Universidad de Huelva

Departamento de Ingeniería Electrónica, de Sistemas Informáticos y Automática

Contribution to road safety through devices and applications based on artificial intelligence

Memoria para optar al grado de doctor presentada por:

José Manuel Lozano Domínguez

Fecha de lectura: 11 de marzo de 2022

Bajo la dirección del doctor:

Tomás de Jesús Mateo Sanguino

Huelva, 2022

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CONTRIBUTION TO ROAD SAFETY THROUGH DEVICES AND APPLICATIONS BASED ON ARTIFICIAL INTELLIGENCE

Ph. D. Thesis

JOSÉ MANUEL LOZANO DOMÍNGUEZ

2021

Supervisor:

Dr. Tomás de Jesús Mateo Sanguino

UNIVERSIDAD DE HUELVA

Programa de Doctorado en Ciencia y Tecnología Industrial y Ambiental

Línea de investigación

Ingeniería eléctrica, electrónica, de control y robótica

CONTRIBUCIÓN A LA SEGURIDAD VIAL MEDIANTE DISPOSITIVOS Y APLICACIONES BASADOS EN INTELIGENCIA ARTIFICIAL

Ph. D. Thesis

JOSÉ MANUEL LOZANO DOMÍNGUEZ

2021

Director:

Dr. Tomás de Jesús Mateo Sanguino

D. Tomás de Jesús Mateo Sanguino, Profesor Titular de Universidad de la Escuela Técnica Superior de Ingeniería de la Universidad de Huelva,

CERTIFICA:

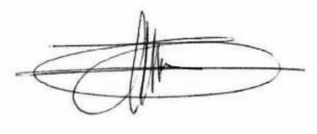
Que D. José Manuel Lozano Domínguez, Graduado en Ingeniería Informática y Máster en Ingeniería Informática por la Universidad de Huelva, ha realizado bajo mi dirección y dentro del Programa de Doctorado en Ciencia y Tecnología Industrial y Ambiental (CyTIA) y en la línea de investigación Ingeniería Eléctrica, Electrónica, de Control y Robótica el trabajo correspondiente a su tesis doctoral titulada:

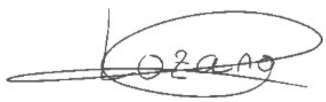
CONTRIBUCIÓN A LA SEGURIDAD VIAL MEDIANTE DISPOSITIVOS Y APLICACIONES BASADOS EN INTELIGENCIA ARTIFICIAL

Revisado el presente trabajo, estimo que puede ser presentado al Tribunal que ha de juzgarlo.

Y para que así conste a efectos de lo establecido en el Real Decreto 99/2011 y por la normativa Reguladora del título de Doctor en la Universidad de Huelva, autorizo la presentación de este trabajo en la Universidad de Huelva.

Huelva a, 30 de Septiembre de 2021





Director: Dr. Tomás de Jesús Mateo Sanguino

Doctorando: José Manuel Lozano Domínguez

CONTRIBUTION TO ROAD SAFETY THROUGH DEVICES AND APPLICATIONS BASED ON ARTIFICIAL INTELLIGENCE

Research memory presented by José Manuel Lozano Domínguez to apply for a PhD. Doctoral degree with International Mention at the University of Huelva.

José Manuel Lozano Domínguez

The present Dissertation has been performed at the Department of Electronic Engineering, Computer Systems and Automatics of the University of Huelva, under the auspices of Dr. Tomás de Jesús Mateo Sanguino, which approves its defense:

Dr. Tomás de Jesús Mateo Sanguino

Huelva, September 30th, 2021

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Chapter 1. General Approach

1.1 Resumen

En los últimos años, las ciudades inteligentes han llegado a ser una realidad mediante el desarrollo de nuevos servicios con el fin de mejorar la vida de los ciudadanos. Entre los sectores más innovadores se encuentran los sistemas de transporte y la seguridad vial. Estos sectores están siendo motores de cambio debido al soporte de las tecnologías de la información y la comunicación (TIC).

La presente tesis doctoral tiene por objetivo contribuir a la mejora inteligente de la seguridad vial, habiendo observado en diferentes estudios que en la actualidad esta es un punto débil en las ciudades. Dichos estudios concluyen que en España se produjeron en torno a 13.475 atropellos durante el año 2018, de los cuales 12.642 ocurrieron en áreas urbanas. De ellos, 237 tuvieron como resultado el fallecimiento del peatón, atribuyéndose 9/10 de los mismos exclusivamente a los conductores. Otros estudios indican que el 40% de los atropellos se producen cuando el peatón cruza la calzada por el lugar adecuado. Por otro lado, el 78% de los accidentes ocurren en condiciones de baja visibilidad de los que el 74% se produce durante la noche y el 4% durante el amanecer y el atardecer. De este modo, los peatones cruzan por pasos habilitados que no siempre se encuentran 100% visibles debido a diferentes factores: (*i*) mantenimiento deficiente de la calzada (e.g., líneas que lo delimitan borrosas por el paso de los vehículos), (*ii*) obstaculización de las señales verticales (e.g., vegetación, vehículos de grandes dimensiones, etc.) o (*iii*) malas condiciones atmosféricas (e.g., lluvia, niebla, oscuridad, etc.). En estas situaciones la distancia a la que se empieza a frenar es determinante en la gravedad del atropello y la prevención del mismo.

Por ello, en esta tesis doctoral se presentan diferentes soluciones hardware y software para ayudar a reducir la siniestralidad vial anteriormente mencionada, así como también se ha presentado una revisión del estado del arte de las comunicaciones inalámbricas utilizadas en el ámbito de los sistemas de transporte y la seguridad vial inteligente. Particularmente, el objetivo de esta revisión es identificar quién, cuando y sobre qué se está investigando, situando el foco en el desarrollo científico e industrial de las comunicaciones de tipo vehículo-a-todos, infraestructura-a-todos y peatón-a-todo. Además de esto, la revisión establece una taxonomía que pretende reducir la ambigüedad de acrónimos alrededor de las comunicaciones entre vehículos, infraestructuras y peatones, así como determinar cuáles son las tendencias y tecnologías futuras que darán lugar a las aplicaciones más útiles.

En cuanto a las soluciones planteadas para mejorar la seguridad vial, en primer lugar, se presenta un sistema de señalización vial inteligente capaz de interactuar con su entorno, discernir entre vehículos y peatones, así como alertar a conductores sobre la presencia de peatones en un paso de cebra. Para ello, se emplea un conjunto de sensores de ultrasonido, variación del campo magnético y detección RADAR junto a técnicas de inteligencia artificial basadas en lógica difusa y fusión sensorial que permiten diferenciar entre objetivos. Dicho sistema destaca además por su capacidad de alimentación autónoma, sus reducidas dimensiones y su instalación en la vía pública sin necesidad de obra civil. Su funcionalidad y viabilidad ha sido probada en un entorno real controlado, obteniendo un alto rendimiento y confiabilidad. Como resultado, dicho sistema se encuentra protegido mediante patente internacional.

La segunda solución propone una mejora del primer sistema desarrollado que permite aumentar la versatilidad al generalizar la detección de vehículos. Su principal ventaja es que no necesita recalibrar las etiquetas utilizadas por la lógica difusa del sistema mediante el uso de técnicas de aprendizaje automático. Con el fin de determinar qué técnica ofrece mejor rendimiento para este problema se utilizaron diferentes enfoques como clasificadores, detectores de anomalías, predicción de series temporales y aprendizaje profundo reforzado. De entre ellos, cabe destacar el uso del agente de aprendizaje profundo reforzado para integrar el uso de redes neuronales recurrentes como parte de su estructura interna. Esta integración es novedosa debido a que, anteriormente, nunca había sido utilizada para la detección de vehículos alrededor de pasos de cebra mediante el uso combinado de sensores. Para ello se generó un conjunto de datos a partir de muestras recogidas en cinco ubicaciones diferentes de España y Portugal bajo condiciones reales de tráfico fluido. La generación de los modelos computacionales obtenidos después del entrenamiento y validación ha ratificado la posibilidad de sustituir la lógica difusa por algunas de las técnicas de aprendizaje automático.

La tercera solución describe una aplicación móvil que permite determinar la intención de cruce de un peatón sobre un paso de cebra y generar rutas seguras en las ciudades. Una de las novedades de la aplicación respecto al estado del arte recae en la capacidad de detectar la intención de cruce de los usuarios en toda la ciudad, y no solo en puntos concretos, ya que esta funcionalidad está integrada en los propios dispositivos de los usuarios y no en la vía. Cabe destacar que esta funcionalidad es robusta frente a condiciones climáticas adversas debido a que usa los sensores internos del dispositivo. La otra funcionalidad de la aplicación permite calcular y trazar rutas seguras por la ciudad haciendo uso de zonas de interés peatonal tales como pasos de cebra, calles restringidas al tráfico y pasarelas elevadas. La inclusión de estos puntos de interés aumenta la seguridad vial de la ruta desde el punto de vista del peatón. Además, la aplicación tiene la capacidad de dictar instrucciones a los usuarios sobre la ruta, así como indicarles cuándo se acercan a puntos que requieren una mayor atención (e.g., pasos de peatones). Como valor añadido, la aplicación incluye también comunicación inalámbrica para transmitir la intención de cruce de un peatón al sistema desarrollado en la primera solución. Los resultados obtenidos han permitido demostrar que los teléfonos móviles pueden ser utilizados como detectores de intención de cruce en torno a pasos de cebra con una alta exactitud y sensibilidad. Así mismo, se ha demostrado que las rutas generadas son más seguras que las ofrecidas por Google Maps.

Estas aportaciones pretenden ayudar a reducir la siniestralidad en la vía pública, mejorando la calidad de vida y facilitando la convivencia de los habitantes. Las soluciones son aportaciones al estado del arte actual sin menoscabo de la necesidad de continuar esta línea de investigación para solucionar las limitaciones actuales y cumplir con el objetivo de la iniciativa «Visión Zero» de la Unión Europea que se resume bajo el concepto de que "no se puede aceptar la pérdida de ninguna vida".

1.2 Summary

In recent years, smart cities have become a reality through the development of new services in order to improve the lives of citizens. Among the most innovative sectors are smart transport systems and road safety. These sectors are being incentive for change due to the support of information and communication technologies (ICT).

The aim of this doctoral thesis is to contribute to the intelligent improvement of road safety, having observed in different studies that this is currently a weak point in cities. These studies concluded that in Spain there were around 13,475 accidents during 2018, of which 12,642 occurred in urban areas. Of these, a total of 237 resulted in the death of a pedestrian, with 9/10 of them being attributed exclusively to drivers. Other studies indicate that 40% of runs over are produced when the pedestrian crosses the roadway at the right place. In addition, 78% of accidents occur in low visibility conditions, where 74% occur at night and 4% at sunrise and sunset. Thus, pedestrians cross the road at authorized crossings that are not always 100% visible due to different factors: (*i*) poor maintenance of the roadway (e.g., lines that delimit it blurred by passing vehicles), (*ii*) obstruction of vertical signals (e.g., vegetation, large vehicles, etc.) or (*iii*) poor weather conditions (e.g., rain, fog,

darkness, etc.). In this regard, it is a fact that the distance at which braking beings is a determining factor in the severity of the collision and its prevention.

For this reason, this doctoral thesis presents different hardware and software solutions to help reduce the aforementioned road accident rate, as well as a review of the state of the art of wireless communications used in the field of intelligent transport systems and smart road safety. In particular, the objective of this review is to identify who, when, and what is being investigated, placing the focus on the scientific and industrial development of vehicle-to-all, infrastructure-to-all and pedestrian-to-all communications. Furthermore, the review establishes a taxonomy that reduces ambiguous acronyms around the communication between vehicles, infrastructure, and pedestrians, as well as determines what the trends and future technologies that will lead to the most useful applications.

Regarding the solutions proposed to improved road safety, an intelligent road marking system capable of interacting with its environment, discerning between vehicles and pedestrians, as well as alerting drivers to the presence of pedestrian at a zebra crossing is presented. For this, a set of ultrasound, magnetic field variation and RADAR sensors are used together with artificial intelligence techniques based on fuzzy logic and sensory fusion allow differentiating between targets. This system also stands out for its autonomous power supply capacity, its small size, and its installation on public roads without need for civil works. Its functionality and viability have been tested in a real controlled environment, obtaining high performance and reliability. As a result, this system is protected by an international patent.

The second solution proposes an improvement of the first system developed that allows increasing versatility by generalizing vehicle detection. Its main advantage is that it does not need to recalibrate the labels used by the fuzzy logic of the system by using machine learning techniques. With the purpose of determining which technique offers the best performance for this problem, different approaches such as classifiers, anomaly detectors, time series forecasting, and deep reinforcement learning were used. Among then, it is worth highlighting the use of the deep reinforcement learning agent to integrate the use of recurrent neural network as part of its internal structure. This integration is novel because, previously, it has never been used for the vehicle detection around zebra crossings through the combined used of sensors. For this, a dataset was generated from samples collected in five different locations in Spain and Portugal under real conditions of fluid traffic. The generation of the computational model obtained after training and validation has validate the possibility of substituting fuzzy logic for some of the machine learning technique.

The third solution describes a mobile application that allows determining the intention of a pedestrian to cross a crosswalk and generating safe routes in cities. One of the novelties of the application with respect to the state of the art lies in the ability to detect the intention to crossing user through the city, not at specific points, since this functionality is integrated into the users' devices and not in the road. It should be noted that this functionality is robust against adverse weather conditions because it uses the internal sensors of the devices. The other functionality of the application allows calculating and tracing safe routes through the city using areas of pedestrian interest such as zebra crossings, streets restricted to traffic and elevated walkways. The inclusion of these points of interest increases the road safety of the route from the pedestrian's point of view. In addition, the application has the ability to dictate instructions to users about the route, as well as indicate when they approach to points that require greater attention (e.g., pedestrian crossings). As an added value, the application also includes wireless communication to transmit the intention of crossing of a pedestrian to the system developed in the first solution. The results obtained have shown that mobile phone can be used as crossing intention detectors around pedestrian crossing with high accuracy and sensitivity. Likewise, it has been shown that the routes generated are safer than those offered by Google Maps.

These contributions are intended to help reduce accidents on public roads, improving the quality of life and facilitating the coexistence of the inhabitants. These solutions are contributions to the current state of the art without detracting from the need to continue this line of research to solve the limitations and comply the objective of the Vision Zero of the European Union, which is summarized under the concept that "no loss of life is acceptable".

1.3 Innovations Provided by the Doctoral Thesis

In this section, the novelties brought by each paper included in the doctoral thesis –in reference to what has been previously published in the state of the art– are highlighted.

In the first place, a set of autonomous intelligent sensor nodes installed on roads without the need for public works is collected. Among the main characteristics of the nodes, it is remarked the ability to discern between vehicles and pedestrians through a sensory fusion process –at both low and high level– based on data obtained by local sensors and shared between them. This process is performed by means of fuzzy logic. In the case of determining the presence of pedestrians on a crosswalk, the system makes use of wireless communications to transmit an activation message to the node's network. Thus, the nodes generate a light barrier oriented towards the drivers, so they can safely stop their vehicles. This innovation has been published as an international patent and in a journal article.

In the second place, an extensive review of the scientific literature is presented. It allows any researcher to identify the main characteristics of the existing wireless communication types and applications in smart cities in which road safety actors are involved (i.e., infrastructures, vehicles, pedestrians and cyclists). In this scientific review, the main technical details, agent involved, use cases and applications have been analyzed. In addition, a thorough bibliometric analysis has been carried out. The analysis allows to locate the milestones achieved in this field from a temporal point of view and –together with the study of the current future trends– lets readers to contextualize and identify the advantages and disadvantages of each technology in this field.

In the third place, an approach based on machine learning (ML) techniques has been proposed to improve the detection of vehicles by the system indicated in the first contribution. The use of ML techniques allows the detection of vehicles in different locations with no need to recalibrate the fuzzy labels used in the previous sensory fusion process. Several ML techniques have been employed to improve the vehicle detection. For this purpose, classification, anomaly detection, time-series forecasting and the use of a DRL agent based on a double-deep recurrent Q-network (DDRQN) is remarkable. More specifically, this agent integrates a long short-term memory (LSTM) neural network layer into its DDRQN. In this way, the developed agent uses current and previous data to recognize in which state it is (i.e., whether there is the presence of a vehicle or not). As far as it is known, this approach has been used for the first time to detect the presence of vehicles in a crosswalk through the combination of sensor data set.

Finally, in fourth place, a mobile application with two innovative features is proposed. The first innovative feature permits to calculate, generate and trace safe routes for pedestrians by adding point of interests (POIs) thanks to an optimizing algorithm. This includes crosswalks, streets restricted to traffic and pedestrian walkways through the city. The second innovative feature is the ability to detect the crossing intention of pedestrians near crosswalks by means of the sensors embedded in a smartphone and fuzzy logic. Furthermore, the application has the capability to wirelessly communicate the detections of users to the system described in the first contribution of the doctoral thesis, thereby allowing the generation of a visual light barrier to alert drivers.

1.4 Achievement of the International Stay

During the development of this doctoral thesis, a three-month predoctoral stay at the University of Algarve (Portugal) in the Faculty of Science and Technology was carried out. This stay was performed under the supervision of Dr. Noélia Susana Costa Correia. In this stay, new techniques and points of view were acquired to carry out the research. Among the main knowledge acquired, machine learning techniques and the ability to transmit ideas in languages other than the PhD's mother language stand out.

As a result of the international stay, a journal article published in Sensors in 2020 (Article no. 3 in Section 1.5.2 of this document) and a paper published in the SSD conference in 2021 (Article no. 6 in Section 1.5.3 of this document) were achieved. In addition, the scientific relationship between the origin and destination research groups were strengthened during the stay. Among them, the participation in joint research projects such as the projects entitled *"Improvement of Road Safety through and Intelligent Service Platform for Pedestrian, Sensors and Environment"* and *"Improving Road Safety Through Photoluminescent Signaling and Fog Computing"* stand out. Both research groups also contributed members to the international scientific committee of ScienCity, a conference held by the University of Huelva since 2018.

1.5 Scientific Contributions of the Doctoral Thesis

This section aims to highlight the scientific context where the doctoral thesis has been developed and the main results obtained. With this intention, the scientific publications indexed in international journals will be detailed, as well as the contributions made to international and national congresses. Finally, the intellectual property document published will be detailed. In addition, with the aim of offering a better vision of the scientific background where the doctoral thesis has been developed, the research projects that have financed the developments are indicated. In brief, the main objective of this section is to show the scientific support and results carried out for three years.

1.5.1 Scientific Projects Funding the Thesis

Project 1. *Reducción de la Siniestralidad en Pasos Peatonales Mediante Dispositivos Sensores de Bajo Coste*

Funding entity: Fundación MAPFRE – Ayudas a la Investigación "Ignacio H. Larramendi"
Reference: BIL/15/P3/047
Participating entities: University of Huelva
Period: 03/02/2016 – 03/02/2017
Principal investigator: T.J. Mateo Sanguino
Number of researchers: 6
Amount: 24,000 €

Project 2. *Industrialization of an Autonomous Road Signaling System for Intelligent Pedestrian Crossings*

Funding entity: Andalusian Government – Aid for knowledge transfer activities among the agents of the Andalusian knowledge system and the Andalusian productive fabric
Reference: 1155452
Participating entities: University of Huelva
Period: 01/06/2019 – 01/06/2020
Principal investigator: T.J. Mateo Sanguino
Number of researchers: 9
Amount: 52,562.50 €

Project 3. *Improvement of Road Safety through an Intelligent Service Platform for Pedestrian, Sensors and Environment*

Funding entity: Junta de Andalucía – Programa Operativo FEDER Andalucía 2014-2020
Reference: UHU-120596
Participating entities: University of Huelva, University of Granada, University of Algarve (Portugal), Polytechnic Institute of Beja (Portugal)
Period: 01/01/2020 – 31/12/2021
Principal investigator: T.J. Mateo Sanguino
Number of researchers: 11
Amount: 33.632,65 €

1.5.2 Publications in International Journals

Below, the works published in scientific journals indexed in Journal Citation Reports (JCR) during the completion of the doctoral thesis are listed. The items are indexed in chronological order.

Article 1. *Design, Modelling, and Implementation of a Fuzzy Controller for an Intelligent Road Signaling System*

Authors: J.M. Lozano Domínguez, T.J. Mateo Sanguino
Journal: Complexity
Reference: Article ID 1849527
Year: 2018
Doi: 10.1155/2018/1849527
Quality index: Journal included in JCR, position 21/105 in the category of "Mathematics, Interdisciplinary Applications", and position 25/69 in the category of "Multidisciplinary Sciences"
IF (2018): 2.591
Number of citations: 11 (Scopus), 14 (ResearchGate) and 13 (Google Scholar)

This paper presents a system based on a set of intelligent nodes capable of interacting with the environment to detect and differentiate between pedestrians and vehicles around a crosswalk. The system also has the ability to generate a sequence of light pulses to alert drivers about the presence of one or several pedestrians. The main feature of the system is the capability to be energetically sustainable by means of solar panels, as well as to have a reduced size.

The paper describes the hardware used to build the system (e.g., low-cost sensors, photovoltaic panels and control units, among other elements), as well as an explanation of the electronic housing. A description of the software used to detect and alert drivers has also been included. This consists in using various fuzzy controllers that work in series and in parallel to determine the presence of pedestrians and vehicles in a crosswalk and to act accordingly.

Finally, a description of the experimentation carried out in real environments has been included, since this test allows to determine the viability of the system and its reliability.

Article 2. *Review on V2X, I2X and P2X Communications and Their Applications: A Comprehensive Analysis over Time*

Authors: J.M. Lozano Domínguez, T.J. Mateo Sanguino
Journal: Sensors
Reference: vol. 19 (12), Article ID 2756
Year: 2019
Doi: 10.3390/s19122756

Quality index: Journal included in JCR, position 77/266 in the category of "Engineering, Electrical & Electronic", position 15/64 in the category of "Instruments & Instrumentation", and position 22/86 in the category of "Chemistry, analytical"
IF (2019): 3.275
Number of citations: 22 (Scopus), 23 (ResearchGate) and 34 (Google Scholar)

This paper presents a study on the state of the art of wireless communication systems and their applications according to the different players found on public roads (i.e., infrastructure, pedestrians and vehicles). The work makes a comparison of the kind of communication used in smart cities depending on the application, actors involved and type of technology. On the one hand, the analytical review allows any technician or researcher to know the current state of the art. On the other hand, it allows to know what type of technology to use in smart cities considering the use case or application to be implemented. From the comparison, the work proposes a taxonomy to reduce the ambiguity of acronyms used in this field.

Furthermore, the paper carries out an exhaustive bibliographic research covering a total of 3422 contributions of which the 100 most cited works among patents and scientific papers published between 1997 and 2018 have been referenced. Finally, the paper foresees future trends and challenges in this field.

Article 3. *Analysis of Machine Learning Techniques Applied to Sensory Detection of Vehicles in Intelligent Crosswalks*

Authors: J.M. Lozano Domínguez, F. Al-Tam, T.J. Mateo Sanguino, N. Correia
Journal: Sensors
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Year: 2020
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Quality index: Journal included in JCR, position 82/273 in the category of "Engineering, Electrical & Electronic", position 15/64 in the category of "Instruments & Instrumentation", and position 26/83 in the category of "Chemistry, analytical"
IF (2020): 3.576
Number of citations: 1 (Scopus), 1 (ResearchGate) and 1 (Google Scholar)

In this paper, the starting point is a drawback observed in the first article of the doctoral thesis when installing the system's nodes at a specific location. This disadvantage requires calibrating the labels of the fuzzy controller in charge of detecting the presence of vehicles due to variations in the Earth's magnetic field. Such variations depend both on the place of installation on public roads and on the presence of ferromagnetic elements.

To solve this issue, a methodology has been followed to validate the feasibility of replacing the fuzzy logic controller by a computational model based on machine learning techniques. As a main benefit, they do not require a calibration process to detect the presence of vehicles around a crosswalk. To this end, the paper proposes different machine learning approaches with the aim of determining which model is the optimal one. The approaches used have been classifiers, anomaly detectors, recurrent neural networks (RNN), time series prediction as well as DRL. In the latter case, DRL is based on a DDRQN that includes an RNN in its interior, thus applying this technique for the first time to detect the presence of vehicles in pedestrian crossings.

The training and validation of the computational models, as well as the feasibility study to replace the fuzzy controller in charge of determining the vehicle presence, was carried out using a dataset generated from measurements of the sensor nodes placed in real environments.

Article 4. *Walking Secure: Safe Routing Planning Algorithm and Pedestrian's Crossing Intention Detector Based on Fuzzy Logic App*

Authors: J.M. Lozano Domínguez, T.J. Mateo Sanguino
Journal: Sensors
Reference: vol. 21 (2), Article ID 519
Year: 2021
Doi: 10.3390/s21020529
Quality index: Journal included in JCR, position 82/273 in the category of "Engineering, Electrical & Electronic", position 15/64 in the category of "Instruments & Instrumentation", and position 26/83 in the category of "Chemistry, analytical"
IF (2020): 3.576
Number of citations: 2 (Scopus), 3 (ResearchGate) and 4 (Google Scholar)

This paper contributes a mobile application that allows detecting the user's intention to cross a crosswalk by means of smartphone's sensors and fuzzy logic. The application is also capable of computing, tracing and guiding users through safe routes in the city thanks to the use of a route optimization algorithm that includes pedestrian areas.

The paper describes the software developed for the application, including its functionalities and architecture. The algorithm designed to optimize safe routes as well as the sensory fusion strategy carried out to detect the pedestrian`s crossing intention is depicted in depth. Moreover, this paper also covers how a pedestrian to infrastructure (P2I) communication was utilized to send an alert message to the system previously described in Article no. 1. In this way, the mobile application allows to automatically alert drivers about the presence of pedestrians intending to cross a crosswalk.

Finally, the experimentation carried out to validate the application has been described. The tests have been divided into two main blocks. The first one is responsible for evaluating the crossing intention detector for which a receiver operating characteristic (ROC) analysis has been used to determine its reliability. The second block aims to compare the routes generated by the application against Google Maps. To this end, a compound performance metric (CPM) was utilized to determine the route quality based on the walking time, travel distance and number of pedestrian safe areas.

1.5.3 Publications in International Conferences

This subsection presents the contributions made in international congresses, which are complementary works to these published in scientific journals. The article no. 5 presents a fault-tolerant mechanism for wireless communications that gives support to the intelligent crosswalk system. The article no. 6 describes a procedure that allows evaluating the possibility of replacing the fuzzy logic strategy to detect vehicles with a machine learning model.

Article 5. *Evaluation of a Robust Fault-Tolerant Mechanism for Resilient IoT Infrastructures*

Authors: J.M. Lozano Domínguez, T.J. Mateo Sanguino, M.J. Redondo González
Event: International Conference on Broadband Communications, Networks and Systems (Broadnets)
Publication: Lecture Notes of the Institute for Computer Sciences, Social Informatics and Telecommunications Engineering (LNICST). Book series vol. 263, pp. 3-12
Date: September 19-20, 2018. Faro (Portugal)

Article 6. *Vehicle Detection System for Smart Crosswalks Using Sensors and Machine Learning Techniques*

Authors: J.M. Lozano Domínguez, F. Al-Tam, T.J. Mateo Sanguino, N. Correia
Event: 18th IEEE International Multi-Conference on Systems, Signals & Devices (SSD)
Publication: Proceedings book, pp. 984-991
Date: March 22-25, 2021. Monastir (Tunisia)

1.5.4 Publications in National Conferences

This subsection includes other minor scientific publications made during the doctoral thesis in the field of smart road safety. Specifically, two contributions in national conferences containing preliminary results for Article no. 7 and Article no. 8 are collected.

Article 7. *Detección de Vehículos en Pasos Peatonales Inteligentes mediante Machine Learning*

Authors: J.M. Lozano Domínguez, F. Al-Tam, N. Correia, T.J. Mateo Sanguino
Event: II Jornadas ScienCity, Fomento de la Cultura Científica, Tecnológica y de Innovación en Ciudades Inteligentes
Publication: Libro de Actas de las II Jornadas ScienCity, pp. 11-14
Date: November 27-29, 2020. Huelva (Spain)

Article 8. *Walking Safe. Aplicación Móvil para el Trazado de Rutas Peatonales en las Ciudades*

Authors: J.M. Lozano Domínguez, T.J. Mateo Sanguino
Event: III Jornadas ScienCity, Fomento de la Cultura Científica, Tecnológica y de Innovación en Ciudades Inteligentes
Publication: Libro de Actas de las III Jornadas ScienCity, pp. 32-36
Date: November 17-19, 2021. Huelva (Spain)

1.5.5 Intellectual Property

This subsection aims to collect the international publication of the patent that protects the system described in the first article of this doctoral thesis. This patent complements the contributions made in journals and conferences by expanding the use of the proposed solution to the exit or entrance of garages as well as to intersections or crossings with reduced visibility, among others.

Patent 1. System and Autonomous Device for Road Signac and Signage and Detection

Authors: T.J. Mateo Sanguino, M.A. Rodríguez Román, J.M. Lozano Domínguez
International reference: WO2018050945 A1
Spanish reference: ES2663655 B1
Current state: Awarded since September 17, 2018

1.6 Justification and Hypothesis

An increasing concern about road safety has been observed recently, which has led to the creation of several platforms –both public and private– focused on reducing the victims due traffic accidents to zero. Some examples are Vision Zero, a multinational road safety project that seeks to achieve a traffic system without deaths or serious injuries in Europe, as well as AXA and «Ponle Freno» foundation that finance social projects to reduce road accidents in Spain. The growing concern about road safety is motivated by the increase or stagnation of traffic accident rates. One of the most worrying cases studied is that of pedestrian accidents, which have increased in recent years due to factors such as the use of mobile phones, poor signaling of crosswalks and other distractions for drivers.

To improve road safety, the research hypothesis that this doctoral thesis wants to demonstrate is whether improving the mutual perception of pedestrians and drivers –connected through an intelligent architecture of nodes– helps to improve the reaction time to minimize accidents and severity of injuries. This has been attempted to achieve through four objectives:

Objective 1. Provide a solution based on a set of smart wireless nodes to create an intelligent road signaling system that helps reduce pedestrian and vehicle accidents related to crosswalks.

Objective 2. Improve vehicle detection on urban roads by applying ML techniques derived from the stay at the University of Algarve.

Objective 3. Identify technical considerations in wireless communications around road safety useful for the different players present in smart cities, allowing to know the main relationships between the players, their strengths and weaknesses.

Objective 4. Develop a mobile application that detects the crossing intention of a pedestrian at crosswalks and that can generate safe routes for them, especially for vulnerable people. This application will be part of a distributed architecture that will allow its integration into the solution described in the first objective to create a new form of intelligent road signaling. This distributed architecture contributes to create a new relationship between pedestrian and road infrastructure using wireless communications.

1.7 Methodology

To achieve the goals defined in the previous section, a research methodology has been followed in this doctoral thesis. This can be briefly resumed in a generic procedure according to the following points:

1) Study of the state of the art.
2) Definition of requirements for the solution.
3) Development of new solutions through an incremental implementation until reaching the final solution.
4) Data collection and analysis of results through objective procedures.
5) Generate conclusions from the results obtained.

This methodology has been applied to the research done in this doctoral thesis as follows, resulting later in the scientific publications presented in Chapter 4:

Objective 1. The procedure consisted in reviewing the state of the art to know the pros and cons of other road safety solutions. Then, the requirements of the proposed road signaling system were defined. After the system was developed, its performance was tested in a real environment and validated using quantitative techniques. Finally, a general conclusion about the system was obtained for which the limitations and possible improvements were identified.

Objective 2. In the first place, a review of the state of the art was carried out to learn the different approaches based on ML techniques used to detect vehicles on public roads. In the second place, different ML techniques addressing the specific problem to be solved were established. In the third place, the dataset used to train and test the ML models was collected in real urban scenarios. In the fourth place, the various ML models were implemented and validated using the cross-validation technique. Finally, the results obtained with the different models were analyzed to provide the general conclusions and limitations of these techniques.

Objective 3. This goal followed a different methodology than the others presented in this section. First, an exhaustive review of the current state of the wireless communication technologies available in smart cities was completed. This study was especially focused on communications between the different actors participating in road safety, highlighting their main characteristics. Second, a technical and taxonomic analysis of the acronyms used to refer to each technology and applications was conducted. Third, a comprehensive bibliometric analysis was carried out to establish a comparison between different emerging technologies over time. Finally, the conclusions were obtained and the main trends in communications for road safety were provided.

Objective 4. Similar to the first and second goal, the first task performed was a study of the state of the art to find out the advantages and disadvantages of other solutions available to detect the crossing intention of pedestrians. This study also included other solutions available to generate safe routes for pedestrians. Then, the requirements of a mobile application to guide pedestrians safely through the city and detect their crossing intention were established. Subsequently, the application was iteratively developed until reaching its end point. Then, the crossing intention detector was tested in a real controlled environment to determine its reliability and performance. Later, the improvement in terms of road safety was compared against other application by means of a proposed metric. Complementary, this app was also designed to be connected with the infrastructure resulting from objective 1 and interact with it when the crossing intention of a user is detected around a crosswalk. At the same time, this solution aims to contribute also to one of the fields studied in the state of the art reviewed in objective 3 (i.e., pedestrian to infrastructure communications). Finally, the general conclusions of the mobile app were obtained along with its limitations and future improvements.

1.8 Structure

The doctoral thesis has been organized into five chapters according to the following order:

Chapter 1, *General Approach*, aims to place the reader in this doctoral thesis. It offers an overview of the doctoral thesis, describes the innovations provided and the scientific contributions made, shows the objectives and the methodology followed, as well as the structure of the doctoral thesis itself is presented.

Chapter 2, *State of the Art*, makes a description of the problem of pedestrian accidents around crosswalks. This chapter takes a tour of both different solutions proposed in the literature to increase road safety and different techniques applied for the detection of targets around pedestrian crossings.

Chapter 3, *Research Resources*, the different sensors, tools and techniques used for the development of the contributions made in the different works that composed this doctoral thesis are detailed.

Chapter 4, *Results & Discussion*, includes the set of scientific contributions that support this doctoral thesis. Specifically, this chapter compiles four contributions in high-impact indexed journals.

Chapter 5, *General Conclusions,* shows the most relevant conclusions obtained in the doctoral thesis as well as the different research lines currently open that can be carried out in future works.

Chapter 2. State of the Art

2.1 Introduction

In this chapter the reader is placed in the research field of the present doctoral thesis. In the first place, several statistics about the current situation of pedestrian accidents in Spain and how this phenomenon is similar in other territories are showed. Next, a tour of the different solutions proposed in the state of the art used to detect the presence of pedestrians at crosswalks is made. Later, other approaches to detect the presence of vehicles around pedestrian crossings based on ML are presented. Subsequently, a review of the current state of the communications used between the different actors involved in Intelligent Transport Systems (ITS) is exposed. Finally, the current state of mobile applications used to improve road safety in smart cities is revised.

2.2 Statistics on Pedestrian Accidents

Around 13,475 accidents of pedestrians occur every year in Spain according to a report published by the National Road Safety Observatory of Spain. Among them, 12,642 (94%) happened in urban areas, 237 resulted in death and 9/10 were attributed to drivers [1]. Other studies also estimate 40% of the accidents when pedestrians are crossing through the right place [2]. These data have been confirmed by a recent study carried out by DGT (acronym for General Administration of Traffic of Spain). This study describes that during 2018, 40.48% of the accidents were pedestrians crossing the street in the right place [3]. According to a barometer from CIS (Spanish acronym for Sociological Investigation Center), the main causes of accidents are mistakes and distractions of drivers (8.25%), lack of civic education (7.87%), poor road conditions (6.80%) and deficient signaling of tracks (6.58%), among others [4]. A similar study published in United States of America (USA) estimated in 70,000 the number of traffic accidents in 2015 with pedestrians and vehicles concerned. Of them, 5,376 resulted in deceased people, which has significantly increased in the last decade up to 15% according to the National Highway Traffic Safety Administration (NHTSA) [5]. These values are significant because the number of accidents remains constant over time since in 2017 there were 71,000 runs over, of which 8.42% caused the death of the pedestrian [6]. NHTSA has determined that 78% of the accidents occur in low visibility conditions, resulting 74% at nighttime and 4% during sunrise or sunset [5]. This concentration of accidents is not only maintained over the years, but an increasing trend is observed over time as evidenced by the Fatality and Injury Reporting System Tool (FIRST) [7].

2.3 Hardware Systems Proposed to Detect Pedestrians on Crosswalks

Pedestrian crossings are not always 100% visible due to different factors: (*i*) poor road maintenance (e.g., blurring lines due to the vehicle passing), (*ii*) occlusion of vertical signs (e.g., vegetation, large vehicles, etc.), and (*iii*) adverse weather conditions (e.g., rain, fog or obscurity), among others. The distance at which drivers begin to brake the vehicle is decisive in the severity of the accident and the prevention of it. Hence, improving drivers' perception of pedestrians is a key goal in reducing accidents or injury severity at zebra crossings. [8] - [9].

There are different solutions in the state of the art with the common aim of decreasing the number of accidents in crosswalks. They are classified into devices on board vehicles to detect pedestrians and approaches located on the road to detect both pedestrians and vehicles.

Regarding the first group, techniques and devices being included in vehicles aim to actively detect pedestrians to alert drivers. Such is the case of a prototype based on RADAR, camera and sensory fusion devised to warn of possible collisions [10]. This system is similar to that of cameras, sensors on windshields, and bumpers that other proposals such as Ford Mondeo, Mercedes S Class or Nissan from Universidad Carlos III of Madrid (UC3M) implement on cars [11] - [12]. However, these systems require the collaboration of the automotive industry to standardize and implement electronics on board. Moreover, these approaches represent personal devices not available to all users. That is, the system belongs to the car's owner and it is not permanently available on public roads to all users.

In relation to the second group, there are very different concepts regarding the type of installation, size and price. For instance, a road sign formed by a luminous marquee over a pedestrian crossing that incorporates spotlights oriented towards the pavement to improve the driver's visualization on pedestrians [13]; a trapezoidal speed bump placed on the road composed of passive lighting such as small light bulbs, light emitting diodes (LEDs) or optical fiber [14]; a section elevated above the track level like a trapezoidal highlight, where the road sign is made of electroluminous diodes activated by the pedestrian presence in zones of pressure placed at the sidewalk [15]; the control of traffic lights by means of the activation –by weight– of a tile placed on the sidewalk [16]; a horizontal road signaling system for crosswalks consisting of long-range and short-range optical sensors on a vertical support to detect pedestrians and vehicles [17]; a system with photoelectric emitters/receivers placed on the sidewalk to detect pedestrians that activates luminous devices located both in the periphery of the crosswalk and vertically on the sidewalk [18]; a proposal of super-safe smart crosswalk that detects persons at the entrance and exit of the zebra crossing and projects a virtual light barrier to warn drivers [19]; an embedded system on the sidewalk that carries a camera in charge of taking images of the crosswalk to visually warn drivers when people is traversing [20]; a Japanese system implemented by Philips that warns pedestrians about the proximity of electrical silent vehicles near crosswalks [21]; a device that protects zebra crossings through warning lights placed on the sidewalk, which contains presence sensors for pedestrians and vehicles [22]; and a crosswalk alert system based on a mast over the sidewalk that includes intermittent lights, solar cells and wireless communication to synchronize the signaling with the opposite mast and where the trigger is a mechanical switch operated by pedestrians [23].

As a summary, a comparative table of the different solutions described in the state of the art with respect to the first proposed solution can be found in article 1 of this doctoral thesis called “Design, Modelling, and Implementation of a Fuzzy Controller for an Intelligent Road Signaling System”.

2.4 Machine Learning Techniques Used to Detect Vehicles on Crosswalks

The improvement of road safety in smart cities concerns not only the detection of the pedestrian presence on public roads, but also vehicles as an important issue. The detection of pedestrians and vehicles around crosswalks are included among the possible smart technological solutions that allow increasing road safety in means of transport in cities [24]. In this sense, there are several artificial intelligence (AI) and ML-based solutions in the literature for ITS that serve different purposes. For example, a detection system based on bioinspired algorithms, autonomic computing and IBM’s MAPE-K is proposed to control vehicle queues at traffic lights [25]. This makes it possible to reduce pollution, accidents and economic losses that are generated when vehicles are stopped for too long at the traffic light. In other applications, as in [26] - [28], historical data is used to detect accidents and generate alternative routes by combining radio frequency identification (RFID), 5G communication and cloud services. These works use logistic regression (LR), multi-layer perceptron (MLP) neural networks, particle swarm optimization, adaptative boosting and decision trees to release cognitive services over Microsoft Azure. Vehicle telemetry was also used to classify and detect abnormal situations on roads (e.g., traffic jams) using a support vector machine (SVM) [29]. This method offers advantages over clustering methods because the data is not normally distributed. As a disadvantage, this method requires a feature selection preprocess to properly define the different types of situations.

Another contribution of AI to turn urban environments into smart cities has been the monitoring of vehicles on public roads. Video surveillance systems have been widely used with this purpose mainly because they are flexible and versatile, allowing the identification of vehicle movements and trajectories [30]. Many papers describe solutions based on vision techniques and the AdaBoost learning algorithm due to the ability to detect and track vehicles in highly changing environments [31] - [33]. In [34], outdoor security cameras were integrated with the Mobilenet V1 single-shot detector (SSD) and a neural network classifier to detect and track vehicles, whilst a method based on random forest (RF) was proposed in [35] to detect vehicles under non-optimal lighting conditions. With the same intention, a system that subtracts the background from images and then detects vehicles using neural networks is described in [36]. Contrarily to the solutions based on cameras, the system proposed in [37] uses a 3D Laser Imaging Detection and Ranging (3D-LIDAR) sensor and a Deep Convolutional Neural Network (ConvNet) to detect vehicles in low light conditions. Nevertheless, both vision-based and LIDAR sensor-based systems still have difficulties in detecting vehicles under adverse weather conditions (e.g., rain, fog or snow). To improve detection, sensors can be also used on the pavement to classify vehicles according to the vibration produced when they are moving [38]. The pattern in the time–frequency domain generated by the sound of the vehicles when circulating is used as source of information to detect targets [39].

AI techniques –and ML in particular– also enable the development of smart road safety (SRS) solutions for smart cities. In [40], for instance, a rear collision detection system for drivers was modelled using the vehicle's acceleration and distance from the preceding car for which both RF and neural networks were used. For the detection of vehicles moving in the wrong direction along highways, a camera-based system classifying the direction of the vehicle was proposed in [41]. As a main benefit, this solution allows traffic authority to be notified and act against such dangerous situations.

Other solutions focus on preventing damage to cyclists. In [42], for example, the telemetry of a motorcycle was used to detect the road roughness and determine the probability of an accident due to the state of the pavement. A method to detect the risk of accident and activate airbags has been developed in [43] using accelerometer signals from a vehicle.

The detection of pedestrians and animals on the road to improve road safety has also been studied. This is the case of systems designed to detect the intention to cross the road and alert drivers through cameras [44] - [46] and LIDAR technologies

[47] applying dense, recurrent or ConvNet [48]. Other work focuses on the detection of pedestrians on zebra crossings using cameras and different classification schemes such as Haarcascade, histogram of oriented gradients (HOG), SSD and you-only-look-once (YOLO) [49]. The detection of animals stopped or in transit on the road was also studied in [50] to avoid accidents. For this goal, vision techniques, k-nearest neighbors (KNN) and RF were used.

To summarize, a comparative table of the different solutions proposed in this state of the art with respect to the second solution proposed can be found in article 3 of this doctoral thesis entitled "Analysis of Machine Learning Techniques Applied to Sensory Detection of Vehicles in Intelligent Crosswalks".

2.5 Wireless Communications Applied to Smart Road Safety

In the ecosystem of smart cities, there are several regulations for the use of wireless communications related to the different actors of road safety (i.e., vehicles, pedestrians, cyclists and infrastructures). The first regulation regarding vehicular communications began in Japan in 1994, which reserved frequencies in the 760 MHz and 5.8 GHz spectrum for ITS [51]. Later in 1998, the Department of Transportation (DOT) and the Federal Communications Commission (FCC) of United States (US) regulated the use of a 75 MHz band in the 5.9 GHz spectrum for unlicensed access to these technologies [52]. Similarly, the European Union (EU) and the European Telecommunications Standards Institute (ETSI) allocated in 2008 a 30 MHz band for safety-related applications of ITS in the same spectrum region [53]. This activity was also followed by other countries in the Asia Pacific region such as Korea, Singapore, China and Australia, which defined their spectrum allocations between 2016 and 2017 [54].

Meanwhile, the Institute of Electrical and Electronics Engineers (IEEE) formed in 2004 a task force to work in an IEEE 802.11-based draft for wireless access in vehicular environments (WAVE), that resulted in the IEEE 802.11p amendment by 2010. This protocol has been subsequently integrated into the IEEE 1609 and SAE J2735 standards to offer a complete standardized protocol stack, which was considered by DOT for dedicated short-range communications (DSRC) in vehicle-based applications (e.g., toll collection, emergency vehicles, road works, braking warnings, etc.). According to the previous scenario, the greatest effort for the development of wireless communications in ITS has been the regulation of the radioelectric spectrum and the standardization of the technology by the different regulatory bodies. Despite this, nowadays there are still some limitations such as the locations of the radio bands, which are different for each country and not interoperable across territories [55].

In the current state of the art, there is a set of works that offer a broad vision of the relationship that wireless communications have between vehicles and other actors such as infrastructures and pedestrians [56]. The most analyzed aspects in vehicular communications come from studies related to the propagation of wireless signals in the 5 GHz band. These include vehicle to vehicle (V2V) and vehicle to infrastructure (V2I) communications. Some of the most studied factors are the vehicle density, relative speed between vehicles and average speed of vehicles [57] - [59]. In addition to these, the distance between transmitter and receiver, and the line-of-sight (LOS) occluded by stationary and moving vehicles have been other issues of interest [60] - [64]. Another field of study extensively analyzed by researchers has been the IEEE 802.11p standard. The literature includes many proposals of improvement since this standard is the most used in vehicular communications. The enhancements are mainly focused on the media access control (MAC) layer due to the high mobility of the network targets, which can cause failures in the estimation of communication channels and a decrease in network reliability [65] - [66]. This layer of the network is responsible for guaranteeing fast, reliable and collision-free access to the medium in vehicular ad-hoc network (VANET) applications, as mentioned in [67] - [69].

Although IEEE 802.11p is the most widespread standard used in vehicular communications, it is not the only field of research and development (R&D). Cellular networks are also relevant for vehicular communications because they may offer better performance in some cases than the 802.11p-based networks [70] - [71]. Other viewpoints considered by some authors argue that the access technologies should be selected based on the vehicle speed [72]. This approach proposes Long Term Evolution (LTE) for V2I communication and IEEE 802.11p for V2V communication [73] - [74]. In addition to these approaches, other authors propose the use of Name Data Network (NDN), where the main advantage is the fast exchange of information between vehicles (i.e., V2V) or vehicles and infrastructure (i.e., V2I). As the main drawback, NDN requires an adequate density of vehicles and low distance between the participants [75] - [76]. Apart from that, other authors claim a network model based on the Software-defined Networking (SDN) and fog computing paradigms due to the higher flexibility, scalability, location capability and fewer delays than the current network models [77] - [78].

Road safety is one of the main goals of vehicular communications since it allows saving lives and preventing injuries to vehicle occupants. With this purpose, road safety admits researching on concerns related to the safe access to highways, secondary roads or areas with reduced visibility, as well as researching on traffic congestion management. Several noteworthy examples in the literature describe a protocol based on emergency warning messages (EWM). This approach has a low delay constraint to ensure the reception of messages on time, which has been utilized to avoid collision accidents on highways [79]. Another use of vehicle networks is traffic jam prevention, for which cooperation techniques between vehicles [80] - [81] or traffic jam detection algorithms are introduced [82] - [83]. However, other authors have focused their work on avoiding collisions in urban intersections using V2V communications, fuzzy control mechanisms [84] - [85] or methods based on formal analysis [86].

There are also different proposals with the aim of increasing the passenger safety. One of them is an RFID-based application whose signal is recognized to adapt the vehicle speed to the road [87]. Another solution is a distributed cruise control that adapts the car speed in function of the road status [88]. In this sense, a speed control system that improves the road flow considering data from accelerations and decelerations of nearby vehicles was shown in [89].

The industry in general –and especially the automation industry– is currently developing systems to increase road safety on public roads based on vehicular communications. An example is Honda, which has patented a system that exchanges information between vehicles and pedestrians (e.g., location, speed, etc.) to alert and avoid accidents in road intersections [90]. Hitachi has also implemented a system that helps pedestrians to cross the road using in-vehicle displays that report future vehicle actions (e.g., give way and go) [91]. In this line, Samsung has developed a system that offer vehicle data to all the actors in critical areas of the road such as crosswalks [92]. Another approach used is an I2V communication system to detect pedestrians at zebra crossings and alert both nearby vehicles wirelessly and their drivers by acoustic and/or light signals [93]. Other systems use pedestrians as a transmitter of wireless communications (i.e., pedestrian to all). This is the case of a solution that uses a signaling device that alerts drivers about pedestrians or cyclists on the road through a luminous totem wirelessly activated by smartphones and personal devices [94]. In a similar way, a procedure to avoid accidents between pedestrians and vehicles based on the historical position –to determine the future location– and user context (e.g., age, response capability, etc.) is used to alert about potential collisions by means of visual and/or acoustic signals [95]. A comparative table of the different solutions collected in the current state of the art is presented in article 2 of this doctoral thesis entitled “Review on V2X, I2X, and P2X Communications and Their Applications: A Comprehensive Analysis over Time”.

In summary, most of the examples mentioned above use V2V or V2I communication, as well as other combinations of these means. Currently, pedestrian to vehicle communications (P2V) is an emerging technology with great potential to be developed to increase road safety and improve the efficiency of traffic flow.

2.6 Solutions Intended to Detect the Pedestrian's Crossing Intention

In addition to road safety solutions based on sensors located on public roads, there is another approach in the current state of the art based on the use of mobile applications. An example is the use of mobile devices to send information between vehicles and alert drivers on traffic jam situations in cities. For example, there is a solution that indicates the presence of road incidents using an algorithm that makes decisions based on a list of events. Nevertheless, this method does not make use of contextual information, which could facilitate the calculation and detection of incidents [96]. A similar proposal that covers the previous drawback is the one presented in [97]. It uses Google Maps and Google Directions to determine the best routes; it also uses contextual and historical information to estimate the probability of a route to has incidents. Another example is the application developed to determine the risk of a driver, cyclist or pedestrian having an accident [98]. To this end, the app uses sensory fusion combined with a history of data and information entered by the users (e.g., age, weight and quantity of alcoholic beverages consumed).

The use of an app on mobile devices also includes route customization within cities according to the specific needs of users (e.g., avoiding slopes up or down, reducing the distance traveled, etc.). This helps prevent user exposure to certain health risks. Besides, this allows generating routes that require travelling a shorter distance than those offered by Google Maps thanks to the use of Open Street Maps (OSM) and the A* algorithm [99]. In addition to the previous application, there is another proposal called *UniBS4All* based on Google Directions, which allows generating routes adapted to the needs of people with physical disabilities. To do this, the points of the routes are modified to avoid architectural barriers stored in a database. Nevertheless, it does not remove all barriers to visually impaired people [100]. Another approach developed for people with visual difficulties is found in [101]. This app uses a Dijkstra algorithm to calculate the best possible route based on people's preferences and limitations, as well as considering the traffic congestion and obstacles on the route. The main limitation of this application resides in its algorithm, since Dijkstra consumes a lot of resources to calculate a route. Route optimization has also been focused from a personal point of view, allowing routes to be customized based on user preferences. The eligible preferences are the number of green areas, number of social places, street noise and total length of the journey. Later, routes are calculated thanks to an algorithm based on weights and OSM [102]. This application does not consider the hours of the day when the query occurs, which could modify the routes to avoid dark places at night or very crowded places during the day.

Other studies focus on road safety around crosswalks, especially on pedestrian detection. An approach in line with this doctoral thesis is the detection of the person's crossing intention using a camera-based system and ML algorithms that monitor zebra crossings [49]. This study shows that the YOLO scheme offers higher performance than the traditional HOG and Haarcascade schemes. Despite this, when pedestrians are partially hidden, there is a drop in performance. With the same approach, several systems capable of detecting pedestrians while crossing a crosswalk have been proposed [44] - [46]. They combine cameras and ML techniques such as region-based convolutional neural networks (CNN), SVM or MLP neural networks. These studies show that ML based on SVM and the use of cameras are adequate to detect the presence of pedestrians in zebra crossings. Another solution also supported by cameras consists in analyzing the body movements and orientation of the person's head to determine whether a pedestrian intends to cross the public road or not [45]. The best performance was obtained by a combination of CNN and SVM. This suggests that the contextual information is very useful to determine the pedestrian's crossing intention. In this sense, LSTM neural networks using images and characteristics (i.e., gender, walking direction and group behavior) has been proposed to estimate the crossing intention with great accuracy. Nonetheless, this results in a slightly high false positive rate (FPR) when trying to classify the type of pedestrian movement [103].

Another approach is a crossing intention detector based on the use of cameras onboard vehicles, which can determine –besides the intention to cross– whether a pedestrian is crossing or standing, as well as if he/she is turning or beginning to cross. This is achieved thanks to the use of RF and SVM, resulting in faster detection than traditional methods [104]. Another study used laser imaging LIDAR sensors along with dense neural networks (DNNs), CNN or RNNs to detect the pedestrian's crossing intention [48]. The best model is DNN, which offers a significant improvement over SVM. Another solution is based on the joint use of cameras and laser sensors. For this, the implemented techniques are LSTM with an attention mechanism (AT-LSTM) and SVM, corresponding the best results to AT-LSTM even in small intervals of time [105].

Chapter 3. Research Resources

3.1 Introduction

This chapter presents the material resources used during the development of the research carried out in the doctoral thesis. These have been grouped according to their nature (i.e., software and hardware elements). Likewise, the software used has been divided into two categories: (*i*) AI techniques applied to the road signaling system; and (*ii*) software used to develop a mobile application. To this end, the chapter begins exposing the hardware used during the development of the road safety system. Next, the AI techniques are described. Finally, the software elements used to create the mobile application are detailed.

3.2 Hardware Elements

During the doctoral thesis, an interactive road signaling system has been designed, implemented and validated. The system consists of a set of autonomous wireless nodes longitudinally located at the limits of a crosswalk –until covering the total width of the road– and spaced several centimeters from each other. In that way, each one controls a road sector to discern between pedestrians and vehicles (Fig. 1). Each node has several sensors to determine the presence of pedestrians inside the zebra crossing and a signaling unit looking towards the approaching vehicles. If a pedestrian is detected, the nodes are synchronized with each other by means of a network communication and emit an intermittent visual signal to create the sensation of a virtual barrier on the asphalt. This is perceived by drivers as a warning light signal.

In sum, each node of the system comprises a control unit, detection unit, signaling unit and power supply unit, among other elements. The elements of each of these units have been selected according to the criteria of reduced dimensions, low consumption and lower price. In the following subsections, the different characteristics of the components of the system and their usefulness are exposed.

3.2.1 Control Unit

The control device selected to develop the signaling nodes is based on a 32-bit reduced instruction set computing (RISC) microcontroller (80MHz, 1MB RAM). The control unit selected is the ESP8266-12 model from Espressif. Its function is to manage the electronics within the same node, process both the internal and external data, and provide intelligence to the overall system. Each microcontroller integrates a wireless module compliant with the IEEE 802.11 b/g/n/d/e/i/k/r standard [106]

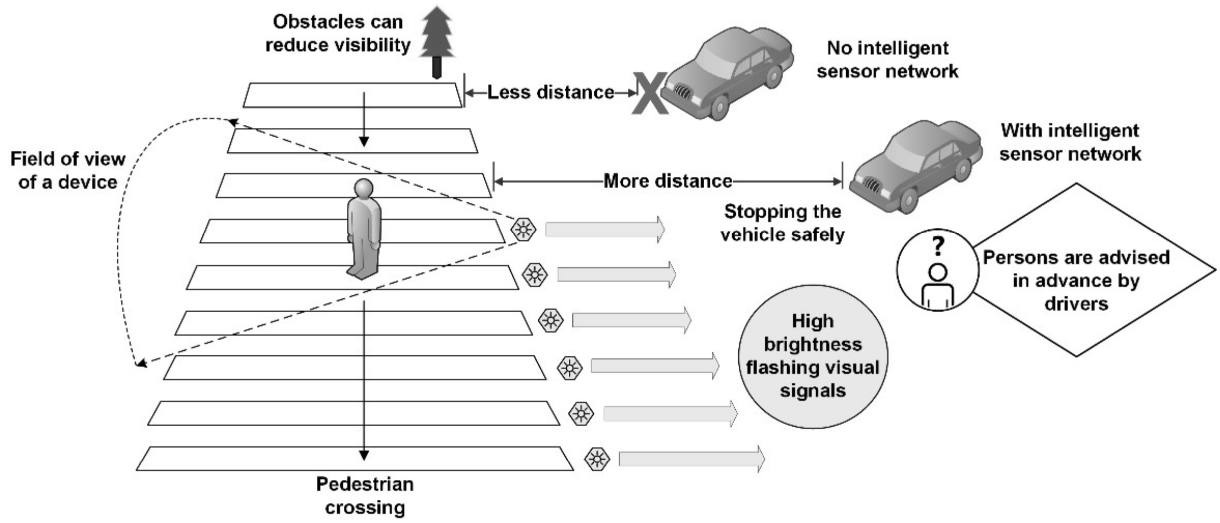


Figure 1. General depiction of the smart road signaling system

that connects them through a wireless local area network (WLAN). Its function is to synchronize the data through the overall system and thereby the visual signage.

The microcontroller selected has a 32-bit core, which is the L106 model from Tensilica. Its central processing unit (CPU) works at a frequency of 80 MHz although it can reach up to 160 MHz. The microcontroller has a RAM memory of 94 KB for data and 64 KB for instructions, and a FLASH memory of 1 MB. It includes several communications interfaces such as Inter-Integrated Circuit (I^2C), Serial Peripheral Interface (SPI), Universal Asynchronous Receiver-Transmitter (UART), Pulse-With Modulation (PWM), Analog-to-Digital Converter (ADC) and several General-Purpose Input/Output (GPIO). The microcontroller works at 3.3V and has different energy schemes to save energy, which are active mode, modem-sleep mode, light-sleep mode and deep-sleep mode. A summary of the main features of this microcontroller can be found in Table 1.

3.2.2 Detection Unit

The developed devices utilize proximity sensors that provide values proportional to distance unlike presence sensors used in other road signaling approaches that deliver binary data of type “all/nothing”. This feature allowed to perform analysis on object proximity over time, which offers a major operation capability in contrast to conventional presence sensors that only determine whether an obstacle exists or not. As a main benefit, this lets us to locate the detection sensors on the road along the crosswalk (i.e., the sensors are not located in the sidewalks as for the most approaches available in the state of the art).

Table 1. Main characteristics of the control unit

Property	Characteristic
Model	ESP8266-12 from Espressif
Core	32 bits Tensilica L106 (80 MHz, RISC)
ROM memory (boot)	64 KB
RAM memory (data /instructions)	94 KB / 64 KB
FLASH memory	1 MB
Communication interfaces	GPIO, I^2C, SPI, ADC, PWM, UART
WiFi communication	IEEE 802.11 b/g/n/e/i/k/r
Operating voltage	3.3 V
Input voltage	3.3 V
Number of GPIO	16
Maximum current output	12 mA
WiFi communication consumption	Transmission with 802.11n (135mA) Reception with 802.11n (62 mA) Modem-sleep (15 mA)

To this end, three sensors based on ultrasound, magnetic field variation and RADAR were used to sense different objects around the crosswalks. Each of the sensors is oriented towards the type of target to be detected (i.e., ultrasound to pedestrians, magnetic and RADAR to vehicles). It is thereby possible to detect a pedestrian when entering the crosswalk from a sidewalk entry point or any intermediate position on the road (e.g., when walking diagonally). In addition, it is possible to determine if there are vehicles circulating at the crosswalk. As a result, when a detection unit senses a pedestrian approaching, the control unit activates the warning signaling. On the contrary, when a detection unit identifies a vehicle, the system disables the luminous barrier to avoid false positives.

The ultrasound sensor used is the SRF485WPR model from Robot Electronics. This sensor works at 42KHz and can detect pedestrians at a distance between 0.6 and 5 meters. As a main advantage, it can operate outdoors as it is waterproof. The LIS3MDL model from STMicroelectronics is the magnetic sensor selected for this solution. This sensor provides detection in the x-, y-, and z-axes with a sensibility up to ±16 Gauss, being capable of detecting vehicles circulating at 50Km/h with a resolution in the order of centimeters. Additionally, the RADAR improves the sense of other vehicles that come frontally to the crosswalk from a distance between 10 and 20 meters (e.g., bicycles composed of materials as aluminum or carbon not detected by the magnetic sensor). To this end, we utilized a Doppler-based RADAR working in the X-band in continuous wave (CW) acquisition mode with effective isotropic radiated power (EIRP) of 15 dBm. The

HB100 model from AgilSense is the sensor used for this implementation. As a summary, the main characteristics of the sensors used is available in Table 2.

3.2.3 Signaling Unit

The system's nodes include a set of high brightness LEDs which are visible under both low contrast and high contrast conditions (i.e., during day and night). An array of four LEDs per node is oriented to drivers to alert of the pedestrian detection while another one is oppositely directed towards pedestrians as a telltale light to indicate the system activity. The selected LEDs produce white cold light (7000 ºK) up to 140,000 mCd (4.82 lm) and can be seen from an angle of vision of 12º ± 6º. The nodes also include a LED oriented towards pedestrians. This permits to them perceive that the system has detected their presence. This LED produces amber light up to 15,000 mCd (1.43 lm) and can be seen from an angle of vision of 20º ± 10º. The main characteristics of the signaling units have been collected in Table 3.

The road signaling presents an intermittent pattern (i.e., activation of 75ms during 5s) managed by the control unit through a low consumption strategy based PWM control. The frequency has been experimentally selected so that the refreshment of the LED light is not perceived by the human eye while it reduces the system consumption.

Table 2. Main characteristics of the detection unit

	Sensor		
Characteristic	SRF485WPR	LIS3MDL	HB100
Based on	Ultrasound	Magnetic field variation	Doppler effect
Range	60 – 500 cm	± 16 Gauss	0 – 20 KHz / 2.5 - 5 V
Operating voltage (V)	12	3.3	5
Current consumption (mA)	10	0.270	50
Dimensions (mm)	40.5 x 40.5 x 30.5	2 x 2x 1	46.5 x 40.0 x 8.90
Operating temperature (ºC)	-30 to +50	-40 to +85	-15 to 55
Ouput	RS485 over UART	I^2C / SPI	Frequency and voltage

Table 3. Main characteristics of the signaling unit

	LED oriented to	
Characteristic	Drivers	Pedestrians
Color	Cool withe	Amber
Brightness intensity (mCd)	140,000	15,000
Brightness intensity (lm)	4.82	1.43
Operating voltage (V)	3.4 – 3.8	1.9 – 2.3
Current consumption (mA)	20	20
Scattering angle (º)	12 ± 6	20 ± 10

3.2.4 Power Unit

The power unit is based on a set of solar cells connected to the energy storage module, which comprises a rechargeable battery that provides autonomy to the node through a charger. This unit is one of the most important because it allows the node to be autonomous without the need for external power sources. In this way, the Sun is used as an energy source that is stored in the battery in cases where the solar panel cannot power the system (e.g., nights or intensely cloud days).

The power unit consists of a matrix of 12 solar cells of monocrystalline Silicon of $92 \times 54 \times 3$ mm^3 with maximum power of 15W, a rechargeable lithium polymer battery (Li-Po) of 9000mAh (3.7V, 1C) with autonomy up to 29.89 hours, and a smart charger with power path management (PPM). The BQ25892EVM-664 model of Texas Instruments is the charger selected for this research. The set of solar cells, battery and charger allows supporting 25.52 Wh/day –or energy consumed in a day by the system– without getting any additional energy. To size the power supply unit, we used the latitude of Huelva (37.2583N, -6.9508W) during December as the period of minor daily solar insolation (2.12kWh/m^2/d) –or energy produced by the Sun in one m^2 per day– and a solar cell performance of 75% as reference. In this way, the battery charging time can be estimated in 2 hours and 12 minutes. See Table 4 for further details.

To increase the autonomy of the system's nodes, a strategy to reduce the power consumption depending on the hour of the day was implemented. For it, a study carried out by means of Google™ Maps allowed us to know the time of the major pedestrians' attendance taking several regions of interest (ROI) of the city as reference (e.g., shopping centers and historic city center). It was determined that the hours with major agglomeration of people were mainly distributed in the time slots between 12-14 hours and 18-20 hours. Accordingly, in Figure 2, "Activated" (blue label) indicates the estimated percentage of the hourly section in which crosswalks

Table 4. Average daily insolation in Huelva per month

Month	Insolation (kWh/m^2/day)
January	2.15
February	3.20
March	4.53
April	5.52
May	6.82
June	7.25
July	8.13
August	7.27
September	6.00
October	4.10
November	2.60
December	2.12
Average of year	**4.98**

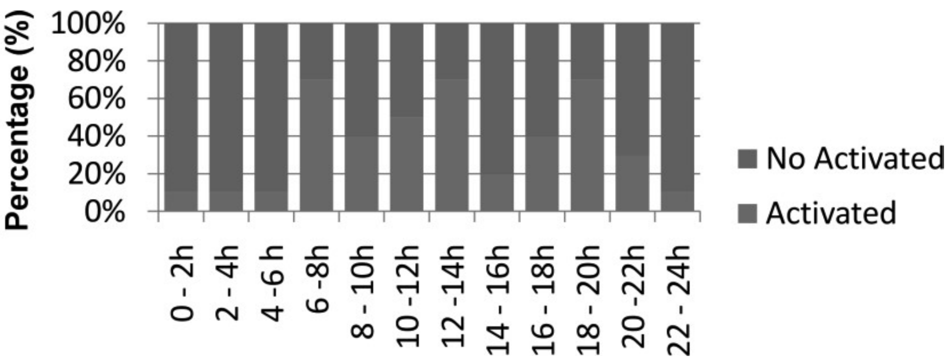


Figure 2. Timetable for the low-power consumption strategy
In blue, the estimate percentage of time that crosswalks are typically used by people. In red, the estimated percentage of time that crosswalks are not used by people.

are utilized by pedestrians, while “No Activated” (red label) means the percentage in which crosswalks are not utilized by people. The strategy consisted in fitting the LED lighting and the reading frequency of the system’s transducers in function of the pedestrians’ attendance and battery level. This allows increasing the battery life up to 5.8% in average. Although not significant, the electrical consumption has been one of the major challenges in this research.

3.2.5 Additional Units

To count the operations performed by the system (e.g., number of pedestrian detections or errors in units), each node incorporates a data storage unit and a real-time clock unit. The storage electronics comprises an external solid-state memory (i.e., 8GB microSD card) that allows extending the storage capacity to implement a local database in each node. The microSD card selected is the SDC10G2/8GB model from Kingston Technology whilst the adapter module from microSD card to SPI bus is from the manufacturer Tinxi. This database stores all the events that happen both in the surrounding environment and within the node for further analysis. To this end, the real-time unit provides a date and hourly stamp for all the actions carried out by a device. The real-time unit selected is TiniRTC, which includes the DS1307 module of Maxim Integrated.

3.2.6 Wireless Communication

The wireless communication unit is responsible for transferring data between the system's nodes within the WLAN. One of the nodes has the role of access point (AP), whose function is to manage and control the network operation. The rest of the network nodes work as clients so that when one of them detects a target, a broadcast message is sent to the rest of the nodes in the WLAN through the AP.

The physical (PHY) layer has been implemented in the microwave band at 2.4GHz, the MAC layer utilizes the IEEE 802.11n standard at 300Mbps with optional Wi-Fi protected access (WPA/WPA2) encryption [107], the network layer uses unicast and broadcast Internet Protocol version 4 (IPv4) addresses and the transport layer has been implemented with the user datagram protocol (UDP) since it accelerates the message delivery with regard to transmission control protocol (TCP) by dispensing with acknowledgment (ACK) messages as discussed in [108]. On the application layer, a fault-tolerant mechanism has been designed to prevent the total loss of network operability due to a failure in the network AP. This mechanism establishes a node hierarchy to prevent loss of communication against AP failures. It automates the management of the node roles by means of an election and promotion process between stations in search of designated and backup APs.

3.2.7 Printed Circuit Board Manufacturing

The hardware described in the previous subsections has been integrated into a printed circuit board (PCB). To this end, the followed methodology consisted of a three-stage process: (*i*) validation of functional concepts on protoboards; (*ii*) design, manufacturing and testing of PCBs in a research laboratory at the University of Huelva; (*iii*) export of final PCB design and fabrication through a professional company.

The complete electronic circuit was designed using KiCAD, a free software tool that allows making designs without size restrictions. This tool allows exporting the designs developed for later professional manufacturing. Once the PCB was designed, two photoliths were printed on an acetate support to generate the boards on which to carry out the photosensitive development and acid etching process (Fig. 3). Later, the electronic components were integrated into the manufactured PCB (e.g., microcontroller, resistors, capacitors, etc.). Subsequently, the correct operation of the hardware functions was validated and then the design was commissioned to an external company. Finally, the integration of hardware into a professional quality PCB (Fig. 4a) was mounted within the protective housing designed to install the system's nodes on public roads (Fig. 4b).

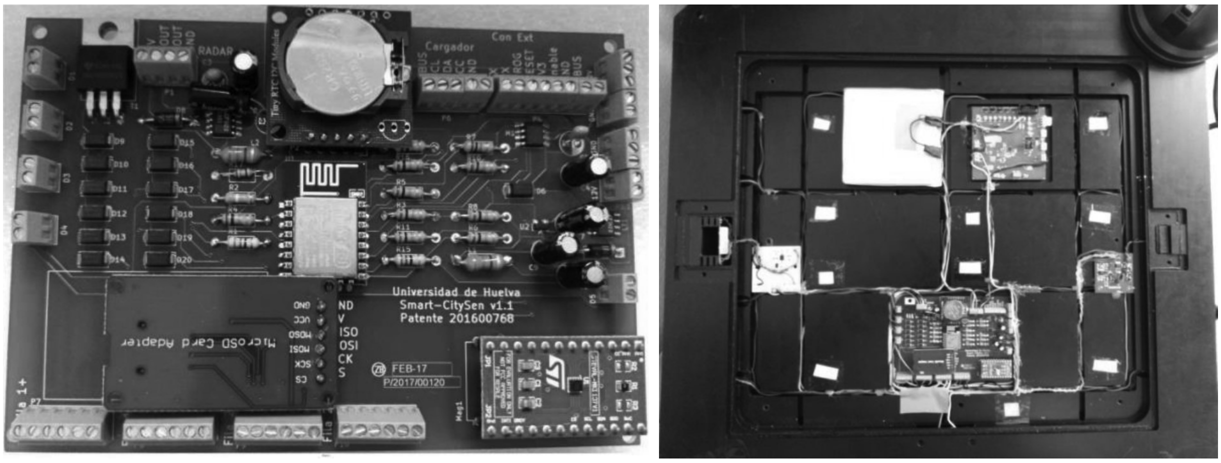
3.2.8 Construction and Placement of the System

The electronics described in the previous subsections are contained in a protective housing to act as a horizontal lighting beacon. The design requirements were the use of non-ferromagnetic material, high durability (min. 6 months), high rigidity (min. 3500 Kg in compression), non-slip ribbed surface, IP67 protection, interior LEDs and sensors with adjustable tilt mount, as well as space inside for PCB mounting. In total, six custom housings have been produced by machining 50 mm thick plates made of high mechanical strength plastic material, which supports large tons of weight without deforming (up to 17 Bar). The manufacturing has been made with a computer numerical control (CNC) milling machine as shown in figure 5a.

The case is arranged in a matrix of 4 × 3 high quality tempered glasses (10H hardness, transmittance of 88-92%) with enough thickness to support the weight of the vehicles up to $8.16 \cdot 10^6$ N/m^2 in compression and preventing the solar panels' surface from being damaged. The complete structure fulfills the IP67 standard of protection against dust and liquids. It can be fixed on the road by means of

(a) (b)

Figure 3. Insolation machine and acid etching during PCB manufacturing



(a) (b)

Figure 4. Electronics mounted on professional PCB and electronics mounted in protective housing

bituminous adherent (e.g., warm tar), epoxy glue (i.e., thermostable polymer hardened by a catalyst agent) or mechanical anchorage by means of screws (e.g., wall plug and lag screw). The housing does not need public works for its installation on the road. Moreover, it is reusable when a re-asphalting of the road surface is required. The shape of the case presents a non-slipping knurling texture to avoid falls of pedestrians or bicycles, as well as a trapezoidal profile with a maximum size of $540 \times 500 \times 45$ mm^3 and 45º of angle of attack to facilitate the vehicle movement. These features comply with the recommendations of the Spanish Ministry of Promotion [109] (Fig. 5b).

3.3 Software Elements

3.3.1 Artificial Intelligence

This section exposes the different AI techniques applied during the development of the doctoral thesis to provide the road signaling system with the ability to discern between vehicles and pedestrians. This section also describes the algorithms applied to improve the vehicle detection around pedestrian crossings. In addition, the section explains the strategy followed to determine the crossing intention of a pedestrian around a crosswalk. In summary, two different techniques supported by fuzzy logic and ML have been used.

3.3.1.1 Fuzzy Logic

The intelligence of the road signaling system consists of a sensory fusion process of association, correlation and combination of information based on fuzzy logic. Specifically, the three-level abstraction model of Dasarathy [110] has been

(a) (b)

Figure 5. CNC manufacturing of the housing and node installed on the public road

used to combine sensor measurements and high-level decisions (e.g., if a pedestrian exists or not upon the crosswalk). The measurements are fused in a cooperative way when coming from different sensors within the same device (i.e., ultrasound, RADAR and magnetic field) and redundantly when belonging to the same sensor in several neighboring devices. This strategy helps to decrease the number of false positives and to improve the accuracy of the system [111]. The fuzzy logic technique has been used as a basis for sensory fusion in the intelligent road signaling system so that it can differentiate between pedestrians or vehicles on a crosswalk. This technique has been selected for its ease of implementation on any device with memory constraints as well as for its versatility and easy correlation between data input and the resulting output, allowing the reason for a possible malfunction to be quickly detected. As an example, the typology of cases with pedestrians and vehicles –either circulating, stopped or parked– interacting around a crosswalk is shown (Figure 6). The system activity, formed by several nodes, is depicted at the bottom of the zebra crossings. The sensors are colored in green when a target is detected on the crosswalk by the ultrasound sensor, in blue when detected by the magnetic sensor, in red when detected by both the magnetic sensor and RADAR, and in black when there is no presence of pedestrians or vehicles. The various scenarios consist of a crosswalk without any agent (Case 0), a pedestrian entering and walking through the crosswalk (Cases 1 and 2), a vehicle circulating along the road (Case 3), a vehicle approaching the zebra crossing while a pedestrian begins to cross (Case 4), a vehicle approaching the crosswalk when a pedestrian is crossing (Case 5), a vehicle stopping or parking (Case 6), a vehicle stopping when a pedestrian begins to cross (Case 7), a pedestrian crossing and a vehicle stopping near the crosswalk (Case 8), a vehicle detected by the magnetic and ultrasound sensors but not detected

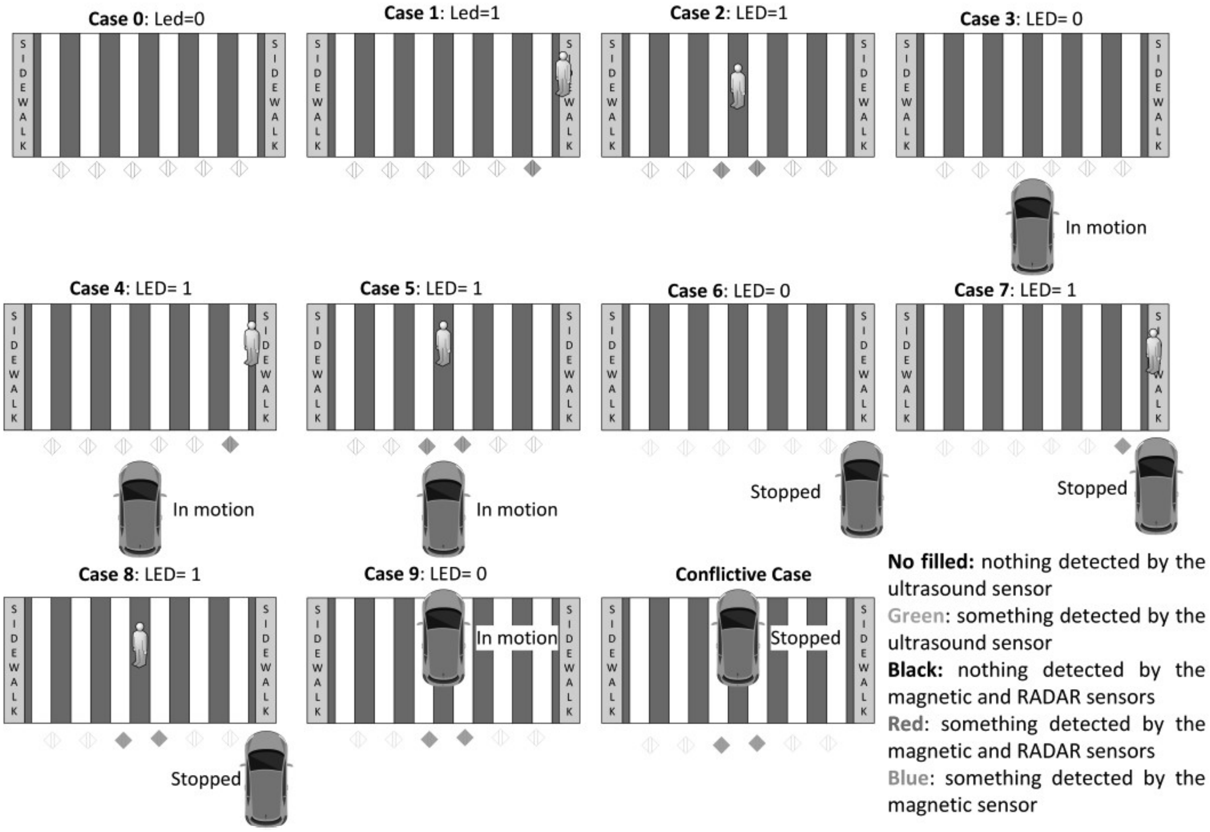


Figure 6. Case studies of the system operation

by the RADAR (Case 9), as well as a vehicle stopping while a pedestrian is crossing (conflictive case). The latter represents the most problematic scenario addressed by the fuzzy logic.

The fuzzy Mamdani model has been implemented in this approach. This model is characterized by using linguistic rules such as "*If X1 is A1 and … and Xn is An, Then Y is B*" in which both antecedents and consequents are labels and rules obtained by an expert system [112]. The membership of a fuzzy set is defined by trapezoidal functions –as they adequately model the system's behavior and are not computationally complex– where the conjunction and implication operators use the minimum T-norm [113]. Moreover, the defuzzification process uses the "First Infer, Then Aggregate" (FITA) method since it is more consistent than "First Aggregate, Then Infer" (FATI) [114] and the Maximum Value Point (MVP) weighting method, also called weighted average method [115].

The system's sensory fusion has been modelled through the Fuzzy Logic Toolbox™ of Matlab® (Figure 7). The "Ultrasound Controller" block manages the data fusion of the ultrasound sensors from the local node and the remote ones at the neighboring nodes; its output indicates whether an obstacle exists on the pedestrian crossing. The "Magnetic Controller" is in charge of fusing the data of the magnetic field sensors and determining vehicles arriving at the zebra crossing; its output updates a temporary variable “T0” useful to control slow traffic or stationary traffic that could generate false positives due to vehicles staying a long period of time over the crosswalk. The “Radar Controller” is responsible for fusing the RADAR sensors and determining if a target approaching the zebra crossing is vehicle or pedestrian. Finally, the “Sensorial Fusion” block determines whether a pedestrian on the crosswalk exists by fusing the outputs from the previous fuzzy controllers. To sum up, the signaling unit within a node is activated in case of positive detection (i.e., a pedestrian) and the whole system is synchronized by a broadcast message sent over the network to activate the nodes’ signaling units. When the sensory fusion detects a vehicle through either the magnetic sensor or RADAR, an inhibition message is sent to avoid false positives.

The specific aspects of the different blocks used in the sensory fusion process are detailed below. The block named “Ultrasound Controller” utilizes three inputs comprising normalized measurements from the ultrasound sensors at the local, right and/or left nodes. The normalization allows using more than one transducer with different radiation patterns to adapt the azimuthal and horizontal range in function of the node position regarding the road (e.g., in the middle of the crosswalk or close to the sidewalk). Each input has three labels meaning the distance of the obstacle in front of the sensor, being *Far*, *Medium* and *Near*. The *Far* label indicates that an object is not detected or is detected in a ROI external to the crosswalk. The *Medium* label means that the object is detected in an uncertainty area or it is not detected by the sensor with enough precision. The *Near* label points out an obstacle existing on the zebra crossing that is clearly perceived. The controller’s output provides values, whose range stands for the grade in which a target exists over the crosswalk by means of two labels (*No* and *Yes*). Thus, a value near zero (0) means that an obstacle

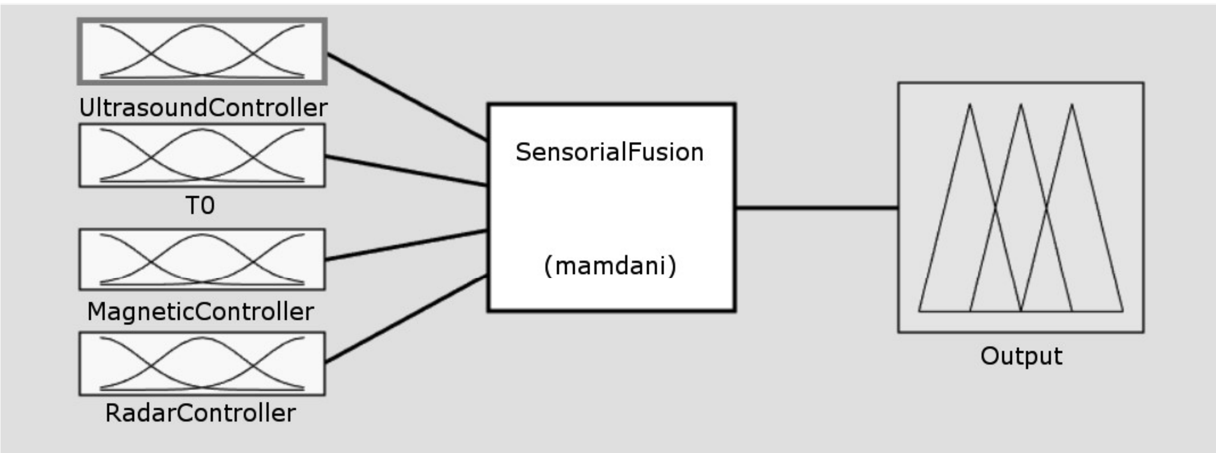


Figure 7. Fuzzy inference structure of the intelligent crosswalk system

does not exist while a value close to one indicates that it exists. In that case, it must be inferred by the rest of the fuzzy system whether the object is vehicle or pedestrian to activate the signaling unit. The rules base and tags of the fuzzy controller were tuned experimentally by an expert system. Since an ultrasound sensor typically has a nonlinear response whose error increases due to distance, it was established that three inputs declaring a *Far* label after the defuzzification process means no obstacle on the crosswalk. On the contrary, two inputs with the *Medium* label or one input with the *Near* label signifies the presence of an obstacle.

The block named "Magnetic Controller" uses an input per axis (X, Y and Z) with three labels for each one called *Farα*, *NearNα* and *Nearα*, being (α) the corresponding axis. The *Farα* tag stands for the value of the magnetic field sensor during the idle state, while *NearNα* and Nearα indicate a magnetic field variation below and above the idle state, respectively. This variation is represented versus temporary samples (Figure 8). The output of the magnetic fuzzy controller has been modelled with two tags ranging from 0 to 1 (*No* and *Yes*), where values near zero mean no vehicle close to the zebra crossing and values near one indicate the presence of a vehicle. Similarly, both the rules base and tags of the fuzzy controller were experimentally fitted by the expert system. It was determined that a variation of the idle state at least in two of three axes of the magnetic sensor indicates presence of a vehicle driving around the zebra crossing. Otherwise, a vehicle does not exist.

The block named "Temporary Variable" has the function of updating a counter called "T0" to measure the time elapsed since the magnetic field sensor did not detect a vehicle. That is, to count the time elapsed since the output of this controller was zero. This variable is useful to resolve conflictive cases –as the one depicted in Figure 7– where it is necessary to know whether a vehicle is sited over the crosswalk. According to this, the temporary fuzzy controller was modelled with three labels called *Little*, *Medium* and *Much*. The *Little* label stands for a small period of time since the magnetic field sensor detected the presence of a vehicle, *Medium* indicates that a certain time has elapsed –but not sufficiently large– since there was a vehicle on the zebra crossing (e.g., stopped), and *Much* indicates an interval of time large enough since the magnetic field sensor detected the presence of a vehicle (i.e., parked).

The block called "RADAR Controller" has two inputs defined, which are the *State* and *Speed* variables. The first one stands for a digital output from the RADAR that points out the presence of an object in the field of view (FOV) of the sensor. So, the *State* tag indicates if there is a target present, where values close to zero (0) specify no object existing (*Low*) and values close to one indicate an object being

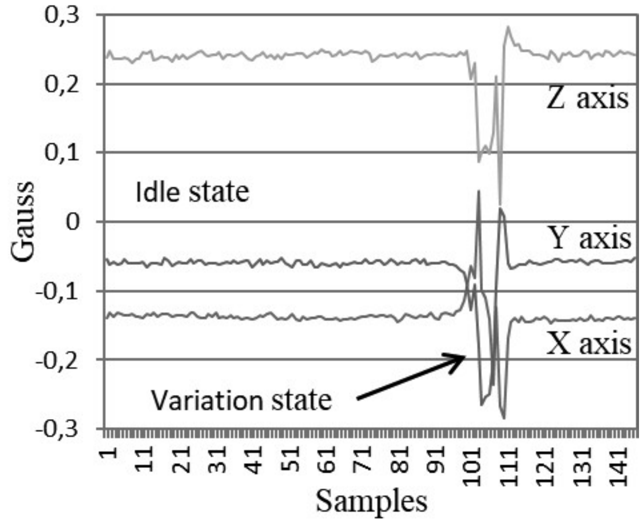


Figure 8. Detection of a vehicle by the magnetic sensor. The idle and variation states are caused by the penetration of a car in the magnetic field. The Gauss measurements taken by the sensor are shown on the *y*-axis while the temporary samples are observed on the *x*-axis

detected (*High*). The *Speed* variable consists of two tags (*Minor* and *Major*) to designate values higher and lower than 5 Km/h. This value –experimentally determined (Figure 9)– stands for a speed threshold above which any detection belongs with certainty to a vehicle (i.e., everything that is not a pedestrian moving on foot). The output of the fuzzy controller is represented by the *Pedestrian* and *Vehicle* labels, meaning the values near zero (0) a pedestrian and the values near one (1) a vehicle. The rules base of the fuzzy controller has been made experimentally by the expert system, which determined that an object speed declared as *Major* with a state designed as *High* stands for a vehicle. In any other case, the object will be potentially a pedestrian or a vehicle at low speed, whose nature must be inferred by the rest of the fuzzy system.

The block named "Sensorial Fusion" is in charge of fusing all the fuzzy controllers previously described (i.e., ultrasound, magnetic, RADAR and "T0") to generate an output to control the LED signaling unit. The output values have a range, where values near zero (0) indicate that the signaling unit must not be activated and values near one (1) indicate that the signaling unit must be activated to alert drivers about pedestrians on the crosswalk. The expert system settled that a pedestrian is detected when the output of the ultrasound controller is *Yes*, the magnetic controller points out *No*, the "T0" variable indicates the *Little* or *Medium* labels, and the output of the RADAR controller designates *Pedestrian*. In this case, it is necessary to activate the LED signaling unit. Otherwise, the pedestrian warning lighting will be disabled.

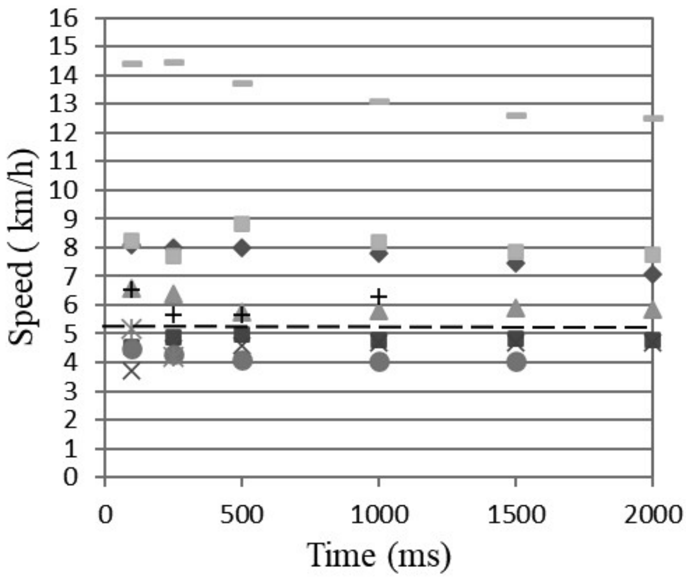


Figure 9. Estimation of the speed threshold between pedestrians and vehicles. Red squares, purple cross and orange circles below the dashed line stand for a pedestrian. The rest are vehicles

3.3.1.2 Machine Learning Techniques

This subsection describes the different ML techniques applied to improve the vehicle detection around zebra crossings. The use of these techniques avoids having to recalibrate the fuzzy labels *n* times in each location where the system is installed, where *n* indicates the number of nodes per crosswalk. To this end, the structure of the dataset used and the resulting parameter settings for each ML algorithm are exposed.

To avoid the inconvenience of requiring recalibration of fuzzy labels, the research took a step forward to improve the system performance while using a single configuration for multiple locations by using ML techniques. The problem was treated upon different points of view such as the binary classification, anomaly detection and even time-series prediction. Moreover, DRL is also used –even as an unsupervised method– assuming a reward function with a binary classification nature. Therefore, the techniques used were organized into classifiers, anomaly detectors, time-series forecasting and DRL.

The reasons for choosing the previously mentioned models are: (*i*) from each category of techniques, an approach was selected. For instance, logistic regression was chosen among linear classifiers. Other alternatives like Fisher's linear discriminant (FLD) are possible. However, these have the same nature and choosing any of them is appropriate. Moreover, (*ii*) the problem can be better understood if tackled in different ways, allowing a multi-unit seamless model to be developed in the future. This may require a new hardware setting to orchestrate multiple nodes at the same time. The approach used to implement the ML models and determine their performance is shown in Figure 10. The yellow block must be replaced by one of the techniques described below.

3.3.1.2.1 Classifiers

The classifiers used are logistic regression, random forest, extra-tree, k-nearest neighbors and multi-layer perceptron, which are all widely known supervised methods. These classifiers were all implemented with the scikit-learn library of Python [116]. The first one –LR– was designed to detect two different classes and the L2 norm was used to control the overfitting. This method is easy to implement and effective because it does not require data scaling. However, it can easily fall short to handle non-linear mappings [117].

The second classifier –RF– was configured with 15 estimators. RF offers the advantage of handling large amounts of data and does not suffer from overfitting. Nevertheless, it is slow to predict and hard to interpret how it performs [117].

The third classifier, extra-tree, was configured with 16 estimators. Its advantages are the high success rate and accuracy as for other algorithms based on assembled trees. In addition, this algorithm stands out for its low computational complexity [118].

The fourth classifier –KNN– was implemented with 4 neighbors. Among the advantages is the conceptual ease to implement the method. However, the amount

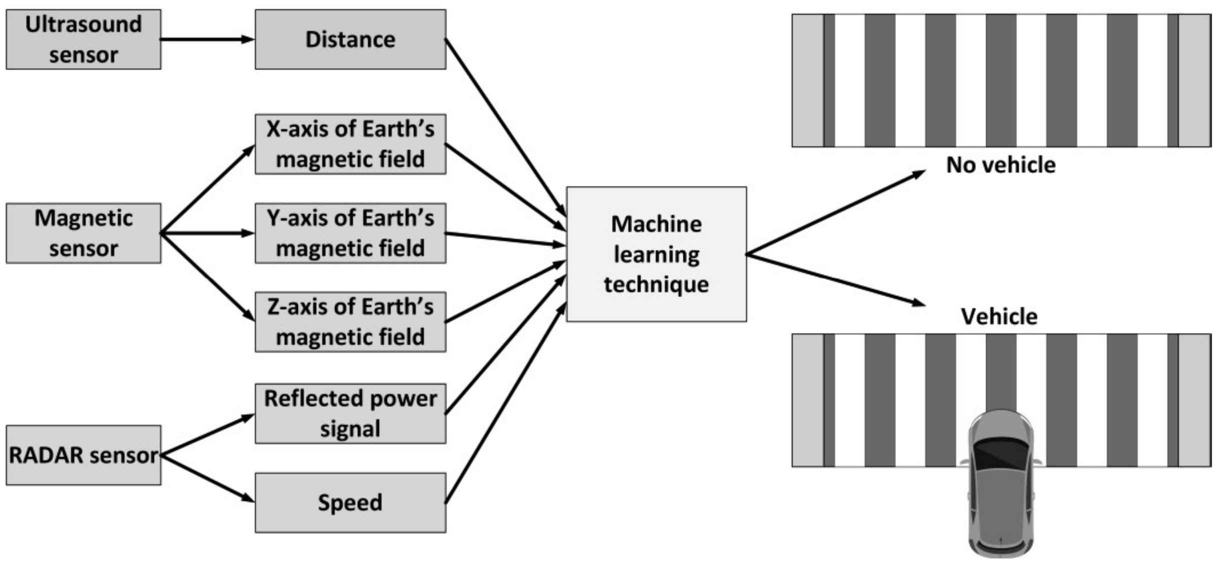


Figure 10. Machine learning approach implemented in the system

of memory, time to store the model and train the method when the dataset is large could be the main drawbacks [117].

Finally, the last classifier –MLP– was optimized with the Adam optimizer. MLP consists of 4 hidden layers –each one with 100 neurons– and 20% of the training data was used for validation to ensure the model stability. This has the capability to learn and model non-linear complex relationships, as well as to make predictions using data that have not been previously observed. Conversely, it can be difficult to tune its hyperparameters and it may require long training for large neural networks [117].

3.3.1.2.2 Anomaly Detector

The anomaly detector used is the one-class SVM, which is an unsupervised outlier detector implemented in Python with scikit-learn. One-class SVM allows the detection of outliers –or anomalies– in the data. The use of this technique allows to treat vehicles as outliers and the "No vehicle" state (i.e., the most frequent state of pedestrians crossing) as the "normal" state. The uniqueness of this method, when compared to the others, is that it only needs to be trained with data belonging to the "No vehicle" class. It has the advantage of providing a good handling of imbalanced classes, it only needs to train instances of the target class and it is very sensitive to outliers. Nevertheless, it requires the right selection of hyperparameters and kernels [119].

3.3.1.2.3 Time-Series Forecasting

To avoid the system generating inconsistent visual alerts, it is necessary not only to consider current measurements from the sensors but also the last few ones. This way, the system output will depend on a sequence of observations. This means that the vehicle detection problem can be treated as time-series forecasting, allowing the use of an LSTM architecture. LSTM networks are an important piece in modern time-series forecasting and to sequence deep learning models. The reason for using an LSTM instead of others (e.g., statistical autoregressive models) is that LSTM networks can be integrated into DRL architectures, as explained below. LSTM is a recurrent neural network equipped with gated cells able to remember important information and forget the irrelevant. LSTM converts the input sequence into memory and hidden states. These can be used to forecast future data based on some training samples and it provides better long-term modeling and a more robust vanishing gradient than conventional RNN. However, LSTM requires more computational and memory capacity due to the multiple memory cells [120]. As shown in Figure 11, the LSTM-based neural network architecture used consists of a total of 42 input neurons, corresponding to the number of time instants and different sensor measurements for each time instant. Then, the LSTM layer is made up of 10 units that are fully connected to the input layer. Finally, the output layer is made of a single neuron completely connected to the LSTM layer, being this neuron responsible for predicting whether a vehicle is –or is not– currently over a crosswalk. The neural network structure has been determined following the instructions described later in the Parameter Settings subsection.

3.3.1.2.4 Deep Reinforcement Learning

DRL is an emerging learning scheme whereby an agent learns by interacting with the environment. It is an unsupervised method that can be trained online. However, it was trained offline in this research to be compared with the other established methods. In this sense, an online training system will be explored as a future work.

The agent –usually represented as a deep neural network for efficiency purposes– observes a state from the environment and performs actions. According

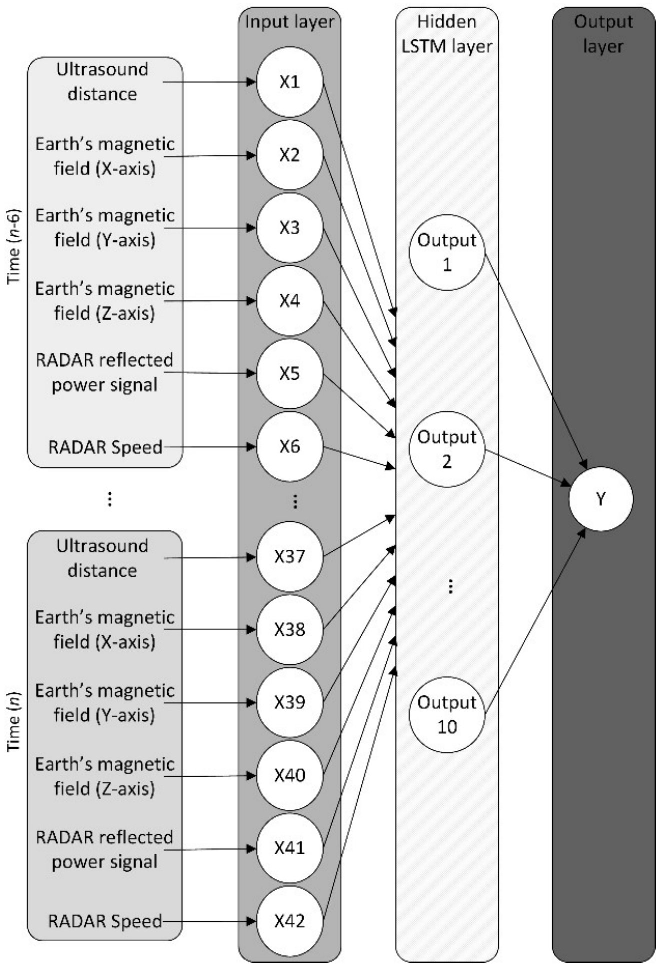


Figure 11. Structure of the LSTM-based neural network

to the action performed, it receives a reward and a new state. The agent's objective is to maximize the accumulated future reward. Therefore, training an agent means finding a policy that maps states with actions in a way that maximizes the cumulative reward received by the agent. In this research, the DDRQN model was utilized [121]. DDRQN uses an LSTM layer (i.e., LSTM–DRL) to obtain time relevance between consecutive states. This allows to reduce the overestimations and the number of operations to calculate them [122]. Therefore, the agent developed in this work uses current and historical data in its state to recognize time-related events. The reward function is as simple as 1 if the agent selects the right class, and -1 otherwise. This rewards the agent for the correct selections and penalizes the wrong ones. The action space of the agent is {"No vehicle", "Vehicle"}, where the LSTM–DRL agent decides if there is a vehicle approaching the crosswalk –or not– according to the sequence of observations received from the sensors.

As shown in Figure 12, the neural network architecture used in the DRL model has a total of 48 input neurons. These correspond to the measurements of the different sensors of the system according to each instant of time (n), including historical data (up to n-7). The hidden layers of the neural network are initially made up of a fully connected layer of 15 neurons, followed by an activation layer where the Rectified Linear Units (ReLU) function is used as activator. At the output of this layer, an LSTM layer with 10 units is completely connected with the previous layer. This output is linked to a second fully connected layer of five neurons. The output of this layer is connected to a second ReLU activation layer. Then, two neurons (Y1 and Y2) fully connected to the previous layer are used. The neural network structure has been determined following the instructions described later in the Parameter Settings subsection.

3.3.1.2.5 Dataset Structure

The proposed approach uses data generated by three different sensors –described in the previous sections– as predictor variables. Table 5 shows such set of predictor variables and their range values. The data are used by the models to identify whether there is –or is not– a vehicle circulating through the intelligent pedestrian crossing.

For this purpose, two classes are used: "Vehicle" and "No vehicle", represented as 1 and 0, respectively. These classes are used as ground truth (GT). The measurements from the sensors were normalized using the Min–Max method for an adequate performance of the ML algorithms [123]. The normalization values are also shown in Table 5.

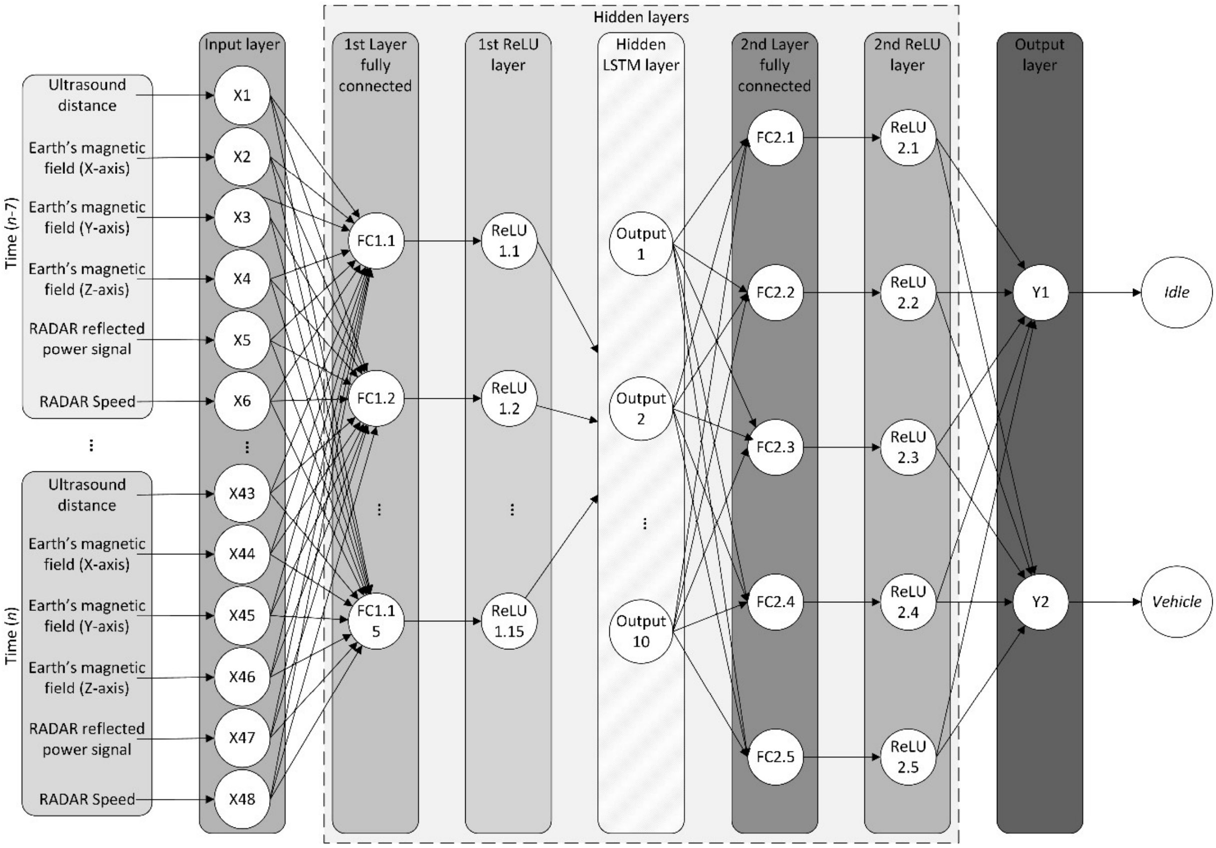


Figure 12. Structure of the DRL neural network

The dataset used to train the ML models –to determine whether a vehicle is approaching a pedestrian crossing or not– was collected from a real environment and is publicly available at the researchers' website [1]. The dataset includes a total of 86,960 tuples labeled, which is imbalanced. The "No vehicle" class has a total of 80,915 tuples (93.05%) whilst the "Vehicle" class has a total of 6045 tuples (6.95%). To balance the dataset, the NearMiss subsampling technique was used [124]. The dataset balanced ends up having 6,362 tuples for the "No vehicle" class and 6,045 tuples for the "Vehicle" class, which corresponds to 51.28% and 48.72% respectively. Therefore, the size of the dataset used at the classification stage consists of 12,407 tuples labeled. The dataset is ordered by a tuple index to keep time linearity, which is necessary for some ML models to work properly.

The data collection process has been carried out in several real environments under fluid traffic conditions. The nodes were placed on the roadway near the line of the pedestrian crossing, while the vehicles passed over the nodes –or on their sides– with an average speed of 18.20 ± 26.16 Km/h. The data collection procedure consisted in monitoring the system's interactions with vehicles and environment,

[1] http://www.uhu.es/tomas.mateo/investigacion/dataset.zip

Table 5. Sensor measurement ranges and corresponding normalization

Measurement	Range Value	Normalized Value
Ultrasound distance	60 – 500 cm	0 – 1
Magnetic X-axis	-32.768 – 32.767 Gauss	0 – 1
Magnetic Y-axis	-32.768 – 32.767 Gauss	0 – 1
Magnetic Z-axis	-32.768 – 32.767 Gauss	0 – 1
Reflected signal power RADAR	0 – 1 n/a	0 – 1
Speed RADAR	0 – 100 Km/h	0 – 100
Ground truth	0 – 1	0 – 1

and then storing the data with both vehicles and no vehicles circulating. Because of this, cases involving pedestrians were filtered out and no data was recorded. The tests were performed both in Portugal and Spain, more specifically in the urban areas of Gambelas (Faro) and Bollullos Par del Condado (Huelva). Four points were in the University of Algarve, two points were in Rua Manuel Gomes Guerreiro, one point was in Rua Comandante Sebastião da Costa, one point was in Praceta Orlando Sena Rodriguez, and another point was in Sector Pp1 Cruz de Montañina. These locations present different terrestrial magnetic fields either due to their nature or to different elements found on public roads (e.g., traffic signs and streetlights among other ferromagnetic elements). To illustrate the different magnetic field values at these locations, Table 6 shows the average values and standard deviations for the X, Y and Z axes of the magnetic sensor for both circulating and non-circulating vehicles. On the one hand, the table shows that there is a small difference between the values for “Vehicle” and “No vehicle” conditions at each location (i.e., a minimum of 0.0051% and maximum of 0.6532%), which is in practice very difficult to calibrate. On the other hand, the average values for the magnetic field sensor have no correspondence between sites with very similar values (e.g., X-axis for the column “No vehicle” of Praceta Orlando *vs*. X-axis for the column “Vehicle” of Cruz de Montañina). This means that a calibration process at one site is unrelated to another, being necessary to start a new system labeling procedure to differentiate between circulating and non-circulating vehicles. The complexity of generating a single vehicle-classifier for multiple locations elevates to $N \times L$, being N the number of nodes of the intelligent pedestrian crossing and L the number of locations.

Table 6. Normalized average magnetic sensor measurements by location, axis and vehicle presence

	No vehicle			Vehicle		
Calibration site	**X-axis**	**Y-axis**	**Z-axis**	**X-axis**	**Y-axis**	**Z-axis**
Campus 1	0.499 ± 0.000	0.458 ± 0.001	0.581 ± 0.001	0.493 ± 0.009	0.461 ± 0.009	0.587 ± 0.012
Campus 2	0.510 ± 0.060	0.500 ± 0.023	0.582 ± 0.010	0.504 ± 0.027	0.502 ± 0.032	0.586 ± 0.031
Campus 3	0.501 ± 0.001	0.455 ± 0.004	0.582 ± 0.001	0.499 ± 0.006	0.455 ± 0.008	0.587 ± 0.010
Campus 4	0.495 ± 0.000	0.458 ± 0.000	0.581 ± 0.001	0.490 ± 0.008	0.460 ± 0.010	0.586 ± 0.012
Manuel Gomes Guerreiro	0.513 ± 0.001	0.513 ± 0.001	0.584 ± 0.001	0.509 ± 0.010	0.514 ± 0.007	0.589 ± 0.009
Praceta Orlando Sena Rodriguez	0.480 ± 0.001	0.480 ± 0.01	0.587 ± 0.001	0.476 ± 0.007	0.481 ± 0.009	0.592 ± 0.010
Comandante Sebastião da Costa	0.511 ± 0.000	0.456 ± 0.000	0.584 ± 0.000	0.504 ± 0.005	0.458 ± 0.010	0.586 ± 0.013
Cruz de Montañina	0.478 ± 0.001	0.492 ± 0.001	0.585 ± 0.001	0.479 ± 0.006	0.492 ± 0.007	0.587 ± 0.010

Finally, the system used wireless communication to collect the data from the sensors. To this end, a portable AP, a laptop with WampServer software and the hypertext transfer protocol (HTTP) were used. The WampServer software has the capability to handle HTTP requests from the nodes –through an Apache server– and store the data in a MySQL database. The collected tuples were manually labelled as "No vehicle" or "Vehicle".

3.3.1.2.6 Parameter Settings

The hyperparameter tuning of the LR, RF, MLP and one-class SVM methods has been carried out using the Grid Search Cross Validation technique implemented in scikit-learn [116], while the tuning of the LSTM and DRL methods has been empirically determined. The method used to determine the best fit for LSTM and DRL is as follows. A combination matrix of the hyperparameter values is generated, the models undergo learning with these hyperparameters using cross-validation to get the metrics for that learning model, and these metrics are added to the combination matrix. The metrics used in this process have been the accuracy and, in case of a tie, the true positive rate (TPR) and then the false positive rate (FPR).

Once the metrics of the first iteration are compared, the best metrics are selected and, therefore, their hyperparameters. Then, a new matrix is established with values close to the best hyperparameters as well as a linear distribution of the values among the best hyperparameters. This process continues iteratively and ends when similar metrics are reached in all cases. The values adopted for each method are shown in Table 7.

3.3.2 Mobile Application

This section describes the features of the application implemented to guide pedestrians through the city and detect their crossing intention around a crosswalk to provide safer routes.

The mobile app has been programmed through Android Studio and the Integrated Development Environment (IDE). This framework allows developing smartphone applications in Java, C/C++ or Kotlin language. The app developed includes the following features: (*i*) calculation and tracing of safe routes for pedestrians through a city; (*ii*) safe guidance of people with hearing and visual impairments by means of haptic, visual and acoustic signals; (*iii*) detection of the pedestrian's crossing intention at crosswalks; (*iv*) visual aid system for drivers to improve the perception of zebra crossings by means of Bluetooth communication. The app's functionalities are summarized through the use case diagram shown in Figure 13. The app developed makes use of the application programming interfaces (API) of the Android operating system. At least, version 5 of Android is required for the execution of the app on a mobile device. This limitation is imposed by the APIs used, these being the following: Android maps, Directions, TextToSpeech and Sensors. In addition to these APIs, the application makes use of the SQLite API to manage a local database (i.e., destination points) and the jTDS library [125] to query an external database hosted on Microsoft SQL Server (i.e., pedestrian POIs). The APIs require the use of a network in addition to the internet connection required to access the cloud-hosted database. The app architecture and interaction with the APIs is shown in Figure 14.

The installation file of the mobile app takes 3345 KB of disk space and requires 9.37 MB in the phone memory. It has been determined through the Android Profiler tool of Android Studio that the main thread of the app consumes 20.03% of the app's runtime process and 20.94% of RAM. The application was monitored for 60s during which the CPU was used for 25.95s (44.46%). The highest usage belongs to the graphical environment with 16.79% of the CPU, followed by the main thread of the app with 8.91% of CPU. During the monitoring, it was determined that the total use of the RAM was 106.5 MB, of which 44.1 MB belongs to the graphical environment and 22.3 MB to the app code.

Table 7. Optimized parameters for the ML models.

Technique	Variable	Value
LR	C	0.09
	Penalty	L2
	Random state	1
	Solver	Newton-cg
RF	Random state	1
	Number of estimators	15
Extra-tree	Random state	1
	Number of estimators	16
KNN	Number of neighbors	4
MLP	Solver	Adam
	Hidden layers	4
	Learning rate	0.0001
	Hidden layer neurons	100
	Maximum iterations	1000
	Validation fraction	20%
One-class SVM	Nu	0.01
	Gamma	0.77
	Kernel	Radial basis function (RBF)
LSTM	Number of time instants	7
	Intermediate layer	10
	Output layer neurons	1
	Optimizer	Adam
	Learning rate	0.0005
	Epochs	20
	Validation fraction	20%
Deep reinforcement learning (RDDQN)	Historical length	8
	Episodes	100
	Steps	2470
	Neurons of first layer fully connected	15
	Neurons of LSTM layer	10
	Neurons of second layer fully connected	5
	Neurons output layer	2
	Learning rate	0.0001

Figure 13. Application functionalities

3.3.2.1 Calculation, Tracing and Guiding of Safe Routes

Among the main features of the app is the ability to calculate and plot safe maps in cities. The calculation and tracing of these maps are based on the Directions APIs and Android Maps, both from Google. The process to calculate a route begins with the detection of the user's location through the Global Positioning System (GPS). Once the current position has been obtained, the user can indicate the destination to which he/she wants to go using two options. The first one is to select the destination location by clicking on the map and then starting of the route. The second option is to press the route start button that will prompt the user to enter the address and city of the destination point by text. Once the origin and destination points of the route are known, an algorithm responsible for calculating, optimizing and plotting safe routes is invoked (Algorithm 1). This process is done in background to avoid congesting the main thread. The algorithm begins by obtaining

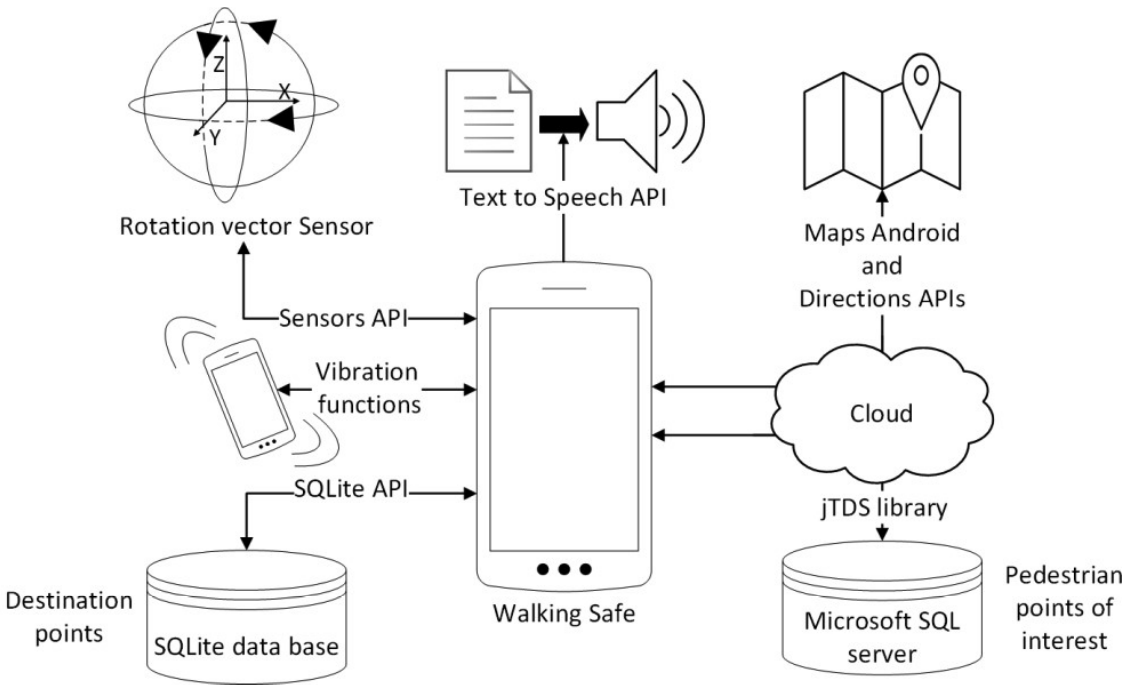


Figure 14. Application architecture

Algorithm 1

Purpose: To obtain a safe route to go from an origin to a destination point
Inputs: origin and destination points
Output: representation of the route on a city map and guidance of the user's safe route

routePoints = get the default route (origin, destination);
pedestrianPoints = pedestrian areas near the route (routePoints)
if size (pedestrianPoints) ≠ 0 **then**
    optimizedRoute = false
    Repeat
        routePoints ← route optimization (origin, destination, pedestrianPoints)
        pedestrianPoints ← calculation of new pedestrian points near the route (routePoints)
        if size(pedestrianPoints) = 0 **then**
        optimizedRoute = true
        end
    until (!optimizedRoute)
end if
trace safe route on city map
highlight the safe point included in the route with a special icon

the default route provided by the Addressing API from the origin to the destination points. Once the default route is known, a query is made to an external database located in the cloud that stores pedestrian POIs (e.g., zebra crossings, walkways and/or pedestrian areas). The jTDS library is used to carry out these queries. Subsequently, the algorithm calculates possible pedestrian POIs near the default route that would increase the safety of the journey. To do this, the points should not be more than 30m away from the route so as not to excessively increase the distance. Similarly, the total distance of the route to be traveled will never be more than 300m from the original route. Once the POIs have been determined in the first query, a second query is made to the Directions API to get a new route including the origin and destination points along with the POIs obtained from the previous step. This optimization is calculated iteratively until the safest possible route is reached without an excessive increase in the distance to be traveled by the user.

Once the final route is calculated, it is plotted using Android Maps and the corresponding guidance instructions are stored. These instructions include both the waypoints of the default route (e.g., “go straight on”, “turn right”, “turn left”) and the specific points introduced by the application (e.g., “you are approaching a pedestrian zone”). These instructions are dictated by the app with voice as users move along the path generated, as well as indicated by haptic signals through the smartphone (i.e., vibrations). These functions enhance the user experience and facilitate the warning to people with visual and/or hearing disabilities, included the elderly. To generate the indications correctly, the app waits until the user is near the waypoint while moving along the route. Once the user is in the zone, the directions are dictated using the TextToSpeech API. This API allows to convert text into a human voice, a function that has been specially designed for people with visual impairments. In addition to this option, guidance by vibration has also been implemented for people with hearing impairments to alert on areas where the route direction should be changed (e.g., taking a zebra crossing, walking down a street or through a pedestrian walkway). This functionality is based on the use of the basic vibration functions implemented on Android and can be configured in the options menu of the app to set how often the instructions should be dictated. The setting of each warning mode (i.e., voice-guided or vibration-driven) is independent, as is the volume at which the application transmits instructions.

3.3.2.2 Fuzzy Logic

The approach used to detect the pedestrian’s crossing intention at a zebra crossing is based on a sensory fusion strategy carried out on mobile devices (i.e., smartphones). This sensory fusion is a fuzzy process that follows the same strategy described in Section 3.2.1, except that it is used to defuzzy the voting method [126]. The solution addressed (Figure 15) combines: (*i*) distance at which the user is located from a POI belonging to the safe route (e.g., crosswalk); (*ii*) walking mode

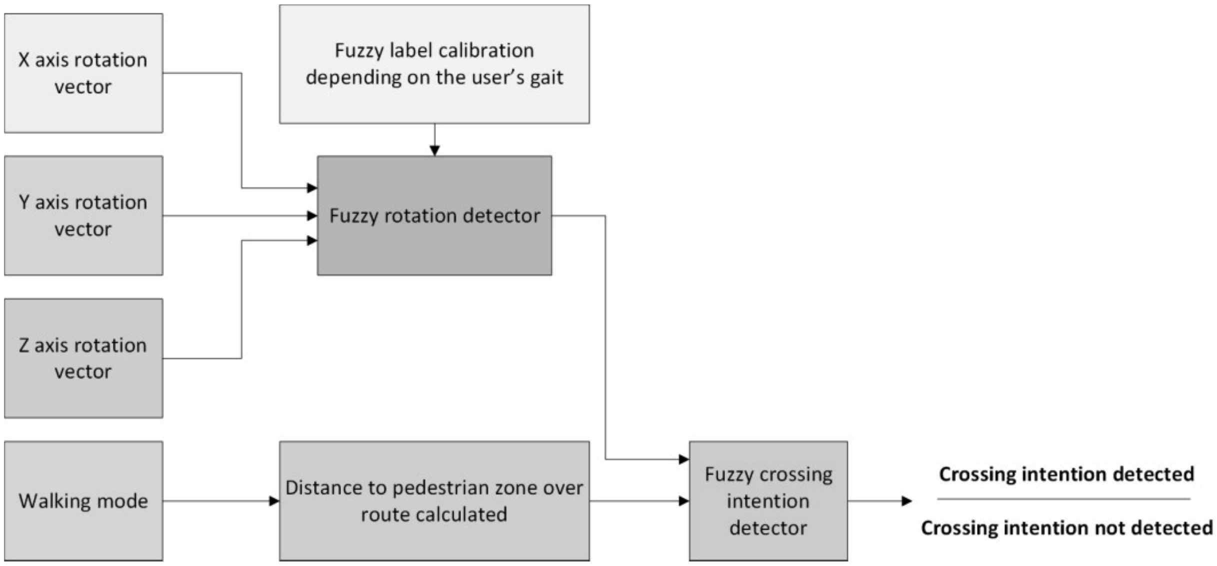
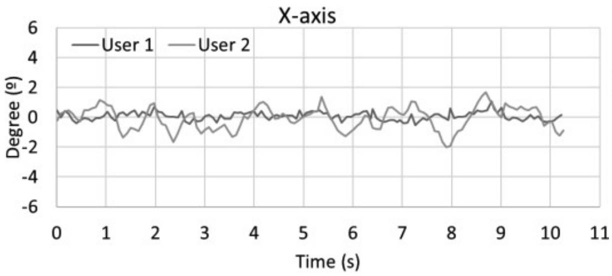


Figure 15. Structure of the Fuzzy system to detect the pedestrian's crossing intention

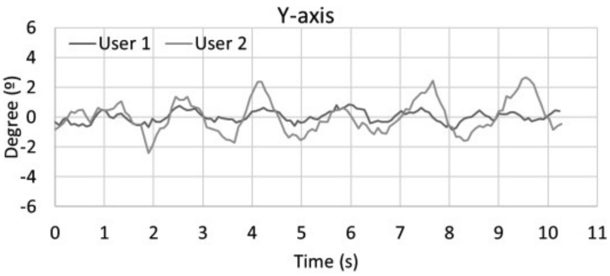
established by the user in the app's options menu (e.g., running, walking or sightseeing); and (*iii*) a fuzzy rotation detector responsible for tracking the user gait.

The block named "fuzzy rotation detector" has been constructed over the Android Sensors API. Specifically, this API asks the operating system for the sensor data related to the rotation vector; this can be hardware or software. The sensor is commonly used to measure movements and rotations, so it has been selected because the movements that pedestrians usually perform when approaching a crosswalk are rotational. In other words, pedestrians make turns as they approach a zebra crossing, thus being captured by this type of sensor. The data generated by the rotation sensor stands for the device's angle variation –and hence that of a pedestrian– at a specific time. To obtain a more accurate measurement of the pedestrian movement, a sliding window method with 10 averaged values was used. In this way, a total of 2s of pedestrian gait is kept in memory. By averaging 2s of movement, it is possible to determine if a pedestrian makes changes in his/her path or if he/she continues to walk straight. The user's rotation is determined through the average variation of the rotation on the XYZ axes. This rotation is never determined if a rotation on the Z-axis is not detected because, regardless of the smartphone's position, the Z-axis always indicates the rotation that a user performs on the ground. It is important to note that there is never a single axis rotation independent of the other axes when a pedestrian is walking.

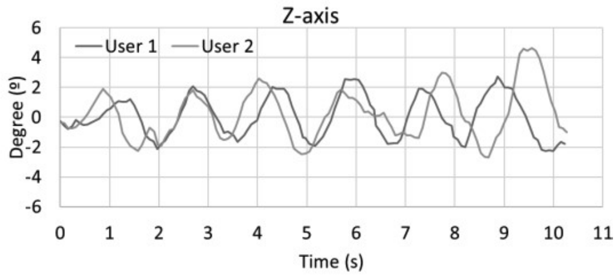
An advantage of the strategy developed is that the fuzzy labels used as rotation detector inputs are automatically established from the sensor calibration process performed by the user. This process is necessary since, as shown in Figure 16, two different individuals have different gaits (i.e., walking styles) and generate



(a)



(b)



(c)

Figure 16. Comparison of two pedestrian gaits over a straight line for 10 seconds

Table 8. Comparison of the rotation values expressed in degrees (º) for each user while walking in a straight line for 10 seconds

	User 1				User 2			
Axis	**Avg**	**Std. Dev.**	**Max.**	**Min.**	**Avg.**	**Std. Dev.**	**Max.**	**Min.**
X	0.079	0.278	1.080	-0.520	-0.089	0.772	1.670	-2.030
Y	0.018	0.380	0.860	-0.830	0.046	1.010	2.680	-2.390
Z	0.059	1.397	2.710	-2.280	0.222	1.702	4.630	-2.690

different rotations. The graphs in Figure 16 depict the rotation on the X-, Y- and Z-axes produced by two volunteers as they take a straight line for 10s. As seen in all cases, the first user produces more complex oscillations than the second user. As a result, it is obviously found that user 2 causes more movements when walking than that generated by user 1. Complementarily, Table 8 lists the average, standard deviation, maximum and minimum values of each user for each axis. These values comprehensively demonstrate that it is necessary to calibrate the fuzzy detector due to the very high differences that exist between the two users when walking.

The label calibration process of the "fuzzy rotation detector" consisted in instructing the user to stop still for 5s to prevent from wrong oscillations and then walking for 12s in a straight line. At the end of the calibration, the maximum and minimum rotation values generated by a pedestrian for each of the XYZ axes were determined. From these values, the membership set of the input variables for each axis is determined as set out in Equation (1) and Table 9. The value "axisDifference" in Table 9 corresponds to the top plateau of the trapezoid in Figure 17 labeled as "Stable difference". V1, V2, V3 and V4 values are calculated according to the form expressed in Table 9.

$$axisDifference = |minimum\ axis\ value| + |maximum\ axis\ value| \quad (1)$$

The "fuzzy rotation detector" block is used as the input for the "fuzzy crossing intention detector" block that performs the system sensory fusion (Figure 15). Besides this, the sensory fusion method requires –as input– the distance between the pedestrian areas and the optimal route calculated. The latter is computed from the pedestrian's current position to the pedestrian's next point collected on the route. To this end, the user should indicate the walking mode to set a greater or lesser distance and fix the detection time around a zebra crossing (i.e., 15, 10 or 5s). The membership functions used to calculate whether a pedestrian is near or far from the POI are shown in Figure 18, which are based on trapezoidal membership sets. The set of values of the membership functions is determined by selecting the walking mode that the user does. These fuzzy sets have been built considering a GPS sensor position error around one meter. In the worst case, the crossing intention can be

Table 9. Definition of membership sets for each axis

Label	V1	V2	V3	V4
Negative difference	-90º	-90º	Min. axis value - axisDifference	Min. axis Value
Stable difference	Min. axis value - axisDifference	Min. axis value	Max. axis value	Max. axis value + axisDifference
Z-axis	Max. axis value	Max. axis value + axisDifference	90º	90º

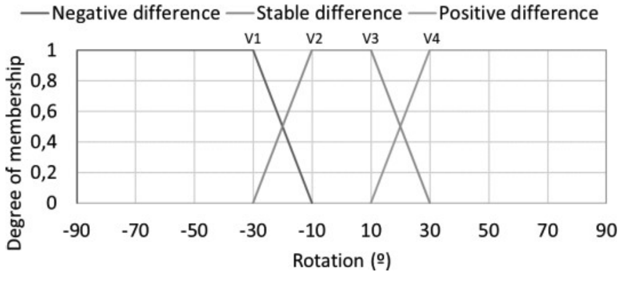


Figure 17. Fuzzy inference system structure to detect the pedestrian's crossing intention

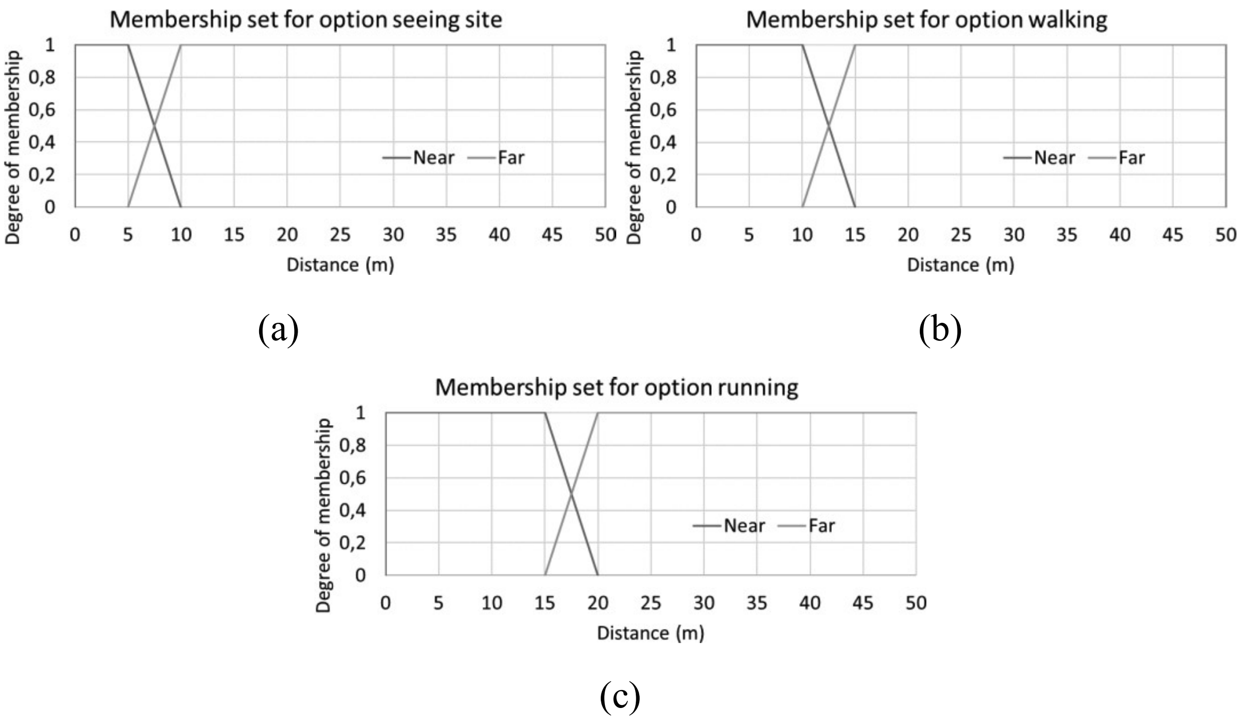


Figure 18. Fuzzy sets used to determine how far a user is from the next pedestrian POI based on its options

safely determined with at least a distance of 5m to the POI, although it could be determined from 7.5 m with enough certainty as shown in Figure 18a. Finally, as in the case of the rotation detector, the output is also a singleton that allows to indicate whether the intention to cross a crosswalk has been detected or not. The set of fuzzy rules used settles that the pedestrian's crossing intention will only be detected when he/she is near the next pedestrian POI on the safe route and he/she is also performing a rotation.

3.3.2.3 Pedestrian Visualization Aid System

An additional function has been included to add value to the app. This can communicate with the intelligent crosswalk –described in the previous sections– to alert drivers about the presence of pedestrians with the intention to cross a zebra crossing. The interaction between the app and the intelligent crosswalk is managed by a gateway that can communicate with the app via Bluetooth and with the nodes of the intelligent crosswalk via Wi-Fi (Figure 19). To this end, a Raspberry Pi 3 device has been selected to implement the functions of that gateway.

The app makes use of the Bluetooth Low Energy (BLE) service implemented in Bluetooth 4.0. For this purpose, a BLE server has been deployed in the mobile application to provide information about the crossing intention of pedestrians. The service can send the values "intent to cross detected" or "intent to cross not detected"

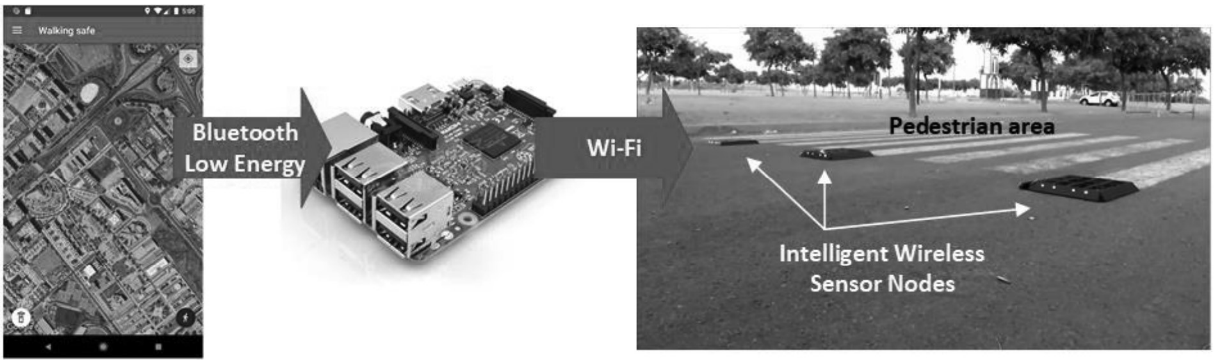


Figure 19. Communication scheme used between the app and the intelligent crosswalk

from the fuzzy detector described above. To do this, the app makes use of the basic BLE profile called Alert Notification Profile, a communication profile that implements the "New Alert" feature. The goal is to allow any BLE client to subscribe to the service to receive any status change and then read the status of the pedestrians' smartphones regarding their crossing intention.

In the gateway, a script that allows converting the Raspberry Pi 3 into a BLE client of the app has been implemented in NodeJS. The client relies on the Noble library [127] to make use of the BLE services and on the dgram library [128] to make use of the Wi-Fi communication with the intelligent crosswalk network. The client running on Raspberry Pi 3 connects to the smartphones once they enter the Bluetooth range and subscribes to the New Alert feature offered by the app. In case the app issues a notification, it is processed by the client; if it indicates that the person intends to cross the intelligent crosswalk, the client sends an activation message to the crosswalk's smart nodes to generate a visual barrier on the roadway that allows vehicles to stop safely, further increasing the smartphones' safety functions.

It is important to note that the application allows to indicate optionally how often the Bluetooth communication is activated. The option allows to keep Bluetooth always on or to activate it automatically when the smartphone is 30m away from a crosswalk. This way, it is possible to reduce the energy consumption of the resources.

Chapter 4. Results & Discussion

4.1 Article 1

Design, Modelling, and Implementation of a Fuzzy Controller for an Intelligent Road Signaling System

Lozano Domínguez, J.M., Mateo Sanguino, T.J.

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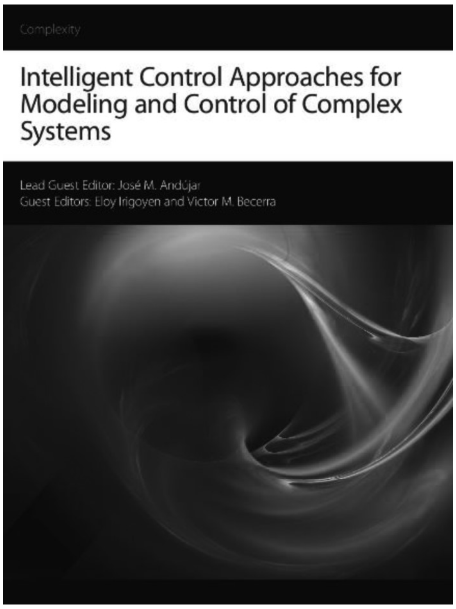

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Research Article

Design, Modelling, and Implementation of a Fuzzy Controller for an Intelligent Road Signaling System

José Manuel Lozano Domínguez and Tomás de J. Mateo Sanguino

Departamento de Ingeniería Electrónica, Sistemas Informáticos y Automática, University of Huelva, Ctra. Huelva-La Rábida S/N, Palos de la Frontera, 21819 Huelva, Spain

Correspondence should be addressed to José Manuel Lozano Domínguez; josemanuel.ldominguez@alu.uhu.es

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Crossing points are not always 100% visible for drivers due to different factors (e.g., poor road maintenance, occlusion of vertical signs, and adverse weather conditions). USA estimated in 2015 the number of traffic accidents involving pedestrians and vehicles in 70,000 of whom 5,376 resulted in deceased people. To contribute in this field, this paper presents the design, implementation, and testing of a smart prototype system applied to pedestrian crossings—not regulated by semaphores—which try to reduce the accident rate on roads. The hardware and software system consists of a set of autonomous, intelligent, and wireless low-cost devices that generate a visual warning barrier perceived by drivers from a suitable distance when pedestrians traverse a crosswalk. In this way, drivers can reduce the speed of their vehicles and stop safely. The system's intelligence is carried out by a fuzzy controller that performs sensory fusion at both low level and high level with various types of sensors from local and neighboring devices. The tests conducted have determined an average success of 94.64% and a precision of 100%, thus corresponding with a very good test according to a ROC analysis. As a result, the system proposed has been patented and extended to international PCT.

1. Introduction

According to a recent report published by Goodyear and RACE (acronym for Real Automobile Club of Spain), around 10,000 accidents of pedestrians occur every year in Spain of whom 9,289 happened in urban areas, 222 resulted in death, and 2/3 were attributed to drivers [1]. Other studies also estimate 40% of the accidents when pedestrians are crossing through the right place [2]. According to a barometer from CIS—a Spanish sociological investigation center—the main causes of the accidents are mistakes and distractions of drivers (8.25%), lack of civic education (7.87%), poor road conditions (6.80%), and deficient signaling in some tracks (6.58%), among others [3]. A similar study published in USA estimated in 70,000 the number of traffic accidents in 2015 with pedestrians and vehicles involved. Of them, 5,376 resulted in deceased people, which has significantly increased in the last decade up to 15% according to the National Highway Traffic Safety Administration [4]. Its study determined that 78% of the accidents occur in low visibility conditions, resulting in 74% at nighttime and 4% during the sunrise or sunset. Thus, pedestrian crossings are not always 100% visible due to different factors: (i) poor road maintenance (e.g., blurring lines due to the vehicle passing), (ii) occlusion of vertical signs (vegetation, large vehicles, etc.), and (iii) adverse weather conditions (e.g., rain, fog, or obscurity), among others. The distance at which drivers begin to brake the vehicle is decisive in the severity of the accident and the prevention of it. Hence, to improve the perception of drivers upon pedestrians is a key goal whether accidents or the severity of injures in zebra crossings needs to be reduced [5, 6].

There are different solutions in the state of the art with the common aim of decreasing the number of accidents in crosswalks. They are classified into devices on board vehicles to detect pedestrians and approaches located on the road to detect both pedestrians and vehicles.

Regarding the first group, techniques and devices being included in vehicles aim to actively detect pedestrians to alert drivers. Such is the case of a prototype based on RADAR,

Table 1: Comparison of features and capabilities for various approaches in the state of the art.

System reference	Safety	Autonomous	Wireless communication	Environment interaction	Public work	Cost
[7–9]	On car	No	No	√	No	High
[10]	On road	No	No	No	√	High
[11]	On road	√	No	No	√	High
[12]	On road	No	No	√	√	High
[13]	On road	No	No	√	√	High
[14]	On road	No	No	√	√	High
[15]	On road	No	No	√	√	High
[17]	On road	No	No	√	√	High
[19]	On road	No	No	√	√	High
[20]	On road	√	√	No	√	High
Proposed	On road	√	√	√	No	Low

camera, and sensory fusion devised to warn of possible collisions [7]. This system is similar to that of cameras, sensors on windshields, and bumpers that other proposals such as Ford Mondeo, Mercedes S Class, or Nissan from the UC3M (Universidad Carlos III de Madrid) implement on cars [8, 9]. However, these systems require the collaboration of the automotive industry to standardize and implement electronics on board. Moreover, these approaches represent personal devices not available to all users. That is, the system belongs to the car's owner and it is not permanently available on public roads to all users.

In relation to the second group, very different concepts exit as for the type of installation, size, and price. For instance, a road sign formed by a luminous marquee over a pedestrian crossing that incorporates spotlights oriented towards the pavement to improve the driver's visualization on pedestrians [10]; a trapezoidal speed bump placed on the road composed of passive lighting such as small light bulbs, LEDs (light-emitting diode), or optical fiber [11]; a section elevated above the track level like a trapezoidal highlight, where the road sign is made of electroluminous diodes activated by the pedestrian presence in zones of pressure placed at the access [12]; the control of traffic lights by means of the activation by weight of a tile placed on the sidewalk [13]; a horizontal road signaling system for crosswalks consisting of long-range and short-range optical sensors on a vertical support to detect pedestrians and vehicles [14]; a system with photoelectric emitters/receivers placed on the sidewalk to detect pedestrians that activates luminous devices located both in the periphery of the crosswalk and vertically on the sidewalk [15]; a proposal of super-safe smart crosswalk that detects persons at the entrance and exit of the pedestrian crossing and projects a virtual light barrier to warn drivers [16]; an embedded system on the sidewalk that carries a camera in charge of taking images of the pedestrian crossing to visually warn drivers when people is traversing [17]; a Japanese system implemented by Philips that warns pedestrians about the proximity of electrical silent vehicles near crosswalks [18]; a device that protects zebra crossings through warning lights placed on the sidewalk, which contains presence sensors for pedestrians and vehicles [19]; and a crosswalk alert system based on a mast over the sidewalk which includes intermittent lights, solar cells, and wireless communication as a means of synchronizing the signaling with the opposite mast and where the trigger is a mechanical switch operated by the pedestrians [20].

The solution proposed in this paper is classified into the second group presented in the state of the art, that is, experimental systems placed on the road that detect both pedestrians and vehicles. Despite the variety of proposals found in the literature about this, they have not been widely deployed in our cities yet. The main reason is the high cost of some approaches requiring a fixed installation on the road pavement or the need for large supporting structures over the sidewalk. Our proposed system comprises a set of smart sensor devices with capability to alert drivers. The action performed consists in differentiating if there are people traversing the zebra crossing, then communicating that situation to the rest of the system nodes, and turning on synchronously the signaling as a visual barrier to alert drivers in order to safely stop their vehicles.

In summary, Table 1 compares the main features of some representative proposals in the state of the art in relation to our solution. The proposed system has several innovative features: (1) low-cost installation since it does not require public works; (2) minimum impact on traffic and users due to its small size; (3) autonomy since it does not require an electrical wiring infrastructure; and (4) intelligent control since it interacts with the environment.

Since the system is based on modular devices acting autonomously, this allows us to adapt the number of nodes depending on the crosswalk topology (one-way route, two-way route, multilane route, etc.). This in turn constitutes another advantage because if a node stays out of service, the rest of the system can keep on operating. Another interesting aspect is its low cost compared with other existing proposals, being an advantage for the final real deployment in urban environments. The system neither needs expensive installation in roads nor mobilizes large machines to do electrical wiring ditches. The size of the system modules is small, being placed on the road directly. Neither big luminous panels nor infrastructures placed in the road or sidewalks are necessary,

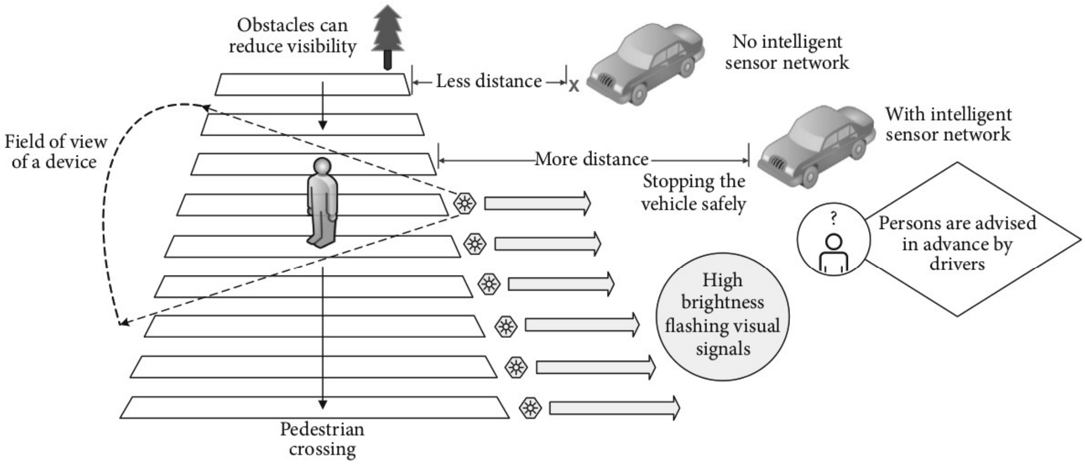

Figure 1: General depiction of the smart road signaling system.

thus presenting a minimal impact on users. Moreover, it is not necessary to connect the system to the power grid, thus obtaining energetic and economical savings. Nevertheless, the proposed system presents some disadvantages regarding the other solutions mentioned as it can be the autonomy beyond ~30 hours at full capacity. Finally, devices can get dirty by the vehicle transits and then loose energy-gathering capacity by being formed by solar cells.

This paper aims at the following significant contributions: (1) design, implement, and prove the feasibility of an autonomous smart system able to actively interact with the environment to detect pedestrians on zebra crossings; (2) generate an innovative way of light signaling to prevent drivers from pedestrians traversing roads; (3) quantitatively measure and analyze the system impact on the improvement of the road safety. Thus, this manuscript is structured as follows: Section 2 describes the general system, hardware elements, and modelling software designed for doing sensory fusion. Section 3 shows the experiments carried out and the results. Finally, Section 4 presents the findings as well as the future works of the proposed system.

2. Smart Road Signaling System

Based on the goals, the intelligent road signaling system consists of a variable number of devices which has been patented and extended through an international cooperation treaty to ARIPO (African Regional Intellectual Property Organization), OAPI (Organisation Africaine de la Propriété Intellectuelle), Eurasia, and Europe [21]. The devices aforesaid are arranged on longitudinal form around the crosswalk limits—depending on the lane topology—until covering the total road width and separated several centimeters between them so that each one covers a sector (Figure 1). Hence, when a pedestrian is detected by a device, the system is wirelessly synchronized to generate a visual intermittent signal which creates the sensation of a visual barrier over the road. This is caught by drivers and perceived as a warning light signal.

2.1. Hardware Description. The system is based on small autonomous devices that comprises a control unit, detection unit, signaling unit, power unit, real-time unit, and data storage unit (Figure 2). A transducer for the pedestrian detection is oriented towards the interior of the crosswalk while another transducer for the vehicle detection and the signaling unit is oriented towards the traffic flow. The cost of the prototype including the electronics and housing is about 1225€ per device, which maintains the advantage over other higher cost solutions.

2.1.1. Control Unit. The prototype is based on a 32-bit RISC (reduced instruction set computing) microcontroller (80 MHz, 1-MB RAM) with integrated wireless module including the IEEE 802.11 b/g/n/d/e/i/k/r standards [22]. Its function is to manage the electronics within the same node, process both the internal and external data, and provide intelligence to the overall system. To this end, the developed prototype utilizes proximity sensors that provide measurements proportional to distance unlike the presence sensors used in other road signaling approaches that only deliver binary signs of type "all/nothing." This feature allowed us to perform analyses on object proximity over time, which offers a major operation capability in contrast to conventional presence sensors that only determine if an obstacle exists or not. As main benefit, this lets us to immerse the detection sensors within the road along the pedestrian crossing (i.e., the sensors are not located in the sidewalks as for the most approaches in the state of the art).

The intelligence is supported by operating rules based on fuzzy logic—which helps to decrease the number of false positives [23]—and other coordinated techniques [24] that process the information of the internal sensors of the same device and from other neighboring devices. This strategy allows improving the system accuracy and discerning between vehicles and people to generate visible signs only when objects are pedestrians and not vehicles. Furthermore, the nodes are connected through a WLAN (wireless local

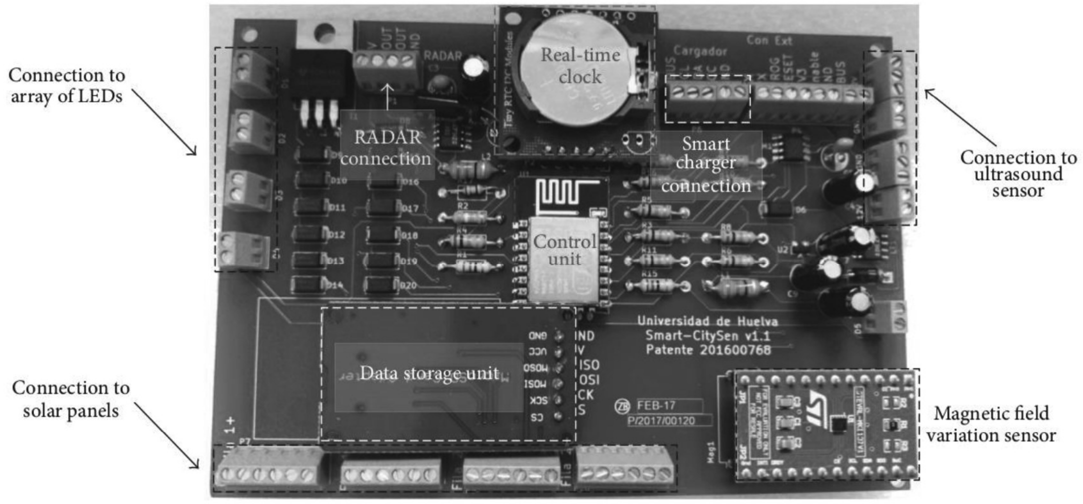

Figure 2: Outline of the inner electronics of the prototype system.

area network) with RF (radio frequency) technology whose function is to synchronize the devices' visual signposting through the system.

2.1.2. Detection Unit. Three sensors based on ultrasound, magnetic field variation, and RADAR were used in order to sense different objects around the crosswalks. Each of the sensors is oriented towards the type of object to be detected (i.e., ultrasound to pedestrians, magnetic and RADAR to vehicles). It is thereby possible to detect a pedestrian when entering to the zebra crossing from the entry points at the sidewalks or across any intermediate position from the road (e.g., when walking diagonally). In addition, it is possible to determine if there are vehicles circulating upon the pedestrian crossing. As an example, when a detection unit perceives a pedestrian approximation, the control unit activates the signaling. On the contrary, when a detection unit identifies a vehicle, the system disables the luminous barrier to avoid false positives.

The ultrasound sensor works at 42 KHz and can detect pedestrians at a distance between 0.6 and 5 meters. The magnetic field sensor provides detection in the x-, y-, and z-axes with a sensibility up to ±16 Gauss, being capable of detecting vehicles circulating at 50 Km/h with a resolution in the order of centimeters. Additionally, the RADAR improves the sense of other vehicles that come frontally to the crosswalk from a distance between 10 and 20 meters (e.g., bicycles compounded of materials as aluminum or carbon not detected by the magnetic sensor). To this end, we utilized a Doppler-based RADAR working in the X-band in CW (continuous wave) acquisition mode with EIRP (effective isotropic radiated power) of 15 dBm.

2.1.3. Signaling Unit. The prototype system includes a set of high brightness LEDs which are visible under both low contrast and high contrast conditions (i.e., during day and night). An array of four LEDs is oriented to drivers to alert the pedestrians' detection while another one is directed oppositely towards the pedestrians to indicate the system activity and facilitate the decision-making before crossing. The selected LEDs produce white cold light (7000°K) up to 140,000 mCd (4.82 lm) and can be seen from an angle of vision of $12^{\circ} \pm 6^{\circ}$. The road signaling presents an intermittent pattern (i.e., activation of 75 ms during 5 s) which is managed by the control unit through a low consumption strategy performed by means of a PWM (pulse-width modulation) control. The frequency has been selected experimentally so that the refreshment of the LEDs is not perceived by the human eye at the same time that it reduces the system consumption.

2.1.4. Power Unit. The supply of the system consists of a matrix of 12 solar panels of monocrystalline Silicon of $92 \times 54 \times 3\,\text{mm}^3$ with maximum power of 15 W, a rechargeable Li-Po (Lithium polymer battery) of 9000 mAh (3.7 V, 1 C) with autonomy up to 29.89 hours, and a smart charger circuit with PPM (power path management). This allows supporting 25.52 Wh/day or energy consumed in a day by the system without getting any additional energy. To size the power supply unit, we used the latitude of Huelva (37.2583N, −6.9508W) during December as the period of minor daily solar insolation (2.12 kWh/m^2/d)—or energy produced by the Sun in one m^2 per day—and a solar cell performance of 75% as reference. See Table 2 for further details.

In order to increase the autonomy of the system, a strategy to reduce the power consumption depending on the hour of the day was implemented. For it, a study carried out by means of Google™ Maps allowed us to know the time of the major pedestrians' attendance taking several ROIs (region of interest) of the city as reference (e.g., shopping centers and the historic city center). It was determined that the hours with major agglomeration of people were mainly distributed in the time slots between 12–14 hours and 18–20 hours. In addition, it gave us an idea of the hourly intervals of highest danger for pedestrians. Accordingly, in Figure 3, "Activated"

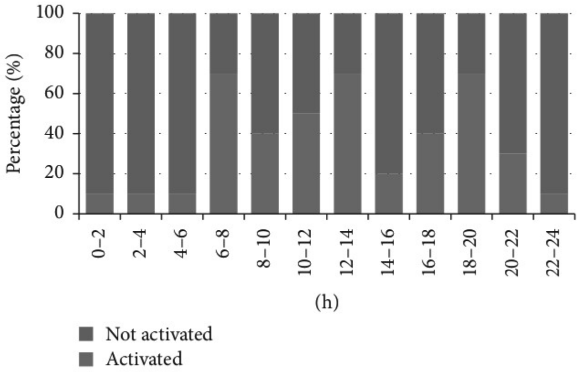

FIGURE 3: Timetable for the low-power consumption strategy. In blue, the estimated percentage of time that pedestrian crossings are typically used by people. In red, the estimated percentage of time that pedestrian crossings are not used by people.

TABLE 2: Average daily solar insolation (kWh/m^2/day) in Huelva order by month.

Month	Insolation
January	2.15
February	3.20
March	4.53
April	5.52
May	6.82
June	7.25
July	8.13
August	7.27
September	6.00
October	4.10
November	2.60
December	2.12
Average of year	4.98

Estimated time of battery charging: 2 hours and 12 minutes.

(blue label) indicates the estimated percentage of the hourly section in which pedestrian crossings are utilized by people, while "No Activated" (red label) means the percentage in which the pedestrian crossings are not utilized by people. The whole strategy consisted in fitting the LED lighting and the reading frequency of the system's transducers based on the pedestrian attendance and battery charge level. This allows increasing the battery life up to 5.8% in average. Although not significant, the electrical consumption has been one of the major challenges in this project.

2.1.5. Additional Units. To take a count of the operations carried out by the system such as the pedestrian detection, errors in units, and operating parameters, each device incorporates a data storage unit and a real-time clock unit. The storage electronics comprises an external solid state memory (i.e., 8-GB microSD card) that allows extending the storage capacity to implement a local database in each device. This database stores all the events that happen both in the surrounding environment and in the inner device for further analysis. To this end, the real-time unit provides a date and hourly stamp for all the actions carried out by a device.

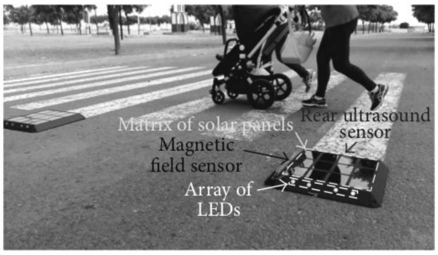

FIGURE 4: Example of the prototype developed on the road.

2.1.6. Wireless Communication. The wireless communication unit is entrusted to transfer data between the system's nodes within the WLAN. One of the devices has the role of AP (access point), whose function is to manage and control the network operation. The rest of the devices work as clients such that when one of them detects an object, a broadcast message is sent towards the rest of the nodes in the WLAN.

The PHY (physical) layer has been implemented within the microwave band at 2.4 GHz, the MAC (media access control) layer utilizes the IEEE 802.11n standard at 300 Mbps with optional WPA/WPA2 (Wi-Fi protected access) encryption [25], the network layer uses unicast and broadcast IPv4 (Internet Protocol version 4) addresses, the transport layer has been implemented with UDP (user datagram protocol) since it accelerates the message delivery with regard to TCP (transmission control protocol) by dispensing with ACK (acknowledgment) messages as discussed in [26], and the application layer is based on the M3 (Machine-to-Machine Measurement) framework to exchange structured information between nodes [27, 28]. This standard declares semantic rules that help to identify clearly the source of a message, what fields it contains, the values of the fields, and its units.

2.1.7. Placement of the Device. The prototype's housing has been constructed with a CNC (computer numerical control) machine that protects the inner electronics (Figure 4). The case is arranged in a matrix of 4 × 3 high quality tempered glasses (10*H* hardness, transmittance of 88–92%) with enough thickness to support the weight of the vehicles up to $8.16 \cdot 10^6$ N/m^2 in compression and preventing the solar panels' surface from being damaged. The complete structure fulfills the IP67 standard of protection against dust and liquids. It has been fixed on the road by means of bituminous adherent (e.g., warm tar), epoxy glue (i.e., thermostable polymer hardened by a catalyst agent), or mechanical anchorage by means of screws (e.g., wall plug and lag screw). The housing does not need public works for its installation on the road. Moreover, it is reusable when a reasphalting of the road surface is required. The shape of the case presents a nonslipping knurling texture to avoid falls of pedestrians or bicycles, as well as a trapezoidal profile with

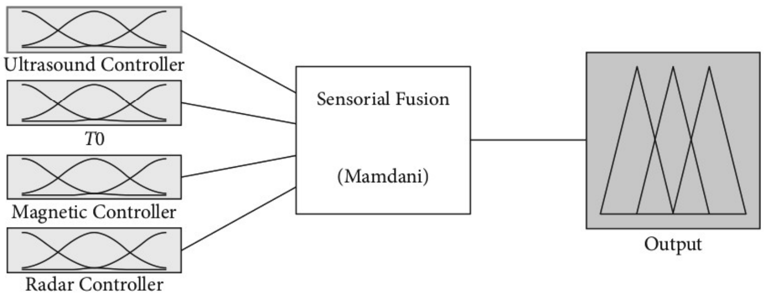

FIGURE 5: Structure of the fuzzy inference system.

a maximum size of $540 \times 500 \times 45\,\mathrm{mm}^3$ and 45° of angle of attack to facilitate the vehicle movement. These features comply with the recommendations of the Spanish Ministry of Promotion [29].

2.2. Fuzzy Model. The device's intelligence consists of a sensory fusion process of association, correlation, and combination of information based on fuzzy logic. Specifically, we have used the three-level abstraction model of Dasarathy [30] to combine sensor measurements and high-level decisions (e.g., if a pedestrian exists or not upon the crosswalk). The measurements are fused in a cooperative way when coming from different sensors within the same device (i.e., ultrasound, RADAR, and magnetic field) and redundantly when belonging to the same sensor in several neighboring devices.

The model implemented is based on a Mamdani fuzzy controller with linguistic rules such as "*If X1 is A1 and* ... *and Xn is An, Then Y is B*" in which both antecedents and consequents are labels and rules obtained with an expert system [31]. Systems described in [32, 33] present an inference system similar to that described in this paper. Considering the number of tags (t) and input variables (n) to use, the complexity is raised to (t^n). Since the system has a high number of inputs and tags, a hierarchical structure with several controllers was designed to keep the rules in a number easily manageable by the expert. The membership of a fuzzy set is defined by trapezoidal functions—as they adequately model the system behavior and are not computationally complex—where the conjunction and implication operators use the minimum T-norm [34]. Moreover, the defuzzification process uses the FITA method (i.e., First Inter, Then Aggregate) since it is more consistent than FATI [35] and the MVP (Maximum Value Point) weighting method, also called weighted average method [36].

The system's sensory fusion has been modelled through the Fuzzy Logic Toolbox™ from Matlab® (Figure 5). This implementation is similar to that described in [37]. The "Ultrasound Controller" block manages the fusion of the ultrasound sensors from the local device and the remote ones at the neighboring nodes; its output indicates whether an obstacle exists on the pedestrian crossing. The "Magnetic Controller" is in charge of fusing the sensors of magnetic field variation and determining vehicles arriving at the zebra crossing; its output updates a temporary variable "$T0$" useful to control slow traffic or stationary traffic that could generate false positives due to vehicles staying a long period of time over the crosswalk. The "Radar Controller" is entrusted of fusing the RADAR sensors and determining if an object approaching the zebra crossing is vehicle or pedestrian. Finally, the "Sensorial Fusion" block determines whether a pedestrian on the crosswalk exists by fusing the outputs from the previous fuzzy controllers.

To sum up, the signaling unit within a device is activated in case of positive detection (i.e., a pedestrian) and the whole system is synchronized by a broadcast message sent over the network to activate the nodes' signaling units. When the sensory fusion detects a vehicle, through either the magnetic sensor or the RADAR, an inhibition message is sent to avoid false positives. As an example, a number of cases with pedestrians and vehicles—either circulating, stopped, or parked—interacting around a crosswalk is shown (Figure 6). The system activity, formed by several nodes, is depicted at the bottom of the zebra crossings. The devices are colored in green when an object is detected on the pedestrian crossing by the ultrasound sensor, in blue when detected by the magnetic sensor, in red when detected by both the magnetic sensor and the RADAR, and in black when there is no presence of pedestrian or vehicle.

The various scenarios consist of a crosswalk without any agent (Case 0), a pedestrian entering and walking through the crosswalk (Cases 1 and 2), a vehicle navigating along the road (Case 3), a vehicle approaching the zebra crossing while a pedestrian begins to cross (Case 4), a vehicle approaching the crosswalk when a pedestrian is crossing (Case 5), a vehicle stopping or parking (Case 6), a vehicle stopping when a pedestrian begins to cross (Case 7), a pedestrian crossing and a vehicle stopping near the crosswalk (Case 8), and a vehicle detected by the magnetic and ultrasound sensors but not detected by the RADAR (Case 9), as well as a vehicle stopping while a pedestrian was crossing (conflictive case). The last example represents the most problematic scenario, which is addressed for the following fuzzy logic.

2.2.1. Ultrasound Fuzzy Controller. This block utilizes three inputs comprising normalized measurements from the ultrasound sensors at the local, right, and/or left nodes. The normalization allows using more than one transducer with different radiation patterns to adapt the azimuthal and horizontal range based on the device's position regarding

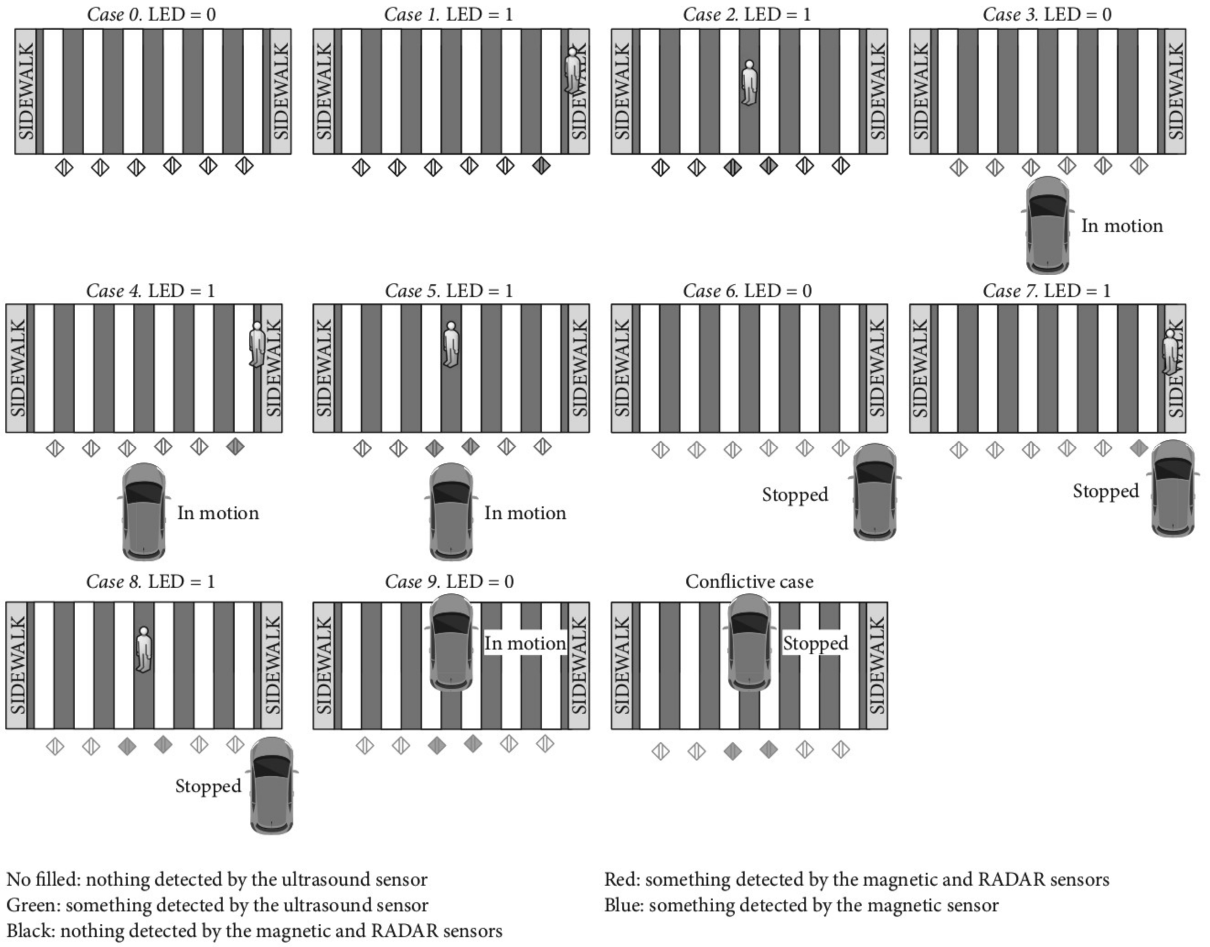

Figure 6: Case studies of the system operation.

the way (e.g., in the middle of the crosswalk or close to the sidewalk). The behavior of the ultrasound sensor versus temporary samples can be observed in Figure 7.

Each input has three tags meaning the distance of the obstacle in front of the sensor, being *Far*, *Medium*, and *Near* (Figure 8). The *Far* tag indicates that the object is not detected or is detected in a ROI external to the crosswalk. The *Medium* tag means that the object is detected in an uncertainty area or it is not detected with enough precision by the sensor. The *Near* tag points out an obstacle existing on the zebra crossing that is clearly perceived.

The output of the controller provides values within [0, 1], whose range stands for the grade in which an object exists over the crosswalk expressed by means of two labels (*No* and *Yes*). Thus, a value near zero (0) means that an obstacle does not exist while a value close to one (1) indicates that it exists. In that case, it must be inferred by the rest of the fuzzy system whether the object is vehicle or pedestrian to activate the signaling unit.

The rules base and tags of the fuzzy controller were tuned experimentally by an expert system (Table 3). Since an ultrasound sensor typically has a nonlinear response whose error increases due to distance, it was established that three inputs declaring a *Far* tag after the defuzzification process means no obstacle on the crosswalk. On the contrary, two inputs with the *Medium* tag or one input with the *Near* tag signifies the presence of an obstacle.

2.2.2. Magnetic Fuzzy Controller. This block uses an input per axis (x, y, and z) with three labels for each one called *Far*α, *NearN*α, and *Near*α, being (α) the corresponding axis (Figure 9). The *Far*α tag stands for the value during the idle state of the magnetic field sensor, while *NearN*α and *Near*α indicate a magnetic field variation below and above the idle state, respectively. This variation is represented versus temporary samples (Figure 10).

The output of the magnetic fuzzy controller has been modelled with two tags ranging from 0 to 1 (*No* and *Yes*), where values near zero mean no vehicle close to the zebra crossing and values near one indicate the presence of a vehicle. Similarly, both the rules base and tags of the fuzzy controller were experimentally fitted by the expert system (Table 4). It was determined that a variation of the idle state at least in two of three axes of the magnetic sensor indicates

Table 3: Rule base for the ultrasound fuzzy controller.

Rule number	Local device	Left neighbor	Right neighbor	Obstacle
1	Far	Far	Far	No
2	Far	Far	Medium	No
3	Far	Far	Near	√
4	Far	Medium	Far	No
5	Far	Medium	Medium	√
6	Far	Medium	Near	√
7	Far	Near	Far	√
8	Far	Near	Medium	√
9	Far	Near	Near	√
...	...	...	...	...
27	Near	Near	Near	√

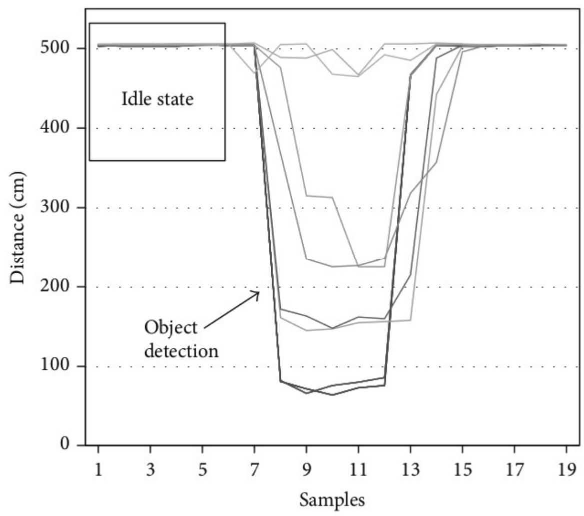

Figure 7: Detection of a pedestrian when crossing a crosswalk at different distances expressed in several colors. Blue and red show the detection of a pedestrian crossing at 100 cm away from the sensor, green and purple crossing at 200 cm, orange and light blue crossing at 300 cm, and pink and light purple crossing at 400 cm. For each distance there are two colors meaning the test crossing from right to left and vice versa. The range measurements taken by the sensor are shown on the y-axis while the temporary samples are observed on the x-axis.

presence of a vehicle driving around the zebra crossing; otherwise a vehicle does not exist.

2.2.3. Temporary Variable. The output of the magnetic fuzzy controller has the additional function of updating a counter called "$T0$" to measure the time elapsed since the sensor did not detect a vehicle, that is, to count the time elapsed since the output of this controller was near zero. This variable is useful to resolve conflictive cases—as that depicted in Figure 6—where it is necessary to know whether a vehicle is sited over the zebra crossing (i.e., constant values close to one).

Table 4: Rule base for the magnetic fuzzy controller.

Rule number	x-axis	y-axis	z-axis	Vehicle
1	Far$x$	Far$y$	Far$z$	No
2	Far$x$	Far$y$	NearNz	No
3	Far$x$	Far$y$	Near$z$	No
4	Far$x$	NearNy	Far$z$	No
5	Far$x$	NearNy	NearNz	√
6	Far$x$	NearNy	Near$z$	√
7	Far$x$	Near$y$	Far$z$	No
8	Far$x$	Near$y$	NearNz	√
9	Far$x$	Near$y$	Near$z$	√
...	...	...	...	...
27	Near$x$	Near$y$	Near$z$	√

According to this logic, the temporary fuzzy controller was modelled with three tags called *Little*, *Medium*, and *Much* (Figure 11). The *Little* tag stands for a small period of time since the magnetic sensor detected the presence of a vehicle, *Medium* indicates that a certain time has elapsed—but not sufficiently large—since there was a vehicle on the zebra crossing (e.g., stopped), and *Much* indicates an interval of time large enough since the magnetic sensor detected the presence of a vehicle (i.e., parked).

2.2.4. RADAR Fuzzy Controller. The inputs defined in this controller block are the *State* and *Speed* variables (Figure 12). The first one stands for a digital output from the RADAR that points out the presence of an object in the FOV (field of view) of the sensor. So, the *State* tag indicates if there is an object present, where values close to zero (0) specify no object existing *(low)* and values close to one (1) indicate an object being detected *(high)*. The *Speed* variable consists of two tags (*Minor* and *Major*) to designate values higher and lower than 5 Km/h. This value—experimentally determined (Figure 13)—stands for a speed threshold above which any detection belongs with certainty to a vehicle (i.e., everything that is not a pedestrian moving on foot).

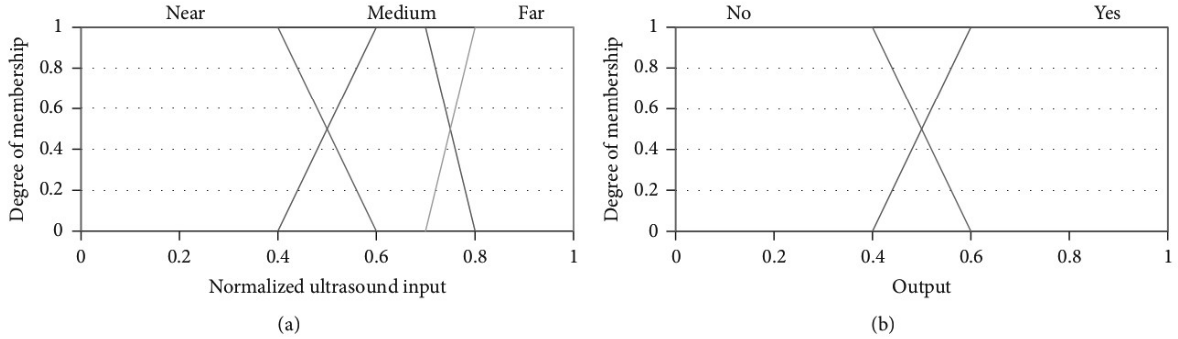

FIGURE 8: Labels for the ultrasound fuzzy controller: (a) input and (b) output.

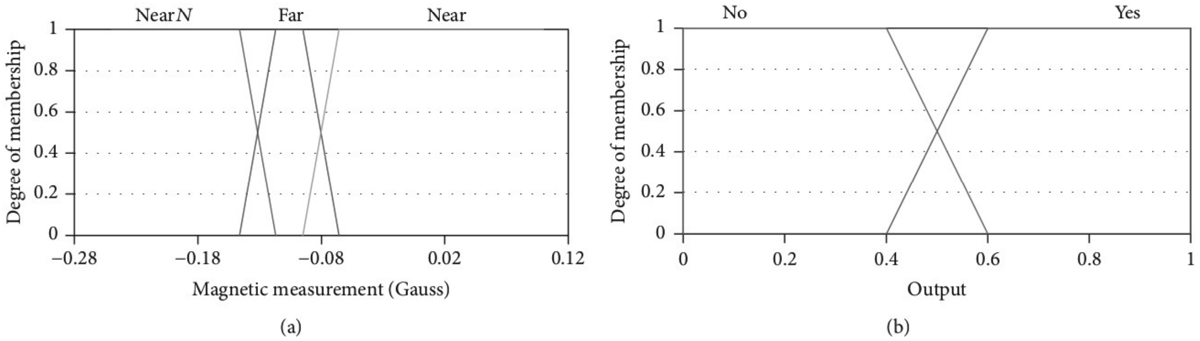

FIGURE 9: Labels for the magnetic fuzzy controller: (a) input for an axis and (b) output.

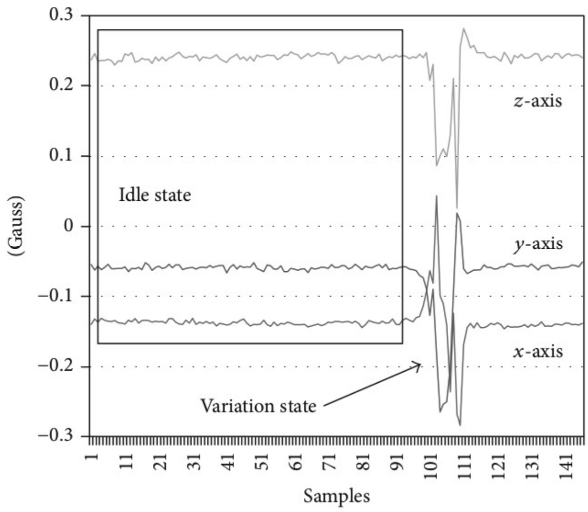

FIGURE 10: Detection of a vehicle by the magnetic sensor. The idle state and variation state are caused by the penetration of a car in the magnetic field. The Gauss measurements taken by the sensor are shown on the y-axis while the temporary samples are observed on the x-axis.

The output of the fuzzy controller is represented by the *Pedestrian* and *Vehicle* tags in the range within $[0, 1]$, meaning the values near zero (0) a *Pedestrian* and the values near one

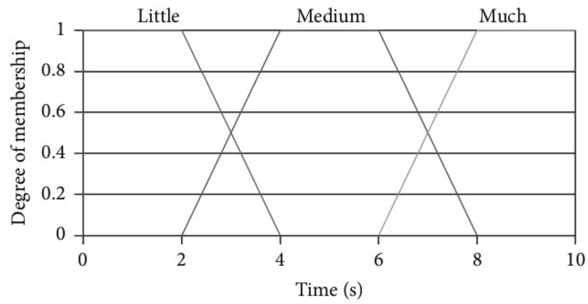

FIGURE 11: Labels for the temporary variable ($T0$).

(1) a *Vehicle*. The rules base of the fuzzy controller has been made experimentally by the expert system, which determined that an object speed declared as *Major* with a state designed as *High* stands for a vehicle (Table 5). In any other case, the object will be potentially a *Pedestrian* or a Vehicle at low speed, whose nature must be inferred by the rest of the fuzzy system.

2.2.5. Sensory Fusion Controller. This block is entrusted to fuse all the fuzzy controllers previously described (i.e., ultrasound, magnetic, RADAR, and "$T0$") whose function is generating an output to control the LED signaling unit. The output values have a range within $[0, 1]$, where values near zero (0) indicate that the signaling unit must not be activated

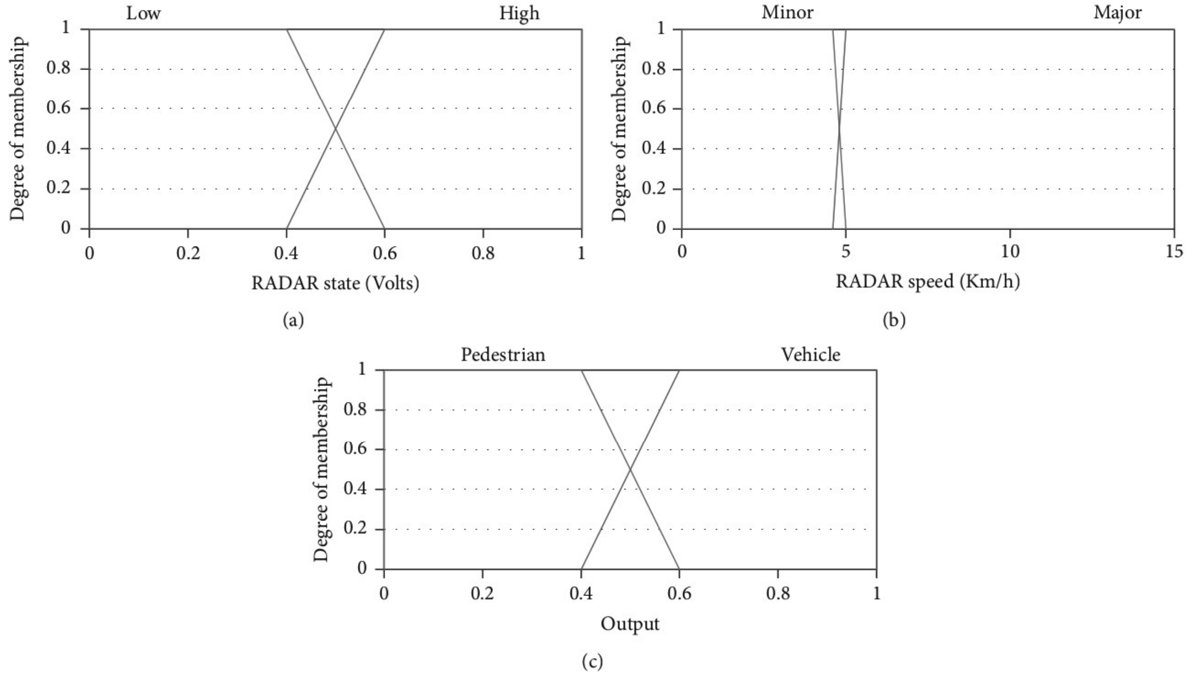

Figure 12: Labels for the RADAR fuzzy controller: (a) input for State, (b) input for Speed, and (c) output.

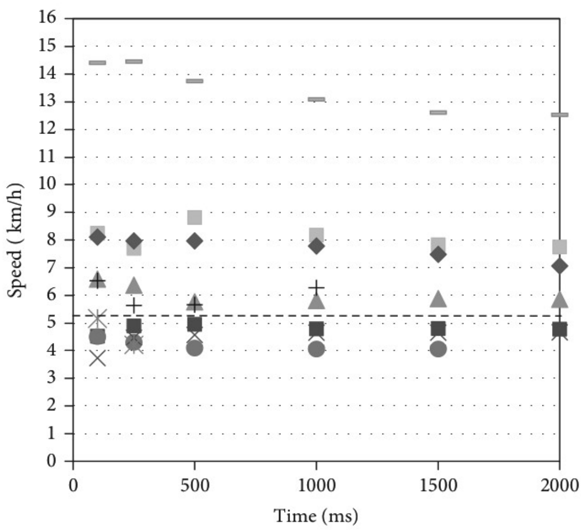

Figure 13: Estimation of the speed threshold between pedestrians and vehicles. Red squares, purple cross, and orange circles below the dashed line stand for a pedestrian. The rest are vehicles.

and values near one (1) indicate that the signaling unit must be activated to alert drivers about pedestrians detected on the crosswalk.

The expert system settled that a pedestrian is detected when the output of the ultrasound fuzzy controller indicates *Yes*, the magnetic fuzzy controller points out *No*, the "$T0$" variable indicates the *Little* or *Medium* tags, and the output of the RADAR fuzzy controller designates *Pedestrian*. In

Table 5: Rule base for the RADAR fuzzy controller.

Rule number	State	Speed	Output
1	Low	Minor	Pedestrian
2	Low	Major	Pedestrian
3	High	Minor	Pedestrian
4	High	Major	Vehicle

this case, it is necessary to activate the LED signaling unit. Otherwise, the pedestrian warning lighting will be disabled (Table 6).

3. Results and Discussion

The experimentation carried out with the prototype system consisted in a total of 240 hours of hardware and software integration, 160 hours of tests in laboratory under controlled conditions, and 65 hours of tests in a real environment. ROC (receiver operating characteristic) analysis, as described in [38], was conducted on the data test achieved from the real scenario to obtain the sensibility against specificity of the system (Table 7). The performance was obtained from a confusion matrix of 2 × 2 elements that relates positive (p) and negative (n) results. In this way, the sensibility or true positive rate (TPR) can be defined as the success rate as follows:

$$\mathrm{TPR} = \frac{\mathrm{TP}}{(\mathrm{TP} + \mathrm{FN})}, \quad (1)$$

where TP stands for the true positives and FN stands for the false negatives. Anyway, the false positive rate (FPR) or

Table 6: Rule base for the whole sensory fusion controller.

Rule number	Ultrasound	$T0$	Magnetic	RADAR	Output
1	No	Much	No	Pedestrian	Deactivate
2	No	Much	No	Vehicle	Deactivate
3	No	Much	Yes	Pedestrian	Deactivate
4	No	Much	Yes	Vehicle	Deactivate
5	No	Medium	No	Pedestrian	Deactivate
6	No	Medium	No	Vehicle	Deactivate
7	No	Medium	Yes	Pedestrian	Deactivate
8	No	Medium	Yes	Vehicle	Deactivate
9	No	Little	No	Pedestrian	Deactivate
10	No	Little	No	Vehicle	Deactivate
11	No	Little	Yes	Pedestrian	Deactivate
12	No	Little	Yes	Vehicle	Deactivate
13	Yes	Much	No	Pedestrian	Deactivate
14	Yes	Much	No	Vehicle	Deactivate
15	Yes	Much	Yes	Pedestrian	Deactivate
16	Yes	Much	Yes	Vehicle	Deactivate
17	Yes	Medium	No	Pedestrian	Activate
18	Yes	Medium	No	Vehicle	Deactivate
19	Yes	Medium	Yes	Pedestrian	Deactivate
20	Yes	Medium	Yes	Vehicle	Deactivate
21	Yes	Little	No	Pedestrian	Activate
22	Yes	Little	No	Vehicle	Deactivate
23	Yes	Little	Yes	Pedestrian	Deactivate
24	Yes	Little	Yes	Vehicle	Deactivate

Table 7: Contingency table for the ROC analysis.

	Actual value		Total
	p	n	
Prediction			
p'	True positives (TP)	False positives (FP)	P'
n'	False negatives (FN)	True negatives (TN)	N'
Total	P	N	

1 − specificity can be defined from Table 7 as the false alarm rate according to the following expression:

$$\mathrm{FPR} = \frac{\mathrm{FP}}{(\mathrm{FP} + \mathrm{TN})}, \quad (2)$$

where FP means false positives and TN means true negatives. Finally, the accuracy (ACC) can be defined as follows:

$$\mathrm{ACC} = \frac{(\mathrm{TP} + \mathrm{TN})}{(P + N)}, \quad (3)$$

where P and N stand for the total positives and negatives, respectively. The tests involved two types of trials: (i) activation of the LED signaling by pedestrians on the zebra crossing and (ii) inhibition of the LED signaling by vehicle traffic on the road. The first trial included the following categories: one pedestrian, two or more pedestrians walking in the same direction, two or more pedestrians walking in opposite directions, a buggy baby, and a bicycle. The second trial included a car, a bicycle, and a motorcycle passing the crosswalk.

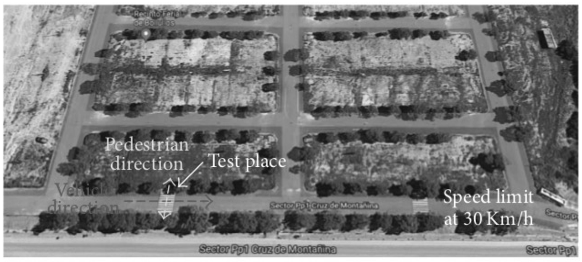

Figure 14: Location of the scenario under study.

To this end, the scenario utilized consisted of a crosswalk sited in "Sector Pp1 Cruz de Montañina" of Bollullos Par del Condado, Huelva, Spain (37.34N, −6.55W). This zebra crossing was selected because it is located on a 180-meter straight track being the speed limited to 30 Km/h (Figure 14). Three prototypes of smart device were installed to cover a crosswalk of 9 meters wide by 5 meters depth. According to (1)–(3), a positive discrimination threshold was established when the object detection was triggered on the first 2/3 of the crosswalk. In other words, a detection on the last 1/3 of the zebra crossing was considered negative in the tests for not achieving the minimum safety requirements for pedestrians.

Table 8: Results obtained in the ROC analysis.

Study case	Test	Speed (m/s)	TPR	FPR	ACC	Success (%)
Pedestrian	148	0.88 ± 0.04	0.8133	0	1	81.33
Buggy baby	33	0.84 ± 0.05	0.972	0	1	97.2
Pedestrian group in same direction	17	0.94 ± 0.05	0.95	0	1	95
Pedestrian group in opposite directions	16	1.05 ± 0.04	0.9433	0	1	94.33
Bicycle as pedestrian	13	1.88 ± 0.14	1	0	1	100
Vehicle (i.e., car, bicycle, and motorcycle)	17	≥ 2.22 <5.55	1	0	1	100
Average	40.66 ± 53.1	1.18 ± 0.43	0.9464	0	1	94.64
Total number of tests	244					

The detection of persons in the direction of the crosswalk consisted in traversing the zebra crossing in different directions: (i) longitudinal movement from right to left and from left to right, meaning as the movement crossing the road from side to side; (ii) transversal movement from back to front and from front to back, meaning as the movement by which a user can enter the crosswalk through any interior point of it; and (iii) diagonal movement from front to back, from right to left and vice versa, meaning as the oblique movement that a user can make to shorten path.

The tests for detecting the vehicle flow over the crosswalk in the direction of the road consisted in inhibiting the lightning barrier and detecting true negatives with a speed higher than 5 Km/h. Recall that this type of vehicles should not activate the LED lighting by themselves when crossing over the system.

The series of tests attained an average speed of 1.18 $\pm$ 0.43 m/s for pedestrians and a speed between 2.22 and 5.55 m/s for vehicles. After the experimentation, an average success of 94.64% and a precision of 100% were obtained. According to the ROC analysis, this corresponds to a very good test with TPR = [0.9, 0.97) and lack of false positives. Specifically analyzing the different case studies (Table 8), we found that the best result was obtained for the detection of vehicles in the road direction, as well as bicycles, buggy babies, and group of pedestrians in the crosswalk direction. On the contrary, we found worse results in both the detection of a person and several people crossing simultaneously in opposite directions. On the one hand, this suggests that the greater the volume of the objects to be detected, the more efficient the intelligent road signaling system (e.g., bicycles or buggy babies versus a person). This is explained due to the collocation of the sensors at the asphalt level, which reduces the effectiveness when detecting low limbs from persons compared to the chest or other parts of the body with major size. On the other hand, the study suggests that bicycles and motorcycles passing the crosswalk are not a trouble for the type of sensors used, both the RADAR and the ultrasound. To sum up, Figure 15 shows a comparative graphic with the case studies addressed and their TPR values.

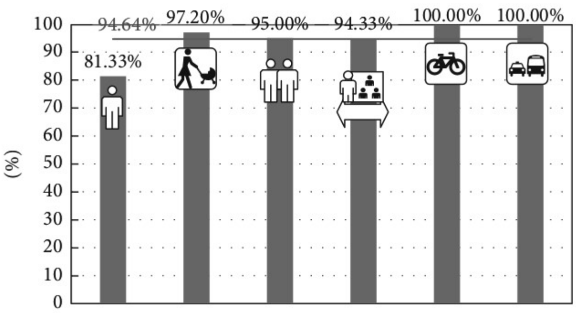

Figure 15: TPR of the classifier modelled by the fuzzy controller.

4. Conclusions

According to studies, 40% of the accidents in which pedestrians are involved are produced when crossing for the right place. This happens—in part—because crosswalks are not 100% visible for drivers due to different reasons: (i) poor road maintenance, (ii) occlusion of vertical signs, and/or (iii) adverse weather conditions, among others.

To help reduce accidents, this paper proposed a prototype signaling system set on the road that alerts drivers when they are approaching zebra crossings when a pedestrian is traversing. This system, formed by a set of autonomous, intelligent, and low-cost devices, implements an object detection and alerts fuzzy controller that activates luminous signals so that drivers can stop safely.

A study on the state of the art about several patents and commercial solutions—including luminous road markers, speed bumps, and vertical signs—revealed that the main innovative features of the prototype system are the artificial intelligence and low-cost installation. On the one hand, the intelligence allows contradistinguishing whether an obstacle traversing a crosswalk is pedestrian or vehicle, thus interacting actively with the environment. On the other hand, the installation is based on a low-cost fitting that removes the need for public works on the road since the autonomous device includes solar-based rechargeable technology instead of a power grid infrastructure.

The tests conducted to validate the system over a total of 65 hours consisted in (i) detecting different types of users walking over a crosswalk (i.e., individual pedestrians or grouped, buggy babies, and bicycles) and (ii) trying the intelligent discrimination of vehicles to avoid false positives (i.e., cars, bicycles, and motorcycles). An exhaustive ROC analysis with a total of 244 tests provided an average success of 94.64% and a precision of 100%. This suggests a very good test in global terms, while the greater the volume of the object to be detected, the better the detection (e.g., bicycles or buggy babies versus a single person). By way of conclusion, a video with the construction and validation of the prototype is available in the web page of the project at http://www.uhu.es/tomas.mateo/smartcitysen.

Future works are focused to improve several technical and functional aspects of the prototype, including size, power consumption, electronics, and code. Regarding the hardware, the energetic deficit supported by the system can be still considered somewhat high. Incorporating elements of lower consumption and/or inducing the control unit to sleep periods without affecting the detection capacity (e.g., modem-sleep, light-slip, or deep-sleep) can reduce the number of PV (photovoltaic) panels at the same time that reduces the case size. Regarding the software, the upgrade to more advanced control techniques would improve the system accuracy and reliability. On the one hand, the object detection would be enhanced by means of pattern analysis and recognition based on FFT (fast Fourier transform) techniques. On the other hand, the implementation of machine learning techniques (e.g., based on genetic algorithms) would automate the calibration of the system variables—and their translation into diffuse linguistic labels to form the knowledge base—regardless of the system installation (i.e., road conditions). Finally, the developed prototype could also be improved by extending its functionalities to enhance the safety of dependent people (e.g., acoustic signaling for blind people).

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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Supplementary Materials

The supplementary material includes a video that shows the prototype construction process, the tests to which the devices have been subjected, and the results obtained. *(Supplementary Materials)*

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4.2 Article 2

Review on V2X, I2X, and P2X Communications and Their Applications: A Comprehensive Analysis over Time

Lozano Domínguez, J.M., Mateo Sanguino, T.J.

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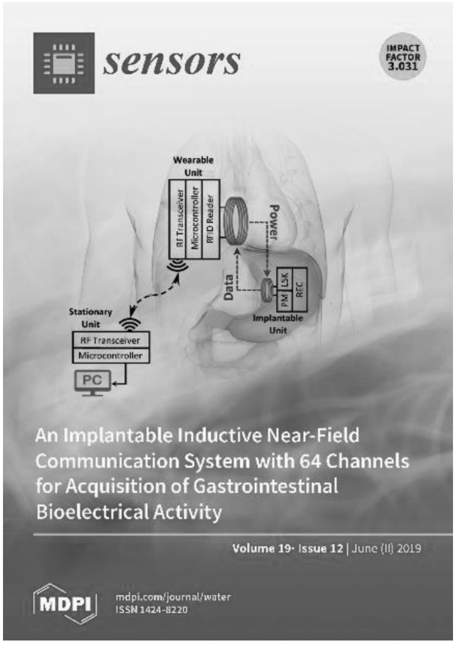

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Review

Review on V2X, I2X, and P2X Communications and Their Applications: A Comprehensive Analysis over Time

José Manuel Lozano Domínguez and Tomás Jesús Mateo Sanguino *

Department of Electronic Engineering, Computer Systems and Automatics, University of Huelva, Av. de las Artes s/n, 21007 Huelva, Spain; jose.lozano@diesia.uhu.es
* Correspondence: tomas.mateo@diesia.uhu.es; Tel.: +34-959-217-665; Fax: +34-959-217-348

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Abstract: Smart cities are ecosystems where novel ideas and emerging technologies meet to improve economy, environment, governance, living, and mobility. One of the pillars of smart cities is transport, with the improvement of mobility and the reduction of traffic accidents being some of the current key challenges. With this purpose, this manuscript reviews the state-of-the-art of communications and applications in which different actors of the road are involved. Thus, the objectives of this survey are intended to determine who, when, and about what is being researched around smart cities. Particularly, the goal is to situate the focus of scientific and industrial progress on V2X, I2X, and P2X communication to establish a taxonomy that reduces ambiguous acronyms around the communication between vehicles, infrastructure, and pedestrians, as well as to determine what the trends and future technologies are that will lead to more powerful applications. To this end, this literature review article presents a comprehensive study including a representative collection of the 100 most cited papers and patents published in the literature together with a statistical bibliometric analysis of 14,364 keywords over 3422 contributions between 1997 and 2018. As a result, this work provides a technological profile considering different dimensions along the paper, such as the type of communication, use case, country, organization, terminology, and year.

Keywords: 5G; autonomous and connected vehicle; communication technology; cybersecurity; infrastructure-to-everything; literature review; pedestrian-to-everything; safety; smart city; vehicle-to-everything

1. Introduction

Smart cities are scenarios of innovation, challenge, and opportunity where the information and communication technologies (ICTs) are being exploited at the service of people to improve economy, environment, governance, living, and mobility (Figure 1). Investment in smart cities is growing, evolving from small projects to great technological market opportunities around universities, governments, and industries [1]. As a consequence, global spending on emerging technologies for the progress of the smart cities reached $80 billion in 2018 and will progressively increase up to $135 billion by 2021 according to a report made by IDC Research [2].

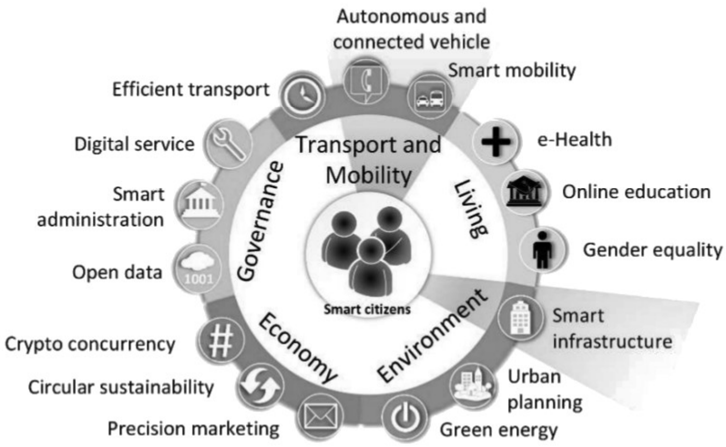


Figure 1. Person-centric adaptation of the Smart City Wheel proposed in [1]. The topics shaded in orange and green concern this research.

Most of the investment is devoted to intelligent connected transport (ICT) and sustainable mobility, followed by smart lighting and environmental monitoring with cross-country variations. Specifically, the US, Japan, and Europe invest in transport and mobility first (e.g., driving safety, traffic efficiency, or telematics services), China spends more in video surveillance systems (e.g., facial recognition or license plate recognition), while environmental monitoring (e.g., water, waste, or air pollution) will be relatively more important in Japan [3]. From this, the US and China are currently the two largest markets for smart city technologies with $22 billion (annual growth rate of 19%) and $21 billion (annual growth rate of 19.3%), respectively [2].

Smart cities are often referred to as digital or connected cities since they implicate the intelligent use of technology to add value and attain more efficient services (e.g., to alleviate the problems resulting from the massive urbanization and population growth). A key aspect of a smart city is the use of sensing, communication, and social capabilities as part of a wider concept around the Internet of Things (IoT) [4]. This approach has been made possible by providing intelligence, mobile sensing, and wireless capability to infrastructures (e.g., green buildings), persons (e.g., wearable devices), and vehicles (e.g., intelligent transport systems) to facilitate data access, which is fundamental to make smart cities a reality [5–7].

According to a recent study, the IoT market (i.e., manufacturing, transport, logistics, and public services) will increase the investment to spend $123.8 billion on IoT platforms and services by 2021 [8]. For instance, the Spanish market achieved 5 million connected objects in 2018 and this is expected to increase up to 8 million IoT lines in 2022 (annual growth rate of 10.9%) [9]. That growth, in line with other EU countries such as France, Germany, Sweden, or the UK (up to 1.3 billion connected objects worldwide) is mainly being demanded by the personal market and the industry 4.0 (i.e., financial, banking, retail, security, transport, logistics, and automotive sectors).

In particular, IoT is pivotal in transforming classic transport and automotive services into intelligent transport systems (ITS) by enabling detection (e.g., image or video), artificial intelligence (e.g., sensor fusion), and data processing (e.g., big data and analytics) for autonomous and/or connected vehicles [10]. In this area, vehicular communications are gaining primary attention from both research community and industry, where vehicles are the third type of connected device with the greatest growth potential, after smartphones and tablets [11]. In this sense, the total average cost of implementing connected vehicle technology in the US is projected to increase from ~$1.2 billion to ~$3.75 billion in 2022 with investments of ~$2.9 billion annually from 2025 [10].

Outline

The current scenario of investment, research, and development described above is being traduced in numerous manuscripts and patents published in leading scientific journals, conferences, and intellectual property databases. When referring to vehicular communication, the research includes a very rich literature, but mostly oriented to cover specific aspects of the technology. As an example, this is the case of ad-hoc networks [12], information management systems [13], security [14], and access technologies [15] around vehicle-to-everything (V2X) communication published in 41 review and survey manuscripts between 1997 and 2018 (i.e., secondary research).

Nonetheless, there is hardly a mention in the bibliography—neither primary research nor secondary research—to other types of communication, such as infrastructure-to-everything (I2X), pedestrian-to-everything (P2X), and their variants. The main reason is that they stand for more emerging markets and do not enjoy yet a standardized definition in the state-of-the-art to be used by the research community (i.e., there is no uniformed consensus about these terms). Moreover, as far as we know, most surveys do not always emphasize on the historical evolution (i.e., they are frequently limited to specific aspects and/or contemporary technologies), do not cover statistical profiles, and do not conduct bibliometric studies with a broad perspective of the context over time.

For this reason, the research question this paper aimed to examine was: What are the past, current, and future interests in V2X, I2X, and P2X communication? It had four main objectives:

1. To situate the industrial and scientific progress through the examination of who, when, and about what the research has been done on emerging technologies for smart cities, especially focused on V2X, I2X, and P2X communications;
2. To systematically collect features on the type of vehicular communication, field of study, technologies, and applications to establish a time reference frame on significant characteristics;
3. To undertake a comprehensive bibliographical analysis on the relationship of the publications comparing the most productive countries and organizations along time, as well as to the inference of an emerging technology over other;
4. To review what future milestones lead technologies to more powerful applications on V2X, I2X, and P2X.

To this end, the present paper is designed as a review article—which is not a primary research article—and structured as follows. The following section provides a taxonomy on V2X, I2X, and P2X communication and their variants. Then, the paper describes the recent attention attracted from governments, academics, and industries around V2X, I2X, and P2X applications. As a result, a summary table about the profile of the most representative applications present in the R&D literature is provided in Appendix A. The next section provides a contextual bibliographic study on the most influential technologies around smart cities. Finally, the paper presents the future trends and emerging technologies to reach the conclusions.

2. Taxonomic and Technical Analysis

Although the term for communication between machines (M2M) or devices (D2D) is a traditional and clear concept for the entire research community, it does not present always clear definitions when applied to vehicles, infrastructure, or pedestrians. As an example, the terms for car to car (C2C), vehicle to vehicle (V2V), car to everything, or car to all (C2X) are used indistinctly as vehicle to everything (V2X) communication in [16–18], among others. This is even more ambiguous when the different actors are included in the interaction but the origin of the data source is not properly considered in the communication process. Therefore, it is necessary to deepen their definitions and make a classification of the various existing forms.

The taxonomy proposed below aims to correct errors, to provide further clarification on frequently misunderstood concepts and to include new acceptations such as for the infrastructure-to-everything (I2X) and pedestrian-to-everything (P2X) communications. To this end, the taxonomy has been elaborated based on the full spectrum of terms collected around V2X, I2X, and P2X communications. Therefore, we provide functional definitions for the different variants. This classification does not intend to provide specifications or impose technical requirements on the various types of communication, but to harmonize terms with the following purposes:

1. To provide clarity and stability regarding the role played by the V2X, I2X, and P2X communications;
2. To provide a useful framework that saves time and effort during the development of specifications and technical requirements (e.g., in standards);
3. To respond to issues of scope for the writing of future regulations, laws, and policies.

As can be appreciated in the following section about the state-of-the-art, the different types of communications can be classified as V2X, I2X, and P2X depending on the origin of the communication. Then, the following taxonomy is proposed (Figure 2).

- **Vehicle-to-Everything** (V2X): Communication from vehicle to any entity, which includes in-vehicle connectivity (IN-V) with sensors (V2S) or other onboard devices (V2D) such as infotainment systems. This definition often encompasses the terms for car to all/car to everything (C2X), car to car (C2C) or vehicle to other vehicles (V2V) such as motorcycles (V2M). This classification group also includes other more specific types of interactions, such as vehicle to grid (V2G) to communicate with smart grids to receive or return electricity, car to infrastructure (C2I) or vehicle to infrastructure (V2I) to communicate with the road (V2R), such as road side units (RSUs) acting as stand-alone units or relay nodes that provide safety and traffic updates (e.g., traffic lights), vehicle to networks (V2N), heterogeneous vehicular networks (HetVNET) or vehicular sensor networks (VSN). These last also include vehicle to broadband cloud (V2B) or vehicle to cloud (V2C) communications utilized for software upgrades or information updates. V2I also includes vehicle to home (V2H) appliances such as lighting or air conditioners, while the car to pedestrian (C2P), vehicle to pedestrian (V2P), or vehicle to phone (V2P) communications may include smartphones and wearables worn by persons. Note that the term vehicle-to-home must be disambiguated with respect to the term vehicle to humans (V2H).
- **Infrastructure-to-Everything** (I2X): Communication from infrastructure to any entity, which may include other infrastructures (I2I), vehicles (I2V), or pedestrians (I2P). This term must be disambiguated with respect to the term individual to individual (I2I).
- **Pedestrian-to-Everything** (P2X): Communication from pedestrian to any entity including other pedestrians (P2P), infrastructure (P2I), and vehicles (P2V). Note that these terms must be disambiguated with respect to the peer to peer (P2P) and payment to individual (P2I) approaches.

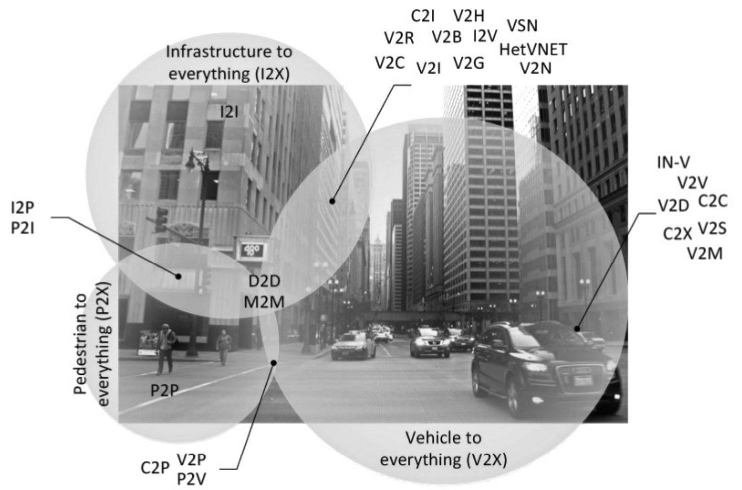
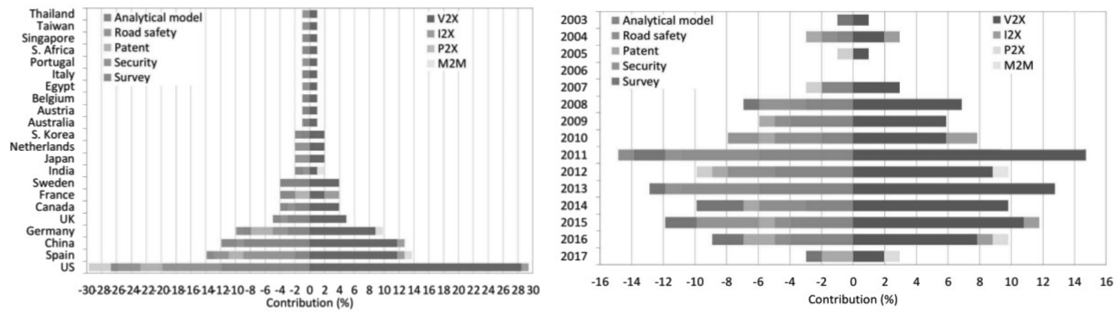


Figure 2. Diagram of interactions between vehicle, infrastructure, and pedestrian communications.

Technological Profile of the Survey

As stated in the previous section, there is no developed methodology to uniformly divulgate the development of applications based on V2X, I2X, or P2X communications. Nevertheless, it is possible to elaborate a set of basic features that they must fulfill. In order to assess one of the contributions made by this work to the field of V2X, I2X, and P2X communications, a comparison of the characteristics and capabilities including a set of 100 representative manuscripts collected in this review is shown in Table A1 (Appendix A). The followed methodology uses the number of citations as criteria to select the most representative papers based on the guidelines to make a literature review mentioned in [19]. Although the criteria could cause a potential bias in the results, since the number of citations increases with time and, thus, the selection could disqualify the most recent papers in the area, we have obtained the following distribution: 20.79% of the documents were published between 2000 and 2009, 45.54% of the documents were published in the period 2010–2013, and 33.67% were published between 2014 and 2018. This means that one third of the papers were published in the last five years, giving a significant insight on the current state-of-the-art.

The analysis about the current research shows that the most productive country is the US (29.7%), with the study of analytical models for vehicular communications (11.88%) and road safety applications (7.92%) being its main contributions (Figure 3a). The next largest contributor is Spain (13.86%), which is mainly focused on road safety applications (6.93%), followed by China (11.88%) in the study of analytical models (8.91%). On the other hand, 2011, 2013, and 2015 were the most representative years (14.85%, 12.87%, and 11.88%, respectively) with contributions in analytical models (15.84%), road safety applications (9.9%), and cybersecurity (3.96%). Moreover, the results show that V2X is the type of communication most investigated (92.14%), with 2011, 2013, and 2015 being the most productive years (14.71%, 12.75%, and 10.78%, respectively) (Figure 3b). I2X is the second type of communication most studied (4.9%), focusing its contributions in 2004, 2010, 2015, and 2016 (0.98%, 1.96%, 0.98%, and 0.98%, respectively). Finally, P2X has barely been studied, only becoming a field of study in recent years (1.96%) where 2016 and 2017 were the main years of contribution (0.98% and 0.98%, respectively).



(**a**) (**b**)

Figure 3. For a representative sample of the 100 most cited publications in the state-of-the-art: (**a**) Type of communication and use case versus country, and (**b**) type of communication and use case versus year.

3. State-Of-The-Art

The purpose of this section is to present a historical review of the most representative technological initiatives that have promoted the development of different V2X, I2X, and P2X approaches over time, from the early regulations carried out by governments and regulatory bodies to the current research and development (R&D) being performing by industries and universities.

3.1. Government and Regulatory Agencies

The history of connected cars dates officially from 1996 with OnStar, a company created by General Motors—collaborator of Electronic Data Systems and Hughes Electronics Corp—whose goal was to request medical help by routing a phone call to an emergency center after a car accident [20]. The e-Call system, which initially started as a voice service activated by airbag deployments only aboard some Cadillac models, has evolved nowadays into a complete sensor-based automatic crash response system capable of determining the severity of the car impacts. To this end, the system comprises GPS location, remote diagnosis, network access device, 4G, and WiFi spot to process up to 5 million phone calls per month in the US.

This milestone in the field of the ITS development has been able to progress thanks to several facilitating entities such as the US Department of Transportation (DOT) and the Federal Communications Commission (FCC) who regulated in 1999 the use of a 75 MHz band in the 5.9 GHz spectrum (i.e., 5850–5925 MHz) for unlicensed access technologies [17]. This effort was preceded by Japan, whose country reserved its radio spectrum for ITS applications in the 760 MHz and 5.8 GHz frequency bands after initiating its deliberations on regulation policies by 1994 [21]. Similarly, the EU and the European Telecommunications Standards Institute (ETSI) allocated in 2008 a 30 MHz band for safety-related applications of ITS in the same spectrum region (i.e., Commission Decision 2008/671/EC). This activity was also followed by other countries in the Asia Pacific region, such as Korea, Singapore, China, and Australia, who defined their spectrum allocations between 2016 and 2017 [22].

Meanwhile, the Institute of Electrical and Electronics Engineers (IEEE) formed in 2004 a task force to work in an IEEE 802.11-based draft for wireless access in vehicular environments (WAVE) that resulted in the IEEE 802.11p amendment by 2010. It was the basis for the future European standard for cooperative ITS environments—such as the one used in the V2V and V2I communications—where the first version was released in 2014 by ETSI and the European Committee for Standardization (CEN) as ETSI ITS-G5. IEEE 802.11p was integrated with IEEE 1609 and SAE J2735 to provide a complete standardized message protocol stack, which was considered by DOT in 2012 for dedicated short-range communications (DSRC) in vehicle-based applications (e.g., toll collection, emergency vehicles, road works, braking warnings, etc.).

Consequently, the EU announced in 2010 that ITS applications were already interoperable (2010/40/EU) and started working by 2014 in a regulatory framework to improve some key areas in V2X technology such as cybersecurity and radio interferences. At the same time, the US National Highway Traffic Safety Administration (NHTSA) published a report in 2014 stating that the V2X technology was technically proven and ready for real deployment in markets. Additionally, China formally proposed in 2015 its own national development program for intelligent connected vehicles (ICV), which has to be finished in 10 years according to its strategic plan known as Made in China 2025 [15]. As a result, this progress has led some countries to mandate all vehicles to carry V2V technology in order to reduce collision-based accidents (e.g., EU from 2018 and US from 2021) [10].

While DSRC proved to be an adequate ad-hoc technology enabling V2V applications due to the short range (300–1000 m), low latency (200 µs), and medium data transmission rate (27 Mbps), cellular networks help to support V2I solutions due to the broad spread and commercial success of the mobile communications. Cellular V2X (C-V2X) has been standardized since 3G/UMTS and 4G/LTE proved to be useful (i.e., up to 2 km, 1.5–3.5 s, and 75–300 Mbps) but not versatile for time-critical scenarios. In this sense, the Third Generation Partnership Project (3GPP) has been a standardization body especially active in the development of 5G technology. It has regulated C-V2X from releases 14 and 15 in early 2016 and early 2019, respectively [23,24].

According to the previous scenario, although the major shift lever for the development of ITS applications has been the regulation of the radio spectrum and the technology standardization by the various regulatory bodies, there are still some limitations that hinder worldwide adoption. On the one hand, the locations of the radio bands are unique to each country and not interoperable across different territories (e.g., the Japanese ITS system in the 760 MHz band overlaps with the 4G/LTE mobile network operating in New Zealand) [25]. On the other hand, the degree of investment required by some other applications (e.g., V2I) will take time to be implemented due to the numerous infrastructures existing [26]. This means a different adoption rate of LTE versus DSRC-based solutions.

For all the above, an increase in the efforts of governments, regulatory bodies, industries, and scientific community is still necessary due to the ambiguity of the communication technologies, lack of supporting infrastructures, overall implementation cost and attention to certain technical challenges, such as the improvements in cybersecurity [27].

3.2. Primary Research in Literature

The work of many governments around the world to legislate wireless technologies is still underway to support V2V and V2I communications, thus being responsible for facilitating and regulating the development of the automotive industry in the coming years [13,28]. This regulation must support the agreements reached in the standards of the different regulatory agencies of each geographical area. In line with this activity, there are studies in the state-of-the-art that provide a broad vision about the relationship of wireless communications in vehicles and other actors on roads, such as infrastructures and pedestrians [29]. The most cited papers found in the literature were initially concerned with the study of different communication approaches, technological challenges, and their applications. This is the case, for instance, of the IEEE 802.11 standard adopted in DSRC communication [30,31]. In this sense, the interest on the proposal of a bandwidth of 10 MHz in the 5 GHz band for vehicular communications based on the IEEE 802.11p standard stands out [32–35].

One of the most analyzed aspects in the history of vehicular communications is the propagation of wireless signals in the 5 GHz band, as well as how different factors affect V2V and V2I communications. Some of the most studied factors include the vehicle density, relative speed between vehicles, and average vehicle speed [36–38]. In addition, the distance between transmitter and receiver as well as the line-of-sight (LOS) occluded by both stationary and moving vehicles were other factors studied [39–43]. In order to understand and improve these concerns, both theoretical and experimental studies were carried out. One example of this is the characterization of the signal loss through stationary and non-stationary models made in [44], while a new method that offers better approximations to determine this signal loss was exposed in [45]. Some authors use geometric modeling since it provides more accurate results for mobile and stationary objects (e.g., vehicles, trees, and buildings) than traditional signal propagation models [46–48]. There are also other authors who take advantage of radio-cognitive techniques for the study of the spectrum as these techniques provide precise information. This is the use case of vehicles that circulate on public roads whose information on the spectrum is shared by other vehicles. The availability of the spectrum allows to know future positions of vehicles [49,50]. Also related to the communication aspects, other studies have determined that the Doppler effect should be taken into account in vehicular communications because different reflections of the same signal can be received in different times and interfere [51]. Therefore, a new approach to palliate Doppler interferences based on a new inter-carrier scheme more efficient and less complex than previous used schemes is presented in [52]. Other authors have proposed the use of RADAR integrated in vehicles—as transmitters and receivers in V2V communication—in conjunction with conventional communication units in order to improve communication performance through the transmission of modulated information in the 24 GHz or 76 GHz spectrum provided by RADARs [53]. Nevertheless, other proposals go beyond the transmission based on radio frequency (RF) waves and propose the use of car headlights and taillights as a means of communication. As the main drawback, the use of light in the visible spectrum limits the range of communication with other vehicles to the cover range of the car lights [54].

Another field of study extensively analyzed by researchers has been the IEEE 802.11p standard. The state-of-the-art includes many proposals of improvement with respect to this standard since it is the most used in vehicular communications. The improvements mainly focused on the media access control (MAC) layer due to the high mobility of the network actors [55], which can cause failures in the estimation of communication channels and a decrease in network reliability [56]. This part of the network is responsible for guaranteeing fast, reliable, and collision-free access to the medium in vehicular ad hoc network (VANET) applications, as mentioned in [57–59]. These documents also proposed that media-access protocols should follow a time division multiple access (TDMA) scheme rather than the scheme currently used based on carrier sense multiple access (CSMA), because TDMA offers better performance in delivering packets on time than CSMA. Improvements to the current standard include the utilization of contention windows [60], a better estimation of communication channels [61], as well as the improvement of the performance of the MAC layer to minimize the bit error rate [62]. To solve these problems, Eichler, Ma and Zhao [30,31,63] offer a new perspective to solve the problems detected in the MAC layer (e.g., MAC congestion control to avoid collision or channel estimation through channel interleaving and channel coding). Despite all these advances, not all problems have yet been solved or are not yet perceived by users as advantages [12].

Although IEEE 802.11p is the most widespread standard in vehicular communications, it is not the only field of R&D. Cellular networks are also relevant for the vehicular communication because they may offer better performance in some cases than the 802.11p-based networks [64,65]. Other viewpoints considered by some authors argue that the access technologies should be selected on the basis of the vehicle speed [66]. This approach uses LTE for V2I communication and IEEE 802.11p for V2V communication [67,68]. The combination of both approaches, known as HetVNET, is a better solution than separately. According to a study, the use of HetVNET networks requires further research and development of new network topologies, as well as better network selection schemes (i.e., effective vertical handover techniques) [69]. Therefore, there are other works that propose the use of device-to-device (D2D) communication to support vehicular communications, where schemes promise suitable performances for V2V communications as mentioned in [70].

In addition to the communication models based on IEEE 802.11p or cellular networks, there are authors who propose other network approaches. An example is Name Data Networking (NDN), where the main advantage is the fast exchange of information between vehicles (i.e., V2V) or vehicles and infrastructure (i.e., V2I). As the main drawback, NDN requires an adequate density of vehicles and low distance between the participants according to [71,72]. Apart from that, other authors claim a network model based on the Software-defined Networking (SDN) and fog computing paradigms due to the higher flexibility, scalability, location capability, and fewer delays than the current network models [73,74]. Another point of view preferred by other authors to develop their communication approaches is the use of position-based routing protocols as they offer more performance in highly dynamic mobile networks [75].

Once the main technologies used in this area have been described, a set of additional outstanding papers are grouped below by the use case to which they belong.

3.2.1. Road Safety

Road safety is one of the main use cases of vehicular communications since it allows saving lives and avoiding injuries to the vehicle occupants. For this purpose, road safety admits research on problems related to the safe access to highways, secondary roads, or areas with reduced visibility, as well as research on traffic congestion management. Several noteworthy examples in the literature describe a protocol based on emergency warning messages (EWM). As the main advantage, this approach has a low delay constraint to ensure the reception of the messages on time, which has been utilized to avoid collision-based accidents on motorways [76]. Similarly, a protocol that prevents network congestion so that emergency notifications sent to users arrive on time was presented in [77]. To achieve this, the protocol exploits the chain effect and removes redundant messages. Moreover, various systems that allow the prediction of traffic congestion in an area and then warn users were developed. On the one hand, approaches based on cooperative vehicular communication techniques were presented in [78,79]. On the other hand, algorithm-based solutions to detect situations of congestion were developed in [80,81]. However, other authors have focused their works on avoiding collisions in urban intersections using V2V communication. Some of them solve this problem by means of Fuzzy logic as a control mechanism [82,83], while others prefer algorithms based on formal theoretic methods [84].

There are also different proposals with the aim of increasing passenger safety. One of them is an RFID-based application whose signal is recognized to adapt the vehicle speed to the road [85]. Another application is a distributed cruise control that adapts the car speed in function of the road status [86]. One more is a system that facilitates the incorporation of vehicles to a main road coming from a secondary one by adapting their speeds [87]. In this sense, a speed control system that improves the road flow by taking account of data from accelerations and decelerations of nearby vehicles was shown in [88].

Another perspective analyzed in research by some authors has been ecological driving, a strategy that adjusts the vehicle speed so that the total fuel consumption around an intersection is optimized through the use of V2I communication [89]. Another field also exploited through different approaches is that concerning traffic monitoring systems. The first one analyzes routes and helps in decision-making through cloud computing so that drivers avoid traffic congestion [90]. The second one utilizes IoT and machine-to-machine (M2M) communication to create maps of road conditions based on data shared from in-vehicle smartphones [91]. Another aspect examined in this field is the real-time driving assistance system. One solution is based on cameras and V2V communication, which prevents vehicles from becoming obstacles to the drivers' field of view (FOV) in a vehicle platoon [92–94]. Other examples are based on various planning methods that allow autonomous vehicles (AVs) to analyze possible maneuvers, select the safest movements, and determine the best trajectories to achieve their destinations [95]. Finally, an adaptive traffic control system that improves road flow by preventing long queues of vehicles intended to cross a given intersection was presented in [96]. This system also includes strategies for special vehicles such as ambulances or fire trucks.

In summary, all the examples previously collected make mention to V2V or V2I communications. Nevertheless, none of them involve vehicular communication with pedestrians or similar. At the moment, V2P communication is an emerging technology with great potential being developed, not only to improve the safety of the road users, but also to improve the efficiency of the traffic flow. To cite a few, some potential applications based on V2P communication can be found in [97,98].

3.2.2. Cybersecurity

Another important aspect extensively studied in vehicular communications is security, since all vehicles can be exposed to security breaches that can produce fatal consequences to the occupants [99,100]. Several approaches in V2X communication are listed in [101] and [16], where the most used is the public key scheme [102–106] as it provides integrity and authentication through the IEEE 1609.2 standard [16]. In this field, other techniques such as the group signature [107] or the symmetric authentication schemes [108] also stand out but are less used as they are not part of the IEEE 1609.2 standard. However, the LTE authentication and key agreement protocol (LTE-AKA) is proposed to protect communications against possible attacks when 4G/LTE—or the coming 5G—is used as an access technology [11]. Beyond these studies, there are other novel works aimed at developing secure approaches applied to specific scenarios such as Tesla++, a protocol suitable for minimum data transmission and low energy consumption that prevents and protects against denial of service (DoS) attacks in VANETs. Despite of the deep understanding on security, there are aspects still unresolved. Among the most important for VANETs is to evaluate the reliability of the nodes that communicate through the network, to detect and revoke the trust on a rogue node, to guarantee the security and/or privacy—in terms of the vehicle traceability—as well as to detect malicious software [14].

3.2.3. Commercial Applications

Vehicular communications, in addition to increasing road safety in the various ways described above, also provide a new approach for multimedia broadcast services and applications (MBMS). It is noteworthy that the development of new technologies, such as the vehicular communications, will greatly help the multimedia content to migrate to mobile platforms [109]. An example of this new contribution is the ability of communications to support streaming video while vehicles circulate on public roads [110]. This is possible thanks to the combination of real-time and non-real-time data; the first one is used to send inter-vehicle messages for safety purposes while the latter is used to transmit multimedia content (e.g., video or audio) [111].

3.2.4. Other Directions of Research

Other miscellaneous contributions include simulations, algorithms, theorems, and other applications not classified in the previous groups. These contributions can be useful for the research on V2X, I2X, and P2X communications, because they allow the optimization of parameters on models. An example of a simulation can be found in [112], whose model allows the simulation of intelligent transport systems and the introduction of elements such as traffic lights or roadside stations, among others. As the main advantage, this work provides results on the traffic flow of vehicles, communications, and RF emissions. Another example of outstanding work in algorithms is [113], whose authors present an approach that determines the optimal number of roadside units (RSU) required per area as a function of the vehicle density. Other works in theorems can also be found to provide network stability and scalability based on the topology of the communication flow [114]. In this sense, a novel model has been proposed to solve problems of shared resources by means of graphs, which offers better results than the traditional methods [115]. Finally, another notable work proposed the use of wireless energy in electric vehicles not only to transfer power, but also to support V2I communication in areas of high traffic density and data transfer rate [116].

3.3. Industry Interest in V2X, I2X, and P2X Communication

The consolidation of the industry concerning the R&D in communication technologies for vehicles, pedestrians, and infrastructure has been mainly motivated by the progress around the connected and/or autonomous vehicles (AVs). Some technological milestones in this regard have been the early functions of the e-Call system demonstrated in 1996, the remote diagnosis capability introduced in 2001, the network access device utilized for vehicle health reporting and turn-by-turn navigation in 2003, the only-data telematics used by Continental, and the 4G/LTE communication with WiFi hotspot access included by Audi, Volvo, and General Motors from 2014 [26].

An example of effort in the development of V2X communication is a car system that identifies traffic lights on public roads and communicates with a cloud server to predict how fast a vehicle should go to encounter green lights, as well as to predict waiting times when lights are red [117,118]. This technology, developed by Traffic Technology Service (TTS) for Audi, BMW, and Continental, allows more environmentally friendly driving and is less harmful for the vehicle components (e.g., tires). On the other hand, Honda has patented a system to communicate data (e.g., location, speed, etc.) from vehicles and pedestrians to alert and avoid accidents in path intersections [119]. Hitachi also worked on helping pedestrians to cross the road through a display-based system aboard vehicles that informs people and other nearby vehicles on future actions (e.g., give way and go) [120]. Moreover, Continental described a V2V/V2I communication system with redundant units to avoid shadow areas and enable the exchange of information [121]. In this line, Samsung developed an advanced information method and system to provide data from vehicles to all the surrounding actors (i.e., infrastructure, pedestrians, and cyclists) in critical areas of the road such as pedestrian crossings [122]. However, not all the communication systems patented are focused on avoiding accidents. This is the case of a vehicle used to record and manage road items in which a communication method based on queries and responses from/to a central node is described in [123].

Regarding the I2X communication, mostly techniques, methods, and communication systems in smart cities are implemented to make urban infrastructure safer and avoid accidents. For instance, an I2V communication system was used to detect pedestrians at zebra crossings and alert both nearby vehicles wirelessly and their drivers by acoustic and/or light signals [124]. In this sense, an apparatus was proposed to synchronize vehicles with pedestrians and facilitate crossings without accidents [125].

Also, a system that transmits auditory information for disabled people about road elements (e.g., traffic lights) when their personal devices are oriented to the infrastructure is described in [126].

Finally, there are several techniques, methods, and systems applied to P2X communication to interact between pedestrians or cyclists to everything. The state-of-the-art includes solutions such as a signaling device that alerts drivers about pedestrians or cyclists on the road through a luminous totem wirelessly activated by smartphones and personal devices [127]. In a similar way, a procedure to avoid accidents between pedestrians and vehicles based on the historical position—to determine the future location—and user context (e.g., age, response capacity, etc.) is used to alert about possible collisions by means of visual and/or acoustic signals [128].

4. Bibliographic Analysis

A more comprehensive and systematic bibliometric analysis has been conducted considering the online abstract and indexing service provided by Scopus® from Elsevier. The reason for its choice—as opposed to others, such as the IEEE Xplore® digital library, Google Scholar, ResearchGate, ArXiv, or DBLP—is that Scopus® is considered the world's largest scientific database. Furthermore, Scopus® is available for free and has also been used in many previous bibliometric analyses [129–132].

The search range was focused on the period from 1997 to 2018 and performed with the following structure: TITLE-ABS-KEY ("*term_1*" OR "term_2" OR "*term_n*" AND "*term_i*" [...] AND NOT "*term_j*" [...]) AND (LIMIT-TO (SUBJAREA, "COMP") OR LIMIT-TO (SUBJAREA, "ENGI")) AND (EXCLUDE (PUBYEAR, 2019)). The publications were gathered to compare whole annual periods, limited to the categories of Computer Science and Engineering, then filtered to avoid the misuse of terms belonging to other disciplines (i.e., acronyms with various meaning) and finally processed using spreadsheets to sort the results. The publications in Scopus® were evaluated considering the following factors: Number of manuscripts per year, source type, keywords, country, and affiliation of the authors. Note that the analysis made in this section has no potential bias, since all the manuscripts stored in Scopus® have been entirely considered unlike the previous section.

Evolution of Mobile Devices, Sensors, and Intelligent Applications for Smart Cities

Regarding the technological context, the sample analyzed in this work included 10,867 articles within the "Smart City" category, 35,537 for "WSN", 41,485 for "Internet of Things", 19,475 for "Smartphone", and 3422 for "I2X, V2X, P2X" and their variants (Figure 4). The survey showed a recent research in all fields in general with a major disruption of the "Internet of Things" (37.4%) over "WSN" (32.1%), "Smartphone" (17.6%), "Smart City" (9.81%), and "I2X, V2X, and P2X" (3.31%). A comparison between the evolution of the publications showed an outstanding correlation for "Smart City" versus "Internet of Things" ($r^2 = 0.967$, $p << 0.01$). The analysis also showed a good correlation for "Smartphone" versus "I2X, V2X, and P2X" ($r^2 = 0.881$, $p << 0.05$), "Internet of Things" versus "I2X, V2X, and P2X" ($r^2 = 0.878$, $p << 0.05$), and "Smart City" versus "I2X, V2X, and P2X" ($r^2 = 0.809$, $p << 0.05$). On the contrary, the bibliographic evolution showed a lower association in the publications of "WSN" versus "Internet of Things" ($r^2 = 0.279$, $p = 0.013$) and "Smart City" versus "WSN" ($r^2 = 0.295$, $p = 0.008$). This study suggests that the I2X, V2X, and P2X technologies are strongly related to smart cities, IoT, and smartphones. At the far side, WSN is less related with IoT and smart cities.

An analysis on the publications per territory focused specifically on I2X, V2X, and P2X communications showed significant activity mainly in Asia (39.65%), Europe (32.25%), and North America (20.55%), followed by South America, Africa, and Oceania to a lesser extent (7.53%). A study on the most productive countries and their relationship was then conducted. To this end, VOSviewer was chosen as the software tool for creating, visualizing, and exploring maps based on network data [133]. The results are resumed in Figure 5 and Table 1 for which thesaurus files and the Lin-Log clustering technique were used to filter inconsistencies over a total of 80 countries.

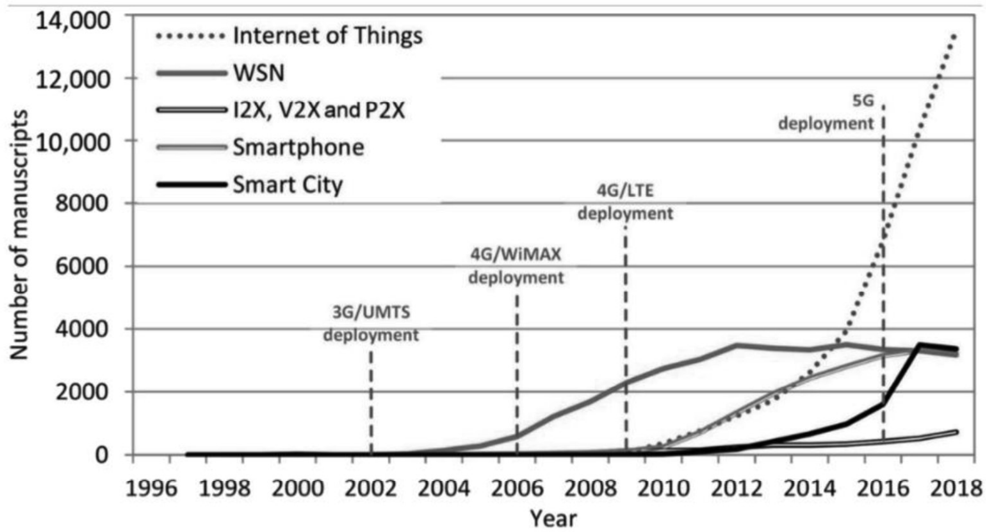


Figure 4. Evolution of key technologies for mobile devices, sensors, and intelligent applications in smart cities.

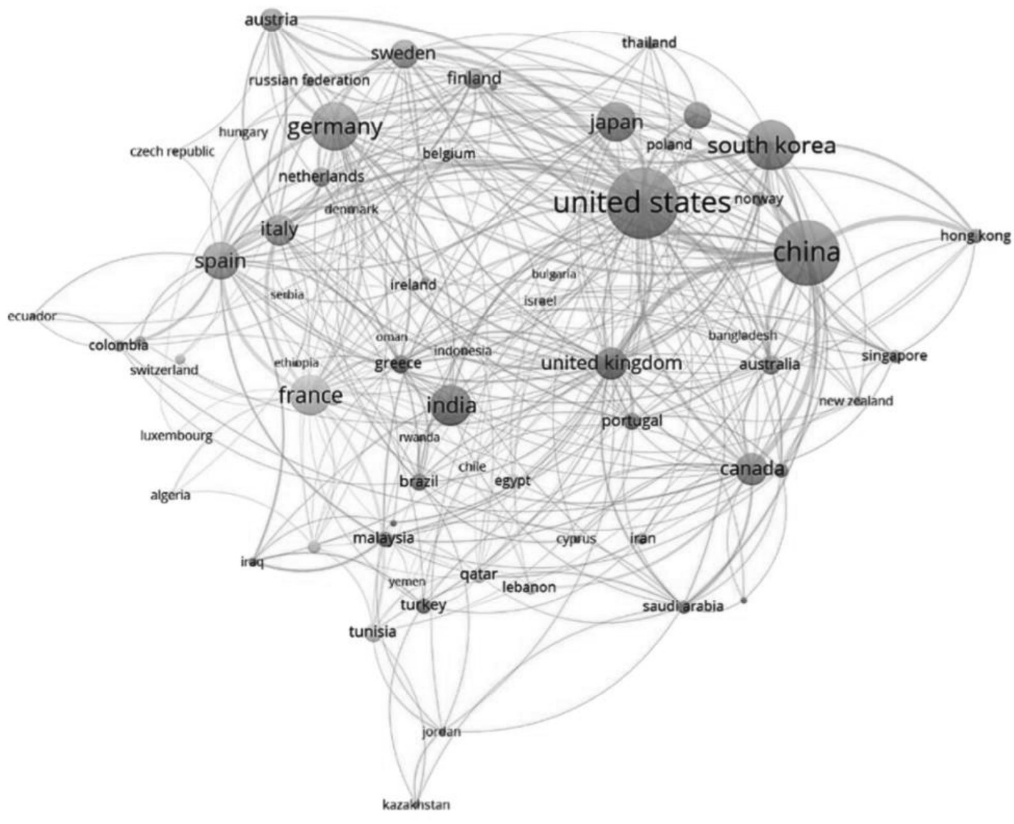


Figure 5. Cooperation between countries based on the publication co-authorship from 1996 to 2018.

Table 1. Most productive countries in I2X, V2X, and P2X research from 1996 to 2018.

R	Country	MP	MP (%)	CA	IC	CR	CR (%)
1	USA	667	19.24	344	46	7856	31.55
2	China	538	15.52	340	30	3573	14.35
3	S. Korea	332	9.57	101	22	1266	5.08
4	Germany	302	8.71	175	32	3600	14.46
5	France	221	6.37	167	36	1690	6.78
6	India	219	6.31	26	14	676	2.71
7	Japan	207	5.97	72	19	919	3.69
8	Spain	178	5.13	133	29	2337	9.38
9	Canada	139	4.01	109	29	1465	5.88
10	UK	133	3.83	131	39	1706	6.85

R: Ranking position; MP: Manuscripts published; CA: Co-authorships with other researchers; IC: International collaborations; CR: Citations received.

A study about the distribution of the organizations showed the leadership of universities (74.48%) over research institutions (15.85%) and private corporations (9.65%). The study on the correlation encountered a good relationship in the research carried out from 1996 to 2018, which confirms the close relationship between the different organizations (r^2 = 0.869 and $p << 0.05$ for "Universities" versus "Institutions", r^2 = 0.717 and $p << 0.05$ for "Universities" versus "Corporations", and r^2 = 0.691 and $p << 0.05$ for "Institutions" versus "Corporations"). The study also encountered that the universities started the research in this field three years earlier than the other organizations (Figure 6). This, in addition to the greatest number of publications, suggests that universities mainly carry the weight of the investigation in this field. This can be derived from the most productive organizations resumed in Tables 2 and 3, where the top of universities, institutions, and corporations is shown.

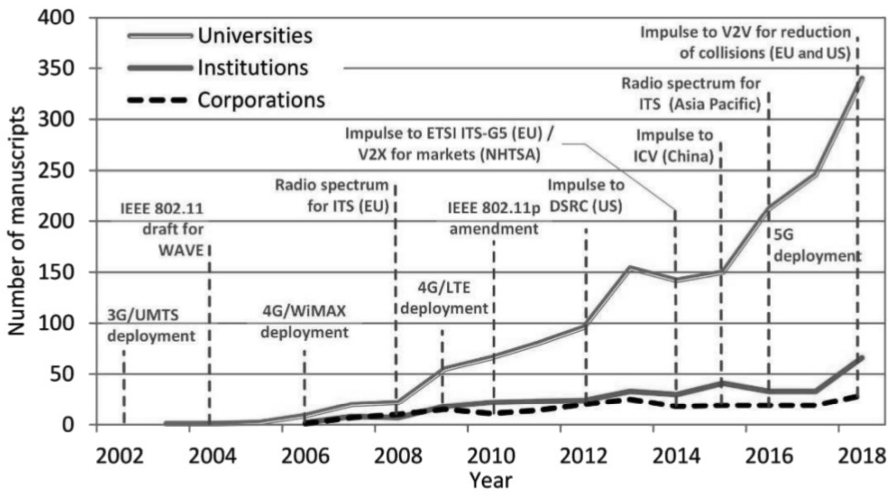


Figure 6. Bibliographic evolution of the contributions on I2X, V2X and P2X research per organization.

An analysis on the source type of the publications (Figure 7) shows a major contribution through conferences (62.41%) followed by journals (30.96%) and books (6.62%). The study confirms a good correlation between the different sources, which suggests that a rapid and strong growth in conferences is also reflected in scientific journals and textbooks (r^2 = 0.849 and $p << 0.05$ for "Conference Proceedings" versus "Journals", r^2 = 0.887 and $p << 0.05$ for "Conference Proceedings" versus "Book Series", and r^2 = 0.891 and $p << 0.05$ for "Book Series" versus "Journals"). The study on the document type found a total of 219 open access manuscripts (6.37%) as well as 41 surveys and short reviews (1.19%) over a total of 3439 manuscripts. These results reflect the weight of primary research versus secondary research.

Table 2. Most productive institutions in I2X, V2X, and P2X research from 1996 to 2018.

R	Organization	CL	MP	MP (%)	NC	CR	CR (%)
1	Beijing Univ. Posts and Telecom. (BUPT)	U	66	1.92	47	345	1.38
2	Beijing Jiaotong Univ. (BJUT)	U	60	1.74	50	455	1.83
5	Univ. Politècnica de València (UPV)	U	39	1.13	27	350	1.41
6	Hanyang Univ.	U	39	1.13	12	95	0.38
7	Electronics and Telecom. Research Institute (ETRI)	I	38	1.10	21	156	0.63
8	Tsinghua Univ.	U	38	1.10	43	303	1.22
15	DeutschesZentrum fur Luft-Und Raumfahrt (DLR)	I	31	0.90	29	131	0.53
25	ConsiglioNazionaledelleRicerche (CNR)	I	24	0.69	18	200	0.80
27	Qatar Mobility Innov. Center (QMIC)	I	24	0.69	15	233	0.94
30	Instituto de Telecomunicações (IT)	I	22	0.64	29	428	1.72

R: Ranking position; CL: Classification; U: University; I: Institution; MP: Manuscripts published; NC: Collaborations with other organizations; CR: Citations received.

Table 3. Most productive enterprises in I2X, V2X, and P2X research from 1996 to 2018.

R	Organization	MP	MP (%)	NC	CR	CR (%)
3	General Motors (GM)	49	1.43	56	641	2.57
22	Volvo	26	0.76	54	322	1.29
40	Toyota Info Tech. Center	19	0.55	21	235	0.94
45	Volkswagen AG	18	0.52	23	137	0.55
57	Forschungszentrum Telekom. Wien (FTW)	16	0.47	16	500	2.01
60	DENSO Corporation	16	0.47	8	9	0.04
61	NXP Semiconductors	16	0.47	4	30	0.12
64	Renault	15	0.44	20	46	0.18
81	Ford Motor Company	13	0.38	33	49	0.20
93	Huawei Technologies Co., Ltd.	12	0.35	18	89	0.36

R: Ranking position; MP: Manuscripts published; NC: Collaborations with other organizations; CR: Citations received.

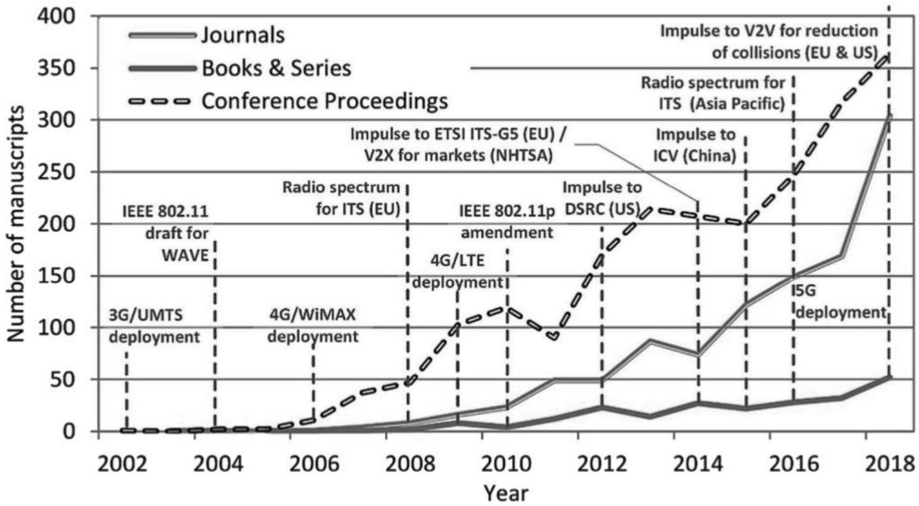


Figure 7. Bibliographic evolution of the contributions on I2X, V2X, and P2X research per source type.

An in-depth review on the co-occurrence of the keywords between the publications—both indexed by authors and publishers—is shown in Figure 8. The network visualization corresponds to the 1000 most popular terms over a total of 14,364 keywords within the 3422 manuscripts. Accordingly, the number of documents in which some representative keywords related to this survey appear resulted as follows: "V2V" (2476), "V2I" (896), "VANET" (872), "intelligent systems" (669), "V2X" (286), "IEEE 802.11p" (191), "LTE" (116), "MANET" (112), "WAVE" (103), "5G" (98), "VLC" (83), "IoT" (79), "sensors" (52), "D2D communication" (52), "WSN" (37), "I2V" (37), "IEEE 802.11s" (27), "smart city" (27), "mobile devices" (21), "smartphone" (21), "RFID" (21), "3G" (20), "WiMAX" (19), "Bluetooth"

(15), "ZigBee" (15), "4G" (14), "LTE-V" (11), "V2R" (11), "IEEE 1609" (10), "V2P" (8), "RFID" (21) and "V2G" (7), among others. The frequency in which the terms appear allows us to assess the weight of research in this field.

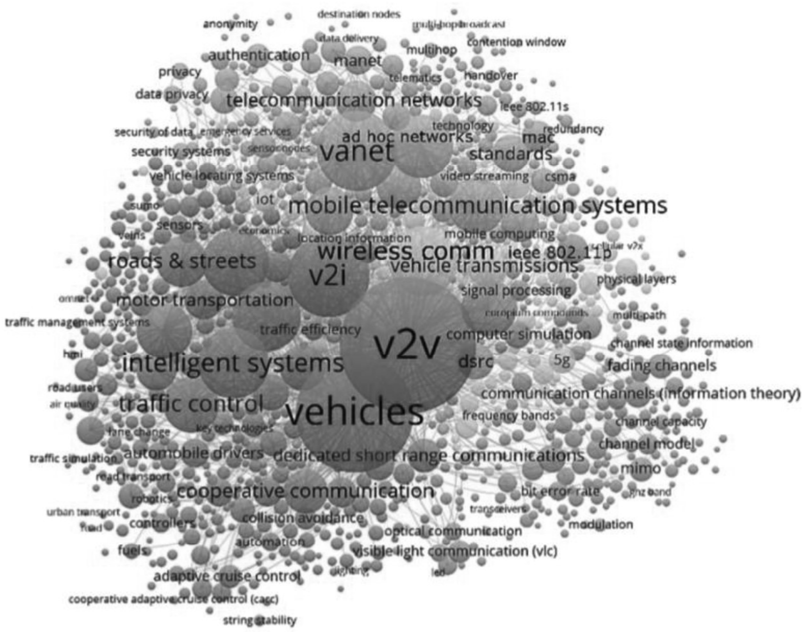


Figure 8. Co-occurrence of the keywords in publications on I2X, V2X, and P2X from 1996 to 2018.

5. Future Trends and Challenges

One of the most promising technologies and driving forces in the medium term is 5G. This access technology has been defined to work in three different usage scenarios: Mobile broadband (e.g., smartphones), machine-type communication (e.g., IoT sensors), and low-latency communication (e.g., industry 4.0 and connected vehicles). So, to boost the R&D on applications at the service of smart cities, 5G must provide higher reliability (up to 100%), data rates (20 Gbps), energy efficiency (10 mW/Mbps/sec), positioning accuracy (sub-meter range), quality of Service (QoS) for mobility (500 km/h), and lower latency (1 ms) than the previous cell-based technologies [134]. Although the 5G worldwide commercial launch is expected to be in mid-2020 after the approval of Release 16 by the International Telecommunication Union Radiocommunication Sector (ITU-R), there was in the past a strong early adoption in the form of pre-standards due to the great interest generated by the industry. This comprised service providers, hardware manufacturers, and national regulatory bodies (e.g., the 5G Technical Forum trial network of Verizon in 2010, the allocation of the 5G band by the FCC in 2016, or the 5G modems launched by Qualcomm and Intel in 2016-17).

In this context, the connected, cooperative, and automated mobility (CCAM) has been identified as one of the main vertical services of 5G by 2020 [135]. With this purpose, some efforts in terms of cooperation to adopt and test the capability of the 5G networks for AVs are becoming visible as that from the 5G Automotive Association (5GAA) since 2016, the European Automotive and Telecom Alliance (EATA) since 2017, or some providers in South Korea (i.e., BMW, Ericson, and SK Telecom). This will provide the autonomous and/or connected vehicles with the possibility of implementing multi-tier convergence networks to address road safety and transport needs for a smarter future mobility, involving ITS, ubiquitous connectivity, AI systems, and transport as a service (TaaS) [10]. Nevertheless, the higher the cost of the 5G infrastructure to be deployed, the higher the losses of the 5G millimeter waves (i.e., indoor coverage up to 2 m), security, and privacy; these are some of the main issues yet to be solved [136].

Although 5G networks can certainly support a larger number of users at much higher data rates than 3G/4G networks, operating at millimeter wavelengths (i.e., 24–86 GHz) drastically reduces signal propagation in closed scenarios [137]. From a research point of view, this could be taken as an advantage rather than a handicap. That is, keeping interferences to a minimum allows multiple users and devices reuse the same spectrum at the same time. Therefore, future works seek to cover the need of users and devices to massively communicate wirelessly while having a high bandwidth. This opens up a new world of possibilities, particularly in the mobility context and for IoT-based HetNets connected indoors (e.g., smart fridges, intelligent thermostats, building health monitoring, or security systems). Hence, proposals beyond 5G must include radically new approaches to operate new high-speed data and energy-efficiency waveforms at frequencies above 90 GHz up to THz. This brings new opportunities to investigate around physical (PHY) layer technologies such as in antenna design, signal processing, information theory, and coding to optimize and reach speeds in the Tbps range [138].

Regarding the aforementioned handicap of 5G (i.e., it suffers severely from attenuation in indoor stages), 3GPP proposed in 2016 a new set of radio access standards to solve it by enabling wide-range cellular devices and services. This is the case of LTE-M and NB-IoT, two types of low power wide area networks (LPWAN) specially focused on machine-type communication approaches that need to transmit small amounts of data to the Internet at low cost—both in terms of hardware and service subscription—with a high battery life (e.g., traffic management, parking monitoring, or street lighting). The main features defined by 3GPP in Release 13 for LTE-M are 1 Mbps of maximum data rate, 10–15 ms of latency, and a cost of $10–15 per module, while for NB-IoT, these values are 250 kbps, 1.6–10 s and $5–10, respectively. Among the main drawbacks, no radio technology excels in all the features and the specific usage must be established on a case-by-case basis (i.e., there is no one-size-fits-all solution). So, while voice and roaming services are well supported in LTE-M, NB-IoT is more suitable for stationary devices. Furthermore, data-intensive and time-critical applications cannot be performed, for instance, in road safety, traffic control, or autonomous driving. In addition, the use of a licensed band—unlike other approaches such as the long-range WAN (LoRaWAN)—precludes coverage in regions without an Internet service provider (ISP) network infrastructure. As a result, although LTE-M and NB-IoT represent cutting-edge technologies aimed at creating new applications and business models, there is still much work to do in terms of adoption and maturity of this technology [139].

An example of development of more advanced services and business models at the expense of smart cities is the Internet of Things Application (IOTA), an accounting open-source technology that allows the secure and wireless exchange of information with special focus on the automotive sector [140]. In this area, the IOTA Foundation and the International Transportation Innovation Center (ICIT) have cooperated since 2018 to test AV solutions through its own IOTA node-based service network (i.e., Tangle). In addition, Volkswagen, Bosch, Orange, Accenture, and Schneider Electric have progressively joined this newfangled initiative, who plan to kick off an IOTA bill platform in Q1 2019, called DigitalCarPass, to automatically pay for certain services such as parking or recharging electric vehicles [141]. This young technology is considered as part of the future smart car economy model so-called mobility as a service (MaaS) also envisioned by BMW, GM, Ford, Hyperledger, and IBM to form one of the world's largest consortia in crypto applications. As a result, IOTA has achieved a market capitalization of ~$800 million since 2017. Nonetheless, the lack of an intelligent contract system, the energy cost of the crypto mining process, the need for a decentralized network, and security are some of the main disadvantages that still need to be worked out at the moment [142].

An example on the need to solve issues related to security and privacy is the social IoT (SIoT), a paradigm of peer interaction through public networks where smart objects such as smartphones, vehicles, and RSUs socialize. SIoT has enormous potential to provide new high-level services using different access technologies (e.g., Wi-Fi, LTE, WiMAX, etc.), with vehicles being a leading exponent of application by exchanging information such as infotainment, traffic status, parking, routes, or weather [143]. Clear examples of Social Internet of Vehicles (SIoV) already operational in markets are a voice chatting system for dynamic vehicular communications (RoadSpeak), a car navigator that integrates traffic voice tweets (NaviTweet) or a mobility data sharing system based on social networks (Caravan Track) [4]. However, despite the enormous possibilities regarding social interaction between vehicles, infrastructure, and pedestrians, future works should focus on trusting social media and confronting ethical dilemmas in decision making. Therefore, social capabilities become the next barrier on the road to developing full self-driving cars to increase passenger safety, comfort, and efficiency, where intermediate steps from 2019 to 2027 will comprise awareness, sensing, cooperative, and synchronized driving [10].

As these skills become key for local decision-making (not only in vehicles but also in the interaction with infrastructure and pedestrians), new technological concepts and innovations must emerge. With this purpose, fog computing was introduced in 2014 by Cisco, and later promoted by the OpenFog Consortium, also joined by Dell, Intel, Microsoft, ARM, and Princeton University, as a technology to reduce the gap between cloud computing and IoT devices [16]. This new architecture allows things, apps, and devices to take advantage of the decentralization of the computing infrastructure and extend the services to the network border. Therefore, data, computation, and storage are distributed in the most logical and efficient place between data source and cloud. As a result, fog computing allows artificial intelligence (AI) to be brought to sensors. This paradigm, well-named as the Artificial Intelligence of Things (AIoT), will allow the performance of short-term analysis, which improves efficiency, reduces raw data traffic, and takes care of legal aspects about security and privacy (e.g., sensitive data subject to regulations in different countries). Popular fog computing applications include smart grid, smart city, smart buildings, software-defined networks, and vehicle networks. In particular, the benefits for vehicular fog computing (VFC) are large computation capacity, low latency, high mobility support, and low deployment cost. However, limitations in storage space, new computing architectures, and the operation of these systems in heterogeneous environments must still be investigated [144].

In relation to self-driving, future trends aim to protect the communications used in AVs against cyber-attacks to prevent the car occupants from suffering personal damage or data theft. To avoid potential security threats (e.g., such as in cybercrime-as-a-service), the automobile industry has set cybersecurity as a critical aspect to be included from the vehicle design to its decommissioning (i.e., to cover the full vehicle lifecycle) [145]. In order to achieve this goal, the car industry is currently involved in the development of the ISO/SAE 21434 standard to provide cybersecurity to road vehicles, which is expected to be published by 2020 [146]. Also with the goal of providing security to AVs, both Europe and the USA are promoting new strategies to include the auditing and certification of cybersecurity aspects beyond the own car functionalities. This includes validating the entire value chain from original equipment manufacturers (OEMs) and multi-tier suppliers to manufacturers [147]. Future steps should therefore be directed to consider the auditing and certification processes as an investment instead of a cost, also provided in the form of new industry approaches (e.g., automobile consortiums) to face the same security concerns [132].

6. Conclusions

Smart cities are scenarios of innovation, challenge, and opportunity to improve citizens' lives, where intelligent transport and mobility are key pieces of interest. Autonomous and/or connected vehicles are an example of cooperative effort made in this area, with the communications to interconnect different road users such as vehicles, infrastructure, and pedestrians being the main topic of this paper. This literature review includes I2X and P2X, in addition to V2X, as the current R&D emerging technologies in this field. To this end, an analysis considering the 100 most representative documents of the state-of-the-art since the beginning of vehicular communications until today has been performed. To avoid disqualifying the most recent papers in the area, the followed methodology included 20.79% of the manuscripts published between 2000 and 2009, 45.54% published in 2010–2013 and 33.67% published between 2014 and 2018 (i.e., one third of the most significant papers were published in the last five years).

From the sample, we confirmed that governments, industries, and universities around the world closely cooperate to respond to needs in the development of regulatory laws, standards, and technologies. The key enabler aspects in the development of communications between vehicles, infrastructure, and pedestrians have been the spectrum regulations carried out around the world (e.g., the US Department of Transportation, the Federal Communications Commission in the USA, or the European Telecommunications Standards Institute in the EU), the IEEE 802.11p standard, the development of the 4G/LTE and 5G technologies, as well as the strategic development programs conducted in different countries (e.g., Made in China 2025). On the contrary, the main drawback for the progress of vehicular communications is the different step of adoption and the non-unification of the radio band locations in countries, which results into non-interoperable technologies across different territories.

Following the bibliographic analysis, we encountered that wireless signals and the improvement of road safety have been the main focus of the V2X, I2X, and P2X communications. In this sense, we found that most of the research and development in communications has centered on V2X (92.14%), I2X to a lesser extent (4.9%), and lastly on P2X (1.96%). These results suggest that the I2X and P2X communications have been barely studied, becoming an emerging field of research in recent years according to the publications. The study also analyzed the influence of one emerging technology over another from 1997 to 2018. Such is the case of the V2X, I2X, and P2X communication, which were strongly influenced by the progress of smartphones (r^2 = 0.881), IoT technologies (r^2 = 0.878), and smart cities (r^2 = 0.809). As a result of the review, we found that the developments around the V2X, I2X, and P2X communications have been promoted mainly by universities (74.84%), followed by other research institutions (15.85%) and private corporations (9.65%). In this sense, the analysis encountered that most of the research was published in conferences (62.41%), followed by journals (30.96%) and books (6.62%).

On the other hand, as one of the conclusions of this review, it has been found that not all authors use the same expressions or acronyms to refer to the same concept. An example can be the indifferent use of car-to-car (C2C) versus vehicle-to-vehicle (V2V) communication, or car-to-everything (C2X) versus vehicle-to-everything (V2X) communication. In order to help solve these misuses, this work proposed a taxonomy to homogenize terms, avoid errors and provide long-term stability for the V2X, I2X, and P2X communication and their variants. In addition, this classification aims to contribute a useful framework that helps save time and effort to researchers and developers when designing future specifications and technical requirements around these communications.

As for future research, we confirmed that one of the most promising and leading technologies in the medium term is 5G. Although 5G networks will provide better performance than 3G/4G networks in general (i.e., reliability, data rate, power consumption, positioning, QoS, and latency), the cost of the 5G infrastructure, the signal loss of the millimeter band, and some aspects on security and privacy are some of the main concerns yet to be solved. In the meantime, other noteworthy proposals beyond 5G, such as LTE-M, NB-IoT or new ways of waveform at frequencies up to THz, have to prove their worth. This would open up a new world of possibilities to more advanced services and business models. In this sense, the Internet of Things Application (IOTA) or the Social Internet of Vehicles (SIoV) are current examples from the automotive sector aimed at increasing the safety, comfort, and efficiency of passengers in the path to developing fully self-driving cars by 2027.

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Abbreviations

3G	Third Generation
4G	Fourth Generation
5G	Fifth Generation
5GAA	5G Automotive Association
AV	Autonomous Vehicle
C2C	Car to Car
C2I	Car to Infrastructure
C2X	Car to All/Everything
CSMA	Carrier Sense Multiple Access
C-V2X	Cellular V2X
D2D	Device to Device
EATA	European Automotive and Telecom Alliance
eV2X	Enhanced V2X
EWM	Emergency Warning Messages
FCC	Federal Communications Commission
FOV	Field of View
HetVNET	Heterogeneous Vehicular Network
I2I	Infrastructure-to-infrastructure
I2P	Infrastructure-to-pedestrian
I2V	Infrastructure-to-vehicle
I2X	Infrastructure-to-everything
ICT	Information and Communication Technologies
ICT	Intelligent Connected Transport
ICV	Intelligent Connected Vehicle
IEEE	Institute of Electrical and Electronics Engineers
IN-V	In-vehicle
ITS	Intelligent Transport Systems
IoT	Internet of Things
IOTA	Internet of Things Application
ITU	International Telecommunication Union
ITU-R	ITU Radiocommunication Sector
LoRaWAN	Long Range WAN
LOS	Line-of-sight
LPWAN	Low Power Wide Area Network
LTE	Long Term Evolution
LTE-M	LTE Machine
LTE-V	LTE for vehicles
M2M	Machine-to-machine
MANET	Mobile Ad Hoc Network
MBMS	Multimedia Broadcast Multicast Service
NB-IoT	Narrow Band IoT
NDN	Name Data Networking
P2I	Pedestrian-to-infrastructure
P2P	Pedestrian-to-pedestrian
P2V	Pedestrian-to-vehicle
P2X	Pedestrian-to-everything
QoS	Quality of Service
R&D	Research and Development
RFID	Radio Frequency Identification
RSU	Roadside Unit

SDN	Software-defined Networking
TaaS	Transportation as a Service
TDMA	Time Division Multiple Access
V2B	Vehicle-to-broadband Cloud
V2C	Vehicle-to-cloud
V2D	Vehicle-to-device
V2G	Vehicle-to-grid
V2H	Vehicle-to-home
V2I	Vehicle-to-infrastructure
V2N	Vehicle-to-network
V2M	Vehicle-to-motorcycle
V2P	Vehicle-to-pedestrian
V2R	Vehicle-to-road
V2S	Vehicle-to-sensor
V2V	Vehicle-to-vehicle
V2X	Vehicle-to-everything
VANET	Vehicular Ad Hoc Network
VFC	Vehicular Fog Computing
VLC	Visible Light Communication
VSN	Vehicular Sensor Network
WAVE	Wireless Access in Vehicular Environments
Wi-Fi	Wireless Fidelity
WSN	Wireless Sensor Network
WiMAX	Worldwide Interoperability for Microwave Access

Appendix A

Table A1. Technological profile of the 100 most cited publications in the state-of-the-art.

Reference	Type	Case of Use	Players	Technology	Application	Country	Year
[12,13,28,37,43,55,56, 59,63,66,71–75,86, 93–95,98,104,107, 108,113,115,121]	V2V and V2I	Survey, Analytical model, Road safety, Security, Others, Patent	Vehicles and Infrastructures	2G, 3G, 4G, LTE, Cell band, 802.11p, 802.11 standards, WiFi, IEEE 1609.4, VLC, WiMax, 802.11b/g and WLAN-based	VANET, ITS, Communications and Smart cities	UK, India, US, Germany, Singapore, China, Australia, France, Canada, S. Korea, Spain, Japan	2008, 2009, 2010, 2011, 2012, 2013, 2014, 2015, 2016, 2017
[29–31,50]	V2I and V2R	Survey, Analytical model	Vehicles, Infrastructures and Road	802.11, 802.11p, 802.11e-based and 802.11a-based	Communications, VANET and ITS	US, Germany, US, France	2003, 2007, 2014
[32–36,39–42,44–47, 49,51,52,55,57,58,60–62,70,76–82,84,88,92, 100,105,106,109–111, 114,120]	V2V	Analytical model, Survey, Road safety, Security, Multimedia, Patent	Vehicles, RSUs and APs	802.16, 802.11 standards, 802.11p, IEEE 1609.4, Visible light, 2G, 3G, 4G, LTE, WiMax, RFID and Bluetooth	Communications, ITS, VANET and Smart cities	US, UK, Sweden, China, Belgium, Germany, Italy, Austria, S. Africa, Canada, Thailand, Spain, Portugal	2004, 2005, 2007, 2008, 2009, 2010, 2011, 2012, 2013, 2014, 2015, 2016, 2017
[38,48,68,83,87,89,96, 102,103,116,123]	V2I	Analytical model, Security, Road safety, Patent	Vehicles, Infrastructures and RSUs	802.11 standards, 802.11p, SFN, 3G, RFID	Communications, ITS, VANET and Smart cities	Spain, UK, Canada, Taiwan, Germany, US	2008, 2009, 2010, 2012, 2015, 2011
[53]	C2C	Analytical model	Vehicles	5 GHz, 24 GHz and 76 GHz	ITS and Communications	Germany	2011
[64,65,69,101,112, 117–119,122]	V2X	Analytical model, Survey, Security, Simulation, Patent	Vehicles, Pedestrians, Infrastructures, etc.	802.11p, 3GPP, 4G, LTE, Cell band, WiMaxand 802.11 standards	Communications, ITS, VANET and Smart cities	China, S. Korea, Canada, Netherlands, US	2011, 2015, 2016, 2017
[67]	V2V, V2I and V2C	Survey	Vehicles, Infrastructures and Cloud	802.11 standards and LTE	Communications, ITS, VANET and Smart cities	China	2015

Table A1. *Cont.*

Reference	Type	Case of Use	Players	Technology	Application	Country	Year
[99]	V2V, V2I and I2V	Security	Vehicles and Infrastructures	-	ITS, VANET, Communications and Smart cities	Netherlands	2015
[85,124]	I2V	Road safety, Patent	Infrastructures and Vehicles	AM or FM radio, GPS, RFID and Cell band	Smart cities and ITS	Spain, US	2010
[90]	V2C and V2V	Road safety	Vehicles and Cloud	-	ITS, VANET and Smart cities	China	2016
[91]	M2M	Road safety	Smartphones and Cloud	802.11 standards	Smart cities, Smartphones and IOT	India	2012
[97]	C2P	Survey	Vehicles and Pedestrian	802.15.4, 802.11p, 3G and 4G	ITS and Smart cities	China	2017
[119]	V2P	Patent	Vehicles and Pedestrians	802.11 standards	Smart cities and ITS	US	2016
[125]	I2X	Patent	Vehicles, Infrastructures, Pedestrians, etc.	LAN, MAN, WAN, Cell band, WLAN, Bluetooth andWiMax	Smart cities and ITS	France	2015
[126]	I2P and I2V	Patent	Infrastructure, Pedestrian and Vehicles	High frequency carrier	Smart cities	France	2004
[127]	P2I	Patent	Pedestrian and Infrastructures	Wireless, GPS and Bluetooth	Smart cities and ITS	Spain	2016
[128]	P2V	Patent	Pedestrian and Vehicles	Cell band, WLAN, PAN andWiMax	Smart cities and ITS	Germany	2010

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4.3 Article 3

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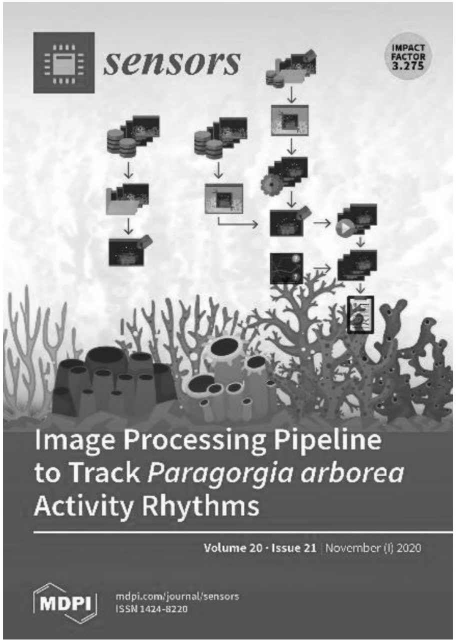

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Article

Analysis of Machine Learning Techniques Applied to Sensory Detection of Vehicles in Intelligent Crosswalks

José Manuel Lozano Domínguez [1], Faroq Al-Tam [2], Tomás de J. Mateo Sanguino [1,*] and Noélia Correia [2]

[1] Department of Electronic Engineering, Computer Systems and Automatics, University of Huelva, Av. de las Artes s/n, 21007 Huelva, Spain; jose.lozano@diesia.uhu.es

[2] Center for Electronic, Optoelectronic and Telecommunications, Faculty of Science and Technology, University of Algarve, 8005-139 Faro, Portugal; ftam@ualg.pt (F.A.-T.); ncorreia@ualg.pt (N.C.)

* Correspondence: tomas.mateo@diesia.uhu.es; Tel.: +34-959-217-719

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Abstract: Improving road safety through artificial intelligence-based systems is now crucial turning smart cities into a reality. Under this highly relevant and extensive heading, an approach is proposed to improve vehicle detection in smart crosswalks using machine learning models. Contrarily to classic fuzzy classifiers, machine learning models do not require the readjustment of labels that depend on the location of the system and the road conditions. Several machine learning models were trained and tested using real traffic data taken from urban scenarios in both Portugal and Spain. These include random forest, time-series forecasting, multi-layer perceptron, support vector machine, and logistic regression models. A deep reinforcement learning agent, based on a state-of-the-art double-deep recurrent Q-network, is also designed and compared with the machine learning models just mentioned. Results show that the machine learning models can efficiently replace the classic fuzzy classifier.

Keywords: smart road safety; pedestrian crossings accidents; vehicle detection; machine learning; time series forecasting

1. Introduction

The so-called intelligent cities can now provide more responsible and efficient solutions to several problems, thanks to information and communication technologies (ICTs) and the many sources of information available [1]. Two fundamental facilitators of this new reality are wireless communication technologies and information analysis/treatment techniques [2] based on artificial intelligence (AI)—machine learning (ML) in particular—which will allow the era of "big data" to be embraced [3,4]. Its joint use is now enabling the development of processes that will transform sectors such as energy, economy, environment, health, and transportation, among others, into smart sectors [5].

An important area of intelligent cities is the intelligent transport system (ITS), which is a set of technological solutions designed to coordinate, improve, and increase transport safety on public roads [6]. Within this area, an intelligent road-marking system was first developed to reduce the rate of accidents around pedestrian crossings—a prior work from the same team [7,8]. The system has the ability to distinguish vehicles from pedestrians by means of a fuzzy classifier that performs sensor fusion using the following elements: (i) ultrasound sensors that detect people passing through the pedestrian crossing; (ii) magnetic field sensors to detect vehicles near a pedestrian crossing; and (iii) radar sensors to detect vehicles approaching the pedestrian crossing. As a disadvantage, the fuzzy labels need to be readjusted n times in each location where the system is placed, n being the number of system nodes per location.

Motivated by this drawback, the present article investigates the possibility of applying ML techniques to the detection of vehicles at pedestrian crossings. Unlike the previous work, this document does not cover techniques aimed at detecting pedestrians, which research work was already addressed in [9]. Applying these techniques would avoid the previously mentioned drawback, facilitating the installation of these systems. The ML techniques under analysis include classifiers, anomaly detectors, time-series forecasting (TSF), and deep reinforcement learning (DRL). More specifically, the contributions of this manuscript are the following: (i) to present a discussion on ML techniques used in literature for the detection of vehicles at pedestrian crossings; (ii) to go further and investigate the possibility of applying the long short-term memory (LSTM) and DRL techniques using a combination of sensors to detect vehicles at pedestrian crossings for the first time; (iii) to integrate LSTM with DRL to produce an even more robust data model than separately; (iv) to provide a general approach that aims to facilitate the installation of safe crosswalks; and last but not least, (v) to test our approach by assembling a new dataset, which has made available to the community. The proposed approach avoids the need for calibration, present in classic label-based fuzzy classifiers, and may also be suitable in systems that use magnetic sensors and are time-dependent, like intrusion detectors in security areas, traffic light controllers, overtaking assistance systems in autonomous vehicles, and vehicle detection in parking areas, among others.

The remainder of this article is organized as follows. Section 2 provides a discussion on work related to smart cities, and the ITS in particular. Section 3 describes the approach developed for vehicle detection, including the system description, problem formulation, and machine learning techniques used. Section 4 exposes the dataset structure, parameter settings, and experiments carried out, and shows the main results. Finally, Section 5 presents the conclusions as well as the future work.

2. Related Work

There are several AI- and ML-based solutions in the literature for ITSs that serve different purposes. In [10], for example, a vehicle detection system based on bioinspired algorithms and autonomic computing, and IBM's MAPE-K is proposed to control the queues at traffic lights. In other applications, as in [11–13], historical data is used to detect accidents and generate alternative routes by combining radio frequency identification (RFID), 5G communication, and cloud services. These works use logistic regression (LR), multi-layer perceptron (MLP) neural networks, particle swarm optimization, adaptative boosting, and decision trees to release cognitive services over Microsoft Azure. Vehicle telemetry was also used to classify and detect abnormal situations on the roads (e.g., traffic jams) using a support vector machine (SVM) [14].

Another contribution of AI to turn cities into smart cities has been the monitoring of vehicles on public roads. Video surveillance systems have been widely used in this type of application, mainly because these systems are flexible and versatile, allowing the identification of movements and paths traced by vehicles [15]. Many papers describe solutions based on vision techniques and the AdaBoost learning algorithm due to their ability to detect and track vehicles in highly changing environments [16–18]. In [19], outdoor security cameras were integrated with a neural network classifier and the Mobilenet V1 SSD object detection model to detect and track vehicles, while in [20] a random forest (RF)-based method was proposed to detect vehicles under non-optimal lighting conditions. With the same intention, a system that subtracts the background from images and then detects vehicles using neural networks is described in [21]. Contrarily to the solutions based on cameras, the system proposed in [22] uses a 3D Laser Imaging Detection and Ranging (3D-LIDAR) sensor and a Deep Convolutional Neural Network (ConvNet) to detect vehicles under poor lightning conditions. Nevertheless, both vision-based and LIDAR sensor-based detection still have difficulties in detecting vehicles under adverse weather conditions (e.g., rain, fog, or snow). To improve detection, sensors can be used on the pavement to classify vehicles according to the vibration produced when they are moving [23]. The pattern in the time–frequency domain, generated by the sound of the vehicles when circulating, is used as source of information to detect targets [24].

AI techniques—and ML in particular—also enable the development of smart road safety (SRS) solutions for smart cities. In [25], for instance, a rear collision detection system for drivers was modelled using the vehicle acceleration and distance from the preceding car, and both random forest and neural networks were used. For the detection of vehicles moving in the wrong direction along highways, a camera-based system classifying the direction of the vehicle was proposed in [26], allowing traffic authority to be notified and act against such dangerous situations. Other solutions focus on avoiding damage to bikers. In [27], for example, the telemetry of a motorcycle was used to detect the roughness of the road and to determine the probability of an accident due to the state of the pavement. A method to detect the risk of an accident and activate airbags has been developed in [28] using accelerometer signals from the vehicle. The detection of pedestrians and animals on the road, to improve road safety, has also been studied. This is the case of systems designed to detect the intention to cross the road and alert drivers through cameras [29–31] and LIDAR technologies [32] applying dense, recurrent, or convolutional neural networks [33]. Other work focuses on the detection of pedestrians on zebra crossings using cameras and different classification schemes such as Haarcascade, histogram of oriented gradients (HOG), single-shot detector (SSD), and you-only-look-once (YOLO) [34]. The detection of stopped or transiting animals on the road was also studied in [35] for crashes to be avoided. Vision techniques, k-nearest neighbors (KNN), and random forest were used.

Table A1 (Appendix A) summarizes the main features of the previously described state-of-the-art proposals, together with our proposal for comparison. In general, most of the approaches to detecting targets are based on optical cameras or LIDAR sensors. This makes the systems vulnerable to poor lightning scenarios or adverse weather conditions. In addition, these are mainly on-board systems and their actions are limited to the presence of vehicles on the public roads. In contrast, the system proposed in this manuscript will be permanently located on streets so that vehicles are detected, and road safety is improved. Furthermore, the proposed approach is robust against low visibility and bad weather conditions due to the type of sensors used. Besides analyzing LR, RF, MLP, and SVM techniques also used by other authors although in different contexts, this article goes further and investigates the possibility of applying LSTM and DRL techniques for the first time. The reasons behind including the last two techniques are the following: (i) time-series forecasting in LSTM uses not only the immediate observation from the sensors but also the historical observations to produce coherent visual alerts; (ii) LSTM and DRL can be integrated (i.e., LSTM–DRL) to produce an even more robust model; (iii) unlike other classifiers, LSTM–DRL can be extended for online training.

3. Approach Description

3.1. System Description

The system previously developed by the authors was aimed at reducing road accidents. Initially, the way to interact with the environment was to distinguish pedestrians from vehicles on zebra crossings, so that visual alerts could be generated. The system controller was implemented using a fuzzy classifier whose logic performed sensory fusion, combining data from different sensors. A general overview of the system, along with the orientation and field of view (FOV) of each sensor, is depicted in Figure 1. The ultrasound sensor measures the distance at which an obstacle is from the pedestrian crossing, offering a range from 60 cm to 5 m. The SRF485WPR sensor (Robot Electronics, Attleborough, UK) is the one used in this implementation. The magnetic sensor measures the Earth's magnetic field for the X, Y, and Z axes, whose values are altered when a vehicle approaches or stops over a pedestrian crossing. The sensor used in this implementation is the LIS3MDL (STMicroelectronics, L'Hospitalet de Llobregat, Spain). The RADAR sensor provides measurements of the speed and signal strength reflected by an object, the latter being very useful to determine the volume of the target. The HB100

(AgilSense, Ang Mo Kio, Singapore) is the model used for implementation. Further technical details on the sensors used in this implementation can be found in [7,8].

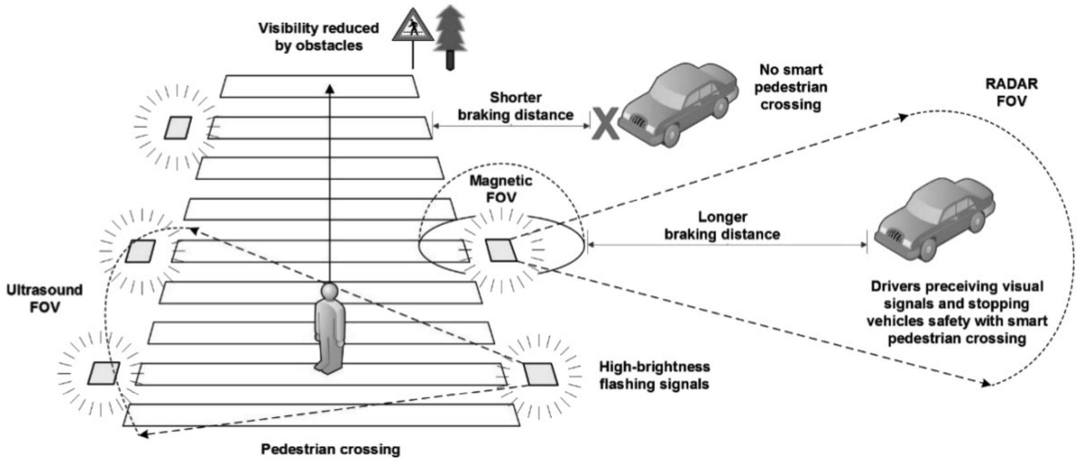

Figure 1. General description of the system and field of view for each sensor.

3.2. Problem Formulation

The previously fuzzy classifier achieved an accuracy of 96.64% and a precision of 100% after calibrating the system for a specific geographical place. Nevertheless, this classifier has the disadvantage of requiring a readjustment of labels according to its physical location on the public road, as mentioned in Section 1. More precisely, the labels used were the following: (a) "Near", "Medium", and "Far", for the ultrasound sensor to indicate how far is a target; (b) "Near-negative", "Far", and "Near-positive", for the magnetic sensor to indicate, along the XYZ axes, if there is a vehicle stopped or approaching a pedestrian crossing; (c) "Low" and "High", for the RADAR sensor to denote the presence of a target based on its reflected signal, together with "Minor" and "Major" for the RADAR to indicate whether the target approaches slowly or quickly. Since a magnetic field can be altered by the presence of power cables, pipes, and other ferromagnetic elements, often present on roads, the magnetic sensor labels must be readjusted according to the location of the system, which is a drawback.

3.3. Methodology

The following workflow is required for the development of the proposed AI-based approach: (1) a data collection and labeling procedure is carried out that takes into account diversity when collecting data (i.e., collection at different places and times); (2) the resulting dataset is analyzed and preprocessed to make it ready for ML models, keeping in mind that the dataset was intrinsically imbalanced, and that some models require time dependency between samples, among other requirements; (3) a set of AI-based models are applied to vehicle detection, the ones considered most appropriate for vehicle detection; (4) a DRL agent based on a state-of-the-art double-deep recurrent Q-network (DDRQN) algorithm is designed; (5) a set of experiments that are appropriate to the problem under study are outlined; (6) a statistical analysis including area under the curve (AUC) metrics and receiver operating characteristic (ROC) curves is performed, for model comparison. As far as it is known, the just-mentioned type of DRL agent and statistical analysis have not been previously applied to vehicle detection.

3.4. Machine Learning Techniques Used

To avoid the drawback of requiring recalibration of fuzzy labels, in this article we take a step forward and improve results with a unique detector for several places using ML techniques. The problem is treated as binary classification, anomaly detection, and even time-series prediction.

Moreover, DRL is also used—even as an unsupervised method—assuming a reward function with a binary classification nature. Therefore, the techniques used were organized into classifiers, anomaly detectors, time-series forecasting, and DRL.

The reasons for choosing the previously mentioned models are: (i) from each category of techniques we have chosen an approach. For instance, logistic regression was chosen among linear classifiers. Other alternatives are possible, like Fisher's linear discriminant (FLD). However, these have the same nature and choosing one of them is appropriate. Moreover, (ii) the problem can be better understood if tackled in different ways, allowing a multi-unit seamless model to be developed in the future, which may require a new hardware setting to orchestrate multiple devices at the same time. The approach used to implement the ML models, and determine their performance, is shown in Figure 2. The yellow block is to be replaced by one of the techniques described in the next subsections.

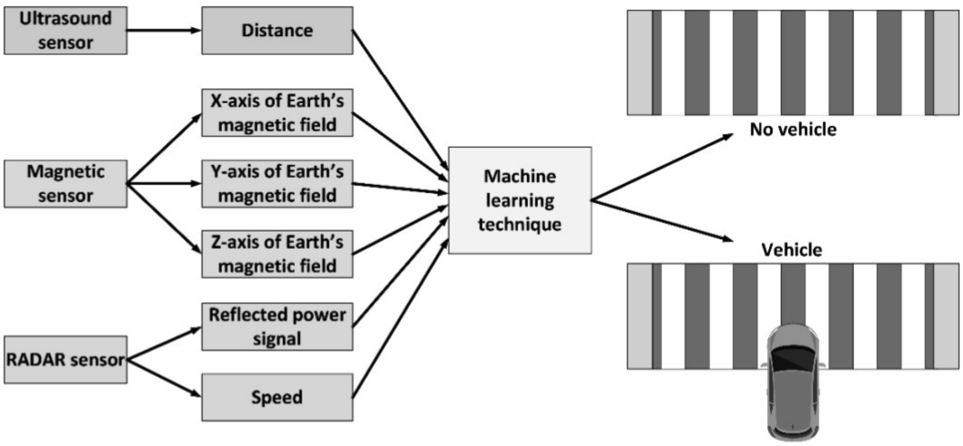

Figure 2. Machine learning approach implemented in the system.

3.4.1. Classifiers

The classifiers used are logistic regression, random forest, and multilayer perceptron, which are all widely known supervised methods. These classifiers were all implemented with the scikit-learn library of Python [36]. The first one, the logistic regression, was designed to detect two different classes and the L2 norm was used to control the overfitting. This method is easy to implement and effective because it does not require data scaling. However, it can easily fall short to handle non-linear mappings [37].

The second classifier, random forest, was configured with 15 estimators. Random forest offers the advantage of handling large amounts of data and does not suffer from overfitting. On the other hand, it is slow to predict and hard to interpret how it performs [37].

Finally, the last classifier is the multi-layer perceptron, which was optimized with the Adam optimizer. The multi-layer perceptron consists of 4 hidden layers, each with 100 neurons, and 20% of the training data was used for validation to ensure the stability of the model. This has the capability to learn and model non-linear complex relationships, as well as to make predictions using data that have not been previously visited. On the other hand, it can be difficult to tune its hyperparameters and it may require long training for large neural networks [37].

3.4.2. Anomaly Detector

The anomaly detector utilized is the one-class support vector machine (one-class SVM), which is an unsupervised outlier detector. This method was also implemented in Python with scikit-learn. The one-class SVM allows the detection of outliers (or anomalies) in the data. The use of this technique allows us to treat vehicles as outliers and the "No vehicle" state (i.e., the most frequent state of pedestrian crossings) as the "normal" state. The uniqueness of this method, when compared to the others, is that it only needs to be trained with the "No vehicle" class data. It has the advantage of offering a good handling of imbalanced classes, it only needs to train instances of the target class and it is very sensitive to outliers. On the other hand, it requires the right selection of hyperparameters and kernels [38].

3.4.3. Time-Series Forecasting

To avoid the system generating inconsistent visual alerts, it is necessary not only to consider the current measurements from sensors but also the last few ones. This way, the output of the system will depend on a sequence of observations. This means that the vehicle detection problem can be treated as time-series forecasting, allowing the use of an LSTM architecture. LSTM networks are an important piece in modern time-series forecasting and to sequence deep learning models. The reason for using an LSTM instead of others (e.g., statistical autoregressive models) is that LSTM networks can be integrated into DRL architectures, as explained below. An LSTM is a recurrent neural network (RNN) equipped with gated cells able to remember important information and forget the irrelevant. An LSTM converts the input sequence into memory and hidden states. These can be used to forecast future data based on some training samples, and it offers better long-term modeling and a more robust vanishing gradient than conventional RNN. However, an LSTM requires more computational and memory capacity due to the multiple memory cells [39]. As shown in Figure 3, the used LSTM-based neural network architecture consists of a total of 42 input neurons, corresponding to the number of time instants and different sensor measurements for each time instant. Then, the LSTM layer is made up of 10 units that are fully connected to the input layer. Finally, the output layer is made of a single neuron completely connected to the LSTM layer, being this neuron responsible for predicting whether a vehicle is—or is not—currently over a crosswalk. The neural network structure has been determined following the instructions described in the Parameter Settings section.

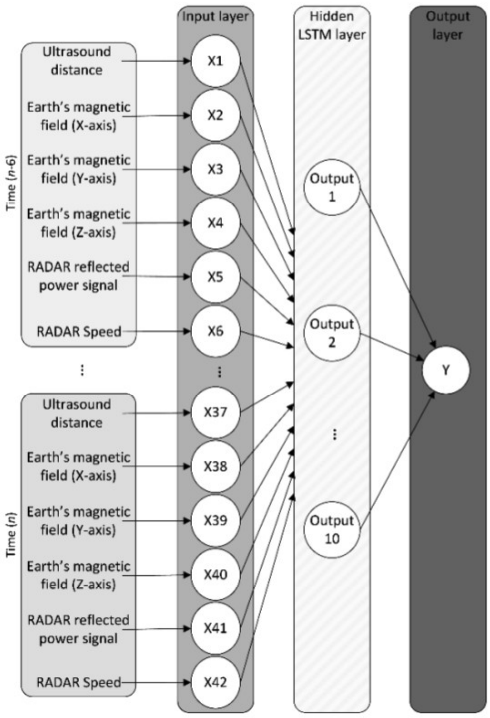

Figure 3. Long short-term memory (LSTM)-based neural network structure.

3.4.4. Deep Reinforcement Learning

DRL is an emergent learning scheme whereby an agent learns by interacting with the environment. It is an unsupervised method and can be trained online. Here in this work it is trained offline for it to be compared with the other well-established methods. An online training system will be explored in the future.

The agent (usually represented as a deep neural network for efficiency purposes) observes a state from the environment and performs actions. According to the performed action, it receives a reward and a new state. The agent's objective is to maximize the accumulated future reward. Therefore, training an agent means to find a policy that will map states to actions such that the accumulated reward received by the agent is maximized. In this work, the DDRQN model is used [40]. DDRQN uses an LSTM layer (i.e., LSTM–DRL) to obtain time relevance between consecutive states. This allows to reduce the overestimations and the number of operations to calculate them [41]. Therefore, the agent developed in this work uses the current and historical data in its state to recognize time-related events. The reward function is as simple as 1 if the agent selects the right class, and −1 otherwise. This rewards the agent for correct selections and penalizes it for wrong ones. The action space of the agent is {"No vehicle", "Vehicle"}, where the LSTM–DRL agent decides if there is a vehicle approaching the crosswalk, or not, according to the received sequence of observations from the sensors.

As shown in Figure 4, the neural network architecture used in the DRL model has a total of 48 input neurons corresponding to the measurements of the different sensors of the system according to each instant of time (n), including historical data (up to n-7). The hidden layers of the neural network are initially made up of a fully connected layer of 15 neurons, followed by an activation layer where the Rectified Linear Units (ReLU) function is used as activator. At the output of this layer, an LSTM layer with 10 units is completely connected with the previous layer. This output is linked to a second fully connected layer of five neurons. The output of this layer is connected to a second ReLU activation layer. Then, two neurons (Y1 and Y2) fully connected to the previous layer are used. The neural network structure has been determined following the instructions described in the Parameter Settings section.

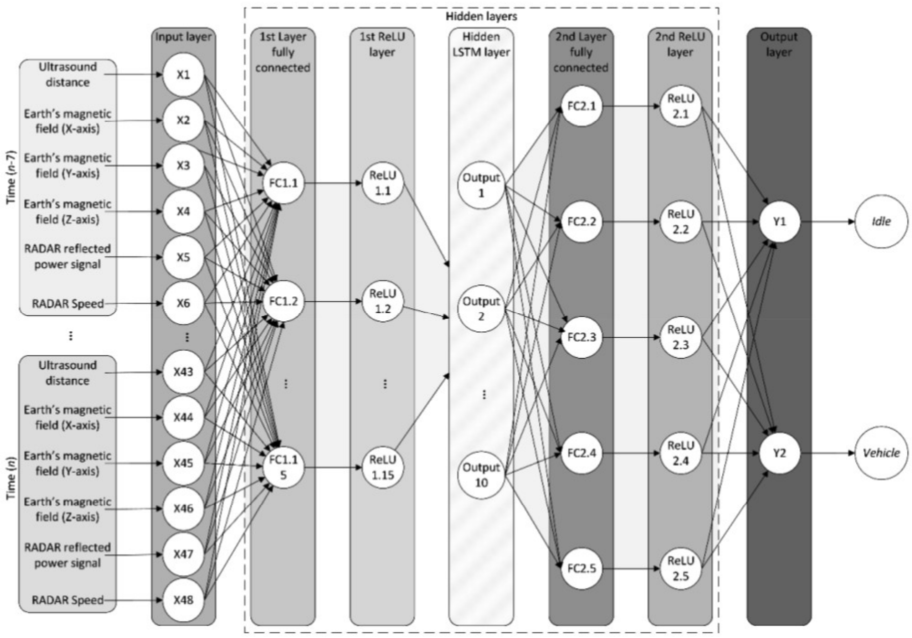

Figure 4. Neural network structure for the DRL used.

4. Experimentation

4.1. Dataset Structure

The proposed approach uses data generated by three different sensors as predictor variables. Table 1 shows such set of predictor variables and range values. The data are used by the models to identify whether there is, or is not, a vehicle circulating through the intelligent pedestrian crossing.

Table 1. Sensor measurement ranges and corresponding normalization.

Measurement	Range Value	Normalized Value
Ultrasound distance	60–500 cm	0–1
Magnetic *X*-axis	−32.768–32.767 Gauss	0–1
Magnetic *Y*-axis	−32.768–32.767 Gauss	0–1
Magnetic *Z*-axis	−32.768–32.767 Gauss	0–1
Reflected signal power RADAR	0–1 n/a	0–1
Speed RADAR	0–100 Km/h	0–100
Ground truth	0–1	0–1

For this purpose, two classes are used: "Vehicle" and "No vehicle", represented as 1 and 0, respectively. These classes are used as ground truth (GT). Measurements from sensors were normalized using the Min–Max method for an adequate performance of the ML algorithms [42]. Normalization values are also shown in Table 1.

The dataset used to train the ML models, for these to determine whether a vehicle is approaching a pedestrian crossing or not, was collected from a real environment and is available at http://www.uhu.es/tomas.mateo/investigacion/dataset.zip. This dataset includes a total of 86,960 labeled tuples. The dataset is imbalanced: the "No vehicle" class has a total of 80,915 tuples (93.05%); whereas the "Vehicle" class has a total of 6045 tuples (6.95%). To balance the dataset, the NearMiss subsampling technique was used [43]. The balanced dataset ends up having 6362 tuples for the "No vehicle" class and 6045 tuples for the "Vehicle" class, which corresponds to 51.28% and 48.72%, respectively. Therefore, the size of the dataset used at the classification stage consists of 12,407 labeled tuples. The dataset is ordered by a tuple index to keep time linearity, which is necessary for some ML models to work properly.

The data collection process has been carried out in several real environments under fluid traffic conditions. The devices were placed on the roadway near the line of the pedestrian crossing, while the vehicles passed over devices—or on their sides—with an average speed of 18.20 ± 26.16 Km/h. This paper focuses on the detection of vehicles only as the basis to study the feasibility of using ML techniques instead of a fuzzy logic approach. So, the data collection procedure consisted of monitoring the system's interactions with vehicles and environment, and then storing the data with both vehicles and no vehicles circulating. Because of this, cases involving pedestrians were filtered out and no data was recorded. Tests were performed both in Portugal and Spain, more specifically in the urban areas of Gambelas (Faro) and Bollullos Par del Condado (Huelva). Four points were in the University of Algarve, two points were in Rua Manuel Gomes Guerreiro, one point was in Rua Comandante Sebastião da Costa, one point was in Praceta Orlando Sena Rodriguez, and another point was in Sector Pp1 Cruz de Montañina. These locations present different terrestrial magnetic fields either due to their nature or to different elements found on public roads (e.g., traffic signs and streetlights among other ferromagnetic elements). To illustrate the different magnetic field values at these locations, Table 2 shows the average values and standard deviations for the X, Y, and Z axes of the magnetic sensor for both circulating and non-circulating vehicles. On the one hand, the table shows that there is a small difference between the values for "Vehicle" and "No vehicle" conditions at each location (i.e., a minimum of 0.0051% and maximum of 0.6532%), which is in practice very difficult to calibrate. On the other hand, the average values for the magnetic field sensor have no correspondence between sites with very similar values (e.g., X-axis for the column "No vehicle" of Praceta Orlando vs. the X-axis for the column "Vehicle" of Cruz Montañina). This means that a calibration process at one site is unrelated to another, being necessary to start a new labeling procedure of the system to differentiate circulating and non-circulating vehicles. The complexity of generating a single vehicle-classifier for multiple locations elevates to $N \times L$, N being the number of nodes of the intelligent pedestrian crossing and L the number of locations. Details on the weather conditions for which the data were collected as well as the duration of each data collection process are given in Table 3. Finally, the system uses wireless communication to collect the data from the sensors. A portable access point (AP), a personal computer with WampServer software, and hypertext transfer protocol (HTTP) were used. The WampServer software has the capability to handle HTTP requests from the nodes (through an Apache server) and store the data in a MySQL database. The collected tuples were manually labelled as "No vehicle" or "Vehicle".

Table 2. Normalized average magnetic sensor measurements by location, axis and vehicle presence.

	No Vehicle			Vehicle		
Calibration Site	**X-axis (avg. ± dev.)**	**Y-axis (avg. ± dev.).**	**Z-axis (avg. ± dev.)**	**X-axis (avg. ± dev.)**	**Y-axis (avg. ± dev.).**	**Z-axis (avg. ± dev.)**
Campus 1	0.499 ± 0.000	0.4580 ± 0.001	0.581 ± 0.001	0.493 ± 0.009	0.461 ± 0.009	0.587 ± 0.012
Campus 2	0.510 ± 0.06	0.500 ± 0.023	0.582 ± 0.01	0.504 ± 0.027	0.502 ± 0.032	0.586 ± 0.031
Campus 3	0.501 ± 0.001	0.455 ± 0.004	0.582 ± 0.001	0.499 ± 0.006	0.455 ± 0.008	0.587 ± 0.010
Campus 4	0.495 ± 0.000	0.458 ± 0.000	0.581 ± 0.001	0.490 ± 0.008	0.460 ± 0.010	0.586 ± 0.012
Manuel Gomes Guerriro	0.513 ± 0.001	0.513 ±0.001	0.584 ± 0.001	0.509 ± 0.010	0.514 ± 0.007	0.589 ± 0.009
Praceta Orlando Sena Rodriguez	0.480 ± 0.001	0.4803 ± 0.001	0.587 ± 0.001	0.476 ± 0.007	0.481 ± 0.009	0.592 ± 0.010
Comandante Sabastião da Costa	0.511 ± 0.000	0.456 ± 0.000	0.584 ± 0.000	0.504 ± 0.005	0.458 ± 0.010	0.586 ± 0.013
Cruz Montañina	0.478 ± 0.001	0.492 ± 0.001	0.585 ± 0.001	0.479 ± 0.006	0.492 ± 0.007	0.587 ± 0.010

Table 3. Weather and temporal conditions of data collection.

Site	Temperature (°C)	Humidity (%)	Weather	Date	Day Time	Duration (min)
Campus 1	24	57	Partly cloudy	25 July 2019	19:34	22
Campus 2	23	62	Sunny	5 August 2019	19:34	39
Campus 3	24	83	Partly Sunny	9 August 2019	13:37	18
Campus 4	24	83	Sunny	23 August 2019	10:36	29
Manuel Gomes Guerriro	25	58	Partly cloudy	4 September 2019	10:37	23
Praceta Orlando Sena Rodriguez	26	59	Partly cloudy	4 September 2019	11:22	25
Comandante Sabastião da Costa	25	68	Partly cloudy	4 September 2019	19:38	18
Cruz Montañina	21	67	Partly cloudy	9 September 2019	10:32	77

4.2. Parameter Settings

The hyperparameter tuning of LR, RF, MLP, and one-class SVM methods has been carried out using the Grid Search Cross Validation technique implemented in scikit-learn [36], while the tuning of the LSTM and the DRL methods has been empirically determined. The method used to determine the best fit for LSTM and DRL is as follows. A combination matrix of the hyperparameter values is generated, the models undergo learning with these hyperparameters using cross-validation to get the metrics for that learning model, and these metrics are added to the combination matrix. The metrics used in this process have been the accuracy and, in case of a tie, the true positive rate and then the false positive rate. Once the metrics of the first iteration are compared, the best metrics are selected and, therefore, their hyperparameters. Then, a new matrix is established with values close to the best hyperparameters as well as a linear distribution of the values among the best hyperparameters. This process continues iteratively and ends when similar metrics are reached in all cases. The values adopted for each method are shown in Table 4.

Table 4. Optimized parameters for machine learning (ML) models.

Technique	Variable	Value
Logistic regression	C	0.09
	Penalty	L2
	Random state	1
	Solver	Newton-cg
Random forest	Random state	1
	Number estimators	15
Multi-layer perceptron	Solver	Adam
	Hidden layers	4
	Learning rate	0.0001
	Hidden layer neurons	100
	Maximum iterations	1000
	Validation fraction	20%
One-class support vector machine	Nu	0.01
	Gamma	0.77
	Kernel	Radial basis function (RBF)
Long short-term memory	Number of time instants	7
	Intermediate layer	10
	Output layer neurons	1
	Optimizer	Adam
	Learning rate	0.0005
	Epochs	20
	Validation fraction	20%
Deep reinforcement learning (RDDQN)	Historical length	8
	Episodes	100
	Steps	2470
	Neurons of first layer fully connected	15
	Neurons of LSTM layer	10
	Neurons of second layer fully connected	5
	Neurons output layer	2
	Learning rate	0.0001

4.3. Results and Discussion

The experiments carried out consisted of submitting the balanced data to the techniques described in the previous section. The cross-validation approach was used for this purpose [44]. The 12,407 tuples, resulting from the preprocessing and data balancing process, were divided into five folds, each one having a total of 2480 tuples. Among them, four folds were used for training whilst one was used for testing. The splitting of the dataset was performed to keep the required temporal linearity. The class distribution of the dataset, according to the folds, is shown in Table 5.

Table 5. Distribution of entries in "No vehicle" and "Vehicle" classes.

Fold	Class "No Vehicle"	Class "Vehicle"
1	680	1800
2	1965	515
3	1111	1369
4	1254	1226
5	1350	1130

To determine the efficiency of each algorithm, the ROC analysis [45] was used (i.e., sensitivity of each algorithm to detect vehicles). The performance was obtained from a confusion matrix of 2×2 elements that relates positive (p) and negative (n) outcomes (Table 6). A vehicle detection is considered positive whilst the detection of the "No vehicle" class is considered negative.

After training the models, taking into account the previous considerations, these were subjected to tests with data not previously used in the training phase. The model that best detected the vehicles was random forest, which achieved a true positive rate (TPR) of 96.82%, false positive rate (FPR) of 1.73%, precision of 98.63%, F1 of 97.68%, accuracy (ACC) of 97.85%, and AUC of 0.98. This can be considered as excellent in a scale of [0.97, 1), as argued in [46]. One drawback of RF is that its decisions are difficult to interpret. The following best-performing models are those that consider the time dimension of the data. These were the deep reinforcement learning (TPR = 92.94%, FPR = 3.73%, precision = 95.00%, F1 = 93.70%, ACC = 94.51%, and AUC = 0.98) and LSTM (TPR = 92.60%, FPR = 5.07%, precision = 95.14%, F1 = 93.18%, ACC = 93.83%, and AUC =0.97), both considered as excellent. The anomaly detector model, one-class SVM, also offers very good results—although lower than the previous models—achieving a TPR of 93.38%, FPR of 15.59%, ACC of 92.08%, and AUC of 0.94. Finally, the multi-layer perceptron and logistic regression had a performance that can be considered as good. Nevertheless, their accuracy rate is reduced when compared to the other models. A summary of these results is shown in Table 7, while the ROC curves for each of the ML techniques are shown in Figure 5. The blue color represents the average ROC curve, the gray shaded area shows the standard deviation, and the soft-blue, orange, green, pink, and purple colors stand for each of the folds used to test the models. Table 7 also includes the performance achieved with the fuzzy classifier used previously. This classifier provided an excellent performance as it was calibrated for a specific location prior to testing. Despite a slight performance drop, the proposed machine learning approaches allow generalization of vehicle detection without the need to calibrate the system.

Table 6. Confusion matrix for the receiver operating characteristic (ROC) analysis.

	Real Value		**Total**
	P	***N***	
Prediction			
p'	True positives (TP)	False positive (FP)	P'
n'	False negatives (FN)	True negatives (TN)	N'
Total	P	N	

Table 7. Results for the machine learning models.

Technique	TPR (%)	FPR (%)	P (%)	A (B/W) (%)	F1	AUC
LR	82.02 ± 22.85	0.22 ± 0.37	99.77 ± 0.25	91.08 (99.96/75.00)	0.88 ± 0.16	0.91 ± 0.09
RF	96.82 ± 4.05	1.73 ± 1.69	98.63 ± 0.53	97.85 (99.60/95.32)	0.98 ± 0.02	0.98 ± 0.01
MLP	82.11 ± 22.88	0.93 ± 1.95	99.77 ± 0.25	90.98 (99.96/75.00)	0.88 ± 0.16	0.87 ± 0.12
One-class SVM	98.38 ± 2.24	15.59 ± 23.19	89.91 ± 14.27	92.08 (99.96/75.44)	0.93 ± 0.08	0.94 ± 0.07
LSTM	92.60 ± 8.47	5.07 ± 3.26	95.14 ± 2.76	93.83 (99.02/86.78)	0.93 ± 0.06	0.97 ± 0.04
DRL	92.94 ± 9.92	3.73 ± 3.71	95.00 ± 4.37	94.51 (99.80/87.05)	0.94 ± 0.06	0.98 ± 0.01
Fuzzy logic	100	0	100	100	1	N/A

TPR: true positive rate; FPR: false positive rate; P: precision; A: accuracy with the best (B) and worst (W) values; F1 score in range [0, 1]; and area under the curve (AUC) in range [0, 1]. All measurements include the standard deviation except for the fuzzy logic technique and the accuracy.

The overall results are summarized as follows. Firstly, LR offers a good result but is not as outstanding as other techniques. The LR reaches an accuracy of 90.84%; its performance is good, but its accuracy, TPR, and ACC are easily surpassed by other models. Its FPR is, however, the lowest of all the techniques used. Additionally, this model is not very reliable because it presents a high standard deviation for the TPR and ACC. Secondly, RF offers the best success rate from all the models, complying with the theory of its ability to optimize the accuracy. Moreover, this model is very stable as it achieves a low standard deviation in all measurements. Thirdly, the model based on MLP offers good results (ACC of 90.98%), but it is not reliable due to the high standard deviation of the TPR and the ACC. Fourthly, the one-class SVM is the least reliable of all the methods because it presents the highest FPR and the highest standard deviation. Fifthly, LSTM offers excellent and stable results, as expected in a theorical way, since it considers the time series. In this regard, the vehicle detection depends largely on the time because two representations of the crosswalk state can be similar for different situations in different locations. Finally, DRL also offers excellent and stable results due to the construction of a specialized agent. The input structure based on current and historical data allows this method to identify the temporal events generated by vehicles when approaching a pedestrian crossing.

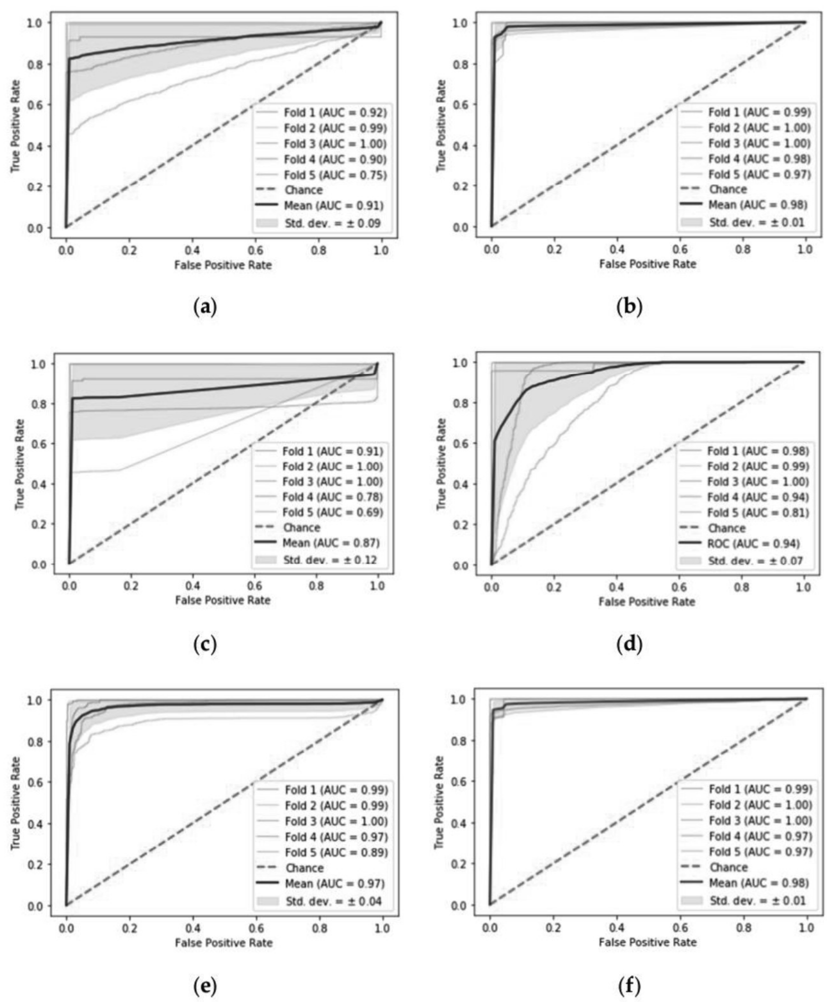

Figure 5. ROC analysis: (**a**) logistic regression; (**b**) random forest; (**c**) multi-layer perceptron; (**d**) one-class SVM; (**e**) long short-term memory; (**f**) deep reinforcement learning.

In addition to the previous analysis, the AUC was studied to empirically determine the performance of each model used. The results obtained confirm the outcomes previously exposed, being that the models based on RF and DRL are the best techniques, with an AUC of 0.98 and a standard deviation of 0.01 each. That is, they have similar separability of classes, which can be confirmed by the shape of their ROC curves in Figure 5. These were followed by LSTM, which achieved an AUC of 0.97 and a standard deviation of 0.04. The one-class SVM offered a very good performance, reaching an AUC value of 0.94 and a standard deviation of 0.07. Finally, the methods based on LR and MLP presented the lowest performance, which is in line with the AUC results of 0.91 and 0.87, respectively.

From all the results exposed it is possible to state that ML techniques are an adequate solution to detect vehicles near pedestrian crossings, and a better choice than the fuzzy classifiers used in our previous work. Although the results obtained with the ML techniques offer a lower performance than those achieved with the fuzzy classifier calibrated for a specific site, the experimentation carried out demonstrate their feasibility to replace the fuzzy classifier. These techniques allow us to place the system in any location without it needing to be calibrated, with a very good or excellent performance. The most effective and reliable ML methods were RF and LSTM–DRL due to their high performance and stability, as shown in Table 7 and Figure 5. On the contrary, the least-recommended methods to detect vehicles, under this system, were LR, MLP, and one-class SVM in particular. LR and MLP are least-recommended due to the high deviations present in their TPR and ACC, and one-class SVM is least-recommended due to its high FPR and standard deviation. In general, the temporal recognizing methods, like DRL and LSTM, offer better performance than the other methods, except for RF. From another perspective, the datasets can be seen as having a limitation: the locations used for data collection were always around the 37th parallel.

This fact, however, does not prevent us from confirming that the models under analysis are capable of replacing the classic fuzzy calibration method. Furthermore, the current dataset—although being representative and including captures of cars, motorcycles and buses—does not reflect all types of possible vehicles that can circulate on public roads (e.g., bicycles, electric scooters, trucks or vans, among others). This lack of samples in the current dataset may have limited the performance of the system for these kinds of targets.

5. Conclusions

Thanks to the support of ICTs, smart cities are becoming a reality and can now improve or create new services that enhance the lives of their inhabitants. Intelligent transport systems and intelligent road safety are among those services in which a significant amount of innovation has emerged. This paper contributes to such field by investigating how different machine learning techniques can be applied—as an alternative to classic fuzzy logic—to generalize vehicle detection using sensor data from intelligent pedestrian crossings. To achieve this goal, several machine learning techniques were implemented in our system and their performance was evaluated. The methods were divided into classifiers (i.e., LR, RF, and MLP), anomaly detector (i.e., one-class SVM), time-series forecasting (i.e., LSTM) and DRL.

The training and testing of the different techniques were carried out with real data collected from a total of five different locations in both Portugal and Spain, under fluid traffic conditions. The dataset created from tests performed in real environments has been assembled and made public for the community. Training and validation data were obtained using a cross-validation scheme with five folds. The best results were obtained by the RF model, having a TPR of 96.82%, FPR of 1.73%, ACC of 97.85%, and AUC of 0.98. The next best results were obtained by DRL and LSTM models, with high ACC (94.83% and 93.83%, respectively) and high AUC (0.98 and 0.97 respectively). In contrast, LR and MLP offered the least reliable performance from all methods due to the low AUC obtained (0.91 and 0.87, respectively). Therefore, the results suggest that it is feasible to use RF, DRL, and LSTM—which present similar metrics—to replace the fuzzy logic approach for vehicle detection.

Future work will focus on real-time vehicle detection deployment, using machine learning techniques, with infotainment purposes. This could allow the system to be used as a traffic monitoring device, being able to count the number of vehicles circulating and to record when these detections take place. In addition, more samples will be collected in real environments, with a broader spectrum of vehicles (i.e., not only cars, motorcycles, and buses but also bicycles, scooters, trucks, or vans), creating more robust and generalized machine learning models. In this sense, samples should also be taken considering other locations (e.g., mountain areas and latitudes different from the 37th parallel) and at different times of the day (e.g., at the sunrise or sunset). This way, models—especially those that detect changes or patterns in time series—are expected to improve their reliability even more. This study can be generalized to applications studying a phenomenon that changes over time, as well as those that may occur in different locations (e.g., detection of intruders, overtaking or avoiding obstacles in autonomous vehicles, or vehicle detection in parking lots).

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Appendix A

Table A1. Features of related work discussed in Section 2.

Reference	Field of Application	Target to Detect	Sensing Device	AI Technique	Metric Used	Year
[7,8]	SRS	Pedestrians & vehicles	Ultrasound; magnetic field; RADAR	Fuzzy logic	ACC; TPR; FPR; Precision; AUC	2018; 2018
[10]	ITS	Traffic jams	Simulated	Bio-inspired algorithm; autonomic computing	Queue of vehicles in a traffic light	2015
[11]	ITS	Traffic jams	5G; RFID	Microsoft Azure cognitive services	N/A	2019
[12]	ITS	Traffic jams	Smart phone	LR; bagging; AdaBoost; voting; trivial	ACC	2017
[13]	ITS	Traffic jams	Camera; security software	MLP; particle swarm	Free flow traffic	2019
[14]	ITS	Traffic jams	Telemetry	One-class SVM; logit	ACC: Recall; Precision	2018
[16]	ITS	Vehicles	Camera	AdaBoost	TPR; FDR	2014
[17]	ITS	Vehicles	Camera	AdaBoost	Detection time	2019
[18]	ITS	Vehicles	Camera	AdaBoost	TPR; FPR	2019
[19]	ITS	Vehicles	Camera	SSD MobileNet V1 model	ACC	2019
[20]	ITS	Vehicles	Camera	RF	N/A	2019
[21]	ITS	Vehicles	Camera	Naive Bayes; KNN; ANN	ACC	2019
[22]	ITS	Vehicles	3D-LIDAR	ConvNet	ACC	2018
[23]	ITS	Vehicles	Vibration	Naive Bayes; RBFN; SVM; MLP	TPR; FPR; Precision; Recall	2016
[24]	ITS	Vehicles	Audio	CNN	ACC	2019
[25]	SRS	Vehicles	Smart phone sensors and camera	ANN; RF; KNN	RScore; TScore	2018
[26]	SRS	Vehicles	Camera	KNN	N/A	2018
[27]	SRS	Accident risk	Telemetry	LR; DT; Discriminant analysis; Naive Bayes; SVM; KNN;	ACC	2019
[28]	SRS	Accident risk	Accelerometers	SOM	FPR; Miss detection; Detection delay	2014
[29]	SRS	Pedestrians	Camera	Region-based CNN; SVM; MLP	AUC	2019
[30]	SRS	Pedestrians	Camera	KNN; SVM; ANN; DT	Performance	2018
[31]	SRS	Pedestrian	Camera	HOG based on SVM	Error rate	2017
[32]	SRS	Pedestrian	LIDAR	KNN; Naive Bayes; SVM	Error rate; AUC; Sensitivity; Specificity; Precision; ACC; F1-score	2017
[33]	SRS	Pedestrian	LIDAR	DNN; LSTM; CNN	Classification rate vs. Time to cross; Classification rate vs. Distance to cross	2016
[34]	SRS	Pedestrian	Camera	Haarcascade based on OpenCV library; HOG based on SVM; SSD based on MobileNet; YOLO based on DNN	ACC	2019
[35]	SRS	Animals	Camera; presence sensor	KNN; RF	F1-score	2019
Proposed	SRS	Vehicles	Ultrasound; magnetic field; RADAR	LR; RF; MLP; One-class SVM; LSTM; DRL	TPR; FPR; Precision; ACC; F1-score; AUC	2020

ACC: accuracy; ANN: artificial neural network; AUC: area under the curve; CNN: convolutional neural network; ConvNet: deep convolutional neural network; DNN: dense neural network; DRL: deep reinforcement learning; DT: decision tree; FDR: false discovery rate; FPR: false positive rate; HOG: histogram of oriented gradients; ITS: intelligent transport system; KNN: k-nearest neighbors; logit: logistic regression linear model; LR: logistic regression; LSTM: long short-term memory; MLP: multi-layer perceptron; RBFN: radial basis function network; RF: random forest; SSD: single shot detector; SOM: self-organizing map; SRS: smart road safety; TPR: true positive rate; YOLO: you-only-look-once.

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4.4 Article 4

Walking Secure: Safe Routing Planning Algorithm and Pedestrian's Crossing Intention Detector Based on Fuzzy Logic App

Lozano Domínguez, J.M., Mateo Sanguino, T.J.

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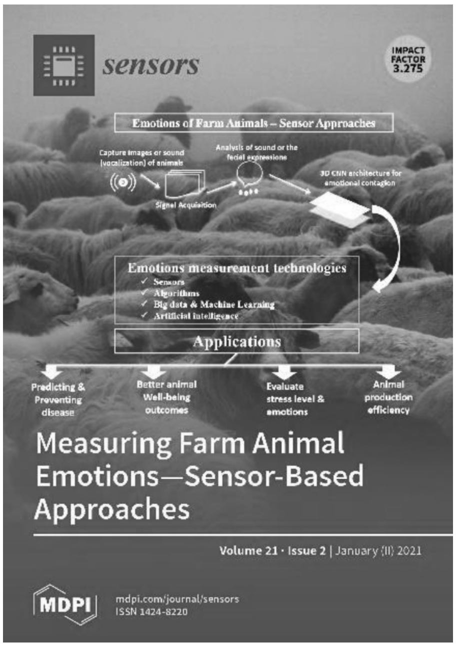

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Article

Walking Secure: Safe Routing Planning Algorithm and Pedestrian's Crossing Intention Detector Based on Fuzzy Logic App

José Manuel Lozano Domínguez and Tomás de J. Mateo Sanguino *

Department of Electronic Engineering, Computer Systems and Automatics, University of Huelva, Av. de las Artes s/n, 21007 Huelva, Spain; jose.lozano@diesia.uhu.es
* Correspondence: tomas.mateo@diesia.uhu.es; Tel.: +34-959-217-719

Abstract: Improving road safety through artificial intelligence is now crucial to achieving more secure smart cities. With this objective, a mobile app based on the integration of the smartphone sensors and a fuzzy logic strategy to determine the pedestrian's crossing intention around crosswalks is presented. The app developed also allows the calculation, tracing and guidance of safe routes thanks to an optimization algorithm that includes pedestrian areas on the paths generated over the whole city through a cloud database (i.e., zebra crossings, pedestrian streets and walkways). The experimentation carried out consisted in testing the fuzzy logic strategy with a total of 31 volunteers crossing and walking around a crosswalk. For that, the fuzzy logic approach was subjected to a total of 3120 samples generated by the volunteers. It has been proven that a smartphone can be successfully used as a crossing intention detector system with an accuracy of 98.63%, obtaining a true positive rate of 98.27% and a specificity of 99.39% according to a receiver operating characteristic analysis. Finally, a total of 30 routes were calculated by the proposed algorithm and compared with Google Maps considering the values of time, distance and safety along the routes. As a result, the routes generated by the proposed algorithm were safer than the routes obtained with Google Maps, achieving an increase in the use of safe pedestrian areas of at least 183%.

Keywords: crossing intention detector; Android application; road safety; smart cities; safe routes; pedestrians

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1. Introduction

Currently, smart cities are becoming a reality thanks to the use of information and communication technologies (ICTs), which allow to improve the services offered to their inhabitants [1]. Wireless communications together with data analysis and processing techniques such as big data, machine learning and artificial intelligence (AI) are promoting the development of technologies applied to smart cities, among other approaches [2–4].

An important area of smart cities is intelligent transport systems (ITS). These are made up of a set of technological solutions designed to coordinate, improve and increase transport safety on public roads [5,6]. At present, road safety of pedestrians represents a weak point of smart cities as stated in a study carried out by the General Administration of Traffic (DGT), in Spain. This study describes that there was a total of 13,545 accidents in urban areas involving pedestrians and vehicles in 2018, of which 5483 (40.48%) were pedestrians run over while crossing the street in the right place [7]. This number of outrages is not a unique concern of Spain. For example, a total of 71,000 run-overs occurred in the U.S. during 2017, of which 8.42% ended in death according to the annual report of the National Highway Traffic Safety Administration (NHTSA) [8]. These values are significant, not only because of the high number of accidents but also because of their upward trend as demonstrated by the Fatality and Injury Reporting System Tool (FIRST) [9].

As a result of this data, there is a growing concern about pedestrian road safety. In this field, there are several solutions in the state of the art based on the use of mobile applications aimed at improving road safety through different approaches. An example is the use of mobile devices to send information between vehicles and alert drivers on traffic jam situations in cities. For example, there is a solution that indicates the presence of road incidents using an algorithm that makes decisions based on a list of incidents. This method does not make use of context information, which could facilitate the calculation and detection of incidents [10]. A similar proposal to the previous ones is presented in [11]. It uses Google Maps and Google Directions to determine the best routes; it also uses contextual and historical information to estimate the probability that a route has incidents or not. Another example is the application developed to determine the risk of a driver, cyclist or pedestrian having an accident [12]. To this end, the app uses sensory fusion combined with a history of data and information entered by the users (e.g., age, weight and quantity of alcoholic beverages consumed). The use of apps on mobile devices also includes route customization within cities according to the specific needs of users (e.g., avoiding slopes up or down, reducing the distance traveled, etc.). In this way, this app avoids exposing the user to certain health risks. Besides, this app generates routes that require travelling a shorter distance than those offered by Google Maps thanks to the use of Open Street Maps (OSM) and the A * algorithm [13]. In addition to the previous application, there is another proposal called *UniBS4All* based on Google Directions, which allows generating routes adapted to the needs of people with physical disabilities. To do this, the points of the routes are modified to avoid architectural barriers stored in a database. Nevertheless, it does not remove all barriers to visually impaired people [14]. Another approach developed for people with visual difficulties is found in [15]. This app uses a Dijkstra algorithm to calculate the best possible route based on people's preferences and limitations, as well as the traffic congestion and dynamic obstacles on the route. The main limitation of this application resides in its algorithm, since Dijkstra consumes a lot of resources to calculate a route. The route optimization has also been focused from a personal point of view, allowing routes to be customized considering the user preferences. To do this, the eligible preferences are the number of green areas, number of social places, noise of the streets and total length of the journey. Later, routes are calculated thanks to an algorithm based on weights and OMS [16]. This application does not consider the hours of the day when the query occurs, which could modify the routes to avoid dark places at night or very crowded places during the day.

Other studies focus on road safety around crosswalks, especially on pedestrian detection. An approach in line with this paper is the detection of the person's intention to cross using a camera-based system and machine learning algorithms that monitor zebra crossings [17]. This study shows that the "you-only-look-once" (YOLO) scheme offers higher performance than the traditional histogram of oriented gradients (HOG) and Haar-cascade schemes. Despite this, when pedestrians are partially hidden, there is a drop in performance. With the same approach, several systems capable of detecting pedestrians while crossing a zebra crossing have been proposed [18,19]. They combine cameras and machine learning techniques such as region-based convolutional neural networks (CNN), vector support machines (SVM) or multilayer perceptron neural networks (MLP). These studies show that machine learning based on support vector machines (SVM) and the use of cameras are adequate to detect the presence of pedestrians in zebra crossings. Another solution also supported by cameras consists in analyzing the body movements and orientation of the person's head to determine whether a pedestrian intends to cross the public road or not [20]. The best performance was obtained by a combination of CNN and SVM. This suggests that the contextual information is very useful to determine the intention to cross of a pedestrian. In this sense, long short-term memory (LSTM) neural networks using images and characteristics (i.e., gender, walking direction and group behavior) has been proposed to estimate the crossing intention with great accuracy. Nonetheless, this results in a slightly high false positive rate when trying to classify the type of pedestrian movement [21]. Another approach is a crossing intention detector based on the use of cameras onboard vehicles, which can determine—in addition to the intention to cross—if a pedestrian is crossing or standing, as well as if he/she is turning or beginning to cross. This is achieved thanks to the use of random forest (RF) and SVM, resulting in faster detection than traditional methods [22]. Another study used laser imaging detection and ranging (LIDAR) sensors along with dense neural networks (DNNs), CNN or recurrent neural networks (RNNs) to detect the pedestrian's crossing intention [23]. The best model is DNN, which offers a significant improvement over SVM. Another solution is based on the joint use of cameras and laser sensors. The implemented techniques are long short-term memory with an attention mechanism (AT-LSTM) and SVM, corresponding the best results to AT-LSTM even in small intervals of time [24]. A complete list of features on the several state-of-the-art approaches described above is given for comparison purposes (Table A1, Appendix A).

With the aim of contributing to improve road safety, this work presents an AI-based application developed on Android that detects the intention of pedestrians to cross zebra crossings and creates safe routes throughout the city. Among the advantages, the solution allows to detect the people's crossing intention at all points of a city, unlike camera-based or LIDAR sensor systems that operate at fixed specific points of the road. Besides, the proposed solution offers robustness against adverse weather or low visibility conditions, as it only uses the internal sensors of a smartphone. Moreover, the proposed solution is based on fuzzy logic, which generates a low computational cost compared to those approaches described in the state of the art to detect the intention of a pedestrian to cross streets. In contrast, solutions based on cameras or LIDAR sensors can suffer under these conditions (e.g., snow or rain). Moreover, the deployment of the solution proposed has a zero cost for the municipalities or private entities that manage the cities because the system is implemented in the own citizens' mobile devices.

To sum up, the novelties proposed in this manuscript regarding the state of the art are (i) the development of a fuzzy logic approach with low computational cost to detect the pedestrian's crossing intention through the own smartphones' built-in sensors; (ii) the development of an optimization algorithm for calculating, tracing and guiding people through safe routes within a city considering pedestrian areas such as crossings, streets and walkways; (iii) in case of detecting the pedestrian's intention to cross, the app has the additional capability to communicate with a luminous intelligent crosswalk previously developed by this research team [25]. As a result, such an intelligent crosswalk creates a light barrier to alert drivers so they can safely stop their vehicles. According to the contributions, this manuscript has been structured as follows. Section 2 describes the fuzzy-based crossing intention detector and its implementation. Section 3 shows the experimentation performed and the main results obtained. Finally, Section 4 presents the conclusions and future works.

2. Mobile Application Description

The mobile app has been developed through the Android Studio Integrated Development Environment (IDE). This programming environment allows developing smartphone applications in Java, C/C++ or Kotlin language. The app developed includes the following features: (i) calculation and tracing of safe routes for pedestrians through a city; (ii) safe guidance of people with hearing and visual impairments using haptic, visual and acoustic signals; (iii) detection of the pedestrian's intention to cross zebra crossings; (iv) visualization aid system for pedestrians at zebra crossings through the use of Bluetooth communications. The app's functionalities are summarized through the use case diagram shown in Figure 1a.

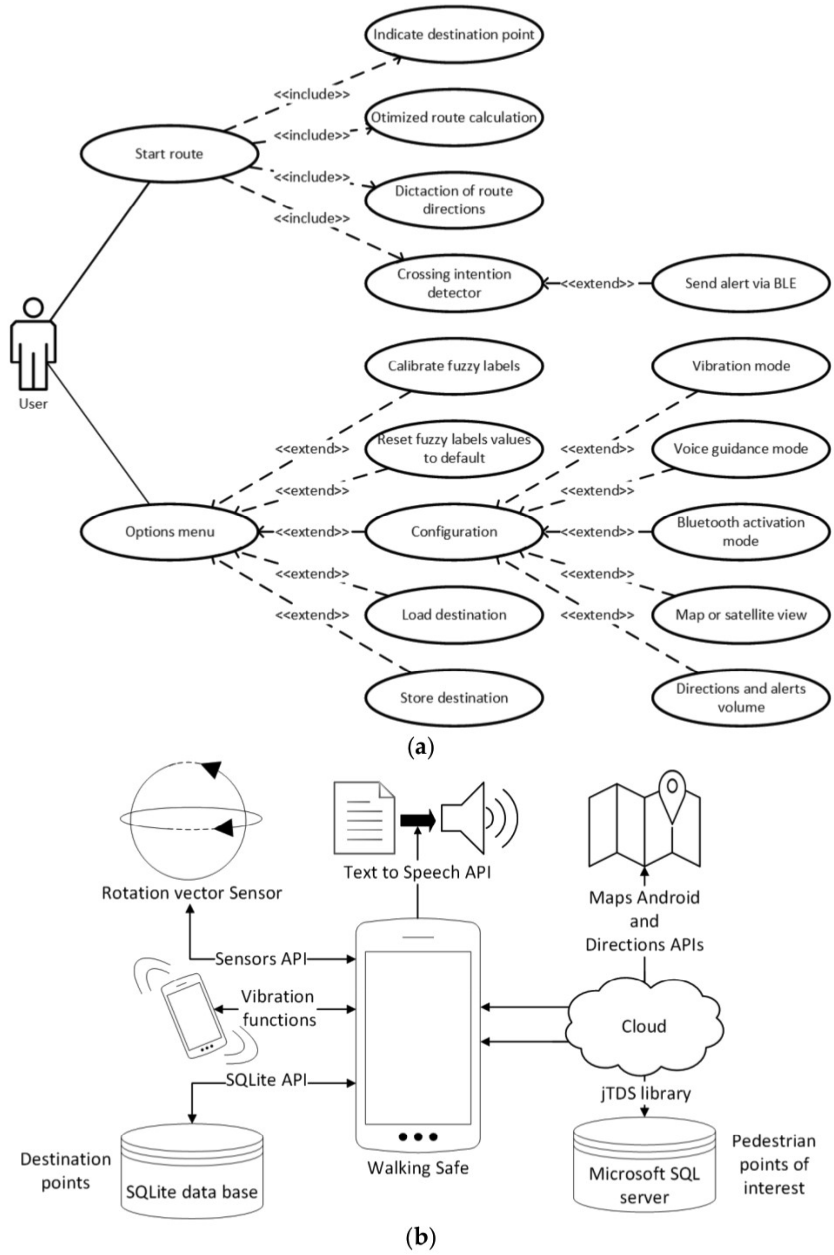


Figure 1. (**a**) Application functionalities. (**b**) Application architecture.

The app developed makes use of the application programming interfaces (APIs) of the Android operating system. At least, version 5 of the Android operating system is required for the execution of the app on a mobile device. This limitation is imposed by the APIs used in the app development, these being the following: Android maps, Directions, TextToSpeech and Sensors. In addition to these APIs, the application makes use of the SQLite API to manage a local database (i.e., destination points) and the jTDS library [26] to query an external database hosted on Microsoft SQL Server (i.e., pedestrian points of interest). The use of APIs requires the use of a network, and the app itself uses a database hosted in the cloud, so a constant connection to the Internet is needed. The app architecture and interaction with the APIs is shown in Figure 1b.

The installation file of the mobile app takes 3345 KB of disk space, and requires 9.37 MB in the phone memory. It has been determined through the Android Profiler tool of Android Studio that the main thread of the app consumes 20.03% of the app's runtime process, and 20.94% of RAM is used by the application. The app was monitored for 60 s, and it used the CPU for 25.95 s (44.46%) during this time. The highest CPU usage belongs to the graphical environment with 16.79% of the total CPU usage, followed by the main thread of the application with 8.91% of usage. During monitoring, it was determined that the total use of the RAM was 106.5 MB, of which 44.1 MB belongs to the graphical environment and 22.3 MB to the application code.

2.1. Calculation, Tracing and Guiding of Safe Routes

Among the main features of the application is the ability to calculate and plot safe maps in cities. The calculation and tracing of these maps are based on the Directions APIs and Android Maps, both from Google. The process for calculating a route begins with the detection of the user's location through the Global Positioning System (GPS). Once the current position has been obtained, the user can indicate the destination to which he/she wants to go using two options. The first one is to select the destination location by clicking on the map and then activating the start of the route. The second option is obtained by pressing the route start button that will prompt the user to enter the address and city of the destination point by text. Once the origin and destination points of the route are known, an algorithm responsible for calculating, optimizing, and plotting safe routes is invoked (Algorithm 1); this process is done in the background to avoid congesting the main process thread. The optimization algorithm starts with getting the default route provided by the Directions API from the origin and destination points. Once the default route is known, a query is made to an external database located in the cloud, which stores pedestrian points of interest (e.g., zebra crossings, walkways and/or pedestrian areas). The jTDS library is used to carry out these queries. Subsequently, the algorithm calculates possible pedestrian points of interest near the default route that would increase the safety of the route. To do this, the points should not be more than 30 m away from the route in order to not to increase the distance excessively. Similarly, the total distance of the route to be traveled will never be more than 300 m from the original route. Once the points of interest have been determined in the first query, a second query is made to the Directions API to get a new route including the origin and destination points along with the points of interest obtained from the previous step. This route optimization is iteratively calculated to reach the safest possible route without an excessive increase of the distance to be traveled by the user.

Algorithm 1

Purpose: obtaining a safe route to go from an origin point to a destination point
Inputs: origin and destination points
Output: representation of the route on a city map and guidance of the user's safe route

```
routePoints ← get the default route (origin, destination)
pedestrianPoints ← pedestrian areas near to the route (routePoints)
if size (pedestrianPoints) ≠ 0
optimizedRoute = false
repeat
routePoints ← route optimization (origin, destination, pedestrianPoints)
pedestrianPoints ← calculation of new pedestrian points near to the route (routePoints)
if size(pedestrianPoints) = 0
optimizedRoute = true
end if
until (!optimizedRoute)
end if
trace safe route on city map
highlight the safe pedestrian points included in the route by means of a special icon
```

Once the final route is calculated, it is traced onto the map using Android Maps and the corresponding guidance instructions are stored. These instructions include both the waypoints of the default route (e.g., "go straight on", "turn right", "turn left") and the specific points introduced by the application (e.g., "you are approaching a pedestrian zone"). These instructions are dictated by the app with verbal language as users move along the path generated, as well as indicated by haptic signals through the smartphone (i.e., vibrations). These methods have been implemented to enhance the user experience and facilitate notice to people with visual and/or hearing impairments, as well as to elderly people. To generate the indication correctly, the application waits until the user is near the waypoint while moving along the route. Once the user is in the zone, the directions are dictated using the TextToSpeech API. This API allows to convert text into a human voice, a function that has been specially designed for people with visual impairments. In addition to this option, guidance by vibration has also been implemented for people with hearing impairments to alert on areas where the route direction should be changed (e.g., taking a zebra crossing, walking down a street or pedestrian walkway). This functionality is based on the use of the basic vibration functions implemented on Android and can be configured in the options menu of the application to set how often the instructions should be dictated. The setting of each warning mode (i.e., voice-guided or vibration-driven) is independent, as is the volume at which the application transmits instructions.

2.2. *Sensory Fusion*

Unlike the different approaches described in the state of the art, the solution proposed herein determines the pedestrian's crossing intention using sensory fusion. To do this, the flow diagram depicted in Figure 2 has been followed. The strategy addressed to detect the pedestrian's crossing intention is based on: (i) the distance at which the user is located from a point of interest collected in the safe route (e.g., zebra crossing); (ii) walking mode established by the user in the app's options menu; and (iii) a fuzzy rotation detector responsible for tracking the user movements. The main contribution of this work lies in the combination of these blocks to detect a pedestrian's crossing intention around a point of interest. Each detail of the sensory fusion is explained in the following subsections.

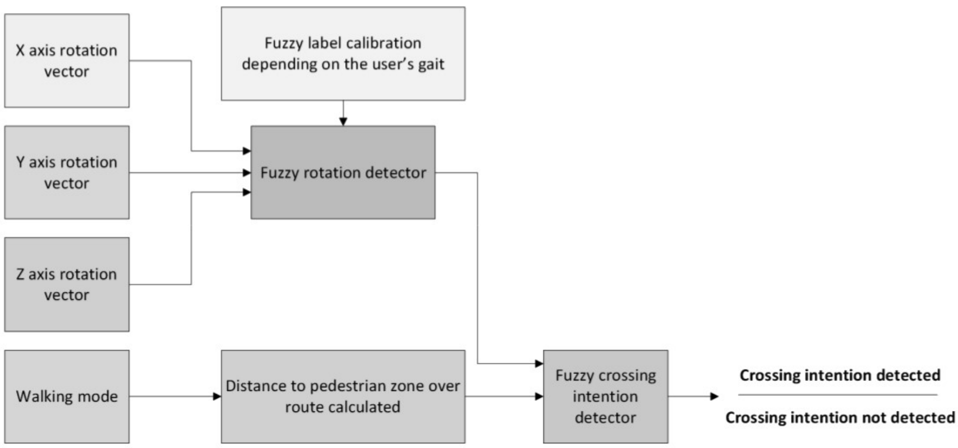


Figure 2. Sensory fusion scheme.

2.2.1. Fuzzy Rotation Detector

The block named "fuzzy rotation detector" has been constructed over the Android Sensors API. Specifically, this API asks the operating system for the sensor data related to the rotation vector; this can be hardware or software. The sensor is commonly used to measure movements and rotations, so it has been selected because the movements that pedestrians usually perform when approaching a crosswalk are rotational. In other words, pedestrians make turns as they approach a zebra crossing, being captured by this type of sensor.

To use it, it is necessary to enable the sensor in the main thread of the app, as well as to set the sample rate of the sensor. The frequency used for this application was 5 Hz (i.e., periods of 200 ms). To avoid saturating the main thread of the app due to the sample rate and the subsequent processing of the values, this task has been moved to an Android service. This represents a separate execution thread responsible only for processing the data generated by the sensor.

The data generated by the rotation sensor stands for the device's angle variation—and therefore that of a pedestrian—at a specific time. To obtain a more accurate measurement of the pedestrian movement, the average value of a sliding window with 10 values was used. In this way, a total of 2 s of pedestrian movement is kept in memory. By averaging 2 s of movement, it is possible to determine if a pedestrian makes changes in his/her path or if he/she continues to walk straight.

The rotation is determined by using the "fuzzy rotation detector" block depicted in Figure 2, which considers the average variation of the rotation on the XYZ axes. The detector is based on fuzzy logic of Mamdani type with linguistic rules such as "If X1 is A1 and … X*n* is X*n*, then Y is B", where the predictor and resulting variables have been established by an expert system [27]. The membership functions of the fuzzy set have been defined in a trapezoidal way—since its suitability to the data model is correct and not computationally complex—where the conjunction and implication operators utilize the minimum T-norm [28]. In addition, the First Infer, Then Add (FITA) method has been used for the defuzzification process because it is more consistent than the First Add, Then Infer (FATI) method [29]. Also, the voting method [30] has been used to produce a singleton (i.e., a single value), which results in a label that can be "go straight" or "rotation detected". The set of fuzzy rules used for the rotation detector is included in Table 1. It can be seen in the rule set that, to determine that a user is rotating, at least a rotation on the *Z*-axis must occur. The user's rotation is never determined if the *Z*-axis does not detect a rotation. This has been determined experimentally because, regardless of the position of the smartphone, the *Z*-axis always determines the rotation that the user performs on the ground. It is important to note that a rotation never exists on a single axis regardless of the other axes when a pedestrian walks.

One advantage of the developed strategy is that the fuzzy labels used as inputs of the rotation detector are automatically established from the calibration of the sensors performed by the user. This process is necessary since, as shown in Figure 3, two different individuals have different gaits (i.e., walking styles) and generate different rotations. The graphs in Figure 3 show the rotation on the XYZ axes produced by two users as they take a straight line for 10 s. As seen in all cases, the first user produces more complex oscillations than the second user. As a result, it is found from this test that user 2 causes more obvious movements when walking than that generated by user 1. Complementarily, Table 2 lists the average, standard deviation, maximum and minimum values of each user for each axis of the graphs represented. These values comprehensively demonstrate that it is necessary to calibrate the fuzzy detector due to such high differences that exist between the two users when walking.

Table 1. Rule set for the fuzzy rotation vector.

Rule Number	X-axis	Y-axis	Z-axis	Output
1	X-negative diff.	Y-negative diff.	Z-negative diff.	Rotation detected
2	X-negative diff.	Y-negative diff.	Z-stable diff.	Go straight
3	X-negative diff.	Y-negative diff.	Z-positive diff.	Rotation detected
4	X-negative diff.	Y-stable diff.	Z-negative diff.	Rotation detected
5	X-negative diff.	Y-stable diff.	Z-stable diff.	Go straight
6	X-negative diff.	Y-stable diff.	Z-positive diff.	Rotation detected
7	X-negative diff.	Y-positive diff.	Z-negative diff.	Rotation detected
8	X-negative diff.	Y-positive diff.	Z-stable diff.	Go straight
9	X-negative diff.	Y-positive diff.	Z-positive diff.	Rotation detected
10	X-stable diff.	Y-negative diff.	Z-negative diff.	Rotation detected
11	X-stable diff.	Y-negative diff.	Z-stable diff.	Go straight
12	X-stable diff.	Y-negative diff.	Z-positive diff.	Rotation detected
13	X-stable diff.	Y-stable diff.	Z-negative diff.	Rotation detected
14	X-stable diff.	Y-stable diff.	Z-stable diff.	Go straight
15	X-stable diff.	Y-stable diff.	Z-positive diff.	Rotation detected
16	X-stable diff.	Y-positive diff.	Z-negative diff.	Rotation detected
17	X-stable diff.	Y-positive diff.	Z-stable diff.	Go straight
18	X-stable diff.	Y-positive diff.	Z-positive diff.	Rotation detected
19	X-positive diff.	Y-negative diff.	Z-negative diff.	Rotation detected
20	X-positive diff.	Y-negative diff.	Z-stable diff.	Go straight
21	X-positive diff.	Y-negative diff.	Z-positive diff.	Rotation detected
22	X-positive diff.	Y-stable diff.	Z-negative diff.	Rotation detected
23	X-positive diff.	Y-stable diff.	Z-stable diff.	Go straight
24	X-positive diff.	Y-stable diff.	Z-positive diff.	Rotation detected
25	X-positive diff.	Y-positive diff.	Z-negative diff.	Rotation detected
26	X-positive diff.	Y-positive diff.	Z-stable diff.	Go straight
27	X-positive diff.	Y-positive diff.	Z-positive diff.	Rotation detected

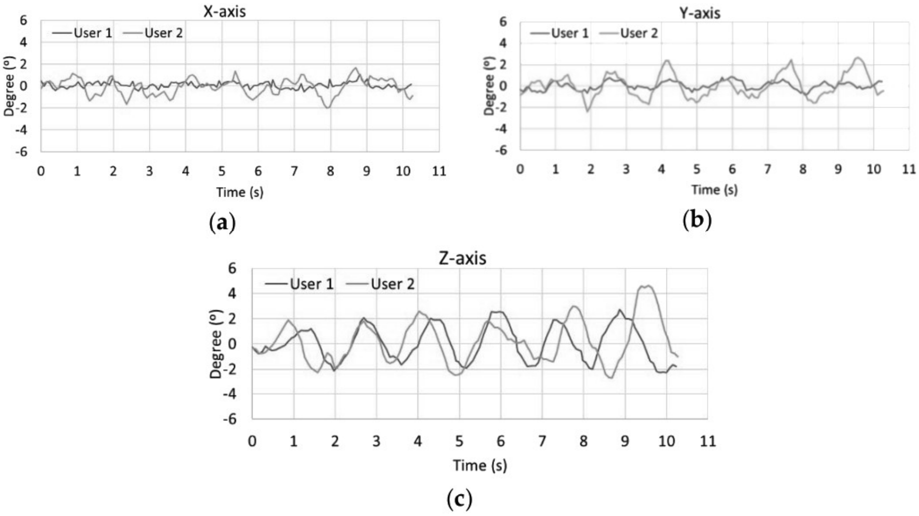


Figure 3. Graphical comparison of two pedestrian gaits over a straight line for 10 s. (**a**) *X*-axis comparison. (**b**) *Y*-axis comparison. (**c**) *Z*-axis comparison.

Table 2. Comparison of the rotation values expressed in degrees (°) for each user while walking in a straight line for 10 s.

	User 1				User 2			
Axis	**Avg.**	**Std. Dev.**	**Max.**	**Min.**	**Avg.**	**Std. Dev.**	**Max**	**Min**
X-axis	0.079	0.278	1.080	−0.520	−0.089	0.772	1.670	−2.030
Y-axis	0.018	0.380	0.860	−0.830	0.046	1.010	2.680	−2.390
Z-axis	0.059	1.397	2.710	−2.280	0.222	1.702	4.630	−2.690

As a result of the previous comparison, the application has included a functionality that allows the automatic calibration of the smartphone sensors. The calibration task can be performed by the user through the options menu located in the upper left area of the app. Once the option is selected, the application indicates the user how to get a correct calibration. This consists in standing still for 5 s to avoid generating incorrect oscillations and then walking for 12 s in a straight line. At the end of the calibration, the maximum and minimum rotation values generated by a pedestrian for each of the XYZ axes are determined. From these values, the membership set of the input variables for each axis is determined as set out in Equation (1) and Table 3. The value "axisDifference" in Table 3 corresponds to the top plateau of the trapezoid in Figure 4 labeled as "Stable difference". V1, V2, V3 and V4 values are calculated according to the form expressed in Table 3.

$$\text{axisDifference} = |\text{minimum axis value}| + |\text{maximum axis value}| \quad (1)$$

Table 3. Definition of the membership sets for each axis.

Label	V1	V2	V3	V4
Negative difference	−90°	−90°	Min. axis value − axisDifference	Min. axis value
Stable difference	Min. axis value − axisDifference	Min. axis value	Max. axis value	Max. axis value + axisDifference
Positive difference	Max. axis value	Max. axis value + axisDifference	90°	90°

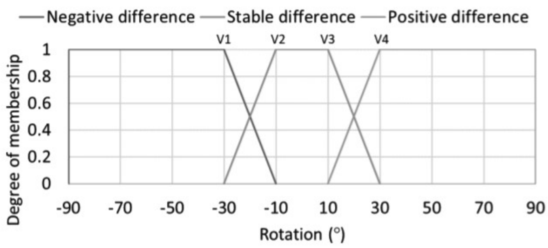


Figure 4. Example of fuzzy labels used for rotation detection inputs.

2.2.2. Fuzzy Crossing Intention Detector

The output of the "fuzzy rotation detector" is used as the input for the block called "fuzzy crossing intention detector" that performs the system sensory fusion (Figure 2). Besides this, the sensory fusion requires—as input—the distance between the pedestrian areas and the optimal route calculated. The distance to the pedestrian zone with respect to the calculated route is computed from the current pedestrian position to the next pedestrian zone collected on the route. To this end, the user can select the walking mode from the following options: "running", "walking" or "sightseeing". This sets a greater or lesser distance to fix the time of detection around a zebra crossing (i.e., 15, 10 or 5 s). The membership functions used to calculate whether a pedestrian is near or far from the point of interest are shown in Figure 5, which are based on trapezoidal membership sets. The set of values of the membership functions is determined by selecting the walking mode that the user does. These fuzzy sets have been built considering a GPS sensor position error around one meter. In the worst case, the crossing intention can be safely determined with at least a distance of 5 m to the point of interest, although it could be determined from 7.5 m with enough certainty as shown in Figure 5a. Finally, as in the case of the rotation detector, the output is also a singleton that allows to indicate whether the intention to cross a crosswalk has been detected or not. The set of fuzzy rules used in this case is listed in Table 4. This sets that the pedestrian crossing intention will only be detected when he/she is near the next pedestrian point of interest on the safe route and he/she is also performing a rotation.

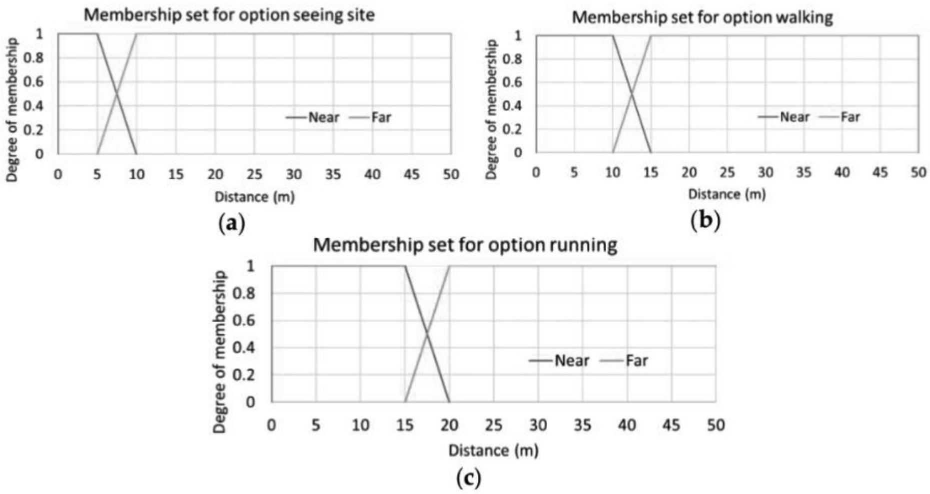


Figure 5. Fuzzy sets used to determine how far the pedestrian is from the next pedestrian point of interest base on its options. (**a**) Sightseeing; (**b**) walking; (**c**) running.

Table 4. Definition of the membership sets for each axis.

Rule Number	Fuzzy Rotation Detector	Pedestrian Point of Interest	Crossing Intention (Output)
1	Go straight	Near	Not detected
2	Go straight	Far	Not detected
3	Rotation detected	Near	Detected
4	Rotation detected	Far	Not detected

2.3. Pedestrian Visualization Aid System

Additional functionality has been included to add value to the app. This can communicate with a smart crosswalk as the one described in [25] to alert drivers about the presence of pedestrians with the intention to cross a zebra crossing. The interaction between the app and the intelligent crosswalk is managed by a gateway that can communicate with the app via Bluetooth and with the nodes of the intelligent crosswalk via Wi-Fi (Figure 6). To this end, a Raspberry Pi 3 device has been selected to implement the functions of that gateway.

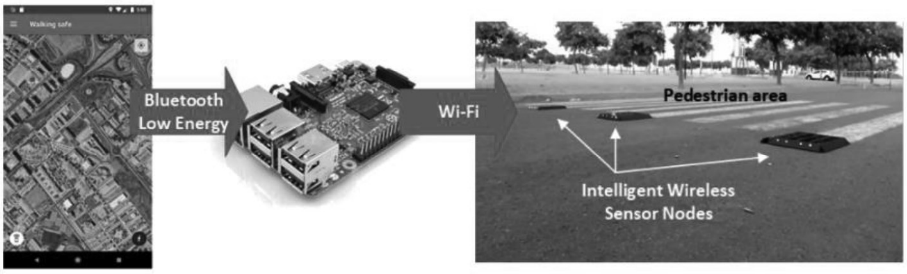


Figure 6. Communication scheme used between the application and the smart crosswalk.

The app makes use of the Bluetooth Low Energy (BLE) service implemented in Bluetooth 4.0. For this purpose, a BLE server has been created in the mobile application to provide information about the pedestrian's crossing intention. The service can send the values "intent to cross detected" or "intent to cross not detected" from the fuzzy detector described above. To do this, the app makes use of the basic BLE profile called Alert Notification Profile, a communication profile that implements the New Alert feature. The goal is to allow any BLE client to read the current state of the pedestrian phones regarding their crossing intention or subscribe to the service to receive any change of state.

In the gateway, a script that allows converting the Raspberry Pi 3 into a BLE client of the app has been implemented in NodeJS. The client relies on the Noble library [31] to make use of the BLE services, and on the dgram library [32] to make use of the Wi-Fi communication with the intelligent crosswalk network. The client running on Raspberry Pi 3 connects to the smartphones once they enter the Bluetooth range and subscribes to the New Alert feature offered by the app. In case the app issues a notification, it is processed by the client; if it indicates that the person intends to cross the intelligent crosswalk, the client sends an activation message to the smart nodes of the crosswalk to generate a visual barrier on the roadway that allows vehicles to stop safely, further increasing the safety of the smartphone's users.

It is important to note that the application allows to indicate optionally how often the Bluetooth communication is activated. The options allow to keep Bluetooth always on or to activate it automatically when the smartphone is 30 m away from a crosswalk. This way, it is possible to reduce the energy consumption of the resources.

3. Experimentation

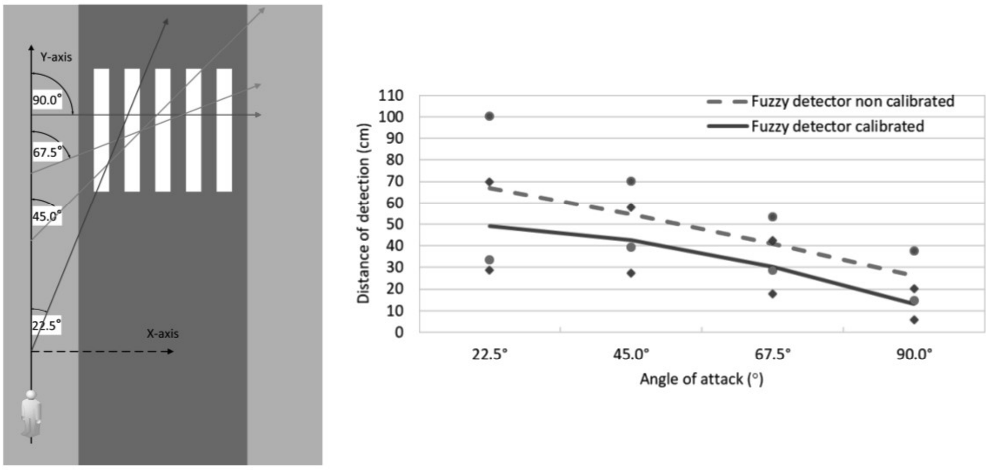
This section describes the experimentation performed with the application and its main results, which consisted of: (i) evaluating the fuzzy rotation detector; (ii) evaluating the sensory fusion strategy developed for the crossing intention detector; and (iii) comparing the performance of the safe route planning algorithm against the same routes generated by default with Google Maps. To carry out the experimentation, a BQ Aquaris V smartphone with an eight-core Qualcomm Snapdragon 435 processor (1.4 GHz), Adreno 505 graphics processing unit, 4 GB RAM and 64 GB storage capacity over Android 8.1.0 was used. This smartphone was distributed to all volunteers to carry out all the tests listed below.

3.1. Description of the Volunteers Set

The tests corresponding to the evaluation of the fuzzy rotation detector and the sensory fusion developed for the crossing intention detector have been carried out with a total of 31 volunteers, of whom 51.61% were men and 48.39% were women. The average age of the subjects is 39.74 years with a standard deviation of 13.85 years. The set of users has an average height of 168.74 cm and a standard deviation of 11.47 cm. If the subjects are analyzed according to gender, the group of men has an average height of 176.47 cm and a standard deviation of 8.59 cm, while the group of women has an average height of 160.47 cm in height and a standard deviation of 7.79 cm. The average age of the male group is 37.19 years and a standard deviation of 12.74 years, while the average age of the female group is 42.47 years and a standard deviation of 14.90 years.

3.2. Evaluation of the Fuzzy Rotation Detector

To evaluate the fuzzy approach of the rotation detector, a series of tests have been designed to determine how far the pedestrian's rotation is detected from the crosswalk considering a reference system (Figure 7a). The goal is to reproduce the conditions under which pedestrians typically cross a zebra crossing using different angles of attack. To do this, the rotations used have been 22.5°, 45°, 67.5° and 90°. As an example, the reference system used for the angle of attack of 22.5° has been represented in Figure 7a. Besides, the tests have been performed to compare the performance of the fuzzy detector both calibrated and uncalibrated.



(**a**) (**b**)

Figure 7. (**a**) Description of the test scenario. (**b**) Average results of the calibrated and uncalibrated rotation detector, where vertical lines represent the standard deviation for each average value.

The results show that the calibrated rotation detector offers a better response than the uncalibrated detector (Figure 7b). The main improvement is seen at 22.5°, where a reduction of 17.78 cm (26.51%) in the distance of detection of the calibrated detector versus the uncalibrated detector was obtained. Similarly, the calibration improved the detection distance in 12.04 cm (21.99%) for an angle of 45°, 10.90 cm (26.56%) for an angle of 67.5°, and 13.06 cm (49.84%) for a rotation of 90°. As a result, it can be asserted that the automatically calibration of the fuzzy labels established in the fuzzy detector improves the detection of angles of the app. In addition, it can be affirmed that the percentage of improvement is greater the less perceptible is the angle of attack used by the pedestrian to cross. However, the detection distance is generally better the greater the angle of rotation used by a pedestrian (i.e., less error). This suggests that abrupt angles of rotation (e.g., 90°) are easier to detect than more subtle angles of rotation (e.g., 22.5°).

3.3. Evaluation of the Sensory Fusion of the Crossing Intention Detector

The performance of the crossing intention detector has been evaluated using a receiver operating characteristic (ROC) analysis as described in [33]. The experimentation was carried out in a real environment under controlled conditions similar to that of Figure 7a to obtain sensitivity against specificity of the detector. The performance has been measured by means of a confusion matrix of 2 × 2 elements that relates positive (p) and negative (n) values (Table 5). To do this, the detection of the intention to cross of a pedestrian is considered positive while the nondetection of the turn intention is considered negative.

Table 5. Confusion matrix for the receiver operating characteristic (ROC) analysis.

	Real Value		**Total**
	P	***N***	
Prediction			
p'	True positives (TP)	False positive (FP)	P'
n'	False negatives (FN)	True negatives (TN)	N'
Total	P	N	

The experimentation carried out has obtained a total of eight confusion matrices, which provide the performance of the sensory fusion for each of the angles shown in Figure 7a, both calibrated and uncalibrated. To this end, 390 samples were used for each confusion matrix, totaling 3120 samples. The distribution of individuals who have undergone the tests is as described in Section 3.1. To carry out the collection of the samples, each subject was provided with a mobile device with the Android operating system, the application installed and containing the route with the test crosswalk. First, each volunteer performed the tests with the uncalibrated device; subsequently, the fuzzy labels of the fuzzy rotation detector were calibrated, and the same tests were repeated with the turn detector calibrated.

The series of tests consisted of (i) walking straight without intending to cross a pedestrian crossing; (ii) walking straight and then crossing the crosswalk according to the rotation angle set in each confusion matrix (i.e., 22.5°, 45°, 67.5° and 90°). It was established that, to consider a sample as true positive, the intention to cross had to be detected before entering the crosswalk; it was considered a false negative if the intention to cross was not detected or if the intention to cross was detected once a pedestrian entered the crosswalk; it was considered a false positive if a pedestrian was walking straight (i.e., no intention to cross the zebra crossing); and finally, it was considered a true negative when a pedestrian was walking straight and no intention to cross was detected.

After the experimentation, the average accuracy for the uncalibrated crossing intention detector was 84.74% with an F1-Score of 87.77%, whilst the calibrated crossing intention detector obtained an average accuracy of 98.63% with an F1-Score of 98.97%. As seen, the sensory fusion of the calibrated crossing intention detector offers better performance than the uncalibrated detector in all case studies and improves all the metrics in Table 6. Specifically, the average rate of true positives is 98.27% for the calibrated crossing intention detector. This is an excellent and fairly accurate value given a precision rate of 99.7%. Moreover, we found that the specificity is quite high reaching a level of 99.39%. Due to this, it can be affirmed that the sensory fusion of the calibrated crossing intention detector has high sensitivity and specificity, which makes the app very suitable for real use in cities.

Table 6. Results of the crossing intention fuzzy detector.

Fuzzy Crossing Intention Detector	Rotation Degree (°)	TPR (%)	FPR (%)	SPC (%)	ACC (%)	P (%)	F1-Score (%)
Non-calibrated	22.5	86.92	22.31	77.69	83.85	88.63	87.77
	45	98.83	18.05	81.95	71.28	91.37	94.95
	67.5	99.61	23.66	76.34	91.77	89.24	94.14
	90	100	23.85	76.15	92.05	89.35	94.37
	Average	96.34	21.97	78.03	84.74	89.64	92.81
	Std. Dev.	6.30	2.70	2.70	9.74	1.19	3.38
Calibrated	22.5	94.64	1.68	98.32	95.79	99.2	96.86
	45	98.85	0.77	99.23	98.97	99.61	99.23
	67.5	99.62	0.00	100	99.74	100.00	99.81
	90	100.00	0.00	100	100.00	100.00	100.00
	Average	98.27	0.61	99.39	98.63	99.7	98.97
	Std. Dev.	2.47	0.80	0.80	1.94	0.38	1.45

TPR: true positive rate; FPR: false positive rate; SPC: specificity; ACC: accuracy; P: precision.

It can be said—looking into the results obtained by the sensory fusion of the calibrated crossing intention detector—that the best results are found when detecting the crossing intention with 90° rotation. On the contrary, less relevant metrics are observed when the sensory fusion of the crossing intention detector is related to 22.5° rotation. This confirms, as in the case studied in Section 3.2, that the detection of rotation at smaller angles is more difficult to identify and because of this, the performance is reduced. Despite this, the sensory fusion of the calibrated crossing intention detector offers a better metric in the worst case than the best case for the uncalibrated detector. The best results obtained with the crossing intention detector are those achieved at angles of 90°, where it is observed that a value of 100% is always obtained in all the metrics except in the false positive rate (FPR), which is 0%, as expected. The following better metrics are obtained with angles around 67.5°. In this case, it is observed how the true positive rate (TPR) is reduced a little—although it is still very good like the rest of the rates—indicating that there have been some turns that have not been correctly detected by the calibrated crossing intention detector. The metrics corresponding to the rotations with an angle of 45° are found as the following better results for which a decrease in the TPR is observed. However, the biggest concern could be considered that the FPR is no longer 0%. Therefore, it suggests that the classifier detected the crossing intention at the wrong time. The same occurs for angles close to 22.5°; since the FPR rate increased to 1.68, the rest of the metrics are also reduced. This way, the calibrated crossing intention detector achieves the least robust set of metrics around an angle of 22.5° (TPR of 94.64%, accuracy (ACC) of 95.67% and F1-Score 96.86%). This is due to, in these cases, the rotation produced by the user is very slight and difficult to detect by the sensors currently used. In the same way, a limitation could be that all volunteers reside in the province of Huelva (Spain). This could have a bias due to the way they walk or cross the pedestrian crossing because they belong to the same specific geographical area. Another limitation can also be the calibration of the fuzzy labels at a specific moment. This calibration could become invalid if the user changes their gait for reasons such as it starts to rain, or he/she receives a phone notification (e.g., call, SMS or WhatsApp). It is important to highlight that the limitations on precision generated by a GPS sensor have been eliminated with the use of the fuzzy logic as mentioned in Section 2.2.2. For all the above, it can be confirmed that the fuzzy logic strategy using a mobile phone as a crossing intention detector on public roads offers good results, being demonstrated by the data generated by the experimentation carried out.

3.4. Comparison of Routes Generated

To evaluate the contribution made with the routing algorithm developed in the mobile application, a cloud-hosted database was created with a total of 79 pedestrian points of interest. These test points represent zebra crossings, walkways and pedestrian streets in different cities of Spain and Portugal (i.e., Huelva, Seville, Bollullos Par del Condado, Almonte, Camas, Tavira and Faro). In order to determine the safety improvement achieved by the routes traced with the application, these have been compared to the routes generated by Google Maps. The points of interest proposed have been used to demonstrate the errors made by Google Maps and how the proposed application improves the routes it generates.

The comparison makes it possible to study how Google Maps falls into various conflicting routes. For instance, it indicates pedestrians to circulate as if they were vehicles (e.g., using roundabouts), it does not direct people to take available pedestrian streets and it does not use walkways to cross three- or four-lane tracks. Table 7 shows a comparison of the routes generated by Google Maps versus the routes generated by the proposed algorithm. It shows the number of cases per route typology, average time difference, average distance difference, and average improvement achieved regarding safe zones. In summary, Table 7 shows that the routes calculated by the algorithm are safer than those generated by Google Maps by making use of a greater number of pedestrian zones. In contrast, the routes generated by the algorithm generally increase the time and distance of the path. The percent difference in each of these cases has been calculated as shown in Equation (2):

$$\text{difference} = (\text{app route value} * 100)/(\text{Google Maps route value}) - 100 \tag{2}$$

Table 7. Comparison of routes generated by the algorithm proposed and Google Maps.

Typology of Route Tested	Cases Tested	Diff. in Time	Diff. in Distance	Increase in Safe Areas	App CPM	Google Maps CPM
Avoid roundabouts	8	48.80%	23.65%	243.75%	0.65	0.62
Avoid circulating as a vehicle	5	23.41%	35.24%	183.00%	0.58	0.56
Use pedestrian street	14	10.71%	−0.66%	215.48%	0.66	0.62
Use pedestrian walkways	3	147.62%	129.26%	266.67%	0.61	0.61
Total	30	36.68%	24.80%	222.72%	0.64	0.61

CPM: Composed performance metric.

In addition to these values, a composed metric has been proposed to evaluate the performance of the routes generated by the application against the routes generated by Google Maps. This metric has been called Composed Performance Metric (CPM) and it expresses the quality of the route—through a single value—as a function of the time, distance and number of safe pedestrian areas of the route. To make use of this metric, it is necessary for the values to be normalized from 0 to 1. For this, the min-max method described in [34] has been used. Once the values have been normalized, it is important to highlight that the values referring to the time and distance used in the route are better the closer to zero they are, while the values referring to the number of pedestrian areas are better the closer to one they are. Therefore, they will be represented by subtracting the normalized time and distance values from 1. Moreover, the number of pedestrian areas is represented according to the value obtained in the normalization. The metric is expressed mathematically by Equation (3):

$$\begin{aligned}\text{CPM} = {} & (1 - \text{normalized value of time}) * K_1 + (1 - \text{normalized value of dis}\\ & \text{tance}) * K_2 + (\text{normalized value of pedestrian areas}) * K_3\end{aligned} \tag{3}$$

where K_1, K_2 and K_3 represent the weight for each of the values in the compound metric. The sum of K_1, K_2 and K_3 must add up to 1. For the current case, an equitable weight has been used (i.e., K_1, K_2 and K_3 have been set to 0.333). This compound metric supports modifying these weights to give greater importance to the factor to be highlighted (i.e., time, distance or safety). This metric has been used to evaluate each of the 30 routes studied, being better the closer its value is to 1. To this end, an average result for each type of route has been included in Table 7.

Table 7 presents a comparison of the routes generated by the app developed and Google Maps. The first case shown in the table prevents a pedestrian from taking roundabouts as a vehicle, which is what happens with the routes generated by Google Maps. The routes generated by the app to avoid this scenario offer an improved safety of 243.75% compared to Google Maps, although this entails an increase in time and distance of 48.80% and 23.65%, respectively. In the same way, the app achieves a better CPM than Google Maps (0.65 and 0.62, respectively). The main improvement of this type of routes lies in indicating to pedestrians that they must move to the nearest zebra crossing instead of taking a roundabout as a vehicle (an example is shown in Figure 8a). On the contrary, Google Maps generates an unsafe route for the same origin and destination points. These route types are unsafe because pedestrians circulate through roundabouts regardless of whether they are walking in the opposite direction to the vehicles or if they are crossing the roundabout through the center, thereby generating a road safety problem for pedestrians and drivers, as it is shown in Figure 8e.

The second case aims to prevent a pedestrian from crossing public roads regardless of where the crossing is made. In other words, the application can generate routes that allow a pedestrian to avoid dangerous crossings by guiding pedestrians to zebra crossings so that they can safely cross the road. This type of route generated by the app obtains an average improvement in road safety of 183.00%, and in CPM (0.58 and 0.56, respectively). This also leads to an increase in time and distance required to complete the route (23.41% and 35.24%, respectively). An example of this route type is found in Seville (Spain), where, to cross a four-lane road, the developed app indicates the pedestrian to move to the closest crosswalk to avoid a possible run-over when crossing the street in the wrong place (Figure 8b). For this same crossing, Google Maps indicates the pedestrian to cross in a straight line regardless of his/her physical integrity. This poses a risk to the life and road safety of persons, which increases if they do not know the city, suffer from a visual problem, or have reduced mobility. The calculated route by Google Maps can be seen in Figure 8f.

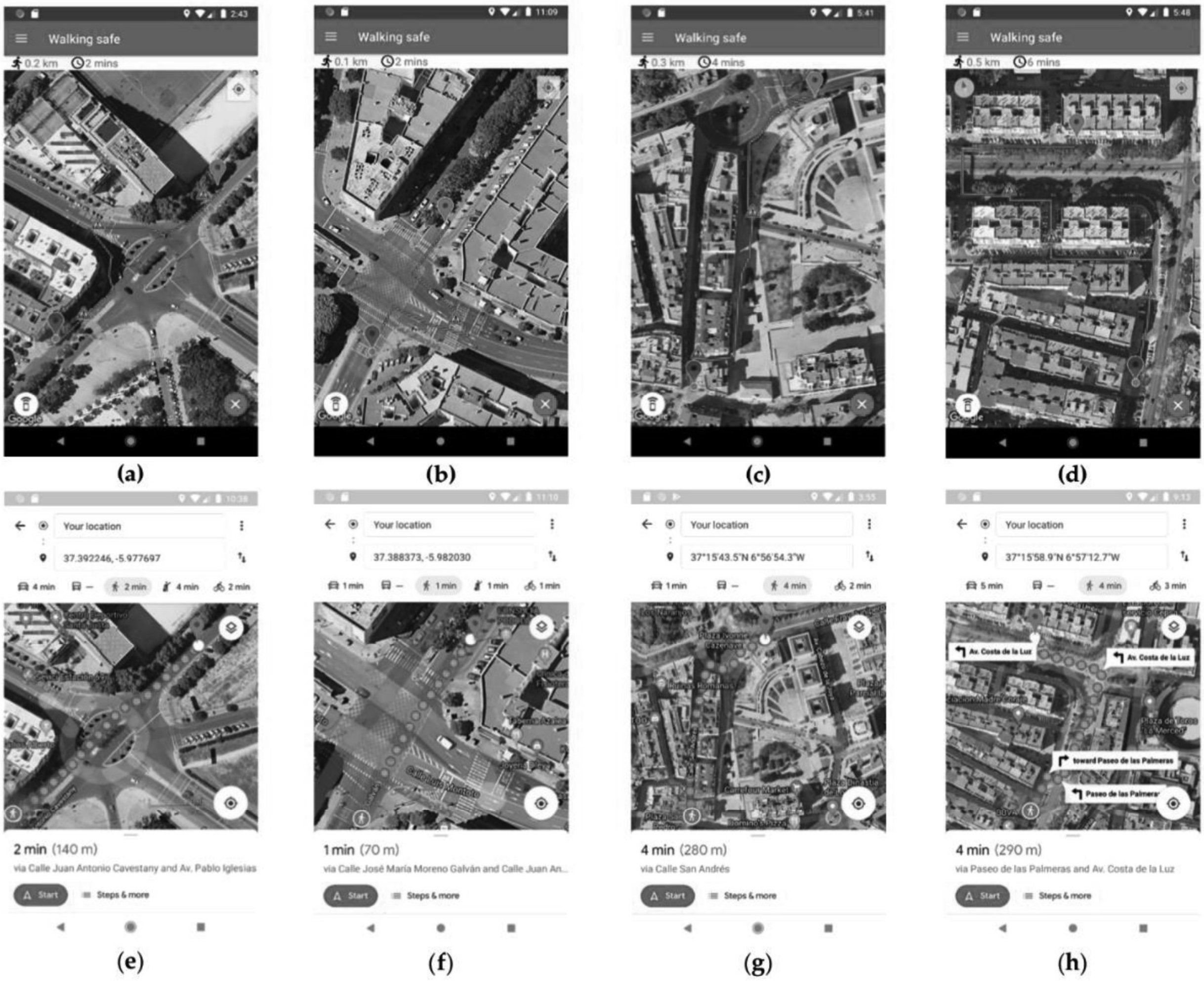


Figure 8. (**a**) Route calculated by the app where it is observed how to avoid the incorrect use of a roundabout. (**b**) Route calculated by the app where it is depicted how to avoid circulating like a vehicle. (**c**) Route calculated by the app where pedestrian areas are used. (**d**) Route calculated by the app where the pedestrian walkway is used. (**e**) Route calculated by Google Maps where a pedestrian is introduced into a roundabout. (**f**) Route calculated by Google Maps where a pedestrian is introduced into an intersection without respecting the signals. (**g**) Route calculated by Google Maps where pedestrians are not introduced through pedestrian areas. (**h**) Route calculated by Google Maps where the pedestrian walkway is not used.

The third case shows that Google Maps does not make efficient use of pedestrian streets in the cities, these being the ones that provide the most road safety to pedestrian because vehicles cannot circulate through them. In the proposed comparison, it is observed that the app manages to increase road safety by 215.48% on average compared to Google Maps, as well as reducing the distance to travel by 0.66%. Additionally, the CPM of the app is better than the CPM achieved with Google Maps (0.66 and 0.62, respectively). In this case, despite reducing the distance to travel, the Google Directions API does not show a reduction in time but an increase of 10.71%. An example of the aforementioned improvement is described in Figure 8c, where the app makes use of pedestrian areas such as the one that persons pass through. In this way, the road safety of pedestrians increases when walking through areas where there should not be cars circulating or parking. For the same route, Google Maps offers a trajectory where the use of pedestrian areas is not prioritized. In this case, Google Maps prefers to give the pedestrian a less safe route to travel a total of 20 m less than the route generated by the app, as it can be seen in Figure 8g.

Last but not least, the best results from the point of view of road safety comes from the routes that make use of pedestrian walkways to cross a road with three or four lanes. These routes improve safety by 266.67% on average. It is necessary to indicate that this increase in safety also increases the times and distance of the routes on average (147.62% and 129.26%, respectively). This is due to the need to move the user to the pedestrian walkways instead of crossing roads where the user's integrity is in danger. These highly dangerous roads can be especially problematic for people with reduced mobility or with severe auditory or visual problems. In these cases, the route generated by the developed app provides even more significant safety than the route generated by Google Maps, despite the increased time and distance included. For these reasons, the CPM shows a tie between the routes generated by the app and Google Maps. An example of these routes is shown in Figure 8a, where it is observed how the pedestrian is indicated to move to the beginning of the pedestrian walkway used to cross a four-lane road that separates the origin and destination points. This way, the pedestrian needs to walk more time and a larger distance, improving at the same time its road safety. Moreover, when the pedestrian is in the most dangerous point of the route—near the access to a highway—he/she is at the safest point of the route since he/she is walking by a walkway only used for people. On the contrary, Google Maps provides a shorter distance and time, but it does not consider the road safety of the pedestrian. Thus, it tells the pedestrian to walk in the opposite direction of the vehicles on a road that does not have sidewalks. Google Maps also tells the pedestrian to walk along a road called "Av. Costa de la luz", which is an access to join a highway. So, at the most dangerous point of the route, the pedestrian is more vulnerable to being run over because drivers do not expect to find a pedestrian on the access to a highway.

The limitations observed in this experimentation refer to the number of sites collected in an external database, since the ideal would be to have all the locations of pedestrian zones in the different cities studied and not just a sample of some dangerous locations. Another limitation refers to the drawing of the routes based on the Google Maps engine, which does not allow modifying the routes to make them pass on the sidewalk and always represents the routes on the road. Finally, based on the results obtained, it can be said that the routes generated by the app are safer than those generated by Google Maps. It has been achieved by guiding pedestrians for a longer time through reserved areas or by guiding them to a crossing where pedestrians have priority. Moreover, the total CPM shows that the routes generated by the app (0.64) are better in general than those obtained by Google Maps (0.61), since the increase in road safety provided by the application is greater than the increase in time and distance caused.

To finish, it is important to highlight that—to use the app—the smartphone always needs to be connected to the Internet because it uses several APIs and an external database that requires cloud connectivity. For this reason, we recorded the times taken by the app to calculate several routes based on the number of pedestrian points of interest and a 4G connection. The experimentation consisted in grouping the routes by the number of points of interest and averaging a series of 20 times. Accordingly, the results obtained were 1.9 ± 0.22 s to calculate the routes with one point of interest; 2.13 ± 0.37 s for routes with two points of interest; 2.13 ± 0.32 s for routes with three points of interest; 2.29 ± 0.28 s for routes with four points of interest; and 2.25 ± 0.41 s for routes with six points of interest. As a rule of thumb, the more points of interest added, the more time the algorithm takes to calculate the route. In this sense, the need for the Internet can be considered as a limitation in itself because, if the smartphone does not have connectivity to the cloud, the app cannot calculate the requested routes.

4. Conclusions

Smart cities are becoming a reality thanks to the support of wireless communications, along with the use of analysis techniques and data processing. Transport and road safety are an important pillar within smart cities. Currently, road safety is a weak point as demonstrated by several studies, which indicate that 40% of accidents involving pedestrians occur when people cross roads in the right place.

To help reduce accidents, this study presents a mobile application developed on Android that makes two contributions. On the one hand, the app can determine the intention of a pedestrian to cross through the public road using rotation sensors and sensory fusion based on fuzzy logic. This approach is integrated into the people's smartphones. Therefore, the crossing intent detection system offers the advantage of being able to be used throughout the city instead of fixed specific points like other camera-based or LIDAR-based solutions. It should also be noted that the proposed solution—unlike other state-of-the-art systems—is robust against adverse weather conditions with low visibility, as it only makes use of simple sensors built into smartphones and requires no cameras. On the other hand, this work presented an algorithm for the calculation, tracing and guidance of pedestrians through safe routes. This includes the use of more zebra crossings, streets and pedestrian areas than other routing applications such as Google Maps. As an added value, the app has Bluetooth communication to interact with intelligent crosswalks and create a light warning barrier that allows drivers to safely stop their vehicles in case of detecting the crossing intention of pedestrians.

The experimentation carried out consisted in crossing a test zebra crossing with a set of 31 pedestrians using different entry angles, totaling of 3120 samples. From the tests, the fuzzy logic-based crossing intention detector has proven that it improves the crossing pedestrian intention detection after the automatically calibration of the fuzzy labels. Specifically, the accuracy rate of the calibrated fuzzy crossing intention detector was 98.63%, with an F1-Score of 98.97%, a true positive rate of 98.27%, a false positive rate of 0.61%, and a specificity of 99.7%. This suggests that the proposed solution has the capability to determine the intention of pedestrians to cross with high sensitivity and specificity.

Regarding the second contribution of this work, the experimentation carried out proved that the set of 30 routes computed by the proposed algorithm increased the safety of pedestrians against Google Maps between 183.00–266.67% by using a greater number of pedestrian areas (i.e., pedestrian crossings, streets and walkways). As a consideration, it should be mentioned that—in most cases—it entails an increase in the distance and time of the trips.

Future work focuses on improving the current functionalities of the app or include new ones. Among the possible improvements would be to implement an infrastructure-to-person (I2P) communication to alert on the presence of vehicles at high speed to avoid possible fatalities for pedestrians (i.e., communication with smart crosswalks). It also includes a person-to-vehicle (P2V) communication to notify the drivers' smartphones about the existence of pedestrians intending to cross a crosswalk. In addition to this, another functionality to investigate is the possibility of changing the route calculation and map engines to OSM, which could offer more complete information about pedestrian areas in cities than Google Maps. Also, the possibility of using machine learning techniques to detect the crossing pedestrian intention with the mobile sensors will be studied, which could offer better performance than the current strategy. In this sense, one-class SVM techniques to detect anomalies, RNNs such as the long short-term memory (LSTM) to analyze time series or MLPs are candidates to be used as a crossing intention detector. In the second stage, the objective would be to increase the number of pedestrian interest points of the cities stored in the external database to increase the road safety provided by the app. In this task, the use of OSM can be very useful because it allows the community to update the maps of its city. In the third stage, the app would be uploaded to application stores such as Android's Play Store or Apple's App Store, among others. This would allow the massive download of the app by the users. In the fourth stage, the task would be to disseminate the app through traditional media (e.g., press or television) and social networks, as well as to attend entrepreneur fairs and exhibitions to publicize the product and its advantages for decision-makers. Finally, the results obtained from the research and the app itself would be transferred to third parties to continue with the maintenance of the project, either publicly or privately.

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Appendix A

Table A1. Comparison of the proposals described in the state of the art.

Ref.	Type	Application	Information Extracted From	AI Implemented	Year
[10]	App	Traffic jams	Smartphone sensors	Decision algorithm in function of the via status	2018
[11]	App	Traffic jams and incidents	Smartphone sensors and third parties	-	2019
[12]	App	Accident risk	Personal information and historical data	Fuzzy harmonic systems and fuzzy patterns	2017
[13]	App	Improve pedestrian routes	Open Street Maps and Google APIs	A * algorithm	2018
[14]	App	Improve pedestrian routes	Data base with architectural barriers and Google APIs	Optimizing iterative algorithm	2020
[15]	App	Improve pedestrian routes	Maps stored in Google Drive and Sensors	Dijkstra algorithm	2020
[16]	App	Improve pedestrian routes	Open Street Maps	Optimizing algorithm	2018
[17]	Camera on the road	Detect crossing intention	Cameras	Haarcascade based on OpenCV library; HOG based on SVM; SSD based on MobileNet; YOLO based on DNN	2019
[18]	Camera on the road	Detect crossing intention	Cameras	Region-based CNN; SVM; MLP	2019
[19]	Camera on the road	Detect crossing intention	Cameras	HOG based on SVM	2017
[20]	Camera on the road	Detect crossing intention	Cameras	KNN; SVM; ANN; DT; CNN	2018
[21]	Camera on the road	Detect crossing intention	Cameras	LSTM	2020
[22]	Camera on board vehicles	Detect crossing intention	Cameras	RF; SVM	2017
[23]	LIDAR sensor on the road	Detect crossing intention	LIDAR	DNN; LSTM; CNN	2016
[24]	Cameras and laser sensor on the road	Detect crossing intention	Cameras and laser sensors	AT-LSTM; SVM	2020
Proposed	App	Detect crossing intention and improve pedestrian routes	Google APIs, external data base and rotation vector	Fuzzy logic and optimizing algorithm	2020

ANN: artificial neural network; AT-LSTM: long short-term memory network with attention mechanism; A* algorithm: A-Star search algorithm; CNN: convolutional neural network; DNN: dense neural network; DT: decision tree; HOG: histogram of oriented gradients; KNN: k-nearest neighbors; LSTM: long short-term memory; MLP: multilayer perceptron; RF: random forest; SSD: single shot detector; SVM: support vector machine; YOLO: you-only-look-once.

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Chapter 5. General Conclusions

5.1 Introduction

The purpose of this chapter is to present the main conclusions, limitations and future works obtained during the development of the solutions presented in this doctoral thesis. These outcomes have been written in both English and Spanish to enhance their usefulness.

5.2 General Outcomes

Smart cities are scenarios of innovation, challenge and opportunity to improve the citizens' lives, where intelligent transport and mobility are key areas of interest. ITS and SRS are scenarios in which a significant amount of innovation has emerged hand in hand with wireless communications, data analysis and processing techniques.

Given this scenario, wireless communications are currently being used to interconnect different road users such as vehicles, infrastructures or pedestrians to give rise to communications called V2X (i.e., vehicle to all), I2X (i.e., infrastructure to all) and P2X (i.e., pedestrian to all) as it has been collected in the literature review presented in this doctoral thesis. To carry out this review, the 100 most representative documents of the state of the art from the beginning of vehicular communications until today have been analyzed. The analysis confirmed that governments, industries and universities around the world closely cooperate to respond to needs in the development of regulatory laws, standards and technologies. In addition, 4G/LTE, 5G and IEEE 802.11, among others are the most used technologies to support V2X, I2X and P2X communications currently. From this analysis, it was also shown not all authors use the same expressions or acronyms to refer to the same concept. An example can be the indifferent use of car-to-car (C2C) versus vehicle-to-vehicle (V2V) communication, or car-to-everything (C2X) versus vehicle-to-everything (V2X) communication. To help resolve these misuses, a taxonomy was proposed to homogenize terms related to V2X, I2X or P2X communications. Finally, the analysis showed that most of the innovations developed to improve road safety are focused on V2X communications (92.14%), followed by I2X communications (4.90%) and lastly by P2X communications (1.96%). This suggests that I2X and P2X communications have been hardly studied to improve SRS, thus allowing an open field of study in the coming years.

Currently – and despite the progress made – road safety is nowadays a weak point of smart cities as it has been shown in several studies, which indicate that 40% of accidents involving pedestrians occur when they cross the right place on the road.

This happens –in part– because crosswalks are not 100% visible for drivers due to different reasons: (*i*) poor road maintenance*,* (*ii*) occlusion of vertical signs, and/or (*iii*) adverse weather conditions, among others.

This doctoral thesis proposes the use of several innovative solutions to help reduce the accident rate at crosswalks. The first article presents a prototype of a road signaling system located on public roads that alerts drivers when they approach a zebra crossing where there are pedestrians. This system is composed of a set of autonomous, intelligent and low-cost sensor nodes, which can detect targets and discern between pedestrians and vehicles. This ability has been achieved by means of a sensory fusion approach. Thus, if a pedestrian is crossing a crosswalk, the system generates visual signals to alert drivers and therefore stop their vehicles safely. If the proposed solution is compared with other commercial and/or patented solutions, the main differentiating characteristics are the use of AI, the ability to power the system sustainably and the no need for public works to install it on the road. This solution was subjected to different tests to determine how the different users of a crosswalk were detected (i.e., group or individual pedestrians, baby carriages, bicycles, cars and motorcycles). A total of 244 tests were performed and validated through a ROC analysis, which achieved 94.64% accuracy and 100% precision. This suggests that –in global terms– the target classification achieved a good performance, although it has been found that the larger the volume of the target, the better the detection (e.g., bicycles or baby carriages *vs* a pedestrian). In addition to this limitation, the system requires the recalibration of the fuzzy logic tags to detect vehicles in function to its location.

The third article provides an improvement to the limitation found in the first approach. This solution is not only applicable to this doctoral thesis, but it also can be generalized for applications that study a changing phenomenon in time or need to work in different locations with the same configuration (e.g., intrusion detection, overtaking or avoiding obstacles in autonomous vehicles, or vehicle detection in parking lots). The article proposes the use of ML-based techniques instead of a fuzzy logic approach to obtain a generalized target detection regardless of the system location. To achieve this goal, a dataset from the smart road signaling system has been used to generate the ML computational models and validate their performance. The ML techniques have been divided into classifiers (i.e., LR, RF, extra-tree, KNN and MLP), anomaly detectors (i.e., one-class SVM), time-series forecasting (i.e., LSTM neural network) and DRL. To determine the technique that achieves the best performance, the dataset was collected in five different locations in Portugal and Spain under fluid traffic conditions. A total of 86,960 tuples were labeled, thus presenting a high class imbalance. The dataset was preprocessed to balance it resulting in 12,407 tuples labelled. This balanced dataset has been used to carry out the training and testing of the different ML techniques, for which a cross-validation scheme with five subsets was used. The best results were obtained with the RF model, achieving a TPR of 96.82%, FPR of 1.73%, accuracy of 97.85% and area under curve (AUC) of 0.98. The following best results were obtained by the DRL and LSTM models with a high accuracy (94.83% and 93.83%, respectively) and high AUC (0.98 and 0.97, respectively). In contrast, LR and MLP achieved the least reliable results of all the methods tested due to their low AUC (0.91 and 0.87, respectively). Therefore, the results suggest that the most feasible techniques to generalize the vehicle detection in environments that change over time and in different locations are RF, DRL and LSTM since they present similar metrics to the fuzzy logic approach.

The fourth article aims to increase road safety for pedestrians using a mobile application as a complementary strategy. On the one hand, the application can determine the pedestrian's crossing intention through a crosswalk using rotation sensors and sensory fusion based on fuzzy logic. This functionality is built into the own users' smartphones, allowing the detection of the crossing intention throughout the city and not only in specific points at streets in contrast to other solutions found in the state of the art. It is also important to note that this solution –unlike others in the state of the art– is not affected by adverse weather conditions since it only makes use of the sensors included in a smartphone. The main contribution of this work lies in the novel combination of fuzzy blocks used to detect the pedestrian's crossing intention around a POI (i.e., crosswalk). On the other hand, the article also proposes an algorithm for calculating, tracing and guiding pedestrians through safe routes in a city. The safe routes make greater use of crosswalks, streets and pedestrian walkways unlike other applications. As an added value, the application includes the ability to communicate –via Bluetooth– with the road signaling system proposed in the first article. The interaction is used to indicate the pedestrian's crossing intention to the intelligent nodes, creating a light barrier that allows drivers to stop their vehicles safely. The experimentation consisted in crossing a crosswalk with different entrance angles by 31 subjects, resulting in 3120 samples. This made possible to determine the quality of the crossing intention detector, obtaining an accuracy of 98.27%, F1-score of 98.97%, TPR of 98.27%, FPR of 0.61% and specificity of 99.70%. This suggests that the proposed solution can determine the pedestrians' crossing intention with high sensitivity and specificity. Moreover, a second experimentation was carried out to analyze 30 routes and compare them with Google Maps to validate the benefits of the app as a safer route planner. The results indicate that the routes generated by the application increased the safety between

183.00% and 266.67% compared to that generated by Google Maps. The routes include a greater number of pedestrian areas, although this increase in safety is due to the increase in the distance and time of the routes.

5.3 Limitations of the Thesis

In this section, the limitations found during the development of this doctoral thesis will be exposed depending on whether they are technical, methodological or scientific limitations. The discussion includes article 1, article 3 and article 4, but not article 2 since it presents a review and analysis of the state of the art.

5.3.1 Technical & Methodological Limitations

A technical limitation observed in the first article is the difference in the quality of detection between different targets. This variation lies mainly in the ultrasound and RADAR sensors, which detect higher volume targets (e.g., vehicles, motorbikes, bicycles, buggy babies and groups of people) with greater reliability and precision than lower volume targets (e.g., a pedestrian walking alone). The limitation in reliability and precision influences the sensory fusion process used to determine the presence of targets in a crosswalk. Despite using fuzzy logic, the low quality of the measurements achieved for a pedestrian generates too much uncertainty in the far limits of the crosswalks to be able to adequately determine the presence of a pedestrian on the zebra crossing. Another technical limitation is the energy consumption of the nodes with an autonomy of approximately 30 hours, despite the improvement achieved with the optimization of consumption based on the time zones with more pedestrian activity. Most of this consumption is associated with the ultrasound and RADAR sensors due to the supply voltage necessary for their operation.

In relation to the third article, a methodological limitation was found due to the dataset used to train and validate the computational models. The current dataset –although it is representative and includes captures of cars, motorcycles and buses– does not reflect all types of vehicles that could circulate on public roads (e.g., bicycles, electric scooters, trucks or vans, among others). This would allow to create more robust ML models. Moreover, the samples must be also collected considering other locations (e.g., mountain areas and different latitudes of the 37th parallel) and different times of the day (e.g., at sunrise or sunset). In this way, models –especially those based on detecting changes or patterns in time series– are expected to improve the system confidence.

Regarding the fourth article, the methodological limitations are divided according to the app functionalities. In relation to the detection of a pedestrian's crossing intention around a crosswalk, it is noteworthy that all the volunteers reside in the region of Huelva (Spain). This could be considered a limitation because people could have very similar ways of walking or crossing streets due to potentially acquired behaviors in their city. In addition, the way of calibrating the fuzzy labels could be considered as a limitation since this process is performed only at a specific time. Occasionally, the calibration process may be invalid when the user changes his/her gait while calibrating the application due to various factors. (e.g., it may start to rain, a phone call or SMS could be received, etc.). The technical limitations with respect to the calculation and tracing of safe routes are related to the number of POIs for pedestrians stored in the database. Currently, the database only collects a set of conflict zones available in various cities as an example, when the ideal scenario would be to include all pedestrian areas in a vast number of cities. Another technical limitation to highlight is the representation of routes on the map, which is directly linked to the map engine used (i.e., Google Maps) and only allows routes to be traced on the road instead of sidewalks. In addition, it should be noted as a limitation the need for an Internet connection for the application to calculate and trace routes through the city. Without this connection, it is not possible to carry out communications with the different APIs necessary for the operation and neither to consult the different pedestrian points of interest collected in the database located in the cloud.

5.3.2 Scientific Limitations

Among the scientific limitations found in the first article, the need to recalibrate the fuzzy labels n times in each location of the system –where n is the number of nodes per location– stands out. This occurs because fuzzy logic uses a set of rules and fuzzy sets that support the reasoning of the system. These fuzzy sets are made up of a set of cut-off points that force the need to recalibrate the system based on the location of each node. This limitation has been solved through the ML algorithms proposed in the third article of the doctoral thesis.

The main scientific limitation presented in the third article is the partial detection of vehicles on public roads. This occurs because each node observes and detects what happens in each section of the public road. Therefore, the vehicle is not classified or detected in the total environment of the road. If a complete classification of vehicles had been chosen, the ML models generated with the techniques used would generally be very complex and computationally costly, thus making it difficult to implement these techniques in a real-time system. Another limitation is the computing capability of the electronics where the ML models must be integrated. These devices are the control units used in the first article, which present a low amount of memory and computing capability. Due to this, it is not possible to use on-line learning algorithms or train ML models directly in these control units because the time required would be too high. Consequently, the algorithms to be selected to detect the presence of vehicles must have low computational consumption for the actual deployment to be viable.

In relation to the fourth article of the doctoral thesis, a scientific limitation found is that the current strategy detects crossing intentions better through large or sharp angles than small angles (e.g., 22.5º). This could be inherent to the fuzzy logic used itself, which could cause these angles to be on the boundary of the fuzzy set labels. Regarding the calculation and tracing of routes, it is found that the optimization algorithm used currently offers an optimal path, being it the safest but no the shortest in distance or time. This is because the current algorithm tries to insert the largest number of pedestrian POIs without considering another characteristic other than not increasing the distance of the route by 300m compared to the original route.

5.4 Future Works

First, future works and trends in the current state of the art of wireless communications used in ITS and SRS will be presented. Subsequently, the work to be done to improve and advance each one of the solutions proposed in this doctoral thesis to improve road safety on publics road will be described.

From the analysis of the state of the art of wireless communications used in ITS and SRS, it was determined that one of the most promising and leading technologies in the medium term is 5G. Although 5G networks will provide better performance than 3G/4G networks in general (i.e., reliability, data rate, power consumption, positioning, QoS, and latency), the cost of the 5G infrastructure, the signal loss of the millimeter band, and some aspects on security and privacy are some of the main concerns yet to be solved. In the meantime, other noteworthy proposals beyond 5G, such as LTE-M, Narrow-Band IoT (NB-IoT) or new ways of waveform at frequencies up to THz must prove their worth. This would open up a new world of possibilities to more advanced services and business models. In this sense, the Internet of Things Application (IOTA) or the Social Internet of Vehicles (SIoV) are current examples from the automotive sector aimed at increasing safety, comfort, and efficiency of passengers on the path to fully autonomous car development by 2027.

Future work for the solutions proposed in this doctoral thesis is detailed bellow. Works on hardware will be focused on improving various technical aspects and functions of the prototype including size, energy consumption and electronics. On the one hand, the energy deficit supported by the system is still considered high. This could be improved including low-consumption devices and/or inducing the control unit to idle periods without affecting the system capability. As a result, it could reduce the number of photovoltaic panels as well as the size of the prototype. Considering the software, the use of more advanced control techniques could improve the accuracy and confidence of the prototype. Among the possible techniques, analysis and recognition of patterns based on the short-time Fourier transform (STFT) are included, as well as the ML techniques to recognize these patterns (e.g., one-class SVM, KNN, RF or RNN). Furthermore, the possibility of optimizing or calibrating these labels by using a genetic algorithm could be considered as complementary research to that carried out in the third article of this doctoral thesis to solve the limitations of the fuzzy logic labels. Finally, the road safety prototype developed can be improved by including functionalities for dependent people (e.g., acoustic signals for blind people).

Furthermore, future work on vehicle detection is aimed at developing a real-time vehicle detection using ML techniques (e.g., DRL, LSTM, RF o MLP) for infotainment purposes. This could allow the use of the prototype system as a traffic analysis tool, being able to count the number of vehicles that circulate, as well as record detentions or traffic jams on public roads. Another possible improvement is to develop a vehicle detector using ensemble learning techniques (e.g., LogitBoost, RF or Gradient Boosting). This could be based on using multiple nodes of the system installed along the line of the crosswalk and each one in charge of monitoring a road section. Thus, each node observes or takes data from a partial view of the road different from that of other nodes. Then, using wireless communications, this information would be sent to a central node that combines the points of view of each node. Thus, several simpler detectors could be used to obtain a single strong and robust detection. From another perspective, the computing capacity –and therefore the vehicle detection– could be improved by implementing the fog computing paradigm. This would allow the use of a central device with greater computing capability than the system nodes, which in turn will communicate with servers in the cloud. Thus, training could be carried out with large amounts of data, which will generate more robust ML models that can then be introduced in each of the system nodes. In the same way, the central unit could also be used to conduct on-line trainings with the data collected from the system nodes and therefore improve the ML models in real time.

Finally, future work to improve the safe guidance application will be aimed at including new functionality or optimizing those already included. Among them are the implementation of an infrastructure to pedestrian (I2P) communication to alert pedestrians on the presence of vehicles traveling at high speed to avoid possible accidents (i.e., communication with the intelligent pedestrian crossings of the first article, being the system nodes the sender of the information). Also, a pedestrian to vehicle (P2V) communication could be addressed to directly notify drivers through their smartphones –in a non-disruptive way– on the existence of pedestrians with the intention of crossing the road. In addition, another functionality that could be investigated is the possibility of changing the map and route calculation engine to OSM, which could offer more complete information related to pedestrian zones in cities than Google Maps. Likewise, the possibility of using ML techniques to determine the pedestrian's crossing intention by means of the sensors included in the smartphones will be studied. This could provide better performance than the current strategy based on Fuzzy logic. The possible techniques to be considered would be one-class SVM as anomaly detectors, RNNs such as LSTM to analyze time series, as well as neural networks of MLP as a general-purpose classifier. Moreover, the objective should be to increase the number of pedestrian points of interest in the cities included in the current external database to increase the road safety offered by the app. In this sense, OSM could be very useful because this tool allows the updating of city maps by the community. In addition, the route optimization could be addressed by using more specific techniques such as a graph resolution using Dijkstra or ant colonies. In the same line, route optimization could also be carried out using a multi-objective genetic algorithm to optimize safety, distance and time spent on the route. After carrying out these tasks, the application would be hosted in app stores such as Android Play Store, among others. Additionally, the application would be advertised using traditional techniques and social networks to attract the attention of users and increase road safety in cities.

5.5 Conclusiones Generales

Las ciudades inteligentes son escenarios de innovación, retos y oportunidades para mejorar la vida de los habitantes, donde los sistemas inteligentes de transporte y movilidad son piezas clave de interés. Los ITS y SRS son escenarios en los que ha surgido una importante cantidad de innovaciones de la mano de las comunicaciones inalámbricas y de las técnicas de análisis y procesado de datos.

Dado este escenario, las comunicaciones inalámbricas para interconectar a los diferentes usuarios de la vía (i.e., vehículos, infraestructuras y peatones) están siendo utilizadas para dar lugar a las comunicaciones denominadas V2X (i.e., vehículo a todo), I2X (i.e., infraestructura a todo) y P2X (peatón a todo), como ha sido recogido en la revisión literaria presentada en esta tesis doctoral. Para llevar a cabo esta revisión, se han analizado los 100 documentos más representativos desde el inicio de las comunicaciones vehiculares hasta nuestros días. El análisis confirmó que los gobiernos, industrias y universidades de todo el mundo están cooperando para responder a las necesidades del desarrollo de leyes reglamentarias, estándares y tecnologías. Además, el 4G/LTE, 5G e IEEE 802.11p, entre otras, son las tecnologías que más soporte están ofreciendo a estas comunicaciones. Este análisis también demostró que no todos los autores usan las mismas expresiones o acrónimos para referirse al mismo concepto. Un ejemplo puede ser el uso indiferente de comunicación car-to-car (C2C) frente a vehicle-to-vehicle (V2V) o comunicación car-to-everything (C2X) frente a vehicle-to-everything (V2X). Con el fin de ayudar a resolver estos usos incorrectos, se propuso una taxonomía para homogenizar términos relacionados con las comunicaciones V2X, I2X y P2X. Por último, el análisis demostró que la mayoría de las innovaciones desarrolladas para mejorar la seguridad vial están enfocadas en las comunicaciones V2X (92,14%), seguida de las comunicaciones I2X (4,9%) y por último las comunicaciones P2X (1,96%). Todo ello sugiere que las comunicaciones I2X y P2X apenas han sido estudiadas para mejorar la seguridad vial inteligente, permitiendo de este modo crear un campo de estudio para los próximos años.

Actualmente –y a pesar de los avances conseguidos– la seguridad vial es un punto débil de las ciudades inteligentes, como ha sido demostrado en diversos estudios, los cuales indican que el 40% de los accidentes que involucran a peatones se producen cuando el peatón cruza por el lugar adecuado de la vía. Esto ocurre –en parte– porque los pasos de peatones no se encuentran 100% visibles para los conductores debido a diversos factores: (*i*) mantenimiento de la vía deficiente, (*ii*) obstaculización de las señales verticales y/o (*iii)* condiciones climáticas adversas, entre otros.

Esta tesis doctoral propone el uso de diversas soluciones innovadoras para ayudar a reducir la tasa de accidentes alrededor de pasos peatonales. El primer artículo presenta un prototipo de señalización vial ubicado sobre la vía púbica que alerta a los conductores cuando se aproximan a un paso de cebra y se encuentran cruzando uno o varios peatones. Este sistema está compuesto por un conjunto de nodos sensores autónomos, inteligentes y de bajo coste, los cuales tienen la capacidad de detectar objetivos y discernir entre peatones y vehículos. Esta capacidad se ha conseguido por medio del uso de fusión sensorial. De este modo, si un peatón está cruzando un paso de peatones, el sistema genera una señal visual que alerta a los conductores para que estos puedan detener los vehículos de forma segura. Si se compara la solución propuesta con otras soluciones comerciales y/o patentadas, las principales características diferenciadoras son el uso de inteligencia artificial, la capacidad de alimentar al sistema de manera autónoma y la modalidad de instalación en la vía pública sin necesidad de obras públicas. Esta solución se sometió a diferentes pruebas para determinar cómo se detectaban los diferentes usuarios de un paso de peatones (i.e., peatones individuales o grupos, carritos de bebé, bicicletas, coches y motocicletas). En total se realizaron 244 pruebas que fueron analizadas mediante análisis ROC, el cual ofreció un 94.64% de exactitud y una precisión del 100%. Esto sugiere que –en términos globales– el clasificador ha obtenido un buen rendimiento, aunque la detección es mejor cuanto mayor es el volumen del objetivo (e.g., bicicletas o carritos de bebé frente a un solo peatón). Además de esta limitación, el sistema necesita recalibrar las etiquetas en función de su ubicación para poder detectar los vehículos.

El tercer artículo ofrece una mejora a la limitación encontrada en el primer enfoque. Esta contribución no solo es aplicable a esta tesis, sino que también puede ser generalizada para aplicaciones que estudien un fenómeno cambiante en el tiempo, así como aquellas aplicaciones que necesiten funcionar en diferentes localizaciones con la misma configuración (e.g., detección de intrusos, detección de vehículos en aparcamientos, adelantamientos o evasión de obstáculos en vehículos autónomos). El artículo propone el uso de técnicas de ML en lugar de técnicas de lógica difusa para obtener una detección de objetivos generalizada sin importar la ubicación del sistema. Para lograr este objetivo, se ha utilizado un conjunto de datos generado a partir del sistema de señalización vial inteligente con el objetivo de generar los modelos de ML y validar su rendimiento. Las técnicas utilizadas se han dividido en clasificadores (i.e., LR, RF, extra-tree, KNN y MLP), detectores de anomalías (i.e., one-class SVM), predicción de series temporales (i.e., LSTM) y aprendizaje profundo reforzado (también llamado deep reinforcemnt learning). Para determinar la técnica que mejor rendimiento ofrece, se recogió un conjunto de datos en cinco ubicaciones diferentes de España y Portugal bajo condiciones de tráfico fluido. En total se obtuvieron 86.960 tuplas etiquetadas, presentando un gran desbalanceo de clases. El conjunto de datos fue preprocesado para balancearlo, obteniendo como resultado un total de 12.407 tuplas etiquetadas. Este conjunto de datos balanceado ha sido utilizado para llevar a cabo el entrenamiento y test de las diferentes técnicas. Para ello, se utilizó un esquema de validación cruzada con cinco subconjuntos. Los mejores resultados se obtuvieron con el modelo RF, ofreciendo un TPR del 96,82%, un FPR del 1,73%, una exactitud del 97,85% y un área bajo la curva (AUC) de 0,98. Los siguientes resultados fueron obtenidos por los modelos

DRL y LSTM, con una alta exactitud (94,83% y 93,83%, respectivamente) y una alta AUC (0,98 y 0,97, respectivamente). En contraste, RL y MLP ofrecieron los resultados menos confiables de todos los métodos probados debido a su baja AUC (0,91 y 0,87, respectivamente). Por tanto, los resultados sugieren que las técnicas más factibles a utilizar para generalizar la detección de vehículos en entornos cambiantes en el tiempo y diferentes localizaciones son RF, DRL y LSTM, ya que presentan unas métricas similares al enfoque de lógica difusa utilizado previamente.

El cuarto artículo persigue aumentar la seguridad vial de los peatones usando una aplicación móvil como estrategia complementaría. Por un lado, la aplicación puede determinar la intención de cruce de un peatón a través de un paso de cebra en la vía pública usando sensores de rotación y fusión sensorial basada en lógica difusa. Esta funcionalidad está integrada en los smartphones de los usuarios, permitiendo la detección de la intención de cruce en toda la ciudad y no solo en puntos específicos de la misma como ocurre con otras soluciones del estado del arte. Es importante destacar que esta solución –a diferencia de otras del estado del arte– no se ve afectada por condiciones climáticas adversas, ya que solo hace uso de los sensores incluidos en el propio smartphone. La principal contribución de este trabajo recae en la combinación de bloques difusos para detectar la intención de cruce de los peatones alrededor de POI (e.g., pasos de cebra). Por otro lado, el artículo también ofrece un algoritmo para el cálculo, trazado y guiado de peatones a través de rutas seguras en una ciudad. Estas rutas seguras hacen un mayor uso de pasos de peatones, calles y pasarelas peatonales a diferencia de otras aplicaciones. Como valor añadido, la aplicación incluye capacidad para comunicarse –mediante Bluetooth– con el sistema de señalización vial inteligente propuesto en el primer artículo. Esta interacción es utilizada para indicar la intención de cruce de un peatón a los nodos inteligentes, creando así una barrera luminosa que permita a los conductores detener los vehículos de forma segura. La experimentación llevada a cabo consistió en cruzar un paso de peatones con diferentes ángulos de entrada por 31 sujetos, obteniendo un total de 3.120 muestras. Esto permitió determinar la calidad del detector de intención de cruce, siendo las métricas obtenidas las siguientes: exactitud del 98,27%, F1-score del 98,97%, TPR del 98,27%, FPR del 0,61% y especificidad del 99,70%. Esto sugiere que la solución propuesta puede determinar la intención de cruce de los peatones con una alta sensibilidad y especificad. Además, una segunda experimentación se llevó a cabo para analizar 30 rutas y compararlas con Google Maps para validar los beneficios de la aplicación como planificador de rutas seguras. Los resultados obtenidos indican que las rutas generadas por la aplicación incrementan la seguridad entre 183,00 % y 266,67% frente a las generadas por Google Maps. Esto se produce porque la ruta generada incluye un mayor número de áreas peatonales, aunque este aumento de seguridad se produce a cambio de aumentar la distancia y el tiempo de la ruta.

5.6 Limitaciones de la Tesis Doctoral

En esta sección se describirán las limitaciones encontradas durante el desarrollo de la tesis doctoral en función de si estas son limitaciones técnicas, metodológicas o científicas. La discusión incluye al artículo 1, artículo 3 y artículo 4, pero no incluye el artículo 2 ya que este es una revisión y análisis del estado del arte.

5.6.1 Limitaciones Técnicas y Metodológicas

Una limitación observada en el primer artículo es la diferencia de la calidad de detección entre los diferentes objetivos. Esta diferencia radica principalmente en el sensor de ultrasonidos y RADAR, los cuales detectan los objetivos de mayor volumen (e.g., vehículos, carritos de bebé, bicicletas y grupos de personas) con una mayor fiabilidad y precisión que los objetivos de menor volumen (e.g., personas caminando en solitario). La limitación de fiabilidad y precisión influye en el proceso de fusión sensorial basado en lógica difusa utilizado para determinar la presencia de objetivos en el paso de peatones. A pesar del uso de fusión sensorial, la baja calidad de las medidas obtenidas para peatones genera demasiada incertidumbre en los límites alejados del paso de peatones como para ser capaz de determinar adecuadamente la presencia de un peatón sobre el paso de cebra. Otra limitación técnica es el consumo energético que presenta el dispositivo, ya que solo ofrece una autonomía de 30 horas aproximadamente a pesar de la mejora conseguida con la optimización de consumos en función de los tramos horarios de más actividad peatonal. La mayor parte de los consumos están asociados a un consumo constante de energía generado por los sensores de ultrasonido y RADAR, en especial al sensor de ultrasonidos por el voltaje de alimentación necesario para su correcto funcionamiento.

En relación con el tercer artículo, se encontró una limitación metodológica debido al conjunto de datos utilizado para entrenar y validar los modelos computacionales. El conjunto de datos actual –aunque es representativo e incluye capturas de vehículos, motocicletas y autobuses– no refleja todos los tipos de vehículos que pueden circular por la vía pública (e.g., bicicletas, patinetes eléctricos, camiones o furgonetas, entre otros). Esto permitiría crear modelos de ML más robustos. Además, las muestras deben ser recogidas considerando otras ubicaciones (e.g., áreas de montaña y latitudes diferentes del paralelo 37º) y en diferentes tramos horarios (e.g., al amanecer y atardecer). De este modo, se espera que la confianza del sistema sea mejorada por nuevos modelos computacionales, especialmente aquellos que detectan cambios o patrones en series temporales.

Las limitaciones encontradas en el cuarto artículo han sido divididas en dos grupos de acuerdo con las funcionalidades de la aplicación. En relación con la detección de la intención de giro de un peatón en torno a un paso de cebra, se destaca que todos los voluntarios residen en la provincia de Huelva (España). Esto se considera una limitación debido a que al vivir en una misma zona geográfica pueden tener formas de caminar o de cruzar la vía pública similares. La detección y posterior señalización de la intención de cruce de un peatón presenta como limitación la forma de calibrar las etiquetas de la lógica difusa, la cual es calibrada en un momento concreto. Ocasionalmente, esto podría provocar una calibración no válida si, mientras se está calibrando la aplicación, el usuario cambia su manera de caminar en base a diversos factores (e.g., comienza a llover, recibe una llamada de teléfono o un SMS, etc.). Las limitaciones técnicas con relación al cálculo y trazado de rutas seguras están relacionadas con el número de lugares de interés peatonal recogido en la base de datos externa. En este momento, la base de datos recoge muestras de zonas conflictivas de varias ciudades a modo de ejemplo, cuando el escenario ideal sería incluir todas las áreas peatonales en un gran número de ciudades. Otra limitación técnica a resaltar es la representación de la ruta segura sobre un mapa debido a la restricción presentada por el motor de mapas utilizado (i.e., Google Maps), el cual solo permite trazar rutas por la vía en lugar de trazar rutas por la acera. Además, sería necesario destacar como una limitación la necesidad de una conexión a Internet en el momento de calcular y trazar las rutas por la ciudad. Sin esta conexión, no es posible realizar las comunicaciones con las diferentes APIs necesarias para el funcionamiento de la aplicación y tampoco para consultar los diferentes puntos de interés peatonal recogidos en la base de datos ubicada en la nube.

5.6.2 Limitaciones Científicas

Entre las limitaciones científicas encontradas en el primer artículo destaca la necesidad de recalibración de las etiquetas del conjunto difuso *n* veces en cada ubicación del sistema, donde *n* representa el número de nodos por localización. Esto se produce debido a que la lógica difusa utiliza un conjunto de reglas y conjuntos difusos que rigen el razonamiento del sistema. Estos conjuntos difusos están compuestos por un conjunto de puntos de corte que obligan a la necesidad de recalibrar el sistema en función de la ubicación de cada nodo. Esta limitación ha sido solventada mediante el desarrollo del tercer artículo recogido en esta tesis doctoral.

La principal limitación científica que presenta el tercer artículo de la tesis doctoral es la detección de vehículos de forma parcial en la vía pública. Esto se produce porque cada nodo observa y detecta qué ocurre en cada tramo de la vía pública. Por tanto, no se clasifica o detecta al vehículo en el entorno total de la vía. Si se hubiera seleccionado una detección completa del vehículo, los modelos de ML generados con las técnicas utilizadas serían generalmente muy complejos y costosos computacionalmente, dificultando así la posibilidad de implementar estas técnicas en un sistema en tiempo real. Otra limitación es la capacidad de cómputo de los dispositivos finales donde debe ser integrado el modelo de ML. Estos dispositivos son las unidades de control utilizadas en el primer artículo de la tesis doctoral, los cuales presentan una cantidad de memoria reducida y baja capacidad de cómputo. Debido a ello, no se pueden utilizar algoritmos de aprendizaje on-line ni entrenar directamente en las unidades de control porque el tiempo requerido sería demasiado elevado. Además, los algoritmos que se seleccionen para detectar la presencia de vehículos deben tener un bajo consumo computacional para que el despliegue real pueda ser viable.

En relación con el cuarto artículo de la tesis doctoral, una limitación científica encontrada es que la actual estrategia detecta mejor las intenciones de cruce cuando se realiza mediante ángulos grandes o bruscos que para ángulos pequeños (e.g., 22,5º). Esto podría deberse al propio uso de la lógica difusa, que podría provocar que estos ángulos estuvieran en la frontera de las etiquetas de los conjuntos difusos. Atendiendo a las limitaciones científicas del cálculo y trazado de rutas, se encuentra que el algoritmo de optimización utilizado actualmente ofrece un camino óptimo, siendo este el más seguro, pero no el más corto o con menor tiempo de recorrido. Esto ocurre porque el algoritmo actual intenta insertar el mayor número de puntos de interés peatonal sin considerar otra característica que no sea aumentar la distancia de la ruta en 300 m en comparación con la ruta original.

5.7 Trabajos Futuros

En primer lugar, se expondrán los trabajos y tendencias futuros en el estado del arte de las comunicaciones inalámbricas utilizadas en los ITS y SRS. Posteriormente, se describirán los trabajos a realizar para mejorar y avanzar en soluciones para mejorar la seguridad vial en la vía pública propuestas en esta tesis doctoral.

Del análisis del estado del arte se determinó que una de las tecnologías más prometedoras y punteras a medio plazo es el 5G. Aunque las redes 5G ofrecerán mejores prestaciones que las redes 3G/4G en general (i.e., fiabilidad, velocidad de datos, consumo de energía, posicionamiento, calidad de servicio y latencia), el coste de la infraestructura 5G, la pérdida de señal de la banda de milímetros y algunos aspectos y privacidad son algunas de las principales preocupaciones aún por resolver. Mientras tanto, otras propuestas dignas de mención más allá del 5G como LTE Machine (LTE-M), Narrow Band Internet of Things (NB-IoT) o nuevas formas de ondas en frecuencias hasta THz tienen que demostrar su valía. Esto podría abrir un nuevo mundo de posibilidades a servicios y modelos de negocio más avanzados. En este sentido, la Internet of Things Application (IOTA) o el Intenet Social de los Vehiculos (SIoV) son ejemplos actuales del sector de la automoción destinados a aumentar la seguridad, comodidad y eficiencia de los pasajeros en el camino hacia el desarrollo de coches totalmente autónomos para el año 2027.

A continuación, se detallan los trabajos futuros para las soluciones planteadas. Los trabajos sobre el hardware irán enfocados a mejorar diversos aspectos técnicos y funciones del prototipo, incluyendo el tamaño, consumo energético y hardware. Por un lado, el déficit energético soportado por el sistema todavía se considera elevado. Esto podría mejorarse incluyendo elementos de bajo consumo y/o induciendo a la unidad de control a periodos de reposo sin afectar a la capacidad del sistema. Como resultado, esto podría reducir el número de paneles fotovoltaicos al mismo tiempo que reduce las dimensiones del prototipo. Si se atiende al software, se podría mejorar la detección de peatones y vehículos mediante el uso de técnicas de control más avanzadas con el fin mejorar la exactitud y confianza del prototipo. Entre las posibles técnicas se puede destacar el análisis y reconocimiento de patrones basado en la transformada en tiempo corto de Fourier (STFT), así como el uso de técnicas de ML para reconocer estos patrones (e.g., SVM one-class, KNN, RF o RNN). Además, se podría estudiar la posibilidad de optimizar o calibrar estas etiquetas mediante el uso de un algoritmo genético como estudio complementario al realizado en el tercero artículo de esta tesis doctoral para solventar las limitaciones de las etiquetas difusas. Finalmente, se podría mejorar el prototipo desarrollado por medio de la inclusión de funcionalidades que permitan mejorar la seguridad vial de personas dependientes (e.g., señales acústicas para personas invidentes).

Además, los trabajos futuros de la detección de vehículos estarán enfocados a desarrollar un sistema de detección de vehículos en tiempo real, utilizando técnicas de ML con fines informativos (e.g., DRL, LSTM, RF o MLP). Esto podría permitir la utilización del prototipo como dispositivo analizador de tráfico, siendo capaz de contar el número de vehículos que circulan por las vías públicas y registrar cuándo se producen detenciones o atascos en las mismas. Otra posible mejora es el desarrollo de un detector de vehículos basado en técnicas de aprendizaje en conjunto (e.g., LogitBoost, RF o Gradient Boosting). Esto se basaría en utilizar múltiples nodos del sistema instalados a lo largo de la línea del paso de peatones y que cada uno se encargue de observar un tramo de la vía pública. De este modo, cada nodo observa o toma datos desde una vista parcial de la vía pública diferente a la de otros nodos. Posteriormente, mediante el uso de las comunicaciones inalámbricas, esta información sería enviada a un nodo central que combinaría los puntos de vista de cada uno de los nodos. De este modo, se podrían utilizar varios detectores de vehículos más simples para obtener una única clasificación o detección fuerte y robusta. Desde otra perspectiva, la capacidad de cómputo –y por tanto la detección de vehículos– podría ser mejorada mediante la implementación del paradigma de computación en la niebla o «fog computing». Esto permitiría el uso de un dispositivo central con mayor potencia de cómputo que los nodos del sistema, el cual a su vez se podrá comunicar con servidores en la nube. De este modo, el entrenamiento podría llevarse a cabo con grandes cantidades de datos, lo cual generará modelos de ML más robustos que luego podrán ser introducidos en cada uno de los nodos del sistema. Del mismo modo, la unidad central podría también ser utilizada para realizar entrenamientos on-line con los datos recogidos por los nodos del sistema y por tanto mejorar los modelos de ML en tiempo real.

Finalmente, los trabajos futuros para mejorar la aplicación móvil de guiado seguro están orientados a incluir nuevas funcionalidades u optimizar las ya incluidas. Entre las posibles mejoras a incluir se encuentra la implementación de una comunicación infraestructura a peatón (I2P) para alertar al peatón de la presencia de vehículos a una velocidad elevada y evitar posibles accidentes (i.e., comunicación con los pasos de peatones inteligentes de la primera solución, siendo el emisor de la información los nodos del sistema). También se podría incluir una comunicación peatón a vehículo (P2V) para notificar directamente a los conductores a través de su dispositivo móvil –de manera no disruptiva– sobre la existencia de un peatón con intención de cruzar la vía por el lugar adecuado. Además, otra funcionalidad que podría ser investigada sería la posibilidad de cambiar de motor de mapas y de cálculo de rutas a OSM, el cual podría ofrecer información más completa relacionada con zonas peatonales de las ciudades que Google Maps. Igualmente, se estudiará la posibilidad de usar técnicas de ML para determinar la intención de cruce. Esto podría ofrecer mejor rendimiento que la estrategia basada en lógica difusa. Las posibles técnicas a ser consideradas son SVM one-class como detector de anomalías, RNNs como LSTM para analizar series temporales, así como las MLP como clasificador de propósito general. Además, el objetivo debería ser incrementar el número de puntos de interés peatonales de las ciudades incluidos en la actual base de datos externa con el fin de aumentar la seguridad vial ofrecida por la app. En este sentido, el uso de OSM puede ser muy útil debido a que esta herramienta permite la actualización de los mapas de la ciudad por parte de la comunidad. Además, la optimización de rutas podría abordarse mediante el uso de técnicas más específicas para ello como resolución de grafos mediante Dijkstra o mediante colonias de hormigas. En esta misma línea, la optimización de rutas también se podría llevar a cabo utilizando un algoritmo genético multi-objetivo para optimizar la seguridad vial de la ruta, la distancia y el tiempo utilizado para recorrerla. Posteriormente a la realización de estas tareas, la aplicación sería alojada en tiendas de aplicaciones tales como Play Store de Android, así como se procedería a publicitar la aplicación mediante las técnicas tradicionales y redes sociales para atraer la atención de los usuarios y aumentar la seguridad vial en las ciudades.

LIST OF ACRONYMS

3D-LIDAR	3D Laser Imaging Detection and Ranging
ACK	Acknowledgement
ADC	Analog-to-Digital Converter
AI	Artificial Intelligence
AP	Access Point
API	Application Programming Interface
AT-LSTM	Long Short-Term Memory with an Attention Mechanism
AUC	Area Under Curve
BLE	Bluetooth Low Energy
C2C	Car to Car Communication
C2X	Car to everything Communication
CIS	Spanish Sociological Investigation Center
CNC	Computer Numerical Control
CNN	Convolutional Neural Networks
ConvNet	Deep Convolutional Neural Network
CPM	Compound Performance Metric
CPU	Central Processing Unit
CW	Continuous Wave
DDRQN	Double-Deep Recurrent Q-Network
DGT	General Administration of Traffic of Spain
DNN	Dense Neural Networks
DOT	United States Department of Transportation
DRL	Deep Reinforcement Learning
DSRC	Dedicated Short-Range Communications
EIRP	Effective Isotropic Radiate Power
ETSI	European Telecommunications Standards Institute
EU	European Union
EWM	Emergency Warning Messages
FATI	First Aggerate, Then Infer
FCC	Federal Communications Commission
FIRST	Fatality and Injury Reporting System Tool
FITA	First Inter, Then Aggregate
FLD	Fisher's Linear Discriminant
FOV	Field Of View
FPR	False Positive Rate

GPIO	General Purpose Input/Output
GPS	Global Positioning System
GT	Ground Truth
HOG	Histogram of Oriented Gradients
HTTP	Hypertext Transfer Protocol
I^2C	Inter-Integrated Circuit
I2P	Infrastructure to Pedestrian
I2X	Infrastructure to all Communication
ICT	Information and Communication Technologies
IDE	Integrated Development Environment
IEEE	Institute of Electrical and Electronics Engineers
IOTA	Internet of Things Application
IPv4	Internet Protocol version 4
ITS	Intelligent Transport Systems
JCR	Journal Citation Reports
KNN	K-Nearest Neighbors
LED	Light Emitting Diode
Li-Po	Lithium Polymer Battery
LOS	Line-Of-Sight
LR	Logistic Regression
LSTM	Long Short-Term Memory
LTE	Long Term Evolution
LTE-M	LTE Machine
MAC	Media Access Control
ML	Machine Learning
MLP	Multi-Layer Perceptron
MVP	Maximum Value Point
NB-IoT	NarrowBand IoT
NDN	Name Data Network
NHTSA	National Highway Traffic Safety Administration
OSM	Open Street Maps
P2I	Pedestrian to Infrastructure Communications
P2V	Pedestrian to Vehicle Communications
P2X	Pedestrian to all Communication
PCB	Printed Circuit Board
PHY	Physical
POIs	Point of Interests
PPM	Power Path Management
PWM	Pulse-Width Modulation
R&D	Research and Development
RADAR	Radio Detection and Ranging

RELU	Rectified Linear Units
RF	Random Forest
RFID	Combining Radio Frequency Identification
RISC	Reduced Instruction Set Computing
RNN	Recurrent Neural Network
ROC	Receiver Operating Characteristic
ROI	Regions of Interest
SDN	Software-Defined Networking
SIoV	Social Internet of Vehicles
SPI	Serial Peripheral Interface
SRS	Smart Road Safety
SSD	Single-Shot Detector
STFT	Short-Time Fourier Transform
SVM	Support Vector Machine
TCP	Transmission Control Protocol
TIC	Tecnologías de la Información y la Comunicación
TPR	True Positive Rate
UART	Universal Asynchronous Receiver-Transmitter
UC3M	Universidad Carlos III de Madrid
UDP	User Datagram Protocol
US	United States
USA	United States of America
V2I	Vehicle to Infrastructure Communications
V2V	Vehicle to Vehicle Communications
V2X	Vehicle to all Communication
VANET	Vehicular Ad-hoc Network
WAVE	Wireless Access in Vehicular Environments
WLAN	Wireless Local Area Network
WPA/WPA2	Wi-Fi Protected Access
YOLO	You-Only-Look-Once

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