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A Survey of Machine Learning in Pedestrian Localization Systems: Applications, Open Issues and Challenges

VÍCTOR F. MIRAMÁ[1], LUIS ENRIQUE DÍEZ[2], ALFONSO BAHILLO[2], AND VÍCTOR QUINTERO[1]

[1]Faculty of Electronics and Telecommunications Engineering, Universidad del Cauca, Popayán, Cauca 190003, Colombia
[2]Faculty of Engineering, University of Deusto, 48007 Bilbao, Spain

Corresponding author: Víctor F. Miramá (vmirama@unicauca.edu.co)

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ABSTRACT With the popularization of machine learning (ML) techniques and the increased chipset's performance, the application of ML to pedestrian localization systems has received significant attention in the last years. Several survey papers have attempted to provide a state-of-the-art overview, but they usually limit their scope to a particular type of positioning system or technology. In addition, they are written from the point of view of ML techniques and their practice, not from the point of view of the localization system and the specific problems that ML techniques can help to solve. This article is intended to offer a comprehensive state-of-the-art survey of the ML techniques that have been adopted over the last ten years to improve the performance of pedestrian localization systems, addressing the applicability of ML techniques in this domain, along with the main localization strategies. It concludes by indicating the underlying open issues and challenges associated with the existing systems, and possible future directions in which ML techniques could improve the performance of pedestrian localization systems. Among other open issues, most previous authors have focused their attention on position estimation accuracy, which wastes the potential of ML techniques to improve other performance parameters (e.g., response time, computational complexity, robustness, scalability or energy efficiency). This study shows that there is a strong trend towards the application of supervised learning. Consequently, there are many potential research opportunities in the use of other learning types, such as unsupervised and reinforcement learning, to improve the performance of pedestrian localization systems.

INDEX TERMS Localization system taxonomy, machine learning, machine learning taxonomy, pedestrian localization systems, reinforcement learning, scene analysis, supervised learning, unsupervised learning.

I. INTRODUCTION

There is currently a high demand for pedestrian localization systems in various application areas, and which are expected to work in diverse scenarios with a reasonable accuracy. Many of these systems are integrated in safety-of-life services and mission-critical communication systems, such as disaster management for search and rescue personnel. On a daily basis, many firefighters find that they are in trouble because they become disoriented in forest fires or large buildings on fire, among others. Pedestrian localization systems are not only restricted to the professional market but their demand is also widespread for all kinds of location-based services (LBSs), such as guidance in airports, hospitals or shopping malls. Such LBSs have particular requirements and they demand specific attention, not only with respect to the accuracy but also to many other system performance parameters (e.g., precision, time response, computational complexity, robustness, scalability or energy efficiency). Depending on the purpose of the LBS, the algorithms addressing the

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pedestrian localization systems will follow different strategies, which could have a direct impact on those system performance parameters [1], [2].

Due to the explosion in the availability of data and computational power, machine learning (ML) techniques have improved significantly in recent years and their use has become extremely popular in many fields, including in pedestrian localization systems. Fig. 1 shows the number of papers published in Scopus in the last ten years that have featured ML application in localization. ML can be used for many different purposes, such as classification, prediction, optimization, clustering or data dimensionality reduction, among others. Thus, ML techniques allow a pedestrian localization system to scrutinize the raw data and to obtain new knowledge, which can be used to improve the location estimation. For example, it is common to find localization systems that incorporate ML techniques for tasks such as estimating step length, recognizing different types of movement, or detecting and then mitigating certain environmental conditions that may interfere with location estimation.

Due to the growing interest in the application of ML in localization systems, several studies have examined the use of ML in localization. However, these works tend to limit their scope to only one type of technology (radio frequency [3], [4]), or to exclusively only one type of localization technique (e.g., scene analysis [5], simultaneous localization and mapping (SLAM) [6], device-free localization [7]), or to only one type of ML techniques (e.g., deep learning (DL), [5], [6], [8]). In general, works that present the use of ML in localization systems do so from the point of view of ML techniques and their practice, not from the point of view of localization systems and the benefit that they obtain [9].

This paper aims to provide a comprehensive state-of-the-art study on the use of ML techniques in localization systems, from the following points of view: considering the different localization system typologies, focusing on the specific processes that benefit from the use of ML, the diversity of ways to quantify the performance of localization systems, and the obtained improvements.

To make this study more tractable, the scope has been narrowed to indoor pedestrian positioning systems. The target users, pedestrians, have been chosen given the fact that more than half of the works addressing localization systems focus on pedestrian localization [10]. The target systems, indoor positioning systems, have been chosen given the fact that pedestrians spend more than 90% of their time in indoor scenarios [11]. For the contrary, outdoor environments, Global Navigation Satellite System (GNSS) is a mature technology that can be considered to be a de facto standard. The main reason for this choice is that GNSS is widespread and is able to provide robust solutions for many applications in a wide range of performance/price ratios, while there are several different indoor positioning solutions, each one specialized for a given scenario and generally expensive, making the survey a more useful tool [12].

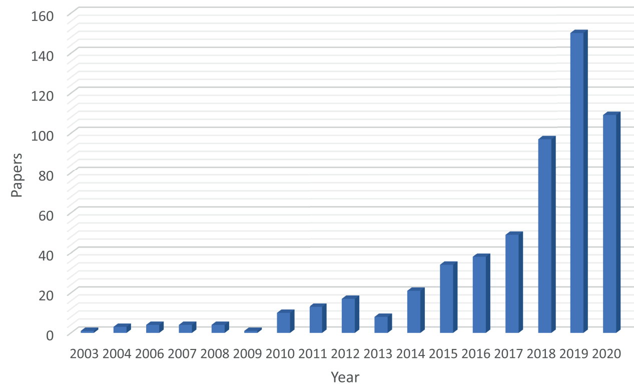

FIGURE 1. Number of papers published on Scopus using "machine learning" and "localization" as keywords.

This survey shows the trends in the application of ML in pedestrian localization systems in the last 10 years. The main contributions follow:

- A systematic literature review on the application of ML techniques in pedestrian localization systems, focusing on the specific localization stage or process in which the ML technique is applied.
- Identification of the underlying open issues and challenges associated with the existing systems, and possible future directions in which the ML techniques might improve the performance of pedestrian localization systems.

The rest of this survey is structured as follows. Section II presents related papers with the main topic of this survey, and the definition of taxonomies used for papers classification. Section III presents the applied method in the systematic literature review, highlighting the main aspects of the methodology and its application. Section IV presents the compendious of the ML applications in pedestrian localization systems, identifying the point in the location estimation chain where the ML technique intervenes. Finally, section V summarizes the lessons learned during the survey construction, including the open research opportunities and the challenges.

II. BACKGROUND AND SUPPORTING TAXONOMIES

This section presents the important papers that allow us to build the state-of-the-art of both localization systems and the use of ML techniques. The constraints, weak points, and obtained improvements from the application of ML in pedestrian localization systems are also highlighted in this section.

A. PEDESTRIAN LOCALIZATION BACKGROUND

There are two general approaches in the study of pedestrian localization systems to estimate the location of a pedestrian. The first is based on information from satellites, where the GNSS uses mature technologies that are able to provide robust solutions for a wide range of outdoor applications.

The second, and the focus of this survey, is the use of different technologies applied in indoor scenarios, where the use of satellite signals cannot be considered [12]. In an effort to complement or to find alternative solutions to the GNSS, many researchers have defined and proposed techniques using a range of technologies to estimate the pedestrian's localization. The authors of the surveys in [13]–[18] introduce localization techniques, including multiangulation, multilateration, scene analysis, proximity, and dead reckoning (DR), among others. These surveys also present the most common metrics that are used as input information by the localization techniques. Metrics such as time of arrival (ToA), time difference of arrival (TDoA), roundtrip time of flight (RToF), received signal strength (RSS), angle of arrival (AoA) and the phase of arrival (PoA) are commonly used to estimate the distance and/or relative angle between a fix node and a mobile device. Meanwhile, metrics such as accelerations, angular rates and magnetic field strength are commonly used to estimate the displacement of a moving object.

From these surveys, a basic general taxonomy of localization systems has been defined (see Fig. 2), which will be used to classify the papers reviewed in this paper from the perspective of pedestrian localization systems. In this taxonomy, there are two main families of localization techniques: position fixing and DR. In position fixing, the signals collected from the scenario are used to estimate the location of a pedestrian by applying geometric or scene analysis localization techniques. The geometrical localization approach is based on using ranging or bearing information obtained from the signal metrics and then applying localization techniques, such as multiangulation or multilateration. The scene analysis localization technique, which is also known as fingerprinting, requires a reference localization map to be created using features related to the signals available in the scenario. Received power is the most commonly used signal feature because it is relatively easy to obtain and allows getting an acceptable performance. The other main family of localization techniques (i.e., DR) is based on the knowledge of a previous position, which is continuously updated by integrating consecutive displacements. Inertial measurement units (IMU) are the most common technology for its implementation. Two main types of DR techniques have been differentiated in this survey: inertial navigation systems (INS) and pedestrian dead reckoning (PDR). INS is a self-contained localization and navigation technique that tracks changes in the orientation, velocity and position of an object by using the measurements provided by accelerometers and gyroscopes mounted on it. PDR makes use of the fact that a human moves by taking steps, so it updates a known position by integrating step lengths and orientations. Position fixing and DR methods have complementary pros and cons, so it is common to merge them to compensate their limitations with their advantages; as shown in Fig. 2. Commonly, the fusion process uses Bayesian filtering, which estimates a state of a dynamic system from noisy observations. In the most basic form of location estimation, the state of interest is the localization of a pedestrian using signals or information provided by sensors that are either placed in the scenario or carried by a pedestrians.

FIGURE 2. Taxonomy of pedestrian localization system techniques.

When different localization systems are compared, the position accuracy is the most common performance parameter. However, there are other parameters that are also important, such as the precision, the computational complexity, the robustness, the scalability, the computational cost or the energy consumption [13], [14], [16]. The lack of standard evaluation methodologies has been one of the biggest barriers in the adoption of non-GNSS pedestrian localization systems by the mass market. Recent works, such as the ISO/IEC 18305 standard, try to deal with this problem [19] but they should be extended to also include good practices related to the evaluation and comparison of pedestrian localization systems that make use of ML techniques.

B. EXISTING SURVEYS ON MACHINE LEARNING AND LOCALIZATION

Keeping in mind the aim of improving the performance of localization systems, many researchers have considered the application of ML as a powerful alternative to solve some of the complex problems related to the localization process. ML approaches are more effective than traditional mathematical tools when used to solve the complex non-linear problems that are usually too complicated for classical methods. The literature includes some surveys of ML application in pedestrian localization; for example, in [4], where the authors perform their study from the point of view of ML, its features, the associated methods, the used datasets, the availability of the datasets and the application of ML in pedestrian localization systems based on wireless signals, specifically radio frequency signals. The authors in [8] focus on the ML application in LBS supported by radio frequency signals. The authors consider that transfer learning (TL) and DL are the best ML approaches to LBS, due to the complexity and diversity of the positioning environment, so they concentrate their efforts only on these ML techniques and the challenges of their application. DL is a special learning architecture that is applied in ML applications, which offers an alternative to improve a specific performance parameter in pedestrian localization systems because DL provides better results with unstructured data.

The authors in [3] present a review of positioning using radio frequency technologies and they dedicate a subsection to study the ML approaches. The authors describe the main ML approaches applied in localization processes, and they list the specific ML algorithms used in procedures related to classification, clustering and matching.

Some studies have focused on particular cases of localization. For example, the authors in [7] study the state-of-the-art of device-free localization, including a review of the main training-based algorithms that are used in device-free localization, such as extreme learning machine (ELM), hidden Markov models (HMM), conditional random fields (CRF) or DL.

The authors in [5] present a specific review of the application of DL in localization systems that are based on fingerprinting, describing the use of DL according to the raw data used to create the fingerprint, identifying the benefits and highlighting the improvement on its performance, mainly by handling large amounts of data to obtain an accurate estimate of the location of a pedestrian. The authors in [6] focus on how DL is applied in SLAM. Meanwhile, the authors in [9] study ML applications in indoor localization and navigation, focusing especially on robots. Table 1 summarizes a comparison between the referenced surveys and this survey to highlight the common topics and the differences.

Based on referenced surveys, a basic taxonomy of ML techniques is defined to support this review. There are three main learning approaches in ML: supervised learning, unsupervised learning, and reinforcement learning. In supervised learning, the algorithm is trained using a set of labeled measurements or data to infer a function or model that maps the input data into the output label. This type of learning is commonly used in problems that are viewed as a classification or regression. In contrast, unsupervised learning explores the hidden features of measurements or data to identify patterns in unlabeled data. Typically, the problems solved by unsupervised learning could be seen as clustering and dimensionality reduction. Reinforcement learning is another type of learning, in which the algorithm is trained by trial and error through interaction with the environment to learn how to make decisions. Semi-supervised learning exists between supervised and unsupervised learning, meaning that only one part of the training data is labeled. Thus, the problems that are handled are of classification or clustering. There are several alternative learning methods, such as TL, which is used to reduce the time of learning in a new end-device or node in a localization system because of the transfer of the knowledge previously acquired; and federated learning (FL), in which the process of learning is performed in a distributed manner from different devices. Considering the types of learning in the existing surveys, a ML taxonomy has been defined as shown in Fig. 3, which includes the typical ML purpose that was developed in each type of learning.

TABLE 1. Comparisons among the surveys on machine learning and localization.

Reference	Motivation	Technological scope	Comparison to this survey
[3]	Localization systems	Radio frequency	It describes the use of ML in scene analysis-based systems.
[4]	ML	Radio frequency	It is mainly motivated on the features of ML techniques (learning approaches) and not so much on the localization problem that ML could solve.
[5]	ML	Radio frequency, computer vision	Its scope is limited to the use of DL techniques in scene analysis-based systems.
[6]	ML	Inertial signals	Its scope is limited to the use of DL techniques in SLAM-based systems.
[7]	Localization systems	Radio frequency	Its scope is limited to device-free localization systems, with only one section on ML techniques.
[8]	ML	Radio frequency	It is a short survey that discusses the use of DL and TL techniques.
[9]	ML	Radio frequency	It is mainly focused on the features of ML techniques (learning approaches) and indoor robot localization.
This survey	GNSS-denied areas pedestrian localization	Radio frequency, inertial signals, ultrasound and magnetic field	The motivation of this paper is the different localization problems that can be solved by the application of ML techniques, considering in its scope the different types of existing localization systems.

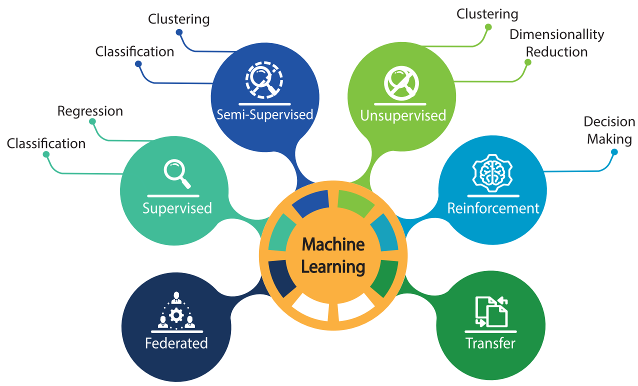

FIGURE 3. Taxonomy of types of learning in ML.

Depending on the number of layers that are used to extract the input features from the obtained data, two main architectures can be used for ML implementation: shallow learning (SL) and DL. SL is used in simple problems where the system learns from predefined data features using a few layers, while in DL the system automatically extracts features from the data using several layers [20].

Considering that the related surveys of ML applications in pedestrian localization are focused on the ML techniques and their application in the localization of robots and general targets, this survey focuses on the pedestrian localization systems, the localization techniques, and learning techniques in ML.

III. METHODS

It is necessary to study recent research and scientific contributions on the use, benefits, limitations, and applications of using ML in pedestrian localization systems if we wish to establish its potential application, open issues and challenges. The construction of this survey and its literature review are based on the Kitchenham methodology [21], [22]. The main elements of the scientific literature review are specified in this section.

A. RESEARCH QUESTIONS

This study aims to understand why and for what purpose ML techniques are applied in localization systems, and what benefits are obtained from them. It is important to identify the most commonly applied techniques, their drawbacks, their opportunities and the achieved performance. Consequently, we have developed the following research questions:

- *Research Question 1 (RQ1):* What is ML used for in localization systems? That is, for which sub-blocks of localization systems is ML used? Does it differ according to the type of localization system?
- *RQ2:* What are the benefits of the application of ML in pedestrian localization systems? That is, which performance parameters are improved by the use of ML techniques?
- *RQ3:* What type of ML is applied in pedestrian localization? That is, what learning approaches (supervised, unsupervised, reinforcement, etc.) and learning architectures (shallow or deep) are used?
- *RQ4:* What are the challenges and opportunities in the application of ML for pedestrian localization?

B. SEARCH RESULTS

Considering these research questions, the following chain of keywords was used during the scientific literature search: *(machine OR reinforcement OR supervised OR unsupervised OR semi-supervised OR transfer OR federated) AND (learning) AND (pedestrian) AND (positioning OR localization)*, focusing on the title, abstract, and keywords. The following databases were considered: IEEE Xplore, Elsevier, ACM, and MDPI. Fig. 4 shows the process that we used in the systematic

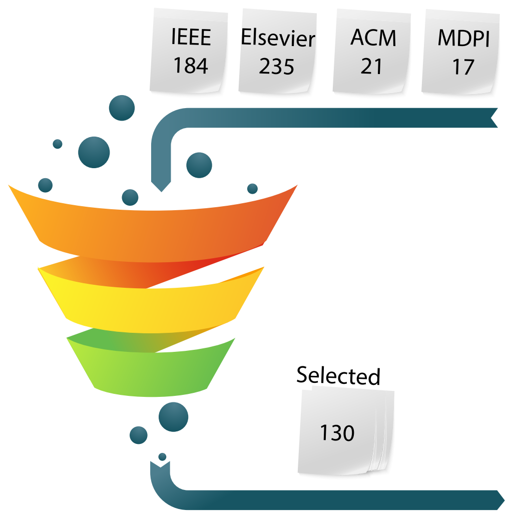

FIGURE 4. Selection process.

literature search. The initial search brought 457 documents in the last 10 years. Selection criteria were defined to filter and to identify the appropriate papers according to the research interests. The main criteria applied in the scientific literature review were: the paper uses ML for pedestrian localization, the paper describes how ML improves some performance metrics, and the paper brings complete information about the research study. Likewise, several exclusion criteria were considered, such as papers that focus on GNSS and papers that only do pedestrian detection. Taking into account these selection and exclusion criteria, 130 papers were selected to be considered in this survey.

The 130 papers were classified considering the defined ML and pedestrian localization taxonomies. In the classification process, discrete and general terms were defined to obtain comparison figures and analytical results. For instance, the classification did not consider a specific technology of radio frequency, such as WiFi, Bluetooth, or other related technologies. Instead, the technologies were classified as ‘‘radio frequency technologies’’. In addition, the raw data were classified by taking the general technology into account. For example, in inertial systems, we do not distinguish between the different forces monitored in a sensor; instead, these types of inertial raw data were considered as ‘‘inertial signals’’.

IV. MACHINE LEARNING APPLICATIONS IN PEDESTRIAN LOCALIZATION

In the last decade, the use of ML techniques in pedestrian localization has been growing. As shown in Fig. 5, the main application of ML in localization is in scene analysis-based systems, in which their use is obvious and straightforward. They have also been applied in other types of pedestrian localization systems. Consequently, it is necessary to identify which problems of the localization processes can be addressed with ML techniques and how ML improves the

TABLE 2. Machine learning application in scene analysis.

		Raw Data				
		Signal Strength	Magnetic Field	ToF	AoA	Image
Supervised	Regression	[23]–[46]	[47]–[49]	[50]	[51], [52]	-
	Classification	[53]–[79]	[80]	[81]	-	[82], [83]
Semi-supervised	Classification	[84]	-	-	-	-
	Clustering	[85]	-	-	-	-
Unsupervised	Clustering	[86], [87]	-	-	-	-
	Dim. reduction	-	[88]	-	-	-
Reinforcement	Decision Making	[89], [90]	-	-	-	-
Transfer		[91], [92]	-	-	-	-

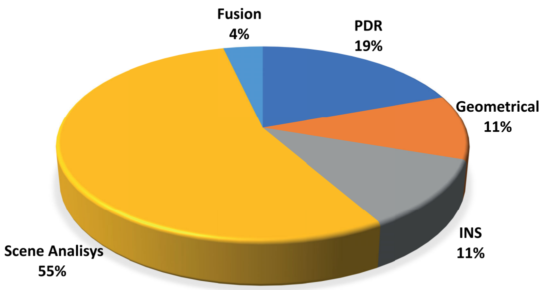

FIGURE 5. Distribution of ML applications in pedestrian localization techniques.

performance of pedestrian localization systems, due to its application in different techniques.

Considering the ML and localization taxonomies that were explained in Section II, Fig. 6 shows a clear tendency towards the application of supervised learning and a low use or exploration of the other types of learning. This happens because supervised learning and scene analysis provide high accuracy, which is the most commonly used performance parameter evaluated in the found papers. Similarly, classification and regression are the most common ML purposes. It is important to note here that the SL architecture is used in many of the considered papers, due to the relatively easy implementation and training, but the use of the DL architecture has been growing in the last years, as shown in Fig. 7, due to the processing capacity improvements in new devices.

In Fig. 6, it is possible to note that techniques such as unsupervised learning and reinforcement learning are little explored in pedestrian localization. Therefore, there are opportunities to look for their application to analyze their advantages and disadvantages. For the techniques of localization, there are few papers related to the application of ML in the fusion technique, which offers another avenue for research. In the remainder of this section, the application of ML in several localization techniques is discussed.

A. MACHINE LEARNING IN SCENE ANALYSIS

Scene analysis is the most commonly used technique in pedestrian localization, due to the relatively easy implementation and acceptable performance. In addition, scene analysis is the localization technique that is more common in the use of ML because this type of pedestrian localization systems considers the localization problem as a classification or regression problem. This type of pedestrian localization systems offers a high degree of flexibility in relation to the type of signals used from the environment in the location estimation process. It is possible to create a fingerprint using radio frequency signals, magnetic fields, visible light, sound, and images, among others. In addition, scene analysis localization could be implemented by signals measured from the environment using technologies such as WiFi, Bluetooth, cellular networks, ultra wide band (UWB), frequency modulated (FM) radio, radio frequency identification (RFID), among others. Although, in general, the pedestrian localization systems based on scene analysis require a device associated with the pedestrian, there are some device-free approaches that use ML to improve their performance. Table 2 lists the works in which ML techniques are applied on pedestrian localization systems based on scene analysis, which are classified according to the type of learning and objective of the ML technique, and the type of data used as input.

Radar diagrams are used in the following sections to show the use of the different types of learning and their application purposes, respectively. The value of each corner corresponds to the proportion of papers using a given type of learning (blue curve) and the ML purpose (orange curve) with respect to the total searched papers. In scene analysis, Fig. 8 shows a clear tendency in the application of supervised learning, with 88% of the papers using this type of learning, and 12% distributed among unsupervised learning, reinforcement learning, and semi-supervised learning. Additionally, Fig. 8 shows that most of the papers use ML for classification and regression because the main application of ML in scene analysis is direct location prediction. This is due to the good performance obtained by using labeled datasets, despite the effort required to collect the labeled data and the high computational cost required for training. Additionally, Fig. 8 shows that a small proportion of papers applied other types of learning, such as semi-supervised, unsupervised, reinforcement, and transfer, which can also be see in Table 2.

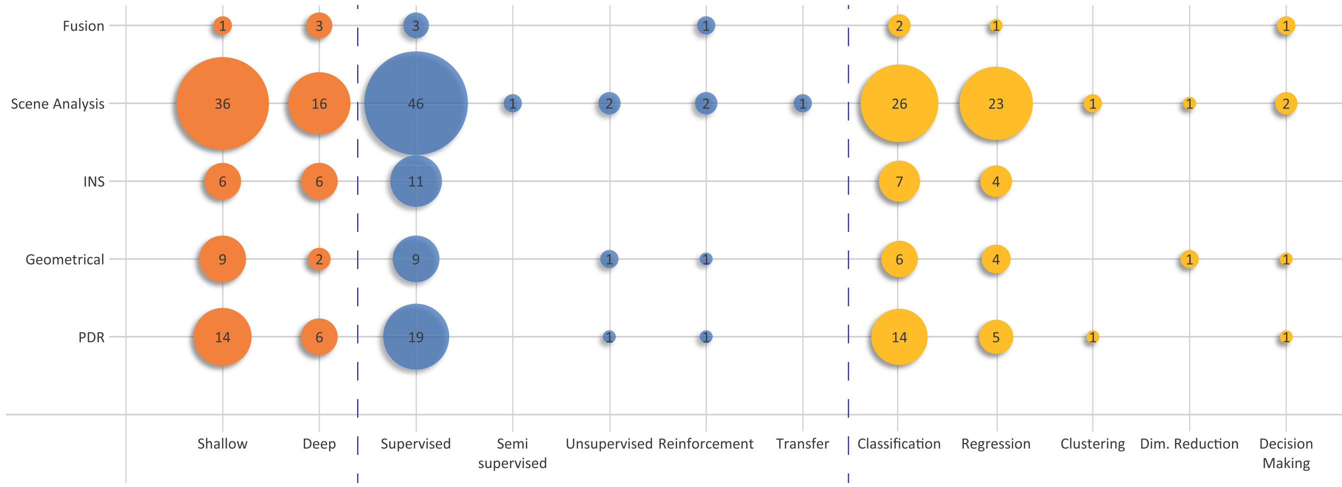

FIGURE 6. ML application in pedestrian localization techniques. The value shown corresponds to a percentage that is calculated based on the 130 papers considered in the systematic literature review.

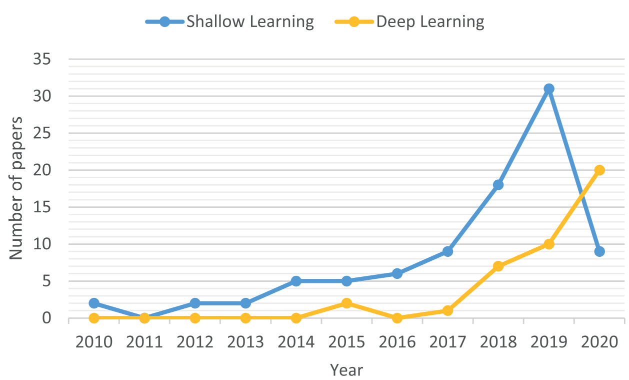

FIGURE 7. Trend in the use of ML architectures in the found papers.

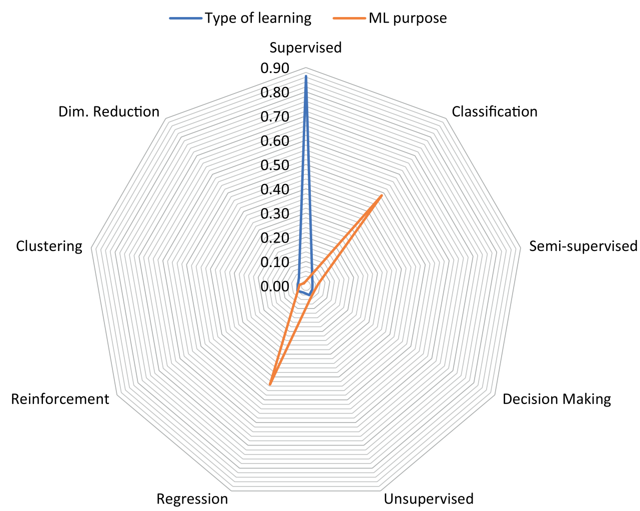

FIGURE 8. ML application in scene analysis. The values represents the proportion of papers reviewed using a given type of learning (blue curve) and the ML purpose (orange curve) with respect to the total searched papers.

In the application of ML in scene analysis, the use of the classical SL architecture and supervised learning have been the most common approaches during the last decade. Typically, localization has been seen as a regression process, as can be seen in the first row of Table 2, in which the authors in [23], [29]–[32], [40], [41], [47], [52], and [46] use classical methods as Gaussian process (GP), k-nearest neighbors (KNN), and support vector machine (SVM) to estimate the location of a pedestrian. Most of these authors focus on improving the pedestrian localization accuracy. Note that accuracy in scene analysis refers to the Euclidean distance between the estimated location and the ground truth. The authors in [47] use magnetic fields to create a fingerprint. Using the KNN method, they are able to achieve a response time that is 30 times faster than conventional pedestrian localization systems. In a different implementation, the authors in [31] use GP to keep the accuracy and reduce the recovery time from a random failure, and remark on the additional benefits that can be obtained from the use of ML.

Seeking to improve the accuracy of pedestrian localization in less time, the ELM technique has increased in popularity because it is a fast and robust type of feed-forward neural network. ELM provides a fast response due to its non-iterative learning mechanism, in which the parameters of the hidden layers are set randomly and do not need to be tuned. In addition, ELM allows the system to learn the output weights analytically from fixed or variable-size data [93]–[95]. The authors in [25], [28], [34], [35], [39], [42], [43] use ELM to improve the accuracy in the localization, achieving a major improvement in [42] where the accuracy with respect to a localization system that does not use ML is improved by 55%.

An interesting SL approach can be found in [33], in which the authors combine RSS and images to infer a localization model by the training of a regression random Fourier features algorithm. For localization, the system uses the inferred model and only the RSS measurements, achieving an improvement in accuracy of 27% considering the Kalman filter (KF) as a reference. Similarly, the authors in [37] compare KNN, random forest (RF), gradient boost, and decision tree (DT) in pedestrian localization, concluding that KNN and RF provide the best performance in scene analysis.

With the increased computational capability of new devices, DL architecture has become a viable alternative to improve the performance of pedestrian localization systems. The authors in [52] compare the shallow and deep architectures. They consider shallow neural network (SNN), convolutional neural networks (CNN), and Long Short Term Memory (LSTM) to reduce the estimation time and improve the accuracy, getting the best results with the deep approaches.

In the DL approaches, the most commonly used techniques are CNN and recurrent neural network (RNN). CNN is a feed-forward neural network that reduces the number of parameters in each convolution step. In contrast, RNN uses memory to save previous reusable output to predict the next outputs, with LSTM being the most widely used RNN algorithm. Both techniques are widely used thanks to their high accuracy and relatively low processing cost. For instance, the authors in [24], [26], [27], [44], [49], and [51] use CNN and RNN to estimate the pedestrian localization, improving the fingerprint creation process, using different data-training, and reducing the noise effects. The best result shows an improvement on accuracy by 75% when compared to the pedestrian localization system without the use of ML. In [36], the authors use a CNN to estimate the relative vertical positioning of a pedestrian, and provide a three-dimensional pedestrian localization with an accuracy of up to 94%, without requiring antenna rotation like other approaches. The authors in [45] use RNN to estimate the orientation and velocity of the pedestrian, and estimate the movement model to track the pedestrian. They then implement a fingerprint update with a conditional generative adversarial network (CGAN) model, which adapts the fingerprint features according to the hour of the day. The authors conclude that the use of multi-connected RNN improves the accuracy by 37% compared to a single RNN.

Other authors assume that the localization problem in scene analysis is a classification problem. Classical ML techniques such as KNN, SVM, DT, RF GP, logistical regression and support vector regression (SVR) and näive Bayes (NB), have been used in [55], [57], [60], [63]–[65], [72], [74], [76], [78], [80], and [81], to improve location accuracy by reducing the continuous problem into a discrete problem, in some cases as an area reduction to estimate the pedestrian localization with a simpler technique. For instance, the authors in [60] apply the DT to reduce the continuous localization area to obtain a small area that corresponds to the location of a pedestrian. In some cases, ML is used for classification purposes to reduce the localization area and other techniques are used to accurately estimate the location. For example, in [57] the authors use ML in the two stages of fingerprinting technique: they apply SVR to classify RSSI data in the offline stage and in the online stage they apply a regression with SVR to estimate the location of a pedestrian, improving the accuracy by 55% with respect to a KNN application. An interesting ML application can be found in [72], where the authors propose a pedestrian localization system for fifth generation (5G) cellular systems based on scene analysis. They use RF to estimate the localization of pedestrians, and conclude that their proposal obtains an accuracy similar to that obtained with a global positioning system (GPS).

Some researchers have evaluated different types of ML techniques to find the ML technique that provides the best performance. The authors in [70], [73], and [77] compare KNN, DT, NB, Bayesian network, sequential minimal optimization (SMO), AdaBoost, gradient boost, SVM, RF and logistic regression. In the tests, the best performance was obtained with KNN, SVM, NB and RF. The most important result is that the use of KNN reduces the computation time by 33%, and RF reduces it by 70%, concerning pedestrian localization systems without ML. Similarly, the authors in [80] propose a pedestrian localization system using exclusively magnetic fields and test several ML techniques such as SVM, KNN, RF and NB to create a fingerprint and estimate whether the pedestrian is in an indoor or outdoor environment.

ELM is used also for classification purpose in [58], [66] and [86]. The latter makes an interesting proposal in which they use the k-means algorithm to divide the area into small subareas. They then use ELM to identify the subarea and pedestrian localization, improving accuracy by 12% over the system without area subdivision.

A different and interesting proposal is presented in [54], in which the authors propose two algorithms: large margin nearest neighbors and neighborhood component analysis, to find out the best metric to improve the accuracy of a pedestrian localization system and its adaptability. The basic concept of this study is to select the metric that brings best performance in a KNN based localization system without overloading the system.

In DL architectures for pedestrian localization, classification techniques could be used to improve the accuracy through a previous site detection or feature classification in the fingerprint. The authors in [56], [61], [67], [69] and [83] use CNN to improve the pedestrian localization system performance. The authors in [69] use continuous wavelet transforms as features to construct the fingerprint. Then, they use CNN to estimate the room and the location of a pedestrian. In [67], the authors present a novel system in which they use WiFi dual band fingerprint. They use SVM to line of sight (LOS) and non-LOS (NLOS) detection, and to select the work band. Then, they use a CNN variation called capsule neural network for pedestrian localization, which reduces the computational cost and improves the accuracy of the localization system. In [56], the authors use CNN in two stages: first, to recognize the scenario; and second, to estimate the pedestrian location in the identified scenario. This proposal, improves the accuracy and reduces the computational cost of pedestrian localization, achieving 80 times faster pedestrian localization estimation than a pedestrian localization system based on a weighted KNN. Another interesting proposal is presented in [48], in which the authors combine CNN and LSTM to improve the accuracy in an infrastructure-free localization system. The authors of [62] use a RNN to predict the trajectory in a multi-person localization and tracking system, improving accuracy by 8% with respect to localization without the use of ML. The authors in [82] propose a pedestrian localization system by applying a combination of deep neural networks on video images to then predict the movement of the pedestrians.

Although it is more common in scene analysis for the existence of a device on the pedestrian to be localized, some researchers, such as in [43], [50], [68], [71], [75], [78], [79], are interested in device-free localization. An interesting proposal for device-free localization is presented in [75], in which the authors use RF to classify the error caused by environment changes and correct the fingerprint errors. In [71], the authors create the fingerprint using magnetic fields and signal strength, and they apply CNN to achieve independence with smartphone pose, due to the fact that the training data fuse the multiple poses of the smartphone into two general poses. In a novel proposal presented in [43], the authors use ELM for pedestrian localization by detecting propagation perturbations caused by the presence of the pedestrian in the scenario. The authors in [68] use a Gaussian mixture model for pedestrian localization and KNN-HMM to track the movement of the pedestrian. The ML application cause an accuracy improvement of 14% with less computational cost when compared to the state-of-the-art of device-free pedestrian localization system.

The ensemble approaches are another alternative to improve the performance of pedestrian localization systems, where the system combines multiple learning techniques to build a better predictive model. The authors in [50] and [66] use an ensemble ELM improving the accuracy by around 10% respect the use of a singe ELM. In [53], the authors propose the use of an ensemble HMM (eHMM) in a multi-layer localization system, improving the zone prediction to posterior pedestrian localization using fusion of localization information. The authors in [59] test the ensemble of multiple ML techniques, such as SVM, KNN and Bayes network, and conclude that weighted ensemble approaches improve the performance of pedestrian localization systems without an ensemble approach.

In scene analysis-based pedestrian localization systems, fingerprint calibration requires a lot of effort and time investment by the installers. Thus, researchers have implement semi-supervised learning to improve the efficiency of the system's implementation. The authors in [84] use semi-supervised with deep ELM, keeping the accuracy respect to SVM based pedestrian localization system, but reducing the calibration effort and the response time. The authors in [85] use semi-supervised with a time-series Laplacian SVM to generate a pseudolabel data for the training process. Their most important result is the high accuracy achieved with a small amount of labeled data.

Unsupervised learning is another alternative to bring to pedestrian localization systems real self-learning because in unsupervised learning the data is unlabeled and the machines learn about the data relation without human intervention, which allows the use of crowd-sourced data but sacrificing the accuracy of the system. This is the case of [86], in which the authors use, in a first stage, k-means algorithm to cluster the raw data, identifying the area division, and then they use ELM for pedestrian localization in a particular area. The authors in [88] use HMM to reduce the raw data dimension to construct a fingerprinting based on magnetic field measurements. In [87], the authors use HMM to learn about the pedestrian presence perturbation in the radio frequency links in a sensor network. The localization process then detects the crossing or no crossing link condition.

Reinforcement learning is another alternative to bring real self-learning to these machines, in which the learning is done as a function of the experience or benefit achieved with past decisions. They then make decisions in future situations. The authors in [89] use Q-Network in a deep reinforcement learning structure to estimate the location of a pedestrian device, with an improvement in the accuracy of 37% in comparison to the unsupervised multilateration localization. The authors in [96] propose a method to learn about the movement of people. They define a maximum entropy deep inverse reinforcement learning (MEDIRL) approach to predict the pedestrian trajectories. They found that the predicted trajectories have an accuracy that is similar to the LSTM-based localization system. The authors in [90] propose a semi-supervised deep reinforcement learning for distance estimation in a pedestrian's localization. The accuracy of the system improves by 23% with respect to supervised learning. TL is another ML technique to speed up learning. It reuses the previous knowledge to reduce the learning time or improve the learning of a related process. In [91] and [92], the authors use TL in pedestrian localization systems. The authors in [92] use deep CNN to pedestrian localization and a TL strategy, reducing the training time by 50% and saving up to 45% of the training data.

Table 3 summarizes the advantages and disadvantages of applying ML to scene analysis-based localization.

B. MACHINE LEARNING IN GEOMETRICAL LOCALIZATION

Geometrical techniques are more general than scene analysis, due to the fact that they are not linked to the data obtained from a specific environment. Instead, geometrical techniques obtain a model of the effect of the relative position between two nodes on properties or metrics of the signals transmitted between these nodes. The most commonly used metrics to estimate the distance between the nodes and the orientation are the RSS and the propagation time. The most accurate models are associated with free space and LOS conditions. Thus, multipath or NLOS conditions adversely affect the range and bearing estimation, and therefore the pedestrian

TABLE 3. Advantages and disadvantages of the type of learning used in scene analysis.

Type of learning	Advantages	Disadvantages
Supervised	- Robust scene analysis construction. - Recognition of pedestrian activity. - Error estimation and correction. - High accuracy.	- Sensible to changes in the scenario - The estimation time as a function of the scenario size. - It requires a significant investment of time in the training process.
Semi-supervised	- Flexible to changes in the scenario. - Reduce the effort in the data labeling and the training.	- Less accuracy compared to the supervised.
Unsupervised	- Learning without human intervention - The use of crowd-sourced data for training. - Adaptable to changes in the scenario.	- Lower accuracy.
Reinforcement	- Identification of movement patterns by trial and error - Learning without human intervention. - Prediction of pedestrian trajectories.	- Low accuracy improvement. - Little explored.
Transfer	- Previous knowedge can be shared to new devices. - Reduces the training time. - Reduces the required training data.	- Little explored.

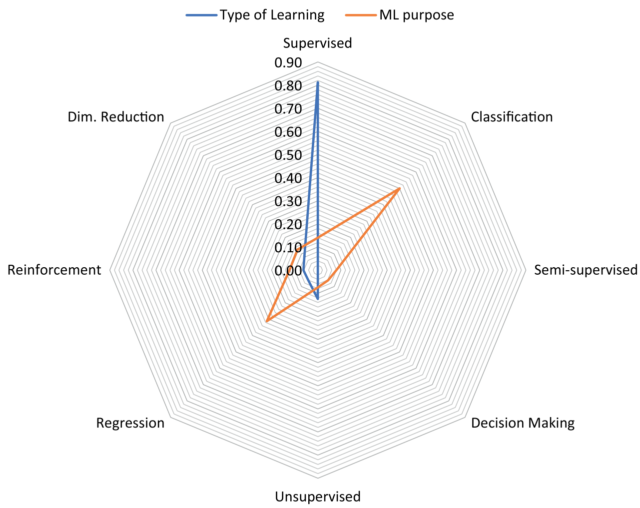

FIGURE 9. ML applications in geometrical localization. The values represents the proportion of papers reviewed using a given type of learning (blue curve) and the ML purpose (orange curve) with respect to the total searched papers.

TABLE 4. Machine learning applications in geometrical localization.

		Raw Data		
		Signal Strength	ToF	AoA
Supervised	Regression	[97], [98]	[99], [100]	[101], [102]
	Classification	[103]–[107] [109], [110]	[108]	-
Unsupervised	Dim. reduction	[103]	-	[102]
Reinforcement	Decision Making	[111]	-	-

localization. The basic stages in geometrical localization are: to obtain the metric, to detect the scenario conditions, to use a model to estimate the distance or bearing, and to combine the obtained data from multiple nodes to estimate the pedestrian localization.

ML could be used in any of these stages to improve the performance of the pedestrian localization system. There are two types of learning applied to geometrical pedestrians localization: supervised (which is the most popular) and reinforcement learning. As shown in Fig. 9, 81% of papers are focused on supervised learning, distributed among classification and regression; as can also be seen in Table 4. Fig. 9 shows that, considering the purpose of ML application in geometrical localization, 50% of papers use classification and 31% regression, stating that the geometrical localization problem could be considered in both orientations. In addition, the radar chart in Fig. 9 shows the rise of unsupervised learning and reinforcement learning in pedestrian localization systems, with 13% and 6%, respectively.

In geometrical localization, ML has been applied most often to define a data-driven model to improve the ranging or bearing estimation, due to the estimation requiring calibration by propagation conditions, even in LOS conditions. Supervised learning in shallow architecture is widely used in geometrical pedestrian localization. For example, in [109] and [110] the authors combine a wireless local area network (WLAN) and a wireless sensor network (WSN) to estimate the location of sensors placed on the body of a pedestrian and infer the location of a pedestrian without the use of inertial sensors. The authors use a linear regression to estimate the ranging and logistic regression to estimate the heading of the pedestrian. In [110], the authors use an ANN for ranging classification and speed classification, improving the accuracy by 25% related to the pedestrian localization system without ML. It is necessary to clarify here that in the geometrical localization systems, the accuracy corresponds with the Euclidean distance between the ground truth and the estimated location. The authors in [105] use a DT to improve the estimation of the direction of pedestrians in a PDR system, improving the accuracy of localization by 80%, respect to the conventional PDR.

The distance estimation has a high dependency on the propagation conditions. Consequently, in geometrical localization, the researchers study propagation conditions detection,

TABLE 5. Advantages and disadvantages of the type of learning used in geometrical localization.

Type of learning	Advantages	Disadvantages
Supervised	- Estimation of channel propagation conditions. - Estimation of data-driving ranging models. - Detection and mitigation of NLOS and multipath errors.	- A large amount of training data.
Unsupervised	- Estimation of kernel density and use the full probability distribution function.	- Little explored.
Reinforcement	- Use of some prior knowledge and considering it as an optimization problem. - Detection and mitigation of NLOS and multipath errors.	- Little explored.

such as NLOS or multipath, which makes the distance estimation difficult. The authors in [104] and [108] propose the NLOS detection using ML in shallow architecture, in [104] the authors use multilayer perceptron (MLP) and boosted DT to NLOS detection, improving accuracy by 11%, taking as reference the localization without NLOS detection. The authors in [108] use an SVM to improve the accuracy of the pedestrian localization system by at least 20%. Similarly, the authors in [107] test SVM, RF and MLP to identify LOS, NLOS and multipath conditions achieving better accuracy with the RF technique.

ML has been used to detect NLOS conditions and mitigate the adverse effect. For example, the authors in [106] and [98] use ML techniques such as GP, KNN, DT, and SVM to identify the NLOS conditions and mitigate the errors that are caused. In the tests, they achieve an improvement in the localization accuracy in the order of 20% to 40%, while reducing the computational cost. In a similar study, the authors in [99] use ANN to predict the error caused by multipath conditions and correct the ranging estimation.

The authors in [97] use ML regression techniques as ANN, GP, and SVM to predict the error caused for anomaly channel conditions without detection of NLOS or multipath. In contrast, the authors study the bad conditions present in NLOS and LOS. The tests of these works achieve an improvement of 25% in the accuracy, related to the systems without error mitigation.

To improve the AoA estimation, in [101] the authors use GP, NN, and regression tree, achieving the best performance with GP, which improves the accuracy by 20%, related to the conventional pedestrian localization systems.

In [103] and [102], the authors use physical feature, principal component analysis and Laplacian eigenmap in the generative models, which are applied in the dimension reduction of the training data set to reduce the data processing time and improve the accuracy of the system. In addition, the authors propose a novel localization technique called soft range information (SRI) localization, which uses ML to estimate a localization model with SRI and fusion. These achieve accuracy improvement of around 40%, in relation to the conventional geometrical localization systems.

Supervised learning in a DL architecture has been used to mitigate the error without multipath detection, such as in [100], where the authors use ANN for ranging error prediction to correct ranging estimation, achieving an improvement of accuracy of 90% compared to localization without the use of ML. The authors in [111] apply reinforcement learning to the estimation of RSS variations of the visible light localization system and mitigate the possible errors. In this work, ML improves the accuracy by 70% with respect to supervised learning models.

Table 5 describes the advantages and disadvantages of the application of ML in geometrical pedestrian localization systems.

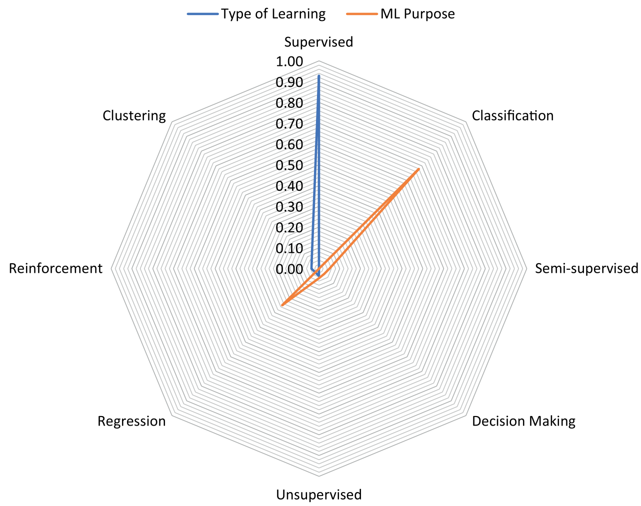

FIGURE 10. ML application in PDR. The values represents the proportion of papers reviewed using a given type of learning (blue curve) and the ML purpose (orange curve) with respect to the total searched papers.

C. MACHINE LEARNING IN PEDESTRIAN DEAD RECKONING

In PDR, the localization or tracking of a pedestrian requires some parameters to be obtained, such as pedestrian motion, step occurrence, step length or pedestrian heading, among others, whose correct prediction can improve the accuracy of the localization system with the use of ML. The radar chart in Fig. 10 shows that around the 94% of the found papers use supervised learning, and the remainder 6% is distributed between unsupervised and reinforcement learning. Additionally, Fig. 10 shows that the purposes of the application of ML in PDR are classification (68%) and regression (26%). In PDR, accuracy is usually defined as the distance between the last position estimated and the last actual position, with respect to the total distance traveled.

TABLE 6. Machine learning applications in PDR.

		Raw Data	
		Inertial Signal	Magnetic Field
Supervised	Regression Classification	[112]–[116] [118]–[132] [133]–[135]	[117] [105], [127]
Unsupervised	Clustering	[136]	-
Reinforcement	Decision Making	[137]	-

The papers have been classified in Table 6 according to the type of learning, application of ML and type of signal used by the PDR system.

In PDR localization systems, the ML application has a clear tendency to use supervised learning in a shallow architecture with the purpose of classification, as shown in Fig. 6. Consequently, some researchers use DT in [121], [122] and [123] to classify the type of movement or activity that the pedestrian is doing. This classification improves the accuracy of the system by at least 50% in comparison to a system without motion recognition. Other proposals of supervised learning applied to motion detection can be found in [118] and [124], in which the authors use the AdaBoost and SVM, respectively, to recognize the activity of a person, evidencing the importance of motion recognition to improve the accuracy of PDR based localization. The localization accuracy of the system is increased by 2% in comparison to systems that do not use motion recognition.

In PDR systems based on smartphones, the pose affects the performance of the localization system. Consequently, supervised learning has been used for smartphone pose detection to improve the accuracy of the system. In [125], [126], [128], [129] and [132], the authors use classical ML models such as SVM, DT, gradient boost and ANN. They get a good performance in the localization and navigation, with an accuracy between 95% and 97% related to the real distance traveled. An interesting study can be found in [127], in which the authors propose a double use of DT in smartphone pose classification and later for corner detection. The authors classify multiple smartphone poses into two specific poses: fixed or unfixed. They achieve an improvement of 20% in the localization accuracy with respect to the PDR system without pose classification.

Other studies use supervised learning to step length estimation, such as [133] and [134], which propose the use of gradient boost trees for step length estimation, and to estimate the activity and location of a pedestrian. The authors in [105] use a MLP model to identify the magnetic disturbances and they exclude this measurement to avoid errors in heading estimation, which produced an accuracy improvement of 79% in comparison to conventional PDR systems.

The step length and heading estimation are often seen as regression problems. For example, the authors in [115] show the use of inertial signal and magnetic field to train an online sequential ELM to estimate the heading and step length, achieving an accuracy of 97% with respect to the real trajectory. The authors in [114] estimate the vertical position of a pedestrian using linear regression. With this proposal, the accuracy of the system can be improved in all scenarios, including those with stairs. In [117], the authors use the magnetic field to estimate the heading of a pedestrian and they compare the performance obtained by SVM, logistic regression, NB, DT and MLP in the estimation. Logistic regression provided the best results, improving accuracy by 80% tin comparison to the systems PDR without heading estimation based on ML.

The authors in [112] explore the features of an electromyographycal signal for pedestrian navigation, using KNN for velocity estimation and pedestrian localization. Although their proposal achieves low accuracy, it is another alternative to using inertial sensors for PDR and could be explored further.

Some authors studied how to handle the problems in PDR localization using DL architectures. The authors in [119] and [120] apply a CNN and LSTM to estimate the pedestrian motion and heading, which improves the accuracy of localization and navigation systems by giving correct motion recognition.

Other authors study the use of DL architectures to step length estimation in [113], [116] and [131]. In [131] the authors use a combination of LSTM and RNN and in [113], the authors use a deep neural network; specifically, they use a stacked autoencoder for step length estimation by adapting the system to different smartphone positions. The accuracy achieved in these papers is up to 97% with a low response time, but it depends on the number of neurons in the neural network. The authors in [116] use a combination of CNN and LSTM, which is called a StepNet architecture, to identify the location of a smartphone and to estimate the step length. The tests got an accuracy of up to 97% in comparison to the real pedestrian trajectory length.

In [130], the authors test shallow and DL for heading and turning point estimation. In particular, they apply RF, linear regression, quadratic discriminant analysis, and ANN, and conclude that quadratic discriminant and ANN have the best response, the accuracy is improved by at least 37% respect the conventional PDR systems.

Other researchers have explored a range of alternatives to improve the performance of the PDR system. For example, in [135], the authors use an ANN to learn about the response of an IMU placed on the foot from an IMU placed in pocket. With this learned model, the system could correct the errors caused by an eventual failure.

Some studies have explored the use of unsupervised learning. For example, in [136], the authors use it to extend the types of motion identified, applying the k-means algorithm to context recognition to identify walking patterns of pedestrians in a marketplace, improving the accuracy by 8%, in comparison to conventional PDR systems.

TABLE 7. Advantages and disadvantages of the type of learning used in pedestrian dead reckoning.

Type of learning	Advantages	Disadvantages
Supervised	- Accurate identification of pedestrian movements. - Accurate identification of movement features (e.g. step length).	- Each researcher needs to create his/her own dataset. - Big effort to labeling data.
Unsupervised	- Accurate identification of different types of pedestrian motions without labeled data.	- Little explored.
Reinforcement	- Calibration of heading estimation without labeled data.	- Little explored.

TABLE 8. Machine learning applications in INS.

		Raw Data
		Inertial Signal
Supervised	Regression	[138]–[143]
	Classification	[144]–[153]

In [137], the authors use reinforcement learning in a deep Q-network (DQN) model to direction calibration in heading estimation. The authors define a policy for moving direction, such that the localization accuracy improves by 72% in comparison to localization systems based on WiFi and particle filter (PF).

Table 7 summarizes the main advantages and disadvantages in the application of ML in pedestrian localization systems based on PDR.

D. MACHINE LEARNING IN INERTIAL NAVIGATION SYSTEMS

In INS, the localization process uses inertial sensors, which are generally mounted on the foot, to obtain information about the person's displacement or movement to estimate the location or trajectory. Meanwhile, ML techniques have been applied to stages such as motion recognition, activity recognition or zero velocity update (ZUPT), among others. Supervised learning in shallow and deep architecture is a unique type of learning applied in INS, probably because of the high accuracy that they can provide. Table 8 shows a paper classification considering the ML purpose.

Considering the use of ML in shallow architecture, the authors in [144]–[146] implement SVM for motion recognition, achieving an accuracy between 85% to 99%. The authors in [152] use RF to classify the motion of a pedestrian using inertial information and images. The system error in the trajectory length has a reduction of 14%. This accuracy in INS is defined as the distance between the last position estimated and the last actual position, with respect to the total distance traveled. A similar application can be found in [153], in which the authors used RF and gradient boost to develop an adaptable solution to ZUPT. They improved the accuracy and computational cost in comparison to the DL method. Similarly, in [147], the authors use SVM to improve the ZUPT estimation, and the accuracy of localization and tracking. They obtained an accuracy improvement of 6% in comparison to the classic INS.

The authors in [149] propose the use of a CNN to identify door transitions in a pedestrian trajectory, although the accuracy that they achieved is lower than conventional pedestrian localization systems.

In INS systems, errors frequently accumulate over time. Consequently, it is necessary to adjust of the system. In [151], the authors use RF to calibrate the raw data obtained from sensors and improve the estimation of the localization parameters, such as attitude and velocity.

In some studies the authors use DL architecture to improve the accuracy of the INS. The ML techniques used are CNN, RNN and ANN, but the localization stages in which ML has been applied is diverse. For instance, the authors in [150] propose motion recognition using classification with ANN in a rescue application. The first prototype is able to achieve an accuracy similar to other traditional localization systems. In addition, the authors in [148] use LSTM to ZUPT detection, and obtain an accuracy of up to 90%.

A recent and promising application of ML is for tracking or displacement estimation by regression. For example, the authors in [138] use a deep RNN-LSTM to estimate a smartphone location and to track it. They use multiple previous estimations obtained only from the inertial data to make the localization prediction. This proposal achieves an improvement of 50% in comparison to the system without the use of ML. The authors in [139] and [140] use deep RNN for localization estimation, employing odometry data. They generate public datasets for the training process and then use them to test different RNN configurations to improve the accuracy and reduce the computational cost. They achieve an improvement in the accuracy of at least of 50% and the processing is 10 times faster than conventional PDR systems. The authors in [141] use a combination of CNN with Binary LSTM for a hybrid estimation of the pedestrian's velocity, obtaining an accuracy greater than similar works and with lower computational cost. They train the Binary SLTM with two IMUs and implement the localization with only one IMU. The authors in [142] use RNN-LSTM to learn about the information obtained from a micro-IMU (MIMU) to construct a virtual-IMU (VIMU), and with this they can then estimate the zero velocity moments. The accuracy achieved in this proposal was improved by 2% in comparison to the pedestrian localization system that uses one MIMU.

In [143], the authors use an ANN to update the extended Kalman filter (EKF) by regression. They get a complete localization parameters as position, velocity and orientation, with lower drift and only one IMU. Table 9 describes the advantages and disadvantages of the application of ML in INS.

TABLE 9. Advantages and disadvantages of the type of learning used in inertial navigation systems.

Type of learning	Advantages	Disadvantages
Supervised	- Accurate in zero velocity detection. - Accurate displacement estimation.	- Required a large training datasets. - Displacement estimation is quite novel. Its generalization is still under study.

TABLE 10. Machine learning applications in fusion frameworks.

		Raw Data		
		Signal Strength	Inertial Signal	Not specific
Supervised	Regression	[154]	-	-
	Classification	-	[155]	[156], [157]
Reinforcement	Decision Making	-	[53]	[82]

E. MACHINE LEARNING IN FUSION FRAMEWORKS

In fusion localization, because Bayesian filters are the most commonly used in localization systems, ML is applied in two stages: the first stage is to define the dynamic localization model to update the estimation, and the second stage is estimation correction using available observations from any source. In Table 10, the papers are classified by the type of learning and the raw data used; note that some of these papers use positioning data bases without specifying the type of raw data.

In the application of ML, many researchers think that DL architectures are better for fusion approaches than shallow architectures. For example, considering the observation model, the authors in [155] use a RNN to construct an adaptable PF where the weight of particles is updated by a CNN. They achieve an improvement in the accuracy of 21% in comparison to the conventional PF, seeing the accuracy as the difference among ground truth and the estimated location. Another application of the observation model can be found in [82], in which the authors use CNN for the observation model and reinforcement learning in a deep CNN to estimate the dynamic model of the movement, reducing the number of the process and improving the accuracy by 35% over approaches without ML application.

Some studies have focused on estimation correction using classification techniques. For example, in [156] and [157], the authors use RNN for pedestrian localization in topological digital maps. They adapt a LSTM neural network, which is used in language translation, to the pedestrian localization process. To this end, they use the estimation of the angle between the possible trajectories in a digital map without the need for initial positioning and direction in a sensor network. The pedestrian localization and tracking trajectory achieves an accuracy of up to 95%.

Shallow architectures have been used to improve the performance of the pedestrian localization systems employing

TABLE 11. Advantages and disadvantages of the type of learning used in fusion.

Type of learning	Advantages	Disadvantages
Supervised	- High accuracy. - Accurate data-driven observation model.	- It requires a large amount of training data.
Reinforcement	- Reduction of the training effort. - Reduction of the response time. - Improve the robustness of the system. - Facilitates optimal configuration of Bayesian filters	- Little explored.

ML in any stage of the PF implementation. The authors in [53] use Q-learning in the resample stage of PF to improve the robustness of the system and reduce the convergence time. Similarly, in [154], the authors use the kernel model, in a shallow architecture, to infer the probability of the test scenario and, together with a PF, they reduce the computational cost and improve the accuracy by 33% in comparison to the classical approaches, such as KNN. Table 11 summarizes the advantages and disadvantages of the application of ML in pedestrian localization systems based on fusion methods.

V. OPEN ISSUES AND CHALLENGES

The application of ML techniques to pedestrian localization systems has opened up a diverse set of performance improvements, as seen through the survey, and there is a considerable amount of research interest in this field. However, the potential that ML techniques can offer to this field is far wider than the current state-of-the art and much of it is still unexplored. Indeed, in this review we encountered many open issues.

A. OPEN ISSUES IN THE TYPE OF LEARNING

Supervised learning has been the most commonly applied learning type in pedestrian localization in the last 10 years, due to the high accuracy it provides; such as shown in Fig. 11. However, other types of learning could provide a range of advantages; for example, semi-supervised learning could be used to reduce training time and to enable faster response; unsupervised learning and reinforcement learning could be used to improve the time response or calibrate the time of pedestrian localization systems, thanks to the increasing processing power of modern chipsets; and, TL and FL could provide faster learning.

In methods using neural networks, there is currently growing popularity in the use of ELM in pedestrian localization systems thanks to its fast response, low computational cost, and high accuracy.

Many different ML techniques have been proposed for most pedestrian localization system problems, but it is not yet clear what the standard is for any of them. Thus, ensemble learning for pedestrian localization (i.e., a combination of

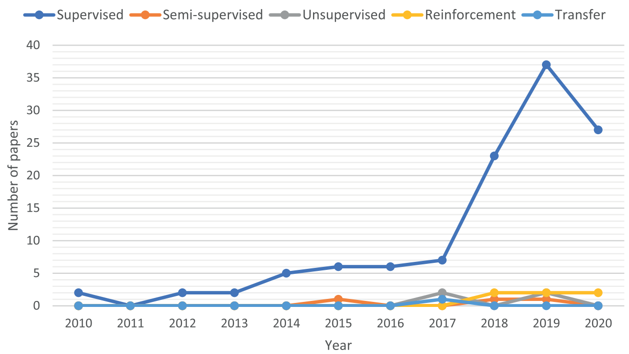

FIGURE 11. Type of learning trends.

multiple ML algorithms) may be an alternative to facilitate the generation of new approaches in pedestrian localization systems and improve accuracy or robustness.

In DR there is no standard of types of motion detected by ML to improve the performance of pedestrian localization. Each researcher establishes the type of motion that they want to identify with the use of ML, and they then analyze the benefit achieved. Therefore, the definition of which type of movements are relevant to DR-based pedestrian localization systems is another research opportunity.

The application of ML in fusion-based pedestrian localization has been less explored. However, the application of supervised learning and reinforcement learning in fusion techniques has been shown to provide good results. Therefore, the use of the heterogeneity of ML techniques to improve the performance of fusion-based pedestrian localization systems is an open field of research.

B. OPEN ISSUES IN ML APPLICATION

Given that adverse scenario conditions negatively affect the performance of pedestrian localization systems, ML can be employed in the detection of these anomalies; for example, NLOS for geometric pedestrian localization systems, the presence of multipath in radio frequency based systems, disturbances in magnetic field based systems. In addition, ML can be used for the correction of the caused detrimental effects.

C. OPEN ISSUES IN ML ARCHITECTURE

There is a clear growing trend towards the use of DL architectures in any type of pedestrian localization system and subblock. However, DL requires large amounts of training data, which is usually not easy to obtain. Most authors in the literature review build their own datasets for their investigations. However, they do not publish the resulting datasets, which makes comparison between different proposals very difficult. Thus, standardization of the size or format of these datasets is necessary.

D. OPEN ISSUES IN STANDARDIZATION

There are no standard parameters to evaluate the application of ML in pedestrian localization. Therefore, it is necessary to define common practices and evaluation parameters to ease the comparison of results among different proposals.

E. OTHER OPEN ISSUES

Accuracy is the most commonly used performance parameter that is evaluated in the literature. However, it is possible to explore other performance parameters to be considered by ML, such as response time, computational complexity, training time, and robustness, among others, which are of paramount importance in many pedestrian LBS applications.

VI. CONCLUSION

In summary, the ML techniques that have been adopted in the last 10 years to improve pedestrian localization performance have been reviewed. Several applications of ML techniques on pedestrian localization systems have been identified, from different types of learning approaches. In addition, the development trends of ML techniques that have been applied and a variety of representative scenarios have been highlighted. A case by case description of numerous compelling applications relying on ML techniques in pedestrian localization systems has also been provided. In comparison to other state-of-the-art survey articles, this survey focuses on the localization stage or process in which the ML technique has been applied. Finally, our review has shown that powerful ML techniques are poised to occupy an important position in addressing scenarios and applications in pedestrian localization systems in the future.

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VÍCTOR F. MIRAMÁ received the B.Sc. and M.Sc. degrees in electronics and telecommunications engineering from the Universidad del Cauca, Popayán, Colombia, in 2008 and 2013, respectively, where he is currently pursuing the Ph.D. degree in electronic sciences. His Ph.D. degree was supported by the Universidad del Cauca, and the Administrative Department of Science, Technology, and Innovation of Colombia (Colciencias) and the Fund for Science, Technology and Innovation of General system royalties in Colombia (FCTeI-SGR), under the Bicentennial Scholarships of Doctoral Excellence. His research interests include mobile and wireless communications, localization systems, and machine learning.

LUIS ENRIQUE DÍEZ received the degree in telecommunications engineering from the University of Deusto, Bilbao, Spain, in 2005, the M.Sc. degree in communication technologies and systems from the Polytechnic University of Madrid, in 2012, and the Ph.D. degree from the University of Deusto, in 2019. From 2005 to 2011, he worked with Everis, as a Senior IT Consultant. From 2013 to 2014, he was with the SoftLab Research Group, Carlos III University of Madrid (UC3M), as a Research Support Technician. Since 2014, he has been with the Mobility Research Group, DeustoTech, University of Deusto. His research interests include pedestrian navigation systems, data fusion techniques, and context-aware applications.

ALFONSO BAHILLO received the degree in telecommunications engineering from the University of Valladolid, Spain, in 2006, the Ph.D. degree from the University of Valladolid, in 2010, and the PMP Certification from PMI, in 2014. From 2006 to 2010, he was with CEDETEL, as a Research Engineer. From 2006 to 2011, he was an Assistant Professor with the University of Valladolid. From 2010 to 2012, he worked with LUCE Innovative Technologies, as a Product Owner. From 2013 to 2017, he held a postdoctoral position. He was the Project Manager with DeustoTech-Fundación Deusto, Bilbao, where he trains Ph.D. students and collaborates in several national and international research projects. He has worked in more than 25 regional, national, and international research projects and contracts (leading some of them). He is currently the Director of DeustoTech-Fundación Deusto, University of Deusto. He has coauthored more than 35 research manuscripts published in international journals, more than 40 communications in international conferences, and three national patents. His research interests include local and global positioning techniques, ambient-assisted living, intelligent transport systems, wireless networking, and smart cities.

VÍCTOR QUINTERO received the B.Sc. and M.Sc. degrees in electronics and telecommunications engineering from the Universidad del Cauca, Popayán, Colombia, in 1999 and 2011, respectively, and the Ph.D. degree in electrical engineering from the Université de Lyon, Lyon, France, in 2018. He is currently an Assistant Professor with the Universidad del Cauca. He is also the Director of the GRIAL Research Group. His research interests include information theory, signal processing, and wireless communication systems. He received the 2017 Best Ph.D. Thesis Award in the domain of information and digital societies from INSA de Lyon, Villeurbanne, France.