Machine Learning Techniques in Indoor Positioning Systems

Mert Bayraktar
Department of Computer Engineering Akdeniz University Antalya, Turkey 202151075008@ogr.akdeniz.edu.tr

***Abstract*—Interest for indoor localization has recently increased due to lack of effectiveness of GPS in indoor environments. Different techniques, wireless technologies and algorithms have been proposed in the literature to provide indoor localization services in order to improve the services provided to the users. In this paper, main goal is to provide a survey of different machine learning algorithms for indoor localization such as K-NN, support vector machine, decision tree, naive bayes, ANN.**

***Index Terms*—Indoor positioning, indoor localization, wireless signals, fingerprinting technique, RSSI, bluetooth low energy, Wi-Fi.**

I. Introduction

Accuracy is important for location based services. Although the global positioning system (GPS) is widely used for localization in outdoors, the usability of GPS is not possible in indoor environments. Indoor environments are complex with obstacles such as walls, doors, moving objects. These conditions alter radio signal propagation causing fluctuation, shadowing, scattering and degrade the accuracy significantly. However, due to high demand for IPS, considerable attention has been made on the development of these systems recently. Different ranging techniques based on received signal strength indicator (RSSI), time of arrival (TOA), angle of arrival (AOA), time difference of arrival (TDOA) have been suggested using various wireless signals such as Wi-Fi, Bluetooth, visible light communication (VLC), ultra wide band (UWB) and radio-frequency identification tags (RFID) for indoor positioning. All these approaches suffer from challenges such as poor accuracy, high complexity and unreliability.

In recent years, artificial intelligence (AI) and machine learning (ML) algorithms find good results in indoor localization [1]–[4]. The main advantage of AI and ML approaches is their ability to make decisions effectually using stored data without the need of accurate mathematical formulations.

For instance, the authors in [5]–[8] have applied supervised and unsupervised ML techniques for none line of sight (NLOS) identification and mitigation while deep learning (DL) technique is applied for NLOS mitigation in [2].

ML has also proven as an efficient way to combine multi-dimensional data collected from multiple positioning sensors, devices, technologies and methods.

The rest of the paper is structured as follows: A basic discussion of indoor localization is presented in Section II. An overview of common ML techniques is presented in Section III. In Section IV the restrictions in ML approaches and future challenges discussed. Finally in Section V conclusions are given.

II. Distance Measurement Techniques

A. Received Signal Strength Indicator (RSSI)

The received signal strength (RSS) is one of the simplest and most widely used signal metrics for indoor localization. RSS is the signal strength received from a transmitter device, usually measured in decibel-milliwatts (dBm). The RSS can be used in estimating the distance between the transmitter (Tx) and the receiver (Rx) devices; RSS decreases with the distance between Tx and Rx. RSSI is an indication of the signal strength received by the Rx [1]. The distance d between Tx and Rx can be estimated using RSSI and a path loss propagation model from (1) as

$$RSSI = -10n\log_{10}(d) + A, \tag{1}$$

where n is the path loss exponent and A is the signal strength received at a reference distance from the Rx.

The relationship between RSS and distance is not necessarily linear, especially in indoor environments due to shadowing, scattering, fading, refraction, multipath. Therefore, to increase the accuracy, different filters like Gaussian Filter, Kalman Filter, Moving Average Filter have been used. RSS-based systems do not rely on time information and synchronization between devices is not needed. RSS-based localization systems provide poor accuracy in long-range distances compared to time-based methods and angle-based methods; however, in short-range distances, RSS-based systems are more accurate [2].

B. Angle of Arrival (AoA)

The angle of arrival (AoA) or direction of arrival (DoA) of a signal is the direction from the signal which is coming from a known location at a base station. In AoA, the desired location can be found by the intersection of angle direction lines. Angle-based approaches use antennae arrays at the receiver side to calculate the angle by measuring the time difference of arrival (TDoA) between individual elements of the antennae array [1]. To estimate the location of the target in the 2D environment, at least two known reference points and two measured angles are needed [3]. AoA-based techniques have their limitations. AoA requires complex hardware requirement(s) and more careful calibration compared to RSS-based techniques. For increasing the accuracy in the indoor environment, the angle measurements need to be accurate, but AoA-based methods can be affected by multipath, NLOS propagation of signals, the directivity of the measuring aperture. These reasons can significantly change the direction of the arrival angle and thus reduce the accuracy of the positioning systems [4].

C. Time of Arrival (ToA)/Time of Flight (ToF)

Time of Arrival (ToA) based systems uses propagation delay of the radio signals between transmitter and receiver devices [5], [6]. To obtain the ToA measurements, sensors first receive signals from the source, when the signal is received, the distance between devices can be calculated from the transmission time delay and propagation speed of the signal [4]. The time synchronization between devices is essential to ensure the accuracy of the arrival times, and the signal must include the time stamp information [7]. The 3D range equation for localization using ToA is

$$st_i = \sqrt{[(x-x_i)^2 + (y-y_i)^2 + (z-z_i)^2]} \tag{2}$$

where s is the signal propagation velocity, t_i is the signal traveling time. The terms x, y, z are the coordinates of the receiver device, and x_i, y_i, and z_i are the coordinates of the transmitter device in three dimensional space (i = a, b, c). The best results are achieved when ToA is used jointly with ultra-wideband(UWB) technology [8].

D. Time Difference of Arrival (TDoA)/Time Difference of Flight (TDoF)

TDoA technique is developed to overcome the restrictions of the ToA technique. TDoA technique has two approaches: the multi-node TDoA and multi-signal TDoA [9]. The first approach uses ToA measurements of signals from temporally synchronized receivers. The transmitter device broadcasts a signal periodically, and when this signal is received, the timestamp is recorded [5], [9], [10]. Therefore, the receiver device can predict the distances of each signal by calculating the time differences. This technique does not require time synchronization between the Tx and Rx devices. The second approach uses different kinds of signals with different propagation velocities. This approach requires different hardware since different waves move at different speeds, and there is a difference between the times the signals travel the equal distances [5]. Similar to the ToA technique, the TDoA technique is only applicable when LOS is available. Equations below indicates the TDoA calculations from three anchor nodes and one unknown node.

$$\Delta d_{BA} = \sqrt{(x_b-x)^2 + (y_b-y)^2} - \sqrt{(x_a-x)^2 + (y_a-y)^2} = c * \Delta t_{BA} \tag{3}$$

$$\Delta d_{CA} = \sqrt{(x_c-x)^2 + (y_c-y)^2} - \sqrt{(x_a-x)^2 + (y_a-y)^2} = c * \Delta t_{CA} \tag{4}$$

III. Wireless Technologies Used For Indoor Localization

In this subsection, most commonly used radio frequency wireless technologies are presented.

A. Wi-Fi - IEEE 802.11n

The IEEE 802.11 standard, Wi-Fi is mainly used in Wireless Local Area Network (WLAN) devices. Wi-Fi operates in the Industrial, Scientific, Medical (ISM) band and Wi-Fi devices communicate in 2.4GHz or 5GHz frequency bands. Wi-Fi has covered a reception range of 50-100 meters but has now increased to about 1 kilometer [11]. Wi-Fi-based localization systems have several benefits. One of the benefits of using Wi-Fi is, today, almost every building has Wi-Fi infrastructure. Thus, Wi-Fi-based systems do not require any additional hardware deployment. Besides this, in WLAN, LOS is not necessary. There are also limitations of WLAN, such as signal fluctuation and interference in the ISM band.

B. Bluetooth Low Energy (BLE)

BLE (IEEE 802.15.1 protocol) or "Bluetooth Smart" is a Wireless Personal Area Network (WPAN) technology introduced by Bluetooth Special Interest Group in 2010. In the BLE protocol, 40 channels spaced at 2MHz apart, around the ISM frequency band of 2.4 GHz are used for transmission. A BLE device is only advertising on channels 37, 38, and 39. These channels are chosen to mitigate interference with existing Wi-Fi infrastructure. BLE can cover a range of 70-100 m and provide a data rate of 24 Mbps with higher power efficiency [1]. The BLE-based protocol iBeacon announced by Apple allows BLE-enabled devices known as beacons to transmit packets of information periodically [12]. We used Aruba BLE beacons in our experiment.

C. ZigBee

ZigBee (IEEE 802.15.4 protocol) is a cost-effective, energy-efficient, and low-data-rate wireless communication technology designed for applications that need long battery life but not high data transfer rates. ZigBee compatible wireless devices can transmit data at 10-75 meters depending on the RF environment and operate at 2.4 GHz in global, 915 MHz in America, or 868 MHz in Europe. The data rate is 250 kbps, 40 kbps, and 20 kbps respectively. IEEE 802.15.4 defines the physical and data link layer, while ZigBee defines the layers from the network to the application layer [13].

D. Radio-Frequency Identification (RFID)

E. Ultrasound (US)

F. Infrared (IR)

G. Ultra-Wide Band (UWB)

H. Frequency Modulation (FM)

IV. Localization Methods

The commonly used localization methods are listed below:

A. Triangulation

The triangulation method uses the geometric characteristics of triangles to estimate the target position. It can be divided into two: lateration and angulation.

1) Lateration: Lateration or multilateration is a method for position estimation of the obscure node with the help of several nodes with known positions and distance measurements. Trilateration is a special case of lateration where at least three known nodes are used. Time-based techniques (ToA, TDoA, RToF) and RSS-based techniques are called lateration techniques. The distance between the target and reference point can be calculated with two equations in a 2D environment [2]. To have better accuracy, three equations are required, and the location of the target can be determined with the intersection of these equations.

2) Angulation: Angulation estimates the location of an object by measuring the AoA information relative to multiple nodes. Location accuracy in this technique relies on the accuracy of the angle measurement. Increasing the number of nodes can enhance the localization performance. For 2D measurements, two AoA measurements and single distance measurement between two arrays are needed to predict the position of an object. For 3D measurements, in addition to those measurements, a single azimuth measurement is also needed [16].

B. Weighted Centroid Localization (WCL)

Within the WCL technique for estimation, weight is doled out to signals when measuring the distance from a tag device. The weight is the inversed distance consulted to a degree (g). The main advantage of this strategy is that it continuously confines location estimation interior the locale encompassed by devices. Moreover, any reference point close the tag gadget will have the highest weight, so that the ultimate area estimation is pulled towards this device. For m beacons, WCL is defined by the following set of equations:

$$x_w = \sum_{i=1}^{m} x_i \frac{w_i}{\sum_{i=1}^{m} w_i} \tag{5}$$

$$y_w = \sum_{i=1}^{m} y_i \frac{w_i}{\sum_{i=1}^{m} w_i} \tag{6}$$

$$w_i = \frac{1}{d_i^g} \tag{7}$$

where (xw, yw) is the estimated coordinate of the WCL method, di is distance between the tag and beacon i, g is the degree of weight and m is the total number of beacons considered at any time for location estimation. Some typical values of g are 0.5, 1, and 2.6.[12]

C. Fingerprinting/Scene Analysis

Fingerprinting technique usually requires an environmental survey to collect features (fingerprints) of the environment and then determine the location of the target by matching real-time measurements with the closest fingerprints stored in the database [1]. A fingerprint is a vector of statistical attributes of a received signal from multiple nodes such as mean, variance and histogram [17]. Fingerprinting method does not require LOS measurements, and it does not require any additional hardware since it uses the existing wireless signal infrastructure in the environment. Fingerprinting technique involves two phases: the offline phase and the online phase. During the offline phase, either a site survey in an environment or a signal propagation model must be used to create radio maps. The radio map is a database of known locations coupled with radio signal characteristics such as RSS, signal phase, propagation time, signal angles in an environment. Construction of the radio map begins with dividing the area into cells. Signal vectors from APs are collected inside these cells for some time and stored in the database. During the online phase, the localization algorithm uses the real-time signal vector and stored signal vectors in the database to estimate the location of the device. For the localization algorithm, deterministic or probabilistic approaches can be used. The main drawback of the fingerprinting technique is that position estimation accuracy depends on the accuracy of the data collected at the offline phase and environmental changes. Due to these reasons and time-consuming measurements, automatic radio map update methods based on the crowdsourcing technique should be used [18]-[23]. The fingerprinting technique requires a site survey to collect and store signals for further learning stage [24].

V. Filtering Approaches

Filtering the data is necessary for eliminating the outliers. In this subsection common filtering technique in IPS is presented.

A. Moving Average Filter

Moving average is averaging strategy of continuously calculating numerous associated data. It is called moving average since it counts out the oldest variable and adding new variable as time pass. Moving normal channel is improved technique to solve deluding expectation of data alter. Also, it is commonly utilized when input information isn't constant. Formula of moving normal channel is given below. n represents size of a subset and Pd represents the data value. [13]

$$MA = \frac{\sum_{i=0}^{n-1} P_d - i}{n} \tag{8}$$

Due to the attribution of wireless signals, signals tends to be unstable. In this case, the result of indoor positioning algorithm can vary from user's exact location. To cover this problem [12] and [13] proposed moving average filter to eliminate the outliers and get better accuracy.

VI. Machine Learning For IPS

ML algorithms are efficient for solving many of the problems of the techniques used for localization in indoor environments. Conventional IPS methods are not very resilient for dynamically changing environments. Fluctuation of RSSI values is the most important problem in IPS and it affects the location accuracy.

A. Machine Learning Algorithms Used in IPS

1) K-Nearest Neighbours Algorithm: The K-NN algorithm can be used to improve the accuracy of fingerprinting techniques because it has the advantages of good accuracy and ease of implementation. Model is also good for fingerprinting because it functions acts as a normal if the measured position is spread across multiple cells. In [26], they devised the Wk-NN technique for position estimation in the online phase of fingerprinting. They used 14 beacons and used the Wk-NN algorithm to implement the Wk-NN method for different numbers of reference points. In [27], they propose combining the K-NN method and the moving average filter for improved accuracy. The suggested method had an average accuracy of 80 percent for 24 cells, which was greater than the fingerprinting technique (68.81 percent) and triangulation method (25.68 percent) in the same paper.

2) Support Vector Machine: The Suppor Vector Machine (SVM) is a machine learning technique with a modest level of complexity that is used to solve categorization problems. SVM is based on the notion of calculating margins. It divides the training data-set into n classes by plotting data items in high-dimensional space and drawing a hyper-plane in such a way that the distance between the class and the hyper-plane is maximized. They converted a multiclass problem into a binary class problem in [29]. When compared to the other proposed approaches, the average accuracy rate is 97.75 percent, which is second only to K-NN.

3) Decision Tree: To address the classification or regression problems, a decision tree shapes a learning tree structure. Based on specific constraints, this model divides the recorded data into a few names. The model guesses the names of real-time data by iterating the input data through the learning tree after creating a tree structure. According to [30], when compared to other algorithms such as K-NN, Naive Bayes, and Bayesian network, the J48 DT algorithm has poor accuracy in creating categorization.

4) Naive Bayes: A naive Bayes classifier is a supervised learning algorithm that is resistant to noisy data, easy to build, fast when connected to large databases, and capable of performing more complex classification models. As a result, it is widely employed in categorization tasks. It assesses the likelihood of each trait in the data, assuming that they are all equally relevant and unrelated. [29] demonstrates that the Naive Bayes method is ineffective for classifying buildings, floors, and regions.

5) Graph Neural Networks: We may consider the localization problem in the context of Graph Signal Processing using the graph Graph Neural Networks (GNN). Indeed, each RSSI measurement X may be viewed as a signal over graph G, with each node I having an associated vector x_i. As a result, the goal is to classify this graph signal into one of the n_z categories. To do so, we'll use the Graph Neural Networks framework, which we'll go over briefly presently. GNNs can be thought of as a graph-based extension of CNNs. In order to do so, we must first define convolution on graphs, which is accomplished using the Graph Shift Operator (GSO) $S \in \mathbb{R}^{n_{AP} \times n_{AP}}$. When there is an edge between nodes I and j, this is a matrix representation of the graph that should respect its sparsity (i.e. $S_{i,j} \neq 0$). We employed the normalized adjacency matrix in our work, but other instances, such as the Laplacian, might be used instead. By computing the matrix product SX = Y (with $Y \in \mathbb{R}^{n_{AP} \times F_{in}}$) we ended up with another graph signal that aggregates at each node the information of its neighbors. We can see that by writing S^KX = S(S^{K-1}X), we may aggregate the information K hops away. The weighted sum of these K signals is what graph convolution is defined as (i.e. $\sum_k S^k X h_k$, where scalars h_k are the taps of the filter). It's worth noting that instead of scalar taps, we could use a F_{in} x F_{out} matrix H_k to modify the output dimension. Applying a pointwise non-linear function to this convolution yields a single-layer GNN (or graph perceptron), and concatenating numerous perceptrons yields a deep GNN.

$$\mathbf{Y} = \sigma\left(\sum_{k=0}^{K-1} \mathbf{S}^k \mathbf{X} \mathbf{H}_k\right)$$

We can combine the GNN with a fully connected neural network whose output size is precise n_z to classify the original signal X into the possible n_z areas. Finally, the softmax function can be used, and the projected zone is the result's maximum value. The cost function utilized to optimize the parameters was cross-entropy. It's worth noting that the GNN's output can be viewed as a node embedding designed expressly for localization, which is an intriguing by-product that could be investigated further. Figure 1 shows an example graph structure for indoor positioning system.

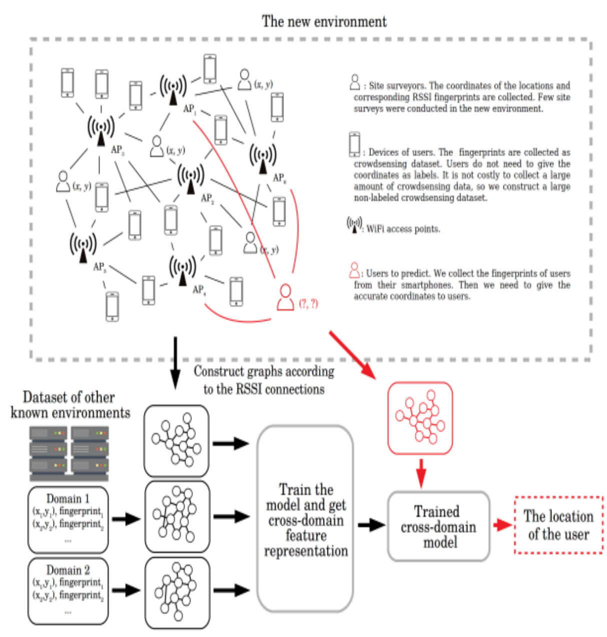

Fig. 1. Structure of the indoor positioning system. Source: Adapted from: [25].

VII. Future Challenges and Limitation of ML

Countless ML based indoor positioning methods have been proposed in the recent years. However, adaptation of ML-based solutions in indoor localization is still in its infancy. A number of problems need more investigation.Mainly, ML based models are very much application specific. For example, a well-trained deep learning model developed on RSSI based fingerprinting can provide good results for the same, but it cannot be applied for CSI based fingerprinting.

VIII. Conclusion

In this paper, challenges in indoor localization discussed and founded that ML approaches have great potential to handle these challenges while traditional localization algorithms have restricted success. The state-of-the-art ML based research efforts have surveyed in solving various challenges associated with indoor localization. Furthermore, challenges related to successful deployment of ML-based localization techniques have been identified and listed for future research directions in this regard.

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