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Indoor Localization System Based on Mobile Access Point Model MAPM Using RSS With UWB-OFDM

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ABSTRACT Indoor tracking is one of the most attractive topics in communication and information technology. Indoor localization mechanisms can help people for navigating in complex environments. Those with complex structures such as airports, shopping malls, hospitals, and others have a massive population (Crowdsourcing) that blocks the visibility (NLOS) between the access points and the users. Accordingly, we present the mobile access point model MAPM as a new algorithm for positioning users indoors based on the mathematical model of received signal strength RSS using UWB-OFDM. MAPM participates in crowdsourcing indoors by using users as mobile access points (MAP). That may decrease the use of several static access points (SAP) indoors and increase the localization precision. First, we use ultra-wideband UWB with orthogonal frequency division multiplexing OFDM as a communication gadget between the users and the system. Those have good quality in terms of accuracy, time response, energy consumption, and efficiency against interference. Second, we measure the received signal strength then, we estimate the distance between users and the access points using the mathematical model of RSS. These can be more adapted to changing environments and device heterogeneity than RSSI fingerprints. Third, we calculate the position information by using the Euclidean distance formula. In this way, we can reduce the effect of most of the problems on the indoor positioning system. We simulate the proposed algorithm in a platform based on three tools, MATLAB for system information processing, MYSQL as a system database, and a control interface coded in Java. In the given simulation results, we find that the average MAPM error in the case of 30 users is 10.19 cm, and the detection rate has a value of 86.66%.

INDEX TERMS MAPM, RSS, UWB, OFDM, machine learning, DNN, SVM, RMSE, crowdsourcing, NLOS.

I. INTRODUCTION

The Global Positioning System (GPS) is the most widely used localization system for outdoor use. However, GPS doesn't work well indoors because walls block the direct view between the satellites and the passengers [1]. For this reason, researchers are trying to use some of the telecommunications tools available indoors. Such as Wi-Fi, Bluetooth, inertial sensors (Accelerometer, gyroscope, magnetometer, barometer, etc.), RFID, cameras, light, and others. In the field of indoor localization, we have six categories [2], [25]:

- Received Signal Strength (RSS) approaches based on Wi-Fi or Bluetooth
- Pedestrian Dead Reckoning (PDR) or Inertial Measurement Unit (IMU) approaches
- Triangulation and Trilateration-based approaches
- Tag/Reader identifications approaches
- Localization by Vision
- Multimodal localization

First, RSS is an indoor positioning technique that estimates the position coordinates by measuring received signal strength during communication [3]. This method can use the mathematical model (the telecommunication equation) that relates signal strength to distance. The second one performs the site survey to build the offline power database, then compares the two online/offline databases to estimate the user position. The third is used to construct the automatic online reference database without a site survey. Some researchers

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proposed using a robot to simultaneously build the offline database. This type is known as Simultaneous Localization and Mapping (SLAM).

Second, some approaches have participated in the existence of inertial sensors in smartphones to offer indoor localization-based services [4]. Most of the proposed PDR-based methods use an accelerometer and gyroscope to get the step length and heading angle. To deduce the floor changes, we analyze the captured barometer data. The magnetometer is applied in indoor positioning systems to distinguish the most weighted reference point when comparing the online/offline magnetic fingerprint database. We determine the coordinates of position by using the following equations:

$$x_{i+1} = x_i + L * \cos(\theta) \tag{1}$$

$$y_{i+1} = y_i + L * \sin(\theta) \tag{2}$$

where,

$$L = \sqrt[4]{a_{max} - a_{min}} \tag{3}$$

where a_{max} is the maximum acceleration, a_{min} is the minimum acceleration, L is the step length, and θ is the heading angle. Third, triangulation and trilateration-based localization techniques are widely used. This category uses the communication between base station antennas and smartphones to deduce the position of users either by calculating the temporal or angular deviation [5], [6]. Time Of Arrival (TOA) estimates the distance between a peer of a client and an access point. We calculate the distance by the following equation:

$$d = C * \tau \tag{4}$$

where C is the light speed, τ is the time of arrival. AOA angle of arrival estimates the angle between two access points and the client. TDOA (Time Difference of Arrival) is a trilateration technique that calculates the time difference between two access points and the client. TOF (Time of Flight) uses two communications. One internal and one external between four antennas, two TX and two RX. ADOA (angle difference of arrival) calculates the difference in an angle of arrival between the base stations and the client. Fourth, radio frequency identification (RFID) [7], near field communication (NFC), and Bluetooth Low Energy (BLE) [8] beacons are localization tools that use identification between Tag/Reader to infer position coordinates. Fifth, visual tracking is a kind of indoor positioning that uses camera data to position people. We either use image processing operations or store images in an offline database, then compare them with those captured online. Multimodal localization merges several types of indoor positioning systems to take advantage of the benefits of each kind [9]. Ultra-wideband radio [27] communication is a technology developed to transfer large quantities of data wirelessly over short distances, over a very wide frequency spectrum, in a short period. UWB has low cost, low power consumption, multipath immunity, etc. These techniques suffer from several constraints that reduce their qualities, making these systems limited in specific conditions of use. Therefore, the researchers proposed integrating other mathematical tools to improve their system's qualities. These methods are bisecting into two categories, one deterministic and another probabilistic. These two types use filters or machine learning algorithms to reduce the acquired error. The KALMAN filter is one of the most used filters for indoor localization systems. This filter had used to reduce the instability of the measurements and the errors due to noise. We also have the Bayesian filtering, the maximum a posteriori (MAP), the maximum likelihood, Gaussian filter, Viterbi algorithm, and least-squares algorithm, which can improve the system's qualities. There are several types of machine learning [10]: unsupervised learning, supervised learning, and reinforcement learning. For example, supervised kth-nearest neighbor (K-NN) learning is a simple and effective machine learning (ML) [11]. It ranks the data in the feature space based on distance. This model predicts the value of the new data points by comparing the similarity of this value with the training data and then finds the kth neighbors that have maximum proximity to the novel data. The support vector machine (SVM) is a supervised learning algorithm with low computational complexity used for classification and regression problems. The SVM places data items in an n-dimensional space and draws n-1 hyperplanes to divide the training data set into n classes. So, the distance is maximized between the class and the hyperplane. The ANN artificial neural network is known as a back-propagation learning algorithm. It is based on the human brain model, which contains hundreds of billions of neurons. ANN network is composed of input, output layers, and hidden layers. ANNs are used for indoor positioning because of their robustness against noise and interference, which is one of the main factors affecting the accuracy of the systems. Further, unsupervised learning, such as K-MEANS is a clustering algorithm. It partitions the data set based on its characteristics into a number k of distinct predefined clusters or subgroups that do not overlap. Deep Learning DL is a kind of machine learning based on the ANN concept [13]. DL can be supervised or unsupervised using both labeled and unlabeled data. The principal aspect of DL is the iterative adjustment of the weight between each pair of neurons. DLs are trained using large labeled data sets. These learn features directly without the need to manually extract features. In addition, Reinforcement learning is a machine learning type approach for optimal control and decision making, where an agent learns an optimal policy of actions on a set of system states by interacting with the system environment [12]. Data matching and overfitting are challenging for fingerprint-based localization systems. K-NN is widely used for pattern matching in the fingerprint technique. However, K-NN does not work well with large datasets and high-dimensional data. In noisy environments such as airports, subway stations, and underground mines, RSSI has a high dimensionality due to the presence of time-varying, attenuation, and noise factors. In such instances, SVM is more efficient. It adopts the kernel mechanism to find the difference between two points of two distinct classes. It also models both linear and nonlinear relationships with better generalization performance. However, SVM-based methods are time-consuming and memory-intensive when the number of support vectors (SV) becomes large. In practice, a fingerprint card generated in the offline phase contains a large data set. Thus, it is necessary to compare the data acquired in the online measurement with each data point on the fingerprint card. To solve this problem, researchers proposed to divide the fingerprint map into several clusters. Then compare the data of the target node to the data center point of the corresponding cluster and estimate the location. If the number of reference points remains large in each group after clustering overfitting problem is likely to occur. Despite the positive impact of machine learning algorithms on indoor location systems, they still face some challenges and limitations, such as [10]:

- The high cost of training and the time it consumes
- Deep learning models need computation and storage time to automatically extract complex features from large volumes of unlabeled data. Therefore, for real-time localization in complex environments, it is difficult to retrain the deep learning model on time for frequently changing input information
- The machine learning approach lacks variability in cases where historical data is unavailable
- The success of DL depends on data.

Most DL algorithms need adequate data. Even in reinforcement learning, the agent learns an action based on the reward/penalty feedback, which can also be considered training data. The amount and quality of available data significantly influence the performance of ML algorithms, and determining the appropriate amount of data is a challenging task. Multipath is one of the major challenges of the indoor positioning system. Therefore, most of the systems calibrated either by filters or by machine learning algorithms are not fully adapted to eliminate the errors created by the non-direct visibility between the base stations and the clients. Crowdsourcing is the situation that brings the phenomenon of multipath. For this reason, we propose a new approachable to avoid the crowdsourcing case. The main contributions of this work are summarized as follows:

- **Mobile Access Point Model (MAPM)**
  In this work, we propose a new algorithm based on a mobile access point model (MAPM). Instead of being limited to a static access point that does not cover all users inside well. We participate in crowdsourcing to provide direct visibility between users and the system. The approach uses a threshold to confirm the line of sight (LOS) between the mobile access point (MAP) and other users.
- **UWB-OFDM telecommunication tool**
  In this work, we choose UWB-OFDM as a telecommunication channel due to the positive qualities of UWB and OFDM. These allow IPS to respect some criteria presented in [26]. In addition, UWB-OFDM can work perfectly with RSS compared to the other techniques.
- **The mathematical method of the received signal strength (RSS)**
  Received signal strength fingerprints are the most widely used in the IPS field because they are easy to deploy. However, they require calibration between online and offline measurements due to environmental changes and also are not suitable for device heterogeneity and others. Therefore, we choose the mathematical method that provides user tracking information.
- **Simulation structure**
  We simulate the proposed approach in a collaborative platform that employs Matlab, Mysql, and Java interfaces. Matlab is used to perform the MAPM processing operations. Mysql is used as MAPM's database for writing and reading information. The control interface is coded in Java. This is used to feed the system with random initial data and analyze the results.
- **Improvement of the positioning criteria**
  We evaluate our positioning system in four test scenarios. The simulation results show that the system achieves an average RMSE error of 10.19 cm in the 30-users case after one round. Furthermore, the detection rate has a value of 86.66%, which respects the major IPS criteria. In the face of repetitions, the average error value remains satisfactory with a value of 53.25 cm and a detection rate of 66% in the case of 30 users after five repetitions.
  In the following, related work is reviewed in Section II. Section III presents the mobile access point model (MAPM). Section IV describes and discusses the evaluation results. Finally, Section V concludes the paper.

II. RELATED WORK

In this section, we begin the presentation of some approaches trending in the literature on indoor positioning systems.

For instance, in [13], the author presents a vehicle people localization technique using a deep neural network (DNN) model. The approach used an impulse radio ultra-wide-band (IR-UWB) radar installed inside the vehicle. Further, the design of a network is updated by changing the type of activation function, the number of layers, and the number of nodes in each DNN's hidden layer. The approach had compared with conventional machine learning algorithms such as support vector machines (SVM). The proposed method is not needed to extract features from a given radar signal. The classification accuracy of DNN is 99.5% higher than the Gaussian SVM, which their classification accuracy is about 74.6%.

The techniques had based on federated learning, which guarantees privacy by using private local data. In this way, the data had kept on the user's device. It's generated by sharing only the local models. In [14], a novel method utilizing federated learning to improve the accuracy of RSS fingerprint-based localization while preserving the privacy of the crowdsourcing participants. The approach proposed demonstrates the prominence of federated learning for improving localization accuracy up to 1.8 m. The localization heterogeneity has affected both centralized and federated learning, thus the convergence time increase. In the area of 390 × 270 m^2, the proposed method localized users within 4.98 m using RSS fingerprint federated learning-based localization.

In [15], the author has developed an effective hierarchical model that unifies both single-floor and multi-floor indoor localization based on deep reinforcement learning (DRL). The approach has formatted the problem as a Markov decision process (MDPs) other than the traditional classification or regression problem. The method detects the target location by consecutively bisecting the search space into a small cube or window. The indoor localization based on DRL runs faster than the existing machine learning. Further, the approach does not require prior knowledge about the search space, such as floor plans and others. The DRL framework allows the model to automatically adapt to environmental dynamics caused by the variation of RSSI and the impact of the dynamic environment.

The approach had tested on three datasets in both single-floor and multi-floor. The proposed method had compared with other machine learning algorithms such as KNN, SVM, and regression algorithms. The evaluation part had shown that the time complexity of brute force neighborhood search is proportional to the size of the training dataset in the KNN-based algorithm. This method is not scalable with massive data in complex indoor environments. 75% of the targets were detected within 0.2 m, and KNN has 4.882 m.

Indoor localization approaches based on the received signal strength fingerprint had influenced by RSS variance, device heterogeneity, and environmental complexity. In [16], HAIL is an accurate and robust indoor localization approach that designs a new algorithm that leverages the advantages of both AP rank and RSS value efficiently to improve the localization accuracy. HAIL has used the RSS value based on the backpropagation Neural Network (BPNN) to fit different environments, which is engaged in measuring the fingerprint's similarities based on absolute RSS values. With this aid, the characteristics of the applied area had learned, such that HAIL could be adaptive to different environments. The experiments demonstrated that HAIL achieved high accuracy with an average error of 0.87 m.

The ultra-wideband (UWB) technique is a good carrier of indoor positioning information due to certain qualities, such as low power consumption, low cost, ease of deployment, etc. [17] The received signal strength RSS as a function of the distance is also a localization simulator for an RSSI-based fingerprint positioning technique has been carried out with conventional wireless USB sticks using OFDM HDR (High Data Rate) UWB radio technology. The approach has been compared to simulation results using TOA-based positioning. The technique measured the log-normal fading process with a standard deviation of 0.53 dB. However, the TOA-based positioning provided that the synchronization inaccuracy is larger than 1ns. The mean estimation error depends on the number of anchor nodes. The error is below 0.2 m.

Received signal strength (RSS) is a simple and less expensive localization method in wireless sensor networks (WSNs). It is also of significant interest for ambient intelligence technologies. In [18], the approach has used the belief theory (the Dempster-Shafer theory) to improve the accuracy of RSS values because the power received by the target is not linear with distance. Therefore, there are shades constraints, NLOS non-direct visibility, etc. Experiments conducted in two indoor environments show the effectiveness of the proposed approach in terms of accuracy. The average error is less than 3 m. Wi-Fi fingerprints have attracted a lot of attention recently, as They allow high applicability in complex indoor environments. In [19], the author presents a survey that gives an overview of advances in two major areas of Wi-Fi fingerprint localization. The survey has shown how we could use temporal or spatial signal patterns, which results in a collaboration between users and motion sensors. For efficient deployment of RSS-based systems, the author discussed recent advances in reducing offline labor-intensive surveys, adapting to changes in RSSI values, and calibrating heterogeneous devices. The survey studied and compared some techniques through experiments to measure the impact of signal collection and energy efficiency for smartphones.

In general, Wi-Fi-based localization systems suffer from calibrations constraints also the divergence of some measurements. The best accuracy is less than 1 m. Further, Wi-Fi fingerprints consume high levels of energy compared to other approaches. For this reason, in our system, we would choose the mathematical model (telecommunication equation), which does not require much cost and offline site survey. Reference [20] has proposed Gradient Fingerprinting (GIFT), which exploits a more stable RSSI gradient. GIFT first built a fingerprint map based on a GMAP gradient by comparing the absolute RSSI values at nearby positions, and then it runs an online extended particle filter (EPF) to locate the user. GIFT is more adaptable to the time-varying RSSI in indoor environments, thus effectively reducing the overhead of fingerprint card calibration. The approach implemented GIFT on Android smartphones and tablets and conducted extensive experiments on a five-story campus. GIFT's error is 5.6m for 80% of the results. Reference [21] A survey studied the indoor positioning techniques based on digital fingerprinting without offline site surveys. The survey had classified the evaluated approaches into three categories: SLAM, inter/extrapolations, and Crowdsourcing systems. The survey compared the approaches' performance on the following parameters: accuracy, operation time, robustness, versatility, security, and participation. The results had shown that SLAM-based techniques are accurate, their security high, their participation good, but their operation time and robustness are poorly satisfied. Otherwise, the

TABLE 1. Evaluation of RSS-based approaches on the root mean square error.

The approach	Error
GP-LVM	3.97 m
Graph SLAM	2.18 m
WiSLAM	5.4 m
TIX	5.4 m
SDM	3 m
Walkie-Markie	1.65 m
RCILS	3 m

inter/extrapolation techniques are good in the criteria of the operation time, safety, and participation. However, accuracy, versatility, and robustness are not satisfied. The crowdsourcing-based positioning technology is accurate and may have low operation time. Also, their versatility and robustness are good, but their safety and participation are low in front of environmental obstacles. Table 1 shows the evaluation results of the RSS-based approaches in terms of the mean square error. Walkie-Markie scored well in terms of accuracy. In [22], MPILOC is a multi-floor indoor localization system that uses data provided by smartphone users via participatory sensing for the automatic construction of a floor plan and radio map. The system does not require manual calibration, prior knowledge, or infrastructure support. MPILOC merges annotated walk paths with the sensor and received signal strengths to derive an annotated walk path map with radio signal strength in multi-floor environments. The average error is 1.82 m. Reference [23] The approach proposed a novel indoor subarea localization scheme based on passive fingerprint crowdsourcing and unsupervised clustering. The approach classifies unlabeled RSS metrics into several clusters and then connects the clusters to indoor subareas to generate subarea fingerprints. The experimental results had shown that the proposed scheme could achieve a sub-area hit rate of 95%. The reference point (RP) based methods such as KNN and K-means are frequently used for indoor localization using fingerprints (RSS). These traditional clustering algorithms do not use the geometric proximity information between RP and the test point for position determination. In [24], to eliminate incorrect neighboring RPs and avoid selected RPs located only on one side of the test point, the geometric proximity between neighboring RPs and the test point is analyzed in the online phase. The nearest neighboring RPs are selected based on their physical distances to the test point instead of the widely used positions of the RPs. The proposed algorithm had tested by experiments conducted in an office building. The results indicate that the proposed method outperforms the traditional KNN, WKNN, and TPIC (Test point Irrelevant Clustering) algorithm. The RMSE of the proposed algorithm is 3.74 m. In this work [25], the author has proposed a novel fingerprint-based passive positioning scheme for ZigBee-based IoT networks. The proposed algorithm merges time and RSS information and designs an improved pattern matching algorithm based on random forests. The approach recovers the time and compensates it by synchronizing DTDOA and GPS. The technique showed that the time information used as additional information for fingerprinting and that DTDOA-based fingerprinting achieves comparable positioning accuracy to RSS-based fingerprinting. By merging and normalizing RSS-DTDOA features into a single long feature vector, they found that RSS and DTDOA could improve positioning accuracy over fingerprint algorithms relying solely on a single fingerprint modality (RSS or DTDOA). This approach designed an improved three-stage pattern matching algorithm, KNN-RF, which outperforms the traditional WKNN pattern matching algorithm for fingerprinting. The system implemented the proposed algorithm (RSS-DTDOA) using KNN-RF in software-defined radio (SDR) based positioning system. The proposed method achieved an average positioning accuracy of 1.6 m, a 36.1% improvement over traditional RSS-based fingerprinting.

III. MOBILE ACCESS POINT MODEL MAPM

A. SYSTEM OVERVIEW

In this paper, we present MAPM that used the mobile access point model and the mathematical received signal strength model (RSS) to deduce the information about the user's position. We use OFDM-UWB as a communication tool between access points and users thanks to their qualities in terms of energy consumption, low response time, and effectiveness against interference. Our interest is to participate in Crowd-sourcing to implement a decentralized indoor positioning system, which ensures the direct visibility between transmitter and receiver. The mobile access point model MAPM is an intelligent algorithm that uses the notion of mobile access points instead of being limited to fixed access points (SAPs) only. So that MAPM can decrease the use of fixed access points SAP, increasing the localization accuracy. The mathematical method RSS is used to estimate the distance between the access point and the user by using the telecommunication equation (Friis equation). After the distance estimation, we use the Euclidean distance equation to find the passenger position coordinates. The objective of our approach is to meet the criteria that determine the quality of the systems.

B. INDOOR LOCALIZATION CRITERIA

In our previous work, [26], we presented a survey based on the results acquired during the bibliography phase. This survey showed that most approaches use only accuracy as a criterion for choosing an efficient indoor positioning system. However, the performance of the techniques depends strongly on other criteria. The choice of an efficient indoor localization system depends on the use objectives. Thus, the location objective is the one that determines the quality of the desired system by choosing the level qualities of the following criteria:

- Precision
- Energy consumption
- Cost
- Easy to deploy

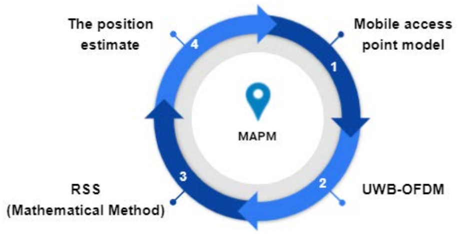

FIGURE 1. The MAPM architecture.

FIGURE 2. The system ranks.

- Stability
- Response time
- Adaptation to changes in the environment & the heterogeneity of devices
- Complexities

C. THE MAPM ARCHITECTURE

The MAPM model uses the mobile access point concept instead of limiting itself only to the fixed access point usage. The system offers three grades. The first one is the SAP (Static Access Point) grade second is the USER grade for all undetected users. The third grade is the MAP (Mobile Access Point) grade, only for detected users. The initialization phase consists only of initializing the system by communication between SAP and USER. In the second phase, if the user position is already known. MAPM changes the user rank to the large MAP. In this way, other users who have direct visibility with this MAP can communicate with them to determine their positions. In the final phase, we use the positioning part of the algorithm to estimate the user's location. After that, we store the position information in the system database. In general, each user must make two communications to define their position. Figure 1 presents the system architecture. Figure 2 presents the system ranks.

In Algorithm 1, we use the algorithm's initialization part to measure the distance between the user and the static access point. These can help to filter out non-direct communications we apply a distance threshold. In the main part, we exploit the direct communications to estimate the distances between them then we deduce the user position coordinates. Afterward, the system changes the user rank to the large MAP. The system proposes after the initialization step other communications with large MAP users that are mobile access points only for users not yet detected (users who don't have direct visibility with SAPs). So, the user can now find their position information, thanks to local communications with MAPs.

Algorithm 1 MAPM Localization Algorithm

Input
X_{sap}: The horizontal coordinate of the SAP position
Y_{sap}: The vertical coordinate of the SAP position
Id_{SAP}: SAP ID number
F_s: Sampling frequency
F_0: Signal frequency
Ns: Number of samples
Ge: Transmitter gain
d_0: The threshold distance
Gr: Receiver gain
Pe: Transmitting power
x_r: The real abscissa of user
y_r: The real ordinate of user
Output
x_e: The estimated abscissa of user
y_e: The estimated ordinate of user
de: The estimated distance
Pr: The received strength
Dr: The detection rate
Grade: The user's rank
RMSE: The root mean square error
Begin
Algorithm initialization
1-Insert SAP data into the system database (x_{sap}, y_{sap}, Id_{sap})
2-Insert user data randomly into the system database (x_r, y_r, Id_{user})
3- Select Id_{user} and Id_{sap}
4- Communication between user/SAP
5- Measure the received strength (Pr) between SAP/User(We used the equation (2))
6- We used the equations (3),(4),(5) for measuring the distance(de) between user/SAP
if $d_e \leq d_0$ **then**
  8- insert to the database the SAPs connected with client X
end if
9- **Main function**
10- Select Id_{user} and Id_{sap}
11- Select the SAPs connected with the client X
12- SAP/User X communication
if the number of communications is greater than or equal to two **then**
  13- estimate client position
  14- Rank = ⋆ MAP ⋆
end if
MAP part
15- Select unpositioned user data
16- Select MAP grade customer data
17- Calculate the distance between MAP/ User Y
if $d_e \leq d_0$ **then**
  18- insert the MAPs connected to the client into the database
end if
for each client **do**
  19- select the MAPs connected with the client
end for

If the user can't communicate with two SAP or two MAP, the system proposes the third choice to participate in unitary user communication with MAP and SAP.

Algorithm 2 The Sequence of MAPM Algorithm

20- MAP/user Y communication
21- Estimation of distance between MAP/ user Y
if he number of communications is greater than or equal to two **then**
  22- estimate client position(we use equation (6))
  23- Rank = ⋆ MAP ⋆
end if
SAP-USER-MAP part
24- Select unpositioned user data
25- Select the SAPs connected with the client Z
26- Select the MAPs connected with the client Z
27- Select the distances estimated between User/SAP and User/MAP
if the number of communications is higher than tow **then**
  28- Choose tow minimum values of distances
  29- Estimate the position of user
end if
30- Eliminate the position out of area
31- Rank = ⋆ MAP ⋆
End

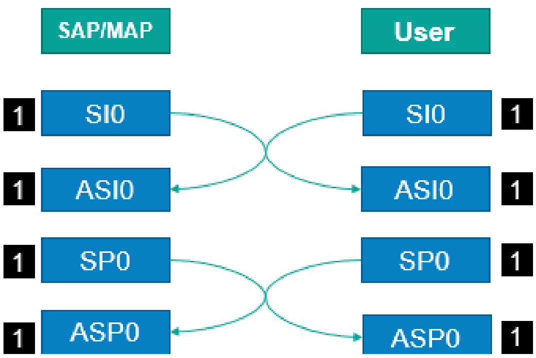

FIGURE 3. The communication protocol.

IV. EVALUATION RESULTS

A. SYSTEM PARAMETERS

Our approach had articulated in three main steps. The first step is the communication between the user and the access point. Second, after measuring the received signal strength, we estimate the distance between the user and access points using the telecommunication equation (Friis equation). In the third step, we use the Euclidean equation for calculating the position's coordinates. Figure 3 represents the communication protocol between the system's elements. SI0 and SP0 represent the bits of the initialization signal and the pilot signal, respectively. ASI0 and ASP0 are the bits of the acquisition of the initialization signal and the pilot signal, respectively. We use a signal S(t) written in the following form:

$$S(t) = A * cos(2 * pi * f0 * t) \tag{5}$$

where A is the signal amplitude, f_0 is the signal frequency. For the simulation part, we estimate the received signal strength by the following relation:

$$Pr = (1/N) * sum(S(t)) \tag{6}$$

With N is the signal length. To estimate the value of the distance between the user and the access point, we benefit from the telecommunication equation written as:

$$Pr = Pe + Ge + Gr - Aiso - PL \tag{7}$$

where

$$Aiso = 20 * log(d) + 20 * log(f) + 32,44 \tag{8}$$

where

$$PL(d) = PL_0 + 10 * \gamma * log(d/d0) + S(d) \tag{9}$$

where Pr is the received signal strength, Pe is the transmit power, Ge is the transmitter antenna gain, Gr is the received antenna gain, and Aiso is the attenuation. PL is the strength loss, f is the frequency, d is the distance, d_0 is the threshold distance, PL_0 is the power loss at d = d0, γ is the slope, and S(d) is the shadow fade. If the distances are already ready, we exploit the Euclidean equation of a circle to deduce the position coordinates:

$$d_{ij}^2 = [(x_j - x_i)^2 + (y_j - y_i)^2] \tag{10}$$

where x_i, y_i is the user position coordinates, x_j, y_j is the access point position coordinates and d_{ij} is the distance between the i user and the j access point. Intending to measure the performance of our approach, we take advantage of the two error estimation tools, RMSE (the squared error) and the detection rate Dr. Drx is worth 1 when the value of RMSE is below certain thresholds. The error functions had defined by the following equations:

$$RMSE = \sqrt{((x_r - x_e)^2 + (y_r - y_e)^2)} \tag{11}$$

$$Dr = Drx/Nu \tag{12}$$

where RMSE is the root mean square error, x_r, y_r, x_e, y_e are the reference coordinates and the estimated position coordinates respectively. Nu is the number of users. Figures 4 and 5 show the information carrier signal in the UWB band before and after OFDM modulation. Table 2 shows the parameters of MAPM.

TABLE 2. Simulation parameters.

Nu	F0	The number of samples	NS	Gr and Ge	Pe	The threshold Distance	Fs	The number of SAP	Size of area
10 /30 /50	3×10^9 Hz	4	256	2.5 dB	20 dB	250 cm	12×10^9 Hz	4 /5 /6	5m x 2m

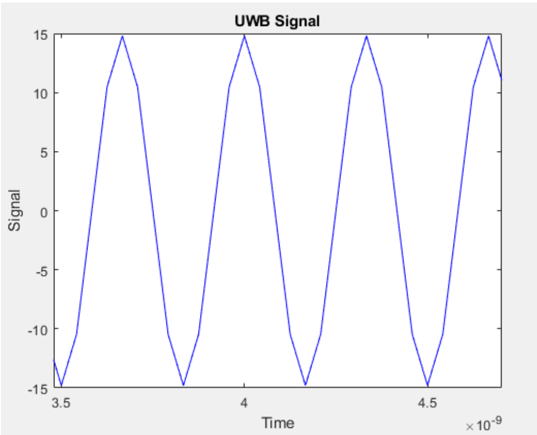

FIGURE 4. UWB signal.

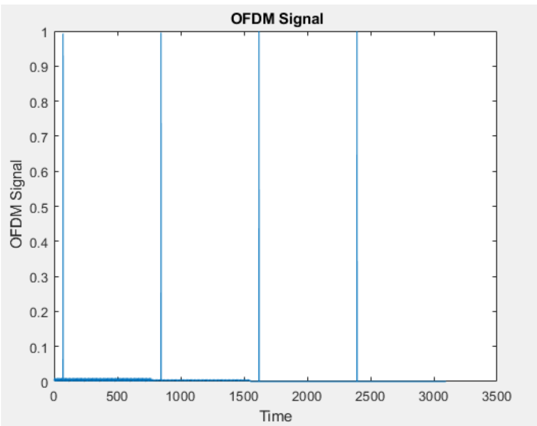

FIGURE 5. Signal after OFDM (TX).

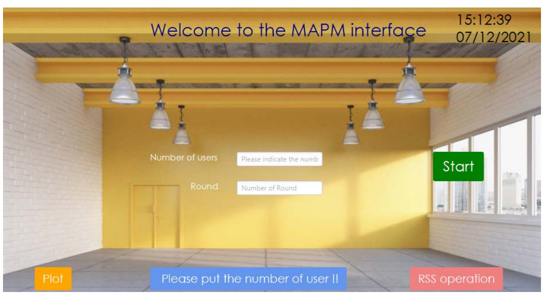

FIGURE 6. The MAPM control interface.

FIGURE 7. Simulation result in the case of 10 users with one round.

FIGURE 8. Simulation result in the case of 30 users with one round.

TABLE 3. The simulation results based on the RMSE and the detection rate Dr with three and five rounds.

Nu	CDF-10 users with five rounds	CDF-30 users in the case of RSS with MAPM with five rounds	CDF-30 users in the case of RSS without MAPM with five rounds	CDF-50 users with three rounds
Average of RMSE(cm)	8.65	53.25	69.6	43.83
Detection rate	66%	52%	36%	55%

B. SIMULATION SETUP

In this framework, we present the simulation that validates the performance of our approach. In this simulation part, we used three platforms:

- ***MATLAB:*** MATLAB is used to make the system processes
- ***MYSQL:*** MYSQL is used as a database of the system
- ***Eclipse (JAVA):*** Eclipse is the control interface of the system, is used to feed the system with random data, also the visualization of the results

Then the MAPM interface (as shown in figure 6) feeds the database with random user information and static SAP access points, such as IDs, reference position coordinates, and algorithm parameters. After the application finishes the initialization step, MATLAB stars the MAPM algorithm to estimate the user's positions. In addition, MATLAB inserts the results into the database of our system. The next step is to analyze the simulation results on the MAPM interface. The interface takes the available results from the database and draws the results and curves of the different laps. We have chosen a certain number of rounds because of the random values that don't always give us the same results. We proposed a simulation environment of size 5m x 2m with four well-positioned static access points.

Figures 7, 8, 9, and Table 3 show the results acquired during the three proposed scenarios. Figures 10, 11, 12 represent the

FIGURE 9. Simulation result in the case of 50 users with one round.

FIGURE 10. Simulation result in the case of 10 users with five rounds.

FIGURE 11. Simulation result in the case of 30 users with five rounds.

FIGURE 12. Simulation result in the case of 50 users with five rounds.

TABLE 4. Evaluation of the simulation results based on the RMSE and the detection rate Dr with one round.

Nu	10	30	50
Minimum of RMSE(cm)	5.68×10^{-14}	2.84×10^{-14}	1.42×10^{-14}
Average of RMSE(cm)	13.21	10.19	9.13
Maximum of RMSE(cm)	108.70	156.05	273.72
Detection rate	80%	86.66%	92%

simulation results in the case of 10 and 30 users with five rounds and 50 users with three rounds. Figures 13, 14, and 16 show the CDF functions in the cases of RSS with MAPM with 10 users and five rounds, 30 users with five rounds, and 50 users with three rounds, respectively. Figure 15 shows the CDF function in the case of RSS without MAPM with 30 users and five rounds. Table 4 presents the simulation results based on the RMSE and the detection rate Dr with three and five rounds. Figure 17 presents the average value of CDF in the case of 30 users. We notice that more than 80% of the positions of the passengers their errors are less than 10 cm.

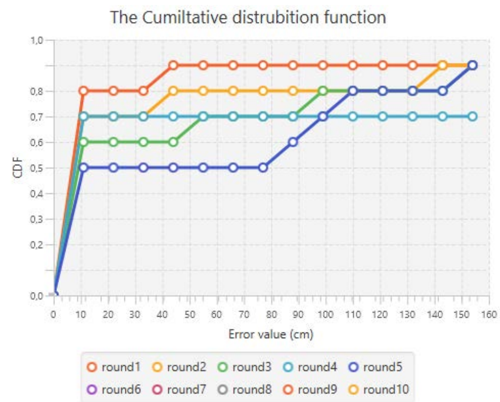

FIGURE 13. The CDF in the case of 10 users with five rounds.

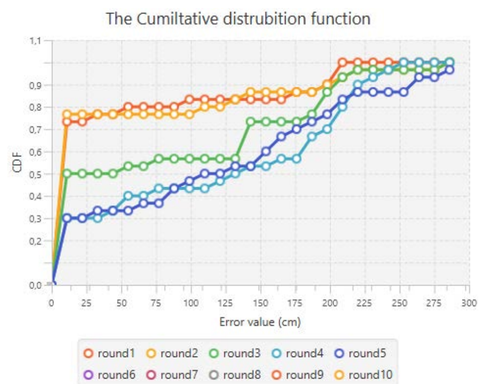

FIGURE 14. The CDF in the case of RSS with MAPM with 30 users and five rounds.

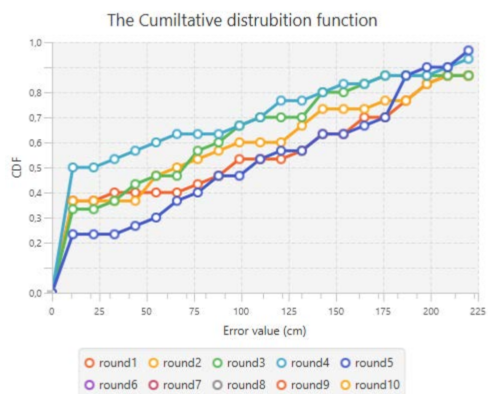

FIGURE 15. The CDF in the case of RSS without MAPM with 30 users and five rounds.

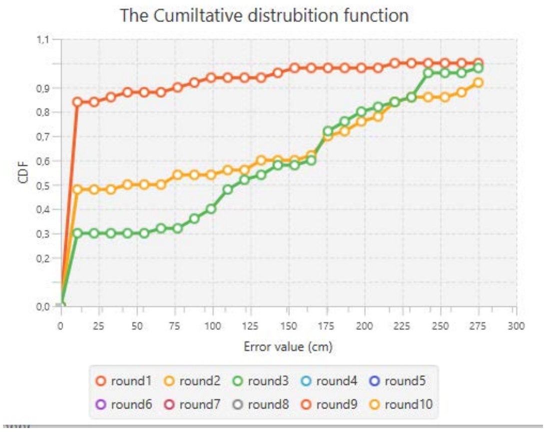

FIGURE 16. The CDF in the case of 50 users with three rounds.

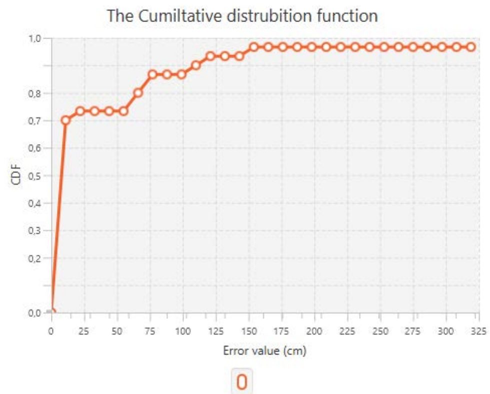

FIGURE 17. The CDF averages the case of 30 users with one rounds.

FIGURE 18. Simulation results in the case of RSS matrix model.

In the following, we use two types of algorithms to show the performance of the approach, the first one based on a neural network and the other one based on the matrix model of received signal strength RSS.

Figures 19, 20, and 21 present the step of comparing the qualities of the approaches with and without MAPM and the RSS matrix positioning model. The results presented in

FIGURE 19. Simulation results in the case of RSS without MAPM.

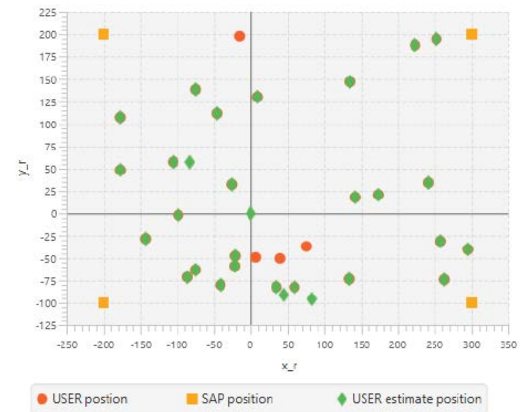

FIGURE 20. Simulation results in the case of RSS with MAPM with one rounds.

TABLE 5. Comparison result between RSS matrix model, RSS without MAPM and RSS with MAPM.

Nu = 30	RSS matrix model	RSS with MAPM	RSS without MAPM
Minimum of RMSE(cm)	17.36	2.84×10^{-14}	$7,10 \times 10^{-15}$
Average of RMSE(cm)	130.05	10.19	93.57
Maximum of RMSE(cm)	288.72	156.05	254.68
Detection rate	0.0%	86.66%	36.66 %

Table 5 show the performance of the proposed method compared to the others. In addition, we evaluated the performance of the proposed approach by integrating the Neural Network that links the received powers with the positions by effective uniform laws, as presented in Figures 21, 22, and Table 6. Figures 23, 24, 25, 26, 27, and 28 show the effectiveness and robustness of the proposed approach to reduce the number of SAPs by comparing the evaluation factors in different scenarios.

FIGURE 21. Neural network simulation results without MAPM with one rounds.

FIGURE 22. Neural network simulation results with MAPM with one rounds.

TABLE 6. Comparison result between NN-with and without MAPM.

For Nu = 30 and 4 SAP	NN-With MAPM	NN-Without MAPM
Average value of RMSE	11.56	33.06
Detection rate	93.33%	83.33%

C. DISCUSSION & RESULTS

In the previous section, we presented the simulation results of the proposed approach. We show the performance of the MAPM system by evaluating the system on four levels.

In the first stage, we evaluate the technique on the number of users (Figures 7, 8, 9). MAPM has shown the quality of indoor localization, despite the high number of users in a 5m x 2m environment. The approach reduced the problem of direct non-visibility between the SAP static access points and the users. Table 4 shows the system performance with the growth of the number of users. The average RMSE error decreased when moving from 10,30 to 50 users. The average RMSE error for 10 users is equal to 13.21 cm, for 30 users RMSE is equal to 10.19 cm, and for 50 users RMSE is 9.13 cm, which validates the proposed algorithm. The detection rate in the case of 50 users, which represents a crowdsourcing case is 92%. This result means that the

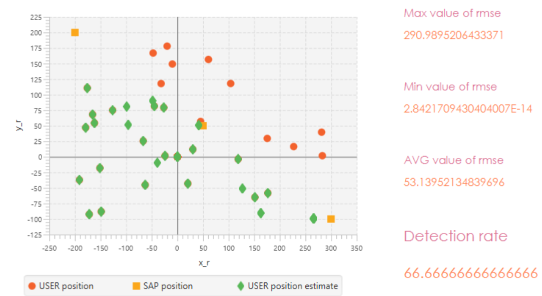

FIGURE 23. The influence of a number of SAP on the performance of the system (The case of 3 SAP with one rounds).

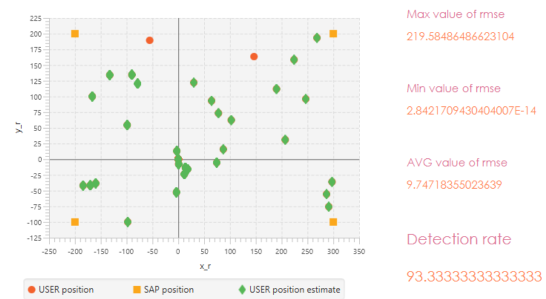

FIGURE 24. The influence of a number of SAP on the performance of the system (The case of 4 SAP).

92% of RMSE is less than 10 cm. Since the algorithm inputs are random, the CDF values can vary between rounds, as shown in Figures 13, 14, and 16. On the other hand, the system's qualities vary in a short interval. We have discussed the nature of the initialization parameters, which are random and affect the results obtained. The system error had influenced by algorithm inputs variation. This issue can only be another challenge for system evaluation. Table 3 and figures 13, 14, and 16 show a decrease in accuracy during the repetitions. The results obtained validate the quality of MAPM despite the negative impact of the rounds on the average error value remains satisfactory with a value of 53.25 cm in the case of 30 users after five repetitions. Table 3 validates the proposed approach by comparing the CDF function in the case of 30 users with and without MAPM. The RSS case with MAPM is very robust and performs well with an error value of 53.25 cm and a detection rate of 66% compared to the other case, which has an error value of 69.6 cm and a detection rate of 36% (see figures 14,15 and table 3).

In the second stage, we compare the proposed system with other approaches, such as the RSS matrix method and mathematical method without and with MAPM, as shown in Figures 18, 19, and 20. Table 5 shows the quality of MAPM, which managed to reduce the average error to 10.19 cm compared to the approach without MAPM and the RSS matrix model. Also, the detection rate has a value of 86.66 %. In the third stage, we used the neural network (Levenberg-Marquardt backpropagation), which has a good revenue on indoor positioning systems. The NN is integrated with MAPM to reduce the squared error from 33.06 cm to

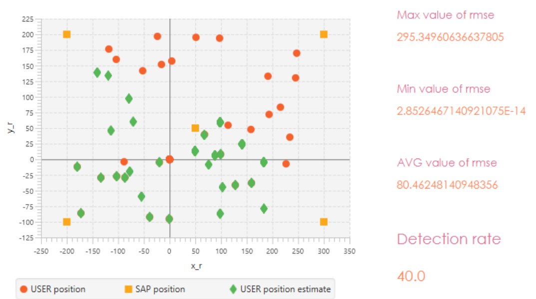

FIGURE 25. The influence of a number of SAP on the performance of the system (The case of 5 SAP with one rounds).

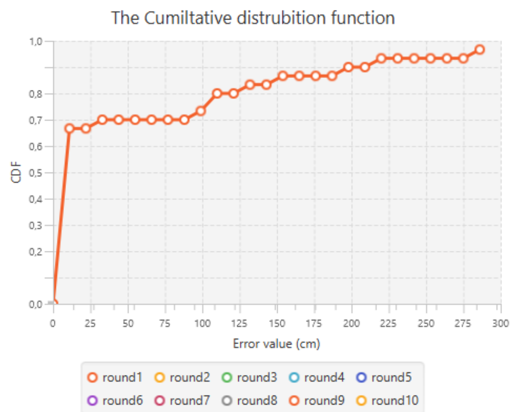

FIGURE 26. The CDF of the proposed approach in the case of 3 SAP with one rounds.

11.56 cm. However, the detection rate increases up to 93.33%, which validates the performance of MAPM.

In the last part of the simulation, we examined the system performance on the number of Static Access Points SAP variations. The results presented in Figures 18, 19, 20, 23, 24, 25, 26, 27, and 28 show the system's effectiveness in different scenarios where the number of access points is unable to infer the positions of indoor passages. The 4 SAP case is the best one because the Static Access Points had positioned correctly to do the initialization step of the MAPM algorithm. Otherwise, in the case of 3 SAP, the detection rate decreased by almost 30% compared to the case of 4 SAP. In the case of 5 SAPs, the system's quality decrease since the 5 SAPs isn't positioned rightly. Therefore, the system's quality does not depend on the use of a large number of access points.

The system qualities decrease between rounds in the range of 0% to 10% (see figures 13, 14, 16). The proposed approach maintains its quality despite using several static access points less than the regular state (4 SAPs). In practice, we can use lower SAP than the number used in the simulation. To conclude, the simulation results have shown the quality of the proposed MAPM algorithms, the positive impact of the UWB-OFDM communication tool on the approach, and the mathematical method of RSS received signal strength adaptation. Our algorithm has successfully limited the NLOS multipath problems by using the concept of mobile access point MAP and signal interference by exploiting UWB-OFDM, which offers a wide communication range.

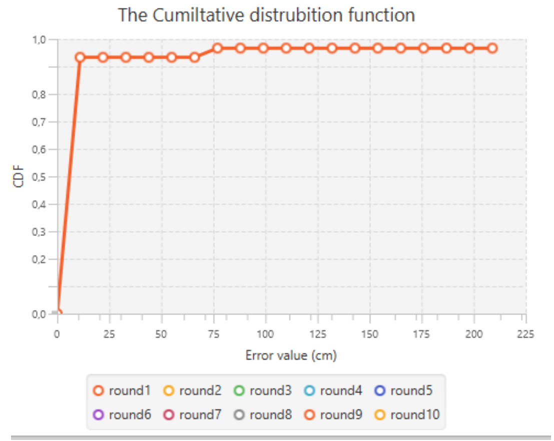

FIGURE 27. The CDF of the proposed approach in the case of 4 SAP with one rounds.

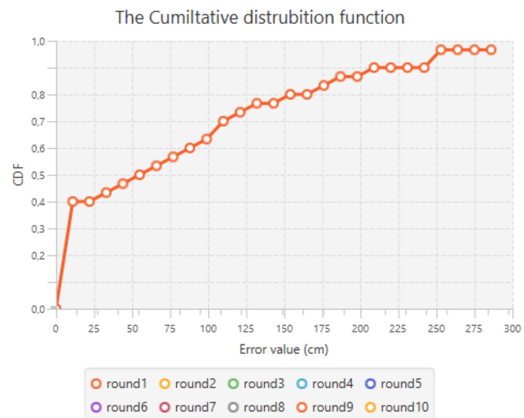

FIGURE 28. The CDF of the proposed approach in the case of 5 SAPwith one rounds.

The system is well adapted to the change of environment, as it has used the mathematical model of received signal strength, which does not require calibration between offline/online measurements.

The simulation results show that MAPM can reduce the need for high Static Access Points numbers since SAPs are only system initialization tools.

In future work, we were trying to realize a magnetic badge capable of linking smartphones with the proposed system, which leads to smoother switching between the system parts.

D. TOOLS PERFORMANCE

Our purpose is to develop an indoor localization system of good quality. We respect the criteria mentioned in section III subsection B. To achieve this goal; we have chosen the following three tools as the basis of our system, each with its role in improving the system:

- The RSS received signal strength method (mathematical method)
- OFDM-UWB
- Mobile Access Point Model (MAPM)

First, the received signal strength (RSS) method is a useful positioning tool in the literature on indoor localization

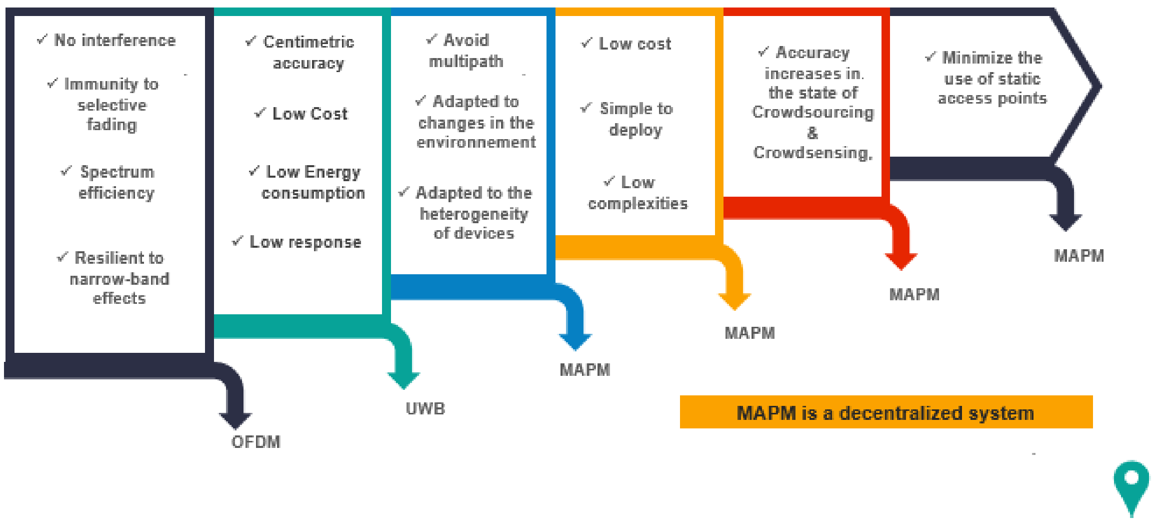

FIGURE 29. The advantages and performance of the system.

systems. We have two types of RSS methods. The first one uses a fingerprint map of the received powers. The second one uses the mathematical model of received signal strength (Friis equation) as a basis for estimating distances between static access points (SAPs) and users. Second [26] ultra-wideband UWB is a technique developed to transfer large amounts of data wirelessly over short distances, over a wide frequency spectrum. The UWB technique can handle the large bandwidth required to carry multiple audio and video streams. This technique operates at a level that allows most systems to interpret the noise and does not interfere with other radios such as cell phones.

We have used crowdsourcing as a source of inter-localization data between crowd elements. For this reason, we restricted the direct non-visibility NLOS problem by using a new mobile access point algorithm (MAPM), which provides a line of sight between users and access points.

UWB-OFDM is the part of the system that provides communication between clients and access points. UWB-OFDM has a wide frequency band based on orthogonal modulation between signals against interference, capable of bringing data from the crowd without interruption. So, the approach can be used in a public place (indoors) that provides navigation services, guidance, etc. This method can facilitate life indoors by participating in Crowdsourcing/Crowdsensing. Figure 29 presents the advantages and performance of the proposed approach. The mixture of UWB, OFDM, RSS (the mathematical model), and MAPM algorithm can manage the different system processes. Therefore, it allows to solve most indoor positioning problems and respect the criteria mentioned in section III subsection B.

V. CONCLUSION

In this paper, we presented MAPM which is a new localization algorithm that participates in crowdsourcing indoors. The concept of a mobile access point MAP had used to provide direct visibility between users and the access point. This approach has been successful in most cases in eliminating the NLOS problem.

We have used the UWB-OFDM technique, which has good qualities (figure 29) in terms of accuracy (its precision is centimetric), low cost, low response time, and reliability against interference. The MAPM algorithm uses the RSS received signal strength telecommunication equation to estimate the distances between the client and the access point. This method is more suitable for changing environments as it does not require calibration between online and offline measurements.

The simulations showed that MAPM is able to meet most of the criteria listed in section III subsection B. MAPM has centimeter accuracy, low cost, low complexity, low operation time, and is adapted to the environment changing. From our perspective, we move on to the implementation of the system. We have discussed the nature of the initialization parameters, which are random and affect the results obtained. In the face of repetitions, the average error value remains satisfactory with a value of 53.25 cm and a detection rate of 66% in the case of 30 users after five repetitions. The case of RSS with MAPM remains more robust than the other without MAPM. The average MAPM error in the case of 30 users is 10.19 cm and has a detection rate of 86.66% for only one round.

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