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Cooperative Localization in Mines Using Fingerprinting and Neural Networks

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***Abstract*—Localizing people in confined and underground areas is one of the topics under research in mining labs and industries. The position of personnel and equipments in areas such as mines is of high importance because it improves industrial safety and security. Due to the special nature of underground environments, signals transmitted in a mine gallery/tunnel suffer from severe multipath effects caused by reflection, refraction, diffraction and collision with humid rough surfaces. In such cases and in cases where the signals are blocked due to the non-line of sight (NLOS) regions, traditional localization techniques based on the RSS, AOA and TOA/TDOA lead to high position estimation errors. One of the proposed solutions to such challenging situations is based on extracting channel impulse response (CIR) fingerprints with reference to one wireless receiver and using an artificial neural network as a matching algorithm to localize. In this article we study this approach in a multiple access network where multiple access points are present. The diversity of the collected fingerprints will allow us to create artificial neural networks that will work separately or cooperatively using the same localization technique. The results will show that using cooperative artificial intelligence in the presence of multiple signatures from different reference points improves significantly the accuracy, precision, scalability and the overall performance of the localization system.**

***Index Terms*—Indoor localization, channel impulse response, artificial neural network, fingerprinting technique, multiple access technique**

I. Introduction

In the mining industry, knowing the position of miners and/or equipments is an important safety measure that reduces risks and improves the security of that facility. Like any indoor environment, wireless signals transmitted in mines are affected by extreme multipath and non-line of sight (NLOS) conditions. Since mines have their own environment that is made up of connected tunnels, localization using traditional techniques is challenging and fails to provide accurate positioning. Most traditional geo-location systems use the triangulation techniques and are mainly based on the received signal strength (RSS), angle of arrival (AOA), time of arrival (TOA) or the time-difference of arrival (TDOA). Other systems use scene-analysis or fingerprinting techniques, and these include the probabilistic methods , k-nearest neighbours (kNN), support vertex polygon (SMP), support vector machine (SVP), and neural networks. Surveys on wireless indoor positioning techniques [1],[2] provide detailed discussion of each approach. Underground localization using traditional systems would result in an unstable behavior due to the fact that the received signals in an underground environment undergo several reflections, refractions and diffractions that can dramatically change the amplitude, time of arrival and phase at the receiver.

A novel approach to localization has been presented in [3] and it is based on studying the CIR at a specific distance from the transmitter and registering its specifications as a fingerprint to be matched using the neural network technique. The same concept was also used in [4] with less input parameters. The uniqueness of the CIR at each position enhanced the accuracy and precision of localization in indoor facilities. Unlike other approaches [5],[6],[7],[8] which mainly base their fingerprints on the RSS with reference to one or more access points, this approach uses several parameters extracted from one CIR as a fingerprint with reference to one receiver.

One of the drawbacks of using the RSS as a fingerprint is the fact that the signal's strength vary with time at the same position [2],[5], and that the accuracy of localization is mainly enhanced when the number of access points (APs) increases in the same area [9].

In this article we will enrich the localization technique in [3] and open it to a wide range of possibilities where the mobile user is capable of transmitting multiple signals to different access points present in the network. Unlike the approach in [3] which estimates the position based on one receiver, this work will consider the inputs of more than one receiver before giving a position estimate. The received signatures at several references form fingerprints and the position will be estimated using multiple neural network techniques in a cooperative localization concept. In the following section, the fingerprinting technique is discussed, and the neural network is presented as the matching algorithm for localization. In the third section, we introduce the localization system and its functionality in the areas containing only one receiver shedding the light on major problems encountered. In section 4, several techniques to localization are discussed in the presence of two receivers. The results are compared and analyzed in section 5. Finally, the paper is closed by a conclusion in section 6.

II. LOCALIZATION USING FINGERPRINTING AND NEURAL NETWORKS

A. Fingerprinting technique

The fingerprinting technique is based on collecting information about specific events and then matching the presence or absence of those events based on the pre-acquired data. Fingerprinting techniques can be used in indoor localization approaches in order to identify the channel at different parts of the covered area [10],[11],[12]. It is similar by analogy to the human fingerprints and it is used here to ensure uniqueness and precision to the indoor channel behavior present in mines. In this paper, the fingerprinting technique is used to identify a position based on the CIR. This technique consists of two phases: the offline phase which is the process of collecting several impulse responses at several distances from the receiver and then storing the information in a database. The second phase of the fingerprinting technique is the real-time phase where in online scenarios the CIR is extracted and then compared to the saved database in order to match a specific position. In the following, the same approach in [3] is discussed along with the different parameters that form the fingerprint of any position. A signature or a fingerprint is a set of seven parameters at a specific distance to the transmitter (discussed below).

Real-time measurement campaigns were carried out 70 meters underground in the CANMET gold mine in Val d'Or city [3],[4]. The measurements in [3] were used in this work and they were recorded at a central frequency of 2.4 GHz in order to have a compatibility with WLAN systems. These measurements consist of 450 measurements along a tunnel as shown in Fig. 1. The complex CIR of the wideband measurements was obtained using the frequency channel sounding technique [3]. Once a signal is received, the channel impulse response is extracted and by applying the inverse fast Fourier transform (IFFT), the time impulse response is obtained. Using this impulse response, one can extract several parameters to form a specific signature. Seven parameters for each CIR guarantee uniqueness to the position of the transmitter. The parameters are as follows:

- The mean excess delay ($\bar{\tau}$) that is the first moment of the power delay profile measured at the first detectable signal that arrives at the receiver and is related to the power of that profile. In other words it is related to the amplitudes of the multipath components, and it is given by:

$$\bar{\tau} = \frac{\sum_k a_k^2 \ \tau_k}{\sum_k a_k^2}.$$

- The root mean square (τ_{rms}), and it represents the square root of the second central moment of the power delay profile and it is given by:

$$\sigma = \sqrt{\bar{\tau^2} - (\bar{\tau})^2},$$

where:

$$\bar{\tau^2} = \frac{\sum_k a_k^2 \ \tau_k^2}{\sum_k a_k^2}.$$

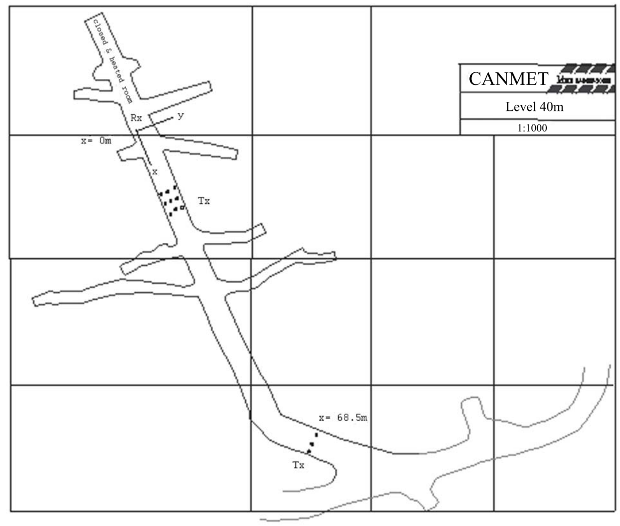

Fig. 1. Map of the tunnel.

- The maximum excess delay (τ_{max}) which is the time at which the signal drops below X dB of the maximum power measured in the power delay profile. It can be seen as the time that a signal stays above a given threshold based on the highest received power in a profile. In the following, the value of 20 dB is taken as a threshold.
- The total power of the received signal (P) measured in dBm.
- The number of multipath components (N) which form the entire received signal measured at a 20 dB floor level.
- The power of the first arrival (P_1) which is the power of the first multipath component.
- The delay of the first path component (τ_1) and it is used along with P_1 in order to distinguish between the LOS and NLOS scenarios.

B. Artificial neural network

Once the database is ready, the system would need a matching algorithm that can study the spatial variation of the channel with respect to the distance, here comes the importance of neural networks. Artificial neural networks (ANN) are computational models able to perform complex computational operations such as classification, control optimization, and function approximation. The advantage of using a neural network is its ability to find the mathematical relation between the set of signatures and the estimated positions. A trained artificial neural network is suitable for real-time applications because it is capable of matching the set of inputs (sets of signatures) to a set of outputs (distances) forming a mathematical model that can estimate new positions based on new signatures [13].

Several types of neural networks are found and can perform different techniques of computations but the main interest among all is to minimize the error and precisely map the set of inputs to the desired output. In the case of localization problems, function approximation is based on non-linear regression modelling. Thus two types of neural networks can be used which are the Multi-Layer Perceptron (MLP) networks and Radial Basis Function (RBF) networks. Both networks are feed forward and perform specific learning algorithms. These algorithms have an important role in adjusting the weights and biases and in minimizing the estimation errors. The use of an MLP-type feed forward neural network with a back-propagation learning algorithm has been proven to give better estimation results in underground localization systems [3],[4].

First, the ANN has to be trained on the set of data collected through measurement campaigns. A neural network is mainly made up of input, output, and hidden layers. Each layer contains several neurons that hold weights and biases. In the offline phase, part of the collected data is used to modify the weights and biases leading to a minimum mean square error. However, initializing the network with random weights and biases would lead to different performances [13], and that is why some training iterations are needed before reaching a desirable performance of the neural network. Once a desired performance is reached, the network can be saved and used to estimate trained and untrained data in real-time scenarios.

III. LOCALIZATION USING ONE RECEIVER

Traditional techniques of localization mainly require two or more reference points in order to precisely estimate the position of the mobile. Geo-location can also be done in the presence of one receiver only using the fingerprinting and the neural networks techniques, and it can give an accurate distance location of 2 meters for 90% and 80% of the trained and untrained patterns, respectively [3]. The neural network used in this work is a feed forward network with a back propagation learning algorithm. It consists of 7 inputs, one hidden layer, and one output. The inputs correspond to the extracted parameters of the CIR while the output is the distance *(d)* to the transmitter as shown in Fig. 2.

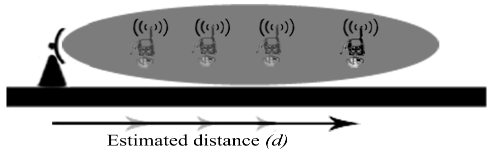

Fig. 2. Localization using one fixed receiver. The CIR is extracted at different distances to the transmitter with 1 meter step size.

The use of one dimensional position estimation is convenient in mine galleries and is later discussed in the following section. The hidden layer consists of 10 neurons and uses a differential tan-sigmoid transfer function unlike the output layer which has a linear type transfer function. The network is trained at several distances away from the transmitter and then the system may estimate the position of the mobile unit (transmitter) based on the received signal. Localization using the CIR in the presence of one receiver is the same technique used in [3] and it is used here as an example of a non-cooperative technique[1]. It was shown that position estimation is precise and that the error is less than 1.5 meters for 90% and 80% of trained and untrained data, respectively.

Despite the fact that the results are promising, there are obstacles that prevent using the same technique in underground environments such as mines due to the following reasons:

- The need of a global localization system that can cover all the areas of interest.
- The existence of junctions and connected tunnels, these tunnels may result in misleading information about the exact position of the mobile user or miner.

On the other hand, using cooperative artificial intelligence in a localization technique is encouraging because it would lead to better estimation results. The estimated distance to the transmitter in LOS might be precise using one reference point, but the position of the miner can be in different directions depending on how much the tunnels are interconnected. For these reasons, using a cooperative technique where at least two receivers are available will introduce localization as a system applicable in mines and would better estimate the position of the mobile user.

IV. COOPERATIVE LOCALIZATION USING TWO RECEIVERS OR MORE

The main interest of deploying a wireless transmission system is to insure constant communications between mobile units and base stations, and this can only be possible if the system is able to provide coverage to the whole area of interest. Localization in the area where signals from two acess points intersect is the main interest of this work. Unlike the first approach in Sec. III which used one signature to estimate the distance, the following techniques will use several signatures of more than one receiver (AP) in order to estimate the same distance taking one receiver as a reference point. This concept will enrich the training set of data that will be fed to the neural network. It is more like collecting multiple fingerprints of the same person which is in our case the distance to the transmitter. If one fingerprint caused a wide error, the others will be there to calibrate the location of the transmitter. Cooperative localization in a 2D/3D topology might involve the participation of more than two access points present in the area of interest. However due to the special one-dimensional topology of mines' galleries, two access points should be enough to provide wireless coverage of the whole area in between.

As shown in Fig. 3, at each position of the transmitter, the two receivers collect the transmitted signal extracting two different sets of parameters (CIRs). This diversity technique opens a wide range of possibilities and helps the neural network exploit a better position estimation model. A full database is saved containing 14 parameters (2 signatures) for each location which is the distance with respect to one

[1]Unlike the system in [3] which uses both x and y coordinates to estimate the position, the proposed system uses a one-dimension estimation concept (x position) neglecting the small variation of y in mine galleries.

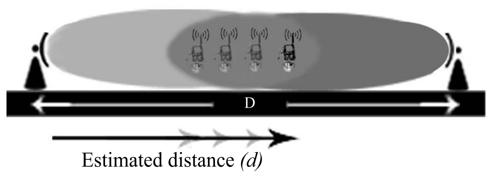

Fig. 3. Localization using two signatures of two receivers in the area where two signals intersect.

receiver. These sets of fingerprints can be treated by different localization techniques.

A. Localization based on separate neural networks

This technique uses two of the same neural network exploited in the case of one receiver as in Sec. III. The system receives the signature of receiver 1 and estimates the distance to the transmitter, and uses the signature of receiver 2 to estimate another distance to the transmitter. Two neural networks are needed as shown in Fig. 4. In this case, the system has to know the exact location of both receivers on a saved digital map of the connected straight lines (tunnels). The new estimated position would be the midpoint of the two estimated locations; localization here is based on averaging both estimation errors.

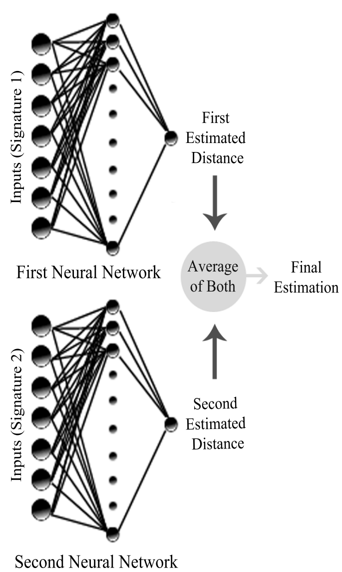

Fig. 4. Localization based on two separate estimations.

B. Localization based on one neural network

In this approach the system collects the signals from both receivers and forms a set of two CIRs with a total of 14 parameters. The transmitter's position is estimated based on the distance to one of the receivers. As shown in Fig. 5, a super neural network is created and trained to localize a mobile with reference to one of the receivers (fixed points or anchors) based on two different signatures. This network trains 75% of the collected data. Several trainings lead to several performances based on the random initialization of the weights and biases. The best performance was achieved with 18 neurons in the hidden layer. In order to test the network's performance, the transmitter is simulated to move across the same path then the system uses the -previously trained- neural network to localize the transmitter based on the two received signals. Usually in most network implementations, access points are placed to cover a wide region and the coverage fields intersect in a handoff region. The length of this region varies from one configuration to another which results in a change in the training set of data (inputs and outputs). In each scenario (i.e., separation distance D in Fig. 3), a new neural network needs to be trained.

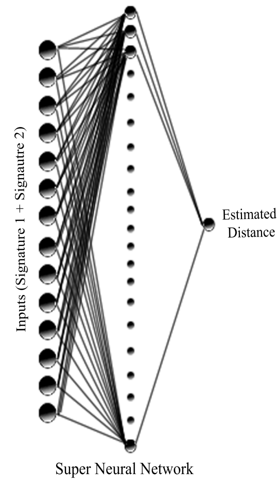

Fig. 5. Neural Network based on multiple signatures.

V. RESULTS OF DIFFERENT TECHNIQUES

The performance of the presented localization techniques will be evaluated using the CDF graph. The first parameter of the CDF is the estimation error which represents the difference between the estimated and the real position measured in meters. The second parameter is the percentage of occurrences for such an estimation error in the collected data. In the following, the coverage of a transmitter is assumed to be 68 meters[2], the results are shown for several distances separating two receivers. Each CDF graph shows four CDF plots of the position estimation errors using different estimation techniques. The first two plots show the results of the localization technique based on receiver 1 and receiver 2. The third plot represents the position errors when using the super neural network, and the last plot shows the results of using the localization technique based on averaging the two separate estimation errors of both receivers. CDF plots of the trained data for separation distances 60m, 80m and 100m are shown in Figs. 6, 7 and 8, respectively.

[2]In real-time measurement scenarios, the transmitted signals fade after this distance resulting in weak signatures.

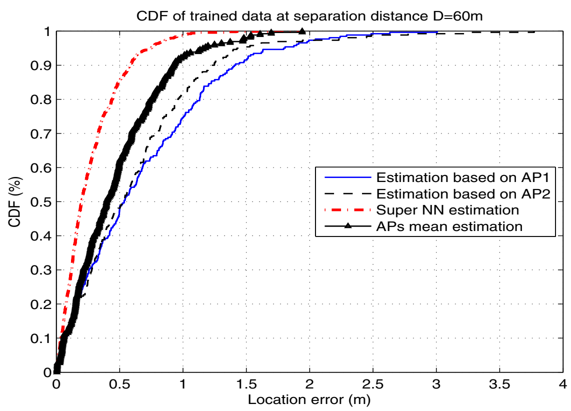

Fig. 6. CDF plots of the position estimation errors at a receivers' separation distance D=60m using several localization techniques.

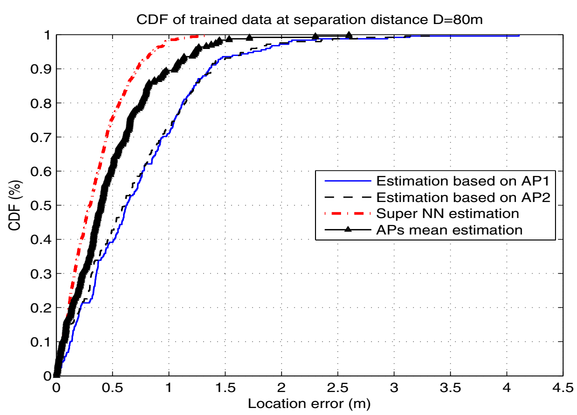

Fig. 7. CDF plots of the position estimation errors at a receivers' separation distance D=80m using several localization techniques.

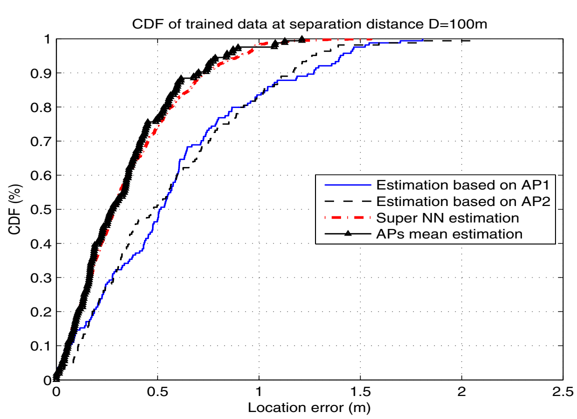

Fig. 8. CDF plots of the position estimation errors at a receivers' separation distance D=100m using several localization techniques.

In the trained set of data, the position error for one receiver estimation technique ranged between 1.2 and 1.5m for 90% of data. The accuracy of position estimation using receiver 1 is slightly different from that of receiver 2 because for each receiver there is a different neural network that trains the collected corresponding set of data. However, it is obvious from the first two CDF plots that the results of using separate neural networks are almost the same no matter if the estimation is based on receiver 1 or 2. On the other hand, the estimation based on averaging the two position errors showed a better performance and it was recorded to be less than 1m for 90% of data. For the super neural network, the performance was recorded to be less than 60 cm for 90% of trained data at close separation distances. When the separation distance increases, the handoff region becomes narrow resulting in a reduced amount of signatures to be trained. This, in fact, has an effect on the training process of the neural networks because training insufficient data results in finding an inaccurate model for localization. The estimation based on averaging shows better accuracy than that of the super neural network at a separation distance of 100m. The reason is that the separate neural networks are trained using the data acquired throughout the whole tunnel while the super neural network is trained using the few signatures in the narrow handoff region. However, due to the fact that the input of the super neural network is a combination of two signatures at the same time, it may be noticed that the super neural network manages to be more precise than the two separate neural networks in most scenarios and it can almost provide the same position accuracy even at far separation distances.

CDF plots of the untrained data for separation distances 60m, 80m and 100m are shown in Figs. 9, 10 and 11, respectively. For the untrained set of signatures, it should

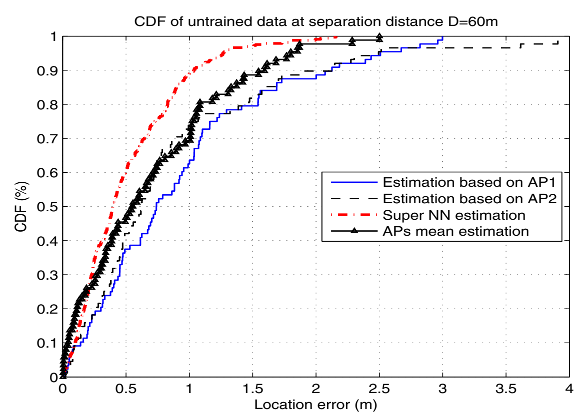

Fig. 9. CDF plots of the position estimation errors at a receivers' separation distance D=60m using several localization techniques.

be noted that data was taken at specific distances between the receivers and that none of the neural networks was trained on the signatures at those distances, i.e. the average was based on two untrained separate estimations. As shown in Figs. 9, 10 and 11, the positioning error of the localization technique

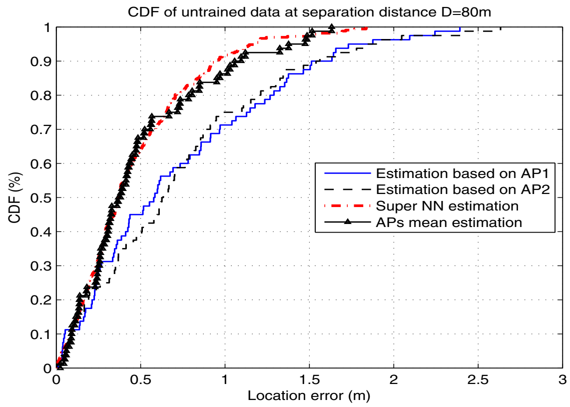

Fig. 10. CDF plots of the position estimation errors at a receivers' separation distance D=80m using several localization techniques.

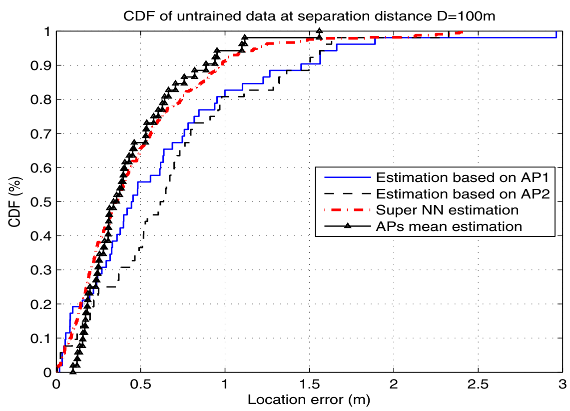

Fig. 11. CDF plots of the position estimation errors at a receivers' separation distance D=100m using several localization techniques.

based on one receiver varies between 1m and 2m for 90% of the untrained data. For the cooperative localization based on averaging, the performance was again dependent on the accuracy of the two neural networks. As shown in Figs. 6 and 9, the results of averaging were precise for the trained data. However, this precision affected the estimation of the untrained data. Using the super neural network, the positioning error was the same for all distances and it gave an error of approximately 1m for 90% of untrained data.

The use of multiple connected neural networks or one super neural network is suitable for indoor localization since both new cooperative localization schemes provide high accuracy, precision and scalability at different separation distances.

VI. Conclusion

This paper studied the results of using the channel impulse responses as fingerprints for position estimation in the presence of different receivers. While other localization techniques fail to be accurate in environments such as mines, this approach is able to estimate the location of personnel and/or equipment with an error of less than 1m for 90% of trained and untrained data. The use of cooperative neural intelligence not only enriches the set of data to be trained but also improves the overall performance of the system and introduces the cooperative localization concept. The diversity of the captured signatures provides rich training sets for the neural networks leading to a more accurate, precise, scalable and robust positioning system.

This system may be designed for remote or self positioning purposes and may use any of the two techniques introduced in the paper. In the first technique, the user collects several signatures from different receivers and uses separate neural networks to estimate the distances to the transmitter. Then, using a saved map that shows the position of each receiver, the system will be able to average the position of the transmitter. In the second technique, the different signatures are fed into a super neural network to provide one position estimation with significantly increased accuracy. This system may be implemented for other indoor environments such as corridors or arcade type indoors. On the other hand, the system can use different wireless technologies such as UWB, WLAN, or mobile radio.

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