Cooperative Localization in Mines Using Fingerprinting and Neural Networks

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ABSTRACT

This work is a special investigation in the localization of users in underground and confined areas such as gold mines. It sheds light on the basic approaches that are used nowadays to estimate the position and track users using wireless technology. Localization or Geo-location 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 suffer 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 the channel impulse response fingerprints with reference to one wireless receiver and using an artificial neural network as the matching algorithm.

In this work we study this approach in a multiple access network where multiple access points are present. The diversity of the collected fingerprints allows us to create artificial neural networks that work separately or cooperatively using the same localization technique. In this approach, the received signals by the mobile at various distances are analysed and several components of each signal are extracted accordingly. The channel impulse response found at each position is unique to the position of the receiver. The parameters extracted from the CIR are the received signal strength, mean excess delay, root mean square, maximum excess delay, the number of multipath components, the total power of the received signal, the power of the first arrival and the delay of the first arrival.

The use of multiple fingerprints from multiple references not only adds diversity to the set of inputs fed to the neural network but it also enhances the overall concept and makes it applicable in a multi-access environment. Localization is analyzed in the presence of two receivers using several position estimation procedures. The results showed that using two CIRs in a cooperative localization technique gives a position accuracy less than or equal to 1m for 90% of both trained and untrained neural networks. Another way of using cooperative intelligence is by using the time domain including tracking, probabilities and previous positions to the localization system. Estimating new positions based on previous positions recorded in history has a great improvement factor on the accuracy of the localization system where it showed an estimation error of less than 50cm for 90% of training data and 65cm for testing data.

The details of those techniques and the estimation errors and graphs are fully presented and they show that using cooperative artificial intelligence in the presence of multiple signatures from different reference points as well as using tracking improves significantly the accuracy, precision, scalability and the overall performance of the localization system.

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Notations and Abbreviations

ANN	Artificial Neural Network
AOA	Angle Of Arrival
AP	Access Point
BP	Back Propagation
CIR	Channel Impulse Response
GPS	Global Positioning System
GRNN	Generalized Regression Neural Network
GSM	Global System for Mobile communication
IFT	Inverse Fourier Transform
LOS	Line Of Sight
MLP	MultiLayer Perceptron
MS	Mobile Station
NLOS	Non Line Of Sight
PDP	Power Delay Profile
PL	Path Loss
RF	Radio Frequency
RMS	Root Mean Square
TDOA	Time Difference Of Arrival
TOA	Time Of Arrival
UWB	Ultra Wide Band
WLAN	Wireless Local Area Network

CHAPTER 1 – INTRODUCTION TO THE THESIS

Telecommunications is one of the fields that are rapidly growing nowadays and its main goal is to provide communication services and data transfer anywhere anytime. Many of those services are wireless and they range from simple remote controls to complex satellite systems. One of the vast numbers of applications of wireless telecommunication systems is position estimation or localization. Outdoor localization systems such as Global Positioning System (GPS) are already in the market and are available to anyone providing an important service that can locate the user's position precisely showing the road names and the direction to take in order to reach any destination within a city or a country. On the other hand, indoor localization is still a controversial topic due to the fact that the signals transmitted indoor undergo several deformations due to reflections and multipath effects caused by the indoor environment. Unlike outdoor mediums where signals travel freely in open-spaces, indoor environments are more complicated channels that need to be modeled in order to estimate how the signal would be received after being reflected, refracted or scattered. The main purpose of this work is to study localization in one special indoor environment which is the mines.

Localization or Geo-location is still one of the major topics under research in mining labs and industries. The position of personnel and/or equipments in areas such as mines is of high importance because it improves the factors of industrial safety and security. Mines have their own nature which is made up of connected tunnels and humid rough surfaces. For that reason, wireless signals transmitted in mines' tunnels would reflect, refract and scatter forming multipath components or simply decay after short distances. Due to that and in the cases where signals can no longer travel due to the presence of interconnected tunnels and non line of sight regions, localization using traditional techniques based on calculating the received signals' strength, angle of arrival, or time of arrival would no longer give a precise estimation of the user's position [3][4]. One of the new approaches to localization in confined areas and mines used the channel impulse response (CIR) as a fingerprint and it proved to give accurate positioning results. The characteristics of wireless signals that define what a CIR is will be covered later.

1.1. Research Problematic:

Localization using the CIR as a fingerprint is one of the accurate solutions that estimate the position of transmission precisely in a mine's gallery. However, research was conducted based on one receiver and is only applicable in a single gallery. Despite the fact that the results are promising, there are several 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 which involves the use of more than one Access Points (AP) or receiver in the whole area 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 where more than one receiver is available is a promising alternative because it leads to better estimation results.

1.2. Objective of the Research

The main objective of this research is to introduce localization in a cooperative technique where more than one receiver shares the responsibility of estimating the position of the transmitted signal underground. This work enhances the previously used method [3] of geo-location and makes it more accurate and precise. The different signals received at different locations add more diversity to the positioning system allowing the neural networks to create good estimation models. The study is performed in both space and time domains, i.e. in space domain, two different receivers in different locations will receive the same transmitted signal to give one position estimation result, while in time domain, the neural networks will record the study the history of fingerprints as a function of time and then localize the position based on two or more fingerprints. Here, the fingerprints of the previous positions play an important role in estimating the new position of the transmitter.

1.3. Research Methodology

Several localization approaches are discussed in the thesis and they are divided under two categories: triangulation and scene analysis techniques. In the triangulation approaches, the same theory is used for both indoor and outdoor systems and it mainly relies on the received signal's components such as the received signal's strength (RSS), angle of arrival (AOA) or time of arrival (TOA); those components are used to calculate the distance to the transmitter. In the second approach, information about the received signals is collected throughout the area of interest and then it is stored in a database. After collecting the data, artificial neural networks are presented as the matching algorithms that can be trained to form a specific model of localization in that special environment. Those estimations can be made based one transmitter or in a cooperative manner where two or more transmitters are used. The details of those techniques and the estimation errors are fully presented in the chapters that follow.

In the following, we present a specific localization approach based on the multiple impulse-response fingerprinting combined with neural networks in a multi-access environment. In this approach, the received signals by the mobile at various distances are analysed and several components of each signal are extracted accordingly. The channel impulse response found at each position gives a precise uniqueness to that position and forms a signature or a fingerprint at a specific distance from the transmitter. One signature is a collection of extracted parameters which are the RSS, mean excess delay, root mean square, maximum excess delay, the number of multipath components, the total power of the received signal, the power of the first arrival, and the delay of the first arrival.

1.4. Structure of the thesis

In the second chapter, a survey of wireless localization techniques shows the modern localization systems and methodologies. This will discuss the basic methods and parameters used in localization system and their respective performance in indoor environments.

In chapter three, a short investigation of wireless signals characteristics will be conducted which leads to identifying essential parameters used in most localization systems. This chapter will discuss the choice of the fingerprinting technique and neural networks as a technique used in geolocation in mines highlighting its major advantages and drawbacks.

Chapter four will introduce the cooperative localization system used in this work including the algorithms and neural network architectures. In this chapter, position estimation is discussed in a cooperative manner where two or more receivers get involved in collecting the fingerprints of a transmitter, then they feed these fingerprints to the artificial neural networks which handle position estimation using different techniques. The results of all techniques and methodologies are presented afterwards using multiple neural networks and testing all the data, the techniques of localization are compared together and analyzed in different graphs.

Chapter five introduces the concept of tracking based on the adding the previous positions of the miners as parameters that contribute in estimating the current position. The theory of tracking and the random walk model are fully discussed and tested. The results of localization using tracking are interpreted at the end of the chapter.

Finally, a conclusion is drawn out in chapter six showing the advantages of the different techniques that were introduced to the localization system and the major future challenges these techniques encounter.

CHAPTER 2 – INTRODUCTION TO LOCALIZATION

2.1. An Overview of localization

Localization, position estimation and geo-location are all synonyms used in wireless networks and they hold the same concept which is the estimation of the position or location of a mobile user based on the wireless transmission of electromagnetic signals. Localization was recently used in a variety of applications and services that are both commercial and military. These services may be essential for outdoor purposes such as the detection of emergency calls, fraud and the management of traffic, at the same time, several applications involve indoor localization used for home automation, tracking of fire-fighters and miners, patient monitoring and intruder detection [1].

Geo-location is a process where the system locates the position of the person or/and equipment based on the wireless transmission between terminals. Based on that, we can distinguish several types of positioning algorithms. For example if the mobile user is the one that receives the signals and based on that information it localizes itself, the system would be a self-positioning system. On the other hand, if the base stations were the nodes that localize a mobile unit, this would be a remote system. Due to the fact that wireless transmission travel between both nodes most of the times, some systems use the indirect positioning algorithms that allow one node to estimate the location of the mobile and then send the information back to the other node. These systems are called indirect and they may be indirect remote systems where a mobile localizes itself and informs the base station of its position. On the other hand, the system may be indirect self positioning, where the remote localizes the mobile unit and sends its location to that unit using data transfer.

In order to estimate the source of a wireless transmission, several techniques are used and will be discussed in the literature. The first key point to localization is to understand the characteristics of wireless communications and electromagnetic signals travelling between the transmitter and the receiver. These singles carry information and hold certain characteristics such as frequency, power, phase, etc ... so each wireless signal may have its own power, frequency and phase once it was transmitted. However, those parameters may change at the receiver's level after being affected by the transmission medium or what is called the channel of communication. For example, the power of any wireless transmitted signal decreases once the distance increases causing the signal to fade. The frequency of a transmitted signal may be altered if the receiver is at a speed travelling towards or away from the transmitter. To make it simple, our minds are able to localize someone calling us at a distance away from us by using the frequency of that person, direction of arrival of his/her voice and amplitude. In wireless communications the concept is the same, once a signal is received; several parameters are extracted and compared to the original signal transmitted. Then several algorithms and techniques may be used in order to estimate the position of transmission.

2.2. The Triangulation Algorithms

Most of the algorithms used in localization follow the triangulation technique. The concept of the triangulation technique is based on collecting information from at least three reference points and then estimating the position of the user in an area of intersection. Several algorithms are present and depend on parameters extracted from the received signals. These parameters classify the type of the triangulation technique, for example using the received signal's strength or the time of arrival as a parameter to estimate the position of the transmitter is categorized under the lateration techniques whereas using the angle of arrival as a parameter for position estimation classifies the technique as angulations technique. A detailed discussion about each kind is presented along with the difficulties each algorithm faces in different environments.

2.2.1. Lateration Technique

The main purpose of geo-location is to find the distance that separates the transmitter from the receiver(s). Here, the medium or environment plays an important role in defining which technique to use. In a lateration technique, at least three reference points are required to localize a transmitter. The number of reference points needed depend on whether localization is two or three dimensional. The following techniques summarize the major localization concept.

2.2.1.1. TECHNIQUE BASED ON THE RECEIVED SIGNAL'S STRENGTH:

Signals transmitted through an open space or specific channels are subject to energy loss on the way to the receiver. One of the methods of calculating the distance to the receiver is by analyzing how much energy the signal has lost on its way to the receiver. Knowing some specifications about the transmitted signals such as the power, the frequency of transmission and the antenna gains allows us to calculate the distance traveled by the signals before reaching the receiver and this allows estimating the position of the transmitter unit.

In the case of free space, the Free Space Path Loss (FSPL) is a simple example that is modeled using simple mathematical equations. An example of localizing a transmitter in a free space channel may be helpful to understand the basic concept of localization using the received signal's strength. For instance, after transmitting a wireless signal in free space with initial power (P_T) the power of the received signal (P_R) at a specific distance d away from the transmitter is given by:

$$P_R = \frac{P_T G_T}{4\pi d^2} A = \frac{\lambda^2}{(4\pi d)^2} G_T P_T G_R. \qquad (2.1)$$

where P_R is the received signal's strength measured in dB, P_T is the transmitted signal's strength, G_T and G_R are the antennas gains at the transmitter and the receiver respectively. λ is the wavelength related to the central frequency of the wireless transmitted signal, and d is the distance separating the transmitter and the receiver.

The distance d which is the main parameter used for position estimation is inversely proportional to the received signal's strength, and it can be derived from equation (2.1) given the other parameters. In a free space model where wireless signals travel freely without being reflected or attenuated, the path loss can be easily calculated using the following equation:

$$\mathrm{FSPL} = \left(\frac{4\pi d}{\lambda}\right)^2 = \left(\frac{4\pi df}{c}\right)^2. \tag{2.2}$$

This can be rewritten in dB as:

$$\mathrm{FSPL} = 10\log_{10}\left(\left(\frac{4\pi d}{\lambda}\right)^2\right) \tag{2.3}$$

$$= 20\log_{10}\left(\frac{4\pi df}{c}\right) \tag{2.4}$$

$$= \ 20\log_{10}(d) + \ 20\log_{10}(f) - 147.55. \tag{2.5}$$

However, some channel models are more complicated such as indoor and confined areas where the signals are attenuated by other factors like reflection, refraction, scattering, etc… These factors change when altering the medium where the wireless transmission is taking place. Unlike free space models where the distance and frequency are the main factors of path loss, in different channel models (like indoor models) the path loss is also dependent on the channel's response to wireless signals. Thus, in each medium, several factors affect the transmitted signals such as reflection, refraction, small and large scale fading, shadowing, etc … In these cases, equation (2.5) no longer calculates the real path loss of a transmitted signal and a more generalized equation can be written as follows:

$$P_{R-d}(dB) = P_T(dB) - P_{e-d}(dB) + G_T(dB) + G_R(dB). \quad (2.6)$$

where P_{R-d} is the received signal's strength at a distance d away from the transmitter, and P_T is the transmitted signal's strength. G_T and G_R are the gains of the antennas at the transmitter and at the receiver, respectively. P_{e-d} is the distance function and it is of the following form:

$$P_{e-d}(dB) = P_{e-d_0}(dB) + 10n\log\left(\frac{d}{d_0}\right) + X. \quad (2.7)$$

where P_{e-d_0} is the loss measured for a distance d_0 which is taken as 1 meter, n is the attenuation coefficient and X is a random variable depending on the nature of the channel. Replacing this equation in equation 2.6 leads us to the following equation:

$$P_{R-d}(dB) = P_T(dB) - P_{e-d_0}(dB) - 10n\log\left(\frac{d}{d_0}\right) - X + G_T(dB) + G_R(dB). \quad (2.8)$$

Equation 2.8 gives the PL including the factors that are affected by the channel, as well as other parameters represent the specifications of the transmission such as the gains of the antennas at both the transmitter and receiver. Another formula is given in [15] as follows:

$$P_{d_i} = P_t\left(\frac{c}{4\pi f_0 d_0}\right)^2 \left(\frac{d_0}{d}\right)^\alpha \left(\frac{f_0}{f}\right)^\beta + e_i. \quad (2.9)$$

$$2 \le \alpha = \beta \le 4$$

In Free Space $\alpha=\beta=2$, and the values of f_0 and d_0 represent a specific frequency and distance taken as a reference while e_i is a variable used to model the transmission power.

In a 2D scenario, the estimated distance represents a radius of a circle where the transmitter lies. Thus three reference points or receivers are needed in this technique and the estimated position would be located at the intersection point of the three circles as shown in figure 2.1. Due to the fact that the transmitted signals are made up of multipath components and non line of sight regions, the estimated distance does not represent the real distance that separates the BS from the MS. The error that is produced by three different references forms an error region which is the area where the three circles intersect.

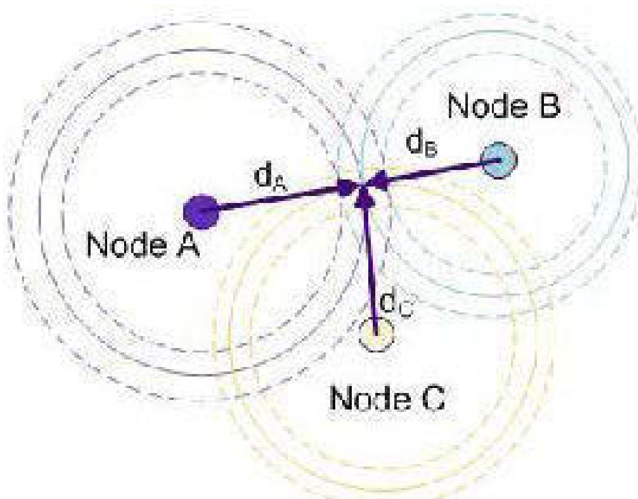

Figure 2-1. Position estimation using three RSS measurements from nodes A, B and C.

The use of direct measurement of the distance from the RSS cannot be reliable because it mainly depends on the path loss model that has been considered. It also may depend on the channel characteristics, thus RSS-based positioning techniques are sensitive to the variations of the channel. In fact, due to the severe multipath fading and shadowing present in the indoor environment, path-loss models do not always hold. In our case of study which is the mines and underground environments, the use of this technique is not convenient due to the presence of connected tunnels that guide the transmitted signals and forces the multipath components to use a direction of transmission after bumping into the walls of the tunnel. It is also shown in [13] that the accuracy of an RSS-based positioning system deteriorates once the distance between the reference points increases.

2.2.1.2. TECHNIQUE BASED ON THE TIME OF ARRIVAL (TOA):

Localization using the time of arrival of a transmitted signal is an accurate technique that relies on the fact that the distance from the mobile target to the measuring unit is directly proportional to the propagation time. The concept of this technique is to calculate the time needed for a wireless transmitted signal to reach each of the three measuring reference points as shown in Fig. 2.2. This is only possible if the receivers are precisely synchronized or if they are exchanging timing information using certain protocols such as a two-way ranging protocols [19], [20], [21].

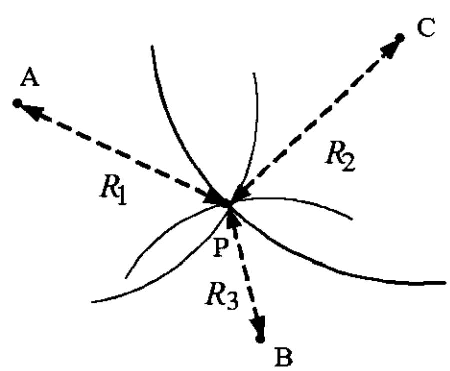

Figure 2-2 Localization based on the TOA

Different techniques are used to measure the TOA such as direct sequence spread-spectrum [16][17] or ultra wide band (UWB) measurements [4], [18]. Once the one way time is measured, the distance between the transmitter and the receiver is calculated. A straightforward approach uses a geometric method to compute the intersection points of the circles of TOA as presented earlier in the case of the RSS. The position of the target can also be computed by minimizing the sum of squares of a nonlinear cost function, i.e., least-squares algorithm [22], [23]. It assumes that the mobile terminal, located at (x_0, y_0), transmits a signal at time t_0, the N base stations located at (x_1, y_1), (x_2, y_2), . . . ,(x_N , y_N) receive the signal at time t_1, t_2, . . . , t_N . As a performance measure, the cost function can be formed by:

$$F(x) = \sum_{i=1}^{N} \alpha_i^2 f_i^2(x). \tag{2.10}$$

where α_i can be chosen to reflect the reliability of the signal received at the measuring unit i, and $f_i(x)$ is given as follows:

$$\mathrm{f_i(x) = c(t_i - t) - \sqrt{(x_i - x)^2 + (y_i - y)^2}}. \tag{2.11}$$

where c is the speed of light, and $x = (x, y, t)^T$. This function is formed for each measuring unit, $i = 1, \ldots, N$, and $f_i(x)$ could be made zero with the proper choice of x, y, and t. The location estimate is determined by minimizing the function $F(x)$.

However, in real time scenarios and in indoor environments, multipath components arrive at the receiver resulting in different time stamps. In such multipath environments, accurate TOA estimation requires high-resolution time delay estimation techniques. Another difficulty that faces the use of this technique is in the areas where there is no direct line of sight. In the cases of non line of sight (NLOS), the received signal is not necessarily that of the direct path. This results in misleading information about the real distance that separates the transmitter from the receiver.

2.2.1.3. TECHNIQUE BASED ON THE TIME DIFFERANCE OF ARRIVAL (TDOA):

Position estimation using TDOA depends on the difference in time at which the signal arrives at multiple measuring units. Since this technique is a triangulation technique, three reference nodes must be present in order to localize the transmitter. The base stations receiving the transmitted signal must be synchronized in order to precisely calculate the time difference of arrival at each base station. Correlation techniques are used to compute the TDOA estimates. Suppose that the received signal at a receiver *i* is $x_i(t) = s(t - d_i) + n_i(t)$ where $s(t)$ is the transmitted signal, d_i and n_i are the delay and noise at receiver *i*, respectively. Similarly, at receiver *j*, the received signal is $x_j(t) = s(t - d_j) + n_j(t)$. The cross-correlation function of the two signals is calculated after integrating the lag product of the two received signals over a time period *T* to give:

$$\hat{R}_{x_i, x_j}(\tau) = \frac{1}{T}\int_0^T x_i(t)x_j(t-\tau)\,dt. \tag{2.12}$$

The TDOA estimate is the value *t* that maximizes $\hat{R}_{x_i, x_j}(\tau)$. Given the case where there are three base stations A, B, and C with three TOA distances R_1, R_2, and R_3, each TDOA parameter determines a hyperbola for the position of the transmitter (*P*) as shown in Fig. 2.3.

The transmitter must lie on a hyperboloid with a constant range difference between at least two of the receivers. The equation of the hyperboloid is as follows:

$$R_{i,j} = \sqrt{(x_i - x)^2 + (y_i - y)^2 + (z_i - z)^2} - \sqrt{(x_j - x)^2 + (y_j - y)^2 + (z_j - z)^2}\,. \tag{2.13}$$

where (x_i, y_i, z_i) and (x_j, y_j, z_j) are the coordinates of the fixed receivers i and j respectively, and (x, y, z) is the position of the transmitter [24]. In a 2D scenario, two hyperbolas are formed from TDOA measurements taken from the receivers A, B and C. The intersection of the two hyperbolas allocates the position of the transmitter P. The solution of the hyperbolic equation can be conducted through nonlinear regression. It can also be solved using the Taylor-series expansion creating an iterative algorithm as shown in [25].

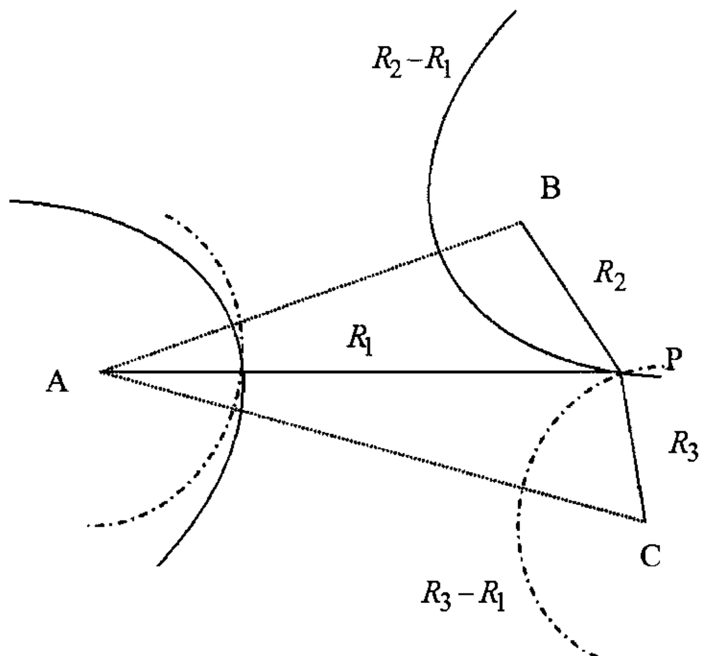

Figure 2-3 Localization based on TDOA measurements

Time synchronization must be performed between the base stations only unlike the TOA technique where synchronization involves the transmitter too. Nevertheless, some other methods were proposed for the 802.11 wireless LANs which eliminates the need of synchronization even between the base stations [17].

2.2.2. Angulation technique based on the Angle of Arrival:

In order to localize a transmitter based on the angle of arrival (AOA) in a 2D scenario, at least two receivers should be present at a known separation distance. The transmitted signals from the mobile device are detected using directional antennas or an array of antennas that are able to measure the angles of arrival at each receiver. In a simple 2D scenario as shown in Fig.2.4, suppose that the transmitter is located at point P and the two receivers are located at points A and B. The receivers measure the angles of arrival of the transmitted signals. The position of the transmitter (P) is estimated based on the intersection point of the two lines formed by the AOAs θ_1 and θ_2.

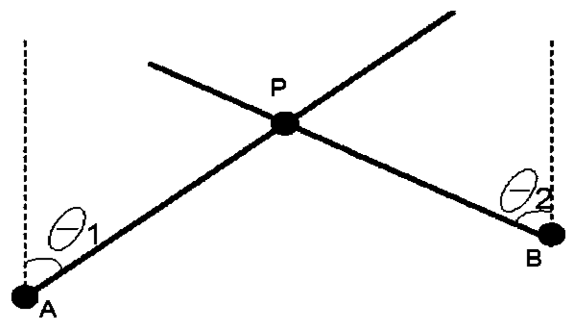

Figure 2-4 Localization based on the AOA

This method needs no synchronization but it requires more expensive antennas that need to be accurate in measuring the AOA. The precision of this localization technique depends on the environment and material used.

Localization based on the AOA is more applicable in open-space and in outdoor scenarios because the transmitted signals travel using the same path towards the receiver. However, in indoor scenarios signals are reflected and multipath components are formed. In the case of a reflected signal, the angle of arrival no longer represents the angle from which the signal was transmitted. These scattered signals arrive from different angles causing position estimation errors about the real position of the transmitter. The accuracy of this technique also depends on the precision of the antenna in detecting the AOA because a small variation of the angle may cause a wide distance error.

2.3. Scene analysis or Fingerprinting

The fingerprinting technique is based on conducting a study campaign on the medium or environment where the localization system will work. This study collects information about how the transmitted signals are received at different positions away from the transmitter. At each position, the desired parameters of the received signals are extracted then they are saved in a database as signatures or fingerprints for their specific distances. Once the study is conducted for all the area of interest, the measurement campaign is over and the system would need a matching algorithm in order to find a relationship between the set of fingerprints and their corresponding positions. In the online stage, this matching algorithm uses the currently observed signal and previously collected information to figure out an estimated position of the transmitter.

The fingerprinting technique is mostly used in the scenarios where the channels cannot be easily modeled due to the distortions that the signals encounter before reaching a specific position. In an indoor environment, for example, the signals are reflected several times before reaching a measuring unit which weakens the signal and causes the RSS to decrease. The same thing applies for the other parameters such as AOA, TOA, or TDOA. Simple mathematical models will no longer hold for such scenarios, and a special investigation may be performed for such a channel using the fingerprinting technique. The main challenge facing this technique is its ability to match different recorded parameters at different positions and create a new mathematical model that can estimate any new received signal with low distance error. Several matching algorithms are present and used in the field of scene analysis such as probabilistic methods, *k*-nearest-neighbor (*k*NN), artificial neural networks, support vector machine (SVM), and smallest M-vertex polygon (SMP). A summary of each technique is presented below:

2.3.1. Probabilistic Methods

The probabilistic method is one of the algorithms that deal with position estimation as a classification problem. Considering that there are several locations $L_1, L_2, L_3 \ldots L_n$, and p is the observed signal vector holding information about the RSS, AOA and/or TOA of the received signal, a position is estimated based on the highest probability of the signal's vector as follows:

$$\text{Choose Li if } P(Li\backslash p) > P(Lj\backslash p) \text{for } i,j = 1,2,3\, ..n \text{ and } i \neq j. \quad (2.14$$

Here $P(L_i \backslash p)$ is the probability that a signal vector p is at a location L_i. Given that the signal vectors are recorded for all the locations in the area interest, once a signal is received the vector p is extracted and classified giving the location with the highest probability. Another method uses the Bayes' formula assuming that $P(L_i) = P(L_j)$, the decision rule becomes:

$$\text{Choose Li if } P(p\backslash L_i) > P(p\backslash L_j) \text{for } i,j = 1,2,3\, ..n \text{ and } i \neq j. \quad (2.15$$

$P(p\backslash L_i)$ is the probability that the signal vector p is received given that the mobile node is located at L_i.

Unlike the histogram approaches discussed above, other methods use the kernel approach assuming that the likelihood of each location has a Gaussian distribution with a calculated mean and standard deviation. If we consider that the measuring units in the medium are independent, we may calculate the overall likelihood of a location by directly multiplying the likelihoods of all measuring units. The estimated 2D location $(\hat{x}, \hat{y})$ may interpolate the position coordinates and give more accurate results. It is a weighted average of the coordinates of all sampling location and it is of the form:

$$(\hat{x},\hat{y}) = \sum_{i=1}^{n}\left(P(L_i|p)\left(x_{L_i},y_{L_i}\right)\right) \; . \qquad (2.16$$

Probabilistic methods also include issues such as memory, history and calibration where learning and assisted tracking takes place. This helps the localization system to be "smarter" avoiding any illogical estimation caused by mathematical errors.

2.3.2. K-Nearest-Neighbor (kNN)

Another way of matching the received signal to the set of signatures saved in the database is based on the kNN. This technique searches for the k (positive integer) closest matches or candidates in the saved set of measurements according to the root mean square principle. These nearest neighbors are averaged by adopting the distances in the signal space as weights and the technique is called weighted kNN. The weights w_i are proportional normalized distances of the nearest neighborhood vectors as:

$$w_i = \frac{\left(\frac{1}{d_i}\right)}{\sum_{i=1}^{k}\left(\frac{1}{d_i}\right)} \;\; , \;\; i = 1,2,3,\ldots k \; ; \qquad (2.17$$

$$\sum_{i=1}^{n} w_i = 1 \; ; \qquad (2.18$$

where d_i is a distance to the i^{th} neighborhood vector, and k is the number of nearest neighbors. The sum of all weights equals to one in order to ensure that the nearest neighbors in the vector space get weighted more heavily. In a 2D space, the estimated location is then calculated using a vector location $L(x,y)$ as follows:

$$(x, y) = \sum_{i=1}^{n} (w_i * p_i) \quad (2.19$$

where $p_i = (x_i, y_i)$ is the location of the nearest neighborhood vector.

2.3.3. Artificial Neural Networks (ANNs)

Artificial neural networks are defined as computational models capable of approximating a function. Each neural network is made up of three layers, the input, hidden, and output layer. The main role of the ANN is to model the mathematical relations between the set of inputs and outputs that are under study. As shown in Fig. 2.5, each layer consists of neurons that are connected through weights and biases. In the case of localization; the input layer would consist of a set of parameters extracted from the received signals such as the RSS, TOA, TDOA and/or the AOA, while the output is mostly the coordinates of the transmitter or the distances separating the transmitter from the measuring units.

Two phases are needed in every neural network technique; the first is the training phase while the second is the recall phase. In the training phase, the weights and biases are adjusted between the neurons in order to model the mathematical relationship between the set of inputs and outputs. After a specific number of iterations or when the performance reaches a desired value, the training phase stops saving the weights and biases at specific values. The neural network would be ready to perform the second phase which is the estimation of any input as a result of the computed model. The difference between the real value of the output and the estimated value is the estimation error.

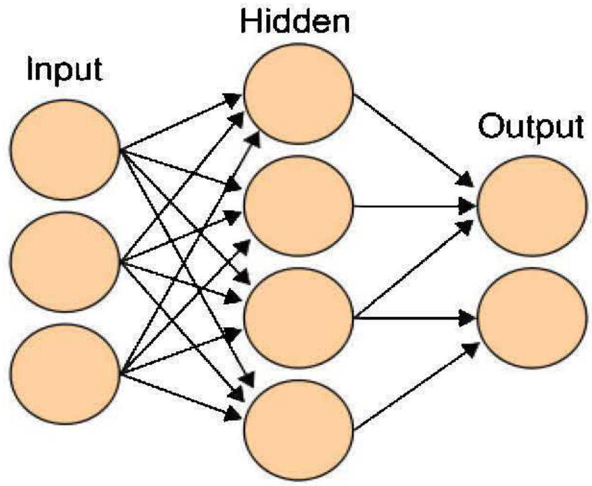

Figure 2-5 Sample Neural Network

Localization problems need nonlinear regression models, and there are two types of neural networks that perform non linear regressions. The first is the multilayer perceptron (MLP) which represents the most prominent and well researched class of ANNs in classification, implementing a feedforward, supervised and hetero-associative paradigm. The second is the radial basis function (RBF) network which is also a multi-layer network that can be used for function approximation and classification, but it works in a significantly different way. In perceptron-type networks, the activation of hidden units is based on the dot product between the input vector and a weight vector. While in RBF networks, the activation of hidden units are based on the distance between the input vector and a prototype vector.

Measurement campaigns are always needed for such a technique in order to collect the fingerprints to be used for the training process. The merit of using neural networks is its ability to predict positions that are not introduced to the network before, which makes the localization system more flexible with the simple variations of the signature values.

2.3.4. Support vector machine (SVM) and Smallest M-Vertex Polygon (SMP)

Support vector machine (SVM) is a new technique that uses the statistical approach and machine learning algorithms for the purpose of classification and data regression. It is widely discussed in [26] and [27] and it has been proposed for localization using the fingerprinting technique. Support vector classification (SVC) is used to classify the location of the user between several locations based on the extracted parameters of the received signal. Other techniques use the support vector regression (SVR) which have been successful in position estimation using fingerprinting [28][29].

On the other hand, the Smallest M-Vertex Polygon (SMP) uses several measuring units in order to estimate the position of the transmitter. After estimating several locations at each receiver, one candidate is taken for each node forming vertices in the shape of a polygon. M is considered to be the number of candidates whose coordinates are averaged in order to estimate the location of the transmitter [30].

2.4. Modern Localization Systems

So far, we have discussed major localization techniques and algorithms that are proposed or used in the localization theory. In real time applications and products in the market, one can find different systems designed using different positioning techniques. There are advantages and disadvantages for each type of design based on its performance and compatibility with the medium where it functions. Before listing different systems, we will discuss a pattern of comparison by studying the major factors that increase or decrease the performance of each system.

2.4.1. Fundamentals of localization systems

For every localization system there are several measures to consider before using the system for any outdoor or indoor application [31]. The performance of a positioning system depends on several factors such as accuracy, precision, scalability, complexity, robustness, and cost.

2.4.1.1. ACCURACY

Accuracy is the most important factor of a positioning system. It is usually defined as the location or position error. It is the difference between the estimated location and the real location of the transmitter. In some applications such as military positioning systems, accuracy is the most important factor and it can be traded for complexity and cost, whereas in commercial positioning systems, accuracy and cost must balance in order to attract the attention of a consumer.

2.4.1.2. PRECISION

The positioning system may be accurate but not all the time, this defines how precise the system is. Precision considers how consistently the system works in different scenarios and given different measurements and types of data. The accuracy of a positioning system may hold for a typical set of data. However, different accuracies may be recorded for other measurements at different positions. A study can be made to measure both the accuracy and precision of the system using the Cumulative Density Function (CDF) plot, which defines the probability that a system holds for a given accuracy.

2.4.1.3. COMPLEXITY

The complexity of the positioning system involves factors like computation time, memory, hardware structure, software design, energy consumption, and implementation. If the localization system is installed at the mobile unit, the factors of memory and battery life are to be considered in addition to the processing speed. Other localization systems may be perfect but lack the simplicity factor of software and hardware design. Complexity is mostly imposed with high accuracy and precision of positioning systems.

2.4.1.4. ROBUSTNESS

In real time scenarios, signals transmitted sometimes fade or scatter forming new sets of signatures, the more robust the localization system is, the more capable it is to predict these variations in the time and space domain. Robustness is the ability to keep the system stable once the received information is corrupted. A robust system is capable of overcoming factors such as reflections, distortions and instability of wireless communications.

2.4.1.5.SCALABILITY

Scalability is an important factor to consider in localization techniques. The system is considered scalable in space once the variation of the distance separating the transmitter and receiver has no effect on the position estimation. In crowded areas where there are several transmitters to be localized, system's scalability may be measured based on its ability to localize several units throughout the whole 1D, 2D or 3D space.

2.4.1.6. COST

The cost of the localization system depends on the complexity of its hardware and software designs, it also depends on the integration factor and time compensation. By integration we mean whether the system can be built using a ready infrastructure or whether it needs a new communications infrastructure. The time the system needs to be implemented increases the cost and so does the complication in hardware design. The margin of acceptable price of a localization system depends on whether the system is used by armies or individuals and whether the system is worth paying for or not.

2.4.2. Examples of modern positioning systems

The localization systems present nowadays are both for outdoor and indoor applications. On the same hand, we can differentiate between two different types of localization systems depending on whether the system works separately or combined with an existing technology. Systems that work separately need their infrastructure and their main application is to localize the mobile unit or transmitter using special hardware and software solutions. From those systems we can mention the GPS which needs at least three synchronized satellite systems in order to localize a 2D position and four satellites to localize a 3D position. Other types of systems rely on existing technologies such WLAN, UWB, or Bluetooth. In the following some indoor localization systems are presented shedding the light on the algorithms of localization they use and their major performance attributes.

2.4.2.1. GPS- BASED

The most successful positioning system used for outdoor applications is the Global Positioning System (GPS) [32]. The main concept of GPS is the use of up to four satellite systems which are time synchronized. These satellites transmit signals at the same time to earth; these signals are received by a measuring unit that uses the time information to localize itself. Based on that technology, several companies started other localization systems in order to cover indoor environments too and increase the accuracy of GPS in indoor applications.

SnapTrack is one system; it is an assisted GPS (A-GPS) system that provides 5 to 50 meters accuracy in indoor environments. The concept of this technique is to use a location server with a reference GPS receiver that detects the satellite signals at the same time as the wireless mobile unit. The mobile unit collects both the satellite and location server signals in order to produce a position estimation.

Atmel and U-blox announced a new technology called SuperSense using a GPS software for indoor positioning. Another system was also produced by *Locata Corporation* and it was called *Locata*. This technology is based on the time-synchronized pseudolite transceiver called a LocataLite [33]. Using *Locata*, GPS-like signals are transmitted and used for position estimation based on the carrier-phase measurements.

2.4.2.2. RFID BASED

RFID is a technology based on transmission and reception of electromagnetic signals in order to retrieve certain information. An RFID system is made up of three major components which are the RFID tags, RFID receivers, and the RFID communication that connects the tags to the receivers [34]. The tags are supposed to emit data which is received by the RFID receivers through a communication link that is governed by a specific radio frequency and a defined protocol of communication. RFID tags may be active or passive. Passive tags are lighter and less complicated than active tags. They can operate without a battery and their major goal is to reflect the signals transmitted from the RFID receiver after adding information to that signal by modulating it. The range of passive tags is limited to 1 or 2 meters and a good example of such systems are the RFID passive tags manufactured by Bewator.

On the other hand, active tags are more advanced because of their ability to transmit signals up to tens of meters (usually they transmit their IDs). They are ideally suited for the identification of high-unit-value products moving in a harsh assembly process. One known manufacturer of Active RFID is WaveTrend Technologies and one of the known position sensing systems that use this technology is SpotON [35]. SpotON depends on the RSS in order to estimate the distance to the tags.

Another system that uses the RFID technology is LANDMARC [36]. This system also relies on the RSS from the tags and uses the kNN algorithm in order to estimate the position.

2.4.2.3. CELLULAR-BASED

In cellular networks such as GSM or CDMA, the position of the users is an important measure used for detecting fraud and emergency calls. Some systems base their estimation on the cell ID where the client is connected, but this technique remains inaccurate and dependant on the area of the cell itself and the error ranges between 50 to 200m [37].

Some work has been presented for indoor localization purposes using the GSM network and it uses the fingerprinting technique combined with the kNN matching technique [38]. The idea of this localization solution is to use the wide signal's strength from multiple base stations covering the area and different channels. These measurements form signatures that are matched using the kNN in order to estimate the position of the mobile phone with an accuracy as low as 2.5 meters [38]. Nevertheless, this technique is considered inaccurate in places where there is lack of coverage from different base stations at the same time.

2.4.2.4. ULTRA WIDE BAND (UWB)

Ultra wide band technology is one of the growing domains due to its special characteristic over the communication channels. UWB works by sending short pulses with low duty cycle over a wide band (even greater than 500Mhz). This technology has important advantages ranging from its low power consumption to its great propagation abilities. UWB tags need less duration to be transmitted than RFID tags and can operate across a board area of the radio spectrum. UWB is considered suitable for indoor environments due to the fact that the received signals may be easily filtered excluding the multipath components.

Some systems use UWB for indoor localization such as the Ubisense system which is a unidirectional UWB location platform with a conventional bidirectional time division multiple access (TDMA) control channel. This system works by creating sensor cells where each cell needs at least four sensors. The sensors use the TDOA combined with the AOA techniques in order to locate the tags that transmit the UWB signals. Another system is used in Siemens local position radar (LPR), it uses the frequency modulated continuous wave radar principle (FMCW) which relies on the received time-of-flight (RTOF).

2.4.2.5. WIRELESS LAN (WLAN IEEE 802.11)

WLANs are the most growing communication networks in industries and enterprises. In the last couple of years, almost most applications including data transfer, communications, networking and voice applications were developed using the IEEE 802.11 standards. For that purpose, localization systems working under such standards would attract the attention of many people that would prefer to use the IEEE 802.11 infrastructure instead of installing a new one. The positioning systems that use the WLAN use the RSS as a parameter to build on and record an accuracy of 3 to 30m.

One of the systems was proposed by *Bahl et al* for in-building user location and tracking system-RADAR using the kNN in signal-space technique. The accuracy of the RADAR system is about 2-3meters and it has two approaches. The first works on the empirical measurements of access point signal strength in offline phase while the second uses the signal propagation modeling.

Another system is called the Horus system and it is discussed in [39] [40]. This system uses the probabilistic method with an accuracy of 2.1m for more than 90% of precision. Other systems use the neural network techniques with fingerprinting in order to estimate the position of the transmitter and report an error of less than 3 meters for 90% of precision [3]. One uses UWB technology [4] while others develop a grid-based Bayesian location sensing system [41].

There are several other localization systems that were designed to work under the WLAN technologies and it would be useful to check [42]-[55] for more approaches and designs.

2.4.2.6. BLUETOOTH

Bluetooth is a wireless technology based on the 2.4 GHz ISM band with a bit rate around 1Mbps and a typical range between 10 to 15 meters. Some localization systems used this technology to launch their approaches and designs such as Topaz local positioning solution which is based on Tadlys' Bluetooth infrastructure and accessory products. This system provides local accuracy of 2 meters for 95% of precision. Another system is proposed in [56] as the Bluetooth Local Positioning Application (BLPA). This system uses a simple propagation model and Kalman filter to compute a 3D position estimate with a 3.76m distance error.

These are some of many localization systems and approaches present in the literature and in modern research laboratories. These systems along with their performance factors are summarized in Appendix B by referring to [1, Table 1].

CHAPTER 3 – LOCALIZATION IN MINES USING FINGERPRINTING AND NEURAL NETWORKS

Localization using 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 [8], [10], [11]. It is similar by analogy to the human fingerprints and it is used here to ensure uniqueness and precision to the indoor channel behaviour present in mines. In this work, the fingerprinting technique is used to identify a position based on the channel impulse response (CIR). This technique consists of two phases: the offline phase which is the process of collecting several parameters from the 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 parameters are extracted from the CIR 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 (discussed below) at a specific distance to the transmitter. The characteristics of the channel and the way to extract those seven parameters out of the received signals are fully presented below. In the second part of this chapter, the principle of using those fingerprints with the neural network technique is discussed and analyzed shedding the light on the major merits and drawback this technique may encounter when used in underground environments such as mines

3.1. Fingerprinting and Wireless Signals

When a signal is transmitted wirelessly through a medium, it is affected by the nature of the environment where propagation is taking place. For wireless signals transmitted in underground mines, the signals are reflected and scattered several times before being received, and these reflections create multiple copies of the same signal with different phase shifts and time delays. Multiple copies of the same signal are called the multipath components of that signal. So practically, at the receiver's end, one can record multiple versions of the same signal with different variations (or distortions) of its original characteristics. The mathematical model that represents how a transmitted signal is received at another end is called the transfer function of the medium and it can be in both the frequency and time domains as follows:

$$H(s,t,f) = \sum_{i=1}^{L(s,t)} \rho_i(s,t).\ e^{j\theta_i(s,t)}.\ e^{-j2\pi f \tau_i(s,t)}. \tag{3.1}$$

$$h(s,t,\tau) = \sum_{i=1}^{L(s,t)} \rho_i(s,t).\ e^{j\theta_i(s,t)}.\delta(\tau - \tau_i(s,t)). \tag{3.2}$$

where $\rho_i(s,t)$, $\tau_i(s,t)$ and $\theta_i(s,t)$ are random variables that represent the sequence amplitude, time of arrival and the phase of arrival, respectively. $L(s,t)$ is the total number of multipath components defined at time t and spatial position s. $\delta(\tau - \tau_i(s,t))$ represents the Dirac distribution and i stands for the index of the multipath component.

In the following we will consider that the channel is time invariant, i.e. there is no spatial variation between the transmitter and receiver due to any human or natural activity. In such case the time can be eliminated from the above equations and a simple representation of the channel impulse response becomes:

$$H(s,f) = \sum_{i=1}^{L(s)} \rho_i(s).\ e^{j\theta_i(s)}.\ e^{-j2\pi f \tau_i(s)}. \tag{3.3}$$

$$h(s,t) = \sum_{i=1}^{L(s)} \rho_i(s).\ e^{j\theta_i(s)}.\delta(\tau - \tau_i(s)). \tag{3.4}$$

where $\rho_l(s)$, $\tau_l(s)$ and $\theta_l(s)$ are functions of space only. The received signal is a result of convolution between the transmitted signal and the complex channel impulse response. After finding how the signals are affected by the medium by comparing the transmitted and received signals, the CIRs are concluded in both the frequency and time domains.

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. They consist of 450 measurements taken along a gallery as shown in Fig. 3.1. The complex CIR of the wideband measurements has been 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.

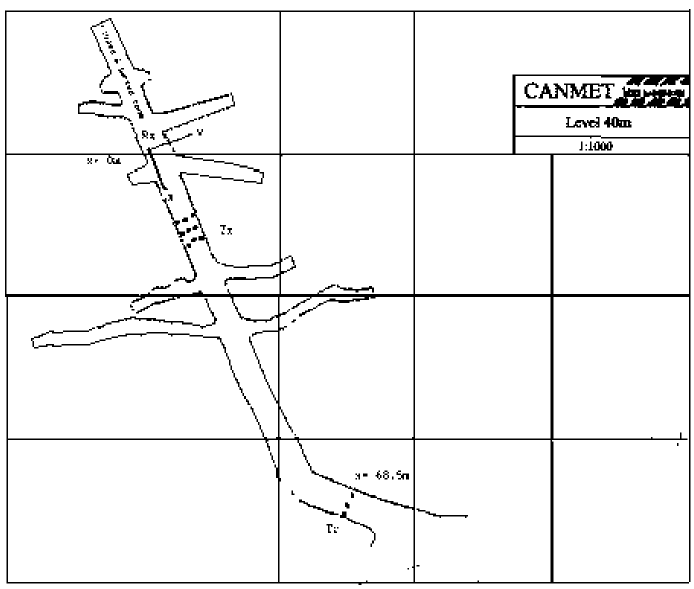

Figure 3-1- Map of the gallery

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 $a_k$of the multipath components k, and it is given by:

$$\bar{\tau} = \frac{\sum_k a_k^2 \tau_k}{\sum_k a_k^2}. \tag{3.5}$$

- 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:

$$\sigma = \sqrt{\overline{\tau^2} - (\bar{\tau})^2}, \tag{3.6}$$

$$\text{and} \quad \overline{\tau^2} = \frac{\sum_k a_k^2 \tau_k^2}{\sum_k a_k^2}. \tag{3.7}$$

- The maximum excess delay (τ_{rms}) 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), it is measured in dam. It can be calculated by combining the square of the amplitudes of all the multipath components as follows:

$$P_{total} = \sum_{k=1}^{N} a_k^2 \ . \tag{3.8}$$

- The number of multipath components (N) which form the entire received signal, it is 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.

3.2. Artificial Neural Networks

Once the database is ready, the system would need a matching algorithm that can study the special 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 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 [12]. 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 perfectly map the set of inputs to the desired output.

The most used artificial neural networks (ANNs) models are the well-known Multi-Layer Perceptron (MLP) [12]. The training process of MLPs for localization problems consists of two tasks, the first one is the selection of an appropriate architecture for the problem, and the second is the adjustment of the connection weights of the network. The use of a feed forward neural network with a back-propagation learning algorithm has been proven to give good estimation results in underground localization systems [3],[4]. The structures of the networks are determined by the number of inputs, outputs and neurons that are needed in order to optimise the results of the mathematical model being built. A neural network is mainly made up of input, output, and hidden layers. Each layer contains several neurons that hold weights and biases. First, the ANN has to be trained on the set of data collected through measurement campaigns (training data). This is called the offline-phase where the network learns the relationship between the parameters extracted from the wireless signal and the relative distance or position of the transmitter. In the offline phase, part of the collected data is used to modify the weights and biases leading to a minimum mean square error while the other part of the data is kept for testing the ability of this network to estimate new positions using data that has not been seen in the training process (testing data).

The training process is launched after initializing the network with random weights and biases. Different initializations would lead to different performances [12] because of the availability of multiple local minimums in most mathematical models, and that is why some training iterations are needed before selecting an optimum performance of the neural network. Once a desired performance is reached, the network can be saved and used to estimate training and testing data in real time scenarios.

3.3. 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 training and testing 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 from the CIR while the output is the distance *(d)* to the transmitter as shown in Figure 3.2:

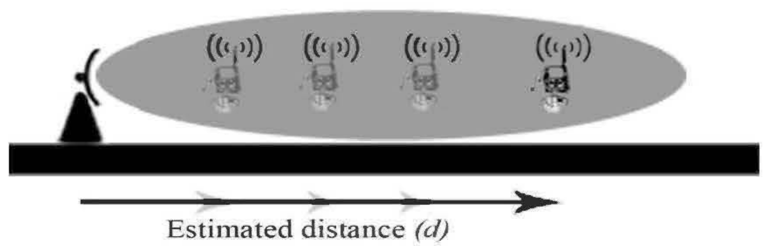

Figure 3-2- Localization using one fixed receiver. The CIR is extracted at different distances to the transmitter with 1 meter step size

The use of one dimensional position estimation is convenient in mine galleries and is later discussed in the following chapter. 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. The results of this localization system are discussed in Chapter 4, however despite the fact that localization using this technique gives promising results; this technique faces challenges that prevent it from being deployed in underground environments such as mines.

3.4. Challenges of the localization system

The presence of junctions and connected tunnels in mines makes it difficult to precisely estimate the direction of transmission which leads to several possible positions. In wireless network architecture, a transceiver might be located at a junction in the mine providing wireless coverage to different parts of the mine. Figure 3.3 shows a map of a level in a mine and it is given to illustrate a major drawback of using one-receiver localization system. Consider an antenna placed at a junction, as shown in Fig. 3.3, supposing that this antenna is collecting a wireless signals transmitted by one miner at a distance d away from the junction. Based on the trained neural network discussed before, the receiver would estimate that the miner is at a distance:

$$d_{est} = d + e\,. \tag{3.9}$$

where e represents the error produced by the neural network.

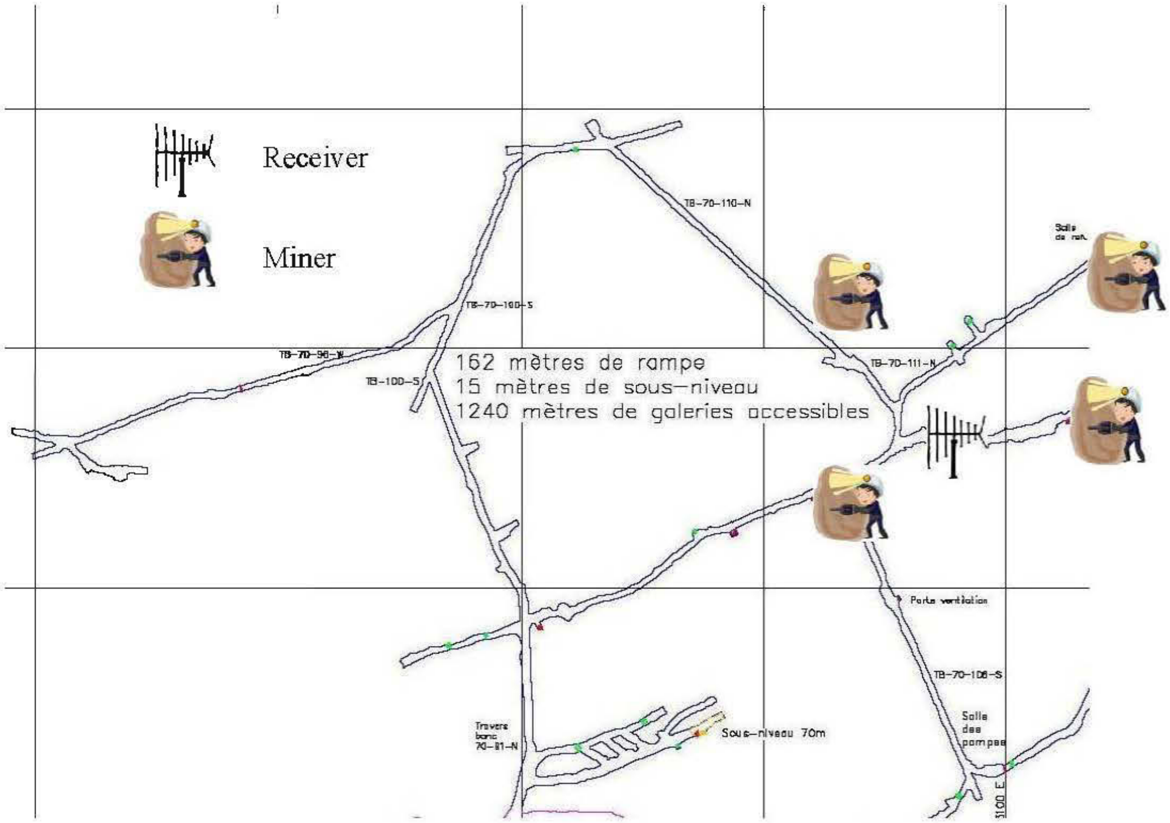

Figure 3-3. Example of a localization error in mines

This neural network would be able to estimate the distance only, and it cannot specify the direction of arrival of the received signal. Thus the system will have to decide between four different choices for such situation (i.e., four possible miner locations).

One might propose adding omni-directional antennas that can measure the angle of arrival of the received signal, but even this might fail in underground environments because the transmitted signals are always being reflected by the walls of the tunnels changing the original path (i.e., angle of arrival) of the transmitted signal. For that reason a new approach was based on using the same technique in multiple parts of the tunnels. This way, the new localization system will work in a cooperative manner as one system applicable in the mining industry

CHAPTER 4 – 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 access points intersect is the main interest of this work. Unlike the first approach in Chapter 3 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. 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.

4.1. Fingerprinting Methodology

The concept of fingerprinting using multiple receivers is based on collecting multiple signatures from different end points forming one fingerprint that corresponds to a transmitter located between the reference endpoints. . It is by analogy 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 tunnel topology of mines' galleries, two access points should be enough to provide wireless coverage of the whole area in between.

As shown in Fig. 4.1, a transmitter at distance d_1 away from receiver 1 is also at a distance d_2 from receiver 2. Since we are supposing that the localization system already knows the digital map of the environment, then the distance D separating the two receivers is also known and it is:

$$D = d_1 + d_2 \qquad (3.10$$

Once a transmitter sends a wireless signal, both receivers collect it at different locations forming two different signatures. A new fingerprint in a cooperative technique is made up of the two signatures collected by the two receivers. Since each signature is a collection of 7 parameters extracted from one CIR, the new fingerprint is a collection of 14 parameters extracted from 2 CIRs. The position of the miner can be localized either by estimating d_1 or d_2.

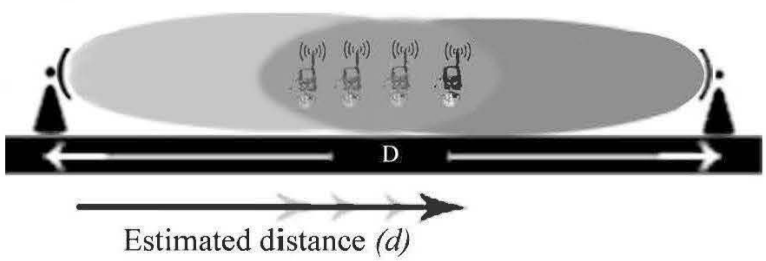

Figure 4-1- Localization using two signatures of two receivers in the area where two signals intersect

As shown in Fig. 4.1, at each position of the transmitter in the offline phase, the two receivers collect the transmitted signal extracting two different sets of parameters (CIRs). The distance to one of the receivers is taken as a reference distance for each extracted fingerprint.

Mine tunnels vary in length and structure and for that reason the fingerprints are affected by the intersection zone of the wireless coverage of both transmitters (handoff region). Once the handoff region expands, more fingerprints may be collected. However in narrow handoff scenarios, the new collected fingerprints will be linked to few positions in the tunnel. In real mine structures, the separation distances and handoff regions would be known and the localization system could be trained on those specific scenarios. However in this work studies the precision of the localization system at different scenarios (i.e., different separations distances D). It showed be noted that the maximum wireless coverage of the conducted measurements was reported to be 68 meters for each of the receivers after which no significant signal responses were recorded [3]. In Chapter 3, the measurement campaign recorded the CIR of every position while moving the transmitter one meter away from receiver. Here, a mobile is simulated to move in the handoff region with a 1 meter step size. At each position, both CIRs extracted by receiver 1 and 2 are recorded and the corresponding parameters are collected to form the fingerprint of the location. One of the receivers is taken as a reference point and the distance that separates the transmitter from one of the receivers is also saved with the corresponding fingerprint. The fingerprint here is made up of two CIRs. After moving the transmitter all across the handoff region for each scenario *D*, a full database is formed showing all the possible fingerprints with their respective distances.

4.2. Structure of the neural networks

This diversity technique opens a wide range of possibilities and helps the neural network exploit a better position estimation model. This concept will enrich the training set of data that will be fed to the neural network. The structure of the neural network will be based on the technique of the position estimation system. For each scenario *D*, a new neural network should be trained because fingerprints change when the handoff region changes. In the following, two different approaches to cooperative localization are presented.

4.2.1. Localization based on separate neural networks

The localization system that is proposed in this work is the one that collects the observations of several access points at the same time once a signal is received by different parties in the tunnel. One simple way of localizing the miners is to compromise their location by observing which access points are receiving their signals. Using this technique, each AP works as a localizing unit of its own using the localization technique discussed in Chapter 3. The goal of this approach is to collect the estimations of different nodes and combine them together to form a higher level position estimation model. The system assumes that the positions of the APs along with the digital map of the mine are both known and that the received signals are collected from different parts of the tunnels.

To narrow the research, we will examine one tunnel with two receivers deployed at its ends. The transmitter sends wireless signals to both ends which at their part inform the localization system using two different readings of the transmitted signal. 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 same transmitter from different angle. The neural networks used to estimate the position of the transmitter are the same used in Chapter 3, however two neural networks are needed as shown in Figure 4.2:

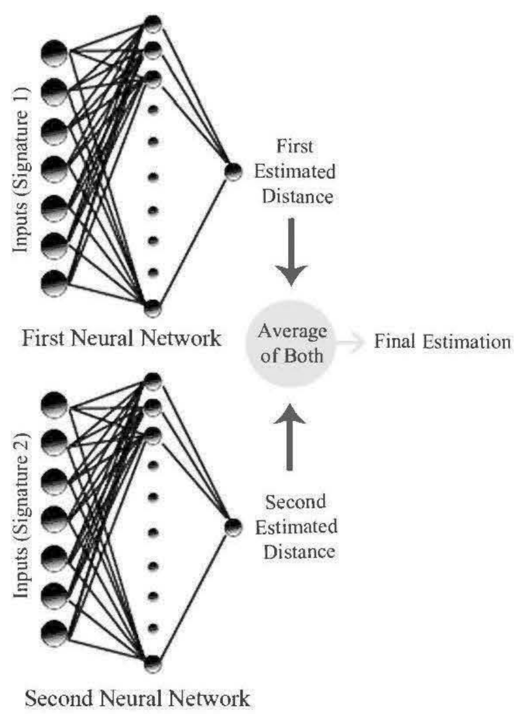

Figure 4-2- Localization based on two separate estimations

The first neural network estimates the position based on the signature collected from receiver 1 while the second neural network estimates another position based on signature 2. The two estimated distances are:

$$d_{1_{est}} = d_1 + e_1. \quad (3.11$$

$$d_{2_{est}} = d_2 + e_2. \quad (3.12$$

where d_1 and d_2 are the real distances to the transmitter from receivers 1 and 2, respectively. And e_1 and e_2 are the estimation errors of neural networks 1 and 2, respectively. The estimated distances would create two estimated positions on the map, the localization system calculates the final estimation position by taking the midpoint of the two estimated locations; in other words localization here is based on averaging both estimation errors.

4.2.2. Localization based on one neural network

Another way of estimating the transmitter's position in a cooperative way is to use the parameters extracted from the CIRs collected by different nodes as one fingerprint to be fed to a new neural network. Unlike the approach used before which uses two separate neural network estimations, this approach is based on one position estimation made by one neural network. In order to create such a network, the fingerprints of both receivers are collected in the whole tunnel forming a set of fingerprints with their corresponding distance. The localization system collects the signals from both receivers and forms a set of two CIRs with a total of 14 extracted parameters. The transmitter's position is estimated based on the distance to one of the receivers. As shown in Fig. 4.3, 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.

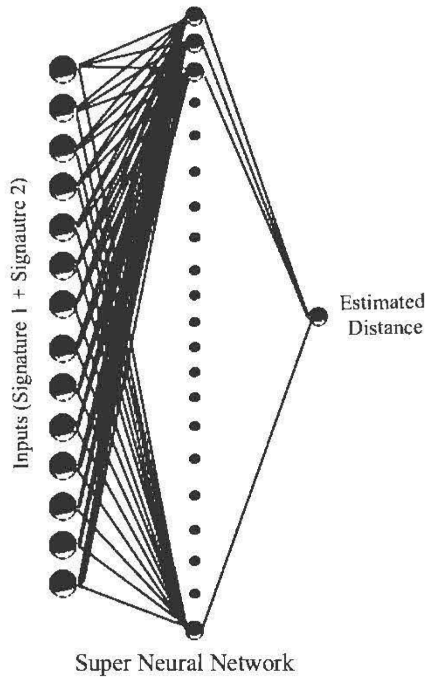

Figure 4-3- Neural Network based on multiple signatures

Instead of making two decisions and averaging the errors as used in the separate networks approach, this neural network is able to provide one decision which is the estimated distance to the transmitter. Like all the neural networks used before, this network also trains 75% of the collected data and leaves 25% for testing. 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 (*D*), a new neural network needs to be trained.

4.3. Results of the cooperative 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; 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 training data for separation distances 60m, 80m and 100m are shown in Figs. 4.4, 4.5 and 4.6, respectively.

In the training 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.

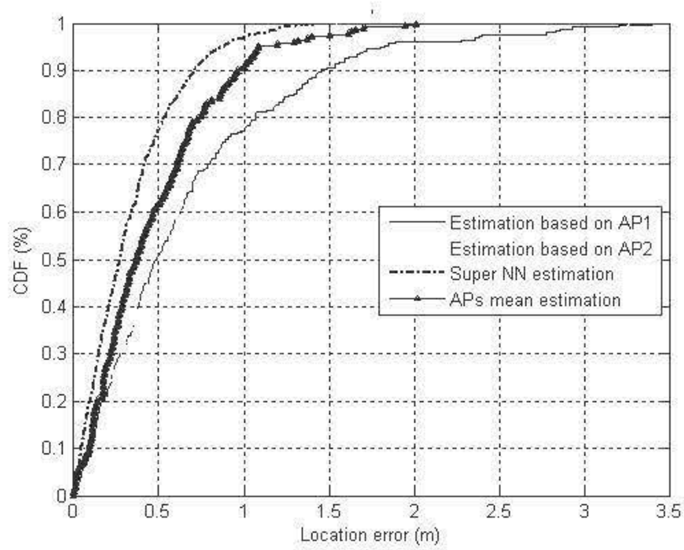

Figure 4-4- CDF plots of the position estimation errors at a receivers' separation distance D=60m using several localization techniques.

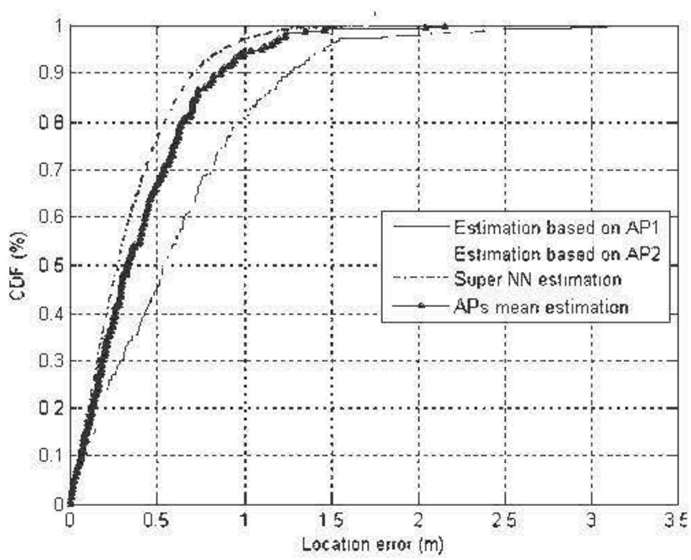

Figure 4-5- CDF plots of the position estimation errors at a receivers' separation distance D=80m using several localization techniques.

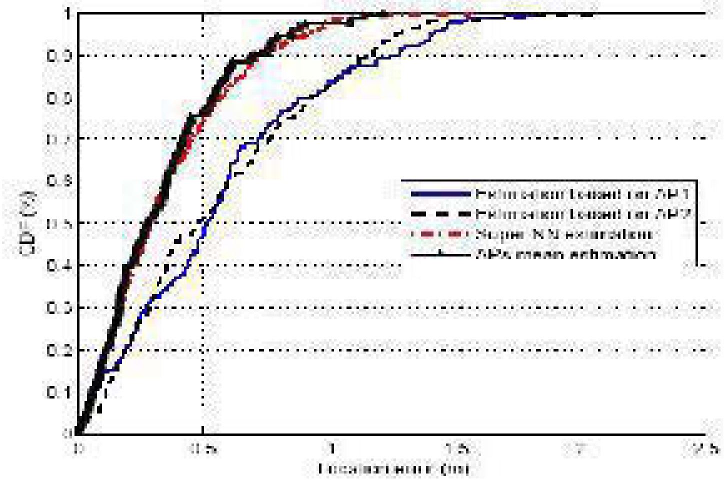

Figure 4-6- CDF plots of the position estimation errors at a receivers' separation distance D=100m using several localization techniques.

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 training data at close separation distances. When the separation distance increases, the handoff region becomes narrow resulting in a reduced amount of training signatures. 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. 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 and it can almost provide the same position accuracy even at far separation distances.

CDF plots of the testing data for separation distances 60m, 80m and 100m are shown in Figs. 4.7, 4.8 and 4.9, respectively.

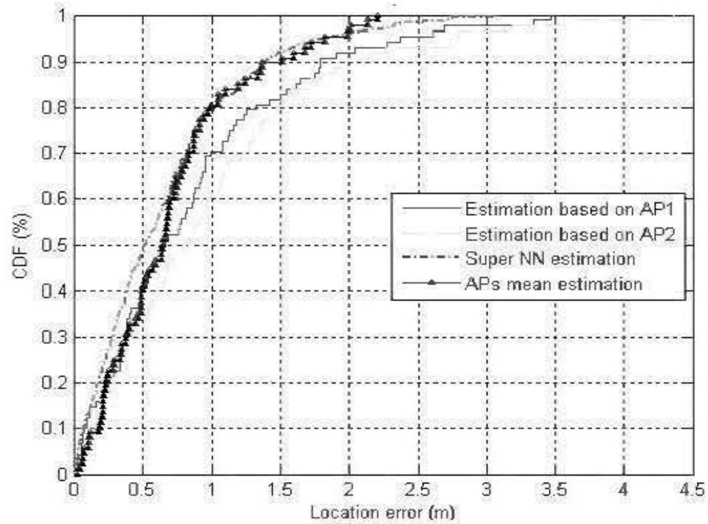

Figure 4-7- CDF plots of the position estimation errors at a receivers' separation distance D=60m using several localization techniques.

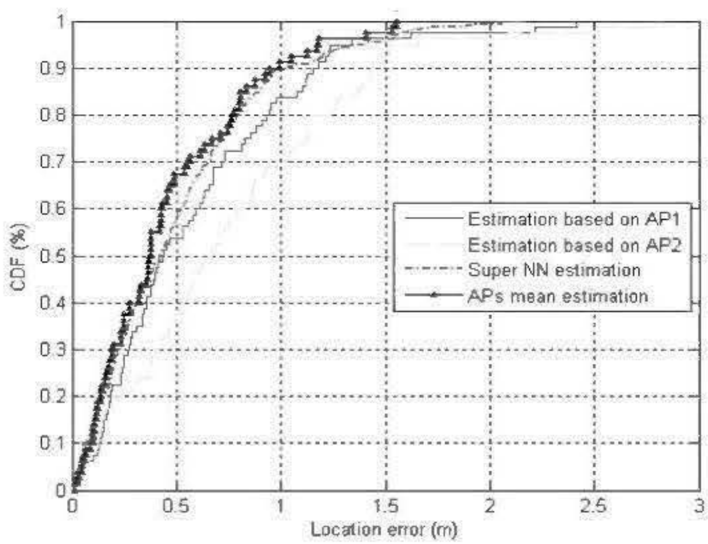

Figure 4-8- CDF plots of the position estimation errors at a receivers' separation distance D=80m using several localization techniques.

For the testing set of signatures, it should 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.

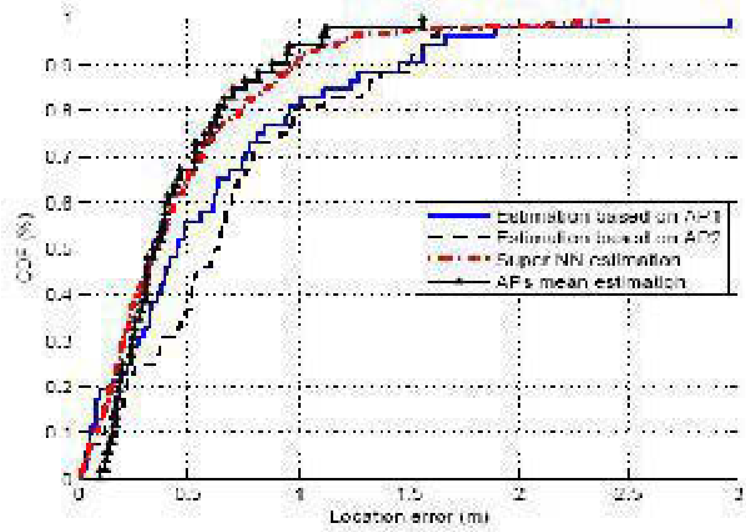

Figure 4-9- CDF plots of the position estimation errors at a receivers' separation distance D=100m using several localization techniques

As shown in Figs. 4.7, 4.8 and 4.9, the positioning error of the localization technique based on one receiver varies between 1m and 2m for 90% of the testing data. For the cooperative localization based on averaging, the performance was again dependant on the accuracy of the two neural networks. As shown in Figs. 4.4 and 4.7, the results of averaging were precise for the training data; however this precision affected the estimation of the testing 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 testing data. The use of multiple connected neural networks or one super neural network is suitable for indoor localization since they both provide high accuracy, precision and scalability at different distances.

CHAPTER 5 – LOCALIZATION USING TRACKING

The last of this research is localization in the presence of memory or history. The concept adds time diversity to the localization system involving speed and prediction of the current position of the miner taking in consideration the previous positions registered in the database. Space diversity was discussed in the previous chapters, two or more access points may be taken as references in space. In this chapter, we introduce a localization system that properly exploits the time domain where the CIRs of the previous positions play an important role in estimating the new position within the ANN through tracking. Consider a walking miner who is transmitting wireless signals across the tunnel. One receiver is fixed and set on a time axis in a way that it starts localizing the miner after saving the CIRs from its transmitter up to a certain memory level l. Using one reference in time ($l=1$) is the same as using one reference in space; i.e., one CIR is recorded and the position is estimated for each location separately using the localization technique in Chapter 3 with one receiver only. In order to estimate the miner's position based on two references in time, a fingerprint should be formed from two CIRs. The first CIR is extracted for the position to be estimated at t_0 while the other CIR is that for previous the position registered in memory at t_{-1}. The speed of motion plays an important role in defining all possible fingerprints a priori, but it does not vary too much between the two typical stationary and pedestrian speeds in the considered underground mining application. Due to the fact that a miner may come from different directions before reaching a current position, the neural network is trained on chains of all possible fingerprint combinations for each position in a tunnel. The results of localization using tracking are discussed at the end of the chapter.

5.1. Fingerprinting Methodology

In the case of tracking, fingerprints vary with the case study which is defined by the number of input levels (l) that need to be considered. Two different models are discussed below which show the methodology that is used in order to collect those fingerprints. In the theoretical approach, all the possibilities of previous positions are considered with equal probabilities of occurrence, whereas in the Random-Walk Model, an artificial miner is simulated to walk in a tunnel with defined probabilities leading to a set of recorded signatures.

5.1.1. Theoretical Model

A miner may reach a current position from different directions in the mine gallery. Localization using tracking with two memory levels ($l = 2$) exploits temporal diversity in the same way as cooperative localization (i.e, as in Chapter 4) does with spatial diversity using two references in space. The accuracy of the neural network increases when increasing the memory level of the system. In this work, we study localization based on tracking using up to five references in time. Since a miner's movements in a 1D-curved topology space are predictable, we are able to add valuable information to our model by creating chains of possible fingerprint combinations to be fed to the neural network. We assume that a miner may walk to a position from different directions in the tunnel-shaped mine gallery taking into consideration the boundary conditions of the tunnel. Using a time domain motion model, the number of input levels (l) that needs to be considered defines the combinatorial number of possible CIRs from which each fingerprint may be extracted. In the simplest case where $l = 2$, each fingerprint is made up of 14 parameters extracted from two CIRs. The first CIR is that of the position to be estimated at t_0 while the other CIR may be one of the five possible previous positions, as illustrated in Fig. 5.1 and listed in Table 5.1.

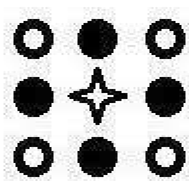

Figure 5-1 Possibilities of previous positions for l=2

The star represents the transmitter at t0 while the filled circles are four possible previous locations at $t-1$ other than the current position (which is also among possible previous positions). For simplicity, motion across diagonals is excluded although our technique can easily take it into account.

Fingerprint	Source of Parameters
1	CIR_{t-1} & CIR_{to}
2	CIR_{to} & CIR_{up}
3	CIR_{to} & CIR_{down}
4	CIR_{to} & CIR_{left}
5	CIR_{to} & CIR_{right}

Table 5-1 Fingerprint combinations for l=2

For each position in the tunnel, those fingerprints are collected with their respective distance to the receiver. The boundary conditions are taken into considerations because at the borders some of the previous positions won't hold.

Once l increases, more positions get involved in forming the paths (fingerprints) to the current position of the transmitter. Fig. 5.2 shows the positions that may be considered for creating a path to the current position for $l = 3$. Once again, if the path taken exceeds the boundary conditions of the geometry of the mine gallery, this path is automatically excluded from being listed as a possible fingerprint. The positions involved in drawing the path are highlighted in Fig. 5.2, while the maximum number of fingerprints (*Nf*) extracted for the miner's position at level l may be calculated using the following formula:

$$Nf\ per\ position = 5^{(l-1)}\ . \tag{5.1}$$

All possible fingerprints are gathered for all positions in the tunnel after specifying a certain level *l*; then the signatures and paths are saved in a database.

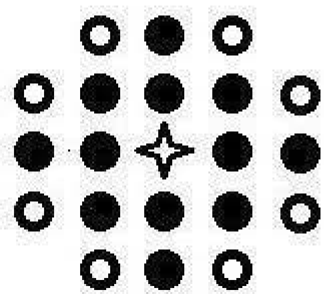

Figure 5-2 Possibilities of previous positions for l=3

All possible fingerprints are gathered for all positions in the gallery after collecting specifying a certain level; then the signatures and paths are saved in a database.

5.1.2. Random-Walk Model

The random-walk model is different from the one used in the theoretical approach where all possible paths are considered. A directed motion is designed in this approach with defined probabilities. To start with, a mobile user is simulated to walk through a tunnel with different probabilities and constraints (boundary conditions). For example, a miner might step forward but cannot suddenly take a step backwards unless it is preceded by a full stop. Giving all directions equal probabilities of occurrence resulted in a movement that takes place around the starting point or the center, that's why the need of a directed motion is essential in order to create a model that can cover all the area of interest. This model simply creates an artificial miner walking across the tunnel with a directive "intention" to proceed forward. As the miner crosses the gallery using this random motion, the system records the positions that the miner took with their corresponding fingerprints.

Several directive random walks were conducted in both directions of the tunnel resulting in different signatures across the gallery. These paths were sorted as positions with different memory levels l, i.e. in case we are studying localization based on one previous position only, that information was extracted for the different positions where motion took place.

5.2. Structure of the Neural Network

The neural network used is the same feed forward neural network with a back propagation learning algorithm. The purpose of this choice is to compare the results of tracking with the original localization system used in Chapter 3. In this part, the ANN is scalable to the number of input levels to be used. Since we have 7 parameters for each CIR signature, adding more signatures in time increases the number of inputs (N) of the neural network where N obeys the rule:

$$N = 7l \tag{5.2}$$

where l is the input level under study which specifies the structure of the neural network used in the positioning system. For $l=2$, the structure of the ANN is similar to the one used in Fig 4.3. The number of neurons used in the hidden layer is based on the number of inputs of the neural network:

$$\begin{aligned} number\ of\ neurons &= 2N + 1 \\ &= 14l + 1 \end{aligned} \tag{5.3}$$

The output layer contains one neuron which represents the distance in meters to the receiver at time t_0. The combinatorial number of possible paths increases the combinatorial number of possible chains of CIRs from which the possible fingerprints or input parameters are extracted without necessarily requiring any increase in the number of CIR measurements. As a matter of fact, while keeping the size of measurement data unchanged, the combinatorial exponential increase in the size of the training data (from where stems temporal diversity) overwhelmingly surpasses the linear increase in the number of neurons required to match the corresponding increase in the so-called memory level l. Throughout the training process, 75% of the collected data are classified to train the neural network while 25% are left in order to test the performance of the neural network with data not seen in the training process. The study was conducted up to level 5 using both approaches discussed earlier. For each level, a neural network was created and trained accordingly.

5.3. Results of Localization using Tracking

Once again the CDF plot is used in order to show the results of localization using tracking at different memory levels. The input level l is the number of signatures a neural network accepts including the current position at time t_0. Since there is no tracking with history at level $l=1$, and the localization system would simply be estimating based on the signature of the current position, level one is not included in the charts, however it would be the same as using one AP as in Chapter 3 . The analysis is classified based on the type of model used and based on whether the neural network is simulated with familiar or new sets of data.

For the theoretical model, estimating the fingerprints of the data used in the training process and those kept for testing the efficiency of the neural network are all shown for differeut levels in figures 5.3 and 5.4.

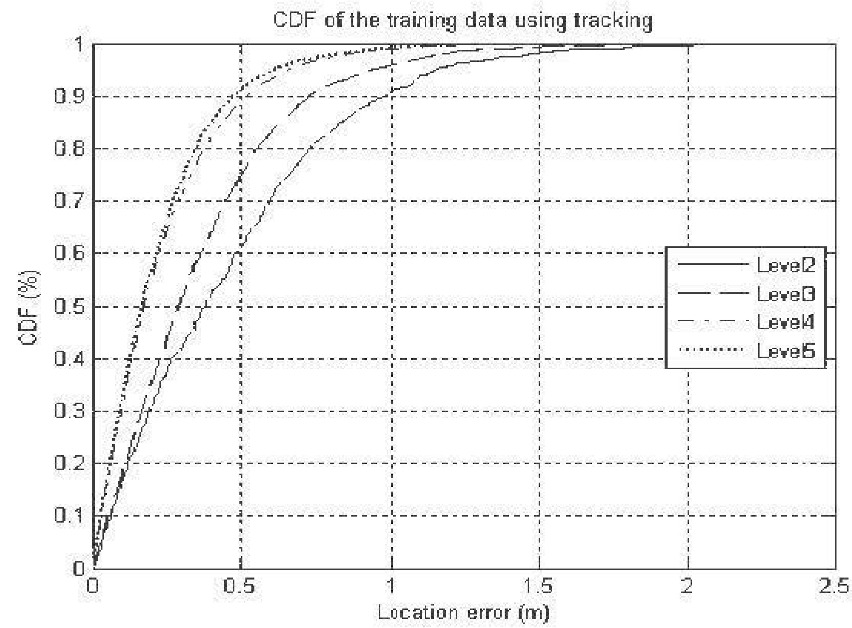

Figure 5-3 CDF plots for the training data using the theoretical model

Note that for each CDF plot at each level, a new neural network's results are shown. For level 2, localization using tracking with only one previous position shows an estimation error of 1 and 1.25 meters for 90% of training and testing data respectively.

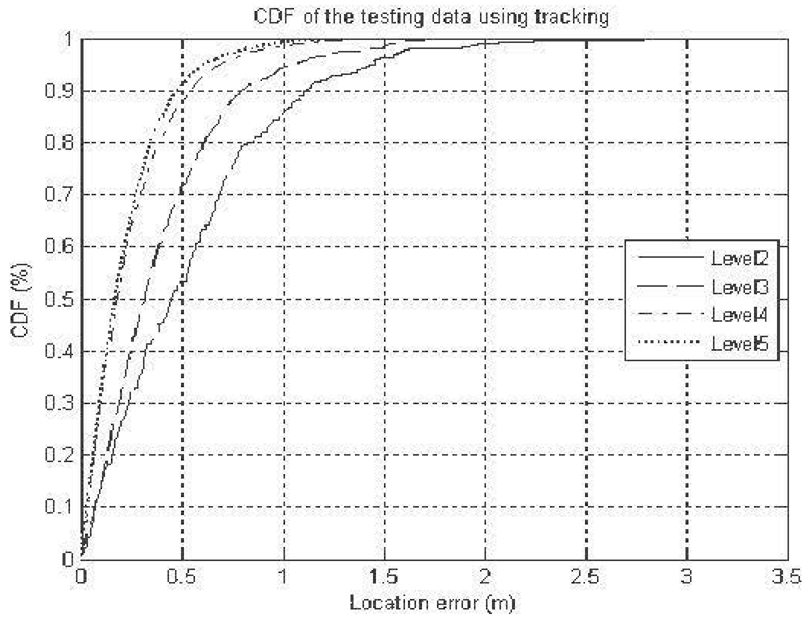

Figure 5-4 CDF plots for the testing data using the theoretical model

When adding a new previous position to the model, the neural network gave a better estimation and understanding of the motion principle and variation of the CIR with respect to distance. At level three, an estimation error of 0.75 and 0.8 meters was recorded for 90% of training and testing samples respectively. The performance was again ameliorated when adding another previous position to the modeling process, and now at level four, the estimation error decreased to around 50 cm for 90% of training and testing data. After this level, the addition of one more previous position increased the number of possible fingerprints for each position making the process of data collection and training of the neural network time consuming. However, once again, testing the data for level five was surprising with increased accuracy and precision of the exact position of the transmitter. An error of less than 50 cm was reported for the localization system with tracking based on the theoretical model at level five. At this level the inputs of the neural network is five times the input of a neural network using one CIR and the number of neurons used is 71 neurons. Calculating the performance of localization at level 6 was conducted using a 3.2 GHz computer with 2GB system memory, however after waiting 3 days till the collection of data and simulation was finalized, the results were almost similar to that of level five clearly showing a saturation in performance after which no significant gain can be obtained.

For the random walk model, the results were different. The data was collected based on a random walk between the two receivers. Not all the possibilities were considered as in the theoretical model, and at the same time there might be some repetitions of the same possibilities in the set of data because different random walks were combined together and fed to the neural network at different levels.

The number of sample data was more than that in the theoretical analysis because the artificial miner was registering more random steps to reach a destination even though the motion was with higher probability to move forward. The results of the random-walk model are shown in figures 5.5 and 5.6 for the training data and testing data respectively.

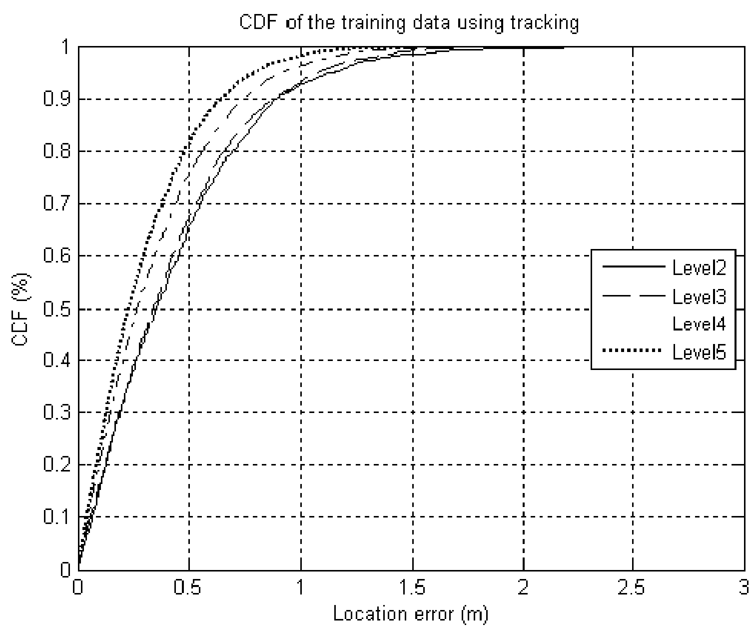

Figure 5-5 CDF plots for training data using the random-walk model

The performance of this model was less accurate than the theoretical model if we compared it at levels three, four and five. However, at level two the model reported a location error of around 90cm for 90% of both the training and testing data. This may be due to the simplicity of the motion with only one previous position taken into account. However when considering more previous positions, the random assignment of fingerprints might cause loss of information which leaded to a neural network that is less accurate than the one used in the theoretical model. The accuracy of level three using the random walk model is almost the same as level two. The estimation error in this model started decreasing at level four where the error was 0.75 meters and 0.82 meters for the training and testing data respectively. At level five, the estimation error was less and it is reported to be 64 cm and 74cm for 90% of the training and testing data respectively.

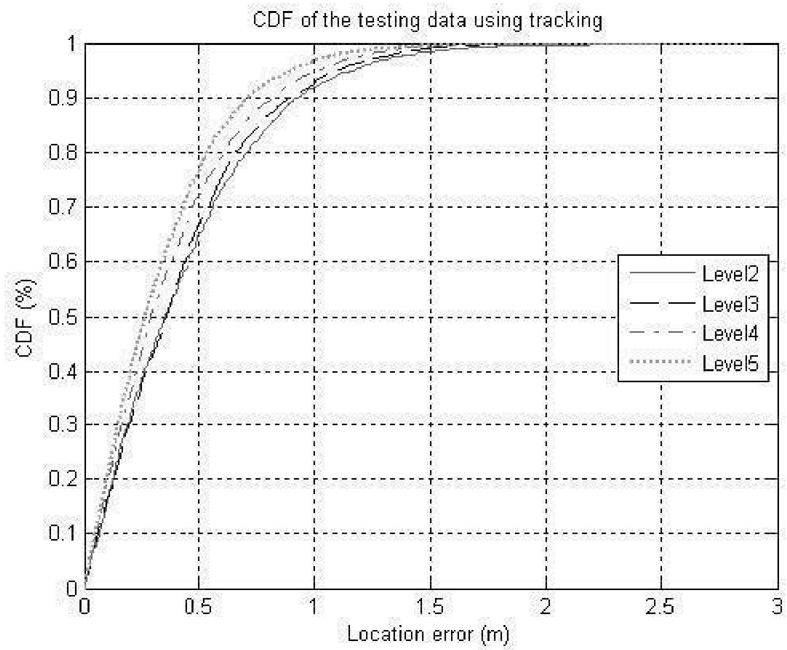

Figure 5-6 CDF plots for testing data using the random-walk model

It is clear that the more the level increases the more the accuracy increases in both the training and testing data. As in the theoretical approach the neural network was capable of registering the best estimation errors at level five with an error of less than 50cm for 90% of training and testing data.

CHAPTER 6 – CONCLUSION

The first part of this study has shown 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 training and testing data. The use of cooperative neural intelligence not only enriches the set of data training the neural network 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.

On the other hand, this work presented a new localization approach that exploits time diversity for radio-localization in underground tunnel-shaped mines. With an in-built tracking algorithm, this technique uses ANNs to localize a transmitter based on fingerprints extracted from chains of CIRs recorded in time. The proposed system is able to estimate the position of a wireless transmitter in 1D-curved topology tunnels with high accuracy and precision of 50 cm for 90% of both training and testing data. Compared to cooperative localization in the spatial domain, geo-location using tracking is more accurate and precise with flexible scalability of fingerprint lengths.

Using any wireless technology, the system may be designed for remote or self positioning purposes and may use any of techniques introduced in the study. 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. In the third technique, different signatures collected in time can be fed into one neural network that can also provide one accurate estimation of the separation distance separating the transmitter from the receiver.

The major future challenge is to integrate the proposed system into a wireless technology by introducing a circuit to any end of the communication that is capable of extracting the CIR of the received signal and transmitting that information into a server. After gathering different samples in a real-time scenario, the server will be able to train and save the neural networks before the localization system becomes active. The collection and training of data may be based on the random movement of the miners for each mine, then estimating any new position will be spontaneous.

Another challenge is the fact that the activity that takes place in the mine which may lead to different signatures, the study was conducted in a tunnel without human interference. The possibility of using live updating of neural networks might be one of the solutions that need to be tested in real time scenarios too. Since the channel is dynamic, classifying the neural networks based on receivers' locations and the time of day would be an interesting feature that may lead to better estimation results. The variation of the channel due to human activity may also be adjusted by implementing some fixed transmitters along the galleries for calibration purposes.

The question of whether the tracking system may be integrated in a cooperative localization technique that exploits spatial diversity is to be investigated. Although this system is studied for an underground environment such as mines, but it can be used for different indoor localization purposes. In fact, it's a concept that can be added to any localization technique in order to increase the accuracy of the system. The discussed system may use different wireless technologies such as UWB, WLAN, or mobile radio.

APPENDIX A – REFERENCES

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APPENDIX B – WIRELESS-BASED INDOOR POSITIONING SYSTEM AND SOLUTION

Table B-1Performance of Wireless based indoor positioning system and solutions

System/ Solution	Wireless technologies	Positionin g algorithm	Accu -racy	Precision	Comple xity	Scalabitli ty/ Space dimensio n	Robust ness	Cost
Microsoft RADAR	WLAN Received Signal Strength (RSS)	kNN Viterbi-like algorithm	3~5 m	50% within around 2.5m and 90% within 5.9m	Moderat e	Good /2D3D	Good	low
Hours	WLAN RSS	Probalistic method	2m	90% within 2.1m	Moderat e	Good /2D	Good	Low
DIT	WLAN RSS	MLP, SVM, etc	3m	90% within 5.12m for SVM; 90% within 5.40m for MLP	Moderat e	Good /2D3D	Good	Low
Ekahau	WLAN RSSI	Probalistic method (tracking-assisted)	1m	50% within 2m	Moderat e	Good /2D	Good	Low
SnapTrack	Assisted GPS TDOA		5m-50m	50% within 25m	High	Good /2D3D	Poor	Mediu m
WhereNet	UHF TDOA	Least Square/R WGH	2-3m	50% within 3m	Moderat e	Very good/2D-3D	Good	Low
Ubisense	Unidirectiona l UWB TDOA+ AOA	Least Square	15c m	99% within 0.3m	Real time respons e (1Hz-10Hz)	2-4 sensors per cell (100-1000m); 1UbiTag per object/2D, 3D	Poor	Mediu m to High
Sappire Dart	Unidirectiona l UWB TDOA	Least Square	<0.3 m	50%withi n 0.3m	Frequen cy respons e (0.1Hz-1Hz)	Good /2D3D	Poor	Mediu m to High

SmartLOC US	WLAN(RSS) + Ultrasound(R TOF)	N/A	2-15c m	50% within 15cm	Medium	Good /2D	Good	Mediu m to High
EIRIS	IR +UHF(RSS)+L F	Based on PD	<1m	50% within 1m	Medium to High	Good /2D	Poor	Mediu m to High
SpotON	Active RFID RSS	Ad-Hoc lateration	Depe nds on clust er size	N/A	Medium	Cluster at least 2 Tags/2D	Good	Low
LANDMAR C	Active RFID RSS	KNN	<2m	50% within 1m	Medium	Nodes placed densely	Poor	Low
TOPAZ	Bluetooth(RS S)+IR	Based on PD	2m	95% within 2m	Position ing delay 15-30s	Nodes placed every 2-15m	Poor	Mediu m
MPS	QDMA	Ad-Hoc lateration	10m	50% within 10m	1s	Excellent/ 2D,3D	Good	Mediu m
GPPS	DECT cellular system	Gaussian process(GP), kNN	7.5m for Gp, 7m for kNN	50% within 7.3m	Medium	Good/2D	Good	Mediu m
Robot-based	WLAN (RSS)	Bayesian approach	1.5m	Over 50% within 1.5m	Medium	Good/2D	Good	Mediu m
MultiLoc	WLAN (RSS)	SMP	2.7m	50% within 2.7m	Low	Good/2D	Good	Mediu m
TIX	WLAN (RSS)	TIX	5.4m	50% within 5.4m	Low	Good/2D	Good	Mediu m
PinPoint 3D-ID	UHF (40Mhz) (RTOF)	Bayesian approach	1m	50% within 1m	5s	Good /2D3D	Good	low
GSM fingerprin ting	GSm cellular network (RSS)	Weighted kNN	5m	80% within 10m	Medium	Excellent/ 2D,3D	Good	Mediu m

APPENDIX C – ARTICLES AND MANUSCRIPTS

The first article "Cooperative Localization in Mines Using Fingerprinting and Neural Networks" discusses the cooperative neural network technique and it was accepted at the IEEE Wireless Communications & Networking Conference in Sydney Australia 2010.

The second article "Localization in Mines: A Cooperative Neural Network Technique in Spatial and Time Domains" introduces both the cooperative technique and tracking and it was accepted at the International Conference on Wireless Communications in Underground and Confined Areas August 2010, Val-d'Or – Québec – Canada

The third article: "Radio-Localization in Underground Tunnel-Shaped Mines Using Neural Networks with In-built Tracking and Time Diversity" is still under review by the committee of IEEE GLOBECOM 2010. This article discusses localization using tracking solely.

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 techniques. 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 vector 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 these events based on the pre-recorded 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:

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

where:

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

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.

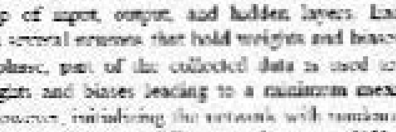

Fig. 2. Localization using one fixed receiver. The CIR is extracted at different distances to the transmitter with 1 meter step size.

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 as 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 access 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 11 parameters (7 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 employed 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

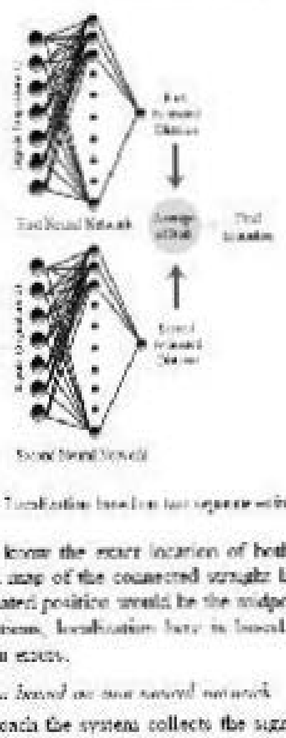

Fig. 4. Localization based on two separate estimations.

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.

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

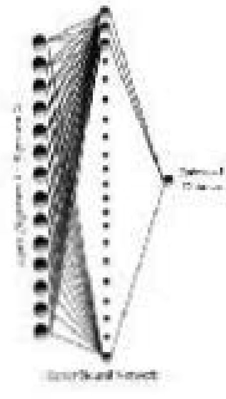

Fig. 5. Neural Network based on multiple signatures.

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.

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 60 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.

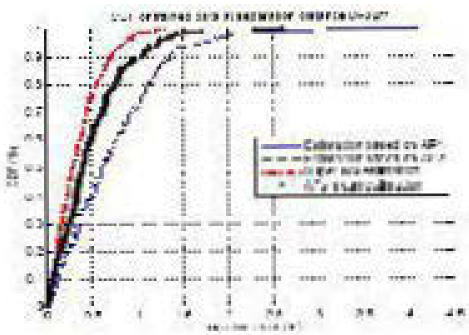

Fig. 7. CDF plots of the position estimation errors at a receivers' separation distance D=80m using several localization techniques.

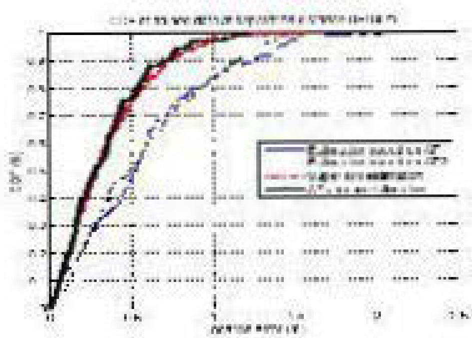

Fig. 8. CDF plots of the position estimation errors at a receivers' separation distance D=100m using several localization techniques.

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

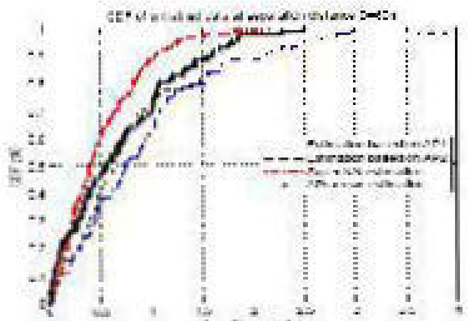

Fig. 9. CDF plots of the position estimation errors at a receivers' separation distance D=60m using several localization techniques.

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 these 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

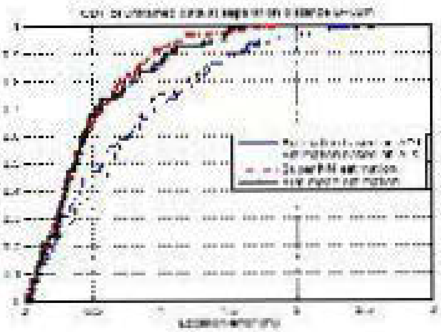

Fig. 10. CDF plots of the position estimation errors at a receivers' separation distance D=60m using several localization techniques.

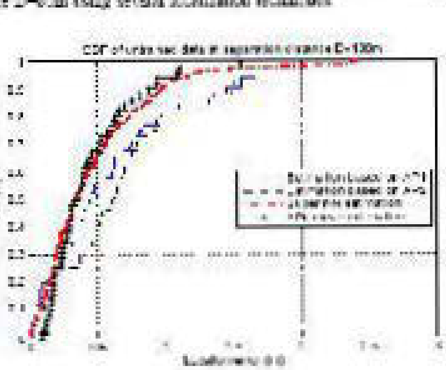

Fig. 11. CDF plots of the position estimation errors at a receivers' separation distance D=100m using several localization techniques.

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. 8 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 in 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 deployed 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 outside type tunnels. On the other hand, the system can use different wireless technologies such as UWB, WLAN, or mobile radio.

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Localization in Mines: A Cooperative Neural Network Technique in Spatial and Time Domains

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Abstract—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. 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. A proposed solution to such challenging situations is based on extracting the channel impulse response (CIR) fingerprints with reference to one wireless receiver and using an artificial neural network (ANN) as a matching algorithm to localize. In this article we study this approach in a cooperative neural network setting where multiple reference points are considered before estimating the position of a transmitter. 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. Multiple reference points in both the time and spatial domains will show that using cooperative artificial intelligence in the presence of different signatures 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, tracking.

I. INTRODUCTION

One of the vast numbers of applications of wireless telecommunication systems is position estimation or localization. Outdoor localization systems such as Global Positioning system (GPS) are already in the market and are available to anyone providing an important service that can locate the user's position precisely. On the other hand, indoor localization is still a controversial topic due to the fact that the transmitted signals indoor undergo several deformations caused by reflections and multipath effects. Unlike outdoor mediums where signals travel freely in open spaces, indoor environments are more complicated channels that need to be modeled in order to estimate how the signal would be received after being reflected, refracted or scattered. Most traditional positioning 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 neighbors (kNNs), support vector polygon (SMP), support vector machine (SVP) and neural networks. Surveys on wireless indoor positioning techniques [1],[2] provide detailed discussion of each approach.

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. Unlike other approaches [5],[6],[7],[8],[9] 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.

In this article we will enrich the localization technique in [3] and open it to a wide range of possibilities where the system uses multiple signatures collected at different parts of the tunnel as one fingerprint that pins the position of transmission. This will also be followed by an investigation that shows that memory and previous positions of mobile users are valuable inputs that help the neural network be more accurate in real-time estimations. In the following section, the fingerprinting and neural network localization technique is discussed in the presence of one reference point. In the third section, we introduce the concept of cooperative localization in the spatial domain. Section 4 discusses the use of signatures recorded in the time domain as an enriched ANN input to estimate new positions more accurately. The results are compared and analyzed in section 5. Finally, the paper is closed by a conclusion in section 6.

II. LOCALIZATION IN MINES USING FINGERPRINTING AND NEURAL NETWORKS

A. The fingerprinting and neural network 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]. 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. Once the database is ready, the system would need a matching algorithm that can study the spatial/time variation of the channel with respect to the distance. And here comes the importance of neural networks.

ANNs 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].

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].

B. Localization using one reference point

Traditional techniques of localization mostly 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 network techniques. 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 150 measurements along a tunnel. The complex CIR of the wideband measurements was obtained using the frequency channel sounding technique [8]. 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. A signature or a fingerprint is a set of seven parameters at a specific distance to the transmitter and these parameters are the mean excess delay ($\bar{\tau}$), the root mean square (τ_{rms}), the maximum excess delay (τ_{max}), the total power of the received signal (P), the number of multipath components (N), the power of the first arrival (P_1) and the delay of the first path component (τ_1). The simple form of a neural network consists of 7 inputs, one hidden layer, and one output. 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 inputs correspond to the extracted parameters of the CIR while the output is the distance (d) to the transmitter.

As shown in Fig. 1, the network is trained at several

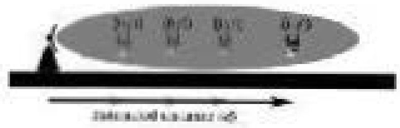

Fig. 1. Localization using one fixed receiver. The CIR is extracted at different distances to the transmitter with 1 meter step size.

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. 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. It was shown that position estimation is precise and that the error is less than 1.5 meters for 90% and 80% of training and non-training data, respectively.

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 that reason, 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.

III. COOPERATIVE LOCALIZATION USING TWO REFERENCES IN SPACE

The concept of fingerprinting using multiple receivers is based on collecting multiple signatures from different end points forming one fingerprint that corresponds to a transmitter located between the reference endpoints.

Fig. 2. Localization using two signatures of two receivers in the area where two signals intersect.

Due to the special one-dimensional topology of mines' tunnels, two access points should be enough to provide wireless coverage of the whole area in between. As shown in Fig. 2, at each position of the transmitter in the offline phase, the two receivers collect the transmitted signal extracting two different sets of parameters (CIRs). The distance to one of the receivers is taken as a reference distance for each extracted fingerprint. 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 CIRs) for each location which is the distance with respect to one receiver. These sets of fingerprints can be treated by two different localization techniques:

A. Localization based on separate neural networks

Using this technique, each AP works as a localizing unit of its own; it would be estimating a distance and not a location. The goal of this approach is to collect the estimations of different nodes and combine them together to form a higher level position estimation technique as shown in Fig. 3. The

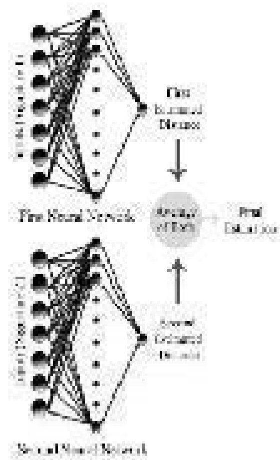

Fig. 3. Localization based on two separate estimations.

transmitter sends wireless signals to both ends which in turn feed the localization system with two different readings of the transmitted signal. The system receives the signature of receiver 1 and estimates the distance to that transmitter, and uses the signature of receiver 2 to estimate another distance to transmitter 2. The localization system creates a new estimation position by taking the midpoint of the two estimated locations; in other words localization here is based on averaging both estimation errors.

B. Localization based on one neural network

Another way of estimating the transmitter's position in a cooperative way is to use the CIRs collected by different nodes as one fingerprint to be fed to a new neural network. Unlike the approach used before which uses two separate neural network estimations, this approach is based on one position estimation made by one neural network. As shown in Fig. 4, only one

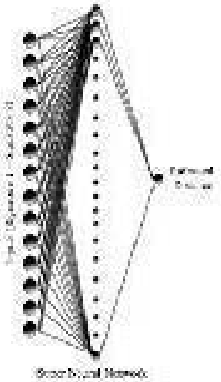

Fig. 4. Neural network based on multiple signatures.

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.

IV. COOPERATIVE LOCALIZATION USING TRACKING

All localization systems studied in the literature use the space domain in order to estimate the position of the transmitter. In other words, the reference points or APs that collect the RSS, TOA, AOA, or fingerprints are fixed in space and they collect the transmitted signal from different angles. In the previous sections, we defined localization using one reference point and a cooperative localization technique using two references in space. Cooperative localization in mines using fingerprinting and neural networks in the spatial domain only is fully discussed in [14]. Using these techniques, the position of the transmitter is estimated regardless of the CIR at its previous position.

In this section, we will introduce a localization system that properly exploits the time domain where the CIR of the previous position plays an important role in estimating the new position within the ANN. For example, if a transmitter is moving with a constant speed across a tunnel, one receiver is fixed and set on a time axis in a way that it starts localizing after saving the CIRs in a certain memory level l. Using one reference in time (l=1) is the same as using one reference in space, one CIR is recorded and the position is estimated for each location separately using the CIR localization technique in the presence of one receiver only. However, the estimation of the same position would be more accurate if the neural network considered two signatures.

In order to estimate the miner's position based on two references in time, a fingerprint should be formed of two CIRs. The first CIR is extracted for the position to be estimated at t_0 while the other CIR is that of the previous position registered in memory at t_{-1}. This can be viewed the same as using two references in space where two signatures help pin the position of the transmitter more accurately. The accuracy of the neural network (as shown in the following section) increases when adding more CIRs to the input layer of the neural network. In this work, we study localization based on tracking using up to five references in time. Since our movements in a 2D space are predictable, we are able to add valuable information to our model by creating chains of possible fingerprint combinations to be fed to the neural network.

Fingerprints of each position are collected using a theoretical approach. We assume that a miner may reach a position from different directions in the mine gallery taking into consideration the boundary conditions of the tunnel. Using the time domain tracking localization model, the number of input levels (l) that needs to be considered defines the number of possible fingerprints each position may have. For the simplest case where $l = 2$, each fingerprint is made up of two CIRs and the outcome gives four different fingerprints for each position as illustrated in Fig. 5.

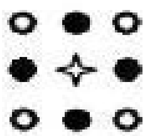

Fig. 5. Possibilities of previous positions for $l=2$.

The star represents the transmitter at t_0 while the filled circles are the previous possible locations at t_{-1}. The possible fingerprints for one position when $l = 2$ are shown in Table I. It should be noted that $CIR_{i_{-1}j}$, $CIR_{i_{+1}j}$, $CIR_{ij_{-1}}$ and $CIR_{ij_{+1}}$ correspond to the CIR that may have been recorded at t_{-1} for a given position and d_{ij} represents the distance to the transmitter.

TABLE I
FINGERPRINTS OF EACH POSITION FOR $l=2$

Fingerprint	Input of ANN	Output of ANN
1	CIR_{ij} & $CIR_{i_{-1}j}$	d_{ij}
2	CIR_{ij} & $CIR_{i_{+1}j}$	d_{ij}
3	CIR_{ij} & $CIR_{ij_{-1}}$	d_{ij}
4	CIR_{ij} & $CIR_{ij_{+1}}$	d_{ij}

Once l increases, more centers get involved in drawing the paths (fingerprints) to the current position of the transmitter. All possible fingerprints are gathered for all positions in the tunnel after specifying a certain level, then the signatures and their corresponding distances are saved in a database. A new neural network and fingerprint database are created for each input level. For $l = 2$, the structure of the neural network is the same as in Fig. 4. Once l increases, the number of inputs and neurons increase accordingly. ANNs throughout this study are trained using 75% of the collected data while leaving the rest for testing. Localization using tracking is analyzed up to level 5 (5 CIRs as a fingerprint).

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.

A. Results of cooperative localization in the spatial domain

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 training data for separation distances 60m, 80m and 100m are shown in Figs. 6, 7 and 8, respectively.

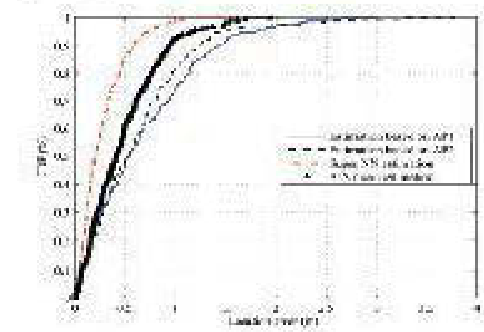

Fig. 6. CDF plots of the position estimation errors for the training data at a receivers' separation distance D=60m using several localization techniques.

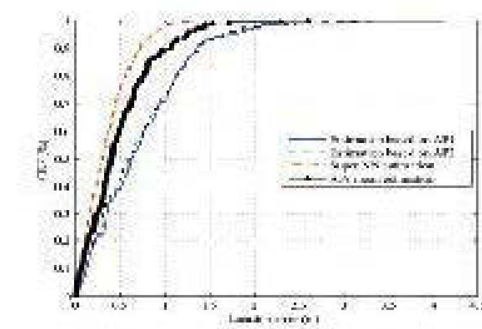

Fig. 7. CDF plots of the position estimation errors for the training data at a receivers' separation distance D=80m using several localization techniques.

In the training set of data, the position error for one receiver estimation technique ranged between 1.2 and 1.5m for 90% of data. On the other hand, the estimation based on averaging the

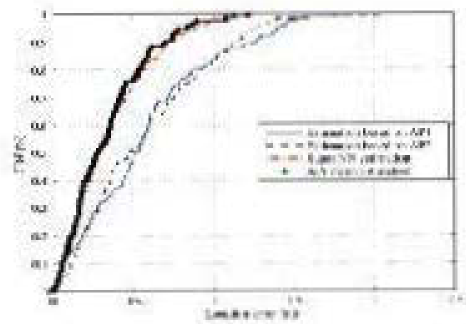

Fig. 8. CDF plots of the position estimation errors for the training data at a receivers' separation distance D=60m using several localization techniques.

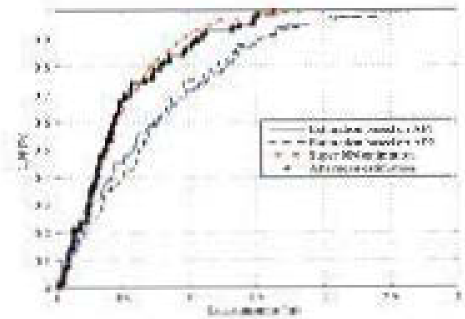

Fig. 10. CDF plots of the position estimation errors for the testing data at a receivers' separation distance D=80m using several localization techniques.

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 training data at close separation distances. When the separation distance increases, the handoff region becomes narrow resulting in a reduced amount of collected signatures. 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 non-training data for separation distances 60m, 80m and 100m are shown in Figs. 9, 10 and 11, respectively. For the non-training set of signatures, it should

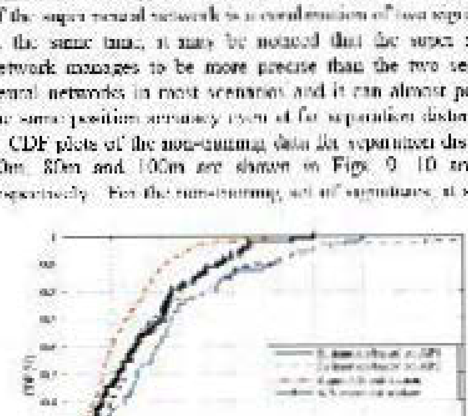

Fig. 9. CDF plots of the position estimation errors for the testing data at a receivers' separation distance D=60m using several localization techniques.

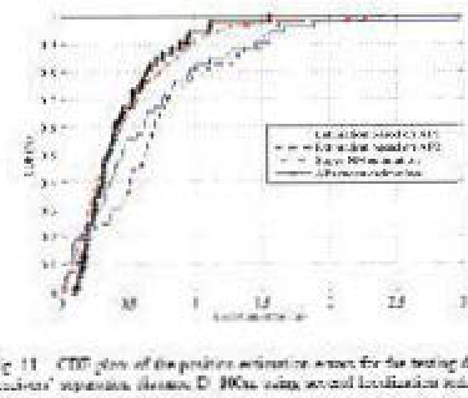

Fig. 11. CDF plots of the position estimation errors for the testing data at a receivers' separation distance D=100m using several localization techniques.

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 non training separate estimations. As shown in Figs. 9, 10 and 11, the positioning error of the localization technique based on one receiver varies between 1m and 2m for 90% of the non-training 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 training data. However, this precision affected the estimation of the testing 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 testing data.

The use of multiple connected neural networks in 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.

B. Results of cooperative localization in the time domain

Once again the CDF plot is used in order to show the results of localization using tracking at different memory levels. The input level L is the number of signatures a neural network accepts including the CIR extracted at time t_1. The results of estimating the fingerprints of the training and testing data are shown for different levels in Figs. 12 and 13. For level

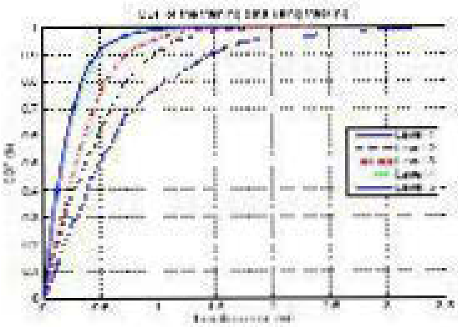

Fig. 12. CDF plots for the training data using tracking

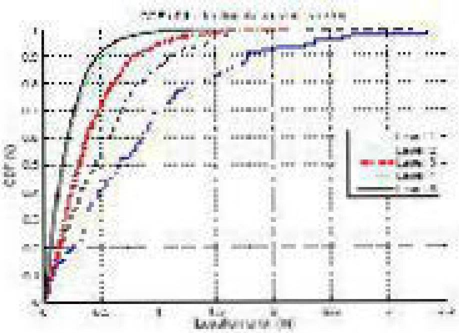

Fig. 13. CDF plots for the testing data using tracking

two, localization using tracking with only one previous CIR shows an estimation error of 1 and 1.23 meters for 90% of training and testing data, respectively. As the input level increases, more paths get involved in the estimation of the current positions. As t increases, the accuracy and precision of the neural network are enhanced forming a better estimation model of the motion trajectory and the variation of the CIR with respect to distance. At level three, estimation errors of 0.75 and 0.8 meters were recorded for 90% of training and testing samples, respectively. The performance was again ameliorated when adding another previous position to the modeling process, and now at level four, the estimation error decreased to 50 cm for 90% of training and testing data. An error of little less than 50 cm was reported for the localization system with tracking based on the theoretical model at level five. At this level, the input of the neural network is five times larger in size than that of a neural network using one CIR and the number of neurons in the hidden layer is 71, clearly suggesting a saturation in performance at level 4 beyond which no significant gain is observed.

VI. Conclusion

This paper studied the results of using the channel impulse responses as fingerprints for position estimation in the presence of different references in both the spatial and time domains. 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 and 50cm for 90% of both training and non-training data in the spatial and time domains, respectively. On the other hand, using references in time was a concept introduced under the topic of localization using tracking and it showed that not only diversity in space can lead to better estimation results, but in fact, introducing time as a dimension for localization purposes helps improve the accuracy and precision of the system. Although this work was conducted for an underground environment such as mines, but the presented approaches are methodologies which may be used for different indoor/outdoor localization systems. The discussed system may also use different wireless technologies such as UWB, WLAN, or mobile radio.

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Radio-Localization in Underground Tunnel-Shaped Mines Using Neural Networks with In-built Tracking and Time Diversity

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Abstract—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. Being an indoor environment, wireless transmitted signals in mines suffer multiple kinds of distortions due to extreme multipath and non-line of sight (NLOS) conditions. One of the proposed solutions to accurate localization in such challenging environments is based on extracting the channel impulse response (CIR) of the received signal and using the fingerprinting technique combined with cooperative artificial neural networks (ANNs). Such localization systems use the spatial domain where the reference localizing units are implemented at different positions away from the transmitter. In this article, we introduce a localization technique that uses tracking as an alternative method to localize. Unlike the spatial domain technique where cooperative localizing units collect multiple fingerprints from different locations, this technique uses one localizing unit and is capable of estimating the position of a transmitter precisely using its current and previous registered fingerprints in time. Localization using time domain fingerprinting (i.e., tracking) and ANNs is introduced as a new method that exploits time diversity and improves the accuracy, precision and scalability of the positioning system.

Index Terms—Indoor localization, channel impulse response, artificial neural network, fingerprinting technique, cooperative localization, tracking, time diversity.

I. Introduction

One of the vast numbers of applications of wireless communication systems is position estimation or localization. Outdoor localization systems such as the Global Positioning System (GPS) are already in the market and are available to anyone providing an important service that can locate the user's position precisely. Different localization techniques base their estimations on one or more extracted parameters out of the received signal such as 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 which include using ANNs as matching algorithms. Once a transmitted signal is received at different locations in space, the variation in the signals' fingerprint, RSS, AOA, TOA, or TDOA is calculated and the position of the transmitter is estimated accordingly. Nevertheless, indoor localization is still a challenging topic due to the fact that the transmitted signals indoor undergo several distortions caused by reflections, refractions, NLOS regions and multipath effects. Unlike outdoor mediums where signals relatively travel almost freely in open spaces, indoor environments such as underground mines stem from more complicated scenarios that need to be modeled in order to estimate how the signal would be received after reacting with the channel. Surveys on wireless indoor positioning techniques [1],[2] provide multiple detailed discussions of different localization approaches.

A new approach to localization in underground tunnel-shaped mines is presented in [3] and is based on extracting the CIRs of the received signal as fingerprints of the transmitter's positions, then using these fingerprints to localize the source of transmission with one receiver or Access Point (AP). Several parameters extracted from the CIR give this approach uniqueness unlike other approaches [5],[6],[7],[8],[9] that mainly base their fingerprints on the RSS only. However, this technique was not able to cover the whole 1D-curved topology of underground mines until the cooperative localization concept was introduced in [4]. Cooperative localization using the CIR technique benefits from the presence of multiple receivers which collect multiple fingerprints in tunnels before estimating the position of the transmitter. Leading to increased accuracy and precision, the developed technique in [4] uses different cooperative neural network techniques and exploits the spatial diversity of the collected fingerprints.

In this article, we will study localization in tunnel-shaped mines using the time-domain fingerprint diversity (i.e., tracking) technique combined with ANNs. The time-domain fingerprint is made up from a chain of CIRs which are collected for the same transmitter along its path to the position which has to be estimated. ANNs are properly then designed based on different chain length or memory levels then trained on all possible path scenarios. Because of the 1D curved topology nature of tunnels, information about the path that the transmitter as following adds valuable input to the ANNs and creates an accurate in built localization system. The following section summarizes the concept of cooperative localization using fingerprinting and neural networks in the spatial domain. In section 3, localization using tracking is introduced along with the theoretical fingerprinting approach. The results of both the spatial (i.e. cooperation) and time (i.e. tracking) diversity-based localization techniques are compared in section 4. In section 5, the major complexities/challenges that face the design are highlighted along with their proposed solutions. Finally, the article is closed by a conclusion in section 6.

II. Localization using Fingerprinting and Neural Networks

In this part, we will study as a background reference a localization technique that uses the spatial domain in order to localize a transmitter in a mine tunnel. The system is capable of localizing a transmitter using two receivers that work separately or cooperatively using different neural network techniques. A more detailed discussion of these techniques can be found in [4]. Before doing so, we will study below the underlying fingerprinting technique from which extension using multiple APs was developed in [4].

A. Localization in the presence of one receiver

Due to the special nature of mines which are made of underground connected tunnels, traditional wireless localization systems fail to provide accurate positioning services. This is mainly caused by the distortions of the basic parameters used in localization systems due to the multipath components and NLOS scenarios present in such environments. In such cases, the fingerprinting technique becomes a very promising alternative in that it confers to each position a specific fingerprint that is then identified by the localizing units using different matching algorithms. In this work, the fingerprinting technique is used to identify a position based on the extracted CIRs at that position.

After conducting a real-time measurement campaign in the CANMET gold mine in Val d'Or city [3], CIRs were collected. For each position across the tunnel, seven parameters were then extracted from the corresponding CIR forming overall a set of fingerprints at different distances (d) away from the receiver as shown in Fig. 1. These parameters are: the mean

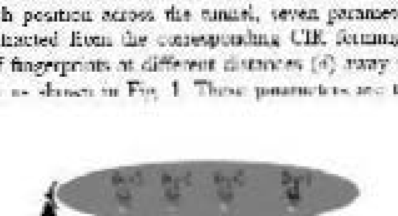

Fig. 1. Localization using one fixed receiver. The CIR is extracted at different distances to the transmitter with 1 meter step size.

excess delay ($\bar{\tau}$), the root mean square (τ_{rms}), the maximum excess delay (τ_{max}), the total power of the received signal (P), the number of multipath components (N), the power of the first arrival (P_1) and the delay of the first path component (τ_1). Estimating the position based on the fingerprints is performed using ANNs.

Being able to perform complex computational operations such as classification, control optimization, and function approximation, ANNs proved to be reliable computational models that are widely used for different localization approaches [3],[4],[10],[11],[12]. Every ANN needs to be trained using a set of training data which, in our case, is made up of 75% of the collected fingerprints, leaving 25% of the data for testing. The use of an MLP-type feed forward neural network with a back propagation learning algorithm has been proven to give accurate estimation results in underground localization studies [3],[4]. The simple form of the ANN used in localization in the presence of one receiver consists of 7 inputs, one hidden layer and one output that is the distance to the transmitter. The hidden layer for this system consists of 10 neurons and it uses a differential tan-sigmoid transfer function, whereas the output layer uses a linear-type transfer function. It was shown that position estimation using one receiver only is precise and that the error is less than 1.5 meters for 90% and 80% of training and non training data, respectively [4]. Despite the promising accuracy of estimating the distance to the transmitter, this technique cannot by itself guarantee full coverage of the whole tunnel network of an underground mine.

B. Cooperative localization using two references in space

Precisely, a search for an upgraded technique that can serve as a complete localizing system in underground mines led to the idea of cooperative artificial neural intelligence [4]. The concept of ANN-based cooperative localization using multiple receivers is based on collecting multiple signatures from different receivers forming one fingerprint that corresponds to a transmitter located between the reference endpoints as shown in Fig. 2. Because of the 1D-curved topology nature of mine tunnels, two APs should be enough to provide wireless coverage of the whole area in between.

Fig. 2. Localization using two signatures of two receivers in the area where two signals intersect.

The first cooperative localization approach is based on separate neural network estimations. Two neural networks at both receivers estimate two distances to the transmitter based on an extracted CIR at each end. Then, knowing the positions of the fixed receivers, the final estimation is drawn after averaging both estimation errors. The structure of the model that employs the cooperative neural network technique based on separate position estimations is shown in Fig. 3.

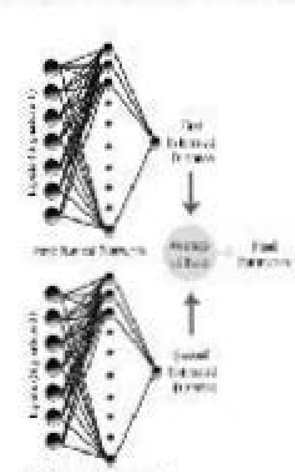

Fig. 3. Localization based on two separate estimations

The second way of estimating the position of the transmitter is by using a single neural network as shown in Fig. 4. Two extracted signatures of the transmitter from two different receivers are fed to this neural network. The latter, which has 14 inputs, is trained to localize a transmitter by estimating the distance to one of the receivers. The separation distance D affects the number of fingerprints that are collected given that each AP (receiver) has a limited wireless coverage. For each separation distance D, a new neural network is created and trained. Unlike the first cooperative approach that uses separate neural networks, this approach is based on one position estimation made by one neural network.

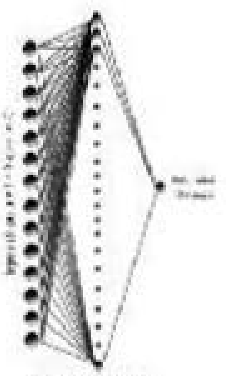

Fig. 4. Neural network based on multiple signatures

III. Localization using Tracking in the Time Domain

The major localization systems studied in the literature use the space domain in order to estimate the position of the transmitter. In other words, the reference points or APs that collect the RSS, TOA, AOA, or fingerprints from the transmitted signal at different positions are fixed in space. In the previous sections, we defined localization using one reference point and a cooperative localization technique using two references in space. Using these systems, the position of the transmitter is estimated regardless of the CIR at its previous positions. In this section, we will introduce a localization system that properly exploits the time domain where the CIRs of the previous positions play an important role in estimating the new position within the ANN through tracking.

A. Concept of time domain diversity with tracking

Consider a walking miner who is transmitting wireless signals across the tunnel. One receiver is fixed and set on a time axis in a way that it starts localizing the miner after saving the CIRs from its transmitter up to a certain memory level ℓ. Using one reference in time (ℓ=1) is the same as using one reference in space; i.e., one CIR is recorded and the position is estimated for each location separately using the localization technique in sec. II-A [3] with one receiver only. However, the estimation of the same position would be more accurate if the neural network considers two signatures representing a motion pattern within the limits of the tunnel topology.

In order to estimate the miner's position based on two references in time, a fingerprint should be formed from two CIRs. The first CIR is extracted for the position to be estimated at t_i while the other CIR is that for previous the position registered in memory at t_{i-1}. The speed of motion plays an important role in defining all possible fingerprints a priori, but it does not vary too much between the two typical stationary and pedestrian speeds in the considered underground mining application. Due to the fact that a miner may come from different directions before reaching a current position, the neural network is trained on chains of all possible fingerprint combinations for each position in a tunnel. Localization using tracking with two memory levels ($\ell = 2$) exploits temporal diversity in the same way as cooperative localization in [4] does with spatial diversity using two references in space. The accuracy of the neural network (as shown in the following section) increases when increasing the memory level of the system. In this work, we study localization based on tracking using up to five references in time.

Since a miner's movements in a 1D-curved topology space are predictable, we are able to add valuable information to our model by creating chains of possible fingerprint combinations to be fed to the neural network. We assume that a miner may walk to a position from different directions in the tunnel-shaped mine gallery taking into consideration the boundary conditions of the tunnel. Using a time domain motion model, the number of input levels (ℓ) that needs to be considered defines the combinational number of possible CIRs from which each fingerprint may be extracted. In the simplest case where $l = 2$, each fingerprint is made up of 14 parameters extracted from two CIRs. The first CIR is that of the position to be estimated at t_0 while the other CIR may be one of the five possible previous positions, as illustrated in Fig. 5 and listed in Tab. I.

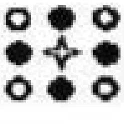

Fig. 5. Possibilities of previous positions for $l = 2$

The star represents the transmitter at t_0 while the filled circles are four possible previous locations at t_{-1} other than the current position (which is also among possible previous positions). For simplicity, motion across diagonals is excluded although our technique can easily take it into account.

TABLE I
FINGERPRINTS OF EACH LOCATION FOR $l=2$

Fingerprint	Source of Parameters
1	CIR_{t_0} & CIR_{center}
2	CIR_{t_0} & CIR_{up}
3	CIR_{t_0} & CIR_{down}
4	CIR_{t_0} & CIR_{left}
5	CIR_{t_0} & CIR_{right}

Once l increases, more positions are involved in forming the paths (fingerprints) to the current position of the transmitter. Fig. 6 shows the positions that may be considered for creating a path to the current position for $l = 3$. Once again, if the path taken exceeds the boundary conditions of the geometry of the mine gallery this path is automatically excluded from being listed as a possible fingerprint. The positions involved in

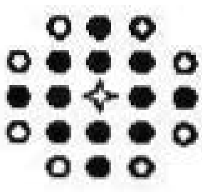

Fig. 6. Possibilities of previous positions for $l = 3$

forming the path are highlighted in Fig. 6, while the maximum number of fingerprints (N_f) extracted for the same x position at level l may be calculated using the following formula.

$$N_f = 5^{(l-1)}.$$

All possible fingerprints are gathered for all positions in the tunnel after specifying a certain level l, then the signatures and paths are saved in a database.

B. ANN structure with time domain diversity using tracking

The ANN used here is the same feed forward neural network with back propagation learning used in sec. II. The purpose of this choice is to properly compare the results of tracking with the original localization system in [3] and its first extension to spatial diversity (i.e., cooperation) in [4]. Here, the ANN is scalable up to the number of input levels to be used. Since we extract 7 parameters from each CIR signature, adding more signatures in time increases the number of inputs (N_{inputs}) of the neural network such that:

$$N_{inputs} = 7l.$$

The memory level l under study specifies the structure of the neural network used in the positioning system. For $l = 2$, the structure of the ANN is the same as in Fig. 4. On the other hand, the number of neurons (N_n) used in the hidden layer is based on the number of inputs of the neural network:

$$N_n = 2N_{inputs} + 1 = 14l + 1.$$

The output layer contains one neuron which represents the distance in meters to the receiver at time t_0. The combinatorial number of possible paths increases the combinatorial number of possible chains of CIRs from which the possible fingerprints or input parameters are extracted without necessarily requiring any increase in the number of CIR measurements. As a matter of fact, while keeping the size of measurement data unchanged, the combinatorial exponential increase in the size of the training data (from where stems temporal diversity) overwhelmingly surpasses the linear increase in the number of neurons required to match the corresponding increase in the so called memory level l. Throughout the training process, 75% of the collected data are classified to train the neural network while 25% are left in order to test the performance of the neural network with data not seen in the training process. Localization using tracking is analyzed up to level 5 (i.e., using as a fingerprint 35 input parameters extracted from 5 CIRs).

IV. RESULTS OF DIFFERENT TECHNIQUES

The performance of the presented localization techniques is evaluated using the Cumulative Distribution Function (CDF) graph. In CDF graphs, the accuracy of the system is compared to its precision. The x axis 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 precision or the percentage of occurrences for such an estimation error in the collected data.

A. Results of cooperative localization in the spatial domain

For the spatial localization approaches, each graph in Fig. 7 or 8 shows four CDF plots that correspond to the position estimation errors of the different techniques used in sec. II. The first two CDF plots represent the position errors caused by the separate estimations (i.e., cf. sec. II A) of the first and second receivers, respectively. The third plot represents the result of cooperative localization based on separate estimations (i.e., averaging both estimation errors, cf. sec. II D). The fourth CDF plot represents the position estimation error of the cooperative neural network technique using one neural network (cf. sec. II-B). At a separation distance (D) of 80 m, the CDF plots of the training and non training data are shown in Figs. 7 and 8, respectively. Other plots for different

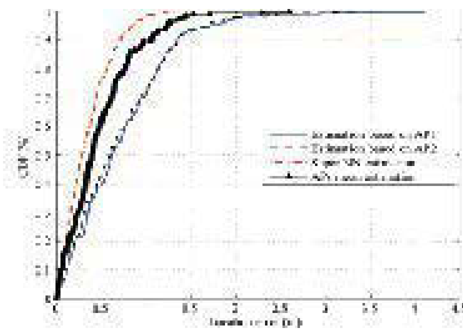

Fig. 7. CDF plots of the position estimation errors for the training data at a receivers' separation distance $D = 80$ m using several localization techniques.

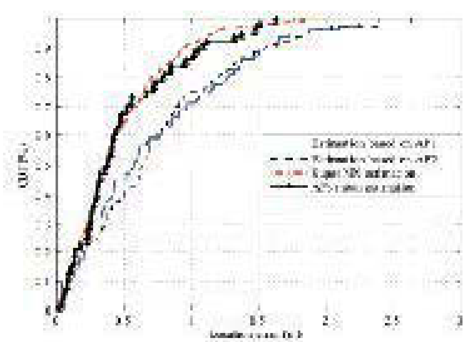

Fig. 8. CDF plots of the position estimation errors for the testing data at a receivers' separation distance $D = 80$ m using several localization techniques.

separation distances (D) are presented in [4]. The accuracy of position estimation using one of the receivers is found to be around 1.2 and 1.5 m for 90% of the training data at different separation distances (D). In the non-training set of data, the error varied between 1m and 2 m for 90% of the cases. The accuracy of the cooperative localization method based on averaging the two position errors was recorded to be around 1m and 1.5 m for 90% of the training and testing data, respectively. For the cooperative localization method using one neural network, the position estimation error was recorded to be less than 60 cm and 1m for the training and testing data, respectively.

B. Results of localization using tracking in the time domain

The CDF plot is used again in order to show the results of localization using tracking at different memory levels. The input level L is the number of signatures a neural network accepts including the fingerprint extracted from the CIR at time t_0. They are shown for the training and testing data in Figs. 9 and 10, respectively. For level two, localization using

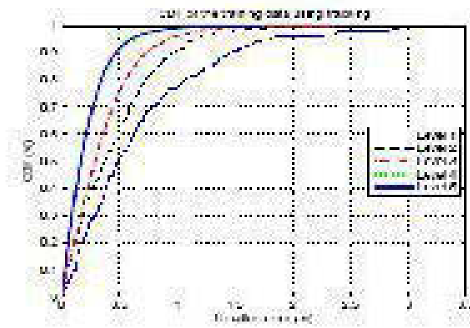

Fig. 9. CDF plots for the training data using tracking

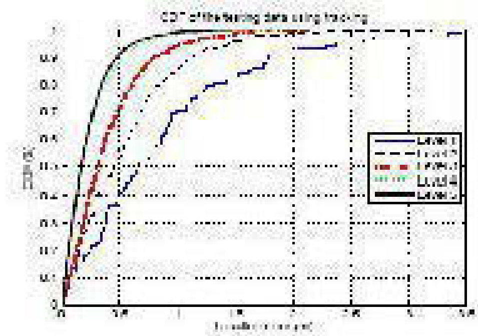

Fig. 10. CDF plots for the testing data using tracking

tracking with only one previous CIR shows an estimation error of 1 and 1.25 meters for 90% of training and testing data, respectively. As the input level increases, more paths get involved in the estimation of the current positions. As L increases, the accuracy and precision of the neural network are enhanced forming a better estimation model of the motion principle and the variation of the CIR with respect to distance. At level three, estimation errors of 0.75 and 0.8 meters were recorded for 90% of training and testing samples, respectively. The performance was again improved when adding another previous position to the modeling process, and now at level four, the estimation error decreased to 50 cm for 90% of training and testing data. An error of little less than 50 cm was reported at level five clearly suggesting saturation in performance at level 4 beyond which no significant gain is observed. At this level, the input of the neural network is five times larger in size than that of a neural network using one CIR and the number of neurons in the hidden layer is 71

Both cooperative and tracking localization techniques provide high accuracy of position estimation with high precision. The limitation in space, however, prevents us from decreasing the position estimation errors with more than two APs in a mine tunnel given its tunnel-shaped topology. On the other hand, due to the flexible scalability of localization using tracking, more inputs are introduced to the neural network resulting in better localization accuracy. At $D = 80$ m, it appears that using cooperative localization has almost the same estimation errors as that of localization using tracking when $l = 8$ and $l = 2$ for the training and testing data, respectively.

V. System Design: Complexity vs. Accuracy

The accuracy of the proposed techniques is high compared to simple localization techniques because it uses the CIR as a fingerprint. The major challenge that faces this approach is to extract the CIR at the receivers' end. Being part of a wireless network, each receiver would be capable of transmitting the extracted CIRs to a main server that should handle the process of training the neural network using the separate or cooperative techniques discussed in sections II and III. The transmitting unit is supposed to be, in our case, a mini transmitter on the miner's cap. Since such system works using the fingerprinting technique, collecting multiple fingerprints in different parts of the tunnels is another essential step that builds up the database. Instead of taking measurements manually, collecting the fingerprints in real-time scenarios is easier once the infrastructure is ready i.e. the miners are automatically transmitting signals and the CIRs are collected at a computer server from the receivers.

Since the channel is dynamic, classifying the neural networks based on receivers' locations and the time of day would be an interesting feature that may lead to better estimation results. The variation of the channel due to human activity may also be adjusted by implementing some fixed transmitters along the galleries for calibration purposes.

Considering a system that uses tracking alone does not create a global localization system in underground mines because it uses one localizing unit as in [3]. The question arises as to whether we are capable of integrating the tracking system in a cooperative neural network technique where two references in space localize using the tracking algorithm and then a final estimation is drawn using one of the two cooperative neural network topologies discussed in sec. II. An ongoing study investigates whether integrating the tracking technique at a given memory level l in a cooperative spatial localizing system (i.e., diversity both in space and time) would lead to higher performances that could match those of tracking alone with higher memory levels l (i.e., only time diversity).

VI. Conclusion

This article presented a new localization approach that exploits time diversity for radio-localization in underground tunnel-shaped mines. With an in-built tracking algorithm, this technique uses ANNs to localize a transmitter based on fingerprints extracted from chains of CIRs recorded in time. The proposed system is able to estimate the position of a wireless transmitter in 1D-curved topology tunnels with high accuracy and precision of 50 cm for 90% of both training and testing data. Compared to cooperative localization in the spatial domain, geo-location using tracking is more accurate and precise with flexible scalability of fingerprint lengths. The question of whether this system may be integrated in a cooperative localization technique that exploits spatial diversity is currently under investigation. Although this work was conducted for an underground environment such as mines, localization using tracking may be used in different indoor/outdoor environments. The proposed system may also use different wireless technologies such as UWB, WLAN, or mobile radio.

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