GEOLOCATION IN MINES WITH AN IMPULSE RESPONSE FINGERPRINTING TECHNIQUE AND NEURAL NETWORKS

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Abstract—The location of people, mobile terminals and equipments is highly desirable for operational and safety enhancements in the mining industry. In an indoor environment such a mine, the multipath caused by reflections, diffraction and diffusion on the rough sidewall surfaces, and the non-line of sight (NLOS) due to the blockage of the shortest path between transmitter and receiver are the main sources of range measurement errors. Due to the harsh mining environment, unreliable measurements of location metrics such as RSS, AOA and TOA/TDOA result in the deterioration of the positioning performance. Hence, alternatives to the traditional parametric geolocation techniques have to be considered. In this paper, we present a novel method for mobile station location using wideband channel measurement results applied to an artificial neural network (ANN). The proposed system, the Wide Band Neural Network-Locate (WBNN-Locate), learns off-line the location 'signatures' from the extracted location-dependent features of the measured channel impulse responses data for LOS and NLOS situations. It then matches on-line the observation received from a mobile station against the learned set of 'signatures' to accurately locate its position. The location accuracy of the proposed system, applied in an underground mine, has been found to be 2 meters for 90% and 80% of trained and untrained data, respectively. Moreover, the proposed system may also be applicable to any other indoor situation and particularly in confined environments with characteristics similar to those of a mine (e.g. rough sidewalls surface).

Index terms—Geolocation in mines, Channel impulse response fingerprinting technique, Artificial neural network.

I. INTRODUCTION

A problem of growing importance in indoor environments is the location of people, mobile terminals and equipments. In underground mines, geolocation with good performance is essential in order to improve operational efficiency, workers' safety and remote control of mobile equipments. Since indoor radio channels suffer from extremely serious multipath and non-line of sight (NLOS) conditions, traditional parametric indoor geolocation techniques (RSS, AOA TOA/TDOA) or their combinations (TDOA with RSS) fail to provide adequate location accuracy. For these techniques, all the paths used for triangulation must have a line of sight (LOS) to ensure an acceptable accuracy, a condition that is not always met in an indoor environment. An improvement of the accuracy may be obtained by using the location fingerprinting technique in which the effect of multipath is used as constructive information.

This paper provides a novel method for mobile station location using a fingerprinting technique based on wideband channel measurement results in conjunction with an artificial neural network (ANN). In section 2, we discuss the various wireless fingerprinting geolocation techniques used in outdoor and indoor environments. In section 3, we present our proposed system (WBNN-Locate) and give the position location results by applying the measured indoor data to an artificial neural network. Finally, we close this paper with a conclusion in section 4. For the studied underground mine, results show a distance location accuracy of 2 meters for 90% and 80% of trained and untrained patterns, respectively.

II. WIRELESS FINGERPRINTING GEOLOCATION TECHNIQUES

A. Fingerprinting geolocation techniques

The process of geolocation based on the received signals' fingerprint is composed of two phases: a phase of data collection (off-line phase) and a phase of locating a user in real-time (real-time phase). The first phase consists of recording a set of fingerprints (in a database) as a function of the user's location, covering the entire zone of interest. During the second phase, a fingerprint or a 'signature' pattern is measured and compared with the recorded fingerprints of the database. A pattern-matching algorithm is then used to identify the closest recorded fingerprint to the measured one and hence to infer the corresponding user's location (Fig. 1).

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To constitute a fingerprint or a ‘signature pattern’, several types of information [1] can be used such as received signal strengths (RSS), angular power profile (APP) and power delay profile (PDP) corresponding to the channel impulse response (CIR). For high location accuracy, the estimated set of fingerprint information must be unique (no aliasing in the signature patterns) and reproducible. Moreover, several types of pattern-matching algorithms may be employed which have the objective to give the position of the mobile station with the weakest location error. Among the commonly used algorithms, one can find algorithms based on the measure of proximity, on the cross correlation of signals and on artificial neural networks. Due to physical constraints of indoor environments, the database containing the set of fingerprint information may not contain all the necessary fingerprints to cover the entire zone of interest. Hence, the pattern-matching algorithm must be robust and respect the generalization property against perturbations and lack of fingerprint data, respectively.

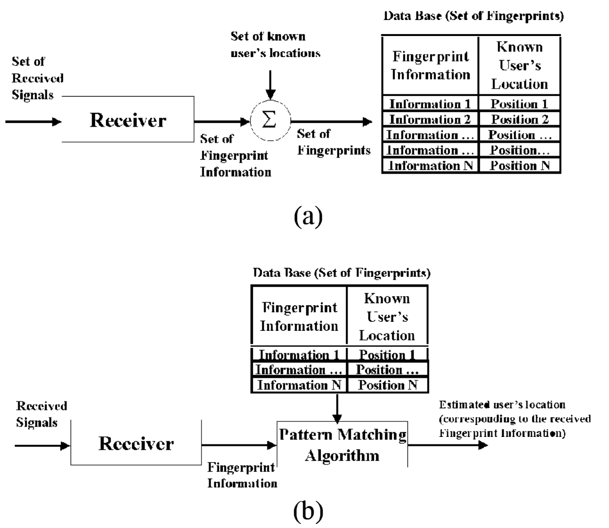

Figure 1. Process of geolocation using received signal's fingerprint, a) off-line phase, b) real-time phase.

B. Wireless geolocation systems using the fingerprinting technique

Several geolocation systems, using the fingerprinting technique, have been recently deployed in outdoor and indoor environments. The main differences between these systems are the types of fingerprint information and pattern-matching algorithms. RSS-type of information has been used in [2], [3], [4] while APP and CIR-types of information have been used in [5] and [6], [7], respectively. In these systems, algorithms based on the measure of proximity [2], [3], [5], [7], on the cross correlation of signals [4], [6] and on artificial neural networks [4] have been employed as the pattern-matching algorithm. As a measure of performance, the median resolution of the location estimation for these indoor and outdoor geolocation systems, is reported to be in the range of 2 to 3 meters and 20 to 150 meters, respectively.

Channel impulse responses have the advantage of being reproducible and unique, especially when the localization is performed on a continuous basis (user tracking). Moreover, the use of an artificial neural network (ANN) as the pattern-matching is essential since an ANN is robust against noise and interference, has a good generalization property and the localization process, during the real-time phase, is almost instantaneous [1], [4]. Consequently, it has been decided to choose location-dependent parameters extracted from the CIR in conjunction with an ANN for the geolocation of mobile units in the considered underground mine.

III. Geolocation In A Mine Using The Fingerprinting Technique

A. Collection of fingerprint information (CIR)

Wideband measurements were conducted in an underground gallery of a former gold mine, the laboratory mine ‘CANMET’ in Val d’Or, 700 kilometers north of Montreal, Quebec Province, Canada. Located at a 40-meter underground level, the gallery stretches over a length of 75 meters with a width and height both of approximately 5 meters. Figure 2 illustrates the map of the gallery with all its under-adjacent galleries. Due to the curvature of the gallery, the existence of a non-line of sight propagation is noted.

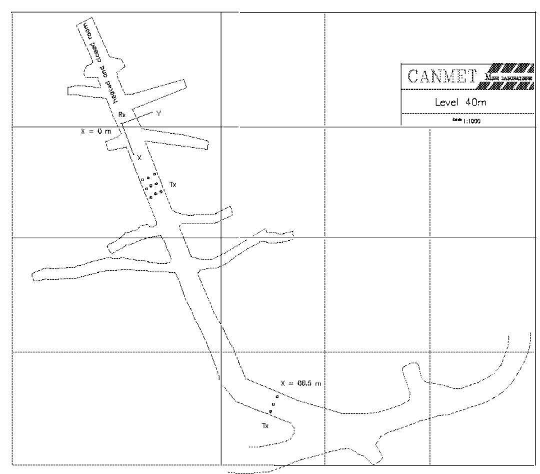

Figure 2. Map of the underground gallery.

A central frequency of 2.4 GHz has been used throughout the measurements in order to have a compatibility with WLAN systems, which may be used for data, voice and video communications as well as for radiolocation purposes. The complex CIR (wideband measurements) has been obtained using the frequency channel sounding technique [8]. The inverse Fourier transform (IFT) has been applied to the measured complex transfer function of the channel in order to obtain its impulse response with an estimated time resolution of about 8 nanoseconds. For fingerprinting radiolocation purposes, the experimental procedures [9] given in this article are different from those encountered in previous works. As shown in figure 2, the receiver was stationed at a predefined referential (x=0, y=0). The transmitter was moved to different locations within the underground gallery by varying its position of 0.5 meter widthwise (6 positions distant of 0.5 meter for the gallery width of 5 meters) and 1 meter lengthwise (70 positions distant of 1 meter for the gallery length of 70 meters). Some other extra intermediate positions have also been used for the LOS and NLOS cases giving a total of 490 location measurements (Fig. 2). During the measurements, transmit and receive antennas were both mounted on carts at a height of 1.9 meters simulating an antenna placed on the helmet of a miner.

The time domain magnitude of the complex impulse response was obtained at all 490 measurement locations and the mean excess delay (τ_m), the rms delay spread (τ_{rms}), the maximum excess delay (τ_{max}), the total received power (P), the number of multipath components (N), the power of the first path (P_1) and the arrival time (delay) of the first path (τ_1) of the channel have been computed at all 490 measurement locations by using a predefined threshold of 20 dB for the multipath noise floor. The first five parameters characterized the time-spread nature of the indoor channel and the last two parameters emphasized the difference between LOS and NLOS situations. Then, these seven relevant parameters (instead of the magnitude of the impulse response), defining the location-dependent features, have been used as the input for the ANN (positioning algorithm). The choice of these parameters was based on the necessity to have a good reflection of the user's location 'signature' (good location-dependent features of the channel impulse measurements) without having an excessive ANN input vector size to avoid the over-fitting of the ANN during its training phase.

B. ANN-based pattern-matching algorithm

A trained artificial neural network can perform complex tasks such as classification, optimization, control and function approximation. The pattern-matching algorithm of the proposed geolocation system can be viewed as a function approximation problem (nonlinear regression) consisting of a nonlinear mapping from a set of input variables containing information about the relevant parameters of the CIR (τ_m, τ_{rms}, τ_{max}, P, N, P_1, τ_1) onto two output variables representing the two dimensional location (x, y) of the mobile station.

The feed-forward artificial neural networks that can be used as a function approximation are of two types, Multi-Layer Perceptron (MLP) networks and Radial Basis Function (RBF) networks. A generalized regression neural network (GRNN), which is an RBF-type network with a slightly different output layer, and an MLP type network have been tested for the proposed geolocation system. The MLP network showed a higher location error, compared to the GRNN, during the memorization of the data set. However, it showed a lower location error during the generalization phase of the network. Since the generalization property of the system was of greater importance, the MLP-type network has been chosen for the pattern-matching algorithm used in the proposed geolocation system.

During the off-line phase, the MLP network is trained to form a set of fingerprints as a function of user's location and acts as a function's approximation (nonlinear regression). Each fingerprint is applied to the input of the network and corresponds to the seven channel's relevant parameters extracted from the CIR data received by the fixed station. This phase, where the weights and biases are iteratively adjusted to minimize the network performance function, is equivalent to the formation of the database seen with other fingerprinting systems. During the real-time phase, the aforementioned relevant parameters from a specific mobile station (extracted from the measured CIR) are applied to the input of the artificial neural network (acting as a pattern-matching algorithm). The output of the ANN gives the estimated value of the user's location (Fig. 3).

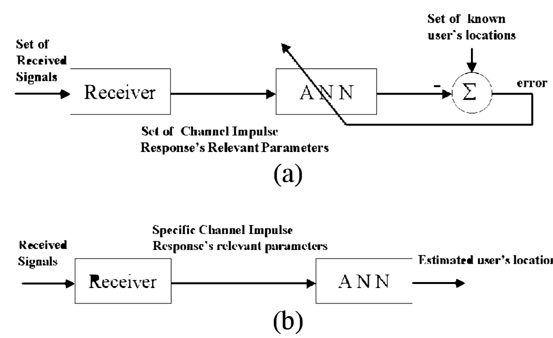

Figure 3. Operation of the proposed system, a) learning phase (off-line phase), b) recalling phase (real-time phase).

It has to be noted that when the size of an ANN is increased, the number of internal parameters (weights and biases) increases inducing more local and global minima in the error surface, and making the finding of a global or a nearly-global minimum by the local minimization algorithm easier [10]. However, when the size of the ANN is large (number of internal parameters is large for the selected training set), an over-fitting problem occurs. It means that the error on the training set is driven to a very small value, but when new data is presented to the network, the error is large. This is a case where the network has memorized (look-up table) the training set, but it has not learned to generalize to new situations [10]. Hence, to have a network with a good generalization property, the size of the network must be chosen just large enough to provide an adequate fit.

In order to have a good generalization property, the used MLP architecture consisted of seven inputs corresponding to the channel's relevant parameters, one hidden layer and an output layer with two neurons corresponding to (x, y) location of the user (Fig. 4). A differentiable tan-sigmoid type of transfer function has been associated for neurons in the hidden layers and a linear one for the output layer.

The simulation results, obtained with the Neural Network Toolbox of Matlab [10], showed that ten neurons corresponding to the hidden layer are adequate to achieve the required regression. Special attention has been given to the ANN's over-fitting problem to respect the generalization property. With seven inputs, two output neurons and ten hidden neurons, the total adjustable number of weights and biases was equal to 102 ([7*10]+[10*2] for the weights, and [10]+[2] for the biases). This is almost four times smaller than the total number of the training set, which is equal to 367 and corresponds to the 75% of the measured wideband data. As a rule of thumb, to have a good generalization property and to avoid the memorization of the network, the number of the patterns in the training set has to be around four times the number of the internal adjustable ANN parameters. Hence, the use of ten hidden neurons was justified.

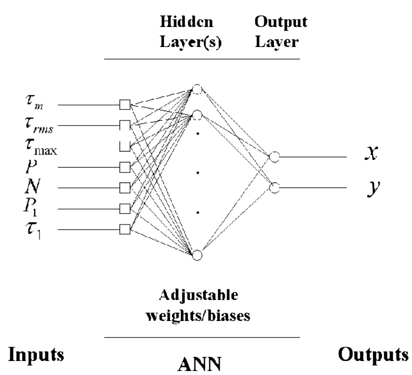

Figure 4. Proposed pattern-matching ANN.

C. Location estimation results

The proposed neural network architecture has been designed using the Neural Network Toolbox of Matlab [10]. In the learning phase, the seven relevant parameters of the CIR and the measured true mobile station positions have been used as the input and as the target of the ANN, respectively. From the 490 measured data, 367 patterns have been employed to train the network. For the recalling phase, as a first step, the same 367 patterns have been applied to the pattern-matching neural network to obtain the location of the mobile station (validation of the memorization property). The location errors as well as their cumulative density functions (CDF) have been computed for analysis purposes. The plots of the corresponding location errors and CDFs of location errors are given in figures 5 and 6. It has to be noted that the localization error has been calculated as the difference between the exact position of the user and the winning position estimate given by the localization algorithm, and hence represents the RMS position location error.

For the training set of data, it can be seen (fig. 5) that the location error in x varies between –2.9 meters and 4.6 meters, the location error in y varies between –1.8 meters and 1.7 meters and the maximum error in Euclidean distance, between the estimated and the true positions, is equal to 4.6 meters.

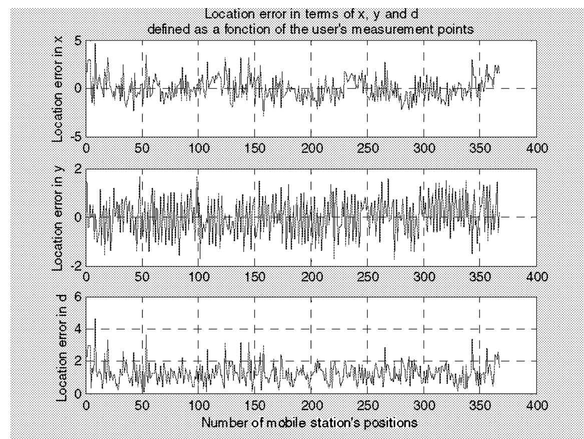

Figure 5. Location errors in *x*, *y* and *d*, with inputs corresponding to the training set of data defined by the number of positions of the mobile station.

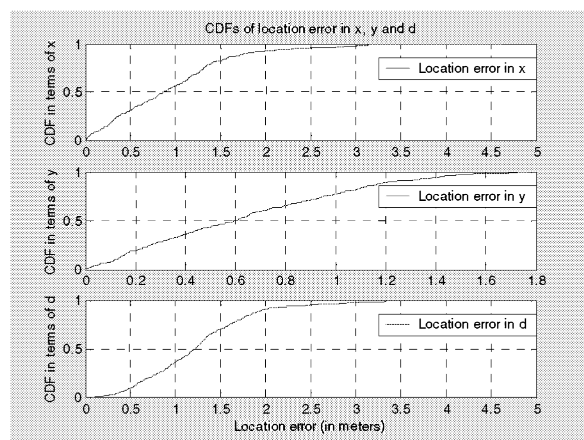

Figure 6. CDFs of location errors in *x*, *y* and *d*, with inputs corresponding to the training set data defined.

Moreover, it can be seen, from figure 6, that a distance location accuracy of 2 meters is found for 90% of the trained patterns. An improvement of the location accuracy is feasible at the cost of the generalization property.

As a second step, the remaining 123 non-trained patterns have been applied to the network to verify the generalization property of the proposed geolocation system. The location errors as well as their cumulative density functions (CDFs) have been computed and plotted (Figs. 7 and 8).

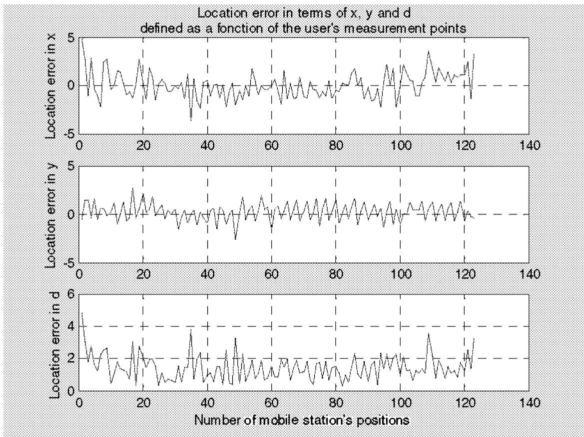

Figure 7. Location errors in *x*, *y* and ***d***, with inputs corresponding to the untrained set of data defined by the number of positions of the mobile station.

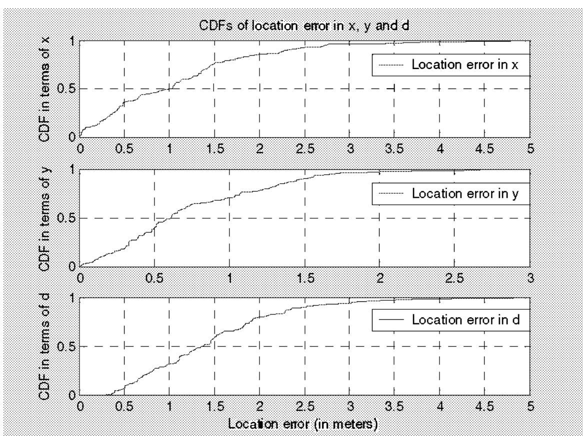

Figure 8. CDFs of location errors in *x*, *y* and ***d***, with inputs corresponding to the untrained set of data.

For the untrained set of data, it can be seen (Fig. 7) that the location error in x varies between –3.8 meters and 4.8 meters, the location error in y varies between –2.6 meters and 2.7 meters and the maximum error in Euclidean distance, between the estimated and the true positions, is equal to 4.8 meters. Moreover, the accuracy of the position estimate depends on the resolution of the map, which in turn depends on the distance threshold used in the map building process. After localization has been achieved, the theoretical error between the actual and estimated position (localization error) should therefore vary between zero and the distance threshold. Since the size of the grid used in the indoor wideband measurements was 0.5 meter widthwise and 1 meter lengthwise, the geolocation accuracy that one may expect with the proposed fingerprinting technique, should be between 0 and 1.12 meters (distance threshold) in terms of the Euclidean distance.

It can be seen, from figure 8, that the location accuracy corresponding to the distance threshold is achieved for 40% of all the untrained patterns.

IV. Conclusions

This paper has shown that a fingerprinting technique using the CIR information is a novel approach for geolocation in mines or other confined environments with rough sidewall surfaces. The technique exhibits superior reproducibility properties compared to other two fingerprint information (RSS and APP) based techniques.

The use of an artificial neural network as a pattern-matching algorithm for the proposed system is a new approach that has the advantage of giving a robust response with a generalization property. Moreover, since the training of the ANN is off-line, there are no convergence and stability problems that some control (real-time) applications encounter. The transposition of the system from two to three dimensions is easy (addition of a third neuron in the ANN's output layer corresponding to the z position of the user) and constitutes an advantage of the ANN.

The proposed fingerprinting technique used for the geolocation of the studied mine, gave an accurate mobile-station location. The results showed that a distance location accuracy of 2 meters has been found for 90% and 80% of the trained and untrained patterns, respectively. This location accuracy, which may be enhanced at the cost of the generalization property, is smaller compared to the one reported in the literature for indoor geolocation using fingerprinting techniques.

On the other hand, the fingerprinting technique needs the digital map of the environment and is not well suited for dynamic areas. Preliminary measurements in mine showed that the influence of low human activity is negligible on the wideband measurement results at the specific frequency of operation. However, heavy machinery or vehicles may considerably change the properties of the channel, requiring an update of the database's information (a new training of the neural network).

As indicated previously, this novel method may also be applicable to any other indoor applications (shopping centers, campuses, office buildings). In addition, some advanced simulation programs may be used to generate impulse responses as a function of user's location (for the training set of data of the neural network) instead of getting these impulse responses via wideband measurements. This approach will reduce the database generation time for the proposed geolocation system and would facilitate the proposed system's implementation.

Finally, for an effective implementation of the proposed system, one may employ different radio access technologies such as WLAN, impulse radio (UWB) or mobile radio.

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