Geolocation in Mines With an Impulse Response Fingerprinting Technique and Neural Networks

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***Abstract*— The location of people, mobile terminals and equipment is highly desirable for operational enhancements in the mining industry. In an indoor environment such as a mine, the multipath caused by reflection, diffraction and diffusion on the rough sidewall surfaces, and the non-line of sight (NLOS) due to the blockage of the shortest direct path between transmitter and receiver are the main sources of range measurement errors. Unreliable measurements of location metrics such as received signal strengths (RSS), angles of arrival (AOA) and times of arrival (TOA) or time differences of arrival (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 for line of sight (LOS) and non-line of sight (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*— Indoor geolocation, underground mine, fingerprinting technique, radio propagation parameters, artificial neural network.**

I. Introduction

A Problem of growing importance in indoor environments is the location of people, mobile terminals and equipment. In underground mines, geolocation with good performance is essential in order to improve operational efficiency, worker's safety and remote control of mobile equipment. Since indoor radio channels suffer from extremely serious multipath and non-line of sight (NLOS) conditions, they have to be modeled and analyzed appropriately to enable the design of radio equipment for geolocation applications. As voice or data services and geolocation applications have different performance criteria [1], existing radio channel models are not fully appropriate for localization purposes. Therefore, different models and techniques have to be applied to provide adequate location accuracy.

In traditional wireless geolocation applications, the basic function of the location system is to gather parametric information such as received signal strengths (RSS), angles of arrival (AOA), times of arrival (TOA) or time differences of arrival (TDOA) about the position of a mobile station (MS) and process that information to form a location estimate [2]. In indoor environments where conditions of signal propagation are severe (multipath, NLOS) and in a mine where the rough sidewall surfaces also impact these conditions [3], the traditional parametric geolocation techniques (RSS, AOA, TOA, TDOA) or their combinations (TDOA with AOA or RSS) fail to provide adequate location accuracy. For these techniques, all the paths used for triangulation must have a LOS to ensure an acceptable accuracy, a condition that is not always met in an indoor environment. Geolocation based on the received signals' fingerprint performs better in such an environment [4] when appropriate signatures and pattern-matching algorithms are used.

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). For the studied underground mine, results show a distance location accuracy of 2 meters for 90% and 80% of the trained and untrained patterns, respectively. In Section II, we discuss the various wireless geolocation techniques used in indoor environments with their limitations and advantages. In Section III, we present our proposed system (WBNN-Locate) and give the position location results by applying the measured indoor data to an artificial neural network. Some implementation issues are discussed in Section IV. Finally, we close this paper with a conclusion in Section V.

II. Indoor Wireless Geolocation Techniques

Most of the indoor geolocation applications use a network-based system architecture in which base stations (BS) or access points (AP) extract location-dependent parameters or metrics (RSS, AOA, TOA or TDOA) from the received radio signals transmitted by the mobile station (MS) and relay the information to a control station (CS). Then the position of the user (MS) is estimated and displayed at the CS.

Manuscript received December 22, 2003; revised September 21, 2004; accepted December 29, 2004. The associate editor coordinating the review of this paper and approving it for publication was Y.-C. Liang.

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Digital Object Identifier 10.1109/TWC.2006.03017

A. Parametric Geolocation Techniques

In the parametric indoor geolocation techniques, the concept of the line of position (LOP) with at least two observations is used in order to obtain a two-dimensional position fix. The main measurement errors introduced during the extraction of the location-dependent metrics (RSS, AOA, TOA and TDOA) are due to the indoor environment. The LOP due to these errors do not intersect at a point resulting in large estimation errors.

In general, the time-based TDOA geolocation technique is the most popular one and may be combined with other techniques to improve the location accuracy [5]. The location accuracy of current systems which use the time-based indoor geolocation technique is in the range of 3 meters in a LOS environment. Results given in section III, show that the location accuracy obtained by the time-based geolocation technique applied to the underground mine is not fully satisfactory for safety purposes. Hence, for a non-line of sight indoor environment alternatives to the parametric geolocation techniques have to be considered.

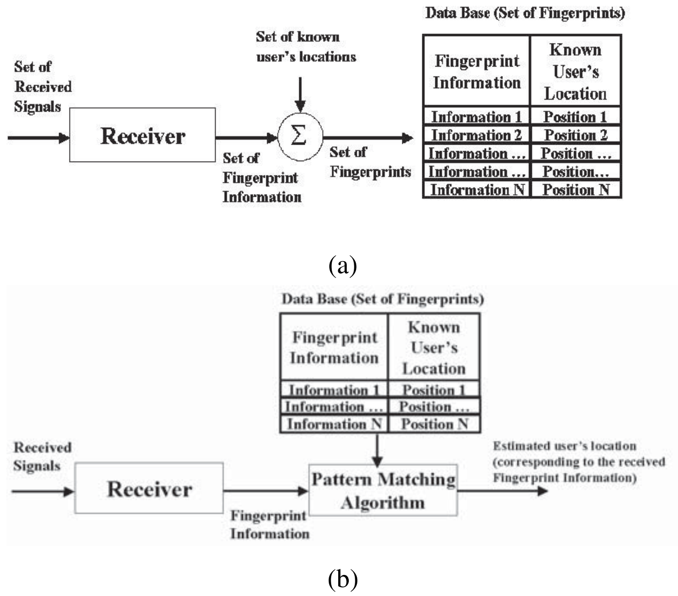

Fig. 1. Operation of the proposed system, a) learning (off-line) phase, b) recalling (real-time) phase.

B. Fingerprinting Geolocation Techniques

To improve the accuracy of the user's location in a harsh environment, the effect of multipath has to be mitigated or multipath has to be used as constructive information. A radio frequency signal transmitted from a given geographical MS location has a distinct pattern by the time it reaches a receiver. Interference caused by natural or man-made objects causes the signal to break up into a number of different paths (multipath). Hence, each location produces a unique 'signature' pattern called fingerprint.

The process of geolocation based on the received signals' fingerprint is composed of two phases: a phase of data collection called off-line phase and a phase of locating a user in real-time. 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 is measured by a receiver and compared with the recorded fingerprints of the database. A pattern matching or positioning 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).

To constitute a 'signature' pattern or a fingerprint, several types of information [4] can be used such as 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 and reproducible. Reproducibility means achieving almost the same estimated set of fingerprint information in one location for different observation times. Uniqueness means that the set of fingerprint information in one location is relatively different from the one in another location and that there is no aliasing in the signature patterns.

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 (ANN). 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. Since an ANN respects these properties, an architecture based on neural networks has been used in the proposed geolocation system as the pattern-matching algorithm.

C. 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. RADAR [6] is an RF-based system for locating and tracking users inside buildings. It uses RSS information gathered at multiple receiver locations to estimate the user's coordinates. The system, operating with WLAN technology, has three access points or fixed stations and covers the entire zone of interest. A pattern-matching algorithm, which consists of the nearest neighbor(s) in signal space, is used to estimate the user's location. Another system similar to RADAR, EKAHAU [7], uses RSS information gathered at multiple receiver locations to perform an indoor positioning using a WLAN infrastructure. In the framework of Trento University's project WILMA (Wireless Internet and Location Management Architecture), RSS fingerprint information has been used to estimate user's location in a building equipped with a WLAN technology. The pattern-matching algorithm employed has been an ANN [8] to achieve the generalization needed when confronted with new data not present in the training set. RadioCamera (product of US Wireless Corporation), DCM (Database Correlation Method) [9], [10] and a third system found in [11] use fingerprinting techniques to locate and track mobile units in metropolitan outdoor environments. RadioCamera, operating with a cellular technology, uses multipath APP gathered at one receiver to locate the user's coordinates. A measure of proximity is used as the pattern-matching algorithm [12]. DCM, operating with cellular GSM (Global System for Mobile communication) and UMTS (Universal Mobile Telephone Service) technologies, uses RSS and CIR measured fingerprint information with a cross-correlation metric algorithm to perform the localization process. As a measure of performance, the median resolution of the location estimation for indoor and outdoor fingerprinting geolocation systems is reported to be in the range of 2 to 3 meters and 20 to 150 meters, respectively. In Table I, different geolocation techniques are presented in order to underline and compare their main features, strengths and weaknesses.

RSS type of information used by RADAR, EKAHAU and WILMA for indoor environments requires the involvement of several fixed stations to compute the user's location. Moreover, values of RSS can vary greatly for different locations thus implying a reproducibility concern. Angular power distribution type of information requires the use of an antenna array and the need for high angular resolution for indoor geolocation since the scatterers are around both the transmitter and the receiver. A set of several characteristics of multipath power delay profiles or channel impulse responses has the advantage of being reproducible and unique, especially when the localization is performed on a continuous basis. Therefore, a signature based on the impulse response of the channel may give the best location accuracy for an indoor geolocation. However, its implementation involves the use of a wideband receiver. On the other hand, the pattern-matching algorithm used in RADAR and DCM systems may show a lack of generalization yielding an incorrect output for an unseen input, a lack of robustness against noise and interference and a long search time needed for a real-time localization, especially when the size of the environment or the database is large. Hence, the use of an artificial neural network as the pattern-matching is essential since an ANN is robust against noise and interference, has a good generalization property and the time of localization during the real-time phase is almost instantaneous.

To respect the reproducibility, the uniqueness and the generalization properties, 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

The proposed geolocation system called WBNN-Locate is an RF-based system for locating and tracking users in an indoor mine. It uses the CIR information obtained from wideband measurements [4] gathered at one receiver to locate the user's coordinates with an uplink-network-based approach. The system which can be operated with different radio access technologies has one fixed station and covers the entire zone of interest. A second fixed station can be used as redundancy.

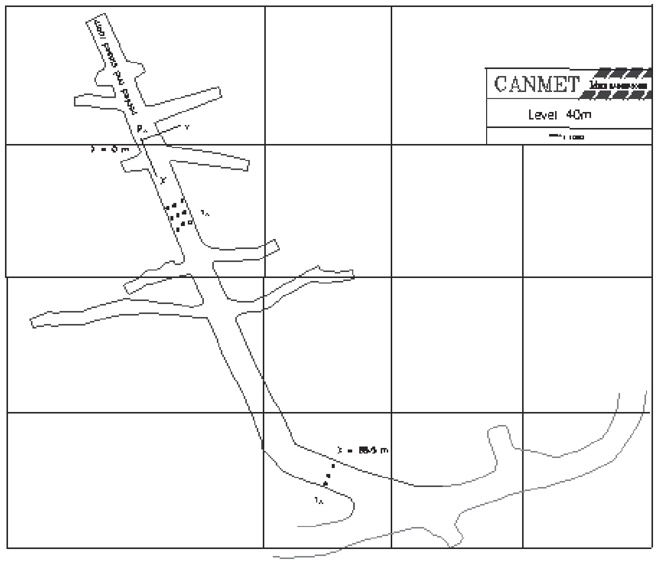

Fig. 2. Map of the underground gallery.

A. Collection of Fingerprint Information (CIR)

Measurements were conducted in an underground gallery of a former gold mine, the laboratory mine "CANMET" in Val d'Or, 700 kilometres north of Montreal in the province of Quebec, 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. Fig. 2 illustrates the map of the gallery with all its under-adjacent galleries. Due to the curvature of the gallery, the existence of NLOS propagation is noted.

The digital photograph given in Fig. 3 shows a part of the underground gallery. It can be seen from the photograph that the walls are very rough, the floor is not flat and it contains some water plaques. It has been found that the roughness of the sidewall surfaces has a substantial impact on the propagation characteristics of the channel [3]. 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 impulse response of the channel has been obtained using the frequency channel sounding technique. During the measurements, a vector network-analyzer has performed the transmission and the reception of the RF signal. The inverse Fourier transform (IFT) has been applied to the measured complex transfer function of the channel in order to obtain its impulse response. The chosen frequency band was centered at 2.4 GHz with a span of 200 MHz corresponding to a theoretical time resolution of 5 nanoseconds. In practice, due to the use of windowing, the time resolution is estimated to be around 8 nanoseconds. The sweep time of the network analyzer has been decreased to validate the quasi-static assumption of the channel. Each sweep consisted of 201 complex samples spaced of 1 MHz from each other giving an unambiguous delay time of 1 microsecond, which was far beyond the sum of the maximum excess delay for the studied mining environment and the propagation delay of the

TABLE I
OVERVIEW OF DIFFERENT GEOLOCATION TECHNIQUES

Geolocation Technique	System	Application	Positionning Algorithm	Implication Technology	Receiver Type	Minimum Bs or AP Per cell	Reported Accuracy (position error)
RSS Parametric	Many	Outdoor	Non linear Least square	Cellular Radio	Narrowband	3	100m-10km
AOA Parametric	Many	Outdoor	Geometric	Cellular Radio	Beamforming	2	50-150m
TOA/TDOA Parametric	Many	Outdoor	Non linear Least square	Cellular Radio	Wideband	3	40-150m
	3D-iD	Indoor	Non linear Least square	Proprietary (40 Mcps)			3m
RSS Finger-printing	DCM	Outdoor	Correlation	GSM	Narrowband	3	40-100m
	RADAR	Indoor	Nearest Neighbor(s) Euclidian	WLAN			3m
	Battiti et al.	Indoor	ANN	WLAN			2m
APP Finger-printing	Radio-Camera	Outdoor	Nearest Neighbor(s) Kullback-Liebler	AMPS	Beamforming	1	50-150m
PDP or CIR Finger-printing	DCM	Outdoor	Cross Correlation	UMTS	Wideband	1	20-70m
	Nypan et al.		Nearest Neighbor(s) Box-Cox	GSM/UMTS			25-55m
CIR Finger-printing (Proposed System)	WBNN-Locate	Indoor (mine)	ANN	Possibility of different technologies	Wideband	1	1-2m

Fig. 3. Digital photograph of the underground gallery.

cable. The wideband experimental procedures [3] were defined to characterize the relevant parameters of the channel and to utilize these parameters in order to perform a radiolocation of workers in the underground gallery. Hence, as a result of the radiolocation purpose using the fingerprinting technique, the experimental procedures given in this article are different from those encountered in previous works. The network analyzer and the PC were stationed with the receive antenna and the other receiver components at the predefined referential. The equipments were tested for a flat response in the measurement band and calibrated in the presence of the RF cable. The transmit antenna and the other transmitter components were moved to different locations within the underground gallery by varying their position of 0.5 meter widthwise and 1 meter lengthwise. Six positions distant of 0.5 meter for the gallery width of 5 meters, seventy positions distant of 1 meter for the gallery length of 70 meters and some other extra intermediate positions for the LOS and NLOS cases gave a total of 490 location measurements (Fig. 2). During the measurements, the mine was empty and the shadowing effects were absent. Transmit and receive antennas were omni-directional and were vertically polarized. They were both mounted on carts at a height of 1.9 meters simulating an antenna placed on the helmet of a miner.

The complex transfer function was obtained at all 490 measurement locations. For each location, a temporal average has been performed on a set of ten measurements of different observation times. The time domain magnitude of the complex impulse response has been obtained from the measured samples of the frequency domain response using the inverse fast Fourier transform (IFFT). From the magnitude of the complex impulse response seven relevant parameters, namely, 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 [13]. The first three parameters characterized the time-spread nature of the indoor channel and the last two parameters gave an emphasis about the difference between LOS and NLOS situations. Then, these seven parameters 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' without having an excessive ANN input vector size to avoid the over-fitting of the ANN during its training phase. This is why the use of all the CIR magnitude samples has been ruled out.

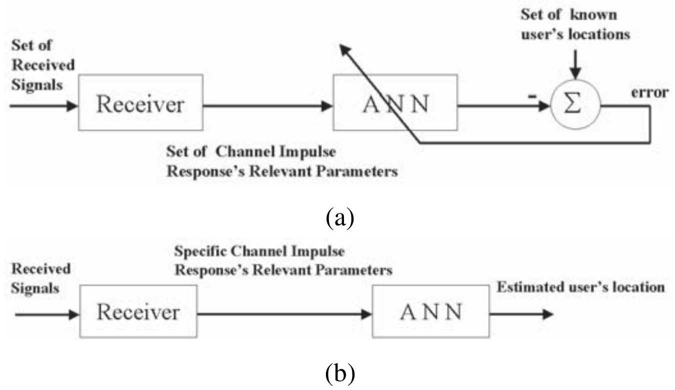

Fig. 4. Operation of the proposed system, a) learning (off-line) phase, b) recalling (real-time) phase.

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 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. Either type of the two networks can approximate any nonlinear mapping to an arbitrary degree of precision provided the right network complexity is selected [14]. A specific learning algorithm is associated for each type of the two networks, which has the role of adjusting the internal weights and biases of the network based on the minimization of an error function, and defines the training of the network. MLP networks can reach globally any nonlinear continuous function due to the sigmoid basis functions present in the network. Since these functions are nonzero over an infinitely large region of the input space, they are capable of achieving a generalization in regions where no training data are available. On the other hand, RBF networks can reach the given nonlinear continuous function only locally because the basis functions involved cover only small and localized regions. However, the design of an RBF network is easier and the learning is faster compared to the MLP network.

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.

The MLP-type ANN, used in the proposed system, consisted of two phases: a supervised learning or training phase and a recalling or testing phase. 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. Each fingerprint is applied to the input of the network and corresponds to the channel's relevant parameters (τ_m, τ_{rms}, τ_{max}, P, N, P_1, τ_1) extracted from the impulse response 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 are applied to the input of the ANN. The output of the ANN gives the estimated value of the user's location (Fig. 4).

It has to be noted that when the size of an ANN is increased, the number of internal parameters such as the weights and the 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 [15]. However, when the size of the ANN is large or equivalently, when the number of the weights and biases 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 [16]. 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. A way of improving the generalization property is the use of a regularization method. The method modifies the performance function by adding to the mean sum of squares of the network errors a term that consists of the mean of the sum of squares of the network weights and biases. Moreover, to have an automated regularization where the optimal regularization parameters are determined in an automated fashion, Bayesian regularization in combination with Levenberg-Marquardt algorithm may be used [17]. Finally, properly trained MLP networks tend to give reasonable answers when presented with inputs that they have never seen [16]. Typically, a new input will lead to an output similar to the correct output or target for input vectors used in training that are similar to the new input being presented. Hence no

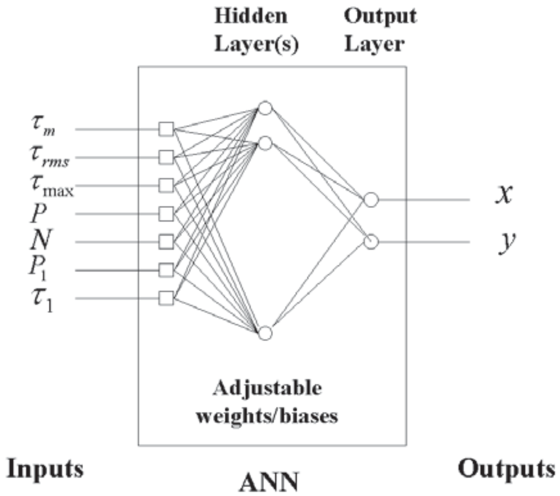

Fig. 5. Proposed pattern-matching ANN.

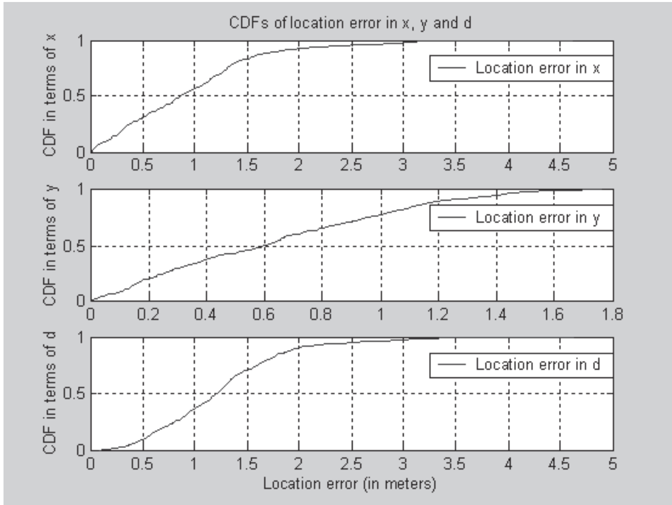

Fig. 6. Cumulative distribution functions (CDFs) of location errors in *x*, *y* and *d*, with inputs corresponding to the training set of data defined by the number of positions of the mobile station.

need to train the network on all possible input/output pairs.

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.5). 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 [16], showed that ten neurons corresponding to the hidden layer are adequate to achieve the required nonlinear regression. Special attention has been given to the ANN's over-fitting problem to respect the generalization property (use of the trainbr.m function of Matlab which applies the Bayesian regularization with the Levenberg-Marquardt algorithm). Hence, the designed network was robust to perturbations at its input such as errors in the measurement data, and was able to accomplish a generalization rather than a memorization by providing the right location for an unseen and non-trained input. Moreover, since an MLP has an inherent low-pass filter property, it may remove the high frequency components present in the location-error signal.

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.

It has to be noted that before training, the inputs and the targets have been scaled or normalized using the premnmx.m function of Matlab so that they fall in the range [-1, +1]. The outputs of a trained network, having scaled inputs and targets, will fall in the range of [-1, +1]. To convert these outputs back into the same units, which were used for the original targets, the postmnmx.m function of Matlab has been used. The normalization of the inputs and targets is essential for the performance improvement of the ANN optimization process. Moreover, typical data sets often contain redundant information or measured values which are highly correlated. It is useful in this situation to reduce the dimension of the input vectors by transforming the full set of training examples into a compressed set that contains only essential information. The prepca.m function of Matlab has been used to execute this operation based on the principal component analysis which performs three tasks: it orthogonalizes the components of the input vectors (the vectors become uncorrelated with each other), it orders the resulting orthogonal components or principal components so that those with the largest variation come first, and it eliminates those components which contribute the least to the variation in the data set [16].

C. Location Estimation Results

The proposed neural network architecture has been designed using the Neural Network Toolbox of Matlab. 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. This step corresponded to the validation of the memorization property. The location errors as well as their cumulative density functions (CDFs) have been computed for analysis purposes. The plots of the CDFs of location errors are given in Fig. 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. Moreover, by analogy with FCC requirements [18], the CDF of the location error has been used as the performance measure of the system.

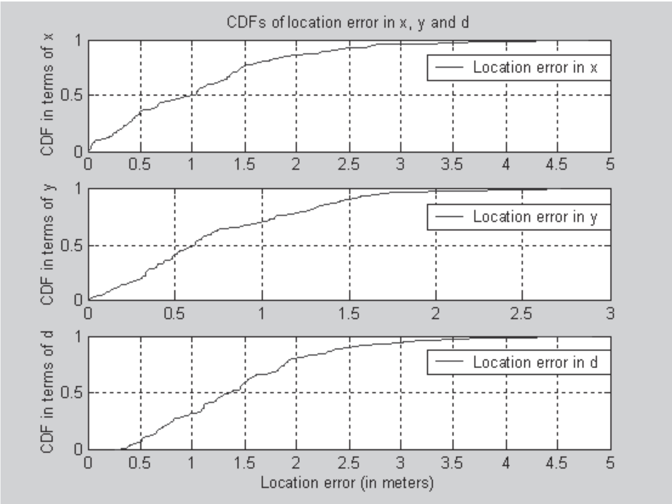

Fig. 7. Cumulative distribution functions (CDFs) of location errors in *x*, *y* and *d*, with inputs corresponding to the untrained set of data defined by the number of positions of the mobile station.

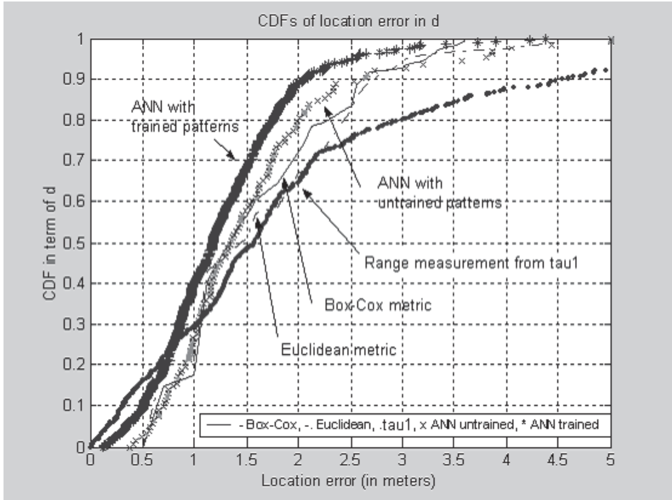

Fig. 8. Cumulative distribution functions (CDFs) of location errors in *d*, using the range measurement technique and the fingerprinting technique with three positioning algorithms (Euclidean metric, Box-Cox metric and Artificial neural network).

For the training set of data, the computed location errors show a variation in x between -2.9 meters and 4.6 meters and in y between -1.8 meters and 1.7 meters. The maximum error in Euclidean distance, between the estimated and the true positions, is found to be equal to 4.6 meters.

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 the CDFs of location errors have been plotted (Fig. 7). For the untrained set of data, computed results show 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. The maximum error in Euclidean distance, between the estimated and the true positions, is found to be equal to 4.8 meters.

It can be seen from Fig. 6 and 7 that a distance location accuracy of 2 meters is found for 90% and 80% of the trained and untrained patterns, respectively. The location accuracy is thus far superior to accuracies found in the literature [6]–[8] for other indoor geolocation processes that use fingerprinting techniques.

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.

First, in order to see the advantage of the fingerprinting technique compared to the parametric one, data corresponding to the arrival time of the first path (τ_1) have been used for localization purposes (range measurement). Secondly, in order to see the advantage of employing an ANN in an indoor geolocation system that uses the fingerprinting technique, three different pattern-matching algorithms (nearest neighbor minimizing the Euclidean distance, nearest neighbor minimizing the Box-Cox metric [19] and artificial neural network) have been used with the same empirical data set (untrained patterns). The three of the five curves seen in Fig. 8 give the CDFs of location errors in Euclidean distance (d) for the involved three pattern-matching algorithms. Only the CDF of location errors using the ANN with the trained patterns is added on the figure since the associated curves for the two other algorithms are not necessary (their location errors tend to zero due to the memorization of the two algorithms). It can be seen that, for the generalization property (the most important property for the fingerprinting technique), the artificial neural network works the best giving an error less than 2 meters for 80%, for all the untrained patterns, compared to 68% and 72% for the Euclidean and Box-Cox metrics, respectively. Although the result of the Box-Cox algorithm is close to the one achieved by the ANN, its computation time will be higher when the zone of interest is large. Finally, the fifth curve in Fig. 8 corresponds to the CDF of location errors using a range measurement technique based on the time of arrival of the first path and without using any ANN. The results yield a distance location accuracy of 2 meters for only 65% of the measured data. This accuracy is far less than the one achieved with the proposed fingerprinting technique assessed above.

IV. Implementation Issues

In indoor environments, the largest excess delay corresponding to the detectable multipath component is in the order of 500 nanoseconds [20]. On the other hand, to characterize the discrete-time impulse response model or equivalently the multipath power delay profile, a reasonable bin (small time interval) resolution is needed. The value chosen for a bin depends on the indoor environment of interest.

The resolution of the measured channel impulse response depends on the system bandwidth. The effect of a limited bandwidth is that multiple reflections may end up in the same time bin on the delay axis, implying the vector combination of the reflections and yielding a resultant signal large or small depending on the distribution of phases among the component waves. This will give rise to a reproducibility problem of the measured channel impulse responses.

For an efficient operation of the proposed system, it is of prime necessity to be able to resolve all multipath components to obtain the power delay profile or the impulse response as a function of the user's location. Hence the radio access technology used for an effective implementation of the system must satisfy this requirement (resolution of the multipath differential delays in the nanosecond range). Several existing technologies, with some modifications (high-resolution algorithms [21]), are good candidates for such an application. The most promising technologies found in practice are, mobile radio systems, impulse radio systems [22], [23] and WLAN systems [24]. The choice of the wideband receiver technology and its implementation depend on the specific application and is still an open area of research.

Moreover, an important issue in the proposed geolocation system is the synchronization between the transmitter and the receiver as well as the choice of multiple-access technique, e.g. Time Division Multiple Access - TDMA, Code Division Multiple Access -CDMA and Carrier Sense Multiple Access - CSMA to support the simultaneous localization of several mobile stations. WLAN-based systems with CSMA tend to be more cost-effective than CDMA and TDMA but issues may arise with respect to the continuous channel access and handoff capabilities for WLANs.

V. Conclusions

This paper has shown that a fingerprinting technique using the channel's impulse response information in conjunction with an artificial neural network 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 main 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 (the location fingerprint does not have to be in the fingerprint database). 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 an important issue that will be investigated in the near future.

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 is improved with respect to the one reported in the literature [6]–[8] 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. Heavy machinery or moving objects may considerably change the properties of the channel, requiring an update of the database's information (a new training of the neural network). This channel variation issue can be addressed by using a master neural network. After detecting the changes in the channel's properties, the system identifies the specific situation (channel state) via a scanning process and activates the trained neural network corresponding to this specific situation.

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. If the generated CIRs are close to the measured ones, this approach will reduce the database generation time for the proposed geolocation system and would facilitate the proposed system's implementation.

Acknowledgment

The authors wish to thank Professor Gilles Delisle for his precious advice and M. Mourad Djadel for his collaboration in the wideband measurements campaign. The financial support of Bell Nordic Group Inc. is also acknowledged.

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