The 17th Annual IEEE International Symposium on Personal, Indoor and Mobile Radio Communications (PIMRC'06)

Neural network and fingerprinting-based geolocation on time-varying channels

Chahé NERGUIZIAN [1], Charles DESPINS [2,3], Sofiène AFFÈS [2], Gilles I. WASSI [4] and Dominic GRENIER [4]

[1] École Polytechnique de Montréal, Canada
http://www.polymtl.ca
chahe.nerguizian@polymtl.ca

[2] INRS-EMT, Montréal, Canada
http://www. emt.inrs.ca
affes@inrs-emt.uquebec.ca

[3] PROMPT-Québec, Montréal, Canada
http://www.promptquebec.com
cdespins@promptquebec.com

[4] Université Laval, Québec, Canada
http://www.ulaval.ca
wassi@gel.ulaval.ca, dominic.grenier@gel.ulaval.ca

Abstract— In a harsh indoor environment, fingerprinting geolocation techniques perform better than the traditional ones, based on triangulation, because multipath is used as constructive information. However, this is generally true in static environments as fingerprinting techniques suffer degradations in location accuracy in dynamic environments where the properties of the channel change in time. This is due to the fact that the technique needs a new database collection when a change of the channel's state occurs. In this paper, a novel solution based on a hierarchy of artificial neural networks (*ANNs*) is proposed to enhance such a geolocation system. It is shown that the enhanced system detects the change in the channel's properties via geolocation reference points, identifies the new channel state and activates a new database that best represents the current radio environment.

Keywords— Indoor geolocation, Fingerprinting technique, Artificial neural network, Time-varying channel.

I. INTRODUCTION

In a harsh indoor environment where conditions of signal propagation are severe (multipath, non-line-of-sight *NLOS*), traditional geolocation techniques (received signal strength-*RSS*, angle of arrival-*AOA*, time or time difference of arrival-*TOA*/*TDOA*) fail to provide adequate location accuracy. For these techniques, all the paths used for triangulation must have a line-of-sight (*LOS*) to ensure acceptable accuracy, a condition that is not always met in an indoor environment [1]. Fingerprinting geolocation techniques, which use multipath as constructive information, perform better in such environments, as long as they are static, and if such is the case, can provide location accuracy within two to three meters [2-4]. However, in dynamic areas where the channel is subject to changes in topology (building construction, movement of people, presence of moving objects), the fingerprint database has to be regularly updated. An off-line updating process is very onerous, whereas a real-time update of the database is almost impossible. To the best of our knowledge, few papers [5], [6] have considered the impact of the dynamic channel's behaviour on the fingerprinting technique typically without giving any detailed solution and dealing only with outdoor environments.

This paper provides a novel geolocation solution, for a channel with a dynamic behaviour, by using a hierarchy of artificial neural networks applied to a fingerprinting geolocation technique. Moreover, it represents the first paper that tries to solve the time-varying channel issue specifically for indoor geolocation applications. In the next section, we give a description of the fingerprinting geolocation technique applied to harsh indoor environments (i.e. underground mine) but initially designed for static channels, followed by the proposed solution based on artificial neural networks, for fingerprinting indoor geolocation over time-varying channels. Prior to a conclusion, section 3 describes how the performance of this proposed solution has been validated in a standard indoor environment.

II. FINGERPRINTING GEOLOCATION WITH TIME-VARYING CHANNELS

A. Fingerprinting geolocation technique designed for static indoor environments

The *RF*-based geolocation system [2], [3] employed in an underground mine uses the channel's impulse response (*CIR*) data, i.e. seven impulse response characteristics obtained from wideband measurements [7], [8], as the fingerprint information or 'signature', gathered at one receiver to locate the user's coordinates and to track the mobile station (figure 1).

The pattern-matching algorithm of the system uses an artificial neural network, which is robust against noise and interference, and has a good generalization property.

During the off-line phase, a Multi-Layer Perceptron (*MLP*) type artificial neural network is trained to form a set of fingerprints as a function of user's location, and acts as a function approximator (nonlinear regression). Each fingerprint is applied to the input of the *ANN* and is composed of a set of the seven channel's location-dependent parameters extracted from the impulse response data received by the fixed station.

1-4244-0330-8/06/$20.00©2006 IEEE

This phase, where the weights and biases are iteratively adjusted to minimize the network performance function, is equivalent to the formation of the database (recording of the set of fingerprints as a function of user's location) seen with other fingerprinting geolocation systems.

During the real-time phase, the seven impulse response characteristics from a specific mobile station (obtained from the measured channel's impulse response) 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.

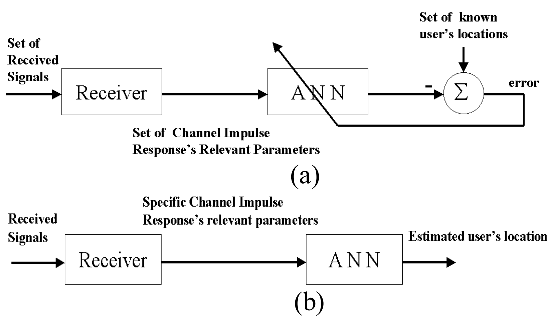

Figure 1. Process of geolocation using received signal's fingerprint, a) off-line phase, b) real-time phase.

Properly trained *MLP* networks tend to give reasonable answers when presented with inputs that they have never seen (generalization property) [9]. Typically, a new input will lead to an output similar to the correct output (target) for input vectors used in training that are similar to the new input being presented (no need to train the network on all possible input/output pairs). Moreover, a *MLP* type artificial neural network has an inherent low pass filter property, which can remove the high frequency components present in the location error signal. Furthermore, since the training of the *ANN* is off-line, there is no convergence and stability problems, and the estimation of the user's location (real-time phase) is almost instantaneous.

Figure 2 gives the cumulative density functions (*CDF*s) of location errors in *d* (Euclidean distance) for the trained and untrained set of data in an underground mine, respectively [2], [3].

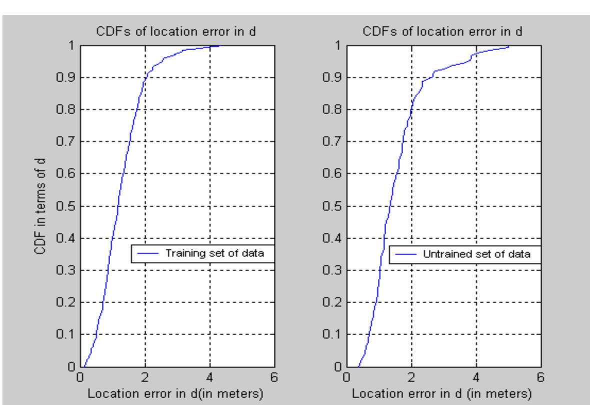

Figure 2. CDFs of location errors in *d*, with inputs corresponding to the training and untrained set of data.

The results show a distance location accuracy of 2 meters for 90% and 80% of the trained and untrained patterns, respectively.

B. Proposed artificial neural network based solution to mitigate the degradation in precision resulting from the channel's temporal variation

Multipath is strongly influenced by the layout of the indoor environment, the number of people and the presence of moving objects in the environment. As the number and the distribution of people vary, and/or as one or several moving objects are present, the propagation characteristics of the *RF* signals change as well, causing variations in the channel's impulse response (*CIR*) at various locations. Consequently, a database or an artificial neural network (*ANN*) respectively created or trained at a particular time may not accurately reflect the environment at a different time due to the radio environment change, causing a considerable reduction of the geolocation accuracy. Hence, to avoid this degradation, the geolocation system has to detect the change of the channel's properties or states, and then identify and activate dynamically the trained *ANN* that best represents the current radio environment.

To be able to perform these three functions adequately, *M* fixed radio transmitters with known locations (geolocation reference points-*GRPs* [10] or light access points-light *APs* [4]) and a continuous user tracking process are of the utmost importance. The knowledge of the *GRP*s' locations (distributed along the zone of interest) serves to detect any significant change in the received channel's impulse response (time average of several *CIR*s) due to a change in the radio environment. Moreover, the continuous user tracking process is a complementary piece of data that may inform the geolocation system about any environmental changes. The underlying idea is to exploit past information in order to detect any changes in the channel's properties. The physical contiguity constraint refrains an indoor user from jumping across large distances at random (the location of a user at a given instant t_2 is likely to be close to its previous position at a nearby time instant t_1). For example, a pedestrian's position cannot undergo a change of more than Δd m in a time interval (time window) of Δt sec. Continuous user tracking mainly amounts to determining a sequence of the user's location. A time window $\Delta t = t_2 - t_1$ is used to compute the time average of consecutive samples of the channel's impulse response (collection of several impulse responses) on a continuous basis. This information is then used with the geolocation system described in the previous sub-section to estimate the user's location on a continuous basis. A second advantage of continuous user tracking is that the uniqueness problem, which occurs in the fingerprinting techniques, may be alleviated i.e. the unambiguous user's location of the recent past in conjunction with the physical constraints, will yield a correct location estimate even if two distant locations give similar fingerprint information.

Accordingly, the proposed solution uses a master *ANN* with *N* trained *ANN* candidates reflecting different environment states (figure 3). The wideband receiver measures the channel impulse response from a specific mobile station location. From this *CIR*, the location-dependent parameters are extracted and then applied to the inputs of the N trained *ANN* candidates. The deployment of M fixed transmitters or *GRP*s in the zone of interest and the process of continuously tracking the user will enhance the geolocation system by detecting the change in the channel's properties and by activating dynamically the trained *ANN* candidate that best represents the current radio environment. The methodology for enhancing the geolocation process is detailed in the following sub-section.

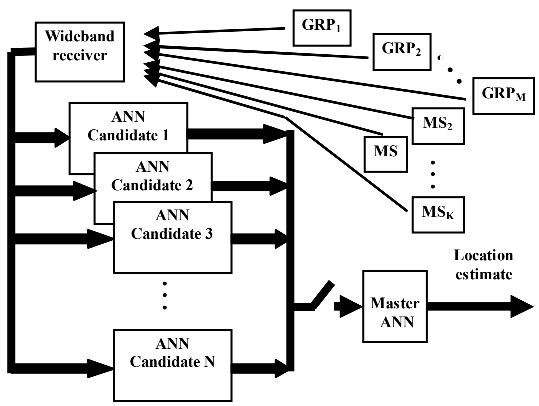

Figure 3. Operation of the neural network based solution.

C. *Methodology for enhancing the geolocation system*

The description of the environmental states depends in general on the indoor channel. Several possible realistic scenarios (environmental states) may exist depending on the indoor channel application. In particular, the number and the distribution of people may vary during the course of a day. Moreover, one or several fixed obstacles at specific locations may be present in the environment. Each configuration corresponds to an environmental state that is associated to a set of channel's impulse responses obtained from wideband measurements at different locations. Hence, for each channel state, there exists a database collection (trained *ANN*) of channel's location-dependent parameters.

In practice, several (N) realistic scenarios (environmental states) in indoor environment may occur:

- Low human activity with no moving objects (a nearly empty environment)
- Medium human activity with no moving objects
- High human activity with no moving objects (an environment with a heavy traffic)
- Low human activity (one fixed object at location A)
- Medium human activity with one fixed object at location A
- High human activity (one fixed object at location A)
- K *human* activity with one fixed object at location L with K=low, medium, high and L representing different locations of the object (*A, B, etc.*)
- K human activity with P fixed objects at locations L_P with K=low, medium, high and L_P representing different locations of the P objects. For example, low human activity (K=low), two objects (P=2) at different locations (location L_1 for the first fixed object and location L_2 for the second fixed object).

The system starts by choosing the most appropriate trained *ANN* between the N candidates. To do so, the received fingerprint information (i.e. the received impulse response parameters) obtained from the M fixed transmitters with known locations (the *GRP*s), are applied to all of the *ANN* candidates. The output of each *ANN* candidate will have M location estimates. One of the candidates will have location estimates very similar to the correct locations of the fixed transmitters. This *ANN* candidate will correspond to the most appropriate environmental state and the master *ANN* will be associated to this specific candidate. Then, the master *ANN* will do the geolocation of the user(s) until a change of the channel's characteristics is detected.

When the location estimate of a user, at time t_j, varies considerably from the estimated value at time t_i (violating the physical contiguity constraint), it implies that the geolocation system has resulted in a large location error due to its limitation (error distance situated at the tail of its cumulative distribution function) or due to a significant change in the indoor environment. To be able to identify the right cause for this large error, the M *GRP*s are, once again, exploited to select the most appropriate trained *ANN* that represents the current environmental state. If the selected *ANN* candidate corresponds to the master *ANN*, it means that the error is due to the geolocation system. Otherwise, it can be concluded that the error is due to a change in the channel's properties. Therefore, the content (old *ANN* candidate) of the master *ANN* is discarded and a new association is made between the new selected *ANN* candidate and the master *ANN*. Then, the same principle applies during the entire geolocation process of the enhanced system. The enhanced geolocation algorithm (figure 4) and the procedure may be summarized as follows:

➡ Start

- Train off-line the N *ANN* candidates corresponding to N different environmental states defined by the specific application.
- Apply the M fingerprints received from the *GRP*s to the N *ANN* candidates. The output of each *ANN* candidate yields a set of M location estimates ($x_{i,j}$ y_{ij}), where i = 1, 2,…, M and j = 1, 2,…, N.
- Compute the set of errors between the M location estimates and the M true locations of the *GRP*s for each *ANN* candidate (e_{xij}=x_{ij}-x_{ic}, e_{yij}=y_{ij}-y_{ic}, $e_{dij} = \sqrt{(x_{ij}-x_{ic})^2+(y_{ij}-y_{ic})^2}$, where (x_{ic}, y_{ic}) represents the true or the correct location of the i^{th} *GRP*; e_{xij}, e_{yij} and e_{dij} represent the errors in x, in y and in Euclidean distance d respectively, between the estimated and true locations of the i^{th} *GRP* and the j^{th} *ANN* candidate).
- Choose the *ANN* candidate with the lowest set of Euclidean distance errors (i.e. mean values of the M Euclidean distance errors) as the one that best

represents the actual radio environment and associate it with the master *ANN*.

- Apply continuously the received fingerprint information, from a specific user *k*, to the master *ANN*. The master *ANN's* output yields the location estimate of user *k* (continuous user tracking).

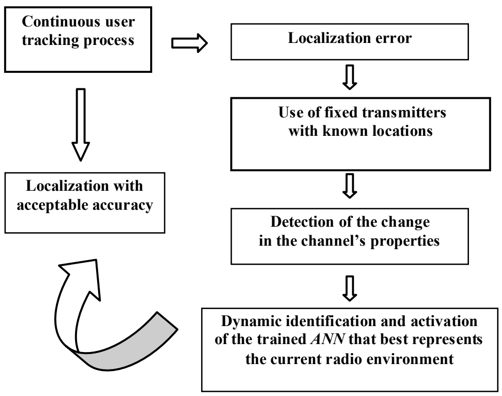

Figure 4. Enhanced geolocation algorithm for time-varying channels.

When a large location error occurs violating the physical contiguity constraint (large value of location error difference between two consecutive instances, i.e. large $e_d(t_j)$-$e_d(t_i)$),

- Identify the cause of the error (geolocation system limitation or change of channel's properties) by applying the *M* fingerprint information received from the *GRP*s to the *N ANN* candidates.
- Compute the set of errors between the *M* location estimates and the *M* true locations of the *GRP*s for each *ANN* candidate
  1. If the selected *ANN* candidate corresponds to the master *ANN*, then the error comes from the geolocation system (the Euclidean error distance is situated at the tail part of its *CDF*). Hence, discard the obtained location estimate value at time t_j and obtain a position estimate for the following instant t_k. The probability to have a location estimate with an acceptable error will be higher than before.
  2. If the selected *ANN* candidate does not correspond to the master *ANN*, then the error comes from a change of the channel state. Therefore, discard the content of the master *ANN* and associate the new selected *ANN* candidate with the master *ANN*.
- Apply continuously the received fingerprint information, from a specific user *k*, to the master *ANN*. The master *ANN's* output yields the location estimate of user *k* (continuous user tracking).

Repeat the same procedure during the entire geolocation process.

III. Performance Validation Of The Proposed Solution

Due to equipments availability, the performance of the solution proposed in this paper for indoor fingerprinting geolocation over time-varying channels has been validated using signatures based on received signal strength (*RSS*) as opposed to *CIR* characteristics. The set of signatures, applied to the input of the *ANN*, has been obtained from a narrowband measurement campaign (using a wireless local area network-*WLAN* narrowband receiver) and was conducted in a standard indoor office environment i.e. a corridor stretching over a length of 75 meters with a width varying from 3 to 4.5 meters (figure 5).

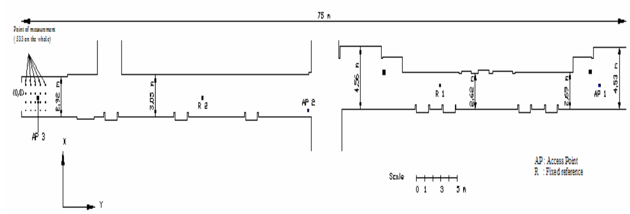

Figure 5. Map of the measurement corridor.

Five different environmental states have been defined reflecting each a realistic channel scenario. The first state corresponded to the corridor where the mobile station alone is present; the second, third and fourth states represented situations where the access points 1, 2 and 3 are obstructed by people or moving objects, respectively. Finally, the fifth state corresponded to the corridor with three *AP*s obstructed.

Two geolocation reference points-*GRP*s have been used in order to detect any significant change in the wireless channel's properties.

For each state, 533 location measurements have been conducted by keeping the indoor channel static for the entire measurement campaign. The location points were separated by 0.6 meter widthwise and lengthwise, and each point corresponded to a signature composed of the mobile station received powers (P_1, P_2 and P_3) from three *WLAN* 802.11b access points (a carrier frequency of 2.4 GHz and a transmitted power of approximately 16 dBm) situated at the beginning, at the middle and at the end of the corridor. The mobile station to be localized was composed of a laptop with 802.11b *PCMCIA* card and antenna. Consequently, the employed *RSS*-type fingerprint information was different from the one (*CIR*-type fingerprint information) used in [2]. As for the pattern-matching algorithm, an *MLP*-type artificial neural network has been trained with the 433 location points leaving the remaining 100 points for localization purposes. Figure 6 gives the cumulative density functions (*CDF*s) of location errors in *d* (Euclidean distance) for the trained and untrained set of data in the indoor corridor (first state), respectively.

The results show a distance location accuracy of 5 meters for 72% and 64% of the trained and untrained patterns, respectively. It has to be noted that the accuracy resulting from the use of the *CIR* fingerprint information (that would be used in practice) will be higher than the one obtained from the *RSS*-type signature which was used herein for this validation process.

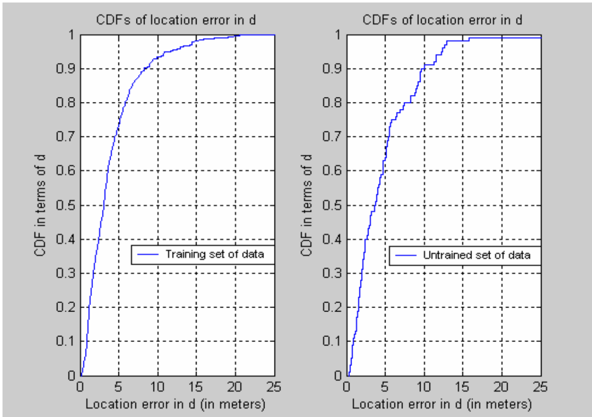

Figure 6. CDFs of location errors in *d*, with inputs corresponding to the training and untrained set of data for the first state (static channel).

Concerning the performance analysis, it has to be noted that for location-based services, the FCC (Federal Communication Commission) rules require carriers to provide location information to 911 call centers on calls from mobile phones. For network-based solutions, the implementation must ensure accuracy of 100 m for 67% of calls and it represents standard location accuracy for outdoor mobile phone applications. However there is no comparable location accuracy standard for indoor geolocation applications. Nonetheless since the purpose of the process is to locate people within a room or a corridor, it is fair to consider an accuracy ranging from 3 to 5 meters as an indoor location precision standard. For fingerprinting techniques, accuracies of 3 and 5 meters may be obtained from location-dependent parameters extracted from wideband and narrowband measurements, respectively. The reason is that for a wireless fading indoor channel, the received total powers (narrowband measurements) vary considerably for short distances compared to the channel impulse responses (wideband measurements) because of the superiority of the latter with respect to reproducibility and uniqueness properties.

After defining the five different channel states and training the corresponding *ANN*s, another measurement campaign was conducted in the corridor with the wireless channel varying continuously in time (dynamic movement of people and reflective materials in the corridor). During the measurements, two geolocation reference points (*GRP*s) were placed in the corridor at two fixed and known locations (1/3 and 2/3 of the corridor). Then, 100 sets of three received powers were recorded at the mobile station and the two *GRP*s, giving 100 location points in the time-varying channel. The 100 location point states were different from each other and from the defined five channel states with which five trained *ANN* were associated.

The algorithm is described in figure 7 and the objective of the process is to estimate the 100 mobile station positions with an acceptable accuracy using the five trained *ANN*.

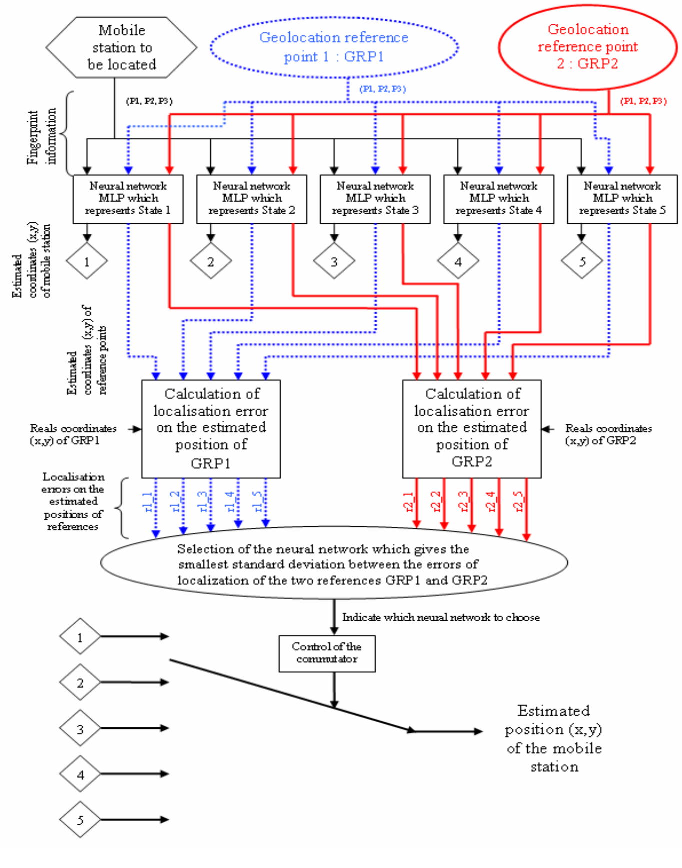

Figure 7. Schematic of the enhanced geolocation algorithm.

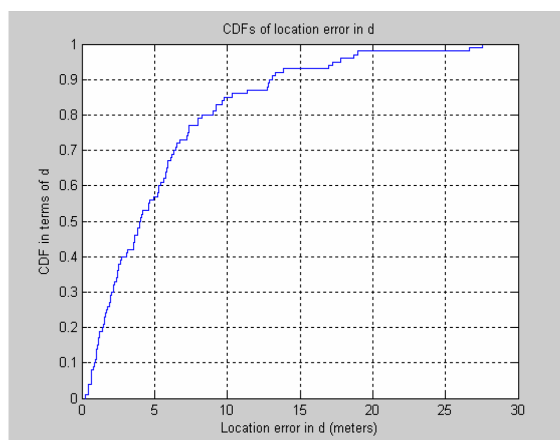

Figure 8. CDFs of location errors for the time-varying channel with inputs corresponding to the untrained set of data.

For the 100 location points, each *ANN* gives an estimated position for each of the two *GRP*s. Since their exact positions are known, location errors resulted from the five *ANN*s and applied to the two *GRP*s are computed. The retained estimated position of the mobile station corresponds to the *ANN*'s output with the least standard variation between the errors resulted from the two *GRP*s. Consequently, the chosen *MLP*-type *ANN* corresponds to the channel state (between the five) that best represents the current radio environment. Figure 8 gives the cumulative density functions (*CDF*s) of location errors in *d*. The results show a location accuracy of 5 meters for 57% of the untrained patterns, i.e. only a very slight accuracy decrease compared to the static channel case (64% of the untrained patterns in figure 6). As these results were obtained with a *RSS*-type signature, and as the hierarchical *ANN* selection process will be identical with *CIR*-type signatures, similar performance degradation from static to time-varying channels should be expected with *CIR*-type signatures whose performance over static channels has already been shown to yield a location accuracy of 2 meters for 80% of untrained patterns [2], [3].

IV. Conclusion

This paper has described the implementation of a novel algorithm, based on a set of artificial neural networks (*ANN*s) and geolocation reference points (*GRP*s), that mitigates the degradation in location estimation resulting from the channel's temporal variation.

The neural network based algorithm makes the enhanced geolocation system resilient to variations in the radio propagation environment and has several advantages:

- The training of the *N ANN* candidates is done off-line.
- The dynamic sweeping process, required for the choice of the right *ANN* candidate, is almost instantaneous since it corresponds to the recall phase of the *ANN* candidates.
- The channel-switching algorithm is simple.
- The process of continuously tracking a user is easy since it corresponds to the recall phase of the master *ANN*.

For *CIR*-type fingerprint information applied in a static indoor channel, a distance location accuracy of 2 meters is obtained for 90% and 80% of the trained and untrained patterns, respectively. As for the *RSS*-type fingerprint information applied in a static indoor channel, the location accuracy corresponded to 5 meters for 72% and 64% of the trained and untrained patterns, respectively. Moreover, a comparison between the distance accuracies of a static channel and a dynamic one, using in both cases a *RSS-ty*pe signature, has shown only a light accuracy decrease for the dynamic case with the enhanced geolocation solution.

In fact, results obtained over narrowband channels suggest a relatively weak accuracy loss of about 10% due to channel time-variations. Given the top-mark performance previously achieved by the location system over static wideband channels (2 meters of location accuracy for 80% untrained patterns [2]), a similar accuracy could therefore be expected in a prospective validation over time-varying channels with rich signatures.

It should be also noted that a check of the *GRP*s' true locations, done regularly, may be helpful for the detection of a possible change in the environmental state. Finally, the implementation results show that for a dynamic environment, the algorithm chooses a trained *ANN* corresponding to a channel state that is the closest to the current radio environment, thus yielding acceptable location estimates.

References

[1] C. Nerguizian, C. Despins and S. Affès, 'A Framework for Indoor Geolocation using an Intelligent System', 3rd IEEE Workshop on WLANs, Boston, USA, September 2001.

[2] C. Nerguizian, C. Despins and S. Affès, 'Geolocation in Mines with an Impulse Response Fingerprinting Technique and Neural Networks', IEEE Vehicular Technology Conference VTC2004fall, Los Angeles, USA, September 2004.

[3] C. Nerguizian, C. Despins and S. Affès, 'Geolocation in Mines with an Impulse Response Fingerprinting Technique and Neural Networks', IEEE Transactions on Wireless Communications, March 2006.

[4] P. Bahl and V.N. Padmanabhan, 'A Software System for Locating Mobile Users: Design, Evaluation, and Lessons', Technical Report MSR-TR-2000, Microsoft Research, February 2000.

[5] T. Nypan, K. Gade and T. Maseng, 'Location using Estimated Impulse Responses in a Mobile Communication System', 4th Nordic Signal Processing Symposium (NORSIG 2001), Trondheim, Norway, October 2001.

[6] S. Ahonen, J. Lähteenmäki, H. Laitinen and S. Horsmanheimo, 'Usage of Mobile Location Techniques for UMTS Network Planning in Urban Environment', IST Mobile and Wireless Telecommunications Summit 2002, Thessaloniki, Greece, June 2002.

[7] C. Nerguizian, M. Djadel, C. Despins and S. Affès, 'Narrowband and Wideband Radio Channel Characteristics in Underground Mining Environments at 2.4 GHz', IEEE 14th International Symposium on Personal, Indoor and Mobile Communication (PIMRC2003), September 2003, Beijing, China.

[8] C. Nerguizian, M. Djadel, C. Despins and S. Affès, 'Radio Channel Characterisation of an Underground Mine at 2.4 GHz', IEEE Transactions on Wireless Communications, September 2005.

[9] H. Demuth and M. Beale, Neural Network Toolbox for use with Matlab (User's Guide), The MathWorks Inc., 1998.

[10] X. Li, K. Pahlavan, M. Latva-Aho and M. Ylianttila, 'Indoor Geolocation using OFDM Signals in HIPERLAN/2 Wireless and Mobile Radio Communication', IEEE 11st International Symposium on Personal, Indoor and Mobile Communication (PIMRC2000), September 2000, London, UK.