Fingerprinting Localization Using Ultra-Wideband and Neural Networks

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***Abstract*-In this paper, the interest in localization is basically for security issues in a big industry that is still considered to be one of the most dangerous working places, the mines. Mines conditions make solutions based on TOA (Time of Arrival), AOA (Angle of Arrival), or even RSS (Received Signal Strength) subject to big errors. The system we discuss relies on fingerprinting technique to overcome those inconveniences. The use of UWB with its high temporal resolution and its multipath beneficial properties will constitute the basic pillar in overcoming much of indoor localization problems. Neural networks with their interpolation characteristics have the role of replacing any database correlator (or search engine) that usually exists in fingerprinting techniques. Measurements of the channel response in the investigated medium, in addition to the choice of the appropriate parameters, will be explored. Evaluation of the neural network performance and comparison with other indoor techniques will help identifying the utility of the proposed system. Finally, future work to be done will be described.**

***Index Terns* —** Localization, UWB, CIR, Neural Network.

I. Introduction

In recent years, implementing localization as an extended service in indoor RF equipment (such as servers) took a big part of indoor localization literature. The idea was, any network that covers an entire indoor area will make it possible for any location finding system to cover the same area and with ideally no additional cost [17]. Systems were designed based on the same concepts of outdoor localization, but they had the drawback of less accuracy [1,3]. Most of the errors in indoor localization were due to the absence of line of sight and to the multipath reflections. But as UWB was introduced to the wireless world, lots of improvements have been made possible.

UWB signal has a very high time resolution making it an ideal signal for location finding systems. In addition to that, UWB spans a large frequency band, and at lower frequencies, it has a better penetrating capability. Moreover, in UWB, multiple paths are resolvable which turns a previous inconvenience into a present benefit [15]. Additionally UWB is expected to coexist with other existing wireless technologies with no considerable interference [16]. These are the reasons that led to thorough study of localization using UWB [6, 8-13].

All of geo-location techniques fall under one of six big technologies: 1) Signal direction detection; 2) Signal time of arrival; 3) GPS systems; 4) Server assisted GPS; 5) Signal strength; 6) The final technique would be fingerprinting technique. As a physical media, UWB can in reality exist for five out of the six technologies, and it is clear that the GPS case is the one to be excluded. On the other hand, in a server assisted GPS system, the server system could be based on UWB technologies, but it would have to use one of the remaining four techniques as an actual localization method [11]. So to summarize, UWB can have an application in one of the following: Signal Strength, Angle of arrival, fingerprinting, and time of arrival.

The UWB fingerprinting will be investigated in this paper. The scenario of in mines localization is one of the best case scenarios for fingerprinting. The area being small in size, gives a small database of fingerprints. Fingerprinting is supposed to overcome usual errors in TDOA and in RSS that are mainly due to the absence of LOS. This is done by using direct fingerprints that projects the usual variations in the traveling signal in that environment. Furthermore, the proposed system will use Neural Network to play the role of the correlator; allowing higher robustness and a better interpolation of the covered area measurements. NN will also provide real time response and reduce the overhead of database search algorithms which means less required computing-power. The proposed system will be thoroughly discussed; the choice of the fingerprint elements that would constitute the NN inputs will be explained. Results and conclusions will be presented. And finally, future further work will be explained.

II. Fingerprinting Location-Finding Technique

The technique of location fingerprinting might be considered as a relatively new term or technique but in fact it is based on an older idea: that of scene analysis; which has been studied for robots and other moving objects that use self localization. The advantage of fingerprinting scheme is that instead of exploiting signal timing or signal strength [2], location is inferred using passive observations and features that are independent of geometry or distances in the sense that once the dataset is built localization will only depend on this dataset [7].

In almost all the studied systems, functionality and deployment of a fingerprinting based positioning system is usually divided into two phases. The first one is called offline phase during which the dataset (database) of location fingerprints is built by performing a survey of the site where the system will be deployed [4]. Most of the developed schemes usually use RSS measurements in this phase. But in fact, choice of fingerprints largely depends on available parameters and the performance of those ones in the localization process itself. The second on-line phase consists of having the mobile equipment or station reporting a sample vector of fingerprints (RSS or other) to the BS (or AP) that will use those obtained information in an algorithm to estimate location. The most common algorithm is computing the Euclidean distance between the obtained vector and the vectors present in the dataset to find the closest set and thus the closest distance. Other algorithms use Bayesian modeling or neural networks which would be the case of this system [4, 5]. Thought those algorithms have relatively different characteristics and offer a variety of advantages and disadvantages, the overall performance (accuracy and precision) of all of them remains relatively similar [4].

The number of BS's that should be combined together to provide the best fingerprint and the grid spacing in the dataset building phase, are two of the basic parameters for fingerprinting. Having a grid spacing of 10 meters can reduce the accuracy to 10 meters. Conversely, having smaller grid spacing might improve accuracy but probability of getting the right fingerprint match would decrease, and precision might decrease; In addition to the fact that constructing the dataset would require more work.

For the system proposed in this paper, a single BS is used in the localization process. The use of Neural Networks, on the other hand, would require the extension of the offline part so as to include the NN training phase. It would also require a good choice of NN inputs that gives the entire system an accuracy and precision up to the required level. For the grid spacing problem, a spacing of one meter was chosen in this case, because 1 meter would provide us with the required accuracy. And on the other hand, it gives the system enough distance to easily distinguish different dataset elements and consequently provide a good precision.

For further details, it should be mentioned that, at an initial stage, the system covered the distance of up to ten meters. The localization performed is a 1D localization since it would only estimate the distance from the starting point (the BS), but in a later stage 2D localization will be investigated.

III. UWB FOR FINGERPRINTS

UWB is projected to be the new Golden horse of the wireless technology. Many are the reasons that make UWB so attractable: starting form the very large bandwidth that it provides with all what this reflects as high bit rate, the high bit rate makes of UWB the common physical medium that is able to support different applications starting with the least demanding up to the most demanding ones (live video); passing through the very low power consumption which makes of it an ideal candidate for battery systems in addition to normal fed systems; then comes the easy direct sequence transmitting technique with what it offers in less complicated transceivers and most importantly lower cost transceivers; its very wide spread spectrum and power emission standards what makes of UWB noise like, therefore, making such systems less interfering with already existing techniques and giving them high security capabilities. All those reasons stated above and many others make of UWB the right candidate for any new system. But in fact, the real reasons and the most important causes of our choice have to do more basically with the propagation characteristics of UWB.

Usually an UWB indoor propagation channel can be identified by different characteristics that are drown from a traveling signals [18]. Such characteristics help identify the impulse response of a given medium, and in our case some of those characteristics would be used as fingerprints for the localization system. In order to get the impulse response and consequently the parameters, a measurement campaign was conducted in the underground location. A PNA (Power Network Analyzer) was used to get the impulse response of the channel. The analyzer swept the frequency band going from 3GHz up to 10 GHz in the frequency domain and then IFFT was used to get time domain channel response. All parameters and values were then extracted from the time domain results.

$$r(t) = \sum_{n=1}^{N(t)} a_n(t) p(t - \tau_n(t)) + n(t) \qquad (1)$$

With $\tau_n(t)$, $a_n(t)$,$N(t)$ being the delay, the gain and the number of identifiable multipath components of the channel. If the channel is considered as stationary, the signal becomes

$$r(t) = \sum_{n=1}^{N} a_n p_n(t - \tau_n) + n(t) \qquad (2)$$

$$r(t) = s(t) * h(t) + n(t) \qquad (3)$$

And the CIR would be

$$h(t) = \sum_{n=1}^{N} a_n \delta(t - \tau_n) \qquad (4)$$

From all the available parameters we chose three in particular to form our fingerprint. The first one is excess delay, defined as a measure of time delay relative to the first component; it is directly related to distance.

$$\bar{\tau} = \frac{\sum_{n=1}^{N} |a_n|^2 \tau_n}{\sum_{n=1}^{N} |a_n|^2} \qquad (5)$$

Fig.1 below draws the behaviour of excess delay relative to distance.

The second fingerprint component is the Total multipath Gain: which is the sum of all the received power from different detected multipath components of the same signal.

$$G = \sum_{1}^{N} |a_n|^2 \qquad (6)$$

In theory, total multipath gain should decrease with distance due to 2 phenomena, the longer the distance the lower the power contained in a signal, and the longer the distance the more multipath components that will have energy levels beneath the noise level and accordingly would not be detected. In fact by using a fingerprinting technique we are no longer interested by the direct path signal energy or by the arrival of the highest energy signal. We only use the total power as a localization parameter because by doing so we overcome a lot of synchronization problems and other errors due to false alarm or early detection. Fig.2 represents how total gain varies with respect to distance in our measurements.

Finally our third parameter is the RMSDS (root mean square delay spread). By definition, it is the square root of the second central moment of the power delay profile. It measures the effective duration of the channel impulse response [15]. Usually RMDS is a fundamental parameter for evaluating the presence of

ISI (inter symbol interference). Its variation is highly dependent on the characteristics of the spot where the measurement was made; in fact the number of received multipath components in addition to power level of those components highly influences the value of this parameter.

$$\tau_{rms} = \sqrt{\frac{\sum_{n=1}^{N} |a_n|^2 \tau_n^2}{\sum_{n=1}^{N} |a_n|^2} - \left(\frac{\sum_{n=1}^{N} |a_n|^2 \tau_n}{\sum_{n=1}^{N} |a_n|^2} \right)^2} \tag{7}$$

This third parameter was chosen as to provide the network with spatial diversity and uniqueness, being that the variation of this parameter is neither directly nor inversely proportional to the distance and it is nevertheless related to the indoor area it was used as to provide, in combination with the two other fingerprint, a unique print at each location. Variation of this parameter's values with respect to distance is presented in Fig.3 bellow.

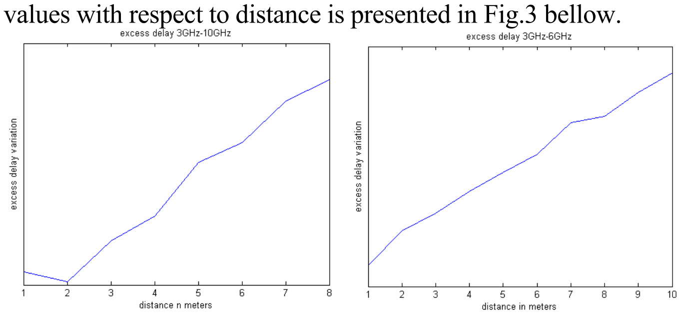

Fig.1 excess delay versus distance

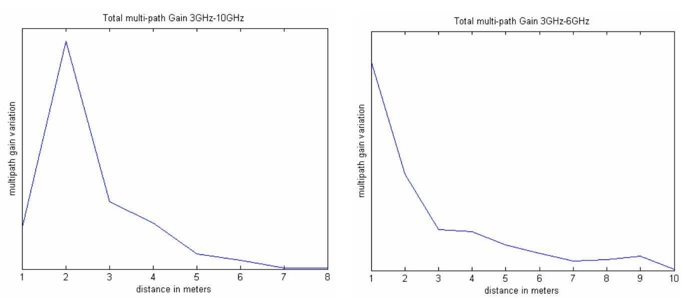

Fig.2 variation of multipath gain versus distance

Our choice of neural network was based on many criteria. NN provides real time response that surpasses the fastest database searching techniques. In reality the time consuming task of NN training would be done in the offline phase.

Furthermore, NN are known for their capabilities to interpolate on values that fall within their training set [14], this would allow our method to give a more precise localization approximation; in the Euclidean distance case, the target would be localized to the nearest fingerprinted location, while in NN, estimated distance to the target would surpass this constraint to approximate the precise location (by interpolation). We should finally add that neural networks are considered to be very robust once they have been properly trained [14].

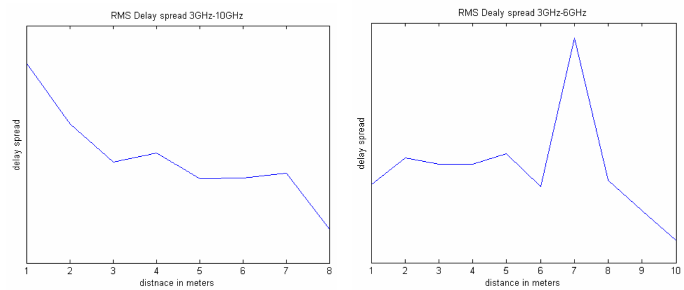

Fig.3 variation of RMSDS with distance

IV. NEURAL NETWORKS FOR DATABASE CORRELATION

Another important prospect of using neural network is its ability to combine techniques. Having three different input parameters, the network -and hence the system- could be considered as a hybrid localization method. To further explain this, one should take a look at the input parameters, one of them being time related (excess delay) while the second is power related (total multipath gain). The Neural Network performance is therefore influenced by both criteria and the system would react to the combined information of both parameters as well as to any variation in only one of them. Accordingly, this method can be thought of as a hybrid method combining both time and power techniques.

Multi-layer perceptron is the most used type of neural network. It has been used to successfully solve many problems by training it using back propagation algorithms. The good performance of the network relies heavily on the relation -linear or not- between the input and output parameters that are used as a training set and later those that are used for real time assessments. So in order to anticipate the performance of our network, we investigated the cross-correlation of the different parameters, and table.1, below, summarizes the results.

It is clear that the correlation values project an obvious relation between the different parameters especially for both 'Multipath Gain' and 'Excess delay' with respect to the output 'Distance' parameter. And based on those values, one can assume that the NN will be able to well enclose the problem at hands. On the other hand, the performance of the network is also highly influenced by the chosen structure of the network. In this case, a network with only one hidden layer with seven elements (neurons) provided very good results (Fig.4).

We already specified that the NN uses back propagation for learning; specifically, we adopted a Bayesian regularization algorithm. Used to overcome over-fitting problem in the training process, Bayesian regularization gives the network a higher ability of generalization [19] which lead to our choice.

TABLE 1: correlation between the different parameters

Correlation values	**Multipath gain** (Input)	**RMSDS** (Input)	**Excess delay** (Input)	**Distance (m)** (Output)
Multipath gain	1.00	0.4146	-0.9445	-0.9655
RMSDS	0.4146	1.00	-0.6354	-0.5936
Excess delay	-0.9445	-0.6354	1.00	0.9972
Distance	-0.9655	-0.5936	0.9972	1.00

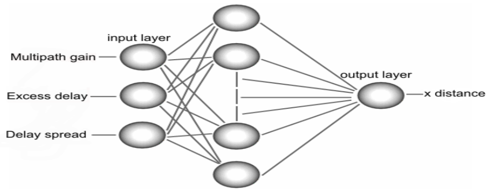

Fig.4 the final neural network architecture

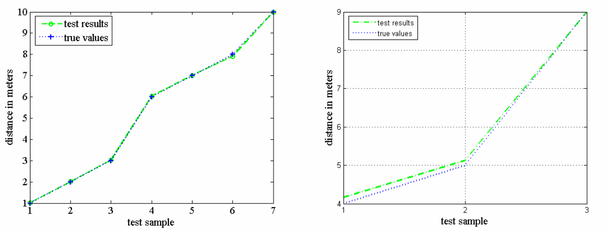

Fig.5a-5b localization results for training and new data (3GHz-6GHz)

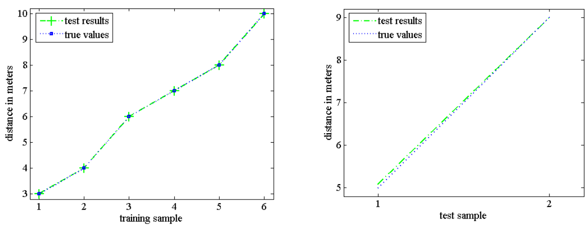

Fig.6a-6b localization results for training and new data (3GHz-10GHz)

V. Results and Interpretations

After training a neural network, we usually have two sets of results the first tests the performance using the same data set that was used in the training process. On the other hand, the second set uses new data to evaluate the performance. The criterion for performance is the error between the real distance and the estimated one. The error we obtained for a distance of up to 10 meters was in the order of centimeters. This error was nearly the same for both frequency bands: the 3 to 6 GHz as well as for the 3 to 10 GHz case. Figures 5a-5b illustrate the case for the smaller band. For the training set (Fig.5a) estimates almost completely overlap with true values and error had a maximum of 0.091 meters. On the other hand, for new untrained values, maximum error was of 0.16 meters at a distance of 4 meters and this error drops as we see at further distances. Likewise Figures 6a-6b, show the case of the 3GHz to 10GHz. Once again, we see that the training set estimates overlap the true distance values, with a maximum error of 0.003meters. Additionally, the test case gives results with a maximum error of 0.081 meters. All of the above results show that the proposed system has a performance that falls within the expected performance of an UWB based localization system. Moreover, obtained error is lower than many reported errors in proposed indoor localization systems based on UWB [8-10,12].

VI. Conclusion

To conclude, we recapitulate by saying that this paper presented a localization technique based on the fingerprinting technique and using UWB CIR. The obtained results showed high accuracy. The system performance seams to take advantage of the UWB propagation characteristics in the indoor channel. But this work will be further pursued, in order to design and test for 2D cases (3D being not required in our case). This may require a higher complexity in the NN architecture as well as in the fingerprint used (increase in the number of parameters that constitute the fingerprint). Additionally, future work will cover farther distances with NLOS scenarios. Nevertheless, and based on the current results, we expect a good performance of the higher complexity system.

References

[1] J. Hightower, and G. Borriello, "Location Sensing Techniques", *University of Washington, Computer Science and Engineering,* Aug. 2001

[2] H. Koshima, and J. Hoshen, "Personal Locator Services Emerge", *IEEE: Spectrum,* Vol.32 Iss.2, pp. 41-48, Feb. 2000

[3] J. Hightower, and G. Borriello, "Location Systems for Ubiquitous Computing", *IEEE: Computer,* Vol.34 Iss.8, Aug. 2001

[4] K. Kaemarungsi, and P. Krishnamurthy, "Modeling of Indoor Positioning Systems Based on Location Fingerprinting", *IEEE: Twenty_third Annual Joint Conferrence Of the IEEE Computer and Communications Societies,* Vol.2, pp. 1012-1022, Mar.2004

[5] C. Nerguizian, C. Despins, and S. Affes, "Geolocation in Mines with an Impulse Response Fingerprinting Technique and Neural networks", *IEEE: Transactions on Wireless Communications,* Vol.5 Iss.3, pp. 603-611, Mar. 2006

[6] S. Gezici, T. Zhi, G.B. Giannakis, H. Kobayashi, A.F. Molisch, H.V. Poor, and Z. Sahinoglu, "Localization Via Ultra-Wideband Radios: a Look at Positioning aspects for Future Sensor Networks", *IEEE: Signal Processing Magazine*, Vol.22 Iss.4, pp. 70-84, Jul. 2005

[7] E. Elnahrawy, X. Li, and R.P. Martin, "Using Area Based Presentations and Metrics for Localization Systems in Wireless LANs", *IEEE: Annual International Conference on Local Computer Networks,* pp. 650-657, Nov. 2004

[8] R. Zetik, J. Sachs, and R. Thoma, "UWB Localization – Active and Passive Approach", *IEEE: Instrumentation and Measurement Technology Conference, 2004. IMTC 04. Proceedings of the 21st IEEE,* Vol.2, pp. 1005-1009, May 2004

[9] Z. Guoping, and S.V. Rao, "Position Localization with Impulse Ultra Wideband", *IEEE: International Conference on Wireless Communications and Applied Computational Electromagnetics,* pp. 17-22, Apr. 2005

[10] Y. Zhang, and J. Zhao, "Indoor Localization Using Time Difference of Arrival and Time-Hopping Impulse Radio", *IEEE: International Symposium on Communications and Information Technology,* Vol.2, pp. 964-967, Oct. 2005

[11] G.R. Opshaug, and P. Enge, "Integrated GPS and UWB Navigation System: (Motivates the Necessity of Non-Interference), *IEEE: Ultra Wideband Systems and Technologies,* pp. 123-127, 2002

[12] C. Zhang, M. Kuhn, B. Merkl, A.E. Fathy, and M. Mahfouz, "Accurate UWB Indoor Localization System Utilizing Time Difference of Arrival Approach", *IEEE: Radio and Wireless Symposium,* pp. 515-518, Jan. 2006

[13] J.Y. Lee, R.A. Scholtz, "Ranging in a Dense Multipath Using an UWB Radio Link", *IEEE: Journal on Selected Areas in Communications,* Vol.20 Iss. 9, pp. 1677-1683, Dec. 2002

[14] S. Haykin, "Neural Networks a Comprehensive foundation", *Prentice-Hall In.* ,2de edition, 1999

[15] M.G. Di Benedetto, and G. Giancola, "Understanding Ultra Wide Band Radio fundamentals", *Prentice Hall: Communications Engineering and Emerging Technologies Series,* 1st printing, 2004.

[16] J. Lansford, "Wimedia UWB: Coexistence with Other Wireless technologies", *Alereon*

[17] A.M. Ladd, K.E. Bekris,A.P. Rudys, D.S. Wallach, and L.E. Kavraki, "On the Feasibility of Using Wireless Ethernet for Indoor Localization", *IEEE: Transactions on Robotics and Automation,* Vol.20 Iss.3, Jun. 2004

[18] A. Chehri, P. Fortier, H. Aniss, P. -M Tardif, "UWB Spatial Fading and Small Scale Characterization in Underground Mines," *IEEE: 23th Biennial Symposium on communications*, Kingston, Ontario, 1 Jun. 2006.

[19] C.D. Doan and, S.Y. Liong, "Generalization for Multilayer Neural Network Bayesian Regularization or early stopping", *APHW 2004: The 2nd APHW Conference*, Jul. 2004