Neural Networks for Fingerprinting-Based Indoor Localization Using Ultra-Wideband

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Abstract—**This paper discusses the use of neural networks in an underground radio-localization system. In a highly aggressive environment such as mines, reliability and robustness are essential to any operational system. Using UWB as the physical wireless propagation medium and combined with fingerprinting-geolocation and neural networks, this work tends to overcome many of the problems encountered in indoor environments. Full description of the system and the adopted approach will help accentuate the role of neural networks in improving the overall performance. Moreover a comparison between MLP and RBF performance is presented, providing a clear evidence of the role and importance of the neural networks in offering good accuracy and precision to the final system.**

Index Terms—**Indoor localization, LOS, NLOS, fingerprinting-localization, ultra-wide-band (UWB), impulse response (IR), neural networks (NN), multi-layer perceptron (MLP), radial basis functions (RBF).**

I. INTRODUCTION

In the last decade, and with the improvement in neural networks on both theoretical and hardware levels, a lot of effort was made for introducing them into practical applications. As a result, neural networks have been adopted in many systems. In this work, we try to benefit from neural network theory and capabilities in order to investigate the feasibility of an underground localization system. An emerging service with many domains of applications [1][2], indoor localization, nevertheless faces many challenges that have to do basically with the surroundings and the propagation properties of electromagnetic waves in those environments.

The primary reason for this work is security in a mining industry that is considered one of the most dangerous and hazardous professions with a very aggressive environment. Additional applications would involve the use of the system in an efficient environment control scheme (energy, proper lighting, ventilation...) One major challenge in such environments (as in the case of indoor localization) is the absence of line of sight (LOS), which renders the typically used information like the RSS, TOA, or TDOA incorrect or not accurate because their values no longer echo the real distances travelled by the EM wave [3][4][5]. Another challenge is due to the very nature of the galleries that deteriorate the signal because of the multipath effect. In fact, underground surfaces are very rough, which causes severe multipath and fast fading phenomena and this represents the second major problem for wireless communication of any type and more importantly for localization that relies on time or power information. A brief description of this issue will be presented thereafter when discussing the localization technique of choice.

In addition to the previous considerations, many practical factors can and must be thought of when choosing the final system; factors like the total cost of the system, its coverage capabilities, its interoperability with other existing systems and techniques, etc. One should finally note that the accuracy and precision of the overall system are the key evaluation features.

In accordance with what have been presented in this introduction, this paper will present a location finding system that is based on UWB and neural networks combined together in order to overcome many of the discussed problems. After a description of the chosen local-

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ization technique, we will elucidate the use of UWB and of neural networks. Then a depiction of the conducted measurement campaigns and of the different scenarios will be provided. Subsequently results will be interpreted including an analysis of the overall system performance and the importance of neural networks. Finally some concluding remarks will help bring this work to a close, and will offer some future perspectives.

II. Localization Technique

As previously mentioned, indoor environments present many challenges. Usually, to estimate a location, traditional systems perform triangulation using one out of three possible information parameters: time (TAO.TDOA), power (RSS), or angle (AOA). In the first case, by assuming EM wave traveling at the speed of light and by acquiring the time of flight from three[1] different transmitters, we can estimate a point of presence of the receiver (user). Nevertheless with the absence of line of sight, the time delay will no longer represent the time consumed by direct flight. Many other factors contribute to this parameter and thus evaluation of the distance is erroneous. For the power (RSS) related algorithms, the theoretical concept relies on power loss due to travel. Therefore, by calculating the received power and comparing it with the transmitted one, the total dissipated power can be estimated. Assuming that this power is due to path-loss, it is consequently proportional to the distance (first order or higher). Here again the absence of line of sight and more importantly multipath diversity and the numerous reflections due to the irregularities in the architecture makes the power loss information inaccurate, thereby resulting in high errors. Finally it is clear that due to NLOS, reverberation, and multipath, the angle of arrival cannot convey useful information. This led us to investigating the fingerprinting localization technique.

The fingerprinting localization concept is relatively new. It has been first proposed for dense urban areas tracking systems, and the results were comparable to the most advanced and more complicated outdoor localization techniques. This technique is based on the notion of identifying a specified position by relying on some data that can represent this location. More precisely, it has the same concept as human fingerprinting. In a given area were the system needs to be implemented, different information can be used to construct a fingerprint that can identify different parts of the area [6][7][8]. The technique consists of two phases: the first comprises the choice of the appropriate data to constitute a fingerprint and subsequently to collect this information. The second phase consists of using the already built database in order to find locations in real time by comparing a target related signature (fingerprint) with the database content [9].

A. UWB Fingerprint

Theoretically any information can be used as part of the signature with the limitation that this information is consistent, it helps forming a unique signature and it is reproducible. This led to some works proposing different time-based or power-based signatures [9][10]. Here we use UWB and try to benefit from its advantages in building the fingerprint [11][12][13]. UWB allows high time resolution at the receiver, which is crucial on every level of a localization scheme [14][15]. This would also allow a better multipath resolvability [16]. Another feature that increases multipath resolvability is the very small cycle duration, which gives the receiver enough time between successive transmissions to clearly identify different copies (versions, components) of the same originally transmitted signal. Additionally, the small cycle reduces any possible ISI effects. Moreover, the small cycle and high multipath resolvability permit higher collection of energy, regarded as a gain. Normally in narrow band transmissions, any energy outside of the considered peak is lost. This is not the case with UWB, where energy can be gathered from different replicas of the same signal [17],[18],[19], [20],[21]. Another important aspect in the choice of UWB is in fact its wide frequency range. In indoor environments, frequency selectivity is a typical behaviour of the channel. But the very large frequency span assures that most or part of the transmitted signal will reach the receiver. On the other hand, low frequency components tend to be more penetrating and have a better chance of overcoming an obstacle that can block the channel.

Subsequently, UWB was selected as the basis of the fingerprint where the CIR[2] would constitute the origin of the different signature components. To this end, multiple measurement campaigns have been conducted in the desired environment, each representing a different scenario. The accumulated data was afterwards analyzed in order to identify a possible fingerprint. A final three-component signature was selected, two of which are directly synthesized from the CIR and the third is related to both the measurement campaign and neural networks performance.

Considering that the received UWB signal is presented by:

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

With $a_n(t)$ being the path gain, $\tau_n(t)$ the path delay, and $N(t)$ the total number of multipath. This represents the summation of the different multipath components reaching the receiver. All parameters are time dependent including the total number of multipath.

Considering that the channel variations are very slow with respect to the pulse repetition rate, the channel can then be seen as stationary and the above parameters will become time independent. The final received signal presentation would be [12]:

$$\begin{aligned} r(t) &= \sum_{n=1}^{N} a_n p_n(t - \tau_n) + n(t), && (2) \\ &= s(t) * h(t) + n(t). && (3) \end{aligned}$$

[1]Additional transmitters provide higher precision.

[2] Channel Impulse Response.

where n and p_n identify the different copies of the same originally transmitted pulse, $h(t)$ is the channel impulse response, $s(t)$ is the originally transmitted signal, and $n(t)$ is the noise. The IR[3] would be:

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

This IR takes into consideration the multipath phenomenon, and it can be used to derive many time, power, and frequency parameters that specify the characteristics of a given channel. The two CIR related signature components are derived from this formula:

1. The total multipath gain is represented by the following formula:

$$G = \sum_{n=1}^{N} |a_n|^2. \quad (5)$$

   It is one of the principle components of the IR. Total multipath gain as the name indicates is highly related to the multipath phenomenon; consequently it is related to the architecture of the environment. Moreover, the total multipath gain is one of the advantageous parameters of UWB due to the previously discussed reasons concerning power collection in UWB. This is our first signature component.

2. The excess delay, frequently used to characterize the PDP[4], is the second chosen parameter, with a mathematical representation :

$$\bar{\tau} = \frac{\sum_{n=1}^{N} |a_n|^2 \tau_n}{\sum_{n=1}^{N} |a_n|^2}. \quad (6)$$

   Excess delay is in fact the delay of all received components relatively to the first received one. Moreover it is directly affected by multipath and energy loss conditions of the channel.

So in addition to the propagation characteristics of UWB that help overcome the aggressive environment of a mine, the choice of UWB related components of the signature further increase the efficiency of the system in that environment. Both chosen parameters are related to the multipath and to the power loss behaviour of the channel.

In fact, by using the fingerprinting technique, we are no longer tied to any defined propagation model of the channel in order to estimate and interpret time and power information. We limit our interest to the chosen parameters and their relation with the position of their computation. Here comes the importance of using Neural Networks. MLP's are known for their ability to estimate a given function [22], and to approximate it to a high order of accuracy if proper training was conducted. This is discussed in the following section.

[3] Impulse Response.

[4] Power Delay Profile.

B. Neural Networks For Fingerprit Interpretation

The theoretical maximum error for a fingerprinting-based system would be equal to:

$$e_{\max} = \frac{d_{sep}}{2}. \quad (7)$$

with d_{sep} being the distance separating two consecutive measurement positions during the dataset building phase. We stress the fact that this is a theoretical maximum, because in real systems, errors have been found to be higher. In fact, any small change in the received data can lead to an error that is 3 times the theoretical one. But for neural networks, due to interpolation capabilities (and limited extrapolation) [23], the theoretical error can be zero, and as will be shown in the results section, the real obtained error is much smaller than those obtained using other algorithms. In order for the neural networks to provide such a performance, we need to find the best architecture with the most convenient training algorithm. In our case, we are not studying the convergence theory of neural networks; a trial and error approach has been adopted in order to find the best combination of both architecture and training. Furthermore, once training has been adopted for a given neural network in a given scenario, it does not need to be changed or re-processed during the active real-time localization process, and this is one of the reasons why we adopted trial and error for finding a suitable combination.

Another benefit to the use of neural networks is their ability to combine information and techniques. In database search methods, the system would only use values of the fingerprint and find its nearest Euclidian distant entry in the database. On the other hand, given the fact that neural networks approximate functions, and given the fact that the used fingerprint components are to a large extent related to delay and power loss which in turn are related to distance, the neural network appears to be combining both received signal strength (RSS) and time delay (TDOA-TDA) based systems. The system can then be thought of as using a hybrid technique, but with the advantage of not requiring any additional computational time or power, and without increasing the complexity of the system itself.

In concordance with the previous statements, it should be noted that neural networks would be having an impact on both phases of the fingerprinting technique. In the first phase, it influences the build-up of the dataset of signatures as well as the signature itself. This is a mutual influence because the total number of a signature's components would influence the architecture of the neural network starting from the input layer and up. Additionally, the training process would vary accordingly. In order to give a proof of the importance of the network architecture and training process, this work included a comparison of two different back propagation networks, namely: an MLP[5], and an RBF[6]. Both will use the same training and testing sets, but as will be seen, the final results will be

[5] Multilayer perceptron.

[6] Radial Basis Function.

dissimilar. The same training process is used for all the RBF networks, but different algorithms are used for the MLPs in the different scenarios. On the other hand, the second phase of the fingerprinting algorithm, really consists of the real-time localization, which in our case would be to use the test set in order to validate the performance of the system.

We should mention that a third component of the signature, a flag, is included. This flag indicates the good functioning of the neural network and will be discussed in the section describing the measurement campaigns.

Finally, our network inputs consist of the three signature components previously discussed (total multipath gain, excess delay, flag), and the outputs are the (x, y) coordinates. All additional information on the neural networks architecture and learning algorithm will be stated when considering the corresponding scenario.

III. Measurement Scenarios

This work is about underground indoor localization and hence the measurement campaigns scheduled to build datasets for the proposed system were conducted in an underground mine at a level situated 40m beneath the surface. Such an environment presents many difficulties as for example unlevelled ground that limits mobility of the equipment. In order to conduct UWB measurements, a network analyzer was used. It would perform frequency sweeping over all the bandwidth of choice. The received sample is then translated into the time domain using IFFT. The measurement equipments included an UWB power amplifier at the transmitter and an LNA at the receiver end, in order to increase the range of the analyzer. Additionally, UWB omnidirectional antennas were used. Antennas where placed at 1.5m from ground, but due to the geology of the environment, most of the time the transmitter and the receiver were not at equal heights. All measurements were in the band going from 3 GHZ to 10 GHZ, which is the entire UWB allowable band. During each sample measurement, the channel should be stationary and in fact due to the very short duration of a sweep the channel can be considered as such. Furthermore, in order to make the measurement sample as representative of the channel as possible, we used averaging over 10 consecutive sweeps for the same location. Measurements were taken at distances of 1 m apart, following a line crossing through the middle of the gallery. This distance from the transmitter antenna represents the 'x' component. On the other hand, two additional measurements are conducted at the same 'x' but with 1 m meter away to the left and to the right of the center measurement in such a manner as to cover the width of the gallery. So at the same 'x' ordinate we have three different measurements located at different 'y' abscissa values. In order to study the performance of the localization system in different scenarios, both LOS and NLOS campaigns were conducted.

For the LOS case, the campaign covered a total distance of 40 meters after which the received signal became too weak so as to provide useful fingerprinting information. Furthermore, during the analysis of the final dataset, we were constrained to use measurements going only up to 36m. "Fig. 1" below shows the topology of the gallery and the placement of the measurements.

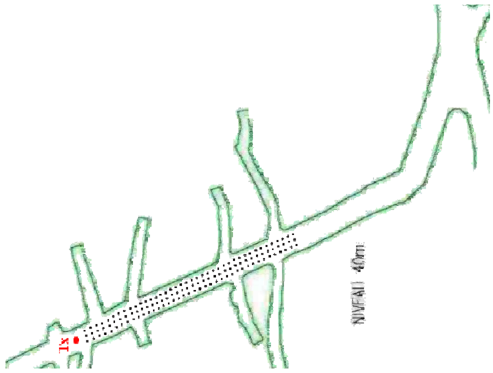

Fig.1 LOS measurement campaign.

The NLOS campaign was conducted in the same condition as for the LOS. Nevertheless, due to the higher power loss, it only extended to a distance of 36m after which the signal was completely overwhelmed by noise. Moreover, during the analysis phase, only measurements covering up to 27m proved to be utilizable.

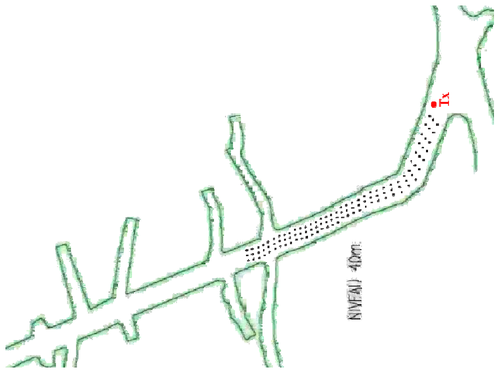

Fig.2 NLOS measurement campaign.

"Fig. 2" gives an insight into the actual measurement placements. In this campaign, the first 6 meters present a line of sight and a partial line of sight exists up to 9 meters after which we have a complete absence of sight. Furthermore, the ground is unlevelled with a slope of more than 6 degrees.

After the dataset was built, and during the treatment of the data, it was realized that due to the structure of the gallery combined with the placement of the measurements, some samples had the same 'y' abscissa value for what is to become different fingerprints. This fact led to a deterioration of the learning ability of the neural network. In fact this network is exposed to different signatures but is supposed to give identical locations for them. Moreover, those similar 'y' values are contradictory with the uniqueness of the fingerprint concept. In order to overcome this inconvenience, neural networks theory proposes the use of a sentinel marker. This approach was used, where we incorporated an additional third component –a flag– to the fingerprint. This flag has one of three values {1, 2, and 3}, indicating left, center and right correspondingly. This proved to be very helpful in improving the performance of the network.

IV. RESULTS AND INTERPRETATION

Usually to evaluate the performance of a localization system, there exist two principal parameters, namely: accuracy and precision. The first one refers to the difference between the real and estimated positions; it is usually the error between the two positions in meters or in centimetres. The second parameter is the percentage of time at which the given accuracy is respected. In order to evaluate our system with respect to both parameters, we will present the CDF[7] functions of the error, this error being the difference between the real and estimated coordinates of the locations. In this way, the graph plots will present different accuracies with their relative precisions. On the other hand, with the aim of further portraying the use of neural networks, their susceptibility to the different localization scenarios, and the importance of the training algorithms of choice, for each set of results we will indicate the neural network architecture including the number of layers and the elements per layer. Then, we will indicate the training algorithm that provided the network with the best outcome. It should be reminded that an additional comparison of RBF and MLP potentials for our system is included.

GRNN[8] (RBF) are used in general to approximate functions. They are easier to construct and easier to train than the MLPs. In fact, their architecture consists of one hidden layer, with radial activation functions. This layer has as many elements as the number of inputs, and thus it will have the same number of elements for our different scenarios. GRNN also has an output layer with linear activation functions. This layer also has as many elements as the inputs. So in general, this architecture for the GRNN networks is the same in all the analysis.

Normally two sets of results can be analyzed, the error for the training data set and the one for the testing data set. The first set is seen by the network during the learning process while the second is only used for testing.

A. First Scenario (LOS)

In the case of LOS campaign, the adopted MLP had 2 hidden layers with respectively '8' and '12' elements. The learning algorithm was based on Bayesian regularization which is normally known for its high generalization capabilities. The following figures give the CDF for both 'x' and 'y' coordinates for the training and testing values.

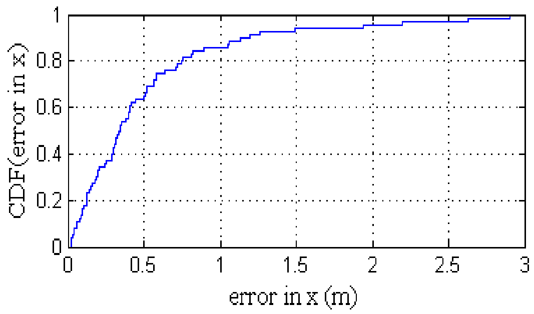

Fig.3: CDF for the error in 'x', MLP training, LOS.

For the 'x' coordinate (as shown in "Fig. 3"), and by using the training set to which the network has been previously exposed, the error is of less than 0.5m accuracy for a less than70% precision.

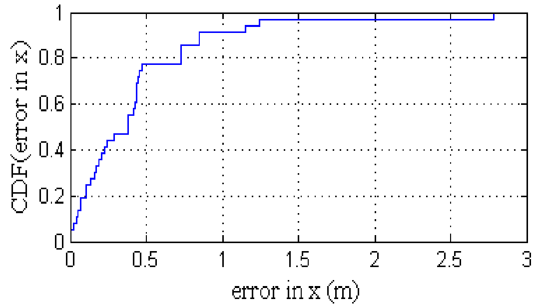

Fig.4: CDF for the error in 'x', MLP testing, LOS.

The maximum error for this case is of 2.7m for 2% of the cases. On the other hand, for the test data ("Fig. 4") to which the network is being exposed for the first time, the error is bellow 0.5m for more than 75% of the cases. This clearly shows the capability of the network to generalize, and further proves that the error obtained for the training set is not due to memorization.

Similar results can be observed for the 'y' coordinate in "Fig. 5" and "Fig. 6" with an error of 0.5m in 80% of the cases for the training and testing data.

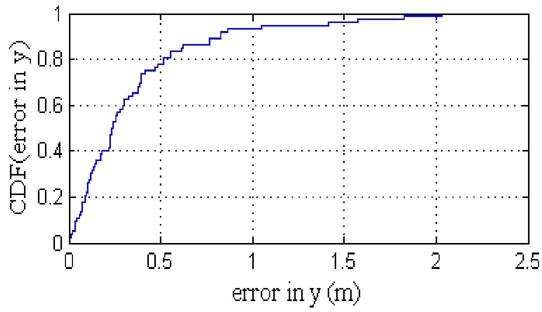

Fig.5: CDF for the error in 'y', MLP training, LOS.

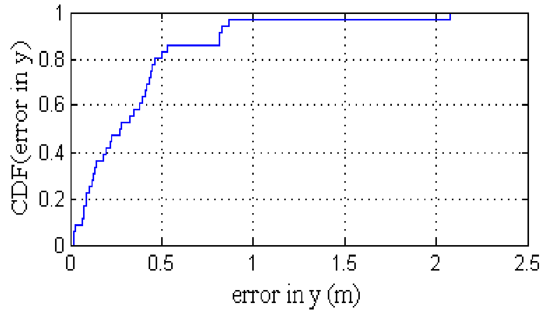

Fig.6: CDF for the error in 'y', MLP testing, LOS.

It should be mentioned that the maximum real 'y' value is 26 m in comparison to a 36 m for x. This can partially explain the higher precision in 'y', but in fact the ratio of error to maximum coverage distances is relatively identical.

For the GRNN network, the architecture has been discussed previously but it remains to mention that the spread which provided the best results was equal to '0.1524'.

The error was larger than the one for the MLP network where in this case the accuracy of 0.5m had a precision of only 51% for training data. The error was even

[7] Cumulative Distribution Function.
[8] General Regressive Neural Networks.

worse for the real time testing dataset. Another deterioration found for GRNN is that the maximum error for the test dataset is not bound by the maximum error of the training phase. “Fig. 7 to 10” below show GRNN results.

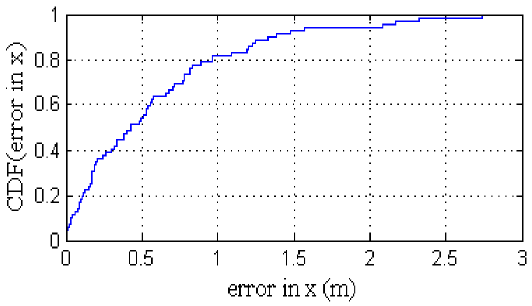

Fig.7: CDF for the error in ‘x’, GRNN training, LOS.

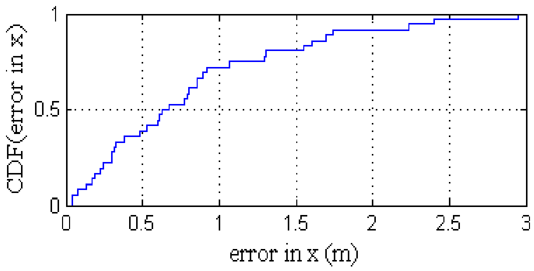

Fig.8: CDF for the error in ‘x’, GRNN testing, LOS.

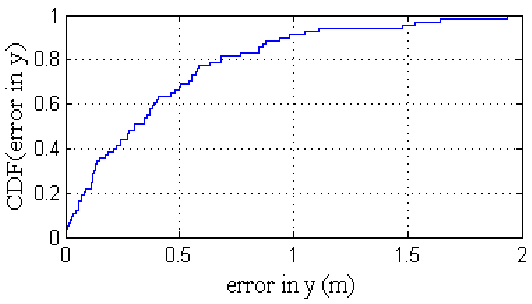

Fig.9: CDF for the error in ‘y’, GRNN training, LOS.

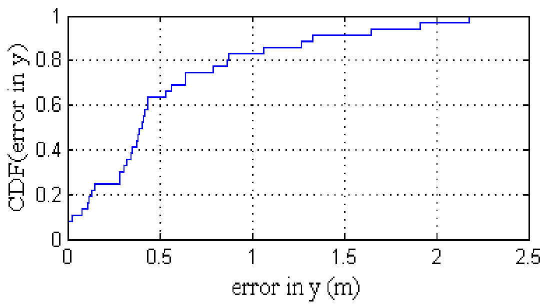

Fig.10: CDF for the error in ‘y’, GRNN testing, LOS.

B. *Second Scenario (NLOS)*

In this case, one can expect less performance compared to the LOS case. In this scenario, the maximum distance with analyzable data was 27 m. In fact, for distances up to 20 m the error was very small and the performance deteriorates significantly between 20 m and 27 m.

The MLP network that gave the best results had ‘7’ elements in the first hidden layer and ‘12’ in the second one. The training algorithm in this case used the scaled conjugate gradient (SCG) with a total of 800 iterations. The scaled gradient is very efficient in the training process. “Fig. 11 through 14” show the CDF’s of the error for the different coordinates.

For data previously seen by the network (training data), the system presents an accuracy of 0.2m with a 74% precision (“Fig.11”). The maximum error is of 0.79m for 2% of the cases, the medium error is of 0.1825m, a very good result for NLOS.

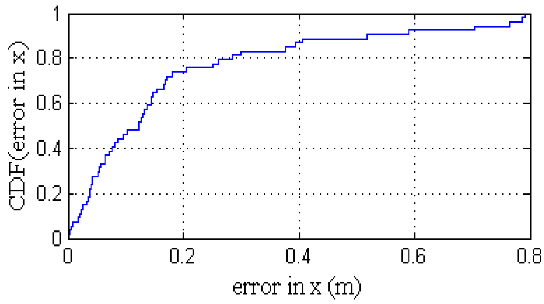

Fig.11: CDF for the error in ‘x’, MLP training, NLOS.

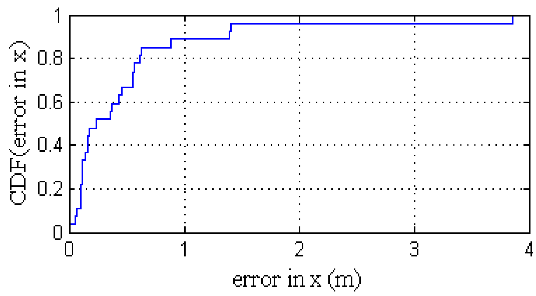

Fig.12: CDF for the error in ‘x’, MLP testing, NLOS.

As for the testing set, “Fig.12” shows a degraded performance where it is expected that SCG is less performing than the Bayesian on the generalization level. The accuracy is of 0.5m for 67% precision. This error is, however, very close to that of the LOS scenario error.

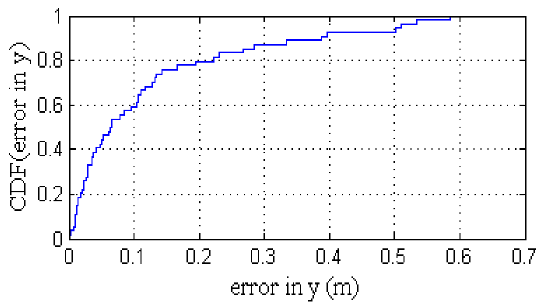

Fig.13: CDF for the error in ‘y’, MLP training, NLOS.

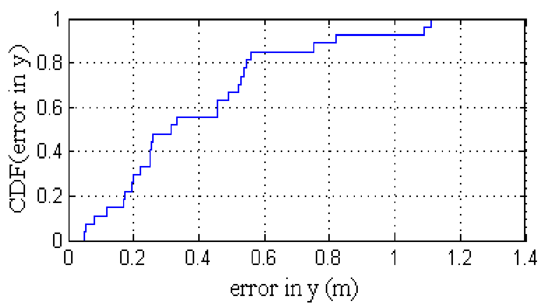

Fig.14: CDF for the error in ‘y’, MLP testing, NLOS.

The error in ‘y’ follows the same behaviour as the one in ‘x’, with a 0.195m for 80% of the cases (“Fig.13”), and a maximum error of 0.59m for 2% for the training set. As for the testing set, “Fig. 14” shows an acceptable accuracy of 0.5m for a precision of 60%. The maximum error in this case is 1.1m for 7%.

In the case of the GRNN network, having the same architecture as previously (LOS case), the spread value used here is 0.1456. In this scenario as for the LOS one, GRNN does not provide a better performance than the MLP. In this case, however, GRNN has better results than in the LOS case.

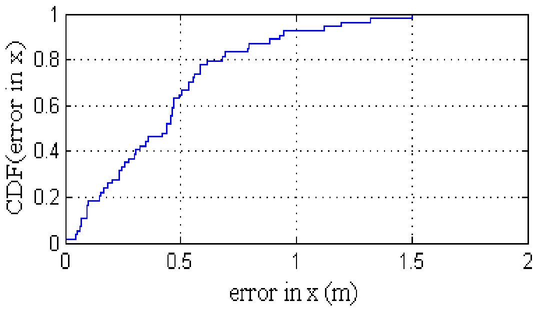

Fig.15: CDF for error in ‘x’, GRNN training, NLOS

For the ‘x’ coordinate, the training set presents an error of 0.6m for 80% of the cases, the maximum error being 1.5m with a precision of 2% (“Fig.15”).

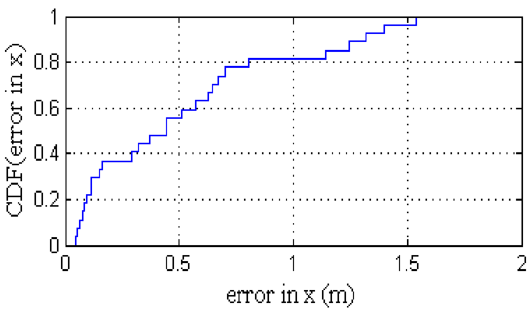

Fig.16: CDF for error in ‘x’, GRNN testing, NLOS

As for the testing set, the values in “Fig. 16” are of 0.6m for 60% precision. It is clear that in this scenario, GRNN network has a comparable performance to that of the MLP. Moreover, in this scenario, the generalization capabilities of the GRNN are much better than for LOS one and this can be seen by looking at the testing set error. The results for the ‘y’ coordinate, shown thereafter, further support this statement.

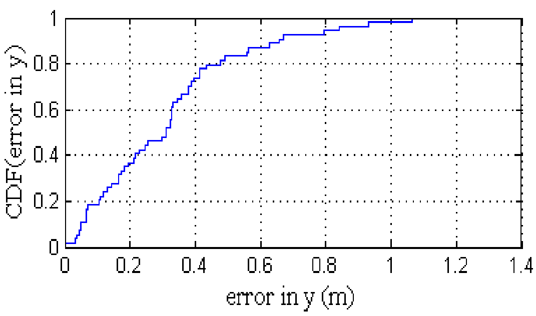

Fig.17: CDF for error in ‘y’, GRNN training, NLOS

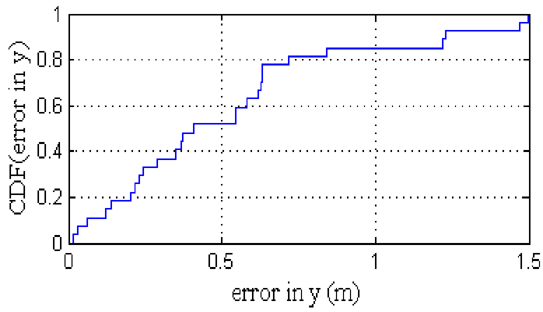

Fig.18: CDF for error in ‘y’, GRNN testing, NLOS

The results obtained by using training data present an accuracy of 0.4m with a precision of 73% (“Fig. 17”). The maximum error is 1.5m with 8% of recurrence. On the other hand, results obtained by using the testing data have a value of 0.65m error for 70% of the time (“Fig. 18”).

According to the previous set of results and interpretations, one can see a small difference between the results obtained by using training and testing sets, but the combined performance of both is comparable and even better than most of the results found in the literature and especially for a medium with very high multipath. If we look at the results in [7] we see a 25% percentile of 1.92 m, which is excessively high when compared to our case of less than 0.5m for more than 75% percentile for LOS, we should mention here that in [7] they are covering a wider area but the maximum covered distance is of around only 7m more than the 36 meters we covered. On the other hand if we compare our results to those obtained in [10], although the authors are using the same system as ours, their system performance is lower than ours especially if we look at the overall percentiles for error, where the authors report an error of less than 2 meters for 80% of the cases, we should keep in mind that in [10] the distance covered was almost twice as ours. We were not able to compare our results with any NLOS results because both of these reference systems only discuss LOS results.

The high performance of our proposed system in this hostile underground environment is due to the use of UWB and neural networks. In fact the use of neural networks directly impacts the performance of the entire system by allowing a better interpretation of the parameters. If we look at the LOS and NLOS cases, although we are using the same parameters in order to localize the target, the performance is relatively stable, which surpasses classical systems expectations. In fact, for other systems, a degradation of more than 30% is observed for NLOS scenarios. Additionally, neural networks provide a better performance for the fingerprinting technique, where in the classical case and using database search techniques, the system extensively deteriorates for new data. This is overcome by using the generalization and interpolation properties of neural networks.

V. CONCLUSION

The overall performance surpasses many of the expected results for indoor localization. This is mainly due to the combination of UWB and neural networks, a combination that provides better propagation characteristics of the wireless transmitted signal, in addition to a better interpretation of the signature parameters due to the neural networks. This way, the system overcomes many of the difficulties encountered in such environments.

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