A Hybrid Neural Network-Data base Correlation Positioning in GSM Network.

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Abstract— **Mobile terminal localization in a GSM environment has been of big interest in the recent years. This work exploits the use of position estimates from different sources in a robust fusion algorithm to reduce the positioning error. A hybrid neural network (NN)-data base correlation method (DC) is discussed. Moreover, the DC position estimates are first corrected by an already trained NN in order to reduce the DC positioning error before its fusion with the NN positions. The NN is trained first offline before it use in the positioning unit. Function approximation and classification properties of the NN will be investigated and the best NN architecture will be chosen from a series of candidates. During positioning phase both positioning results from NN and DC are fused with a robust tested method in order to increase the precision of the position estimate. Results show that, the post processing of the DC result decreases the DC positioning error and fusion process get the MT estimate with a better accuracy.**

Keywords- localization, mobile positioning, data fusion, database correlation, neural network.

I. INTRODUCTION AND STATE OF ART

Satellite-based positioning provides the most accurate positioning systems today. However, the GPS has to be used only in case of a clear sky. This makes its use impossible or not reliable in urban areas, mountainous terrains and covered spaces. Many researchers have worked on alternative positioning systems suited for such environment. There are several types of Localization Based Systems:

Cell ID, the precision of this method is 300m in urban areas, 2km in suburban areas and 3-4km in rural zones.

Enhanced Cell ID With this method one can get a precision similar to Cell ID, but for rural areas, with circular sectors of 550 meters.

Time of Arrival and Angle of arrival suffer in case of environment with severe multipath.

E-OTD: This is similar to TOA, but the position is estimated by the mobile phone, not by the base station. The precision of this method depends on the number of available LMUs in the networks, varying from 50 to 200 m.

Fingerprint methods have been preferred as they perform better in areas with severe multipath propagation compared to others [1-5], moreover, they do not require any additional equipment for their implementation.

This paper fuses both NN position estimates and the location estimations from the database correlation in order to get better results. The major problem for both NN and DC localization methods is the realization of the fingerprint database. The signal fingerprint can be collected either by measurements or by a computation network planning tool. Measurements collection is time consuming but produces more accurate fingerprint data. In this work we used both methods. Collected data are used for the NN training and predicted data [6] for the database correlation method. Our algorithm is tested with real collected data.

II. LITERATURE OVERVIEW

Many researchers have paid have paid attention on positioning of a mobile system within a GSM environment using the received signal strengths [1-4]. Some works exploit the use of data fusion techniques combining information from different sources in order to have better results [5, 7-9]. In “in press” [5], a fusion of DC position estimates and NN is presented, but due to the fact that, in that work the DC algorithm is a conventional and simple one, the maximum DC positioning error is 320m with 67% and 720m with 95%. In this work, we use a trained NN to correct the position estimate got from the DC algorithm before the fusion process is made. Other works focus on the dead reckoning technique [10, 11], which estimates the present position by projecting heading and speed from a known past position. This method suffers from an accumulation of the positioning error. A constant update can be made in order to remedy to this issue.

In [12] a mobile positioning using GSM cellular phone and artificial NN has been presented. Classification and Function approximation properties of NN have been exploited, but only one method for classification was considered.

In this work, a survey of different neural training algorithms and architectures adapted to this RSS fingerprint positioning is conducted. Function approximation and classification properties of the NN are investigated in order to consider the best candidate suited for a given scenario. Two types of classifications are presented and implemented for the conducted experiments. The benefit from a fusion process between the NN position estimate and Database correlation method position estimate is exploited. The DC position estimates are corrected with an extra NN to decrease the DC positioning error.

III. POSITIONING METHOD USING NN.

The NN acquires intelligence during training. This process is performed off line before using it in the positioning algorithm. During training, the NN parameters are set in order to make a good mapping between RSS and location with the least squared error.
Positioning using NN can be tackled in two different ways: as a function approximation problem and as a multi-class classification problem.

A. Function approximation

During training, the NN parameters are set in order to approximate a function which represents the mapping between the RSS and positions (x-y) with the least squared error.

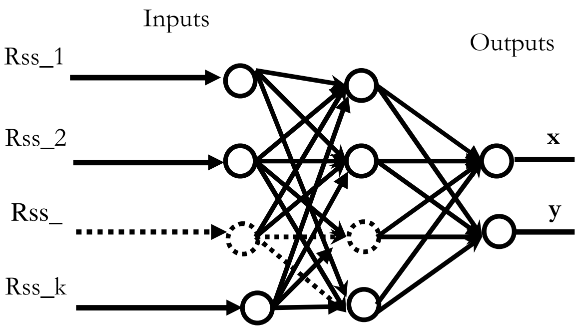

Figure 1. NN architecture for function aproximation

The number of inputs corresponds to the number of Cell antennas considered. In our case, 10 inputs were used. The outputs in this function approximation case are two (i.e. x,y-coordinates of the location position) as shown on Fig.1. The number of hidden layers and their corresponding number of neurons are fixed experimentally.

B. Classification

In classification case, the experimental area is divided into squared sections. During training, predicted RSS together with their corresponding section numbers are provided to the NN which makes a generalization. In positioning phase, the location estimation of the MS section using received power levels from different base stations is the classification task.
The difference here is that the number of outputs corresponds to the number of sections to which we divides the experimental area.
A set of RSS is given at the input. If these data were taken at a point belonging to sector number 2, then all the target inputs are 0 except for the second target which value is 1 as shown on Fig. 2. This series of 01000 is referred to in this work as codeword.

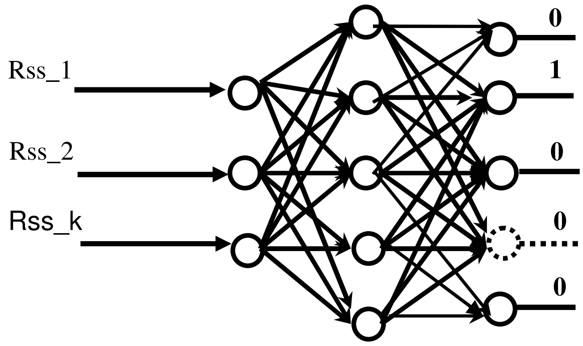

Figure 2. NN architecture for classification

During positioning phase, it appears that these values of the codeword change and are not 0 at all the positions and 1 at the rank corresponding to the location estimate section number. They take values lying in interval 0-1. This is due to the fact that, the training error is not null and the training and testing points are different.

Two different methods of deciding on the section estimate at the NN output can be applied: First, choose the rank of the maximum value in the codeword to be the section number. We will refer to this method as Absolute Maximum method. Second, consider all rank with values greater than a certain weighted value. These considered ranks contribute to the choice of the section estimate by finding their center. We will refer to this as Weighted Method.

At the NN output, the so called weighted quadratic average value ($q_{average}$) and so called weighted variance (sigma) are calculated at every tested point as shown in "in press" [5]. All the rank of the output values laying in the interval $\left[q_{average} - sigma, q_{average} + sigma\right]$ are taken into account. The center of the selected sections is then calculated and considered to be the location estimate.
The training process of the NN is illustrated in Fig.3. This process is done off line. During Test or positioning phase, there is no need of the yellow colored part of the figure. Only a set of the real rss is enough to know the position estimate of the MS.

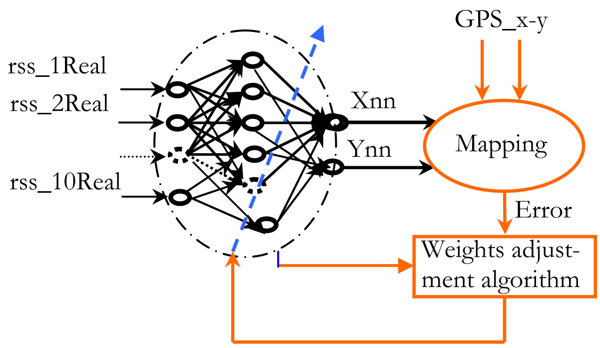

Figure .3. NN training and positioning block diagram (In the NN positioning phase, only black colored part of the figure is used).

C. *Comparative results*

Experiment 1

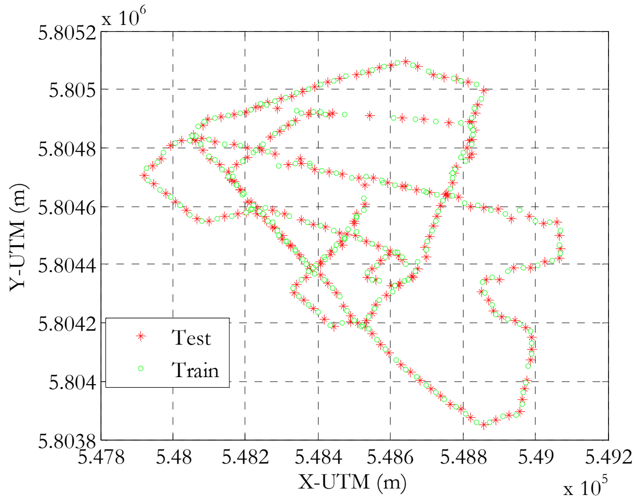

Figure 4. Sample positions used for training and test.

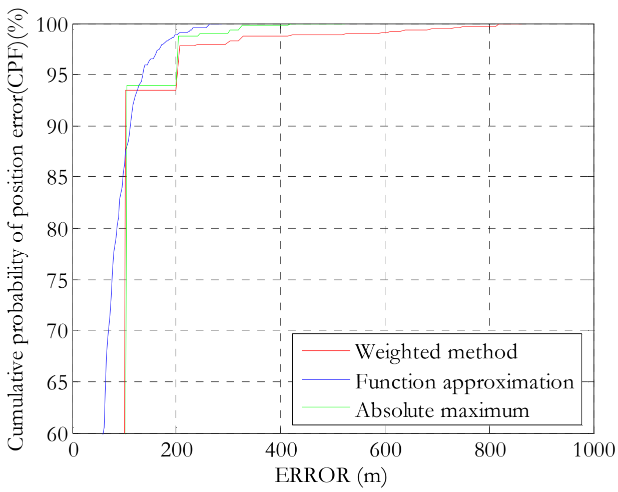

Figure 5. Cumulative distribution functions for the three methods

Figure 4. shows the sample positions of our experimental area which were used for the training of the NN and which were used in the positioning phase. The training and testing points are 10m distant one from another. The three methods perform good as we can see in fig.5. Absolute maximum appears to perform better than the weighted because of a good representation of the training data in the entire concerned area. As a result, in the codeword at the NN output, the rank of the maximum value is more likely to be the true position.

We can see also that for both types of classification methods, we can get true position estimates of the sectors with 93% of probability. The size of the sectors is considered 100mx100m which makes a maximum error of 100m.

Experiment 2

In Fig.6, we have another case. Here, the training is made with a small quantity of data and which are not uniformly located on the experimental area. This is a case whereby, data at the entire area can not be available for training or in order to remedy to time consuming process during data collection, only a small sample is used for this purpose.

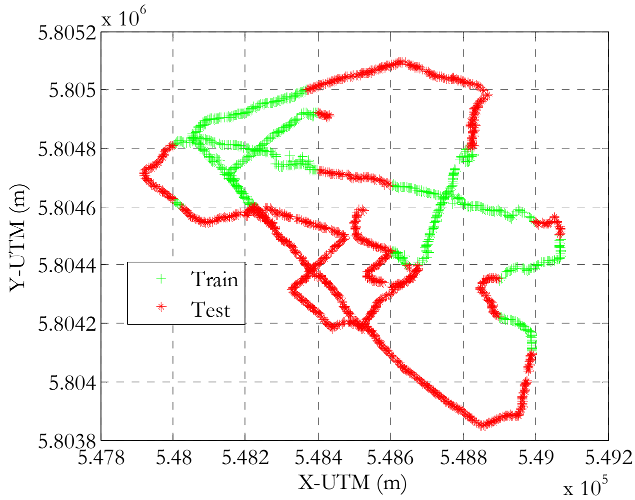

Figure 6. Sample positions used for training and test.

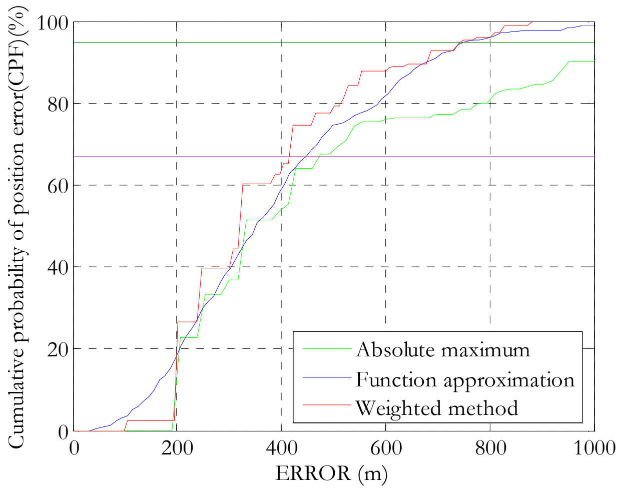

Figure 7. Cumulative distribution functions for the three methods

In Fig.7, it turns out that the Weighted Method could be the best solution. This can be explained by the fact that, the error is more likely to be bigger and the max value at the NN output codeword does not indicate the position estimate. A contribution of values bigger than a weighted limit could be a better indication for the location estimate.

IV. POST PROCESSING OF THE DATABASE CORRELATION RESULTS

The key Idea of the DC is to store any location-dependent signal information that can be measured by a MS and corresponding positions in a database for the whole interested area that is used by a location server [3]. In this work we use predicted RSS as the signal fingerprint. When the MS need to be located, the necessary measurements are performed and transmitted to the location server. The location server then calculates the MS location by comparing the transmitted fingerprint and the fingerprint of the database. In DC method, searching time should be reduced by limiting the searching process around the area where the mobile unit is located. The Timing Advance and Cell Identification information help to limit the searching area Fig.9. Other robust pattern matching methods for database correlation such as, those using Bayer filter have been investigated in [4] and could be used for better results. In this work, the metric used to decide on the matching location is the mean quadratic error. The coordinates associated with the fingerprint that provides the smallest mean quadratic error is returned as the estimate of the position.

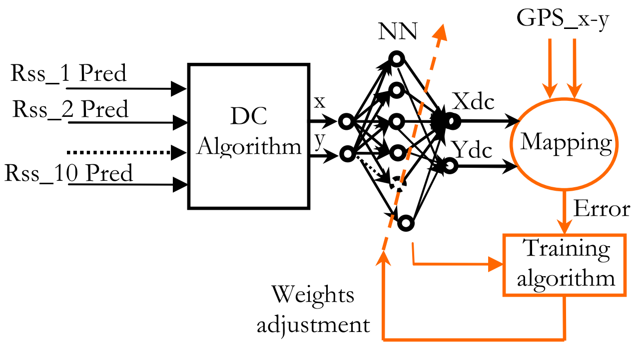

Figure 8. Block diagram of the DC positioning correction

Figure 8, illustrates the algorithm used to correct the position estimates from the classical or conventional DC method. In order to perform the training process of the NN, a few sample of location predicted fingerprints from the database are used. Position estimates for theses points are obtained from the classical DC algorithm. These position estimate samples are used as input to the NN, the corrisponding GPS target are introduced to the NN as well, Fig.8. A mapping function is approaximated so that, during DC positioning phase, the yellow part of the figure is not needed anymore. During DC positioning phase, a set of real rss is introduced to the classical DC algorithm. Position estimate with coordinates (x,y) is produced at the DC output, as shown in Fig.8. A post processing of these position estimates is made with an already trained NN, in order to get new position estimates with a better accuracy. Without this post processing of the DC position estimates, the max positioning error with 67% was 320m, “in press” [5]. In this work, post processing reduces the DC positioning error to a maximum of 220m with 67%.

V. FUSION

Training of the NN is made off line and takes time for a good generalization. After training, a positioning test can be performed in order to decide whether it satisfies our requirements or the training set should be reselect, NN architecture should be changed for a new training to be performed. As result, we have at the NN output the position estimate A with a known variance σ_1^2 got from the performance tests.

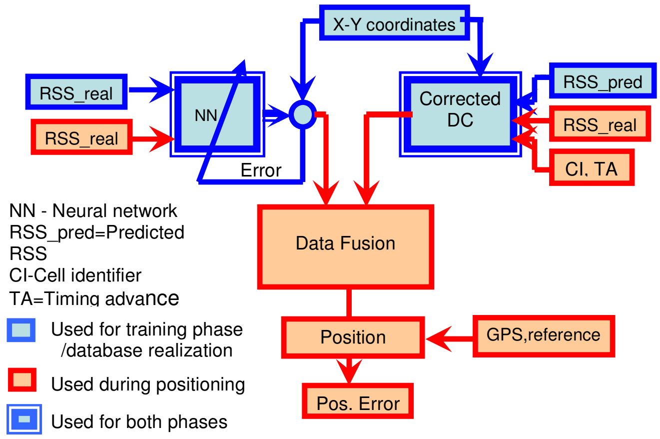

Figure 9. Block diagram of the fusion process

From the probability theory, we know that in case of a Gaussian density function, 68% of the probability is contained within the band σ unit to each side of the mean.

The same way, DC method provides us with an output B having a certain variance σ_2^2 which is also known after some tests. Having both positions and their corresponding variances, a fusion unit processes these information to produce a new location estimate C with a variance σ_3^2 .

The new position estimate C and variance are found through the formulas bellow:

$$C = \left(\frac{\sigma_2^2}{\sigma_1^2+\sigma_2^2}\right).A + \left(\frac{\sigma_1^2}{\sigma_1^2+\sigma_2^2}\right).B \qquad (1)$$

$$\frac{1}{\sigma_3^2} = \left(\frac{1}{\sigma_1^2}\right) + \left(\frac{1}{\sigma_2^2}\right) \qquad (2)$$

We should note that σ_3 is less than either σ_1 and σ_2 , which is to say that the error in the position estimate has been decreased by combining the two pieces of information [5,7].

The NN and the corrected DC blocks from Fig.9. are clearly illustrated in Fig.3. and Fig.8. respectively.

VI. FUSION RESULTS AND AREA USED FOR EXPERIMENT

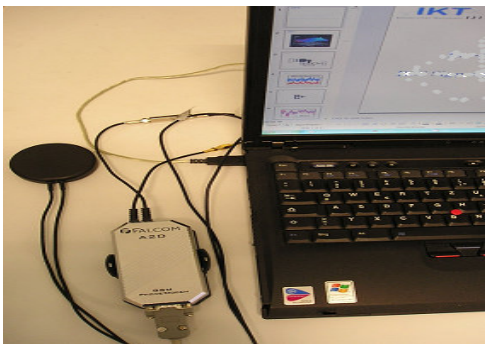

Figure 10. GSM-GPS antenna and Modem used

The experimental environment is an urban area with some high buildings. Experiments were performed in an area of size, 3km by 3km in which 10 GSM cell antennas were considered. The collected and predicted RSS used are from Eplus mobile network, Germany. A deterministic method was applied to predict the rss of our concerned area [6]. The pixel resolution of these provided predicted RSS is 5m.

In positioning phase, real collected RSS with a GSM-GPS antenna and modem were used in the algorithm, Fig.10.

Fig.11, shows us the fusion impact on the positioning accuracy. For this part of the experiment, the training of the NN was made with 1/15th of the 2000 location points collected along the area used for the experiment. In training the NN used for the DC positioning correction, 200 location data were used.

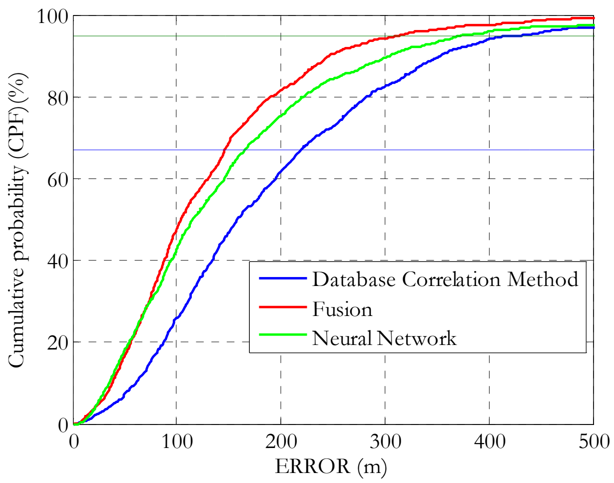

Figure 11. CPF for NN,DC and Fusion of both

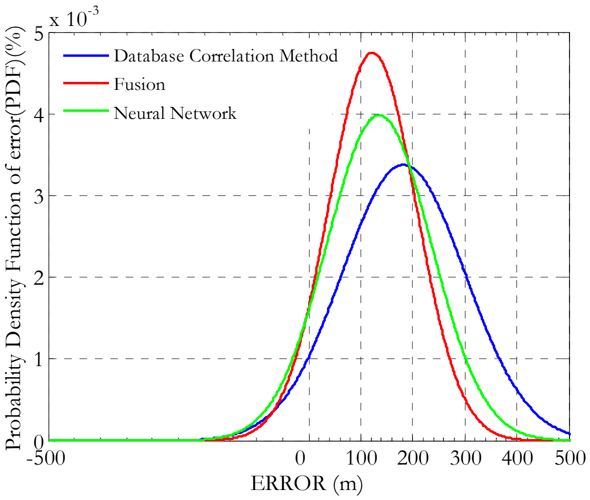

Figure 12. PDF of NN, DC and Fusion methods

The impact post processing of the DC positions can be seen from Fig. 11. With 67%, the DC error is less than 220m instead of 320m in the conventional DC method.

The positioning error got from the fusion process is having the least variance as shown in Fig. 12.

VII. CONCLUSION

In this work, the accuracy of different methods to yield the position estimate of a MS in a GSM network has been presented. An investigation of different NN positioning method was undergone for the given problem. Results from the second experiment show that using classification properties of NN in positioning issue can provide better results compared to function approximation, in case where training data are available for only some sectors of the whole experimental area.

A conventional database correlation positioning method was presented. The performance of this conventional DC method was further improved by involving a NN for post processing purpose. Result of the post processing reduces 100m in the positioning error compared to the conventional methods.

A fusion theory was investigated in order to combine positioning results from NN and corrected DC sources for the accuracy improvement. Results illustrated on Fig.11,12 show that, positioning error can be reduced by fusing positioning information coming from the different sources.

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