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Transmitter source location estimation using crowd data☆

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The problem of transmitter source localization in a dense urban area has been investigated where a supervised learning approach utilizing neural networks has been adopted. The cellular phone network cells and signals have been used as the test bed where data are collected by means of a smart phone. Location and signal strength data are obtained by random navigation and this information is used to develop a learning system for cells with known base station location. The model is applied to data collected in other cells to predict their base station locations. Results are consistent and indicating a potential for effective use of this methodology. The performance increases by increasing the training set size. Several shortcomings and future research topics are discussed.

1. Introduction

Massive use of mobile phones utilizing cell-based technologies created huge opportunities for the society and changed the life style in a fundamental way. As almost all of the smart mobile devices are equipped with GPS (Global Positioning System) support, the mobile users can easily locate themselves provided that the satellite based GPS signals are available. In outdoor environments, this has allowed service providers and third party developers to supply numerous location based services to the customers spanning fields of navigation support, active marketing, and social networking [1]. A serious and everlasting problem has been the estimation of the location of the mobile user when GPS is not available, e.g. in indoor environments or when GPS signals are not available because of the buildings and other environmental conditions. There are several solutions to the problem with varying levels of accuracy and cost. A simple and inaccurate solution can be to use the location of the base station as broadcasted by the base station itself provided that the service provider allows such a transmission. Assisted GPS is a more accurate solution where the GPS module of the mobile phone and the service provider's servers work together in different modes for better positioning. Assisted GPS is an enhanced GPS technology commonly used on smartphones. In the Assisted GPS system, an assistance server in the mobile network provides accurate time stamps and accurate GPS satellite orbital information. By using this information, it is possible to obtain initial position information in seconds. The overall accuracy is between 5 m and 10 m in Assisted GPS. Just like GPS, it has several pros and cons. The main advantage of Assisted GPS is its high accuracy. Moreover Assisted GPS can be helpful in densely populated areas where clear GPS signals may not be available. The quick location collection, which is useful for location-based services, is another advantage of Assisted GPS. One of the main disadvantages is the dependency on the mobile network provider. Assisted GPS can only work where mobile network reception is possible [1].

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In this work, we have investigated the inverse problem of locating the transmitting station based on the data collected by a crowd of devices. The problem of determining transmitter location based on sensors is a research area that is well developed for certain techniques. Common techniques utilized for this purpose are based on TOA (Time Of Arrival), TDOA (Time Difference Of Arrivals), AOA (Angle Of Arrival), RSS (Received Signal Strength), and the hybrid use of those mentioned. In all of those methods the major requirement is that the location of the receiving sensors are known. The computations of the transmitter location can be based on geometrical lateration techniques which may be converted to the solution of nonlinear set of equations employing methods of least squares or other optimization techniques. The reader may refer to the surveys for a comprehensive list of applications [2–8]. The major advantages and disadvantages, or requirements of these methods are as follows. Both TOA and TDOA based methods offer a high accuracy provided that LOS (Line Of Sight) conditions are met. Moreover, TOA requires time synchronization of both the transmitter and the receiver sensors whereas TDOA requires time synchronization for the received signal among the receivers only. AOA methods offer also high accuracy for LOS conditions where special smart antenna arrays are needed to determine the angle of the signal at its highest intensity whereas time synchronization is not required. RSS based methods also do not require synchronization however an accurate signal propagation model is necessary for accuracy. A major concern in all those methods is that fading in signals would change the accuracy drastically. The use of hybrid approaches for non LOS conditions tries to remove this problem to a certain extent. The problems associated with the transmitter location estimation get complicated in heterogeneous environments such as in dense urban environments where the propagation models cannot be determined accurately. The errors arising in the computations of sensor locations and received signal strengths also cause difficulties. The lack of necessary hardware capabilities in the sensor nodes to perform the required complex calculations is another obstacle hindering effective use of those methods [3,6,8].

A major and novel problem is the use of information collected by a crowd to determine the transmitter location even if there is no synchronization among those receiver sensors. The active research area for wireless sensor networks can be extended to this field where TOA, TDOA, and AOA methods cannot be utilized. In the literature, there are papers using the RSS and sensor location information to predict the source location. Among them, [9] describes an iterative method that estimates source location and the other unknown parameters of power and path loss coefficients based on each other where RSS values are used. The simulations assuming zero mean Gaussian noise, indicate convergence to the theoretical lower bounds (Cramer–Rao Lower Bound), however, there is no real life data. Similarly, in [10], the authors employ a novel weighted least squares algorithm for source localization where the simulation results are given for an area of 40 m by 60 m. The results indicate that the prediction accuracy will be enhanced if the signal to noise ratio of the transmitter is increased. The recent work of [11] employs a Bayesian theory for data fusion which is simulated for an evenly distributed set of sensors within an area of 1 km by 1 km. This approach does not estimate the source location directly; it is used to predict the source in the closest proximity. The experimental work in [12] fits histograms of RSS measurements to spline functions in order to predict the source location in a 150 m^2 area where the mean error comes out to be between 10 m and 34 m depending on the position of the transmitter above the ground. The authors conclude that an “alternative approach to solving the positioning equations that takes into account the variations in the path-loss” has to be developed. A field work paper compares different propagation models in an urban area using real life measurements of GSM signals [13]. As the focus of the paper is not source localization, there is no performance data about this, however, the comparison yields that the SUI model ([14]) is the closest one for the dense urban environment. The deviation between the closest model and the experimental data is more than 10 dB in distances less than 1 km and this reduces the applicability of such propagation models in source localization as the location error becomes 80% for typical values of propagation coefficients. Lastly, the work in [15] deals with the problem of estimating the theoretical bounds of source localization. The methods are based on using the RSS measurements, however, the paper states that non-Bayesian methods have to be deployed if the propagation model is not known. Review of those papers mentioned above indicates that hard computing methods would not suffice in dealing with our problem where an accurate propagation model cannot be obtained from the collected data only. However, research indicates that soft computing methods such as neural networks can be efficiently used for source localization in a setting where the nonlinear propagation model is highly unpredictable [16]. A recent review of RF based indoor positioning methods also indicates that there are soft computing methods utilized for proper source localization [17]. Based on those work in the literature, we have investigated the problem of transmitter location estimation using machine learning from data supplied by a set of heterogeneous sensors which only supply RSS and location data. To the best of our knowledge, there is no work that utilizes GSM signals in outdoor for source localization. As the case study, we have performed real life tests using the GSM signals of base stations received by mobile phones in a dense urban area. In the remaining of the paper, Section-2 describes the problem settings and the methodology employed. Section-3 includes the experimental data collected and processed. Finally Section-4 concludes the paper by discussing the results, shortcomings and future research topics.

2. Problem and methodology

2.1. Problem statement

In its most general form, the research problem is to determine the location of a transmitter source using the data collected by a crowd of sensors where the data includes the “id” of the transmitter, the strength of the received signal (RSS)

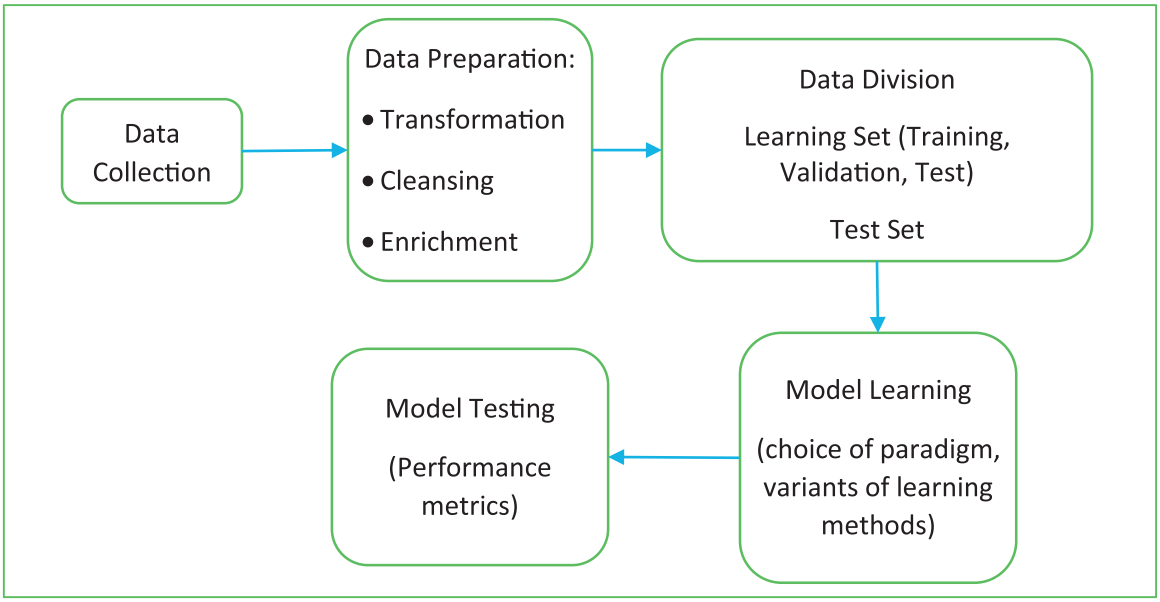

Fig. 1. Block diagram of the learning process.

and the location of the sensor at the time of the measurement. The transmitter sources are the base stations of GSM cellular mobile phone network operating at 900Mhz. Receiving sensors are smart mobile phones that can identify the “id” of the base station, RSS at the antenna, and its own location using the integrated GPS module. The environment is a dense urban area where an accurate propagation model of signals is not available. Even though there are many models available for dense urban areas in the literature [14,18,19] their accuracy depends on the topology of the area and the characteristics of the buildings and other structures. The parameters of the model span a certain range of values making it difficult to make accurate predictions unless the parameters are calculated by extensive measurements for the area of interest. Furthermore, the receivers are limited at two aspects: they have no direct communication capability with other sensor devices (similar receivers), hence they cannot utilize the measurements of other sensors in real time. Also, their computational power and memory are not adequate to perform complex calculations. Hence, it would be impossible to implement computationally intensive łateration based techniques locally in sensor nodes. A server based solution would be possible but this would be costly in terms of time and the hardware requirements for data communications.

Due to the nature of the aforementioned problem, there are some features which may be exploited for better performance. Firstly, the base stations in dense urban areas have a special signal radiation pattern where a set of three transmitters are deployed to cover a 360° of angle. That is, each transmitter has an effective region of 120° sector (one third of a circular disk) so that the sensors can only be connected to that transmitter when they are within this disk sector. Secondly, the sensors (mobile phones) do not make consistent RSS measurements as they are not equipped with same types of antennas. The measurements among different devices at the same location would be different because of hardware differences, battery level, and even software differences. At first sight, this seems to be a disadvantage, but using a large pool of sensor data from the crowd, those variations may be regarded as noise in measurements so that a methodology capable of dealing with noise would be able to make accurate predictions. Lastly, the density of available transmitters in a dense urban area is high: the distance between adjacent transmitters is approximately less than 500 m so that each “cell” identified by the transmitter can be assumed to exhibit similar characteristics of disturbances in signal propagation. Therefore, a system can be developed based on measurements in a representative set of cells which can be deployed for other similar cells. This system can be based on hard computing paradigms such as lateration based techniques or on soft computing paradigms which can include machine learning algorithms. As hard computing paradigms would require accurate propagation models or synchronization, they are not useful for our problem. On the other hand, machine learning based on neural networks can be a good candidate to model the noisy environment displaying a high degree of uncertainty. Especially supervised learning employing MLP (Multi Layer Perceptron) neural networks can be utilized in many regression and function approximation tasks [20,21] including problems of the wireless sensor networks domain [22,23].

2.2. Methodology

The process of a generic machine learning system is given in Fig. 1. The process is based on data. After data collection, data will be processed to suit the needs of the system to be used. The data are divided into learning and test data where the learning data are again divided into training, validation and test sets. Training data are used to tune the parameters of

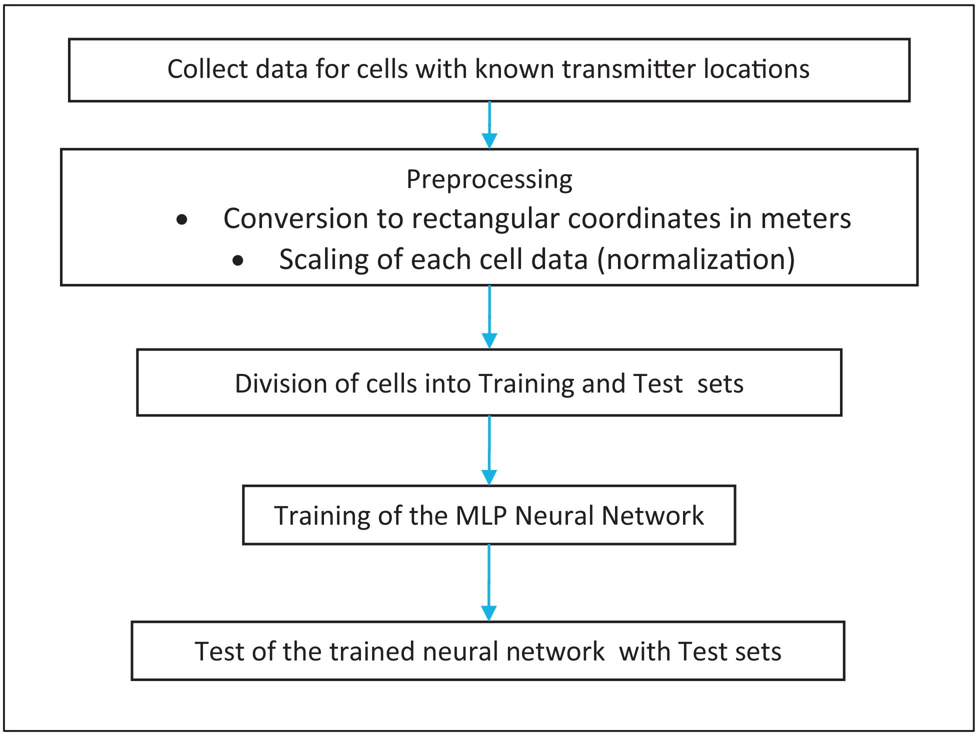

Fig. 2. Algorithm of the learning system.

the model whereas the validation set is used to determine when to stop training (to avoid overfitting in learning). Then the test set is used to verify the performance of the model. Finally, the model can be further tested for performance using independent test data to obtain the performance metrics.

As a crowd of mobile phones navigate, each device may collect GPS based position information and some basic data about the base station of the current cell in which the device navigation occurs. They are the identification of the base station including country, network, and station codes, and the RSSI (RSS Indicator) value obtained via the antenna module. The raw data obtained can be expressed as a quadruple:

$$\{id, longitude, latitude, RSSI\}.$$

The basic methodology to develop a learning system based on this data is given in Fig. 2.

The longitude and latitude values will be converted to coordinates in meters where the 0.00E, 0.00N (the point on the equator where the Greenwich meridian passes) is chosen as the origin [24]. Then our data set will be made up of the following quadruples:

$$\{id, x\_in\_m, y\_in\_m, RSSI\}$$

Collected sets of coordinates for each cell are assumed to be mapped to a flat surface neglecting any deviations in elevation as the outputs of the GPS module have less accuracy for the elevation component especially in a dense urban area. Then, all cells will be scaled within themselves, that is, based on the collected coordinates, a new origin will be determined for each cell so that absolute values of coordinates will be normalized. For this purpose, the centroid of the collected coordinates is chosen as the origin of the cell for practical reasons: the points will be distributed evenly around the origin. The origin for each cell is calculated as

$$orig_{x(id)} = \frac{1}{n_{id}} \sum_{i=1}^{n_{id}} \mathrm{x\_in\_m}(i) \tag{1}$$

$$orig_{y(id)} = \frac{1}{n_{id}} \sum_{i=1}^{n_{id}} \mathrm{y\_in\_m}(i) \tag{2}$$

where n_{id} is the number of measurement points in cell number “id.” Then each point is normalized according to this origin in each cell giving the final coordinates of x and y as follows:

$$x(i) = \mathrm{x\_in\_m(i)} - orig_{x(id)} \;\; for \;\; i = 1, \;\; n_{id} \tag{3}$$

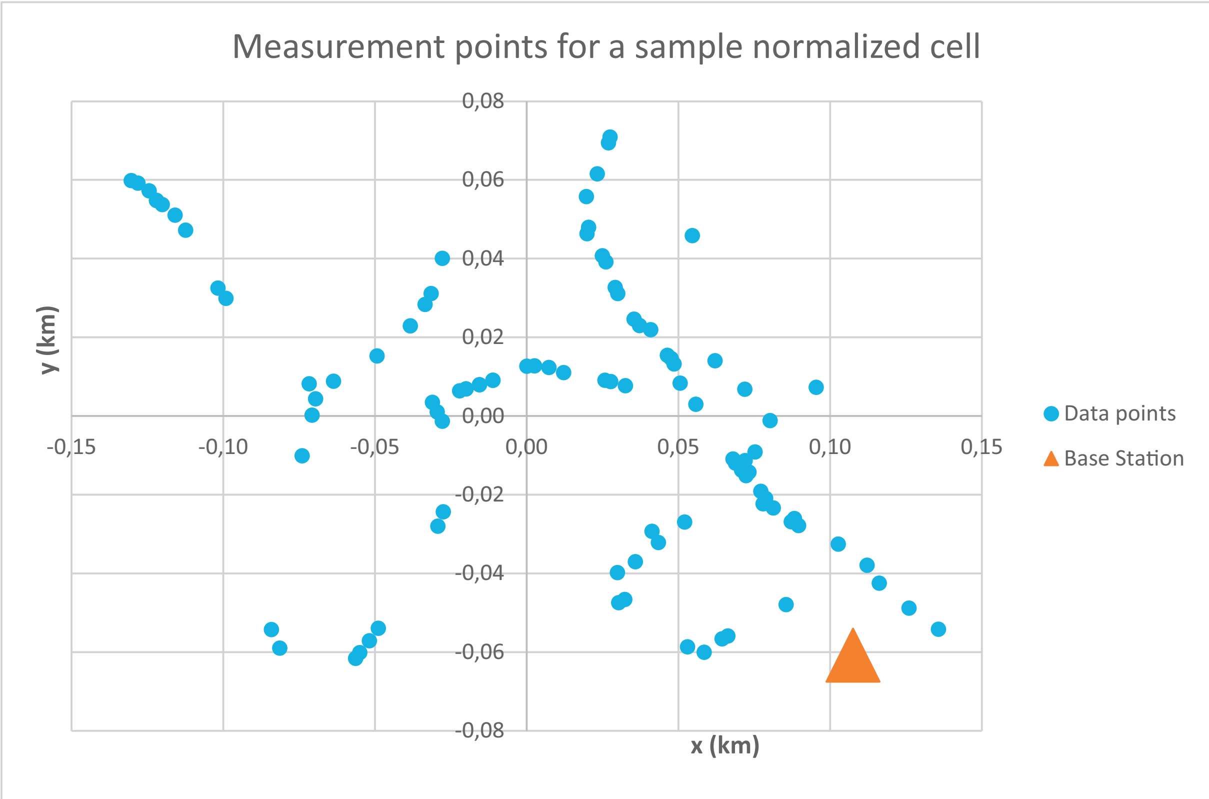

Fig. 3. Scaled and normalized measurement points for a sample cell with the location of the transmitter.

$$y(i) = \mathrm{y\_in\_m(i)} - orig_{y(id)}\ \ for\ i = 1,\ \ n_{id} \tag{4}$$

A sample result for this normalization at each cell is given in Fig. 3.

After this normalization, cells are randomly divided into two groups: training set and test set. The ratio of this division may vary. The cells in the training set will be used for the training of a MLP neural network whereas the test set will be used for the validation of this learning approach. The neural network topology consists of the input layer having three inputs (x, y, RSSI), a single hidden layer with N neurons, and the output layer having two output neurons for the coordinates of the base station x_{base} and y_{base}. During the training several variants of backpropagation have been tested along with different number of hidden units. Furthermore both versions of the supervised learning with respect to weight updates in the neural network have also been tested: online and batch updates. Details of the training process will be given in the next section with real life measurements. The training of the network has been achieved in MATLAB Neural Network Toolbox. The collection of normalized coordinates and RSS values along with the normalized coordinates of the base station, has been further grouped into three divisions for training, validation, and test of the neural network training process. This division is necessary to prevent overfitting of the neural training where the validation group data will be used to determine when to stop the training process. A standard approach for this random division is to use 70% of the data for training (updates of weights), 15% for validation and the remaining 15% for test [25]. The stopping criteria for the network have been threefold: a maximum for the iteration count (epochs), a minimum threshold of MSE (Mean Square Error), and a maximum number of iterations (usually six in practice) where the error in validation set increases in a row.

The main idea of the proposed method is to utilize data obtained in cells with known base station location to develop a model based on supervised learning in MLP neural networks. Then, this model will be tested on cells which have not been used in the learning process to yield the base station locations. Once the training is completed, the crowd data of the "new" cells will be fed to the neural network. For each measurement point, the neural network model will give us a pair of coordinates which have to be condensed to a single pair as the candidate base station location. The adopted approach for this purpose is to use the average of the outputs to yield the final coordinates. However, other approaches can also be utilized in case of the availability of sensor nodes navigating in real time which will be discussed in the final section.

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Table 1
Summary of sizes of 31 cells where crowd data are gathered.

Cell sizes	Length (m)	Width (m)
Min	210	130
Average	520	320
Max	1100	940

Table 2
Comparison of mean error (m) in base location for supervised learning by regression (REG) and by the MLP neural network (NN).

	Number of cells used in the training set							
	6		12		21		30	
	REG	NN	REG	NN	REG	NN	REG	NN
Training data set	388	258	583	232	506	174	461	153
Test data set	491	304	437	290	467	226	387	106

Fig. 4. Map of the region where data are collected: the most crowded commercial and residential area of Istanbul.

```
for k=6, 12, 21, 30
LOOP
    for i=1..10
    LOOP
        Select k cells randomly to form training set;
        for N=5, 10, 15, …,60
        LOOP
            Train the MLP neural network with N hidden units
            5 times, store the NN structure with minimum error;
            Store the outputs, and errors;
        end LOOP;
        determine minimum MSE hidden unit count;
        forward run of NN having minimum MSE with test set;
        determine error for each cell in test set;
    end LOOP;
    determine minimum and average distance error for this grouping;
end LOOP;
```

Fig. 5. Training of the MLP neural network.

3. Experiments and results

Based on the methodology described above, we have carried out experiments based on real life measurements in a dense urban environment. Firstly, a mobile application has been developed to gather the required data during navigation. The application stores the GPS based location information, base station information, and the RSSI value in a local text file based on a sampling period supplied. The default value for sampling period has been set to 3 s. This mobile app has been loaded into a smart phone which has been kept in the “pocket” of one of the authors as he traveled by foot or by car during the day. The actual implementation of this approach would be to use the data collected by a crowd of people. As a pilot study, we have performed data collection using two samples of a smart phone. The data collection process has been carried out covering a total geographical area of approximately 3.2 km by 2.4 km including 45 different base stations during a period of 2 weeks in December 2016. The data are collected in the most densely populated areas of Istanbul (districts of Fatih and Beyoglu) during the daytime. Fatih is the commercial centre of the city with an approximate count of 2.5 million people at daytime during the weekdays. Hence, there is a need for a huge capacity of GSM network which can only be achieved by

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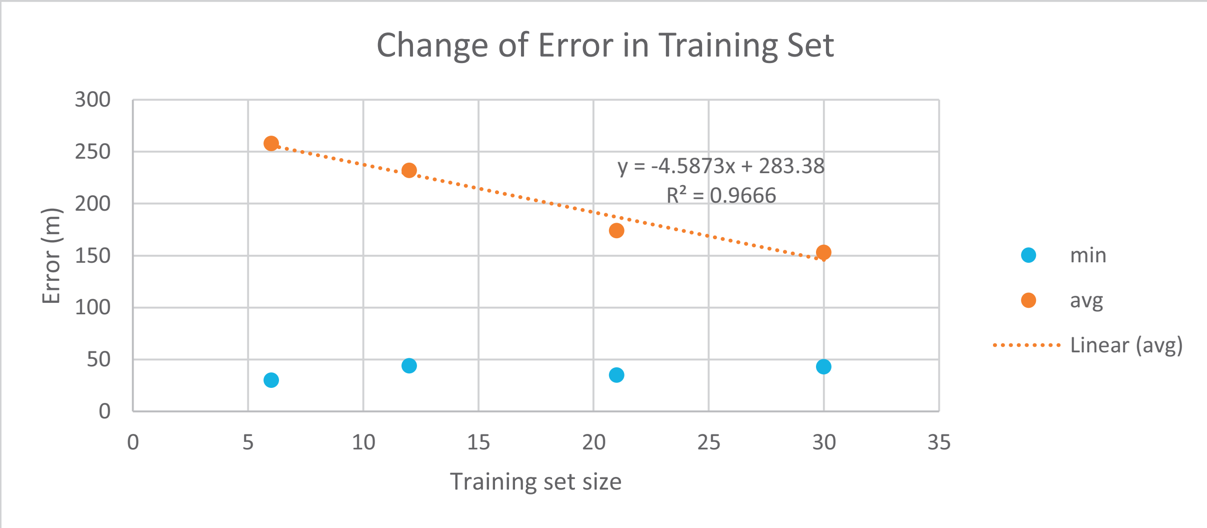

Fig. 6. Variation of minimum and average location error in the training set depending on the number of cells used in training set.

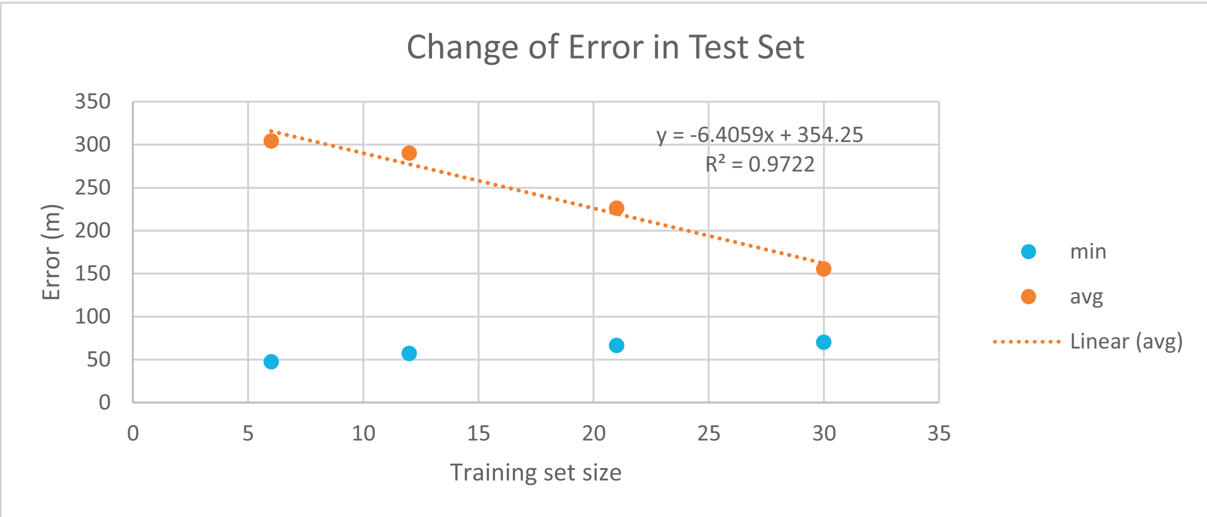

Fig. 7. Variation of minimum and average location error in the test set depending on the number of cells used in training set.

a dense allocation of base stations. The map of the region is given in Fig. 4 where data are collected. The accuracy of the data set is bound to the hardware and the software of the mobile device used. We have uploaded the application to two different models of Android based smart phones and their readings exhibited a maximum variation of $+/-3$ dB which can be regarded as noise. The raw data has been pre-processed. Data without the GPS based location information are discarded. Cells are also excluded that have less than 50 data points. Moreover, duplicated records are removed which are collected as the phone was not moving. Lastly, the number of data points in each cell are reduced to 100 by iteratively removing one of the two data points in the closest pair of points. This would prevent the domination of cells with relatively larger number of data points in the training process. Finally, the remaining 31 cells have been taken into consideration. A summary about the sizes of the cells is given in Table 1.

For the training of the neural network, several alternative groupings are prepared for the training set of the cells. Four groupings have been identified including k cells for the training of the neural network where k ϵ {6, 12, 21, 30}. Those numbers have been selected as they constitute 20%, 40%, 60%, and 97% of the total cells respectively. For each grouping, 10 different subsets of k cells are randomly selected from the 31 cells and the training is carried out using those subsets. The training of the MLP performs a function approximation job: weights of the MLP neural network are updated in the backpropagation algorithm, so as to minimize the mean error between the actual output (what the neural network predicts as the base station location) and the desired output (true position) for the set of training samples. The backpropagation training will be repeated 5 times for different number of hidden units N where N takes values between 5 and 60 with

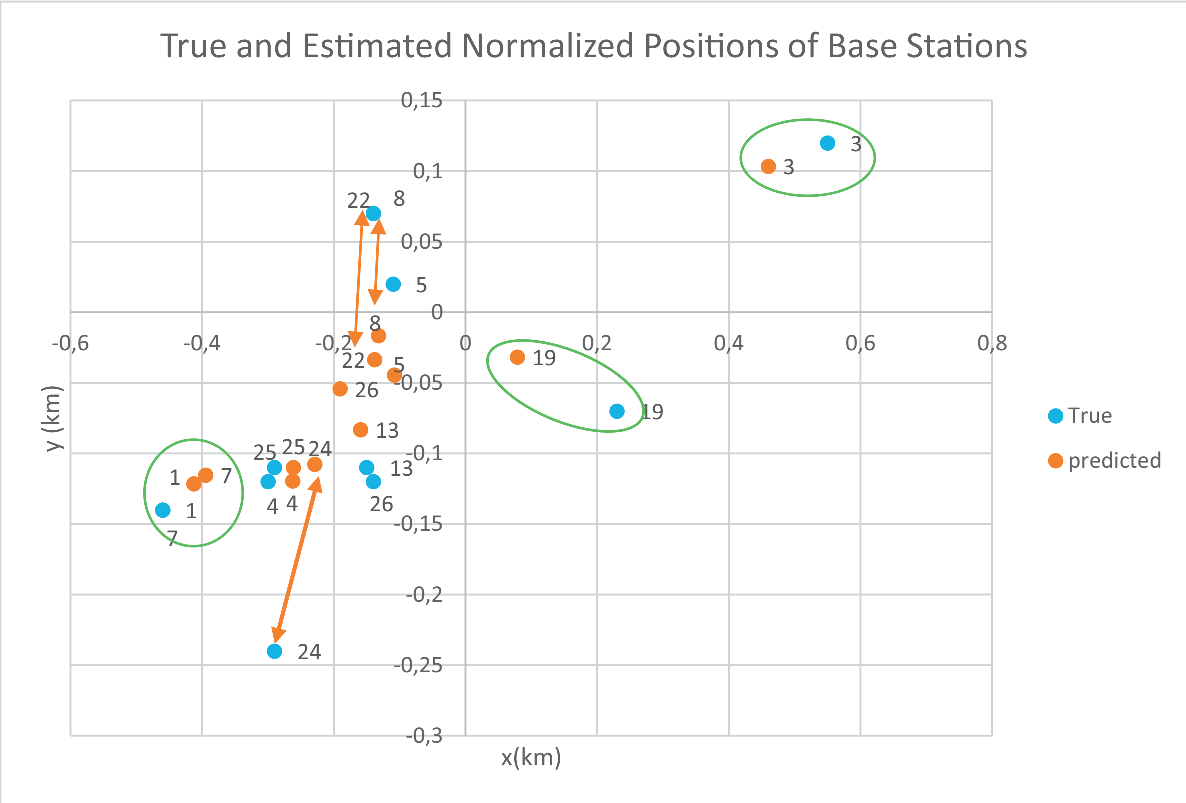

Fig. 8. True and predicted locations of base stations for a sample training set of 12 cells.

increments of 5. That is, for each set with k cells, the effect of hidden unit count is also monitored. The results indicate that the neural network training error is at its minimum for a hidden unit count between 20 and 30 for different groupings. However, extensive trials have shown that using a hidden unit count of 20 is optimal. The training has been repeated for 5 times in order to overcome premature convergence to a local minima in the training. Each time, the training with minimum MSE (Mean Squared Error) is recorded. Then, a forward propagation run is executed using the best performing hidden unit count with the test set data to determine the predictions for the base station locations. Furthermore, the minimum and average errors (distance between actual location and predicted location) are computed for each grouping. This algorithm is given in Fig. 5.

The training process based on the use of groupings allowed us to make the following useful observation: The accuracy of the learning has improved as the training set size increased. Fig. 6 displays the change of average and minimum error for base station locations in the “training set” with respect to the training set size, whereas Fig. 7 displays the same variation for the test set. It is clear that the test set has larger average errors in comparison to the training set. Furthermore, the trend lines indicate a linear decrease in the average error as the training set size increases.

True and estimated base station locations for a sample training run with 12 cells are given in Fig. 8. Location of some of the base stations have been predicted with a good accuracy (distance between the actual location and the predicted one is less than 50 m for cells numbered 1, 4, 13, 25), whereas prediction error is between 50 m and 100 m for cells numbered 3, 5, 7, 8, 26). Finally, locations of the base stations numbered 19, 22, 24 are predicted by an error larger than 100 m.

We have also implemented a supervised learning based on regression in order to make a comparison with the use of the neural network. Sets of cells with counts of {6, 12, 21, 30} are selected randomly. The data collected within this training set are used for nonlinear regression. For this, the log-normal function as given in Eq. (5) is used which resembles the standard path loss model where **RSS** is the received signal strength, **d** is the distance to the source, and the parameters **A, B**, and **C** are to be found using nonlinear regression.

$$RSS = A + B\ \log\frac{d}{C} \tag{5}$$

The remaining cells are used for testing the validity of the regression approach. The average error for the base station location (distance between the actual position and the predicted position) in the training set and the test set are given in Table 2 for both approaches.

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The results indicate that using a log-normal function approximation is not adequate to model the complex behavior of signal propagation in the dense urban environment. The results of the MLP neural network are superior to the approach where nonlinear regression to log-normal function is employed.

This result is in accordance with the findings in the literature as many papers report poor performance in using the log-normal propagation model with real data [12–14,19]. The simulation results of [9–11,15,16] are based on a certain propagation model and/or a stationary noise characteristics. However, the real urban environment is much more complex than those models. The deviations in the nonlinear behavior can be held responsible for the performance degradation in our approach. For the limited set of cells, the overall performance enhancement seems to be promising as the cell count in the training data increases.

4. Conclusion

A methodology for base station source localization of the GSM network in a dense urban area has been developed. The research may yield useful results in the field of object tracking, wireless sensor networks, and reverse engineering of a network. The essential contribution of this work is the development of a supervised learning system by using MLP neural networks which is trained by real life measurements in cells of known base station locations. Then, the system can be used to predict the base station location of cells using the crowd data made up of location and signal strength components. This offline method assumes that the nonlinear propagation models of those dense urban areas will be similar and neural networks are capable of approximating noisy, uncertain information. Based on the data collected for 31 cells, different training runs are carried out for varying number of cells used for training in groupings. The results indicate that the performance increases by increasing the training set size.

The major limitation of this approach is that the measurements may have an unpredictable variability as the transmitter powers are not necessarily uniform. The dense urban structure and the random or unplanned collection of data may deteriorate the prediction performance. However, in comparison to many simulation based research in the literature, actual field measurements are successfully used in a machine learning process. As future research, a normalization of signal strength values in form of a scaling can be investigated. Another possible topic would be to employ a polar coordinate system for the cell data collected. In any case, increasing the cell counts for training and a wider coverage of the cells will certainly increase the prediction ability. An interesting potential for this methodology can be the development of a server or cloud system where each sensor node (e.g. mobile phone) can work in online mode to communicate with other sensors in order to carry out a superior source localization by sharing data and by possible synchronization. In such a system, the transmitter location can also be predicted by a single sensor that navigates in the region where the changes of received signals may also be utilized.

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