RBF Network Design for Indoor Positioning based on WLAN and GSM

Maja Stella, Mladen Russo, Matko Šarić

Abstract— Location-based services aim to improve the quality of everyday lives by enabling flexible and adaptive personal services and applications. In order to provide context-aware services and applications, key issue is to enable accurate estimation of user location. Localization methods based on Received Signal Strength (RSS) fingerprints are gaining huge interest as localization solution, where, as pattern matching algorithm, different methods are used. In this paper we investigate the usage of Radial Basis Function (RBF) neural network as approximation function that maps RSS fingerprints to user locations. We provide detailed analysis on network training performance considering different number of neurons and radial basis functions' spread values. We developed two real world indoor positioning systems in WLAN and GSM environment based on RBF neural networks. Compared to GSM based approach, WLAN system has the advantage in terms of lower localization error, but generally GSM signal coverage by far outreaches WLAN coverage and if less accurate positioning is required, GSM can also present a good solution.

Keywords— Localization, Received Signal Strength (RSS), fingerprinting, RBF neural network, WLAN, GSM.

I. Introduction

ACCURATE localization is important and novel emerging technology [1, 2]. Ability of a positioning system on mobile device to determine its position accurately, leads to substantial context aware computing [3] and a great number of useful Location Based Services (LBS), from asset tracking in warehouses, mobile advertising, and various personal applications requiring different localization accuracies. Currently many scientific groups are involved in research in the area of localization in order to develop accurate and robust localization system.

GPS presents the best localization solution for outdoor environment since it offers maximum coverage and GPS capability can be added to various devices by adding GPS cards and accessories in these devices, enabling location-based services. In indoor environment satellite based localization can't be applicable, since there is severe attenuation of satellite signals and line-of-sight between receivers and satellites is not possible [3, 4].

Many systems for indoor localization using different wireless technologies - from ultrasound [5, 6, 7], radio-frequency identification (RFID) [8, 9], Bluetooth [10], wireless local area network (WLAN) [11,12], infrared [13, 14], sensor networks [15-18], ultra-wideband (UWB) [19] have been developed. Each system has unique advantages in performing location sensing and differing with respect to accuracy, coverage and installation cost. Active Bat [5] and Cricket [6] are based on combination of RF and ultrasound signals. For estimation of the distance between transmitter and receiver, time difference of arrival (TDOA) is used. Active-Badge, as one of the first localization systems, uses low range infrared signals and performs poorly in presence of direct sunlight. It provides room-grained localization, using wall-mounted sensors that pick up an infrared ID broadcast by tags worn by the building's occupants [13].

Some of the proposed localization systems require specially designed infrastructure, and they can be expensive and hard to implement in every indoor environment, which is a main drawback of their practical implementations. Thus, for practical localization purposes it is preferable to employ the existing wireless communications infrastructure. Since in indoor areas, the wireless communication infrastructure is primarily based on the wireless local area networks (IEEE 802.11 WLANs) and WLANs are already widely implemented in all public area such as schools, universities, airports, hospitals, shopping centers, their use for localization purposes makes it a cost effective localization solution.

Localization is based on dependency of RSS values on location, this dependency can be expressed by a propagation model or by a location fingerprinting model. RSS indicator can be easily read in every 802.11 interface. On user side, their devices such as smart phones, tablets and laptops are already equipped with WLAN interface and they can be easily used as positioning devices, only software deployment is required.

Propagation models are accurate for open space, but in indoor area multipath conditions lead to degradation of localization accuracy. Having the major advantage of exploiting already existing 802.11 network infrastructures, currently the most viable solution for RSS-based indoor positioning is the fingerprinting architecture [20-24].

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A location fingerprint is typically based on RSS signal characteristic. RSS represents a unique position or location. It is created under the assumption that each position or location inside a building has a unique RF signature. Localization is composed of two phases: data collection and real-time user localization. The first phase consists of recording a set of RSS fingerprints in a database as a function of user's location covering the entire zone of interest and using this data as input and as the target of pattern matching algorithm. During the second phase, a RSS fingerprint is measured by a receiver and applied on pattern-matching algorithm to obtain location. In literature, traditional approaches used as localization algorithm are nearest neighbor [11], multilayer perceptron [21], maximum likelihood [12] and probabilistic approach [25].

In this paper we propose fingerprinting positioning system based on Radial Basis Function (RBF) network to construct nonlinear relation between RSS and user location. We conducted real life experiment in our university building, where we collected realistic RSS measurements. Key parameters determining the performance of the RBF network are the number of neurons and radial basis functions' spread values, and the choice of appropriate values is most important. We provide detailed analysis on RBF network training performance considering different number of neurons and radial basis functions' spread values. We developed two positioning systems in real world indoor environment based on WLAN and GSM. Experimental results indicate advantage of WLAN based approach in the sense of lower localization error compared to GSM based approach, but GSM-based indoor positioning system has advantages over WLAN in terms of far outreaching signal coverage and high acceptance of mobile phones among users. As a part of GSM standard (e.g. [26]) which is required for successful handovers, mobile phones are required to report signal strength of 6 neighboring cells and a fingerprint could be easily obtained just by software.

The rest of the paper is structured as follows. Section 2 describes location fingerprinting and radial basis networks. In Section 3, measurement setup, RBF network design and positioning results for the proposed systems based on WLAN and GSM are given. We close this paper with a conclusion in Section 4.

II. Localization based on fingerprinting and Radial Basis Function Networks

A. Location fingerprinting

Fingerprinting based system works like the process of pattern matching. It is based on some RF characteristics (typically on RSS) which is the basis for representing a unique location within some area. It is created under the assumption that each location has a unique RF signature. The process can be divided in two phases: a phase of data collection (off-line phase) and a positioning phase in real-time (on-line phase).

In the first phase a set of RSS fingerprints are recorded as a function of the user's location covering the entire zone of interest and using this data as input and as the target of pattern matching algorithm. During this phase, a set of predefined reference points is used, where RSS values from N APs are measured. A set of reference fingerprints is collected at each reference location and stored in a database (radio map) together with the referent physical coordinates.

During the second phase, an RSS fingerprint is measured by receiver, at unknown location. Radio map from off-line phase is used in order to obtain a location estimate by applying a pattern matching algorithm. Location estimation is obtained by minimizing an error function, typically Euclidean distance between unknown and reference signal.

Pattern matching algorithms can be classified into deterministic and probabilistic types based on the approaches that model the relationship between location fingerprints and location. The deterministic types of algorithms are those that are based on the nearest neighbor classifiers [11, 27] and the neural network classifiers [4, 20, 21, 24]. The probabilistic types of algorithms treat RSS as a statistical random variable and likelihood value for each location is calculated based on estimated probability distributions, typically with Gaussian kernel function. For unknown location, conditional probability of each referent location in radio map is calculated. In literature some pick location of largest conditional probability distribution [12, 25] or take an average of k locations with largest conditional probability distribution [27].

Several localization systems using the fingerprinting technique have been recently deployed in outdoor and indoor environments. The main differences between these systems are the types of fingerprint information and pattern matching algorithms [11, 20, 22]. Neural networks, as a pattern matching algorithm, have been employed in wide range of positioning systems and have demonstrated good results [4, 21, 24]. A trained artificial neural network can perform complex tasks such as classification, optimization, control and function approximation [28].

B. Radial Basis Function Networks

A radial basis function (RBF) network is a special type of feed-forward neural networks trained using a supervised training algorithm. They are typically configured with a single hidden layer of units that uses a radial basis function as its activation function.

RBF networks have been applied in many applications, such as real time approximation [29] pattern classification [30], system identification, nonlinear function approximation [31], adaptive control, speech recognition [32].

The radial basis function network is different from other neural networks, possessing several distinctive features. Because of their universal approximation ability, more compact topology, faster learning speed, and avoiding solution of falling into local minima, RBF networks have attracted considerable attention and they have been widely applied in many science and engineering fields [33].

Generally, a radial basis function network can be described as a parameterized model used to approximate an arbitrary function by means of a linear combination of basis functions [34].

RBF networks typically have three layers: an input layer, a hidden layer with a non-linear RBF activation function and a linear output layer. The weights connecting the basis units to the outputs are used to take linear combinations of the hidden units to produce the final classification or output. The network training is divided into two stages: first the weights from the input to hidden layer are determined, and then the weights from the hidden to output layer.

The output of the network *f(x)* is function of the input vector

$$f(x) = \sum_{i=1}^{N} w_i \varphi\left(\| x - c_i \|\right) \qquad (1)$$

where N is the number of neurons in the hidden layer, c_i is the center vector for neuron i, and w_i is the weight of neuron i in the linear output neuron, all inputs are connected to each hidden neuron. The norm is typically taken to be the Euclidean distance.

RBF networks belong to the class of kernel function networks where the inputs to the model are passed through kernel functions which limit the response of the network to a local region in the input space for each kernel or basis function. The output from each basis function is weighted to provide the output of the network. As a basis function, a Gaussian kernel is most commonly taken.

Some of the used basis functions are given in Table 1.

TABLE I
BASIS FUNCTIONS

Function		
Gaussian	$\varphi(x) = \exp(-x^2/2\sigma)$	$\sigma > 0$
Multi-Quadric	$\varphi(x) = (x^2+\sigma^2)^{1/2}$	$\sigma > 0$
Generalized Multi-Quadric	$\varphi(x) = (x^2+\sigma^2)^{\beta}$	$\sigma > 0,\ 0 < \beta < 1$
Inverse Multi-Quadric	$\varphi(x) = (x^2+\sigma^2)^{-1/2}$	$\sigma > 0$
Generalized Inverse Multi-Quadric Functions	$\varphi(x) = (x^2+\sigma^2)^{-\alpha}$	$\sigma > 0,\ \alpha > 0$

This network offers advantages over the standard multi-layer perceptron (MLP) in terms of long training time needed for MLP network, where backpropagation is used for finding the optimal weights – it modifies the weights of the network in order to minimize the mean square error between the desired and actual outputs of the network. Unlike MLP, RBF avoids problems associated with local minima since optimum weight values are easy to find [34].

In context of indoor localization in WLAN/GSM system, a RBF network can be viewed as a function approximation problem, consisting of nonlinear mapping from a set of N input variables (RSS fingerprints from N access points/base stations) into two output variables representing unknown two-dimensional location (x, y) in physical space, Fig 1.

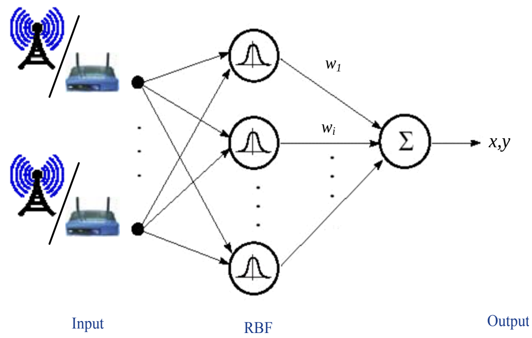

Fig. 1 Architecture of a RBF network in WLAN/GSM system

III. RBF NETWORK BASED POSITIONING SYSTEM

A. Measurement Setup

Localization system setup was carried out in the part of the fourth floor of our university building, dimensions of approximately 28m×15m, total area 420m2. Area includes 4 offices, 3 laboratories, a classroom and a hallway. The layout of the floor with APs and measurement locations is shown in Fig.2.

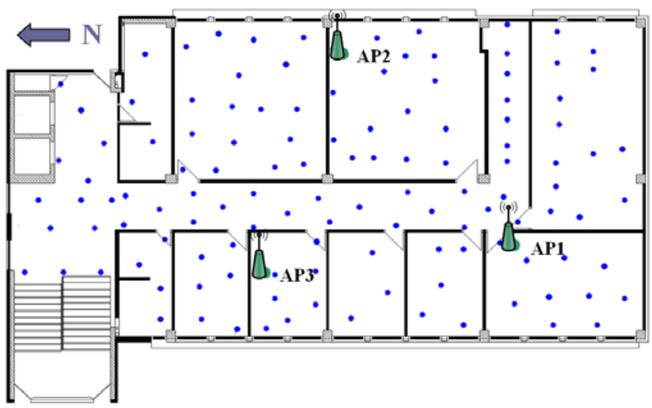

Fig.2 The test location layout with positions of the access points and measurement locations

For collection of the RSS samples from APs we used a laptop with Proxim Orinoco card and Network Stumbler software [35], screenshot in Fig 3. The information that is available to the user include the MAC address, SSID and the access point name, channel number on which works, connection speed, manufacturer name, signal to noise ratio (dB), the current and maximum signal-to-noise (dBm). At each location signal parameters are recorded in log file. As can be seen from the figure, three access points are configured to operate on non-overlapping channels 1, 6 and 11. Their MAC addresses are 0016B6A32A3F, 0016B6A32A42 and 0016B6A33909, and are marked in the text as AP1, AP2 and AP3.

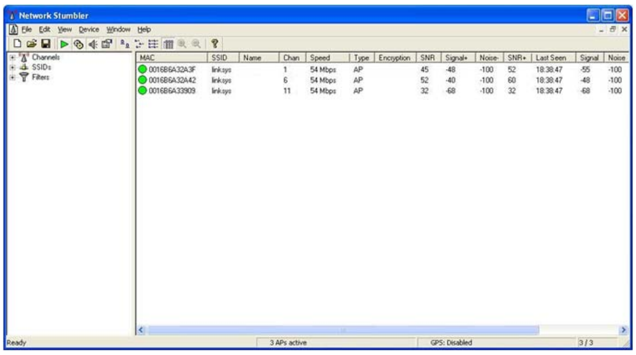

Fig. 3 Network Stumbler application for WLAN data collection

For GSM measurements we used Sony Ericsson MD300 device which works like an ordinary GSM mobile phone, but provides more advanced programming capabilities, e.g. AT command for reading neighboring cells signal strength – AT*E2EMM. For such purpose, we built an application for reading data from MD300 device. Application screenshot is shown in Fig. 4.

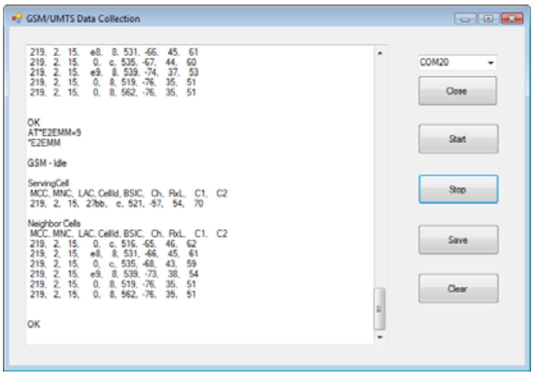

Fig. 4 Application for GSM data collection from MD300 modem

Locations in terms of coordinates for the measurement of RSS have been chosen and stored together with measurements of RSS values for any given location. The RSS sampling period in our measurement was one second, with 400 samples per location.

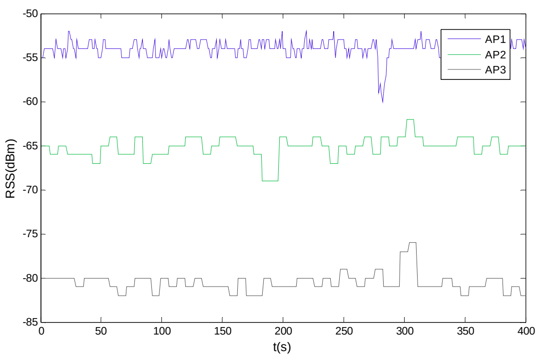

Fig. 5 RRS values from three AP

In Fig. 5, RSS values from three APs are shown at one measurement location. It can be seen that the measured signal strength at a fixed position varies over time and the variations can be up to 10 dBm.

In Fig. 6, signal strength values from seven GSM channels from one GSM provider are shown at one measurement location. Compared to Fig. 5, it can be seen that the measured signal strength appears to be more stable than WLAN signal.

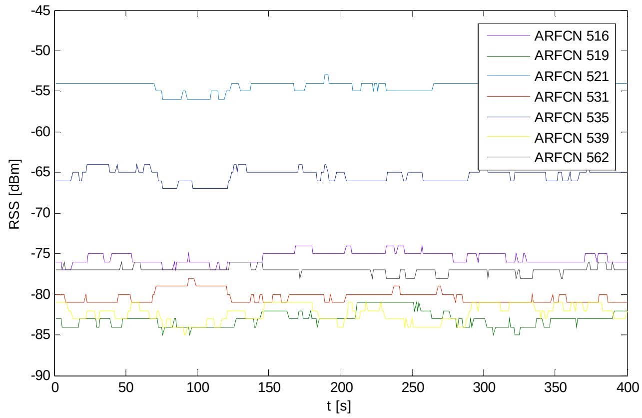

Fig. 6 Measured signal from seven GSM 1800 channels from one GSM provider

The measurements were conducted at 125 locations, 2-3 meters apart from each other, not forming the regular grid due to office and laboratory equipment, inaccessible areas, etc.

B. *RBF Network Design and Positioning Results*

As a pattern matching algorithm in our positioning systems, we used a Radial Basis Function feed-forward artificial neural network (Fig. 1) consisting of three inputs (received RSS from three APs). Network further contains one hidden layer with radial basis neurons and an output layer with two neurons (corresponding to location of a user *(x,y)*).

From the data from 125 measurement locations, 100 patterns have been employed to train the network, 10 patterns we used for the validation purpose and the remaining 15 non-training patterns have been applied to the network for testing the developed positioning system.

RBF network is created iteratively by adding one neuron at a time (Matlab function *newrb*). Neurons are added to the network until the sum-squared error falls beneath an error goal or a maximum number of neurons has been reached. Determination of the number of neurons in the hidden layer is very important since it affects the generalizing capability of the network and the network complexity. If the number of the neurons in the hidden layer is insufficient, the RBF network cannot learn the data adequately; on the other hand, if the neuron number is too high, poor generalization or an overlearning situation may occur [34].

Key parameter defining the network behavior (besides number of neurons) is the spread of radial functions. It is important that the spread parameter be large enough that the radial basis neurons respond to overlapping regions of the input space, but not so large that all the neurons respond in essentially the same manner.

Designing a radial basis network often takes much less time than training a sigmoid/linear network, and can sometimes result in fewer neurons' being used. Using large numbers of neurons can result in creating a network with zero error on training vectors, but the key issue here, as with all neural networks, is to create a network with good generalization capabilities so it could perform well with new unknown data.

In order to better choose the network parameters and to give some insight on RBF network design issues, we first investigated how the network performance depends on the spread values and the number of neurons. 3D plot in Fig. 7. shows RBF network performance (mean square error) for the training data set as the function of spread and number of neurons.

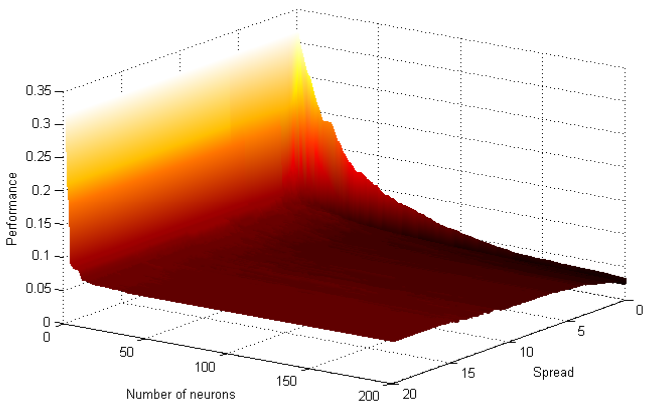

Fig. 7. 3D plot of the training set performance as the function of spread and number of neurons

Generally, when training starts (with 1 neuron) network performance is drastically improved with increasing number of neurons, but soon becomes constant and increasing the neuron number has no effect on the performance except for the very small values of spread, where the network could eventually reach zero error (as mentioned above).

Much more important than the performance for the training set, is how the network will perform for the unknown test data. It wouldn't be fair to optimize the network for the test data set, so we used the validation data set to investigate the network behavior and to choose the optimal network parameters. Fig. 8. (top plot) shows network performance for the validation data set as the function of spread and number of neurons.

It is plotted with "hot" colormap where we deliberately chose to "burn" higher performance values in order to better differentiate areas with lower values (which are of interest). Bottom plots show validation performance for several single values of spread (1, 2, 10 and 20). Higher number of neurons in the areas with lower spread values results with increasingly worse performance since the network can not generalize well for small spread values. Increasing the spread means better generalization capabilities, but for values higher than 15, performance becomes practically constant regardless of spread and number of neurons. The best performance is generally achieved in the areas with about 20 neurons (black areas), the actual minimum of the whole plot is for 18 neurons and the spread value of 2.7. Choosing lower number of neurons is also desirable in terms of computational performance.

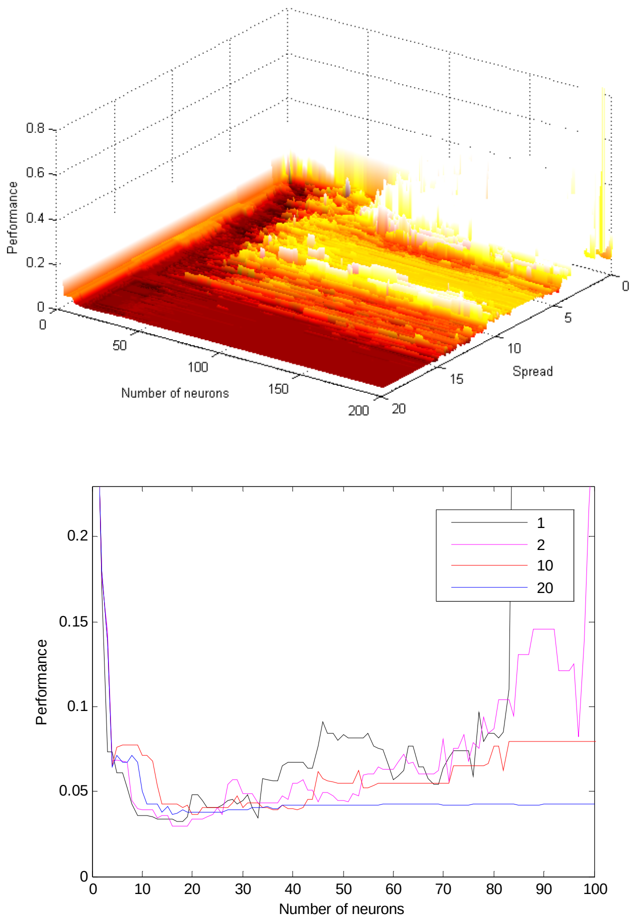

Fig. 8. 3D plot of the validation set performance as the function of spread and number of neurons (top) and validation performance for several single values of spread (bottom)

This investigation showed us the most likely area (in terms of network parameters) for achieving the best performance, shown in more detail in Fig. 9. So, in order to successfully train a RBF network, one should simply try several configurations (number of neurons and spread values) corresponding to this area and should be able to quickly achieve desired performance.

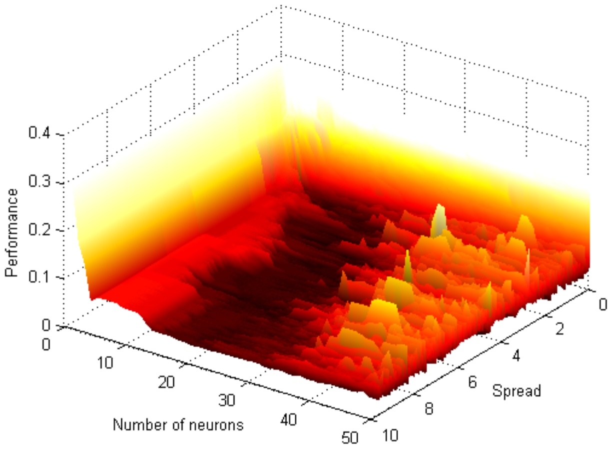

Fig. 9. More detailed plot of the validation set performance in the area of interest

For the final evaluation of RBF network performance for localization of the actual test data measurements, we used RBF network with 18 neurons and the spread value of 2.7 (where the best performance was achieved for the validation data set). Mean localization error of 2.33 m (with standard deviation of 1.52 m) was achieved.

Besides positioning in WLAN network, in this paper we have also developed a GSM based positioning system. Following the guidelines from the above RBF network design, we were able to quickly determine the optimal values for spread and neuron number in GSM based system. Fig. 10. shows GSM validation set performance. Best performance is achieved in the areas denoted with black color, where the actual minimum of the whole plot is for 12 neurons and the spread value of 0.6.

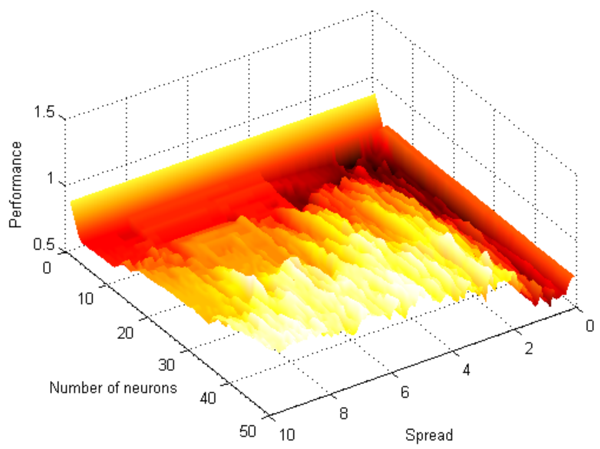

Fig. 10. 3D plot of the GSM validation set performance as the function of spread and number of neurons (top) and validation performance for several single values of spread (bottom)

For the evaluation in the actual GSM based positioning system, we used RBF network with 12 neurons and the spread value of 0.6 (where the best performance was achieved for the validation data set). Mean localization error of 4.61 m (with standard deviation of 1.94 m) was achieved.

The results of positioning accuracy for both WLAN and GSM based positioning systems are given in Table II (mean error, 50 percentile error and 95 percentile error) in meters. Localization errors are calculated as Euclidian distances between estimated and actual location coordinates.

TABLE II
LOCATION ESTIMATION ERRORS

Method	Mean ± Variance	50%	95%
WLAN	2.33 ± 1.52	2.18	5.15
GSM	4.61 ± 1.94	3.58	7.43

Positioning accuracy indicated by the cumulative percentage of localization error is given in Fig. 11.

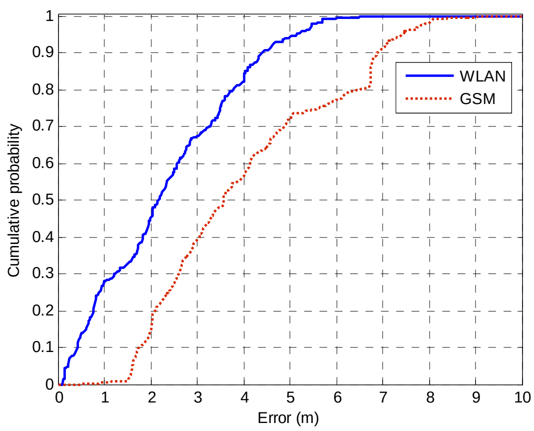

Fig. 11. Cumulative distribution of localization error

Results are quite similar to results in our previous work with MLP neural network [21], but considering the analysis given above, it is much easier/quicker to create the network with optimal parameters than using the MLP networks.

Our results also show that localization error in WLAN based system is lower than in GSM based system; mean errors are 2.33m and 4.61m for WLAN and GSM, respectively. Compared to GSM based approach, WLAN system has the advantage in terms of lower localization error, but generally GSM signal coverage by far outreaches WLAN coverage and if less precise accuracy is required, our results indicate that GSM positioning can also be a viable solution.

IV. CONCLUSION

In this paper we have developed a RBF neural network based positioning system in indoor WLAN and GSM environment. It offers more compact topology and faster training than traditional MLP networks.

Key parameters determining the performance of the RBF network are the number of neurons and radial basis functions' spread values, and the choice of appropriate values is most important. In this paper we provide detailed analysis on network training performance considering different number of neurons and spread values. We evaluated the developed positioning system in real world WLAN and GSM indoor environment and obtained good positioning results.

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