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GSM-Based Approach for Indoor Localization

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***Abstract*—**Ability of accurate and reliable location estimation in indoor environment is the key issue in developing great number of context aware applications and Location Based Services (LBS). Today, the most viable solution for localization is the Received Signal Strength (RSS) fingerprinting based approach using wireless local area network (WLAN). This paper presents two RSS fingerprinting based approaches – first we employ widely used WLAN based positioning as a reference system and then investigate the possibility of using GSM signals for positioning. To compare them, we developed a positioning system in real world environment, where realistic RSS measurements were collected. Multi-Layer Perceptron (MLP) neural network was used as the approximation function that maps RSS fingerprints and locations. Experimental results indicate advantage of WLAN based approach in the sense of lower localization error compared to GSM based approach, but GSM signal coverage by far outreaches WLAN coverage and for some LBS services requiring less precise accuracy our results indicate that GSM positioning can also be a viable solution.

***Keywords*—**Indoor positioning, WLAN, GSM, RSS, location fingerprints, neural network.

I. Introduction

LOCALIZATION techniques enable location estimation of people, mobile devices or equipment. Although Global Positioning System (GPS) is the most popular positioning system for open outdoor environments, there is an unmet need for a reliable positioning system that can work indoors, where the microwave radio signals used by the GPS are greatly attenuated [1-3].

Accurate indoor localization is an important and novel emerging technology [1]. There are numerous important applications in industrial, commercial, public safety, everyday life and military settings [4]. The ability of an accurate location determination leads to substantial context aware computing [5] and a great number of useful LBS.

As new mobile technology comprising highly sophisticated devices as smartphones or tablets experiences a massive growth these days, context defined by location of the mobile devices grows in importance.

To determine the location of the users within the network it is preferable to employ the existing wireless communications infrastructure. Most research in indoor localization systems use the wireless communication infrastructure primarily based on the wireless local area networks (WLANs), in particular the IEEE 802.11 standard since its widely deployed equipment and the RSS measurement can be easily obtained from IEEE 802.11 MAC software. Currently, the most popular solution based on WLAN's RSS is the fingerprinting architecture [6-12].

In this paper we investigate if an indoor positioning system based on GSM fingerprints can achieve high accuracy comparable to WLAN fingerprints performance. 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. [13]) which is required for successful handovers, mobile phones are required to report signal strength of 6 neighboring cells. So, a fingerprint could be easily obtained just by software thus obviating the need for investments in infrastructure. Increasing the number of channels would result in larger fingerprint and potentially increased localization accuracy, but it would require changes in GSM specification and phones' operation, so we are, in this paper, interested only in building a GSM positioning system which could be easily implemented on every mobile phone without any modifications in their operations and investments in network infrastructure thus enabling ubiquitous positioning applications.

Section 2 describes the localization technique based on location fingerprinting and neural network. Measurement setup and localization results of the developed positioning systems in WLAN and GSM networks are given in Section 3. We close this paper with a conclusion in Section 4.

II. Localization based on Fingerprinting and Neural Network

A location fingerprint based on RF characteristics such as RSS is the basis for representing a unique position or location. It is created under the assumption that each position or location inside a building has a unique RF signature. The process is composed of two phases: a phase of data collection called off-line phase and a phase of locating a user in real-time called on-line phase (Fig. 1).

The first phase consists of recording a set of RSS fingerprints in a database 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 we use a set of predefined reference points $L_i = (x_i, y_i),\ i = 1, ..., M$, where RSS values from N APs are measured. A reference fingerprint $F = \left[f_1, f_2, ..., f_N\right]^T$ is a vector of RSS samples where f denotes the RSS value related to particular AP. A series of reference fingerprints is collected at each reference point and stored in a database together with the referent physical coordinates (x_i, y_i).

During the second phase, an RSS fingerprint is measured

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by receiver. Given a new fingerprint $F' = \left[f_1', f_2', \ldots, f_N' \right]^T$ measured at unknown location L' we use the reference data from off-line phase in order to obtain a location estimate by applying a pattern matching algorithm.

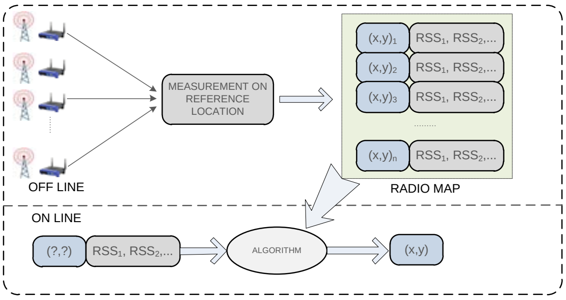

Fig. 1 Location determination based on RSS fingerprints

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 and the neural network classifiers. Location is typically estimated by minimizing an error function, e.g. the Euclidean distance between F' and the reference fingerprints in the database. The probabilistic types of algorithms are those that are based on the statistical learning theory. 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 [9, 11, 14].

Neural networks, as a pattern matching algorithm, have been employed in wide range of positioning systems and have demonstrated good results [2, 15-17]. A trained artificial neural network can perform complex tasks such as classification, optimization, control and function approximation [18, 19]. Artificial neural network (ANN) can be used to establish a relationship between pattern of RSS samples and location. The pattern-matching algorithm of the system can be viewed as a function approximation problem consisting of a nonlinear mapping from a set of input variables (RSS from N access points) into two output variables representing the two dimensional location *(x, y)* of the mobile station.

An ANN is consisting of processing units which communicate by sending signals to each other over a large number of weighted connections. The total input to unit k is simply the weighted sum of the separate outputs from each of the connected units plus a *bias* or offset term θ_k:

$$s_k(t) = \sum_j w_{jk}(t) y_j(t) + \theta_k(t) \qquad (1)$$

Generally, for activation function y_k some sort of threshold function is used: a hard limiting threshold function (a sgn function), or a linear or semi-linear function, or hyperbolic tangent function. One of the most popular ANNs is the MultiLayer Percepton (MLP), Fig. 2.

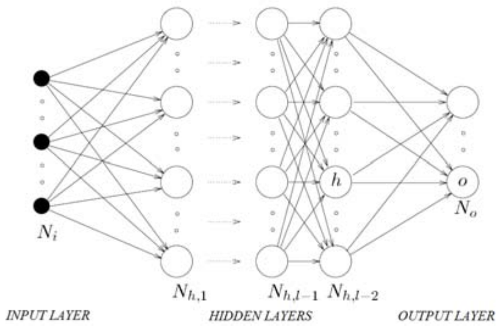

Fig. 2 General structure of multi-layer perceptron [18]

The MLP is a feed-forward multi-layer network which uses a supervised error-based learning mechanism. Each layer consists of units which receive inputs from units from layer directly below and send their output to units in a layer directly above. There are no connections within a layer. 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.

III. Experimental Setup and Results

Localization of users in the widely available IEEE 802.11 WLAN environments is an emerging technology. Unlike other positioning systems, like IR and ultrasonic, WLAN-based positioning systems reuse the existing WLAN infrastructures, which lowers the cost of indoor positioning. Also, many persons already carry possible positioning devices around with them in their daily life (smart phones, laptops and tablets with WLAN interface). The RSS indicator can be easily read in every 802.11 interface which makes the solution cost effective since only software deployment is required. Besides that, GSM has additional advantage in terms of far outreaching signal coverage and high acceptance of mobile phones among users. GSM fingerprint can also be easily obtained since every mobile phone is required to report signal strength of 6 neighboring cells. Thus, in this paper we aim to investigate the possibility of using GSM signals for positioning. For comparison, we developed two positioning systems – WLAN and GSM based, in the same indoor environment.

A. Location Fingerprinting

Measurements were made in the part of the fourth floor of our university building, dimensions of approximately 28m×15m, total area 420m^2. Area includes 4 offices, 3 laboratories, a classroom and a hallway. The layout of the floor and locations of the APs are shown in Fig. 3.

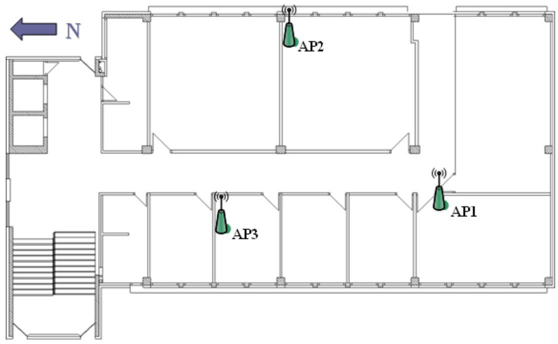

Fig. 3 The test location layout with positions of the access points

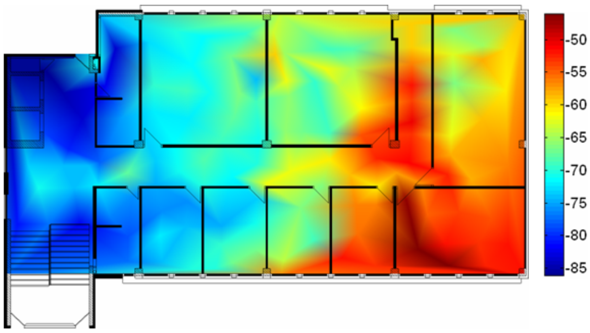

Fig. 5 2D propagation of the signal strength of AP1

We used three Access Points (AP) WRT54GS from Linksys which are IEEE 802.11b/g compatible. For collection of the RSS samples from APs we used a Fujitsu-Siemens laptop with the Network Stumbler software [20]. The WLAN Proxim Orinoco card was plugged into the PCMCIA slot on the right side of the laptop. To collect the RSS samples, the laptop was placed on the box approximately one-meter high.

Locations in terms of coordinates for the measurement of RSS have been chosen and stored together with three measurements of RSS values for given location. Total number of measurements was 125, 110 for training and 15 for testing. Collecting enough statistics for creating location fingerprints is the key to achieving good performance with any indoor positioning system.

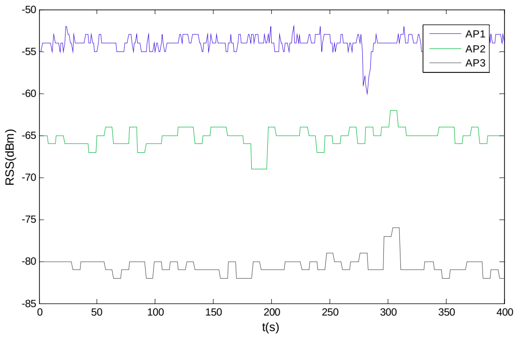

Fig. 4 RRS values from three AP

The RSS sampling period in our measurement was one second, with 400 samples per location. Measurement locations were not forming the regular grid due to office and laboratory equipment, inaccessible areas, etc. In Fig. 4, 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. 5, 2D propagation of the signal strength of AP1 is plotted. Colors denote signal strength; blue presents the weakest signal and red the strongest signal. For AP1 signal strength is from -86.4 dBm to -45.8 dBm.

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. 6.

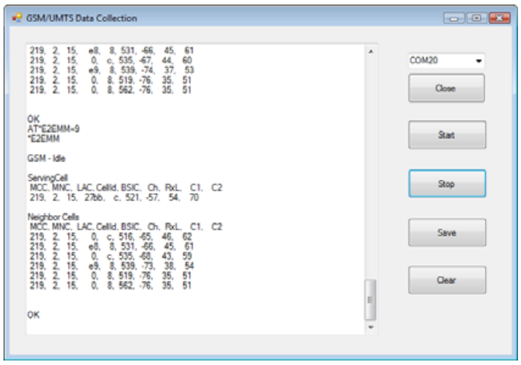

Fig. 6 Application for data collection from MD300 modem

In Fig. 7, signal strength values from seven GSM channels from one GSM provider are shown at one measurement location. Compared to Fig. 4, it can be seen that the measured signal strength appears to be more stable than WLAN signal.

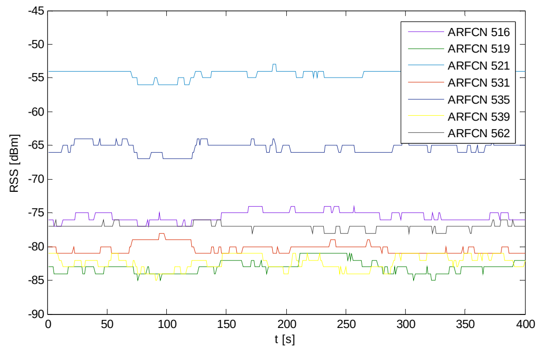

Fig. 7 Measured signal from seven GSM 1800 channels from one GSM provider

In Fig. 8, 2D propagation of the GSM signal strength (Cell ID E9, ARFCN 539) is plotted. Colors denote signal strength, from -98.04 dBm to -66 dBm.

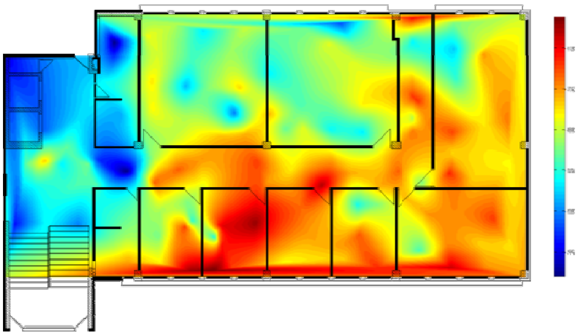

Fig. 8 2D propagation of the GSM signal strength (Cell ID E9, ARFCN 539)

B. Neural Network based Positioning and Results

As a pattern matching algorithm in our positioning systems, we used the Multi-Layer-Perceptron (MLP) feed-forward artificial neural networks (Fig. 9) – one consisting of three inputs (received RSS from three APs) for WLAN positioning and one consisting of seven inputs (corresponding to seven GSM channels) for GSM positioning. Networks further contain one hidden layer and an output layer with two neurons (corresponding to location of a user (x,y)).

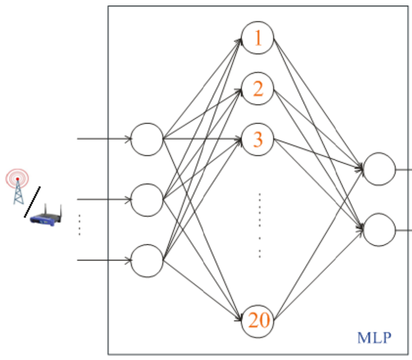

Fig. 9 MLP neural network

From the 125 measured data, 100 patterns have been employed to train the network, 10 for the validation purpose and the remaining 15 non-training patterns have been applied to the network for testing developed positioning systems. In order to train the network, these patterns have been applied to the pattern-matching neural network together with location coordinates. Criterion for stopping of the network training was chosen as a moment after which the performance of validation set terminated to enhance.

During the training, we experimented with several topologies with a different number of hidden layers, but the results were quite similar. Experimenting with a number of hidden layer neurons, we found that 20 neurons are adequate to achieve minimal mean distance test error.

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

TABLE I
LOCATION ESTIMATION ERRORS

Method	Mean ± Variance	50%	95%
WLAN	2.35 ± 1.62	2.23	6.38
GSM	4.86 ± 1.43	5.22	7.32

Positioning accuracy indicated by the cumulative percentage of localization error is plotted in Fig. 10.

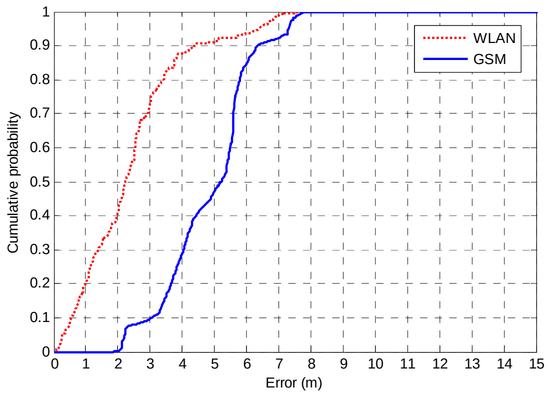

Fig. 10 Accuracy comparison

As expected, localization error in WLAN based system is lower than in GSM based system; mean errors are 2.35m and 4.86m for WLAN and GSM, respectively. But it is also visible from results that both distributions are quite similar, GSM errors are practically shifted 2-3m compared to WLAN, and they are both always within 8m, so if a bit less precise positioning services are required, GSM positioning can also be a viable solution.

IV. CONCLUSION

In this paper we investigated the possibility of using GSM signals for positioning. First as a referent one, we developed a localization system based on RSS fingerprinting in WLAN network, since most relevant research in indoor positioning is based on WLAN networks and RSS fingerprinting. Then we developed a GSM based system in the same indoor environment, for adequate comparison. Multi-Layer Perceptron neural network was used as the approximation function that maps RSS fingerprints and locations.

Results have shown that errors are comparable, both distributions are quite similar, GSM errors are practically shifted 2-3m compared to WLAN so if a bit less precise positioning services are required, GSM positioning can also be a viable solution since GSM signal coverage by far outreaches

WLAN, and it can be applied practically everywhere without any new infrastructure deployments.

REFERENCES

[1] A. H. Sayed, A. Tarighat, and N. Khajehnouri, "Network-based wireless location," IEEE Signal Processing Magazine, vol. 22, pp. 24-40, Jul 2005.
[2] S. H. Fang and T. N. Lin, "Indoor Location System Based on Discriminant-Adaptive Neural Network in IEEE 802.11 Environments," IEEE Transactions on Neural Networks, vol. 19, pp. 1973-1978, 2008.
[3] K. Pahlavan, X. R. Li, and J. P. Makela, "Indoor geolocation science and technology," IEEE Communications Magazine, vol. 40, pp. 112-118, Feb 2002.
[4] F. Gustafsson and F. Gunnarsson, "Mobile positioning using wireless networks," IEEE Signal Processing Magazine, vol. 22, pp. 41-53, Jul 2005.
[5] J. Hightower and G. Borriello, "Location systems for ubiquitous," Computer, vol. 34, pp. 57-+, Aug 2001.
[6] S. H. Fang, T. N. Lin, and P. C. Lin, "Location fingerprinting in a decorrelated space," Ieee Transactions on Knowledge and Data Engineering, vol. 20, pp. 685-691, May 2008.
[7] G. L. Sun, J. Chen, W. Guo, and K. J. R. Liu, "Signal processing techniques in network-aided positioning - [A survey of state-of-the-art positioning designs]," IEEE Signal Processing Magazine, vol. 22, pp. 12-23, Jul 2005.
[8] M. Kjærgaard, G. Treu, and C. Linnhoff-Popien, "Zone-based RSS reporting for location fingerprinting," Pervasive Computing, pp. 316-333, 2007.
[9] M. Brunato and R. Battiti, "Statistical learning theory for location fingerprinting in wireless LANs," Computer Networks, vol. 47, pp. 825-845, 2005.
[10] M. A. Youssef, A. Agrawala, and A. Udaya Shankar, "WLAN location determination via clustering and probability distributions," in Pervasive Computing and Communications, 2003.(PerCom 2003). Proceedings of the First IEEE International Conference on, 2003, pp. 143-150.
[11] S. H. Fang and T. N. Lin, "A Dynamic System Approach for Radio Location Fingerprinting in Wireless Local Area Networks," IEEE Transactions on Communications, vol. 58, pp. 1020-1025, Apr 2010.
[12] S. Guolin, C. Jie, G. Wei, and K. J. R. Liu, "Signal processing techniques in network-aided positioning: a survey of state-of-the-art positioning designs," Signal Processing Magazine, IEEE, vol. 22, pp. 12-23, 2005.
[13] ETSI, "Digital cellular telecommunications system (Phase 2+); Handover procedures, GSM 03.09 version 5.1.0," ed, 1997.
[14] P. Bahl and V. N. Padmanabhan, "RADAR: an in-building RF-based user location and tracking system," in INFOCOM 2000. Nineteenth Annual Joint Conference of the IEEE Computer and Communications Societies. Proceedings. IEEE, 2000, pp. 775-784 vol.2.
[15] M. Stella, M. Russo, and D. Begusic, "RF Localization in Indoor Environment," Radioengineering, vol. 21, pp. 557-567, Jun 2012.
[16] C. Nerguizian, C. Despins, and S. Affes, "Geolocation in mines with an impulse response fingerprinting technique and neural networks," IEEE Transactions on Wireless Communications, vol. 5, pp. 603-611, Mar 2006.
[17] C. Laoudias, P. Kemppi, and C. Panayiotou, "Localization using radial basis function networks and signal strength fingerprints in WLAN," in Global Telecommunications Conference, 2009. GLOBECOM 2009. IEEE, 2009, pp. 1-6.
[18] B. Kröse, B. Krose, P. van der Smagt, and P. Smagt, An introduction to neural networks: University of Amsterdam, 1996.
[19] S. Haykin, Neural networks: A comprehensive approach, 1994.
[20] NetStumbler.com. Available: http://www.netstumbler.com