A Low-cost Fingerprint Positioning System in Cellular Networks

Claude Takenga
Institute of communications engineering
Leibniz University of Hannover
Appelstrasse 9A, 30167 Hannover, Germany
takenga@yahoo.fr

Kyandoghere Kyamakya
Department of Smart System Technologies
Alpen Adria University Klagenfurt
Klagenfurt, Austria
Kyandoghere.kyamakya@uni-klu.ac.at

Abstract — **An ultimate aim of mobile positioning research is to find a method providing high estimation accuracy to the user within minimum delay and at minimum cost. Conventional location techniques based on trilateration and triangulation rely on line-of-sight path between the base station antenna and the mobile unit. In densely built urban areas, this assumption is rarely valid. This fact degrades the location performance of the conventional techniques and motivates the need for development of more accurate technique suited for these areas. Positioning system developed in this research is divided into three sub-systems. The first sub-system solves the problems related to fingerprint localization and involves neural network as key element of the positioning algorithm. The post-processing tasks which include tracking and map-matching are performed in the second and third sub-systems respectively.**

Keywords — Fingerprint Positioning, Mobile Localization, Kalman Filter, Map-Matching, Neural Networks.

I. INTRODUCTION

Mobile localization techniques have been under strong development during the last years. There is a broad agreement that localization will play a central role in enabling value-added services in the new generation cellular networks and that these services require high accuracy at low cost. The Global Positioning System (GPS) is a popular solution for providing location in terrestrial wireless communication networks. GPS is a proven technology and provides high accuracy when a line-of-sight (LOS) path exists between the receiver and at least four satellites. However, GPS is often inoperable in areas where satellites are blocked, such as in buildings and built-up urban areas.

Much of the activities in the area of wireless positioning have been driven by the 1996 Report and order of the Federal Communications Commission (FCC) [1]. Since then, different positioning systems working within a cellular network have been developed [2-4]. Parameters that are often measured and used for location include received signal strength (RSS), angle-of-arrival (AoA), time-of-arrival (ToA) and time differences of arrival (TDoA).

Direction finding and ranging methods perform well in environment characterised with LOS. In dense urban area, additional algorithms should be added which deal with non-line-of-sight (NLOS). Moreover, these methods require additional equipment for their implementations (directional antennas at every base station (BS) for AoA and very accurate clock for ranging methods).

Fingerprint localization methods perform relatively better in urban area compared to other methods. Moreover, this approach does not require any additional equipment for its implementation to the existing cellular networks.

The main achievement of this research is, the development of a low-cost fingerprint positioning system working within cellular networks with positioning accuracy satisfying the federal communications commission requirements in areas where other methods have poor performance (urban).

In [5, 6] numerical results of the Cramer-Rao lower bound performed for the case of RSS-fingerprint-based localization showed that:

- The location accuracy improves when the number of network measurement reports (NMR) used in a sample fingerprint increases from 1 to 10. Using more than 10 RSSs in one location fingerprint sample only helps slightly improving the location accuracy.
- The location error increases linearly with the BS separation distance. In order to get reasonable accuracy (satisfying the FCC requirements), the distance range between BSs should not be greater than 1500m. This shows that this method is not suitable for rural areas, where the BSs are located more than 5Km distant from one another.
- The measurement error (which is caused by the RSS map resolution, small-scale fading, MS orientation, Antenna polarization distortion…) affects the location accuracy. A higher standard deviation of the measurement error leads to more inaccurate location estimation. The standard deviation of measurement error should not be greater than 8dB in order to obtain the location error lower than 130m when 6 BSs are reported in a NMR.
- The location accuracy is poor if measurements are more correlated (because the BSs are sectorized, several RSSs reported in one NMR come from the same BS).
- For environments with high multipath propagation characteristc, the location performances are better because this fact increases the uniqueness of the RSS fingerprint. Such an algorithm is suited for urban and indoor environments.

The above conclusions of the analytical results performed in [5] demonstrate that the suited environments for a possible successful implementation of the RSS fingerprint based location are urban and indoor environments.

The positioning system developed in this research can be divided into three sub-systems. The first sub-system solves the problems related to fingerprint localization and involves neural network as key element of the positioning algorithm. Such a positioning system based on received signal strengths from base stations as location fingerprints is highly sensitive to the effects of signal attenuation, reflection and scattering. As a result, the accuracy obtained from the first sub-system is poor and this creates the need for post-processing. The post-processing tasks which include tracking and map-matching are performed in the second and third sub-systems respectively.

II. Fingerprint Positioning Method

The key idea of the fingerprint concept lies in the fact that each mobile station (MS) location has a unique set of RSSs from neighbouring base stations as illustrated in Figure 1. Exploiting this concept, a mobile unit can be localized based on a set of RSS it receives from its neighbouring BSs.

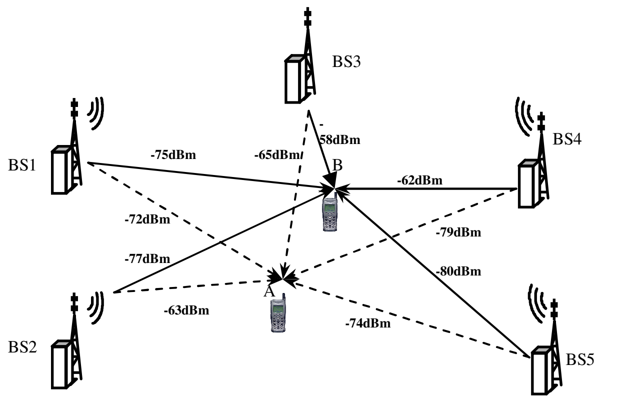


Figure 1 RSS Fingerprint Concept.

Due to the unstable propagation channel in the urban environment, the RSSs at one location keep on fluctuating. These fluctuations are caused by many factors such as dynamics in the environment, user effect, user orientation, multipath propagation. Figure 2, shows samples of histograms of the RSS at one location depending on the mean RSS value.

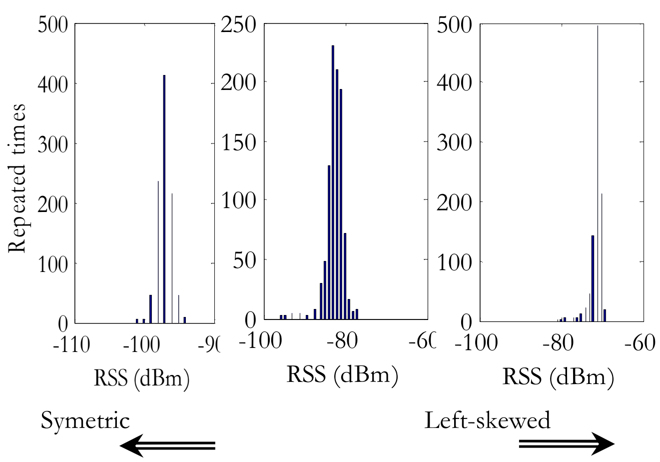


Figure 2 Dependence of the distribution on the mean RSS values

We collected RSSs at one location for a period of 2 hours from neighbouring GSM cell antennas. Results of Figure 2 show that, the weaker the mean RSS value, the more symmetric is the distribution. The stronger the mean RSS value, the more distribution is left skewed.

Fluctuation in the RSS is the major source of error in the methods based on RSS-fingerprinting. There is a need of processing the collected values in order to consider in the positioning algorithm, the most expected RSS at a location.

Figure 3, shows the algorithm used for RSS processing. Time delayed neural network is used. This unit performs a linear averaging of RSS values as they are collected. With such an algorithm, there is no need of collecting many samples at a location in order to perform averaging.

Results in Figure 4 show the performance of the noise reduction unit. As we can notice, a big portion of noise has been cancelled. The values at the output of this unit could be considered in the positioning algorithm.

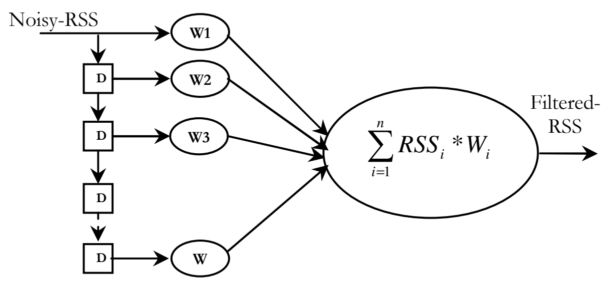


Figure 3 Noise reduction system with TDNN

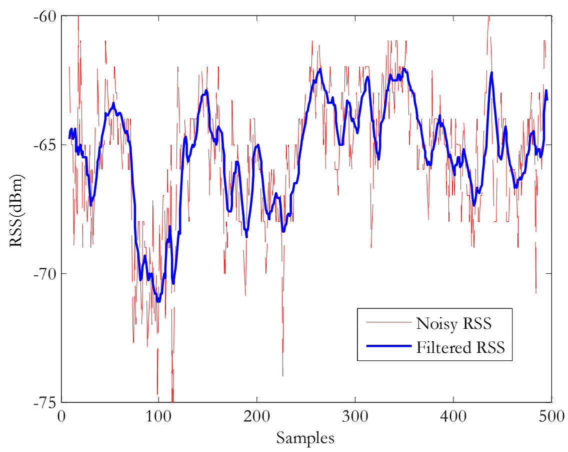


Figure 4 Noisy RSS and filtered RSS

In the fingerprint positioning algorithm applied, NN is the key element. The NN is used to map the relationship between the set of fingerprints and their locations as applied in [7-11]. The NN acquires intelligence during training. This process is performed off-line before using it in the positioning phase. During training, the NN parameters are set in order to make a good mapping between RSS and location with the least squared error

We collected 2000 data records from 2000 locations. A data record contains signal strengths from a number of BSs and actual GPS position. A half of this collected data was used for calibration of the predicted RSS map of the area. The calibration system developed in our previous work[12], was of great importance since the prediction data differ to the real values. The other half of collected data was used for testing the system. The NN was trained with predicted data. A number of candidates NN were tested for this given problem, and architecture with 10 inputs, 2 hidden layers with 48 and 36 neurons respectively, 2 outputs was the best choice for the given case.

The positioning error provided from the NN was still big because of some of these reasons:

- Instability and availability of the RSS fingerprint
- Difficulties in the choice of the appropriate NN architecture, parameters and training algorithm.

In order to reduce the positioning error, we perform in the next section, the post-processing of the location estimate obtained from a NN positioning algorithm. The post-processing includes tracking using Kalman filter algorithm and Map matching.

III. POST-PROCESSING OF THE POSITION ESTIMATION

Two post-processing algorithms are applied in this section. The first is tracking and the second map-matching. Kalman Filter tracking algorithm is chosen in this work because it has the feasibility to model noise and can allow the system to filter state values in noisy environments. The State equation x of the KF algorithm are the coordinates of the position to be estimated and the measurement equation z are the obtained position coordinates from the NN algorithm. The KF algorithm is found in [13, 14] and illustrated in Figure 5.

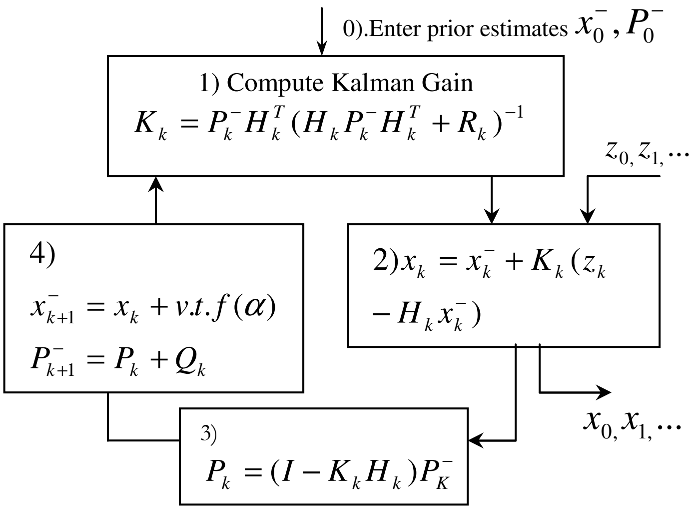


Figure 5 Kalman Filter algorithm

α is the heading direction and it is obtained using a simple digital compass.

The error variance R of the measurement is known, as we can test the NN performance. The idea behind this tracking algorithm is to get the new position estimate with error variance P less than the one obtained from NN algorithm.

By setting the prior estimate for the state x_0^- and its error covariance P_0^-, the KF recursion can be followed as 1-2-3-4-1-2… this is continued as long as new NN positions $z_0, z_1, \ldots$ are available, Figure 5. The a posteriori or new position outputs from the KF tracking algorithm are $x_0, x_1, \ldots$. These new position estimates are having less error as shown in Figures 9,11.

In cases where the user is located on the road, combining the result with map information does improve the performance. The process of projecting the location estimate to the nearby road using matching algorithms is the the second post-processing of our system. Several map-matching techniques have been developed in order to match the estimated location to the nearby road. In general, they are divided into three classifications. The first is geometric map-matching, the second one is geometric and topological map-matching and the third is probabilistic algorithms. In the first geometric map-matching technique, only geometric relationships between the estimated location and a digital road-map are considered, whereas in the second approach, not only geometric relationships but also the topology of the road network is taken into account. In probabilistic algorithms, some information about the accuracy of the estimated position is needed. If Kalman Filter is used, this is very convenient because the variance of the error is available. This covariance information can be used to make a confidence region, which sets the boundary within which, the true MS location lies with a certain probability. The confidence region is superimposed on the road network and the shape points that fit in this region are selected. The selected shape points are evaluated further in order to determine which of these points that is the most probable MS location.

If the heading is stored in the shape point, this could be compared with the MS heading. The comparison of the headings is a very important criterion, especially at road intersections. More details about map-matching algorithms and implementation can be found in [15, 16].

There are three main techniques for map-matching: Point-to-point matching which will match the KF estimated locations to the closest reference point (shape point) on the road database, Point-to-curve matching will match the KF estimated location to the closest arc or segment in the road network, in curve-to-curve, if ($L_{11}+L_{21}$) < ($L_{12}+L_{22}$), two consecutive points P_1, P_2 are matched to the Road 1, whereas, if ($L_{12}+L_{22}$) < ($L_{11}+L_{21}$), P_1, P_2 are matched to the Road 2, see Figure 6.

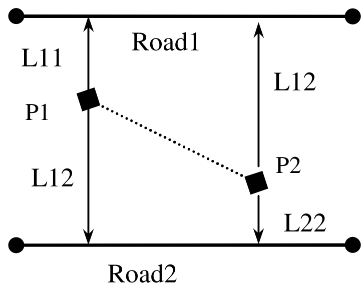


Figure 6 Curve-to-curve map-matching

IV. PERFORMANCE EVALUATION RESULTS

For the software implementation, Matlab was chosen to be the best choice for some of these reasons: The work focused on the application of NN as MS positioning system. Matlab was ideal for this, because of its built in NN toolbox that has more than adequate set of NN functionalities. In addition, serial I/O required for communication between the GSM modem and the notebook during data collection was easy with matlab.

A simple data acquisition script was written in Matlab to collect GPS and GSM information from the GSM modem via a serial connection. The dual 900/1800 with GPS antenna connected to the modem was mounted to a horizontal surface to minimise data inconsistency due to antenna orientation to the ground. The height was also kept constant and was 1 m from the ground, Figure 7.

Figure 7 GSM Modem (a) and Dual GSM/GPS antenna (b)

The experimental area is an urban area in Germanny-Hannover. The experiments were made within GSM1800, of the E-Plus mobile network. 10 neighbouring BSs were considered for the experimental region. For every network report measurement (NMR), the average of 4 BS could be reported in one fingerprint.

Figure 8 maps the location positions obtained from the NN (in black circles) and from the KF tracking algorithms (in red triangles) to the map of our experimental area. It is clearly seen that, after NN positioning, the error variance is still big, and it is difficult know to which roads some locations belong.

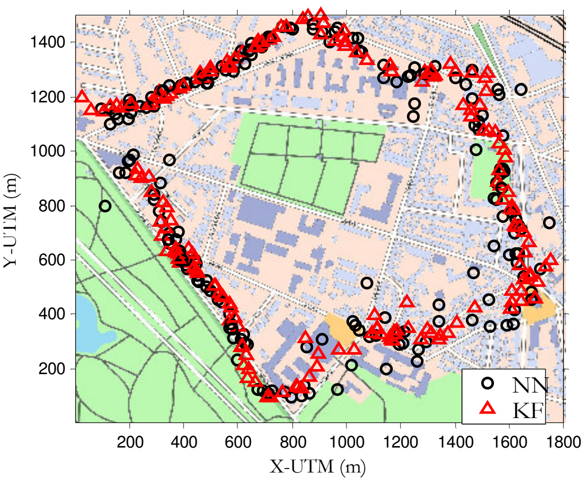
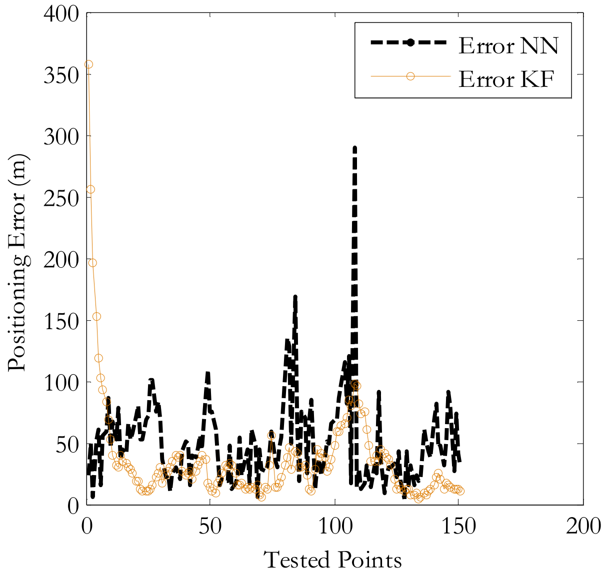


Figure 8 Estimated routes with NN and KF (1800m x1500m)



Fugure 9. Comparison of positioning error for NN and KF locations

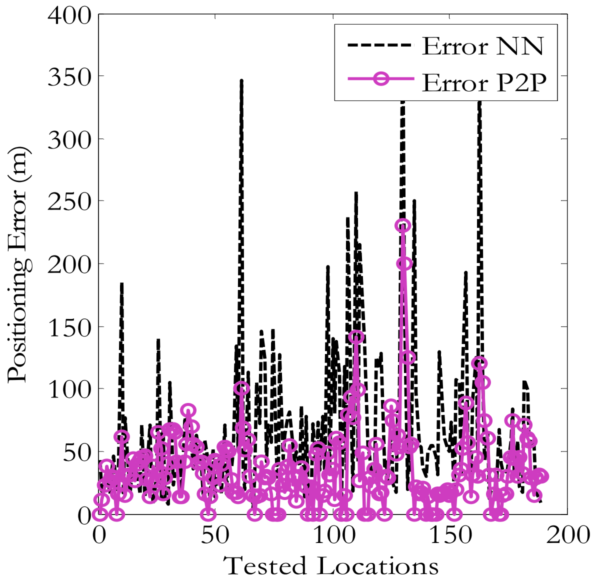


Figure 10 Comparison of positioning error for NN and point-to-point matching method

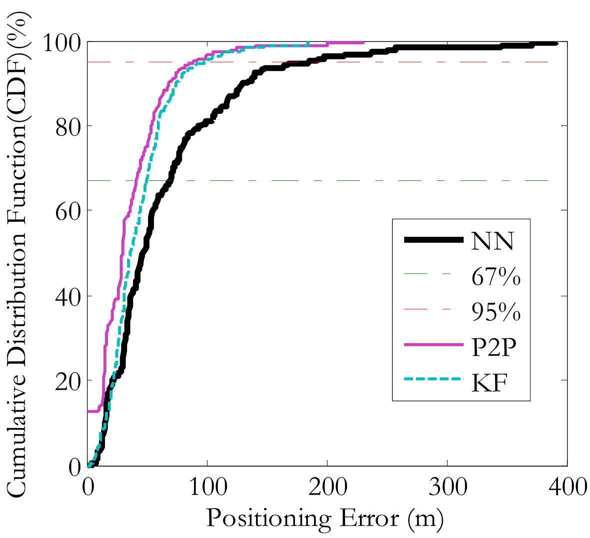


Figure 11 CDF for NN, KF and P2P

Figure 9 shows the convergence ability of the KF algorithm. After the 20-th location (iteration), the KF could converge the positioning error to the minimum value it could, for the settings applied for the experiment. The remaining error variance is due to the stochastic behaviour of the fingerprints.

From the Figures 10,11 we can clearly see that the positioning error obtained at the output of the NN positioning algorithm is the biggest 80m with CEP-67 and 190m with CEP-95. KF tracking algorithm could reduce the positioning error obtained from NN to a value of 50m with CEP-67, and 100m with CEP-95. The choice of map-matching algorithm or deciding whether map-matching should be applied, depend on the error variance and the nature of the road network. In the case of the experiments conducted, map-matching could further reduce the positioning error to a value 40m with CEP-67 and 95m CEP-95. In some cases, very dense road network, map matching should not be included, due to the big error variance in localization within cellular networks. From Figure 11, we can see that after map-matching, 13% of the tested locations were mapped to the correct roads and correct locations.

V. SUMMARY OF THE RESULTS COMPARISONS

The basic performance metric for localization is the accuracy. But the location system must also provide the location information quickly, reliably and the cost for implementation should be reasonable as we have mentioned already.

In Table 1 the performance comparison between the standardized GSM location techniques and the ones based on RSS fingerprinting is made. Data for the existing methods were found in [17-19]. The RSSI-based fingerprint method developed in this work is relatively good when pre-processing of the RSS and post-processing of the location estimate are performed.

TABLE 1 PERFORMANCE COMPARISON OF STANDARDIZED GSM POSITIONING TECHNIQUES AND RSS FINGERPRINT-BASED ONES

	Cell-ID	*E-OTD*	*A-GPS*	*RSSI-based fingerprint (no pre and postprocessing)*	*RSSI-based fingerprint (with pre and postprocessing)*
Accuracy	Poor 200m~ 20km	Average 100- 500m	Excellent 5~50m	Poor 200~600m	Good < 100m
Time-to-first-fix (TTFF)	Excellent ~1s	Very Good ~5s	Very Good 5~10s	Excellent 1~3s	Execllent 1~3s
Reliability	Poor	Average	Very Good	Poor	Good

In Table 2, comparison is made based on the cost metric. The implementation of the location algorithm must support an efficient cost for the operator to be able to benefit from the service. The cost analysis should include costs in all stages of the service. The Handset cost, cost of infrastructure and cost on maintenance are the major factors that we consider as cost-metrics.

TABLE 2 COMPARISON OF STANDARDIZED GSM POSITIONING TECHNIQUES AND RSS-BASED FINGERPRINTING BASED ON COST METRICS

	Cell-ID	*E-OTD*	*A-GPS*	*RSSI-based fingerprint (no pre and postprocessing)*	*RSSI-based fingerprint (with pre and postprocessing)*
Handset Cost	Low (no change)	Low (software)	Medium (Hard+software)	Low (no change or software)	Low (no change or software)
Cost of Infrastructure	Low	High (LMUs+ ..)	Low	Medium (Location servers)	Medium (Location servers)
Cost on maintenace	Low	High (LMUs)	Low	High (New predictions)	Medium (Database calibration)

The handset cost is low if the existing MS can be used in the location system without modifications or by adapting the software. Otherwise the cost is considered to be medium or high.

The cost of infrastructure depends on the number of additional LMUs, number of equipments for precise timing, Number of location servers and additional software.

The developed in this thesis method, RSSI-based fingerprint uses the existing handsets without modification. However, location servers should be placed at some mobile switching centers and the maintenance of the RSSI map should be periodically performed by calibrating the predicted map.

The basic metrics compared for implementation issues are the roaming capability, scalability and need of additional signalling, Table 3. Location solutions should support roaming across wide geographic areas and into other networks. With scalability, we mean that with the network expansion, the location solution should be easily expanded as well. Additional signalling are the measurements which are not available in the network report measurements.

TABLE 3 COMPARISON OF STANDARDIZED GSM POSITIONING TECHNIQUES AND RSS-BASED FINGERPRINTING BASED ON IMPLEMENTATION ISSUES

	Cell-ID	*E-OTD*	*A-GPS*	*RSSI-based fingerprint (no pre and postprocessing)*	*RSSI-based fingerprint (with pre and postprocessing*
Roaming	Excellent	Poor	Excellent	Good	Good
Scalability	Excellent	Poor	Excellent	Good	Good
Additional Signalling	No	OTD-measurements	Pseudo range measurements	No	No

V. CONCLUSION AND OUTLOOK

The main achievement of this paper is, the development of a low-cost fingerprint positioning system working within cellular networks with positioning accuracy satisfying the FCC E-911 requirements for the case of urban environments, where other method provide poor performance.

Pre-processing of the fingerprints has a great impact on the accuracy of the fingerprint-based approaches. In the conducted experiments, we applied a TDNN to remedy to stochastic effect of the RSS and then calibration of the predicted RSS was performed.

Three sub-systems, namely NN positioning, KF-tracking and Map-matching were developed in order to create a reliable positioning system working within cellular networks and providing a reasonable positioning accuracy with low demanding effort and minimum cost. Such a localization system can have many applications, some of which are listed below:

- Serve as complementary system to GPS, i.e Applied at places where GPS does not operate or performs within big errors (urban environment, indoor).
- Location information can be used to support commercial services such as navigation or route guidance, location-sensitive billing
- Tracking of lost patients and criminals.
- Emergency calls, stolen vehicle recovery, local traffic information, security issues such as improved fraud detection, also accurate location information is essential in allowing law enforcement to respond quickly to reports of suspicious activities.

Outlook:

There are still several challenging issues related to RSSI-based fingerprint positioning which are to be solved:

- The positioning experiments carried out in this work included data from a relatively small area (3x3km). Thus, the training time needed for mapping the relationship between RSS and locations was reasonable (around 1hour). In case of a real commercial solution, the database will contain location fingerprints from a larger area and thus, some problems might occur, such as ability of the NN to map the RSS-locations-relationship, very long time needed for training. In such cases, the area of interest could be divided into sections and for each section a NN could be trained, as we introduced this in [12]. But still more investigations are required on this issue.

- In the conducted experiments it was assumed that the signal power level -113dBm (RxLev=0 or -113dBm) was the best estimated value (most probable) for missing or incomplete data during the positioning process. This might sound logical for RSS fingerprinting cases but still further investigations which could generate better substitutes of the missed values could improve the performance of the system.

- A possible combination of the RSS fingerprinting based positioning and GPS could serve as one of the best candidates for the future localization system. GPS for areas with accurate GPS signals, RSS fingerprint-based for areas where GPS signals are obstructed and a combination of both for areas where GPS signals are weak or signals from only one or two satellites can be received.

ACKNOWLEDGEMENT

We would like to thank Prof. Thomas Kuerner and his research group from the Braunschweig Technical University for providing the network and RSS prediction data of the concerned area of this work.

REFERENCES

[1] Enhanced-911-WirelessServices, "http://www.fcc.gov/911/enhanced/."

[2] A. D. Groote, "GSM Positioning Control," presented at Mobile Business Seminar, Fribourg,Switzerland, 2005.

[3] J. Borkowski and J. Lempiainen, "Practical Network-Based Techniques for Mobile Positioning in UMTS," *EURASIP Journal on Applied Signal Processing*, vol. 2006, pp. 1-15, 2006.

[4] J. Kriegl, "Location in cellular networks," Diploma Thesis, Institute for Applied Information Processing and Communications, University of Technology Graz, Austria 2000.

[5] J. Zhu, "Indoor/Outdoor Location of Cellular Handsets based on Received Signal Strength." Geargia: Doctor Thesis, School of Electrical and Computer Engineering, Georgia Institute of Technology, 2006.

[6] N. Patwari, "Location Estimation in Sensor Neworks," PhD Thesis, University of Michigan, Department of electrical engineering and computer science, Michigan 2005.

[7] D. C. F. Chick and D. C. W. Tai, "Mobile Station Positioning Using GSM Cellular Phones and Neural Networks," Project Report, Department of electrical and computer engineering, Australian National University 2004.

[8] C. Nerguizian, C. Despins, and S. Affes, "Indoor Geolocation with received Signal Strengths Fingerprinting Technique and Neural Networks," presented at ICT, Putten, 2004.

[9] Z. Salcic and E. Chan, "Mobile station positioning using GSM cellular phone and artificial neural networks," *Wireless Personal Communications*, vol. 14, pp. 235-254, 2000.

[10] C. M. Takenga, Q. Wen, and K. Kyamakya, "On the accuracy improvement in Issues in GSM Location Fingerprinting," presented at Vehicular Technology Conference (VTC-Fall), Montreal, Canada, 2006.

[11] C. Takenga, X. Chen, and K. Kyamakya, "A Hybrid Neural Network-Database Correlation Positioning in GSM Network," presented at International Conference on Communication Systems (ICCS), Singapore, 2006.

[12] C. Takenga and K. Kyamakya, "Location Fingerprinting in GSM network and Impact of Data Pre-processing," presented at World Wireless Congress (WWC), San Fracisco, USA, 2006.

[13] Y. Bar-Shalom, X. R. Li, and T. Kirubarajan, *Estimation with Application to Tracking and Navigation*. New York: John Wiley & Sons, inc., 2001.

[14] E. Brookner, *Tracking and Kalman filtering made easy*. New York: John Wiley & Sons, 1998.

[15] D. Anderson and J. Fjellstrom, "Vehicle positioning with map-matching using intergration of dead reckoning system and GPS," Report, Department of Electrical Engineering, Linkopings University, Linkopings, Sweden 2004.

[16] J. Yang and S. Kang, "The map matching algorithm of GPS data with relatively long polling time intervals," *Eastern asia society for transportation studies*, vol. 16, pp. 2561-2573, 2005.

[17] SnapTrack, "Location Technologies for GSM, GPRS and UMTS Networks," Qualcomm Company, http://www.cdmatech.com/download_library/pdf/location_tech_wp_1-03.pdf, 20.05.2007.

[18] G. Wilde, "Performance implications of wireless location technologies- effect on location-based services revenue growth," in *Business Briefing: Wireless Technology*, 2003, pp. 1-4.

[19] H. Laitinen, "Cellular Location Technology," CELLO Consortium Report available at http://www.telecom.ntua.gr/cello/documents/CELLO-WP2-VTT-DO3-007-int.pdf, 2001.