Tracking in WiMAX Networks depending on the available RSS-based information

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***Abstract*—Tracking in WiMAX networks is gaining a lot of interest; especially after that the mobile WiMAX became one of the emerging technologies promoting low-cost deployment and evolving to provide IP-based services of high mobility including providing location-based services (LBS). Therefore, locating users in a cheap way that depends on the available network resources is becoming more and more interesting and an active topic for researchers.**

In this paper we consider the problem of tracking in WiMAX networks depending on the available RSS-based information. The type of the information and its accuracy plays an important role in positioning accuracy. The provided examples show that the available RSS-based information with the help of already available data (street maps), allow to achieve plausible results.

***Index Terms*—GPS, tracking, LBS, positioning, positioning accuracy, radio planning tools, road network information, RSS, timing advance, WiMAX.**

I. Introduction

THE most popular way to track a user is to use the Global Positioning System (GPS), since it provides positioning accuracy that meets all the known location-dependent applications requirements. The main problems with GPS despite that the user's terminal must be GPS enabled are the battery high consumption, the limited coverage and the latency. The battery high consumption means that the user can be positioned during a short period of time. Also GPS performs poorly in urban areas near the high risings and inside tunnels, i.e. it has a poor performance when it is needed the most. And it needs about 4 minutes (cold start) before the first position fix is available. Another way to track a user is to depend on the wireless network itself by using the available information by making measurements on the wireless network. Some of these measurements are hard to obtain like time of arrival (TOA) which needs synchronization, while some are easy to obtain like RSS measurements. Many localization approaches depending on network measurements have been proposed in GSM and sensor networks. Most of the work focused on range measurements depending on TOA, time-difference of arrival (TDOA) observations and RSS observations, surveys [1], [2] and [3]. In [4] an enhanced object tracking with RSS using a Kalman Filter is proposed by obtaining velocity information of the mobile sensor node which is used to improve the accuracy of the tracking. The authors of [5] proposed a grid-based centralized localization based on RSS to locate a target using the maximum and minimum path loss exponents; the proposed method achieves higher localization accuracy than the conventional localization method using the same path loss exponent when the distribution of the path loss exponents over the field is uniform and has worse performance when the distribution of the path loss exponents over the field is normally distributed. An indoor localization method based on received signal strength using discrete fourier transform has been proposed in [6]; the method provided satisfactory positioning accuracy if the environment stay consistent from the radio building phase.

In this paper, we propose the use of particle filters to track users in WiMAX networks depending on the available RSS-based information. A comparison between the positioning accuracies achieved by using different types of RSS-based information is provided. We argue that this approach meets the requirements of most of LBS.

This paper is organized as follows: Section II discusses the available RSS-based information in WiMAX networks; section III discusses the motion model and the implementation of the used particle filters in two cases: 1) the user can be anywhere in the area under study and 2) the user is using the public road network, section IV provides the obtained results, and we conclude in section V.

II. The available RSS-based information in WiMAX networks

The available RSS-based information in WiMAX networks can be divided into two categories, 1) the *measured RSS values* which are obtained by conducting direct measurements on the network and can be divided to subcategories depending on the used instrument in the measurements. 2) The *predicted RSS values* which are obtained by using *Radio planing tools*;

A. The measured RSS values

The RSS values can be measured using one of the following alternatives:

1) A spectrum analyzer;
2) Measurement dedicated modems;
3) Standard modems.

Using a spectrum analyzer gives the most accurate measurements, but it can't be used in realistic applications due to its high price, big size, power consumption and weight. Therefore it was not considered in this study. Using measurement dedicated modems enables obtaining the received signal strength index (RSSI) which can be converted to dBm values by using the modem calibration tables. But the values can be obtained for one frequency (channel) at a time which means that obtaining all the RSS values in the area under study needs several drives. Due to this constraint, the use of RSSI values is limited to building the off-line RSS database in realistic applications. In this study, the RSS values were used to build the off-line database and also they were used as measurements to track users to compare the accuracy achieved by using this type of measurements with the other RSS-based measurements. The SCORE values are used by the standard WiMAX modems to evaluate the connection quality between the subscriber station (SS) and the available base stations (BSs). The advantage of using the SCORE values is the possibility to obtain them for all the available BSs simultaneously, without adding any extra software or hardware. The disadvantage however, lies in their low accuracy comparing to the received signal strength (RSS) values. The relation between the measured SCORE and RSS values has been studied by computing the average error and the covariance between the two quantities. Figure 1 shows good correlation between SCORE and RSS values which means that the use of SCORE values instead of RSS values is possible, but then lower positioning accuracy is expected.

B. The predicted RSS values

The predicted RSS values can be obtained by using the radio planing tools. The used values in this study were obtained from the data provided by Clearwire / Belgium. To evaluate the accuracy of this data, in other words to measure how much it is close to the real RSS measurements, the relation between the predicted and the measured RSS values were studied by computing the average error and the covariance between the two quantities as depicted in figure 2.

The correlation between the predicted values and the measured ones is not that good as is the correlation between the SCORE and RSS values. Therefore, lower positioning accuracy than using the SCORE values is expected.

III. TRACKING USING MOTION MODELS

In static positioning, one does not consider the time information (stamps) available with the measurements. When the target is localized with good accuracy for one measurement, in the next measurement when the user is possibly quite close to the previous location (because only a small amount of time has passed), the previous good accuracy localization is completely discarded and a new localization is done based on the new measurement. This is one type of static target localization and the dynamic information coming from the fact that the user does not move much between consecutive measurements is not used. Two particle filters were used to track the target (user). The first one exploited the target dynamic information and the second filter exploited the public road information map in addition to the dynamic information. Knowing that the user is using the public road network is a valuable information to position him/her. The *TeleAtlas* maps have been used as an assisting data in addition to the measured data. One of the ways to use this extra information in localization is to use a dynamic model for the target (user) position given as:

$$x_{t_{k+1}} = f_{t_{k+1},t_k}(x_{t_k}, w_{t_{k+1},t_k}) \tag{1}$$

where

- $x_{t_k} \in \mathbb{R}^{n_x}$ is the state of the target at time t_k,
- $w_{t_{k+1},t_k} \in \mathbb{R}^{n_w}$ is the process noise representing the uncertainty in the model between time instants t_k and t_{k+1}. If the process noise term is selected to be small, this means that the target model is known with good accuracy and vice versa.
- $f_{t_{k+1},t_k}(.,.)$ is in general a nonlinear function of its arguments.

This type of models is generally used in target tracking [7], [8] to model target motion dynamics. At each time instant t_k, we get a measurement y_{t_k} which is related to the state of the target as

$$y_{t_k} = h(x_{t_k}, v_{t_k}) \tag{2}$$

where

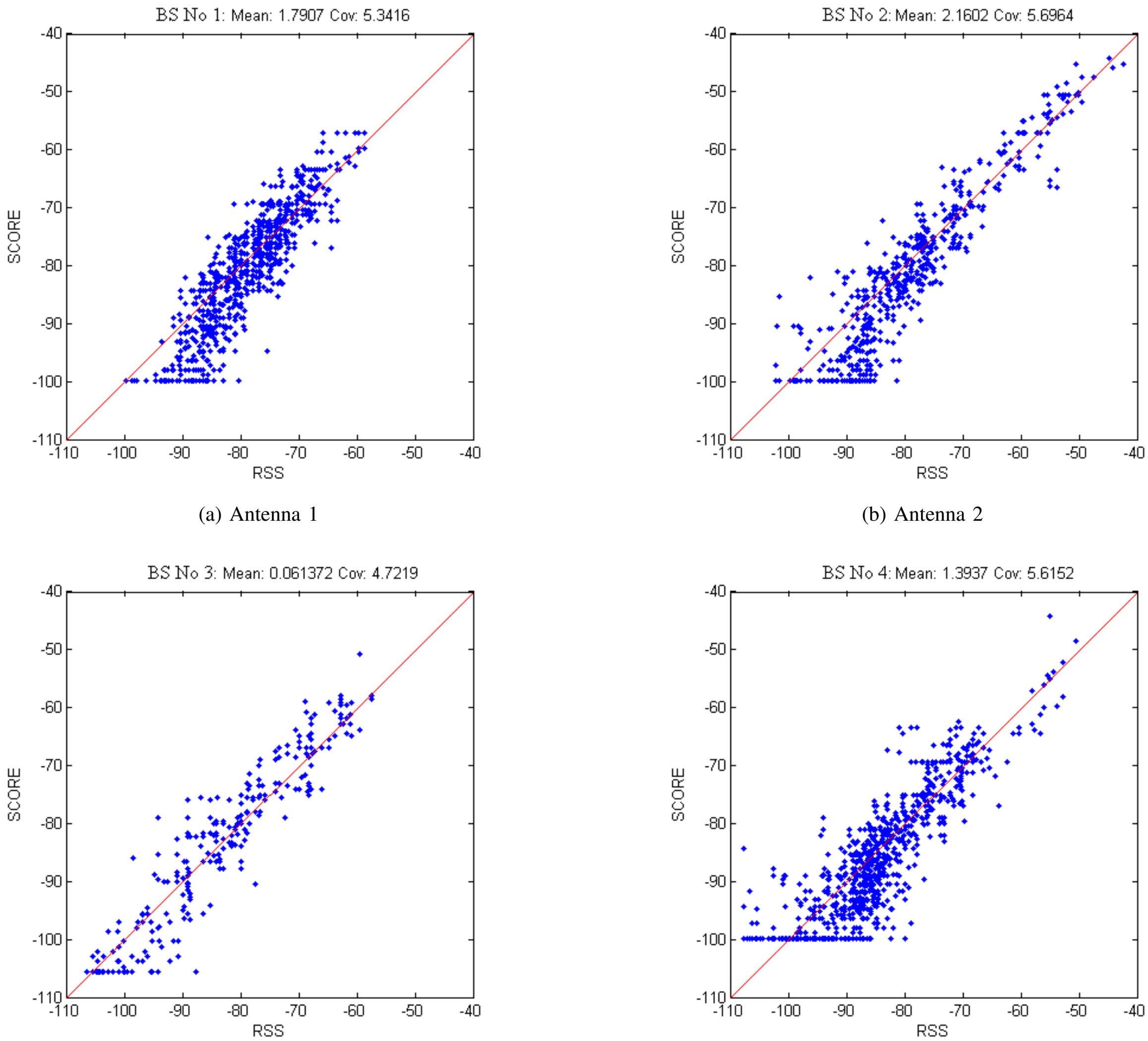
- $h(.,.)$ is, in general, a nonlinear function of its arguments. In our application, the function $h(.,.)$ will be formed from the already built RSS database.
- v_{t_k} is the measurement noise representing the quality of our sensors.

State estimation with this type of probabilistic model given by (1) and (2) is a mature area of research [9], [10]. The optimal solution when the functions $f(.)$ and $h(.)$ are linear and the noise terms w_{t_{k+1},t_k} and v_{t_k} are Gaussian is the well-known Kalman filter [11]. There are some methods which can handle small nonlinearities like extended Kalman filters (EKFs) [12] and unscented Kalman filters (UKFs) [13], [14]. In our case, the measurement function $h(.)$ that we are going to derive from RSS database information is highly nonlinear. Moreover, if one assumes that the user is moving on the road, the state model would be highly multi-modal which can be approximated with a Gaussian distribution quite poorly whereas both EKF and UKF depend on Gaussianity approximation.

Therefore, in this work we are going to use the relatively recent alternative algorithms in the literature called particle filters. Particle filters are recursive implementation of Bayesian density recursions [15], [16], [17]. The main aim in the method, as in many Bayesian methods, is to calculate the posterior density of the state x_{t_k} given all the measurements $y_{t_{1:k}} \triangleq \{y_{t_1}, y_{t_2}, \ldots, y_{t_k}\}$, i.e., we calculate the density $p(x_{t_k}|y_{t_{1:k}})$. While doing this, particle filter approximates the density $p(x_{t_k}|y_{t_{1:k}})$ with a number of state values $\{x_{t_k}^{(i)}\}_{i=1}^{N_p}$ (called particles) and their corresponding weights $\{\eta_{t_k}^{(i)}\}_{i=1}^{N_p}$ (called particle weights) i.e.,

$$p(x_{t_k}|y_{t_{1:k}}) \approx \sum_{i=1}^{N_p} \eta_{t_k}^{(i)} \delta_{x_{t_k}^{(i)}}(x_{t_k}) \tag{3}$$

Then, at each time step, the particle filter needs to calculate the particles and weights $\{x_{t_k}^{(i)}, \eta_{t_k}^{(i)}\}_{i=1}^{N_p}$ from the previous particles and weights $\{x_{t_{k-1}}^{(i)}, \eta_{t_{k-1}}^{(i)}\}_{i=1}^{N_p}$.



(a) Antenna 1

(b) Antenna 2

(c) Antenna 3

(d) Antenna 4

Fig. 1: The relation between the measured SCORE and RSS values

A. State Models

The first particle filter uses a classical (nearly) constant velocity model with state $x_k = \left[\ p^x_{k+1} p^y_{k+1} v^x_{k+1} v^y_{k+1}\ \right]$ where variables p and v denote the position and velocity of the the target respectively. The motion model is given

$$\begin{bmatrix} p^x_{k+1} \\ p^y_{k+1} \\ v^x_{k+1} \\ v^y_{k+1} \end{bmatrix} = \begin{bmatrix} \mathbf{I}_2 & T_{k+1}\mathbf{I}_2 \\ \mathbf{0} & \mathbf{I}_2 \end{bmatrix} \begin{bmatrix} p^x_k \\ p^y_k \\ v^x_k \\ v^y_k \end{bmatrix} + \begin{bmatrix} \frac{T^2_{k+1}}{2}\mathbf{I}_2 \\ T_{k+1}\mathbf{I}_2 \end{bmatrix} w_{k+1} \tag{4}$$

where w_k is a two dimensional white Gaussian noise and $\mathbf{I}_n$ is the identity matrix of dimension n. $T_{k+1} = t_{k+1} - t_k$ is the difference between consecutive time stamps of the measurements. The second particle filter makes use of the road database information and uses a reduced order motion model. The state of the particle filter is denoted by x^r_k where r stands for emphasizing road-information, and it is given as $x^r_k = [p^r_k, v^r_k, i^r_k]^T$ where the scalar variables p^r_k, v^r_k denote the position and speed values of the target on the road segment which is identified by the integer index i^r_k. The following model is used for the dynamics of x^r_k.

$$\begin{bmatrix} p^r_{k+1} \\ v^r_{k+1} \\ i^r_{k+1} \end{bmatrix} = f^r\left(\begin{bmatrix} \mathsf{p}^r_{k+1} \\ \mathsf{v}^r_{k+1} \\ i^r_k \end{bmatrix}, \mathcal{I}_{RN}, w^{r_d}_{k+1}\right) \tag{5}$$

where

$$\begin{bmatrix} \mathsf{p}^r_{k+1} \\ \mathsf{v}^r_{k+1} \end{bmatrix} = \begin{bmatrix} 1 & T_{k+1} \\ 0 & 1 \end{bmatrix} \begin{bmatrix} p^r_k \\ v^r_k \end{bmatrix} + \begin{bmatrix} \frac{T^2_{k+1}}{2} \\ T_{k+1} \end{bmatrix} w^{r_c}_{k+1} \tag{6}$$

The continuous process noise $w^{r_c}_k$ is a scalar white Gaussian acceleration noise and $\mathcal{I}_{RN}$ is the road network information. The predicted position and speed values p^r_{k+1}, v^r_{k+1} might not be on the road segment indicated by i^r_k. The function $f^r(.)$ therefore projects the values p^r_{k+1}, v^r_{k+1} into the road segment denoted by i^r_{k+1}. If there are more than one candidate for the next road segment index i^r_{k+1} due to the junctions, the function also selects a random one according to the value of the discrete

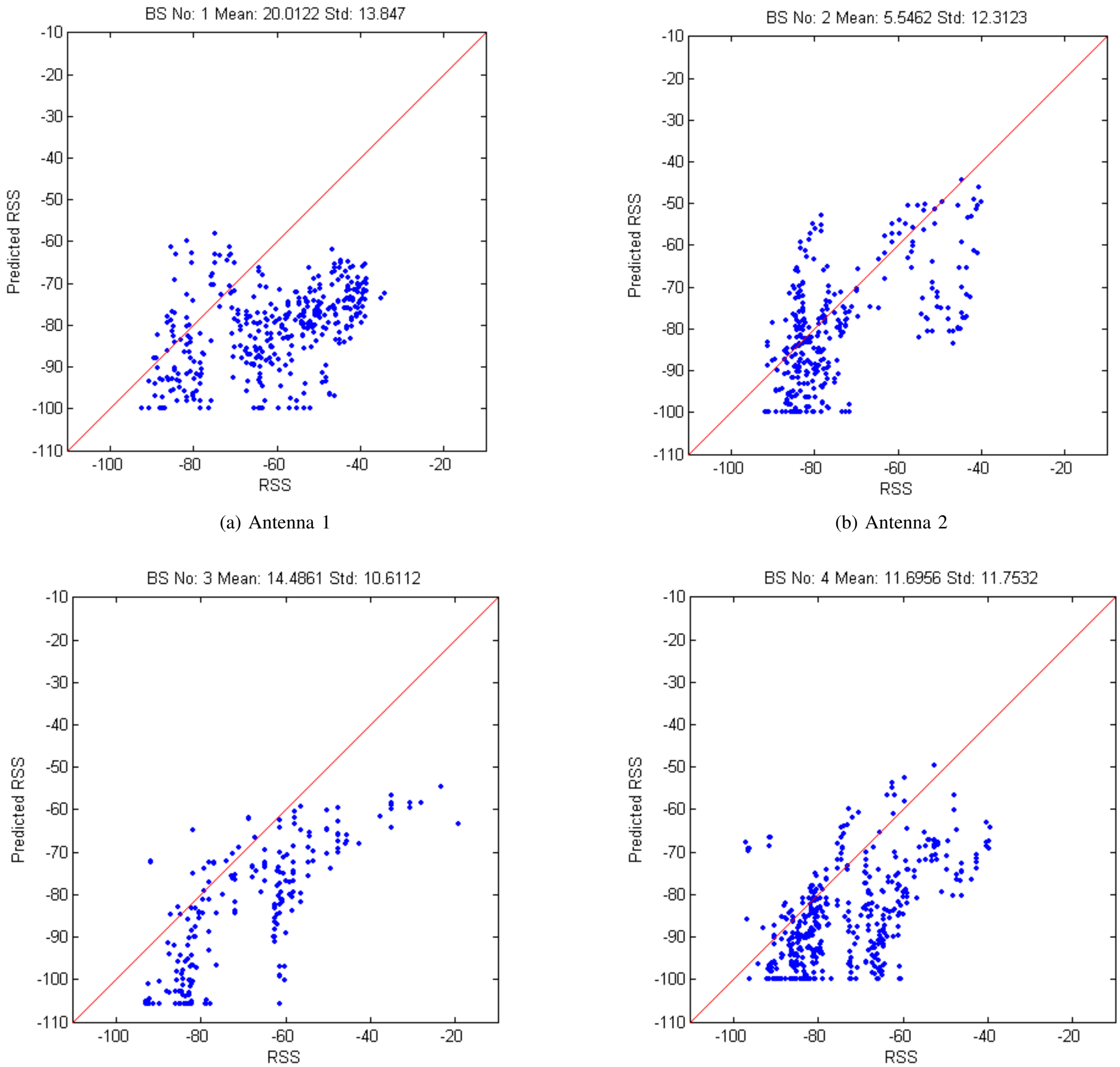


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Fig. 2: The relation between the predicted RSS values and the measured ones

on-road process noise term $w_{k+1}^{r_d} \in \{1, 2, \ldots, N_r(x_k^r)\}$ where $N_r(x_k^r)$ is the number of possible road segments that the target with on-road state x_k^r might go in the following T_{k+1} seconds.

B. Measurement Models

The measurement update is the same for both particle filters. At a single time instant t_k, the measurement vector is in the following form:

$$y_{t_k} = \begin{bmatrix} V_1 & V_2 & \ldots & V_{N_{BS}} \end{bmatrix}^T \tag{7}$$

N_{BS} is the number of base stations. The values V_j can either have the corresponding measured scalar RSS (SCORE) value or the predicted RSS value detected from the jth base station or NaN (Not a Number) which denotes that no measurement from that base station is detected. The RSS database was built depending on the power map for the area under study and consists of vectors in the form:

$$\begin{bmatrix} pos & V_{1..N} \end{bmatrix} \tag{8}$$

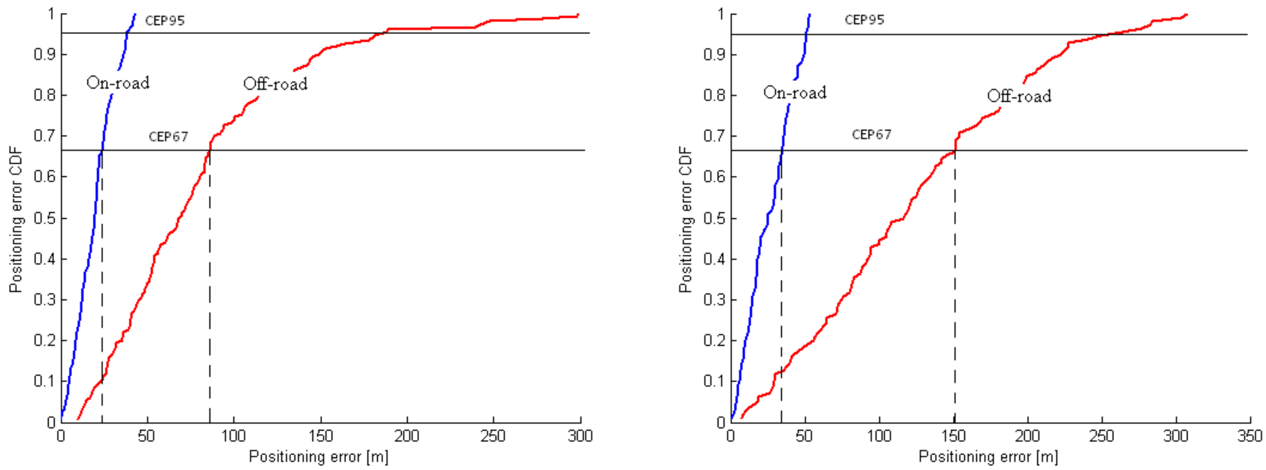
where,

$$pos = \begin{bmatrix} X & Y \end{bmatrix}^T \tag{9}$$

is the position of the power map point, and

$$V_{1..N} = \begin{bmatrix} V_1 & V_2 & \ldots & V_N \end{bmatrix}^T \tag{10}$$

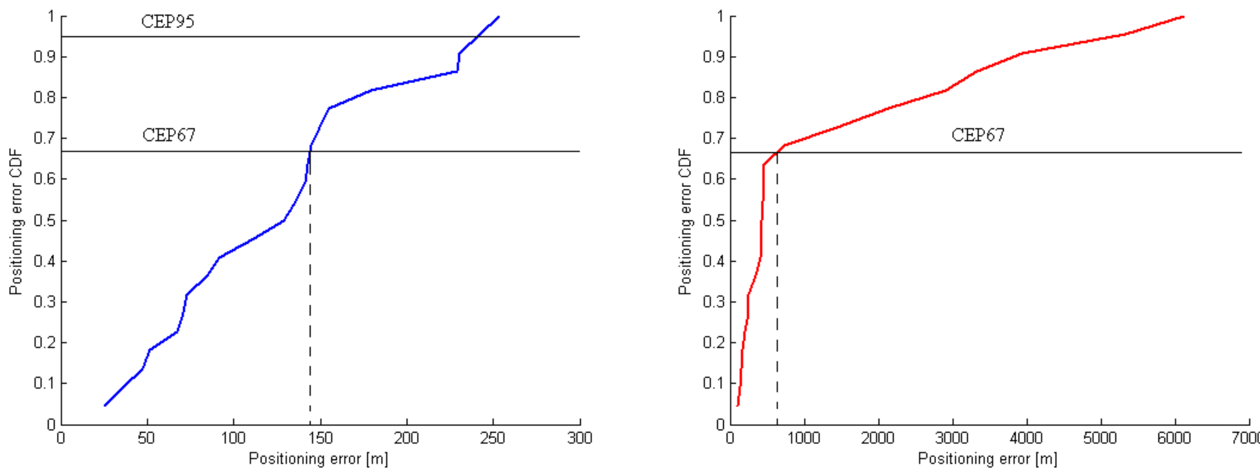
is the received RSSs in the mentioned point, where N is the number of the received BSs. The measurement update is based on finding the closest RSS vector ($V_{1..N}$) in the already built database to the measurement vector y_{t_k}; that is, *fingerprinting*.



(a) Using RSS measurements

(b) Using SCORE measurements

Fig. 3: Positioning error CDF using the measured RSS and SCORE values



(a) With road information (on-road)

(b) Without road information (off-road)

Fig. 4: Positioning error CDF using the predicted RSS values

IV. The results

The results were consistent with what we have expected by examining the quality of the data. The best positioning accuracy was obtained by using he measured RSS values, while the second accuracy was obtained by using the SCORE measurements. The predicted data gave the worst accuracy but still useful for many LBS if combined with the use of road information. Figure 3 depicts the results obtained by using the measured RSS-based values, and figure 4 depicts the results obtained by using the predicted RSS-based values. Figure 5 depicts the instant positioning error using the predicted RSS values in two cases, 1- with the help of road inforamtion(on-road), 2- without the help of road information (off-road). Note that the off-road filter diverged when bad quality of data was used. The road information has helped in keeping the filter working even when poor quality of data was used. And also using the road information has improved the positioning accuracy in notable values.

V. Conclusion

This paper has discussed using the available RSS-based measurements to track users in WiMAX networks. Using RSS values produce the best accuracy but they are hard to obtain in the current WiMAX modems (a special software has to be installed on) and only one channel can be obtained at a time only. SCORE measurements can be obtained using the standard modems and, therefore, can be used in realistic applications and the obtained accuracy is very promising and useful for the most of LBS. Using the predicted RSS values produces the least accuracy, but the advantage is avoiding the time consuming and costly job to build the database by direct measurements. Anyway, using the predicted RSS values has

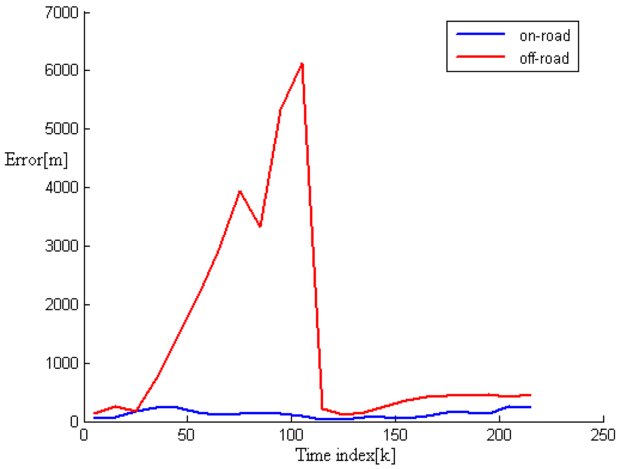


Fig. 5: The instant positioning error using the predicted RSS values

to be done with the road network information to support LBS that don't require high positioning accuracy.

The particle filter has been chosen because of the high non-linear measurement model that depend on the fingerprinting approach. In addition, the use of road network information makes modeling the state by Gaussian distribution is not accurate. However, a potential localization accuracy improvement has been gained from using the road information.

References

[1] F. Gustafsson and F. Gunnarsson, "Possibilities and fundamental limitations of positioning using wireless communication networks measurements," *IEEE Signal Process. Mag.*, vol. 22, pp. 41–53, 2005.

[2] S. Gezici, Z. Tian, B. Giannakis, H. Kobayashi, and A. Molisch, "Localization via ultra-wideband radios," *IEEE Signal Process. Mag.*, vol. 22, pp. 70–84, 2005.

[3] D. Li and Y. Hu, "Energy-based collaborative source localization using acoustic microsensor array," *Journal of Applied Signal Processing*, pp. 321–337, 2003.

[4] M. Nabaee, A. Pooyafard, and A. Olfat, "Enhanced object tracking with received signal strength using Kalman filter in sensor networks," *Internatioal Symposium on Telecommunications*, pp. 318–323, 2008.

[5] J. Shirahama and T. Ohtsuki, "RSS-based localization in environments with different path loss exponent for each link," *Vehicular Technology Conference*, pp. 1509–1513, 2008.

[6] M. Zhang, S. Zhang, J. Cao, and H. Mei, "A novel indoor localization method based on received signal strength using discrete Fourier transform," *Communications and Networking in China*, pp. 1–5, 2006.

[7] Y. Bar-Shalom, X. R. Li, and T. Kirubarajan, *Estimation with Applications to Tracking and Navigation*. New York: Wiley, 2001.

[8] S. Blackman and R. Popoli, *Design and Analysis of Modern Tracking Systems*. Norwood, MA: Artech House, 1999.

[9] B. D. O. Anderson and J. B. Moore, *Optimal Filtering*. Englewood Cliffs, NJ: Prentice Hall, 1979.

[10] P. R. Kumar and P. Varaiya, *Stochastic Systems: Estimation, Identification and Adaptive Control*. Englewood Cliffs, New Jersey: Prentice Hall, 1986.

[11] R. E. Kalman, "A new approach to linear filtering and prediction problems," *J. Basic Eng.*, vol. 82, no. 1, pp. 34–45, Mar. 1960.

[12] A. H. Jazwinski, *Stochastic Processes and Filtering Theory*. NY, USA: Academic Press, 1970.

[13] S. Julier, J. Uhlmann, and H. Durrant-Whyte, "A new method for the nonlinear transformation of means and covariances in filters and estimators," *IEEE Trans. Autom. Control*, vol. 45, no. 3, pp. 477–482, Mar. 2000.

[14] S. Julier and J. Uhlmann, "Unscented filtering and nonlinear estimation," *Proc. IEEE*, vol. 92, no. 3, pp. 401–422, Mar. 2004.

[15] A. Doucet, S. J. Godsill, and C. Andrieu, "On sequential simulation-based methods for Bayesian filtering," *Statistics and Computing*, vol. 10, no. 3, pp. 197–208, 2000.

[16] A. Doucet, N. de Freitas, and N. Gordon, Eds., *Sequential Monte Carlo Methods in Practice*. Springer Verlag, 2001.

[17] S. Arulampalam, S. Maskell, N. Gordon, and T. Clapp, "A tutorial on particle filters for on-line non-linear/non-Gaussian Bayesian tracking," *IEEE Trans. Signal Process.*, vol. 50, no. 2, pp. 174–188, Feb. 2002.