On the Accuracy improvement Issues in GSM Location Fingerprinting

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Abstract **– Determining the position of mobile users in GSM networks has become more and more important. Such services as emergency calls and other location dependent services have been of great importance in the last years. A key factor for the success of any localization technology is its accuracy. This work is focused on localization in a dense urban scenario or in any other area where the GPS signal is not available or its error is very big due to some obstruction of the satellites. Different methods such as those based on neural network localization, database correlation, dead reckoning and a tracking algorithm in case of user mobility have been examined in this work in order to find the optimal in terms of accuracy. The pre-processing of the received signal strengths (rss) is performed to reduce the positioning error due to the rss-stochastic behaviour. Results show that, a tracking algorithm using NN positioning results and an extended Kalman filter (EKF) supplies better results in case of mobility of the user.**

Index Terms **– Dead reckoning, Fingerprint localization, Neural networks, Noise cancellation, Tracking.**

I. INTRODUCTION.

There are three main approaches to positioning, namely satellite based, terrestrial based and stand alone. The first two methods can be called radio-location methods because they rely on the property of radio signal. The most accurate positioning today is achieved using the satellite-based and its combinations. However, GPS is usable only in case of clear sky, which makes it hardly usable in urban areas, mountainous terrain, closed and covered space.

An example of a terrestrial based positioning is the localization within a gsm network. In such positioning systems many methods have been developed: cell ID (CI), which just returns the weighted center of the serving cell as a position estimate. Cell ID plus Timing advance (CI+TA) based methods which take into account an estimate of the distance to the base transceiver station. Angle of arrival (AOA), time of arrival (TOA), time difference of arrival (TDOA) and pattern matching or fingerprint methods. With the TOA, TDOA and AOA methods, location of the mobile system (MS) is calculated under assumption of the line of sight propagation between the base station (BS) and MS. This assumption is not valid in city centers where high buildings often obstruct the line of sight. Moreover, severe multipath propagation characteristic to these environments makes it difficult to detect the angle or time of arrival of the direct component. Consequently, these methods are not suited for dense cellular network of urban environments. The fingerprint method does not need any additional equipment to existing networks and it is designed to obtain better results in the environment with significant multipath.

Another way of improving the positioning accuracy is to combine map matching with the above listed methods. The principle of map matching method is to ensure that a position is matched to the nearest street. However, a street network can be quite complicated, especially when there are several crossroads. Moreover, in case of pedestrian navigation, a pedestrian might use small paths which are not in the available road network database.

Dead reckoning (DR) is one example of the stand-alone approach. DR methods locate a MS by computing its distance (velocity, acceleration, time) and direction of travel from a known fixed initial position. The distance and direction measurements can be made by sensors

In this work, the improvement of the positioning accuracy is achieved with a robust EKF tracking algorithm using the NN positioning results as measurements. The dynamic motion model of the user is developed.

The remainder of this paper is organized as follow: In the second section, we present the literature background of the related works. Fingerprinting methods are summarized in the third part of this work. Our methodology for fingerprint data pre-processing is discussed in section four. Dead reckoning positioning system is developed section five. In section six, the tracking algorithms with extended Kalman filter is presented . In section seven, we describe the experimental environment. Simulation results and a conclusion are found in sections eight and nine respectively.

II. LITERATURE REVIEW

This paper examines the effectiveness of different localization methods within a GSM network. These methods have been explored in a number of papers. A key contribution of this work is to benefit from the position information of different methods in a robust tracking algorithm to get a better position estimate.

Several papers have explored the rss fingerprint method to localize a MS [1-3].In case of outdoor positioning, the rss collection along the streets to realise a fingerprint database is time consuming. In [3] predicted rss generated as described in [4], were corrected with only a few samples of real collected data. These corrected predicted rss were thereafter used as fingerprint database. This was done in order to remedy to the big demanding effort during rss collection. The tracking theory and implementation were developed in [5-9]. The database positioning method is discussed in [10]. The dead reckoning technique has been applied in many positioning systems [11-13], but this method results in a positioning error accumulation with time. An update should be periodically performed to solve this problem.

III. Fingerprinting Methods

Fingerprinting methods, known also as signature-based consist of determining the position of the MS by either comparing the actual signature (fingerprint) to the ones stored in a database or using the actual fingerprint as input to an already trained NN to get the position estimate at the output.

Signatures are location sensitive parameters of radio signals measured or predicted along the streets used for the experiment. These signatures can be channel impulse responses (CIR), radio signal strengths, angle of arrival… In this work we use the rss as signatures. Because of the narrow gsm bandwidth, the use of the CIR as signatures is inefficient.

The first method is called database correlation (DC). The database realization is a time consuming process. Some works have used predicted fingerprint to remedy to this issue. Moreover positioning process takes time while comparison is been performed. Some papers use the cell ID and timing advance information to limit the searching only to the area where the MS is to be found.

The second method is referred to as NN positioning. This method works better compared to the DC one. The positioning time is reduced. This makes the implementation of this method in real time positioning possible. The NN is trained first off line with rss collected or predicted from several cell antennas. GPS coordinates of the collected data points are used as target during training phase. During training process, which needs sufficient time for a good rss-position mapping, a mapping function is approximated. In positioning mode, no target is needed. Only a set of actual signature is given at the NN input and the NN generates the position estimate at its output. The training algorithm used for the weights adjustment is the gradient descent for its low memory requirement and its simplicity.

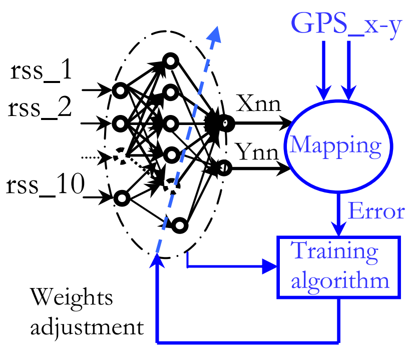


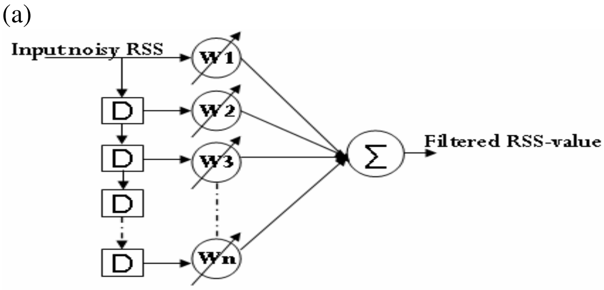
Fig. 1, NN training block diagram.

Fig. 1, illustrates the NN fingerprint positioning method. rss_1,….rss_10, are the signal strengths from 10 cells antennas considered. Xnn and Ynn are the position estimate during positioning mode. GPS_x-y are the reference or target coordinates during training mode. In positioning mode only the black colored part of the figure is used.

IV. RSS Pre-processing

The accuracy of fingerprint positioning methods depends significantly on how the signatures (rss) were pre-processed before their input to the localization unit [3]. The stochastic behavior of the rss makes difficult to consider the best estimated of its value in the algorithm. To remedy to this issue, a simple time delayed neural network (TDNN) or a single input adaptive transverse filter was able to remove a large portion of the noise in the received rss, fig 2.a. It performs this operation by calculating a weighted average over a window. We used five delay units for this purpose. This procedure can be either online or off line conducted. It is clearly seen from fig. 2.b, how the noisy rss at the input has been filtered at the TDNN output.

(a)



(b)

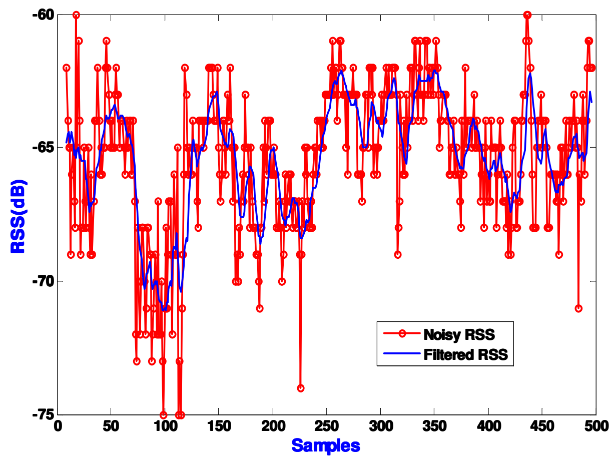


Fig. 2, Time delayed NN for noise reduction (a), Noisy rss at the TDNN input and filtered RSS at the output (b)

V. Dead Reckoning

Dead reckoning is the process of estimating present position by projecting heading and speed from a known past position. It is used widely for navigation, because it can also determine the future position by processing an ordered course and velocity from a known present position as shown in Fig. 3.

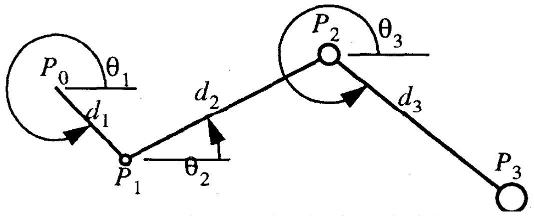


Fig.3, Dead reckoning principle

Where P_0 is the initial position, d_1 and θ_1 are the first path and heading angle. Thereby we can calculate the next position P_1 and so forth.

If we assume that the pedestrian or vehicle is moving on a two dimensional plane, then the dynamic equation to depict the kinematic relationship can be given as follows:

$$\begin{bmatrix} x(k+1) \\ y(k+1) \\ \theta(k+1) \end{bmatrix} = \begin{bmatrix} x(k)+v(k).t.\cos\theta(k) \\ y(k)+v(k).t.\sin\theta(k) \\ \theta(k+1) \end{bmatrix} \qquad (1)$$

Where $x(k)$, $y(k)$ are position coordinates, $v(k)$ is vector of velocity and θ is the heading angle of the pedestrian or vehicle.

In this experiment, the heading angle is read directly from a sensor (inertial measurement unit), fig.4, or digital compass, fig.5.a.

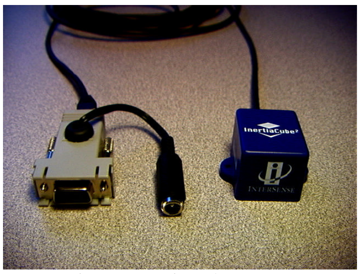


Fig. 4. InertiaCube (IMU)

The Inertia cube gives 1^0 static accuracy and 3^0 dynamic accuracy.

The InertiaCube2 is a monolithic part based on micro-electro-mechanical systems technology involving no spinning wheels that might generate noise, inertial forces and mechanical failures. The Inertia Cube simultaneously measures 9 physical properties, namely angular rates, linear accelerations, and magnetic field components along all 3 axes. Microminiature vibrating elements are employed to measure all the angular rate components and linear accelerations, with integral electronics and solid-state magnetometers. The functional performance of the multisensor unit is better explained in [14]. In this experiment, we do not exploit all the properties of the cube. We just use it to get the orientation information at every collected position.

VI. Extended Kalman Filter

Motion tracking is one of the most important parts of a robustly working system. We use in this work a non linear Kalman filter or Extended Kalman Filter (EKF), because Kalman filter has the feasibility to model noise, even allowing the system to filter state values in noisy environments.

For linear dynamic systems with white noise process and white measurement noise, the Kalman filter is known to be an optimal estimator. For nonlinear systems, the Kalman filter can be extended by linearizing the system around the current parameter estimates. The first step of the EKF algorithm is computing the linearized state matrices and then they are used in the Taylor approximation of nonlinear function as shown in [8].

The EKF addresses the general problem of trying to estimate the state $x \in \Re^n$ of a discrete-time controlled process that is governed by the nonlinear stochastic difference equation,

$$x_k = f(x_{k-1}, u_{k-1}, w_{k-1}) \qquad (2)$$

with a measurement $z \in \Re^m$ that is

$$z_k = h(x_k, v_k), \qquad (3)$$

f and *h* are nonlinear functions. *f* relates the state at the previous step to the current step, and *h* relates the state *x* to the measurement *z*. In this paper, linearization of state and measurement equations is achieved as we consider positions at discrete times. In the case of measurement equation, the NN position estimates are used. These NN positions are considered at discrete points as the user is moving. Linearization is achieved between two near position estimates.

In our case, the state *X* is composed with $\begin{pmatrix} x \\ y \end{pmatrix}$, which are the position estimate coordinates. All the filter parameters are calculated for these both state coordinates.

The random variables w_k and v_k represent the process and measurement noise respectively. They are assumed to be independent of each other, white, and with normal probability distributions

$$p(w) \sim N(0,Q) \text{ and } p(v) \sim N(0,R) \qquad (4)$$

The Kalman algorithm has two steps: the prediction or also called time update process and the corrector, also called measurement update process.

a. Prediction

The a priori state estimate is formed based on the previous estimate of the state and the current value of the input which is got from the dynamic motion model of the pedestrian.

$$\hat{x}_k^- = f(\hat{x}_{k-1}, u_{k-1}, 0) \tag{5}$$

Where, x_k is the state or the position estimate coordinates and u_k is input or the distance got from the pedestrian dynamic motion model, as shown in (1).
And now we can calculate the a priori covariance

$$P_k^- = A_k \; P_{k-1} \; A_k^T + W_k \; Q_{k-1} \; W_k^T \tag{6}$$

A is the Jacobian matrix of partial derivatives of *f* with respect to *x*. *W* is the Jacobian matrix of partial derivatives of *f* with respect to *w*. Q_k is process noise covariance. The determination of the process noise covariance is generally difficult as we typically do not have the ability to directly observe the process we are estimating. Anyway, injecting enough uncertainty into the process via the selection of Q_k does work. In this work we take Q_k to be equal to 25.

In practice, the process noise covariance Q and measurement noise covariance R matrices might change with each time step or measurement. If at time k, the process is performed when the disturbance noise is bigger, Q_k should be also bigger. However, in this work, we assume that *Q is* constant.

b. Correction or measurement update

In order to correct the a priori estimate, we need the Kalman filter gain K_k

$$K_k = P_k^- \; H_k^T \, (H_k \; P_k^- \; H_k^T + V_k \; R_k \; V_k^T \,)^{-1} \tag{7}$$

This KF gain is used to correct the a priori estimate and gives us the a posteriori estimates.

$$\hat{x}_k = \hat{x}_k^- + K_k \, (z_k - \mathrm{h}(\hat{x}_k^-, 0)) \tag{8}$$

We can now calculate the a posteriori covariance.

$$P_k = (\mathrm{I} - K_k \; H_k \,) \, P_k^- \tag{9}$$

Where z_k is measurement matrix, *H* is the Jacobian matrix of partial derivatives of *h* with respect to the state *x*, *V* is the Jacobian matrix of partial derivatives of *h* with respect to *v*.
The determination of the Jacobian matrixes *A,W,H,V* is made as shown in [8,15]. R_k is the measurement noise covariance. In the actual implementation of the filter, the measurement noise covariance R_k is usually measured prior to operation of the filter. In this work, knowing the NN positioning performances, we can determine the variance of the measurement noise. The NN positioning performances gave a standard deviation of 27m, which determines the value of $R = \sigma^2 = 729$.

VII. Experimental environment and Settings

The experimental area is an urban environment in Hannover-Germany. The rss and reference data (GPS) were collected with a GPS-GSM Falcom A2D modem and antenna while walking along the streets. The experimental area size is of 1x1km. In our test, the orientation information at every point was recorded by two sensors: an expensive IMU shown in fig. 4, and a simple two axes-digital compass, fig. 5.a.
Most conventional mobile positioning solutions fitted to the aircraft, boats and automobiles take advantages of speed sensing devices fitted to the vehicle. In case of pedestrian navigation which is the case in this paper, movement associated with walking and running is detected by a simple mechanical or electrical sensor. In this work, we used a cheap sport pedometer for the footsteps count fig.5.b. The distance can be estimated knowing the time and estimating the step size.
NN architecture of three layers, ten neurons on the input layer which corresponds to the number of cells from which the rss are collected was used. Due to the limitation of standard GSM mobile, a maximum of 7 values appear in sample collected data for all the points. For this reason, data record is filled with zeros for those stations for which measurements have not been collected. We used 36 neurons on the hidden layer and two neurons on the output layer which correspond to the x-y position coordinates, Fig.1. The NN training was made first off to perform the rss-position mapping before using it in the positioning algorithm.

a) b)

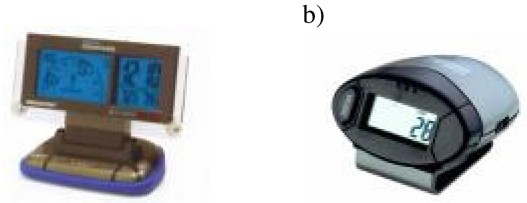


Fig. 5. Digital compass(a) and Pedometer (b)

VIII. Simulation Results

Fig.6,7, show that the positioning error coming from the DR method can keep on accumulating with time. The EKF has a big error at the beginning, because the first estimate was just a guess, and it was 300m away from the real position. But with time, the EKF error is iteratively reduced.

Fig.8, shows the cumulative distribution functions of the three methods. It is clearly seen that, for this experiment, NN appeared to give better result than the DR. This justifies the reason that pushed us to consider the NN output in the measurement equation.
Fig.9, shows the way the a posteriori covariance error is reduced with time. It seen that, after the 20th tested point, the EKF has reduced the error up to the maximum it can for a given set of parameters.

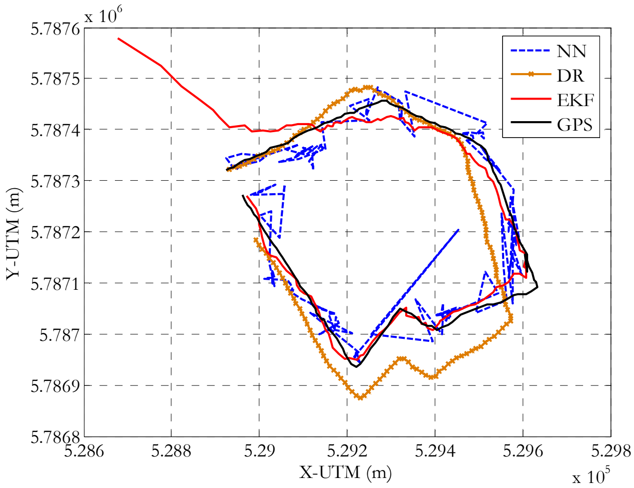


Fig.6. Comparative performances of NN,DR,EKF on the 2D experimental area (1 x 1 km).

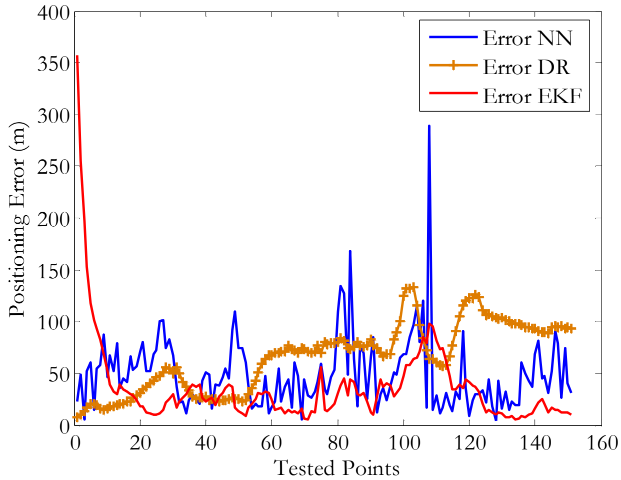


Fig.7, Positioning Error of NN, DR and EKF

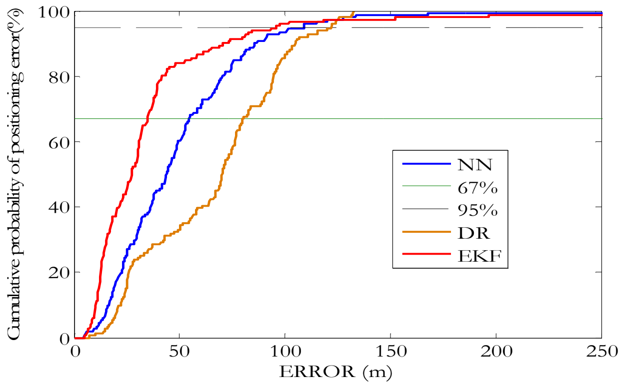


Fig. 8, Cumulative distribution function (CDF) of NN,DR,EKF

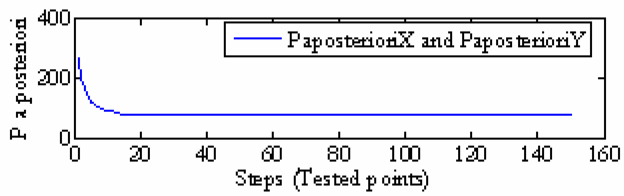


Fig. 9, The a posteriori error covariance of the state

VIII. CONCLUSION AND OUTLOOKS

In this paper we have presented different positioning methods within a GSM cellular environment, those based on : NN, DR and tracking with EKF. A key factor for the success of any localization technology is the positioning accuracy. A pedestrian navigation case has been examined to compare different methods in terms of accuracy and possible implementation. Pre-processing of the position fingerprints has been performed to reduce the error due to the rss stochastic behavior. In case of user mobility, the tracking algorithm using EKF and NN was the best. Such a positioning system could be successfully applied where no GPS is available or working with a bigger error.

Future works should focus on removing the conditions which we made for this work. Further optimization of the EKF parameters at every step should be surveyed. A possible implementation of an unscented Kalman filter or particle filter will be investigated for a robust filtering algorithm independently on the noise nature.

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