Tracking Mobile Terminals in Wireless Networks

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Abstract— **We propose a Bayesian filter algorithm for tracking the position of mobile terminals in wireless cellular networks when the loss of GPS information occurs. Our technique utilizes simulated IMU (inertial measurement unit) data and map-matching according to the received cell-ID in the prediction and update steps of the algorithm respectively. The map used for matching has been generated by correlating geographical data and radio profile prediction information of the experimental area. We show how to maintain location information for mobile terminals in wireless networks using a novel combination of data sources. Our approach provides a reliable solution in street canyons and heavy tree canopies where GPS information is almost always inapplicable. The developed technique could also be applied to vehicle navigation, where dead-reckoning instruments are available and accurate.**

I. INTRODUCTION

The first application of mobile location dates back to World War II, when it was critical to locate military personnel rapidly and precisely in emergency situations [1]. In the nineties, the GPS was made accessible for commercial applications. Furthermore, the EU is most likely to follow the US and Japan in requiring high positioning accuracy of mobile emergency calls from 2010 when the Galileo system will be fully operational [2]. However, the benefits of GPS could be limited where position information is still needed due to obscured view to satellites or degraded accuracy caused by multipath.

A backup to GPS during signal outage with comparable accuracy could be achieved using fusion of inertial measurement unit (IMU) raw data with already existing cell-ID based methods and map-matching. The radio profile of a given area can determine routes that are covered by each cell antenna. Therefore, the computational cost of map-matching algorithms would be reduced to a minimum.

The proposed positioning algorithm is designed to maintain mobile location information during GPS signal blocking using the recursive Bayesian filter [3]. The initial position is assumed as the last GPS position fix. The main task of the algorithm would be to compensate for IMU data errors using map-matching. Our proposed algorithm is assumed to be a mobile-based technique, where map information is provided by network operators. However, the technique could be run as network-based if the IMU data is uploaded from the mobile terminal (MT) to the operator network.

The objective of this paper is to investigate the feasibility of MT location using IMU raw data with cell-ID and geographical map information. We examine this concept by fusing simulated IMU data with real-world cell-id information from cellular wireless networks and map-matching in order to maintain MT location information outdoors with accuracy comparable to that of GPS positioning. Radio maps generated by radio propagation prediction tools are used off-line to determine road areas covered by every cell antenna in our test area. Our experiments will investigate the range of acceptable IMU data errors that would allow reliable positioning when using real IMU data.

The rest of the paper is organized as follows. The next Section presents the basics of the proposed positioning algorithm. Section III discusses the motion and world models utilized in our work. Experimental results are provided in Section IV, and the whole paper is concluded in Section V.

II. THE POSITIONING ALGORITHM

A. Recursive Bayesian Filtering

The recursive Bayesian filter (RBF) [3] is a probabilistic framework for state estimation that utilizes the *Markov assumption*, i.e., past and future measurements are conditionally independent if the current state is known. In the context of the proposed MT localization algorithm, the RBF estimates the posterior belief of the MT position given its prior belief, IMU measurements, cell-ID of the serving base station (BS), and a model of the world. The RBF is stated mathematically as

$$Bel(s_t) = \eta \cdot p(o_t \mid s_t, m) \cdot \sum [p(s_t \mid s_{t-1}, a_{t-1}, m) \cdot Bel(s_{t-1})].$$

(1)

Where $Bel(s_t)$ is the posterior belief over the MT position s_t at time t, and η is a normalization constant to ensure that $Bel(s_t)$ will sum up to one over all states. However, normalization is not crucial for filter implementation. The term $p(o_t | s_t, m)$ is the likelihood of the measurement or observation o_t of the serving cell-ID at time t given the current MT position and the world model m. It is also known as the *observation model*. The expression $p(s_t | s_{t-1}, a_{t-1}, m)$ is the probability that the MT is at s_t given it executed the movement a_{t-1} when it was at s_{t-1} within the space defined by m. It is also called the *motion model*. Finally, $Bel(s_{t-1})$ is the prior belief over the MT position. A complete derivation of expression (1) is provided in [4].

TABLE I shows how Equation (1) is usually computed in two steps called *prediction* and *update*, where $Bel^-(s_t)$ is the posterior belief just after executing action a_{t-1} and before incorporating the observation o_t. Note that MT actions and observations are assumed to occur in an alternative sequence.

TABLE I.   GENERIC RECURSIVE BAYESIAN FILTER

Algorithm **Generic_RBF**($Bel(s_{t-1}), a_{t-1}, o_t, m$)

  for all s_t do

    Prediction Step

    $Bel^-(s_t) = \sum [p(s_t | s_{t-1}, a_{t-1}, m) \cdot Bel(s_{t-1})]$

    Update Step

    $Bel(s_t) = \eta \cdot p(o_t | s_t, m) \cdot Bel^-(s_t)$

  endfor

  return($Bel(s_t)$)

B. Practical Implementation

A single iteration of the positioning algorithm is given in TABLE II. The inputs are the initial position $s_{t-1} = (x_{t-1}, y_{t-1})$, the IMU data $a_{t-1} = (trans_{t-1}, \theta_{t-1})$, where $trans_{t-1}$ and θ_{t-1} are the translation (after twice integration of the IMU acceleration measurement) and orientation (IMU compass) in a 2D Cartesian coordinate system at time $t-1$ respectively, the network measurement o_t, and the corresponding world map m_t where w_j is the weight of the j-th location candidate and initially set to zero. Note that the proposed algorithm updates only one position hypothesis.

The positioning algorithm propagates the known initial MT location s_{t-1} using IMU data in the prediction step. The propagated location is then updated by matching it to the set of candidate locations that are covered by the current serving cell antenna, after descending sort of the candidates w.r.t. weight, the new MT position is simply the candidate of the

minimum Euclidean distance to the location computed in the prediction step.

TABLE II.   THE PROPOSED POSITIONING ALGORITHM

Algorithm **Positioning**($s_{t-1}, a_{t-1}, o_t, m_t$)

  // Inputs

  $s_{t-1} = (x_{t-1}, y_{t-1})$

  $a_{t-1} = (trans_{t-1}, \theta_{t-1})$, $o_t = cell - ID_t$

  $m_t = DB_{cell-ID_t} = < x_i, y_i, w_i >, i = 1..n, < w_i >= 0$

  Prediction Step

  $x_t^- = x_{t-1} + trans_{t-1} \cdot \cos \theta_{t-1}$

  $y_t^- = y_{t-1} + trans_{t-1} \cdot \sin \theta_{t-1}$

  Update Step

  for $i = 1 : n$ do

    $w_i = \dfrac{1}{\sqrt{(x_t^- - x_i)^2 + (y_t^- - y_i)^2}}$

  endfor

  $m_t = sort(m_t)$ // Descending sort w.r.t weight

  $s_t = (x_t, y_t) = (x_1, y_1)$

  return(s_t)

III. MOTION AND WORLD MODELS

A. Motion Model

The motion model used in the prediction step is simply dead reckoning that computes the next location by applying the course and distance traveled since to a previous position according to the following two equations

$$x_t = x_{t-1} + trans_{t-1}.\cos \theta_{t-1}, \tag{2}$$

$$y_t = y_{t-1} + trans_{t-1}.\sin \theta_{t-1}. \tag{3}$$

To investigate the feasibility of IMU raw data we have generated IMU measurements with additive white Gaussian noise (AWGN) as

$$trans_{t-1}^{noisy} = trans_{t-1} + \zeta_{trans}, \tag{4}$$

$$\theta_{t-1}^{noisy} = \theta_{t-1} + \zeta_{orient}. \tag{5}$$

And

$$\zeta_{trans} = N(trans_{t-1}, \sigma_{trans}), \tag{6}$$

$$\zeta_{orient} = N(0, \sigma_{orient}). \tag{7}$$

Where ζ_{trans} is the Gaussian translation error with $trans_{t-1}$ mean and standard deviation of σ_{trans}. And ζ_{orient} is the Gaussian orientation error with zero mean and standard deviation of σ_{orient}. Thus the expressions for the predicted position are

$$x_t = x_{t-1} + trans_{t-1}^{noisy}.\cos\theta_{t-1}^{noisy},\qquad(8)$$

$$y_t = y_{t-1} + trans_{t-1}^{noisy}.\sin\theta_{t-1}^{noisy}.\qquad(9)$$

B. World Model

Two kinds of databases (prior information) have been utilized in this work. The first one is a prediction of the radio profile in a test area of 9 km^2 in Hannover, Germany. The predicted radio profile has been constructed using a 3D deterministic radio propagation prediction model, described in [5], with a resolution of 5 m. These data have been generated to provide predictions of the average received signal strength levels (RxLev), at reference locations, from the surrounding GSM antennas at 1800 MHz in our test area that contains 6 sectorized cells and four indoor antennas. This procedure is produced during the network planning stage, and is a useful source for MT positioning. After several preprocessing steps, as in [6] and [7], the radio profile data was subdivided into separate databases, in each are locations served by a certain cell antenna as illustrated in Figure 1.

The second kind is a digital map of the area, generated from satellite images. Thus, different features, e.g. water, green, building, road, etc., could be easily discriminated.

Because the goal of this work was to introduce a backup to GPS pedestrian positioning, we have extracted locations in which a walking person might exist and correlated their coordinates to the radio profile prediction data. The result is a collection of pedestrian outdoor location databases divided according to GSM antenna radio coverage, see Figure 2. These databases are used in the update step of our proposed positioning algorithm.

IV. EXPERIMENTS AND RESULTS

A. Experimental Setup

A measurement campaign has been carried out in an E-Plus GSM 1800 MHz network by a pedestrian along a route of about 1940 m long. RxLev measurements of the serving base stations and up to six neighboring stations along with GPS position fixes for ground truth have been logged into a file for later offline simulations. Furthermore, the GPS positions have been used to generate IMU pseudo measurements to simulate real ones, so that the feasibility of a real IMU employment could be investigated.

B. Numerical Results

We have investigated the performance of the tracking algorithm by varying σ_{trans} from 1% to 10% of the performed translation and σ_{orient} between 1° and 6°. The quality of performance is determined according to successful tracking, mean, 67 percentile, and 95 percentile positioning errors in meters. We consider the MT position is successfully tracked if the final position estimate over the experiment route of 1940 m is not greater than 50 m away from the true MT

location. All experiments have been repeated 100 times in order to get reasonable results. It can be seen – as expected – in Figure 3 that the higher σ_{trans} and/or σ_{orient} are, the lower the probability of successfully tracking the MT along the test route. However, for σ_{trans} up to 4% and σ_{orient} up to 2°, successful tracking is achieved over 90% of all repeats. With σ_{orient} up to 2° and σ_{trans} up to 10%, slightly less than 70% of successful tracking is achieved. When σ_{orient} is increased up to 5°, successful tracking is achieved 60% of the times with the worst case of σ_{trans}. For σ_{orient} equals 6°, the percentage of successful tracking drops below 60% as σ_{trans} increases above 4%.
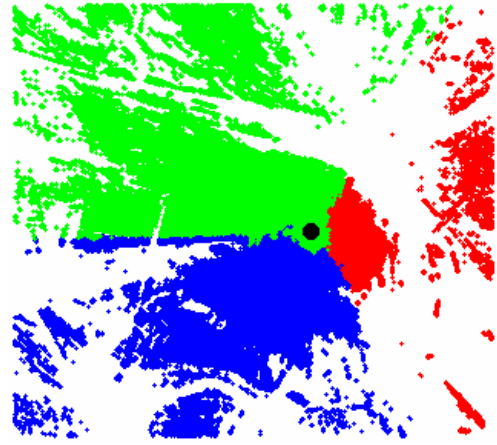

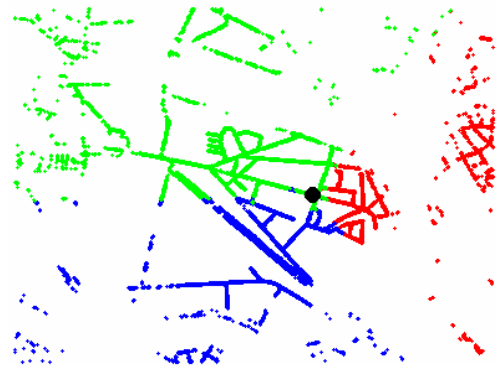Figure 1.   Locations served by three sectors of the same base station.

Figure 2.   Outdoor locations categorized after radio coverage of sector cells.

Figures 4, 5 and 6 show that the mean, 67 percentile, and 95 percentile positioning errors for the different cases are less than 20 m, 20 m, and 62 m respectively. This is very accurate for most positioning applications and confirms the suitability of IMU-based localization to work as a reliable back up in case of GPS information outage.
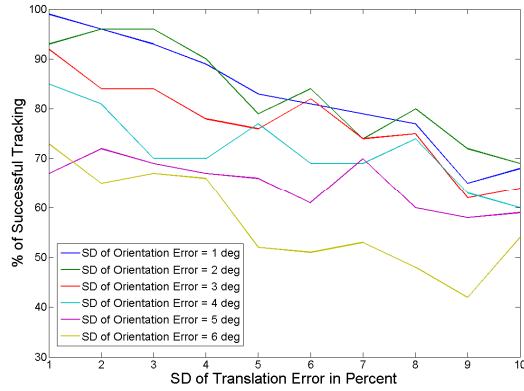
Figure 3.   Percentage of successful position tracking with varying standard deviations of IMU translation and orientation.
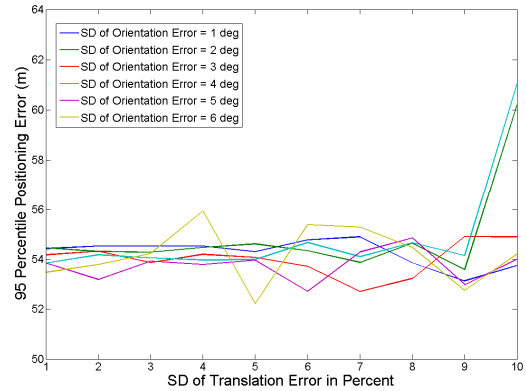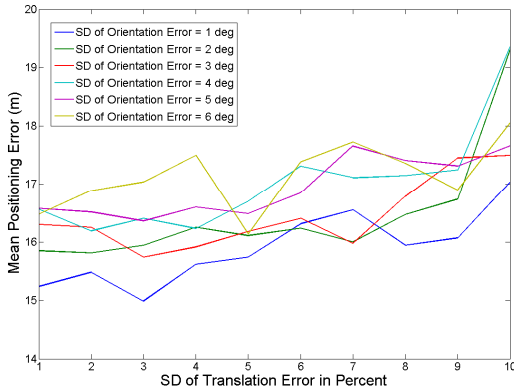

Figure 4.   Mean positioning error.

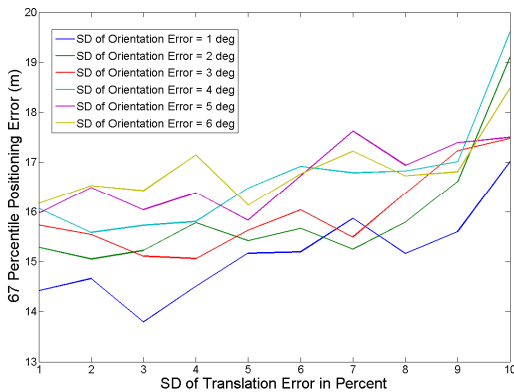Figure 5.   67 percentile positioning error.

Figure 6.   95 percentile positioning error.

V.   CONCLUSION

In this paper we presented a technique based on simulated IMU raw data to maintain location information in cellular wireless environments for MTs in case of GPS outage. The proposed method runs in real time with positioning errors acceptable for most location-based applications. Thus, it could be considered as a reliable alternative in many cases.

The presented algorithm could also be applied to vehicle navigation, where dead-reckoning instruments are available and accurate.

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