POSITION TRACKING AND GLOBAL LOCALIZATION OF MOBILE TERMINALS IN CELLULAR NETWORKS

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ABSTRACT

Dead reckoning (DR) via direction and distance could provide an accurate way of maintaining location information for mobile terminals when loss of GPS signals occurs. Furthermore, DR would provide reliable solutions in indoor/outdoor transitions, street canyons, and heavy tree canopies where GPS information is almost always inapplicable. Thus, DR is a desirable option for security and commercial applications that value position information. This paper describes and investigates how DR could provide accurate and reliable positioning using radio profile databases and map-matching. The proposed technique solves both the position tracking and global localization problems, so that mobile terminal localization could be achieved in case of GPS outage or even without any GPS information at all respectively.

1. 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, lack of a GPS receiver in the mobile terminal to locate, or degraded accuracy caused by multipath.

An alternative to GPS or a backup during GPS 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 solve two problems using the recursive Bayesian filter [3]: *Position tracking* and *global localization*. In the first problem, the initial position is given, either manually or as the last GPS fix in case of GPS signal blocking. The main task of the algorithm would be to compensate for IMU data errors using map-matching. In the global localization problem, no initial position is known to the system and the algorithm has to calculate the mobile terminal location from scratch. This problem is more difficult because the algorithm has to handle multiple and distinct hypotheses. Solving this problem would make our system totally GPS-independent. 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 achieve MT outdoor position tracking and global localization 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 localization algorithm. Sections 3 and 4 discuss the motion and world models utilized in our work respectively. Experimental results are provided in section 5, and the whole paper is concluded in section 6.

2. THE LOCALIZATION ALGORITHM

2.1. Recursive Bayesian Filter

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

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

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 $p(o_t \mid s_t, m)$ 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 $p(s_t \mid s_{t-1}, a_{t-1}, m)$ 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].

Algorithm 1 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.

Algorithm **Generic_RBF**($Bel(s_{t-1}), a_{t-1}, o_t, m$)
for all s_t *do*
Prediction Step
$Bel^-(s_t) = \sum [p(s_t \mid s_{t-1}, a_{t-1}, m) \cdot Bel(s_{t-1})]$
Update Step
$Bel(s_t) = \eta \cdot p(o_t \mid s_t, m) \cdot Bel^-(s_t)$
endfor
return($Bel(s_t)$)

Algorithm 1: The generic recursive Bayesian filter.

2.2. Position Tracking Implementation

In position tracking, the algorithm is designed to propagate the initial MT location s_{t-1} using raw IMU data in the prediction step. In the update step, the propagated location is matched to a set of location candidates that are known to be covered (in radio signal strength terms) by a certain cell antenna with a cell-ID identical to that received by the MT from the current serving cell. The candidate with the minimum Euclidean distance to the location computed in the prediction step is considered as the new position of the MT. This procedure is described in Algorithm 2, where $trans_{t-1}$ and θ_{t-1} are respectively the translation and orientation in a 2D Cartesian coordinate system at time $t-1$. $DB_{cell-ID_t}$ is the database that contains coordinate information of locations, covered by the cell antenna that serves the MT at time t, and w_i is the weight of location candidate i.

Algorithm **PositionTracking**($s_{t-1}, a_{t-1}, o_t, m_t$)
// Initialization
$s_{t-1} = (x_{t-1}, y_{t-1})$, $\eta = 0$
$a_{t-1} = (trans_{t-1}, \theta_{t-1})$, $o_t = cell-ID_t$
$m_t = DB_{cell-ID_t} =< x_i, y_i, w_i >, i = 1...n , < w_i >= 0$
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*
$w_i = \dfrac{1}{\sqrt{(x_t^- - x_i)^2 + (y_t^- - y_i)^2}}$
$\eta = \eta + w_i$
endfor
for $i = 1:n$ *do*
$w_i = \dfrac{w_i}{\eta}$ // Normalize weights
endfor
$m_t = sort(m_t)$ // Ascending sort w.r.t weight
$s_t = (x_t, y_t) = m_t(x_n, y_n)$ where $w_n = \max < w_i >$
return(s_t)

Algorithm 2: The position tracking function.

2.3. Global Localization Implementation

Unlike position tracking, the global localization algorithm has no information about the accurate MT position at the beginning. Thus, it has to resolve the location ambiguity and converge to the true position of the MT by tracking all probable location candidates and determine their weights every time the algorithm is run. When this task is successfully fulfilled, the algorithm is allowed to run in the position tracking mode discussed in 2.2.

As depicted in Algorithm 3, the global localization mode will run as long as the number of location candidates n is greater than a certain threshold α. In this mode, the prediction and update steps will only run if the MT's traveled distance is greater than or equal to the database resolution DB_{res} in order to allow position state transition using the database. The updated candidate will only be added to the new belief if the location it is matched to is not greater than DB_{res} away. Therefore, the number of location candidates will decrease after every run of the algorithm until their total number is equal to or less than the threshold α. In this very event, the updated MT position is simply estimated as the average of the remaining candidates, and the algorithm is switched to the position tracking mode already described above. The global localization procedure is listed in Algorithm 3.

3. 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 added noise as

$$trans_{t-1}^{noisy} = trans_{t-1} + randn \cdot \sigma_{trans} \cdot trans_{t-1} \tag{4}$$

$$\theta_{t-1}^{noisy} = \theta_{t-1} + randn \cdot \sigma_{orient} \tag{5}$$

Where σ_{trans} is the standard deviation of the simulated IMU translation as a percentage of the translation performed, σ_{orient} is the standard deviation of the simulated IMU orientation in degrees, and $randn$ is a normally distributed random number. Thus the expressions for the predicted position are

$$x_t = x_{t-1} + trans_{t-1}^{noisy}.\cos\theta_{t-1}^{noisy} \tag{6}$$

$$y_t = y_{t-1} + trans_{t-1}^{noisy}.\sin\theta_{t-1}^{noisy} \tag{7}$$

4. 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 Fig. 1.

Algorithm **GlobalLocalization**($Bel(s_{t-1}), a_{t-1}, o_t, m_t$)
// Initialization
$Bel(s_{t-1}) = DB_{cell-ID_t} =< x_i, y_i >, i = 1...n$, $trvld\_dist = 0$
$m_t = DB_{cell-ID_t} =< x_j, y_j, w_j >, j = 1...q$, $< w_j >= 0$
$a_{t-1} = (trans_{t-1}, \theta_{t-1})$, $o_t = cell - ID_t$, $\eta = 0$
$Mode = 0$ // Global localization mode
if $Mode == 0$
if $n > \alpha$
$trvld\_dist = trvld\_dist +$
$\sqrt{(trans_{t-1} \cdot \cos\theta_{t-1})^2 + (trans_{t-1} \cdot \sin\theta_{t-1})^2}$
if $trvld\_dist >= DB_{res}$
Prediction Step
for $i = 1 : n$ *do*
$x_i^- = x_i + trvld\_dist \cdot \cos\theta_{t-1}$
$y_i^- = y_i + trvld\_dist \cdot \sin\theta_{t-1}$
Update Step
for $j = 1 : q$ *do*
$w_j = \dfrac{1}{\sqrt{(x_i^- - x_j)^2 + (y_i^- - y_j)^2}}$
endfor
$< w_j >= sort(< w_j >)$ // Ascending sort
if $(\frac{1}{w_q} \le DB_{res})$
add (x_q, y_q) to $Bel(s_t)$
endif
endfor
else if $n \le \alpha$
$Mode = 1$
$s_t = (\frac{\sum x_i}{n}, \frac{\sum y_i}{n})$
endif
else if $Mode == 1$ // Position tracking mode
PositionTracking($s_{t-1}, a_{t-1}, o_t, m_t$)
endif

Algorithm 3: The global localization function.

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 or an alternative 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 (Fig 2). These databases are used in the update step of our proposed localization algorithm.

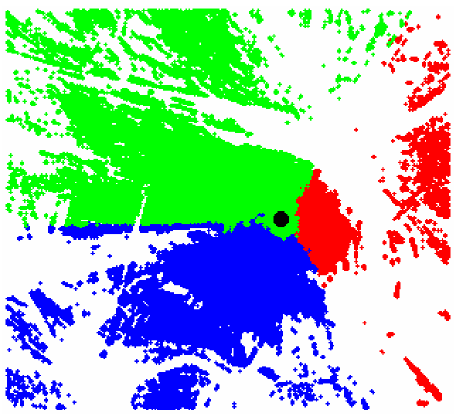

Fig. 1: Locations served by three sectors of the same base station.

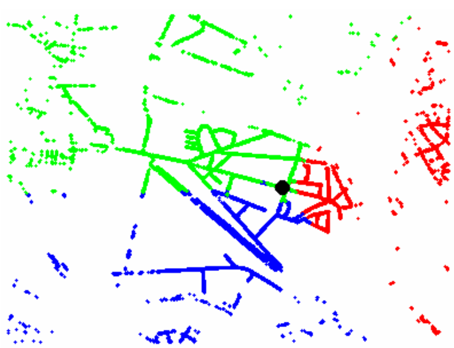

Fig. 2: Outdoor locations categorized after radio coverage of sector cells.

5. EXPERIMENTS AND RESULTS

5.1. 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, equations (4) and (5), so that the feasibility of a real IMU employment could be investigated.

5.2. Results

Within position tracking experiments the initial location of the MT is known. 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 and the mean positioning errors in meters. We consider the MT's 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 Fig. 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%. Note that all IMU data are raw and have not been filtered before map-matching. Thus, adding a filter at the IMU output (e.g. Kalman filter) still could enhance the percentage of successful tracking for the given values of σ_{trans} and σ_{orient}. Fig. 4 shows that the mean positioning error for the different cases is between 15 and 20 m. This is very accurate for most positioning applications and confirms the suitability of IMU based localization as a reliable backup in case of GPS information outage.

In the global localization experiments we have investigated the percentage of successful localization for the different values of σ_{trans} and σ_{orient}. As shown in Fig. 5, the achieved successful global localization is over 80% and 65% for σ_{orient} up to 3° and 6° respectively. The effect of σ_{trans} on the results is almost not significant, because of the 5 m map resolution that makes the update step insensitive to the range of translation errors assumed. Moreover, there is a slight tendency to increase the possibility of successful global localization with increasing σ_{trans} especially when σ_{orient} also increases, which seams counter intuitive. However, the fact is that large errors caused by high σ_{orient} values are compensated by increasing σ_{trans} and the low map resolution that prevents quick deviation from the true path.

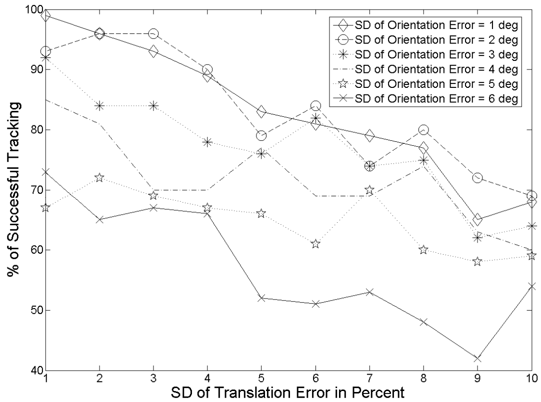

Fig. 3: Percentage of successful position tracking with varying standard deviations of IMU translation and orientation.

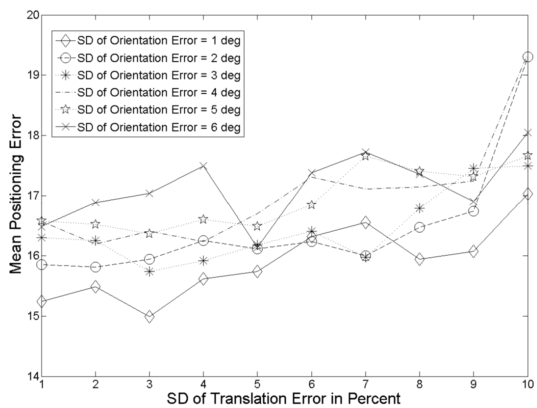

Fig. 4: Mean position error of position tracking.

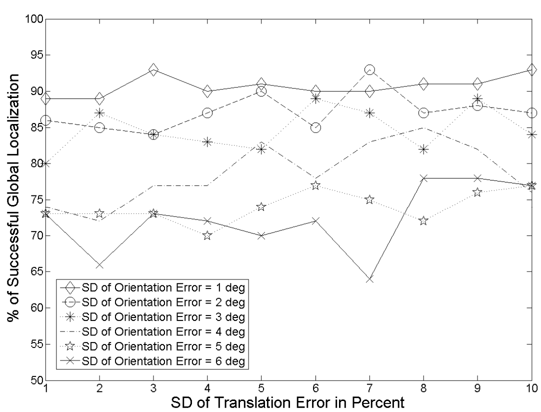

Fig. 5: Percentage of successful global localization with varying standard deviations of IMU translation and orientation.

6. CONCLUSION AND FUTURE WORK

In this paper we presented techniques based on simulated IMU raw data to maintain location information for MTs in case of GPS outage. Moreover, we introduced a novel technique to find the position of a MT without any prior information, so that our location algorithm would be GPS independent. The proposed methods run in real time with positioning errors acceptable for most location-based applications. Thus, they could be considered as reliable alternatives in many cases. The presented algorithms could also be applied to vehicle positioning, where dead-reckoning instruments are available and accurate.

This work can still be extended by filtering (e.g. using Kalman filter) the raw IMU data in order to increase the probability of successful position tracking and global localization. More advanced map-matching techniques might also enhance the overall performance. It is planned to experiment with real IMU data to verify and validate the proposed approach.

7. REFERENCES

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