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A Novel GPS-free Method for Mobile Unit Global Positioning in Outdoor Wireless Environments

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Abstract This paper investigates a Global Positioning system (GPS)-free positioning method for mobile units (MUs) in outdoor wireless environments by using the Bayesian filtering formulation. The procedure utilizes simulated inertial measurements, cell-ID of the serving base station, and pre-determined locations grouped according to cell antennas radio coverage in the experimentation area. The developed algorithm makes no assumptions on the initial position of the MU. However, the algorithm takes some time to converge. Experiments show the range of inertial measurement errors that would maintain reliable location information with accuracy comparable to GPS positioning.

Keywords Mobile location · Global positioning · Recursive Bayesian filtering · Inertial measurement unit (IMU) · Dead reckoning · Cell-ID · Radio mapping · Geographical maps · Global positioning system (GPS)

1 Introduction

Mobile unit (MU) positioning is a key problem in wireless environments. It is the most fundamental problem to providing customers with tailored and location-aware services. MU positioning can be defined as the determination of the MU's geolocation by using location-dependent parameters in a specific coordinate system. The key driver for developing MU location technologies in USA was E-911. In the EU, it was commercial services in the first place, and later E-112 that utilizes the same techniques. Emergency call location has become a requirement in fixed and cellular networks in USA in 1996 [1] and in the EU in 2003 [2]. Positioning of a MU is considered more critical because MU users and thus MU originated emergency calls are continually increasing. It is estimated that about 50% of all emergency calls in the EU are MU originated, and the expected tendency is rising [2].

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The first application of MU location dates back to World War II, when it was critical to locate military personnel rapidly and precisely in emergency situations [3]. Furthermore, non-military interest in this field dates back to about 40 years ago [4,5]. While emergency call location could be considered the most important of location-based services (LBS) due to its urgency for life and property safety, commercial LBS are believed to make increasing revenues for network operators who could provide customers with attractive and tailored services [6]. Therefore, a lot of research is being carried out in this area.

Positioning systems are usually categorized according to the place where location calculations are performed into *network-based* or *mobile-based*, or according to the application environment into *outdoor* or *indoor*. The main approaches of positioning techniques are *satellite-based* methods, *geometric* techniques and *mapping* approaches. These methods differ in terms of accuracy, coverage, cost, power consumption and system impact.

Satellite-based technologies are mainly employed for outdoor applications and come in two flavours: Stand-alone Global Positioning System (GPS) or assisted-GPS (A-GPS), and both are mobile-based solutions. A-GPS needs extra signals from reference GPS receivers and thus the system impact is increased. The main drawbacks are high power consumption, need of clear view to at least four satellites (for stand-alone GPS) and the costs of integrating GPS receivers into the MUs. Furthermore, A-GPS solutions increase overhead costs due to the requirement to install reference GPS receivers. The satellite-based approach is the most accurate MU positioning technique, and it was only made accessible for commercial applications in the nineties. Also 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 [7]. However, the benefits of satellite-based positioning could be limited where location information is still needed due to signal blocking or degraded accuracy caused by multipath. In such cases, other positioning methods should be triggered in order to backup the failed or degraded satellite signals.

Geometric methods estimate the MU location by utilizing, e.g. time of arrival (TOA), time difference of arrival (TDOA), or angle of arrival (AOA) measurements. The main drawback of TOA measurements is the need of mutual synchronization of the involved base stations (BSs) in order to avoid degraded location accuracy, which is difficult to achieve. Exploiting AOA measurements increases overhead costs due to the need for installation of special antennas at the BSs. However, the continuous advancement in MIMO technologies would make AOA estimation more feasible for accurate mobile positioning. At least three BSs are required for TDOA measurements, which cannot always be fulfilled in many non-urban environments. Although geometric techniques are generally more accurate than mapping methods [6], their position estimation accuracy degrades severely in multipath environments, which is the dominant condition in built-up areas, and in non-line-of-site (NLOS) situations without accurate environmental information.

Mapping-based mobile location is one way to achieve accuracy improvement of cell-ID positioning. They also appear in the literature under the names *database comparison* or *correlation*, *location fingerprinting* and *pattern recognition* or *matching*. In these techniques, a *database* or *map* of location-dependent parameters is constructed using radio wave propagation prediction tools or field measurements. Propagation prediction tools are advantageous in terms of cost and map construction time, while field measurements provide more realistic databases but with tedious and longer construction time and higher costs to support performing the measurement campaigns. Later, a moving MU collects measurements to be compared with the entries in the database in order to yield location estimates. Location-dependent parameters usually used for mapping include received signal strength levels (RxLev) from surrounding BSs [8–10], and the channel impulse response (CIR) [11,12]. In Global System for Mobile communication (GSM), the bandwidth is too small, unlike the Universal Mobile Telecommunications System (UMTS), for accurate positioning based on correlation of CIR only [11].

Mapping methods utilize prediction data of RxLev and/or CIR produced during network planning. In the online positioning phase they use only the network available measurements and thus they almost do not require any additional hardware installations at BSs or in MUs. This is advantageous in terms of cost, coverage and system impact compared to the other approaches. Therefore, they seem to be the first alternative to take into consideration, especially for European network operators, since EU location requirements still do not specify any accuracy levels unlike the US mandate.

The location accuracy of mapping approaches ranges between about 100 m and several kilometres depending on cell size, mapping resolution, propagation conditions and significance degree of the mapped location-dependent parameter. While CIR maps generally achieve more accurate estimates than RxLev mapping in urban and dense urban environments, they tend to have comparable performance in suburban and rural areas. However, mapping methods are advantageous, because no LOS conditions are needed, it can work even with one BS, and its implementation costs are pretty low. Moreover, mapping techniques will still be needed also when more accurate technologies are fully available. They will achieve positioning for applications with low accuracy requirements; they will be deployed in areas of the network where more accurate methods are not supported; and finally, they will work as backup in case the accurate techniques fail for any reason. Therefore, improving positioning accuracy of mapping approaches is an active research topic.

In Sect. 2, Categorization of the different positioning problems within the mapping approach is given. The outline of a novel alternative for GPS positioning is introduced in Sect. 3. Section 4 presents the proposed positioning algorithm with an illustrated example. In Sect. 5, the utilized motion and world models are provided. Experiments and numerical results are discussed in Sect. 6, and the whole paper is finally concluded in Sect. 7.

2 Categorization of the Positioning Problems within the Mapping Approach

Estimation of the MU's position in its environment involves using a map of a location-dependent parameter of the environment, network measurement data and motion information. The estimation accuracy could even be enhanced by utilizing any prior knowledge of the MU location when available.

Motion information is generally the most difficult piece of information to extract. Without dedicated motion sensors, e.g. an inertial measurement unit (IMU), motion estimation is either impossible or very inaccurate due to the noisy signal behaviour used to derive the MU motion pattern. Accordingly, the MU positioning problem could be divided into *location estimation* and *tracking* based on the availability of motion measurements. Location estimation (LE) algorithms calculate the MU location without incorporating any motion information or prior knowledge about the accurate initial position. Moreover, tracking algorithms could be further categorized according to the availability of prior knowledge into *position tracking* and *global positioning*. In position tracking (PT), the initial position of the MU is known, and the problem is to find adequate procedures in order to compensate incremental errors in the motion sensor measurements. In the more challenging global positioning (GP) problem, the initial location of the MU is unknown, and consequently the MU position has to be determined from scratch. This positioning problem is more difficult because multiple and distinct hypotheses have to be handled. To the best of the author's knowledge the problem of global positioning has not been investigated within the wireless location context. Therefore, only the global positioning problem will be addressed in the rest of the paper. It is also worthy to note that the position tracking and global positioning problems have been successfully solved for robotics applications [13].

3 An Alternative Approach to GPS Positioning

An alternative to GPS navigation information with comparable accuracy could be achieved using fusion of IMU raw data with a mapping-based positioning method. By correlating geographical and radio profile maps of a given area, the routes that are served by each cell antenna in the environment could be accurately determined and used for position finding. The resulting cross map is called *radio-route map*.

The feasibility of MU positioning using IMU raw data with cell-ID and radio-route maps will be investigated and examined by correlating simulated IMU data and real-world cell-ID information from a working GSM network with radio-route maps in order to achieve MU outdoor global positioning with accuracy comparable to GPS localization. Radio profile maps generated by radio propagation prediction tools are used off-line to determine pedestrian routes covered by every cell antenna in our test environment. The experiments will investigate the range of acceptable IMU data errors, i.e. translation and orientation errors that would allow reliable global positioning when using real IMU data. The proposed algorithm could be implemented as a mobile-based positioning method, where necessary maps are provided by network operators.

4 Global Positioning using the Bayesian Filtering Formulation

4.1 The Basic Recursive Bayesian Filter Algorithm

The recursive Bayesian filter (RBF) [14] 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 MU localization algorithm, the RBF estimates the posterior belief of the MU position given its prior belief, simulated IMU measurements, cell-ID of the serving BS and the model of the world. The RBF is stated mathematically in discrete form as

$$Bel(s_t) = \eta \cdot p(o_t|s_t, m) \cdot \sum \left[p(s_t|s_{t-1}, a_{t-1}, m) \cdot Bel(s_{t-1})\right], \tag{1}$$

where $Bel(s_t)$ is the posterior belief over the MU position $s_t =< x_t, y_t >$ at time t, and η is a normalization constant to ensure that $Bel(s_t)$ will sum up to one in order to represent a valid probability distribution function (PDF). 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 MU position s_t and the world model m. It is also known as the *observation model*. $p(s_t|s_{t-1}, a_{t-1}, m)$ is the probability that the MU is at s_t given it executed the movement a_{t-1} at s_{t-1} within the space defined by m. It is also defined as the *motion model*. Finally, $Bel(s_{t-1})$ is the prior belief over the MU position. A complete derivation of expression (1) is provided in [14].

Table 1 The generic recursive Bayesian filter algorithm

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

Table 1 shows how Eq. 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 MU actions and observations are assumed to occur in an alternative sequence.

Equation 1 cannot be directly implemented on a digital computer. However, non-parametric filters [15] provide implementable techniques for the RBF. They approximate posterior distributions by a finite number of parameters, each associated with a *probability value* or *weight* that determines its importance. Moreover, the number of parameters can be varied during filter operation. The resulting filter is called *discrete recursive Bayesian filter (DRBF)* and it represents the belief $Bel(s)$ at any time as

$$Bel(s_t) \approx < s^{(i)}, \quad w^{(i)} >_{i=1:n}, \tag{2}$$

where $s^{(i)} = \{x^{(i)}, y^{(i)}\}$ is the ith MU location candidate and $w^{(i)}$ is its weight.

4.2 The Global Positioning Algorithm

A Bayesian filtering algorithm for the global positioning problem is given in Table 2. The algorithm has no information about the accurate MU location at the beginning. Thus, it has to resolve the location ambiguity and converge to the true position of the MU 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 (line 26).

As depicted in Table 2, the algorithm is initialized by setting both the traveled distance as measured by the IMU ($trvld\_dist$) and $Mode$ (global positioning mode) to zero (line 2). Inputs (line 3) are: (1) The prior belief distribution $Bel(s_{t-1})$ which covers the whole state space, i.e. $Bel(s_{t-1}) = DB_{cell-ID_t}$ where $DB_{cell-ID_t}$ is the database that contains coordinate information of locations, covered by the cell antenna that serves the MU at time t. (2) The world model, where w_j is the weight of the jth location candidate and initially equals zero. (3) The network measurement o_t, and (4) the IMU data a_{t-1}, where $trans_{t-1}$ and θ_{t-1} are, respectively, the translation and orientation in a 2D Cartesian coordinate system at time $t-1$.

The algorithm will run in the global positioning mode as long as the number of location candidates n in the belief distribution $Bel(s_{t-1})$ is greater than a certain threshold α (line 6). During this mode, the prediction and update steps will only run if the MU's travelled distance is greater than or equal to the database resolution DB_{res} in order to allow position state transition using the database (line 8). 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 (lines 15–17), which is not the case for all candidates. 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

Table 2 The global positioning algorithm

1:	Algorithm **GlobalPositioning**($Bel(s_{t-1}), a_{t-1}, o_t, m_t$)
2:	$trvld\_dist = 0$, $Mode = 0$ // Initialization, only at the first run of the algorithm
3:	// Inputs
4:	$Bel(s_{t-1}) = DB_{cell-ID_t} =< x_i, y_i >, i = 1 \ldots n$, $m_t = DB_{cell-ID_t} = < x_j, y_j, w_j >$, $j = 1...q$, $< w_j >= 0$, $o_t = cell - ID_t$, $a_{t-1} = (trans_{t-1}, \theta_{t-1})$
5:	*if* $Mode == 0$ // Global positioning mode
6:	*if* $n > \alpha$
7:	$trvld\_dist = trvld\_dist + \sqrt{(trans_{t-1} \cdot \cos\theta_{t-1})^2 + (trans_{t-1} \cdot \sin\theta_{t-1})^2}$
8:	*if* $trvld\_dist >= DB_{res}$
9:	*for* $i = 1 : n$ *do*
10:	$x_i^- = x_i + trvld\_dist \cdot \cos\theta_{t-1}$, $y_i^- = y_i + trvld\_dist \cdot \sin\theta_{t-1}$ // Prediction step
11:	*for* $j = 1 : q$ *do*
12:	$w_j = \frac{1}{\sqrt{(x_i^- - x_j)^2 + (y_i^- - y_j)^2}}$ // Update step
13:	*endfor*
14:	$< w_j >= sort(< w_j >)$ // Ascending sort
15:	*if* $(\frac{1}{w_q} \leq DB_{res})$
16:	add (x_q, y_q) to $Bel(s_t)$
17:	*endif*
18:	*endfor*
19:	$trvld\_dist = 0$
20:	*endif*
21:	*else if* $n \leq \alpha$
22:	$Mode = 1$
23:	$s_t = \left(\frac{\sum_i x_i}{n}, \frac{\sum_i y_i}{n}\right)$
24:	*endif*
25:	*else if* $Mode == 1$ // Position tracking mode
26:	**PositionTracking**($s_{t-1}, a_{t-1}, o_t, m_t$) // Table 3
27:	*endif*

α. In this very event, the updated MU position is simply estimated as the average of the remaining candidates, and $Mode$ is set to one, i.e. the algorithm is switched to the position tracking mode (lines 21–24). Note that the algorithm returns position estimates only in the position tracking mode (see Table 3), where only one position hypothesis well be tracked, i.e. n in Expression (2) equals one. The position tracking algorithm propagates the initial MU location s_{t-1} using the raw IMU data in the prediction step (line 4). In the update step, the propagated location is matched to the set of location candidates and the candidate with the minimum Euclidean distance to the location computed in the prediction step is considered as the new position of the MU (lines 5–10).

4.3 The Global Positioning at Work

In this section, solving the global positioning problem for an MU in a GSM network is described and illustrated in Fig. 1. State space, location candidates, ground truth (GPS position

Table 3 The position tracking algorithm

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

  // Inputs

  $s_{t-1} = (x_{t-1}, y_{t-1})$, $a_{t-1} = (trans_{t-1}, \theta_{t-1})$, $o_t = cell - ID_t$, $m_t = DB_{cell-ID_t} = \, < x_j, y_j, w_j >, j = 1 \ldots n, < w_j >= 0$

  $x_t^- = x_{t-1} + trans_{t-1} \cdot \cos\theta_{t-1}$, $y_t^- = y_{t-1} + trans_{t-1} \cdot \sin\theta_{t-1}$ // Prediction step

  $for j = 1 : n do$

    $w_j = \frac{1}{\sqrt{(x_t^- - x_j)^2 + (y_t^- - y_j)^2}}$ // Update step

  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 $w_n = \max < w_j >$

return(s_t)

fix) and position estimation (when available) are depicted in asterisks, circles, diamond and solid pentagram, respectively. At start, the MU location is not known and the algorithm has to handle all probable locations. Therefore, location candidates cover the whole state space (Fig. 1a). After ~ 27 m of motion, many location candidates have been considered improbable and thus have fallen out of consideration (Fig. 1b). After another 38 m of movement, all possible location candidates have been concentrated on two parallel streets (Fig. 1c). The number of candidates has further decreased after another 13 m (Fig. 1d). The location belief has almost converged to the true MU position as in Fig. 1e. Figure 1f shows how the MU location ambiguity has been resolved after a total movement of about 145 m with a position estimate error of ~ 16 m.

5 Motion and World Models

5.1 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

$$x_t = x_{t-1} + trans_{t-1}.\cos\theta_{t-1}, \tag{3}$$

$$y_t = y_{t-1} + trans_{t-1}.\sin\theta_{t-1}. \tag{4}$$

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

$$trans_{t-1}^{noisy} = trans_{t-1} + \zeta_{trans}, \tag{5}$$

$$\theta_{t-1}^{noisy} = \theta_{t-1} + \zeta_{orient} \tag{6}$$

and

$$\zeta_{trans} = N(trans_{t-1}, \sigma_{trans}), \tag{7}$$

$$\zeta_{orient} = N(0, \sigma_{orient}), \tag{8}$$

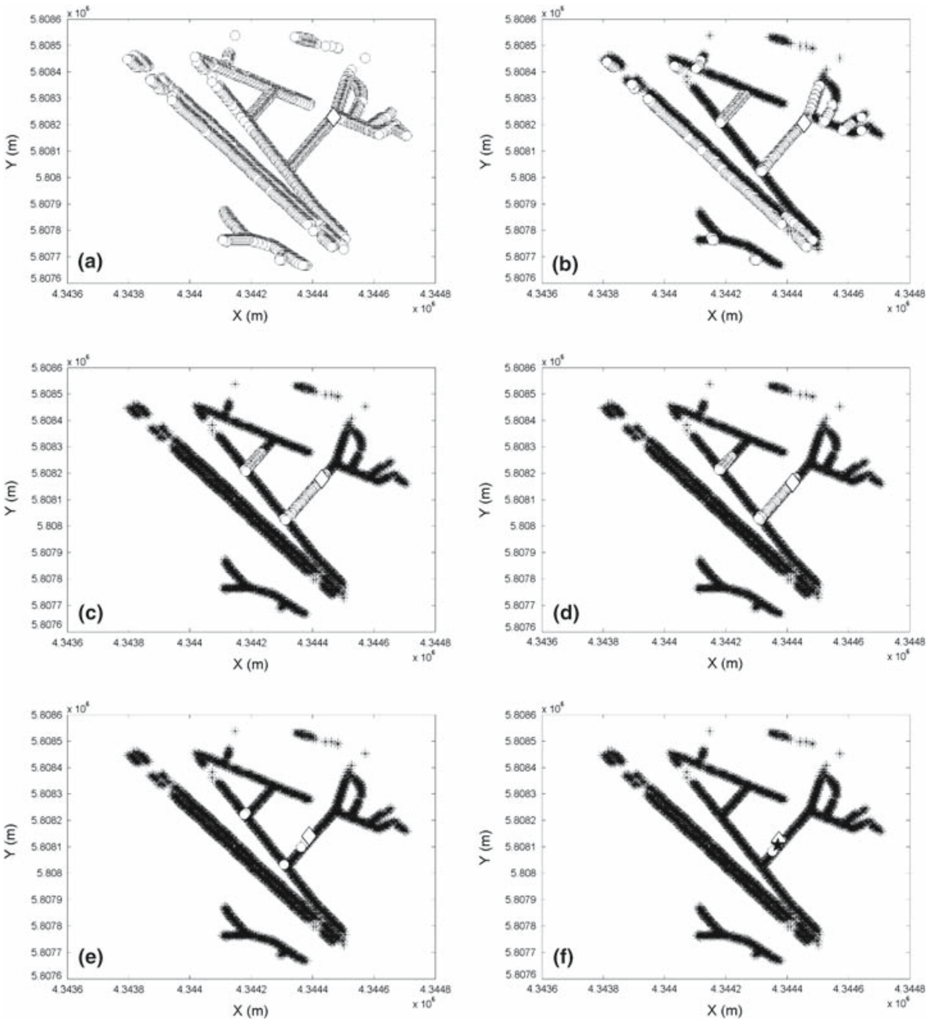

Fig. 1 Global positioning of the mobile unit

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

$$x_t = x_{t-1} + trans_{t-1}^{noisy} . \cos \theta_{t-1}^{noisy}, \tag{9}$$

$$y_t = y_{t-1} + trans_{t-1}^{noisy} . \sin \theta_{t-1}^{noisy}. \tag{10}$$

5.2 World Model

Two kinds of databases (prior information) have been utilized in this work. The first one is prediction databases of the radio profile in a test area of $9\,\mathrm{km}^2$ in Hannover, Germany.

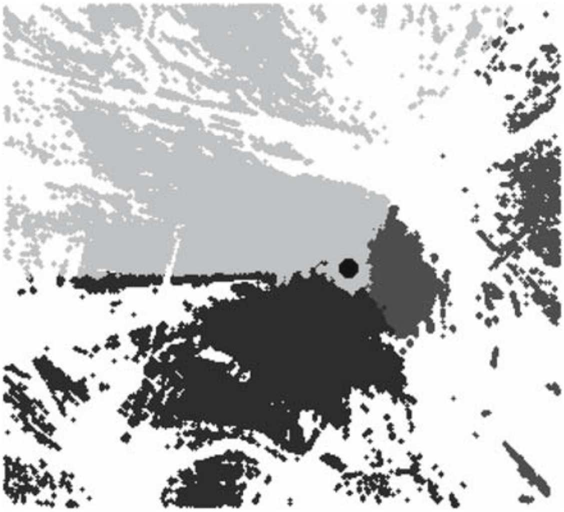

Fig. 2 Locations served by sectorized cell antennas of the same base station (solid circle)

The predicted radio profile has been constructed using a 3D deterministic radio propagation prediction model, described in [16], with a resolution of 5 m. These data have been generated to provide predictions of the average RxLev, at reference locations, from the surrounding GSM antennas at 1,800 MHz in our test area that contains six sectorized cells and four indoor antennas. This procedure is produced during the network planning stage, and is a useful source for MU positioning. After several pre-processing steps, as in [17, 18], the radio profile data was subdivided into separate databases, in each are locations served by a certain cell antenna as illustrated in Fig. 2.

The second kind is a digital map of the area, stored in form of databases containing coordinate information of different land features. These information are generated from satellite images with a resolution of 30 cm, see Fig. 3. The different features, e.g. water, green, building, road, etc. are discriminated using different colours.

Because the goal of this work was to introduce an alternative to GPS pedestrian positioning, we have extracted outdoor locations in which a walking person might exist and correlated their coordinates to the radio profile prediction databases. The result is a collection of pedestrian outdoor location databases (or maps) divided according to the GSM antennas' radio coverage in the experimental area (Fig. 4). These databases (route-radio maps) are used as world models in the update step of our proposed localization algorithms (Tables 2, 3).

6 Experiments and Results

6.1 Experimental Setup

A measurement campaign has been carried out in an E-Plus GSM 1,800 MHz network by a pedestrian along a route of about 1,940 m long. RxLev measurements of the serving base stations and up to six neighbouring 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, refer to Eqs. (5) and (6), so that the feasibility of a real IMU employment could be investigated.

Fig. 3 Digital map of the experimentation area

Fig. 4 Outdoor positions categorized after radio coverage of sectorized cell antennas

6.2 Numerical Results

In the experiments we have investigated the percentage of successful global positioning for the different values of σ_{trans} and σ_{orient}. We consider the global positioning is successfully achieved if the location estimation error just before switching to the position tracking mode is not > 50 m, so that location estimation errors could be bounded and compensated in run of the MU movements. All experiments have been repeated 100 times in order to get reasonable results. As shown in Fig. 5, the achieved successful global positioning 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 calculations insensitive to the range of translation errors assumed. Moreover, there is a slight tendency to increase the possibility of successful global positioning with increasing σ_{trans} especially when σ_{orient} also increases, which seams counter intuitive. However, the fact is that large

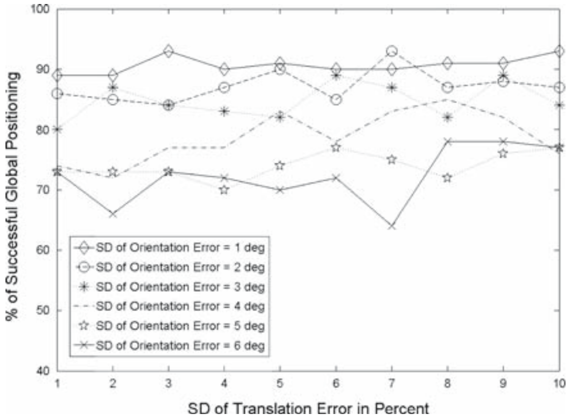

Fig. 5 Results of successful global positioning with varying standard deviations of IMU translation and orientation

Table 4 Mean, 67 and 95% position estimation errors

Mean error	67% Error	95% Error
15–20 m	14–20 m	52–56 m

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.

Table 4 summarizes location estimation errors after successful global positioning of the MU. 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 claim for the proposed localization method as a reliable alternative for GPS navigation signals. The 67 and 95 percentiles positioning errors are almost always not $>$ 20 and 56 m, respectively.

7 Conclusions and Future Work

In this paper, a novel GPS-free global positioning method for mobile units in outdoor wireless environment has been developed. The proposed algorithm is a Bayesian filtering approach that utilizes inertial measurements, cell-ID of serving base station, and pre-determined route-radio maps. The investigated positioning accuracy is quite enough for most location-aware applications. Results thus confirm the potential of using IMU for reliable GPS-free localization, though we will need IMU hardware integration. The presented technique can also be applied in indoor environments and for vehicle navigation.

Increasing the reliability of the global positioning algorithm is a topic for future work. This will be achieved by analysing the behaviour of the algorithm when the MU position is incorrectly estimated. Results should help to develop mechanisms that will recognize and handle such occurrences.

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