Accurate GPS-free Positioning of Mobile Units in Wireless Networks

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BIOGRAPHIES

Mohamed Khalaf-Allah received the MSc in computer engineering from the Leibniz University of Hannover, Germany, in September 2004. After his master thesis, he joined the Institute of Communications Engineering, Group of Positioning and Location-based Services also at the Leibniz University of Hannover, where he is now working towards his PhD thesis in the field of mobile positioning in wireless networks. The research interests of Mr. Khalaf-Allah include positioning and tracking technologies, data fusion and filtering techniques. He has also worked as a consulting engineer for an automotive competence center in the field of GPS/INS vehicle navigation. Mr. Khalaf-Allah is a member of IEEE and VDE (German Association for Electrical, Electronic & Information Technologies).

Dr. Kyandoghere Kyamakya obtained his master of science (Ingénieur Civil) in Electrical Engineering at the University of Kinshasa in 1990. In 1999 he completed his doctorate in Electrical Engineering at the Fernuniversität Hagen in Germany. He then spent two years of postdoc research at the Leibniz University of Hannover in the field of “Mobility Management in Wireless Networks and Location Based Services”. From October 2002 to October 2005 he occupied a junior professorship for “Positioning and Location Based Services”, also at the Leibniz University of Hannover. Since October 2005 he is full professor for “Transportation Informatics” and head of the Department for Smart System-Technologies at the Alpen-Adria University of Klagenfurt.

ABSTRACT

Dead reckoning (DR) via direction and distance could provide an accurate way of maintaining location information for mobile units (MUs) 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 MU 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 were 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 unit 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 MU 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 MU to the operator network.

The objective of this paper is to investigate the feasibility of MU location using simulated IMU raw data with cell-ID and geographical map information. We examine this concept by fusing the simulated IMU data with real-world cell-id information from a working GSM network and map-matching in order to achieve MU outdoor position tracking and global localization with accuracy comparable to GPS location information. Radio maps generated by radio propagation prediction tools are used off-line to determine pedestrian areas covered by every cell antenna in our test environment. The 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 technique with algorithm listings and a working example. Sections 3 and 4 discuss the motion and world models utilized in our work respectively. Experimental results are provided in section 5. Conclusion and suggestions for further developments are given in section 6.

2. 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 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 base station (BS), and the model of the world. The RBF is stated mathematically as

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

Where $Bel(s_t)$ is the posterior belief over the MU position s_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 $p(o_t \mid s_t, m)$ is the likelihood of the measurement or observation o_t of the serving cell-ID at time t given the current MU position s_t and the world model m. It is also known as the *observation model*. $p(s_t \mid s_{t-1}, a_{t-1}, m)$ 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 [4].

Table 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 MU 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) = Σ[ p(s_t | s_{t-1}, a_{t-1}, m) · Bel(s_{t-1}) ]
    Update Step
      Bel(s_t) = η · p(o_t | s_t, m) · Bel^-(s_t)
  endfor
  return( Bel(s_t) )
```

Table 1: The generic recursive Bayesian filter.

Equation (1) cannot be directly implemented on a digital computer. However, nonparametric filters [3] 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

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

Where $s^{(i)}$ is the *i*-th MU location candidate and $w^{(i)}$ is its weight.

2.2. POSITION TRACKING ALGORITHM

During position tracking, the algorithm is designed to propagate the initial MU 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 MU 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 MU. This procedure is described in Table 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 MU at time t, and w_j is the weight of location candidate j. Note that the proposed position tracking algorithm updates only one position hypothesis, i.e. n in expression (2) equals 1.

Algorithm **PositionTracking**($s_{t-1}, a_{t-1}, o_t, m_t$)
// Initialization
$s_{t-1} = (x_{t-1}, y_{t-1})$, $a_{t-1} = (trans_{t-1}, \theta_{t-1})$, $o_t = cell-ID_t$, $\eta = 0$
$m_t = DB_{cell-ID_t} =< x_j, y_j, w_j >, j = 1...n$, $< w_j >= 0$
<u>Prediction Step</u>
$x_t^- = x_{t-1} + trans_{t-1} \cdot \cos\theta_{t-1}$
$y_t^- = y_{t-1} + trans_{t-1} \cdot \sin\theta_{t-1}$
<u>Update Step</u>
for $j = 1:n$ *do*
$$w_j = \frac{1}{\sqrt{(x_t^- - x_j)^2 + (y_t^- - y_j)^2}}$$
$\eta = \eta + w_i$ // Optional
endfor
for $j = 1:n$ *do*
$w_j = \frac{w_j}{\eta}$ // Normalize weights (optional).
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 $w_n = \max < w_j >$

Table 2: The position tracking function.

2.3. GLOBAL LOCALIZATION ALGORITHM

Unlike position tracking, the global localization algorithm has no information about the accurate MU position 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 discussed in 2.2.

As depicted in Table 3, the global localization mode will run as long as the number of location candidates n is greater than a certain threshold α . During this mode, the prediction and update steps will only run if the MU'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 MU position is simply estimated as the average of the remaining candidates, and the algorithm is switched to the position tracking mode already described in Table 2. Note that the algorithm returns no position estimates in the global localization mode. First after switching to the position tracking mode, location estimates are returned at the end of every update run.

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

// Initialization

$Bel(s_{t-1}) = DB_{cell-ID_i} =< x_i, y_i >, i = 1...n$, $m_t = DB_{cell-ID_i} =< x_j, y_j, w_j >, j = 1...q$, $< w_j >= 0$, $trvld\_dist = 0$, $\eta = 0$

$a_{t-1} = (trans_{t-1}, \theta_{t-1})$, $o_t = cell - ID_t$, $Mode = 0$ // 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 $trvld\_dist >= DB_{res}$

<u>Prediction Step</u>

for $i = 1 : n$ *do*

$x_i^- = x_i + trvld\_dist \cdot \cos\theta_{t-1}$

$y_i^- = y_i + trvld\_dist \cdot \sin\theta_{t-1}$

<u>Update Step</u>

for $j = 1 : q$ *do*

$$w_j = \frac{1}{\sqrt{(x_i^- - x_j)^2 + (y_i^- - y_j)^2}}$$

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 $n \le \alpha$

$Mode = 1$

$$s_t = (\frac{\sum_i x_i}{n}, \frac{\sum_i y_i}{n})$$

endif

else if $Mode == 1$ // Position tracking mode

PositionTracking($s_{t-1}, a_{t-1}, o_t, m_t$) // Table 2

endif

Table 3: The global localization function

2.4. AN EXAMPLE COURSE OF THE MOBILE UNIT GLOBAL LOCALIZATION

In this section, solving the global localization problem for a mobile unit in a GSM network in described and illustrated in Figure 1. Location candidates, ground truth, and position estimation (when available) are depicted in green, red, and black respectively. At start, the MU location is not known and the algorithm has to handle all probable locations (Figure 1a). After approximately 27 m of motion, many location candidates have been considered improbable and hence have fallen out of consideration (Figure 1b). After another 38 m of movement, all possible location candidates have been concentrated on two parallel streets (Figure 1c). The number of candidates has further decreased after another 13 m (Figure 1d). The location belief has almost converged to the true MU position as in Figure 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 approximately 16 m.

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

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

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

To investigate the feasibility of IMU raw data we have generated IMU measurements with added noise as

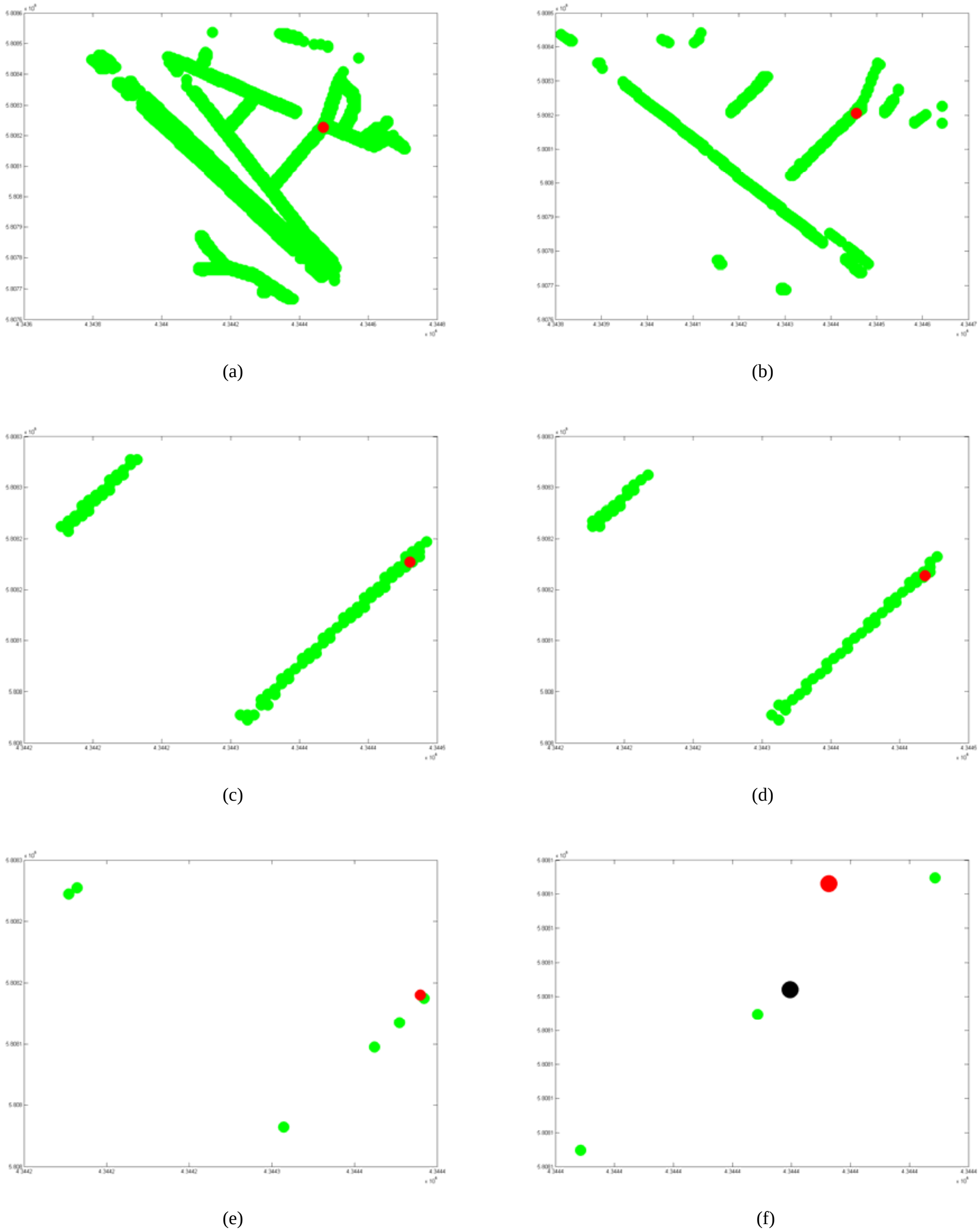
$$trans_{t-1}^{noisy} = trans_{t-1} + randn \cdot \sigma_{trans} \cdot trans_{t-1} \tag{5}$$

$$\theta_{t-1}^{noisy} = \theta_{t-1} + randn \cdot \sigma_{orient} \tag{6}$$

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

$$x_t = x_{t-1} + trans_{t-1}^{noisy}.\cos\theta_{t-1}^{noisy} \tag{7}$$

$$y_t = y_{t-1} + trans_{t-1}^{noisy}.\sin\theta_{t-1}^{noisy} \tag{8}$$



(a) (b)

(c) (d)

(e) (f)

Figure 1: Global localization of the mobile unit using the proposed algorithm

4. 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 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 MU positioning. After several pre-processing 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 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 Figure 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 a backup or 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 divided according to the GSM antennas' radio coverage in the experimental area (Figure 4). These databases are used in the update step of our proposed localization algorithm (Tables 2 and 3).

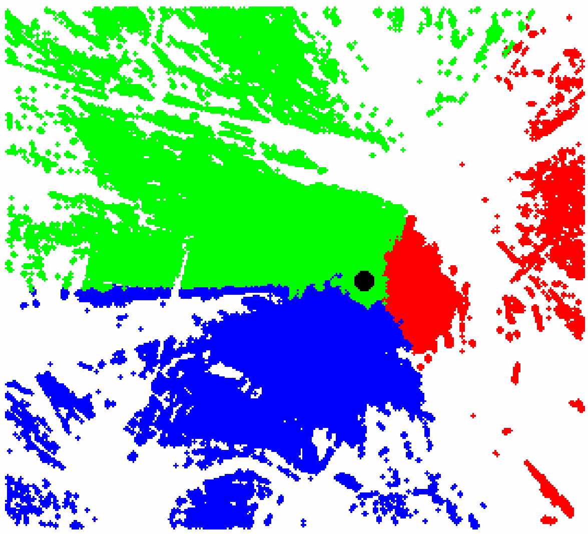


Figure 2: Locations served by three sectors of the same base station (black dot).

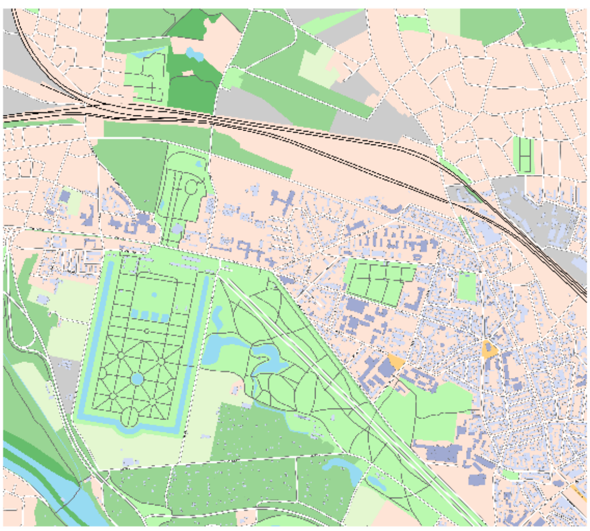


Figure 3: Digital map of the experimental area.

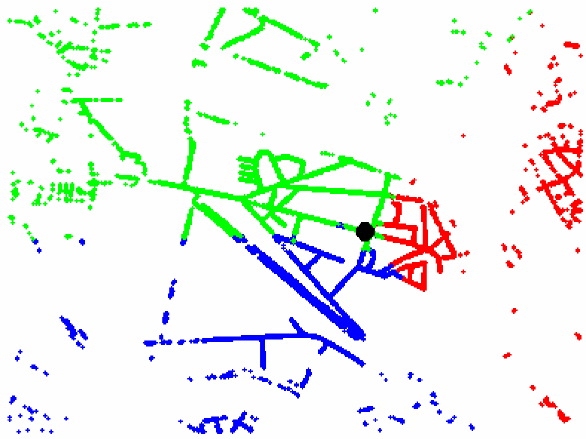


Figure 4: Outdoor locations categorized after radio coverage of sector cells.

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 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 equations (5) and (6), so that the feasibility of a real IMU employment could be investigated.

5.2. RESULTS

Within position tracking experiments the initial location of the MU 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 *positioning errors* in meters. We consider the MU's position is successfully tracked if the final position estimate over the whole experiment route of 1940 m is not greater than 50 m away from the true MU location. All experiments have been repeated 100 times in order to get reasonable results. It can be seen in Figure 5, as expected, that the higher σ_{trans} and/or σ_{orient} are, the lower the probability of successful tracking of the MU's location 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 the cases are successfully tracked. When σ_{orient} is increased up to 5°, successful tracking is achieved at least 60% of all repeats even with the worst case of σ_{trans}. For σ_{orient} equals 6°, the percentage of successful tracking drops below 60% as σ_{trans} is over 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}.

Figure 6 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. The 67 percentile positioning error is always less than 20 m for all cases as illustrated in Figure 7. Figure 8 depicts the 95 percentile position tracking error which is almost always between 52 and 56 m and less than 62 m in the worst cases.

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 Figure 9, 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.

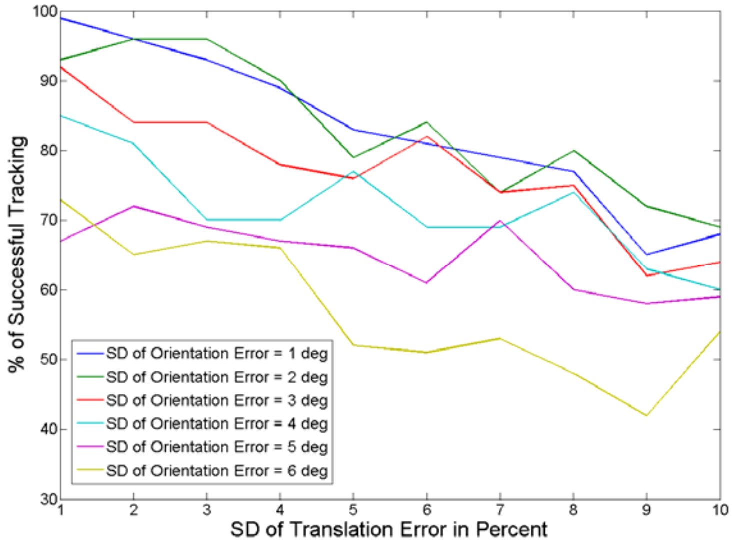


Figure 5: Percentage of successful position tracking with varying standard deviations of IMU translation and orientation.

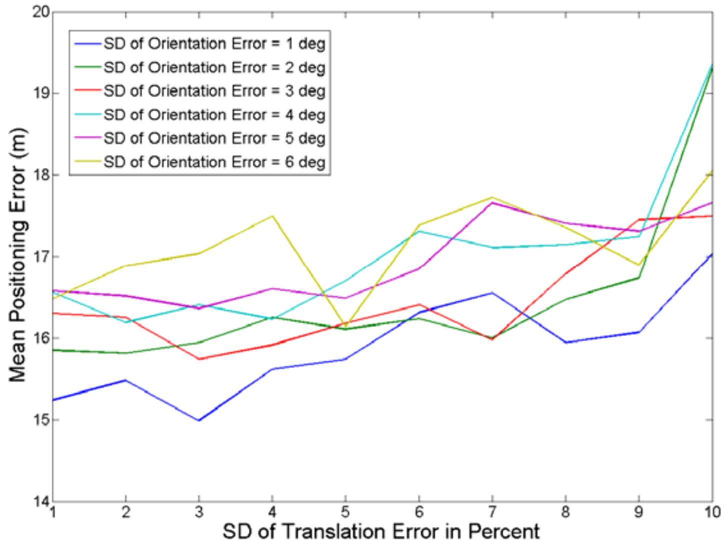


Figure 6: Mean position tracking error.

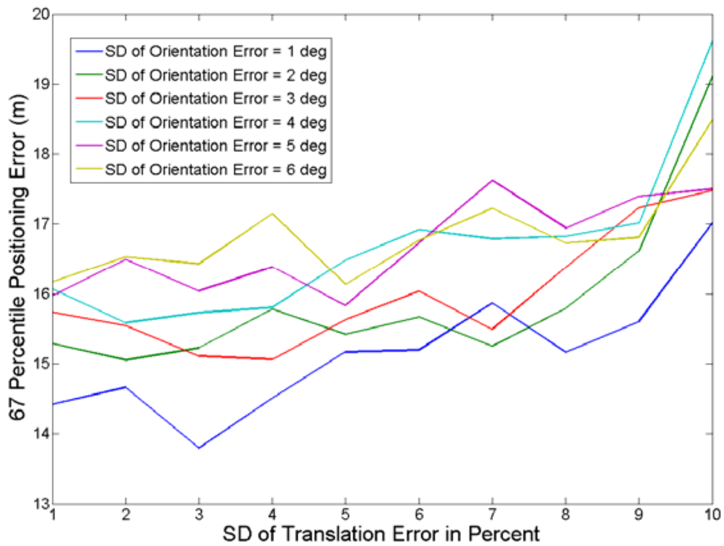


Figure 7: 67 percentile position tracking error.

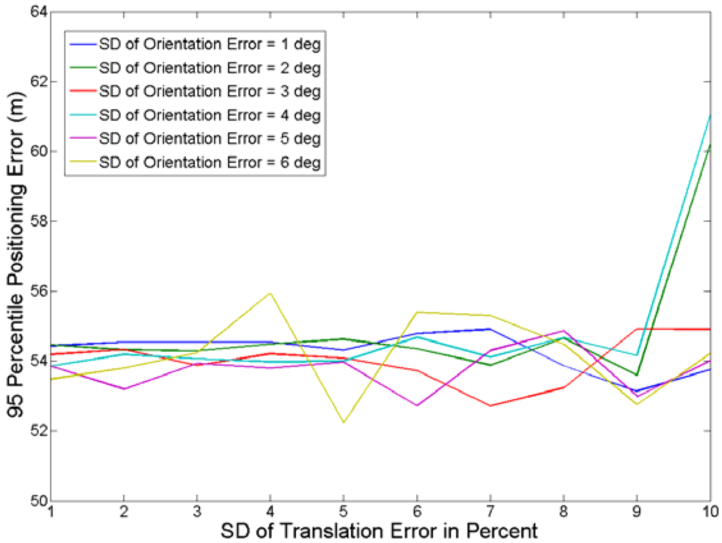


Figure 8: 95 percentile position tracking error.

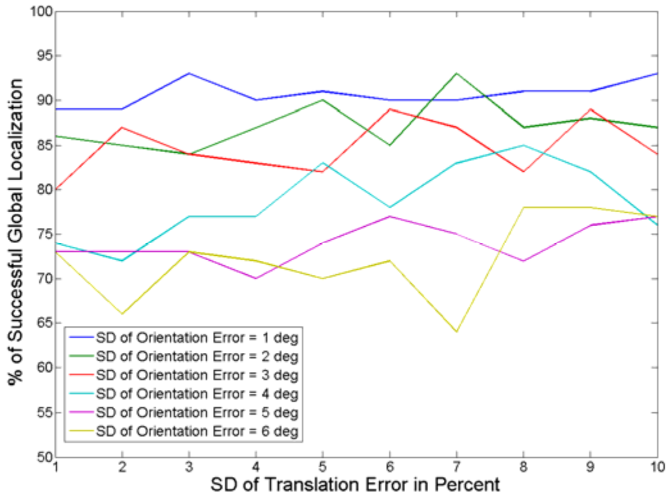


Figure 9: Percentage of successful global localization with varying standard deviations of IMU translation and orientation.

6. CONCLUSION AND FURTHER WORK

In this paper we presented techniques based on simulated IMU raw data to maintain location information for MUs in case of GPS outage. Moreover, we introduced a novel technique to find the position of a MU without any prior information, in the discrete recursive Bayesian filtering framework, 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 use real IMU data to verify and validate the proposed approach.

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