APPLICATION AND PERFORMANCE OF JOINT COOPERATIVE CELL-ID LOCALIZATION AND ROBUST MAP MATCHING

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ABSTRACT

In this paper two extensions to the well known Cell-ID localization technique for handsets in mobile cellular networks are presented: It is firstly shown how the combination of multiple cross-provider Cell-IDs, which may become available from cooperation of one-hop neighbours in mobile adhoc networks (MANETs) or from Dual SIM mobiles phones, can be used to improve the positioning accuracy. Secondly, a robust map matching algorithm for Cell-ID localization is presented. The proposed map matching algorithm is termed robust, as it is capable of dealing with the - compared to GPS - more coarse Cell-ID based position estimates. An implementation of a localization system based on these methods shows, that the positioning accuracy can be significantly improved compared to the simple single Cell-ID technique.

1. INTRODUCTION

There is a rapid development in the area of personal mobile communications: Mobile phones are becoming smart phones, in that they are integrated with features like high-resolution displays, wireless connectivity (802.11x, bluetooth,...), different kinds of sensors and localization technology. The integration of these features will enable the broader evolution of already established and of new location based services (LBS) based on mobile handsets. The key to LBS is the location awareness of the mobile device; and the obvious technology for this purpose seems to be the GPS technology.

A closer look however reveals that GPS is not necessarily the best choice for every kind of LBS. A major drawback of GPS in context of LBS is that GPS usually requires a line-of-sight (LOS) to the satellites. This LOS requirement, however, may be contradicted by the typical use case of a LBS, where the user shall get notified about the occurrence of a certain location triggered event ("pushed LBS") and where the user therefore typically does not carry his device to maintain LOS conditions, but carries it in her/his pocket, backpack or in some case in a car. Thus, for these kinds of services, the user-time coverage is the critical point. In fact it has been shown that a typical user-time coverage of GPS can be below 5% in worst case [1]. In this use case the adoption of GPS would therefore not be preferred, because it makes the usage of the LBS inconvenient or even impossible for the user. A second critical point is the power consumption of the GPS receiver. Using it to constantly track the mobile's position will reduce the battery life time of the mobile device. Finally it should be noticed, that the high positioning accuracy that GPS provides – and which is indeed inevitable for e.g. navigation and routing applications – is not required for every kind of LBS. There are LBS which can be adopted with much lower accuracy. Examples [2, 3] include social and infotainment applications (for example "notification about nearby friends"), service applications (show points of interest on a local map) or commercial applications (location based advertising, traffic analysis).

The conclusion from these considerations is, that for LBS, where GPS-like accuracy is not absolutely required and where user-time coverage is more important, GPS should be replaced by a localization technology which is not dependent on LOS conditions and which is less power consuming. In order to make the adoption of the technology straightforward it is also desirable to avoid intrusive software or hardware changes on the mobile phone platform. These considerations suggest cellular based localization. Cellular based localization includes geometric approaches [4] based on received signal strength (RSS), time-of-arrival (TOA), time-difference-of-arrival (TDOA) or angle-of-arrival (AOA), as well as fingerprint methods [5], which use location dependent fingerprints. While these methods can achieve reasonable accuracy, they all require the access to baseband measurements, which, however, is usually not available to the application developer on most smartphone platforms. An information that can usually be obtained easily is the Cell-ID, the information about the base transceiver station (BTS), the phone is currently connected to.

Cell-ID localization means in the simplest case to estimate the position of the mobile phone as the position of the connected BTS [6]. Its accuracy therefore directly correlates to the cell size of the current BTS and makes it the most inaccurate among the cellular based localization approaches, while being the only approach which is easy to implement across different mobile platforms.

In this paper we analyze two approaches to increase the accuracy of Cell-ID localization. The first approach is the usage of multiple cross-provider Cell-IDs instead of only one Cell-ID. As an example, additional Cell-IDs can become available by means of cooperation effects in already established MANETs, where a mobile phone collects the Cell-IDs from those one-hop neighbours, that are connected to different service providers[7]. Only one-hop neighbours are considered, because the distance between those is limited by the physical communication range and can be assumed to be smaller than or in the order of the expected localization accuracy. Another example would be dual-SIM mobile phones, which are equipped with two simultaneously active SIM cards, so that the mobile phone can be registered to two different service providers at the same time. The second approach is the inclusion of map matching into the localization algorithm. The map matching algorithm is based on matching a set of possible position candidates for each raw position estimate. In order to select the best candidate from each set, metrics, which depend on topological and geometric evaluation of previous and current position estimates, are assigned to each candidate. Using these metrics, sequences of "on street" positions can be constructed, which show an increased positioning accuracy. The developed map matching algorithm differs from traditional approaches, in that it is capable of dealing with less accurate raw position estimates and it is therefore considered as a robust map matching algorithm.

This paper is organized as follows: In section 2.1 background on Cell-ID localization is presented followed by the proposed cross-provider Cell-ID algorithm in Section 2.2. Section 3 starts with a brief introduction to map matching and then presents the developed map matching algorithm. Results from field tests are presented in Section 4 and conclusions are drawn in Section 5.

2. CROSS-PROVIDER CELL-ID LOCALIZATION

2.1 Cell-ID localization

The simplest method among cellular based localization methods is the Cell-ID method: The position of the mobile terminal is estimated as the position of its currently serving BTS. As it only requires the extraction of the Cell-ID and the knowledge about the location of the BTS, it is easy to implement on common smartphone platforms and does not require any intrusive software changes. Its drawback however is the accuracy, which is lower than that of range-, direction- or fingerprint-based methods. The accuracy directly depends on the cell size, which may vary depending on the environment from a few hundred meters up to $20-25km$. It should be noted that in context of localization for LBS, which typically takes place in urban, suburban or highway scenarios, the cell size is at most in range of a few kilometers, usually much smaller. Another point that degrades the performance is the fact that the mobile phone is not necessarily always connected to its closest BTS [6].

It is well-known that incorporation of multiple connectivity informations can increase positioning accuracy. In the following section we thus analyze how cross-provider connectivity information, i.e. multiple Cell-IDs from different providers, can be used to improve the positioning performance. The resulting range-free, handset-based algorithm is formulated in terms of a Kalman filter.

2.2 Cross-provider Cell-ID localization

Assume a mobile terminal at position $(x(i),\ y(i))$ with velocity $(v_x(i),\ v_y(i))$, which has access to N Cell-IDs from different BTS at locations $(x_{BTS,j},\ y_{BTS,j})$, $j = 1 \dots N$. A state space model is then formulated as

$$\begin{aligned} \mathbf{x}(i) &= \mathbf{\Phi}\mathbf{x}(i-1) + \mathbf{\Theta}\mathbf{w}(i), && (1)\\ \mathbf{y}(i) &= \mathbf{H}\mathbf{x}(i) + \mathbf{n}(i), && (2) \end{aligned}$$

where the vectors $\mathbf{x}(i) = [x(i),\ y(i), v_x(i),\ v_y(i)]^T$ and $\mathbf{y}(i) = [x_{BTS,1}(i), \dots x_{BTS,N}(i),\ y_{BTS,1}(i), \dots y_{BTS,N}(i)]^T$ denote position and velocity of the terminal and positions of the BTS at time instant i. The transition matrix $\mathbf{\Phi}$ and the measurement matrix $\mathbf{H}$ are given as

$$\mathbf{\Phi} = \begin{bmatrix} 1 & 0 & \Delta t & 0 \\ 0 & 1 & 0 & \Delta t \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}, \mathbf{H} = \begin{bmatrix} \mathbf{e}_N & \mathbf{0}_{N\times 1} & \mathbf{0}_{N\times 2} \\ \mathbf{0}_{N\times 1} & \mathbf{e}_N & \mathbf{0}_{N\times 2} \end{bmatrix},$$

where Δt is the sampling time and $\mathbf{e}_N$ is the column vector consisting of N ones. The scrambler matrix $\mathbf{\Theta}$ incorporates the sampling time into the velocity noise $\mathbf{w}(i) = [w_x(i) w_y(i)]^T$,

$$\mathbf{\Theta} = \begin{bmatrix} \multicolumn{2}{c}{\mathbf{0}_{2\times 2}} \\ \Delta t & 0 \\ 0 & \Delta t \end{bmatrix},$$

so that the process covariance is given as $\mathbf{Q} = \mathbf{\Theta} E\{\mathbf{w}(i)\mathbf{w}^T(i)\}\mathbf{\Theta}^T$. The measurement covariance is taken as $\mathbf{R}(i) = E\{\mathbf{n}(i)\mathbf{n}^T(i)\}$. Given this state-space model it is straightforward to apply a Kalman filter to estimate the position and velocity of the terminal. As usually there is a prediction step for the state $\mathbf{x}(i)$ and the covariance $\mathbf{P}(i)$,

$$\begin{aligned} \mathbf{P}^-(i) &= \mathbf{\Phi}\mathbf{P}^+(i-1)\mathbf{\Phi}^T + \mathbf{Q}, && (3)\\ \mathbf{x}^-(i) &= \mathbf{\Phi}\mathbf{x}^+(i-1), && (4) \end{aligned}$$

and a correction step,

$$\begin{aligned} \mathbf{K}(i) &= \mathbf{P}^-(i)\mathbf{H}^T \left(\mathbf{H}\mathbf{P}^-(i)\mathbf{H}^T + \mathbf{R}(i)\right)^{-1} && (5)\\ \mathbf{P}^+(i) &= \mathbf{P}^-(i) - \mathbf{K}(i)\mathbf{H}\mathbf{P}^-(i) && (6)\\ \mathbf{x}^+(i) &= \mathbf{x}^-(i) + \mathbf{K}(i)\left(\mathbf{y}(i) - \mathbf{H}\mathbf{x}^-(i)\right), && (7) \end{aligned}$$

where $\mathbf{K}(i)$ is the Kalman gain. Estimated position and velocity are given as the a posteriori state estimate $\mathbf{x}^+(i)$.

The process and measurement covariances are written as

$$\mathbf{Q} = \Delta t^2 \sigma^2 \begin{bmatrix} \mathbf{0}_{2\times 2} & \mathbf{0}_{2\times 2} \\ \mathbf{0}_{2\times 2} & \mathbf{I}_{2\times 2} \end{bmatrix}, \mathbf{R}(i) = \begin{bmatrix} \mathbf{R}'(i) & \mathbf{0}_{2\times 2} \\ \mathbf{0}_{2\times 2} & \mathbf{R}'(i) \end{bmatrix},$$

where $\mathbf{R}'(i) = \mathrm{diag}(r_1^2(i), \dots, r_j^2(i), \dots r_N^2(i))$. The process variance σ^2 is a design parameter, which controls the smoothing of the state estimation; for the measurement variances the squared cell size is used, where the cells are assumed to have circular shape around the BTS. As we only know the positions of the BTS and the sizes are generally unknown, we approximate the $r_j(i)$ as half of the distance between the current and the previously connected BTS. Although both this approximation and the circular cell size assumption are certainly quite coarse, our experiments showed that they improve the filter's performance in case of small cells (urban scenario) compared to choosing all $r_j(i)$ identically. For larger cell sizes (suburban and highway scenarios) the improvement is only marginal.

To justify that the choice of state space model and Kalman filter are reasonable, it is instructive to analyze how the filter behaves in case the modeling of the mobile's dynamics is dropped. Thus setting $\sigma^2 \to \infty$ and starting with an arbitrary $\mathbf{P}^+(0) = \mathbf{I}$, at time instant $i = 1$, the predicted state covariance becomes $\mathbf{P}^-(1) = \mathbf{Q}$. Putting this into (5) and (6) results in

$$\begin{aligned} \mathbf{K}(1) &= \left(\mathbf{H}^T\mathbf{R}^{-1}(1)\mathbf{H}\right)^{-1}\mathbf{H}^T\mathbf{R}^{-1}(1) \text{ and}\\ \mathbf{P}^+(1) &= \left(\mathbf{I} - \mathbf{K}(1)\mathbf{H}\right)\mathbf{P}^-(1)\\ &= \left(\mathbf{I} - \left(\mathbf{H}^T\mathbf{R}^{-1}(1)\mathbf{H}\right)^{-1}\mathbf{H}^T\mathbf{R}^{-1}(1)\mathbf{H}\right)\mathbf{P}^-(1)\\ &= \mathbf{0}, \end{aligned}$$

where the identity

$$\begin{aligned} \mathbf{K}(i) &= \mathbf{P}^-(i)\mathbf{H}^T\left(\mathbf{H}\mathbf{P}^-(i)\mathbf{H}^T + \mathbf{R}(i)\right)^{-1}\\ &= \left(\mathbf{H}^T\mathbf{R}^{-1}(i)\mathbf{H} + (\mathbf{P}^-(i))^{-1}\right)^{-1}\mathbf{H}^T\mathbf{R}^{-1}(i) \end{aligned}$$

has been used. For all consecutive steps, $i \to \infty$, it holds $\mathbf{K}(\infty) = \mathbf{K}(1)$ and (7) becomes

$$\begin{aligned} \mathbf{x}^+(i) &= \mathbf{x}^-(i) + \mathbf{K}(\infty)\left(\mathbf{y}(i) - \mathbf{H}\mathbf{x}^-(i)\right)\\ &= \left(\mathbf{H}^T\mathbf{R}^{-1}(i)\mathbf{H}\right)^{-1}\mathbf{H}^T\mathbf{R}^{-1}(i)\mathbf{y}(i). && (8) \end{aligned}$$

It is now easy to see that (8) is the generalized least squares estimator with weighting matrix $\mathbf{R}^{-1}(i)$, thus it is also the best linear unbiased estimator.

The structure of $\mathbf{H}$ allows further simplification of (8) to

$$\mathbf{x}^{+}(i) = \begin{bmatrix} \frac{1}{\sum_{j=1}^{N} r_j^{-2}(i)} \sum_{j=1}^{N} r_j^{-2}(i)\ x_{BTS,j}(i) \\ \frac{1}{\sum_{j=1}^{N} r_j^{-2}(i)} \sum_{j=1}^{N} r_j^{-2}(i)\ y_{BTS,j}(i) \\ \mathbf{0}_{2\times 1} \end{bmatrix}$$

and it can be seen that the filter reduces to a weighted centroid algorithm in case of unmodelled dynamics. We finally note that for unknown cell radii, i.e. setting all $r_j^2(i)$ identical, it further simplifies to the well known centroid algorithm ([8, 9]):

$$\mathbf{x}^{+}(i) = \left[\frac{1}{N} \sum_{j=1}^{N} x_{BTS,j}(i),\ \frac{1}{N} \sum_{j=1}^{N} y_{BTS,j}(i),\ \mathbf{0}_{2\times 1}^{T} \right]^{T}$$

Thus the proposed algorithm is essentially a weighted centroid algorithm, but extended by a motion prediction model.

3. ROBUST MAP MATCHING

3.1 Overview

The Kalman filter delivers raw position estimates based on the available Cell-IDs. As it usually can be assumed, that the user moves on streets, whether be it in a vehicle or by foot, we can use street map data to introduce a constraint on the raw positions and to improve the positioning accuracy. This task is called map matching.

In general, map matching[10] is the problem of finding the best path on street for a given series of position estimates. It is limited by the inaccuracy of the raw position estimates and street map data. In a map matching algorithm usually three steps are involved: In the first step a candidate set of possible street segments or street trajectories is identified using the data delivered by the position estimator; these data include the raw position itself and optionally confidence, direction or velocity informations. The second step consists in finding the best of the candidates. This can be accomplished for example by using geometric, topological or probabilistic [10, 11, 12] measures. The final position estimate is found by projecting the raw position to the selected street segment. For a more detailed overview on map matching techniques, the reader is referred to [13].

When considering the application of map matching to Cell-ID localization, it is first of all important to realize that most work in the field of map matching is tailored to GPS localization and that there are major differences between the quality of GPS and Cell-ID-based position estimation: Firstly the positioning accuracy of Cell-ID localization is lower. Secondly, the GPS error is known to be correlated in time [14], i.e. it is possible to construct reasonable trajectories from series of position estimates even if the positions themself are less accurate. For the Cell-ID algorithm used in this work, the position estimates are only slightly correlated, depending on the choice of the Kalman filter's process variance σ^2. That means, similarity metrics based on estimated trajectories can hardly be used and, additionally, the estimated headings and velocities are coarse. Therefore, the map matching algorithm presented in this paper puts less focus on the distance of the map matched position estimates to the raw estimates. Instead, the objective is to construct a reasonable, shortest route with respect to estimated positions and topological measures. Estimated velocity and heading are only used for a very coarse prefiltering in some cases. The following section describes the proposed algorithm.

3.2 Algorithm

Given the a posteriori state estimate of the Kalman filter as input data, the map matching algorithm at each time instant i consists of the following three steps:

1. Identify a candidate set of size L with possible matched points on street.
2. Assign a metric $M_j(i)$ to each candidate $j = 1 \dots L$.
3. Find the candidate with minimum metric and select its predecessor at time instant $i - \tau$ as final matched point.

The steps are described in detail in the following:

3.2.1 Candidate set

The candidate set $C(i)$ is formed by generating L perpendicular projections of the raw position estimate to segments of the street network. The candidate points have to meet two conditions:

- The distance measured on street between each pair of candidates is greater than a design parameter Δ_s, which should be selected smaller for a more dense street network.
- The direction of the corresponding street segment is $\in [\phi(i) - \Delta_\phi(i),\ \phi(i) + \Delta_\phi(i)]$, where $\phi(i)$ is the estimated direction computed from the estimated velocity components $v_x(i)$ and $v_y(i)$. The tolerance $\Delta_\phi(i)$ is adaptively assigned at each time instant as

$$\Delta_\phi(i) = \begin{cases} \Delta_\phi & \text{if } \sqrt{v_x^2(i) + v_y^2(i)} > v_T \\ \pi & \text{else,} \end{cases} \tag{9}$$

  where the correlation of higher velocity and more reliable estimated heading is used (cf. [15]): the filtering is only effective if the estimated absolute velocity is greater than a threshold v_T. As mentioned in the previous section, the velocity estimate and therefore the estimated heading $\phi(i)$ is quite coarse, because it is only based on cell transitions. So Δ_ϕ is set very conservatively to $pi/2$ in this work in urban environments. This means that the main effect of this prefiltering is to remove oneway streets and to match on the correct side of two-lane roads. In suburban and highway environment, where the accuracy of $\phi(i)$ is lower due to larger cells and less cell transitions, it is not used as it tends to remove correct street segments.

3.2.2 Metric

A metric $M_j(i)$ is assigned to each candidate point j at time instant i as follows:

a) The set of predecessors $P^j(i)$ of j is formed by those elements $p \in C(i-1)$ that can be reached from j with on-street distance $d_s^{(j,p)} < \Delta_d$.

b) For each $p \in P^j(i)$ a branch metric is computed as

$$\mu^{(j,p)} = (1 + \alpha\ r^{(p)})\ d_s^{(j,p)}, \tag{10}$$

   where α is a design parameter and $r^{(p)} \in [0,\ 1]$ is the distance of p to its corresponding raw position estimate relative to the other candidates in $C(i-1)$. This relative distance is computed as

$$r^{(p)} = \frac{d^{(p)} - d_{min}}{d_{max} - d_{min}}, \tag{11}$$

   with d_{min} and d_{max} being the minimum and maximum distances of candidate points in $C(i-1)$ to the raw estimate $(x(i-1),\ y(i-1))$ and $d^{(p)}$ the distance of p to $(x(i-1),\ y(i-1))$.

c) The metric $M_j(i)$ is computed as

$$M_j(i) = \min_p \lambda M_p(i-1) + (1-\lambda)\mu^{(j,p)}, \qquad (12)$$

where $\lambda \in [0,\ 1)$ is a design parameter. Additionally the best predecessor p_{Best} is stored for the traceback step. Thus the metric $M_j(i)$ depends on the on-street-distance between the candidate j and its best predecessor and on the relative distance of the predecessor to its raw position estimate. The parameter $\alpha \geq 0$ is used to weight between both measures; if the accuracy of the raw position estimate is expected to be lower, then a smaller value α should be used to reduce to influence of the raw position estimates in favor of constructing a shortest route through the street network. The forgetting factor λ results in an exponential window, which controls how many previous metrics have impact on the current metric. In this work $\lambda = 0.9$ has been used, which corresponds to an effective influence of about the past 9 estimates.
We note that for the special case $\alpha = 0$ and $\lambda = 1$, the algorithm would result in finding a shortest path through a graph, where the nodes and vertices are defined by the candidate points and on-street connections between candidate points of consecutive time instants, respectively.

d) Besides the metric $M_j(i)$ the number of predecessors $N_j(i)$ is used as an additional measure. For a candidate j it is computed as

$$N_j(i) = N_{p_{Best}}(i-1) + 1, \qquad (13)$$

where

$$p_{Best} = \arg\min_p \lambda M_p(i-1) + (1-\lambda)\mu^{(j,p)}. \qquad (14)$$

It can intuitively be seen, that a candidate with small $N_j(i)$ is not likely a correct point. On the other hand, in the ideal case, where the candidate set covers the true street in every time step and the parameter Δ_s is chosen large enough, it should hold that $N_j(i) = i$.

If $P^j(i)$ is found to be empty in step a), the steps b)-d) are skipped and

$$M_j(i) = \infty \text{ and } N_j(i) = 0. \qquad (15)$$

3.2.3 Select and Traceback

From all L candidates at time instant i the best one $j_{Best}(i)$ is selected as

$$j_{Best}(i) = \arg\min_j \{M_j(i) \mid N_j(i) > \Delta_p\}. \qquad (16)$$

If no candidate satisfies $N_j(i) > \Delta_p$, j_{Best} is selected as

$$j_{Best} = \arg\max_j N_j(i). \qquad (17)$$

Finally in the case where $N_j(i) = 0\ \forall\ j$ and thus no previous information can be used, j_{Best} is selected as the point with shortest distance to the raw estimate. This case should however only occur if the algorithm is (re-)initalized.

The final position estimate is given by tracing τ steps back from the j_{Best} using the best predecessor in each step, which causes a delay in the position estimate of $\Delta t \cdot \tau$. The selection of τ is thus a trade-off between robustness (larger τ) and real-time requirements.

Table 1: Summary of algorithm parameters.

	Description	Settings: Urban	Suburban	Highway
Kalman filter parameters:				
σ	Kalman process cov.	1e-10 deg/s^2		
$\mathbf{R}'(i)$	Measurement cov.	adaptive		
Δt	Sampling time	4s		
Map matching parameters:				
L	Number of Candidates	10		
Δ_ϕ	Dir. prefilter tolerance	$\pi/2$	-	-
v_T	Velocity threshold for direction prefilter	30km/h	-	-
Δ_s	Minimum distance-on-street betw. candidates	100m	200m	500m
Δ_d	Maximum on-street-distance to predecessor	1000m		
Δ_p	Required number of predecessors	9		
λ	Forgetting factor	0.9		
α	Weighting factor	2.0	1.1	1.1
τ	Traceback depth	15	7	7

4. RESULTS FROM FIELD TESTS

To assess the performance of the algorithm, field measurements using four handsets forming a WLAN-based MANET have been carried out. All four nodes were registered to different GSM network providers. During the tests, all nodes were in one vehicle which covered a distance of about 300km in urban, suburban and highway environments. This resulted in about 14k Cell ID samples. A GPS device connected to the head-node has been used to provide reference measurements. Vectorized street map data has been taken from the OpenStreetMap project; the completeness of these data has been visually verified for the considered terrain. The parameters of the algorithm are summarized in Table 1. An adaption of the terrain dependent parameters is done based on observed cell sizes.

The results are presented in Table 2, where the mean error and the 90%-error ("In 90% of the cases, the error is smaller than x.“) are given in meters for urban, suburban and highway terrain. For the cases where 2 and 4 cross-provider Cell-IDs are used, the mean error of the raw position estimate, of a simple point-to-point matching (marked as "Smpl.“), which just matches the raw position to the closest point on a street, and of the proposed robust matching algorithm ("Rob.“) are given; additionally the result of the localization based on one single Cell-ID at a time is given.

From these figures, we get the following important results:

- The positioning accuracy is improved, if the number of used cross-provider Cell-IDs is increased. It is interesting to compare this result to the results from [1], where the authors point out that the usage of multiple neighbour Cell-IDs (i.e. single-provider) does not necessarily increase the performance in all cases.
- Simple point-to-point matching does not help to improve the accuracy, as it leads to too many wrong matches.
- The proposed robust map matching algorithm, which puts more focus on finding matches on a continuous approximated shortest path, can however improve the positioning accuracy for both the 2 and 4 Cell-ID case even

Table 2: Results in terms of mean error and 90%-error in meters.

	Mean error							90% error						
No. Cells	1	2			4			1	2			4		
Algor.	Raw	Raw	Smpl.	Rob.	Raw	Smpl.	Rob.	Raw	Raw	Smpl.	Rob.	Raw	Smpl.	Rob.
Urban	**209**	158	157	145	135	132	**106**	**495**	369	354	309	340	232	**207**
Suburban	**682**	458	456	444	428	428	**386**	**1429**	870	874	931	881	875	**835**
Highway	**734**	597	600	551	556	555	**487**	**1508**	1150	1157	1109	1044	1040	**1002**

for these relatively coarse position estimates.

- The obvious fact, that the cell sizes correlate with the positioning error, is clearly also reflected in these results, where urban environment, with smallest cell size, shows the highest accuracy.

To give a visual impression of these results, Fig. 1 shows a part of the test route for the highway case. The reference GPS path is plotted along with the raw position estimates, the point-to-point matched positions and the positions resulting from the robust map matching algorithm. It can be seen, that for this part, the proposed algorithm matches all raw positions to the true path. It however also becomes clear that this does not necessarily mean, that the positioning error goes to zero: Although the right street segment is obtained, there is still "temporal shift" between these estimates and the true positions, which results in the remaining error. The reason for this is the principle of the proposed Kalman filter based algorithm, whose position estimates tend towards the centroids of the connected cells and are therefore not equally distributed.

5. CONCLUSIONS

The key to LBS is the position estimation of the user. That the GPS technology is not necessarily a feasible choice for this task and that cellular based approaches can be a suitable alternative, if user-time coverage is critical and location accuracy is less important, has been argued in this paper. For the simplest among these approaches, the Cell-ID localization, it has been shown, that significant improvements in terms of accuracy can be achieved by using multiple cross-provider connectivity data and robust map matching. Even though its lower accuracy compared to GPS, a continuous usertime coverage qualifies it for LBS in the field of e.g. social or infotainment applications.

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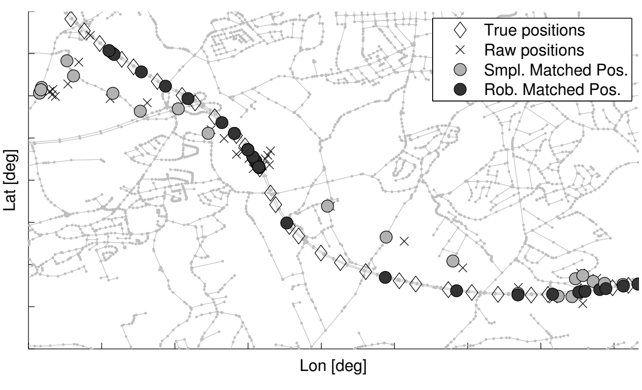

Figure 1: Part of the test route for a highway environment.

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