A Probabilistic Similarity Measure and a Non-Linear Post-Filter for Mobile Phone Positioning using GSM Signal Power Measurements

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Abstract - In this paper we present the design of a particle filter for post filtering instantaneous positioning estimates of GSM mobile terminals. The instantaneous estimates are obtained by comparing signal power levels, which are reported by the mobile terminal to the base station, with a database of predictions using a novel statistically motivated similarity measure. Unlike a simple Euclidian distance measure, the proposed scheme incorporates inherent information about signal power level measurements requested by the serving base station but not reported by the mobile terminal. Furthermore, we show how the Monte Carlo method of particle filtering helps to obtain better position estimates and, surprisingly, also helps to reduce the computational complexity. Results are presented for real field data.

1 Introduction

Location based mobile telephony services, like automatic localization of emergency calls or virtual travel guides, are predicted to have a high market potential. Also network operators could benefit from location information e.g. for location-dependent billing or enhanced hand-over strategies. In particular the regulations put forward by the FCC on enhanced emergency calls [1] have incented major research efforts to obtain precise position estimates of mobile terminals.

Whereas various other proposed localization methods like triangulation based or GPS assisted approaches, ask for extensive modifications of the network infrastructure or the mobile terminal hardware, database assisted positioning is compatible with existing mobile terminals and the GSM network infrastructure. This pattern recognition approach utilizes the location-dependency of signal parameters observed by the mobile terminal such as signal power levels of neighboring base stations, and compares the measured parameter values ("fingerprints") with those stored in a database, where every database entry consists of measured or predicted values along with the position coordinates. Additionally, database assisted positioning is applicable in the whole cellular network coverage area, even for indoor areas and in non line of sight scenarios, which normally cause problems when using triangulation based or GPS assisted approaches.

However, database assisted positioning suffers from limited accuracy. The accuracy of better than 83m in 67% given in [3] seems to be overly optimistic, since the model parameters have been optimized for the given test data. In [2] an accuracy better than 44m for 67% of all estimations has been reported. This excellent result, however, could only be achieved by exploiting map information in addition to the comparison with a database of measured signal power levels. In [4] it has been shown that the accuracy of the database approach can be improved by using robust metrics that are insensitive to variations of the measured signal power levels due to fading or shadowing. Also post filtering using a state-space model of the mobile terminal movement can significantly increase accuracy [5]. By using particle filtering for this purpose and evaluating data of wheel speed sensors within ABS units positioning accuracies similar to GPS were reported in [6].

The approach of database assisted positioning presented here is based on standard GSM system signalling. Measurement reports of signal power levels are evaluated, which are regularly transmitted in the Radio Subsystem Link Control, e.g. utilized when performing hand-overs. Taking a pattern recognition approach, these measurements are compared with a database (map) of predictions using a novel similarity measure. Then particle filtering, which belongs to the family of randomized post filtering methods, was adopted to smooth instantaneous position estimates over time. Using this approach, the probability density function (PDF) of mobile terminal positions is approximated by a set of weighted samples, the so-called particles.

In the next section we will give a brief introduction into the principle of database assisted positioning and analyze the GSM signal power level measurement procedure, from which we will derive a statistically motivated similarity measure in section . In section 4 the principle of particle filtering will be presented and we will show how it can be applied to the domain of database assisted positioning utilizing the presented similarity measure. After the presentation of experimental results, a conclusion ends this paper.

2 Database assisted Positioning

Database assisted positioning (DAP) utilizes the location dependency of signal parameters like signal power levels (SPLs). To this end, a database of location dependent parameters is required. This database contains K entries of the form

$$T_k = (\ell_k, \mathbf{s}(\ell_k)); \qquad k = 1, \dots, K. \tag{2.1}$$

ℓ_k denotes the location of the k-th entry in 2D coordinates and $\mathbf{s}(\ell_k)$ is a vector of signal parameters if the object of interest is located at ℓ_k.

Positioning is carried out by comparing the measurement vector $\boldsymbol{\gamma}'(n)$, where n denotes the discrete time, with all parameters $\mathbf{s}(\ell_k)$ stored in the database using a similarity measure $d(\boldsymbol{\gamma}'(n), \mathbf{s}(\ell_k))$. Then the location of the most similar entry is used as a position estimate:

$$\hat{\ell}(n) := \underset{\ell_k}{\operatorname{argmax}}\, d\left(\boldsymbol{\gamma}'(n), \mathbf{s}(\ell_k)\right). \tag{2.2}$$

Here, the used database contains predicted SPLs of all together 107 GSM-900 and GSM-1800 cells and cell sectors of the Vodafone Network in the area of Stuttgart, Germany. These predictions were calculated using a COST-231 model by our colleagues of the

”Institut für Hochfrequenztechnik” at the University of Stuttgart. The database covers an area of 4,500m × 4,950m containing 223,969 locations in a regular grid with an element spacing of 10m.

DAP faces several critical issues. The first one is the compilation and the maintenance of the database, that can be very cost-intensive. Due to its size and for the ease of maintenance, the database should be stored in a central place in the network resulting in network-based positioning. The second issue is the necessity of an appropriate similarity measure. The measure presented in this paper is based on a probabilistic model of reported measurements, which was derived by analyzing the hand-over procedure, that is part of the GSM Radio Subsystem Link Control. The last problem to be solved is an appropriate post filtering method, since the instantaneous position estimates disregard any constraints arising from the limited mobility of the mobile terminal.

2.1 GSM Measurement Procedure

In order to guarantee stable operation by performing hand-overs if necessary, the serving base station (BTS) periodically requires feedback about the reception conditions at the mobile terminal (MT) position when operating in ”dedicated mode”. Therefore, every 480ms a so-called network neighborhood list of $N_B \leq 16$ neighboring BTSs is transmitted to the MT to initiate the measurement of the SPLs of their broadcast control channels (BCCHs). Additionally, the MT will measure the SPL of the serving BTS. Let the resulting internal measurement list of size $N_B + 1$ in the MT be denoted by $\boldsymbol{\gamma}(n) = (\gamma_0(n), \gamma_1(n), \ldots, \gamma_{N_B}(n))^T$. It consists of the entries $\gamma_j(n)$, where $j = 0$ refers the serving BTS and $j = 1, \ldots, N_B$ denote the neighboring BTS. Without loss of generality, let the N_B measurements of neighboring BTSs be sorted in descending order. Clearly, $\gamma_1(n)$ is the measurement of the neighboring BTS with the largest measured SPL, $\gamma_2(n)$ the measurement of the neighboring BTS with the second-to-largest SPL, etc.

However, not the complete internal measurement list is reported to the serving BTS. To reduce traffic, only the measurement of the serving BTS and the $N_R(n) \leq 6$ largest measurements of the neighboring BTSs together with the corresponding BTS identifiers are reported.

Due to the GSM-internal representation of SPL measurements in a meter called RXLEV, reported measurements can only represent values in the range of -110dBm to -48dBm in steps of 1dBm. Thus all measurements above -48dBm and below -110dBm are clipped before they are transmitted.

Let the resulting measurement report (MR), which is transmitted from the MT to the BTS be denoted by $\boldsymbol{\gamma}'(n) = (\gamma'_0(n), \gamma'_1(n), \ldots, \gamma'_{N_R(n)}(n))^T$. The first entry $\gamma'_0(n)$ refers to the serving BTS and $\gamma'_j(n), j = 1, \ldots, N_R(n)$ refers to the possibly clipped measurement $\gamma_j(n)$ of the neighboring BTS, for which a SPL was measured and ranked on j-th position. Note that at different times n, a different subset of BTSs delivers the $N_R(n)$ largest values.

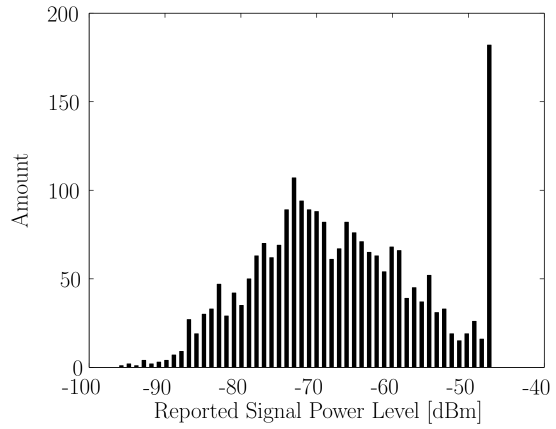

Figure 1: Histogram of recorded measurements.

2.2 Field Data

A measurement campaign has been conducted in the city center of Stuttgart, Germany. Measurements along four different routes, each of a maximum length of approx. 3km, have been recorded. Every 5 seconds on average an MR was recorded together with the geographic coordinates obtained by a GPS unit for validation purposes, amounting to a total of 947 MRs.

The measurement procedure detailed in the last section causes some distortion of the statistical characteristics of the reported data. Figure 1 shows the histogram of the recorded measurement that were reported. Clearly the effect of clipping at -48dBm can be observed due to excellent reception conditions, a significant amount of all reported measurements are reported as being above -48dBm.

3 Similarity Measures

Our novel similarity measure (SM) considers these mentioned effects. Regarding DAP as a pattern recognition problem, the location of that database entry is chosen as an instantaneous estimate of the MT position, which maximizes the conditional probability of the MR when the MT is located at the regarded location. Thus the required SM is equal to a conditional probability:

$$d\left(\boldsymbol{\gamma}'(n), \mathbf{s}(\ell_k)\right) := p\left(\boldsymbol{\gamma}'(n)|\mathbf{s}(\ell_k)\right). \tag{3.3}$$

The required probability density function (PDF) $p\left(\boldsymbol{\gamma}'(n)|s_i(\ell_k)\right)$ can be obtained by analyzing the described measurement procedure, beginning with the SPL measurements of the (N_B+1) BCCHs. Assuming independent and identically distributed (i.i.d.) measurements, the joint probability of this internal measurement list can be split up into the product of the single probabilities of its N_B separate measurements:

$$p\left(\boldsymbol{\gamma}(n)|\mathbf{s}(\ell_k)\right) = \prod_{i=0}^{N_B} p\left(\gamma_i(n)|s_i(\ell_k)\right), \tag{3.4}$$

where $s_i(\ell_k)$ is the corresponding prediction of $\gamma_i(n)$ for position ℓ_k.

In lack of evidence for any other distribution we assume an additive error model for these measurements with a Gaussian distributed measurement error:

$$p\left(\gamma_i(n)|s_i(\ell_k)\right) = \mathcal{N}(\gamma_i(n) - s_i(\ell_k); \mu, \sigma^2), \tag{3.5}$$

here $\mathcal{N}(x; \mu, \sigma^2)$ denotes a Gaussian density with mean μ and variance σ^2, evaluated at x. The bias μ considers systematic prediction or measurement errors.

With these single PDFs, the probability of the MR can be calculated using order statistics [7, 8]. Therefore, the probabilities of having observed $\gamma_j(n)$ and that this observation is ranked on j-th position of all N_B measurements is computed. Note that $j \leq N_R(n)$, since we need to calculate only the probabilities of reported measurements.

Since the resulting formulae are quite unwieldy, the densities are approximated by Gaussians with properly chosen means and variances, denoted by $\tilde{\mu}$ and $\tilde{\sigma}^2$ in the following. So we arrive at a first similarity measure, which is denoted by the subscript "A":

$$p_A\left(\boldsymbol{\gamma}'(n)|\mathbf{s}(\ell_k)\right) = \prod_{i=0}^{N_R(n)} p_A\left(\gamma_i'(n)|s_i(\ell_k)\right) = \prod_{i=0}^{N_R(n)} \mathcal{N}(\gamma_i'(n) - s_i(\ell_k); \tilde{\mu}, \tilde{\sigma}^2). \tag{3.6}$$

This first SM can be enhanced by compensation of clipping, which was disregarded yet. In the following we show how to extract maximum information from a reported measurement $\gamma_i'(n)$ clipped at -48dBm.

Intuitively, it is clear that a clipped value should not be used "as is" in the similarity measure. The information conveyed by a clipped value is that the true, unclipped value is greater than -48dBm. This information can be incorporated using the minimum mean square error (MMSE) estimate

$$\begin{aligned} \hat{p}(\gamma_i'(n) > -48\text{dBm}|s_i(\ell_k)) &= E[p_A(\gamma_i'(n)|s_i(\ell_k))|\gamma_i'(n) > -48\text{dBm}] \\ &= \frac{\int_{-48\text{dBm}}^{\infty} p_A^2\left(x|s_i(\ell_k)\right) dx}{\int_{-48\text{dBm}}^{\infty} p_A\left(x|s_i(\ell_k)\right) dx}. \end{aligned} \tag{3.7}$$

Thus a more reliable position estimation can be obtained by use of this enhanced SM denoted version "B":

$$p_B\left(\boldsymbol{\gamma}'(n)|\mathbf{s}(\ell_k)\right) = \prod_{i=0}^{N_R(n)} p_B\left(\gamma_i'(n)|s_i(\ell_k)\right) \tag{3.8}$$

with

$$p_B\left(\gamma_i'(n)|s_i(\ell_k)\right) = \begin{cases} p_A\left(\gamma_i'(n)|s_i(\ell_k)\right) & \text{if } \gamma_i' \leq -48\text{dBm} \\ \frac{\int_{-48\text{dBm}}^{\infty} p_A^2(x|s_i(\ell_k))dx}{\int_{-48\text{dBm}}^{\infty} p_A(x|s_i(\ell_k))dx} & \text{else.} \end{cases} \tag{3.9}$$

So far we have not yet exploited all available information. The inherent information about all $N_B - N_R(n)$ unreported measurements is, that they are smaller than or equal to the smallest reported SPL, since the SPLs of all N_B base stations have been measured, but only the strongest $N_R(n)$ have been reported to the serving base station by the MT.

This information can be included in a similar way as clipped values are handled: Since these measurements are not known by the serving base station, it is possible to calculate conditional expectations of their probabilities due to the fact that their distribution function is known and that these unreported measurements are bounded by the smallest reported measurement. This allows to extend our SM to all unreported measurements resulting in SM version "C":

$$p_C\left(\boldsymbol{\gamma}'(n)|\mathbf{s}(\ell_k)\right) = \prod_{i=0}^{N_R(n)} p_B\left(\gamma_i'(n)|s_i(\ell_k)\right) \prod_{l=N_R(n)+1}^{N_B} p_C\left(\gamma_l(n)|s_l(\ell_k)\right) \tag{3.10}$$

with

$$p_C\left(\gamma_l(n)|s_l(\ell_k)\right) = \frac{\int_{-\infty}^{\gamma'_{N_R(n)}(n)} p_A^2\left(x|s_l(\ell_k)\right)dx}{\int_{-\infty}^{\gamma'_{N_R(n)}(n)} p_A\left(x|s_l(\ell_k)\right)dx}, \tag{3.11}$$

where $\gamma_{N_R(n)}(n)$ denotes the smallest reported signal power level.

4 Post Filtering

Since instantaneous position estimates disregard any constraints arising from the limited mobility of a MT, post filtering using an appropriate state space model of the MT movement and an appropriate measurement model can be applied to raise accuracy.

The state equation describes the MT movement in a dynamical state model of the object state vector $\mathbf{x}(n)$ driven by a system noise vector $\mathbf{v}(n-1)$:

$$\mathbf{x}(n) = f_n(\mathbf{x}(n-1), \mathbf{v}(n-1)), \tag{4.12}$$

where $\mathbf{x}(n) = (\ell_x(n), \ell_x(n), v_y(n), v_y(n))^T$ consists of position and velocity in Cartesian 2D-coordinates and f_n is the function describing the process dynamics, that can be assumed to be linear here.

The measurement equation describes the dependency of the measurement $\mathbf{z}(n)$ on the state vector:

$$\mathbf{z}(n) = h_n(\mathbf{x}(n), \mathbf{w}(n)), \tag{4.13}$$

where h_n is a possibly non-linear function and the vector $\mathbf{w}(n)$ is called measurement noise.

Our goal is to estimate $p(\mathbf{x}(n)|\mathbf{Z}(n))$, i.e. the a-posteriori PDF of the system state at time n given the measurements $\mathbf{Z}(n) := \{\mathbf{z}(1), \mathbf{z}(2), \ldots, \mathbf{z}(n)\}$ in a recursive manner from $p(\mathbf{x}(n-1)|\mathbf{Z}(n-1))$. With this PDF the MMSE estimate $\hat{\mathbf{x}}(n)$ of the current state can be calculated ("filtering").

In principle the a-posteriori PDF can be updated recursively employing Bayes' rule

$$p(\mathbf{x}(n)|\mathbf{Z}(n)) = p(\mathbf{x}(n)|\mathbf{z}(n), \mathbf{Z}(n-1)) = \frac{p_L(\mathbf{z}(n)|\mathbf{x}(n)) \cdot p(\mathbf{x}(n)|\mathbf{Z}(n-1))}{c(n)}, \tag{4.14}$$

with $c(n) = p(\mathbf{z}(n)|\mathbf{Z}(n-1)) = \int p_L(\mathbf{z}(n)|\mathbf{x}(n)) \cdot p(\mathbf{x}(n)|\mathbf{Z}(n-1)) d\mathbf{x}(n)$ being a normalization constant. $p_L(\mathbf{z}(n)|\mathbf{x}(n))$ is called likelihood function and is (implicitly) defined by the terms of the measurement model. The prediction $p(\mathbf{x}(n)|\mathbf{Z}(n-1))$ can be calculated using the Chapman-Kolmogorov equation

$$p(\mathbf{x}(n)|\mathbf{Z}(n-1)) = \int p(\mathbf{x}(n)|\mathbf{x}(n-1))p(\mathbf{x}(n-1)|\mathbf{Z}(n-1))d\mathbf{x}(n-1), \qquad (4.15)$$

where $p(\mathbf{x}(n)|\mathbf{x}(n-1))$ is (implicitly) defined by the terms of the state model.

In the case of a linear state and measurement model, white Gaussian system and measurement noise the optimal solution to this set of equations is the well-known Kalman filter. In our case, we can assume a linear state equation, but the measurement equation is definitely non-linear, since the measurements, i.e. the MRs depend in a highly non-linear fashion on the MT's position. So, Kalman filtering is not suitable in this context. Instead, particle filtering, which is able to cope with a non-linear system model, has been employed [9, 10].

4.1 Particle Filtering

Particle filtering - also known as bootstrap filtering, condensation algorithm or "survival of the fittest" - is a sequential Monte Carlo method and thus a randomized algorithm, where PDFs are approximated by a weighted set of random samples rather than by moments. It operates on the true measurements, the MRs. If Kalman filtering were to be used, the measurements would first have to be reduced to an instantaneous position estimate, which is obtained by determining the maximum of the PDF, see equation (2.2). By doing so, a lot of information is lost, e.g. a hypothetical position with just a little smaller probability than the position winning the argmax-operation, would be completely disregarded.

This is not the case when using particle filtering. Here, the a-posteriori PDF $p(\mathbf{x}(n)|\mathbf{Z}(n))$ is approximated by a set of N_S discrete samples $\mathbf{x}^j(n), j = 1, 2, \ldots, N_S$ with respective weights $w^j(n)$ tracked over time. These samples, which are called particles, are drawn from a so-called proposal PDF $q(\mathbf{x}(n)|\mathbf{Z}(n))$, since it is not possible to sample from $p(\mathbf{x}(n)|\mathbf{Z}(n))$ directly, causing

$$w^j(n) \propto \frac{p(\mathbf{x}^i(n)|\mathbf{Z}(n))}{q(\mathbf{x}^i(n)|\mathbf{Z}(n))}. \qquad (4.16)$$

Note that the choice of this proposal PDF is a critical design issue for particle filtering. Here, we have chosen $q(\mathbf{x}^i(n)|\mathbf{Z}(n)) = p(\mathbf{x}(n)|\mathbf{x}^i(n))$ resulting in the so called sampling importance sampling (SIR) particle filter.

A set of particles, which represent hypothesized values of the state variable, approximates this PDF very well:

$$p(\mathbf{x}(n)|\mathbf{Z}(n)) \approx \sum_{j=1}^{N_S} w^j(n)\delta(\mathbf{x}(n) - \mathbf{x}^j(n)). \qquad (4.17)$$

Since this estimation is recursive, all particles are handled in an iterative manner.

In a first processing step of every iteration, the corresponding weights are updated by evaluating the new measurement using the likelihood function $p_L(\mathbf{z}(n)|\mathbf{x}^j(n))$:

$$w^j(n) := w^j(n-1) \cdot p_L(\mathbf{z}(n)|\mathbf{x}^j(n)). \tag{4.18}$$

This part is called "measurement update", since the weights modelling the prediction $p(\mathbf{x}(n)|\mathbf{Z}(n-1))$ are updated, delivering an approximation of $p(\mathbf{x}(n)|\mathbf{Z}(n))$. Therefore, the likelihood function is another critical issue when applying particle filtering.

Normalization of the weights allows to calculate the MMSE estimate of the target's state that is obtained as the weighted sum of all particles:

$$\hat{\mathbf{x}}(n) = \frac{\sum_{j=1}^{N_S} w^j(n) \cdot \mathbf{x}^j(n)}{\sum_{j=1}^{N_S} w^j(n)}. \tag{4.19}$$

In a second step, resampling is performed in order to avoid degeneration of the system over time by discarding unlikely hypotheses in order to keep a significant amount of particles with high weights.

In this step, N_S new particles, where generated from the current set of particles by sampling with replacement, where the probability of sampling a particle $\mathbf{x}^j(n)$ is $w^j(n)$. Note that resampling can be done in a deterministic way (systematic resampling). Afterwards, normalization of all particle's weights is done by setting them to $w^j(n) = \frac{1}{N_S}$.

The execution of this resampling step can be adaptively triggered by the effective weight

$$N_{\text{eff}} \approx \frac{1}{\sum_{j=1}^{N_S} \left(w^j(n)\right)^2} \tag{4.20}$$

having fallen below a given threshold N_T (importance sampling).

In the third step, all particles are propagated using the state space model. Here, the system noise must be included for the prediction of every particle by what this algorithm becomes randomized.

4.2 Particle Filtering for DAP

Utilizing particle filtering for DAP, we used a state vector which consists of the MT position and its velocity in Cartesian 2D-coordinates.

Further, a linear state equation was used where the system noise term corresponded to a random acceleration. The measurements on which the designed particle filtering operates on, are the MRs: $\mathbf{z}(n) = \boldsymbol{\gamma}'(n)$.

The required likelihood function $p_L(\mathbf{z}(n)|\mathbf{x}^j(n))$ is the presented conditional probability denoted by similarity measure version "C". By use of this most enhanced similarity measure the MR is compared with the predictions on the particle's positions which are obtained by bilinear interpolation of the 4 nearest locations in the database.

Another critical issue is the initialization of particle filtering. Our designed filter is initialized by placing the particles on the locations of those database entries that achieve highest probabilities for the first MR.

In our context, particle filtering faces the issue of sample impoverishment, since particles can remain in a local minimum of the PDF. This causes the undesired effect of a decreasing variance of all particle locations. Thus, the particles cannot track the object anymore. This can be avoided by a procedure, that will be executed if the variance of particle locations is fallen below a given threshold. Then, the particles will be placed randomly in the area of a circle centered at the mean of all particle locations. In our case, this procedure was triggered when the mean distance of all particle positions to the average of the particle positions is fallen below 24m. The circle in which the particles were randomly placed was defined by a radius of 75m around this average.

Due to efficient interpolation of the SPL predictions for the particle's positions, particle filtering needs much less computing resources than the computation of the instantaneous estimate (2.2). Whereas every database entry had to be accessed for the instantaneous estimations in the time intensive search for the maximum, in our implementation the number of database accesses is reduced to the number of particles.

We employed particle filtering using $N_S = 650$ particles with resampling triggered if the effective weight falls below $N_T = 90$.

5 Experimental Results

In a first step, the three versions "A", "B" and "C" of SMs are compared for instantaneous position estimates in order to use that version, which delivers best results for the likelihood function of particle filtering. Furthermore, the obtained results will serve as a reference for assessing the post filtered results.

In a jackknife procedure, measurements from three routes were used as training data to estimate means and variances of the Gaussians. The data of a fourth campaign was used as test data.

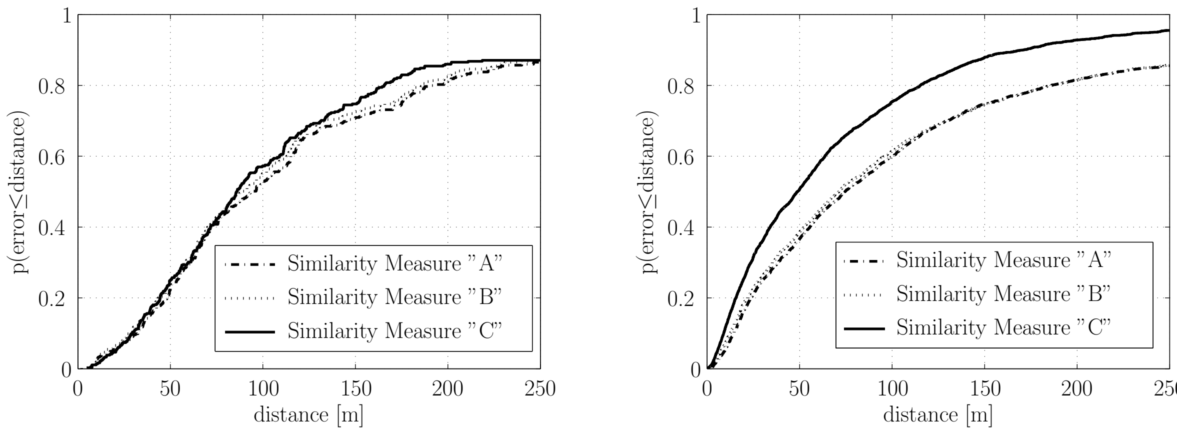

Figure 2: Positioning errors by instantaneous position estimates for real data (left) and synthetical data (right).

Figure 2 depicts the cumulative probability function of the position error for the three presented SMs. The most simple SM version "A" is marked as a dash-dotted line. Using this measure a positioning error of less than 100m was obtained in 52% of the cases

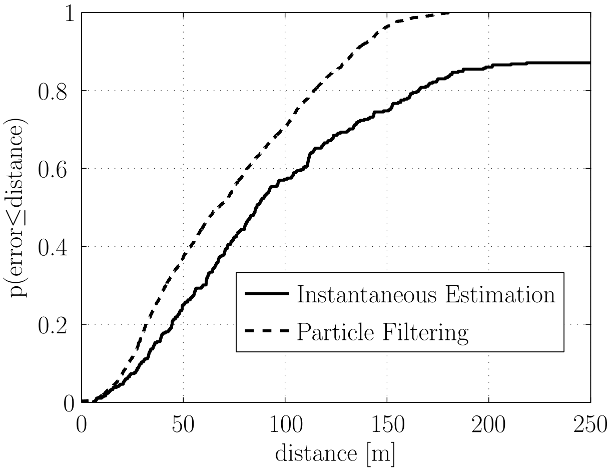

Figure 3: Positioning errors by post filtered position estimates.

and below 250m in 86%, which does not meet FCC's requirements for network based positioning, recommending an error of below 100m in 67% of all cases. The results of clipping compensation are shown as a dotted line. The position estimates are only slightly better, since only 8.7% of all reported measurements were clipped. Therefore, slightly more reliable results can be attained utilizing the inherent information about unreported SPLs.

In control experiments with synthetically generated measurement data and perfect knowledge of the list of neighboring base stations the improvement compared to version "A" by using similarity measure version "C" were much higher, see right part of figure 2. The somewhat disappointed improvements observed on the field data may in part be explained by the fact that the network neighborhood list had originally not been recorded during the measurement campaign and could only partly be reconstructed afterwards.

Now post filtering was applied to the field data. Since particle filtering belongs to the family of randomized algorithms a route was estimated ten times in order to reduce influences caused by the randomization.

The solid line in figure 3 repeats the results for instantaneous location estimates using similarity measure version "C" which is seen in figure 2. The dotted line shows the results obtained from post filtering using particle filtering.

Applying particle filtering, a positioning error of less than 100m was obtained in 70% of the cases and below 300m in 99%. So the accuracy was raised to such an extent, that it meets FCC's requirements for network based positioning.

Compared to the results reported by Laitinen et al.[2] mentioned in the introduction, these results are modest. However, it should be noted that no additional information like a-priori knowledge about allowable positions is used and that the proposed scheme is fully compatible with existing MTs and network infrastructure while the calculation complexity is reduced compared to instantaneous estimates.

6 Conclusions

In this paper, the design of particle filtering for post filtering instantaneous position estimates by database assisted positioning using a novel similarity measure was presented.

The similarity measure was derived from the GSM measurement protocol. While leaving the procedure of reporting measurements unchanged and thus being compatible with existing mobile terminals and base stations, inherent information about clipped and unreported measurements is considered. Experimental results showed raised accuracies by incorporation of this additional information.

Furthermore, we have shown how non-linear post filtering through particle filtering can be carried out to obtain more reliable position estimates fulfilling FCC's recommendations for network based positioning. Due to efficient interpolation, this approach reduces the calculation time. Furthermore, sample impoverishment was detected.

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