COMPARISON OF POSITIONING ACCURACY OF GRID AND PATH LOSS-BASED MOBILE POSITIONING METHODS USING RECEIVED SIGNAL STRENGTHS

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ABSTRACT

In this paper, positioning accuracy of two basic mobile positioning methods based on Received Signal Strength (RSS) measurements is compared via comprehensive simulations. The first method is a path loss-based technique using general free-space loss model and brute-force algorithm. The second method is a grid (fingerprint)-based positioning approach, with averaging over several nearest neighbor grid points. In the analysis, these two methods are compared in various outdoor scenarios using Matlab simulations. It is shown that the grid-based method performs better when fast fading is present and/or shadowing variance is 10 dB or more, even if path loss parameters are perfectly estimated. In addition, for the grid-based method, the optimal choice of the number of neighbor points for averaging is shown.

Keywords: *Positioning, Received Signal Strength, Grid Point, Fingerprints, Path loss, Nearest neighbors.*

1. INTRODUCTION

The number of different positioning applications has been enormously increasing in many fields, ranging from business and leisure time to surveying and health care. The receiver unit for Global Positioning System (GPS) has been included in many new mobile phones, and also applications like Google Maps are available in many new models. However, there is still a demand especially for low cost positioning techniques, e.g., for cheaper mobile phones without GPS or other satellite-based positioning systems. GPS also has performance limitations in certain circumstances, such as urban canyons, and relatively high power consumption when implemented into a cell phone.

Several different cellular mobile positioning techniques for outdoor situation based only on Received Signal Strength (RSS) have been proposed over the years. One approach is a path loss method, where position of the mobile station (MS) is estimated based on some signal propagation model. RSS from several Base Stations (BS) is measured, and the position estimate is then calculated via trilateration using estimated distances between BSs and MS [1, 2]. In order to calculate a unique location estimate for the mobile, distances from at least three BSs are needed. In addition, BS locations are needed as well. [2] In the grid-based or fingerprint positioning methods, RSS values are compared to a database with a number of pre-measured signal strength samples with known locations. The best hit, i.e., the most similar situation is then decided to be the estimated location of MS [3]. The main disadvantage of the grid-based method is database generation and maintenance requirements. However, it has to be taken into account that some pre-measured samples are needed in the path loss approach as well for estimating the path loss channel characteristics.

Even though different RSS based positioning techniques are widely known, a fair comparison of path loss-based and grid-based approaches in terms of positioning accuracy for outdoor case cannot be found in the literature so far to the best of the Authors' knowledge. Most publications related to the subject are evaluating the performance for only one of these methods, such as [4, 5] for fingerprints and [6, 7] for path loss approaches, or are limited to indoor circumstance only (such as [8, 9, 10]). Some related works are also utilizing Wi-Fi networks for outdoor positioning, e.g., [1]. Therefore a comprehensive comparison of these two basic positioning methods for outdoor case with varying fading phenomenon is very interesting and important indeed when an RSS based positioning technique is intended to be implemented for mobile phones or other receiver equipment. Moreover, a small enhancement of grid-based positioning based on averaging over a certain number of neighbor measurements is proposed here.

Brute-force algorithm with path loss model parameter estimates is used for the path loss approach when estimating user location. In the positioning phase of the grid-based method applied in this paper, also averaging over N_{neigh} nearest neighbor grid points is used, starting from some ideas found in [3] and [11] and developed further here with respect to the optimum neighbor points. The differences between RSS levels of the user and RSS values in the database are calculated, and the estimated position for mobile is then calculated as mean of known locations of N_{neigh} grid points with the minimum difference. The analysis is performed in various scenarios, i.e., with/without shadowing, with/without fading and for both sectorized and omni-directional antennas, using Matlab simulations. Both cell radius and number of hearable BSs are varied. Traditional Cell-ID (CID) method is included as benchmark. In addition, the optimal value of N_{neigh} neighbor points for averaging is searched and results are shown here, using both simulated data and real data measurements.

The paper is organized as follows. Path loss-based and grid-based positioning methods are described in Section 2. The simulation and measurement results are shown and explained in Section 3, and the conclusions are drawn in Section 4.

2. RSS BASED MOBILE POSITIONING ALGORITHMS

2.1 Path loss-based positioning method

The path loss model used in this paper is the simplified path loss model with log-normal shadowing [12]

$$Pl_a = k + 10n\log_{10}(d) + X_{shadow}, \qquad (1)$$

where Pl_a is average path loss in dB, k is a constant, d is the propagation distance between BS and mobile unit, n is the path loss exponent and X_{shadow} is a random variable modeling the shadowing effect via a log-normal distribution [12]. The received signal power PR is given by $P_R = P_T - Pl_a$, where P_T is transmission power. Using this together with Eq. 1 and adding also one random parameter X_f for fast fading, the received signal strength can be modeled with

$$P_R = P_{TA} + 10n\log_{10}(d) + X_{shadow} + X_f. \qquad (2)$$

Here, P_{TA} includes both a model constant k and the transmission power P_T, and X_f is modeled via Rayleigh distribution (i.e., typical model for fast fading).

By using Eq. 2 with the RSS level measured by the MS, the distance between the MS and corresponding BS can be estimated. In this paper, the possible shadowing or fast fading effects are not estimated or mitigated when RSS is converted into distance. Then, since the locations of the BSs are assumed to be known, a standard trilateration approach similar than, e.g., in GPS [2] can be used to calculate the user position. The distance approximations lead to circles around the BSs, and the MS is located in the intersection point of the circles. This is illustrated in Fig. 1. The solution is unique if at least three BS are hearable.

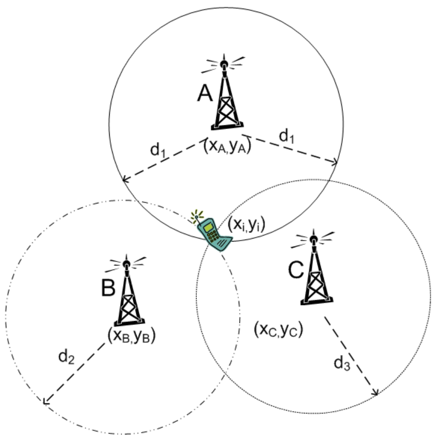

Figure 1*: Example of the standard trilateration method with three BSs.*

When calculating position estimate via trilateration in the simulations, brute-force algorithm is used. As a search method, brute-force converges conveniently, and gives the Maximum Likelihood (ML) solution. In reality, however, due to high number of unknown parameters, some other method, e.g., Newtons optimization approach has to be used.

2.2 Grid-based positioning method

In the grid point positioning method, the position of the MS is estimated based on a database with some location-sensitive parameters, such as the RSS measurements. The main idea with this method is to create a database using pre-measured samples with known locations, and then use only this database in positioning phase. The samples are for now on called grid points.

In this paper, when comparing currently measured RSS levels of the MS to the RSS levels of the grid points, the difference is calculated as a Euclidean distance. If no averaging over nearest grid points is used (i.e., $N_{neigh} = 1$), grid point with smallest distance is selected, and the location of this grid point is returned as MS location. When averaging is used, i.e., $N_{neigh} > 1$, N_{neigh} grid points with smallest distances are selected, and the position of the MS is calculated as an average over corresponding locations. Naturally, as in the path loss-based model as well; one hearable BS is in most cases not enough for an explicit position estimate.

3. SIMULATION AND MEASUREMENT RESULTS

In this Section, the path loss-based (from now on denoted as PL) and the grid-based (GP) positioning methods are compared in various scenarios in 2-dimensional environment. In the traditional CID used here as a benchmark, the estimation of the position is performed simply as a mean over all the measurement locations within the serving cell area. Only circular cells (i.e, omni-directional antennas) or a section of a circular cell (i.e, sectorized antennas) are taken into account. The cell radius is denoted as D_{max} and the grid resolution, i.e., number of measurement samples per cell, is denoted as N_{grid}. The root mean square error (RMSE) based on the distance error is used in the comparison to quantify the difference between the true MS location (x_i, y_i) and the estimated one $(\hat{x}_i, \hat{y}_i)$, as

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\Big((x_i-\hat{x}_i)^2 + (y_i-\hat{y}_i)^2\Big)}. \qquad (3)$$

In the simulations, RMSE was calculated over 1000 random iterations.

In all the simulations presented here for the PL approach, the channel characteristics P_{TA} and n as well as the BS locations are assumed to be known (this would give us a best bound on path loss-based estimation). For the brute-force search method a step of 10 m is used with two different search areas: first, the search is performed for the whole cell area, i.e., from $-D_{max}$ to $+D_{max}$ with a step of 10 m for both x- and y-axis for omni-directional cell. Secondly, the search is carried out only in the neighborhood on chosen grid point, which makes this method basically a combination of PL and GP techniques. In the simulations, the square search area around chosen grid point is from -100 m to 100 m with a

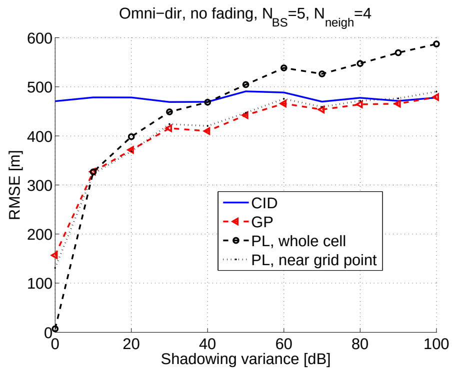

Figure 2: *RMSE vs. Shadowing variance. Omni-directional cell, D_{max} = 1 km, N_{grid} = 100. No fast fading.*

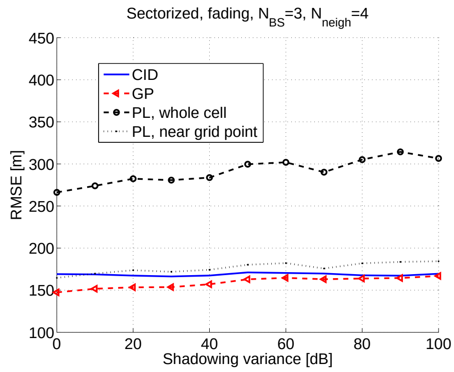

Figure 3: *RMSE vs. Shadowing variance. Sectorized cell, D_{max} = 500 m, N_{grid} = 20. Fast fading included.*

step of 10 m. In the figures shown later on in this Section, the curves for both search areas are included. In the simulations for GP method, the grid resolution is varied. The samples are generated randomly in the sense that both distance from the BS and angle are assumed to be uniformly distributed. The unknown MS position is generated similarly. Also other distributions types (e.g., Gaussian distribution) were tested, but the effect to the results was noticed to be very small. Thus, only the uniform distribution was kept here due to its simplicity.

Figs. 2 and 3 present RMSE versus shadowing variance for all methods. In Fig. 2, the cell is assumed to be omni-directional with D_{max} = 1 km and N_{grid} = 100 points. The fast fading effect is not included here. In Fig. 3, the cell is sectorized with D_{max} = 500 m and $2\pi/3$ angle. N_{grid} = 20 points and fast fading is also included. It can be seen in Fig. 2 that without shadowing and with a small enough search step, PL method can be very accurate especially with search over whole cell area. However, when shadowing is included PL method starts to deteriorate very fast. Even with a relatively small shadowing variance of 20 dB PL approach has clearly higher RMSE than GP method. In urban areas, the standard deviation of shadow fading in log-normal scale is usually between 4 and 10 (as noticed, e.g., in [13]), which is equal to the shadowing variance between 16 to 100 dB. In Fig. 3 it can be noticed that also the fast fading can decrease the positioning accuracy of PL approach quite significantly. Even without shadowing, PL method with whole cell search fails to offer a satisfactory location estimate.

Figs. 4 and 5 present RMSE versus averaging over neighbor grid points N_{neigh} for GP method. Results are shown for both simulated data (Fig. 4) and for real data measurements (Fig. 5). For simulated data, the used cell was sectorized with D_{max} = 400 m and $2\pi/3$ angle, and with both N_{grid} = 2 and N_{grid} = 50 points. Also 10 dB shadowing variance was included. For data measurement case, the measurement area was approximately 1 km x 0.9 km, covering several 3G-cells in the city centre of Tampere, Finland. A Nokia cell phone registering GPS coordinates and the RSS levels with corresponding Cell IDs was used for the data collection. Measurement data was first collected and grid point database was created. The grid resolution was fixed, i.e., the

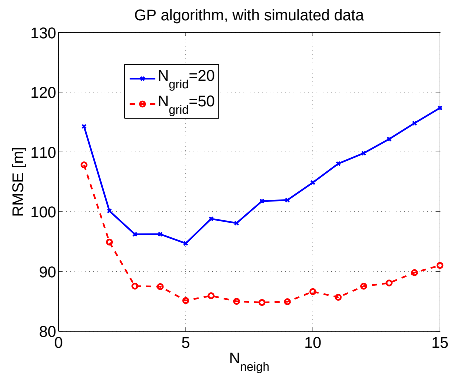

Figure 4: *RMSE vs. averaging over neighbor grid points N_{neigh} for GP method with simulated data.*

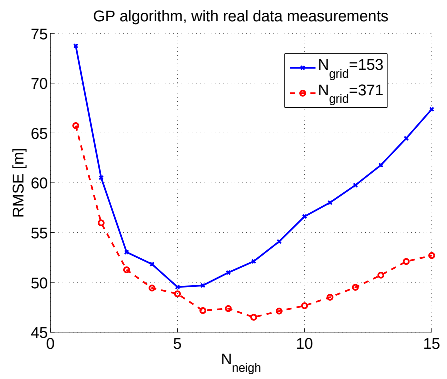

Figure 5: *RMSE vs. averaging over neighbor grid points N_{neigh} for GP method with real data measurements.*

grid points had some pre-defined size (e.g., square of 50 m x 50 m) and all samples measured in this area (GPS was used as a reference) were fixed to the same grid point. Two different grid resolution were used, i.e., with 153 grid points (i.e., fixed grid point size 50 m x 50 m) and 371 grid points (i.e., fixed grid point size 25 m x 25 m) within the whole measured area.

As it can be seen in Figs. 4 and 5, averaging over neighbor points will increase the positioning accuracy, as reported also earlier, e.g., in [3, 11]. It can also be seen that the optimum number of N_{neigh} grid points used for averaging process is dependent on N_{grid} value: if N_{grid} is small, i.e., N_{grid} = 20 for the simulated data or N_{grid} = 153 for the real data, the best results are achieved with N_{neigh} = 5. When N_{grid} is higher, i.e., N_{grid} = 50 for the simulated data or N_{grid} = 371 for measured data, he optimum number of N_{neigh} is from 5 to 10. We remark that also weighted averaging over neighbor points (i.e., by giving more weight to the grid point with best match etc.) was tested at this point. It was noticed, however, that this did not have effect on the results, especially with the real data measurements, and thus, the results related to weighted averaging were not included in this paper.

One limitation in our model is that the variable X_{shadow} modeling the shadowing effect via a log-normal distribution is generated randomly to each generated measurement point. This leads into situation where near-by measurements may have quite different value of X_{shadow} when in practise there is always some correlation in the rx-levels of the measurements close to each others. This also explains why the results with real data measurements in Fig. 5 have better performance than the simulated one in Fig. 4. This feature does not affect however to the general conclusions as can be seen when comparing Fig. 4 to Fig. 5, but only to the achieved performance with simulated data. The work for more realistic simulation model is continued in the future.

4. CONCLUSION

In this paper, it is shown that GP positioning method performs better than PL method in terms of positioning accuracy, when fast fading and/or shadowing is present, even if the estimates for channel characteristics in the assumed path loss model are perfect. However, if shadowing variance is small (i.e., 10 dB or less), PL may offer very good results as well. Especially in macro-cells in rural areas, where number of grid points can be quite small, PL method will probably give better positioning estimate. It was shown in this paper, based on both simulated and measured data, that the optimal value of neighbor points to be used for averaging process N_{neigh} for GP method is usually 5 to 10 points.

Our path loss model assumed equal channel path loss parameters for the whole measured cell areas, which might be a limiting assumption in the performance of path loss models. The general and rather astonishing finding of our paper is however that path loss models are much more sensitive to channel impairments such as fading and shadowing than grid-based approaches, and that by varying the parameters used in a grid-based estimation (such as the grid size and the number of neighbor points used in the estimation) we can enhance substantially the GP-based position estimation. One interesting and important topic for future research would be to compare both methods in different kind of environments using real data measurements.

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