Indoor Positioning Using WLAN Coverage Area Estimates

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***Abstract*—This paper introduces a novel method for positioning using coverage area estimates of wireless communication nodes. The coverage areas are estimated in a Bayesian inference framework using location fingerprints that are collected in an offline calibration phase, and the estimated coverage areas are stored in a database. In the online positioning phase the coverage areas of the heard communication nodes are used to infer the position of the mobile terminal. Floor plan information is used to enhance the positioning accuracy. In a field study comparing Kalman Filter, Box Filter and Particle Filter using real WLAN measurement data, it is found that Kalman Filter achieves almost the same accuracy as Box Filter and Particle Filter but with smaller computational load.**

I. Introduction

Location fingerprinting is a positioning method that determines the location of a Mobile Terminal (MT) using a database of radio characteristics. Fingerprinting methods have been widely studied in indoor positioning and they have been reported to provide adequate accuracy for most location based services in indoor environments. The state of the art methods in indoor positioning collect WLAN Received Signal Strength Indicators (RSSI) at predefined locations and use Weighted K-Nearest Neighbor (WKNN) to estimate the position of MT [1, 2]. Each fingerprint collected during the calibration phase consists of a list of heard WLAN Access Point (AP) Media Access Control (MAC) addresses, corresponding signal strengths, and the coordinates of the calibration point. The scheme is straightforward, but there are several problems. First, the calibration phase is very laborious, and large databases need to be constructed and processed. Secondly, these methods are based on variations of RSSI values as a function of position. However, WLAN chipset vendors use different RSSI definitions and the scales of different RSSI values vary from one chipset to another. As a result, RSSI values collected with different MT models are not easily comparable with each other. Thirdly, even small changes in the environment may have a huge effect on RSSI values, and the positioning performance degrades if the fingerprint database is not up-to-date [3]. Finally, if the positioning calculations are carried out in MT, the data transmission between the network and MT may be too time consuming for real time positioning even if the data is compressed using kernel approximations.

In this paper, we use an approach to location fingerprinting that uses a database of transmitter coverage areas (reception regions), as presented in [6]. Each planar coverage area is assumed to be ellipse-shaped and can be specified by five floating point numbers, and thus is compact to store in a database and fast to transmit to a MT. The parameters of the coverage area are determined by statistical analysis of the locations of fingerprints. In the positioning phase the statistical inference of the MT's location from the list of heard APs is computationally light: the location posterior mean is a weighted average of the location parameters of the coverage areas. Use of RSSI measurements is difficult if the calibration data is collected with different MT models that use different RSSI definitions. We present a novel idea to calibrate RSSI values: each MT collects its own database of observed RSSI values and determines the scale of the RSSI values.

The positioning accuracy can be enhanced using map information. Nowadays the basic geometry of almost any building is available from aerial image databases, and detailed digital floor plans are available for many significant buildings, such as hospitals, shopping malls and airports. Map matching (i.e. projecting the positioning result to an indoor location) is commonly used to improve the performance of indoor positioning systems. The floor plan can also be used in a way more tightly integrated to the estimation, for example by restricting (truncating) the location's probability distribution [4].

Positioning accuracy is also enhanced by time-series filtering. Filters combine new measurements with past measurements and the motion model of MT. The Kalman Filter (KF) has been studied and applied extensively in positioning applications. KF assumes linear motion model, linear measurement function, Gaussian initial distribution, and Gaussian measurement and motion model noises. If these assumptions are met, KF offers a closed form solution for the posterior distribution of the state. If the distribution of position is restricted by a floor plan, the assumptions of KF are no longer valid and the posterior distribution of position cannot be calculated analytically. In situations like this, it is possible to use Particle Filters (PF), which use weighted particles to approximate the posterior distribution. PF usually produces a good estimate for the posterior distribution, but it requires a lot of computation compared to KF. One solution is to approximate the restricted posterior distribution with piecewise constant functions and to use a graph that describes the topology of the indoor environment as the motion model. We call this filter Box Filter (BF).

In this paper, two ways to use a floor plan in indoor positioning are examined. Different methods are tested with real data collected from WLAN APs. The static coverage area based method is compared to Nearest Neighbor (NN) method [1]. We also investigate how the floor plan improves the position estimate, and use PF and BF for the position calculation.

An outline of the paper is as follows. In Section II we show how the multivariate normal linear model can be used in the coverage area estimation. A statistical method for positioning MT using coverage area estimates is presented in Section III. Section IV discusses the use of the restrictive floor plan information in indoor positioning, and Section V describes two ways to use floor plan in filtering. Section VI outlines how fingerprints collected with different MT models can be calibrated. Positioning algorithms are tested with real WLAN data and the test results are presented in Section VII.

II. Coverage area estimation

Fingerprint data is used to model the coverage area of a WLAN AP. For every MAC address there is a list of location reports consisting of the coordinates at which an AP is hearable by the MT. These location reports are used to estimate the coverage area of an AP. We write the measurement model as

$$\mathrm{Y} = \mathbf{1}_n \boldsymbol{\mu}^T + \epsilon, \tag{1}$$

in which Y is an $n \times d$ matrix representing n mutually independent observations of d-dimensional location, $\mathbf{1}_n$ is an n-variate vector of ones, $\boldsymbol{\mu}$ is a d-dimensional vector of coordinates, and ϵ is a $n \times d$ matrix of errors. Let $\boldsymbol{\epsilon}_{(i)}$ denote the (column) vector formed by taking a transpose of the ith row of matrix ϵ. Assume that error vectors

$$\boldsymbol{\epsilon}_{(i)} = \mathrm{Y}_{(i)} - \boldsymbol{\mu} \tag{2}$$

are, for given $\boldsymbol{\mu}$ and Σ, independent and normally distributed with zero mean and covariance Σ, that is, $\boldsymbol{\epsilon}_{(i)} \sim \mathrm{N}_d(\mathbf{0}, \Sigma)$. The parameters of the coverage area are the location parameter μ and the symmetric positive definite matrix Σ that describes the size and the shape of the coverage area. The distribution of the unknown parameters can be solved using the Bayes' rule. The Bayesian approach is used because it allows recursive estimation and update of the coverage area estimates, and the use of a Bayesian prior, which models the subjective information about a typical coverage area. This information is especially important when there are only a few location reports from WLAN AP.

The likelihood can be written as

$$\begin{aligned}
&\mathrm{p}(\mathrm{Y}|\boldsymbol{\mu}, \Sigma) \\
&\propto |\Sigma|^{-n/2} \exp\left[-\frac{1}{2}\operatorname{tr}\Sigma^{-1}(n(\boldsymbol{\mu}-\hat{\boldsymbol{\mu}})(\boldsymbol{\mu}-\hat{\boldsymbol{\mu}})^T + \mathrm{S})\right] \\
&\propto |\Sigma|^{-n/2} \exp\left[-\frac{1}{2}\operatorname{tr}\Sigma^{-1}\mathrm{S}\right] \times \\
&\quad \exp\left[-\frac{1}{2}\operatorname{tr} n\Sigma^{-1}(\boldsymbol{\mu}-\hat{\boldsymbol{\mu}})(\boldsymbol{\mu}-\hat{\boldsymbol{\mu}})^T\right],
\end{aligned} \tag{3}$$

in which $\hat{\boldsymbol{\mu}} = \frac{1}{n}\mathbf{1}_n^T \mathrm{Y}$ is the least squares estimator of $\boldsymbol{\mu}$ and $\mathrm{S} = (\mathrm{Y} - \mathbf{1}_n\hat{\boldsymbol{\mu}}^T)^T(\mathrm{Y} - \mathbf{1}_n\hat{\boldsymbol{\mu}}^T) = \mathrm{Y}^T\mathrm{Y} - n\hat{\boldsymbol{\mu}}\hat{\boldsymbol{\mu}}^T$ is the residual sum of squares.

We use the natural conjugate prior for parameters $(\boldsymbol{\mu}, \Sigma)$, which is the normal-inverse-Wishart distribution [5], namely

$$\mathrm{p}(\boldsymbol{\mu}, \Sigma) = \mathrm{p}(\boldsymbol{\mu}|\Sigma)\mathrm{p}(\Sigma), \tag{4}$$

in which

$$\mathrm{p}(\boldsymbol{\mu}|\Sigma) \propto \exp\left[-\frac{1}{2}\operatorname{tr}\Sigma^{-1}a(\boldsymbol{\mu}-\mathbf{m})(\boldsymbol{\mu}-\mathbf{m})^T\right], \tag{5}$$

$$\mathrm{p}(\Sigma) \propto |\Sigma|^{-(v+d+1)/2}\exp\left[-\frac{1}{2}\operatorname{tr}\mathrm{B}\Sigma^{-1}\right], \tag{6}$$

and where $\mathbf{m}$ is a d-variate known vector, $a \geq 0$ and $v \geq d$ are fixed constants and B is a $d \times d$ positive definite symmetric matrix. Thus $\boldsymbol{\mu}|\Sigma \sim \mathrm{N}_d(\mathbf{m}, \frac{1}{a}\Sigma)$ and $\Sigma \sim \mathrm{W}_d^{-1}(\mathrm{B}, v)$, where W_d^{-1} denotes inverse-Wishart distribution.

The joint posterior density for parameters $(\boldsymbol{\mu}, \Sigma)$ can be found using Bayes' formula and multiplying (3) and (4)

$$\begin{aligned}
\mathrm{p}(\boldsymbol{\mu}, \Sigma|\mathrm{Y}) &\propto \mathrm{p}(\mathrm{Y}|\boldsymbol{\mu}, \Sigma)\mathrm{p}(\boldsymbol{\mu}, \Sigma) \\
&\propto |\Sigma|^{-(n+v+d+1)/2}\exp\left[-\frac{1}{2}\operatorname{tr}\Sigma^{-1}\mathrm{Q}\right],
\end{aligned} \tag{7}$$

where

$$\mathrm{Q} = \hat{a}(\boldsymbol{\mu}-\hat{\mathbf{m}})(\boldsymbol{\mu}-\hat{\mathbf{m}})^T + \hat{\mathrm{S}}, \tag{8}$$

in which

$$\hat{\mathbf{m}} = \frac{1}{n+a}\left(\mathrm{Y}^T\mathbf{1}_n + a\mathbf{m}\right), \tag{9}$$

$$\hat{a} = n + a, \tag{10}$$

$$\hat{\mathrm{S}} = \mathrm{Y}^T\mathrm{Y} + \mathrm{B} + a\mathbf{m}\mathbf{m}^T - \hat{a}\hat{\mathbf{m}}\hat{\mathbf{m}}^T. \tag{11}$$

Also the joint posterior density is a normal-inverse-Wishart distribution. Thus marginal posterior densities of the parameters are $\boldsymbol{\mu}|\mathrm{Y} \sim \mathrm{t}_d\left(\hat{\mathbf{m}}, \frac{1}{\hat{a}(n+v-d)}\hat{\mathrm{S}}, n+v-d\right)$ and $\Sigma|\mathrm{Y} \sim \mathrm{W}_d^{-1}\left(\hat{\mathrm{S}}, n+v-1\right)$ [6].

The posterior distribution of parameters $\boldsymbol{\mu}$ and Σ contains all relevant information about the parameters. For our model, the posterior is completely specified by the posterior means [7, 8]

$$\mathrm{E}(\boldsymbol{\mu}|\mathrm{Y}) = \hat{\mathbf{m}} \text{ and} \tag{12}$$

$$\mathrm{E}(\Sigma|\mathrm{Y}) = \frac{1}{n+v-d-2}\hat{\mathrm{S}}. \tag{13}$$

For each AP only parameters of the coverage area needs to be stored and after the coverage areas are formed, the actual fingerprints do not need to be stored in a database. Also, the posterior means can be computed from measurement data in a recursive fashion, see [9] for details.

III. Positioning

In the positioning phase the MT reports the MAC addresses of the heard APs and uses the corresponding coverage area data to find the posterior probability density function of the MT position. A point estimate of the state can then be computed from the posterior probability distribution function (pdf), e.g., the mean or the maximum a posteriori position. Measures of dispersion can also be computed, if information about the position estimate's accuracy is desired.

Let $\mathbf{c} = c_1, c_2, \dots, c_k$ be a list of APs heard by MT. We assume that sufficient training data has been collected so that the parameters $\boldsymbol{\mu}_i$ and Σ_i of the coverage area of the ith AP c_i can be treated as known. Let $\mathbf{x}$ be a d-variate vector containing the position of the MT and assume that $\mathbf{x}|c_i \sim \mathrm{N}_d(\boldsymbol{\mu}_i, \Sigma_i)$. The probability that the MT located at $\mathbf{x}$ is in the coverage area of c_i can be obtained using Bayes' rule

$$\begin{aligned} \mathrm{p}(c_i \in \mathbf{c}|\mathbf{x}) &\propto \mathrm{p}(\mathbf{x}|c_i \in \mathbf{c})\mathrm{p}(c_i \in \mathbf{c}) \qquad (14)\\ &\propto \mathrm{p}(\mathbf{x}|c_i \in \mathbf{c}). \qquad (15)\end{aligned}$$

The last expression is obtained by assuming that the prior probability of hearing c_i is equal for all $i = 1 \dots k$.

Assuming that the observations are mutually independent given $\mathbf{x}$, the measurement likelihood function for $\mathbf{x}$ can be formed

$$\begin{aligned} \mathrm{p}(\mathbf{c}|\mathbf{x}) &= \prod_{i=1}^{n} \mathrm{p}(c_i \in \mathbf{c}|\mathbf{x}) \\ &\propto \prod_{i=1}^{n} \exp\left[-\frac{1}{2}(\mathbf{x}-\boldsymbol{\mu}_i)^T \Sigma_i^{-1}(\mathbf{x}-\boldsymbol{\mu}_i)\right] \qquad (16)\\ &\propto \exp\left[-\frac{1}{2}(\mathbf{x}-\bar{\mathbf{x}})^T \mathrm{C}^{-1}(\mathbf{x}-\bar{\mathbf{x}})\right], \end{aligned}$$

in which

$$\bar{\mathbf{x}} = \left(\sum_{i=1}^{n} \Sigma_i^{-1}\right)^{-1} \left(\sum_{i=1}^{n} \Sigma_i^{-1}\boldsymbol{\mu}_i\right) \text{ and } \mathrm{C} = \left(\sum_{i=1}^{n} \Sigma_i^{-1}\right)^{-1}.$$

So our measurement likelihood is a normal density $\mathrm{N}_d(\bar{\mathbf{x}}, \mathrm{C})$, where the mean parameter is a weighted mean of ellipse centers and the weights are the inverses of covariance matrices.

IV. Floor plan as restrictive information

In the Bayesian framework, restrictive information can be incorporated by truncating the probability density functions so that no probability mass is located in restricted areas. In indoor positioning, we could restrict the pdf so that no probability mass is located outside the building. This has been already done in [4] to restrict the probability density function of the user's position in Kalman-type filters. The Kalman-type filters propagate Gaussian distributions, so the truncated Gaussians are approximated with Gaussian distributions using moment matching techniques in order to allow analytical treatment of the densities.

Graphs may be used in indoor positioning to model the connections of different parts of the building [10]. In our approach the floorplan is partitioned into convex polygons called boxes. A box may consist of one room but bigger areas, such as long corridors or lobbies, may be partitioned into smaller areas, and there may be several boxes in one area. The floor plan topology is modeled by an undirected graph $G(V, E)$, where the vertices V represent boxes and the edges E indicate the possibility of moving directly between boxes. Fig. 1 gives an example of a floor plan and of the corresponding graph, whose adjacency matrix is

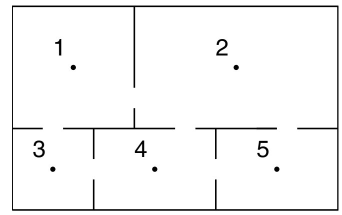


Figure 1: An example of a floor plan

$$\mathrm{G} = \begin{pmatrix} 1 & 1 & 1 & 0 & 0 \\ 1 & 1 & 0 & 1 & 1 \\ 1 & 0 & 1 & 1 & 0 \\ 0 & 1 & 1 & 1 & 1 \\ 0 & 1 & 0 & 1 & 1 \end{pmatrix}. \qquad (17)$$

All diagonal elements in matrix G are equal to one, because it is always possible that the MT stays in the same room.

V. Map Assisted Filtering

We study two filters that use the floor plan and the graph in indoor positioning: a particle filter, which approximates the state pdf with weighted particles, and a box filter, which approximates the state pdf with a piecewise constant function.

A. *Map assisted particle filter*

Map information is easy to incorporate in particle filters. The key idea in map assisted particle filters is that the particles should not occupy impossible positions given the map constraints. For example, since the user cannot pass through walls, the particles that cross a wall are weighted down. This approach is used in [11–13].

Let $\mathrm{B} = \{B_i, i = 1, \dots, n_b\}$ be a set of boxes that partitions the floor plan. We use bootstrap filter to estimate the user's trajectory, but at every time step t_k for every particle $\mathbf{x}_k^i$ we determine the box it is associated with and save the index $j_k^i \in (1, \dots, n_b)$ of the box. The new particle position is determined by the motion model and the new box indices j_{k+1}^i are calculated. The particle weight is assigned as follows:

$$w_{k+1}^i \propto \begin{cases} \mathrm{p}(c|\mathbf{x}_{k+1}^i) & \text{if } \mathrm{G}_{j_k^i j_{k+1}^1} = 1 \\ 0 & \text{if } \mathrm{G}_{j_k^i j_{k+1}^i} = 0. \end{cases} \qquad (18)$$

B. *Box filter*

The box filter approximates the measurement likelihood as piecewise constant functions. This piecewise approximation is commonly used in grid filters [14–16]. The difference between grid filters and the box filter is that in the box filter the state is a vector of probabilities and it uses the matrix G to build a Markov matrix to be used for the state evolution. Let $\mathbf{p} = ((\mathbf{p})_1, \ldots, (\mathbf{p})_{n_B})^T$ be the state vector where $(\mathbf{p})_i$ is the probability mass inside the ith box. It is assumed that all adjacent vertices are equally likely, so the state transition matrix is obtained by dividing the elements of each row of G by the corresponding row sum. For example if G is given by (17) then

$$\Phi^T = \begin{pmatrix} 1/3 & 1/3 & 1/3 & 0 & 0 \\ 1/4 & 1/4 & 0 & 1/4 & 1/4 \\ 1/3 & 0 & 1/3 & 1/3 & 0 \\ 0 & 1/4 & 1/4 & 1/4 & 1/4 \\ 0 & 1/3 & 0 & 1/3 & 1/3 \end{pmatrix}. \tag{19}$$

Now the prior estimate of state at t_k is

$$\mathbf{p}_k^- = \Phi \mathbf{p}_{k-1}. \tag{20}$$

To obtain the posterior estimate, calculate the measurement likelihood of state at t_k and if $(\mathbf{p}_k^-)_i > 0$, update the prior

$$(\mathbf{p}_k)_i = (\mathbf{p}_k^-)_i \pi(i), \tag{21}$$

in which $\pi(i)$ is the probability mass inside the ith box. After update, normalize the probabilities. The mean estimate of the position at t_k becomes

$$\mathbf{x}_k = \sum_{i=1}^{n_B} (\mathbf{p}_k)_i \mathbf{m}_i, \tag{22}$$

where $\mathbf{m}_i$ is the midpoint of the ith box.

For an arbitrary convex polygon, $\pi(i)$ can be calculated using recursive pdf truncation as presented in [4]. This applies one linear constraint at a time and approximates the truncated distribution as a Gaussian. Parallel planes in a box can be processed in a single stage, see [17]. However, here we do not need a Gaussian approximation of the truncated distribution; we need only the probability mass inside the box. The probability mass can be computed exactly as presented in [4] and [17].

VI. RSSI MEASUREMENTS

It is stated in literature that reducing the number of heard APs may increase the accuracy of position estimate [2, 18]. In many publications, the optimal number of APs is determined experimentally. Different studies has provided different results for the optimal number of heard APs and it may be difficult to find a limit that produces good positioning performance in all environments.

In coverage area based positioning the number of APs may be limited in positioning, but also in coverage area estimation. It is typical that each AP is hearable in most of the building. If all the location reports are taken into account during the coverage area estimation, the resulting coverage area database is useless for positioning within the building. One option is to impose some signal strength threshold value during data collection. Then, for every fingerprint, only APs that are hearable with RSSI values exceeding the threshold value are considered in coverage area estimation. Some threshold value, either the same one as in coverage area estimation or some other value, could be used also in the positioning phase. In this case, only coverage areas of APs that are heard with RSSI that exceeds this threshold value are used in positioning. This would lead to smaller estimated coverage areas and more accurate positioning. A difficulty with signal strength is that if training data is collected with a range of MT models, or positioning is done with a different model, then the RSSI values may not be comparable with each other.

To allow comparison of RSSI values, we have devised the following scheme. Each MT, whether for fingerprint collection or positioning, constructs a histogram of RSSI values observed over a long time interval. Generally, the scale of the distribution may vary in different MT models, but if we assume that the shape is similar, the parameters of the distribution, such as mean, median or mode, are comparable with each other and can be used to calibrate RSSI readings.

Fig. 2 gives an example of two histograms of RSSI values collected with different Nokia devices. RSSI values in Fig. 2a are collected from the Tampere University of Technology campus and RSSI values in Fig. 2b are collected from the centre of Tampere. RSSI values in Fig. 2a are negative and low RSSI values mean weak signal strengths while RSSI values in Fig. 2b are positive and high RSSI values mean weak signal strengths. As expected, the scale of the distribution differs but the shape of the distribution is similar in the figures. Both histograms show that the distribution of RSSI values is skewed towards low signal strengths. This is expected, because at any given location there are usually more WLAN APs further away from the MT than there are close to the MT. The figures indicate that the distribution of RSSI values could be used to equate, for example, mean RSSI value between different MT models.

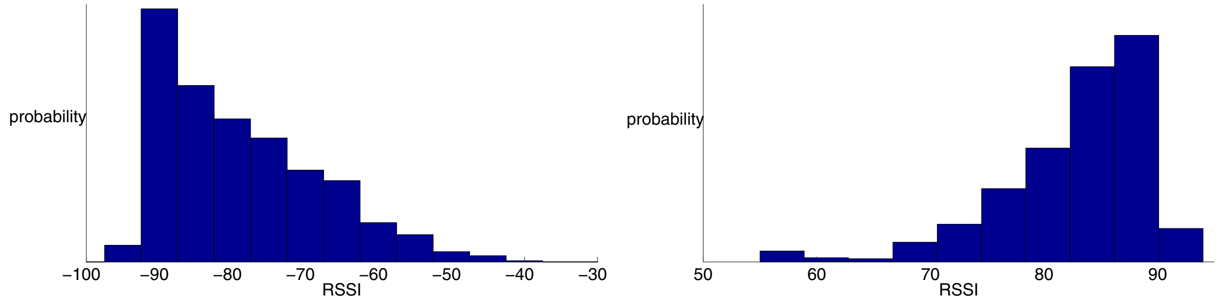
To achieve more reliable understanding about the behavior of RSSI values, more data should be collected in different environments and with different MT models.

VII. TESTS

The radiomap and the test data were gathered with Nokia N900 mobile phone and the data collecting software was implemented with Qt Developer. The phone scans the available WLAN channels and measures RSSI values for each hearable AP. The RSSI values are stored together with their unique MAC addresses.

The calibration data were collected in a building at the Tampere University of Technology. Altogether 96 fingerprints were collected in corridors, lecture rooms, and outside the building. 206 APs were detected during data collection and the average number of heard APs per fingerprint was 29. Two test tracks were gathered in the proximity of the calibration points in the test building. Test tracks and calibration points are shown in Fig. 3.

A static coverage area based positioning method is compared to a Nearest Neighbor method (NN) that uses the 1-norm as the distant measure in the RSSI space. KF uses the solutions of the static coverage area based positioning technique as



(a) (b)

Figure 2: Example of RSSI histogram

linear measurements. KF is compared to Positioning Kalman Filter (PKF), that uses the solutions of the static NN method as linear measurements. Note that NN uses the whole fingerprint database, also the RSSI values of the fingerprints, whereas in coverage area based positioning the fingerprint data is compressed into coverage area estimates and no RSSI values are used. Also, we investigate with BF and PF how the use of floor plan affects the positioning accuracy. We use 500 particles in PF. Lastly, it is tested how the positioning accuracy changes when only location reports that exceed some RSSI value threshold are taken into account in coverage area estimation and in positioning.

The results of the test tracks are shown in Tables I and II. The reported quantities are the mean error in meters (ME), the root mean squared error (RMSE) in meters, the 95th percentile of errors (95%) in meters, and the maximum error (Max) in meters.

The results show that the coverage area based positioning yields almost the same accuracy as the traditional NN method, even though NN uses more information, that is, the RSSI values. In Track 1, the coverage area based positioning outperforms the NN method, but in Track 2, NN shows more accurate positioning performance. Both KF and PKF give more accurate position estimates than the corresponding static methods. KF and PKF achieve similar positioning accuracy. The accuracy of the NN method could be improved by using more sophisticated methods like the Weighted K Nearest Neighbor (WKNN) where the weight function and the number of neighbors K could be optimized [2].

Table I shows that the floor plan information improves the

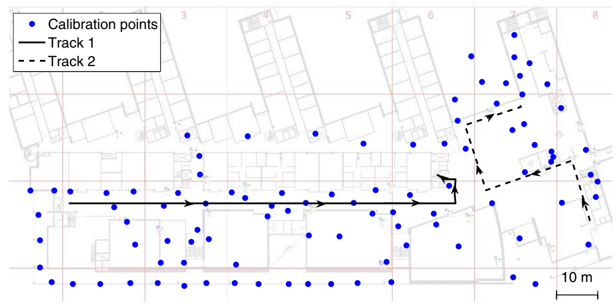


Figure 3: Floor plan of the test area

Figure 4: KF, BF and PF estimates for test track 1

positioning accuracy. There are no significant differences in the positioning accuracy between BF and PF. However, in our tests, PF requires approximitely 80 times more computation time than BF. Mean error is slightly better with BF and PF than with KF but the biggest differences are in the 95th percentile and in the maximum error. Fig. 4 shows the position solutions for Track 1 given by KF, BF and PF.

Table II shows no improvement in positioning accuracy

Table I: Results for Track 1

	ME [m]	RMSE [m]	95% [m]	Max [m]
Coverage area	7.5	9.5	20.3	29.8
NN	9.9	12.5	26.3	31.3
KF	7.4	9.1	20.4	26.4
PKF	7.4	9.0	18.4	21.6
BF	6.4	7.6	14.6	18.2
PF	6.4	7.8	17.6	19.3

Table II: Results for Track 2

	ME [m]	RMSE [m]	95% [m]	Max [m]
Coverage area	8.7	9.8	16.6	27.9
NN	8.1	9.1	14.6	31.3
KF	7.1	7.7	11.7	12.6
PKF	6.7	7.8	13.5	14.4
BF	7.8	9.0	15.4	22.5
PF	8.6	9.3	15.3	21.5

Table III: Results for Track 1 with limited number of APs

	ME [m]	RMSE [m]	95% [m]	Max [m]
KF	5.5	6.9	15.4	18.7
BF	4.5	5.5	10.5	14.2
PF	5.0	6.1	13.2	15.5

when the floor plan information is used. Actually, in Track 2, KF outperforms BF and PF. This is because Track 2 is located in a lobby, and in a big open area the floor plan information has little value. This is why also the accuracy of BF and PF is closer to the static method.

Table III shows results for the coverage area based positioning technique from Track 1 when the weakest signals are discarded. We used the RSSI data we had from the data collection to determine the parameters of the RSSI distribution. The used threshold values were the median of RSSI in coverage area estimation and the mode of RSSI in positioning. Results show that the positioning error is reduced with all filters and also the root mean squared error is reduced. This show that limiting the number of APs is useful also in coverage area based positioning. However, finding RSSI values that work well in all environments is still an open problem.

VIII. Conclusion

In this paper, a coverage area based positioning technique for indoor positioning is presented. The method was tested with real WLAN data and compared with NN. It was tested how the positioning performance changes when the floor plan is used to limit the probability distribution of the position. The performance was studied with BF and PF. Also an idea to calibrate RSSI values was presented.

The results show that the coverage area based method can achieve the same accuracy as the NN method without needing to use the actual fingerprint data and without using the RSSI values in positioning. Also, the results show that the floor plan improves the positioning accuracy. The results indicate that PF and BF have a similar positioning performance. KF, however, achieves almost the same accuracy with significantly lower computational load. Results show that the location accuracy can be improved by limiting the number of heard access points during data collection and positioning. If only the strongest access points are taken into account during data collection, the coverage area estimates become smaller and lead to more accurate position estimates.

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