The Effect of Coverage Gaps and Measurement Inaccuracies in Fingerprinting based Indoor Localization

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Abstract— **In this paper we estimate the effect of coverage gaps and inaccurate Received Signal Strength (RSS) values in fingerprinting based indoor localization using Wireless Local Area Networks (WLAN). The results are based on extensive measurement campaign including two multi-storey buildings with over 700 found WLAN access points in total. We introduce a novel randomized method to artificially create realistic coverage gaps in the database. It is further emphasized that a realistic fingerprint removal process for modeling coverage gaps cannot be based in uniformly distributed probability density function. User positioning performance between the original database and the partial database is compared using the well-known K-Nearest Neighbor (KNN) algorithm. In addition, we model RSS inaccuracies in the database originated from badly calibrated learning data or from a constant bias between learning data collection devices and the device used for positioning. The effect of coverage gaps and RSS inaccuracies on the user positioning accuracy is studied in terms of average horizontal positioning error and in average floor detection probability over several user tracks and randomized removal processes. The presented results and the provided methodology allow error dimensioning of collected learning data and assist in planning measurement campaigns in future indoor positioning studies.**

Keywords-component; fingerprinting, indoor positioning, Received Signal Strenght (RSS), Wireless local Area Networks (WLAN), coverage area

I. Introduction

Whereas Global Navigation Satellite Systems (GNSS) and cellular network based positioning methods are able to provide satisfactory positioning accuracy outdoors, many positioning challenges have yet remained unsolved in the demanding and highly dynamic indoor environment. Increasingly growing availability of Wireless Local Area Networks (WLAN), more specifically the IEEE 802.11 standard [1], has reasserted the feasibility of WLAN-based solutions for indoor positioning. Possibly the most common positioning approach in this context is to exploit Received Signal Strength (RSS) measurements from observed WLAN Access Points (AP). Assuming that AP locations and their transmit powers would be known, positioning can be based on pathloss models with proper parameterization. However, due to unpredictability of indoor environment with walls and floor differences, pathloss models are not usually able to deliver sufficient positioning accuracy. Collecting learning data from the target area might help in creating more accurate pathloss models, but does not avoid the problem of having a good fit with the measurement data due to the highly dynamic environment. Therefore, using the measurements simply as fingerprints from different locations avoids issues in pathloss model fitting and enables higher positioning accuracy at cost of larger learning database size.

Fingerprinting based positioning has been earlier studied in [2]-[10]. In these, the general assumption is that the fingerprints have full coverage over the areas where user tracks are being tested. However, in practice this is not always the case. For example, persons collecting the data might have restricted access into some regions in the target area, or the data collection is decided to cover only the most important areas and routes. In these cases the fingerprint database contains coverage gaps, which have a clear impact on the user positioning performance. Different error sources and performance analysis related to the fingerprint database have been studied in [11]-[14]. In [11]-[12] authors focus on deriving a Dilution of Precision (DOP) like error estimate for the RSS based fingerprinting, and in [13] and [14] the fundamental limits and a Cramer-Rao lower bound for the RSS based fingerprinting are characterized respectively. The effect of coverage gaps in WLAN based fingerprinting has not been yet addressed in the literature to the best of the Authors' knowledge.

In this paper we study the effects of coverage gaps with help of data from an extensive measurement campaign. Data has been collected between November 2013 and February 2014 from two different buildings having totally over 35,000 WLAN measurement scans including over 700,000 RSS measurements and over 800 found APs. Based on these densely covered target areas we study the effect of coverage gaps by artificially removing part of the fingerprints from the database. To the best of our knowledge this has not been studied in the literature before, at least in this extent. Furthermore, we propose a novel randomized procedure for modeling realistic coverage gaps in the fingerprint database by removing a block of adjacent fingerprints at a time. Contrary to removing arbitrary fingerprints based on uniform probability distribution, the model takes into account the fact that the coverage gaps are usually occurring is larger blocks of areas, for example as inaccessible corridors or floors in a building for security reasons.

In addition to coverage gap studies, as a comparison we also study the effect of noisy RSS values in the database. Here the idea is to model insufficient database calibration (i.e., not having enough measurements from the same AP in one fingerprint) and to compare the positioning performance difference with the coverage gap studies. Moreover, also the effect of bias between the learning data and the user device is briefly studied. This type of bias might occur in case that the device used in collecting the learning data is different from the device used for the user positioning.

The paper is organized as follows. In Section II, we introduce the conducted measurement campaign. Then, in Section III, we present the structure of fingerprint database and define the methodology for fingerprint removal and noise addition processes, which are further used in Section IV to analyze the positioning results. Finally, the conclusions are drawn in Section V.

II. MEASUREMENT CAMPAIGN

Measurements have been taken in two different buildings in Tampere, Finland. One building is a four-storey university building in Tampere University of Technology, and the other one is a small three-storey shopping mall next to the university. The university building is a typical office building, where the first two floors are considered as main floors with open spaces and lecture rooms, and the upper two floors contain mainly offices and narrow corridors. In the shopping mall, the lowest floor is a parking hall, the second floor is the main floor including majority of the shops, and the third floor is smaller area, with a few shops. There are also big opened spaces between second and third floors.

The used measurement device was a Nexus 7 tablet from ASUSTeK Computer Inc. (ASUS) with proprietary software provided by HERE, Tampere. In each measurement location we have logged the RSS measurements from all heard APs identified by their Media Access Control (MAC) addresses. The coordinates of the measurement locations were given manually by the user with the help of building floor plans. Minor errors in the measurement coordinates do not affect the fingerprint database, since the measurements are eventually mapped into a rectangular grid as explained further in Section III.

All the presented measurements are taken on 2.4GHz center frequency. In the university building the total number of performed WLAN scans was nearly 25,000 including over half a million RSS measurements from 316 found APs. One WLAN scan includes coordinates and RSS measurements from all heard APs with specific time and location. Essentially all the accessible areas in the university building were covered by the measurement campaign. In the shopping mall approximately 12,000 WLAN scans were taken with over 150,000 RSS measurements from 414 found APs. Here the measurement density was not as high as in the university building.

III. FINGERPRINT DATABASE

A. *Construction of the original database*

To avoid oversized databases and to alleviate the effect of RSS deviation in measurement locations, fingerprints are usually mapped into predefined set of locations as done in [2]-[7]. From these, we consider the approach given in [4]-[5] and use a rectangular grid with a specific grid point spacing g. However, if the building floor plan is assumed to be available, grid point locations could be defined more sensible as done in [3]. In the case when multiple RSS measurements from the same AP are being mapped into the same fingerprint, an arithmetic mean of the RSS values is used. It is worth of noticing that in this point part of the information in the measurements is lost. The distribution of the RSS measurements from the original learning data is part of the Bayesian positioning approach used in the Kernel method in [2]. However, as illustrated in [3], the performance difference between the Kernel method and the widely known K-Nearest Neighbor (KNN) method, used later in the results in Section IV, is relatively small. The obvious downside of the Kernel method is the increased database size, since data from multiple RSS measurement from the same AP need to be modeled in each fingerprint.

The structure of the fingerprint database can be described as follows. The i^{th} fingerprint in the database is given as (x_i, y_i, z_i, $\mathbf{P}_i$), where x_i, y_i, and z_i are the x, y and z coordinates, and $\mathbf{P}_i$ is a vector of RSS measurements in the i^{th} fingerprint. Consequently, $\mathbf{P}_i$ consists of elements $P_{i,j}$, which define RSS values for j^{th} AP in the database. As explained earlier, $P_{i,j}$ is an average of all RSS measurements heard from the j^{th} AP in the i^{th} fingerprint. This is needed in case of multiple scans in the same fingerprint location.

B. *Removing fingerprints from the original database*

In order to study the effect of coverage gaps in the database, an automated procedure for artificially removing part of the fingerprints is needed. Coverage gaps in the database can be found because of several reasons. For example, learning data collection might be scarce, leaving part of the rooms and corridors without coverage. Another reason could be that the learning data might have lost its integrity or it has become outdated. Also, in some buildings there might be restricted access areas, where the fingerprints cannot be collected. Nevertheless, we focus mainly on case of the scarce learning data collection, which describes the situation where the learning data collection has not reached all the regions in the target area. In this case it is more likely that fingerprints are missing from larger areas at a time. Therefore, removing fingerprints randomly using uniform probability distribution is not viable, since on average fingerprints are still found all around the target area.

To remove fingerprints in a way that reflects the considered scenario, we propose the following type of procedure that is completely defined by two separate parameters: the removal percentage μ and the removal block radius d_{block}. Here μ defines the percentage of fingerprints removed from the database, and d_{block} describes the radius of coverage gaps generated in the database. The process is repeated for each

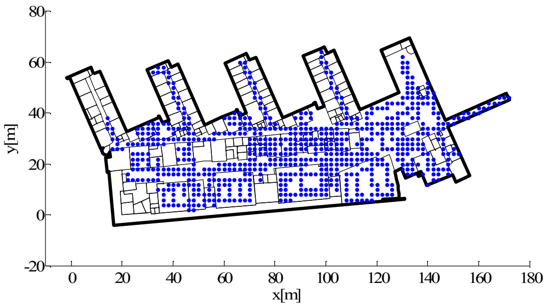

Figure 1. Original fingerprints from the first floor of the university building with g=2m

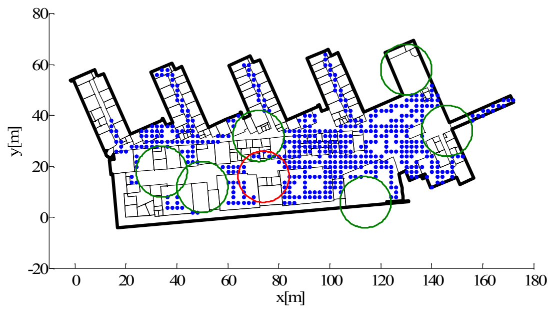

Figure 2. Example of removal process with μ=30% and d_{block}=10m. Circles indicate the removed areas, and the red circle is the last removed area, where part of the fingerprints has been retrieved in order to satisfy the desired μ.

floor separately, because we assume that there is no reason why the gaps should be vertically aligned. By denoting the set of all fingerprint indices as Ω_{full}, the target is to remove a part of the fingerprints, so that the number of remained fingerprint indices is $|\Omega_{partial}|=(1-\mu)|\Omega_{full}|$, where $\Omega_{partial}$ is a set of remained fingerprint indices and $|\cdot|$ gives the number of elements in the set. To achieve this, we initialize $\Omega_{partial}=\Omega_{full}$ and take the four following steps:

1. We select one fingerprint (x_i, y_i, z_i, $\mathbf{P}_i$) randomly from $\Omega_{partial}$ using uniform probability distribution.

2. To create a coverage gap around the selected fingerprint (x_i, y_i, z_i, $\mathbf{P}_i$), we remove all fingerprints whose Euclidian distance in horizontal plane (the xy-plane) to the selected fingerprint is smaller or equal to the block radius parameter d_{block}. The preserved fingerprints are now defining the set of new partial database $\Omega_{partial}$.

3. After removing the fingerprints in the part 2, we check if the desired removal percentage is satisfied: $|\Omega_{partial}|\leq(1-\mu)|\ \Omega_{full}|$. In case the inequality is satisfied, we continue to the part 4, and otherwise go back to the part 1, and remove more fingerprints.

4. If the equality $|\Omega_{partial}|=(1-\mu)|\Omega_{full}|$ is not satisfied with one fingerprint accuracy, we retrieve a required number of the fingerprints from the last removed block starting from the fingerprints with largest distance to (x_i, y_i, z_i, $\mathbf{P}_i$) to satisfy the equality.

After the removal process, the fingerprints defined by the set $\Omega_{partial}$ are now the preserved fingerprints in the database. The number of fingerprints indices in $\Omega_{partial}$ is 1-μ percent of the number of indices in Ω_{full} with one index accuracy. The original fingerprint coordinates with g=2m is shown in Fig. 1 for the first floor of the university building, and an example of one outcome of partial fingerprint coordinates is illustrated in Fig. 2 with μ=30% and d_{block}=10m. As seen in Fig. 2, sometimes a block center can hit on the edge of the target area and result in half circle shaped removal areas. In addition, the removed blocks can overlap with each other and create even larger coverage gaps.

The proposed removal process is fairly simple, but as any random method, to use it for studying its effect on the user positioning accuracy, the process should be run over multiple trials with different random number generator seeds. Moreover, several user tracks covering the whole area should be tested with different removal process outcomes and this has been done in this study, as it will be seen in Section IV.

C. Adding RSS inaccuracies to the original fingerprints

Besides the fingerprint removal process, we also consider adding an artificial error to the fingerprint RSS values. The main purpose here is to compare the magnitude of the impact between the removal process and the noisy RSS values. Here we use an assumption that the RSS values $P_{i,j}$ in each fingerprint are perfectly calibrated and they truly refer to the mean RSS value over infinite number of measurements. This is not true, of course, but because of very large set of data, the assumption is fairly justified. For example in the university building with g=5m, the average number of measurements for defining each $P_{i,j}$ was over 20, which is considered to provide an adequate approximation for the true mean.

We have considered three types of inaccuracies in the RSS values. First we model a case where the calibration of RSS values in the database is inadequate, i.e. the number of measurements for defining the $P_{i,j}$ has been too low. For example, we have observed that the standard deviation of RSS measurements in one location can be even more than 10dB, for which reason taking average of just a few RSS measurements can result in large errors compared to the true average value. This sort of lack of calibration is modeled as

$$\tilde{P}_{Gauss,i,j} = P_{i,j} + W_{i,j}\,, \tag{1}$$

where $\tilde{P}_{Gauss,i,j}$ is the noisy value of $P_{i,j}$ and $W_{i,j}\sim N(0,\sigma^2)$ is zero mean white Gaussian noise with standard deviation σ. Consequently, instead of using the 'true' values $P_{i,j}$, we will use the noisy values $\tilde{P}_{Gauss,i,j}$ in the database. Furthermore, based on the central limit theorem, the Gaussian distribution is a reasonable model also for a set of additive error sources with arbitrary probability distributions.

Another important error source is a constant bias error between the learning data set and the user device. This sort of bias error can occur, for example, if the device used to gather the learning data and the device used for the positioning are originated from different manufacturers. The bias error for the RSS values is modeled as

$$\tilde{P}_{bias,i,j} = P_{i,j} + b \, , \quad (2)$$

where b is a constant describing the bias. In addition, the sign of the bias must be considered carefully, since it is generally recognized that higher observed RSS measurements enable higher positioning accuracy than lower RSS measurements.

IV. Positioning Results

The positioning results presented in this paper are based on the well-known KNN algorithm. The algorithm is often used in the fingerprinting based positioning systems and it can achieve accuracy very close to the Bayesian methods as shown in [3]. The basic idea of the algorithm is to compare the positioning stage measurements with the fingerprints in the database. For this purpose, at each user measurement location, the Euclidian distance between RSS measurements of heard APs in each fingerprint is calculated as

$$D_i = \sqrt{\sum_{j \in \Omega_{user}} \left(P_{i,j} - R_j\right)^2} \, , \quad (3)$$

where R_j is the RSS measurement of the user from the j^{th} AP and Ω_{user} is the set of AP indices heard by the user. As proposed in [2], if a heard AP in the user measurement set is not found in a certain fingerprint, a heuristic RSS value smaller than any other heard RSS value, is used. According to our scarce optimization simulations we have decided to use constantly the value -95dBm, which is 1dB lower than the lowest observed RSS measurement regarding the whole measurement campaign. Finally, the user position estimate can be determined as the average of coordinates of K-nearest fingerprints as

$$(\hat{x}, \hat{y}, \hat{z}) = \frac{1}{K} \sum_{k \in \Omega_{nearest}} (x_k, y_k, z_k) \, , \quad (4)$$

where K is the parameter defining the number of nearest neighbors taken into account, $\Omega_{nearest}$ defines the set of fingerprints with K smallest D_i values, and x_k, y_k, and z_k are the x, y, and z coordinate of the k^{th} fingerprint. Based on algorithm optimization simulations we have used value K=3 in all presented results.

Since our studies regarding the fingerprint removal process and the noisy RSS values introduce random elements, the positioning results are shown as a mean over 100 trials with different random number generator seeds. In addition, the positioning results are based on average of 12 different user tracks in the university building and 4 different user tracks in the shopping mall. Results are studied in two separate categories: as the average positioning error in horizontal plane (2D) and as the average floor detection probability. The latter one is defined as the percentage of estimating the correct floor. The floor is detected correctly, if the z-coordinate estimate is closer to the true user floor than to any other floor.

The average horizontal positioning error as a function of μ is shown in Fig. 3 in the university building for different fingerprint removal approaches, namely uniform and block based based with two different block radii. Here it can be seen that regardless of the fact that μ is the same for all of the cases the results are varying considerably. It is evident that the radius of average coverage gaps, defined by the block radius parameter, has a significant effect on the positioning performance. Moreover, the larger is the grid spacing g the more does the fingerprint removal affect. Nonetheless, our conclusion is that the fingerprint removal with uniform probability distribution, especially with g=2m, is clearly too optimistic approach in modeling gaps in the fingerprint coverage area.

Fig. 4 shows the average floor detection probability as a function of μ in the university building for different fingerprint removal approaches. Compared to the results of horizontal positioning accuracy, the effect of fingerprint removal method is clearly more visible here. For example, for the method with uniform removal process, there is hardly any change in the floor detection probability as μ increases, but again this uniform modeling seems a very optimistic modeling, which is likely to be far from real encountered scenarios.

Similar results are studied also for the shopping mall in Fig. 5 and in Fig. 6, for average positioning error and average floor detection probability respectively. In general the results are aligned with the results of the university building. However, it appears that the grid spacing does not have as large impact on

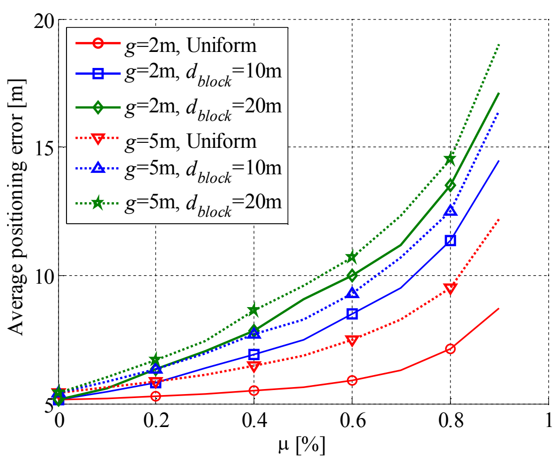

Figure 3. Average horizontal positioning error as a function of μ for different fingerprint removal approaches in the university building

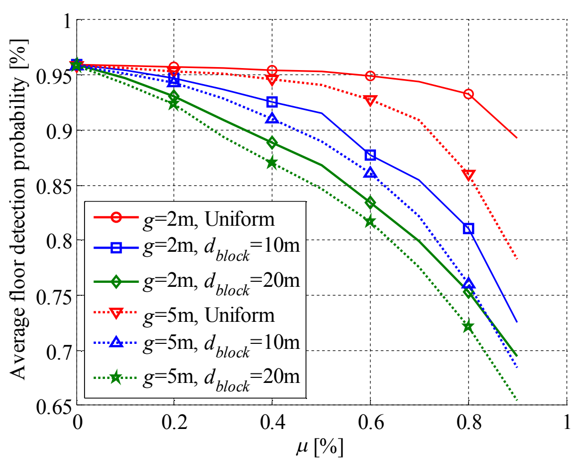

Figure 4. Average floor detection probability as a function of μ for different fingerprint removal approaches in the university building

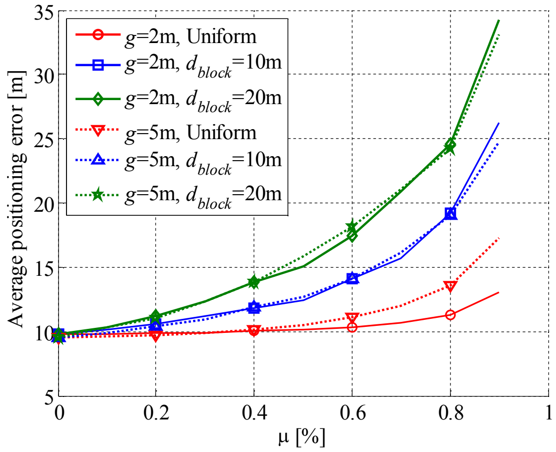

Figure 5. Average horizontal positioning error as a function of μ for different fingerprint removal approaches in the shopping mall

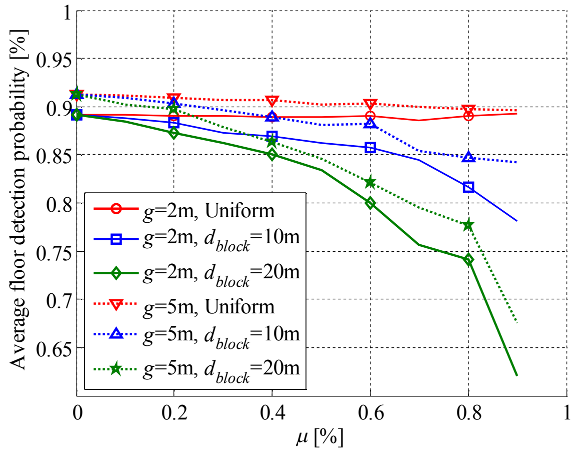

Figure 6. Average floor detection probability as a function of μ for different fingerprint removal approaches in the shopping mall

the curves as in the university building case. This is mainly due to fact that in the university building the measurement density with respect to the building dimensions has been considerably larger. In the shopping mall there are more open spaces and wider corridors for which reason learning data collection has originally left more gaps in the data set than in the university building.

It is worth of noticing that in case there are considerable coverage gaps in the database, KNN method with K= 1, called as Nearest Neighbor (NN) method, cannot estimate the user position inside the gaps, since the estimate is always exactly at the fingerprint with the lowest Euclidian distance. However, with KNN method, if the fingerprints with the smallest Euclidian distance are located around the coverage gap area, the estimate is also located inside the gap making it much more suitable in practical positioning scenarios.

To compare the effect of coverage gaps and inaccurate RSS measurements in the fingerprint database, the average horizontal positioning error is shown in Fig. 7 in the university building for different sort of RSS inaccuracies. Here the Gaussian case refers to Gaussian type of RSS error given in (1), and the bias cases refer to biased type of RSS error given in (2). The plus and minus sign given with the bias indicate whether the bias is positive or negative respectively. Moreover, the x-axis defines the square root of average power for the error source, which is the noise standard deviation σ for the Gaussian noise case, and the amplitude of bias b for the biased cases. As expected, the Gaussian error source induces the smallest impact on the positioning accuracy. Nevertheless, it is slightly surprising that with σ=10dB the positioning error is approximately increased only from 5m to 6m.

The validity of results with high noise levels (σ>10dB) arises a question of useful information included in the RSS measurements. As explained earlier in Section III, the positioning algorithm uses a heuristic parameter in defining the unheard APs in (3). The value of this parameter adjusts the weight of heard APs in the position estimate. Now, by neglecting the RSS values, and using only the number of commonly heard APs as the positioning metric, the average positioning error becomes as 7.3m with g=2m and 7.4m with g=5m. Since here the RSS values are not used at all, the result is constant over the whole x-axis. This corresponds with the performance of the Gaussian case with roughly σ=15dB for

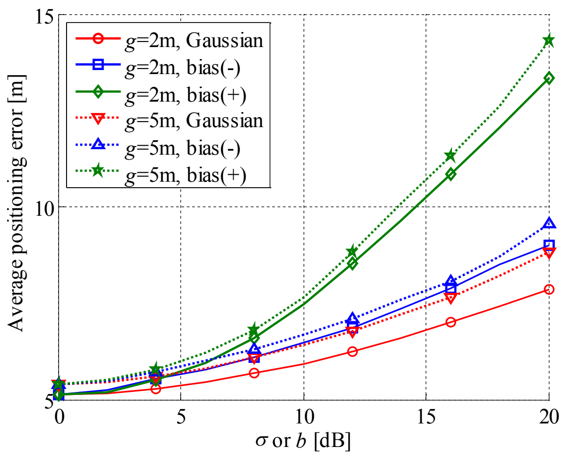

Figure 7. Average horizontal positioning error as a function of error magnitude for different RSS inaccuracies in the university building

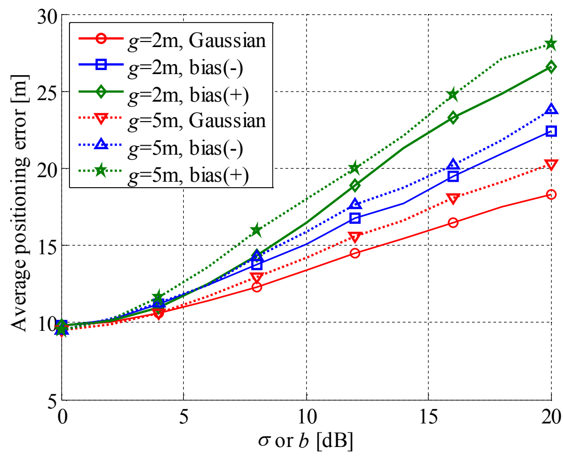

Figure 8. Average horizontal positioning error as a function of error magnitude for different RSS inaccuracies in the shopping mall

g=5m and σ=17dB for g=2m. It means that there's still useful information in the RSS values, even though the learning database calibration is badly incomplete.

The effect of biased learning database is twofold as seen in Fig. 7. If the bias is negative, i.e. the user device observes the RSS values as larger, the performance is only slightly worse than with the Gaussian error. On the contrary, the negative bias, i.e. the user device observes the RSS values as smaller, has more significant effect on the performance. In this case as the bias gets larger, the user device is completely missing the high RSS values leading to decreased positioning accuracy.

Similar results for the shopping mall are shown in Fig. 8. Although in general the average errors are on much higher levels, the results seem to be consistent with the university building results.

Defining a sensible noise source levels in practice is very difficult, especially for the bias error case. However, since here the Gaussian noise is modeling the error of inadequately calibrated database, the noise power σ is connected with the number measurements used to create $P_{i,j}$ in each fingerprint. The worst case happens when only one measurement per $P_{i,j}$ is obtained. In this case the error magnitude can reach the higher values of σ in the presented results.

V. CONCLUSION

We have conducted a study regarding effects of coverage gaps and inaccurate RSS values in a fingerprint database. Based on an extensive measurement campaign it has been shown that that the measurement gaps can cause considerable reduction in the average positioning error. Moreover, besides the results are affected by the number of removed fingerprints, the distribution of removed fingerprints is essential. It was shown that removing fingerprints with uniform probability distribution resulted in rather optimistic results, especially for the floor detection probability.

In addition to fingerprint coverage gaps, inaccurate RSS values were studied in case of Gaussian distributed noise and constant bias error. Although the effect of these with practical noise power values was found to be less severe than with coverage gaps, they should be considered in positioning system design.

The given results are valuable for evaluating requirements for adequate learning data collection. Since the effect of coverage gaps and inaccurate RSS values can be approximated, the learning data collection can be dimensioned properly to achieve the desired positioning accuracy with minimum effort. For example, based on the results in the university building, losing 20% of the fingerprint coverage or having 9dB of Gaussian calibration error will both have approximately 10% reduction in the average positioning accuracy.

Although the results shown in this paper indicate the effect of coverage gaps and inaccurate RSS fingerprint in terms of average error, it would be important to study also the corresponding error distributions. Moreover, analyzing the mapping from the actual measurements to the fingerprint database in more detailed manner would reveal more information on the error statistics and its effect on the positioning performance.

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