REFINING WI-FI BASED INDOOR POSITIONING

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Abstract

The increasing demand for location-based services inside buildings has made indoor positioning a significant research topic. This study deals with indoor positioning using the Wireless Ethernet IEEE 802.11 (Wi-Fi) standard that has a distinct advantage of low cost over other indoor wireless technologies. Most of the proposed Wi-Fi indoor positioning systems use either proximity detection via radio signal propagation models or location fingerprinting techniques, the latter being usually more accurate. The aim of this study is to examine several aspects of Wi-Fi location fingerprinting based indoor positioning that could enhance the positioning accuracy, without demanding a larger radio map with additional signal strength measurements in more locations, namely making use of weakly-sensed access points, making use of the different available Wi-Fi frequency bands, using device's orientation information provided by a built-in digital compass, and augmenting the radio map using Locally Weighted Regression.

Keywords: *indoor positioning, location fingerprinting, Wi-Fi, IEEE 802.11, WLAN, wireless network*

Introduction

The increasing demand for location-based services inside buildings has made indoor positioning a significant research topic. The applications of indoor positioning are many, for instance, indoor navigation for people or robots, inventory tracking, locating patients in a hospital, guiding blind people, tracking small children or elderly individuals, location-based advertising, ambient intelligence etc.

Although the Global Positioning System is the most popular outdoor positioning system, its signals are easily blocked by most construction materials making it useless for indoor positioning. This study deals with indoor positioning using the Wireless Ethernet IEEE 802.11 (Wi-Fi) standard that has a distinct advantage of low cost over other indoor wireless technologies – it has relatively cheap equipment and in many areas usually a Wi-Fi network already exists as a part of the communication infrastructure avoiding expensive and time-consuming infrastructure deployment.

Although Wi-Fi has not been designed for positioning, its radio signals can be used for location estimation by exploiting the Received Signal Strength (RSS) values measured in any off-the-shelf mobile device equipped with Wi-Fi facilities – and no additional special-purpose hardware is required. Such a positioning system can be relatively easily implemented for notebook computers, Personal Digital Assistants, smartphones, and other Wi-Fi enabled mobile devices.

Most of the proposed Wi-Fi indoor positioning systems use either proximity detection via radio signal propagation models (Thomas and Ros, 2005; Widyawan et al., 2007; Yim et al., 2010) or location fingerprinting techniques (Badawy and Hasan, 2007; Brunato and Battiti, 2005; Ferris et al., 2006; Honkavirta et al., 2009; Hossain et al., 2007; Liao and Kao, 2008; Yim, 2008; Yim et al., 2010). Deriving an accurate propagation model for each Wi-Fi access point (AP) in a real-world indoor environment is extremely complex and therefore usually results in a relatively poor positioning accuracy (Widyawan et al., 2007; Yim et al., 2010). On the other hand, location fingerprinting techniques use empirical data to approximate a location. First, a so-called radio map is constructed by measuring RSS at a number of known locations – calibration points. The location of the user is then determined by comparing the obtained RSS values to a radio map. This provides accurate positioning even in very complex environments while the modelling of the complex signal propagation is avoided. In addition, the fingerprinting techniques usually do not require knowing exact locations of APs.

An early example of a positioning system that uses fingerprinting is RADAR (Bahl and Padmanabhan, 2000). In RADAR, user's location is determined by finding a known fingerprint that is most similar to the actual RSS readings. Since then, many studies have been conducted that perform location estimation from a radio map employing Nearest Neighbours (Honkavirta et al., 2009; Lin and Lin, 2005; Yim et al., 2010), Artificial Neural Networks (Battiti et al., 2002; Derr and Manic, 2008; Lin and Lin, 2005), Support Vector Machines (Brunato and Battiti, 2005), Decision Trees (Badawy and Hasan, 2007; Yim, 2008), Bayesian techniques (Honkavirta et al., 2009; Liao and Kao, 2008; Madigan et al., 2005), or other techniques (Ferris et al., 2006; Honkavirta et al., 2009; Widyawan et al., 2007; Yim et al., 2010). In majority of these studies the Nearest Neighbours technique, in addition to its simplicity, turned out to be among the most accurate ones.

The aim of this study is to examine several aspects of Wi-Fi location fingerprinting based indoor positioning that could enhance the positioning accuracy without demanding a larger radio map with additional RSS measurements in more locations.

Making use of weakly-sensed APs: It is considered to make use of (in many studies frequently ignored) weakly-sensed APs located further away, on other floors, and even in nearby buildings. It is demonstrated that the weak APs can provide additional information for at least a slightly more accurate positioning. Furthermore, also a situation, when in the entire building there would be no APs, is considered – the positioning system may use signal strength information from only those APs of the other buildings nearby.
Making use of the two different Wi-Fi frequency bands: The use of either or both 2.4 GHz and 5 GHz Wi-Fi bands using IEEE 802.11b/g and IEEE 802.11a standards is examined.
Making use of device's orientation information: In studies (Bahl and Padmanabhan, 2000; Honkavirta et al., 2009; Kaemarungsi and Krishnamurthy, 2004; Liao and Kao, 2008), it is argued that the mobile device's orientation information can have a significant effect on the RSS values and therefore on estimated location. This study examines the opportunity to improve positioning accuracy using device's orientation information provided by a digital compass – a piece of hardware that is built-in in many newest handheld devices.
Augmenting the radio map: A method is proposed for augmenting the radio map with additional fingerprints predicted by Locally Weighted Regression (LWR), with locality of interpolation optimized individually for each AP. It is shown that the augmented radio map can provide higher positioning accuracy without additional RSS measurements, especially if the original radio map is sparse.
In many existing studies, to perform the positioning experiments, the (usually) three to six APs are carefully distributed across the area of interest specifically for the purposes of the experiments. Therefore, it should be noted that in the experiments of this study no additional APs were deployed and no existing APs were moved – the experiments are performed using an already existing infrastructure with APs that have been deployed for maximum Wi-Fi internet availability.
The remainder of this paper is organized as follows: The next section outlines location fingerprinting, describes Weighted k-Nearest Neighbours algorithm, sketches the idea of the usage of device's orientation information, and proposes radio map augmentation using LWR. Then the performed experiments are described and experimental results and findings are presented. Finally, the last section concludes the paper.

Methodology

Location fingerprinting

Location fingerprinting based positioning systems usually work in two phases (see Fig. 1): calibration phase (also called offline phase) and working phase (also called online phase or run-time phase). In the calibration phase, a mobile device is used to measure RSS values (in dBm) from several APs at the chosen calibration points in the area of interest. Each of the *n* measurements becomes a part of the radio map and is a tuple $(\mathbf{q}_i, \mathbf{r}_i)$ $i = 1,2,...,n$ where $\mathbf{q}_i = (x_i, y_i)$ are the geographical coordinates of the *i*th location and $\mathbf{r}_i = (r_{i1}, r_{i2}, ... r_{im})$ are the *m* RSS values from *m* APs at that location. Usually, an average of several samples recorded per location is stored.

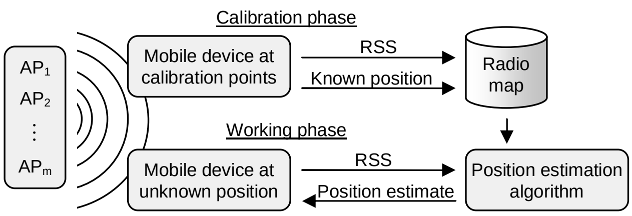

Figure 1. The two phases of location fingerprinting

In the working phase, a mobile device measures the RSS values in an unknown location and applies a location estimation algorithm to estimate its current location using the previously created radio map. As indoor environments have unique signal propagation characteristics, it can be assumed that each location can be associated with a unique combination of RSS values.

Weighted k-Nearest Neighbours

A general Weighted k-Nearest Neighbours (WKNN) algorithm for location fingerprinting can be described as a two step process. First, find within the radio map the *k* indices $i_1, i_2, ..., i_k$ whose $\mathbf{r}_{i_1}, \mathbf{r}_{i_2}, ..., \mathbf{r}_{i_k}$ values are nearest (according to Euclidean distance in the signal space) to the given vector **r** measured at the unknown location. In the second step, calculate the estimated location **q** (for each coordinate separately) as an average weighted by the inverse of the RSS distances:

$$\mathbf{q} = \sum_{j=1}^{k} \frac{w_j \mathbf{q}_{i_j}}{\sum_{l=1}^{k} w_l}, \tag{1}$$

where all weights are nonnegative $w_j = d(\mathbf{r}_{i_j}, \mathbf{r})^{-1}$ and d is the Euclidean distance between the m-vectors. Note that there is a special case when the distance is zero; then as the estimated location just the one with the zero distance is taken without fully computing (1). The reasoning behind this algorithm is that the calibration point with the shortest distance in signal space also has the shortest distance in physical space, and as such acts as a proper location estimate.

WKNN has one tuning parameter, the number of nearest neighbours considered k, which is used to control the locality of the location calculation. When $k = 1$, the algorithm acts as a simple look-up table. For larger values, the location can also be estimated to be somewhere in-between the calibration points. Li et al. (2006) recommends using $k = 1$ only if the density of the radio map is high. However, k should also not be too large as then the location estimates will be too much influenced by calibration points far away. In this study the number is fixed experimentally to $k = 2$.

Making use of device's orientation information

Honkavirta et al. (2009) in their study showed that the positioning accuracy significantly benefit from varying rotation of the measuring device during the calibration phase. This is mostly because of the radio irregularity caused by the direction of a mobile device's antenna, existence of some reflector of the wireless signal, or user's body due to the high proportion of water in human body absorbing wireless signals (Kaemarungsi and Krishnamurthy, 2004; Liao and Kao, 2008). Device's rotation can level out or equalize the impact of its orientation to measure more reliable fingerprint compared to the fingerprint that is measured only to one direction.

In (Liao and Kao, 2008), during the calibration phase RSS values were recorded in four different orientations while in the working phase device's orientation was estimated and employed for a more accurate positioning. It was shown that, when the user movement consists of mostly straight lines, positioning accuracy can be improved. However, if the orientation of the device is estimated incorrectly, the positioning accuracy decreases.

Theoretically, the availability of orientation information from a built-in digital compass can improve the positioning accuracy by using radio map data of only the specific orientation. This study examines the potential to improve positioning accuracy using device's orientation information provided by a digital compass.

Augmenting the radio map

Collecting large numbers of fingerprints in the calibration phase is labour-intensive, which makes a large-scale deployment of accurate indoor positioning non-trivial. Therefore, a variety of techniques have been proposed in order to generate synthetic calibration points with predicted RSS values for adding to the radio map, allowing to collect only a limited number of field measurements. Many proposed techniques (Hossain et al., 2007; Pechac and Klepal, 2001; Widyawan et al., 2007) predict the RSS values using a radio signal propagation model requiring knowing exact locations of all used APs or even complete plans of the whole deployment area with precise locations of all walls. And even with this information available, the derived propagation models may be inadequate for the environment and therefore may not bring the desired positioning accuracy. A number of other proposed techniques do not rely on any propagation model, instead the RSS values are predicted via local interpolation of the original calibration points, approximating the behaviour of the radio signal (Ferris et al., 2006; Li et al., 2006).

This study adopts the latter approach and proposes generating synthetic calibration points using LWR with locality of interpolation optimized individually for each AP. The technique does not require knowing locations of neither APs nor walls. The augmentation of the radio map is done using only the original calibration points. This allows performing augmentation also when the available information on the environment is incomplete, e.g. when locations of some APs are unknown, and without additional software for environment layout analysis.

LWR (Cleveland and Devlin, 1988; Atkeson et al., 1997) is designed to address situations in which the models of global behaviour do not perform well or cannot be effectively applied without undue effort. The LWR interpolation is carried out by point-wise fitting of low-degree polynomials to localized subsets of the data. The advantage of this method is that it is not required to specify a global function of the data.

The assumption of the LWR is that near the query point (i.e. the to-be-added synthetic calibration point) the approximated value changes smoothly and can be approximated using a low-degree polynomial. The coefficients of the polynomial are calculated using the weighted least-squares method giving the largest weights to the nearest (according to the Euclidean distance) calibration points and the smallest weights to the farthest calibration points.

Given a regression model

$$F(\mathbf{q}_i) = \beta_0 + \beta_1 x_i + \beta_2 y_i, \tag{2}$$

the coefficients $\boldsymbol{\beta} = (\beta_0, \beta_1, \beta_2)$ are calculated minimizing

$$\boldsymbol{\beta} = \arg\min_{\boldsymbol{\beta}} \sum_{i=1}^{n} w(q, \mathbf{q}_i)(F(\mathbf{q}_i) - \mathbf{r}_{ij})^2, \tag{3}$$

where j is the index of AP for which the interpolation is done, w is a weight function, and $q = (x, y)$ is the query point (nearest neighbours of which will get the largest weights). The weight function w depends on the distance (in a scaled space) between the point of interest q and a calibration point $\mathbf{q}_i$. In this study, a Gaussian weight function is used:

$$w(q, \mathbf{q}_i) = \exp(-\alpha\mu), \tag{4}$$

where α is a coefficient that controls the locality of the interpolation and μ is scaled distance from the query point to the ith calibration point:

$$\mu = \frac{d(q - \mathbf{q}_i)}{d(q - q_*)}, \tag{5}$$

where d is Euclidean distance and q_* is the farthest calibration point from the query point q so that $\mu = 1$ when $q_* = \mathbf{q}_i$. Consequently, for each query point, the closer calibration points contribute more heavily in formulating regression equation.

The locality of the interpolation is controlled by varying the value of α. The larger its value, the more local is the interpolation; for $\alpha = 0$, the local model transforms into a global model. To automatically find the 'best' value of α for each AP, a simple search algorithm is performed in each step employing Leave-One-Out Cross-Validation (LOOCV) for estimation of LWR's predictive performance. The algorithm starts with $\alpha = 0$ and gradually increments it by 10, in each step performing LOOCV. The search is stopped after the predictive performance could not be improved for 5 steps in a row.

LOOCV involves n iterations where each time $n-1$ calibration points from the radio map are used as training data, and the remaining one point is used as validation data (acting as the query point in LWR). This is repeated so that each calibration point is used exactly once as the validation data. LOOCV estimates the predictive performance by averaging the individual squared errors of RSS prediction from the n iterations.

Once the 'best' α values for each AP are known, the predicted RSS value at a synthetic point is obtained by plugging the two coordinates of a synthetic point and its corresponding three coefficients (computed using (3)) in (2). Note that these computations must be performed for each AP and each synthetic point separately. In other words, for inferring each synthetic point, a different regression equation is obtained for each of the m APs every time.

The Matlab source code of LWR employed in this study is available at http://www.cs.rtu.lv/jekabsons/.

Experimental testbed and data collection procedure

The experiments were performed on the fifth floor of a five-storey building of the Faculty of Computer Science and Information Technology, Riga Technical University. The area of the testbed is approximately 860 m^2, and includes eight classrooms, four offices, and the main hallway.

Fig. 2 displays the layout of the floor where the experiment was performed. The area has five APs installed which have been deployed for maximum Wi-Fi internet availability and can be sensed in at least a third of the area. The largest left-out part of the fifth floor (upwards in the figure) has some additional APs that can be barely sensed from some nearest locations. Furthermore, some APs from the fourth and even third floors can also be sensed in some small areas. This sums up in locally-situated 14 APs. Most of the local APs are Enterasys devices RBT-1002 and RBT-4102 operating in both IEEE 802.11a and IEEE 802.11b/g modes at the same time, allowing getting RSS readings for both 2.4 GHz and 5 GHz Wi-Fi frequency bands. Additionally, there are a total of 43 APs in the nearest other buildings that can be sensed in at least one small location. Note that no additional APs were deployed and no existing APs were moved – the experiments were performed using an already existing infrastructure. The measurements were done mostly in working hours with people walking around and the Wi-Fi internet being used.

The RSS measurements were collected by a human operator using a PC notebook with internal wireless card. The notebook was used for both calibration and working phase. A total of 82 calibration points are defined (see Fig. 2). In the classrooms, the points were placed near the walls and corners, as the walls are responsible for fast drops of signal strength while in the free space the signal strength drops much slower, especially further away from an AP. On average, the distance from one calibration point to the nearest other point is 3.7 m within the same room and 2.6 m when also the points from other rooms are considered. The number of APs that could be sensed from a location ranges from 2 to 13 with average of 7.

To be able to test the usefulness of device's orientation information, for each calibration point the RSS readings were collected in four directions (facing north, east, south, and west), while for each direction a total of 30 RSS samples were collected over a time span of 30 seconds. The readings are then averaged for each direction separately as well as for all the directions combined, resulting in five different average RSS values, each for a separate radio map.

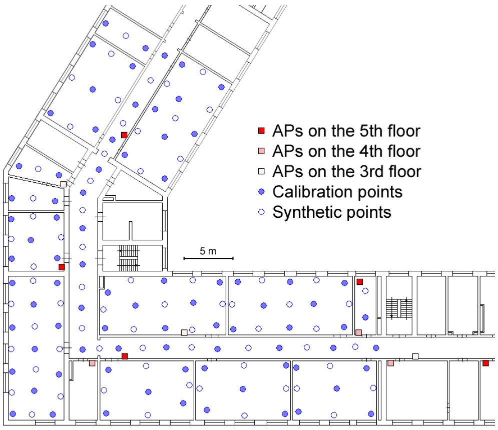

Figure 2. Layout of the testbed environment with calibration points and synthetic points

Finally, a test set of 68 points was created (see Fig. 3). The placement of the testing points mimics a person walking in a route through five classrooms, one office, and the hallway. The route is started at one point and finally ended at the very same point, visiting 34 different locations where each location is visited two times, each time facing a different direction. The measurement process, apart from that it is performed for only two orientations, is the same as for the calibration points.

The averaged RSS values range from -99 dBm (used when the AP is not present) to about -33 dBm in close proximity to an AP. The outcome of the measurement session can be downloaded at http://www.cs.rtu.lv/jekabsons/.

Experimental results

Table 1 summarizes the positioning errors for the experiments.

Making use of weakly-sensed APs: The results suggest that indeed the positioning accuracy can be at least slightly improved if the list of the used APs consists of not only the strongest APs (average positioning error of 2.37 m) but also the weakly-sensed APs located further away, on other floors, and even in nearby buildings as well (average positioning error of 2.10 m).

Additionally, an interesting result is that, if in the entire building there would be no APs and the positioning system could use signal strength information from the 'outside' APs only – those of the other buildings nearby, the average positioning error would still be a decent 7.14 m. This suggests that such a positioning system could still be useful, especially if used together with some supplementary positioning or tracking technology while walking through hallways in the middle of the building (where, in this experiment, the positioning error is the largest).

Making use of the two different Wi-Fi frequency bands: Signals from eight of the local APs were strong enough for the measuring device to be able to detect them in both bands, 2.4 GHz (IEEE 802.11b/g) as well as 5 GHz (IEEE 802.11a). It turned out that, in addition to 2.4 GHz RSS, using also the 5 GHz RSS (as if they would come from additional eight APs) always increased the average positioning accuracy by at least 10%. Apparently, despite the sharply dropping 5 GHz signal strength, the RSS values are still useful for extracting additional information for positioning, even if only near the APs.

Table 1

Test set error (in meters) distribution: mean, median, and percentiles

	Mean	Median	75th	90th	95th
5 strongest local APs					
2.4 GHz	2.56	2.35	3.60	4.64	5.56
Both freq.	2.28	1.87	3.40	4.24	5.36
Both freq. + orientation info.	2.45	1.88	3.76	4.70	5.50
Both freq. + LWR	2.19	1.95	3.03	4.31	5.60
All local APs (14)					
2.4 GHz	2.33	2.16	3.17	3.99	5.12
Both freq.	2.10	1.67	3.12	4.18	5.41
Both freq. + orientation info.	2.40	1.61	3.26	5.03	7.23
Both freq. + LWR	1.94	1.52	2.55	4.00	5.21
All sensed APs (57)					
2.4 GHz	2.44	2.32	3.58	4.62	5.10
Both freq.	2.02	1.62	3.04	4.22	4.52
Both freq. + orientation info.	2.11	1.71	3.10	4.08	4.96
Both freq. + LWR	1.82	1.56	2.35	3.69	4.58
Only the 'outside' APs (43)	7.14	6.51	10.02	13.64	14.55
Reduced radio map, both freq.					
5 strongest local APs	3.48	3.48	4.75	5.99	6.95
5 strongest local APs + LWR	3.22	3.05	4.47	5.33	6.52
All local APs	3.31	3.31	4.61	5.55	6.53
All local APs + LWR	2.83	2.56	3.88	5.03	5.76
All sensed APs	3.43	3.30	4.81	5.87	7.21
All sensed APs + LWR	3.00	2.42	3.99	5.79	7.40

Making use of device's orientation information: For this experiment, four different radio maps where created – one for each orientation. The location estimation for each testing point was done using that radio map corresponding orientation of which is the nearest to the actual orientation of the measuring device at the time of measurement.

While theoretically the availability of orientation information could increase the positioning accuracy, in practice there was no improvement. The reason for this could be the evident signal strength fluctuations, i.e. the noise in the data could be higher than the useful orientation-specific information. Nevertheless, it should be noted that the positioning accuracy significantly benefited from the RSS readings averaged over all four orientations, for example, while using all local APs and both frequency bands, the positioning error decreased from 2.85 m, when RSS information from only the north orientation was used, to 2.10 m, when all four orientations were used.

Augmenting the radio map: For this experiment, the locations of the synthetic points were chosen so that the points in the radio map would retain the uniform distribution. The chosen locations are shown in Fig. 2. Results in Table 1 suggest that there is at least a slight improvement. Fig. 3 shows the location estimation results, where a triangle represents the true location and its corresponding two crosses represent the estimated locations for the two opposite orientations. Note that the estimated locations almost always fall in the correct room providing a near 100% accuracy on the room-level granularity (here, an unaugmented radio map provides similar behaviour). The same experiment was also performed with a reduced radio map formed from the original one by taking only the (one to three) central calibration points for classrooms, one point for each office, and every second point for hallway – a total of 25 calibration points. In the augmentation process, the synthetic calibration points were generated at all the left-out calibration point locations as well. This time the augmented radio map outperforms the unaugmented one more significantly (see Fig. 4a). It can be seen that the gain using an interpolation technique becomes more significant when the radio map is sparse. This also agrees with the results of prior studies (Hossain et al., 2007). The thing to emphasise is that with the significant reduction in the number of measured calibration points, the positioning error increased only to 2.83 m. This means that, if an environment has changed, only a small number of new measurements is needed to quickly generate an updated radio map and get a reasonably accurate positioning.

Finally, Fig. 4b presents the results of an additional experiment where the impact of varying the number of used APs was studied with more detail and without regarding the origin of an AP. The list of all APs was sorted by their overall RSS variance in the full radio map and for each number of used APs only those with the largest variance were used. As expected, the positioning error is not a linear function of the number of APs: the decreasing rate of positioning error gradually slows down and at some threshold it is evident that only little benefit is achieved by further increasing the number of APs. Here, the best results are mostly achieved using about 20 APs. However, the fluctuations of the curves suggest that a better criterion for sorting the APs or a better algorithm for finding the best subsets of the APs could be used delivering smaller subsets with the same or even slightly better positioning accuracy.

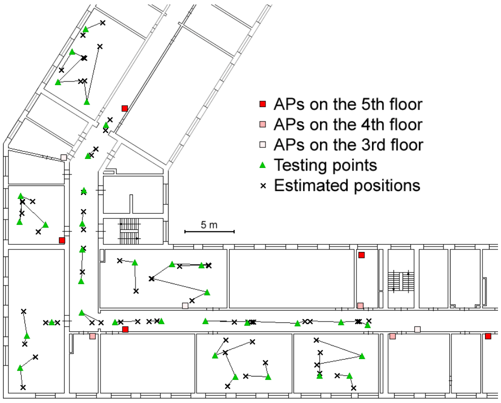

Figure 3. Testing points and their corresponding estimated locations

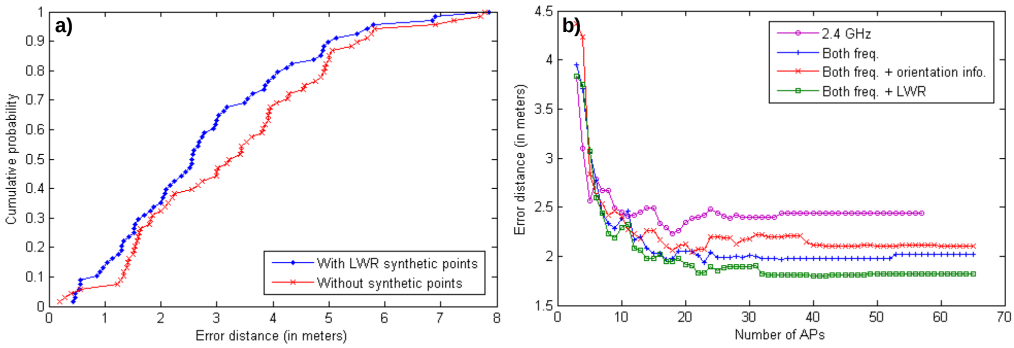

Figure 4. Positioning performance: a) with the reduced radio map; b) with different numbers of APs

Conclusion

This paper examined several aspects of Wi-Fi location fingerprinting based indoor positioning that could enhance the positioning accuracy. Based on the experimental findings, the following conclusions can be drawn.

It was observed that a positioning system can benefit from the availability of additional weakly-sensed APs as well as APs working in 5 GHz frequency band (using IEEE 802.11a/n). RSS readings from these APs gave a notable improvement in positioning accuracy – the average positioning error dropped from 2.56 m to 2.02 m. In fact, in this study, using exclusively the APs from the other buildings nearby, the positioning error was still a decent 7.14 m.

Nevertheless, it must be noted that the benefit from adding more and more weakly-sensed APs quickly decreases and after a certain number of APs, the accuracy actually can deteriorate. This is especially true for sparse radio maps. One of the future work directions here could be consideration of some kind of automatic subset selection technique to filter-out the irrelevant APs. While this may not bring much additional accuracy, at least the size of RSS fingerprint database could be significantly reduced.

In this study, the availability of orientation information could not increase the positioning accuracy. The reason for this could be the evident signal strength fluctuations. However, as this result appears to contradict with some other studies, it should be investigated more extensively with different experimental setups.

The results from experiments with LWR show that the largest potential improvement in positioning accuracy is when the radio map is sparse. This makes the technique especially suitable for larger environments in order to shorten the time required for measurements in the calibration phase and still achieve a reasonable positioning accuracy.

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