Are all the Access Points necessary in WLAN-based indoor positioning?

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***Abstract*—Wireless Local Area Networks are widely used for indoor localization purposes based on Received Signal Strength -based positioning algorithms, due to the increasing demands for Location-based Services indoors. A huge number of hearable Access Points can however increase the complexity of the positioning system and the difficulty of location estimation, since not all of the available Access Points carry useful or significant information. This paper focuses on Wireless Local Area Networks-based indoor location by taking into account the contribution of each hearable Access Point in the location estimation. Several criteria for Access Point selection are examined, and we will show what is the permissible reduction factor without a large deterioration in positioning performance and which criterion is optimal for use in Access Point removal. The fingerprinting estimation method and the deconvolution based path loss positioning approach are both addressed, and the results are based on a large measurement campaign covering five different buildings with several floors each, in two countries.**

I. Introduction

Wireless Local Area Networks (WLAN)-based positioning is becoming more and more popular in indoor areas, where the traditional Global Navigation Satellite Systems generally fail to offer a position estimate due to multipath propagation, low visibility of satellites and weak signal powers [1], [2], [3]. A wide area of location-based services and location-based business models are envisioned for the future, once the barrier of indoor location is crossed [4]. The underlying multiple access schemes for WLANs are both Direct Sequence-Code Division Multiple Access and Orthogonal Frequency Division Multiplexing techniques and the underlying modulations range from Binary Phase Shift Keying to higher order Quadrature Amplitude Modulation. Thus, Time-Of-Arrival or Round-Trip-Time based estimations for WLAN location are still not widespread, due to the many different underlying physical layer features of WLANs on the market. Alternatively, the Received Signal Strength (RSS) or the Received Signal Strength Indicator (RSSI) of the signal can be used for the positioning purposes. RSS-based positioning methods have the advantage of easy accessibility, availability in almost every device and cost effectiveness due to the ability to utilize the current wireless infrastructures.

Alternatively, RSS can be used for the location purpose, either by matching the measured RSSs with some RSSs collected in preamble in a database (fingerprinting method) or by trilateration methods using some signal-to-distance mapping derived from the measured RSS (path-loss estimation). Both methods involve two stages: an initial off-line training phase and an on-line estimation phase [1], [5], [6]. In the training phase, models and databases are built based on collected information about the indoor environment. In the estimation phase, that involves real-time processing, the unknown position of a mobile station (MS) is estimated based on the information saved in the training phase. Due to the high deployment of Access Points (APs) in many buildings, both fingerprinting and path loss-based positioning methods suffer from having to deal with a huge amount of data. Indeed, it is generally believed that some APs are strongly relevant, while others are weakly relevant for the positioning purpose [7], [8].

WLAN transmitters inside buildings can nowadays support multiple BSSID. This means that several MAC addresses can be visible at exactly the same location. In addition, WLAN AP deployment inside a building is optimized for communication purposes, not for navigation purposes. This means that several APs can be placed in the vicinity of each other or can transmit some correlated information. For positioning purposes, it may be that not all of the available APs carry useful or significant information. Redundant, unnecessary APs may increase the difficulty of location estimation and increase the time and space complexity to build a positioning system [9].

To overcome the problems caused by a large amount of available data, the number of APs can be decreased by selecting a subset of APs among all of the availabe APs. With a suitable subset of APs, it is possible not only to decrease the amount of data, but also to improve the positioning accuracy [10], [11]. However, so far there has still been very little work regarding how to choose the subset and measure the significance of an AP [7], [12], [13]. Indeed, the existing studies are limited into one building only, and general rules are difficult to be drawn based on one particular building.

This paper addresses two related questions: first, whether we can reduce the fingerprint database in WLAN-based positioning, by removing some of the available APs and what is the permissible reduction factor without a large deterioration in performance, and secondly, which criterion is the best to be used in AP removal. We continue our previous studies in [11], by introducing two new selection criteria and by addressing both the fingerprinting estimation method and the deconvolution based path loss (PL) positioning approach, based on a

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large indoor measurement data campaign. The data has been collected with two different tablets, a Windows tablet and an Android Nexus tablet, in several buildings in Tampere, Finland and Berlin, Germany (university buildings, office buildings and shopping centers). Nokia HERE indoor maps and proprietary software has been used in the data gathering. In this paper, we will show that the maxRSS-based removal criterion seems to be most consistent and to offer the best results among the other studied methods. Indeed, we will show that it is possible to remove even up to 50% of the APs in the training phase without a significant performance degradation.

II. Positioning Principles

A. Fingerprinting

Fingerprinting has two stages, described below.

1) Training Phase: The fingerprinting (FP) based positioning method is a database correlation technique, where a database is first created using pre-measured samples with known locations in the building of interest (i.e., the training phase) and then only this database and the current real-time measurements are used to calculate the position estimate (i.e., the estimation phase). The measurement points (i.e., grid points or FPs) are formed as (x_i, y_i z_i, $P_{i,k}$), where x_i, y_i z_i are the 3D coordinates of the FP i ($i = 1, ..., N_{fp}$, where N_{fp} is the total number of FPs) and $P_{i,k}$ denotes the measured RSS from kth AP in the ith FP. An AP stands for a MAC address; several APs can transmit from exactly the same location (e.g., as it is the case in WLAN with multiple BSSID). We refer to those WLANs with multiple MAC addresses from the same location as Multiple Input Multiple Output (MIMO) WLANs, by analogy with the most widespread WLAN standard nowadays, 802.11n, which supports MIMO transmissions.

In the training phase, we use so-called synthetic grids with fixed grid resolution. This means that the grid points (i.e., FPs) have a pre-defined size (e.g., 1 m x 1 m, or 5 m x 5 m, building dependent) and all samples measured in this area are fixed to the same grid point. Since the training phase process consists of several different measurement collections at different time instants (and they can be collected also continuously, e.g., by using crowdsourcing), several measurements can occur at the same grid point. Therefore, when a new sample occurs to a grid point that already has a sample, all hearable APs are examined. If a new AP has been detected in the incoming sample, the AP is saved to the grid point data. If an AP is detected both in the old and incoming sample, the old RSS value is replaced by the mean over the old and new RSS values. The architecture of the positioning system used in this paper is mobile-based. This means that the user device, e.g., a mobile station (MS), makes the necessary measurements (here, the RSSs of the heard APs) and calculates the position estimate. The training phase data is saved and continuously maintained and updated on a database (i.e., server) and transferred to the MS when requested.

2) Estimation Phase: When comparing currently measured RSS levels by the MS with the RSS levels of the FPs, based on our studies the best results are achieved by minimizing the power difference between the observed RSS O_k and the RSS of the FP $\hat{P_{i,k}}$ and by maximizing at the same time the number of commonly heard APs N_{AP} in the current measurement and in the FP. This is a common optimization criteria [14] and it can be performed, e.g., by computing a Gaussian likelihood function $\mathcal{L}_i$ for each FP i as a sum of logaritmic likelihoods:

$$\mathcal{L}_i = \sum_{k=1}^{N_{AP}} log\left(\frac{1}{\sqrt{2\pi\sigma_{ap}^2}}exp\left(-\frac{(O_k - \hat{P_{i,k}})^2}{2\sigma_{ap}^2}\right)\right), \quad (1)$$

where σ_{ap} is a noise variance that takes into account both shadowing and measurement error effects. Now, if no nearest neighbour (NN) method is used, the FP $\hat{i}$ with highest Gaussian likelihood $\mathcal{L}_{\hat{i}}$ is selected, and the location of this FP $[x_{\hat{i}}, y_{\hat{i}}, z_{\hat{i}}]$ is returned as MS location ($[x_{\hat{i}}, y_{\hat{i}}, z_{\hat{i}}] = [x_{\hat{MS}}, y_{\hat{MS}}, z_{\hat{MS}}]$). When the NN method is used, FPs with highest Gaussian likelihoods are selected, and the position of the MS is calculated as an average over the corresponding locations of N_n nearest neighbours as

$$[x_{\hat{MS}}, y_{\hat{MS}}, z_{\hat{MS}}] = \frac{1}{N_n}\left(\left[\sum_{n=1}^{N_n} x_{\hat{i}}, \sum_{n=1}^{N_n} y_{\hat{i}}, \sum_{n=1}^{N_n} z_{\hat{i}}\right]\right). \quad (2)$$

B. Deconvolution-based PL positioning

The traditional path-loss model is based on wave propagation in free space [15] and it is assumed that the path loss coefficient n_{ap} for the apth AP remains constant within the distance between the transmitter and receiver. Two modeling parameters, namely the path loss coefficient n_{ap} and the transmit power $P_{T_{ap}}$ for the apth AP, are needed per AP and they are related to the RSS via

$$P_{i,ap} = P_{T_{ap}} - 10\, n_{ap}\, log_{10}\, d_{i,ap} + \eta_{i,ap}, \quad (3)$$

where $P_{i,ap}$ is the measured RSS of the apth AP in the ith measurement point, $d_{i,ap}$ is the distance between the apth AP and the ith measurement point (i.e., $d_{i,ap} = \sqrt{(x_i - x_{ap})^2 + (y_i - y_{ap})^2 + (z_i - z_{ap})^2}$) and $\eta_{i,ap}$ is a Gaussian distributed noise factor with standard deviation σ and zero mean. In our model, it is assumed that the noise standard deviation σ is constant per AP.

As in the fingerprinting approach, the training phase is needed in the deconvolution-based PL approach as well. In the training phase, the AP positions x_{ap}, y_{ap}, z_{ap} and the modeling parameters n_{ap} and $P_{T_{ap}}$ are estimated based on the same database as in fingerprinting method, with x_i, y_i z_i, $P_{i,k}$. Also here, synthetic grids with a fixed resolution are used. In the estimation phase, the mobile position estimate is calculated using the parameters saved per AP in the training phase (i.e., estimates for the AP position x_{ap}, y_{ap}, z_{ap}, path loss coefficient n_{ap} and transmit power $P_{T_{ap}}$) and the measured RSS by the mobile. It can easily be noticed, that the motivation for PL approaches is in the amount of stored data. In fingerprinting approach, not only the amount of fingerprints may be huge, but also the data saved for each fingerprint usually demands more than 10 variables. Besides the fingerprint coordinates (x_i, y_i z_i), also the AP indexes k and the measured power for the kth AP $P_{i,k}$ need to be saved. E.g., if in a certain fingerprint i the number of heard APs is 12, we need to save 27 parameters for this one fingerprint only: 3 parameters for the location, 12 for RSS and 12 for the AP indexes. In the PL-based approaches, we only need to store 5 parameters per AP (i.e., x_{ap}, y_{ap}, z_{ap} , n_{ap} and $P_{T_{ap}}$).

In the deconvolution-based PL approach, the idea is to formulate the estimation problem as a deconvolution problem. In the training phase, the PL model in Eq. 3 can be written in matricial form as [16]

$$\mathbf{P_{ap}} = \mathbf{H_{ap}} \, \mathbf{\Theta_{ap}^T} + \mathbf{n}, \tag{4}$$

where $\mathbf{P_{ap}}$ is a vector of power fingerprints of apth AP (i.e., $\mathbf{P_{ap}} = [P_{1,ap} \, P_{1,ap} \, \ldots \, P_{N_F,ap}]$), Θ_{ap} includes the unknown AP parameters, except the coordinates (i.e., $\Theta_{ap} = [n_{ap} \, P_{T_{ap}}]$), $\mathbf{T}$ is the transpose operator, $\mathbf{n}$ is a Gaussian distributed noise vector with size $N_F x 1$, and

$$\mathbf{H_{ap}} = \begin{bmatrix} 1 & -10\omega_1 log_{10} d_{1,ap} & \ldots & -10\omega_{M-1} log_{10} d_{1,ap} \\ & \ldots & \ldots & \\ 1 & -10\omega_1 log_{10} d_{N_F,ap} & \ldots & -10\omega_{M-1} log_{10} d_{N_F,ap} \end{bmatrix} \tag{5}$$

In order to solve both unknowns, i.e., $\mathbf{H_{ap}}$ and $\mathbf{\Theta_{ap}}$, we use the Least Squares (LS) deconvolution method that is presented in detail in [16]. Moreover, the AP position in this paper is estimated using the Gaussian regression based approach [17].

III. AP Selection Criteria

In this paper, several different AP selection criteria in the training phase were studied. The criteria are:

1) No selection
   - Here, all heard APs are kept. This criterion is included in the results as a reference, in order to see the effect of limiting the number of APs. This also gives the benchmark results.
2) MIMO selection
   - WLAN transmitters inside buildings can support multiple BSSID nowadays, allowing multiple MACs from the same physical location. The reasoning behind the MIMO selection criterion (see the explanations for the terminology in Section II A) is to try to remove redundant information offered by similar (i.e., closely located) APs. The MIMO APs (or other APs with several MAC-addresses) are recognized simply based on the estimated AP location: if there are several APs located with maximum one meter distance of each other, only one (with maximum average RSS) is kept. The unknown AP locations are estimated using the Gaussian regression based approach [17] as in the deconvolution-based positioning approach. Naturally, there may also occur situations where two or more separate APs are truly located next to each others. Since the distance estimation is the only measure to determine closely located APs in our studies, these kind of situations are not taken into account, and only one AP among the closely located APs will be kept. The number of MIMO APs in total is dependent on the measurement scenario.
3) KL
   - APs are sorted in descending order, based on a criterion derived by analogy with Kullback-Leibler (KL) divergence $D_{KL} = [d_{ap_i,ap_j}]_{ap_i,ap_j=1..N_{ap}}$, where
   $$d_{ap_i,ap_j} = \sum_i \sum_j |P_{ap_i} - P_{ap_j}| \, log(|P_{ap_i} - P_{ap_j}|) \tag{6}$$
4) Dissimilarities
   - Here, the APs are sorted in descending order based on dissimilarity matrices, that are calculated based on the difference between the average RSS values between all APs in the building:
   $$\mathbf{D_{Diss}} = \begin{bmatrix} 0 & |\bar{P}_1 - \bar{P}_2| & \ldots & |\bar{P}_1 - \bar{P}_{N_{ap}}| \\ |\bar{P}_2 - \bar{P}_1| & 0 & \ldots & |\bar{P}_2 - \bar{P}_{N_{ap}}| \\ & \ldots & \ldots & \\ |\bar{P}_{N_{ap}} - \bar{P}_1| & |\bar{P}_{N_{ap}} - \bar{P}_2| & \ldots & 0 \end{bmatrix} \tag{7}$$
   where $\bar{P}_a p$ is the mean RSS heard from apth AP.
5) Maximum RSS (maxRSS)
   - APs are sorted in descending order based on their maximum RSS value.
6) Entropy
   - APs are sorted in descending order based on so-called entropy of RSS per AP. The entropy is calculated and derived by the Authors by analogy with classical entropy definition [18]:
   $$E_{ap} = max\,(P_{ap} \times log_2\,(P_{ap})), \tag{8}$$
   where P_{ap} is a vector of power fingerprints of apth AP (i.e., $P_{ap} = [P_{1,ap} \, P_{1,ap} \, \ldots \, P_{N_F,ap}]$) and $\times$ is the point multiplication.

In MIMO selection, the number of MIMO APs in total is dependent on the measurement scenario and on how many APs at a close physical location were available in a certain building. Thus, also the removal percentage for the MIMO case is dependent on the measurement scenario. With the other criteria, only a certain part of APs is removed: e.g., 20%, 30%, or 50% out of all APs, and this removal percentage is flexible and user defined.

IV. Measurement Analysis

A. Measurement scenarios

The measurement data was collected in 5 different buildings (two university buildings, one office building and two shopping malls) in Tampere, Finland and in Berlin, Germany. Measurements for both training and estimation phases were collected manually with two different tablets, a Windows tablet

TABLE I
MEASUREMENT SCENARIOS.

	Building (measurement device)	Location	No. of FPs	No. of user meas.	No. of APs	No. of independent APs	No. of floors	Horizontal grid size [m]
A	University building 1 (Nexus)	Tampere, Finland	4417	606	358	173	4	1 m
B	University building 2 (Windows)	Tampere, Finland	584	176	311	186	3	1 m
C	Office building 1 (Nexus)	Berlin, Germany	624	850	252	166	9	5 m
D	Shopping mall 1 (Nexus)	Berlin, Germany	1633	520	281	236	6	5 m
E	Shopping mall 2 (Windows)	Tampere, Finland	274	215	43	34	3	1 m

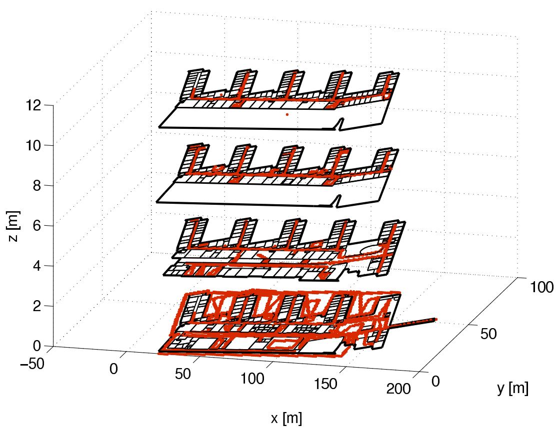

Fig. 1. Illustration of collected measurement grid for the building A.

and an Android Nexus tablet, that included detailed indoor maps for each building. After the training phase, the user tracks used for the positioning analysis here were collected separately during different days and covering several floors in each building. The same exact device was used to collect the training and estimation data for one particular building, but the devices may have been different from one building to another. All measurement scenarios, with building descriptions and main characteristics, are detailed in Table I, showing the number of FPs (i.e., the number of synthetic grid points in the training database), the number of user measurements in the user track, the number of detected APs, the number of independent APs, the number of floors and the horizontal grid size (x-y-dimention) of the particular building. The number of detected APs is the number of individual MAC addresses, but since some WLAN transmitters may have multiple MAC addresses, some of the APs here can be at the same physical location. Therefore, we calculated the number of independent APs by estimating the AP locations and deciding that all APs that are closer than 1 m of each other, are MIMO APs and handled as one AP only.

B. Positioning results

In what follows, the positioning results are presented as mean distance error in 3D. The mean distance error is computed by averaging the Euclidean distances between the estimated location and the true location in a three-dimensional Cartesian coordinate system (x, y, z). In the fingerprinting approach, NN-method is used, with $N_n = 5$.

Figs. 2 and 3 show the mean positioning error for all AP selection criteria for Building A with fingerprinting and deconvolution based PL approach, respectively. The removal percentage varied between $10\% - 70\%$, except for the MIMO case, since the number of MIMO APs is dependent on the measurement scenario. For MIMO selection criteria, the number of removed APs varied so that only one (with the highest mean RSS), two or three APs were kept out of those APs located close to each other. If only one AP was kept, the removal percentage is naturally the highest (e.g., about 50% for Building A with fingerprinting approach, see Fig. 2).

Similarly, Fig. 4 represents the mean positioning error for all AP selection criteria for Building A with fingerprinting and Fig. 5 with deconvolution based PL approach. As the results begin to deteriorate fast after a 50% removal, the figures show the results only up to 50% removal for a clearer visibility of the relative performance of algorithms. When examining the Figs. 2 - 5, it can easily be seen, that APs can be removed with MIMO AP removal criteria keeping only one AP out of closely located APs without deteriorating the positioning results. However, since the number of MIMO APs is dependent on the building, the removal percentage may vary from a few percent up to 50%. From Figs. 4 and 5, it is also very clear, that in the case of less MIMO APs (here, around 17%), it is possible to remove even 50% of the APs with other selection criteria.

Based not only on the Figs. 2 - 5 but also on the results obtained for buildings B, C, and E (that could not all be included here due to the lack of space), it was noticed that the maxRSS-based AP removal criteria offered the best results in general when removing 50% of the APs. This holds for both fingerprinting and deconvolution based PL approach. In Figs. 2 and 3, it can be seen, that with the Dissimilarities-based removal method, the mean distance error is already increased by more than 2 meters, when 30% of the APs are removed. With other removal criteria (MIMO, KL, entropy and maxRSS), 50% of the APs can be removed increasing the positioning errors by less than 0.5 meters. With maxRSS-based and KL-based removal algorithms, even 70% of the APs can be removed in the case of Building A, while the entropy-based algorithm starts to deteriorate very fast after a 50% removal. The results are very similar for both positioning methods.

For Building D (Figs. 4 and 5), the results are slightly different. Also here, the entropy-based algorithm begins to deteriorate faster, but unlike the results for Building A, now

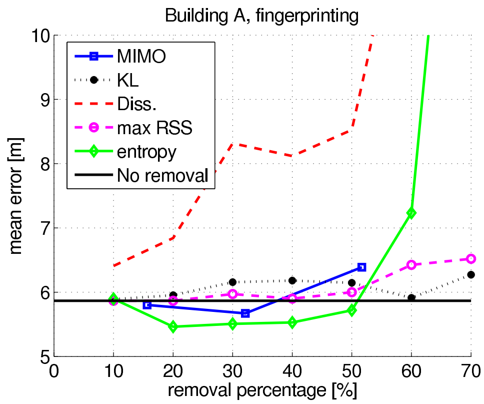

Fig. 2. Mean positioning error for all AP selection criteria. Building A with fingerprinting.

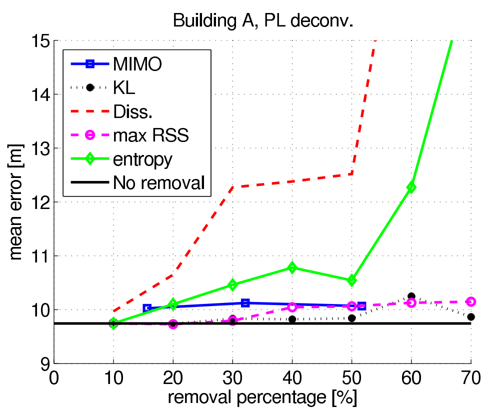

Fig. 3. Mean positioning error for all AP selection criteria. Building A with deconvolution based PL approach.

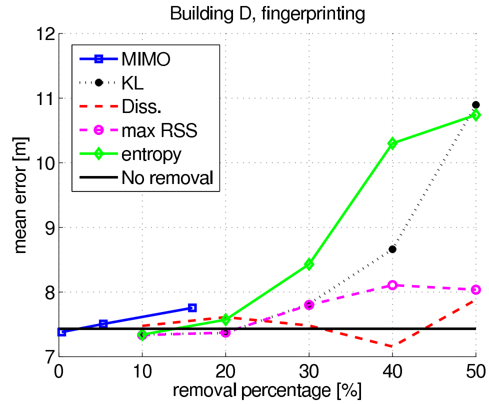

Fig. 4. Mean positioning error for all AP selection criteria. Building D with fingerprinting.

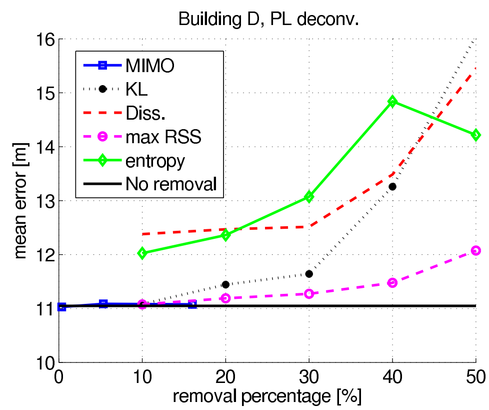

Fig. 5. Mean positioning error for all AP selection criteria. Building D with deconvolution based PL approach.

also the KL-criterion (for fingerprinting) and both the KL- and Dissimilaritied-based criteria (for deconvolution based PL approach) are not giving as good results as the maxRSS-based option for a 50% removal. When comparing all of the results, it can be seen that the simple maxRSS-based algorithm is the most consistent among all criteria. This can be seen also in Table II (for both fingerprinting and deconvolution based positioning), which represent the mean and median positioning errors and Root Mean Square Error (RMSE) in meters for all buildings, with a 50% removal. Results for both maxRSS- and KL-based algorithms are presented, together with a "no removal"-option, that is kept as a reference. When comparing the results for KL- and maxRSS-based algorithms, it can be noticed that the results are quite close to each other and the biggest differences between these criteria are in the case of building D. One reason for this may be large opening areas and smaller AP density of this particular building. In general, the mean positioning error for the fingerprinting approach is increased by only about 8% with the maxRSS-based and about 16.5% with the KL-based approach, when compared with the case without any removal. For deconvolution based positioning, the mean error is increased by about 6% with the maxRSS-method and 11.5% with the KL.

V. CONCLUSION

In this paper, we have shown via an extensive measurement campaign, that it is possible to remove up to 50% of the APs in the training phase with only a $6-8\%$ deterioration in positioning performance. We examined several different removal criteria and noticed that the maxRSS-based removal criterion seems to be most consistent and to offer the best results among the other studied methods. Nowadays, WLAN transmitters inside buildings can support multiple BSSID and due to the AP deployment meant for communication purposes, several APs can be placed in the vicinity of each other or can transmit some correlated information. Keeping only one AP among the many closely located ones can in some cases give the best results by removing most of the repetitive APs, but in some other building with different AP deployment, the removal percentage may be very low using the MIMO criterion. We have shown that even in buildings with less closely located APs, there are still redundant and unnecessary APs, and using the maxRSS-based removal algorithm, the number of APs to be used in the positioning phase can be lowered significantly. To answer the question raised in our paper title, not all APs are needed in the positioning phase in an indoor RSS-based positioning, and, with a properly chosen

TABLE II
RESULTS FOR ALL BUILDINGS, 50% REMOVAL.

	Building	Criteria	mean error [m]	median error [m]	RMSE [m]
FP	A	No removal	5.87	3.11	8.55
		maxRSS 50%	6.00	3.99	8.48
		KL 50%	6.15	4.11	8.71
	B	No removal	9.33	7.59	11.96
		maxRSS 50%	9.77	8.08	12.50
		KL 50%	9.62	7.91	12.30
	C	No removal	4.01	3.59	4.54
		maxRSS 50%	4.92	4.33	5.60
		KL 50%	4.82	4.19	5.63
	D	No removal	7.40	6.44	8.51
		maxRSS 50%	8.04	7.16	9.27
		KL 50%	10.90	8.52	13.98
	E	No removal	17.47	13.58	23.69
		maxRSS 50%	18.47	13.22	25.27
		KL 50%	18.74	13.63	25.42
deconv.	A	No removal	9.74	8.21	11.76
		maxRSS 50%	10.06	8.77	12.06
		KL 50%	9.84	8.66	11.75
	B	No removal	9.01	7.38	12.45
		maxRSS 50%	9.39	7.44	12.69
		KL 50%	9.11	7.19	12.58
	C	No removal	6.09	5.87	6.75
		maxRSS 50%	6.99	7.26	7.73
		KL 50%	6.81	6.46	7.65
	D	No removal	11.05	9.08	13.16
		maxRSS 50%	12.07	10.26	13.77
		KL 50%	16.05	16.57	18.32
	E	No removal	20.46	19.51	23.77
		maxRSS 50%	20.22	19.31	23.48
		KL 50%	20.12	19.72	23.47

removal criterion, we can remove even up to 50% of the available APs without a significant performance degradation.

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