Beacon Selection for Localization in IEEE 802.11 Wireless Infrastructure

Ryangsoo Kim, Hyuk Lim, Daewon Jung, and Kapjin Kim

Abstract

Given the widespread deployment of IEEE 802.11-based access points (APs), received signal strength (RSS)-based localization algorithms, which estimate the location of clients by measuring RSS at the installed APs, have drawn considerable attention due to their simple implementation alongside existing infrastructure. However, the accuracy of RSS-based localization depends heavily on the RF and geometry characteristics between the client and the APs. In order to improve the localization accuracy, the selection of an appropriate AP set without outliers is an important and challenging issue. In this paper, we first propose to use Cramér-Rao Bound, obtained from the average Fisher Information Matrix, as a criterion for selecting an appropriate AP set. Then, based on the proposed selection criterion, we develop a batch beacon selection algorithm that searches all the possible AP sets. Furthermore, to implement real-time mobile client localization by alleviating computational complexity, we devise an online beacon selection algorithm. This employs a simple but effective method to select a portion of APs from all of those possible, such that the number of AP sets is reduced.

Index Terms

Beacon selection; localization; Cramér-Rao bound; Fisher information.

I. INTRODUCTION

In last few years, IEEE 802.11-based WLANs have been widely deployed in areas with a high volume of users, such as universities, airports, office complex, and shopping center. Based on these wireless networking systems, we are able to implement GPS-free localization system as an alternative provider of location information for location-aware services, e.g., indoor navigation for passenger in an airport, location detection for fireman in a building on fire, and inventory control in a shopping center (Liu et al. 2007; Wang et al. 2012; Lee et al. 2006; Carlos et al. 2011; Fang et al. 2012; Kang et al. 2012). Hence, a great deal of research has been carried out on GPS-free localization systems for the existing WLAN infrastructure (Atia et al. 2012; Zhang et al. 2011; Fang et al. 2010;

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Chang et al. 2010). In particular, received signal strength (RSS)-based localization systems have drawn considerable attention, because the RSS measurements are easily obtained by every IEEE 802.11 interface without any additional cost.

However, the RSS-based localization accuracy is heavily dependent on RF and geometry characteristics between client and the access points (APs). RF characteristics, such as multi-path fading and signal attenuation due to changes in temperature, humidity, and object mobility, cause fluctuations in the RSS measurement result that may affect the calculation of geographic distance between client and AP (Lim et al. 2006; Zanca et al. 2008; Santiago et al. 2009; Guo et al. 2011). Furthermore, geometry characteristics, such as the distance and angle to the client, and the array and the number of APs, influence the estimates of client location that utilize the distances to, and geometry information of, APs. Therefore, it is important to reduce the influence of undesirable RF and geometry characteristics, which cause a degradation in the accuracy of the estimated client location, as much as possible.

There are many research results concerning the improvement of RSS-based localization accuracy. In Yang et al. (2009), regression- and correlation-based signal propagation models were proposed that enhance the relationship between geographic distance and RSS measurement data. Further, an adapted multi-lateration method to improve robustness to RSS measurement errors was presented in Kurouglu et al. (2009). Note that, for the analysis of estimation error, Cramér-Rao Bound (CRB) is widely used in localization literature because it represents a lower bound on the covariance of an unbiased estimator. In Catovic et al. (2004), Larsson et al. (2004), Hossain et al. (2010), and Patwari et al. (2003), the localization systems were analyzed with respect to CRB to individually assess the impact of different RF and geometry characteristics. In particular, Patwari et al. (2003) showed that a lower bound on the covariance of a location estimator decreased as more reference nodes were added, assuming that the reference nodes had the same RSS measurement variance.

While these RSS-based research efforts have inspired the existing work, there is still room for localization accuracy improvement, especially with respect to determining an appropriate set of reference nodes (usually 802.11 AP nodes) in areas where a number of APs are deployed. By selecting an appropriate AP set, in which the APs are affected by relatively low RF and geometry characteristics, it is possible to alleviate the localization error. There exists a beacon selection scheme using the CRB as the criterion to select the subset of beacon nodes (Lieckfeldt et al. 2008). *However, the CRB method of selecting the best set of AP nodes cannot be directly adopted because, if only the number of selected AP nodes increases, the CRB accordingly decreases.* This may imply that increasing the number of AP nodes is one method of improving the localization accuracy. However, increasing the number of AP nodes is liable to degrade the localization accuracy when some APs have inaccurate RSS measurement data. Moreover, the large number of APs gradually increases the computational overhead of estimating the client location. In order to resolve this problem, we propose to use the CRB, which is obtained from the average Fisher Information Matrix (FIM), as a criterion to select an appropriate AP set, thereby improving the localization accuracy.

II. System Model

We consider an RSS-based localization in an extended service set (ESS) of an enterprise IEEE 802.11 wireless local area network (WLAN) composed of N basic service sets (BSSs), denoted by $\mathcal{N} = \{1, \cdots, N\}$. The deployed location of the AP in each BSS is assumed to be known and available to all mobile devices belonging to the ESS. Note that the APs in the ESS serve as beacon nodes, with known locations for the localization service. Let $\boldsymbol{\theta} = [\theta_1, \theta_2, \cdots, \theta_N]$ denote the location vector of the APs, where $\theta_i = [x_i, y_i]^T$ is the location of the i-th AP, and $\mathbf{p} = [p_1, p_2, \cdots, p_m]^T$ denote the RSS vector, where p_i is the RSS from the i-th AP to a target node, of which the location is given by $\theta_t = [x_t, y_t]^T$. The distance vector between the APs and the target node is then obtained as $\mathbf{d} = [d_1, d_2, \cdots, d_N]^T$, where d_i is the geographical distance between the i-th AP and the target node and is given by the following Euclidean distance:

$$d_i = ||\theta_i - \theta_t||. \tag{1}$$

We also assume that the RSS follows a log-normal shadowing model, which is given by:

$$\mathbf{p} = p_r \mathbb{1}_N - 10\alpha \log(\frac{\mathbf{d}}{d_r}) + \mathbf{n}, \tag{2}$$

where $\mathbb{1}_N \in \mathbb{R}^N$ is the column vector whose elements are 1, d_r is a reference distance, p_r is the RSS value at the reference distance, α is a path loss exponent, and $\mathbf{n} = [n_1, n_2, \cdots, n_N]^T$ is a measurement noise vector that follows Gaussian distribution with a zero mean and a covariance matrix of $\mathbf{\Sigma} = \text{diag}(\sigma_1^2, \cdots, \sigma_N^2)$. Given a measured RSS vector of $\mathbf{p}$, the distances to the APs can be simply estimated as follows:

$$\hat{\mathbf{d}} = d_r \cdot 10^{(\frac{p_r \mathbb{1}_N - \mathbf{p}}{10\alpha})}. \tag{3}$$

By using the AP locations and estimated distances, the location of the target node is computed via a Linear Least Square (LLS) approach as follows:

$$\hat{\theta}_t = \frac{1}{2}(\mathbf{X}^T\mathbf{X})^{-1}\mathbf{X}^T\mathbf{y}, \tag{4}$$

where

$$\mathbf{X} = \boldsymbol{\theta}^T - \left(\frac{\mathbb{1}_N \cdot \mathbb{1}_N^T}{N}\right)\boldsymbol{\theta}^T,$$

and

$$\mathbf{y} = \text{diag}[\boldsymbol{\theta}^T\boldsymbol{\theta} - \hat{\mathbf{d}}\hat{\mathbf{d}}^T] - \frac{\mathbb{1}_N}{N}(\text{trace}[\boldsymbol{\theta}^T\boldsymbol{\theta}] - \hat{\mathbf{d}}^T\hat{\mathbf{d}}).$$

Because the Euclidean distance formula in (1) is nonlinear, it should be expressed as a linear equation in order to be suitable for the LLS approach. To convert the Euclidean distance formula $d_i = \sqrt{(\theta_i - \theta_t)^T(\theta_i - \theta_t)}$ to a linear equation, we raise equation (1) to the power of 2 and then subtract $\frac{1}{N}\sum_{i \in \mathcal{N}} d_i^2$ to eliminate the second-order terms with respect to θ_t. Based on the converted linear equations and the estimated distances, we are able to apply the LLS approach to compute the location of the target node.

III. Proposed beacon selection scheme

Consider an RSS-based localization in a hotspot area serviced by a number of APs. In such an area, a target node with an unknown location can be localized by utilizing all of the APs within the communication range of the target node as beacon nodes. However, the localization accuracy may become worse if the target node utilizes all of the available APs, rather than a smaller subset. This is because one or more APs leading to inaccurate distance estimation results, i.e., outliers, degrade the localization accuracy. Therefore, we are able to improve the localization accuracy by selecting an appropriate set of APs as beacon nodes. In order to select an appropriate set of APs, we need a selection criterion, and we thus adopt the CRB, which represents a lower bound on the covariance of unbiased parameter estimation.

A. Fisher information and CRB

Under the assumption that the measurement noise follows a Gaussian distribution with zero mean and variance σ_i^2 (in dB), the probability density function (PDF) of p_i can be easily derived, and is denoted by $f_{p_i|\theta_i}(p_i|\theta_i)$ in Patwari et al. (2003). Using $f_{p_i|\theta_i}(p_i|\theta_i)$, the FIM for the i-th AP is obtained as follows:

$$\mathbf{I}_i = \frac{b_i}{||\theta_t - \theta_i||^4}(\theta_t - \theta_i)(\theta_t - \theta_i)^T, \tag{5}$$

where $b_i = \left(\frac{10 \cdot \alpha}{\sigma_i \cdot \ln 10}\right)^2$. Suppose that a set S of $\mathcal{N}$ is available for localization of the target node (i.e. $S \subseteq \mathcal{N}$). The variance of the estimated location for the target node is then bounded below by the trace of the CRB, which is obtained by the inverse of the FIM:

$$\Psi(S) = \text{trace}\left[\left(\sum_{i \in S} \mathbf{I}_i\right)^{-1}\right]. \tag{6}$$

In Patwari et al. (2003), it is shown that the lower bound for the variance of the location estimate decreases as more APs are used to estimate the target node location, because the diagonal terms of FIM increase for a larger set S with more APs. This may imply that the localization accuracy increases as more APs are used, as the variance of the location estimation is proportional to the mean square error (MSE) of the estimated location. However, localization using a large set of APs does not always guarantee an improvement in accuracy compared with that using a smaller set of APs. This is because one or more APs in a large set may disturb the location estimate when the APs lead to inaccurate distance estimation results. Therefore, we need to modify the CRB to use as a selection criterion for an appropriate AP set by excluding the inaccurate distance estimation results.

B. Batch beacon selection algorithm

Instead of using all the APs within a communication range of a target node, we identify and exclude those APs that may lead to inaccurate location estimations. In order to choose an appropriate set of APs, we propose to use an average FIM, rather than the simple summation of FIMs in (6). The average FIM for a set S of APs is obtained by averaging the FIMs of APs belonging to S. Based on the average FIM, we define a new bound $\Gamma(S)$ as follows:

$$\Gamma(S) = \text{trace}\left[\left(\frac{1}{|S|}\sum_{i\in S}\mathbf{I}_i\right)^{-1}\right]. \tag{7}$$

Note that when more APs are added to S, $\Gamma(S)$ does not always decrease. Instead, $\Gamma(S)$ may increase when the added APs result in smaller FIM quantities than the average FIM quantity of the APs already in S.

Using $\Gamma(S)$, we select set of APs that gives the smallest $\Gamma(S)$ from among all the possible AP sets with at least three APs as follows:

$$S^* = \underset{\{S|S\subseteq\mathcal{N},|S|\geq 3\}}{\arg\min}\ \Gamma(S). \tag{8}$$

It is important to note that the computation of the FIM for APs in (7) requires the location of the target node as well as those of the APs. If a prior location of the target node is available, it can be used as an initial guess to evaluate the FIMs of APs. Otherwise, the location obtained by (4) when $S = \mathcal{N}$ is used as an alternative. Because the search space of the batch beacon selection algorithm is all possible sets containing at least three APs, it may incur a rigorous computational overhead, and thus take a considerable time to select an appropriate AP set from an ESS composed of a number of APs. Let n denote the number of APs within the communication range of the target node. The computational complexity is $O(2^n)$, because the number of sets is $\sum_{i=3}^{n}\binom{n}{i}$, which is equal to $\left(2^n - \frac{n(n+1)}{2} - 1\right)$.

C. *Online beacon selection algorithm*

For real-time mobile localization, we now devise a fast algorithm with lower computational complexity. The computational complexity can be alleviated by reducing the search space of the batch beacon selection algorithm in (8). Because the maximum speed of a mobile node is bounded, its new location cannot be especially different from its previous location. In this case, we make the assumption that the appropriate AP set remains unchanged, or is only slightly changed. More specifically, we make assumptions that at most k new APs that do not belong to the previous appropriate AP set can be newly added to the current appropriate AP set, and at most m APs that belong to the previous appropriate AP set can be subtracted for the current appropriate AP set. Under these assumptions, the search space for selecting the appropriate AP set can be significantly reduced. We define an extended AP set as the union of the previous appropriate AP set and a set of, at most, k newly selected APs. Instead of using $\mathcal{N}$, we can then restrict the search space to the APs in the extended AP set.

In order to determine the values of k and m, consider a situation in which a mobile node moves from location A to B over an area where a number of APs are uniformly deployed, as shown in Figure 1. The solid and dashed circles represent the communication ranges of the mobile node when it is in locations A and B, respectively. In such a situation, the APs located in area (c) are newly included in the communication range of the mobile node. Because these newly included APs can be added to the current appropriate AP set, we set the value of k to the number of APs in area (c).

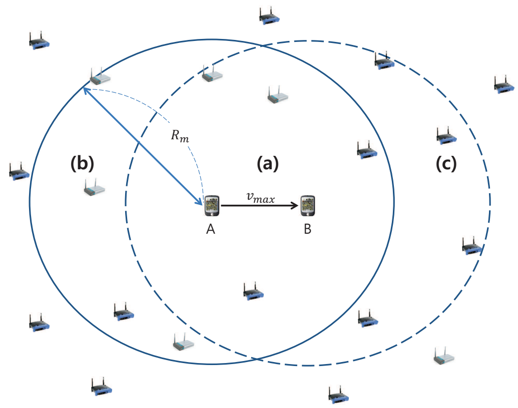

Fig. 1. Variation of APs in the communication range of a mobile node when it moves from location A to B.

On the other hand, in Figure 1, the APs located in area (b) are excluded from the communication range of the mobile node, and these excluded APs can be subtracted from the previous appropriate AP set. In Figure 1, it is obvious that the size of area (c) is equal to that of area (b). This may imply that the number of APs excluded from the communication range of the mobile node is equal to that of newly included APs, i.e., $m = k$. Therefore, we can modify our assumptions as follows: at most k APs can be newly added and subtracted to form the current appropriate AP set.

In order to estimate the number of APs in area (c), i.e., the value of k, we need to know the size of area (c) and the density of the deployed APs. We first compute the size of area (a), because area (c) is obtained by subtracting the size of intersection with area (a) from that of the dashed circle. Let v_{mac} and t denote the maximum speed of the mobile node and the time elapsed from the previous localization, respectively. We can then compute the circle-circle intersection area (a) in Figure 1 as follows:

$$\Delta = 2R_m^2 \cos^{-1}\left(\frac{v_{max} \cdot t}{2R_m}\right) - \frac{1}{2} v_{max} \cdot t\sqrt{4R_m^2 - (v_{max} \cdot t)^2}, \tag{9}$$

where R_m denotes the radius of the communication range. From the size of area (a), we can compute the size of area (c) and then, once the density of the deployed APs is given, we can estimate the average number of APs located in area (c) as follows:

$$k = \lceil (\pi R_m^2 - \Delta) \cdot \rho \rceil, \tag{10}$$

where ρ (number of APs/m^2) denotes the density of the APs in the localization area and $\lceil \cdot \rceil$ denotes the ceiling function. Based on (10), we select k new APs that may contribute to improving the accuracy of the location estimate. Specifically, to achieve the smallest lower bound $\Gamma(S)$ for the new appropriate AP set, we select the k new APs with the largest FIM quantities among the APs that did not belong to the previous appropriate AP set. These are computed as follows:

$$S_r = \underset{\{S \mid S \subseteq (S_p)^C,\ |S| = k\}}{\arg\max} \ \text{trace}\left[\sum_{i \in S} I_i\right], \tag{11}$$

Algorithm 1 Localization using the online beacon selection algorithm

Input: previous appropriate AP set S_p,

previous mobile node location θ_t.

Output: estimated mobile node location $\hat{\theta}_t$

1: Update $\hat{\mathbf{d}}$

2: $S_r = \arg\ \max_{\{S|S\subseteq(S_p)^C,|S|=k\}} \text{trace}\left[\sum_{i\in S} I_i\right]$

3: $S_b = S_1 \cup S_2$

4: $S^* = \arg\ \min_{\{S|S\subseteq S_b\}} \Gamma(S)$

5: $\hat{\theta}_t = LLS(\boldsymbol{\theta}_{S^*}, \hat{\mathbf{d}}_{S^*})$

where $(S_p)^C$ denotes the APs that did not belong to the previous appropriate AP set S_p.

Using the k newly selected APs and those in the previous appropriate AP set, we can generate candidate sets for the new appropriate AP set. We define a bounded AP set $S_b = \{S|S = S_1 \cup S_2\}$ as a set of AP sets such that $S_1 = \{S|S \subseteq S_r\}$ denotes subsets of the newly selected k APs, and $S_2 = \{S|S \subseteq S_p, |S| \geq |S_p| - k\}$ denotes subsets of the previous appropriate AP set, from which at most k APs have been excluded. More specifically, each AP set in the bounded AP set is composed of the union of two different AP subsets that originated from S_1 and S_2, respectively. From the bounded AP set, we select one AP set which gives the smallest $\Gamma(S)$ as follows:

$$S^* = \underset{\{S|S\subseteq S_b\}}{\arg\ \min}\, \Gamma(S). \tag{12}$$

Note that the computational complexity of the online beacon selection algorithm is $O(2^{2k})$, because the number of sets in the bounded AP set is $\left\{\sum_{i=0}^{k}\binom{k}{i}\cdot\sum_{i=|S_p|-k}^{|S_p|}\binom{|S_p|}{i}\right\}$, which is equal to 2^{2k}. In comparison with the batch beacon selection algorithm, which has a computational complexity of $O(2^n)$, the computational complexity is considerably reduced. Further, to construct the bounded AP set, we require the previous AP set from the previous localization phase. If the previous AP set is not available, we perform the batch beacon selection algorithm in (8), and use the AP set selected by that algorithm as an initial guess.

Algorithm 1 describes the localization procedure for a mobile node using the online beacon selection algorithm. At first, the mobile node measures the RSSs of beacon messages transmitted from the APs, and converts the measured RSSs to distances using (3). Next, the mobile node selects k new APs as those with the largest FIM quantities among the APs that do not belong to the previous AP set. From the newly selected APs and the previous AP set, the mobile node generates the bounded AP set and selects one AP set, which has smallest lower bound result, as the appropriate AP set. Finally, the mobile node estimates its location by the LLS estimator using the appropriate AP set.

IV. Simulation and Experiment Results

In this section, we discuss the results of simulations designed to evaluate the localization accuracy of the proposed beacon selection algorithms by comparing them to other heuristic selection algorithms. We consider a RSS-based

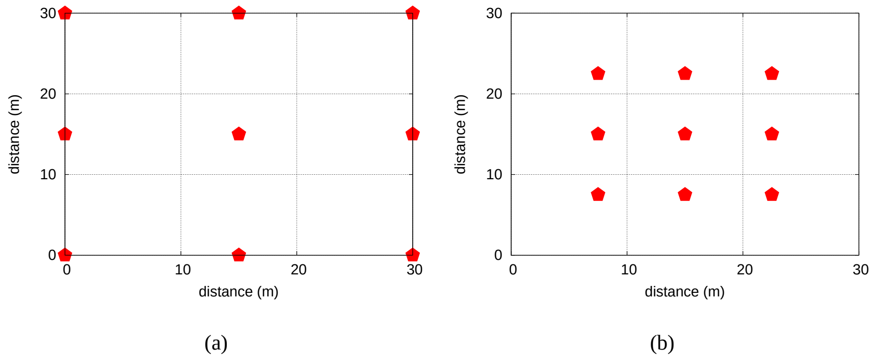

Fig. 2. Deployment of all available APs in a 30(m)x30(m) area.

beacon selection algorithm, which selects a set of APs having high RSS values, and a random beacon selection algorithm, which selects a random set of APs, as the heuristic selection algorithms. Furthermore, we consider a mobile node whose movement follows a random waypoint model with a maximum speed of 6(m/s). For the wireless channel environment, we set the path loss exponent α to 3.8. Moreover, we assume that the standard deviations of the measured RSS data have different values, due to the different RF characteristics between the mobile node and the APs. Therefore, we randomly set the standard deviations within the given range. The measured RSS values are periodically updated every 0.5 (s), and the LLS approach is used to estimate the location of the mobile node. In our simulation results, *RSS-*K and *RAND-*K represent localization using the RSS-based beacon selection algorithm and the random beacon selection algorithm, which both select K APs. Furthermore, *ALL* represents localization using all the available APs, *Batch* represents localization using the proposed batch beacon selection algorithm, and *Online* represents localization using the proposed online beacon selection algorithm.

A. Deployment of APs

In order to verify the robustness of the proposed beacon selection algorithms to the deployment of APs, we consider two different AP deployments, as shown in Figure 2 (a), (b), and a random deployment of the nine APs in a 30 (m) x 30 (m) area.

Figure 3 represents the median distance errors in estimated mobile node location with respect to the range of the standard deviation of the measured RSS data when the APs are deployed as shown in Figure 2 (a). In Figure 3, we note that the RSS-based selection algorithm (RSS-K) has a lower median distance error than both the random based selection algorithm (RAND-K) and localization using all the possible APs (Total), because the accuracy of the distance estimation from converting the measured RSS data is inversely proportional to the geographic distance between the mobile node and the APs. This may imply that localization using the RSS-based selection algorithm is one method of improving the localization accuracy. However, in comparison with the RSS-based selection algorithm, our proposed beacon algorithms achieve a 25% reduction in median distance errors. This is because the beacon messages with high RSS measurement results may be affected by severe noise, thus not always guaranteeing an accurate distance estimation. Moreover, we can see that the online beacon selection algorithm

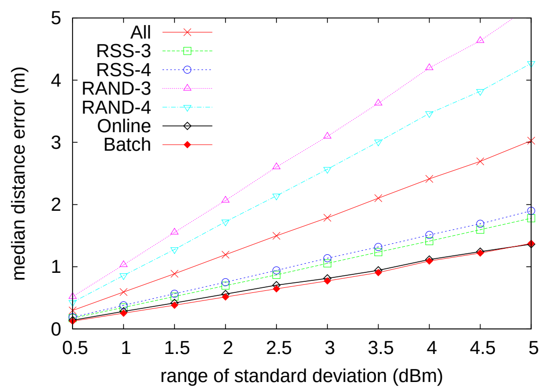

Fig. 3. Median distance errors in estimated mobile client location with respect to the range of standard deviation of RSS measurements when the APs are deployed as in Fig. 2 (a).

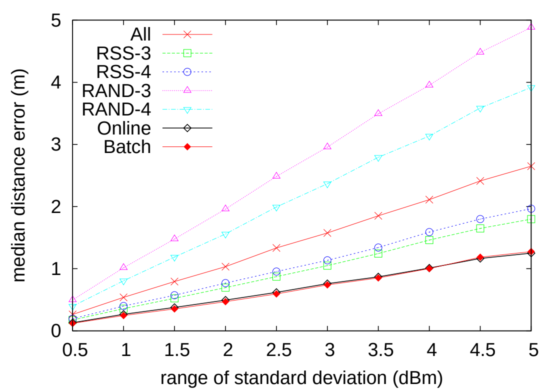

Fig. 4. Median distance errors in estimated mobile client location with respect to the range of standard deviation of RSS measurements when the APs are deployed as in Fig. 2 (b).

achieves similar median distance errors as the batch beacon selection algorithm. This means that the online beacon selection algorithm can estimate the location of the mobile node without sacrificing accuracy.

We now consider the deployment of APs shown in Figure 2 (b). Figure 4 shows that the proposed beacon selection algorithms give a lower median distance error than the other heuristic selection algorithms. The median distance errors using the proposed beacon selection algorithms are 30% lower than those using the RSS-based beacon selection algorithm. In addition, we consider a random deployment of APs in 30 (m) x 30 (m) area and, as shown in Figure 5, the proposed beacon selection algorithms again achieve lower median distance errors than the other selection algorithms. In comparison with the RSS-based beacon selection algorithm, the proposed beacon selection algorithms achieve a 35% reduction in median distance errors. We note that, in Figure 5, the median distance error of RSS-3 is higher than that of RSS-4. This is due to the fact that, once we use three APs for localization, an ill-conditioned matrix may occur in the LLS estimator. This is used to estimate the mobile node location, and thus we are liable to obtain inaccurate estimation results.

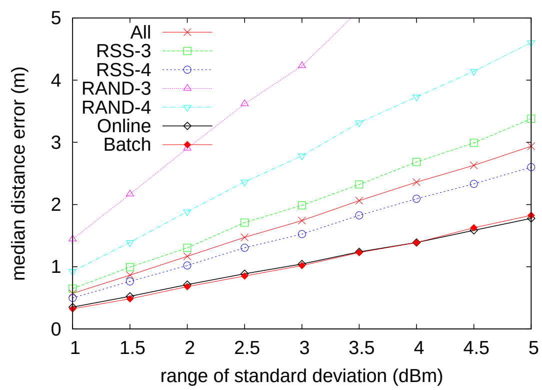

Fig. 5. Median distance errors in estimated mobile client location with respect to the range of standard deviation of RSS measurements when the APs are randomly deployed.

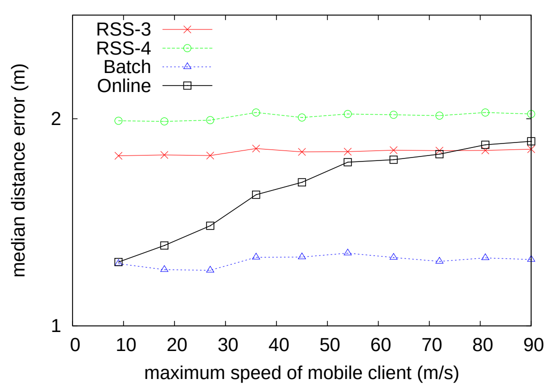

Fig. 6. Median distance errors in estimated mobile client location with respect to the maximum speed of the mobile client when the APs are deployed as shown in Fig. 2 (b) and the range of standard deviation of the measured RSS values is set to 5 (dBm).

From the simulation results, we can state that the proposed beacon selection algorithms improve localization accuracy compared with the other heuristic beacon selection algorithms, regardless of the AP deployment. Furthermore, although the computational complexity is alleviated by using a portion of the APs, the online beacon selection algorithm is able to estimate the location of the mobile node without sacrificing estimation accuracy.

B. Speed of mobile node

To confirm the applicability of the online beacon selection algorithm with respect to the speed of the mobile node, we conduct a simulation to study the median distance errors with respect to the maximum speed of the mobile node when the APs are deployed as shown in Figure 2 (b). Specifically, we simulate two different online beacon selection algorithms, one of which uses a constant value of k. This is because the value of k, which represents the number of newly added or subtracted APs in the appropriate AP set, is related to the bounded AP set and depends on the speed of the mobile node.

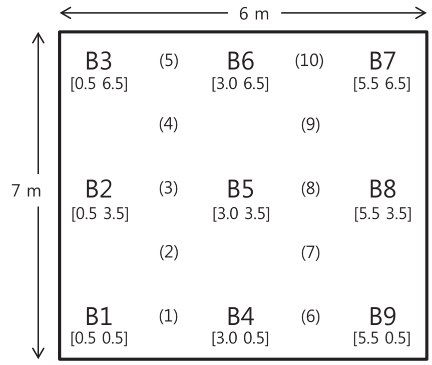

Fig. 7. Experiment setup in 6 by 7 m.

In Figure 6, we can see that when the value of k is set to 1, localization accuracy decreases with respect to the speed of the mobile node. This is because once the speed of the mobile node is sufficiently fast, its current location is far from its previous location, at which the online beacon selection algorithm was last operated. In such a case, the bounded AP set may be considerably different from the appropriate AP set. On the other hand, the localization accuracy using the proposed online beacon selection algorithm does not decrease with respect to the speed of the mobile node, because the value of k is determined properly with respect to the maximum mobile node speed.

C. *Experiment Results*

We have implemented the proposed algorithms in Zigbee wireless sensor network (WSN) nodes (CC2430) manufactured by Crossbow. Each node is compatible with IEEE 802.15.4 standard, and is capable of communicating with each other and measuring RSS of received packets transmitted by the others. The experiments were carried in an outdoor environment on our campus where the ground is covered with grass. Figure 7 shows the experiment configuration. Nine Zigbee nodes serving as a beacon were located within a 6x7 m area, and client nodes were located at ten different positions denoted by (1) to (10).

The experiment results are reported in Table I, where the client location represents the real location of the client node and their unit is meter. The mean distance error for the proposed online beacon selection algorithm was 1.016 m, and those of the other two algorithms were about 1.31 m. During the experiments, we observed that RSS measurements were significantly fluctuating over time, and especially some beacon nodes located far from the client node frequently showed a large variation of RSS measurement. Even in those cases, the proposed beacon selection algorithm dynamically selected the appropriate set of APs by excluding the outliers according to the CRB based selection criterion, and successfully improved localization performance.

TABLE I

EXPERIMENT RESULTS.

ID	Client location		Online			All			RSS-3		
	x	y	x	y	error	x	y	error	x	y	error
(1)	1.75	0.5	2.941	1.602	1.623	3.216	2.054	2.136	2.843	2.326	2.128
(2)	1.75	2.0	2.896	2.233	1.169	3.299	2.110	1.553	2.967	2.292	1.251
(3)	1.75	3.5	1.805	2.824	0.678	2.350	3.082	0.731	1.711	2.589	0.912
(4)	1.75	5.0	2.196	4.970	0.447	2.725	4.556	1.071	2.177	4.985	0.427
(5)	1.75	6.5	2.738	5.064	1.743	3.360	4.711	2.407	2.967	4.861	2.041
(6)	4.25	0.5	4.134	1.745	1.251	4.163	1.962	1.464	4.215	2.325	1.825
(7)	4.25	2.0	4.917	2.908	1.127	4.234	3.012	1.012	4.917	2.908	1.127
(8)	4.25	3.5	5.042	3.289	0.820	4.583	3.201	0.448	4.934	2.911	0.903
(9)	4.25	5.0	4.296	4.725	0.279	4.130	4.216	0.793	4.008	4.174	0.861
(10)	4.25	6.5	4.318	5.479	1.023	3.944	5.026	1.505	4.234	4.893	1.607
Avg. distance error					**1.016**			**1.312**			**1.308**

V. Conclusion

In this paper, we proposed the beacon selection algorithms for a RSS-based localization system. Based on the CRB computed by the inverse of the average FIM, we proposed a batch beacon selection algorithm, which selects the appropriate AP set as that with the minimum lower bound result from among all the AP sets available for localization. Furthermore, we devised an online beacon selection algorithm to implement real-time mobile node localization by alleviating the computational complexity of the batch beacon selection algorithm. The simulation and experiment results verified that the accuracy of client localization using the proposed beacon selection algorithms increased, as they achieved lower median distance errors than localization using other heuristic selection algorithms.

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