Optimized Access Points Deployment for WLAN Indoor Positioning System

Weixiao Meng, Ying He, Zhian Deng
Communications Research Center
Harbin Institute of Technology
Harbin, China, 150001
wxmeng@hit.edu.cn

Cheng Li
Electrical and Computer Engineering, Faculty of Engineering and Applied Science, Memorial University
St. John's, NF, Canada AIB 3X5
licheng@engr.mun.ca

Abstract—**Indoor positioning in wireless local area network (WLAN) has been attracting increasing attentions for its cost effectiveness and reasonable positioning accuracy. Existing positioning methods all pay attention to establish more accurate relationship between received signal strength (RSS) and physical locations. However, the deployment of access points (APs) is ignored. This paper proposes an optimized APs deployment method for improving WLAN positioning accuracy. The objective of APs deployment is to maximize the RSS Euclidean distance between physical locations. We investigate and demonstrate the importance of RSS Euclidean distance to WLAN positioning. Simulation studies and experimental results show that the proposed APs deployment method can improve positioning accuracy significantly.**

Keywords-location-based service; APs deployment; wireless local area network; indoor positioning

I. INTRODUCTION

The rapid development of wireless technology and the increasing demands of location based services (LBS) have made wireless positioning technology become more and more attractive. For indoor environments, the well-known Global Positioning System (GPS) cannot provide enough accuracy due to the limited signal coverage. In contrast, the indoor positioning in wireless local area network (WLAN) has been paid more and more attentions because of its low cost effectiveness and reasonable accuracy [1, 2]. WLAN positioning depends on the relationship between received signal strength (RSS) and physical locations. Since the RSS values from access points (APs) can be collected by pervasively available network card on mobile devices, no extra hardware is required.

WLAN is a kind of LAN constructed by wireless communications technology which can provide all the features of a traditional wired LAN. Compared with wired LAN, WLAN has several features including mobility, flexibility, fast network, low cost, easy management, expansion capability and so on. In addition, WLAN is working at 2.4 GHz which doesn't require license then is ready to construct a network. To satisfy users' need of positioning, WLAN indoor positioning system is based on regular wireless communication service which offers high-accurate real-time to communication systems.

Common positioning algorithm is TOA(Time of Arrival), TDOA(Time Difference of Arrival), AOA(Angle of Arrival), Signal Strength Positioning and Fingerprint which is also called database relevant positioning.

Currently, the most popular WLAN positioning architecture is fingerprinting[3, 4]. Fingerprinting is composed of two stages: offline stage and online stage. In the offline stage, after deploying APs, the RSS values from APs at selected reference points are collected to create the radiomap. In the online phase, the real-time RSS samples are taken as inputs to the pre-constructed positioning model to estimate the user's location.

Fingerprinting can be considered as a pattern recognition process, thus several pattern recognition algorithms have been proposed for positioning, such as weighted k-nearest neighbor (WKNN) [5], maximum likelihood (ML) [6], support vector regression (SVR) [7, 8] and artificial neural network (ANN) [9, 10]. All existing positioning algorithms aim to establish more accurate relationship between RSS and physical locations. However, all these algorithms are developed after APs deployed. Previous APs deployment [11, 12] just concerns about the signal coverage to meet the communication performance. The APs deployment for positioning is ignored in WLAN infrastructure.

This paper proposes a novel APs deployment method for improved WLAN positioning. Under the constraint of seamless signal coverage in WLAN, the APs deployment is designed to improve positioning accuracy. We aim to maximize the RSS Euclidean distance between physical locations. RSS Euclidean distance is defined as the average Euclidean distance of RSS signal between neighbor reference points. The importance of RSS Euclidean distance for positioning is fully investigated. We demonstrate that the larger RSS Euclidean distance, the more the positioning system tolerates the RSS fluctuation, and thus the higher positioning accuracy is achieved. Besides, to avoid the large difference of RSS Euclidean distance between different locations, we also keep the standard variance of RSS Euclidean distance into a certain value. Simulations and experiments in the real WLAN show that, the proposed APs deployment improves positioning accuracy significantly.

The remainder of this paper is structured as follows. Section II demonstrates the importance of RSS Euclidean distance to WLAN positioning. Section III describes the proposed scheme of optimized APs deployment method.

This work was supported by Heilongjiang Province Postdoctoral Science Foundation (Grant No. LBH-210127), and the Fundamental Research Funds for the Central Universities (Grant No. HIT. NSRIF. 2010090).

Section IV explores the simulations and experiments done in a real WLAN environment. Conclusions are given in the last section.

II. Demonstration of the Importance of RSS Euclidean Distance to WLAN Positioning

The basic assumption of the proposed APs deployment is that the larger RSS Euclidean distance renders the higher positioning accuracy. For simplicity, we take the classical nearest neighborhood (NN) algorithm as example.

NN algorithm is the basic search matching algorithm, identifying the nearest reference point with the smallest RSS Euclidean distance is considered as the user's location. The RSS Euclidean distance here means the Euclidean distance between RSS vectors. Then the server searches the fingerprint database, finds the reference point whose RSS Euclidean distance to the real-time RSS values is least and returns its coordinate to the user as positioning result.

NN algorithm computes and stores the average RSS vector for each reference point in the offline stage. In the online phase, compute the Euclidean distance between real-time RSS vector and the average RSS vector of each reference point.

As seen in Fig. 1, the physical space of target region is divided into appropriate size of grids. The center of each grid is represented by a reference point (RP). Denote the two dimensional-coordinates of RP C_1, C_2, C_3, and C_4 as $\mathbf{L}_1$, $\mathbf{L}_2$, $\mathbf{L}_3$, and $\mathbf{L}_4$, the m-dimensional average RSS vectors of C_1, C_2, C_3, and C_4 as $\mathbf{r}_1$, $\mathbf{r}_2$, $\mathbf{r}_3$, and $\mathbf{r}_4$. Assume that the user stands at point P with real-time RSS vector $\hat{\mathbf{r}}$. The point P is nearest to RP C_4. The RSS Euclidean distance between $\hat{\mathbf{r}}$ and $\mathbf{r}_i$ is given:

$$D_i = \left\|\hat{\mathbf{r}} - \mathbf{r}_i\right\|_2,\ i=1,\ldots,4 \quad (1)$$

Then, the user's location $\hat{\mathbf{L}}$ is estimated:

$$\hat{\mathbf{L}} = \mathbf{L}_j,\ \text{subject to } D_j = \min\{D_i\},\ i=1,\ldots,4 \quad (2)$$

Ideally, the user's location can be located into RP C_4, because the real-time RSS $\hat{\mathbf{r}}$ is more similar with $\mathbf{r}_4$. However, due to various propagation factors such as multipath and shade effect, nonline of sight propagation and the user's body, the real-time RSS values always fluctuate to some extent. If the RSS values vary significantly some time, the user's location may be located into the other RPs and leads to a large positioning error.

Assume the signal space is two-dimensional. RSS values at the point P fluctuate in the circle which centers at the point $\hat{\mathbf{r}}_c$ and its radius is $\hat{\sigma}$. As shown in Fig. 1, when enlarge the RSS Euclidean distance to some extent, the probability of locating the user into the wrong RP may become zero. In contrast, when reduces the RSS Euclidean distance, this probability of locating into wrong RPs will increase, thus the positioning accuracy will degrade .

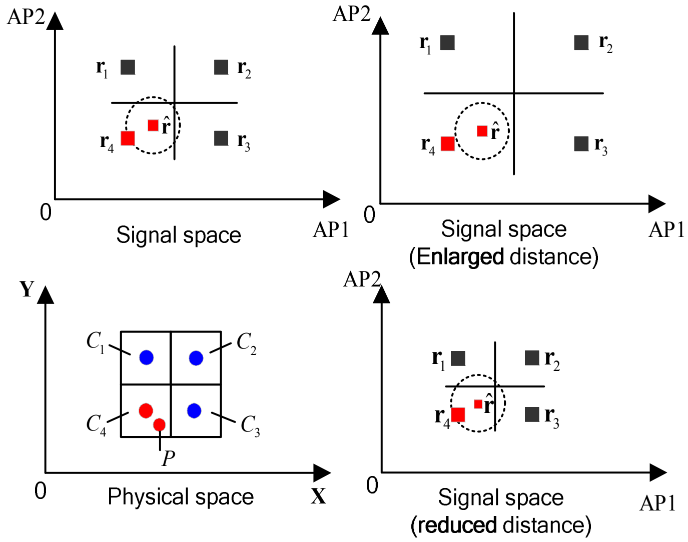

Figure 1. Relationship betweenthe the positioning performance and RSS Euclidean distance.

Then, the question is: can the RSS Euclidean distance be changed by the APs deployment? Generally, the average RSS from AP1 at the RPs can be modeled as following:

$$r = r_0 - 10\alpha \log d/d_0 \quad (3)$$

where, d_0 is the distance between AP and the calibration point, d is the distance between AP and the RP, r_0 is the RSS value of the reference point, and α is the path loss factor. For AP1, the RSS Euclidean distance between C_1 and C_2 is:

$$\Delta r = r_1 - r_2 = 10\alpha \log d_2/d_1 \quad (4)$$

where d_1 and d_2 is the distance to AP1 of C_1 and C_2, respectively. If the position of AP1 changes, the value of d_2/d_1 and the RSS Euclidean distance are also changed. As a consequence, the positioning accuracy may be improved by increasing the RSS Euclidean distance with appropriate APs deployment.

In addition, there is a WKNN algorithm which is an improvement to NN algorithm. Different from NN algorithm by which the only point with the least Euclidean distance is fixed, when searching the fingerprint database in WKNN algorithm, K RPs with the least distances are fixed. Then fuse the coordinates of the K RPs and get the final location coordinates for the unknown point:

$$(\hat{x},\hat{y}) = \sum_{i=1}^{K} (x_i, y_i)/\hat{d}_i \quad (5)$$

where, (x_i, y_i) is the ith reference point among these K points and $(\hat{x},\hat{y})$ is final location coordinates of the unknown point. $\hat{d}_i$ is the normalized Euclidean distance between the real-time RSS vector and the mean RSS vector at the related reference point, whose value can be obtained as in (1). The normalized RSS Euclidean distance $\hat{d}_i$ can be given as follows:

$$\hat{d}_i = D_i \cdot \sum_{i=1}^{K} (1/D_i) \tag{6}$$

III. Proposed optimized APs Deployment in WLAN Indoor Positioning System

A. Find the Reasonable Number of APs

Generally, increasing of the number of APs might have positive influence on the positioning accuracy. However, more APs deployed may bring in more cost in hardware. We has determined the minimum number of APs needed in the offline stage based on the average RSS Euclidean distance. Given the threshold of the average RSS Euclidean distance in the offline training phase, the number of APs deployed is set as the minimum number whose corresponding average RSS Euclidean distance exceeds the threshold. The reasonable number of APs follows the objective function:

$$\begin{cases} \min_{m} \left\{ \max_{\beta} \left\{ \bar{D}(m) \right\} \geq S \right\} \\ \bar{D}(m) = \dfrac{1}{p \cdot q} \sum_{i=1}^{p} \sum_{j \in Neigh(i)} D_{i,j}(m) \\ D_{i,j}(m) = \sum_{k=1}^{m} \left(r_i(k) - r_j(k) \right)^2 \\ \beta = \left\{ (X_1, Y_1), (X_2, Y_2), \cdots, (X_m, Y_m) \right\} \end{cases} \tag{7}$$

where, S is the threshold of the average RSS Euclidean distance; p and m is the number of RPs and APs; β is the positions of the APs; $\bar{D}$ is the average RSS Euclidean distance; $D_{i,j}$ is the RSS Euclidean distance between the $i-$th and $j-$th RP; $r_i(k)$ is the RSS value from the $k-$th AP at the $i-$th RP; $Neigh(i)$ is the neighbor RPs of the $i-$th RP; and q is the number of neighbor RPs.

B. APs Deployment

With the fixed number of APs, APs deployment are designed to maximize the average RSS Euclidean distance while keeping the standard variance of RSS Euclidean distance at a certain value. That is, we aim to make the RSS Euclidean distance as uniform as possible so that big positioning errors may be avoided to some degree, while maximizing the average RSS Euclidean distance. The objective function is given as follows:

$$\begin{cases} \max_{\beta} \left\{ \bar{D} \big/ \sqrt{\mathrm{var}(\bar{D})} \right\} \\ \mathrm{var}(\bar{D}) = \dfrac{1}{p} \sum_{i=1}^{p} \left(\sum_{j \in Neigh(i)} D_{i,j}(m)/q - \bar{D} \right)^2 \\ \beta = \left\{ (X_1, Y_1), (X_2, Y_2), \cdots, (X_n, Y_n) \right\} \end{cases} \tag{8}$$

where, β is the APs deployment for the total n APs, $\bar{D}$ is the average RSS Euclidean distance computed as in (7), and $\mathrm{var}(\bar{D})$ is the variance for the RSS Euclidean distance.

The Positions of APs are assumed at the discrete grids of the target region. We use the genetic algorithm to seek the APs deployment that satisfying (8). The algorithmic steps are shown as follows:

- Step 1: Given the number of RPs and APs at the target region, create the objective function as in (8);
- Step 2: Set the genetic algorithm parameters, including: population parameters, regeneration parameters, fitness calculation parameters, variation parameters, selection parameters, cross parameters, and stop conditions parameters etc.;
- Step 3: Process the genetic algorithm, calculate the objective function, and save the biggest value and corresponding individual (APs deployment);
- Step 4: When one of the stop conditions is met, output the best objective function value and the corresponding APs deployment. The algorithm ends.

IV. Simulations and Experimental Results

A. Simulation and Experimental Setup

We simulated the WLAN positioning using log-distance path loss model [13]. The RSS value is given as follows:

$$r(k) = r_0 - 10\alpha \log(\frac{d}{d_0}) + \chi_\sigma \tag{9}$$

where, d is the Euclidean distance between the receiver and the AP, and χ_σ is the noise variable with zero mean and Gaussian distribution. The reference points in the target region are uniformly distributed and separated by 2 meters. The test points are randomly selected. Total 1000 real-time RSS testing samples per test point are generated by (9). We simulated the APs deployment in four WLAN indoor environments whose sizes are 8m×16m, 16m×16m, 16m×32m and 32m×32m, respectively. The simulation parameters are set to $r_0 = -25$ dBm , $d_0 = 1$m , $\sigma = 4.3$dBm and one second sampling period. The positioning algorithm used in simulation is the widely used WKNN algorithm.

We also carried experiments in a real WLAN indoor environment, part of the hall of our building with size $12\ \mathrm{m} \times 16\ \mathrm{m}$. There were total 4 APs available. 40 reference points separated by 2 m were selected, with 100 samples per reference point. 40 test points were randomly selected at the target positioning region. 100 test samples per test point were collected in the different days to test the performance. An ASUS laptop with Intel PRO/3945ABG IEEE Wireless Card was used to read and collect RSS values from all APs. For comparison, we carried various positioning algorithms including WKNN, ML, SVR and ANN.

B. Simulation Results

Fig. 2 shows the relationship between positioning errors and RSS Euclidean distance with 5, 7, 9, and 11 APs in the environment of 32m × 32m. When the number of APs increases from 5, 7 to 9, the RSS Euclidean distance increases significantly for most of the RPs, and thus the positioning errors reduce greatly. When the number of APs increases from 9 to 11, the addition of RSS Euclidean distance and the reduction of positioning errors are not obvious. Fig. 3 shows the relationship between positioning errors and RSS Euclidean distance in 16m × 32m environment. The blue, red, green and black points represent the RPs with 3, 5, 7, and 9 APs, respectively. When the number of AP increases from 3 to 5, the RSS Euclidean distance increases and positioning errors reduce significantly. Continuing adding the number of APs, the RSS Euclidean distance and the error don't change a lot. As seen in Fig. 2 and Fig. 3, when the average RSS Euclidean distance is above 4.5, most of positioning errors distribute within 2 meters. So we set S=4.5 in (7) to determine the reasonable number of APs during offline stage. Therefore, we give the following conclusions:

- The larger RSS Euclidean distance leads to the higher positioning accuracy. In other words, the larger RSS Euclidean distance renders the smaller positioning error.
- At the same positioning environment, the RSS Euclidean distance for different RPs is different. For the same average RSS Euclidean distance, the smaller variance may improve the positioning performance. This is because the smaller variance renders the smaller probability that small RSS Euclidean distance happens.
- The reasonable number of APs for different size of environments is different. The larger size requires more APs to cover the larger region when aiming to achieve the same positioning performance.
- For the same RSS Euclidean distance, the more number of APs used in positioning may lead to the smaller positioning error, because more number of information sources explored may make the positioning algorithm more robust to noise.

Table I shows the APs deployment in the four environments of 8m×16m, 16m×16m, 16m×32m and 32m ×32m. The reasonable numbers of the APs for these four simulation environments are set to be 2, 3, 5, and 8, respectively. All these reasonable number of APs are determined in (7) during offline stage. The previous APs deployment method follows the strategy that the signal coverage should be as uniform as possible. The optimal APs deployments for different environments are obtained by the proposed APs deployment algorithm.

Table II shows the positioning accuracy comparison between the proposed APs deployment method and previous APs deployment method. The positioning results are based on the most commonly used WKNN algorithm. In contrast to previous method which just considers the signal coverage, the proposed APs deployment further considers maximizing the RSS Euclidean distance under the constraint of seamless signal coverage. Thus, as seen in Table II, the mean positioning error of the proposed APs deployment reduces significantly than the previous method. Mean positioning errors of the proposed APs deployment in the four environments are all within 2 meters, while the mean errors of the previous ones are above 2 meters. Besides, the mean positioning error increases with the number of APs increases, though the size of positioning environment increases. This is because the average RSS Euclidean distance increases with more APs added.

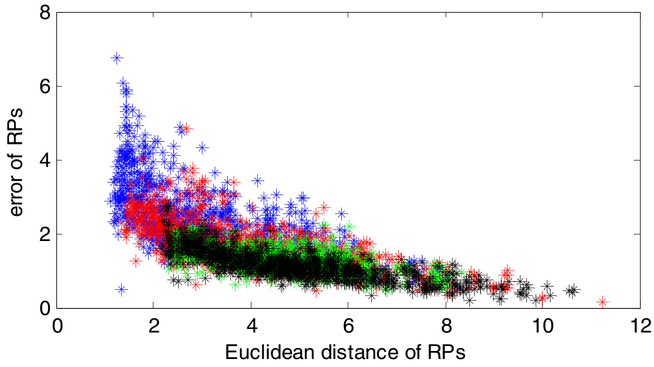

Figure 2. Relationship between positioning errors and RSS Euclidean distance of RPs in 32m×32m simulation environment. The blue, red, green and black points represent RPs with 5, 7, 9, and 11 APs, respectively.

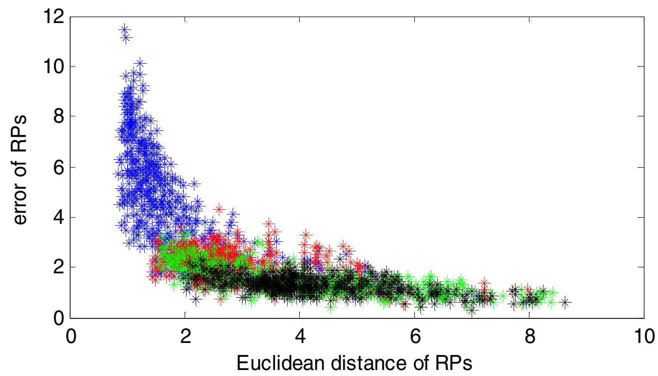

Figure 3. Relationship between positioning errors and RSS Euclidean distance of RPs in 16m×32m simulation environment. The blue, red, green and black points represent RPs with 3, 5, 7, and 9 APs, respectively.

TABLE I. APS DEPLOYMENT IN FOUR ENVIRONMENTS

Environment (m×m)	Previous APs Deployment	Proposed APs Deployment
8×16 (2 APs)	(4.0, 5.33); (4, 10.66)	(3.4, 5.2); (4.4, 9.8)
16×16 (3 APs)	(8.0, 5.33); (4.10.66); (12.0, 10.66)	(2.4, 7.9); (10.3, 12.5); (12.5, 4.0)
16×32 (5 APs)	(4.0, 8.0); (8.0, 16.0); (12.0, 4.0); (4.0, 24.0); (12.0, 24.0)	(12.3, 17.1); (4.2, 20.2); (10.0, 9.5); (6.5, 1.7); (8.2, 28.1)
32×32 (8 APs)	(4.0, 8.0); (12.0, 8.0); (20.0, 8.0); (28.0, 8.0) (4.0, 24.0); (12.0, 24.0); (20.0, 24.0); (28.0, 24.0)	(28.2, 12.95); (6.0, 4.7); (26.1, 24.4); (4.4, 16.4); (16.4, 16.9); (12.3, 28.0); (8.8, 22.7); (18.2, 5.3)

TABLE II. POSITIONIGN ACCURACY COMPARISON BETWEEN THE PROPOSED APS DEPLOYMENT AND THE PREVIOUS ONE

Environment (m×m)	Mean Error (m)		Accuracy within 2 m	
	Proposed	*Previous*	*Proposed*	*Previous*
8×16 (2 APs)	1.94	2.33	60.3%	54.2%
16×16 (3 APs)	1.89	2.21	62.5%	56.1%
16×32 (5 APs)	1.81	2.36	63.4%	52.8%
32×32 (8 APs)	1.73	2.12	65.7%	58.2%

C. Experimental Results

Fig. 4 shows the positioning performance of the proposed APs deployment method in a realistic WLAN environment. To test the performance improvement for different positioning algorithms, we carried the ML, SVR, WKNN and ANN methods. Due to the propagation factors such as multipath and shade effect, more noisy information is introduced into the RSS signal space in real environment. Thus, we deploy four APs to increase the average RSS Euclidean distance.

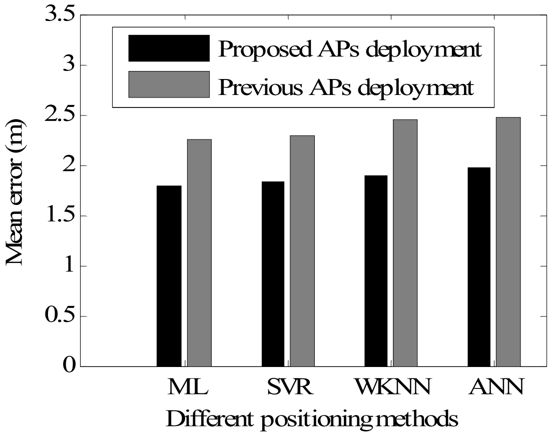

Figure 4. Mean positioning error comparison between different methods.

As seen in Fig. 4, the following conclusions can be given:

- The mean positioning error reduction is obtained by all the positioning methods. This fact supports that the increase of RSS Euclidean distance is beneficial to all positioning methods.
- The improvement of WKNN is larger than the other methods, because WKNN is constructed on RSS Euclidean distance directly. WKNN reduces the mean error by 22.9% while ML, SVR and ANN by 20.4%, 20.0%, and 20.2%, respectively.
- Using the same number of APs, the positioning performance in realistic wireless indoor environment is always worse than that in simulation environment, because the noise strength in real environment is always larger due to the complex propagation factors.
- The smallest mean positioning error is obtained by ML method, because the RSS statistical information is further modeled and explored.

V. CONCLUSIONS

This paper proposes an optimized the APs deployment method for WLAN indoor positioning. Unlike previous APs deployment just for WLAN communication, we further consider improving the positioning accuracy. Under the constraint of seamless signal coverage for WLAN communication, the proposed APs deployment method aims to maximize the average RSS Euclidean distance, while keeping the variance of RSS Euclidean distance into a certain value. After substantive experiments and analysis, we demonstrate that the larger RSS Euclidean distance renders the higher positioning accuracy. Besides, the reasonable number of APs is also determined according to the threshold of average RSS Euclidean distance during offline stage. Both simulations and experimental results show that, the proposed APs deployment method can improve the accuracy of different positioning methods significantly. Experiments show that WKNN reduces the mean error by 22.9% while ML, SVR and ANN by 20.4%, 20.0%, and 20.2%, respectively.

REFERENCES

[1] M. Chon, and H. Cha, “LifeMap: A smartphone-based context provider for location-based services,” *IEEE Pervasive Computing*, vol. 10, no. 2, pp. 58-67, 2011.

[2] L. Wirola, T. A. Laine, and J. Syrjarinne, “Mass-market requirements for indoor positioning and indoor navigation,” *Proceedings of 2010 International Conference on Indoor Positioning and Indoor Navigation*, September 2010.

[3] S. Tagashira, Y. Kanekiyo, Y. Arakawa, and A. Fukuda, “Collaborative filtering for position estimation error correction in WLAN positioning systems,” *IEICE Transactions on Communications*, vol. E94-B, no. 3, pp. 649-657, 2011.

[4] A. Kushki, K. Plataniotis, and A. Venetsanopoulos, “Intelligent dynamic radio tracking in indoor wireless local area networks,” *IEEE Transactions on Mobile Computing*, vol. 9, no. 3, pp. 405-419, 2010.

[5] P. Bahl and V. N. Padmanabhan, “RADAR: An in-building RF-based user location and tracking system,” *Proceedings of INFOCOM 2000*, pp. 775–784, 2000.

[6] M. Youssef, A. Agrawala, and A. U. Shankar, “WLAN location determination via clustering and probability distributions,” *Proceedings of Pervasive and Computer Communications*, pp. 143-150, 2003.

[7] M. Brunato, and R. Battiti, “Statistical learning theory for location fingerprinting in wireless LANs,” *Computer Networks,* vol. 47, pp. 825–845, 2005.

[8] Z.L. Wu, C.H. Li, K.Y.N. Joseph, and L. Karl, “Location estimation via support vector regression,” *IEEE Transactions on Mobile Computing*, vol. 6 no. 3, pp. 311-321, 2007.

[9] U. Ahmad, A.V. Gavrilov, S. Lee, Y.K. Lee, “A modular classification model for received signal strength based location systems,” *Neurocomputing*, vol. 71, pp. 2657-2669, 2008.

[10] M. Borenovic, A. Neskovic, D. Budimir, “Space partitioning strategies for indoor WLAN positioning with cascade-connected ANN structures,” *International Journal of Neural Systems*, vol. 21, no. 1, pp. 1-15, 2011.

[11] S. Kouhbor, J. Ugon, A. Rubinov, A. Kruger, and M. Mammadov, “Coverage in WLAN with minimum number of access points,” *Proceedings of VTC 2006*, pp. 1166-1170, 2006.

[12] M. D. AdickeS R E. Billo, B. A. Norman, S. Banejce, B. 0. Nnaji, and J. Rajgopal, “Optimization of indoor wireless communication network layouts,” *IIE Transaction*, vol. 34, no. 9, pp. 823 – 836, 2002.

[13] T. S. Rappaport, *Wireless Communications: Principles and Practice.* IEEE Press, Piscataway, NJ, USA, 1996.