On the RBF-based Positioning using WLAN Signal Strength Fingerprints

C. Laoudias*, C. G. Panayiotou*, P. Kemppi†
*KIOS Research Center for Intelligent Systems and Networks
Department of Electrical and Computer Engineering, University of Cyprus
Kallipoleos 75, P.O. Box 20537, 1678, Nicosia, Cyprus
Email: {laoudias, christosp}@ucy.ac.cy
†VTT Technical Research Centre of Finland
Vuorimiehentie 3, P.O. Box 1000, FIN-02044, Espoo, Finland
Email: Paul.Kemppi@vtt.fi

***Abstract*—Provision of accurate and reliable location estimates is the key issue for the proliferation of indoor location oriented services and applications. Our positioning method is based on Radial Basis Function (RBF) networks and we exploit Received Signal Strength (RSS) measurements from several WLAN Access Points (AP). We incorporate the RSS covariance matrix into the estimation method and couple that with a methodology that indicates which APs can be ignored during positioning without sacrificing accuracy. We evaluate the RBF method in a real-life setup, and experimental results suggest that the proposed approach performs well.**

I. Introduction

Indoor positioning is challenging due to the complex propagation environment and unpredictable time varying conditions, such as the presence of people or equipment. Improving the localization accuracy and the robustness to these environmental factors is expected to increase the interest in location aware applications, such as indoor guidance and asset tracking.

Different positioning technologies have been discussed in the literature including infrared, Bluetooth, RFID, UWB, ultrasound and WLAN. Several positioning methods rely on WLANs, mainly due to the wide availability of relevant infrastructure in indoor environments. These methods exploit Angle of Arrival (AOA), Time of Arrival (TOA), Time Difference of Arrival (TDOA) and Received Signal Strength (RSS) measurements from Access Points (AP) to infer the unknown user location. An overview of technologies to determine location and a survey of commercial positioning systems is provided in [1], [2].

In the context of WLAN positioning, RSS measurements are usually preferred, because they can be easily collected without the need for specialized and expensive equipment. Indoor radio propagation models have been used to transform RSS values into distances from at least three relevant APs in order to determine the unknown user location. However, this approach has some limitations, mainly due to the multipath effect that renders the use of standard log-distance propagation models inadequate. Another problem is that the exact locations of the APs are required, and such information is either not available or hard to obtain. Fingerprinting methods address both issues by utilizing RSS fingerprints collected a priori at some predefined reference points in the area of interest. Location can then be estimated using the currently measured fingerprint to find the best match between the current and collected fingerprints.

In our approach, we employ a type of Artificial Neural Networks (ANN) called Radial Basis Function (RBF) networks and use the collected reference data to build a mapping between the RSS fingerprints and location coordinates. We investigate the performance of the RBF positioning method, in case the RSS covariance matrix is used. Moreover, variable selection is addressed, and we discuss a suitable cross validation methodology to decide which input variables, i.e. APs, can be eliminated for dimensionality reduction.

The rest of the paper is structured as follows. Previous work related to indoor positioning using RSS fingerprints and AP selection methods is discussed in Section II. The proposed method based on RBF networks is detailed in Section III. In Section IV, we present the WLAN experimental setup used for our performance evaluation, followed by the results regarding the positioning accuracy. Finally, Section V provides the conclusions and discusses some ideas for future work.

II. Related Work

A. WLAN RSS-based positioning

Several approaches utilize a number of RSS fingerprints, collected a priori at some reference points. In the deterministic case, location is estimated as the average of K Nearest Neighbors (KNN) [3], i.e. reference points with the shortest distance between the observed and mean RSS fingerprint at each point. Probabilistic methods determine location by using estimates of probability density functions (PDF). Kernel-based techniques or the histogram density estimate can be used as nonparametric approximations of the required PDFs [4]. Other methods rely on ANNs, including the Multi Layer Perceptron (MLP) [5], [6] or Support Vector Machines (SVM).

In the proposed RBF method, location is expressed as the weighted sum of Gaussian radial, i.e. distance-based, functions and we use the RSS covariance matrix in distance calculation. Weights can be determined easily from the training data using linear algebra. In the positioning phase, the RBF network

978-1-4244-7157-7/10/$26.00 ©2010 IEEE

outputs a location estimate given the currently observed fingerprint.

B. AP Selection Methods

A mobile device may detect a large number of APs due to the ubiquitous coverage of several WLANs that have been deployed independently. However, some APs may provide correlated RSS samples that introduce bias in the location estimates. Moreover, using all available APs has an impact on the computational complexity of the positioning algorithm. On the other hand, ignoring specific APs can lead to accuracy degradation, if the RSS values from these APs affect the ability of the positioning algorithm to discriminate between neighboring reference points. Therefore, the objective of AP selection schemes is to identify a subset of APs that will be used during positioning without compromising performance.

In the SkyLoc fingerprint-based floor positioning system [7], forward selection and backward elimination have been used to select the appropriate GSM Base Stations. In the context of WLAN RSS positioning, Youssef et al. choose the APs with the highest RSS value in the observed fingerprint. The intuition is that these APs provide the highest probability of coverage over time. However, it has been observed experimentally that the variance of RSS measurements at a given location increases with its mean power [8], [9] and thus selecting the strongest APs may not always provide the best accuracy. In [10] the APs that are more capable of distinguishing the reference points, are included in the subset, and the selection process is based on the Information Gain criterion. Authors in [11] rely on divergence measures, such as the Bhattacharyya distance or the Information potential, to deal with correlations between signals from APs and obtain a small subset. In [12], selection is based on the discrimination score of each AP calculated with the Fisher criterion.

In this work we use cross validation to select the appropriate APs. These kinds of techniques, including the leave-one-out and generalized cross validation, are able to predict the performance of a trained model when new unobserved inputs are available. In this way, available APs can be ordered based on their ability to describe the input-output relation, and then we can select only the most important to consider during positioning.

III. Positioning Algorithm

A set of reference points $\ell_i = (x_i, y_i),\ i = 1, \ldots, L$ is used to measure RSS fingerprints $s = [s_1, \ldots, s_n]^T$ from n APs, where s_j denotes the RSS value related to the j-th AP. A series of fingerprints $s(\ell_i, m),\ i = 1, \ldots, L$ and $m = 1, \ldots, M$, are collected at each reference point and associated with the physical coordinates (x_i, y_i). Thus, our training set contains $N = L \cdot M$ fingerprints denoted as $s^i,\ i = 1, \ldots, N$.

In our method, the RBF network has n inputs, corresponding to RSS values from all n APs and two outputs representing the coordinates. Given a fingerprint s measured at location $\ell = (x, y)$, the output of the RBF network may be expressed as the weighted sum of normalized Gaussian basis functions

$$\ell(s) = \sum_{i=1}^{L} w_i u(s, c_i) \tag{1}$$

$$u(s, c_i) = \frac{\varphi(\|s - c_i\|)}{\sum_{j=1}^{L} \varphi(\|s - c_j\|)} \tag{2}$$

where $\varphi(\|s - c\|) = \exp\big(-\frac{1}{2}\|s - c\|^2\big)$ and $w_i = [w_i^x\ w_i^y]$ are 2-dimensional weights. We set each RBF center c_i equal to the mean value fingerprint at each reference point $\overline{s}(\ell_i)$ that is defined as

$$\overline{s}(\ell_i) = \frac{1}{M} \sum_{m=1}^{M} s(\ell_i, m),\ i = 1, \ldots, L. \tag{3}$$

We may determine the unknown weights using the reference data by solving the overdetermined system of linear equations

$$\ell_i = \sum_{j=1}^{L} w_j u\big(s(\ell_i, m), c_j\big),\ i = 1, \ldots, L,\ m = 1, \ldots, M. \tag{4}$$

These equations can be written in matrix form as two linear systems $Uw^t = d^t,\ t \in \{x, y\}$ that represent a separate RBF network for each location coordinate, where

$$U = \begin{bmatrix} u(s^1, c_1) & u(s^1, c_2) & \cdots & u(s^1, c_L) \\ u(s^2, c_1) & u(s^2, c_2) & \cdots & u(s^2, c_L) \\ \vdots & \vdots & \ddots & \vdots \\ u(s^N, c_1) & u(s^N, c_2) & \cdots & u(s^N, c_L) \end{bmatrix} \tag{5}$$

$$w^t = \big[w_1^t,\ w_2^t,\ \ldots,\ w_L^t\big]^T \tag{6}$$

$$d^t = \big[d_1^t,\ d_2^t,\ \ldots,\ d_N^t\big]^T \tag{7}$$

Each row in the $N \times L$ matrix U contains the responses of the basis functions to a particular fingerprint, while w^t are the $L \times 1$ unknown weights and d^t are the $N \times 1$ outputs for each coordinate. The respective weights are calculated in a least squares sense by $w^t = U^+ d^t$, where U^+ is the pseudoinverse defined as $U^+ = (U^T U)^{-1} U^T$.

Subsequently, the weights are used to derive the estimated location, given the currently observed fingerprint $s' = [s'_1, \cdots, s'_n]^T$

$$\widehat{\ell}(s') = \sum_{i=1}^{L} w_i u(s', c_i). \tag{8}$$

A. Distance Calculation

The euclidean norm can be used to calculate the distance between the input fingerprint and RBF centers in the RBF network. However, individual fingerprint elements may differ regarding the distribution of RSS. Thus, we consider a weighted norm as distance measure and use the following set of basis functions that represent multivariate Gaussian distributions with mean c_i and single common covariance matrix Σ.

$$\varphi(\|s - c_i\|) = \exp\big(-\frac{1}{2}(s - c_i)^T \Sigma^{-1} (s - c_i)\big),\ i = 1, \cdots, L. \tag{9}$$

The covariance matrix determines the receptive field of the basis functions [13] that affects the performance of the RBF positioning method, because it has an influence on the subset of the RSS input space for which each basis function has a fairly large output. In our previous work [14], we considered $\Sigma = \sigma^2 I$, where σ^2 is a common variance for all n APs and proposed a heuristic to select an appropriate value for σ^2 according to the maximum distance among RBF centers.

Another option is to use a diagonal covariance matrix

$$\Sigma = diag(\sigma_1^2,\ \sigma_2^2,\ \ldots,\ \sigma_n^2) \tag{10}$$

where σ_k^2 is the sample variance of the k-th AP estimated from the collected reference data. In this way, we are still under the assumption that RSS values from different APs are independent, and we exploit the RSS variance in our AP selection methodology that is described in the following. Note that a non-diagonal covariance matrix could be used to consider correlations between APs. However, when a WLAN is deployed inside a building, non-overlapping transmission channels are usually preferred in order to minimize interference between neighboring APs. Thus, the independency assumption is valid and has been verified experimentally in [8].

B. Cross validation AP Selection

In typical WLAN setups, there are several APs installed throughout the building that can be detected and used for positioning. Thus, the input dimensionality of the RBF networks in our method is increased. This is not a significant limitation regarding the calculation of the RBF weights, because the weights are determined once off-line. However, computational complexity during positioning is increased, which can affect real-time positioning in case low processing power mobile devices are considered.

In this work, we address the need for the joint design of AP selection and distance calculation. We use a single common norm weighting matrix Σ^{-1} by setting

$$\Sigma = diag(\alpha_1\sigma_1^2,\ \alpha_2\sigma_2^2,\ \ldots,\ \alpha_n\sigma_n^2). \tag{11}$$

Vector $\alpha = [\alpha_1,\ \alpha_2,\ \ldots,\ \alpha_n]$ can be considered as a vector of scaling parameters that indicate the importance of each input variable, i.e. AP. Small value of a specific α_k suggests that the respective input is significant, and even small changes are reflected to the output of the RBF network. On the other hand, if α_k is large, then the output does not vary much with respect to the RSS level of that AP. Thus, we may use parameters α to obtain an ordering of the available APs based on their significance.

We use the Generalized Cross Validation (GCV) method to estimate α; see [13] for details. In this context, vector α is selected to minimize the objective function given by

$$V(\alpha) = \frac{\frac{1}{N}\|(I - A(\alpha))d\|^2}{\left[\frac{1}{N}tr(I - A(\alpha))\right]^2} \tag{12}$$

$$A(\alpha) = U(U^T U)^{-1} U^T \tag{13}$$

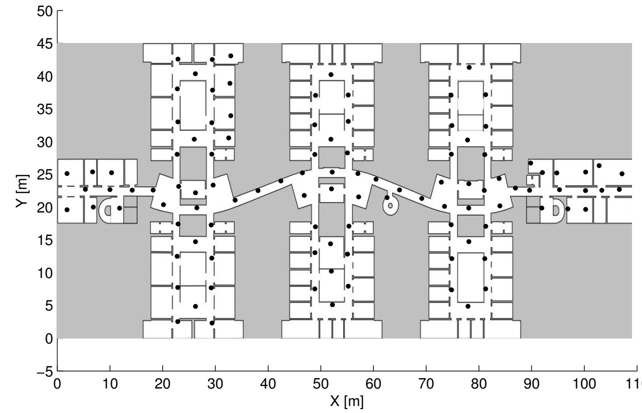

Fig. 1. Floorplan of the experimentation area.

Matrix A depends implicitly on α, because the covariance matrix given in (11) is used for distance calculation. The output of the location coordinate x or y is denoted by d and $tr(\cdot)$ denotes the trace of a matrix. Notice that (12) relies only on the training data. Following this procedure, we obtain two sets of parameters $\alpha^t,\ t \in \{x, y\}$ that scale the inputs in each RBF network appropriately. Subsequently, we can choose the subset of APs that are important for the performance of our positioning algorithm and remove the remaining for dimensionality reduction.

IV. Experimental Evaluation

A. Measurement Setup

The performance evaluation was done using data collected in a typical office environment on the second floor of a three storey building at VTT Technical Research Centre of Finland. The floor consists of eight wings containing offices and meeting rooms connected with corridors. The floorplan of the experimentation area and the locations of the reference points are depicted in Fig. 1. We used a Fujitsu-Siemens Pocket Loox smart phone with Windows Mobile operating system to collect RSS measurements at 107 reference points. These points are separated by 2-3 meters and form a grid that covers all public spaces and meeting rooms.

A total of 3210 reference fingerprints, corresponding to 30 fingerprints per reference point, were collected at the rate of 1 sample/sec. We use all 31 available WLAN APs that are installed throughout the building. Due to the open plan interior design, these APs can be partially detected on the second floor, and the average number is 9.7 APs per reference point. RSS values range from -101dBm to -34dBm and we used a small constant to handle the missing RSS values in the fingerprints. For testing purposes, fingerprints were also collected by walking at a constant speed over a path that consists of 192 locations. One fingerprint is recorded at each location, and the same path is sampled 3 times.

B. Parameter tuning

We reserved the collected fingerprints from one route as validation data and used samples from the other two routes as

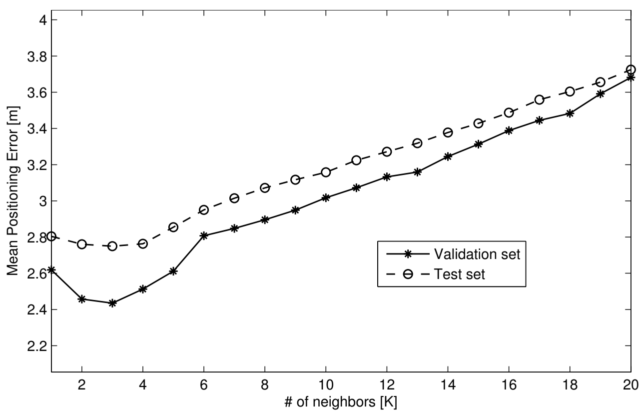

Fig. 2. Mean error pertaining to the validation and test data for KNN method as a function of parameter K.

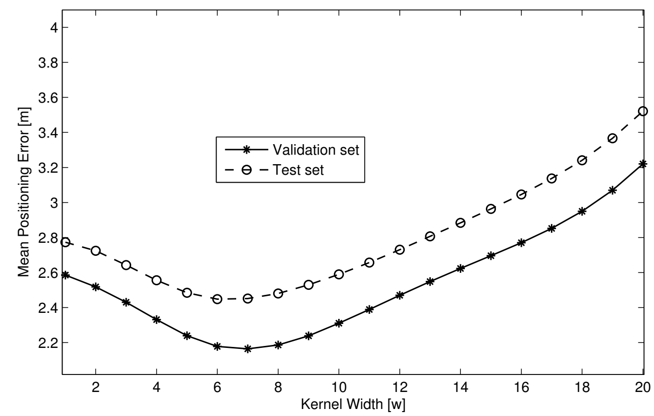

Fig. 3. Mean error pertaining to the validation and test data for KERNEL method as a function of parameter w.

test data. Algorithm specific parameters are selected in order to decrease the mean positioning error on the validation data.

In the Nearest Neighbor method [3], the estimated location $\widehat{\ell}$ is obtained by minimizing the Euclidean distance between the observed fingerprint s' and the mean value fingerprints

$$\widehat{\ell}(s') = \arg\min_{\ell_i} \|s' - \overline{s}(\ell_i)\|^2. \tag{14}$$

The KNN variant determines location as the average of K reference points, whose mean value fingerprints are closer to s'. The mean error pertaining to the validation set for KNN method using variable number of neighbors K is plotted in Fig. 2. The mean error regarding the test set is also included to show that tuning K based on the validation data can provide acceptable and usually near-optimal performance when the test data are considered. The plot indicates that $K = 3$ provides the lowest mean error for the given setup, and this value is used thereafter.

In the probabilistic method [4], denoted as KERNEL, the unknown location is estimated as the expected value of the location variable ℓ

$$\widehat{\ell}(s') = \mathbf{E}[\ell|s'] = \sum_{i=1}^{L} \ell_i p(\ell_i|s'). \tag{15}$$

By application of Bayes rule, the problem reduces to calculating $p(s'|\ell_i)$ and assuming that RSS measurements from neighboring APs are independent, we get $p(s'|\ell_i) = \prod_{j=1}^{n} p(s'_j|\ell_i)$. The conditional probability $p(s'_j|\ell_i)$ is estimated as the average of M equally weighted Gaussian kernel functions. Each kernel is centered on $s_j(\ell_i, m),\ m = 1, \cdots, M$ according to the reference data, and parameter w determines the kernel width. The mean positioning error as a function of the kernel width is depicted in Fig. 3, and w = 7 provides the lowest error with respect to the validation data set.

For the RBF method, a Genetic Algorithm was used to minimize (12) and obtain several solutions for the scaling parameters α^t. We used the validation data to select the best $\alpha^t,\ t \in \{x, y\}$ and for this solution $\alpha^x \in [0.18\ 1.36]$, while $\alpha^y \in [0.13\ 2.07]$. Sorting the scaling parameters indicates which APs are not so important to describe the RSS-position relation. Those APs that have high scaling values can be excluded during positioning without significantly affecting the performance of the RBF method. For the RBF network that corresponds to each location coordinate x or y, we take the ordering of APs with respect to increasing scaling values. The regulating parameter $0 \leq b \leq 1$ denotes the percentage of APs that will be used for position estimation.

The positioning error as a function of b is plotted in Fig. 4. The mean error regarding the validation set is 3.1m in case the 16 most important APs ($b = 0.5$) are used in each RBF network. Note that these two subsets do not necessarily contain the same APs, because the ordering is based on the individual scaling parameters α^t. Using less than 12 APs ($b < 0.4$) leads to further accuracy degradation, because the selected APs are not enough to provide good coverage throughout the experimentation area. Results on the validation set reveal that if we set $b = 0.7$, then the RBF method provides the same level of accuracy compared to KNN and KERNEL methods.

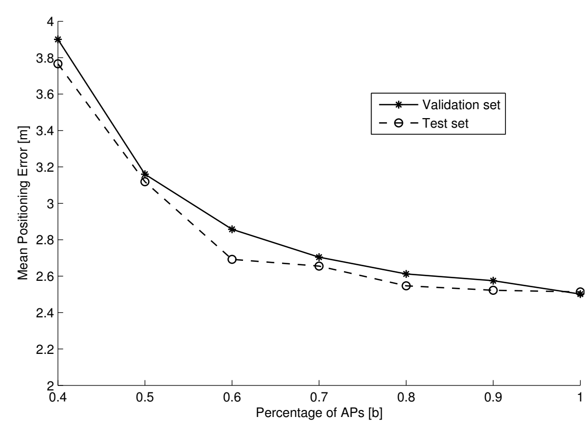

Fig. 4. Mean error pertaining to the validation and test data for RBF method as a function of parameter b.

C. Results

We use the test data, collected by sampling the same path twice, to evaluate the performance of the proposed

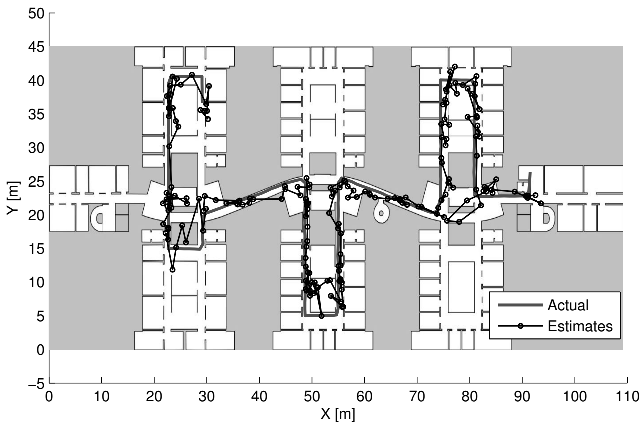

Fig. 5. RBF estimates for Test set 1.

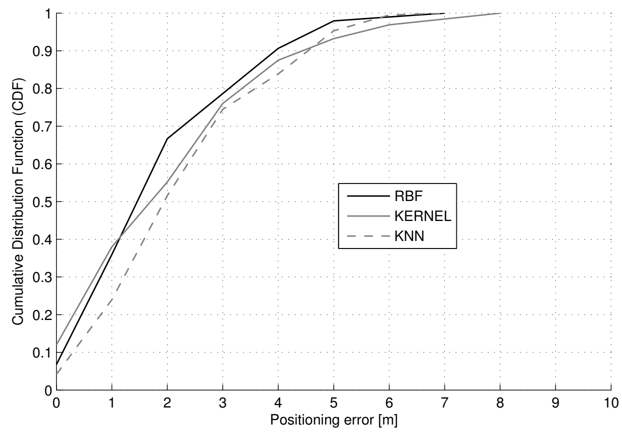

Fig. 7. CDF of the positioning error for Test set 1.

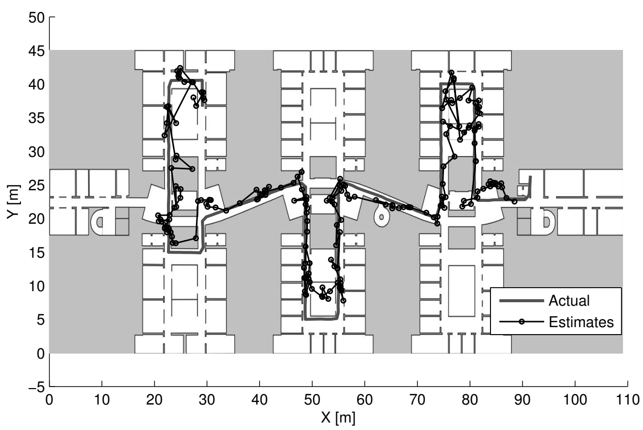

Fig. 6. RBF estimates for Test set 2.

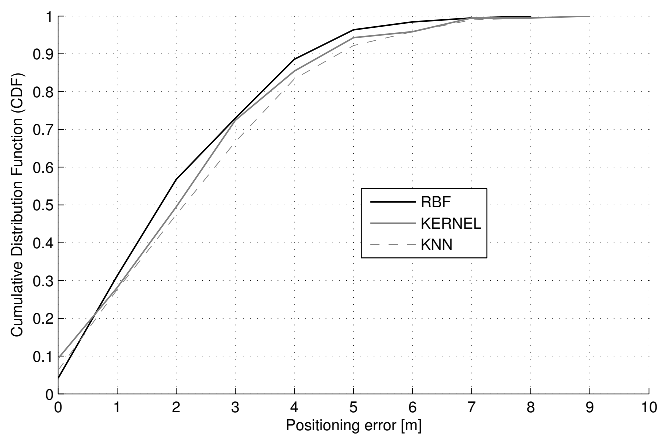

Fig. 8. CDF of the positioning error for Test set 2.

RBF method. First, we employ RSS measurements from all available APs to examine the level of accuracy provided by the RBF method, when the diagonal covariance matrix $\Sigma = diag(\sigma_k^2),\ k = 1, \cdots, 31$ is used in distance calculation. Then, we investigate the effect on the performance in case we use a subset of APs based on the scaling factors calculated in Section IV-B.

The actual locations (shown with dark grey line) and the RBF estimates for each test set are depicted on the floorplan map in Fig. 5 and Fig. 6, respectively. The user follows a path that covers different wings in the floor, and the estimated locations reflect the traveled trajectory.

The RBF method is compared to KERNEL and KNN methods in terms of the positioning error, defined as the Euclidean distance between the actual and estimated location. The Cumulative Distribution Function (CDF) of the positioning error for the first test set is plotted in Fig. 7. The error regarding the 67^{th} percentile is 2.6m, 2.9m and 3.0m for RBF, KERNEL and KNN methods, respectively. When the 95^{th} percentile is considered, the error is 5.1m, 5.7m and 5.5m. Similar performance is achieved for the second test set, as shown in Fig. 8. In this case, the positioning error is increased, but the RBF estimates are still more accurate compared to other methods.

Results pertaining to both test sets are summarized in Table I and indicate that the RBF method improves the positioning accuracy with respect to the mean and median error. Moreover, the RBF method provides the best performance when the maximum positioning error is considered.

TABLE I
POSITIONING ERROR [M].

	Mean	Median	67% CDF	95% CDF	Max
RBF	2.5	2.3	2.9	5.4	7.4
KERNEL	2.6	2.4	3.1	5.3	8.4
KNN	2.7	2.5	3.3	5.7	8.6

The RBF approach outperforms the other methods in our evaluation when RSS values from all available APs are employed. However, our second objective is to achieve a level of accuracy that is comparable to other methods, while reducing the number of APs required during positioning. The CDF of the positioning error pertaining to both test sets is plotted in Fig. 9, assuming that $b = 0.7$ for the RBF method. In this case, the RBF networks utilize RSS measurements from 22 APs contrary to KNN and KERNEL methods that exploit 31 APs.

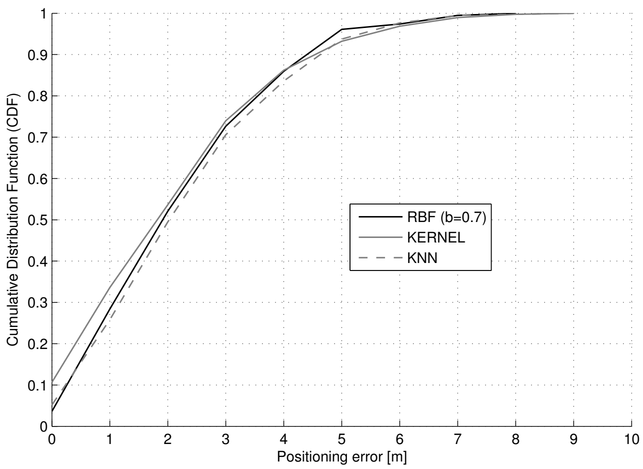

Fig. 9. CDF of the positioning error for Test sets 1 and 2, using AP selection for the RBF method.

The mean error is 2.7m, 2.6m and 2.7m for RBF, KERNEL and KNN methods, respectively. Accuracy results reveal that we can use a fraction of the APs that are spread in the area of interest, without compromising the performance of the RBF method.

The reduction in the number of APs that are used in the RBF networks, results in significant savings with respect to the computational time during positioning. One position estimation using the RBF method takes approximately 0.33msec (mean), for a Matlab implementation on an Intel Pentium 4 processor 3.6GHz with 1GB RAM. We assume that the RBF network weights are calculated offline, all 31 APs are used for positioning, and the execution times are averaged over 100 runs using the data from both test sets. If RSS measurements from 22 APs are used, then the mean calculation time per location estimate is decreased by 24% (0.25msec). We also highlight that in large public places the number of detected APs can be much higher than 31. Therefore, using a small subset of the available APs can indeed be beneficial to minimize the computational complexity during positioning and extend the battery life, especially when low power mobile devices, such as PDAs, are considered.

V. Conclusion

A RBF-based positioning method that exploits WLAN RSS fingerprints is presented. The proposed method uses the RSS covariance matrix in distance calculation and is very efficient, because the weights and scaling parameters of the RBF network are calculated once during training and are used thereafter to estimate the unknown user location. Moreover, computational complexity and thus estimation time can be reduced by using the scaling parameters to identify which APs should be ignored during positioning.

Within WLAN, the variance of RSS is very high and at the same time different subsets of APs may be more appropriate for positioning, depending on the region that the user resides. As a next step, we plan to consider an adaptive approach in order to further improve the performance of the RBF method. In this approach, reference points that are spatially related to the user location are selected dynamically, and the covariance matrix is re-estimated in real-time. Then, an AP selection methodology can be applied. In this fashion, we may adjust the size of RBF networks and re-calculate the weights on-line by exploiting only relevant reference data, instead of calculating them off-line based on all available reference fingerprints.

Acknowledgment

This work is partly supported by the Cyprus Research Promotion Foundation under contract $\mathrm{EN I\Sigma X}/0506/59$.

References

[1] Y. Gu, A. Lo, and I. Niemegeers, "A survey of indoor positioning systems for wireless personal networks," *IEEE Communications Surveys & Tutorials*, vol. 11, no. 1, pp. 13–32, 2009.

[2] M. Kjaergaard, "A taxonomy for radio location fingerprinting," pp. 139–156, 2007.

[3] P. Bahl and V. Padmanabhan, "RADAR: an in-building RF-based user location and tracking system," in *Proceedings IEEE INFOCOM*, vol. 2, 2000, pp. 775–784.

[4] T. Roos, P. Myllymaki, H. Tirri, P. Misikangas, and J. Sievanen, "A probabilistic approach to WLAN user location estimation," *International Journal of Wireless Information Networks*, vol. 9, no. 3, pp. 155–164, Jul. 2002.

[5] M. Brunato and R. Battiti, "Statistical learning theory for location fingerprinting in wireless LANs," *Computer Networks*, vol. 47, no. 6, pp. 825–845, Apr. 2005.

[6] M. Borenovic, A. Neskovic, D. Budimir, and L. Zezelj, "Utilizing artificial neural networks for wlan positioning," in *19th IEEE International Symposium on Personal, Indoor and Mobile Radio Communications (PIMRC)*, 2008, pp. 1–5.

[7] A. Varshavsky, A. LaMarca, J. Hightower, and E. de Lara, "The skyloc floor localization system," in *Fifth Annual IEEE International Conference on Pervasive Computing and Communications (PerCom)*, 2007, pp. 125–134.

[8] K. Kaemarungsi and P. Krishnamurthy, "Properties of indoor received signal strength for WLAN location fingerprinting," in *The First Annual International Conference on Mobile and Ubiquitous Systems: Networking and Services (MOBIQUITOUS)*, 2004, pp. 14–23.

[9] K. Kaemarungsi, "Distribution of WLAN received signal strength indication for indoor location determination," in *1st International Symposium on Wireless Pervasive Computing*, 2006, p. 6.

[10] Y. Chen, Q. Yang, J. Yin, and X. Chai, "Power-efficient access-point selection for indoor location estimation," *IEEE Transactions on Knowledge and Data Engineering*, vol. 18, no. 7, pp. 877–888, 2006.

[11] A. Kushki, K. N. Plataniotis, and A. N. Venetsanopoulos, "Kernel-based positioning in wireless local area networks," *IEEE Transactions on Mobile Computing*, vol. 6, no. 6, pp. 689–705, 2007.

[12] 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.

[13] S. Haykin, *Neural Networks: A Comprehensive Foundation*. Prentice Hall PTR Upper Saddle River, NJ, USA, 1998.

[14] C. Laoudias, P. Kemppi, and C. Panayiotou, "Localization using radial basis function networks and signal strength fingerprints in WLAN," in *IEEE Globecom 2009 Wireless Communications Symposium (to appear)*, Honolulu, HI, USA.