LOCATION FINGERPRINTING IN A DECORRELATED SPACE

Shih-Hau Fang[2], *Member, IEEE,* Tsung-Nan Lin[1,2], *Senior Member, IEEE,* and Pochiang Lin[2], *Member, IEEE,*
[1]Department of Electrical Engineering
[1]Graduate Institute of Communication Engineering
National Taiwan University, Taipei, Taiwan.

***Abstract*—We present a novel approach to the problem of the indoor localization in wireless environments. The main contribution of this paper is four folds: (a) We show that, by projecting the measured signal into a decorrelated signal space, the positioning accuracy is improved since the cross correlation between each AP is reduced. (b) We demonstrate that this novel approach achieves a more efficient information compaction and provides a better scheme to reduce online computation. The drawback of AP selection techniques is overcome since we reduce the dimensionality by combing features. Each component in the decorrelated space is the linear combination of all APs. Therefore a more efficient mechanism is provided to utilize information of all APs while reducing the computational complexity. (c) Experimental results show that the size of training samples can be greatly reduced in the decorrelated space. That is, fewer human efforts are required for developing the system. (d) We carry out comparisons between RSS and three classical decorrelated spaces including Discrete Cosine Transform (DCT), Principal Component Analysis (PCA), and Independent Component Analysis (ICA) in this paper. Two AP selection criteria proposed in literature, MaxMean and InfoGain are also compared. Testing on a realistic WLAN environment, we find that PCA achieves the best performance on the location fingerprinting task.**

***Index Terms*—WLAN, location fingerprinting, decorrelated transformation, PCA, compuation.**

I. INTRODUCTION

THE popularity of wireless access infrastructure and mobile devices fulfils people's desire to access the required services ubiquitously. Meanwhile, the provision of the additional value-added services catches more and more interests. Indoor positioning is one of the possibilities. Many domains get benefits from the location information to provide useful applications and services, such as the museum tour guide and content delivery [1], [2], [3], [4].

Because the client devices are usually small, maintained by constrained battery power, a challenging issue is how to reduce the online computation of positioning system design while achieving a high accuracy at the same time [5], [6], [7]. As the mobile software continues to grow up in complexity and power demand increases, it is critical to reduce the computational burden in the client side. Chen et.al. [8] first selects the most discriminative access points (APs) for minimizing the used AP numbers in the positioning algorithm. This approach selects an appropriate subset of the existing features to the problem of computational complexity. Reducing the number of APs is equivalent to the dimension reduction in a signal space, which reduces the number of calculations required on the mobile device. However, such AP selection technique suffers from a critical disadvantage: it discards all the information from unselected APs, so that decreases the accuracy of estimation.

The question is: is it possible to reduce the online computation while keeping the whole AP's information? This motivates us to explore the possibility to perform the location fingerprinting in a transformed signal space in order to achieve the information reorganization and dimension reduction. It has been proven in several applications that the same algorithm may obtain better results in a decorrelated space. For instance, JPEG compression [9] and color demosaicking [10] are operated in DCT and spectral color difference space respectively. In face recognition, PCA has been a widely used technique [11]. Our preliminary study has showed its efficiency in indoor localization [12]. In speech analysis, ICA is utilized for separating mixed audio signals into independent sources [13].

The first work utilizes the transformation technique for localization is presented in [14], [15]. Kernel canonical correlation analysis (KCCA) is used to maximize the correlation between the physical location and signal space, thus a more accurate mapping function can be constructed. In contrast to that approach, our work aims at minimizing the correlation between each component in the signal space.

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Our location system is deployed in a 802.11 WLAN environment, which is characterized by a number of APs with CSMA/CA protocol. The WLAN-enabled device senses RF signals over the specified frequency band in the physical layer, and then decodes the address of APs in MAC layer such that all detectable APs are indexed [16], [17]. The receiver will first attempt to decode the PHY header when the received power is greater than the physical carrier sense threshold. If the PHY header can not be decoded, the receiver will regard the medium as busy until the power level falls below the threshold. If the PHY header and MAC payload can be decoded, the receiver will operate in accordance to the 802.11 specification. Traditional AP selection technique thus can choose a subset of APs based on a binary-decision vector in the application layer whereas a decorrelated projection is utilized in the proposed approach.

In this paper, we show that, by projecting the measured signals into a decorrelated signal space, the positioning accuracy is improved since the cross correlation between each AP is reduced. Besides, this novel approach achieves a more efficient information compaction and provides a better scheme to reduce the online computational complexity. The whole AP's information can be utilized in our approach since each component in the decorrelated space is the linear combination of all APs with different weights. Moreover, an additional advantage of our proposed technique is that fewer training samples are required to build the localization system. That is, the huge amount of labor work for data collection can be minimized. Chai [18] proposes a learning-based approach to reducing the calibration effort.

We carry out comparisons with three classical decorrelated spaces including *Discrete Cosine Transform* (DCT) [9], [19], *Principal Component Analysis* (PCA) [11], [20] and *Independent component Analysis* (ICA) [13], [21] in this paper. Two AP selection criteria proposed in literature [22], [8], *MaxMean* and *InfoGain* are compared respectively. The experimental results show that mapping to a decorrelated space achieves better performance, in which PCA performs the best.

The rest of the paper is structured as follows. Section II introduces a fingerprinting algorithm of Maximum Likelihood (ML) and Section III describes ML incorporated with the corresponding decorrelated transformation respectively. In section IV, we introduce the experiment environment and tools. Section V presents the experimental results and analysis. The conclusion is given in Section VI.

II. Maximum likelihood based system

Several statistical learning theory have been applied to the fingerprinting technique such as Weighted K-nearest-neighbor (WKNN) [23], [24], Multi-Layer Perceptron (MLP) [25], [26], Neural Network [11], [27] and Support Vector Machines (SVMs) [28], [29]. In this paper, we adopt maximum likelihood (ML) [22], [25], [30], [31], as the baseline positioning system. ML algorithm treats RSS values as random variables, which are statistically dependent on the location. Each reference location is modeled as a Gaussian distribution to make the likelihood estimation practicable. The estimated location can be calculated as the average of all reference locations by adopting their normalized likelihood as weights.

$$\widehat{\mathbf{w}} = \sum_{r=1}^{R} \mathbf{w_r} \cdot \widehat{P}_r \tag{1}$$

where $\mathbf{w_r}$ represents the coordinate of the r-th reference location, and R is the number of reference locations. $\hat{P}_r$ is a normalized likelihood w.r.t summation over r.

Let the measured RSS vector during online stage is a vector, $\mathbf{O} = [o_1, o_2, ...o_D]^T \in \Re^{D*1}$, where D is the total AP numbers and the superscript "T" means the transpose. Since each location is modeled as a Gaussian distribution, the statistic parameters, including a mean vector $\mu_\mathbf{r}$ and a covariance matrix $\mathbf{\Sigma_r}$, are calculated by typical maximum likelihood estimator [20] and stored for each $\mathbf{w_r}$ during the offline stage, where $\mu_\mathbf{r} = [u_{r1}, u_{r2}, ...u_{rD}]^T \in \Re^{D*1}$ and $\mathbf{\Sigma_r} = \{\Sigma_r(i,j)\} \in \Re^{D*D}$.

Under the assumption of the uncorrelation between each AP, the likelihood $\mathbf{P}(\mathbf{O}|\mathbf{w_r})$ can be calculated as

$$\mathbf{P}(\mathbf{O}|\mathbf{w_r}) = \prod_{d=1}^{D} \frac{1}{\sqrt{2\pi\Sigma_r(d,d)}} \cdot exp\left\{\frac{-(o_d - u_{rd})^2}{2\Sigma_r(d,d)}\right\} \tag{2}$$

III. Decorrelated Transformation

Traditional approach builds the model and estimates location in RSS space whereas our approach is constructed in a decorrelated signal space. Define a transformation matrix, $\mathbf{A} = \{a_{ld}\} \in \Re^{L*D}, L = 1, 2, ...D$, where L represents the retained basis number. The basis for new signal space is each row vector of the transformation matrix $\mathbf{A}$ and the transformed output value can be obtained by projection to each basis. After the corresponding transformation, only L dimensions are utilized by the ML algorithm. In that case, Eq.2 is modified as

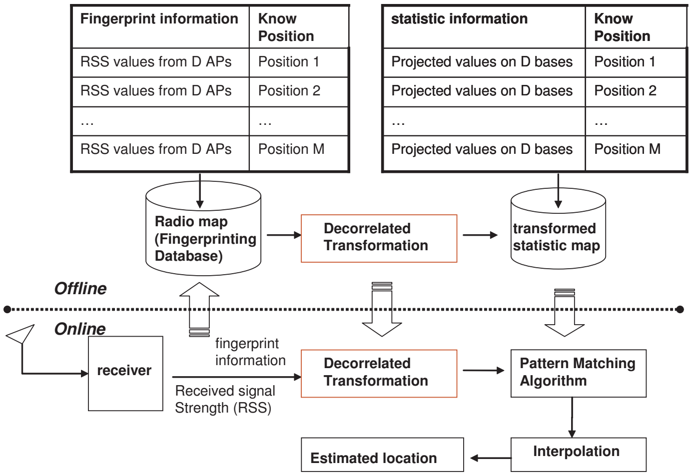

Fig. 1. The architecture of the proposed transform based indoor localization system.

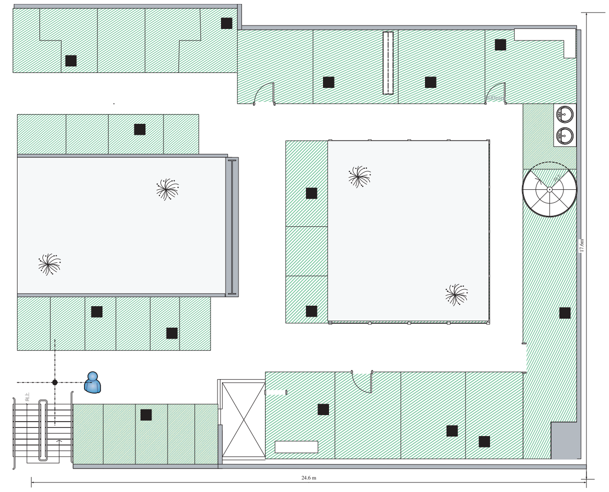

Fig. 2. Part of the fifth floor plane of NTU EE, where we perform the experiment. The black dots show the locations of the APs.

$$\mathbf{P}(\mathbf{O}|\mathbf{w_r}) = \prod_{l=1}^{L} \frac{1}{\sqrt{2\pi\widetilde{\Sigma}_r(l,l)}} \cdot exp\left\{\frac{-(\widetilde{o}_d - \widetilde{u}_{rd})^2}{2\widetilde{\Sigma}_r(l,l)}\right\} \tag{3}$$

where $\widetilde{\mathbf{O}}$, $\widetilde{\mathbf{u}}_\mathbf{r}$ and $\widetilde{\mathbf{\Sigma}}_\mathbf{r}$ respectively represent the transformed observation, mean vector and covariance matrix for the r-th reference location. The l-th component of that can be formulated as follows:

$$\widetilde{o}_l = \sum_{d=1}^{D} a_{ld} \cdot o_d \tag{4}$$

$$\widetilde{u}_{rl} = \sum_{d=1}^{D} a_{ld} \cdot u_{rd} \tag{5}$$

$$\widetilde{\Sigma}_r(l,l) = \sum_{i=1}^{D}\sum_{j=1}^{D} \Sigma_r(i,j) \cdot a_{li} \cdot a_{lj} \tag{6}$$

Once the transformation matrix is available, the modified ML algorithm can be applied. The parameters of Eq.3 could be calculated based on the projected values by means of Eq.5 and Eq.6 during the offline stage. The proposed system architecture is shown in Fig. 1

Now the problem is how to determine a_{ld}. Several techniques have been proposed to find a set of transformation coefficients in order to achieve information reorganization and dimension reduction. For instance, the coefficients of A can be used as a typical Discrete Cosine Transform (DCT), which is a popular approach for color image compression. In DCT, $a_{ld} = cos[\frac{\pi}{D}(d-\frac{1}{2})(l-1)]$, each basis is a cosine wave uncorrelated to each other.

Other approaches design the transformation based on the measured data such as Principal Component Analysis (PCA) and Independent Component Analysis (ICA). In PCA, a_{ld} can be determined by the eigenvector of $\mathbf{\Sigma_\Gamma}$, which is a global covariance matrix of the measured data.

$$\mathbf{\Sigma_\Gamma} \cdot \mathbf{V_i} = \lambda_\mathbf{i} \cdot \mathbf{V_i} \tag{7}$$

where $\mathbf{V_i}$ is the i-th eigenvector of the covariance matrix $\mathbf{\Sigma_\Gamma}$ and a_{ld} is in fact the components of $\mathbf{V_i}$. The method has been shown to be the optimal linear transformation for keeping the subspace that has the largest variance [11]. Compared to DCT transformation, PCA not only reduces the cross correlation between each AP, but also reorganizes the information quantity accordingly. The eigenvectors in Eq.7 rank in descending order of corresponding eigenvalues, $\lambda_1 \geq \lambda_2 \geq ...\lambda_D$, which indicate the importance of each basis in a theoretical view of point.

While the goal in PCA is to maximize the variance in the projection space, the goal of ICA is to find the representation of non-gaussian data as independent as possible. Unlike PCA, there is no closed form to find a_{ld}, but many iterative algorithms based on different search criteria are instead. In this paper, we adopt the FastICA criterion, which is a popular ICA algorithm and the matlab package is publicly available on the web site. For details on FastICA, please refer to [32], [13].

IV. Experimental Setup

In order to evaluate the performance of the proposed technique, we collect realistic RSS data in a WLAN environment in the electronic engineering department area of National Taiwan University as shown in Fig. 2.

The dimension of the corridor is 24.6 x 17.6 meters. Every location in this environment is covered by five IEEE 802.11b APs on average and there are total 15 detectable APs in the environment (D=15). We adopt an IBM ThinkPad T40 laptop as the mobile node, with RedHat 7.1 Linux operating system. A Lucent WaveLan/IEEE Wireless Card with Youssef's driver [33] is installed to gather RSS from nearby APs. For undetected APs, we set a default value,-95, the minimum detectable RSS. We collect 100 samples of signal strength at 86 (R=86) locations separated by 1 meter. Then we adopt the same procedure [8] of partitioning the data set into 2 independent groups, 10 samples for testing and 90 samples for training. We adopt the distance error as the performance metric, which is the Euclidean distance between the estimated location and the true coordinate. The mean and variance of distance error are calculated w.r.t all test results to evaluate the performance versus the number of APs.

For the validity of experimental results, we run the experiments based on an alternative positioning algorithm, Weighted K-Nearest-Neighbor (WKNN) [23], to evaluate the performance of the decorrelated projection techniques. The target environment is modeled as the centroids in WKNN instead of the probability distributions in ML. WKNN calculates Euclidean distances between the measured RSS and all the centroids in the model. Then the location is estimated by linearly combining the k nearest centroids with the weight of corresponding inverse distances. The constant k is set 6 in our experiments.

V. Experimental results

The first experiment evaluates its performance versus different model dimensions L in Eq.3. Instead of AP number in the traditional approach, the basis number in the projected signal space determines the model dimension in our approach. Three decorrelated spaces are compared here: DCT, PCA and ICA as mentioned in section III. Additionally, 2 AP selection criteria: MaxMean [22] and InfoGain [8] are also compared in the decorrelated space. MaxMean selects APs based on the average RSS, where the strongest L APs are selected to estimate client location. The Information Gain-based criteria [8] ranks APs in descending order of their InfoGain values which are calculated as follows: $InfoGain(AP_d) = H(w) - H(w|AP_d)$ where $H(w)$ is the entropy of the location when AP_d's value is unknown, and $H(w|AP_d)$ computes the conditional entropy of the location given AP_d's value. InfoGain calculates the discriminative ability instead of signal strength for each AP and the top L are considered the best.

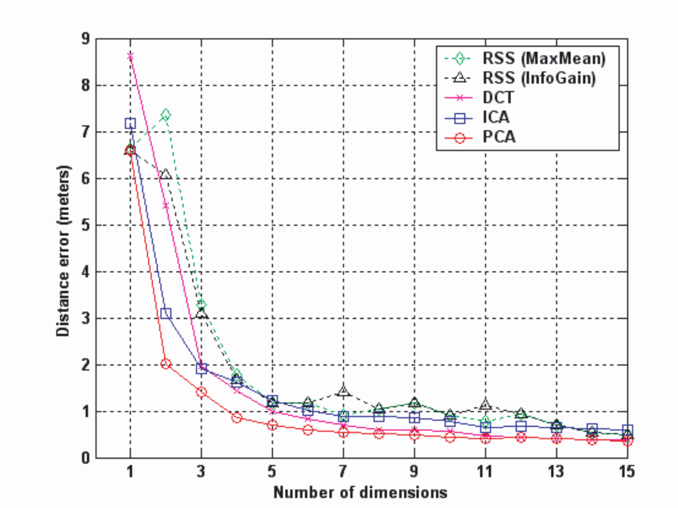

Fig. 3. Mean of error versus number of APs (dimension in the decorrelated space)

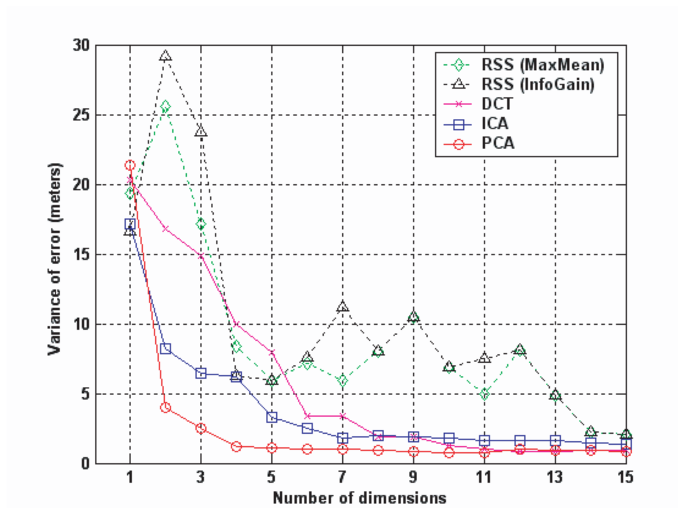

Fig. 4. Variance of error versus number of APs (dimension in the decorrelated space)

A. Positioning Performance

Fig. 3 and Fig. 4 report the mean and variance of error with respect to different signal spaces and dimension L respectively. Both results show that mapping to decorrelated space performs much better than original RSS space, in which the two AP selection approaches are similar. The figures report that the improvement in PCA space is the most significant, especially in the lower dimension. Under 3 APs, the error mean of PCA approach is 1.41 meters while those of MaxMean, InfoGain, DCT, ICA are 3.27, 3.10, 1.97 and 1.91 meters respectively. Compared to DCT and ICA, PCA has a natural property that the basis is ranked based on the corresponding eigenvalue obtained in Eq.7. These eigenvalues quantize the information contribution of each basis in the decorrelated

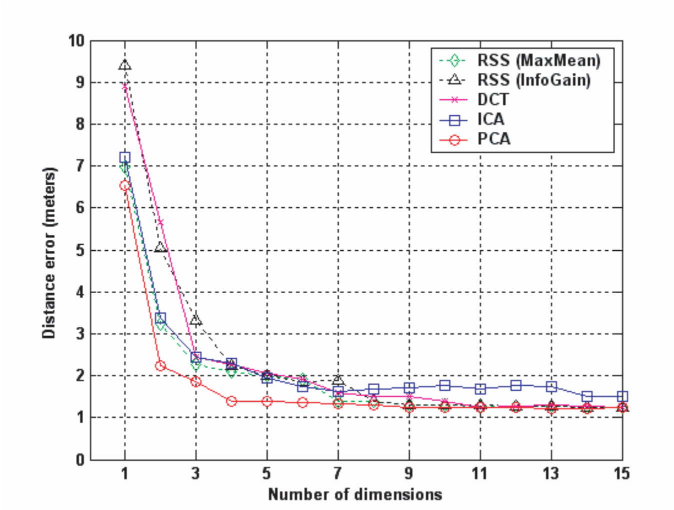

Fig. 5. Mean of error comparison with the decorrelated projection in the $WKNN$ based system) .

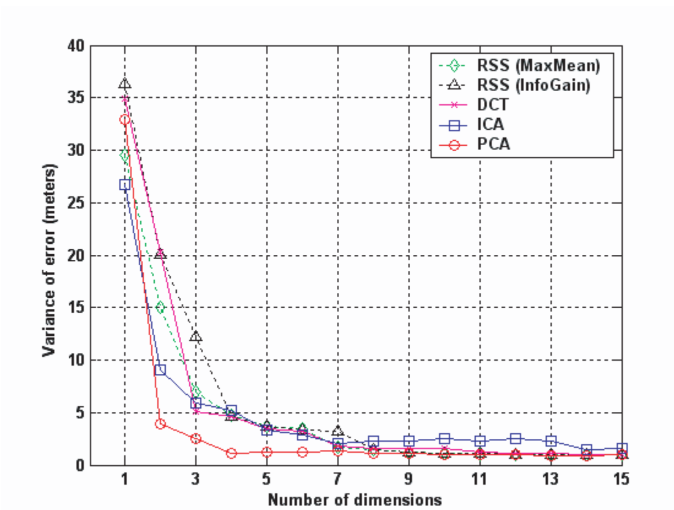

Fig. 6. Variance of error comparison with the decorrelated projection in the $WKNN$ based system) .

space. The bigger the eigenvalue is, the more information the basis has. Therefore PCA based decorrelation algorithm utilizes the maximal information in the positioning system at the same dimension constraint. That's the reason why PCA achieves the best performance among the compared decorrelation techniques. Furthermore, if the whole AP's information is utilized, the performance is still better and presented in the variance of error, which is 0.86 meters in PCA space while those of RSS space is 2.09 meters.

WKNN-based model is also run with the same decorrelated projection techniques in Fig. 5 and Fig. 6 for the validity of experimental results, where the mean and variance of error are reported individually. Fig. 5 and Fig. 6 clearly present a consistent result as compared to

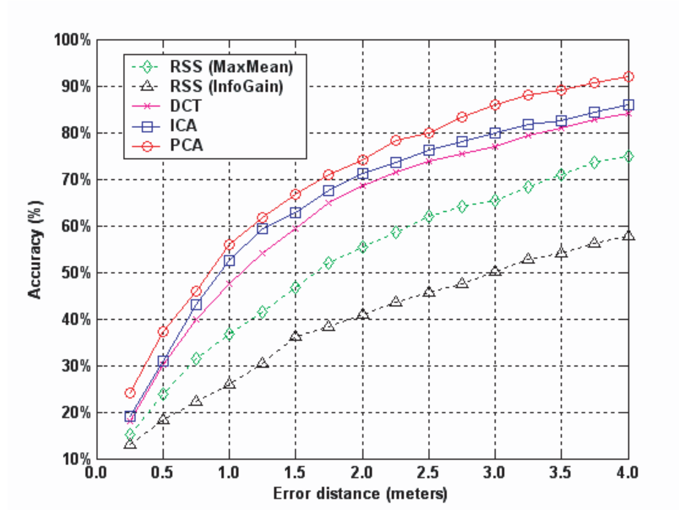

Fig. 7. Accuracy versus error distance under 3 AP numbers condition

Fig. 3 and Fig. 4. That is, positioning in a decorrelated space provides better accuracy under the smaller number of dimensions, and PCA achieves the best performance among the compared techniques. That means the PCA-based decorrelated projection is independent of the back-end positioning algorithm. Besides, the optimum result obtained by WKNN is a little worse than that from ML, as shown in Fig. 3 and Fig. 5. It can be attributed to that the ML-based modeling takes the temporal RSS variation into account while WKNN based modeling only considers the centroids of RSS. When the dimension is reduced to the minimum requirement for positioning (L=3), 23.89% (1.8525 to 1.41 meters) reduction of error mean is obtained by ML technique. In other words, we still recommend the ML-based modeling for smaller dimensions, although the performance difference is minor when full APs are utilized.

If the dimension can be reduced while achieving a high accuracy, an important advantage of saving computation is accomplished substantially. This issue is described in the next subsection.

B. Computational Complexity

In ML based positioning system, the most time consuming and complicated part is the calculation of the exponential function $e(\cdot)$ in Eq.3. It requires 20 operations (10 addition and 10 multiplication) if a 10 order Taylor series is approximated. In that case, the likelihood calculation in Eq.2 requires 25 operations (11 addition and 14 multiplication) for each component and thus once positioning request requires 25*15*86=32250 operations (14190 addition and 18060 multiplication) in our system, where 15 represents the number of APs and 86 represents the number of reference locations. It is intuitive to use as many APs as possible to improve the system accuracy. However, the increased AP numbers increase the online computational complexity and power demand in the client side.

To find the trade-off between the number of used APs and the accuracy can be achieved, AP selection technique is proposed to reduce the online computation. However, the disadvantage is that it may lost important information and thus leads a worse performance as shown in Fig. 3. The mean of error is 0.5m and 3.10m while 15 APs and the most discriminative 3 APs are used respectively. That is, the 80% compuational saving is at the cost of system accuracy.

Our proposed technique overcomes this drawback since we reduce the dimensionality by combining features. Fig. 3 reports that if we want to be below a 1.5m distance error, the AP selection technique requires at least 5 APs whereas PCA space needs only 3 bases. Therefore our approach has the advantage that using the fewest operations to achieve the same accuracy. It should be emphasized that the additional computation incurred by our approach is minor since the linear combination is simple to compute. The extra computation is the decorrelated transformation for the online measured RSS in Eq.4, which requires 30 operations (15 addition and 15 multiplication) for each decorrelated projection.

Fig. 7 reports the accuracy between different spaces while 80% operations are saved (L=3). To be more specific, AP selection technique requires 25*3*86=6450 operations (2838 addition and 3612 multiplication) while our approach requires 6450+30*3=6540 operations (2883 addition and 3657 multiplication) under this computation saving condition. As can be seen, at an error distance of 3.0 meters, the accuracy increased from 65.46% to 85.81% in PCA space. At the same time, the online computation complexity is still reduced and leads power efficient in the client side.

From an implementation perspective, the calculation of the exponential function $e(\cdot)$ can be computed with a pre-stored table in the memory to speed the positioning. In such a case, the power consumption of the positioning software can be further reduced.

C. Reduction in human effort

The limitation of all location fingerprinting systems is that it requires site survey to collect RSS data in order to build the radio map in the initialization and training phase. Data collection can account for large part of the cost of developing a location fingerprinting system. In this experiment, we use only the random subset of the training samples at each location. The number of training samples at each location varies from 10 to 90, and we plot the accuracy at error distance 3.0m under 3 APs case. The results in Fig. 8 clearly show that the size of training samples can be greatly reduced in the decorrelated space. By using only 10 samples at each location, decorrelated space can even outperform RSS space that use full training samples. Therefore the cost of collecting data is accordingly reduced since the time required for site survey is decreased. The reason is the same as mentioned in Section V-A. That is, the PCA-based location technique utilizes information more efficiently in the projected space. In this way, the extracted features have provided sufficient information for the model learning, and thus less training samples are required in the location system. Again, PCA achieves the best performance, where the accuracy is 84.53% while the DCT and ICA are 76.05% and 78.95% when 30 training samples are utilized. It is also because of the rule provided by PCA, where the basis is ranked from an information-theoretical viewpoint.

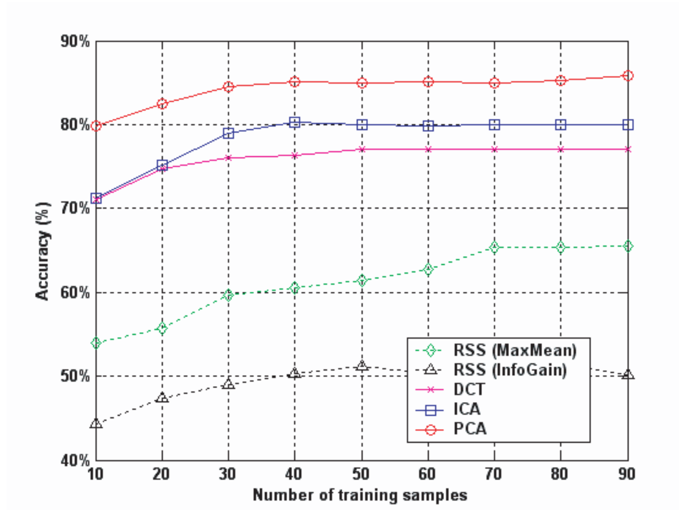

Fig. 8. Accuracy within 3.0 meters versus number of training samples

VI. Conclusion

This paper present a novel approach to the problem of the indoor localization in wireless environments. The work focus on using decorrelated transformation to improve positioning accuracy and reduce online computation at the same time. Our approach provides a more efficient mechanism to utilize information of all APs while reducing computational complexity. Moreover, fewer training samples are required to build the localization system. That is, the labor work for data collection can be reduced as well. We carry out comparisons between RSS and three classical decorrelated spaces including

Discrete Cosine Transform (DCT), Principal Component Analysis (PCA), and Independent Component Analysis (ICA) in this paper. Two AP selection criteria proposed in literature, MaxMean and InfoGain are also compared. Testing on a realistic WLAN environment, we find that PCA outperforms DCT and ICA on the location fingerprinting task.

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Shih-Hau Fang (M'07) received his B.S. degree from the Department of Communication Engineering in National Chiao Tung University, Taiwan, in 1999 and the M.S. degree from the Graduate Institute of Communication Engineering of National Taiwan University, Taiwan, in 2001. From 2001 to 2007, he was a software architect at Internet Services Division at ChungHwa Telecom, Taipei, Taiwan. He is currently pursuing the Ph.D. degree at the Graduate Institute of Communication Engineering of National Taiwan University. His current research interests include signal processing, pattern recognition, and cognitive radio networks.

Tsung-Nan Lin (SM'03) received the B.S. degree in electrical engineering from National Taiwan University, Taipei, Taiwan, in 1989, and the M.A. and Ph.D. degrees in electrical engineering from Princeton University, Princeton, NJ, in 1993 and 1996, respectively. He was a Teaching Assistant with the Department of Electrical Engineering, Princeton University, from 1991 to 1992. From 1992 to 1996, he was a Research Assistant with NEC Research Institute. He has been with EPSON R&D Incorporated and EMC. Since February 2002, he has been with the Department of Electrical Engineering and the Graduate Institute of Communication Engineering, National Taiwan University. Dr. Lin is a Member of Phi Tau Phi scholastic honor society.

Po-Chiang Lin received the BS degree in communication engineering from National Chiao Tung University, Taiwan, in 1996, and the MS degree in communication engineering from National Taiwan University, Taiwan, in 2005. He is currently working toward the Ph.D. degree at the graduate institute of communication engineering, National Taiwan University, Taiwan. His current research interests are in wireless multimedia networking including handoff design, performance optimization, and QoS issues.