A Novel Algorithm for Multipath Fingerprinting in Indoor WLAN Environments

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***Abstract*—Positioning in indoor wireless environments is growing rapidly in importance and gains commercial interests in context-awareness applications. The essential challenge in localization is the severe fluctuation of receive signal strength (RSS) for the mobile client even at a fixed location. This work explores the major noisy source resulted from the multipath in an indoor wireless environment and presents an advanced positioning architecture to reduce the disturbance. Our contribution is to propose a novel approach to extract the robust signal feature from measured RSS which is provided by IEEE 802.11 MAC software so that the multipath effect can be mitigated efficiently. The dynamic multipath behavior, which can be modeled by a convolution operation in the time domain, can be transformed into an additive random variable in the logarithmic spectrum domain. That is, the convolution process becomes a linear and separable operation in the logarithmic spectrum domain and then can be effectively removed. To our best knowledge, this work is the first to enhance the robustness to a multipath fading condition, which is common in the environments of an indoor wireless LAN (WLAN) location fingerprinting system. Our approach is conceptually simple and easy to be implemented for practical applications. Neither a new hardware nor an extra sensor network installation is required. Both analytical simulation and experiments in a real WLAN environment demonstrate the usefulness of our approach to significant performance improvements. The numerical results show that the mean and the standard deviation of estimated error are reduced by 42% and 29%, respectively, as compared to the traditional maximum likelihood based approach. Moreover, the experimental results also show that fewer training samples are required to build the positioning models. This result can be attributed to that the location related information is effectively extracted by our algorithm.**

***Index Terms*—Location fingerprinting, IEEE 802.11, Multipath, WLAN, location estimation.**

I. INTRODUCTION

THE increasing demand of context-awareness computing has motivated the development of wireless-LAN (WLAN) based indoor positioning systems. Positioning in wireless environments is highly desirable for many location-based services such as visitor guidance, fraud detection, and so on [1], [2], [3]. Since the deployments of WLAN infrastructures are widely adopted and the received signal strength (RSS) can be easily obtained from IEEE 802.11 MAC software, RSS-based indoor localization system is growing rapidly in importance and commercial interests [4], [5], [6]. Currently, the most viable solution for RSS-based positioning is the fingerprinting architecture [4], [6], [7]. Location fingerprinting usually works in two stages: off-line and online stage. During the offline stage, RSSs from different Access Points (APs) are collected at various sampling locations to build the database called *radio map* for the target environment. During the online stage, the location can be computed by comparing the measured RSS with RSS values stored in the database.

The propagation of signal in indoor environment is extremely complex and the intensity of a radio signal at a given location usually varies with time for a number of reasons [8]. In general, RSS is composed of both a line-of-sight (LOS) component and numerous delayed signals with different attenuations. The channel variation as a function of position due to the scatter-rich nature of indoor environments can be significant [9]. All such signals combine to an alias version, which may be enlarged or diminished depending on the relative phases of the delayed reflections. Moreover, the observable reflection is affected not only by propagation environment but also by the signal bandwidth for a band-limited system [10], [11]. It is possible to observe more multipath components when a larger bandwidth gives better time resolution. Therefore, the most challenging issue for WLAN location fingerprinting is the unstable RSS value due to the multipath effect caused by reflection, diffraction and diffusion on the indoor scattering-rich walls. The phenomenon influences the radio signal propagation and causes a time-varying RSS even at a fixed location [12], [13], [9], [14].

The performance of localization is often degraded due to the RSS severe variation resulted from multipath. Such a problem is inevitably encountered when the positioning system is deployed in a real indoor environment where the multipath effect is significant. Traditionally, the RSS variation is generalized to an additive noise and, consequently, an average (median) filter is applied to reduce the noisy effect [15], [16], [17]. In this paper, we take a step further to investigate the received signal variation from both communication interference and numerous delayed aliases of the line-of-sight (LOS) component resulted from the phenomenon of the multipath in scatter-rich indoor environments. Based on the analysis, a novel positioning architecture with a noise and fading correction technique is proposed to enhance the robustness of the performance.

The dynamic behavior of the multipath from the environmental change incurs a characteristic mismatch between the off-line recorded data and the online measurement in a location fingerprinting system. The previous restored radio map may no longer reflect the statistical characteristic of the

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current RSS and thus the system performance degrades.

Recently, some approaches utilize a sensor network to assist the location system for adapting the environmental dynamics [18], [19], [20], [21]. A collaborative positioning system with the context-awareness radio map is to measure the unstable factors such as the door opening/closing and humidity detected by the sensors. The multipath problem is claimed to be minimized since the database is temporally updated depending on the current environment. However, these techniques face some difficulties. First, they require a full-scale site survey on numerous factors and need to continuously monitor the changing in the environments. Second, some dynamic information is not easily available such as moving obstacles and the presence of people. Third, the online database adaptation consumes extremely high computation of time. Finally, these approaches rely on additional sensory hardware installations and thus are not cost and time efficient.

The main contribution of this paper is to present a novel mechanism to minimize the multipath disturbance on the accuracy performance of a location-fingerprinting-based system. Our basic idea is to extract the multipath resistant information from the temporal trajectory of the measured RSS in an indoor IEEE 802.11 WLAN environment. The multipath effect can be treated as a convolutional filter operation of the propagated signal based on the observation that the online measured RSS is the superposition of the LOS decayed aliases with different propagation gains. Through analyses, we discover that the dynamic multipath effect can be transformed into an additive random noise variable in the logarithmic spectrum domain. Therefore, the noisy disturbance from the multipath can be efficiently mitigated in the logarithmic spectrum domain and the robust information can be extracted from the measured RSS. We clarify that the proposed approach is operated on the RSS measurements whether receiving LOS or not. This approach is conceptually simple and easy to be implemented with current IEEE 802.11 WLAN environments for practical applications. Neither a new hardware nor an extra sensor network installation is required. To our knowledge, our approach is the first to exploit the multipath effect on the received signal strength provided by IEEE 802.11b and IEEE 802.11g MAC layer software in the context of indoor location fingerprinting.

Experimental results conducted by collecting realistic RSS data in an indoor WLAN environment show that the extracted feature can construct more robust statistical models. The proposed mechanism demonstrate higher positioning accuracy compared to the traditional maximum likelihood approach (ML) [4] and Horus systems [17]. Experimental results show that the mean of error is reduced by 42%, and the standard deviation of error is reduced by 29% on the average. Furthermore, the results show the size of training samples can be greatly reduced in the proposed architecture in order to achieve the similar accuracy of [4], [17]. That is, the cost of collecting data in the offline stage is thus reduced.

The rest of the paper is structured as follows. Section II illustrates the basic principle for the location fingerprinting system and the RSS variation. Section III describes the mathematical analysis for RSS corrupted by multipath in details. We introduce our proposed indoor positioning system in section IV. In section V, we describe the experiment environment. Section VI presents the experimental results and analyses. Finally, the conclusion is given in Section VII.

II. Related Work

Indoor positioning systems in wireless networks could provide ubiquitous and location-aware computing in the indoor environment where the global positioning system (GPS) does not work well [1], [3], [22], [23].

A. *Previous Work on Indoor Localization*

In the past years, many developed indoor positioning systems extract the location-dependent parameters such as time of arrival, time difference of arrival and angle of arrival [2], [3], [14] from the received radio signal transmitted by the mobile station. Such a measurement needs to be estimated accurately and it requires LOS between the transmitter and the receiver. Furthermore, it requires specialized and expensive hardware integrated into the existing equipments. Due to the high implementation cost, the indoor positioning system based on the use of RSS thus gets more and more interests. Since the deployments of WLAN infrastructures are widespread and the RSS sensor function is available in every 802.11 interface, the RSS-based positioning system is obviously a more cost-effective solution.

Presently, the most viable solution for RSS-based positioning is the fingerprinting architecture [24]. The basic design can be divided into two stages: offline and online stages. During the offline stage, a site survey performed in the target environment is required. RSSs are collected at sampling locations to build the database called the radio map as a function of the user's physical coordinates. During the online stage, the positioning techniques measure RSS in real time by the receiver and calculate the estimated location coordinates based on the previously recorded database of RSSs stored in the radio map [25], [26], [27].

Various machine learning techniques can be applied to the location estimation problem [28]. Probabilistic method [6], [29], [30], k-nearest-neighbor [25], neural networks [31], [32], and support vector machines [33], [34] are popular positioning techniques based on the location fingerprinting. Most recently developed indoor localization systems are based on the probabilistic method [7] which utilizes the statistical parameters extracted from the radio map to estimate the location. Kernel canonical correlation analysis [35], [36] is used to construct a more accurate mapping function between RSS and radio map. Chai [37] proposes a learning-based approach to reducing the calibration effort. A decorrelated transformation can be found in [38], [39].

Recently, some approaches utilize sensor network to assist location system for adapting the radio dynamics [18], [19], [21]. The unstable factors such as open/close doors and humidity are detected by the sensors and thus a collaborative positioning system is provided by such context-awareness radio map [40], [41]. Yin [20] proposes a learning approach where the radio map is temporally updated depending on the current environment. In Moraes's work [42], a dynamic RSS mapping architecture is investigated. The dynamic noise problem is in some sense reduced in such mechanisms where the environmental changing is monitored. However, the short-term dynamic multipath is difficultly detected and several difficulties are faced such as a site survey on environmental factors and additional hardware installation in these techniques. More recently, a measured channel impulse response is proposed in [43], [44] for geolocation in mines. Sheng-Po et al. [45] work out a scrambling method which enlarges the RSS comparison space to enhance positioning accuracy.

B. Previous Work on RSS Variation

The fingerprinting-based architecture mentioned above regards localization as a pattern matching problem. Therefore, choosing discriminating and robust features is a key element since it's the first step of the whole matching process and the parameters of the statistical learning algorithm are estimated based on the recorded signals. However, it seems that no other efforts have been reported so far in trying to find a robust feature in application of positioning. To the best of our knowledge, the average (median) filter [31], [17] is the only solution to deal with the RSS variation for indoor localization at present. The rapid RSS fluctuation is generalized to an additive noise and an average filter is consequently applied to reduce the noisy effect [15], [16]. The analysis is obtained from [17]. Let y represent the measured RSS from the m-th access point at a fixed location and x represent the LOS decayed signal in a free space, the relation between RSS and the noise component can be modeled as

$$\begin{aligned} y^m(n) &= x^m(n) + v^m(n) \\ & \quad 1 \leq m \leq M, 0 \leq n \leq N-1 \end{aligned} \tag{1}$$

where m is the index of AP, n is the discrete time index and v is a noise process which is independent from x. The model states that the measured RSS value $y^m(n)$ is an linear combination of the signal intensity $x^m(n)$ and an independent noise $v^m(n)$. In theory, the term $x^m(n)$ should be a constant at a fixed location since the signal degradation depends only on the distance between the transmitter and receiver. The behavior of the radio propagation model between transmitter i and receiver j is given in Eq. 2 [46], [47].

$$PL = \left(\frac{4\pi d_{ij}}{\lambda}\right)^2 \tag{2}$$

where PL is the free-space path loss, λ is the wavelength of the an electromagnetic wave, and d_{ij} is the distance between the sender and receiver. According to Eq. 2, the LOS decayed signal at a fixed location should be a constant since the term d_{ij} is fixed in an ideal LOS case. Therefore the variation of measured RSS is dominated by the additive noise $v^m(n)$, as shown in Eq. 1. To reduce the noisy effect, an average process A is applied to the temporal trajectory of RSS and thus the new feature TA_RSS is generated.

$$\begin{aligned} TA\_RSS^m &= A[y^m(n)] \\ &= \frac{1}{N} \cdot \sum_{n=0}^{N-1} y^m(n) \end{aligned} \tag{3}$$

where A represents an average process with respect to the time index n and N indicates the length of the time sequence. After the operation of the average filter, the variance of TA_RSS^m can be calculated as

$$\begin{aligned} Var[TA\_RSS^m] &= Var(A[y^m(n)]) \\ &= Var(A[x^m(n) + v^m(n)]) \\ &= Var(A[v^m(n)]) \\ &\propto \frac{1}{N} \cdot Var(v^m) \end{aligned} \tag{4}$$

Comparing Eq.1 with Eq.4, the decrease of variance of TA_RSS^m results from the time average (from $Var(v^m)$ to $\frac{1}{N}Var(v^m)$). A more stable feature called TA_RSS can thus be obtained for positioning in such a simple noise model . However, Eq.4 only considers the LOS situations which are less probable in indoor environments. The average in time domain does not cancel out the multipath effect because the multipath can not be separated from an additive noise as Eq.1. Nevertheless, such a procedure is the only solution to deal with the rapid RSS fluctuation in the current localization system.

III. Analysis of Multipath Effect on RSS

Although it is observed that the large variation of RSS is mainly caused by the multipath effect, tackling the problem with the average filter is to simplify the complicated phenomenon as an additive noise behavior. Contrary to traditional approaches, we analyze, in this section, the multipath phenomenon as the superposition of the LOS decayed signal with different transmission gains. In other words, we consider the measured RSS reported by IEEE 802.11b MAC software contains both effects of the convolution filter effect caused by the scatter-rich indoor environments and the communication additive noise. Based on this model, we discover that the dynamic convolution effect can be effectively transformed into an additive random variable in the logarithmic spectrum domain. Then a robust information without multipath disturbance can be efficiently extracted from the measured RSS.

A. Convolution model

The measured RSS is overlapped by multipath components that arrive with short delays, each having its own gain. These different components are combined to generate an alias version, which may be enlarged or diminished depending on the relative phases of the delayed reflections. Besides, the radio bandwidth also affects the number of observed multipath components. In that case, the location-related signal can not be extracted effectively by applying the average filter directly. In this paper, we adopt a discrete channel model to characterize the wireless environment, in which the multipath is viewed as a convolution operation instead of a simple additive noise.

Let $y^m(n)$ represents the measured RSS from the m-th access point at a fixed location, $x^m(n)$ represents the LOS decayed signal in a free space, and $v^m(n)$ represents the communication noise. The time-varying multipath is captured by the attenuation of each reflected path $h^m(n)$, the time delayed LOS signal $x^m(n-l)$, and the number of delayed paths, L. Mathematically, RSS is described in the time domain as:

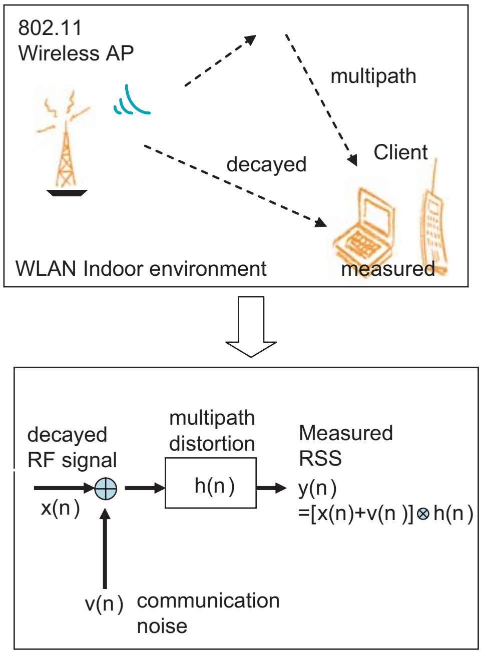

Fig. 1. The convolutional model of the RSS variation due to the multipath effect in a scatter-rich indoor WLAN environment.

$$\begin{aligned} y^m(n) &= \sum_{l=0}^{L-1} h^m(l) \cdot [x^m(n-l) + v^m(n-l)] \\ &= \sum_{l=0}^{L-1} h^m(l) \cdot x^m(n-l) + \sum_{l=0}^{L-1} h^m(l) \cdot v^m(n-l) \\ &= x^m(n) \otimes h^m(n) + v^m(n) \otimes h^m(n) \\ & \quad 1 \le m \le M, 0 \le l \le L-1, 0 \le n \le N-1 \quad (5) \end{aligned}$$

where $h^m(n)$ represents the channel attenuation for each delay arrival signal. The value may be positive or negative based on the relative phase of the different reflections. These signals may add coherently or cancel each other and thus lead to a larger or smaller value of RSS. The symbol $\otimes$ denotes a convolution process. In principle, the multipath effect can be viewed as a convolution noise $h^m(n)$ which models the multipath channel in the wireless environment as shown in Fig. 1.

B. Logarithmic Spectrum Domain

In this subsection, we utilize signal processing techniques to transform the RSS sequence into the logarithmic spectrum domain, and discover that the convolution operation of the multipath can be transformed into an additive random variable. The procedures need to find the autocorrelation function and then apply discrete Fourier Transform (DFT) to transform RSS sequence into the power spectrum domain. The autocorrelation function of the measured RSS is shown in Eq. 6 [48], which provides the correlation measurement between RSS samples at an interval of k.

$$R_y^m(k) = \frac{1}{N-k} \sum_{n=0}^{N-1} y^m(n) \cdot y^m(n+k)$$
$$1 \le m \le M, 0 \le k \le K-1, 0 \le n \le N-1 \quad (6)$$

where k and K are the index and length of the autocorrelation sequence. The term $R_y^m(k)$ represents the autocorrelation sequence with index k for the m-th access point. Substituting Eq. 6 in Eq. 5, it comes out

$$\begin{aligned} R_y^m(k) &= R_x^m(k) \otimes h^m(k) \otimes h^m(-k) \\ & \quad + R_v^m(k) \otimes h^m(k) \otimes h^m(-k) \\ & \quad 1 \le m \le M, 0 \le k \le K-1 \quad (7) \end{aligned}$$

where $R_y^m(k)$, $R_x^m(k)$ and $R_v^m(k)$ are the autocorrelation sequences of the measured RSS, LOS decayed RSS and the communication noise, respectively. As well known, the time autocorrelation sequence and the power spectrum are related to each other through Fourier Transform. For this reason, taking DFT with respect to k on both sides of Eq. 7, we obtain

$$\begin{aligned} S_y^m(f) &= S_x^m(f) \cdot |H^m(f)|^2 + S_v^m(f) \cdot |H^m(f)|^2 \\ &= [S_x^m(f) + S_v^m(f)] \cdot |H^m(f)|^2 \\ &= S_{\tilde{x}}^m(f) \cdot |H^m(f)|^2 \\ & \quad 1 \le m \le M, 0 \le f \le F-1 \quad (8) \end{aligned}$$

where f and F denote the discrete frequency index and total length of the power spectrum. $S_y^m(f)$, $S_x^m(f)$, and $H^m(f)$ are the power spectrums of the measured RSS, LOS decayed signal, and the convolution noise. $S_{\tilde{x}}^m(f)$ represents the power spectrum of the LOS decayed signal corrupted by the communication noise. As shown in Eq. 8, the convolution operation becomes multiplication in the power spectrum domain. Consequently, if we take the logarithm of both sides of Eq. 8, the multiplied variables can be separated as

$$\begin{aligned} logS_y^m(f) &= logS_{\tilde{x}}^m(f) + 2log|H^m(f)| \\ & \quad 1 \le m \le M, 0 \le f \le F-1 \quad (9) \end{aligned}$$

C. Mitigation of Multipath Disturbance

As shown in Eq. 9, we can observe that the convolution noise becomes linearly additive in the logarithmic power spectrum domain. The physical meaning of Eq. 9 implies that the multipath has been transformed into an additive random variable. As the analysis in Eq. 4, the rapid variation caused by the multipath effects can be mitigated efficiently in the logarithmic power spectrum domain. Therefore the average filtering A can be used to extract the robust feature with the minimal disturbance of the multipath since the multipath becomes a linearly additive process in the logarithmic spectrum domain.

Notably, $logS_{\tilde{x}}^m(f)$ still contains the component of the communication noise. Due to the independent assumption, they also can be presented in an additive form as $S_{\tilde{x}}^m(f) = S_x^m(f) + S_v^m(f)$. In an ideal environment where the multipath does not exist, the average operation A applied here is equivalent to the decrease of the communication noise. Moreover, $S_v^m(f)$ can be viewed as a constant upon the additive white Gaussian noise (AWGN) assumption. In that case, the invariable shift does not affect the positioning system. The location correlated signal only contributes to the lower frequency components of $logS_y^m(f)$ whereas the multipath

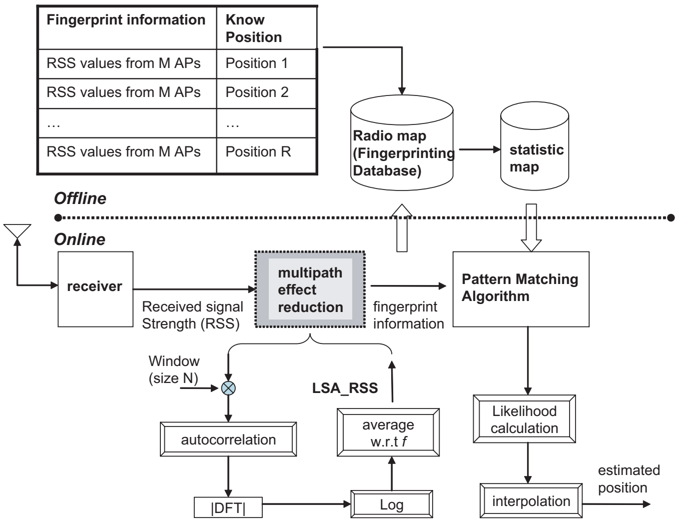

Fig. 2. The architecture of the proposed location fingerprinting system. During the offline stage, the LSA_RSS is previously extracted to generate the database so as to online match the LSA_RSS pattern in a multipath-reduced scenario.

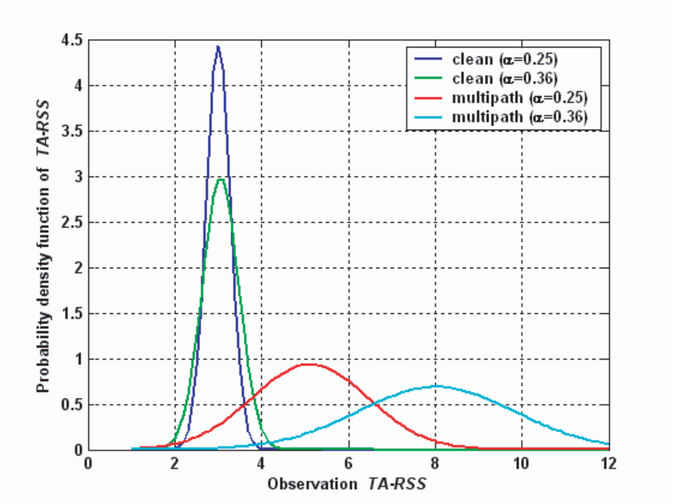

Fig. 3. Gaussian models obtained by TA_RSS under 2 conditions: clean means the clean RSS without the disturbance of multipath, and multipath represent the RSS passing through simulated multipath channels. A larger α indicates the more severe time-varying multipath, where the threshold of β is decreased from 0.7 to 0.6.

effect contributes to all the higher frequency components. Thus, averaging the logarithmic power spectrum with respect to frequency f, we obtain

$$\begin{aligned} LSA\_RSS^m &= A[logS_y^m(f)] \\ &= \frac{1}{F} \cdot \sum_{f=0}^{F-1} logS_y^m(f) \end{aligned} \tag{10}$$

The generated signal named LSA_RSS is used to mitigate the multipath impact to the location fingerprinting. We consider LSA_RSS as the robust signal extracted from the measured RSS because it is less sensitive to the multipath disturbance. In this paper, our location fingerprinting system is developed based on this feature. During the off-line stage, the radio map is constructed by LSA_RSS information. During the online stage, the temporal RSS trajectories are stored and used for calculating LSA_RSS coefficients. Thus the pattern matching algorithms can be applied to estimate locations at the real time. Fig. 2 shows our proposed localization system architecture.

D. Analytical Simulation

An analytical simulation is conducted to observe the effectiveness of the proposed approach in this subsection. We assume only one access point exists in the environment (M=1). The LOS decayed signal x is assumed to be a Gaussian random variable. Each delayed reflection is simulated by a convolution operation in which each attenuation follows different distributions. The random coefficients in $h(n)$ describe the time varying multipath in the indoor environment, where the number of reflected path L is 4 [49]. Furthermore, each path weighting is multiplied by an on-off key $\beta(n)$ which is a binary value controlled by a random sequence. The multipath component is retained if the corresponding β is one; otherwise the component is set zero. This way, the RF signals may propagate to the receiver through different consecutive or nonconsecutive paths with different weightings. The measurement is modeled as $y(n) = x(n) \otimes h(n)$ and the parameters for this simulation are described as follows: $x(n) \sim N(3, \alpha)$, $h(1) \sim U(0, 2\alpha)$, $h(2) \sim U(-\alpha, \alpha)$, $h(3) \sim N(0.2, \alpha)$, $h(4) \sim N(0.1, \alpha)$, where $Y \sim P$ denotes the condition Y has distribution P. 100 samples are generated for the simulation. $N(\mu, \sigma)$ denotes a Gaussian distribution where μ and σ represent the mean and variance, respectively. $U(a, b)$ denotes the uniform distribution where a and b represent the minimum and maximum values. Similar simulation results can be obtained with different sets of distributions. The parameter α and β are used to model the degree of multipath because the observable multipath is affected not only by propagation environment but also by the signal bandwidth for a band-limited system [10], [11]. The initial value of α is 0.25 and the threshold of β is 0.7. A more severe multipath condition is simulated by increasing the value of α to 0.36 and decreasing the threshold of β to 0.6. That is, a more significant RSS fluctuation is generated because the more randomness is presented in both the multipath coefficients and the number of the multipath components.

Fig. 3 reports the distribution obtained by TA_RSS. In Fig. 3, the blue line represents LOS signal. The red line indicates the distribution obtained by passing LOS signal through the simulated multipath. The distribution of the measurement $y(n) = x(n) \otimes h(n)$ is denoted as the multipath($\alpha = 0.25$) in the figure. The distribution of clean($\alpha = 0.36$) and multipath($\alpha = 0.36$) are reported by the green and cyan lines.

Fig. 4 shows the results obtained by the proposed approach. Notably, since LSA_RSS is operated in the logarithmic spectrum domain, the scale is different from Fig. 3. From Fig. 3 and Fig. 4, we can compare the robustness of the proposed approach with respect to the traditional approach under different multipath environments. Obviously, the extracted signal obtained by LSA_RSS is more stable than that by traditional TA_RSS. Fig. 3 shows that the original thin Gaussian becomes a fat distribution. Both mean and variance are enlarged due to the simulated multipath noise. That is,

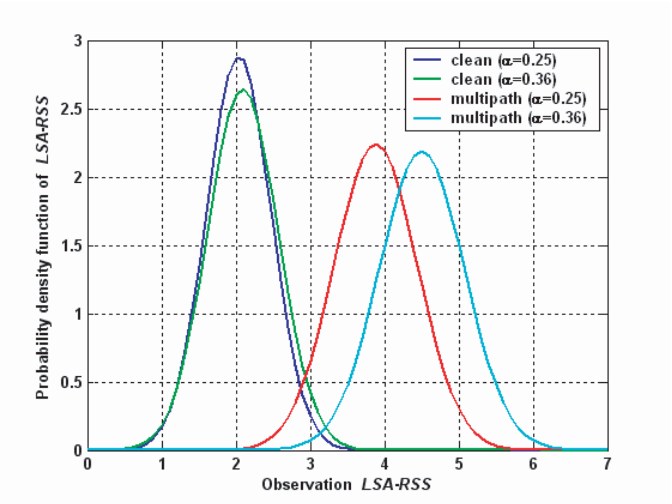

Fig. 4. Gaussian models obtained by LSA_RSS under 2 conditions: clean means the clean RSS without the disturbance of the multipath, and multipath represent that the RSS passing through simulated multipath channels. A larger α indicates the more severe time-varying multipath, where the threshold of β is decreased from 0.7 to 0.6.

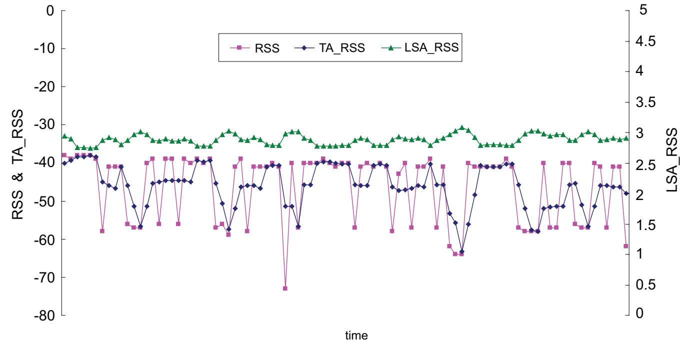

Fig. 5. The sample values of different features at a fixed point in the WLAN test environment. The x axis is the discrete time index of the measurement sequence, the left and right y axis represent the value of the derived TA_RSS and LSA_RSS.

the traditional approach (TA_RSS) can not effectively reduce the noisy variation resulted from multipath, while on the contrary the proposed approach (LSA_RSS) demonstrates its effectiveness. Fig. 4 reports that the extracted signal maintains a similar Gaussian shape even passing through the more severe multipath condition. To provide a more fair comparison, the probabilistic distance measure technique is used here to analyze the degree of distribution changes. We calculate Divergence Distance [50], which is defined as ($J_D(p_1, p_2) = \int_x [p_1(x) - p_2(x)] log[p_1(x)/p_2(x)]dx$), where p_1 and p_2 represent the two compared distributions. If the compared distributions are the Gaussian distributions, Divergence Distance becomes:

$$\begin{aligned} J_D(p_1, p_2) \quad = \quad & \frac{1}{2}(\mu_1 - \mu_2)^T(\Sigma_1^{-1} + \Sigma_2^{-1})(\mu_1 - \mu_2) + \\ & \frac{1}{2} tr[\Sigma_1^{-1}\Sigma_2 + \Sigma_2^{-1}\Sigma_1 - 2I] \end{aligned} \tag{11}$$

where μ_1, μ_2 are the means and Σ_1, Σ_2 are the variances of the compared distributions. The Divergence Distance between clean and multipath(α=0.25) in Fig. 3 is 39.45 whereas it is 14.515 in Fig. 4. That is, the proposed approach shows a better ability to recover LOS signal from the measured data under the corruption of multipath. Moreover, the proposed approach demonstrates satisfactory performance to recover the signal under the condition where the environmental change results in more severe multipath effects. Divergence Distance between multipath(α=0.25) and multipath(α=0.36) in Fig. 3 is 3.8198 whereas it is 1.2084 in Fig. 4. To be more specific, the realistic RSS data in a WLAN environment is collected to observe the property. RSS values at a fixed location are recorded and the values of TA_RSS and LSA_RSS are calculated and shown in Fig. 5. It is clear that the variation of LSA_RSS is significantly smaller than either TA_RSS or RSS, implying that the proposed mechanism can effectively mitigate the disturbance of multipath and extract a robust signal feature in the logarithmic spectrum domain.

IV. The Proposed Fingerprinting Location System

Previous works show that the probabilistic approaches such as maximum likelihood (ML) provide more accurate results than deterministic approaches do in indoor environments [7], [6]. Therefore ML is adopted to be the core of our positioning system and the architecture is described as follows. The 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. In the proposed location system, we extract the robust signal with minimal multipath disturbance to construct the probability distribution between the location and the extracted WLAN signals. The technique works as follows:

During the online positioning stage, LSA_RSS derived from the temporal RSS sequence is treated as a vector $O = [o_1, o_2, ...o_M]^T \in \Re^{M*1}$, where M is the number of APs. The basic localization problem can then be regarded as finding the highest $P(w_r|0)$, where w_r represents the coordinate of the r-th reference location. By means of Bayes' rule, the probability can be calculated as:

$$P(w_r|O) = \frac{P(O|w_r)P(w_r)}{P(O)} = C \cdot P(O|w_r) \tag{12}$$

where C is a constant scale if w_r follows a uniform distribution. In this case, the posteriori probability $P(w_r|0)$ depends only on the likelihood $P(O|w_r)$, which gives the probability of observing O at a given location w_r. Therefore we can easily choose the location coordinate w_r to be our estimation result if its posteriori probability $P(O|w_r)$ is the highest. The decision rule is

$$\widehat{w} = \underset{i}{argmax}\, P(O|w_r) \tag{13}$$

where $\widehat{w}$ means the estimated coordinate of the mobile client. Next, the estimated coordinate can be interpolated as the average of all locations by adopting their normalized likelihood as weights to give more accurate results.

$$\widehat{w} = \sum_{r=1}^{R} w_r \cdot \widehat{P}_r \tag{14}$$

where R is the number of reference locations and $\hat{P}_r$ is a normalized likelihood w.r.t all posterior probabilities as Eq.15

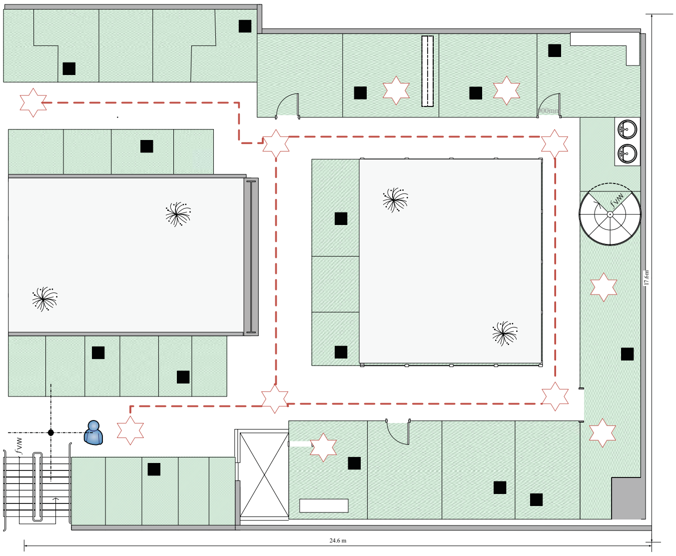

Fig. 6. Part of the fifth floor plane of NTU EE, where experiment had been performed. The dot line represents the path of data collection and test corridors, the black dots show the locations of the APs, the stars indicate the test rooms and the end of the test corridors.

$$\widehat{P}_r = \frac{P(O|w_r)}{\sum_{r=1}^{R} P(O|w_r)} \tag{15}$$

Since the extracted signal at each location is modeled as a Gaussian distribution, the statistic parameters including a mean vector μ_r and a covariance matrix Σ_r are calculated and stored for each w_r during the off-line stage, where $\mu_r = [u_{r1}, u_{r2}, ...u_{rM}]^T \in \Re^{M*1}$ and $\Sigma_r = \{\Sigma_r(i,j)\} \in \Re^{M*M}$. Considering uncorrelated property between each AP, the likelihood $P(O|w_r)$ can be calculated as:

$$P(O|w_r) = \prod_{m=1}^{M} \frac{1}{\sqrt{2\pi\Sigma_r(m,m)}} \cdot exp\left\{\frac{-(o_d - u_{rd})^2}{2\Sigma_r(m,m)}\right\} \tag{16}$$

The architecture of our fingerprinting location system is shown in Fig. 2.

V. Experimental Setup

In order to evaluate the positioning performance of the proposed technique, we collect realistic RSS data in a WLAN environment in the electronic engineering department area of the National Taiwan University (NTU), as shown in Fig. 6.

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 is in total 15 detectable APs in the environment. 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 [51] is installed to gather RSSs from nearby APs. For undetected APs, we set a default value, -95 dBm, the minimum detectable RSS. We collect 100 samples of signal strength at 86 locations separated by 1 meter. Then we adopt the same procedure of [52] to partition the data sets into two independent groups, i.e., 10 samples for testing and 90 samples for training. By parametric learning from the sample data, we can get the statistic parameters used in the probabilistic method. The likelihood is calculated from the Gaussian distributions estimated from the radio map.

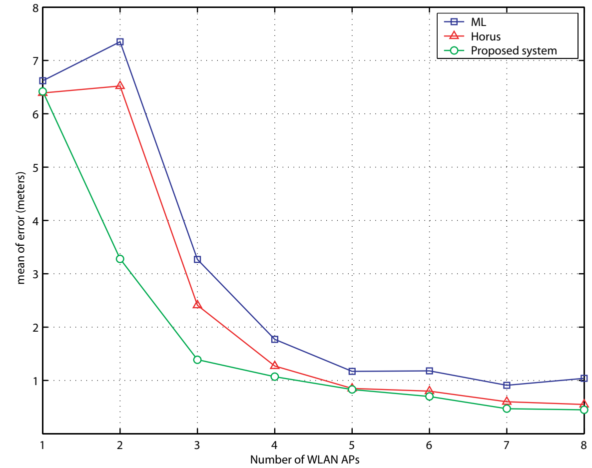

Fig. 7. Performance comparison of mean of the error for the proposed algorithm with different numbers of APs.

We adopt the distance error as the performance metric, which is the Euclidean distance between the estimated location $\hat{\omega}$ and the true coordinate of client ω. The absolute geographical location of a client node is defined in terms of two dimensional coordinates. Thus the error is defined as

$$error = d(\omega, \hat{\omega}) = \sqrt{(\omega_x - \hat{\omega}_x)^2 + (\omega_y - \hat{\omega}_y)^2} \tag{17}$$

where ω_x, ω_y are the coordinates of ω; $\hat{\omega}_x$, $\hat{\omega}_y$ are the coordinates of $\hat{\omega}$.

VI. Experimental Results and Analysis

In this section, we present the mean and standard deviation of the error for different indoor positioning systems. For observing the performance of the proposed technique versus different AP numbers, the ranking of APs is required in our experiment. This work selects eight APs based on InfoGain criterion proposed by Chen et al. [52]. The Information Gain-based criteria ranks APs in descending order according to their InfoGain values which are calculated as follows:

$$InfoGain(AP_i) = H(W) - H(W|AP_i) \tag{18}$$

where $H(W)$ is the entropy of the location when $AP_i^{\prime}s$ value is unknown, and $H(W|AP_i)$ computes the conditional entropy of the location given the AP_i's value. InfoGain calculates the discriminative ability for each AP and the top eight APs are selected to estimate the client location in our experiments.

A. Performance Evaluation

Fig. 7 and Fig. 8 report the comparisons of accuracy performance (mean and standard deviation) with respect to different location mechanisms when the number of APs changes. ML [4] calculates the conditional probability of the physical coordinates depending on the measured signal strength. Horus system [17] uses the moving time-average filter technique to obtain better accuracy.

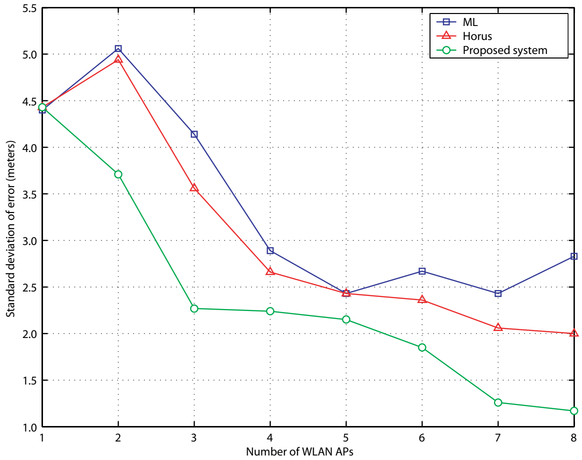

Fig. 8. Performance comparison of standard deviation of the error with different numbers of APs.

When more APs are used, more information is available to determine the physical coordinates. Fig. 7 and Fig. 8 demonstrate that both mean and standard deviation (STD) of the errors decrease as the number of APs increases for the three mechanisms. When the number of APs is increased from 1 to 5, a significant performance improvement can be observed. However, the improvement fades away gradually when the number of APs used is larger than 5. The results demonstrate a trade-off between the online computation and accuracy.

Although it can not tackle the problem efficiently to treat the variation of RSS caused by the multipath as the additive noise, the technique of the moving average filter can alleviate the disturbance in some sense. This can be observed from both results of Fig. 7 and Fig. 8 that Horus system [17] demonstrates a better performance than ML [4] in terms of the smaller mean as well as STD of errors. Numerical results show that Horus system [17] reduces the mean and standard deviation of error by 17% and 9% respectively on the average.

Obviously, the results show that the proposed mechanism outperforms either ML or Horus system under the same AP numbers. For instance, the mean of error is reduced from 3.3 to 1.4 meters when three APs are used, while ML must utilize five APs to achieve the same performance. Meanwhile, STD of error is also much smaller in the proposed system. It is reduced from 4.14 to 2.27 meters when three APs are used, while Horus system must utilize seven APs to achieve the same accuracy. That means that our mechanism has the advantage of using fewer data to achieve the same positioning performance. STD of error could be further reduced to 1.85 and 1.17 meters when six and eight APs are used, respectively. Numerical results show that the proposed system reduces the mean and STD of error by 42% and 29% on the average.

B. Performance Impact of the Filter Size

In order to investigate the performance impact of parameter N of Eq. 5 on the positioning accuracy, we compare the mean of error for different numbers of Ns. The results in Fig. 9 illustrate that the accuracy is enhanced as the window size N increases. In the case of larger N, the average procedure takes more RSS samples and generates more stable features for

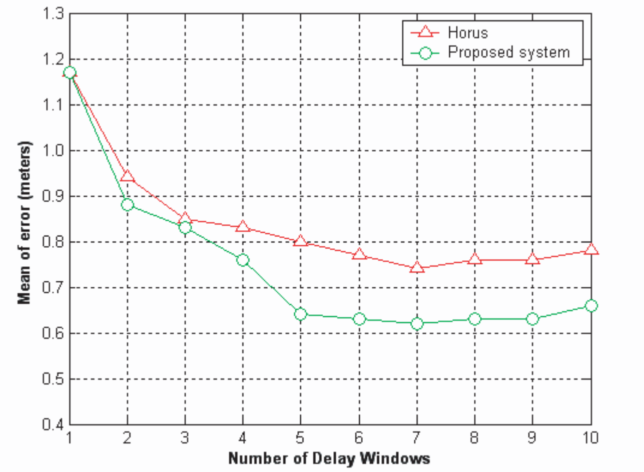

Fig. 9. Performance comparison of mean of the error with different window sizes N.

localization. Horus [17] and the proposed system converge to approximate 0.75 and 0.65 meters correspondingly. However, a side effect of increasing N is the latency of positioning system. The larger the value of N is, the longer the delay will be incurred since more samples are required. The latency can be reduced by using a buffer to store the past RSS samples. In that case, the system does not need to wait for the necessary future RSS samples but utilizes the past data to generate the temporal trajectory of RSS.

C. Reduction of Training Samples

Since the proposed approach can effectively minimize the disturbance caused by the multipath and produce better accuracy performance, we are also going to explore the performance impact. In this section, the number of collected data on the performance between different location systems is considered. Systems of location fingerprinting require the site survey to collect RSS data in order to build the radio map in the initialization phase. Data collection accounts for a large part of the cost in developing a fingerprinting location system. In the experiment, the performance of different location systems has been tested based on different training samples. The number of training samples at each location varies from 10, 20, 40, 60, 80 to 90. Fig. 10 and Fig. 11 show the results.

The results clearly show that the size of training samples can be greatly reduced in the proposed system. This result can be attributed to that the location related information is effectively extracted by our algorithm. That is, the cost of collecting data is accordingly reduced since the time required for site survey is decreased. Our system requires fewer training samples to achieve the same performance. For example, to achieve error mean smaller than 0.75 meters, Horus system needs at least 60 samples while the proposed system only needs about 20 training samples. Fewer training samples mean the human resource is saved.

VII. Conclusion

Positioning in wireless environments are growing rapidly in importance and catches commercial interests for context

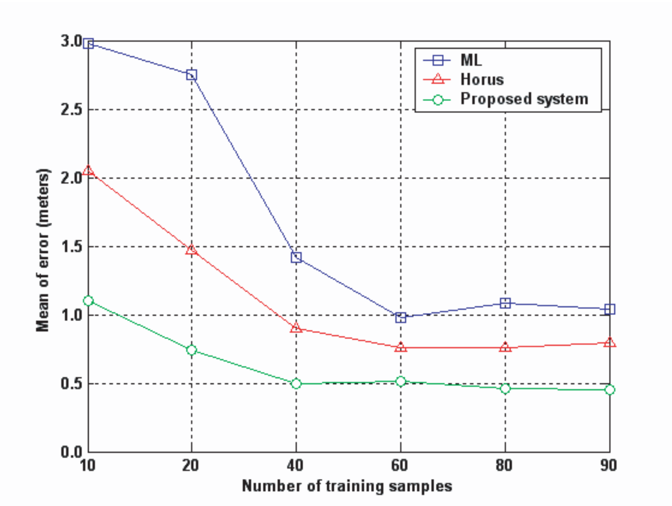

Fig. 10. Performance comparison of mean of the error with different numbers of training samples. The number of APs is fixed at five.

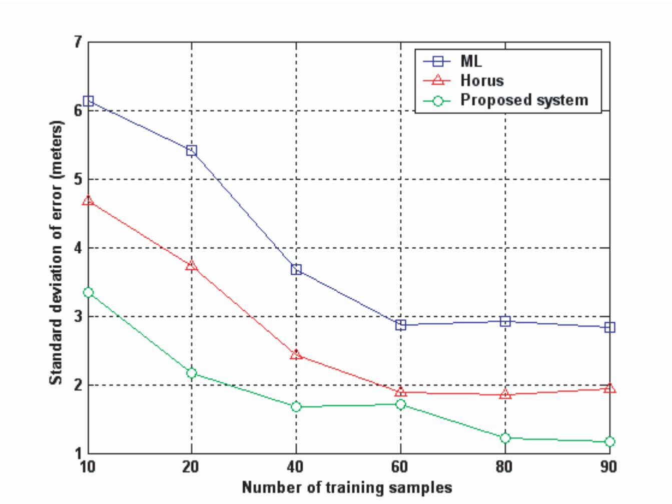

Fig. 11. Performance comparison of standard deviation of the error with different numbers of training samples. The number of APs is fixed at five.

aware applications. The essential challenge in localization is the severe fluctuation of RSS. In this paper, we explore the major noisy source of a geolocation system in indoor wireless environments from the multipath and we present an advanced positioning architecture to reduce the influence. Our contribution is to propose a novel approach to extract the robust feature from RSS which is provided by IEEE 802.11 MAC software. The dynamic multipath behavior can be transformed into a random variable in the logarithmic spectrum domain. That is, the convolution process becomes a linear and separable operation in the logarithmic spectrum domain. To our best knowledge, this work is the first to explore the convolution effect of the multipath on the measured WLAN RSS and is capable of extracting the robust signal efficiently for the location purpose. In contrast to traditional mechanisms, our approach is conceptually simple and easy to implement for practical applications. Not a new hardware or an extra sensor network is required.

Both analytical simulation and experiments in a real WLAN environment demonstrate the usefulness of the system and significant improvements of the location accuracy. The numerical results show that the mean and the standard deviation of estimated error are reduced by 42% and 29%, respectively. Moreover, the experimental results also show that fewer training samples are required by the proposed approach. It reaches as good performance as that of traditional approaches with fewer data and is quite a cost and time saving technique.

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