Real Time Evaluation of RF Fingerprints in Wireless LAN Localization Systems

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Abstract— **RF location fingerprinting has received significant attention as a practical solution to the indoor localization problem due to its use of the available wireless infrastructure (WLANs) and the simplicity of measuring the Received Signal Strength (RSS) fingerprint. The improvement of RSS-based fingerprinting has been limited due to RSS being a weak fingerprint structure; where it has been reported in literature that using more complex pattern recognition algorithms provides diminishing gains. Recently channel-based RF fingerprints such as the channel impulse response (CIR), channel transfer function (CTF) and frequency coherence function (FCF) have been proposed to improve the accuracy at the physical layer. An empirical evaluation of the physical layer fingerprints does not exist in literature and there is a need to understand the advantages/limitations of these fingerprint structures/signatures. As a result in this paper we provide a comprehensive empirical performance evaluation of location fingerprinting with a focus on analytical comparison of the RSS, CIR, CTF and FCF -based fingerprints using the weighted *k*-nearest neighbor (*k*NN) pattern recognition technique. By conducting frequency domain channel measurements in the IEEE 802.11 band at the university campus we evaluate the accuracy of the fingerprints and their robustness to human induced motion perturbations to the channel. We also provide analysis on the impact of system parameters such as the number of access points and the number of nearest neighbors.**

Index Terms— **Channel impulse response fingerprinting, frequency coherence function, RSS location fingerprinting, performance evaluation of localization fingerprinting.**

I. INTRODUCTION

Localization for the indoor environment has received considerable attention recently due to the challenges facing the technology and the lucrative business potential. Location fingerprinting has been the popular and practical approach to indoor localization mainly due to the fact that it takes advantage of existing IEEE 802.11 based wireless infrastructure ubiquitously present in many indoor/urban environments. In addition the simplicity of the RF fingerprint that is based on the received signal strength (RSS) makes it a practical approach. Location fingerprinting combines the use of RF measurements and pattern recognition algorithms in order to find the best correlation between the offline phase (survey locations) and the online phase (the unknown location). In [1] the Radar system was introduced to locate mobile terminals using the RSS measurements from multiple base stations. Further the WLAN user location estimation using the RSS was studied in [2, 3, 4] as a machine learning framework where a model based signal distribution is derived from the collected offline database. In [5] the authors employ machine learning techniques based on information theory and clustering analysis in order to increase the estimation accuracy and minimize power consumption.

The major drawback of RSS based location fingerprinting is that the fingerprint structure/signature itself is not unique to one location which results in localization ambiguity/error [3]. In fact the performance evaluation of RSS-based fingerprinting using different pattern recognition techniques highlighted that adopting more complex pattern recognition algorithms does not provide significant improvement compared to the simple nearest neighbor [6, 7]. As a result of these diminishing gains, researchers recently investigated “channel” based RF fingerprints that focus on improving the fingerprint structure at the physical layer. Channel-based RF fingerprints such as the Channel Impulse Response (CIR) harness the multipath information that is *theoretically* unique to a given location which yields a more accurate fingerprint and location estimate. CIR-based fingerprinting was first introduced by U.S. Wireless Corp. where it was used for cellular networks [8]. The statistics of the CIR (RMS delay spread, number of multipath components, etc.) were used in a neural network framework for fingerprinting localization in mines [9]. CIR fingerprinting for WLAN systems was investigated in [10] using Ray-Tracing (RT) simulations. Ultra Wideband (UWB) based CIR fingerprinting illustrated the benefits of high-time domain resolution in enhancing localization accuracy [11, 12]. However, performance evaluation of CIR-based RF fingerprinting has revealed that system bandwidth and database resolution (grid spacing) are important factors that determine practical achievable accuracy [13]. Recently, other channel based RF fingerprints that are represented in the frequency domain have been proposed. The first is the Channel Transfer Function (CTF) which is the Fourier transform of the CIR [12]. The second is the frequency coherence function (FCF) which is the autocorrelation of the channel in the frequency domain and it has been proposed in a recent U.S. patent application [14].

Although there is significant literature on the performance evaluation of RF fingerprinting; the focus has been on analyzing RSS-based fingerprinting using different pattern recognition algorithms [6, 7]. The performance evaluation of RF fingerprinting from a physical layer perspective (e.g. comparison of CIR, CTF and FCF vs RSS) does not exist in the literature. As a result there is a need for understanding the comparative advantages and limitations of the existing RF fingerprint *structures*. As a result, in this paper we provide an empirical performance evaluation of RF fingerprinting from a physical layer perspective for WLAN systems. Specifically using a frequency domain measurement system we construct a database of RF fingerprints from measurements in a typical indoor environment (in UAE) conducted in the IEEE 802.11 bands. We then evaluate the accuracy gains of different fingerprint structures using the simple weighted k nearest neighbor (*w- k*NN*)* algorithm. Specifically, we provide an empirical analysis on the robustness of RF fingerprints to channel variations due to the motion of people in the vicinity of the transmitter/receiver. Finally the impact of system parameters such as number of transmitters and number of nearest neighbors will be investigated.

The paper is organized as follows. In section II the mathematical formulation is presented. In section III the measurement system and data collection are introduced. The results and analysis are provided in section IV. Finally the paper is concluded in Section V.

II. SYSTEM MODELING

The design of a location fingerprinting system depends primarily on the "radio map" that contains the fingerprints for predefined locations. In this section the mathematical model of location fingerprinting will be introduced.

A. Mathematical Model

The radio map is constructed by creating a grid of points in an indoor area; where the grid points are spaced by Δ which defines the separation between the training points in the $x-y$ plane. The spacing results in a distinct total number of training points N which dictates the radio map density. For each (x_i, y_i) location, where $i \in [1, N]$, there exists a unique fingerprint vector $\mathbf{S_i}$ for this location as follows

$$(x_i, y_i) \Rightarrow \mathbf{S_i} = [s_i^1 \quad s_i^2 \quad \cdots \quad s_i^M]_{1\times M} \tag{1}$$

where, s_i^j is the measured RF signal at the *ith* location from the *jth* AP, where $i = [1, N]$ and M is the number of APs covering the floor or building. The elements of the fingerprint can be a scalar in the RSS case or a vector in the CIR, CTF and FCF cases. Similarly, in the location estimation phase, a fingerprint at an unknown position (x_b, y_b) , is measured and it is given by $\mathbf{Z_b} = [z_b^1 \quad z_b^2 \quad \cdots \quad z_b^M]_{1\times M}$ which is then compared with the radio map database to estimate the target location.

B. Fingerprint Structure

The structure of the RF fingerprints is extracted from the mathematical model of the wireless channel. The transmitted radio signal experiences a multipath channel creating replicas at the receiver side. The multipath wireless channel can be modeled as a transfer function in the frequency domain as:

$$H(f,t) = \sum_{m=1}^{L(t)} a_m(t)\ e^{-j(2\pi f \tau_m(t) - \theta_m(t))} \tag{2}$$

where, $a_m(t)$, $\theta_m(t)$ and $\tau_m(t)$ are the amplitude, phase and delay of the *mth* multipath components. This framework describes the temporal variation of the wireless channel and hence no assumption of time invariant channel has been made.

For RSS-based systems, the fingerprint can be constructed by measuring the received signal strength between a mobile device and a number of access points. The RSS is then given by

$$P(t) = \int_{-\infty}^{\infty} |a_m(t)|^2 df \tag{3}$$

The RSS signature vector is represented as $\mathbf{S_i^{RSS}} = [P_i^1 \quad P_i^2 \quad \cdots \quad P_i^M]_{1\times M}$. The offline database that holds all the RSS fingerprints is defined as a matrix where each row vector represents the RSS fingerprint for a receiver location from the available M APs or

$$\overline{\mathbf{S}}^{\mathbf{RSS}} \Rightarrow \begin{bmatrix} P_1^1 & P_1^2 & \cdots & P_1^M \\ P_2^1 & P_2^2 & \cdots & P_2^M \\ \vdots & \vdots & \ddots & \vdots \\ P_N^1 & P_N^2 & \cdots & P_N^M \end{bmatrix} \tag{4}$$

For the CIR-based systems, the CIR fingerprints can be obtained by taking the Inverse Fourier transform of the frequency transfer function $H(f,t)$ which is modeled by

$$h(\tau,t) = \Im^{-1}\{H(f,t)\} = \sum_{m=1}^{L(t)} a_m(t) e^{j\theta_m(t)} \delta(\tau - \tau_m(t)) \tag{5}$$

Similarly the FCF fingerprints can be obtained by calculating the complex autocorrelation function of the frequency transfer function $H(f,t)$ as [14]

$$R(\Delta f,t) = \int_{-\infty}^{\infty} H(f,t) H^*(f+\Delta f,t) df \tag{6}$$

Equations (2), (5) and (6) correspond to the vector elements entries of the fingerprint $\mathbf{S_i}$, at the *ith* location, which can be represented as, $\mathrm{S_i^\Psi} = [\Psi_i^1 \quad \Psi_i^2 \quad \cdots \quad \Psi_i^M]_{L\times M}$. Where ψ corresponds to CIR, CTF or FCF fingerprint structures. Note that $\mathrm{S_i^\Psi}$ is a matrix since $\Psi_i^j = [\Psi_i^j(1) \quad \Psi_i^j(2) \quad \cdots \quad \Psi_i^j(L(t))]^T$, where L is the number of samples of the ψ measurement. Thus for the CIR, CTF and FCF-based location fingerprinting, the overall offline database is defined as, $\bar{\mathbf{S}}^{\Psi}$ matrix given by:

$$\bar{\mathbf{S}}^{\Psi} = \begin{bmatrix} \Psi_1^1 & \Psi_1^2 & \cdots & \Psi_1^M \\ \Psi_2^1 & \Psi_2^2 & \cdots & \Psi_2^M \\ \vdots & \vdots & \ddots & \vdots \\ \Psi_N^1 & \Psi_N^2 & \cdots & \Psi_N^M \end{bmatrix}_{(N\bullet L)\times M} \qquad (7)$$

C. Pattern Recognition

In the online stage pattern recognition algorithms are used to estimate the mobile device location by comparing the online fingerprint with the offline database of fingerprints to find the best matching entry. A variety of pattern recognition algorithms can be used from the simple NN or *k*NN to the more complex probabilistic (Bayesian) and neural networks [6, 7]. The performance evaluation of RSS-based fingerprinting revealed that there is only a slight advantage in terms of location accuracy that can be achieved by using the more complex algorithms such as Bayesian or neural networks [6, 7]. The diminishing of gains of different pattern recognition techniques support the intuitive conclusion that substantial accuracy can be achieved instead by improving the design/structure of the fingerprint itself. As a result in order to compare different fingerprint structures, the focus of this paper will be on the simple weighted *k*NN approach. The weighted *k*NN algorithm estimates the position by finding the minimum Euclidean distances (maximum correlations) between the online fingerprint vector (matrix) and the offline database of fingerprint vectors (matrices). For the RSS-based system calculation of the Euclidean distance is straight forward since both the training and online fingerprints are vectors. Thus the Euclidean distance between a fingerprint at an unknown location b and the ith location in the training database is given by

$$d_{b,i} = \left\| \mathbf{Z}_b^{RSS} - \mathbf{S}_i^{RSS} \right\| = \sqrt{\sum_{j=1}^{M} (P_b^j - P_i^j)^2} \qquad (8)$$

where $\|(\bullet)\|$ is the norm between the observed vector $\mathbf{Z}_b^{RSS}$ and the offline fingerprint, $\mathbf{S}_\mathbf{i}^{\mathbf{RSS}}$ at the ith calibration point. Thus, the result of comparing the observed signal with the entire database would result in the Euclidean distances vector $\mathbf{d}_b = [d_{b,1} \quad d_{b,2} \quad \cdots \quad d_{b,N}]$. The weights of *k*NN can be then found as the inverse of the Euclidean distances as $\mathbf{w_b} = [1/d_{b,1} \quad 1/d_{b,2} \quad \cdots \quad 1/d_{b,N}]$. For other fingerprint structures, the estimated position can be computed by evaluating first the correlation between $\mathbf{Z}_\mathbf{b}^{\Psi} = [\Psi_b^1 \quad \Psi_b^2 \quad \cdots \quad \Psi_b^M]$ and $\mathrm{S}_\mathrm{i}^{\Psi}$. The correlation between the online fingerprints at location b and the offline fingerprint at location i is given by $\rho_{b,i}$ where, $0 \le \rho_{b,i} \le 1$. Thus, the result would be the correlation vector, $\boldsymbol{\rho}_\mathbf{b} = [\rho_{b,1} \quad \rho_{b,2} \quad \cdots \quad \rho_{b,N}]$. Consequently, the weights of the *k*NN is the same as the computed correlations as $\mathbf{w_b} = [\rho_{b,1} \quad \rho_{b,2} \quad \cdots \quad \rho_{b,N}]$. The locations on the database that yields the highest correlation with the online fingerprint b (minimum Euclidean distance) will be the estimated positions. Thus by using the weighted *k*NN algorithm the estimated position for location fingerprinting based systems can be found by taking the weighted average of the estimated positions as

$$(\hat{x}_b, \hat{y}_b) = \frac{\sum_{k=1}^{\mathrm{K}} w_k * (x_k, y_k)}{\sum_{k=1}^{\mathrm{K}} w_k} \qquad (9)$$

where K represents the nearest neighbors with smallest Euclidean distance (RSS) or largest correlation (CIR/CTF/FCF).

III. MEASUREMENT SYSTEM

In this paper the location fingerprinting database (offline/ online) was collected by conducting a frequency domain channel measurements. Frequency domain channel measurements have been carried out in the past to characterize the wireless propagation channel [15]. We use the same measurement system/approach to construct the RF fingerprints in different locations across a floor plan of interest. This section describes the measurement environment, system components and their setup. Also, it explains the measurement procedures and the parameters that affect the location fingerprinting system.

A. Measurement Environmemnt

The frequency domain channel measurements were conducted at Khalifa University building in Sharjah, UAE. The layout of the floor plan of the tested area is shown in Fig. 1. Four zones, of a 30X25 m^2 total area, were covered in the measurements including vertical and horizontal corridors, lab and student lounge area. Fig. 1 also shows the respective positions of the transmitter antenna under the three fixed WiFi access points.

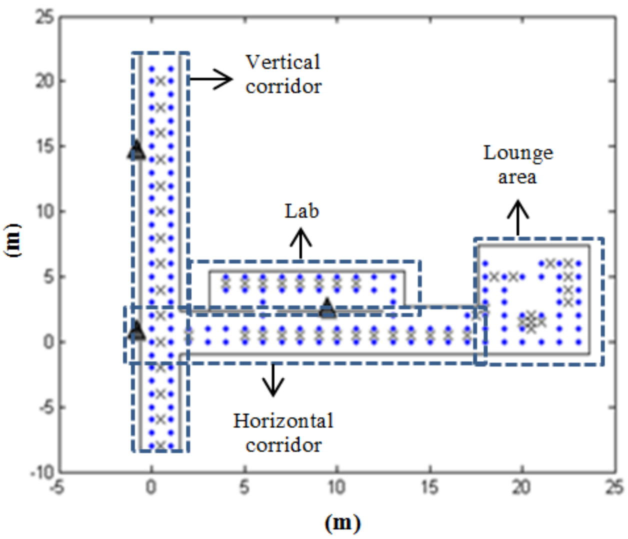


Figure 1. Layout of the floor plan located on the ground floor of the KU building, Sharjah. Triangle- transmitter location; dots- offline locations; 'x' – online receiver locations.

B. Measuremt Setup

The frequency domain measurements (S21) of the wireless channel were carried out using the ZVB14 Vector Network Analyser (VNA) from Rhode&Schwartz. The measurement system consists of the VNA, a 30 dB power amplifier, a 22 dB gain low-noise amplifier, low loss RF cables and omnidirectional antennas at the transmitter and receiver ends. The transmitter and receiver heights were fixed at 1.5 m.

A program script was written for the VNA to measure 40 consecutive sweeps; each sweep contains 601 frequency sample points with spacing of 0.167 MHz to cover a 100 MHz band centered at 2.4 GHz. The former settings provided a high time-domain resolution of 10 nsec (inverse of the bandwidth) and a time span of 5.99 µsec (inverse of frequency step). The measurements were designed to examine the WiFi bands specifically, channels 1, 6 and 11 in the IEEE 802.11g standard. As a result the measured 100 MHz was parsed to fit the channel allocations in the standard. In this paper the analysis is focused on channel 1 because it experienced the lowest interference from deployed APs. In fact by examining the data it is revealed that channel 6 (default channel on deployed APs) experienced the most interference. The study of the impact of interference on location fingerprinting is our future work.

C. Measuremnt Procedure

The test area shown in Fig.1 was divided into uniform grids with a 1 m spacing that resulted in a total number of 152 offline points. In the survey the offline database was first gathered by measuring the channel frequency response at each location, of the 152 points, from a single transmitter fixed in a location close to an actual WiFi AP. The measurements were repeated for the other two access points. In order to test the performance of the location fingerprinting system, the channel frequency responses were collected for 51 online points distributed randomly in the test area, which will be compared later with the offline database. The offline database was measured under a stationary scenario where there were no movements around the TX/RX at the time of the measurements. This is typically achieved in actually systems since the survey is conducted during low-activity time. For the online database, in addition to the stationary scenario, we captured the channel fluctuations due to the motion by having 3 individuals walking around the TX/RX during the 40 snapshots. This set of measurements is specifically important to analyze the impact of motion on the integrity of the RF fingerprint structures.

IV. Results and Discussion

In this section the results obtained from the frequency domain channel measurements are analyzed. A comprehensive performance evaluation of location fingerprinting is provided with a focus on analytical comparison of the RSS, CIR, CTF and FCF -based fingerprints using the weighted *k*NN pattern recognition technique.

A. The performance of location fingerprinting structures

We begin our analysis into analyzing the performance of RF fingerprints in stationary scenarios. Fig. 2 (a) illustrates the CDF of location errors for the RF fingerprints under stationary conditions (stationary offline and online). It is clear that the FCF fingerprint exhibits the best performance. In addition note that CIR fingerprint is slightly worse than RSS. This is mainly due to the fact that CIR is a function of the system bandwidth and at 22 MHz (WiFi bandwidth) it has limited time-domain resolution as verified in [13]. In realistic conditions, the propagation channel can be perturbed by the motion of people/objects around the transmitter and receiver. The performance of the RF fingerprinting structures under motion perturbation is evaluated in Fig. 2(b). The figure clearly shows that FCF exhibits the best performance and is robust to channel variations. On the other hand the performance of CTF deteriorates and this is mainly due to the sensitivity of the frequency response to the changes in each multipath; where changes in a single path can alter the response significantly [14]. The performance of RSS exhibits the worst degradation mainly due to the averaging notion of power where the power fluctuates with channel perturbation which affects the mean (shadowing). It is interesting to note that CIR fingerprints are relatively more robust than CTF and RSS and this again due to the fact that the channel in the time-domain (especially at lower bandwidths – 22 MHz) does not change significantly when the channel is perturbed; when several paths are affected by the motion, the overall impact on the CIR is limited [16].

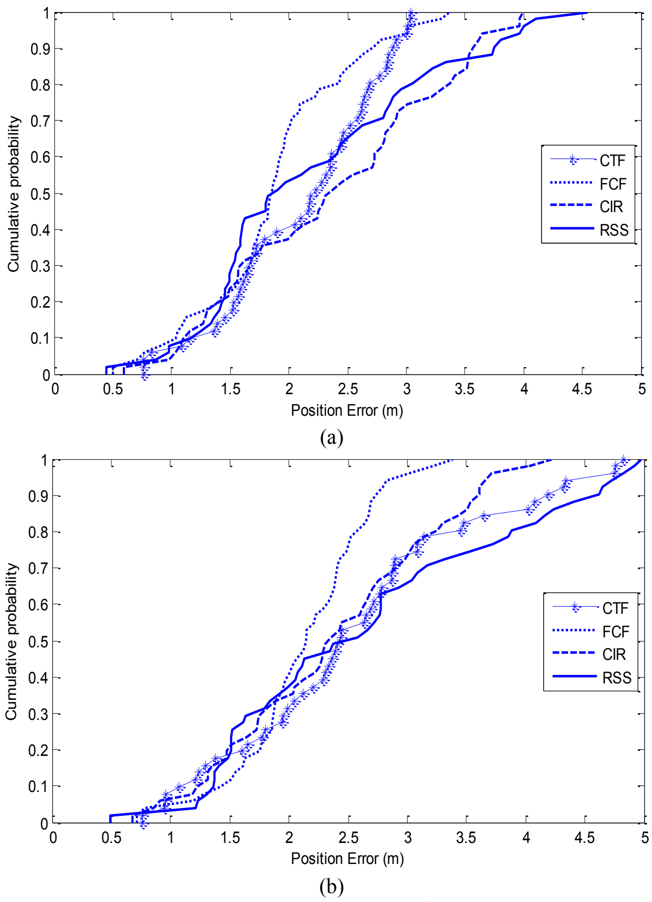


Figure 2. Cumulative Density Function (CDF) of RSS, CIR, FCF and CTF errors in location estimation (a) Stationary- stationary. (b) Stationary-movements.

In order to further understand the robustness of FCF and CIR to time-variations of the channel it is best to examine sample measured complex channel responses. Fig. 3 illustrates the 3 channel-based RF fingerprints (in addition to RSS) in stationary and dynamic channel conditions. Each plot contains 40 consecutive time sweeps. Notice how the CTF exhibits significant fluctuation as motion perturbs the propagation environment. The robustness of FCF and CIR to movements can be clearly seen in the figures. The perturbation is also evident in the time measurements of the RSS which explains the degradation in Fig. 3.

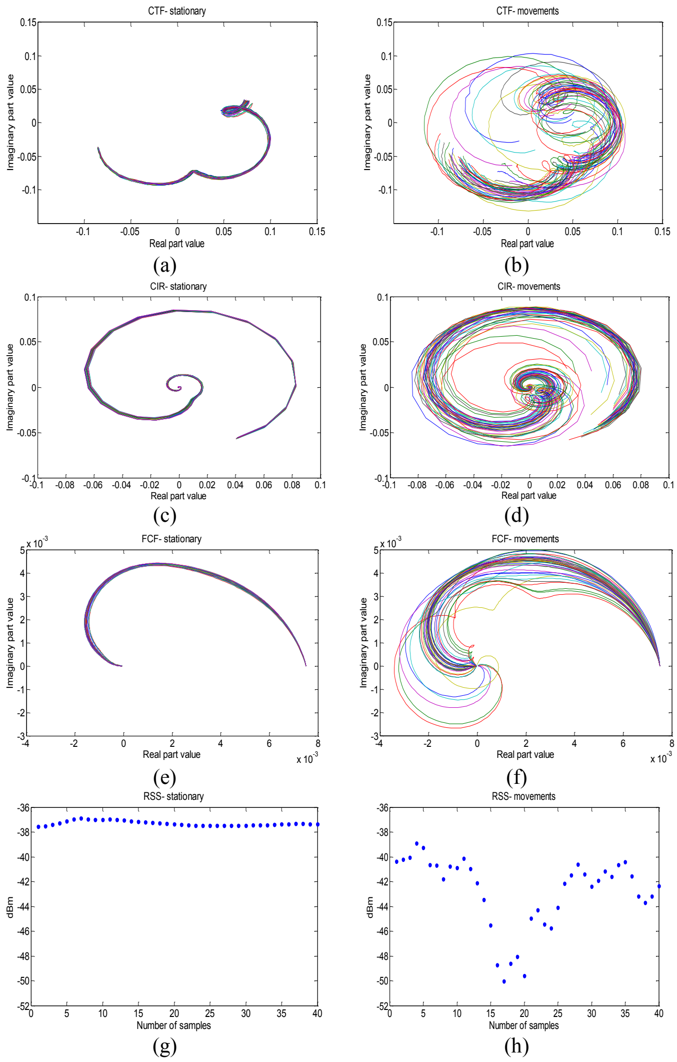


Figure 3. Measured RF Fingerprints at 40 snapshots. (a) CTF- stationary. (b) CTF- movements. (c) CIR- stationary. (d) CIR- movements. (e) FCF- stationary. (f) FCF- movements. (g) RSS- stationary. (h) RSS- movements. The channel based fingerprints are complex vectors while RSS is a scalar.

B. *Effect of varying the number of Access Points (APs)*

The performance of RF fingerprinting is a function of the number of APs; which affects the size and accuracy of the fingerprints structure. The Root Mean Square Error (RMSE) was computed for two scenarios; stationary online fingerprints in Fig. 4 (a), and online fingerprints with motion perturbation illustrated in Fig. 4 (b). 3 nearest neighbors were used. For both scenarios, there is a noticed improvement for all fingerprints as the number of transmitter increase which is a result of having higher dimension fingerprints accumulated from each transmitter location. It is shown that RSS fingerprint structure has the highest RMSE compared to other fingerprint structures in both scenarios. FCF shows the best performance followed by CTF and CIR. Also note that the performance degrades with motion which affects the accuracy of the fingerprint structures.

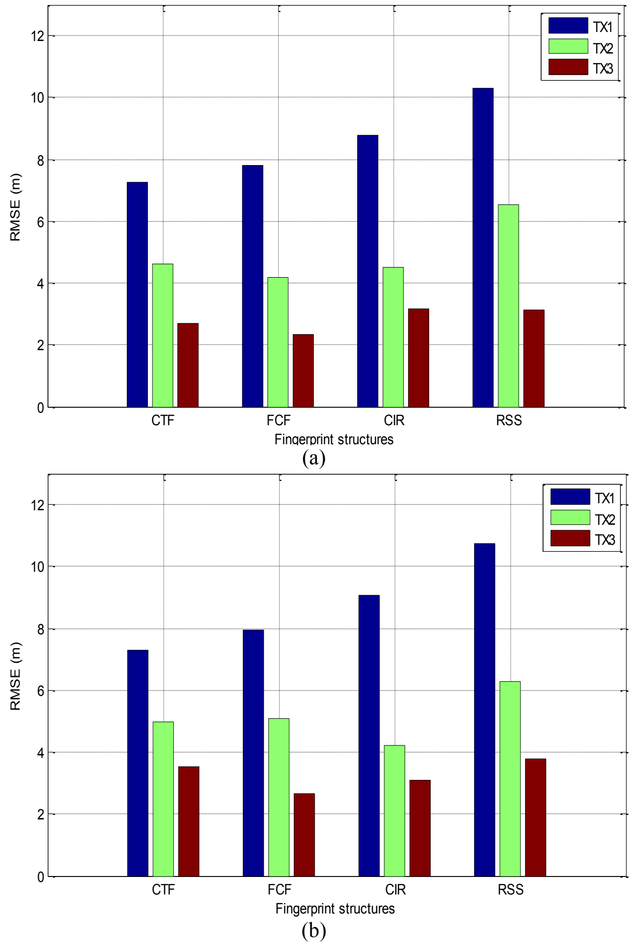
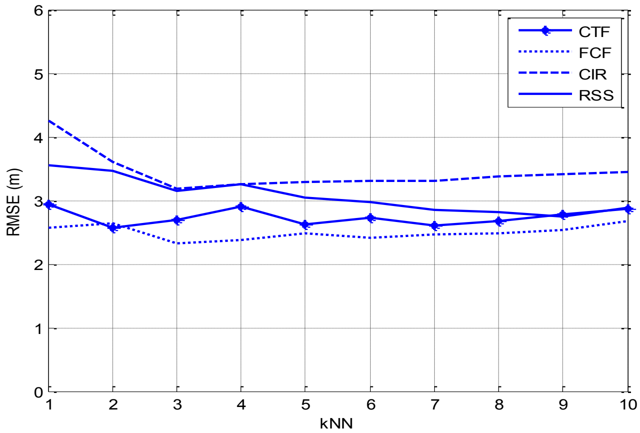


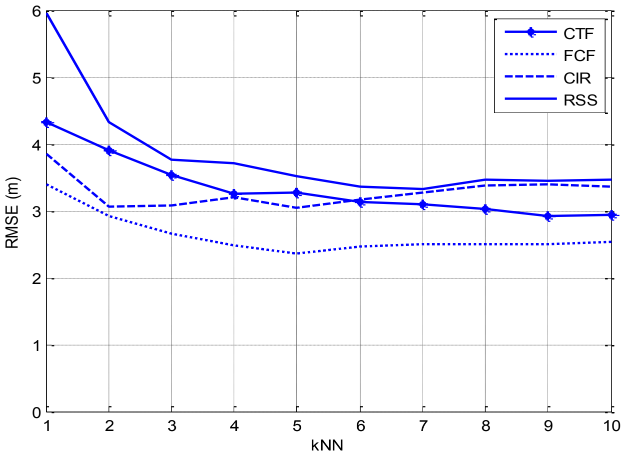
Figure 4. Performance against number of transmitters available using *k*NN = 3 (a) Stationary- stationary. (b) Stationary- movements.

C. *Effect of varying the number of nearest neighbors*

In this section we provide an analysis of the performance in stationary and movement scenarios for different number of nearest neighbors selected. As expected the performance improves as the number of *k*NN increases. The results for varying the number of k nearest neighbor are shown in Fig. 5 where the RMSE of different fingerprint structures is highlighted. The results were generated by taking an average of 40 offline measurements and an average of 40 sequential online measurements. Overall the results shown in Fig. 5 supports the CDF results obtained in Fig. 2 where FCF fingerprint structure has the minimum error. It also shows that increasing the value of k nearest neighbor improves the location estimation accuracy for individual fingerprint structure. However, this improvement is limited since for channel-based fingerprints; there are locations in the corridor that exhibit symmetry and increasing the number of neighbors can degrade the accuracy.



(a)



(b)

Figure 5. Performance against number of nearest neighbors (a) Stationary- stationary. (b) Stationary- movements.

V. CONCLUSION AND FUTURE WORK

RF location fingerprinting has been a practical and popular approach for the indoor localization problem mainly due to the availability of existing wireless infrastructure and the simplicity of measuring the RSS. However due to the weakness of RSS as a fingerprint, researchers recently proposed different channel based RF fingerprints: CIR, CTF and FCF. Performance evaluation of RSS-based location fingerprinting for different pattern recognition algorithms exists in the literature. However the evaluation of the performance from a physical layer "channel" perspective does not exist. Thus there is a need to understand the performance gains/limitations of the proposed fingerprint structures.

In this paper, a comprehensive empirical performance evaluation of RSS, CIR, CTF and FCF -based location fingerprinting is provided. By conducting a frequency domain channel measurement campaign at the university campus the performance of fingerprints structures and the impact of channel variation has been investigated. Results show that FCF has the best performance and is robust to channel variations due to people motion. Although CTF outperforms CIR in stationary conditions, it degrades significantly under motion scenarios highlighting the robustness of CIR to the same channel impairments. Finally RSS exhibits acceptable performance in stationary environments, but degrades even more under motion perturbations. From a system point of view, increasing the number of transmitters and nearest neighbors improves the performance, but has limitations in light of channel impairments; such as motion of people around the transmitter/receiver.

Our future work will focus on analyzing different movement scenarios in the offline database (impact of collecting the survey database in normal activity conditions) and the impact of interference on the performance of RF fingerprinting.

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