Properties of WLAN Indoor Fingerprinting Received Signal Strength for Localization

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Abstract — *Indoor positioning systems that make use of received signal strength-based location fingerprints and existing wireless local area network infrastructure have recently been the focus for supporting location-based services in indoor environment. A familiarity and understanding of the properties of the location fingerprint can assist in algorithm design and improving indoor positioning system deployment. However, most existing research work on the radio signals properties has been conducted, the requirements may differ from various algorithms. This paper investigates the properties of the received signal strength reported by IEE 802.11b wireless network interface cards. Analyses of the data are performed to understand the underlying features of location fingerprints to assist in model design. The measured data also analyses to understand the distribution model to the measured data.*

Keywords — *Indoor, WLAN, RSS, Modelling, Localization, Positioning system.*

I. INTRODUCTION

Indoor localization systems that apply location fingerprints based on available wireless local area network (WLAN) communications have been established for indoor vicinity where specifically the global positioning system (GPS) does not operate well [1,2]. The fingerprinting method is easy to set up in relation to techniques applying time difference of arrival (TDOA) and angle of arrival (AOA) or other related techniques. Rather than relying on accurate approximates of the angle or distance to establish the position, position fingerprinting relates position dependent features such as the received signal strength (RSS) with a position and applies these features to infer the position. For this scenario, there is no necessitate for dedicated hardware at the mobile side (MS) out of the wireless network interface card and the available WLAN environment can be reused straightforward.

Prior a localization system can determine the position, a position fingerprint radio map or database should be created [3,13]. The database is used as simulation environment where the proposed positioning algorithm extracted all necessary data. In case the positioning system needs to interact directly with actual mobile device, the mobile device should send the received signal strength to the radio map to compute the required location. Every entry in the radio map is a mapping among real location and a position fingerprint. The position fingerprint may be in average value as in the RADAR system or probabilistic [4].

Recognizing the statistical features of the position fingerprint (RSS vector) is significant for the design of localization systems model for numerous reasons. It may provide insight on how altering the indoor access points can affect a location accuracy and precision, whether pre-processing of the RSS measurements can give the better accuracy. The current literatures for indoor localization systems mainly focus on the improvement of accuracy performance of the position estimation algorithm and neglect the consideration of the RSS random characteristics [5]. Understanding of the RSS features may in reality assist the development of good algorithms to categorize a measured RSS vector ***P*** as owned to a specific position *L*. Even though a range of statistical radio propagation models available, they were created with signal communications capability, coverage and data rate in consideration. Furthermore, the correlation among RSS values as some transmitter setting parameter altered is not understood well. The distribution of RSS values, their temporal variation, their standard deviation and the relation of RSSs from APs are essential for understanding and modelling the performance of fingerprint based indoor positioning systems. For recent, the distribution of the RSS is thought to be Gaussian distributed in dBm according to the study in [6]. Though, the initial investigation and the study in [7] demonstrated otherwise.

This paper analyses the RSS in indoor surroundings with localization in consideration. Section 2 explains the measurement setup. Section 3 investigates the effect of changing AP height, the effect of changing AP power, the effect of number of samples and the distribution of the RSS. The individuality of the RSS coming from several APs is also examined in Section 3. The paper is concluded in Section 4.

II. MEASUREMENT SETUP

The interactive scanning deriver (ISD) that it returns the signal strength of beacon frames received from all access points in the NIC is developed for Linux. A Dell Ispiron N5050 laptop computer equipped with ISD software was used to collect samples of RSS from access points (APs) at Mbeya University of Science and Technology. The ISD client manager software is a site-survey tool designed to allow user to initiate data collection details such as reference number, number of samples required, transmitter height and transmitter power level before starting scanning process. After finishing scanning process, the tool saves data in comma value separated (CVS) format. The driver is primarily to support this feature under Linux.

For a particular location, vectors of RSS are formed based on measurable signals from APs during the measurement time. The received signal sensitivity of a particular make of WLAN card limits the measurable range of the RSS. For instance, WLAN card has its receiver sensitivity between 100 dBm and 0 dBm. The smallest signal value that most standard 802.11 cards can receive and report corresponds to around -100 dBm. The highest typical value of the RSS found in the experiment using WLAN card is approximately -18 dBm at one meter from any AP. The building used has 3 floors and 5 APs were determined for data measurement. The measurement was carried out in the ground floor with the estimated dimension of 350 m^2. The radio frequency for the APs is 2.4 GHz.

A. *Experimental Design*

To identify and understand different factors which may affect WLAN performance, a couple of different factors settings need to be determined and conducted. The experiment conducted in service is estimated to be 350 m^2 with total number of 74 training locations. All APs are placed at specified meter height on the testing service area. The sampling RSSI during offline learning is collected on grid-shape RPs at distance of (1-1.5) meter. The APs fixed in such a manner that, every location in the service area is reached with sufficient number of different APs signals necessary for positioning purposes. If the sample size for a particular location was estimated to be 20 samples, then the number of collected sample for the whole service area with 74 reference points (RPs) is given by equation 1.

Ns (Number samples) × (APs) × (RPs) =20×5×74=7400 samples. ……………………… (1)

During the experiment different factors settings was varied as shown in Table 1.

Table I: Different factor settings for experiment

Factors	Options
Sampling rate	1 Hz
RPs height	Constant (at floor level)
RPs distribution	1-1.5m
Number samples	20,30,40
RPs density	74
APs density	5
APs distribution	3,4,5
APs height	1m, 2m,3m
APs power	HIGH(≤-18dBm), MEDIUM (≤-30dBm), LOW (≤-43dBm)

III. Properties of the received signal strength

Indoor radio propagation is tricky to envisage due to the dense multipath condition and dissemination effects like scattering, reflection and diffraction [8]. Multipath fading causes the arriving signal to vary around a mean value at specific location. The arriving signal is generally modelled by the mutual effects of small-scale fading and large-scale fading [9]. The large-scale-fading element (of interest here) illustrates the signal decrease as the signal moves with respect to distance and is rapt by material such as floors and walls alongside to the receiver. This element envisages the mean of the RSS and generally has a log-normal distribution [9]. Small-scale fading describes the dramatic reduction of the signal caused by the multipath fading. If the line of-sight (NLOS) component is not available, the small-scale fading is commonly represented with a method of Rayleigh distribution. If the line-of-sight (LOS) component is present, the small-scale fading it can be presented with a Rician distribution. Though, these models are based on realizing the effect of radio propagation on receiver design and signal coverage instead of considering the indoor positioning systems.

The analysis of RSS data in this part is divided into three sections. All measurements were carried at fixed locations. Initially, the investigation of the effect of varying the AP height, AP power and number of samples on the RSS set over time was conducted. Second, the investigation of the statistical properties of the RSS set (the distribution of RSS over different samples). Third, the study of properties of several RSS sets (essentially RSS values offered from multiple APs). The evaluation based on whether every RSS set is independent with the others and either they all show the similar statistical properties.

A. Effects of AP height on RSS

In indoor positioning systems based on WLANs, the user typically carries the mobile station equipped with a wireless NIC. The effect of the AP height plays a significant role in the mean and standard deviation values. The study showed that the AP height in different power settings (HIGH, MEDIUM, LOW) caused a mean and standard deviation difference variation of -15.33 dBm to -19.26 dBm, -15.50 dBm to -21.10 dBm, -19.83 dBm to -24.46 dBm and 15.37 to 17.22, 12.58 to 13.09, 13.00 to 15.43 respectively in RSS level between consecutive heights of 1, 2, 3 meters as shown in Figure 1 and 2 respectively. This suggests that the AP height is an important factor and should be included in designing the user indoor positioning model. Also, it implies that the maximum value to be considered the in designing the user indoor positioning model when AP effect taken in to consideration should range in -24.46 dBm (mean) and 15.43 (standard deviation) at any particular reference point.

B. Effect of AP power on RSS

To study the effect of the AP power on RSS, the measurement of the signal performed considering different power settings in a particular AP at location L in the study area. The distance between the transmitter (AP) and the receiver (MS) is approximately 6 m. The data were recorded for different power while number of samples remains constant. The results were analysed by plotting graph of the RSS for both powers. The change of AP power setting caused RSS level variation up to -24.46 dBm mean difference and 17.22 standard deviation difference respectively as shown in Figure 1 and 2. This suggests that the AP power is an important and should be included in designing the user indoor positioning model.

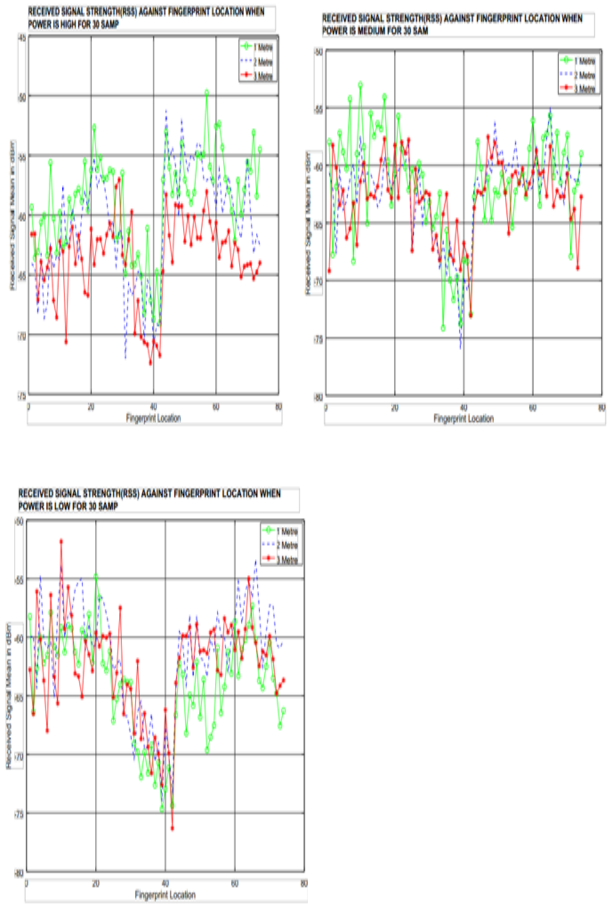

Figure 1: Characteristics of RSS mean over different reference points as power and height settings changes

Figure 2 illustrate the variation between these power variations. The differences in power settings can have significance influence to the RSS variations. The standard deviation difference is increased from approximately 12.58 to 17.22 as the transmitter power settings changes. The mean difference changes from -15.33 dBm to -24.46 dBm as the transmitter power settings changes. Clearly, it is essential to collect data for the radio map based on the application. When the positioning system model is supposed to cater to various transmitter power settings, it is essential to consider power settings while collecting the RSS values for the fingerprint and to take into account the effect of transmitter power setting.

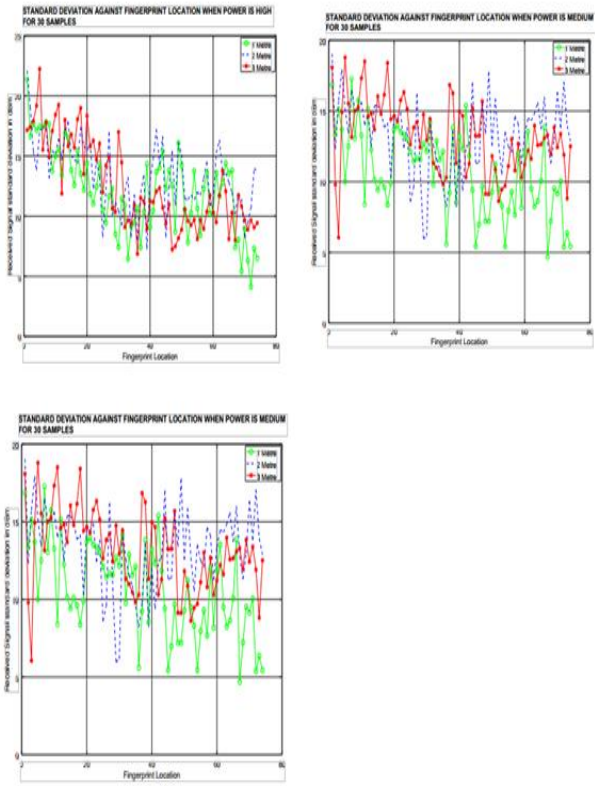

Figure 2: Characteristics of RSS standard deviation over different reference points as power and AP height changes

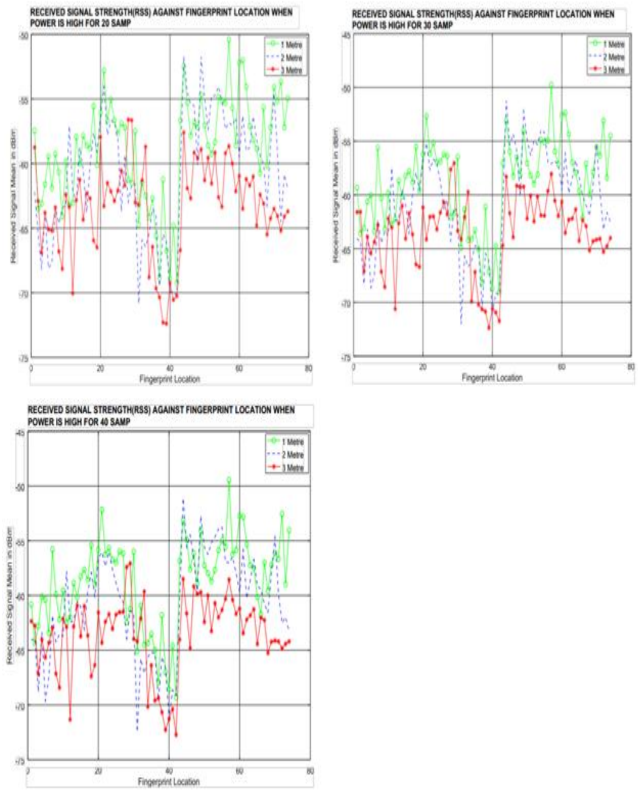

Figure 3: Characteristics of RSS mean over different reference point as samples and height changes

C. Effect of number of sample (Mean and Standard deviation)

To study the effect of number of samples on mean and standard deviation, the measurement was performed at 74 locations inside the building. In this case, the distance between the transmitter and receiver is varies from point to point. The measurement was done for a period of 4 to 5 minutes. The results of the statistics of the RSS values from the transmitters are shown in Figure 3. The results show that the RSS mean and standard deviation difference varies from -14.7 dBm to 21.37 dBm and 14.11 to 17.61 respectively. Although the variation does not depend much on the number of samples as it can be seen in Figure 1 the maximum found mean is estimate to be -50 dBm. This suggests that as the number of samples varies from 20 to 40 there is no significance change in mean. Therefore, applying the sample in the range can give an estimated accuracy.

IV. STATISTICAL PROPERTIES OF THE RSS

Traditionally, the average RSS is believed to be log-normally distributed [10]. The mean value is generally predictable and thought to conform one of several homogeneous path loss models discussed in [11]. However, there are some conflicting conclusions regarding the RSS distribution measured at the software level by the wireless NIC for indoor radio propagation in [5]. Moreover, the standard deviation and the stationarity of the RSS are not understood very well.

A. Distribution of received signal strength

It was observed that the value obtained for both sample after dividing skewness and kurtosis by standard error is ranging from -0.32 to 1.03 for skewness and -0.53 to -0.85 for respectively. The obtained value is within ±1.96 limits, suggesting that the data is normally distributed and the normality is not too extreme. The result also shows that, even though the numbers of sample changes from 20, 30 to 40 the distribution still stay in normal distribution. This suggests that, including more samples does not have more impact in indoor fingerprint distribution.

Even starting by 20 samples can provide a better distribution. The visual histograms in Figure 4 and Table 2 highlight the RSS obtained result from the analysis.

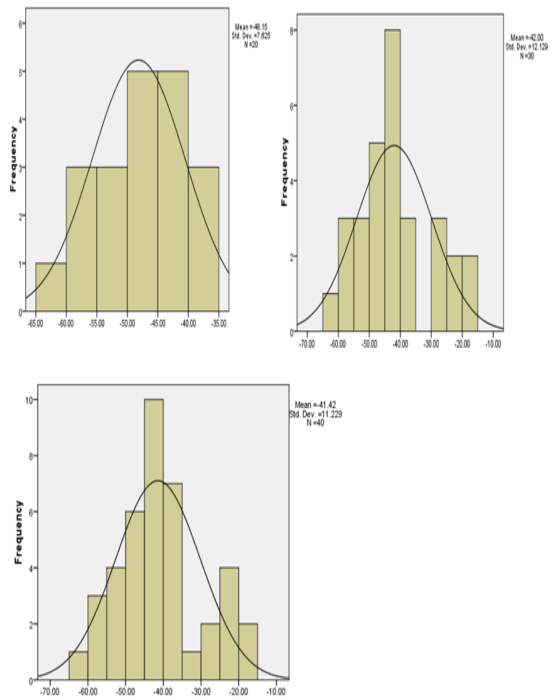

Figure 4: Distribution of received signal strength for various sample

Table II: Parametric detail of received signal strength for various sample

	Received Signal Strength distribution with 20 samples	Received Signal Strength distribution with 30 samples	Received Signal Strength distributio n with 40 samples
N Valid	20	30	40
Skewness	-.164	.425	.387
Std. Error of Skewness	.512	.427	.374
Kurtosis	-.842	-.628	-.391
Std. Error of Kurtosis	.992	.833	.733

V. PROPERTIES OF MULTIPLE RSSS AT A PARTICULAR LOCATION

This subsection analyses the dependency of multiple RSSs from multiple APs. This is to confirm an intuition that the RSS from multiple APs are actually independent. The second part of this subsection discusses the effect of interference on the RSS when there is another AP transmitting in the same frequency channel.

A. Independence of multiple RSSs

The average of the RSS coming from each AP is a value of a position fingerprint vector. To validate statistical independence among these values, a measurement of multiple RSS samples was collected at location 10 (L10) where the mobile device can receive signals from three APs simultaneously. The distances from the five APs were approximately 8, 15, and 10, meters. The correlation values between each pair of RSS data is between -0.26 to 0.21 as shown in Table 3. Therefore, it shows that the RSS from the APs are having weak correlation which implies that both RSSs are independent and any proposed WLAN fingerprinting indoor positioning model should be able to combine features from different pair. This is due to Carrier Sense Multiple Access with Collision Avoidance (CSMA/CA) mechanism which is used in 802.11 based WLANs as also reported by [12].

Table III: The Correlation Coefficients of Different APs Pair

AP Pair	C0:A0:BB:19:78:F8, CC:B2:55:FE:40:12	C0:A0:BB:19:78:F8, 60:E3:27:BC:EF:4C	CC:B2:55:FE:40:12, 60:E3:27:BC:EF:4C
Correlation Coefficient	-0.26556996	-0.052435739	0.214835711

To verify the statistical independence between different samples as the transmitter height varies from 1 meter three meter a measurement of multiple RSS samples was collected at location 10 (L10) where the mobile device receives signals from AP with MAC address *60:E3:27:BC:EF:4C*. The result shows that the correlation between samples in different height ranging from -0.003 to -0.3 as shown in Table 4. Therefore, it reveals that the RSS samples as transmitter height varies are having weak correlation which implies RSSs samples are independent and any proposed WLAN fingerprinting indoor positioning model should be able consider features from different height.

Table IV: The Correlation Coefficients of AP in Different Height

AP in different Height	60:E3:27:BC:EF:4C(1,2)	60:E3:27:BC:EF:4C (1,3)	60:E3:27:BC:EF:4C (2,3)
Correlation Coefficient	-0.109732599	-0.308328222	-0.00314834

To verify the statistical independence between different samples as the transmitter power setting changes from HIGH to LOW a measurement of multiple RSS samples was collected at location 10 (L10) where the mobile device receives signals from AP with MAC address *60:E3:27:BC:EF:4C* while height and samples were fixed to 1 meter and 30 samples respectively. The result shows that the correlation between different power setting ranging from -0.1 to 0.1 as shown in Table 5. Therefore, it reveals that the RSS samples as transmitter power setting varies are having weak correlation which implies RSSs samples are independent and any proposed WLAN fingerprinting indoor positioning model should be able consider features from different height.

Table V: The Correlation Coefficients of AP in Different Power

AP in different Power	60:E3:27:BC:EF:4C(HIGH,MEDIUM)	60:E3:27:BC:EF:4C (HIGH,LOW)	60:E3:27:BC:EF:4C (MEDIUM,LOW)
Correlation Coefficient	0.06759929	0.142783536	-0.16170546

VI. CONCLUSIONS

The paper presents preliminary investigation of the RSS values as accounted by an 802.11 NIC usually applied in indoor positioning systems depends on position fingerprinting. Also, statistical properties of the RSS were analyses and found that APs height, and APs power are important and should be included in designing the user indoor positioning model however as number sample varies from 20 onward there is no significance on mean. The distribution of the RSS is normally distributed and the normality is not too extreme and the standard deviation varies with respect to the signal level.

It is obvious from the study that signals reported from multiple APs are usually independent. The RSS patterns in the study show that the fingerprint may be composed together as a set of mean clusters to mitigate the effect of noise. Different cluster mean can represent one position because of the different modes of the RSS distribution. The future study is to design a model for the distribution of the RSS and to recognise how they influence location. The results investigated this paper and previous work may provide understanding on the technique behind indoor position systems based on fingerprinting localization. In summary, this study investigates the RSS pattern in various aspect. This study elevates an essential aspect of designing a location fingerprinting system that is to examine the properties of the fingerprint itself before applying to a pattern recognition method to solve the positioning challenge. Simple pattern recognition approach can be appropriate and more effective than sophisticated ones.

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