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INFLUENCE OF MOBILE DEVICE RECEIVED SIGNAL STRENGTH INDICATION FOR WLAN FINGERPRINTING INDOOR POSITIONING ACCURACY IMROVEMENT

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ABSTRACT

The indoor positioning services in view of wireless local area network (WLAN) location fingerprinting would be the most part utilized on the mobile devices. This paper explores the distinctions of received signal strength indication (RSSI) among various mobile devices and the distributions of RSSI from these gadgets. The measurable analysis of test results demonstrates the distinctions of RSSI among various mobile devices are not identical. RSSI distribution is not usually Gaussian its left or right skewed. In this way, considering skewness and RSSI mean, is adequate to guarantee a precise demonstration of the RSSI. The impacts of sensitivity versa distance on RSSI distribution are explored and the size of mobile devices revealed to have an impact on distribution. The statistical data analysis could empower mobile device indoor positioning framework planners to enhance positioning performance and to model location fingerprinting based indoor positioning systems.

KEYWORDS: *WLAN; RSSI; Indoor Positioning; Skewness; Mean; Sensitivity; Distance*

1. INTRODUCTION

The broad mobile devices advent and location sensing lead to a widespread demand for mobile device positioning systems with relatively high accuracy. Although the Global Positioning System (GPS) can provide sufficient positioning services in most cases, it suffers in indoor environments because of wall attenuation and excessive multipath (Mrindoko, 2015). As an alternative or complementary solution for indoor environments, Chan and Sohn (2012) proposed a positioning approach based on the RSSI in WLAN networks. These days, the WLAN positioning has turns out to be more alluring for indoor positioning as a result of the expanding accessibility of open and private system Access Point (APs) (Kaemarungsi, 2005).

Positioning systems that fit for the indoor positioning should be adaptable to a variety of mobile devices with comparative positioning accuracy. The basic issue that influences the accuracy of the RSSI based positioning is the versatility of RSSI fingerprint database establishment for various mobile devices. The positioning accuracy of mobile devices such as smart phone and iPod or laptop depends much on the comparison between the offline RSSI fingerprint database and the online RSSI data. If the online RSSI data collected by different mobile devices varies to some degree, the position accuracy contrasts too, this implies that the positioning system is not stable or reliable. At present, there are only a few types of terminals that can be used to gather and establish the offline RSSI fingerprint database. However, there are huge of clients with enormous various types of mobile devices and there will be more distinctive mobile devices going to the business sector consistently. Thus, it is not reasonable to establish the offline RSSI fingerprint database that covers every kind of mobile devices. Therefore, the variations in the RSSI data of various devices should be taken full in consideration for a business indoor positioning framework that is intended for urban application.

The comprehension of the RSSI data is a key for location determination algorithms such as the deterministic approach (Luo *et al.*, 2011). The Gaussian or log-normal distribution is currently used to model the randomness of RSSI. However, the substantial scale measurements in Li (2012) revealed that, the majority of RSSI histograms fitted well with Gaussian distribution and there were a few histograms that could be fit better with bi-modal Gaussian distributions. On the other side, most existing data were collected by laptops. Compared with laptops, the smart phones and IPods are smaller and their computing power is very limited, thus the smart phones and IPods would be more sensitive to the environmental change when collecting the RSSI for indoor positioning application. The measurement results are clearly supported in section 3. This has motivated the current study in influence of mobile devices RSSI for WLAN based indoor positioning accuracy and the popular mobile devices such as Android mobile phones and Dell laptop were selected in the experiments.

By comparing the histograms of RSSI collected in arbitrary direction scenarios, an evaluation of the RSSI collected by laptop device was reported by Kaemarungsi and bi-model distribution was observed (Kaemarungsi and Krishnamurthy, 2004). On the other side, the bi-modal distribution was observed in Kaemarungsi (2006) but the cause of bi-modal distribution had never been revealed.

In this paper, the RSSI information gathered by Android smart mobile phones and portable PC are examined. From the gathered information, hadware differences impacts on the RSSI value are discussed. Furthermore; the dispersion of RSSI data is analyzed and characterized by evaluating the skewness. An extensive assessment on the effects gadget affectability on the dissemination of WLAN RSSI is made and the reason for the distribution is additionally researched. The results of this paper could provide hypothetical support on indoor positioning innovation.

The paper comprises of five sections. Taking after this brief presentation, Section 2 presents the measurement setup and data gathering. Section 3 investigates the impact of various mobile devices on RSSI. The distribution of the RSSI data and the sensitivity impacts of mobile devices explained in Section 4. At last, Section 5 concluded the paper

2. EXPERIMENTAL SETUP AND MEASUREMENT

The investigation was carried basing on precise measurements of the WLAN RSSI using Android smart phones and MS window laptop. Two Android smart phones and one MS window laptop, namely; iNote beyond, HUAWEI Y330-U11 and Dell Ispiron N5050 equipped with RSSI collecting application software were used to collect samples of RSSI data from APs at the Postgraduate research room in the College of Information and Communication Technologies, University of Dar es Salaam. The dimension of the room is nearly 8 m × 5 m. Three wireless APs located at height of 2.0m above the floor were deployed as shown in Fig. 1. The three APs have the same merchant and models. As shown in Fig. 1, a small area is defined as a grid of 8 points (the solid red dots in Fig. 1). The minimum separation between two consecutive locations known as grid spacing was fixed at a distance of one meter. Firstly, the estimation was made to detect the differences of RSSI data gathered by different smart phones and laptops at different APs. Eight estimation places as appeared in Fig. 1 meant as 1, 2, 3, 4, 5, 6, 7 and 8 were gathered the RSSI data. The 1, 2,3 up to 8 represent point 1, point 2 up to point 8.

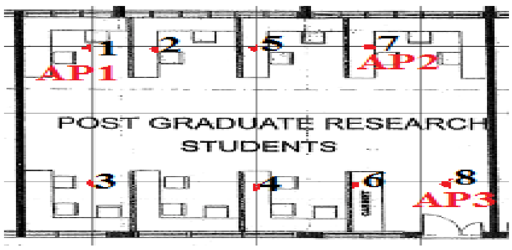

Figure 1. Location of APs and the measurement points on the Postgraduate research room

In the experiment, one laptop and two smart phones were put together on a 1.2-meter high backing. The position of the mobile devices is as appeared in Fig. 2. The purpose behind this plan was to quantify the distinction of RSSI quality gathered by these gadgets at same location and the meantime. Table 1 demonstrates the fundamental setup of two Android mobile phones and one laptop. All mobile devices were activated in the meantime and each gathered 200 RSSI tests in 5 minutes at a rate of 1Hz.

Figure 2. Placement and direction of three Mobile devices to measure RSSI data differences

Table 1. Basic configuration of mobile devices used to measure the RSSI

Configuration	Itel iNote beyond	Dell Aspiron N5050	Huawei Y330 U-11
CPU	Unknown	2.2 GHz Dual core	1.3GHz Dual core
Operating System	Android OS 2.3	MS window 7 Professional	Android OS 4.2
Wi-Fi Module	unknown	Dell Wireless 1702 802.11b/g/n	802.11b/g/n

3. DIFFERENCES OF DIVERSITY MOBILE DEVICES

The investigations of Kaemarungsi and Krishnamurthy (2004) proposed that the area fingerprints with various gadgets could be distinctive. Instinctively, the RSSI measured among different mobile device ought to have distinctive results. To look at the impact of hardware on the RSSI data gathering, the attributes of measurable RSSI data gathered utilizing diverse mobile devices were examined. The genuine got signal vitality is a persistent amount and measured in dBm or decibel milliwatt, while in handy terms, the RSSI is accounted for in dBm as a whole number Mrindoko (2015). Different devices have their own particular way to change over the genuine got signal vitality to RSSI esteem in dBm.

Table 2 lists the manufacturer, phone model, minimum RSSI, maximum RSSI and the RSSI variation range for all the mobile devices used for comparisons. The greatest estimation quality was gotten while putting the mobile devices close to the beacon, while the minimum estimation worth was acquired while setting the mobile devices beyond as possible from the same access point in the postgraduate research room. The variation scope of RSSI showed here won't not be exact in light of the fact that it is conceivable that, the device software will never receive some of the RSSI values in dBm.

As appeared in Table 2, the variation range of RSSI data gathered by Dell Inspiron N5050 seems more prominent than others. This implies it can quantify the signal with higher determination and see more variation of signal contrasted with alternate device utilized as a part of this analysis. Then again, the Huawei Y330 U11 has the shortest range, yet it has appeared to have stronger signal than iNote beyond. This implies, the device to have the more prominent does not suggest the higher sensitivity of a device to a signal. Thusly, various real measured signal levels might be mapped into mean RSSI esteem for position fingerprinting purposes. Mobile devices with the higher sensitivity of the RSSI qualities are better as it permits a positioning system to better separate between two areas notwithstanding for small position change.

Table 2.Min, Max and Variation Range of RSSI Collected By Different Mobile Device

Manufacturer	Device Model	MIN (dBm)	MAX (dBm)	Range (dBm)
Dell Inc	Inspiron N5050	-68	-23	-45
HUAWEI	Y330-U11	-69	-27	-42
Itel	iNote beyond	-88	-39	-44

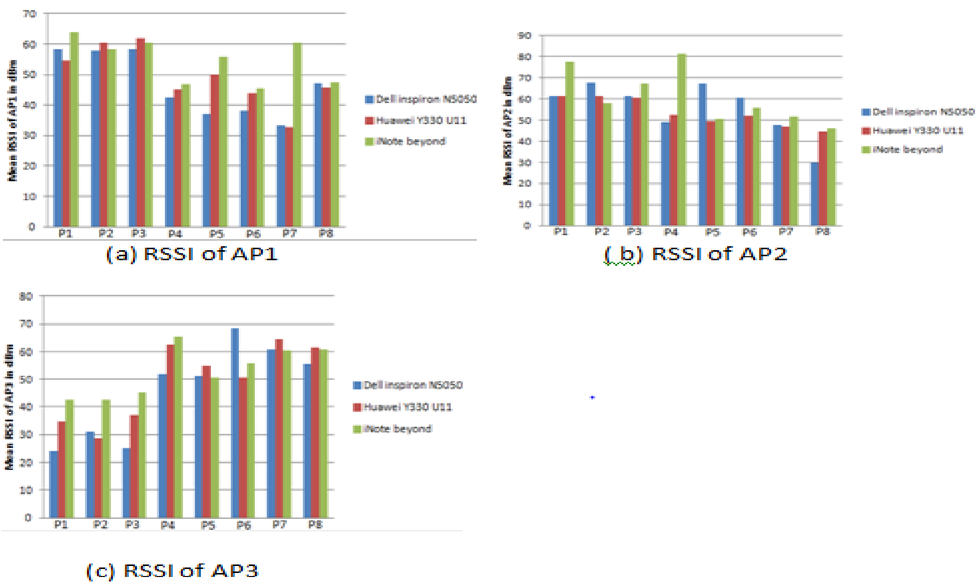

Figure 3. Mean RSSI of three APs collected by three mobile devices at 8 places

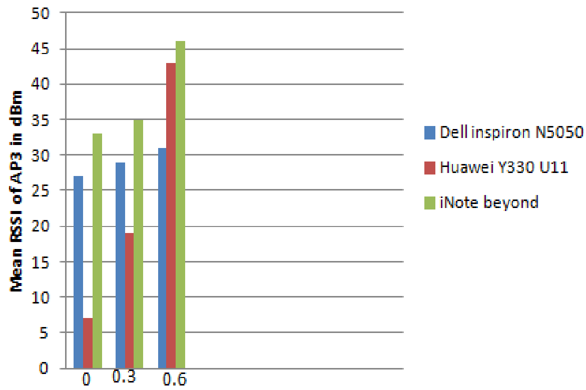

Figure 4. RSSI of AP variation versus distance

The Mean RSSI data gathered among different mobile devices is appeared in Fig. 3. The RSSI contrast fluctuates for the most part, and once in a while the distinction can be as high as 23 dBm, even at the same area and in the meantime and same access point. The average RSSI between three devices from the same reference point are recorded in the Table 3. It demonstrates the average of RSSI between three devices is relative to their variation range of RSSI data and their standard deviation. The bigger the variation scopes of RSSI are, the bigger the average of RSSI qualities could be. Along these lines, the location accuracy would diminish essentially if the variation scopes of RSSI data belong to the devices on offline stage and online stage varies much extensive. The results in Luo (2014) showed the distinctions of RSSI between portable PCs were around 1-2 dBm. Though, the RSSI of the mobile phones in this investigations demonstrates much extensive contrasts, e.g., the average, the average differences of RSSI between Huawei Y330 U11 and Itel iNote beyond are 7.5 dBm and between laptop and smart phone ranging from 7.5 dBm to 15.7 dBm. Also the smart phone of greater RSSI sensitivity it is signal variation in relation to distance is appear to be higher compared to smart phone with less sensitivity as it is shown in Fig. 4. The value of Huawei Y330 U-11 at 0 meter was 7 dBm and 0.3 meter was 19 dBm while the value of itel iNote beyond beyond was 33 dBm and 35 dBm respectively on the same point. The data were recorded at point 7 AP from the Fig. 1.

Table 3. The Average (IN dBm) of RSSI Value Between Three Mobile Devices in Same Reference Point And Access Point

	N	Minimum	Maximum	Mean	Std. Deviation
Dell inspron N5050	10	23	30	25.80	2.300
Huawei Y330 U11	10	30	36	34.00	1.826
Itel iNote beyond	10	38	44	41.50	1.841
Valid N (listwise)	10				

Also Table 3 demonstrates the standard deviation of the RSSI data collected by three different mobile devices. The standard deviation of the RSSI data collected by the Huawei Y330 U11 appears smaller than the Dell inspron N5050 and Itel iNote beyond. This is due to the fact that the variation range of value collected by Dell inspron N5050 and Itel iNote beyond mobile devices is larger than Huawei Y330 U11.

As shown by the measurement results, the RSSI data gathered by different mobile devices differs and sometimes substantially. The offline RSSI fingerprint database consists of the mean of RSSI data or the mean combined standard deviation of RSSI data in generally, while the online RSSI data usually consists of the mean of RSSI data. The substantial difference between RSSI collected by offline device and online device would result in tremendous positioning error. Therefore, it is essential to calibrate the RSSI to adjust the difference in the future work.

4. DISTRIBUTION OF RSSI

Existing works of Luo and Zhan (2014) used the kurtosis coefficient and normalized histogram distribution to study the randomness of RSSI although the impact of sensitivity is not explained. Li (2012) use the Gaussian distribution to model RSSI value with parameters (μ, δ) where μ is the mean of RSSI samples, δ is the standard deviation of RSSI samples. However, Li (2012) claimed an ambiguous conclusion: 'Most of the intensity histograms were very close to Gaussian', but the details of the assessment criteria were not reported. On the contrary, the test results in Chen *et al* (2013) demonstrated that the dissemination or histogram of the RSSI have a long tail to one side, which is called left-skewed dispersion, if the average RSSI is high (−80 dBm or above). On the off chance, the normal RSSI is low (beneath −80 dBm), the dispersion will be practically symmetric or appear to be log-normal distribution without the long tail. Clearly, there are some clashing conclusions with respect to the RSSI dissemination since it is not expressed if the RSSI taken is a mean or single signal value without mean calculation.

A. Skewness of RSSI:-

In the current work, three APs'(as appeared in Fig.1) RSSI data collected by the Dell aspiron N5050, Huawei Y 330 U-11 and itel iNote beyond at 8 grid points as designed in Section 2 were analyzed as well as the distribution of the RSSI data and the impact of sensitivity. Although 50 samples were gathered from each grid point, the numbers of RSSI values were limited and in most cases the numbers of RSSI values were below 10 and above 4. In this subsection, skewness used to roughly assess whether the RSSI data obeys the Gaussian distribution. The skewness is reported by using a scatter plot of the standardized value from the data set, if the data are well normally distributed with the same mean and standard deviation as in the data set. Fig. 5 shows the comparisons of the skewness between 3 AP's RSSI data from 8 locations. Intuitively, it shows that a lot of the skewness is left or right.

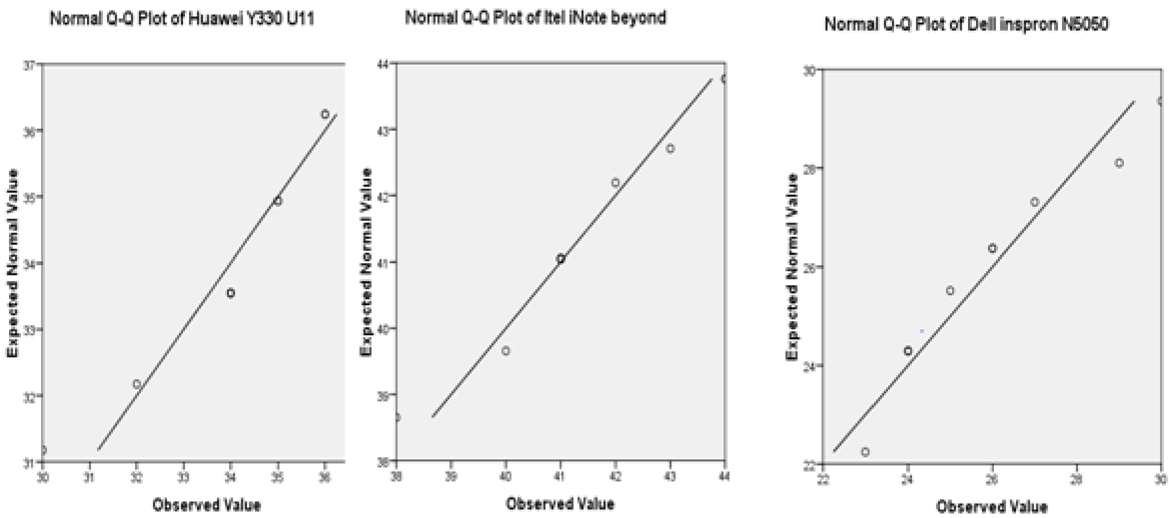

Figure 5. The skewness of three AP's RSSI from 8 locations

5. CONCLUSION

This paper examines the effect of the impact of hardware on RSSI and characterizes the distribution of RSSI. The RSSI data gathered by three mobile devices were analyzed. By comparing the RSSI data of three mobile devices, the differences between different devices in terms of the mean, standard deviation, and range of RSSI are assessed. The test result demonstrates that the mean estimation of the RSSI data gathered by different mobile devices varies significantly, some of the time as large as 26dBm, even in the same time and place. The variation of the RSSI data appears because of the different shifting mechanism and antenna gain of different mobile devices on real received signals to the RSSI values in dBm. Besides, the examination of the RSSI dispersion demonstrates that when skewness and devices sensitivity are taken into account, using the Gaussian distribution to model the RSSI is sufficient for accurate approximation. If Gaussian distribution must be used, adjusting the standard deviation would lead to a better distribution.

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