An Improved Algorithm to Generate a Wi-Fi Fingerprint Database for Indoor Positioning

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A New Approach to Model Wi-Fi Signal Strength

Lina Chen
College of Information Science and Technology, East China Normal University, China;
College of Mathematics, Physics and Information Engineering, Zhejiang Normal University, China;
School of Surveying and Geospatial Engineering, UNSW
+86-579-82282501, chenlina@zjnu.edu.cn
Binghao Li
School of Surveying and Geospatial Engineering, UNSW
+61-2-93854189, Binghao.li@unsw.edu.au
Andrew Dempster
School of Surveying and Geospatial Engineering, UNSW
+61-2-93856890, a.dempsteri@unsw.edu.au
Zhengqi Zheng
College of Information Science and Technology, East China Normal University, China;
+86-21-54345107, zqzheng@ee.ecnu.edu.cn

ABSTRACT

Fingerprinting is a widely used technique for indoor positioning, especially for Wi-Fi positioning systems. It is essential to create the fingerprint database in training phase. A quick survey can save labour effort and time; however it normally means the sacrifice of the positioning accuracy since a small number of measurement the signal strength can't represent the real signal distribution well with current models at each reference points. In order to achieve high accuracy, a better model is required. A new model is proposed in this paper using the Double-Peaks Gauss function to approximate the Wi-Fi signal strength distribution in the offline training phase. The model was created based on the analysing of large amount measurement during the intensive experiments. Testing shows this model worked well even the samples changed from 10000 to 100. The model can be used to improve the efficiency to generate the radio map. The new model can possibly be applied to other types of wireless signal.

KEYWORDS: fingerprinting; radio map; signal strength

1. INTRODUCTION

Location Based Service (LBS) is mobile application which depends on mobile devices and mobile network to calculate the actual geographical location of mobile user, further more to provide the service information relate with the position what users need. It is now becoming one of the standard features in mobile devices and has good application prospect and huge market space. Because the most of actives of LBS are finished in indoor, so the indoor positioning technology is the key issue for LBS. To data, Wireless Location Area Network (WLAN) has already been used as one of the most effective indoor positioning system. Especially, Wi-Fi has become the industry standard, it almost is the best choice for indoor positioning. Fingerprinting has been accepted as an effective technique for Wi-Fi indoor positioning, it consists of the offline training phase and online positioning phase. First, the offline phase is when a site-survey of RSSI from multiple APs is performed to collect patterns of RSSI. The result of this phase is a database that maps between RSSI patterns, which is called location fingerprints, and locations in that area (K. Kaemarungsi and P. Krishnarmurthy 2004). The RSSI database is called a radio map. The location fingerprints can be as simple as patterns of averaged RSSI or distributions of RSSI from a number of APs. In the literature systems that maintain or estimate distributions of RSSI for each location usually have better positioning performance. For instance, lognormal distribution to model the RSSI has been assumed (Youssef and Agrawala et al, 2003), while Xiang et al utilized shape filtered on empirical distribution of actual RSSIs distribution could be a key to improve the performance of indoor positioning systems (Xiang and Song et al, 2004).

To estimate the probability of such occurrence, commonly the mean and standard deviation of received signal strength indicator (RSSI) at each location is computed, the simplest method is to use the average SS of each access point (AP) measured at each reference point (RP) to create the fingerprint database (Bahl and Padmanabhan, 2000; Saha and Chaudhuri et al, 2003), but there has the large variation of the SS measured at each point and has great influence on the positioning determination (Binghao and James et al, 2006). In order to achieve more accurate results, the probabilistic approach has also been developed (Ladd and Bekris et al, 2002; Youssef and Agrawala et al, 2003), however, the behaviour of RSSI is not simple to be expected as propagation of the signals is influenced by several factors and the distribution of the SS is non-Gaussian. Not only that, it varies at different locations, and at the same location when the orientation of the antenna changes (Ladd and Bekris et al, 2002; Wang Y and Jia X et al, 2003). To achieve a good estimation of user location, the more RPs and the more measurements obtained at each point the better positioning accurate, but more RPs and more measurement mean that the training data phase takes more time and labour to generate the radio map for fingerprinting.

In this paper, the location fingerprinting is a technique that exploits presumable a unique relationship between RSSI and an indoor positioning. The RSSI can be obtained by IEEE 802.11b/g WLAN interface cards. There is sampling survey in three indoor areas covered with WLAN signals which respectively is office, building, and classroom. It took eight hours and received more than 10000 samples in each indoor room. An interesting appearance be observed, that is the real distribution of the RSSI almost all have two peaks and have a long tail. Based on this observation, a new approach was proposed which called double-peaks Gaussian function. The simulation experiments showed that the algorithm shape is very same with the occurrence singles, even the samples changed from 10000 to 100.

2. MEASUREMENT SETUP

This study investigated for real distribution of the RSSI based on four different indoor-rooms which are all covered Wi-Fi signals. In order to obtain the real distribution of the RSSI, the received of signals remained 8 hours at each indoor locations. The table 1 explains every indoor area.

Location	Area	Sample time	The number of APs
Office	$20m^2$	9am to 5pm	147
Building	$100\ m^2$	2pm to 10pm	34
Classroom	$200\ m^2$	9am to 5pm	154

Table 1. Experiment conditions

A Lenove ThinkPad X220 laptop was used in all experiments. There is one built-in wireless card which is the Intel Advanced-N 6205. To collect RSSI samples, the laptop was placed on a desk with approximately one-meter height. A user monitored the measurement at each location. In general, the RSSI measured by different cards should have different results. In order to difference between other experiments, table 2 lists the information of model and the chipset of WLAN cards and the information of standard and interface of these WLAN card in this study.

Vendor	Model	Chipset	Interface	Standards
Intel Corporation	Advanced-N 6205	Intel	PCI-E	IEEE 802.11a/b/g

Table 2. WLAN model and standards information

The inSSIDer software is an open-source Wi-Fi scanner by MetaGeek. It can use your current wireless card and connection software works with Windows XP, track the strength of received signals in dBm over time, sort by MAC address, SSID, Channel, RSSI, and time. This scanner was used in this measurement. Then Matlab was utilized to analyse the signal distribution and signal characteristics.

Access points inside each building that can support both IEEE 802.11b and 802.11g WLAN cards. There are total of from 34 to 182 access points placing to serve most area of each building. Three different areas inside building which were used for collecting samples of RSSI is the same device. Using the inSSIDer , samples of RSSI are collected nine hours for a total of more than 10000 samples at each location. The RSSI data is used to calculate statistic propertied and plot graph.

3. MEASUREMENT RESULTS

Many attempts to characterize the properties of indoor received signal strength were done with all kinds of way (K. Kaemarungsi and P. Krishnarmurthy 2004). The results provided preliminary guidelines to better guidelines to better understand the nature of RSSI from the indoor positioning systems perspective. However, the actual distribution of RSSI was not yet known. This study looks into a number of graphs collected in current work, and tries to impose a structure for RSSI’s distribution based on occurred measurement results.

3.1 Distributions of RSSI

Initially, the results obtained showed that the RSSI often exhibits a long tail as depicted in Figure 1. This appearance is called right-skewed distribution in other literature. But expect this, this study also notices that almost all received signals have two peaks as showed in Figure 1.

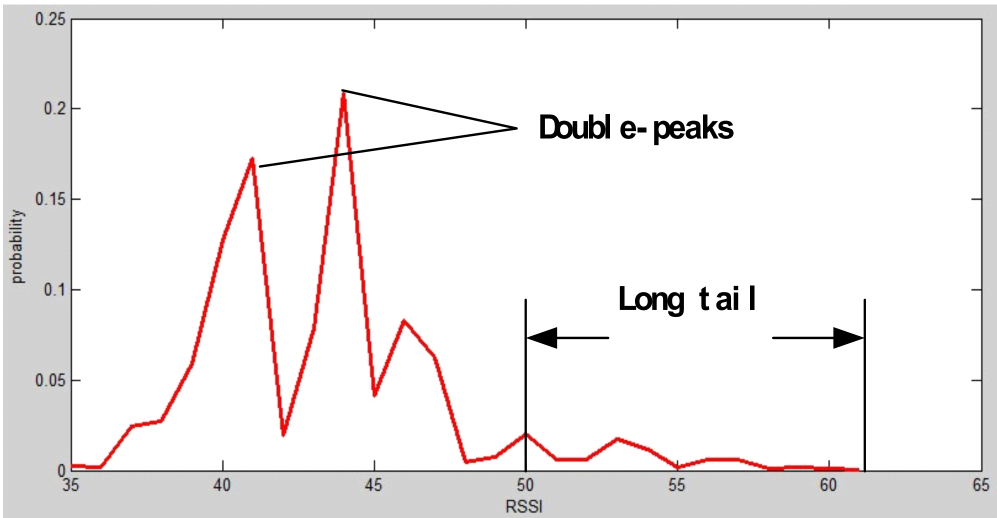


Figure 1. Distribution characteristics of signals

Note that this paper tries to explain for two appearances although the reason maybe is not the foremost or essential. Figure 2 illustrates the value distribution of received signals according to the order of time. The results in figure 2 were from the same data with figure 1, there have three parts that is the first peak, the second peak and the tail area. Another need noticed that the first peak data area and the second peak data area is separated by the mean of the data, and the tail data appears at start of receiving. If want to clear completely that requires additional investigation beyond the scope of the current study.

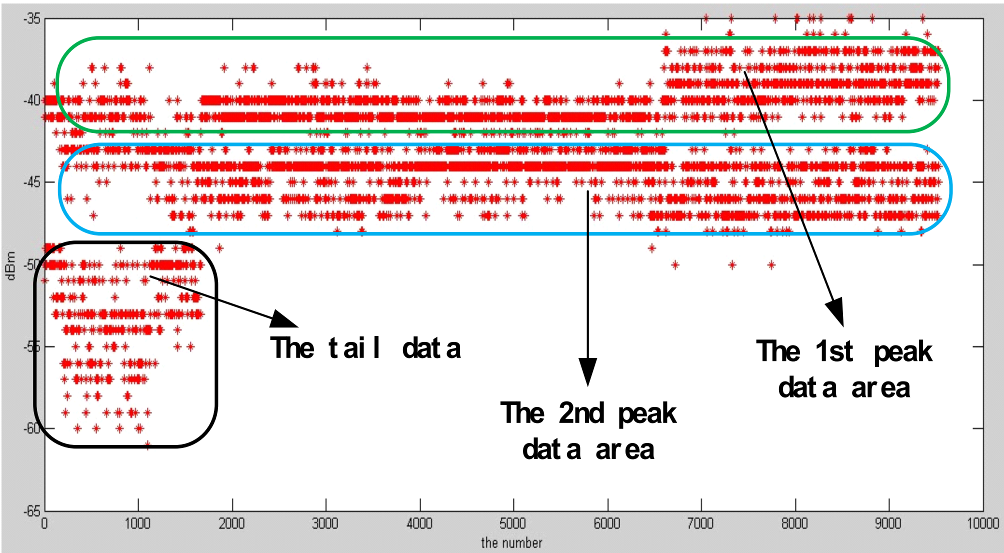


Figure 2. Time distribution of signals in Figure 1

3.2 Fingerprinting Positioning Dependency of RSSI

From theory of wireless communication, a signal of radio frequency attenuates over the distance that it travels. The mean of received signal strength at a receiver can be predicted by one of several path loss models (K. Pahlavan and P.Krishnamurth 2001). This distance dependency property is transformed into location dependency of RSSI when there are multiple signals from different access points in the area. The means of RSSI is often used as location fingerprint that provides unique pattern for location determination. The location dependency of RSSI has been investigated and confirmed (P. Dastro and P.Chiu et al, 2001; Saha and Chaudhuri et al, 2003). The probability density function of RSSI has significant effect for property of positioning. The distribution of RSS regarded as standard Gaussian distribution (M.A. Yousesf, 2004), another literature presents a solution using the Weibull function for approximating the distribution of signal strength (L. Pei and R. Chen et al, 2010). But above arithmetic did not think the characteristic of double-peaks and long tail of signal.

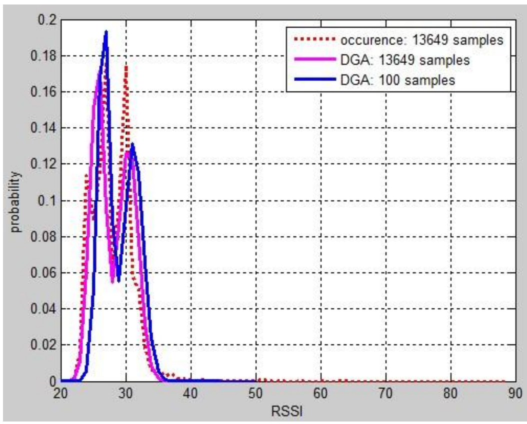
4. DOUBLE-PEAKS GAUSSIAN MODEL

The bin-based solution requires a large training data set in order to obtain a good estimate of the RSSI probability distribution. In this study, a new approach which called Double-peaks Gauss Arithmetic (DGA) was proposed to proximate the probability distribution of RSSI. Gauss function is a traditional method, its probability density function can be expressed as:

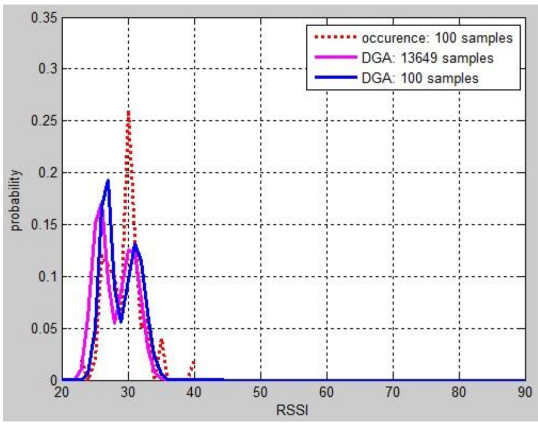
$$F(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(x-u)^2}{2\sigma^2}} \qquad (\sigma > 0) \qquad (1)$$

Where x is the variable of the function, u is the mean of x, and σ is the standard deviation of x. In this paper, the RSSI of each AP was divided into two parts according to the mean, then each part regarded as a Gaussian function, final to add the two functions. Using this approach, some experiment results brought out with the following.

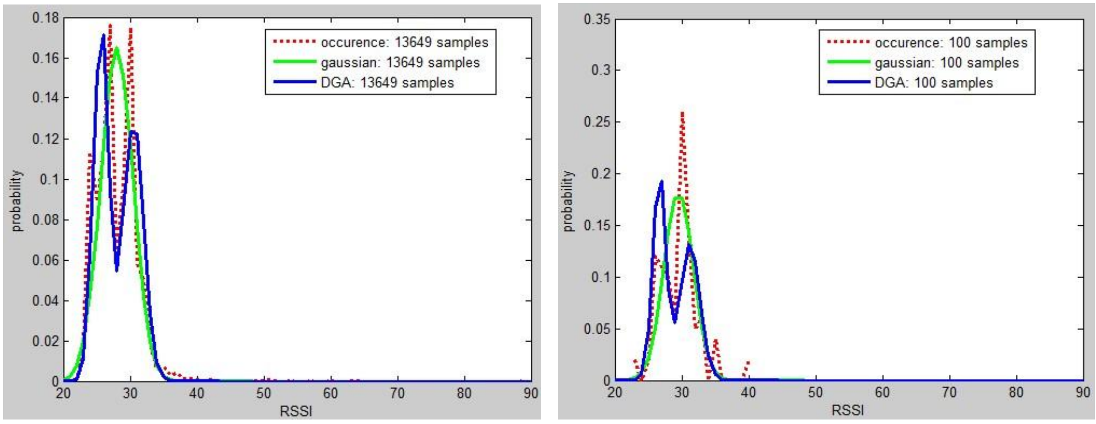
In figure 3 is comparison for office. Where (a) compared the probability distribution derived from a DGA using 13694 RSSI measurement samples and 100 RSSI samples randomly selected from the same data with the benchmark distribution of 13694 samples, (b) showed 100 RSSI using DGA, (c) and (d) compared using DGA and Gaussian with 13694 and 100 RSSI samples. With the same ways, figure 4 and figure 5 is the comparison for a building and a classroom.



(a)

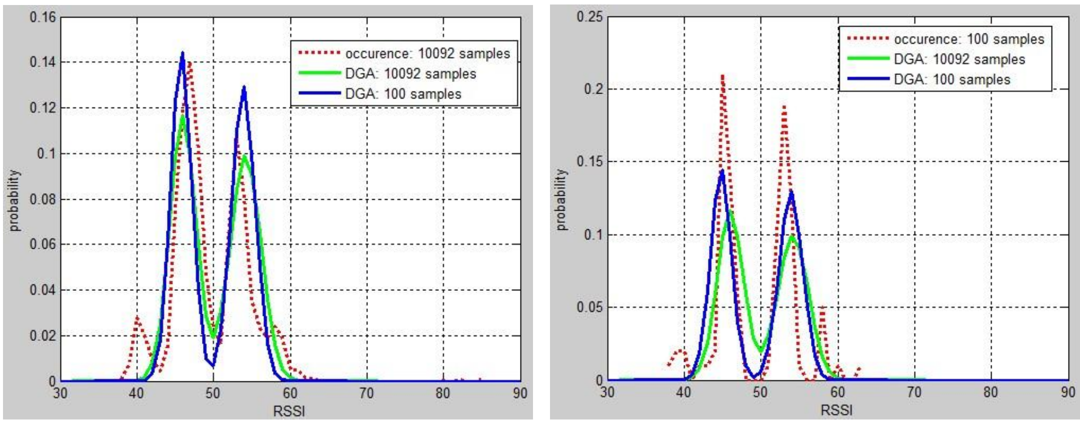


(b)

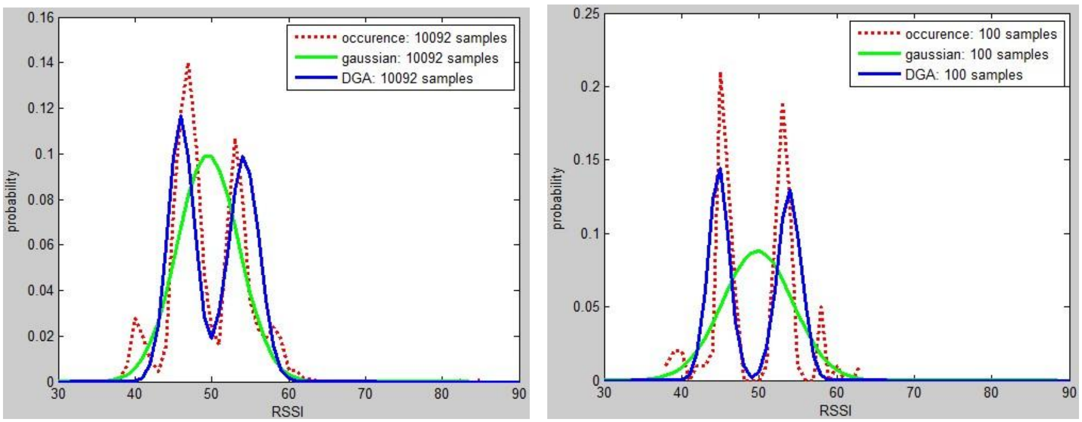


(c) (d)

Figure 3. Comparison of the probability distributions for office: (a) DGA vs. occurrence-based probability distribution with 13649 samples; (b) DGA vs. occurrence-based probability distribution with 100 samples; (c) DGA vs. Gaussian occurrence-based probability distribution with 13694 samples; (d) DGA vs. Gaussian occurrence-based probability distribution with 100 samples

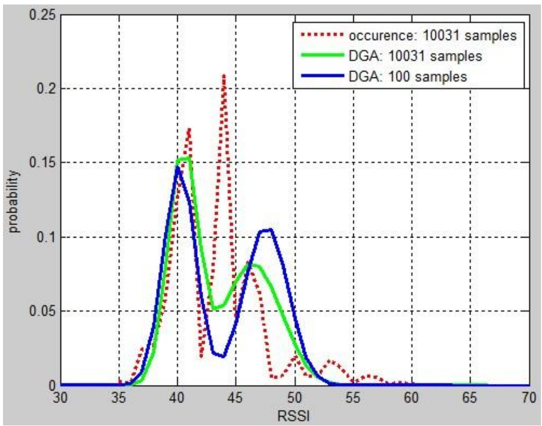


(a) (b)

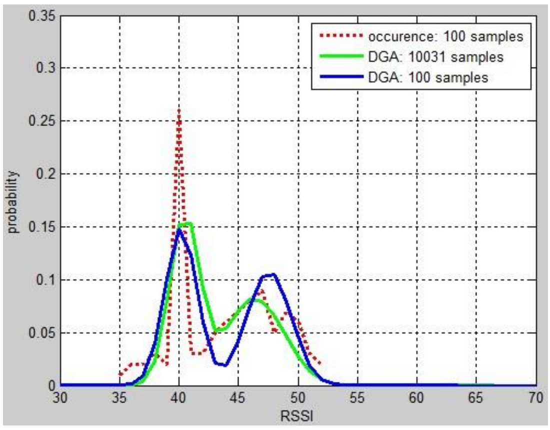


(c) (d)

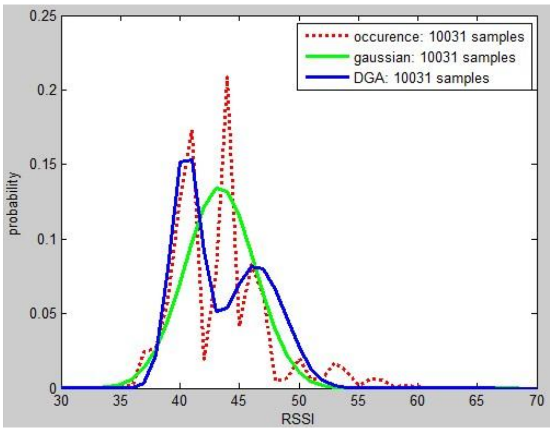
Figure 4. Comparison of the probability distributions for building: (a) DGA vs. occurrence-based probability distribution with 10092 samples; (b) DGA vs. occurrence-based probability distribution with 100 samples; (c) DGA vs. Gaussian occurrence-based probability distribution with 10092 samples; (d) DGA vs. Gaussian occurrence-based probability distribution with 100 samples



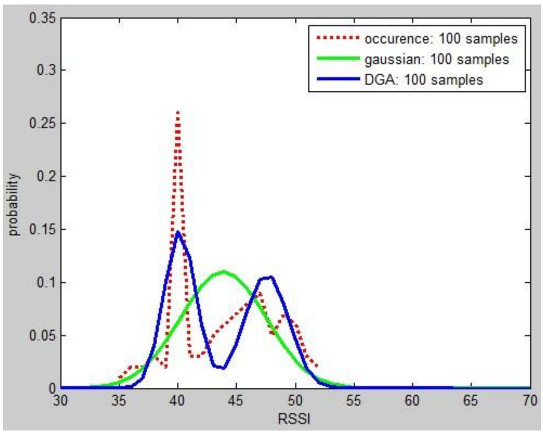
(a)



(b)



(c)



(d)

Figure 5. Comparison of the probability distributions for classroom: (a) DGA vs. occurrence-based probability distribution with 10031 samples; (b) DGA vs. occurrence-based probability distribution with 100 samples; (c) DGA vs. Gaussian occurrence-based probability distribution with 10031 samples; (d) DGA vs. Gaussian occurrence-based probability distribution with 100 samples

From figure 3 to figure 5, it is obvious that the shape of the double-peaks Gaussian function from more than 10000 or 100 RSSI samples is similar to that of actual distribution of RSSI. Another worth notice is that the DAG can better approximate the real distribution of RSSI than Gaussian.

5. CONCLUSIONS

Wi-Fi fingerprinting requires significant amount of labour and time to generate radio map. This paper enlightens a new approach to approximate the distribution of RSSI. The test result showed that RSSI probabilistic approach is a reasonable way for Wi-Fi indoor positioning. Using the double-peaks Gaussian arithmetic to instead probability distribution of RSSI can improve the reliability and accuracy of the fingerprint database than Gaussian. Since this model worked well even 100 the RSSI samples, the amount of work needed for generating the fingerprint database is reduced significantly. The study is for Wi-Fi indoor positioning, but the new approach can be extended and possibly be applied to other types of wireless signal.

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