

# Properties of Channel Interference for Wi-Fi Location Fingerprinting

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**Abstract**—Localization systems for indoor areas have recently been suggested that make use of existing wireless local area network (WLAN) infrastructure and location fingerprinting approach. However, most existing research work ignores channel interference between wireless infrastructures and this could affect accurate and precise positioning. A better understanding of the properties of channel interference could assist in improving the positioning accuracy while saving significant amounts of resources in the location-aware infrastructure. This paper investigates to what extent the positioning accuracy is affected by channel interference between access points. Two sets of experiments compare how the positioning accuracy is affected in three different channel assignment schemes: ad-hoc, sequential, and orthogonal data is analyzed to understand what features of channel interference affect positioning accuracy. The results show that choosing an appropriate channel assignment scheme could make localization 10% more accurate and reduces the number of access points that are required by 15%. The experimental analysis also indicates that the channel interference usually obeys a right-skewed distribution and positioning accuracy is heavily dependent on channel interference between access points (APs).

**Index Terms**—Indoor positioning, Channel Interference, Location Fingerprinting

## I. INTRODUCTION

WIRELESS Local Area Networks (WLANs) are often deployed on a large-scale in a wide range of urban environments. Covering a very large urban environment requires that thousands of access points be placed and installed properly, without interference. The basic requirements of an effective WLAN are, first, adequate coverage where users wish to access location-aware (e.g., pervasive computing-enabled) applications and services. Second, the WLAN should allow accurate localization of mobile devices. The deployment of the network should reduce the interference as much as possible so as to achieve these functions in a cost-effective and resource-efficient manner.

Unfortunately, access points (APs) are usually deployed in an empirical way, manually placed and positioned on the basis of measurements of RSS (received signal strength) taken by engineers. Such an unstructured approach to WLAN infrastructure design implies poor resource utilization and strong channel interference. [1] For example, more APs may be used to improve coverage but this may still leave blind spots or places where there are too many access points packed

too closely together. This can lead to signal overlap, which is wasteful and causes interference.

Location-Fingerprinting-based approaches [1][2][3][4][5][6] locate a device by comparing its coordinates with the received signal strengths (RSSs) and coordinates of other devices within the Wi-Fi footprint as held in an LF database. More specifically, the LF approach requires the collection of data  $\{(\mathbf{Y}_n, C_i), i = 1 \dots N\}$ , for  $N$  locations in an area, where  $C_i$  is the known location of the  $i$ 'th measurement and  $\mathbf{Y}_i = (\mathbf{Y}_{i1}, \dots, \mathbf{Y}_{iN})$  is the received signal strength (RSS) vector when the transmitter is at  $C_i$ . The vector  $\mathbf{Y}_i$  is the "fingerprint" of the location  $C_i$ . When a new fingerprint  $\mathbf{Y}$  is derived from a transmitter at an unknown location  $A$ , I can locate  $A$  by searching for the fingerprint  $\mathbf{Y}_i$  that is closest to  $\mathbf{Y}$  in say  $d$  distance and estimate the location with the corresponding  $C_i$ . The drawbacks of the LF approach are (1) LF requires an initially survey with a very large training dataset and (2) LF is very sensitive to signal fluctuation due to the changes of infrastructure of buildings and channel interference among APs leading to inaccurate positioning.

The IEEE 802.11 standard establishes several requirements for radio frequency transmission, including the canalization schemes and the spectrum radiation of the signal.[7] In IEEE 802.11 b/g WLAN, there are 14 channels. In North America, the 2.4GHz frequency ISM band is divided into 11 channels. Each channel is spread over 22 MHz due to the Direct Sequence Spread Spectrum (DSSS) technique employed by IEEE 802.11b/g. These channels have only five MHz of center frequency separation. Channel interference occurs because frequency spectrum is shared with each adjacent channel. Recent research has focused on reducing channel interference by either creating a new channel assignment scheme [8][9][10] or enhancing existing MAC protocols [11][12] The goal is to improve the data transmission through wireless networks. However, none of existing work on channel interference has focused on the accuracy of the location estimation algorithm. Some researchers have even maintained that interference could increase positioning accuracy.

This paper investigates the influence of channel interference in a location fingerprinting approach. The study of channel interference is essential for accurate indoor positioning system. This paper also describes localization experiments and simulations on the IEEE 802.11 test-bed and investigates the channel assignment of APs, the distribution of received signal strength (RSS) values, the variation of coverage, and distances between APs. The analysis of these features provide insights into how to assign channels, how to space APs so

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as to reduce interference, and how many access points are required to uniquely identify a location at a given accuracy and precision. The results would be of interest and assistance to engineers designing WLAN channel assignments specifically for positioning.

The rest of this paper is organized as follows: Section II describes related work on the deployment of positioning systems, modeling of wireless signal strength properties and infrastructure design of Wi-Fi Network. Section III describes the reason and algorithms of overlapping channel interference. Section IV describes the positioning methodology. Section V defines the characteristics of channel interference metrics. Section VI presents the experiment and result on channel interference matrix. Section VII presents the experiment and result on the effect of channel interference to positioning accuracy. Finally, Section VIII offers our conclusion and future work.

## II. RELATED WORK

In this section, we summarize current research works on positioning systems, modeling of wireless signal strength properties and infrastructure design of Wi-Fi Network.

### A. Positioning Systems

Acoustic [13][14][15], light-based and global positioning systems are most effective in relatively open and flat outdoor environments but are much less effective non-line-of-sight (NLOS) environments such as hilly, mountainous or built-up areas. Moreover, most acoustic localization applications not only require the sound source to have a high intensity and to be continuously propagated, they also are limited to localizing only within the area covered by the sound. The drawbacks of light-based localization approaches include their dependence on contrast of the background light intensity [14][16]. Sequential Monte Carlo (SMC) approaches [17][16] need to have many sampling, weighting and filtering steps to have updated distribution of sensors. After building an overview of sensors' distribution, the sensor estimates its location by the weighted average of all samples. It is not effective and has high computational cost in sensor networks.

The task of localization is not limited to above approaches but is also carried out on other types of networks, in particular, on Wi-Fi - IEEE 802.11b. Wi-Fi networks are increasingly ubiquitous in public places, for example, airports, malls, cafes, campuses, and even public squares. They are fuelling a wide range of location-aware computing applications. Currently, Wi-Fi-enabled devices can be located by applying one of two types of location-sensing approaches, propagation-based [18][19][20] and location-fingerprinting-based (LF)[5][1][19].

Propagation-based approaches measure the received signal strength (RSS), angle of arrival (AOA), or time difference of arrival (TDOA) of received signals and apply mathematical models to determine the location of the device. The drawbacks of propagation-based approaches are needed to compute every condition that can cause wave signal to blend in order to achieve accurate localization. These approaches majorly suffer from signal fluctuation and channel interference. Channel

interference worsens the positioning accuracy and increases the computational complexity.

LF-based approach allows a person to locate himself by using a device to access a database containing the fingerprint (i.e., the RSSs and coordinates) of other devices within the Wi-Fi footprint and then calculate its own coordinates by comparing with the LF database. The drawbacks of LF approach are needed to have extensive training dataset surveying and highly affected by the changing of internal building infrastructure, presence of humans and interference among devices leading to inaccurate localization. These issues have been addressed in our previous work [21].

### B. Modeling of Wireless Signal Strength Properties

The modeling of wireless signal strength properties [2][6] is crucial to deploying efficient indoor positioning systems. Analytical models can be used to improve the design of positioning systems. For example, by eliminating the installation of Wi-Fi access points and shortening the sampling time of Wi-Fi received signal strength (RSS) in location estimation. Yet, we currently lack an analytical model that might be used as a framework for designing and deploying positioning systems. Such an analytical model should have spatial elements to visualize the RSS distribution and to evaluate and predict "precision" performance of indoor positioning systems based on location fingerprinting. Such a model could be used to improve the design of positioning systems, for example by eliminating some fingerprints and reducing the size of the location fingerprint database. Our previous work [22] and [23] made use of fuzzy logic and topographic mapping techniques to visualize the received signal strength (RSS) but did not investigate how channel interference affects positioning accuracy. Most existing research in channel interference has focused on improving wireless data transmission [11][12] and channel assignment [8][9][10]. The study on the relationship between channel interference and positioning accuracy has been insufficient.

### C. Infrastructure Design of Wi-Fi Network

WLANs are made up of many access points (APs) or nodes. These access points (APs) are manually placed and positioned on the basis of measurements of RSS (received signal strength) taken by engineers empirically. An unstructured approach to WLAN infrastructure design implies poor resource utilization. [1] as extra APs may be used to improve coverage but this may still leave blind spots or places where there are too many access points packed too closely together. This can lead to signal overlap, which is both wasteful and causes interference. As long as an ad-hoc approach is used, it is not possible to estimate in advance how many APs are optimally required for localization or where they should be placed. In our previous work [24] and [25], we addressed this issue and proposed a more structured approach which would produce economies of scale and efficiencies as well as improved localization capabilities. However, different Wi-Fi infrastructure designs could cause different patterns of channel interference and to date there has been no in-depth study of how channel interference might affect positioning accuracy.

### III. OVERLAPPING CHANNEL INTERFERENCE

The bandwidth of wireless network is limited because of the property of wireless networks and stations have to share the limited bandwidth. [26] IEEE 802.11b/g has 14 overlapping frequency channels. Channel 1, 6 and 11 are non-overlapping channels.

As shown in 1, IEEE 802.11 b/g spreads through 2,401 MHz to 2,483 MHz. Each channel spreads over 22 MHz. Two adjacent channels are separated only by 5 MHz such that most of existing channels are overlapped.

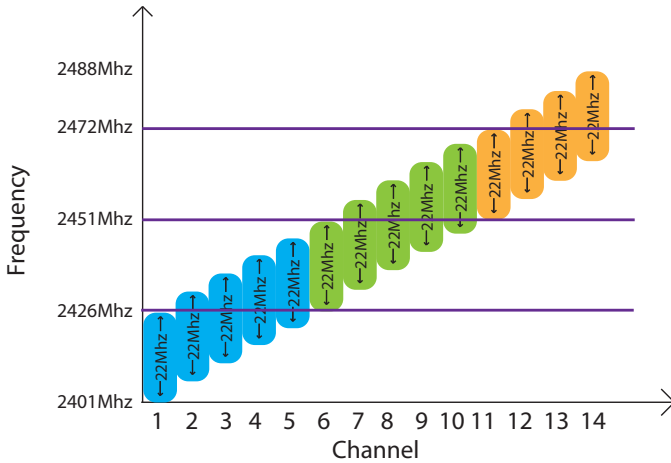


Fig. 1. IEEE 802.11b/g Frequency Spectrum to Channel Number

#### A. Interference-level Function

The interference-level function  $\gamma$  is defined as follows:

$$\gamma(\Delta c) = \max(0, 1 - k\Delta c) \quad (1)$$

where  $\Delta c$  is the absolute channel difference and  $k$  is the non-overlapping ratio of two channels.  $\gamma$  and  $\Delta c$  are in Db unit. When  $\Delta c$  increases,  $\gamma$  decreases. For example, if  $\Delta c = 0$ , then  $\gamma(\Delta c) = 1$  and if  $\Delta c \geq 5$ , then  $\gamma(\Delta c) = 0$ . In other words, for channel 1 and 6,  $\Delta c = 5$ ,  $k = 0$ , then  $\gamma(\Delta c) = 0$ , suggesting no interference. In real case, if APs are installed far enough with others,  $\gamma$  should be at least equal to the above threshold.

#### B. Signal Propagation Loss Algorithm

Signal propagation loss algorithm [5][18][20] calculates the received signal strength (RSS) with path loss as follows:

$$R = r - 10\alpha \log_{10}(d) - wallLoss \quad (2)$$

where  $r$  is initial RSS,  $d$  is a distance from APs to a location,  $\alpha$  is the path loss exponent (clutter density factor) and  $wallLoss$  is the sum of the losses introduced by each wall on the line segment drawn at Euclidean distance  $d$ .

Initially,  $r$  is the initial RSS at the reference distance of  $d_0$  is 1 meter (this is 41.5 dBm for LOS propagation and for 37.3 dBm NLOS propagation for some report measurement). The path loss exponent  $\alpha$  at a carrier frequency of 2.4 GHz

is reported to be 2 for LOS propagation and 3.3 for NLOS propagation [7]. Under other circumstances,  $\alpha$  can be between 1 and 6.

#### C. Signal-to-Interference-plus-Noise-Ratio

Signal-to-Interference-plus-Noise-Ratio (SINR) is a very common indicator to measure interference. SINR is defined as follows:

$$SINR = \frac{R_b}{\gamma(\Delta c) \sum R + n} \quad (3)$$

where  $R_b$  is the highest RSS after path loss calculation.  $R$  is the remaining set of RSS after path loss calculation.  $n$  is the noise signal strength.  $R_b$ ,  $R$ ,  $n$  are in dBm unit. Usually,  $n$  should have the value of -100dbm. Again SINR should be at least equal to above calculated threshold which depends on the distance among APs, the transmission rate, the modulation scheme and the required bit-error rate.

### IV. POSITIONING METHODOLOGIES

Two positioning methodologies are typically applied in WLANs, propagation based approaches and location fingerprinting (LF). Our previous works [21][27] make use of LF to track a WLAN-enabled device. In our later simulations we will use only LF approach. As accuracy obtained using LF approach will also be obtained using a propagation-based approach but for completeness in the following we briefly describe both.

#### A. Propagation-based Approach

Propagation-based approaches measure the received signal strength (RSS), angle of arrival (AOA), or time difference of arrival (TDOA) of received signals and apply mathematical models a set of triangulation algorithms to determine the location of the device.

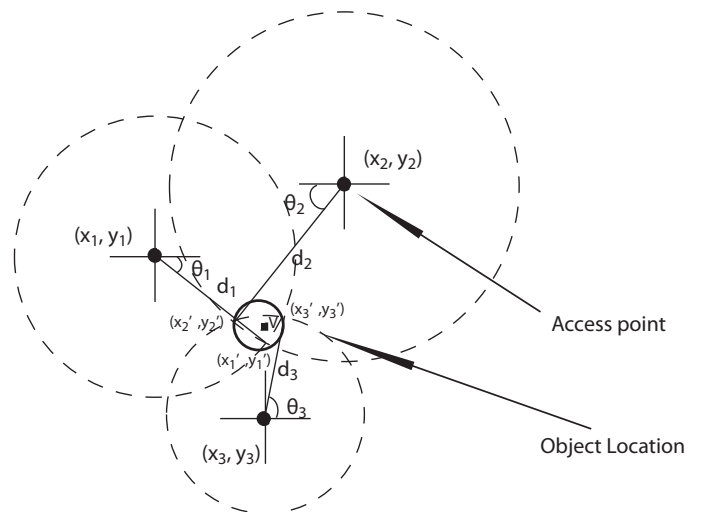


Fig. 2. Triangular Algorithm

The triangular positioning algorithm uses trigonometry and geometry to compute the locations of objects. In a 2D environment, this requires three access points (APs). The locations of

these three APs' location are denoted as  $(x_1, y_1)$ ,  $(x_2, y_2)$ ,  $(x_3, y_3)$  and the object location is  $(x, y)$ . Using the propagation-based theorem in (2), we can denote the distance between the access points and object location as  $d_1$ ,  $d_2$ , and  $d_3$ , where  $d_0$  is the initial RSS at the reference distance. To estimate the location of the object, we use the tri-lateration method as follow.

$$\begin{cases} d_1 = d_0 10^{\frac{r_0 - r_1 - \text{wallLoss}}{10 \cdot \alpha}} \\ d_2 = d_0 10^{\frac{r_0 - r_2 - \text{wallLoss}}{10 \cdot \alpha}} \\ d_3 = d_0 10^{\frac{r_0 - r_3 - \text{wallLoss}}{10 \cdot \alpha}} \end{cases} \quad (4)$$

Initially,  $r_0$  is the initial RSS at the reference distance of  $d_0$  is 1 meter (this is 41.5 dBm for LOS propagation and for 37.3 dBm NLOS propagation for some report measurement) [28]. The path loss exponent  $\alpha$  at a carrier frequency of 2.4 GHz is reported to be 2 for LOS propagation and 3.3 for NLOS propagation [5]. Under other circumstances, can be between 1 and 6.

After calculating the distance, we find the angle  $\theta_1$ ,  $\theta_2$  and  $\theta_3$  between the object location and APs, and then we are able to calculate the possible location matrix of the object as follows:

$$\begin{pmatrix} x'_1 & y'_1 \\ x'_2 & y'_2 \\ x'_3 & y'_3 \end{pmatrix} = \begin{pmatrix} x_1 + d_1 \cos \theta_1 & y_1 + d_1 \sin \theta_1 \\ x_2 + d_2 \cos \theta_2 & y_2 + d_2 \sin \theta_2 \\ x_3 + d_3 \cos \theta_3 & y_3 + d_3 \sin \theta_3 \end{pmatrix} \quad (5)$$

### B. Location Fingerprinting Approach

There are two Location Fingerprinting approaches, the K-Nearest Neighbor (K-NN) and the probabilistic approach.

1) *K-Nearest Neighbor Location Fingerprinting Approach:* The K-Nearest Neighbor (K-NN) algorithm requires two sets of data. The first set of data is the samples of RSS from  $N$  APs in the area. Each element in a vector is an independent RSS (in dBm) collected from APs in the location. The second set of data contains all of the average RSS from  $N$  APs at a particular location. This second dataset forms the location fingerprinting database.  $F = \{f_1 \dots f_n | f_i \in \mathfrak{R}^n\}$  is a set of sampling LF vectors in database. We estimate the location  $d_k$  by clustering the Euclidean distance  $|r - f_i|$  between current received LF vector  $r$  and sampling LF vector  $f_i$  with position  $d_i$  as

$$d = \frac{\sum_{i=0}^n \frac{d_i}{|r - f_i|}}{\sum_{i=0}^n \frac{1}{|r - f_i|}} \quad (6)$$

2) *Probabilistic Location Fingerprinting:* Probabilistic LF applies Baye's theorem to calculate the most probable location out of the pre-recorded LF database,  $F = [f_1, f_2, f_3 \dots f_N]$ . We can estimate  $d$  by

$$\arg \max_d [P(d/F)] = \arg \max_d \left[ \frac{P(F/d) P(d)}{P(F)} \right] \quad (7)$$

Since  $P(F)$  is constant for all  $d$ , the algorithm can be rewritten as:

$$\arg \max_d [P(d/F)] = \arg \max_d [P(F/d) P(d)] \quad (8)$$

As  $P(d)$  can be factored out from the maximization process, the probabilistic positioning algorithm is as

$$P(F/d) = \prod_{i=1}^N P(f_i/d) \quad (9)$$

We make use of probabilistic location fingerprinting to estimate the position in our later part of experiment and simulation.

## V. CHARACTERIZATION OF CHANNEL INTERFERENCE METRIC

This section investigates whether interference is normally or log normally distributed. The signal difference between the preset (maximum) RSS value of AP and sample RSS of an AP could be seen as interference strength value (in dB). Two APs are placed and interfere with each other. We assume that there is a zero (or very short) distance between receiver and APs, In other words, the signal should not be reduced by propagation-loss. The preset RSS value is denoted by  $\rho$  and the interference strength value by  $F = \{f_1, f_2, \dots, f_n\}$ . The interference could then be by:

$$Y = \sqrt{\sum_{i=1}^n (\rho - r_i)^2} = \sqrt{\sum_{i=1}^n f_i^2} \quad (10)$$

where  $n$  represents the number of collected sample. In (10), the difference between a preset RSS value and measured RSS,  $r_i$  considered to be a signal interference strength. In fact, the random variable of interference  $f_i$  should have a zero mean if and only if the wireless RSS obeys a normal distribution. In other words, the random variable of interference  $f_i$  has a non-zero mean when the wireless RSS does not obey a normal distribution.

It is assumed that the random variable  $X = Y^2$  where the random variable  $X$  is the square of the difference between the sample RSS and the preset RSS. Assuming that the RSS is normally distributed, the random variable  $X = Y^2$  has a central chi-squared distribution with  $n$  degrees of freedom, i.e.  $E\{r_i\} = \rho$  or the mean of sample RSS is equal to a preset RSS value. Thus, the difference-squared  $f_i$  obeys a zero mean Gaussian distribution. A probability density function (PDF) of  $X$  will be the chi-square distribution:

$$P_{X_n^2}(x) = \frac{1}{2^{\frac{n}{2}} \sigma^n \Gamma(\frac{n}{2})} x^{\frac{n}{2}-1} e^{-\frac{x}{2\sigma^2}} \quad (11)$$

where the variance of each Gaussian component in  $X$  is  $\sigma^2$ , and  $\Gamma$  denotes Gamma function which has closed-form values at the half-integers.

However, in some real-world scenarios, the distribution of the RSS is not usually Gaussian and it is often left-skewed. The standard deviation for this real distribution varies according to

the signal level. This has been verified in [29]. Actually, the distribution of the RSS is a non-central chi-squared distribution. In this case, the random variable of interference  $f_i$  will have a non-zero mean equal to  $\mu = \rho - E\{r_i\}$ .

Here,  $\lambda$  is defined as a non-centrality parameter of the non-central chi-squared distribution. Parameter  $\lambda$  could be defined as  $\lambda = \sum_{i=1}^n \mu_i^2$ . A larger value of  $\lambda$  indicates that some regions are experiencing higher signal interference. The PDF of non-central chi-square distribution is seen to be a Poisson-weight mixture of central chi-squared distribution. It could be defined by:

$$P_X(x; n, \lambda) = \sum_{i=0}^{\infty} \frac{e^{-\lambda/2\sigma^2} (\lambda/2\sigma^2)^i}{i!} P_{P_{X_n^2}(n+2i)}(x) \quad (12)$$

Alternatively, the PDF can be written as

$$P_X(x; n, \lambda) = \frac{1}{2\sigma^2} e^{-\frac{x+\lambda}{2\sigma^2}} \left(\frac{x}{\lambda}\right)^{\frac{n-2}{4}} I_{\frac{n-2}{2}}\left(\frac{\sqrt{\lambda x}}{\sigma^2}\right) \quad (13)$$

where  $I_k(x)$  is the  $k$ th-order modified Bessel function of the first kind given by

$$I_k(x) = \left(\frac{x}{2}\right)^k \sum_{i=0}^{\infty} \frac{x^{2i}}{4^i i! \Gamma(k+i+1)} \quad (14)$$

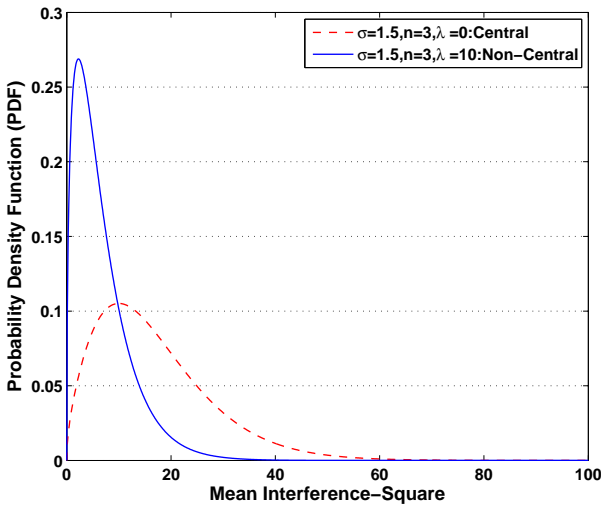


Fig. 3. Theoretical comparison of the PDFs of central and non-central chi-squared distribution of interference under  $\sigma = 1.5$ ,  $n = 3$

In Figure 3 we have the theoretical distribution formed by (11) and (13). The dotted purple line represents the central chi-squared distribution used by (11). The blue line represents a non-central chi-squared distribution used by (13). As can be seen, the use of a central chi-square distribution produces a more evenly distributed interference-square. In other words, the strength of the interference fluctuates widely. When  $\sigma = 1.5$ ,  $n = 3$ , the interference-square of the non-central distribution would be mostly around 10. When a non-central distribution is used, the distribution is skewed more to the right

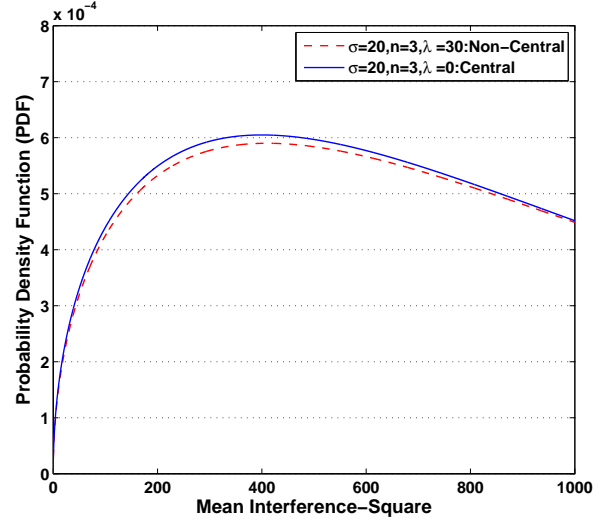


Fig. 4. Theoretical comparison of the PDFs of central and non-central chi-squared distribution of interference under  $\sigma = 20$ ,  $n = 3$

and interference strength is more likely to be a smaller value. When  $\sigma = 1.5$ ,  $n = 3$  and  $\lambda = 10$ , the interference-square of non-central distribution would be mostly at 4.

Figure 4 shows the PDF versus mean interference-square under  $\sigma = 20$ ,  $n = 3$ . The non-central and central chi-square becomes very similar when the standard deviation of the received signal strength has a larger value. This indicates that the larger standard deviation of received signal strength causes the mean interference-square of central and non-central chi-distribution to move closer together.

In conclusion, depending on whether RSS is a central or non-central normal distribution, the interference distribution could be defined by either (11) or (13). Having said this, it should also be noted that experiments with RSS distributions could vary, with some experiment results showing that RSS obeys a normal distribution and some showing otherwise. To our knowledge, however, the distribution of interference has not yet been studied. The later experimental section will show that interference usually follows the distribution described in (13).

## VI. EXPERIMENT & RESULT ON CHANNEL INTERFERENCE METRIC

The following section describes an experiment on channel interference metrics and discusses the experiment results. The purpose of the experiment is to determine whether interference distribution obeys a normal, mean chi-square, or non-mean chi-square distribution.

The experiment places two APs within a short distance of an RSS receiver. The assumption is that all signal fluctuations are caused by interference between two APs. Two APs were set to the same channel and emitted a WLAN signal at the maximum strength -70dBm. A receiver recorded 1,000 samples of signal strength from two APs over two hours. The sample result was compared using (11) and (13). Table I summarizes the

TABLE I  
EXPERIMENT SETTINGS (SET A)

Item	Description
Number of APs	2 APs
Sampling time	2 hours
Samples of Signal Strength	1,000
Wi-Fi coverage from each APs	80 meters
Range of signal strength	-70dBm to -30dBm

experimental settings of Set A. Two parameters,  $\sigma$  and  $\lambda$  are input to adjust the shape of the distribution curve.  $\sigma$  is the standard distribution of interference.  $\lambda$  is a non-centrality parameter.

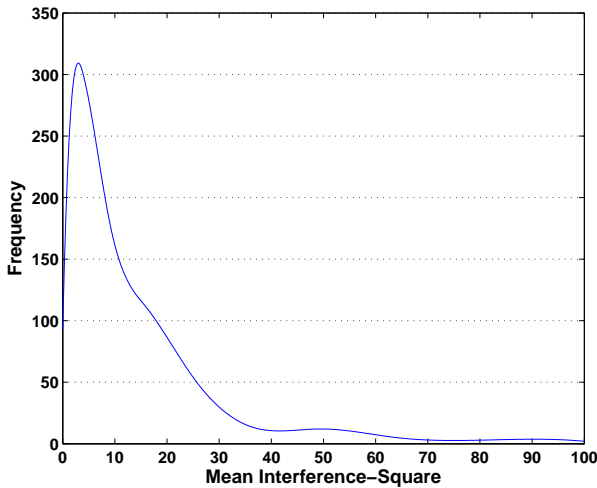


Fig. 5. Result of Frequency to Mean Interference-Square experiment

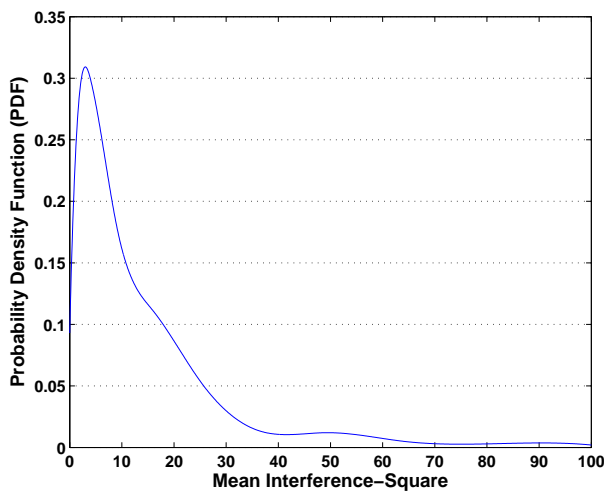


Fig. 6. Result of PDF to Mean Interference-Square experiment

Section V discussed the theoretical distribution of interference. Here, it is compared with the actual experimental result. Figure 5 shows the relationship of the mean interference-square to frequency. Along the Y-axis, frequency represents the

TABLE II  
EXPERIMENT SETTINGS (SET B)

Item	Description
Total area	150m x 100m
Number of APs	9 APs
Positioning resolution	3 meters
Wi-Fi coverage from each APs	80 meters
Range of signal strength	-85dBm to -30dBm

number of occurrences of a particular value of the interference-square. The interference-square is mostly at 7 and is a right-skewed distribution.

Figure 6 shows the relationship of the mean interference-square to the probability density function (pdf). As can be seen in Figure 6, it is again a right-skewed distribution. A smaller value for the mean interference-square means a larger value of the pdf. When the mean interference-square is 4, the pdf has the largest value of 0.31.

In following paragraphs, we could now further discuss on the impact of parameters of the interference based on the visual results presented so far. The visual results so far suggest that interference is a random variable if the received signal strengths from APs are also all random variables. Intuitively this makes sense. The results in these experiments indicate that the interference mostly occurs in a right-skewed distribution, which implies a smaller value for the mean interference-square. It also shows that a non-central chi-distribution (13) could represent the distribution of interference. It would be ideal to have less interference and a smaller fluctuation. The above work helps to understand the features of interference and it could be used to decide a better positioning system.

The following sections will continue to look at some factors that affect interference: channel assignment, number of APs, the SINR value, and distribution of location uncertainty.

## VII. THE EFFECT OF CHANNEL INTERFERENCE ON POSITIONING ACCURACY: EXPERIMENT AND RESULTS

This section describes experiments on the effect of channel interference on positioning accuracy. The experiments were conducted in a 150m X 100m testing area. Accuracy was measured using only the probabilistic LF approach, which is defined by (9). The radius of coverage of each AP is 80m. The signal strength ranges between -85dBm and -30dBm. The positioning resolution is set to three meters. Table II summarizes the experiment settings of Set B.

The following discusses the results and compares the positioning accuracy under three typical channel allocation schemes. Subsection A looks at the impact of channel interference on positioning accuracy. Subsection B investigates the positioning accuracy by varying the number of access points under different channel allocations. Subsections C and D look at how channel interference is affected by varying the number of APs and SINR values.

### A. Effect of Interference on the positioning accuracy

Figure 7 shows the relationship of channel interference to positioning accuracy. In order to see how channel interference

affects positioning accuracy specifically, the number of APs is set to 13. The channel interference is varied from 0 to 25 dBm and the accuracy is in a scale from 0 to 1 (1 represents 100% accuracy). The three different channel allocations do not have major difference of positioning accuracy when the interference value is still small. When the interference strength increases above 15dBm, positioning accuracy deteriorates seriously. It is thus clear that when channel interference increases, the positioning accuracy decreases. However, this interference value is difficult to control because it depends on the environment. One way of improving this is to take more iteration. As can be seen in Figure 7, the positioning performance of orthogonal channel allocation is the most accurate. This result indicates that orthogonal channel allocation is 10% more accurate when the system is burdened with high channel interference.

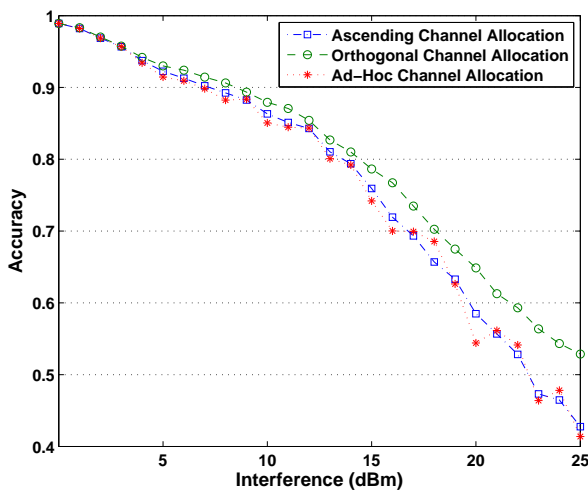


Fig. 7. Relationship of interference to accuracy under ascending, orthogonal and ad-hoc channel allocation

### B. Effect of number of APs on the positioning accuracy

This section considers the impact of the number of APs. Figure 8 shows the relationship of the number of access points to accuracy using each of the three allocation schemes. The resolution is 2m. A higher number of APs improves the precision dramatically up to the point that nine APs are used. If more than nine APs are used, the accuracy does not increase significantly due to the interference between them.

The channel interference between APs increases when the number of APs increases. Figure 8 shows that orthogonal channel allocation with only nine APs achieve 90% accuracy. Perhaps the most important point to note is that orthogonal channel allocation could require 15% fewer APs than either ascending channel allocation or ad-hoc channel allocation. Again, the smaller the interference is, the more accurate the positioning is. This is because orthogonal channel allocation provides less interference than the other two channel allocations. The next subsection further investigates this issue.

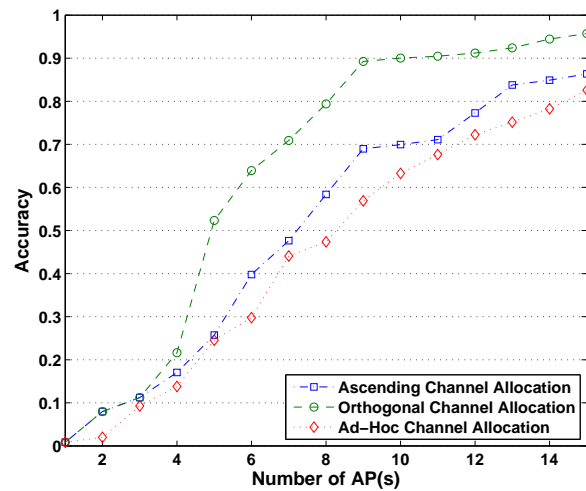


Fig. 8. Relationship of number of access points to accuracy under ascending, orthogonal and ad-hoc channel allocation

### C. Effect of number of APs on the interference

Figure 9 shows the relationship of the number of APs to interference. The result suggests that more APs cause in more interference. Orthogonal channel allocation is associated with less interference in any case, an average of 10.9 dBm, whereas ascending channel allocation and ad-hoc channel allocation respectively average of 13.1 dBm and 14.24 dBm of interference.

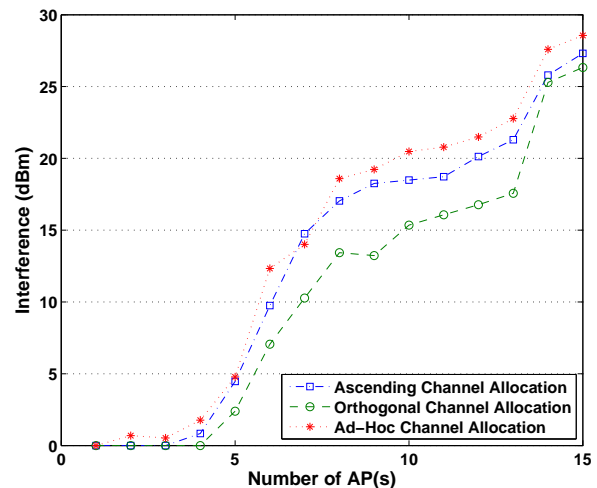


Fig. 9. Relationship of number of APs to interference under ascending, orthogonal and ad-hoc channel allocation

### D. Effect of Signal-to-Interference-plus-Noise-Ratio on the positioning accuracy

In order to see how SINR affects the positioning accuracy, the number of APs is set to 13. The SINR is varied from 0 to 1 and the accuracy was in a scale from 0 to 1 (1 represents 100% accuracy). Figure 10 shows the relationship of SINR to

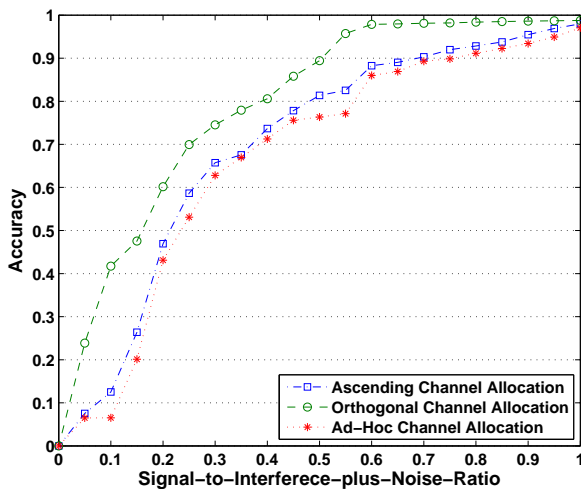


Fig. 10. Relationship of Signal-to-Interference-plus-Noise-Ratio to accuracy under ascending, orthogonal and ad-hoc channel allocation

positioning accuracy. The result indicates that the higher the value of SINR, the more accurate the positioning. Orthogonal channel allocation has the best positioning performance and was 8% more accurate than the other two channel allocations.

## VIII. CONCLUSION

We present a comprehensive analysis of the channel interference to positioning accuracy based on location fingerprinting. The result indicates that channel interference would worsen the positioning accuracy. Higher channel interference implies less accurate positioning. We clear from falsehood that interference could help to achieve more accurate positioning. From our experiment, channel interference among APs using same frequency channel have a significant (worsening) impact on the positioning system. Our experimental analysis also verifies that the channel interference usually obeys a right-skewed distribution. This verification helps to model the environment of channel interference virtually.

The effect of channel interference to positioning accuracy depends on number of APs, SINR and channel assignment scheme. A higher number of APs gives more accurate positioning. Moreover, as the number of APs increases, the channel interferences among APs increase and decrease the rate of increasing positioning accuracy. We also point out that a higher value of SINR is, more accurate positioning could be achieved. In this paper, we emphasize that channel assignment is critical issue to positioning system. Choosing orthogonal channel allocation could save 15% of APs and meanwhile achieve 10% more accurate positioning in average. The results in this paper provide more insight on the stable and robust indoor positioning system based on LF. Our studies address that the positioning accuracy is seriously dependent on channel interference. Thus, reducing channel interference is essential to improve the positioning accuracy and meanwhile could save significant amount of resources of localization infrastructure.

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## REFERENCES

- [1] C. Budianu, S. Ben-David, and L. Tong, "Estimation of the number of operating sensors in large-scale sensor networks with mobile access," *IEEE Transactions on Signal Processing*, pp. 1703–1715, 2006.
- [2] N. Swangmuang and P. Krishnamurthy, "Location Fingerprint Analyses Toward Efficient Indoor Positioning," *The 6th IEEE International Conference on Pervasive Computing and Communications*, pp. 101–109, 2008.
- [3] M. B. Kjaergaard and C. V. Munk, "Hyperbolic Location Fingerprinting—A Calibration-Free Solution for Handling Differences in Signal Strength," *The 6th IEEE International Conference on Pervasive Computing and Communications*, pp. 110–116, 2008.
- [4] S. Fang, T. Lin, and P. Lin, "Location Fingerprinting In A Decorrelated Space," *IEEE Transactions on Knowledge and Data Engineering*, vol. 20, no. 5, pp. 685–691, 2008.
- [5] B. Li, Y. Wang, H. Lee, A. Dempster, and C. Rizos, "Method for yielding a database of location fingerprints in WLAN," *IEEE Proceedings on Communications*, vol. 152, no. 5, pp. 580–586, 2005.
- [6] K. Kaemarungsi and P. Krishnamurthy, "Modeling of indoor positioning systems based on location fingerprinting," *The 23th Conference IEEE Computer and Communications Societies*, vol. 2, 2004.
- [7] W. Sun, Z. Qin, L. Yao, and M. Li, "Research on Interference-Based Channel Assignment Methods in 802.11-Based Wireless Mesh Network," *4th International Conference on Wireless Communications, Networking and Mobile Computing*, pp. 1–4, 2008.
- [8] A. P. Subramanian, H. Gupta, S. R. Das, and J. Cao, "Minimum interference channel assignment in multiradio wireless mesh networks," *IEEE Transactions on Mobile Computing*, vol. 2, pp. 1459–1473, 2008.
- [9] H. S. Chiu, K. Yeung, and K.-S. Lui, "J-CAR: an Efficient Channel Assignment and Routing Protocol for Multi-channel Multi-interface Mobile Ad Hoc Networks," *IEEE Global Communications Conference*, pp. 1–5, 2006.
- [10] M. Haidar, R. Ghimire, H. Al-Rizzo, R. Akl, and Y. Chan, "Channel assignment in an IEEE 802.11 WLAN based on Signal-To-Interference Ratio," *Electrical and Computer Engineering Canadian Conference*, pp. 001 169–001 174, 2008.
- [11] P. Dutta, S. Jaiswal, and R. Rastogi, "Routing and Channel Allocation in Rural Wireless Mesh Networks," *The 26th IEEE International Conference on Information Computing*, pp. 598–606, 2007.
- [12] G. Zeng, B. Wang, Y. Ding, L. Xiao, and M. Mutka, "Multicast Algorithms for Multi-Channel Wireless Mesh Networks," *IEEE International Conference on Network Protocols*, pp. 1–10, 2007.
- [13] R. Stoleru, T. He, J. Stankovic, and D. Luebke, "A high-accuracy, low-cost localization system for wireless sensor networks," *The 3rd international conference on Embedded networked sensor systems*, pp. 13–26, 2005.
- [14] R. Stoleru, P. Vicaire, T. He, and J. Stankovic, "StarDust: a flexible architecture for passive localization in wireless sensor networks," *The 4th international conference on Embedded networked sensor systems*, pp. 57–70, 2006.
- [15] W. Chen, J. Hou, and L. Sha, "Dynamic Clustering for Acoustic Target Tracking in Wireless Sensor Networks," *IEEE Transactions on Mobile Computing*, pp. 258–271, 2004.
- [16] J. Wang, H. Zha, and R. Cipolla, "Coarse-to-Fine Vision-Based Localization by Indexing Scale-Invariant Features," *IEEE Transactions on Systems, Man, and Cybernetics - Part B: Cybernetics*, vol. 36, no. 2, p. 413, 2006.
- [17] B. Dil, S. Dulman, and P. Havinga, "Rangebased localization in mobile sensor networks," *The European Conference on Wireless Sensor Networks*, pp. 164–179, 2006.
- [18] R. Jan and Y. Lee, "An indoor geolocation system for wireless LANs," *International Conference on Parallel Processing*, pp. 29–34, 2003.
- [19] J. Kwon, B. Dundar, and P. Varaiya, "Hybrid algorithm for indoor positioning using wireless LAN," *The 60th IEEE Vehicular Technology Conference*, vol. 7, 2004.



- [20] P. Prasithsangaree, P. Krishnamurthy, and P. Chrysanthis, "On indoor position location with wireless LANs," *The 13th IEEE International Symposium on Personal, Indoor and Mobile Radio Communications*, vol. 2, 2002.
- [21] C. L. Chan, G. Baciú, and S. C. Mak, "Using Wi-Fi Signal Strength to Localize in Wireless Sensor Networks," *The 1st IEEE International Conference on Communications and Mobile Computing*, vol. 1, pp. 538–542, 2009.
- [22] —, "Wireless Tracking Analysis in Location Fingerprint," *The 4th IEEE Wireless and Mobile Computing, Networking and Communications*, pp. 214–220, 2008.
- [23] —, "Fuzzy Topographic Modeling in WLAN Tracking Analysis," *International Conference on Fuzzy Computation*, pp. 17–24, 2009.
- [24] —, "Resource-effective and Accurate WLAN Infrastructure Design and Localization Using a Cell-structure Framework," *The 5th IEEE International Conference on Wireless Communications, Network and Mobile Computing*, vol. 6, pp. 9–15, 2009.
- [25] —, "Using a Cell-based WLAN Infrastructure Design for Resource-effective and Accurate Positioning," *Journal of Communications Software and Systems*, vol. 5, no. 4, 2009.
- [26] K. Y. C. Kwon Kim, "A Channel Management Scheme for Reducing Interference in Ubiquitous Wireless LANs Environment," *Multimedia and Ubiquitous Engineering, International Conference*, pp. 276–281, 2008.
- [27] C. L. Chan, G. Baciú, and S. C. Mak, "Using the Newton Trust-Region Method to Localize in WLAN Environment," *The 5th IEEE International Conference on Wireless and Mobile Computing, Networking and Communications*, pp. 363–369, 2009.
- [28] K. Kaemarungsi and P. Krishnamurthy, "Properties of indoor received signal strength for WLAN location fingerprinting," *The 1st Annual International Conference on Mobile and Ubiquitous Systems: Networking and Services*, pp. 14–23, 2004.
- [29] P. Bahl and V. Padmanabhan, "RADAR: an in-building RF-based user location and tracking system," *The 19th IEEE International Conference on Information Computing*, vol. 2, 2000.



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