國立交通大學

資訊學院　資訊學程

碩 士 論 文

一 個 不 需 帶 裝 置 的 室 內 人 員 偵 測 方 法

A Device-free Location Detection Scheme for Indoor Environment

研 究 生：莊承益

指導教授：曾煜棋　教授

中 華 民 國 一 百 零 壹 年 二 月

一個不需帶裝置的室內人員偵測方法

A Device-free Location Detection Scheme for Indoor Environment

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國 立 交 通 大 學

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一個不需帶裝置的室內人員偵測方法

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國 立 交 通 大 學　　資 訊 學 院　　資 訊 學 程　硏 士 班

摘　　　要

以無線網路為基礎的定位方法中，大多數的定位法都是讓欲定位的目標上帶著訊號傳送器或是訊號接受器來進行定位。然而，目前依然無令人滿意的方法使目標免持裝置且能達到定位效果。在本論文中，我們提出了一個以統計學的角度的方法來定位無持裝置的目標在哪一個房間，其方法是透過不斷的監測無線網路的訊號變化性來判斷目標在哪一個房間。這個方法分為訓練階段與定位階段，我們假設在環境中存在若干的無線網路基地台與一無線網路訊號接收器，在訓練階段我們將收集目標在各房間時各無線網路基地台對無線網路訊號接收器的訊號分佈狀態；而在定位階段時，我們將利用即時的各無線網路基地台對無線網路訊號接收器的訊號分佈狀態與訓練階段中的狀態做比較，進而找出定位目標所在的位置。

A Device-free Location Detection Scheme for Indoor Environment

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Abstract

Among all the wireless localization techniques, most works require users to carry a device, such as a transmitter or a receiver, on the target object to be localized. The need is to develop a device-free localization system, This paper proposes a statistics-based scheme to locate people, where we monitor the received signal strength (RSS) of the Radio Frequency (RF) system in the background environment to recognize that a person may be located in a certain room. This scheme consists of two phases: training phase and online phase. In the training phase, we assume that the building has been deployed with some Wi-Fi APs and a fix receiver; our scheme will measure the RSS distribution while a person is in a room, or not in a room, as the training patterns. In the online phase, we compare the current RSS distribution against the training patterns to detect which room a person is now in. We believe that our framework can provide a valuable solution for device-free localization. A prototype system is developed to verify the practicability of our framework with real data.

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首先要感謝是我的指導教授曾煜棋老師，及一直持續不斷給我加油、指導、啟發的羅棨鐘學長。在實驗的過程中，遇到了很多的挫折，還好有老師、學長的指導與鼓勵，讓我可以不斷地努力嘗試不同的方法、克服一個個艱困的問題，最終論文得以完成。

在就讀研究所的同時，我還在科學園區的公司工作，身為研發工程師，工作量、及工作時間都很長，專案又經常碰到有時間壓力、難度不小的問題，也時常的需要配合工作出差。非常感謝黃昭舜先生、王天助先生兩位主管的體諒，在工作上經常協助我渡過難關。也經常的鼓勵我，讓我可以工作、課業兩頭兼顧。

還有現在是我賢淑的太太，在我寫論文時是貼心女友的張淑紋小姐。為了讓我能夠專心寫論文，無後顧之憂，經常台北、新竹不辭辛苦的兩地通車，感謝親愛的太太的體諒。

這個題目對我來說，一路走來真的不容易，期間還發生相同的題目，卻被國外的學者先行發表。我數度的幾乎要放棄，要是沒有你們，我一個人真的過不了這個關卡，我心裡由衷的感謝你們。謝謝！

最後，僅以此文獻給養育我長大、陪伴我成長、摯愛的雙親。

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A Device-free Location Detection Scheme for Indoor Environment

研究生：莊承益

指導教授：曾煜棋教授

Abstract—among all the wireless localization techniques, most works have to carry a device, such as a transmitter or a receiver, on the target object to estimate locations. For the device-free localization system, a globally acceptable solution is still missing. This paper propose a statistics-based scheme to locate the people, where we monitor the received signal strength (RSS) of the Radio Frequency (RF) system in the background environment to recognize that a person may locate in a room-based area (e.g., a living room). This scheme consists of two phases: training phase and online phase. In the training phase, we assume that the building has been deployed with some Wi-Fi APs and a fix receiver; our scheme will measure the RSS distribution while a person is in a room (or not in a room) as the training patterns. In the online phase, we compare the current RSS distribution against the training patterns to detect which room would a person stay. We believe that our framework can provide a valuable solution for device-free localization. A prototype system is developed to verify the practicability of our framework with real data.

1. Introduction

Location-based services (LBS) have been regarded as a killer application in mobile networks. A central issue of LBS is location tracking. At present, GPS is still the widest used technology for positioning in outdoor environments. However, due to shadowing effects, GPS is not always available or even reliable. Therefore, much research has been dedicated to the wireless positioning system (WPS), which is based on Radio Frequency (RF) signals to locate a mobile user. These systems can be classified into five categories: AoAbased [6], ToA-based [7], TDoA-based [8], signal loss-based [9], and pattern-matching [10]-[14] techniques.

While surveying those existing localization approaches, most works have to carry a device, such as a transmitter or a receiver, on the target object to estimate locations. This constrains the availability of LBS when the user without carrying the mobile devices. Therefore, many device-free solutions have been proposed to track the motion objects. For example, some infrared, ultrasound, and scene analysis based systems have been proposed in [1]. In [2], the authors deploy many sensors on the ceiling and propose a localization model of distance, transmission power and the signal dynamics caused by the objects. However, the main drawback of those systems is their high deployment cost. In [3], the authors detect and track object by monitoring the changes of the received signal strength (RSS) between a transmitter and a receiver that deployed at the environment. However, such a system can only be used near the transmitter and receiver. If a room did not deploy a transmitter or a receiver in the environment, this system can not detect the changes in this room.

In this paper, we propose a room-based device-free location detection scheme, which compare the distribution of RSS that record in the training phase with the current distribution to recognize the room in which a person may locate. We deploy some transmitters (i,e. Wi-Fi access points) and a receiver (i,e. a laptop) in a small scale area, such as a house. Our scheme consists of two phases: training phase and online phase. In the training phase, we will collect the RSS distribution that a user in various rooms. Note that no user in the room is one of the conditions. Then, we use a test distribution set (where to represent a person stay in each room) to compare against the distribution of training RSS and calculate the repetition rate as the training pattern. In the online phase, we will collect the current RSS distribution and compare it against the distribution of training RSS to calculate the repetition rate as the current pattern. Then, we will compare the current pattern with training patterns to find out the most similar one, where it represents a person stay in a specific room. In the end, our system will show a person stay in this room as the output.

The rest of this paper is organized as follows. Section II gives some background knowledge. The room-based device-free location detection scheme is presented in Section III. Some experimental results are shown in Section IV. Conclusions is drawn in Section V.

2. 1 Background

Since civilian *Global Positioning System* was invented in 1970s, the localization demand for numberless applications had been noticed greatly. In recently years, due to the prospering of mobile devices, the focuses of localization demand has changed from measurement, navigation and field sports to personal location-based services such as local search, personal guidance and location-dependent multimedia services. Some critical disadvantages of GPS got more obvious in these application environments. For example, there must be no satellite signals inside a shopping mall, whereas a common location-based coupon service is desired. Even in an outdoor business section of a city, the accuracy of GPS is bad because there is no enough satellite in the sight or the multi-path fluctuation is serious.

For these reasons, a new type of localization method had been invented because of the widely spread wireless base stations. Wireless-based localizations utilized the wireless transmission characteristic to calculate the position of mobile device. The radio type varied from a common IEEE 802.11 Wi-fi to a novel WiMAX metropolitan area network. The data for calculation are time gaps or RSS readings. The wireless positioning techniques can be mainly categorised into two. The first one is triangulation-based. The principle of wireless triangulation-based localization is almost the same as GPS, except the beacons changed from satellites to access points or base stations. It triangulates the location by time gaps or signal decay according to ideal sphere path-loss model. The finer beacon coverage is guaranteed because the high density of base stations. However, the multi-path and signal fluctuation problems still existed. For these drawbacks, a substitution is introduced to alleviate these problems. That is fingerprinting-based, or pattern-matching based localization. The principle is based on collecting a mapping of location labels and signal fingerprinting vector. Once the mapping is collected, we can deduce the location from the immediate fingerprints.

However, those existing localization approaches, most works have to carry a device, such as a transmitter or a receiver, on the target object to estimate locations. This constrains the availability of LBS when the user without carrying the mobile devices. Therefore, many device-free solutions have been proposed to track the motion objects. For example, some infrared, ultrasound, and scene analysis based systems have been proposed in [1]. In [2], the authors deploy many sensors on the ceiling and propose a localization model of distance, transmission power and the signal dynamics caused by the objects. However, the main drawback of those systems is their high deployment cost. In [3], the authors detect and track object by monitoring the changes of the received signal strength (RSS) between a transmitter and a receiver that deployed at the environment. However, such a system can only be used near the transmitter and receiver. If a room did not deploy a transmitter or a receiver in the environment, this system can not detect the changes in this room.

2.2 Related work

Device-free passive (DfP) localization, in which the tracked entity need neither carry devices nor participate actively in the localization algorithm.

“Entity” we mean an object that can cause changes to the environment, such as people. “Environment” we mean the mean and variance of RSSI (Wireless signal strength).

Mean RSSI average

$$\alpha_{l,k} = \frac{1}{w_l} \sum_{i=k}^{k+w_l-1} q_i$$

Variance RSSI

$$\bar{q}_t = \frac{1}{w_l} \sum_{i=k}^{k+w_l-1} q_i$$

$$v_t = \frac{1}{w-1} \sum_{i=k}^{k+w-1} (q_i - \bar{q}_t)^2$$

3. Experimental method

In this paper, we propose a room-based device-free location detection method, which compare the distribution of RSS that record in the training phase with the current distribution to recognize the room in which a person may locate. The main idea of this work is that the human will cause the RSS attenuation if he/she closes to the transmitter or the receiver. Figure 1 and figure 2 show the obvious observation.

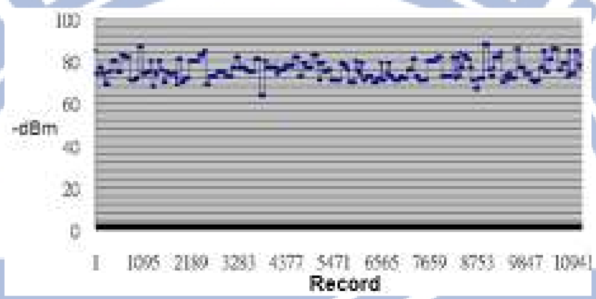

Figure 1. The RSS reading collected from a receiver while a person close to it.

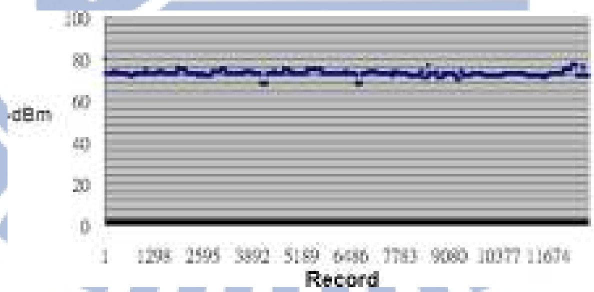

Figure 2. The RSS reading collected from a receiver without any interference.

Considering the RSS changes between Figure. 1 and Figure. 2, we observe that the object may cause the RSS attenuation if the object closes to the transmitter or the receiver. Therefore, we could detect the object location by monitoring RSS in the background environment. To locate a device-free object, we deploy m transmitters (i,e. Wi-Fi access points) and a receiver (i,e. a laptop) in a small scale area, such as a house, which has m rooms (n<m). Figure 3 shows this environment.

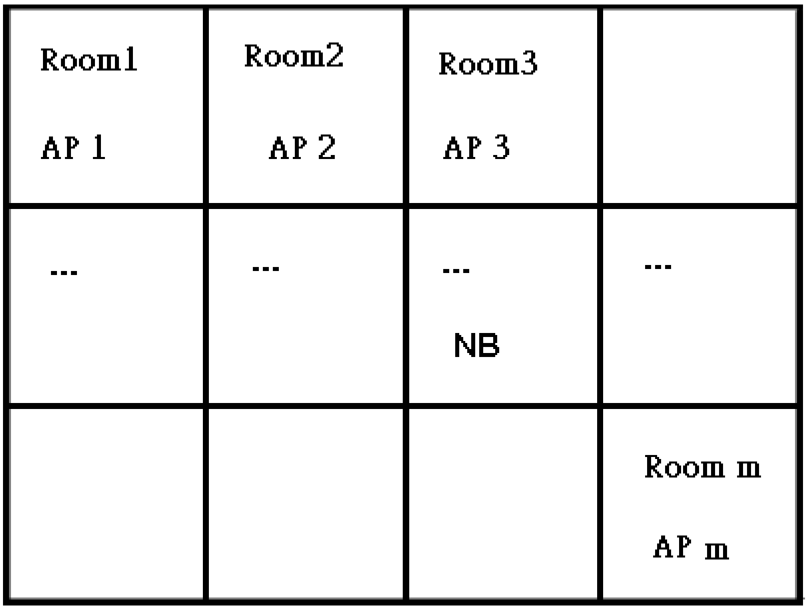

Fig 3

Below, we propose a statistics-based localization scheme to locate the device-free object. This scheme consists of two phases: training phase and online phase, as illustrated in Fig. 4. In the training phase, we will collect the RSS distribution that a user in various rooms. Note that no user in the room is one of the conditions. Then, we use a test distribution set (where to represent a person stay in each room) to compare against the distribution of training RSS and calculate the repetition rate as the training pattern. In the online phase, we will collect the current RSS distribution and compare it against the distribution of training RSS to calculate the repetition rate as the current pattern. Then, we will compare the current pattern with training patterns to find out the most similar one, where it represents a person stay in a specific room. In the end, our system will show a person stay in this room as the output.

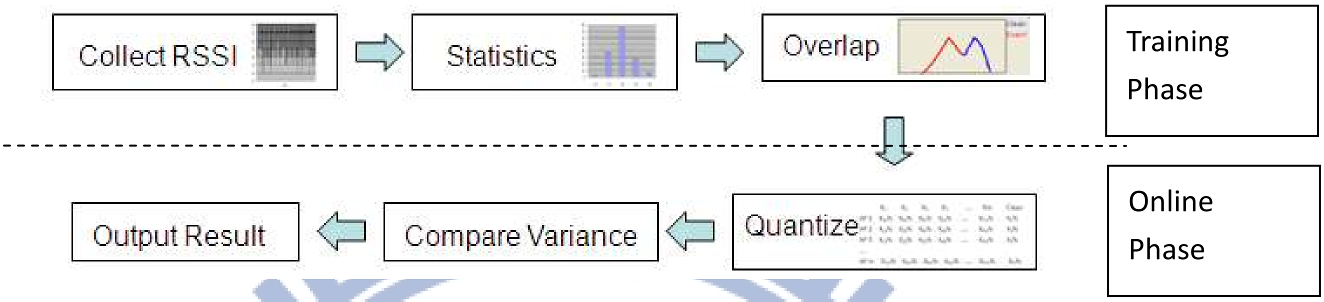

Figure 4. System flow.

3.1 Training phase

In the training phase, we will collect the RSS distribution that a user in various rooms. Note that no user in the room is one of the conditions. Then, we use a test distribution set (where to represent a person stay in each room) to compare against the distribution of training RSS and calculate the repetition rate as the training pattern.

To achieve this goal, we ask a volunteer to stay in each room for 5 minutes. For each room, we will collect 5,000 RSS samples from n APs. For each AP, then, we will calculate the average and variance RSS reading every size (Wi) of the samples. In order to facilitate the calculation, this value will be rounded number. If we assume AP1 was closest to room No.1 among all other AP, we obtained that M=(AP1 Total record)/(Window Size).

$$M_i = \frac{1}{W_i}\sum_{j=0}^{W_i}(AP1)_j$$

Two data, with or without the presence of people, were recorded for each room as {S0,S1},{S0,S2},{S0,S3},…. {S0,Sm}, which were statistically arranged in histograms in Fig. 5. Rmin, Rmin+1, Rmin+2, …, Rmax denote the distribution of RSSI intensities. N is its number and Mi is its total number. We can approximate a distribution curve as in Fig. 6.

$$M_i = N_{Rmin} + N_{(Rmin+1)} + N_{(Rmin+2)} + \cdots . + N_{Rmax}$$

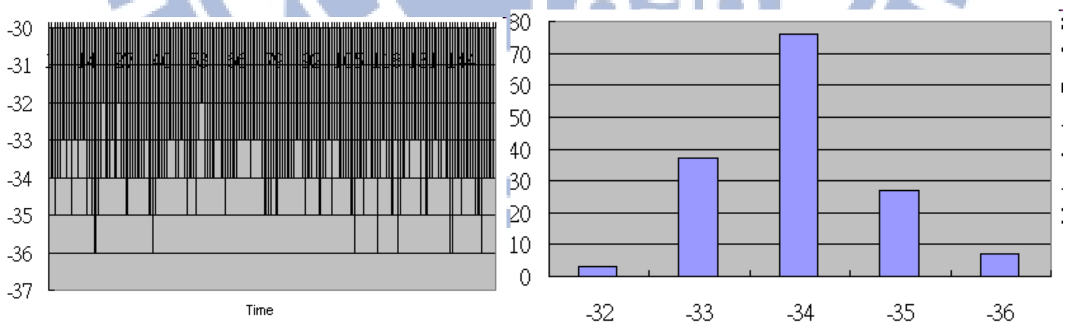

Fig 5. Overlapped the two histograms of signal strength

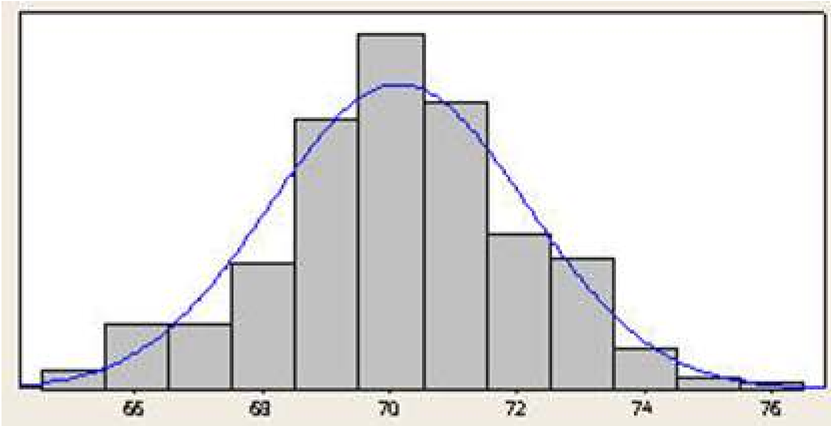

Fig 6. An example of a histogram of the signal strength of an access point

We overlapped the two histograms of signal strength recorded with or without the presence of people (Fig 7)，

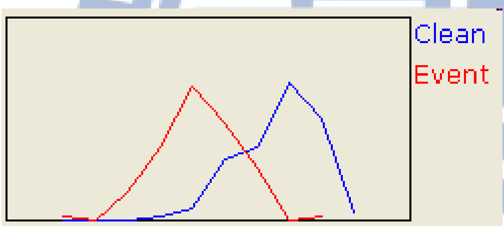

Fig 7

The overlapped parts were those signals with higher frequency (Fig. 8)

Support there are i different Signal Strength,

If $C_i < E_i$, Output E_i

If $C_i > E_i$, Output C_i

C is the number of signals when there were no people in the room while E is the number when there were.

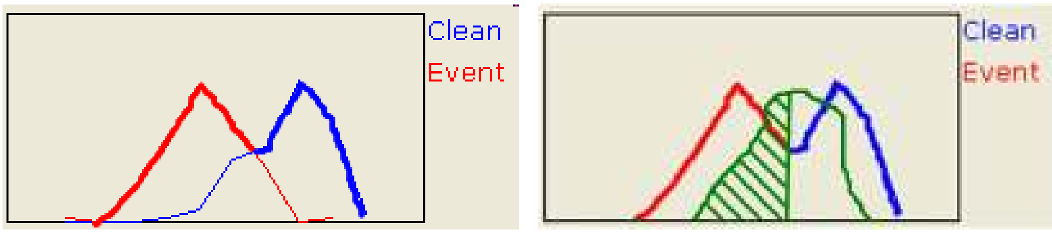

Fig 8

The same process was applied to the real-time record of RSSI. The information was recorded and statistically arranged in histograms before overlapping on Fig. 8, Hi as in the example in Fig. 9.

Hi is the number of E Side outputs overlapped to 3.1.5.

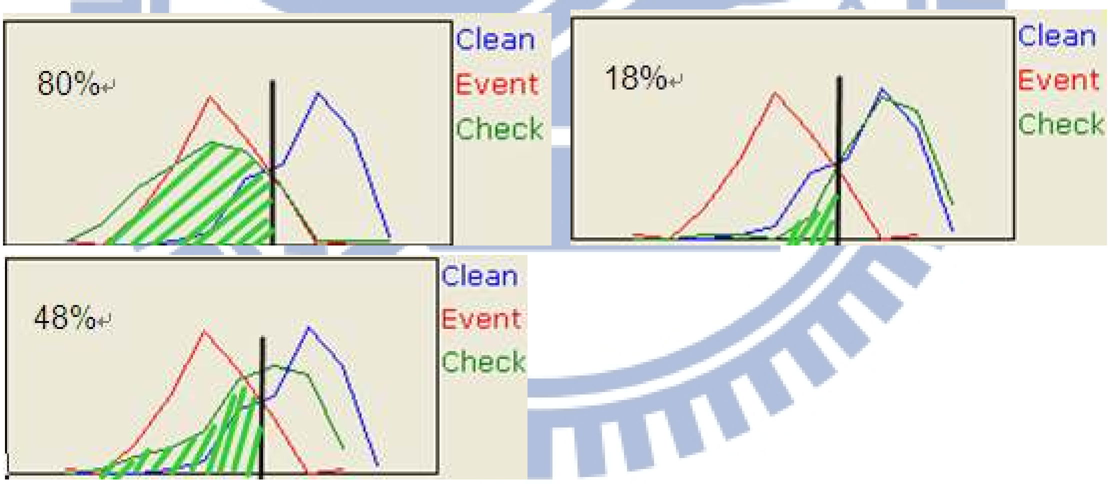

Fig 9

We calculated the percentage of real-time signals indicating the presence (E Side)/ absence (C Side) of people $\frac{1}{\mathrm{Mi}}\sum \mathrm{H}_{\mathrm{Rmin+i}}$. If the percentage was over 50%, the conditions sustained, indicating the presence / absence of people.

Then we quantified our data with vectors. We could determine how high the probability of the presence of people in room No. 1 was by repeating step 3.1.7 with AP 1-AP m recorded when there were people in the room (Node 1).Fig 10

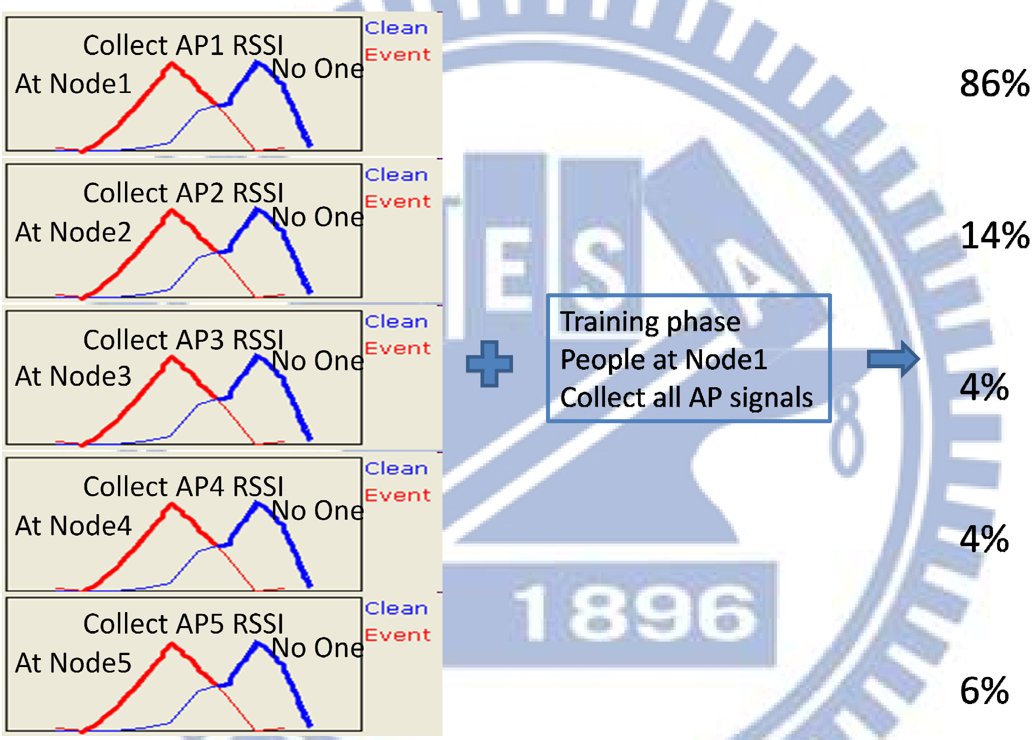

Fig 10

In the following steps, we describe the features of the environment. What data would be close to what we want? The result from overlapping the same data to itself would be closest to what we want and would best represent the features of the environment.

First, the data recorded during offline phase was overlapped to data during offline phase with and without the presence of people.

3.1.4-3.1.6, the ratios for each AP in each room was arranged in the rectangle table of percentages (Table 1). R1 means that there were people in Room No. 1 and Clean means that there was no one in any room. They are Vector Characteristics. After obtaining this feature table, we compared real-time data with Vector Characteristics to identify the most similar data.

	R1	R2	R3	R4	….	Rm	Clean
AP 1	X11%	X21%	X31%	X41%	….	Xm1%	X1%
AP 2	X12%	X22%	X32%	X42%	….	Xm2%	X2%
AP 3	X13%	X23%	X33%	X43%	….	Xm3%	X3%
….							
AP m	X1m%	X2m%	X3m%	X4m%	….	Xmm%	Xm%

Table 1, Vector Characteristic

Then, another rectangle table of percentages (Table 1) was obtained by overlapping real-time data recorded in online phase onto data during offline phase with and without the presence of people.

First, we assume that we didn’t know which room was present with people. After subtracting the square of data in 3.1.9. from data in 3.1.10, we further added the difference for the same room. This means that if the difference (Table 2) between the real-time data recorded so far and the Vector Characteristic was the smallest, indicating that they were most similar, we could conclude which room was present with people.

Variance room#1= (XR11-XV11)2+(XR12-XV12)2+(XR13-XV13)2+…….+(XR1m-XV1m)2

$$\sum_{i=1}^{m}(X_{R1i} - X_{V1i})^2$$

R stands for real time and V stands for Vector Characteristic.

Room	R1	R2	R3	R4	….	Rm	Clean
Variance	xxxx	xxxx	xxxx	xxxx	…	xxxx	xxxx

Table 2, Compare the variance. The location with smallest difference is the location present with people. Clean means there were no people in any room.

3.2 Expansion Scenario 1

How can we infer if there is no AP in a specific room or location? As in Table 3, although AP3 was removed, we still had the recorded value of X31, X32 , X34…., and X3m, from which we were still able to infer which room was present with people by the method in 3.1.11.

$$\sum_{i=1}^{m}(X_{R1i}-X_{V1i})^2, i \notin 3$$

In other words, we may have m rooms or m nodes which are not necessarily in the rooms and n APs. m≠n

	R1	R2	R3	R4	….	Rm
AP 1	X11%	X21%	X31%	X41%	….	Xm1%
AP 2	X12%	X22%	X32%	X42%	….	Xm2%
AP 3	X13%	X23%	X33%	X43%	….	Xm3%
AP 4	X14%	X24%	X34%	X44%	….	Xm4%
….						
AP m	X1m%	X2m%	X3m%	X4m%	….	Xmm%

Table 3

3.3 Expansion Scenario 2

How to infer if there were people in multiple rooms or locations? We could collect data when there were people in multiple rooms in the offline phase, i.e. people are present in Room#1 and Room#2, in Room#1 and Room#3 ,or in Room#1 and Room#3. We can still infer if compare this data with the method described in 3.1.11.

3.4 Simplified procedure

Simplified procedure as in below:

Data collecting ->Statistics->Overlapping-> Rectangle Table of Percentages ->Variance obtained by subtracting ->the resulted inference as in Fig. 4.

4. Experiment Data

4.1 Environment Setup

Inside a 30 level ground apartment, one AP was placed in each room (Fig. 11). There were two notebook receiving intensity signals. During the training phase, all people left all rooms before the signals were recorded for five minutes. Every AP recorded approximately 3,000 intensity signals. Then, one man stood in each of the six rooms for six times and signals were recorded. This completed our training phase.

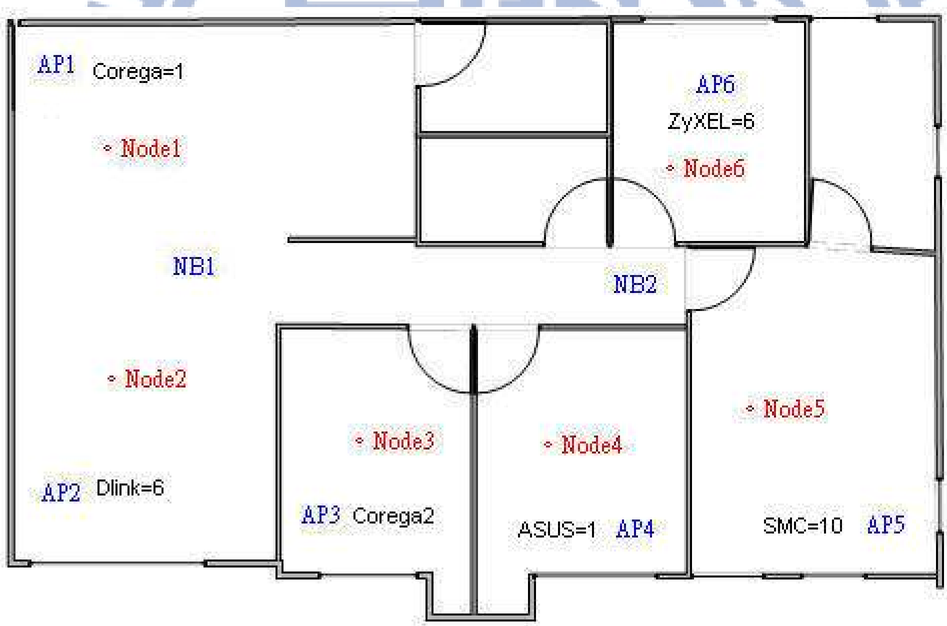

Fig 11. A 30 level ground apartment, 8.9m X 14.8m

During position phase, we assumed that there was one man standing in room No. 1 while the signals were recorded. With MDE, we could tell if the room was really present with any person because we had a set of statistical data for every room present with or without any person recorded during training phase.

Pay special attention during signal recording in following aspects. 1. Recording signals from an environment without any person. We used a timer currently set at three minutes for computer set up before the person left the environment. 2. Signal delay. Some APs still received signals up to 2.5 minutes after shutting down the six APs used in our experiment. Therefore, we extend the recording time to three minutes after AP shutdown.

We recorded signals when there was no one or there was one person in one room a time for every room. The data was saved in Clean, Node 1 to Node n databases.

4.2 Statistical Data

We separately analyzed data under different conditions of the presence of people in the environment and in each node. The results were arranged in histograms.

Example 1

In node 1

With signals from AP1 as reference, the blue part in the histogram is signals recorded when there was no one, and the red/green parts are signals recorded when there was a person present at room No. 1/ node 1 (Fig. 12).

Room#1-AP1

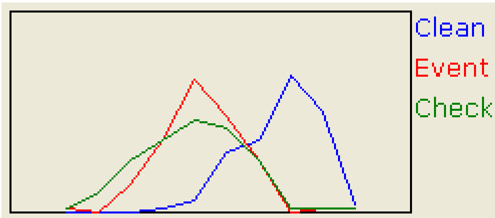

Fig 12

Example 2

In node 1

With signals from AP1 as reference, the blue part in the histogram is signals recorded when there was no one, and the red/green parts are signals recorded when there was a person present at room No. 1/ node 4 (Fig. 12).

Room#1-Ap1

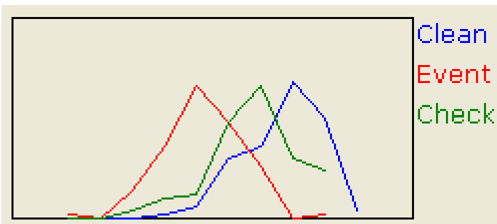

Fig 13

Data analysis was conducted majorly by mean and assisted by variance. According to our experience and actual data, mean is a more precise statistic in data analysis.

Next, we performed 3.1.4 to 3.1.9 to obtain a Vector Characteristic (Table 4).

Each Figure represented the statistical results obtained through 3.1.4 to 3.1.9 based on signals from AP 1 to 5 (column 1 to 5) when there was a person standing in room 1 to 5 (row 1 to 5 and C indicated that there was no one in the room)

Rm	1	2	3	4	5	C
AP 1:	86%	81%	17%	44%	13%	20%
AP 2:	14%	82%	23%	18%	13%	10%
AP 3:	04%	37%	97%	01%	01%	01%
AP 4:	04%	41%	38%	79%	06%	10%
AP 5:	06%	04%	13%	06%	60%	19%

Table 4

4.3 Compare Variance

Real time statistical data as in table 5 was obtained by repeating 3.1.4 to 3.1.8 and

3.1.10. Table 6 was obtained by deducting data in table 4 as in step 3.1.11.

Each row of data represented the result after deducting Vector Characteristic. The probability of the presence of people increases as the figure decreases. Data in each column represented the analyzed results from signals recorded in room 1 to 5 with or without the presence of people respectively. Those circled in red indicated that the prediction was a 100% match.

Rm	1	2	3	4	5	C
AP 1:	83%	80%	12%	39%	16%	20%
AP 2:	13%	56%	28%	07%	07%	10%
AP 3:	02%	30%	42%	00%	01%	01%
AP 4:	04%	31%	46%	58%	17%	10%
AP 5:	07%	13%	09%	11%	46%	19%

Table 5

F/Node	1	2	3	4	5	Clean
File01=	00012	07286	14619	07076	07746	04214
File02=	03145	00935	09538	05869	09892	06978
File03=	08683	07780	03083	03950	06112	03421

File04=05133 09158 10520 00632 05816 02720

File05=06720 13558 10893 06429 00381 00762

FileC6=04547 11388 10084 05593 01729 00000

Table 6

4.4 When There Was No AP in Some Rooms

We tried to remove AP2 (Table 7)

Rm 1 2 3 4 5 C

AP 1:83% 80% 12% 39% 16% 20%

AP 2:13% 56% 28% 07% 07% 10%

AP 3:02% 30% 42% 00% 01% 01%

AP 4:04% 31% 46% 58% 17% 10%

AP 5:07% 13% 09% 11% 46% 19%

Table 7

Repeated the procedures in 4.3 to obtain table 8, which turned out to be a very precise estimation.

F/Node	1	2	3	4	5	Clean
File01=	00011	02558	14519	07056	07746	04203
File02=	01455	00234	08500	04441	08109	04903
File03=	08506	04802	03064	03850	05903	03105
File04=	05072	03474	10243	00508	05771	02708
File05=	06660	07889	10616	06306	00337	00751
FileC6=	04527	06189	09907	05533	01718	00000

Table 8

Table 9 was obtained by removing AP3 and repeating the procedures in 4.3.

F/Node	1	2	3	4	5	Clean
File01=	00007	06100	05659	07075	07745	04213
File02=	02492	00891	05076	05034	09058	06156
File03=	07256	07749	00119	02260	04422	01749
File04=	05113	07813	01140	00630	05814	02718
File05=	06709	12293	01783	06429	00381	00762
FileC6=	04537	10140	01002	05593	01729	00000

Table 9

Table 10 was obtained by removing AP4 and repeating the procedures in 4.3. The estimation indicated no person while there had been one person in room 3.

F/Node	1	2	3	4	5	Clean
File01=	00012	05941	13508	01570	07745	04183
File02=	02434	00835	09493	03601	09239	06533
File03=	06993	07760	03023	02813	04512	02157
File04=	02288	08880	10120	00181	03088	00437
File05=	06571	12960	10448	02502	00258	00718
FileC6=	04516	10420	09313	00817	01709	00000

Table 10

We tried to remove one to more APs to observe the precision of our estimations (Fig. 14)

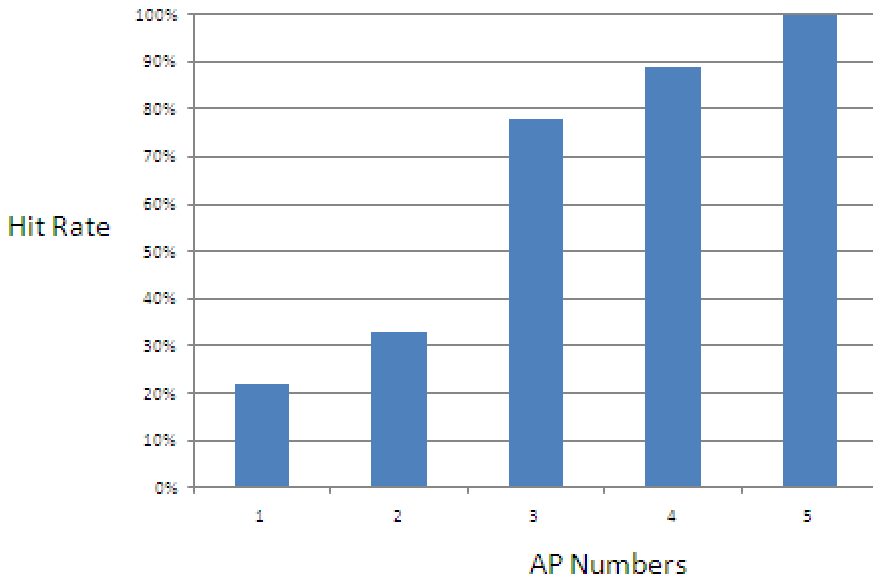

Fig 14. AP Number VS. Hit Rate

4.5 Other environment

We changed to another environment (Fig. 15), where we set up six APs, five nodes and three NBs.

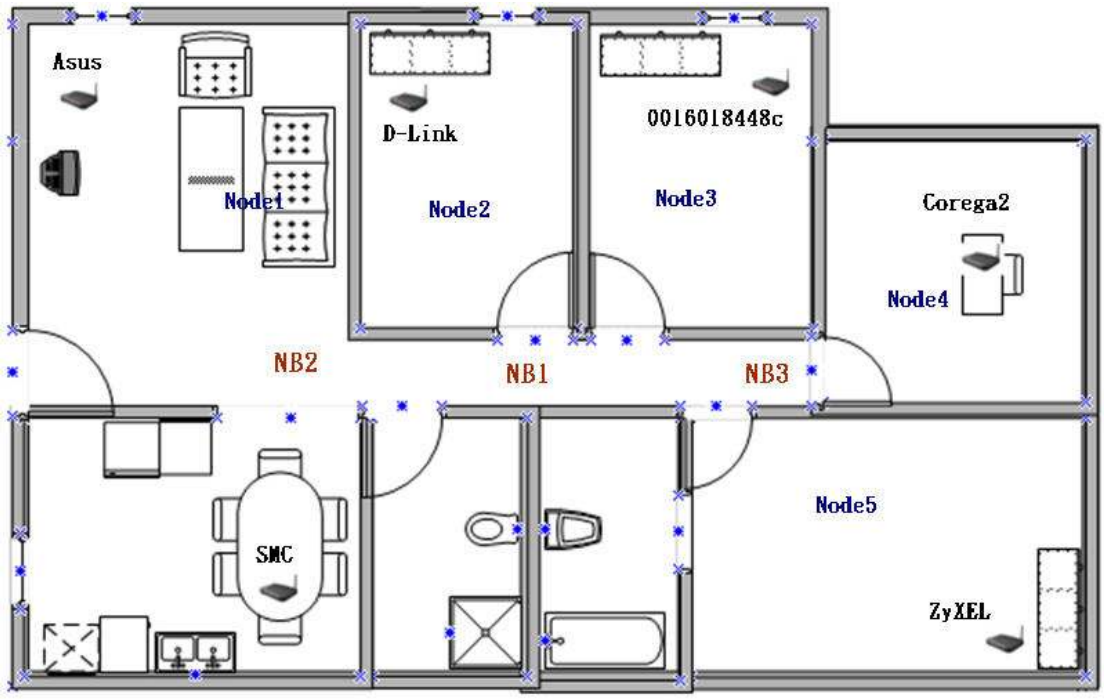

Fig. 15 a 40 level ground apartment, 9.7m X 16.6m

4.5.1

We first observed the precision of estimation when the three different NBs were placed at different locations.

4.5.1.1

NB 1 Offline MDE

Node 1 2 3 4 5 C

AP 1:094% 100% 091% 053% 061% 049%

AP 2:046% 096% 008% 093% 100% 028%

AP 3:084% 064% 100% 080% 053% 017%

AP 4:082% 007% 007% 054% 080% 007%

AP 5:003% 002% 004% 035% 100% 004%

NB 1 Online MDE

Node 1 2 3 4 5 C

AP 1:097% 099% 097% 058% 067% 021%

AP 2:056% 098% 003% 094% 099% 006%

AP 3:086% 096% 063% 089% 059% 006%

AP 4:099% 000% 000% 093% 099% 004%

AP 5:000% 004% 001% 043% 100% 001%

F/Node 1 2 3 4 5 Clean

File01=00404 09600 08982 05335 13715 19052

File02=10436 01086 08652 11366 19041 17664

File03=10893 08233 01455 17464 28008 13758

File04=06609 06291 14327 01656 06828 17783

File05=14691 18941 26841 04714 00430 28124

File06=16252 13747 05087 18444 24696 01400

Hit:100%

4.5.1.2

NB 2 Offline MDE

Node	1	2	3	4	5	C
AP 1:	089%	055%	048%	059%	057%	021%
AP 2:	000%	063%	002%	002%	005%	001%
AP 3:	065%	027%	082%	098%	072%	090%
AP 4:	015%	012%	029%	068%	014%	002%
AP 5:	001%	005%	000%	080%	089%	000%

NB 2 Online MDE

Node	1	2	3	4	5	C
AP 1:	090%	062%	038%	051%	052%	017%
AP 2:	001%	099%	000%	009%	003%	002%
AP 3:	089%	081%	097%	098%	048%	089%

AP 4:012% 011% 017% 099% 013% 001%

AP 5:002% 002% 004% 091% 099% 002%

F/Node 1 2 3 4 5 Clean

File01=00554 10751 03632 17793 11442 05961

File02=08944 04225 09118 22905 12997 09135

File03=02114 09868 00495 13335 11296 01820

File04=10290 18928 08844 01162 05908 12401

File05=08925 16344 08160 07895 00715 09547

File06=04912 11478 00576 18592 12748 00019

Hit:100%

4.5.1.3

NB 3 Offline MDE

Node 1 2 3 4 5 C

AP 1:089% 055% 048% 059% 057% 021%

AP 2:000% 063% 002% 002% 005% 001%

AP 3:065% 027% 082% 098% 072% 090%

AP 4:015% 012% 029% 068% 014% 002%

AP 5:001% 005% 000% 080% 089% 000%

NB 3 Online MDE

Node 1 2 3 4 5 C

AP 1:090% 062% 038% 051% 052% 017%

AP 2:001% 099% 000% 009% 003% 002%

AP 3:089% 081% 097% 098% 048% 089%

AP 4:012% 011% 017% 099% 013% 001%

AP 5:002% 002% 004% 091% 099% 002%

F/Node 1 2 3 4 5 Clean

File01=00554 10751 03632 17793 11442 05961

File02=08944 04225 09118 22905 12997 09135

File03=02114 09868 00495 13335 11296 01820

File04=10290 18928 08844 01162 05908 12401

File05=08925 16344 08160 07895 00715 09547

File06=04912 11478 00576 18592 12748 00019

Hit:100%

The results indicated precise estimations when the three different NBs were placed at different locations.

4.5.2

Then we tried to remove different amounts of AP to observe the precision of our estimations.

4.5.2.1

NB 3 Offline MDE, remove AP 5

Node	1	2	3	4	5	C
AP 1:	094%	100%	091%	053%	061%	049%
AP 2:	046%	096%	008%	093%	100%	028%
AP 3:	084%	064%	100%	080%	053%	017%
AP 4:	082%	007%	007%	054%	080%	007%

NB 3 Online MDE, remove AP 5

Node	1	2	3	4	5	C
AP 1:	097%	099%	097%	058%	067%	021%
AP 2:	056%	098%	003%	094%	099%	006%

AP 3:086% 096% 063% 089% 059% 006%

AP 4:099% 000% 000% 093% 099% 004%

F/Node 1 2 3 4 5 Clean

File01=00392 09600 08978 03735 04371 19048

File02=10432 01082 08652 09658 09437 17663

File03=10877 08233 01448 15917 18792 13751

File04=05360 05309 13171 01592 02646 16627

File05=04691 09725 17106 01503 00430 18389

File06=16236 13747 05080 16896 15480 01392

Hit:100%

4.5.2.2

NB 3 Offline MDE, remove AP 4,5

Node 1 2 3 4 5 C

AP 1:094% 100% 091% 053% 061% 049%

AP 2:046% 096% 008% 093% 100% 028%

AP 3:084% 064% 100% 080% 053% 017%

NB 3 Online MDE, remove AP 4,5

Node	1	2	3	4	5	C
AP 1:	097%	099%	097%	058%	067%	021%
AP 2:	056%	098%	003%	094%	099%	006%
AP 3:	086%	096%	063%	089%	059%	006%

F/Node	1	2	3	4	5	Clean
File01=	00115	02876	02254	03621	04093	12964
File02=	02091	01028	08598	02376	01096	17652
File03=	02536	08180	01394	08635	10450	13740
File04=	03365	02393	10255	00097	00651	14127
File05=	04343	03325	10706	01343	00082	12613
File06=	07895	13693	05026	09615	07138	01381

Hit:100%

4.5.2.3

NB 3 Offline MDE, remove AP 3,4,5

Node	1	2	3	4	5	C
AP 1:	094%	100%	091%	053%	061%	049%

AP 2:046% 096% 008% 093% 100% 028

NB 3 Online MDE, remove AP 3,4,5

Node 1 2 3 4 5 C

AP 1:097% 099% 097% 058% 067% 021%

AP 2:056% 098% 003% 094% 099% 006%

F/Node 1 2 3 4 5 Clean

File01=00111 02732 01827 03600 03484 06880

File02=01607 00004 08598 01768 01074 14288

File03=02340 08164 00050 08507 08796 04904

File04=03329 02137 09977 00022 00224 08651

File05=03231 01447 10592 00047 00037 10436

File06=03087 07399 02848 04431 05317 01268

Hit:100%

4.5.2.4

NB 3 Offline MDE, remove AP 2,3,4,5

Node 1 2 3 4 5 C

AP 1:094% 100% 091% 053% 061% 049%

NB 3 Online MDE, remove AP 2,3,4,5

Node 1 2 3 4 5 C

AP 1:097% 099% 097% 058% 067% 021%

F/Node 1 2 3 4 5 Clean

File01=00011 00028 00007 01296 00711 05280

File02=00007 00000 00011 01764 01067 06188

File03=00036 00064 00028 01111 00576 04900

File04=01935 02115 01877 00021 00195 01024

File05=01295 01443 01248 00011 00035 01600

File06=02303 02499 02240 00075 00323 00784

Hit:50%

4.5.3

The results indicated that estimations were still with high precision when NBs were placed at different locations while the precision declined as the amount of AP decreased.

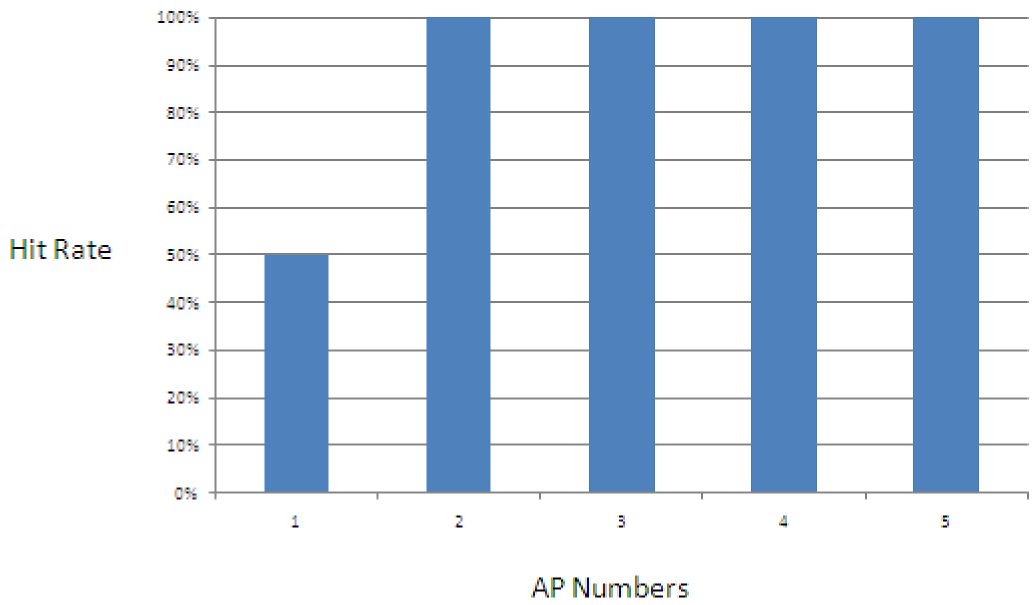

Fig 16. AP Number VS. Hit Rate

1896
E S A

5.1 Other Challenges

Signals are easily influenced by temperature, humidity and object locations, which often result in refraction, reflex, transmission or diffraction. These results not only add to the complexity of studying the signals changes in our survey. And the signal delay collection. Therefore, there is still room for improvement.

5.2 Conclusion

Although this survey can detect and analyzed the changes of environment and whether a human being is getting into a certain space, the variance of signals is so unstable that incorrect output may lead to misjudgments. There is still room for improvement to achieve reliable output.

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