# DESIGN AND IMPLEMENTATION OF A MOBILE BASED GATE PASSING DETECTION METHOD

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***ABSTRACT:*** *Gate passing detection is important information for indoor location based services. The proposed algorithm use Wi-Fi signal strength and accelerometer of user's smart phone to detect gate passing. The variations in Wi-Fi occur when door divides the indoor environment. When parameters of Wi-Fi vary significantly, it indicates a gate passing. The algorithm detects such change based on Wi-Fi distance function and give impression of moving distance corresponding to an accelerometer. The algorithm is evaluated and found out that most doors passing can be detected and existence of doors with identical door passing can be estimated with high accuracy.*

**Keywords:** Wi-Fi, Received Signal Strength Indication (RSSI)

## 1. INTRODUCTION

Gate passing that point out the entrance of a building or room is a critical information for indoor location-based services. This is especially useful for monitoring user activities and identifying user pathways. Traditionally card readers or RF tag readers are attached to gates to detect gate passing. . In these methods, users make physical contact of readers with their cards. Sometime, a gate is detected by vision-based approach [1]. The door is extracted from the images apprehended by the camera attached to a robot or a user. The limitations of camera locations drain general users. Another method uses proximity sensors [2], although general mobile terminals do not have them.

In this paper, We proposed a gate passing detection method. It works on assumption that users have smart phones. We used Wi-Fi signal strength information for detection of gate passing and evaluated the moving distance with the help of accelerometers with which most of the smart phones are equipped. In working environment, access points of Wi-Fi must be placed. However, many of the access points (APs) have already been placed in the places like universities, offices and public building.

The flow of proposed idea is describe here. Wi-Fi signal strength approaches to be block off or minimized through gates like doors. We supposed gates at those locations where strength of Wi-Fi signals deviates. To obtain the order of deviation of the Wi-Fi environments, We introduced and made the comparison of two types of moving distances which are based on Wi-Fi and accelerometers. If the Wi-Fi-based distances diverge from the accelerometer-based distance, It predicts that the user is passing a gate.

## 2. PROPOSED METHOD

Many objects divide spaces like doors, elevators, and walls. Such objects approaches to cut off or lessen strength of Wi-Fi signal. The degree of deterioration depends on the physical contact between object and access points. However, in many cases, Wi-Fi environments divided by objects are very different.

An example is shown in figure 1; a Wi-Fi environment is different due to distinction by door. Wi-Fi environment changes when the user passes through door. It is supposed that when user passes through gate like door, Wi-Fi environment changes effectively.

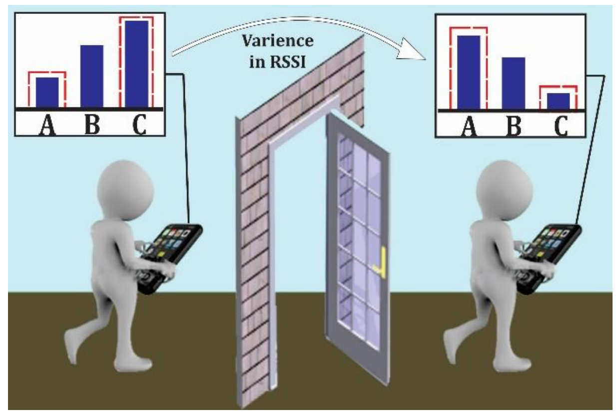


**Figure 1 Variation in Wi-Fi Environment (RSSI list)**

We defined sites where Wi-Fi environments are isolated by significantly different parts of sites as a Wi-Fi significant point. We assumed a condition where users have standard smart phones & walk with their Smartphone's indoors. The method that we have used requires two types of moving distances. One of them is accelerometer-based step estimation and the second method is the distance based. The distance-based method is grounded on the deviation of Wi-Fi signal strengths and the third is propagation model of a signal. If the latter distance varies from the former distance, the method reveals that the user has passed a Wi-Fi significant point.

One of an important model is the Seidel model [3], which is based on signal propagation model and it shows the relationship between the distance to an AP and its received signal strength indication (RSSI). By using this model, distance to an AP using RSSI can be calculated quite accurately.

### 2.1 Fundamental Algorithm for Extracting Wi-Fi Significant Points

A simple environment is defined to formulate Wi-Fi significant point extraction algorithm. It has only one AP whose location is not known. Users walk around freely, thus the route is not necessarily linear. From Wi-Fi and accelerometer information, two kinds of distances are estimated.

The distance approximated by Wi-Fi is user minimum distance. When RSSI distance $rt_1$ at $t_1$ varies to distance $rt_2$ at $t_2$ time, using Wi-Fi propagation model succeeding formula correspond the minimum moving distance $dmin$ by using Wi-Fi propagation model $f$:

$$d_{min} = |f(rt_1) - f(rt_2)|$$

Various possible path examples are shown in figure 2. When the user linearly moves away from the AP, then RSSI is varies from -30 to -40 dBm, the extent of the path distance must be the smallest. The formula for the span calculation is as:

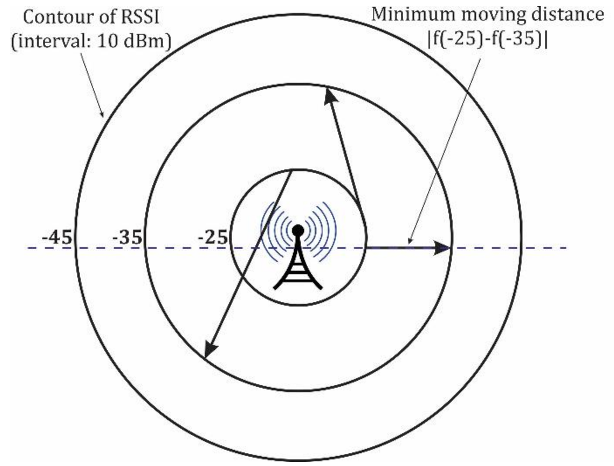


**Figure 2 User trajectory with a variation of 10 dBm signal strength**

$$d_{min} = |f(-30) - f(-40)|$$

If the user undergoes a Wi-Fi significant point, We found that minimum distance ($d_{min}$) must be greater than the actual walking distance.

Maximum walking distance $d_{max}$ between time intervals $t_1$ to $t_2$ is approximated by an accelerometer. Walking steps can be eliminated by taking local maximum and local minimum. Step distance is estimated using local maximum and local minimum along with the user height. If the user walks linearly, the total distance can be calculated by adding up each step's distance. the distance between the positions of the user at $t_1$ and $t_2$ would be smaller then the linear walking if the user's trail is not linear.

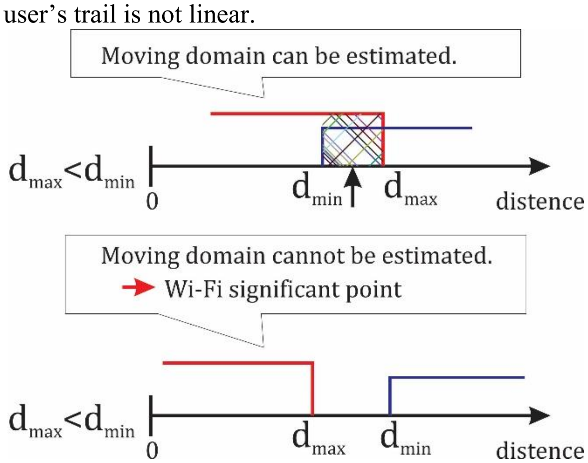


**Figure 3 Significant point extraction mechanism**

It is estimated based on $d_{max}$and $d_{min}$ that the user has passed the Wi-Fi significant point. The basic mechanism of the algorithm is shown in figure 3. If the value of $d_{max}$ exceeds $d_{min}$, we can estimate the actual distance range. In contrary, if value of $d_{max}$ exceeds $d_{min}$, we suppose the value of $d_{min}$ is not reasonable. In this case, we assume the user has crossed the Wi-Fi significant point.

### 2.2 Extending Our Proposed Method for Real Environments

We introduce the effect of the variations of RSSI and multiple Wi-Fi information and extend our recommend method for actual environments. In the actual environment, Wi-Fi signal effects multipath fading that is why RSSI is not fixed. The effect of variations can be reduced by using the average value of RSSI that are observed multiple times. Meanwhile, we assume multiple Wi-Fi information sent by multiple APs installed in different places. Recently, since many APs have been placed in several buildings, we can obtain multiple AP signals at a number of places.

#### 2.2.1 RSSI Fluctuations Effects

Firstly, we initiated the effect of the variations of RSSI and rebuilt our above strategy as a stochastic model. We assumed the variations as a Gaussian distribution. Various researchers acquire Gaussian distribution to estimate RSSI fluctuation [4], [5]. We assumed level of variations is constant.

In ideal environments, the distance can be assessed through function $f$ and RSSI $r_{\mu}$. The distance is specified by $f(r_{\mu})$.

The fluctuation is shown as a Gaussian whose mean is $r_m$ and the standard deviation is $r_s$ as in figure 4. At the time, in the ideal environment, when RSSI is observed, distance $rm - rs$ can be calculated as $f\ (rm) - f\ (rm - rs)$. Using the value, We assessed the distance variation to AP as a Gaussian distribution where the average is $wm = f\ (rm)$ and the standard deviation is $w_{\sigma} = f\ (r\mu) - f\ (r\mu - r\sigma)$.

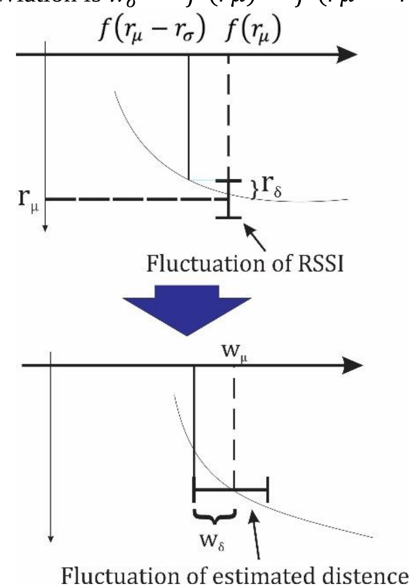


**Figure 4 Estimation of distance from RSSI (as Gaussian distribution of fluctuations)**

Minimum distance $d_{min}$is stated as difference of Gaussian distributions. As a result, $d_{min}$ is denoted as a Gaussian whose average is $d_{\min\_\mu} = w_{\mu 1} - w_{\mu 2}$ and standard deviation is $d_{\min\_\sigma} = \sqrt{w_{\sigma 1} + w_{\sigma 2}}$.

In the earlier section, the existence probability of Wi-Fi significant points is expressed as binary. On the other hand, through introducing variations, the probability based on two kinds of distances $d_{max}$and $d_{min}$ are expressed as growing probability as depicted in figure 5 (shaded area). The likelihood is calculated as:

$$p = \frac{1}{2}\left(1 + erf\left(\frac{d_{ref} - d_{\mu}}{\sqrt{2d_{\sigma}^{2}}}\right)\right)$$

$\mathrm{erf}(x)$ $is\ an\ error\ function$

The top of figure 5 is an example where aggregate probability $p$ is high which explains probable fluctuation in observed RSSI. On the other hand, if $p$ is under threshold $p_{threshould}$ (Figure 5, bottom), the observed RSSI is doubtful even where the variation is concerned. It is assumed that a Wi-Fi significant point is crossed between observation times $t_1$,$t_2$.

A weak RSSI value should not be used for extraction of Wi-Fi significant points. If the RSSI value is weak or varies, the calculated distance to the Access pints (AP) is significantly different. For example, by using the Wi-Fi transmission model from the evaluation section, the distance where the RSSI is -80 dBm is 83 m, and the distance where it is -81 dBm is 91 m. The variance is only 1 dBm, but the difference of the calculated distances is 8 m. Therefore, RSSI values that increase threshold $r_{threshould}$ for the extraction of Wi-Fi significant point are used.

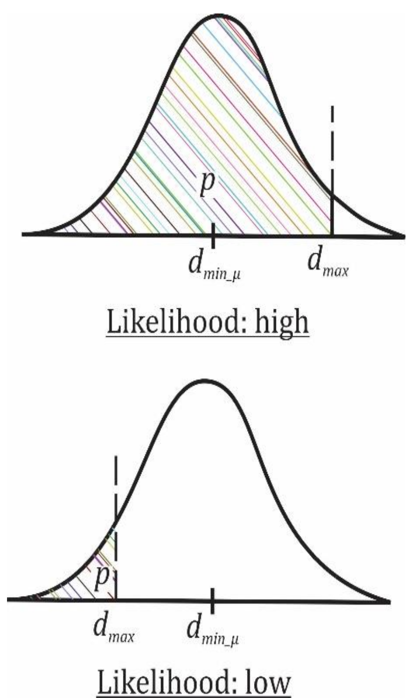


**Figure 5 Distance likelihood**

### 2.2.2 Multiple APs' Wi-Fi information

When the user goes through a point, where the Wi-Fi environment varies significantly, RSSI's are not always altering concurrently due to sensitivity of mobile device and device driver. Thus, the time intervals that Wi-Fi significant points are observed are not always equal. To reduce the problem, Wi-Fi significant points from every AP's RSSI are summed up as one point. Based on the previous section, the presence of Wi-Fi significant points from every RSSI is estimated in each observation in the time interval between $t$ and $t + 1$. The Wi-Fi significant points receive votes for their respective pauses.

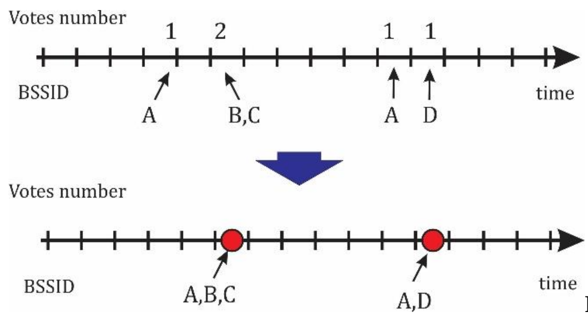


**Figure 6 Voting and Aggregation**

Then the pause that receives the much of votes in a window, the size of window is w, is refer to be one Wi-Fi significant point.

### 2.3 Identical gate-passing detection and passing direction estimation

The sum of the Wi-Fi significant points comprise of multiple Wi-Fi significant points from multiple APs' Wi-Fi information. We believe identical gate-passing detection can be realized using the pattern of the AP's information. The pattern of ith Wi-Fi significant point $S_i$ can be expressed as a vector by using the number of votes and voted BSSIDs b.

$$S_i = [b_{i,0}, b_{i,1}, \cdots, b_{i,n}]$$

The resemblance of two random Wi-Fi significant points $S_i$, $S_j$ is calculated by using Tanimoto coefficient T [6]:

$$T = \frac{N(S_i \cap S_j)}{N(S_i) + N(S_j) - N(S_i \cap S_j)}$$

The Tanimoto coefficient is a similarity metric to evaluate two sets. If they are identical, T is 1 and if they don't have any common element T is 0. Here, $N(x)$ is the number of elements in $x$.

When similarity T increases similarity threshold $t_{threshould}$, Wi-Fi significant points $S_i$, $S_j$ are guess to be the same point, and the user is crossing the gate again.

Moreover, we assessed the passing direction through the configuration of the variance of the RSSIs. For each common BSSID $b$ in $S_i$ and $S_j$, we checked the variance direction to find out whether RSSI increased or decreased. If the variance direction is the same, $Nsame$ is incremented. If the variance direction is different, $Ndiff$ is incremented. If $Nsame$ is larger than Ndiff, the user passed the gate from the same direction, and if $Ndiff$ are larger than $e$ , the user passed the gate from a different direction.

### 2.4 Correction of Wi-Fi significant points using accelerometer

As above, RSSIs do not always change at the gate-passing moment. The difference of the RSSI change timing and actual gate-passing timing is not zero, and the difference may be about ten seconds. Afterword, we modified the Wi-Fi significant point with an accelerometer.

Normally when a person passes a gate, the step interval is long, and length of each step is short, even though the ongoing time of the state is not so long. Based on the heuristics, we developed simple gate-passing timing estimation using an accelerometer. In our method, when the accelerometer's local maximum and minimum are lower than threshold $g_{threshold}$ and the continuing time is lower than $w_{threshold}$, We assumed the time zone is a gate passing. Here, $g_{threshold}$ means threshold of gate-acc and $w_{threshold}$ means threshold of gate-passing time. Various situations probably exist where the estimation is not correct. For example, in a crowdy situation people walk slowly or even stand still for short moment of time.. The method is probably inaccurate when a person slow down to passes a corridor's corner.

### 2.5 Restrictions

This proposed method is very dependent on the physical relationships between gates and APs. Thus, this algorithm cannot detect all gate passing. In absence of APs around a gate, gate passings will not be detected. Even if an AP is present around a gate, there are shapes of physical relationships between the AP and the gate where our method cannot detect gate passing.

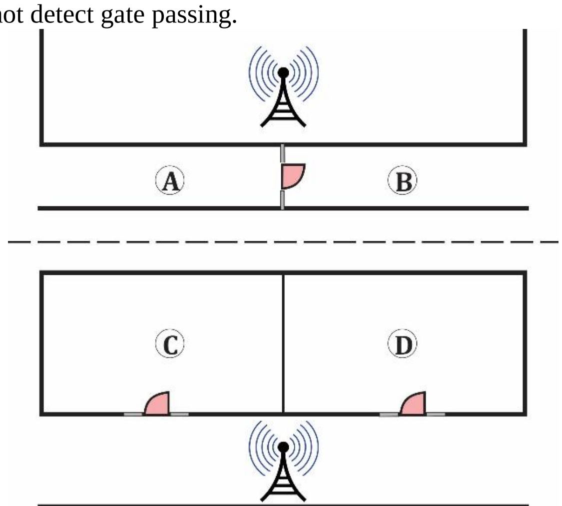


**Figure 7 Examples of unfeasible situations.**

Figure 7 shows two of the examples. In such a situation as the top of figure 7, the RSSIs at points A and B are almost the same, so the gate passings cannot be extracted by the RSSI fluctuations. In such a situation as the bottom of figure 7, the pattern of the RSSI variance of passing rooms C and D is almost the same. Thus, using our method, the doors of the two rooms should be detected as the identical door.

Additionally, there are some restrictions to apply our projected method. First, the gate must physically divide the environment like doors and elevators. Second, the person himself should open a gate to pass. If the door is previously open, capture of RSSI fluctuations difficult.

## 3. EXPERIMENTS

We experimentally assessed the accuracy of proposed method using the gate-passing detection method and the identical gate-passing estimation method.

### 3.1 Experimental environment

The experiment was conducted on the 1st and 2nd floors of the SCF-L of SUPARCO. There were nine doors in the environment with one automatic door.

Table 1 overviews the observation data. The subject is one of the authors of this paper who used an iPhone 4S smartphone. He put it in his waist holder and walked around the experimental environment. His walking speed was not constant; standing and slow walking were involved except for door passing. Our proposed method is applicable when users themselves open and close doors, so he opened and closed doors when passing them.

### 3.2 Settings

**Table 1 Experimental Data**

| | |
|---|---|
| Sampling rate of Wi-Fi observation | 1 Hz |
| Sampling rate of accelerometer | 100 Hz |
| Number of doors | 9 |
| Number of door passing | A-F: 10 times, BG-I: 20 times |
| Total experimental time | 5300 seconds |

We adopted LaMarca's parameter of the Seidel model [7]. $f(r) = -32 - 25\log_{10} r$

Step length $s$ is calculated by the following formula [8].

$$s = 0.26 \cdot height + (peakdiff - peakavg) \cdot 5.0$$

As $peakdiff$ is the difference between the values of the local maximum and the local minimum in each step and $peakavg$ means the average value of $peakdiff$. The user's height is height. In this experiment, We set the values as $height = 1.80m$, $peakavg = 1.11[g]$. The experimental parameters for the setup are provided in table 2.

**Table 2 Experimental Parameters**

| | |
|---|---|
| Fluctuation of RSSI $r_{\sigma}$ | 2.5 dBm |
| Threshold of RSSI $r_{threshold}$ | -60 dBm |
| Threshold of likelihood $p_{threshold}$ | 0.1 % |
| Threshold of similarity $p_{threshold}$ | 0.4 |
| Window size $w$ | 10 sec |
| Threshold of gate-acc $g_{threshold}$ | 0.15 G |
| Threshold of gate-passing time $w_{threshold}$ | 2.0 sec |

## 4. RESULTS

### 4.1 Gate-passing detection method

Table 3 shows the result of gate-passing detection. We defined correct detection when a detected gate passing is within 10 seconds of the actual door passing. The precision of the gate-passing detection was about 59%, and the recall was about 76%. As a result, our proposed method detected about half of the door passing, but it does not always detect them.

**Table 3 Accuracy of gate-passing detection**

| | |
|---|---|
| Gate-passing detected points | 157 |
| Actual gate passing | 120 |
| Successful gate-passing detections | 92 |
| Precision | 59% |
| Recall | 76% |
| F-measure | 66% |

Table 4 shows the accuracy of the gate-passing detection for identical doors. The precision of identical gate-passing detection was about 70%, and the recall was about 48%. Depending on the results, the accuracy of the gate-passing detection significantly differs by door, even though gate-passing detection is possible when the user passes the door many times. Automatic doors provide minimum accuracy. When passing automatic doors, the step length around the door is shorter than manual door.

**Table 4 Accuracy of identical gate-passing estimation**

| | |
|---|---|
| Wi-Fi significant points related to door passing | 92 |
| Pair of Wi-Fi significant points that have identical | 348 pairs |

| | |
|---|---|
| gates | |
| Pairs of Wi-Fi significant points where identical gate detection was correct | 245 pairs |
| Pairs of Wi-Fi significant points where they should be estimated as same gate | 508 pairs |
| Precision | 70% |
| Recall | 48% |
| F-measure | 57% |

One reason is the existence of Wi-Fi hotspots caused by reflections and multipath. For example, corridor's corner tends to be Wi-Fi hotspot. Consequently, the accuracy of identical gate-passing estimation is not as high as gate-passing detection, even though we found doors on which the identical gate-passing estimation method was performed successfully. Therefore, we are sure that our method is useful for restrictive situations. For 245 pairs that were correctly estimated as the same gate. We applied the gate-passing direction estimation method and the accuracy was 92%. Moreover, for door G whose accuracy of identical gate-passing estimation was high, the accuracy of the gate-passing direction estimation was 100%. As a result, the gate-passing direction estimation method is generally useful.

## 5. CONCLUSION

This technique proposed and tested a mobile based gate passing detection method. Proposed method work on the assumption that Wi-Fi environment which are divided by gates, has significant difference. The information from accelerometer of smartphone and Wi-Fi is used for gate passing detection. As a result of several experiments, it has been found that the proposed method detects more the half of gate passing events. Accuracy of identical gate passing is quite low. However, we found gates whose accuracy of identical gate passing methods is high.

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