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Modelling the Effect of Human Body around User on Signal Strength and Accuracy of Indoor Positioning

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Abstract: WLAN indoor positioning system (IPS) has high accurate of position estimation and minimal cost. However, environmental conditions such as the people presence effect (PPE) greatly influence WLAN signal and it will decrease the accuracy. This research modelled the effect of people around user on signal strength and the accuracy. We have modelled the human body around user effects by proposed a general equation of decrease in signal strength as function of position, distance, and number of people. Signal strength decreased from 5 dBm to 1 dBm when people in line of sight (LOS) position, and start from 0.5 dBm to 0.3 dBm when people in non-line of sight (NLOS) position. The system accuracy decreases due to the presence of people. When the system is in NLOS case, the presence of people causes a decrease in accuracy from 33% to 57%. Then the accuracy decrease from 273% to 334% in LOS case.

Keywords: Indoor Positioning System, People Presence Effect, Internet of Thing, WLAN Fingerprinting, Model of Human Body

1. Introduction

IPS based service has great economic potential, it is estimated to reach US$ 10 billion in 2020 [1]. Indoor Positioning market is predicted to reach $54.60 billion in 2026 [2]. IPS are any system that gives a precise position inside of buildings, such as a smart building [3], hospitals [4], airport [5], a subway [6], construction [7], industry [8], and university campuses [9].

One of the performance indicators of IPS is accuracy, the difference between the actual location and the estimated location [10]. There are many applications that need precise IPS, among others for emergency case and patient monitoring. For example, it is essential for 911 to know the location of caller as precisely as possible to control delays in emergency response. Delays in response can make loss of lives. Then they define new standard "next generation 911 (NG911)" [11], [12]. It is also important to build an indoor navigation system that can track firefighters to within a meter [13]. IPS also has an important role in the field of Internet of Thing (IoT) [14]. One of the largest European Union project on IoT (FP-7 Butler project) stated that location information is one of the key enabling technology in the IoT.

WLAN IPS has been chosen because it has high accuration and minimal cost [15]. However, WLAN signal inside indoor area is greatly influenced by environmental conditions such as the people presence effect (PPE) and multipath effect, so it can decrease the accuracy. It needs adaptive IPS that can adapt the multipath effect and the environmental changes, mainly, to provide the high accuracy of IPS.

One of the main problems related to PPE is the position of the user himself who holds mobile device (MD). This problem is known as the user orientation problem. To solve user orientation problem, Liu [16] collected four orientations of radio map (RM) in offline phase and used a K-Nearest Neighbor (KNN) positioning algorithm in online phase. Zhi

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[17] also built up multi orientations RM in offline phase and deployed Rotation Matrix and Principal Component Analysis (RMPCA). Their solutions are time consuming because the multi-vectors of received signal strength indicator (RSSI) had to be collected at each node manually. The systems in previous studies required a large amount of time for collecting data and developing database because they focused on the development of a multi-orientation RM database.

In addition to users who hold MD, people around users also affect RSSI. The people presence has a same effect to obstacles blocking WLAN signals. One of major effects leading to variation of RSSI is the movement of humans [18], [19]. Alshami was presented an experimental result to show that people’s presence between access point (AP) and MD reduced the received signal strength by 2dBm to 5dBm [20]. Only the effect of one or two people to the RSSI is discussed by Alshami and they just considered the single path signal propagation model. However multipath signal such as reflection has significant effect in indoor propagation. This research tries to model the effect of many people around user with several of number and position on signal strength (RSSI) and the accuracy of IPS.

2. Literature Review

The user's body that hold the MD also becomes a barrier to the WLAN signal. Then the user orientation is also important to consider. Bahl and Padmanabhan [21] stated that RSSI is significantly impacted by user orientation, and can therefore also affect the error of position estimation. The error distance is computed by the author for all four combinations of opposing directions. The median of position error is in the range of 2 to 3 meter. It needed big memory for four orientation RM database, and time-consuming process to collect the data (RSSI vector).

King built 8-orientation radio map in offline step manually then use digital compass to select the appropriate radio map in online step. Then system will choose a RM appropriate to user (MD) direction in online step [22]. The distance error is 1.65m. King’s solution is time consuming in offline step because it collects 8 orientation data manually at each node. This technique also spent significant memory for RM database.

Feng [23] proposed a received signal strength (RSS)-based localization scheme in WLAN using the theory of compressive sensing (CS). CS is a framework that used for recovering sparse or compressible signals, and it need fewer noisy measurements than the Nyquist sampling theorem. Clustering by affinity propagation was performed in online phase to address the effects of RSS variation and mobile device orientation. This method needed minimum 4 APs to achieve 2.1m error. This method is time consuming because it needs to collect RSSI four times at each node to get the 4-orientation radio map database.

Four orientations of RM are collected by Zhou [24] then user orientation is integrated into the Bayesian positioning algorithm. They needed 7 APs, 800 samples, and 240 second for every reference location in offline phase to achieve 84% accuracy within 4m of error. The average of position error was 2.89m. This solution still needed high computation and required a lot of devices and times to collect the data and calculate the estimated location.

Fet et al. used single-orientation radio map and signal attenuation model to build multi-orientation radio map [25]. Fet’s solution can reduce the time to build 8 orientations RM. By applying this model, WLAN scanning time could be saved up to 87.5% in the offline phase. Then using multi orientations RM database means extra computational cost and need extra memory. Liu and Wang [16] collected four orientations of RM and used a k-NN positioning algorithm. This system consists of 3 kinds of devices such as servers, APs and smart phones. The accuracy of positioning can achieve 93.3% from 15 test points, but they did not mention the positioning error.

Booranawong et al. [18] stated the effect of the human activity to WLAN signal strength. The people detection and tracking system can be constructed using this effect [19]. The attenuation of WLAN signals in the 60 GHz affected by human blockage has been measured by Koda et al. [26] and Slezak et al. [27]. Then to reduce the variation of RSSI and the error of position estimation caused by the human activity, Booranawong et al. [18] proposed filtering methods. Unfortunately the error is still quit high, above 1m.

An experimental has been presented by Alshami et al. [20] and showed that RSSI reduced in value (-2dBm to -5dBm) because of human’s position between AP and MD. The value of RSSI is affected by the distance between the MD and the people [28]. The result is the improvement of positioning accuracy from 1.9m to 1.7m. Although it could improve the accuracy, but to get better accuracy it still needs further research by modelling the effect of many people around user with several of number and position on signal strength (RSSI) and the accuracy of IPS.

3. Research Method

This research method consists of three phases as shown in figure 1. They are radio map construction, modelling the effect of human body around user on signal strength (RSSI) and accuracy.

3.1 Radio Map Construction

There are three radio maps: manual radio map, automatic radio map using multi wall propagation model (MWPM) and ray tracing propagation model. The first step is manual radio map construction which uses Wi-Fi scanner application to collect information from the beacon frames of IEEE 802.11 broadcasted by APs in the surrounding environment. Wi-Fi scanner is an android application that made by Alshami [29] to record RSSI. Beacon frame of IEEE 802.11 consist of many information such as MAC address, signal strength (RSSI), system time, timestamp, channel, and frequency. This study only recorded MAC address and RSSI data. Data collection procedures in the construction of this radio map refer to procedures that have been carried out by Alshami [29] and Firdaus [30]. Data is recorded at points with a distance of 1m, and there are no people around MD. At each point, 30 RSSI are recorded. Then the median value was used as a radio map data. This database that consist of location data and RSSI are stored in an excel file. It will be used in Matlab to simulate and compute the location prediction.

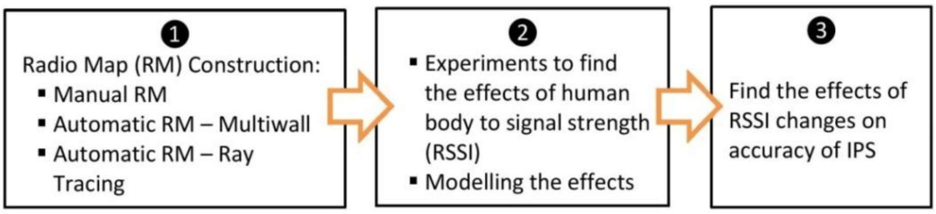

Fig. 1 - Step by step of the research methodology

The second step is automatic radio map construction using multi wall propagation model (MWPM) that comes from previous work by Alshami [29]. MWPM only considered the direct path between the transmitter and receiver, and every wall crossed by this path attenuates the passing ray by a constant amount.

An automatic radio map using ray tracing propagation model (ARM-RT) is developed in the third step. Building map, type of material and relative permittivity become the input of the system. The system also considers the location of transmitter (AP), transmit power of AP, and the height of receiver (MD). The output is the RM database that consists of the RSSI value in the building and location information. In this simulation, the RSSI will be calculated using ray tracing at the same position as in the manual calibration with distance of 1m each point.

The image file of building map will be changed first to .csv file. The .csv file consists of the coordinate that define the floor, ceiling, wall, and their relative permittivity. The server will run the ray tracing model to calculate the RSSI and store the ARM-RT database for the building. To run a ray tracing simulation, a building layout and information on the type of material used are required. Figure 3 shows the layout of the building and the type of material described in Table 1.

Each wall will be defined in its shape, size, and relative permittivity value according to the type of material. Besides walls, floors and ceiling also need to be defined. The ray tracing method provides the estimation of the path loss, time delays, arrival angle, and departure angle [31]. Ray tracing is a promising method for indoor radio propagation modelling because it provides an accurate prediction [32].

The ray tracing (RT) simulation in this research used image method that considered the transmission and reflections to predict the RSS. Two reflection rays were used in this simulation because three reflections are not significant contributors to signal strength [33]. The signal strength changes by only 1 dB when considering 3 to 6 reflections. It increases the complexity and execution time exponentially [34]. Table 2 explains the simulation parameters.

3.2 Effect of Human Body around User on Signal Strength (RSSI)

The aim of PPE testing is to check the effect of people or human body around user on RSSI and accuracy of the IPS. PPE testing consists of 3 experiments. First experiment is conducted to test PPE in the position of Line of Sight (LOS); the position of people is between the AP and MD so that blocking signals from the transmitter. Second and third experiments are conducted to test PPE in Non-LOS (NLOS) positions; people are around MD and do not block signals directly from the transmitter.

There are variations in the position of people and the distance between people and MD. There are 1 to 13 people involved in this experiment. The criteria of people involved were people with normal height, between 160 and 170 cm. All the people involved have first gotten an explanation of this research and they volunteered to be involved in this research.

3.3 Effect of Human Body around User on Accuracy

Many of the machine learning algorithms such as KNN, Support Vector Machine (SVM), Artificial Neural Network (ANN) and others were used as positioning algorithm in the literature [35]–[38] to find the accuracy of the system. KNN is chooseen as positioning algorithm because it is the simplest of all machine learning algorithms. The KNN included in non-parametric and instance-based learning method for classification and regression. The main tools will be used in this phase are Wi-Fi scanner and Matlab. Wi-Fi scanner is used to collect RSSI, and Matlab is used to run the positioning algorithm.

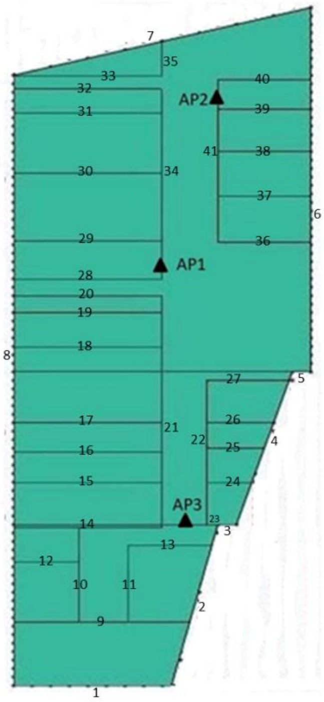

Fig. 2 - Layout of level 3 of Razak Tower

Table 1 - Type material of the walls in Razak (level 3)

Walls	Material	Walls	Material
1	Brick	22	Glass
2	Glass	23	Glass
3	Brick	24	Particle board
4	Glass	25	Particle board
5	Brick	26	Particle board
6	Glass	27	Brick
7	Glass	28	Brick
8	Glass	29	Particle board
9	Particle board	30	Particle board
10	Brick	31	Particle board
11	Particle board	32	Particle board
12	Brick	33	Particle board
13	Particle board	34	Particle board
14	Particle board	35	Particle board
15	Particle board	36	Particle board
16	Particle board	37	Particle board
17	Particle board	38	Particle board
18	Brick	39	Particle board
19	Brick	40	Brick
20	Brick	41	Glass
21	Particle board		

Table 2 - Parameters for ray tracing propagation model simulation

Parameters	Value
Frequency of WLAN	2.4 GHz
Method of RT	Image method
The considered multipath	first reflection, second reflection, and transmission
Transmission power	-30 dBm

In order to evaluate the positioning method, different performance metrics have been proposed such as: accuracy, precision, complexity, scalability, robustness, cost and responsiveness [39] [40] [41]. Accuracy is one of the most important performance parameter of the localization system [42]. This research used the positioning accuracy as performance metric. The accuracy as shown in equation (2) is the difference between the real position and the estimated one [43]. Where (x_p, y_p) is the predicted point, and (x_a, y_a) is the real point.

$$Accuracy = \sqrt{(x_a - x_p)^2 + (y_a - y_p)^2} \tag{2}$$

4. Result and Analysis

4.1 Radio Map Database

Manual radio map of 20 rooms and corridors consist of RSSI vectors that collected at 523 points. The maximum of RSSI that transmit from AP1 is -50dBm Then it become -40dBm, and -45dBm that transmit from AP2, and AP3 respectively. Then the minimum RSSI are -89dBm, -84dBm, and -87dBm. Standard deviation for $RSSI_1$ is 7.1, 11.06 for $RSSI_2$, and 10.45 for $RSSI_3$. The Manual Radio Map (MRM) is used to calibrate of the Automatic Radio Map (ARM) database.

The calibration result of ARM-MW and ARM-RT can be seen in Table 3. RT is ray tracing model, and MW is multi wall model. Mean square error (MSE) of RT model is smaller than MSE of MW model. Its mean that to predict the RSSI, ray tracing model is better than multi wall. This is because multi wall model only counts the direct signal from TX to RX, while ray tracing model calculates the direct and indirect signals such as diffraction and reflection. So that ray tracing are more accurate than multi wall to predict the RSSI.

Table 3 - Prediction error of ray tracing and multi wall propagation model

APs	MSE		RMSE		MAE	
	RT	MW	RT	MW	RT	MW
AP1	14.55	34.14	3.8	5.8	3.2	4.3
AP2	14.05	108.4	3.7	10.4	2.9	7.4
AP3	12.19	92.38	3.5	9.6	2.8	7.1
Mean	13.60	78.30	3.7	8.6	2.9	6.3

4.2 The Effect of Human Body around User on RSSI

First experiment is shown in Figure 3, one person is standing in a position that blocking the LOS path from transmitter (AP) to receiver (MD). The distance from transmitter to receiver is 10 meter. The height of AP1 is 1m from the floor, then 2m and 3m for AP2 and AP3. The height of mobile device is 1m from the floor. One person stands between access point and mobile device by setting the distance between people with mobile device (r) from 1 m to 9 m. We measured 30 data of RSSI at each position. The results can be seen in Figure 4. As a reference, when there is no human blocks the signal (LOS), RSSI received by MD from AP1 is -45 dBm, -45 dBm for AP2, and -46 dBm for AP3. It appears that the people as a barrier between the AP with MD on LOS path can reduce the value of RSSI, especially when the people position is close to the MD. When one people is at a distance of 1 to 3 m from MD, the reduction of RSSI by is 5 dBm in average. When the distance is 4 to 6 m then the RSSI decreases by an average of 3 dBm. It decreases by 1 dBm when the distance is 7 to 9 m. The decrease in RSSI is greater when the distance of people to MD is closer in the LOS position. The more signal from the transmitter is blocked by people when the people is closer to the MD. This applies to RSSI from AP1, AP2, and AP3.

Second experiment, the signal from AP to MD is not block directly by people. There is one people around the MD. There are three rings of people's position in this experiment, the first ring is 1 m from MD, the second ring is 2 m away, and third ring is 3 m apart. Just like the previous experiment, this experiment used 3 APs. AP1 is placed at a height of 1 m from the floor, AP2 is 2 m, and AP3 is 3 m. The height of MD is 1m from the floor. Table 4 shows the average of difference in RSSI between condition of one people around MD and no people (Δ RSSI). The further of the distance between MD and human, so the smaller the impact on RSSI. The RSSI decrease by around 0.5 dB when there is people at a distance of 1m from MD in NLOS position. When the distance is 2m, it decrease around 0.4 dB and around 0.3 dB when 3m. The decrease of RSSI here is much smaller than the LOS case. This is because the direct signal is blocked by people in LOS position and it will make significant attenuation, whereas the reflection signal is blocked by people in NLOS. The power of reflection signal is much smaller than the power of direct signal.

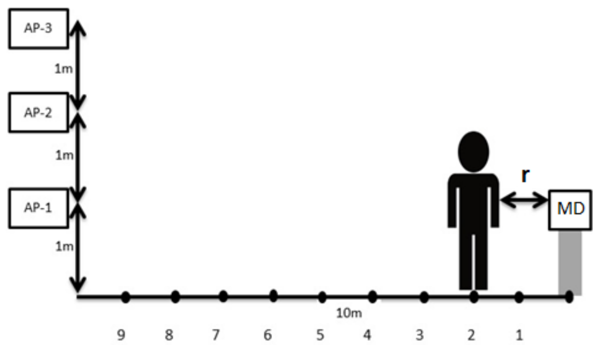

Fig. 3 - People in LOS Position between TX and RX

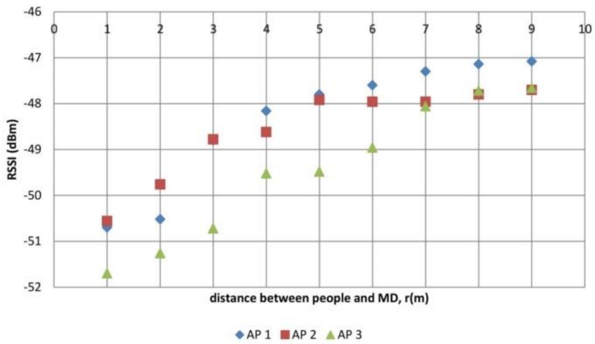

Fig. 4 - The effect of one people in LOS position to RSSI

The effects of many people around MD on RSSI are explored in the third experiment. This experiment involved several people (2 to 13) with variation in their position and distance to MD. The distance start from 1 m (1st ring) then proceeds with a distance of 2 and 3 m. The result also can be seen in Table 4. Greater influence is gained when there are more people and the closer the distance between MD and people. The general equation is shown in Equation 3 for NLOS case.

4.3 The Effect of Human Body around User on Accuracy

There are 3 types of RM databases that will be used to test the accuracy of IPS here: MRM, ARM-MW, and ARM-RT. The KNN algorithm is used as positioning algorithm in this experiment because this algorithm also used in previous research that conducted at the same place (the 3rd floor of Razak Tower UTM Kuala Lumpur) [29]. They nominated

KNN and ANN as positioning algorithms then KKN (k=3) is chosen because KNN more accurate than ANN. KNN is also easier to apply on smartphones because KNN computing is simpler than ANN.

Table 4 - The average of difference in RSSI between condition of one people around MD and no people

Distance of people to MD/User (r)	Number of people (n)	Δ RSSI
1	1	-0.5
1	2	-0.55
1	3	-0.58
1	4	-0.6
1	6	-0.8
1	7	-0.91
2	1	-0.4
2	2	-0.54
2	3	-0.56
2	4	-0.6
2	5	-0.64
2	6	-0.71
2	9	-1.1
2	10	-1.1
3	1	-0.3
3	2	-0.48
3	3	-0.52
3	7	-0.68
3	13	-0.91

Table 5 - The result of multilinear regression analysis from data in table 3

	Coefficients	*Standard Error*
Intercept	-0.52345	0.055078
X Variable 1	0.078936	0.025015
X Variable 2	-0.06129	0.005822

$$\Delta RSSI = -0.52345 + 0.078936r - 0.06126n \quad (3)$$

Table 6 - The average of accuracy for each type of database

Radio Map Database	Accuracy
Manual measurements	0.62 m
Ray Tracing Model	0.97 m
Multi Wall Model	1.27 m

Binghao Li [44] and Xingbin Ge [45] used 30 test points to find the accuracy. Other studies used 43 points [46], 21 points [47], and 7 points [48] for testing to get the accuracy. Iyad did the experiment at same building with this research used 38 test points and 306 reference points to cover a half part of 3rd floor Razak Tower (eastern side) [29]. In contrast, this study covered all parts of the 3rd floor of the Razak Tower which has 527 reference points and 65 test points. This experiment is to conduct a test to find out in detail the influence of the presence of people on IPS accuracy. The presence of people is divided into two, first when people stand in the LOS position and second when people stand in the NLOS position. In the LOS position, people will reduce RSSI -5 dBm, -3 dBm, and -1 dBm. People in the NLOS position will cause RSSI to decrease from -0.5 dBm until 1 dBm.

The maximum error for the MRM database is 1.37m, then 1.47m for the ARM-RT database and 2m for ARM-MW. While the average error for each type of database can be seen in Table 5. The smallest average error of course when using the MRM database is 0.62m. Then followed by ARM-RT and ARM-MW, the averages of accuracies are 0.97m and 1.27m respectively. The best accuracy is achieved by MRM database. However, it is wasteful of time and energy to create a MRM database.

The highest average error is 1.27m when using ARM-MW database. This result is same with the previous studies by Iyad [29] that conducted in same building. Better error average is obtained when using the ARM-RT database which is 0.97m. We need longer time to generate an ARM-RT database than the ARM-MW database. It takes around 25 to 30 minutes to generate ARM-RT database while 5 to 10 minutes is needed to generate ARM-MW database. Based on that result, ARM-RT became a very potential solution.

To find out the effect of the presence of people on accuracy is done by reducing the RSSI value from 65 test points in accordance with the AP that gets influence. For example if AP1 is affected by the presence of people, then the RSSI value from AP1 at 65 test points is reduced by 5 dBm for the case of LOS (r=1m) and 0.5 dBm for the NLOS case (r=1m). The results can be seen in Table 6 and Table 7.It can be seen that the system accuracy decreases due to the presence of people. The accuracy of the system decreases when there are more RSSI are affected by people presence effect. For example, when there is no people effect so the accuracy of the system is 0.48 m (MRM), 0.83 m (ARM-RT), and 1.9 m (ARM-MW). When the system using ARM-RT database, the presence of people causes a decrease in accuracy of 33% (1 AP), 44% (2 APs), and 57% (3 APs) in NLOS case (Δ RSSI = 0.5 dBm).

Table 7 shows that the effect of the people presence in the LOS position is greater than NLOS position. When using the ARM-RT database (Δ RSSI = 5 dBm), the presence of people causes a decrease in accuracy of 273% (1 AP), 322% (2 APs), and 334% (3 APs). These results show that PPE has a significant effect on the accuracy of the system. The worst accuracy (reduced by 334%) is occurred when RSSI from the three APs was influenced by people in LOS position. The greater the change in RSSI and the more the number of APs affected by the presence of people, the decrease in accuracy is also more significant.

Table 6 - People presence effect on IPS accuracy in the NLOS position

Database	Δ RSSI = 0.3 dBm			Δ RSSI = 0.5 dBm			Δ RSSI = 0.8 dBm		
	1 AP	2 APs	3 APs	1 AP	2 APs	3 APs	1 AP	2 APs	3 APs
MRM	0.7	0.8	0.9	0.8	1	1.1	0.9	0.8	1
ARM-RT	1.1	1.2	1.3	1.1	1.2	1.3	1.3	1.1	1.3
ARM-MW	1.3	1.4	1.5	1.3	1.5	1.7	1.5	1.3	1.6

Table 7 - People presence effect on IPS accuracy in the LOS position

Database	Δ RSSI = 1 dBm			Δ RSSI = 3 dBm			Δ RSSI = 5 dBm		
	1 AP	2 APs	3 APs	1 AP	2 APs	3 APs	1 AP	2 APs	3 APs
MRM	1.1	1.5	1.6	2.7	3.7	4	3.5	4.6	5.4
ARM-RT	1.4	1.5	1.7	2.4	2.8	2.9	3.1	3.5	3.6
ARM-MW	1.6	2.1	2.2	3	4.1	4.9	4.3	6.2	8.5

5. Conclusion

There are many applications that need precise IPS, among others for emergency case and patient monitoring. WLAN IPS has been chosen because it has high accuration and minimal cost. However, WLAN signal inside indoor area is greatly influenced by environmental conditions such as the people presence effect (PPE) and it can decrease the accuracy. One of the main problems related to PPE is the position of the user himself who holds MD (user orientation problem). There are many researchers proposed solutions for this problem. In addition to users who hold MD, people around users also affect RSSI. This research modelled the effect of many people around user with several of number and position on signal strength (RSSI) and the accuracy of IPS.

When one people stand in LOS position with a distance of 1 to 3 m from MD, RSSI decrease by an average of 5 dBm. When the distance is 4 to 6 m then the RSSI decreases by an average of 3 dBm. It decreases by 1 dBm when the distance is 7 to 9 m. People at a distance of 1m from MD in NLOS position make the RSSI in MD decrease by around 0.5 dBm. Then it decrease around 0.4 dBm when the distance is 2m and around 0.3 dBm when 3m. The decrease of RSSI at NLOS is smaller than the decrease of RSSI at LOS. This is because the direct signal is blocked by people in LOS position and it has significant attenuation, whereas mainly block the reflection signal is blocked by people in NLOS. The signal strength of reflection signal is smaller than the direct signal. We have modelled the human body around user effects by proposed a general equation of decrease in RSSI as function of position, distance, and number of people. The system accuracy decreases due to the presence of people. When the system using ARM-RT database, in NLOS case (Δ RSSI = 0.5 dBm), the people presence causes a decrease in accuracy of 33% (1 AP), 44% (2 APs), and 57% (3 APs). The people presence causes a decrease in accuracy of 273%, 322%, and 334% when using the ARM-RT database (Δ RSSI = 5 dBm).

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