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INDOOR LOCATION ESTIMATION UTILIZING WI-FI SIGNAL BASED ON BAYESIAN APPROACH

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ABSTRACT

The uses of detection location technology such as GPS and A-GPS have increased by day. However, this technology cause inefficient for indoor environment detection. This is due to the multipath fading and disability of signal to penetrate most of building materials. This study will focus on indoor location estimation which utilizes available signal which is Wi-Fi. Bayesian approach algorithm and MATLAB software are used to estimate the location in order to analyze indoor location and positioning via Wi-Fi by using one of the method named fingerprints. Location fingerprints is a technique of positioning that compares measured of Received Signal Strength (RSS) data to a database of expected values to estimate the location. The performance of Bayesian approach was evaluated and it has greatly performed in this location with low percentage of error. For the future works, the software can be improved by considering the user is in moving mode. It is worthwhile to explore the big variations in historical RSS information as to enhance the system estimation. A MATLAB coding which can automatically measure the RSS value of each access point should be considered in order to make the location estimation calculation easier.

Keywords: Bayesian model, fingerprints technique, indoor location estimation, received signal strength indication, Wi-Fi.

1. INTRODUCTION

Recent years demand for services and systems that depend upon accurate positioning of people and objects have seen rapidly increasing. Thus, it has led to the development and evolution of numerous positioning systems. Positioning system determine the location of a person or an object either relative to a known position or within a coordinate system [1]. In the last few decades, many positioning systems have been motivated by demand and have been developed [2]. There are two types of positioning system which are Indoor positioning and Outdoor positioning.

Indoor positioning make used of signal of opportunity. Signal of opportunity are an existing Radio Frequency (RF) signals around us, which tend to have much higher power levels and wider coverage in urban or indoor environments than Global Navigation Satellite System (GNSS) signals. Furthermore, it can penetrate buildings due to their lower frequencies [3]. Using signals of opportunity may also reduce the costs in terms of system implementation than GNSS [4].

There are significant problems that need to be considered in engaging each of them for positioning, owing to the fact that such terrestrial signals were not designed for location estimation. Signals of opportunity in previous research include analogue or digital television and analogue or digital audio signals transmitted from commercial radio and television broadcasting towers [3]. They also include GSM signals from mobile telephone base stations [3]. Other types of signals of opportunity are Ultra-Wide Band (UWB), ZigBee, and Wireless Local Area Networks (WLAN) such as Wi-Fi and Bluetooth [5].

The critical challenge of using signals of opportunity as ranging signals is synchronization. Some signals of opportunity e.g. Digital Video Broadcasting (DVB), Digital Audio Broadcasting (DAB), WLAN, and Fourth- Generation Communications System 4G use OFDM modulation [6], because of its low sensitivity to radio channel quality, multipath propagation, etc [7].

In other hand, Global Positioning System (GPS) and Assisted GPS (A-GPS) are types of outdoor positioning system. Using satellites, cell towers, and Wi-Fi databases, outdoor positioning does a reliable job of pinpointing location within approximately 20 meters. Standard GPS is a great solution for outdoor positioning products, such as road navigation, photo tagging, and location based searches.

Although GPS is a great solution for many products, GPS suffers from one fundamental problem. The signals sent by GPS satellites are relatively weak. The GPS signals cannot penetrate the structure of most buildings. This makes positioning within a building very difficult. With the help of A-GPS, the position estimation usually within general proximity of the building, nevertheless this technology would never be able to take the next step to achieve accurate indoor positioning using these methods [8].

One of other method is an RF fingerprint. It is a set of location-dependent signal parameters measured by the Mobile Station (MS) or the Access Point (AP) [3].

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Similarly to a human fingerprint, which carries the unique identification of a person, an RF fingerprint is expected to uniquely identify a geographic position. In order to do so, the number of signal parameters in the RF fingerprints must be high enough to allow for a unique correspondence with a given location [3]. For this study, the RF fingerprint is a technique that compares measured of Received Signal Strength Indication (RSSI) data to a database of expected values to estimate the location [3]. In order to estimate the object location, the system needs first to measure received signal strength at particular locations and then search for the pattern or fingerprint with the closest match in the database [9]. This technique used an arbitrary grid pattern [3].

An indoor location estimation utilizing Wi-Fi signal is proposed in this study [10-12]. Although Wi-Fi signal has not been designed for positioning, its radio signals can be used for location estimation by exploiting the Received Signal Strength (RSS) values measured in any device equipped with Wi-Fi facilities and no special hardware is needed [13-20]. Besides, Wi-Fi signal also had been installed in most of the building in over the world and been upgrade from time to time. This is the greater chance for Wi-Fi to be used in detecting the location of a person and things [21-26].

Bayesian is a probabilistic approach where the RSS is treated as a random variable that can be modeled as a lognormal distribution. Assuming the target wireless devices is located at a location $L=[x,y]$, given the online observed RSS values s, that is $s=\{s1,s2,s3,s4,.....sn\}$, the location of the target wireless devices is given by

$$(\hat{x},\hat{y})=\arg\max_L[P(L/s)] \quad (1)$$

Where $P(L/s)$ denotes the probability that the wireless device is at location L.

By using Bayes' rule, equation 1 is equivalent to finding the position L which maximizes

$$P(L/s)=\frac{P(s/L)\times P(L)}{P(s)} \quad (2)$$

Without prior information about the position of the wireless device, probabilistic of wireless device located at different places is assume to be equally likely. Thus, equation 2 can be showed as

$$P(L/s)=c\times P(s/L) \quad (3)$$

where $c=P(L)/P(s)$ is a constant.

Equation (3) can be further simplified by assuming conditional independence of measurement from all access points:

$$P(s/L)=P(s1/L)\cdot P(s2/L)\cdot P(s2/L)\cdots P(sn/L) \quad (4)$$

RSS measurements at each location is assumed as follow a log normal distribution, the expected RSS vector at each location, that is, for every location L can be computed. Thus the location of L can be determined which maximizes [3].

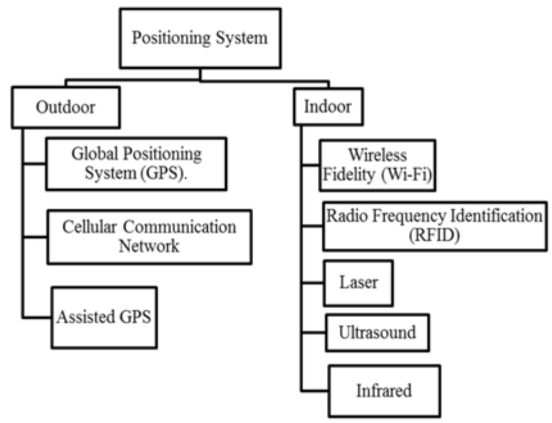

Figure-1. Type of positioning system.

2. METHODOLOGY

Four major phases are involved the study.

A. First phase: Offline phase

In this phase, a personal computer equipped with VisiWave Site Survey Trial software version is used to measure RSS for offline database. All these RSS values are stored as offline database.

B. Second phase: Online phase

RSSI is measured at the certain area at the sample location. These locations are chosen randomly. All the locations then are stored as online phase.

C. Third phase: Build simulation software

In this phase, MATLAB is used as simulation programme to develop and design the simulation software. Bayes Rules is applied in the coding as a determination algorithm.

D. Forth phase: Analyze performance

The performance of the location estimation based on Bayesian algorithm is analyzed by comparing the different between location estimation and actual location.

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E. Methodology of the system

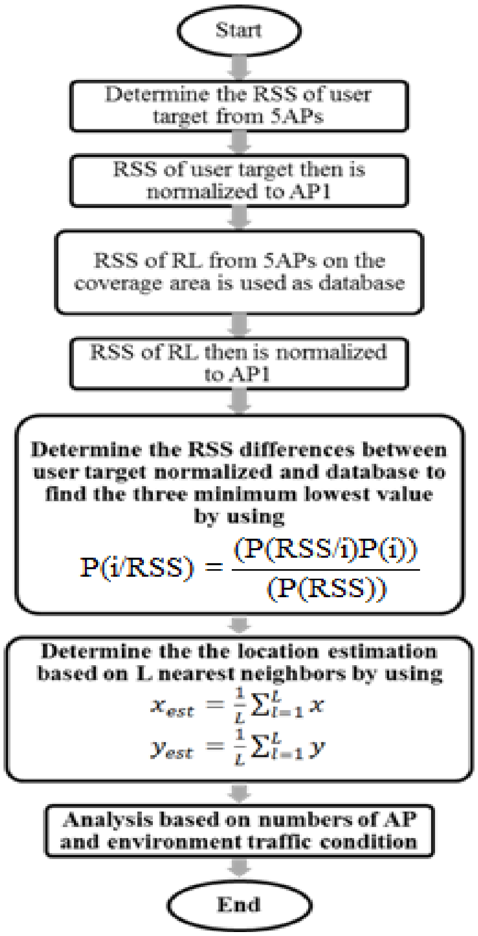

Figure-2. Flowchart of the programme system.

3. RESULTS

The area of the sample location is divided into 2 x 26 constant point based on number of poles. The length from A to C is 2.34m and A to B is 92m. Therefore, the distance from a point to another point at range A to B is 3.7048m. Figure-3 shows the sample area which covers in this study.

- Length A to B: 92m / 26 points= 3.7048m
- Width A to C: 2.34m

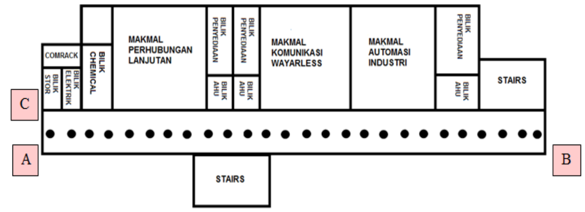

Figure-3. Ground floor of block E FKEKK.

While Table-1 shows how the reference locations are arrange in matrix form. Table-2 shows the offline database.

Table-1. Reference point arrangement in matrix form.

Reference location	Matrix form (x,y)
1-26	(1,1), (2,1), (3,1), (4,1), (5,1), (6,1), (7,1), (8,1), (9,1), (10,1), (11,1), (12,1), (13,1), (14,1), (15,1), (16,1), (17,1), (18,1), (19,1), (20,1), (21,1), (22,1), (23,1), (24,1), (25,1), (26,1)

Table-2. Part of offline database.

Reference point	AP1	AP2	AP3	AP4	AP5
1	-86	-77	-76	-74	-76
2	-86	-72	-73	-76	-65
3	-86	-76	-77	-76	-66
4	-77	-75	-74	-80	-68
5	-78	-75	-75	-83	-66
6	-74	-73	-72	-80	-67
7	-69	-75	-76	-83	-69
8	-71	-72	-72	-75	-69
9	-72	-72	-72	-73	-68
10	-67	-76	-77	-83	-72
11	-56	-76	-76	-66	-79
12	-63	-80	-79	-65	-83
13	-58	-75	-77	-66	0
14	-61	-75	-75	-57	0
15	-51	-78	-78	-58	0
16	-61	-77	-77	-59	-87

ARPN Journal of Engineering and Applied Sciences

Table-3. MAC address of each AP.

AP Label	Name of AP	MAC address
AP1	Makmal Wireless	00:08:30:70:87
AP2	UTeM-X	24:b6:57:F8:ba:12
AP3	UTeM-Student	24:b6:57:F8:ba:11
AP4	Bilik Pasca	00:22:b0:42:de:83
AP5	Makmal Lanjutan	00:08:30:70:88:20

Reference point 1 for Yes location can be calculated as the equation below. References Point will be tabulated as frequency table from RP 1 to 26.

$$\text{Yes} = \left(\frac{\text{normalize target\_AP2}}{\text{normalize AP2}} + \frac{\text{normalize target\_AP3}}{\text{normalize AP3}} + \frac{\text{normalize target\_AP4}}{\text{normalize AP4}} + \frac{\text{normalize target\_AP5}}{\text{normalize AP5}}\right) \quad (5)$$

$$= \left(\frac{-9}{9} + \frac{-7}{10} + \frac{-17}{12} + \frac{-7}{10}\right)$$

$$= -3.8167$$

Table-4 shows the MAC address of each AP.

Table-4. Part of offline database normalize to AP1.

Reference point (RP)	Matrix form (x,y)	AP1 (dbm)	AP2 (dBm)	AP3 (dBm)	AP4 (dBm)	AP5 (dBm)
1	(1,1)	0	9	10	12	10
2	(2,1)	0	14	13	10	21
3	(3,1)	0	10	9	10	20
4	(4,1)	0	2	3	-3	9
5	(5,1)	0	3	3	-5	12
6	(6,1)	0	1	2	-6	7
7	(7,1)	0	-6	-7	-14	0
8	(8,1)	0	-1	-1	-4	2
9	(9,1)	0	0	0	-1	4
10	(10,1)	0	-9	-10	-16	-5
11	(11,1)	0	-20	-20	-10	-23
12	(12,1)	0	-17	-16	-2	-20
13	(13,1)	0	-17	-19	-8	58
14	(14,1)	0	-14	-14	4	61
15	(15,1)	0	-27	-27	-7	51
16	(16,1)	0	-16	-16	2	-26
17	(17,1)	0	-10	-10	7	-18

Based on the values from Table-3, likehood table for reference point 1 by for instant is -0.07677. The entire likehood table for 26 reference points is shown in Table-5 below.

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ARPN Journal of Engineering and Applied Sciences

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Table-5. Likelihood table.

Likelihood table		**Location**	
		Yes (i)	**No** (i2)
Reference point(RP)	1	-0.07677	-0.55524
	2	-0.06466	-0.7584
	3	-0.07498	-0.65326
	4	-0.03911	-0.16037
	5	-0.05062	-0.19224
	6	-0.21455	-0.18171
	7	0.074711	0.380526
	8	0.336918	0.257076
	9	0.306746	0.151768
	10	0.083727	0.547138
	11	0.056408	0.939156
	12	0.197462	0.80303
	13	0.058375	-0.13749
	14	-0.06481	-0.49832
	15	0.058008	0.159621
	16	-0.14544	0.604212
	17	-0.00884	0.378618
	18	-0.01991	0.408969
	19	0.196855	0.815045
	20	0.092033	0.849595
	21	0.03817	-0.05083
	22	0.053521	0.949767
	23	0.055081	-0.32536
	24	0.014629	-2.17149
	25	0.034926	-0.04043
	26	0.102137	-0.51938

Here, considering the Bayesian rule is applied, probability for all reference point for the matrix form from (1, 1) to (26, 1) are tabulated in Table-6 below.

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Table-6. Probability table for x=18.5 and y=1.

Probability table			$P(i/RSS)$
		Matrix form	
Reference point (RP)	1	(1,1)	-0.09309
	2	(2,1)	-0.05543
	3	(3,1)	-0.07608
	4	(4,1)	-0.17677
	5	(5,1)	-0.19359
	6	(6,1)	-2.66667
	7	(7,1)	-0.13757
	8	(8,1)	-4.1875
	9	(9,1)	5.083333
	10	(10,1)	-0.10406
	11	(11,1)	-0.03842
	12	(12,1)	-0.17849
	13	(13,1)	0.207296
	14	(14,1)	-0.08708
	15	(15,1)	-0.28839
	16	(16,1)	0.129121
	17	(17,1)	0.014183
	18	(18,1)	0.029115
	19	(19,1)	-0.17476
	20	(20,1)	-0.07149
	21	(21,1)	0.31627
	22	(22,1)	-0.03596
	23	(23,1)	0.094427
	24	(24,1)	0.004132
	25	(25,1)	0.347272
	26	(26,1)	0.108038

The three highest values from Table-6 then are extracted to obtain its matrix form for location estimation. The highest at RP = 9, 21 and 25 where in matrix form (9, 1), (21, 1) and (25, 1). These matrix forms of x and y is used to determine the location estimation of user by using L nearest neighbor's algorithm:

#

$$x_{est} = 1/3\sum_{i=1}^{3}(9+21+25) \quad (12)$$
$$= 18.333$$

$$y_{est} = 1/3\sum_{i=1}^{3}(1+1+1) \quad (13)$$
$$= 1$$

Then, these x_{est} and y_{est} are multiply with the scale used in actual measurement.

$$x_{est} = x \times 3.5385 = 64.8724\text{m}$$
$$y_{est} = y(2.054/2) = 1.027m$$

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The result obtain has slightly different from the actual location which are (65.4623 m, 1.027 m). The distance error is 0.5099 m. Table-7 shows three different points which randomly picking up at the location. While Table-8 and Figure-4 shows the result of estimation location on the real time and comparison between actual location and estimation location based on point. The dot symbol is the estimation location while the star symbol is the actual location.

Table-7. RSS at different point at the sample location.

Sample location	Actual location	AP1 (dBm)	AP2 (dBm)	AP3 (dBm)	AP4 (dBm)	AP5 (dBm)
Blue	(18.5, 1)	-66	-75	-73	-83	-73
Green	(8, 1)	-72	-74	-76	-75	0
Yellow	(20, 1)	-61	-80	-80	-66	-82

Table-8. Location estimation in real time.

Sample Lo cation	Actual location (m)		Estimate location (m)		Differences (m)		Location error (%)		Display on GUI
	X	Y	X	Y	X	Y	X	Y	
Yellow (18.5,1)	65.46	1.17	64.75	1.17	0.58	0	0.91	0	Graph
Blue (8,1)	28.03	1.17	22.41	1.17	6.89	0	20.83	0	Graph
Green (20,1)	70.77	1.17	69.59	1.17	1.17	0	1.67	0	Graph

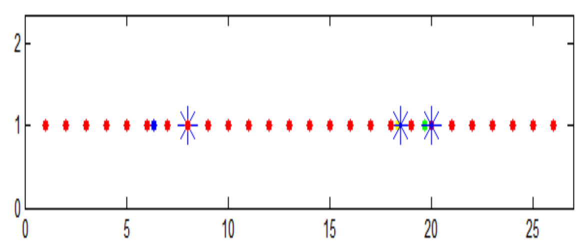

Figure-4. Comparison between location estimation and actual location.

Figures 5 and 6 show the MATLAB GUI for this study. This user interface is for values in AP1, AP2, AP3, AP4 and AP5 which in the measured signal panel and x and y value to be inserted for actual location. Value for x and y are in matrix. Actual location button and location estimation button can be clicked by user in order to know the actual location in meter and the location estimation in matrix and meter. The reset button is used to delete all the pass calculation before inserting another location to be estimated.

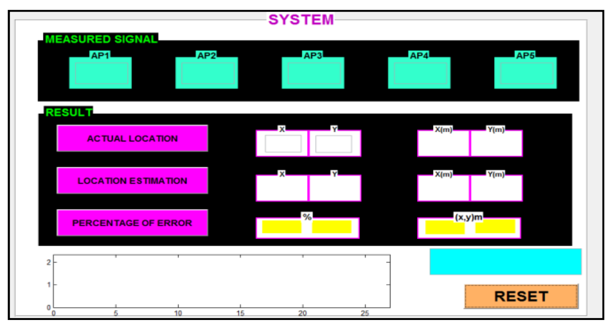

Figure-5. MATLAB general user interface (GUI).

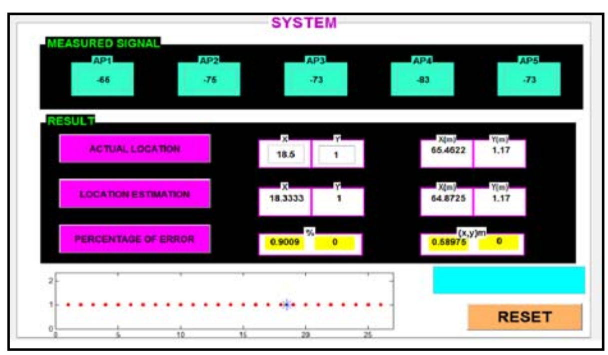

Figure-6. Example location display in MATLAB GUI.

4. DISCUSSIONS

The location used as the testing location for this study was ground floor of block E of FKEKK. This ground floor was divided into 26 points which on each point, the RSS value was measured by using VisiWave Site Survey Trial version. Here, five APs were chosen which have stable RSS value. There are a slightly error between estimation location and actual location. This may due to inaccuracy of indoor AP localization systems. Human body orientation can give impact to the RSS value for each AP. Body of a user can be obstruction blocking a portion of Wi-Fi signals. Specifically, Wi-Fi signals are strong at the Line Of Sight (LOS) propagation from an AP to user and are weak when the user is at the opposite orientation and blocks the signal [27]. Besides, the RSS was very sensitive to the environment. It needs to periodically recalibrate or update the offline database when something in the environment changes in ways that can affect the signal propagation. This also can affect the accuracy of the estimation location.

5. CONCLUSIONS

In this study, the performances of Bayesian Approach was been evaluate and it has greatly performed in this location with low percentage of error. There are several task can be extended in the future works. Firstly, the software can be improve by consider the user is moving. Since a stationary user stays at a location for a very long time period, it is relatively easy to determine the location of a stationary user than a moving user. This is because the RSS samples of a stationary user can be collected for as many time as needed to improve the accuracy, but for moving user, a very few RSS samples of location can be collected. Secondly, it is suggested to explore the big variations in historical RSS information because to enhance the system estimation, RSS pattern plays important role in determination location. Irregular RSS patterns will decrease the accuracy of the estimation location. Furthermore, the accuracy of estimation location can be increases as increase the measurements of RSS sampling thus provide a better system performance. Thirdly, a MATLAB coding which can automatically measure the RSS value of each access point should be consider in order to make the calculation for estimation location easier thus can help user to use this application without need to insert the estimate RSS value for each AP's.

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