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AUTOMATIC WLAN FINGERPRINT RADIO MAP GENERATION FOR ACCURATE INDOOR POSITIONING BASED ON SIGNAL PATH LOSS MODEL

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ABSTRACT

The first step in developing a ubiquitous environment, in which the user can interact with any available electronic device, is the existence of an accurate indoor positioning system. WLAN-based indoor positioning system is considered as one of the best choices for indoor positioning due to its low cost, simple configuration and high accuracy. Although the WLAN Received Signal Strength fingerprinting method is the most accurate positioning method, the offline phase of this method known as radio map creation is a time consuming process. On the other hand, in dynamically changing environments, this radio map will be outdated and this will reduce the positioning accuracy. In this paper the Multi-Wall signal path loss model will be used to automatically generate the radio map based on the knowledge of the environment layout. The results of the experiment show that the indoor positioning by using the generated radio map can achieve high accuracy with average distance error reaching up to 1.2m. This promising results means that an accurate indoor positioning system can be easily developed with time saving features.

Keywords: indoor positioning, WLAN-based Positioning, fingerprinting, radio map, path loss model, distance error, localization, ubiquitous environment .

INTRODUCTION

The last few years have seen the development of smart homes, office or environments and they are known as ubiquitous environments. In this smart environment the mobile user has the ability to interact with the available electronic devices. Indoor positioning is the base of any smart closed environment or ubiquitous application. In addition to this, there is a need to apply many of the location based services (LBS) in indoor environments as well as outdoor. A wide range of technologies have been proposed to be used for indoor positioning such as Radio Frequency Identification (RFID); Ultra Wide Band (UWB); Wireless LAN (WLAN); and Bluetooth. WLAN has been highlighted as the preferred technology due to its accurate positioning results and minimal infrastructure cost [1-5]. These techniques can be divided into three general categories and they are: Proximity, Triangulation and Fingerprinting [1, 2, 4-6]. Proximity is also known as connectivity based. The position of mobile device is determined by the coverage area of the transmitter (access point in WLAN case) – it is fixed in a known position and has limited range [4, 5]. The proximity method has a wide range of distance errors. The Triangulation method uses the triangles' geometric properties of the radio frequency to locate the current location of the mobile device. It has two approaches: distance-based and direction-based. The distance-based (Lateration) approach converts the measurement of the propagation-time of the received signal into distance to estimate the mobile device location, such as in [7] where the Time of Arrival (ToA) is used and as in [1] where the Round Trip Time (RTT) is used; or based on converting the measurement of the receive signal strength (RSS) into distance such as in [8, 9]. On the other hand, the direction-based (angulation) approach estimates the location based on the angle of the received signal [4, 5]. Fingerprinting uses the pattern recognition techniques which combine RF with location information, e.g. coordinates or label from the environment to obtain the real position of a mobile device. Scene analysis techniques include topological analyses, or advanced techniques such as hierarchical fuzzy inference algorithms [4, 5]. Fingerprinting is the most accurate method but its accuracy declines when an environmental change occurs [1, 4, 6].

WLAN Received Signal Strength (RSS) describes the power of the WLAN radio signal in milliwatts and it is always presented as logarithmic value called decibel (dBm) [10] . It has been used as the base of the indoor positioning by Bahl and Padmanabhan [11]. RSS Fingerprinting is considered the most accurate indoor positioning method [1, 4, 6]. In this method the WLAN RSS from multiple access points recorded in reference points or locations in the indoor environment is used to build a fingerprint database called a radio map. In the runtime the location of the mobile device will be determined by matching its RSS with the radio map instances to retrieve the reference location. Although WALN Fingerprinting is an accurate method, however, its radio map building is time consuming and this will be worse in multi-floor environments [12-16]. This means there is a need for an accurate WLAN-based indoor positioning technique and this technique must handle the fingerprinting problem. The accuracy or location error of the indoor positioning technique is the most important performance metric for any positioning model. It is defined as the percentage of the test locations that are accurately estimated by the evaluated technique [1, 4]. Precision or distance error is another important metric which is defined as the average of the Euclidean Distance between the estimated location and the true location [1, 4].

Of course there are many performance metrics as can be found in [1, 4] and a tradeoff between these metrics can be made. Many researches had been conducted to overcome the fingerprinting problem and these researches achieved satisfactorily accurate results. In this paper a simple and effective indoor positioning model will be presented. The contribution of this paper is that it creates a dynamic radio map automatically for indoor positioning based on path loss propagation models. The results of the experiments show that the proposed model can provide an accurate positioning with low distance error.

The rest of this paper is organized as follows: Section II will present the literature review which shows and overview of the path loss model and it will discuss the most related work. Section III will present the methodology used in this research and discussion of the obtained experiment results will be in section IV. The final section will present the conclusion of this research and recommendations on future direction will be given.

LITERATURE REVIEW

Locating the point coordinates on which the mobile device is located is the last step in indoor positioning of mobile device localization in a multi-floor environments. Many researchers have contributed in this area. In this section the path loss model will be presented, first as the base of the proposed method in this paper and this is followed by a discussion on related work in this area. Most of the related work is seen as complex solutions or time consuming solutions. The first one does not fit the recent mobile device because it has limited recourses and the second one is a time consuming solutions because it relied on a manual fingerprinting database creation. However, this paper presents a light solution which fits with the mobile device's limitations and it relies on automatic fingerprinting database creation.

Path loss models

It is acknowledged that the wireless signals propagate into multipath and will run into obstacles in the taken path and these obstacles will cause a reduction in signal strength. Based on this, the path loss or path attenuation models were found to estimate the signal strength, measured in decibel (dB), in a certain path [17, 18]. One-slope model (OSM) [19] is the most commonly used path loss model where the RSS value decreases exponentially with the distance d, distance in meters, between the transceivers.

$$PL(d) = PL(d_0) + 10n \log\left(\frac{d}{d_0}\right) \tag{1}$$

where the $PL(d_0)$ is the free space propagation loss at reference distance d_0, typically 1 meter, and n is the slope factor (power decay index) which becomes 2 for free space and 6.5 for obstructed space[19, 20]. The term free space means that the receiver can be in line-of-sight (LOS) with the transmitter. In addition to the free space path loss, Multi-Wall Model (MWM) [20] considers the penetration parameters such as the wall and floor attenuation factors.

$$PL(d) = PL(d_0) + 10n \log\left(\frac{d}{d_0}\right) + \sum_{i=1}^{I}\sum_{k=1}^{k_{wi}} L_{wik} + \sum_{j=1}^{J}\sum_{k=1}^{k_{fj}} L_{fjk} \tag{2}$$

where L_{wik} is considered the attenuation factor of all types of wall and L_{fik} is the attenuation factor of all types of floors, I and J are number of wall types and the number of floor respectively. For simplicity and as an evolution of MWM, COST231 MWM assumes that all walls have the same properties such as the material and thickness and the entire floor also have the same properties.

$$PL(d) = PL(d_0) + 10n \log\left(\frac{d}{d_0}\right) + \sum WAF + \sum FAF \tag{3}$$

where WAF and FAF represents the wall attenuation factor and the floor attenuation factor respectively.

Related work

Bahl and Padmanabhan [11] proposed RADAR which is a pioneer research in using WLAN fingerprinting indoor positioning system. RADAR applied the first WLAN RSS fingerprinting methods. In the offline phase the radio map will be calibrated and then the online localization phase will be run. The results of the experiment show the validity of using the WLAN's signals in the indoor positioning systems with distance error between 2m to 3m. Although RADAR achieved acceptable accuracy, its offline radio map database which is created manually is a time consuming process and this radio map becomes an outdated database due to any environmental change occurrence. In addition to this any critical location based system could not rely on this large distance error.

Hung-Huan and Yu-Non [21] provided indoor positioning system based on combining the fingerprinting method and path loss models for multi floor environment, because most of the WLAN-based IPS did not consider the multi floor environment. Selected samples per floor have been selected to create the radio map and in the online phase the floor number is localized based on searching the radio map. After determining the floor, the mobile device location is determined by triangulation methods based on the Aps location, estimated by the path loss model. The results of the experiment of the proposed solution show that the floor positioning is highly accurate, close to 100% and point localization precision is close to 1.6m, with 5m distance between each point. Although a high accurate result is important in floor positioning, in any

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fingerprinting system the main drawback is that a database is usually required to rebuild for accurate localization if environmental change occurred.

Vahidnia, Malek [22] proposed a method to improve the performance of the fingerprinting method. They used two layers of classification: a concurrent hierarchical partitioning of both signal and physical space to keep the signal patterns in each part of the environment with highest similarity. Then they combined the proposed classifier with either artificial neural network (ANN) or Bayesian probabilistic model (BPM). The experimental result showed that using BPM achieved the lowest distance error which is 1.35m while ANN achieved 1.46m as distance error. However, the proposed method is a complex method which could not fit with the mobile device limitation and the traditional offline radio map creation is a time consuming process.

Narzullaev and Park [23] proposed algorithm to handle the extensive and time-consuming RSS calibration process in designing the radio map for the indoor localization systems. The proposed algorithm combines the concept of the reference point (feedback point) and the one-slope- model (OSM), equation (1), and it overcomes loss signal prediction to get time-efficient calibration process. It starts by calibrating the RSS of the available Aps by the feedback points, then it estimates the location of the Aps with the strongest RSS based on the distance between the prediction point and it closes the feedback point where the RSS can be predicted by using OSM. However, the experiment results show efficiency of the proposed algorithm in reducing the RSS calibration time without reducing the location prediction accuracy. From the author point of view, the proposed solution has few drawbacks. Firstly, it increases the cost of indoor positioning system by using a feedback point. Secondly, the algorithm increases the computational complexity by searching for the strongest Aps and determining its locations. Thirdly, it uses the OSM model which assumes ideal wireless media which will not fluctuate nor attenuate due to many known and unknown reasons.

Sun, Zheng [15] used FLD, Fisher's Linear Discriminant, as a floor discriminative model. FLD model is based on the manual collected fingerprint database and the output of this model will be matched with the fingerprint database by using weighted KNN (WKNN). After floor determination the positioning accuracy increased and the average distance error reduced from 4.8 to 1.2 meters. However, the high localization accuracy and the low distance error of the proposed model is considered as a complex solution model and time consuming for fingerprint database creation.

As a conclusion, these related work used different techniques and different technologies to overcome the fingerprinting method's problem. Although they achieved high positioning results, they used either complex solution which does not fit with the mobile device limitations or expensive technology which is not good from the organization manager's point of view. On the other hand, this paper proposes a model which can overcome the fingerprinting problem with promising positioning result without any extra infrastructure cost and which contest all related work.

AUTOMATIC RADIO MAP FOR INDOOR POSITIONING MODEL

In order to generate a fingerprint radio map automatically adapted MWM COST321 path loss model with zero-mean Gaussian distributed random variable, equation (4), will be used with knowledge of the environment's layout description.

$$PL(d) = PL(d_0) + 10n \log\left(\frac{d}{d_0}\right) + \sum WAF + X \tag{4}$$

Where PL(d) is the RSS value of desired access point on distance d, $PL(d_0)$ is the free space propagation loss at reference distance d_0, n is the slope factor, $\sum WAF$ represents the sum of walls attenuation and X is a zero-mean Gaussian random number which aims to emulate RSS fluctuation. The model parameters will be discussed in the next section and the environment's layout description contains access points' locations, rooms and walls sizes. In previous works [16, 24] the feasibility of this proposed model has been proven in a one floor environment and its positioning accuracy rate exceeded 91% on the room positioning level. In this paper that model will be used in order to show its efficiency in a finer localization, i.e. determining the coordinates of the point where the mobile device/user is located. The measurement of this work will be the Precision, known as distance error, which is the average of the Euclidean Distance between the estimated location and the true location [1, 4].

RESEARCH METHODOLGY

This section presents the methodology followed in this research. First, the test-bed environment used in this research is the Testing set, whereby a real RSS of the available access points will be collected as described in the next subsection. Second, based on the test-bed layout description files an automatic fingerprint radio map will be created by using modified MWM COST321 path loss model, described in equation (4). Finally, k-nearest neighbor (KNN) algorithm will be used to evaluate the efficiency of the auto-generated radio based on accurate indoor positioning system. Results of the experiment and discussion on the results will be presented in the next section.

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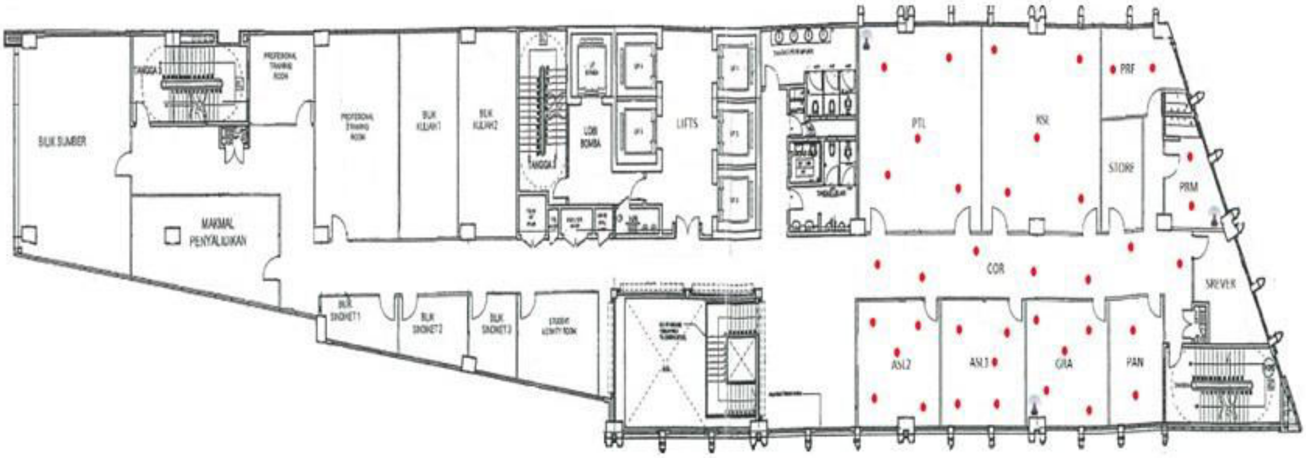

Figure- 1. Menara Razak, level 3 layout.

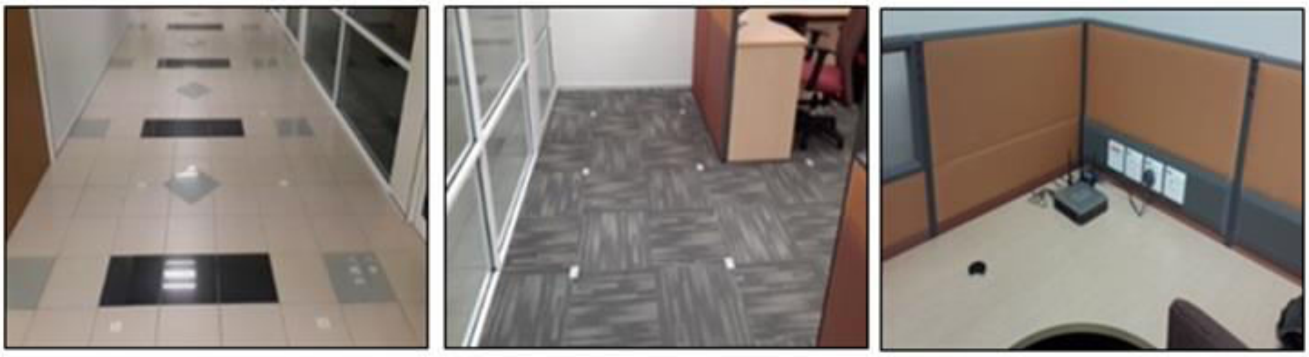

Figure- 2. Gridding the testbed environment.

Test-bed selection and testing set creation

The eastern side on the third floor of the Menara Razak building, Universiti Teknolgi Malaysia (UTM) Kuala Lumpur, has been selected as testbed environment as shown in Figure-1. This test-bed has been gridded into 1m x 1m cell size as shown in Figure-2. The dimension of the selected area is $480m^2$, this area contains a blocked area that means only 300 different points are available for calibrations.

In order to measure the proposed model precision, a manual testing set must be calibrated in well-known points. These points have been shown as red dots as shown in Figure 1. A mobile device, Samsung Galaxy Tab 4 – T231, has been equipped with WifiScanner application, described in [16], to create the desired test-set. WifiScanner has been configured to calibrate RSS from three access points in pre-determined points. At each point the Wifiscanner calibrates RSS for 30 seconds, then RSS represented by its median is calibrated and labeled by the coordinate of calibrated point. The median has been used to avoid the effect of the outlier RSS if it occurs.

Radio map generating

Determining the point's coordinates, where the mobile device/user is located correctly is considered the last step to have a complete indoor positioning system in a multi-floor environment. In addition to this, the mobile device limitations must be taken into account when proposing any method or technology for multi-floor indoor positioning. Hence, after locating the room in which the mobile device is located, in this paper a COST231 MWM path loss model with the shadowing zero-mean random variable, as in "equation (4)", will be used in order to generate a small fingerprint radio map of the pre-determined room to determine the point's coordinates where the mobile device is located.

The parameters of the model have been carefully determined. The floor attenuation factor (FAF) has been excluded from the path loss model in equation (3) because all the access points have been fixed in the same floor. The wall attenuation factor (WAF) equals to -3 dBm as shown in experiments in [16] and this agrees with [20]. The distance (d) between AP and mobile device will be calculated based on the layout description. In the experiment, the path loss at $1m$ distance $PL(d_0)$ is found to be equal to -34 dBm for the used APs. The power decay index (n) has been determined to equal -2.1 dBm because the selected environment is a simple structure environment. Finally, the random shadowing factor (X) is a random integer selected randomly from -1 to 1 in order to simulate any other factors which will affect the received signal strength.

Positioning result

The last step of this research methodology is measuring the effectiveness of the auto generated radio map on indoor positioning. K-Nearest Neighbor (KNN) will be used for positioning algorithm. KNN will search the auto generated radio map in order to retrieve the coordinates of the best match point with each testing point. Then Euclidian Distance geometry will be used to compute the distance error between the selected radio map point, $p = (x_1, y_1)$, and the testing point, $q = (x_2, y_2)$, as shown in equation (5).

$$D(p,q) = \sqrt[2]{(x_1 - x_2)^2 + (y_1 - y_2)^2} \quad (5)$$

RESULTS AND DISCUSSION

The generated radio map, point size radio map, will be used to train the KNN algorithm, matching algorithm and to determine the coordinates of the point where the mobile device is located. With k =1 the best match point in the pre-determined room is selected and the distance error will be computed based on the coordinates of the reference point and the selected one by using equation (5). Table-1 shows the important statistical values related to the computed distance error in each room. The minimum distance error does not exceed 1m. The maximum distance error can be considered relatively small in comparison with other work such as [25, 26]. On the other hand, the achieved average distance error gives very interesting results since the achieved maximum average is 1.8m.

Table-1. Average distance error per the test-bed layout.

Room Label	Testing Points	Min. dist. error	Max. dist. error	Average
ASL2	5	0	3	1.7
ASL1	5	1	2	1.5
GRA	5	0	3	1.2
PAN	2	0	1	0.5
PTL	5	1	3	1.8
RSL	5	1	3	1.8
FPR	2	0	2.24	1.1
MPR	2	0	0	0.0
Corri	7	0	2	1.1
			Average	1.2

This promising result is as expected due to the accurate determination of the parameters of the model especially due to the small size of the predicted radio map of the pre-determined room. In order to have more certainty about the achieved result, the cumulative probability of the distance error is computed and is shown in Figure-3.

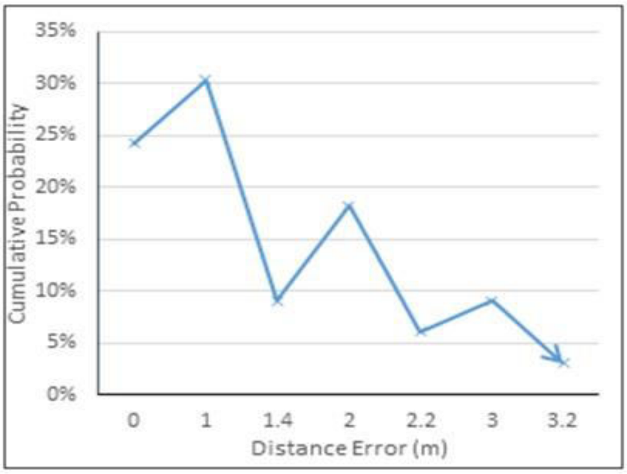

Figure- 3. Cumulative distance error probabilities.

As shown in the previous Figure the highest cumulative probability, which is 30%, occurs with distance error equal to 1m. In addition to this 25% of the cumulative probability occurs with distance error 0m, which means that more than 55% of the cumulative probability occurs with distance error less than or equal to 1m. Also the decrement in the cumulative probability can be noticed easily with the distance error increment.

In comparison with previous works the proposed model achieves accurate positioning result with a lower distance error as shown in Table-2. This averaged distance error, which is equal to 1.2m, is one of the lowest achieved distance error. Hence, the proposed model can generate RSS fingerprinting radio map, and this radio map can be used as base of accurate indoor positioning system. This system can achieve accurate positioning result with low distance error.

Table-2. Comparison with related work based on distance error.

Research	Method	Distance Error
Bahl and Padmanabhan [11]	Manual Radio Map + KNN	2.5
Hung-Huan and Yu-Non [21]	Path Loss model + Triangulation	1.6
Vahidnia, Malek [22]	Manual Radio Map + BPM	1.36
Sun, Zheng [15]	Manual Radio Map + WKNN	1.2
The proposed Model	Path Loss Model + KNN	1.2

CONCLUSIONS

Accurate indoor positioning existence is the base of any ubiquitous environment. Due to its low cost, simple configuration and high accuracy WLAN-based indoor positioning is considered as one of the best choices for indoor positioning. Although the WLAN RSS fingerprinting method is the most accurate positioning method, its radio map calibration is a time consuming process. On the other hand, in the case of dynamically changed environments, this radio map will become outdated and this will reduce the positioning accuracy. This paper proposes to create the radio map automatically by using adapted Multi-Wall path loss model with the knowledge of the environment layout. Results of the experiment show that proposed indoor positioning based on the generated radio map achieved high accuracy where average distance error did not exceed 1.2m. Recommended future research work in this field may be in two directions. The first direction is to test the proposed method, automatic radio map generation in a larger environment. The second direction is to integrate this method with floor detection method in order to have a complete multi-floor indoor positioning system.

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