WI-FI MULTI-FINGERPRINT TECHNIQUE FOR HIGH ACCURACY INDOOR POSITIONING

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Abstract- Determining position is very important because it is easier and faster to search for the best route to the destination with known position. Nowadays, more and more people move to urban areas and live in complex buildings. Indoor positioning, therefore, plays an important role for determining position for indoor areas and also in urban areas. Indoor positioning focuses on using smartphone to receive Wi-Fi signal due to its convenience and ease of operation. The Wi-Fi Fingerprint has been commonly used for indoor positioning. Nevertheless, Fingerprint technique has limitation in multipath rich indoor environment. Thus, this research focuses on improving the efficiency of Fingerprint technique by using multilayer of Fingerprint, named "Multi-Fingerprint Technique" in order to overcome the limitation of Fingerprint technique. Two types of Multi-Fingerprint technique were created in this research, which are (1) Patterned Fingerprint, radio map and converted radio map (or named distance map) with certain reference nodes were used for position determining; each reference node on distance map was calculated by the reversion of radio propagation model equation, and (2) Random Fingerprint, radio map and distance map with random reference nodes were used for position determining; each reference node was randomly defined by computer program. The four layers of radio maps and distance maps mentioned above were integrated (named Multi-Fingerprint map) and k-Nearest Neighbor (k-NN) algorithm was used for classifying position. Experimental results showed the difference in positioning efficiency among patterned distance map, random distance map, and Multi-Fingerprint map. Besides, root mean square error equation was used for measuring errors between real position and estimated position.

Keywords- Indoor positioning, Multi-Fingerprint technique, Received Signal Strength Indicator, Path loss model, k-Nearest Neighbor (k-NN)

I. INTRODUCTION

Nowadays Outdoor Positioning System (OPS) using Global Navigation Satellite System (GNSS) is a very popular and high-accurate method for estimating the user position [2]. Anyway, in urban areas the accuracy of OPS is decreased due to the crowded buildings. Indoor Positioning System (IPS) is commonly used for urban areas or inside the buildings to estimate the position. IPS can be divided into two types; (1) Triangulation technique, this technique measures distance between Access Points (APs) and user position by using geometric properties of triangles, such as, Time of Arrival (TOA) technique [3] and Angulation of Arrival (AOA) technique [4]. (2) Fingerprint technique, this technique is the most popular method because it includes noise environment. The Fingerprint technique are commonly used together with Bluetooth [5], Radio-frequency identification (RFID) [6], RFID combines with Wi-Fi [7], and ZigBee combines with Wi-Fi [8] to build fingerprint map and estimate user position. Although the result is very good but most people use fingerprint technique based on Wi-Fi because smartphones can receive signal from APs and APs are widely installed inside buildings and in urban areas. Fingerprint technique is divided into two phases, offline phase and online phase. In offline phase, data is collected from APs in the building in order to build the fingerprint map. In this phase, King Mongkut's Institute of Technology Ladkrabang used neural network based on ultra wideband (UWB) to update the database of the fingerprint map [9]. In online phase, user receives signal strength indicator (RSSI) from APs then uses approximation algorithm for the user position. A lot of good approximation algorithms are used, such as, k-Nearest-Neighbor algorithm (k-NN), Support Vector Machine (SVM) [10], Artificial Neural Network (ANN) [11], K-means [12] for estimating user position. Moreover, Institute for Infocomm Research used the Inertial Sensing Integrated with the fingerprint technique in order to improve accuracy of the positioning [13]. In this paper, we propose the offline phase of the fingerprint technique by defining the difference map of the fingerprint and reversed logarithm-distance path loss model to find the distance, after that use k-NN algorithm to estimate the user position.

This paper is divided into 4 sections; (I) introduction of IPS, (II) description about the system model of the Dead Reckoning (DR), the radio propagation model, the fingerprint technique, and k-Nearest Neighbor algorithm (k-NN), (III) experimental results both in symmetric and non-symmetric areas, and (IV) summary, conclusion, and future work.

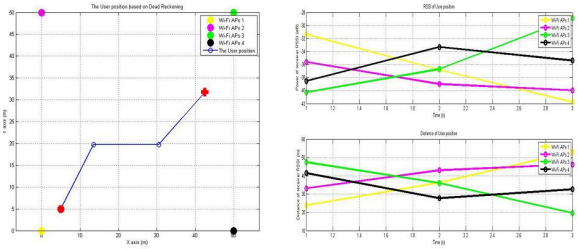
II. METHODOLOGY

A. Kinematics model

The position of human motion is generated based on Dead Reckoning (DR) method in 2-Dimensional Cartesian space. (See Fig.1 (a)) The Dead Reckoning method uses previous position, velocity, and orientation of each sample period to estimate the current position, as shown in Eq1;

$$x_i = x_{i-1} + v_i \Delta t \cos(\theta_i)$$
$$y_i = y_{i-1} + v_i \Delta t \sin(\theta_i) \quad (1)$$

Where x_i, y_i are the current positions and $x_i - 1, y_i - 1$ are the previous position reference in 2 –Dimensional Cartesian space. v_i is velocity of human, Δt is the sampling period, and θ_i is the orientation of the human.



(a) The User position (b) The Power receiver and Distance

Fig. 1: The simulation of DR and the use of position from DR to generate Wi-Fi signal and distance between user position and access point

B. Radio propagation model

The user position can be estimated by using the radio signal propagation from Wi-Fi Access Point (APs). RSSI value can be measured from APs to estimate user position because the RSSI value decreases with the distance according to the characteristics of the signal between transmitter and receiver. The signal from access point uses logarithm-distance Path loss model (see Eq2) to generate the signal, which is used for the simulation (see Fig. 1 (b)). The logarithm-distance Path loss model can be reversed to find the distance (see Eq3) between user position and access point because in real work the user receives RSSI value from access point.

$$P_{rx}(dB) = P_{d_0}(dBm) + 10n \log_{10}\left(\frac{d}{d_0}\right) \quad (2)$$

$$d = 10^{\|P_{rx}(dB) - 10\|/\alpha} \quad (3)$$

Where

rx P is the power receiver in decibel, 0 d P is the power received or RSSI value from APs in first meter of the distance, n is path loss exponent, which value is adjustable depending on the environment. 0 d and d are the distance between transmitter and receiver.

C. Fingerprint Technique

The Wi-Fi Fingerprint has been commonly used for indoor positioning because it includes noise of environment. Fingerprinting is a map for determining the location of the user. Fingerprint technique divides into two parts, the first part is the off line phase, which this part collects the RSSI value in order to build fingerprint map. The first step is to define the reference node in area of building after that collects the data of each reference node and finally the database has RSSI value from each access point in every reference node. The second part is the online phase, for this phase the user position receives the real RSSI of each access point after that uses estimation algorithm to estimate user position in fingerprint map (see Fig. 2). In this paper, we used the different map of fingerprint to estimate the user position because the different map generates different output.

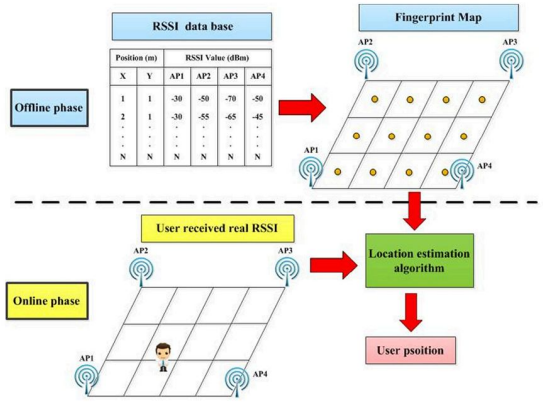
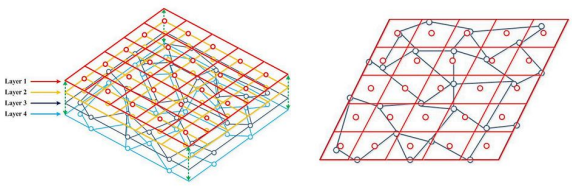


Fig. 2: Two phases of the fingerprint tecnique

D. Multi-Fingerprints Technique

In this paper, we used two different types of fingerprint to estimate user position in order to increase precision and accuracy of the positioning. The fingerprint with two different points, the first point is the difference between the Patten fingerprint and the Radom fingerprint, and the second point is the difference between the Radio map and the Distance map. We used RSSI signal to build the radio map fingerprint after that we used Eq3 to calculate distance from the RSSI signal to build the distance map fingerprint. Two types of fingerprints are divided into 4 layers (see Fig. 3(a)).

Layer 1 : Patterned fingerprint (Radio Map)
Layer 2 : Patterned fingerprint (Distance Map)
Layer 3 : Random fingerprint (Radio Map)
Layer 4 : Random fingerprint (Distance Map)



(a) The layers of fingerprint (b) The Multi-Fingerprint

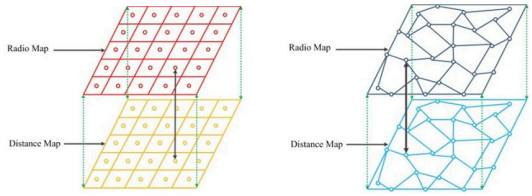
Fig. 3: The layer of fingerprint and the sum of every layer to build the multi-fingerprint

• Patterned fingerprint

Patterned fingerprint is a radio map and converted radio map (or named distance map) with certain reference nodes that are used for position determining (see Fig. 4 (a)) in area of building depending on infrastructure; each reference node on distance map was calculated by the reversion of radio propagation model equation.

• Random fingerprint

Random fingerprint is radio map and distance map with random reference nodes that are used for position determining (see Fig. 4 (b)); the points for random of reference node depend on programmer because programmer limits maximum points for random and then uses points in order to generate RSSI value and distance in reference node on fingerprint map. The first step measuring RSSI value in first meter (0 d P) because there are a lot of APs inside the building and sometimes the APs is not same so the RSSI value is not same.



(a) The patterned fingerprint (b) The random fingerprint

Fig. 4: The Radio and distance map of each type of fingerprint

E. k-Nearest Neighbor algorithm (k-NN)

k-NN algorithm is a measure of distances between RSSI in online phase and the reference nodes in fingerprint map for classifying position by using the Euclidian distance in Eq.4 The Euclidian distance will calculate all of reference nodes after that the shortest distance is used to estimate the position.

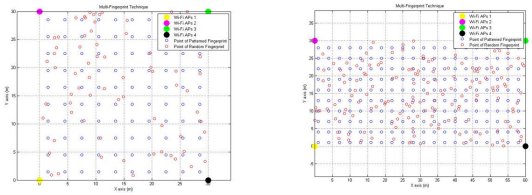
$$d_i = \left| rf_i - rp \right| = \sqrt{\sum_{i=1}^{N} \left(rf_i - rp \right)^2} \qquad (4)$$

Where id is the distance between the RSSI value of user position and the RSSI value of reference nodes, irf is the RSSI value of reference nodes on the fingerprint map, rp is the RSSI value of the user position.

In other researches, they used fingerprint technique by improving classifier algorithm to estimate the user position [1] [14] [15]. However, in this paper, we used original k-NN classifier in different fingerprint map due to the output of k-NN in fingerprint map is different.

III. EXPERIMENTAL RESULTS

In this paper, we used symmetric area for indoor positioning simulation in 30 30 × meter2 and non-symmetric area 60 30 × meter2. We setup 4 access points in 4 corners of the fingerprint map. The yellow circle is access point number 1, the purple circle is access point number 2, the green circle is access point number 3, and the black circle is access point number 4. The initial condition for generating RSSI value follows the Eq.2 010 d P dBm = , 3 n = , 0 1 d m = . The points of reference nodes of the patterned fingerprint map setup all points with equally distance at 3 meters. The first point of reference node is 1.5 x = meter and 1.5 y = meter from 0 x = , 0 x = so in area 30 30 × and 60 30 × meter 2 the patterned fingerprint in symmetric area has 100 reference nodes and non-symmetric has 200 reference nodes (see Fig. 5, the blue dots). The random fingerprint used random function from MATLAB to generate reference nodes in symmetric area (limit to 75 reference nodes) and non-symmetric area (limit to 175 reference nodes) (see Fig. 5, the red dots).



(a) (b)

Fig. 5: The simulation shows reference nodes of the patterned and random fingerprint in symmetric and non-symmetric area.

In this experiment, two types of user positon were simulated. The user position from the DR is shown in Fig. 6 (blue line), the user position estimation from the Patterned fingerprint is shown in Fig. 6 (red line), the user position estimation from the random fingerprint is shown in Fig. 6 (green line), and the user position estimation from the multi fingerprint is shown in Fig. 6 (black line). The graph showed errors between real user position and estimated position (See Fig 6-7).

TABLE I: The initial condition for DR

area	Style	x (m)	y (m)	v (m/s)	Δt (s)	θ	Point
Symmetric	linear	7	7	1.5	1	45	20
	square	7	7	1.3	1	10	45
Non-symmetric	linear	10	10	2	1	10	20
	square	10	5	1.2	1	10	100

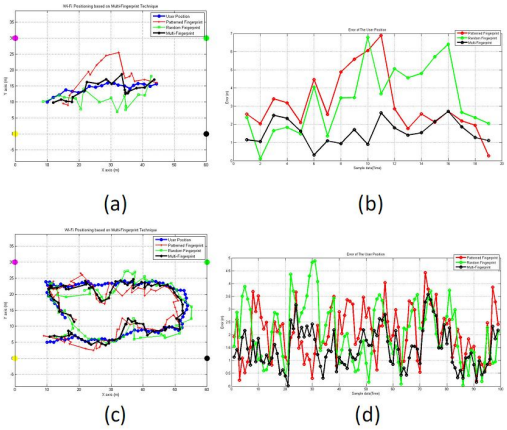


Fig. 7: The simulation of estimating the user position by using patterned, random and multi fingerprint in non-symmetric area

CONCLUSION

The Wi-Fi indoor positioning using the multi fingerprint technique can improve the accuracy of the positioning, we used four layers of fingerprint to determine position and then used k-nearest neighbor to estimate the user position. Root mean square error equation is also investigated for measuring errors between real position and estimated position. TABLE II shows the different output of each fingerprint.

TABLE II: Comparison of the accuracy of the patterned, random, and multi fingerprint.

Fingerprint Technnique		Symmetry		Not symmetry	
		Linear	Square	Linear	Square
Patterned	Min	0.3371	0.1994	0.2782	0.2166
	Mean	2.1366	1.5886	3.1657	2.0643
	Max	4.2673	4.5646	6.8962	4.4226
Random	Min	0.1174	0.0763	0.1067	0.0345
	Mean	1.9061	1.6118	3.3631	2.0770
	Max	4.2712	3.8080	6.7822	4.8857
Multi	Min	0.2989	0.2076	0.3078	0.0180
	Mean	1.2912	1.1626	1.5864	1.4681
	Max	3.2092	2.8442	2.7114	3.5753

From TABLE II, the results showed that multi fingerprint technique is better than patterned and random fingerprint because multi fingerprint has several points near real position and it has slightest mistake. The mean error of multi fingerprint technique is also less than the patterned and random fingerprint. For the future work, we will use other algorithms to estimate the user position such as SVM, ANN, ML in order to improve the accuracy of the positioning.

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