Reduce RSSI Variance for Indoor Localization System Using Frequency Analysis

Piyapan Suwannawach and Sorawat Chivapreecha

***Abstract*—Indoor localization system has been continuously developed. However, there is still an error in the positioning due to the variance of the signal. This paper proposed method to reduce variance of received signal strength indicator (RSSI) using frequency analysis and applied Genetic Algorithm to search the optimal weights for weighted distant fingerprint algorithm (WDF). Experiments are conducted in indoor environment using android mobile received signal strength from access point and the proposed algorithm can be compared with K-Nearest Neighbor (KNN) algorithm and conventional weighted distant fingerprint (WDF) algorithm. Results demonstrate that the proposed algorithm can improve an accuracy increase to 89.75% for identifying correctly 0.5 m × 0.5 m area of target node.**

***Index Terms*—Indoor localization, frequency analysis, fingerprint, genetic algorithm.**

I. Introduction

At present, Indoor localization system is important. It can be observed from the creation of various systems such as employee tracking system [1]-[3], Object tracking system [4], [5] and navigation system [6]-[10].

The techniques used for indoor localization can be divided into 4 types as follows: Time of arrival (TOA), Time difference of arrival (TDOA), Angle of arrival (AOA), and Received Signal Strength Indicator (RSSI).

Time of arrival (TOA) [11]-[14] is considered when the signal from the target node arrives at the sensor. By a magnetic wave that moves very fast (light speed or about 300,000 kilometers per second), which has a very short response time Need to have a device to help synchronize If the speed is constant at the time between transmission and reception, it can be used to determine the location of the target node. This technique provides high accuracy.

Time difference of arrival (TDOA) [15]-[19] is similar to the TOA method. TOA considers the time that the signal is used to arrive at each sensor, but the TDOA method is considered more from the TOA, which measures the time difference that each sensor receives. From the target node.

Angle of arrival (AOA) [20]-[23] considers the direction of the signal that the sensor receives from the target node. Use the antenna to find the path of the signal from the target node. Calculating the position of the target node can be done by sending a route from multiple locations to the target node due to the continuous rotation of the antenna to easily measure the distance. Therefore, the receiver or sensor uses only the cable installed at the specified angle to create the intersection for the position of the device. It is a technique that provides high accuracy. But must use many types of equipment and have a high cost.

Received Signal Strength Indicator (RSSI) [24]-[40] is considered the power of the signal that the sensor measures from the signal that the target node sends. Can determine the location of the target node using reduced signal power when the distance between the target node and the sensor is far greater than this technique is not very accurate due to factors that cause the signal energy to increase and significantly decrease in the environmental building.

Although the RSSI measurement method has lower accuracy than other methods but it is enough to be used to identify the location within the building that requires precision, just specify the rough position or tell the medium size areas such as bedrooms, bathrooms, corridors and balconies, etc. Also, this measurement technique also costs with lower equipment than other techniques Which does not require additional hardware and does not require time synchronization Therefore, the reason why RSSI measurement techniques have received more attention than other techniques.

There are many research projects that offer positioning methods using RSSI measurement techniques. It is known that the use of RSSI measurement techniques makes the cost of equipment cheap. But this technique is not very accurate. Therefore, most researches offer various calculation methods to develop in terms of precision Each research will be discussed in the following order.

Linear Least Squares [24]-[26] is the basic method. Use uncomplicated calculations and very little number of calculations. This method identifies the location of the target node using a linear transformation method.

The Gradient-based search method [27]-[29] is a method that is more accurate than the Linear Least Squares method, but uses a greater number of calculations. Because it is a method that uses the iterative method. This method uses a loop and improves the approximate position in every The cycle from the equation presented to reduce the error of estimating the distance from the target node to the sensor.

Multidimensional Scaling Method [30]-[32] is a technique that analyzes similar data. Which is applied to identify the location Use the calculation of more than 2 methods above but give more accuracy. This method starts from bringing the distance, which consists of the distance between the target node and all the sensors and the distance between the sensors together, analyzing and creating points that represent all

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target nodes and sensors.

K-Nearest Neighbor (KNN) [33]-[35] is a method for storing average signal power from various sensors. That can be read from the target node in every Interested reference coordinates and then record the coordinates and average RSSI of each coordinates into the database as for positioning, the RSSI values will be taken from various sensors. That can be read from the target node to compare with the RSSI value of every reference coordinate that is in the database.

Weighted Distance Fingerprint [36]-[40] is a method that has been improved for precision finger printing techniques. And the computational complexity or number of calculations used depends on the amount of data in the database in improving the accuracy of this method, it took advantage of the weighting or the reliability of the signal data that each sensor could measure in unequal ways.

The method of identifying positions that use RSSI measurement techniques can be classified into two major categories: 1. The method that requires the conversion of measured signals into distances and the distance to calculate mathematically, resulting in coordinates and 2. Method that calculates the coordinates from the signal power without having to go through the conversion before the distance The first type is the positioning method that is presented in the previous 3 research methods. The first consists of Linear Least Squares method, Gradient based Search method and Multidimensional Scaling method. Each of these methods requires calculation of the distance. The way between the target node and the sensor first Calculated from the signal power measured by the sensor from the target node and because the environment in the building has many obstacles, the analysis of the relationship between the signal power and the distance is complex as well. Resulting in bringing these methods to use to achieve high accuracy That is very complicated but the second type of positioning method can avoid the analysis of the relationship between signal power and distance. Therefore, making it easier to use and use Which this type of technique is called the finger print technique

However, the accuracy of positioning within the building using the RSSI technique depends largely on the RSSI value. If the RSSI value is very variable, it will result in low accuracy. In actual use, it is found that RSSI has very high variability. Therefore, if able to reduce the variance of RSSI, it should result in higher accuracy.

The purpose of this study was to ascertain the effect of using conventional received signal strength indicator (RSSI) as compared to RSSI through the process of variance reduction using frequency analysis method. Algorithms for measuring position performance are 3 methods: K-Nearest Neighbor (KNN) algorithm, conventional weighted distant fingerprint (WDF) algorithm, and applied Genetic Algorithm to search the optimal weights for weighted distant fingerprint algorithm (GA-WDF).

II. Background

A. K-Nearest Neighbor Algorithm (KNN)

KNN algorithm is used to identify the position, with two steps. The first step is to average RSSI each reference position, which is called fingerprint. The second step is to calculate the Euclidean distance between RSSI and fingerprint in each position and choose the location at minimum distance.

Calculate Euclidean distance, as in (1).

$$dist_n(x_n, y_n) = \sum_{m=1}^{M} (r_m - rssi_{n,m})^2 \tag{1}$$

Then, choose the location at minimum distance, as in (2).

$$(x, y) = \min\{dist_n(x_n, y_n)\} \tag{2}$$

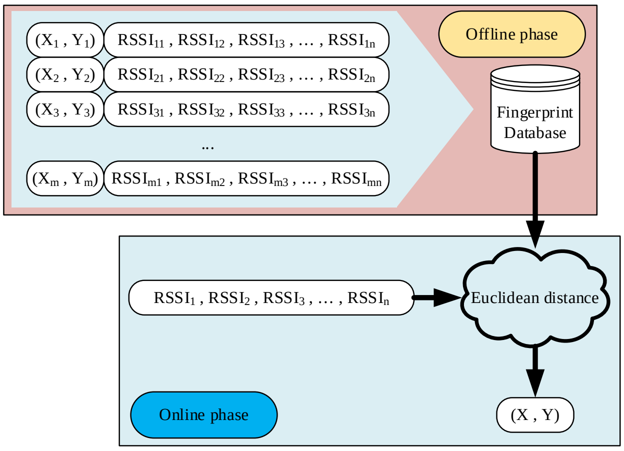

Fig. 1. K-Nearest neighbor algorithm.

B. Weighted Distance Fingerprint Algorithm (WDF)

Weighted distance fingerprint algorithm is improving method the KNN algorithm by adding weight values to the positioning process, as in (3).

$$wdist_n(x_n, y_n) = \sum_{m=1}^{M} w_m (r_m - rssi_{n,m})^2 \tag{3}$$

The weight of each access point (w_m) is inversely to variance of the measured RSSI, as in (4).

$$w_m = \frac{1/Var_m}{\sum_{1}^{M} 1/Var_m} \tag{4}$$

which, Var_m is the RSSI variance of the access point m reading, calculated from equation (5).

$$Var_m = a_m \times r_m + b_m \tag{5}$$

C. Genetic Algorithm (GA)

Genetic Algorithm is process that simulates natural evolution. GA has the following steps:

1) Initial population by random (optimal weight for all access point).
2) Evaluate optimal weight by fitness function, as in (3).
3) Weighted are updated in 3 steps as reproduction, crossover and mutation.

4) Repeated to step 2 and 3 until the criteria is met. Criteria are number of iteration or error is less than given.

Genetic algorithm consists of sub-steps as shown in Fig. 2.

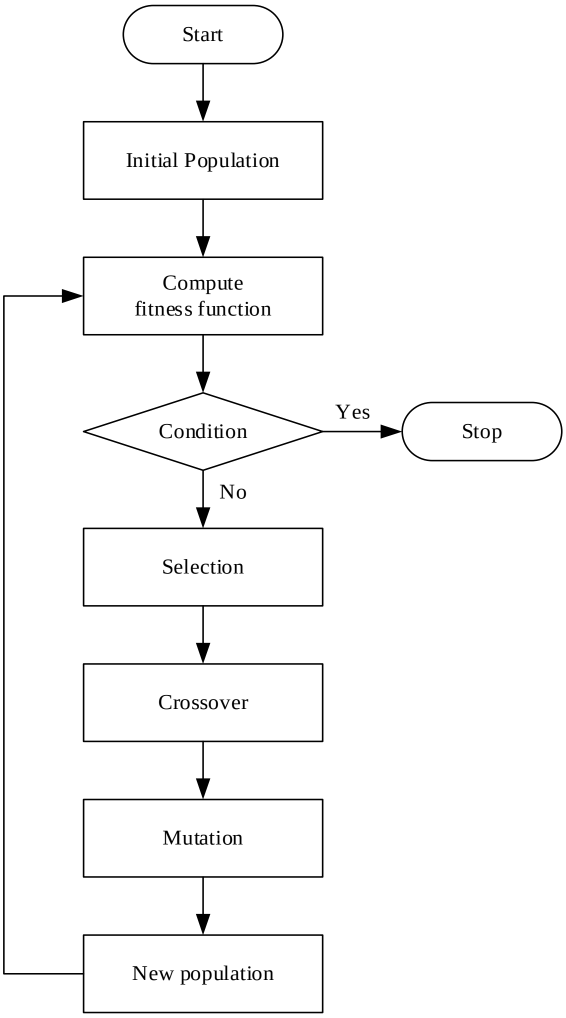

Fig. 2. Genetic algorithm.

D. *Windowing (GA)*

Windowing is a process of selecting groups of data for a given period of time. Fig. 3 shown data set and used size of window is 3.

Input :	5	3	4	1	6	2	2	4	3	1	5	3
1st	5	3	4	1	6	2	2	4	3	1	5	3
2nd	5	3	4	1	6	2	2	4	3	1	5	3
3rd	5	3	4	1	6	2	2	4	3	1	5	3
4th	5	3	4	1	6	2	2	4	3	1	5	3

Fig. 3. Windowing algorithm.

III. System

The proposed system can be divided into two phase: offline phase and online phase. Offline phase is used to created fingerprint database and weight for WDF algorithm. Overall process shown in Fig. 4.

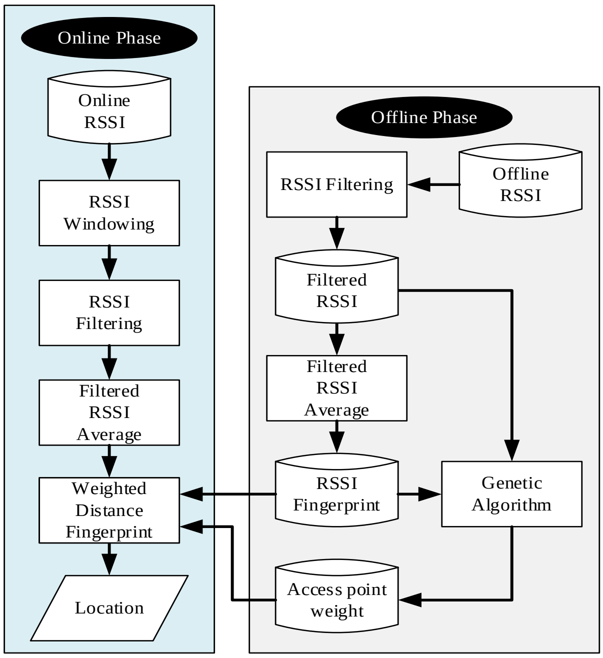

Fig. 4. Overall process.

A. *RSSI Windowing*

This process is used to selected RSSI group by window size is 10. Fig. 5 shown results of RSSI windowing.

1	2	...	9	10	11	12	...	19	20	21	22	...	29	30
-34	-31	...	-31	-31	-29	-29	...	-44	-30	-32	-30	...	-30	-30
group 1					group 2					group 3				

Fig. 5. RSSI stream.

B. *RSSI Filtering*

This process is used to reduce the variance of the received signal strength indicator (RSSI). It is to count the frequency of RSSI and select RSSI that is equal or greater than 15% of the RSSI considered. For example, we collected 15 RSSI values as follows: -31, -30, -30, -31, -30, -30, -31, -31, -31, -32, -32, -31, -33, -33, -34, -34, -31, -31, -31, -31, -29, -29, -32, -44, -30, -30, -30, -30, -30, -30, -33, -31, -31, -31, -31, -31, -31, -31, -29, -32, -33, -31, -31, -31, -31, -31, -31, -31, -29 and -32. The frequency and selected RSSI is shown in Table I.

TABLE I: Frequency of RSSI

No.	RSSI	Frequency	Percent	Group *c*
1	-29	4	8	reject
2	-30	10	20	accept
3	-31	24	48	accept
4	-32	5	10	reject
5	-33	4	8	reject
6	-34	2	4	reject
7	-44	1	2	reject

C. *Filtered RSSI Average*

This process is the result of the previous process to calculate the average. Table 1 shows that when RSSI Filtering process is completed, only 2 values are displayed (-30 and -31) and both data were averaged.

IV. Experimental Setup and Results

This section will be described experimental setup, sensor location and equipment.

A. *Experimental Setup*

Experiments were conducted using a Wi-Fi network in the testing environment. There are four D-Link DIR600 devices and one of them is the Samsung Galaxy J2 Android handsets. The image of the device is distributed and received shown in Fig. 6.

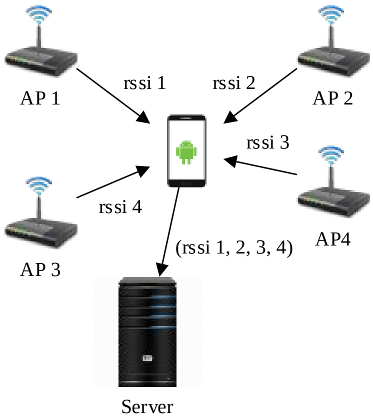

Fig. 6. Overview of indoor localization systems.

Test area is 8 m x 8 m. There are 256 fingerprint locations with size is 0.5 m x 0.5 m. Fig. 7 shown access point location and fingerprint location in test area.

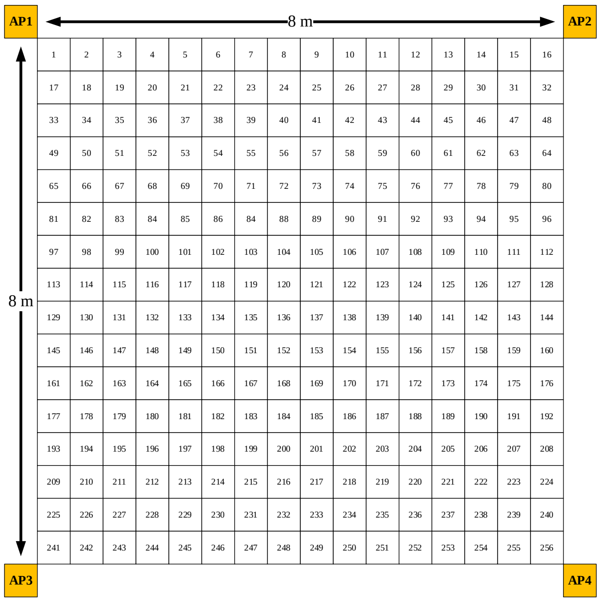

Fig. 7. Fingerprint and access point position.

WDF algorithm must find weight to calculate location. Conventional WDF and GA will be find GA is applied to find the optimal weights for all access point.

TABLE II: Weight for WDF

Algorithm	Weight			
	AP1	AP2	AP3	AP4
Conventional WDF	0.1648	0.4801	0.1679	0.1872
Genetic Algorithm	0.1847	0.4358	0.2900	0.0895

B. *Results*

In the experiment, three algorithms were compared: KNN, WDF and GA. All algorithms will be tested in three methods. The first method was test with immediately RSSI. The second method was test with windowing RSSI. Final method was test with windowing and filtered RSSI. Experiment results can show the accuracy of localization that obtained from three algorithms and three methods as in Table III.

TABLE III: Accuracy (%)

	No preprocess	Windowing	Windowing and filter
KNN	7.73	26.17	87.60
Conventional WDF	7.61	27.73	88.09
Genetic Algorithm	7.89	28.57	89.75

V. Conclusion

This paper presents the development of indoor localization system by using Wi-Fi received signal strength of Android mobile phone. The obtained results in this paper will be compared with previous localization algorithms as KNN, WDF and GA-based WDF algorithm. All algorithms will be tested in three methods. The first method was test with immediately RSSI. The second method was test with windowing RSSI. Final method was test with windowing and filtered RSSI. GA-based WDF algorithm is more effective than KNN and WDF.

Experimental results can show that the proposed method can increase the accuracy of GA up to 89.75% for correct.

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