An Indoor Positioning Method Using Wi-Fi Signals

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Abstract—**This paper presents a fingerprint method to measure indoor position by reducing distance errors. The proposed fingerprint method uses the Gaussian distribution probability of Wi-Fi signals and data of magnetic field sensors to measure indoor positions. The accuracy of the proposed method is measured in the area of 4.5m x 9m. The distance errors are compared with the Gaussian fingerprint method. The experiment results show that the proposed method distance errors are less than 1m range.**

Keywords- WiFi; Indoor Position; Fingerprint; Magnetic Field Sensor

I. INTRODUCTION

Recently the research area on the location-based service is getting interests to apply to find indoor position. Many applications are simulated and experimented to use practically. The measurement method to find indoor positions might be Wi-Fi, RFID, Bluetooth, IMU Sensor(Inertial Measurement Unit Sensor) and so on. RFID method shows high accuracy and low error rate in the indoor positioning but is very expensive to set up the initial indoor positioning facilities. Bluetooth is relatively cheaper than other methods to build indoor positioning facilities initially, but its disadvantage is that its positioning performance is inaccurate[1]. Wi-Fi positioning method has two advantages. One is that its signal range is 35*m* and the other one is that it is possible to use the existing infrastructure without additional set-up cost. Typical Wi-Fi positioning technologies are based on cell-ID, triangulation, fingerprint and so on.

IMU is a device to measure speed, direction and acceleration of moving objects. IMU-based indoor positioning utilizes the PDR(Pedestrian Dead-Reckoning) algorithm that is a method to measure continuously by following the movement direction and the speed. The PDR algorithm is a good method for the position estimation of the pedestrian because it has a short cycle. But it increases the cumulative error if the starting position of a pedestrian is not set [2].

Therefore this paper proposes a fingerprint method using the Gaussian distribution probability of Wi-Fi signals and data of magnetic field sensor.

II. PROPOSED METHOD

A. *Proposed fingerprint method*

In order to configure the radio map, we have installed reference points every 3 meters within the service range and monitored Wi-Fi signals and geomagnetic output data. The Gaussian fingerprint method, which is typical WiFi-based fingerprint method, is configured as a block diagram shown in Figure 1.

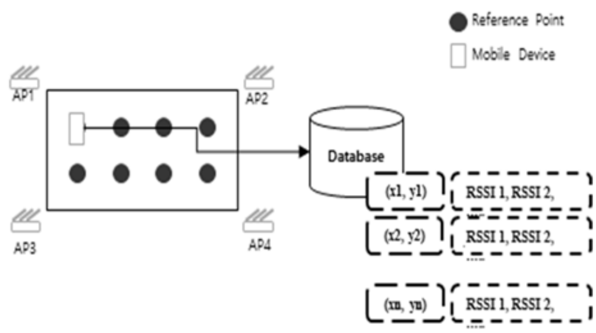

Figure 1. Localization based on Wi-Fi fingerprint

The proposed method is configured as a block diagram shown in Figure 2.

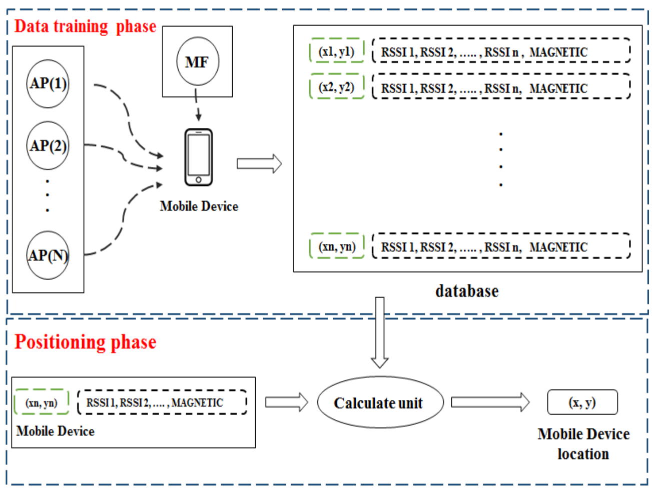

Figure 2. Configuration of proposed fingerprint

The positioning phase estimates the position of users through the data that a mobile device collects the signal strength and geomagnetic output data of nearby APs(access point). The measurements are compared them with the radio map.

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B. Fingerprint based on the Gaussian distribution

The Gaussian distribution function is generally used to decide probability-based fingerprint because the RSSI measurement data is represented with Gaussian probability. In the data training phase, mean and standard deviation of Wi-Fi signal strength of each reference point are calculated. Geomagnetic output data are used to calculate the mean and its standard deviation by Equation (1).

$$\text{magnetic} = \sqrt{(X^2 \times Y^2 \times Z^2)} \tag{1}$$

At the positioning phase, the estimation position (l) is obtained by each reference point of radio map using Wi-Fi signal strength of APs and geomagnetic output data, which is ($\vec{O} = \{O_1, O_2, O_3, \dots, O_k\}$) with the mobile device. The last value (O_k) of $\vec{O}$ means a geomagnetic output data. l is obtained by conditional probability, the likelihood of l is obtained by probability of $p(\vec{O}|l)$ that is calculated according to the Gaussian distribution probability as Equation (2). Also The Gaussian function of geomagnetic output data is obtained by Equation (2).

$$p(\vec{O}|l) = \prod_{i=1}^{k-1} \frac{1}{\sqrt{2\pi\sigma}} e - \frac{(x-\mu)^2}{2\sigma^2} \tag{2}$$

At Equation (2), $x = O_i$ means the signal strength collected by i-th AP. $\mu = AVG_{li}$ and $\sigma = DEV_{li}$ are the mean and the standard deviation of the Wi-Fi signal strength received from i-th AP on location l respectively in the radio map. The likelihood value of geomagnetic output value can be obtained in the same way with the likelihood value of Wi-Fi signal strength.

WKNN(Weighted K-Nearest-Neighbors) algorithm is used to estimate user locations after sorting calculated result by the maximum likelihood of geomagnetic value and Wi-Fi in Equation (2). Furthermore, as shown in Figure 3, the k value of WKNN is configured to reduce errors between estimated positions and real positions before using the WKNN algorithm.

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Sp = { P1 , P2, P3 ,P4 }
K = 3
for i = 1 to 3
  if  Pi.location = P4.location
      K = 4
      break
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Figure 3. k value decision algorithm

S_p in the Figure 3 represents the maximum likelihood probability of Wi-Fi and geomagnetic data calculated by Equation (2). P_1, P_2, P_3 and P_4 are sorted Wi-Fi values according to likelihood probability and the maximum likelihood probability value of geomagnetic. And then, k is configured to reduce errors after comparing the location Wi-Fi and geomagnetic likelihood probability. The estimation position is obtained by Equation (3).

$$(X, Y) = \frac{\sum_{j=1}^{K} [w_j \times (X_j \times Y_j)]}{\sum_{j=1}^{K} w_j} \tag{3}$$

w_j means $\log P_j$ and (X_j, Y_j) means a position coordinate j-th from S_p . (X, Y) is obtained from an estimation position coordinate of users.

III. EXPERIMENT

A. Environment

We experimented with a rectangular area which is 4.5m x 9m, each RP distance is 2.5m. We used Samsung Galaxy S3 as a mobile device for this measurement.

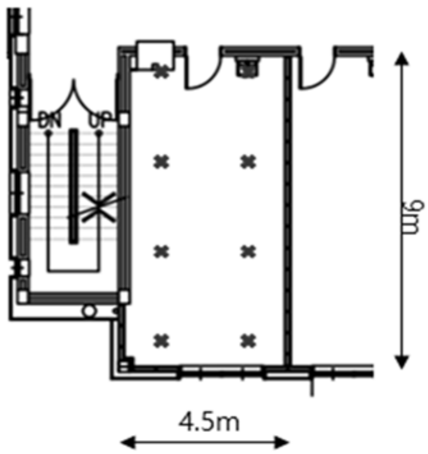

Figure 4. Experimental environment

B. Results

To evaluate the performance of the proposed method, we analyzed the error distance between the real position of users and the measured positions of mobile devices on the same environment. The error distance is shown as Equation (4).

$$\text{diss\_err} = \sqrt{(x - x_0)^2 + (y - y_0)^2)} \tag{4}$$

In the above Equation (4), (x, y) means the measured position coordinate and (x_0, y_0) means the real position coordinate.

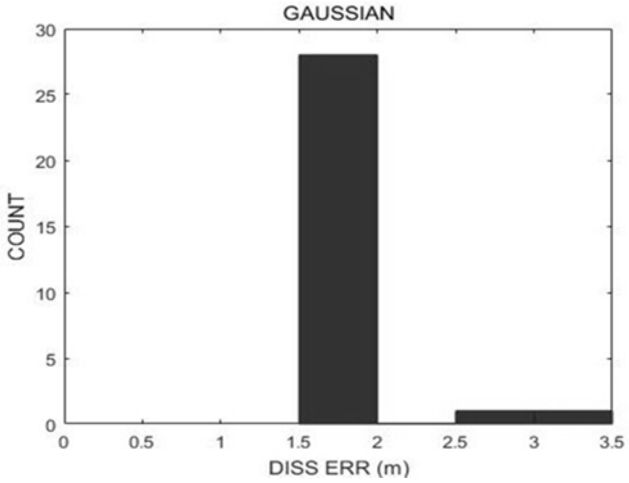

Figure 5. Error distance of the gaussian method

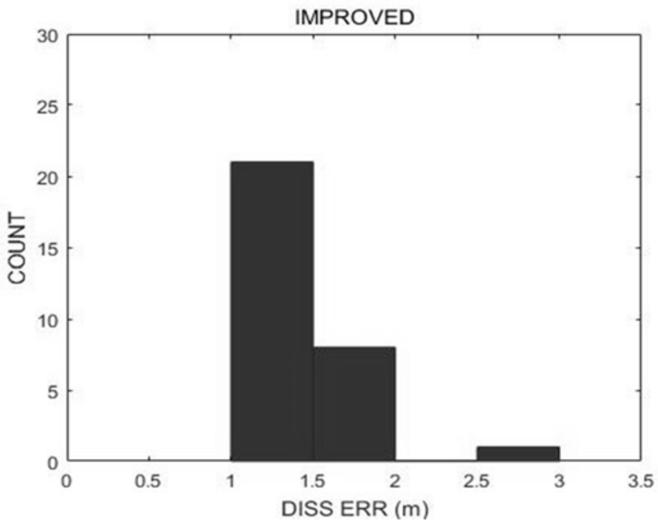

Figure 6. Error distance of the improved method

Figure5 and Figure 6 show the results measured for 30 rounds at the same measurement position and represent a distance errors of the proposed method and the Gaussian method.

Figure7 shows a comparison of probability distribution between the Gaussian method and the proposed method for 30 rounds at the same location. The distance errors of Gaussian method are1.5 *m* to 2.0*m* and those of the proposed method are decreased and error ranges are 1*m* to 1.5*m*.

Table 1 shows the performance comparison of the Gaussian method and the proposed method. As shown in Table 1, when the proposed method is implemented, the average error distance is reduced by 18%. As a result, we verified that the proposed method has better performance than the Gaussian fingerprint.

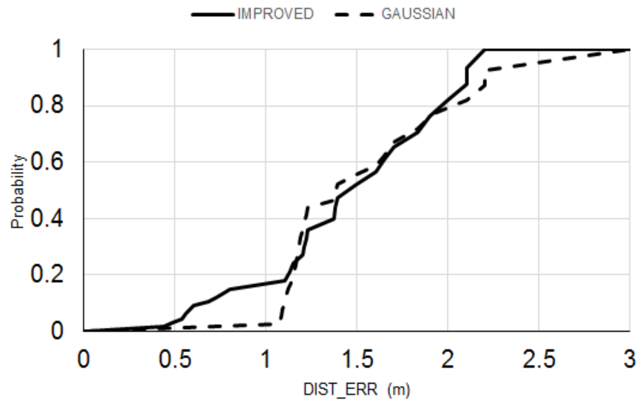

Figure 7. Probability distribution of 30 rounds

TABLE I. DISTANCE ERROR OF EACH TEST

Model	T1	T2	T3	T4	T5	Average
Gaussian Method	1.39	1.56	2.15	1.48	2.01	1.71
Proposed Method	1.19	1.36	1.69	1.16	1.56	1.39

IV. CONCLUSION

We proposed a fingerprint method to reduce the distance error by using magnetic field sensor in smartphone and WiFi-based fingerprint using Gaussian probability. The proposed method shows better performance than the Gaussian method. As far as Wi-Fi signals are stable, the proposed method can get accurate indoor positions by using geomagnetic output data.

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