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Marcin Uradzinski*, Hang Guo, and Min Yu

Improved indoor positioning based on range-free RSSI fingerprint method

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Abstract: As the development of modern science and technology, LBS and location-aware computing are increasingly important in the practical applications. Currently, GPS positioning system is a mature positioning technology used widely, but signals are easily absorbed, reflected by buildings, and attenuate seriously. In such situation, GPS positioning is not suitable for using in the indoor environment.

Wireless sensor networks, such as ZigBee technology, can provide RSSI (received signal strength indicator) which can be used for positioning, especially indoor positioning, and therefore for location based services (LBS).The authors are focused on the fingerprint database method which is suitable for calculating the coordinates of a pedestrian location. This positioning method can use the signal strength indication between the reference nodes and positioning nodes, and design algorithms for positioning. In the wireless sensor networks, according to whether measuring the distance between the nodes in the positioning process, the positioning modes are divided into two categories which are range-based and range-free positioning modes. This paper describes newly improved indoor positioning method based on RSSI fingerprint database, which is range-free.

Presented fingerprint database positioning can provide more accurate positioning results, and the accuracy of establishing fingerprint database will affect the accuracy of indoor positioning. In this paper, we propose a new method about the average threshold and the effective data domain filtering method to optimize the fingerprint database of ZigBee technology. Indoor experiment, which was conducted at the University of Warmia and Mazury, proved that the distance achieved by this system has been extended over 30 meters without decreasing the positioning accuracy. The weighted nearest algorithm was chosen and used to calculate user's location, and then the results were compared and analyzed. As a result, the positioning accuracy was improved and error did not exceed 0.69 m. Therefore, such system can be easily applied in a bigger space inside the buildings, underground mines or in the other location based services.

Keywords: Indoor positioning, navigation, sensor integration, wireless sensor networks, Zigbee technology

1 Introduction

Locating a mobile user anytime anywhere using GNSS positioning is still a challenging task, especially in degraded and denied environments such as urban canyons and indoors. Because of it, some other positioning techniques have been introduced such as pedestrian dead reckoning system based on MEMS sensors (PDR) or pseudolites to obtain a reliable indoor-outdoor positioning results [1, 12, 13, 14, 21]. A conventional Pedestrian Dead Reckoning (PDR) system is based on acceleration obtained from accelerometers to measure the step count to estimate step length and generate the position with the heading received from angular sensors (magnetometers and gyroscopes). Such a solution can be used to about any location: airports, mines or shopping malls. It can also be very helpful to guide blind pedestrians, emergency rescue workers or firefighters. Unfortunately, collected signals are very responsive to the alignment of sensor devices, the built-in instrumental errors and disorders from surrounding environment. For the reason that positioning accuracy decreases over time, supplementary sensors are usually used with IMU such as a time of arrival based on Local Positioning System (LPS) – radio frequency based system with inertial sensor supplementation.

Nowadays, there are needs to support a lot of devices in the wireless personal networks using WiFi, UWB, Blue-

***Corresponding Author: Marcin Uradzinski:** University of Warmia and Mazury, Institute of Geodesy, Oczapowskiego 1, 10-719, Olsztyn, Poland, E-mail: marcin.uradzinski@uwm.edu.pl
Hang Guo: Nanchang University, Institute of Space Science and Technology, P.O. Box 21-1-8, 202 West Beijing Rd., Nanchang, China, E-mail: guo1_2002@hotmail.com
Min Yu: Jiangxi Normal University, School of Computer and Information Engineering, China, E-mail: myu821@163.com

tooth or ZigBee technology [8, 9, 10, 15, 17, 18, 19, 20, 22]. Such systems provide RSSI (received signal strength indicator), which can be a great benefit for indoor navigation/positioning. Considering indoor situation, the fingerprint database solution is more reasonable to calculate the location of a pedestrian. Today, satellite navigation technology is widely used. Unfortunately its signals are easy to degrade (multipath) and can be seriously attenuated. In such case, navigation process is not suitable to use in the indoor applications. In recent years, the usefulness of wireless sensor networks will be generally used in the indoor environment. Improvement of positioning method can be done using RSSI (received signal strength indication) among the reference nodes and coordinator node with usability of prepared positioning algorithms. Considering wireless networks, the positioning modes are divided into two categories which are range-based [16] and range-free positioning modes [6, 4, 11]. In our project we are focused on a method based on RSSI fingerprint database, which is range-free.

There are two stages using fingerprint database to obtain current position. First we need to establish offline fingerprint database and then provide online positioning. In the offline fingerprint database establishment stage, we collect RSSI values of the reference nodes knowing their coordinates. Based on it we can establish the fingerprint database. In the online positioning stage, we compare the real-time RSSI values of the mobile nodes to the fingerprint database's information to calculate the current location.

2 Establishment of Fingerprint Database and Principle of Positioning

The fingerprint database establishment is based on two stages. The first one creates the fingerprint database and the second one is to obtain the coordinates of a moving node within positioning area using RSSI collected from all reference nodes.

The accuracy of fingerprint database has a significant influence on the accuracy of the final node location results. The calibration process of wifi coordinator is usually based on measurements of RSS at distance of 0 or 1 meter, that are suitable for most use cases. However, in order to accommodate more reference distance data, we use the reference RSSI value calibration at different distances (5, 10, 15 or 30 m). You can identify the Tx power for which you are changing the calibrated value. This is specially useful as the Wifi transmitters tend to emit different RSSI signals in different environments. Therefore calibrating them better reflect their behavior in the location they are going to be used in. Based on thisTherefore, the high precision fingerprint database is very important to obtain high accuracy positioning results. The nearest data point for collecting RSSI value will always overlap when selecting the data point and collecting the RSSI values. Therefore, we decided to choose the following sample data processing methods to increase the accuracy of the fingerprint database.

A set of collected data from sample data points is selected and analyzed. Defining rssi (n)i to be n groups of data of RSSI values from the i-th reference node, namely: Rssi (n)iRSSI, n is the data number of the group collected at this point, i represents RSSI values of the i-th reference node.

In the data recording process, some groups of data may change suddenly because of occurring interference.

In order to avoid the harmful data from incorporating into the fingerprint database, an upper and lower threshold binding with experiments is set. The average RSSI value of the collected point received from the

$$u_i = \sum_{1}^{N} rssi(n)_i/N \tag{1}$$

θ as the change factors, i.e.:

$$rssi(n)_i \in [u_i - \theta, u_i + \theta] \tag{2}$$

$$rssi(n)_i \notin [u_i - \theta, u_i + \theta] \tag{3}$$

When Equation (2) makes, it indicates that there is no abnormal of data in data collection process. When equation (3) makes, it indicates that abnormal occur, it should be removed and replaced by its average u_i.

After recording data from each data collection point and eliminating the influence of the abnormal, there was problem found in the data collection. It's that frequency of occurrence of data far away from the data center point at both ends is very low. The emergence of these data is the overlapping of the nearest sampling points, which is incorporated directly into metadata of the fingerprint database, what affects the accuracy of the database. In such case, the influence can be eliminated using a data domain filtering method. This approach can be done as follows: Set domain zone of the data collected as { rssi(n)i |[min, max]|} in which min and max represent the maximum value and the minimum value of the group of RSSI values collected. Mid is the center value, the central offset is ξ, i.e.: the effective data domain of this group of data is { rssi(n)i |[min,max]|} , we select weights of data which appear in [min, Mid-ξ) and (Mid + ξ, max] area in accordance with the order of distance from the center value, and then weight and average, naturally form a new group of data, finally, we weight and average this new group of data and the data in valid data domain in accordance with number of occurrences totally.

Calculations can be made as follows:

$$rssi(n)_{\epsilon 0} = \frac{\epsilon}{\theta} rssi(n)_{\epsilon} + \frac{\theta - \epsilon}{\theta} rssi(n)_{\epsilon+1} \tag{4}$$

$$rssi(n)_{\epsilon 0-1} = \frac{k}{k+\varphi} rssi(n)_{\epsilon-1} + \frac{\varphi}{k+\varphi} rssi(n)_{\epsilon 0} \tag{5}$$

$$K_0 = k + \varphi \tag{6}$$

Where, $rssi(n)_{\epsilon 0}$ denote the new RSSI values which are the weighted averages of the ϵth RSSI value and the (ϵ +1)th RSSI value. θ is the number of groups of different RSSI values of the data center point on both sides. The farther the distance is from the center the bigger is. ϵ is the number of sequence number of these groups.

The $rssi(n)_{\epsilon 0-1}$ denotes the new RSSI values, which are the weighted averages of the RSSI values in accordance with the number of each group of data. φ represents the total number of data of ϵ, $\epsilon + 1$ groups, k represents the number of data of original, K_0 denotes the new the number of data of $\epsilon - 1$ groups. After operation of equations (5), (6), and (7), the edges of the value in the source data are weighted and merged, then the data is optimized.

3 Fingerprint database positioning based on weighted nearest algorithm

While considering indoor environment, measurement error is usually large. Therefore, we are focused on using the weighting factor 1/Dj to weight and average the coordinate values of the location fingerprint information points among the smaller K Euclidean distance. Closer the distance between the fingerprint information points, the larger the weight [5, 7]. Its weight value can be expressed as

$$W_j = \frac{1/Dj}{\sum_{j=1}^{k} 1/Dj} \tag{7}$$

So, the user's location can be calculated using the following formula:

$$L = \sum_{j=1}^{k} W_j \cdot L_j \tag{8}$$

W_j is the weight value of the j-th fingerprint information point, and L_j is the coordinate of the j-th fingerprint information point.

4 Experimental results and analysis

While considering a density of collection points of the fingerprint database data, there is an order: the more intensive the selection of the fingerprint data, the higher positioning accuracy [2, 3]. In previous experimental tests, we realized that while using the ATMEL AT86RF233 2.4GHz Zigbee transceiver and choosing various interval data collection points in the experimental area, the intervals between the collection points are less than 0.5 m, RSSI values ??from four references to nodes nearby- several nearest data sampling points are the same. So in our new experiment, we select 0.84m as the sampling point interval to settle a fingerprint database.

Figure 1: Test area

In the test area (Figure 1)?34 m × 2.52 m), we choose 120 data sampling points shown in Figure 2. The black points stand for the chosen fingerprint data sampling points. The

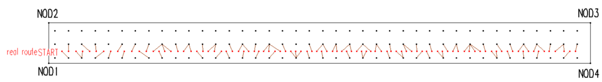

Figure 2: Distribution of the fingerprint data points and Zigbee test results

Table 1: Summary of positioning errors

	Differences in x- axis (dx)	Differences in y- axis (dy)
MIN (m)	0.40	0.01
MAX (m)	0.44	0.69
AVERAGE (m)	0.42	0.24
STDEV (m)	0.02	0.17

distance between the points is 0.84 m. We chose 0.84 m, because choosing four floor tiles gives a summary size of (0.84 m × 0.84 m). It was easier to conduct fingerprinting in offline stage to mark reference points on tiles, which were later used to step on while collecting data in online stage. Narrow and long configuration of the test area, was chosen because the shape of this corridor is like a regular and most common one..At each point we collected 150 groups of data. Next ??we extract RSSI values from the sampling data of each reference node, calculate its mean and variance and establish the positioning fingerprint database of off-line stage. To avoid the anthropogenic influences of operating devices in the beginning and the end phases of the sampling of each data sample point, we remove 25 groups of data which is in the front and rear of the 150 collected fingerprint information point data, respectively.

After removing mentioned 25 groups of data, there were some "jump points" in the remaining 100 groups of data. The accuracy of the fingerprint database will be affected if these points are included in the database.

After processing average threshold values and selecting valid data domains to above sampling data, abnormal data was filtered by the averaging threshold method, and the offset data within a certain range was optimized by the method of selecting valid data domains. After processing the collected data in the method of selecting valid data domains, the fingerprint data is centralized and the edge scatter data reduces.

When we established the fingerprint database and chose actual route, we calculated the real time positions in the location area. In Figure 2, the red dots denotes actual route (with modeled 1-second positions for comparison), and brown directional lines stands for Zigbee test results. The results are shown in Figure 2 and Table 1.

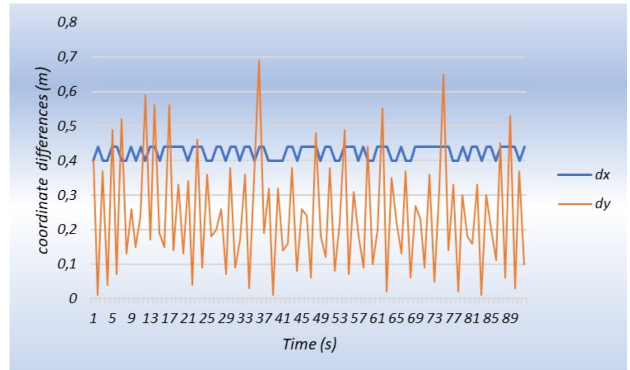

Figure 3: Positioning results

Considering our previous experiments, we have learnt that no matter what algorithm we use to calculate the position, the positioning accuracy of the filtered sampling data is always more accurate than without filtering.

Based on our experience with other positioning algorithms, in presented experiment final Zigbee positions obtained using the weighted nearest algorithm, are the most optimal and at high level of accuracy for presented scenario.

The results show that the standard deviation with the improved fingerprint database is less than or equal to 0.17 m in more than 30 m range. The authors are aware of the differences in y axis and assume that they are caused by interference of 2.4 GHz waves from nearby rooms, where computer labs are located. For next experiments we are going to choose another location scenario, free of any sources of potential wave interferences. The Presented experiment also shows that the used algorithm can effective eliminate the position error which is usually significant in wifi positioning, since many wireless networks transmit their signals in a narrow radio frequency range around 2.4 GHz. It's common for devices on the same frequency to affect the wireless signal. Interference can be also caused by other wireless networks, other 2.4 GHz frequency devices (Bluetooth), and high voltage devices that generate electromagnetic interference. We were focused on checking how the wifi signal is stable, especially in such multipath environment. Unfortunately we were limited by the number of wifi devices/routers to four. In such environment we would suggest to have at least six devices. In the near future we are going to obtain the latest wifi/lte mobile routers working on 2.4 and 5 GHz simultaneously. The 5 GHz band tends to have less overcrowding than the 2.4 GHz band because less surrounding devices use it and because it has 23 channels for devices to use, while the 2.4 GHz band has only 11 channels. The number of channels that are available depends on the regulatory domain. When experiencing a lot of interference from other devices, we would suggest using the 5 GHz band which is more suitable in indoor environmentsThe authors are conscious of interference positioning errors coming from 2.4 GHz wireless network, and to overcome this drawback, additional experimental work with 5GHz mobile equipment is planned in the near future. Such a solution may take advantage of the reduced noise available in the 5 GHz spectrum, providing faster data rates and more stable connection.

5 Conclusions

In this research paper, we proposed a new method about the average threshold and the effective data domain filtering method to optimize the fingerprint database of ZigBee positioning system. Indoor experiment, which was conducted at the University of Warmia and Mazury, proved that the distance achieved by this system has been extended over 30 meters without decreasing the positioning accuracy. The weighted nearest algorithm was chosen and used to calculate user's location, and then the results were compared and analyzed. As a result, the positioning accuracy was improved and error did not exceed 0.69 m. Based on our previous experimental work with other positioning algorithms, presented final Zigbee positions obtained using the weighted nearest algorithm, are the most optimal and at high level of accuracy for chosen scenario. The experiment also shows that the used algorithm can effective eliminate the position error which is usually significant in wifi positioning, since many wireless networks transmit their signals in a narrow radio frequency range around 2.4 GHz. Therefore, such system can be easily applied in a bigger space inside the buildings, underground mines or in the other location based services. For future scientific work, additional experiments with 5GHz mobile equipment is planned. It may take advantage of providing faster data rates, more stable connection and less signal noise in the 5 GHz spectrum.

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