Preliminary Study of Classifier Fusion Based Indoor Positioning Method

Yuki Miyashita, Mahiro Oura, Juan F. De Paz, Kenji Matsui, Gabriel Villarrubia and Juan M. Corchado

Abstract Indoor positioning technology is commercially available now, however, the positioning accuracy is not sufficient in the current technologies. Currently available indoor positioning technologies differ in terms of accuracy, costs and effort, but have improved quickly in the last couple of years. It has been actively conducted research for estimating indoor location using RSSI (Received Signal Strength Indicator) level of Wi-Fi access points or BLE (Bluetooth Low Energy) tags. WiFi signal is commonly used for the indoor positioning technology. However, It requires an external power source, more setup costs and expensive. BLE is inexpensive, small, have a long battery life and do not require an external energy source. Therefore, by adding some BLE tags we might be able to enhance the accuracy inexpensive way. In this paper, we propose a new type of indoor positioning method based on WiFi-BLE fusion with Fingerprinting method. WiFi RSSI and BLE RSSI are separately processed each one by a Naive Bayes Classifier. Then, Multilayer Perceptron(MLP) is used as the fusion classifier. Preliminary experimental result shows 2.55m error in case of the MLP output. Since the result is not as good as the ones using conventional method, further test and investigation needs to be performed.

Keywords Indoor positioning · Classifier fusion · Wi-Fi · BLE · Fingerprint

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H. Lindgren et al. (eds.), *Ambient Intelligence- Software and Applications (ISAmI 2016)*,
Advances in Intelligent Systems and Computing 476,
DOI: 10.1007/978-3-319-40114-0_18

1 Introduction

In case of outdoor positioning, satellite-based GPS positioning works very well. However, indoor positioning [2] [5] is not so straight forward, and that area is glowing research fields in mobile computing because of the popularization of mobile devices, like smartphones, tablets. The technologies currently most used in the development of Real-Time Location System are, RFID (Radio Frequency IDentification) [10], Wi-Fi [6] or BLE (Bluetooth Low Energy) [4] [7]. Indoor positioning technology is commercially available now, however, the positioning accuracy is not sufficient in current technologies. Currently available indoor positioning technologies differ in terms of accuracy, costs and effort, but have improved quickly in the last couple of years. WiFi signal is commonly used for the indoor positioning technology. However, WiFi equipment requires an external power source and more expensive setup costs. WiFi signal is strong and it can cover relatively wide area. Bluetooth Low Energy (BLE) is one of the latest technologies. It is called BLE beacons (or iBeacons) that are inexpensive, small, have a long battery life and do not require an external energy source. Both WiFi and BLE technologies bring a couple of advantages: easy deployment and are integrated in most of the current electronic devices. Thus, it has been actively conducted research for estimating indoor location using RSSI (Received Signal Strength Indicator) level of Wi-Fi access points or BLE tags.

This paper reports a preliminary study of WiFi-BLE mixed indoor positioning engine, which can provide location information of people or objects inside a building with possibly better accuracy and better cost performance. The use of these technologies for location system is mainly based on intensity maps constructed from RSSI levels in different zones. The maps are used as a basis of obtaining the locations. The classifiers use the data of the maps and the data obtained from the devices to determine the position of a person inside a building.

In this article, Section 2 describes our proposed method, Section 3 presents the detailed points of the experiment. Section 4 summarizes the experimental results, and in Section 5, we discuss about our next steps, finally, we conclude our report.

2 Proposed Method

There are various methods in terms of indoor positioning. In the study written by Gabriel [1], he used WiFi RSSI data with Bayesian network based classifier to get the estimated position data. The intensity map has the data structure shown in Figure1. Each data map contains the information of all the WiFi access point MAC addresses, RSSI values, as well as the coordinates (x, y). The RSSI values are considered to be the distance from the WiFi access points. The more data we use, the more processing time we need.

Our objectives are: 1) increase the positioning accuracy, 2) increase the processing speed, and 3) increase the cost-performance. In order to meet those objectives, first, we added more beacons to make the position estimation accurate. For those beacons, we chose simple BLE tags to reduce the additional cost. Then, we introduced the combination of Bayes classifier and Multi-layer Perceptron (MLP) in order to increase the processing speed without losing the accuracy. Similar study was reported by Javier [3]. He proposed the method using fusion classifier.

Figure 2 shows the basic building block of the proposed fusion classifier, where $\sum f(pos_i)$ is the expected location coordinates. The advantages of using BLE tags are not only improving the cost performance, but we might be able to implement many applications associated with BLE tags.

X	*Y*	*MAC Address*	*RSSI*	*MAC Address*	*RSSI*	…	…

Fig. 1 Data format of the intensity map

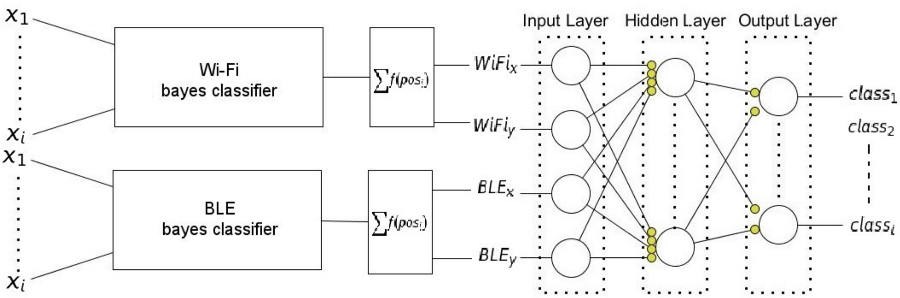

Fig. 2 Block diagram of the proposed fusion classifier

3 Experiment

As for the test environment, we used our office shown in Figure 3. Three square symbols in that figure are WiFi access points, round ones are BLEs, and 100 fingerprints are indicated by X marks. That office is 15 × 20m, approximately 300m^2. There are around 30 additional WiFi access points in the building, and we allocated 8 BLE tags in the office. For the training data collection, one smart phone was utilized to measure the RSSI and other data. We measured the training data from 100 locations in the room as total. At each location, RSSI values were measured 10 times. That means 100 fingerprints were collected. Those collected data were used to train the Bayes classifiers. The output from the Bayes classifier is the estimated location coordinates (x_i,y_i). Both those estimated data and actual measured data were used to tune the MLP.

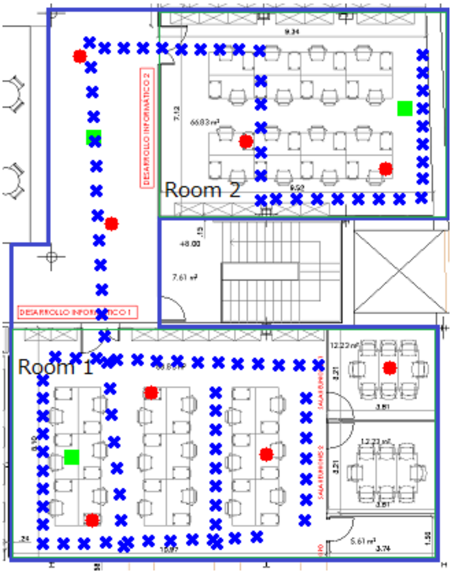

Fig. 3 Environment of evaluation

In this study, our proposed indoor positioning system is based on the fingerprinting [7] on a map of intensities. In terms of the accuracy evaluation, we compared four different positioning methods as shown below. The overall diagram is shown in Figure 4.

1. Bayes classifier with WiFi - RSSI
2. Bayes classifier with BLE - RSSI
3. Bayes classifier with both WiFi - RSSI and BLE - RSSI
4. MLP with Method 1 output and Method 2 output.

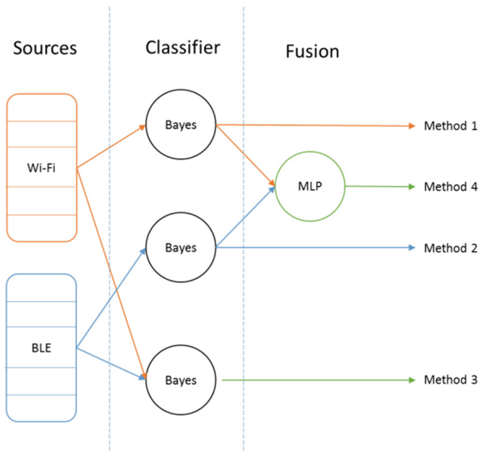

Fig. 4 Block diagram of the experiment system

For the experiment, we used around 30 WiFi signals in the building as well as the three WiFi stations in the room. Those additional access points are the originally installed ones in the building. As for the testing data, we obtained 50 more measurement data, and used for the experiment.

4 Experimental Results

The experimental results are shown in Table 1. The average error shows that the proposed method (method 4) was not as good as other methods. In terms of the BLE tags, both method 2 and method 3 are slightly better than the WiFi based location estimation. More detailed evaluation with various conditions needs to be performed.

Table 1 Errors of estimating [m]

Method	*Max Error*	*Minimum Error*	*Average Error*
1	6.159	0.173	2.525
2	6.367	0.198	2.254
3	6.527	0.240	2.363
4	5.898	0.292	2.555

5 Discussion

There are many issues we need to work further. For instance, how to stabilize the location estimation is very important challenge. Since we did not address about the WiFi intensity signal fluctuation associated with the equipment characteristics, variation in power source, and various room environment, some of the promising directions of improvement are: (1) Updating the fingerprint data based on carefully observed signal intensity behavior. The fingerprints are normally influenced by environmental factors, the brands and models of the devices. (2) Eliminating negatively affect devices by observing intensity level and fluctuation. (3) Applying the each probability distribution functions into the Bayes classifiers.

6 Conclusion

In this paper, we provided a preliminary study of indoor positioning estimation using WiFi-BLE fusion method. As for the classifiers, we tested the combination of Bayes classifer and MLP. We evaluated the overall fingerprint matching performance between the proposed method and conventional method. The average error shows that the proposed method was not as good as other methods. In terms of the BLE tags, both method 2 and method 3 are slightly better than the WiFi based location estimation. Since both WiFi and BLE signal intensity is normally influenced by environmental factors and device characteristics, more detailed evaluation with various conditions needs to be performed.

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