Implementing an iBeacon Indoor Positioning System using Ensemble Learning Algorithm

Kuan-Wu Su[1],He-Yen Hsieh[2],Jen-Chieh Hsu[3],Bo-Han Chen[4],Che-Jui Chang[5],Jenq-Shiou Leu[6]
Department of Electronic and Computer Engineering[123456],
National Taiwan University of Science and Technology, Taiwan(R.O.C.)
{d10102107[1],m10402124[2],m10502103[3],m10502143[4],m10402104[5],jsleu[6]}@mail.ntust.edu.tw

ABSTRACT

Nowadays, there is an increasing requirement for indoor positioning and navigation with Location Based Services (LBSs). Many applications on smartphones exploit different techniques and inputs for positioning. Most of the indoor wireless positioning systems rely on Received Signal Strengths (RSSs) from indoor wireless emitting devices. However, the accuracy of indoor position is easily affected by servals signal interference. In this paper, we propose a LBS system using ensemble machine learning with iBeacon RSSs fingerprint, and hope to achieve higher accuracy for indoor positioning. Preliminary experiments showed very promising results that our approach can improve indoor positioning accuracy at shorter distance.

Keywords

Indoor positioning; iBeacon; ensemble learning; machine learning

1. INTRODUCTION

In recent years, Location Based Services (LBS) have been widely applied in many applications and services in mobile environments, where location awareness is crucial to people's daily lives. However, Global Positioning System (GPS), although is very convenient and accurate outdoor, but has significant signal loss indoor. Recently, more and more important applications required indoor LBS have being applied to places like universities, shopping malls, and hospitals, with huge demand in precision and accuracy for people to find locations inside buildings.

DOI:

Many different kinds of signals can be used for indoor positioning, such as Wi-Fi[2], ZigBee, RFID, Ultrasound, Laser, and Bluetooth Low Energy (BLE). Most popular indoor positioning algorithm is based on fingerprint database[3], where it uses Received Signal Strength Indicator (RSSI) as fingerprint basis, and can be read easily with widely available portable devices. Here, we use iBeacon technology, which utilize BLE for indoor LBS combined with machine learning algorithms. Bluetooth beacons are cost effective, easy to deploy and small in sizes[1], and iBeacon doesn't rely on external power source and can last for months. Therefore, we implement our ensemble learning indoor positioning algorithm with iBeacon and hopefully to achieve high positioning accuracy as other methods.

2. INDOOR POSITIONING WITH ENSEMBLE LEARNING

2.1 System Architecture

2.1.1 Data Collection System

The data collection system consists of two main components - client side on mobile devices, and server side with database and services. Mobile application on the client side collects RSSI signals, and then send its data to the server side. Ensemble learning algorithm running on the server side calculate the results based on RSSI fingerprint stored in the database. The topology of our system is shown in Figure 1.

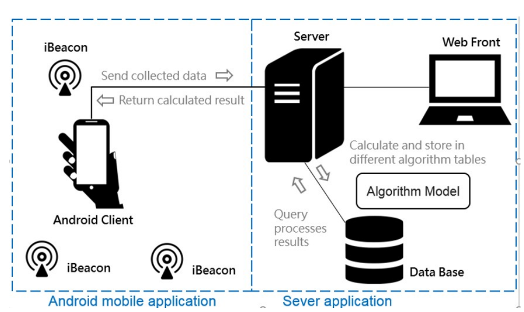


Figure 1: Data Collection System Architecture

2.1.2 Ensemble Learning

We have implemented a positioning application on several different types of mobile devices gathering data and connecting to our servers to evaluate the system performance. Beacon signals collected on the client sides are send to multiple classifiers, and all the results from them are then ensemble into an aggregated prediction result. Several different ensemble learning algorithms were evaluated and algorithms with parameters that generate the highest accuracy results in shorter distance were picked. The ensemble learning process flow is shown in Figure 2.

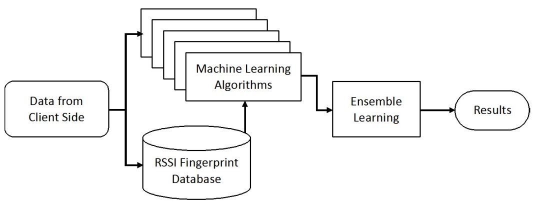


Figure 2: Ensemble Learning Process Flow

2.2 Experiments and Result

2.2.1 Experiment Environment and Setup

In order to evaluate the proposed localization approach, several preliminary experiments were conducted. The test environment is located at the seventh floor of the Electrical and Computer Engineering Building in National Taiwan University of Science and Technology, Taiwan. The tracking area has a dimension of 4.8m by 7.2m by 3m within the red rectangular. Three beacons are deployed on three different walls, two meters high off the ground. The floor plan of our test environment is shown in Figure 3.

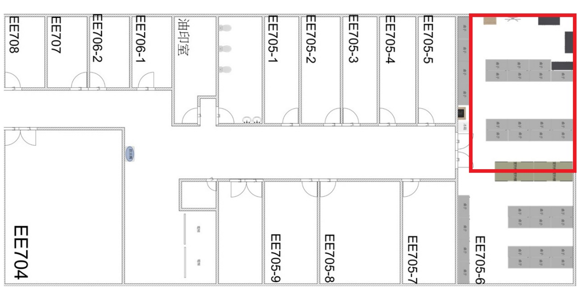
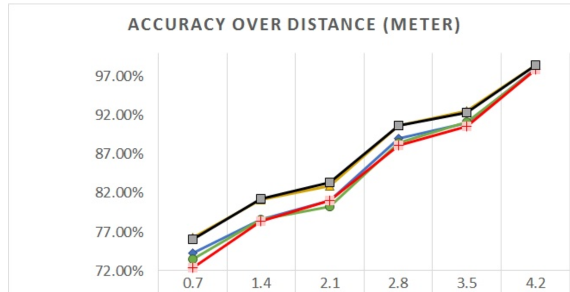


Figure 3: Floor Plan of the Test Area

To evaluate our proposed system in a real environment, we implemented an application for indoor positioning with ASUS Zenfone3, an Android smartphone equipped with Wi-Fi and BLE. Each machine learning algorithm as well as the ensemble learning process are implemented with python using scikit-learn, and deep learning neural network using Keras with TensorFlow backend.

2.2.2 Results

The results of estimated accuracy(ACC) over different positioning displacement distance is shown in Figure 4. And it shows the ensemble learning process can increase the positioning accuracy at the displacement distance around 2 meters, and achieve over 80% of accuracy at the distance less than 1.3 meter, and over 90% around 2.5 meter.



	0.7	1.4	2.1	2.8	3.5	4.2
KNN	76.25%	81.19%	82.94%	90.69%	92.63%	98.44%
Random Forest	74.25%	78.56%	81.06%	89.00%	91.06%	98.06%
3-layer NN	73.50%	78.56%	80.25%	88.50%	91.19%	97.94%
DNN	72.38%	78.38%	81.00%	88.19%	90.56%	97.94%
Ensemble	76.00%	81.31%	83.38%	90.69%	92.38%	98.44%

Figure 4: Positioning Accuracy over Distance

3. CONCLUSIONS

Our prototype indoor positioning system using ensemble learning algorithm has shown great promise to be on par in accuracy with other indoor positioning methods. And there's still more room to improve our system's performance like deploying more BLE beacons, or using other ensemble learning techniques like boosting to make shorter distance accuracy increased further. The low cost and cheap iBeacon also mean our system can be cost effective and energy efficient, and would be a solid foundation for other LBS applications to build upon.

4. REFERENCES

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