Study on the application of indoor positioning based on low power Bluetooth device combined with Kalman filter and machine learning

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***Abstract* – In recent years, outdoor positioning technology has approached maturity, but the Global Positioning System is limited by environmental factors and obstacles, and has no effect indoors. There are many research and discussion on indoor positioning, among which the lower cost construction methods are Bluetooth and Wi-Fi. This study uses a device based on the iBeacon protocol proposed by Apple in 2013 as a tool for this research. Due to the Received Signal Strength Indicator (RSSI) value from the Bluetooth is unstable which will affect the positioning results, this research used Kalman Filter Algorithms to improve the RSSI stability of Bluetooth and used machine learning algorithms to improve indoor positioning accuracy. iBeacon and Android smart phones were used as experimental devices to test and compare the differences between K nearest neighbors (KNN), support vector machines (SVM) and random forest algorithms. The experimental results indicate the optimal signal collection density for indoor positioning is about 1 meter and the accuracy can reach to more than 85%. The statistics show that the model which trained by KNN algorithm has the highest accuracy.**

Keywords- Machine Learning, Kalman Filter, Indoor Positioning, Bluetooth.

I. INTRODUCTION

For the past few years, with the popularity of handheld smart mobile devices, mobile network and wireless network, the related applications of location-based services (LBS) based on spatial positioning have become more widespread. The Global Positioning System (GPS) has become a mature technology which provides convenient and reliable outdoor positioning service. However, there cannot have any obstacle between signal transmitter and receiver because of the GPS feature Line of Sight (LOS). Otherwise it will be affected by the shielding effect of the obstacle or cause signal interference. Therefore, if GPS is to be used for indoor positioning applications, it is easy to cause the problem that the indoor positioning is not accurate enough or cannot be positioned because the signal is not received.

According to the reasons discuss above the application services of indoor positioning should rely on other technologies. For example, Bluetooth, Wi-Fi, Radio Frequency Identification (RFID) and Zigbee. Through the feature None Line of Sight (NLOS) of the technologies mentioned above to compensate for the indoor positioning problem of GPS. Due to environmental factors, wireless signals may cause physical phenomena such as diffraction, reflection, refraction or multiple paths when the signal is in contact with obstacles and resulting in serious signal fluctuation and poor positioning. This research finds that there is still room for improvement in the accuracy of the current positioning algorithm in indoor positioning. However, the recent literature rarely discusses the relationship between the density of signal collection and accuracy (P. C. Ng, J. She and S. Park, 2018), so this study proposes a method for reinforcement of indoor positioning accuracy.

Apple Inc. published iBeacon at the 2013 Apple Worldwide Developers Conference (WWDC). iBeacon is developed as positioning device and it is based on Bluetooth Low Energy (BLE). The reasons we adopted iBeacon as our experimental positioning devices because of its low price, the convenience of establishing connection and the ability to provide Received Signal Strength Indication (RSSI) to the positioning application. To improve positioning accuracy and stability, the solution needs to reduce the impact of signal attenuation and noise, and improve the tolerance of the positioning model to the model. This study first discussed the more commonly used indoor positioning technology and signal attenuation phenomenon. In order to reduce the influence of signal attenuation, a Kalman filter can effectively improve the signal attenuation phenomenon. It only needs to use the signal of the previous prediction and the signal of the observation to achieve the filtering effect. Therefore, this research adopted the Kalman filter as a method to improve signal attenuation. Furthermore, this study took three machine learning algorithms and tried to compare the effects of different algorithms on improving the accuracy and positioning. Finally, we choose the best algorithm and integrate with Kalman Filter to generate positioning prediction model.

II. RELATED WORK

Positioning technology began as early as the 15th century when people began to explore the ocean, but at that time use the very rough methods such as nautical maps and astrological maps to confirm their position. With the advance and development of human science and technology, positioning technology has gradually made good progress in terms of methods, accuracy and usability. From the high-end fields of navigation, aviation, military, natural disaster prevention, etc., various important applications, such as vehicle navigation, traffic management, location search gradually infiltrates into people daily life. The GPS and base station positioning technology has substantially met the demand for location services in outdoor scenarios. However, as human society becomes more urbanized and indoor spaces are becoming more complex, modern people spend most of their time indoors. Wireless or satellite signals are inevitably hindered by indoor building structures during the process of dissemination, so GPS technology is difficult to apply to indoor environment (Feir, 2017; Ciezkowski, 2017). In view of this, more than 20 manufacturers including Nokia, Sony, Samsung, and Qualcomm have formed an In-Location Alliance with the aim of providing devices and solutions that are "high-precision, low-power, mobile, easy to deploy, and usable."

The development of indoor positioning technology is diverse. The mainstream technologies include infrared, ultrasonic, computer vision, Zigbee (Alliance, n.d.), RFID, Wi-Fi, Bluetooth, LED visible light, and Ultra Wideband (UWB). The traditional positioning method includes seven main principles such as triangulation, fingerprinting, proximity, centroid positioning, pole method, multilateral positioning method and dead reckoning. However, Bluetooth-based indoor positioning is not a novel idea. The research (R. Bruno and F. Delmastro, 2003) tried to develop approach which is based on Bluetooth, but by the limitation of technology it has not been widely used. In recent years, intelligent indoor positioning algorithms gradually appear. The main method is to divide the indoor area into some blocks, and obtain the signal intensity characteristic value in each block as the training data of machine learning. During the positioning process, the block with highest matching degree of the current signal is used as the location of the device. The studies (A. Blattner, Y. Vasilev, B. Harriehausen-Mühlbauer, 2015) and (Z. He, B. Cui, W. Zhou, S. Yokoi, 2015) implemented BLE technology on their indoor positioning system, but their approaches do not mention about the signal pre-processing. The rest of the paper is organized as follows: Section III begins with the description of proposed method and experiment process. The experimental results will be given in Section IV. Finally, the conclusions and future works are drawn in Section V.

III. PROPOSED METHOD

The purpose of signal processing filters is mainly to eliminate the noise and distortion of wireless signals. In this study, we use Kalman Filter to improve wireless signal stability. The Kalman Filter is originated from the Hungarian mathematician Rudolph E. Kalman in 1960 (Kalman, 1960). It is described by a series of recursive mathematical formulas. The formulas provide an efficient and computable method to estimate the state of the process and minimize the estimated mean square error. The applications of Kalman Filter are widely used and powerful. Even without knowing the exact property of the model, it can estimate the past, current and future state of the signal (G. Welch and Gary Bishop, 2006).

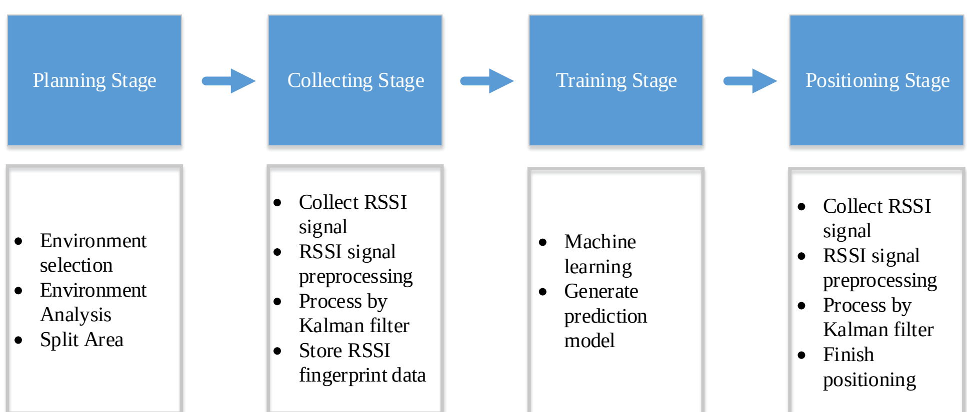

Fig. 1 Magnetization as a function of applied field.

Since the objective of this study is to improve positioning applications on mobile devices, the Kalman Filter is a lightweight algorithm (A. Ozer and E. John, 2016). The original RSSI signal value will fluctuate rapidly due to peripheral interference, so Kalman Filter is needed to smooth the signal value. The raw RSSI noise is reduced to achieve fast and immediate optimization of the RSSI stability. Then the distance between the Beacon and the mobile device is calculated, thereby improving the positioning accuracy. The application of this study is implemented on Android platform. Detailed experimental process is shown in Fig. 1 and discusses each stage in following.

A. Planning Stage

In this stage, we select the experimental positioning test space and try to divide the space into several blocks. After splitting the space, mark each block to facilitate the subsequent machine learning training phase and prediction phase. At present, there is no formula or standard for the separation rules of the space, and it can only be adjusted according to the needs of the experiment and the environment. According to the experience of this study, the size of each block is at least above 1 meter * 1 meter and the distance between the blocks is about 1 meter or more. As for the deployment of iBeacon, it is based on the principle that can cover all the blocks. There are two areas be selected as our experimental environment.

A1. Experimental Area 1

We choose the Science Building 701 room at National Chung Hsing University which show in Fig. 2 as experimental area 1.

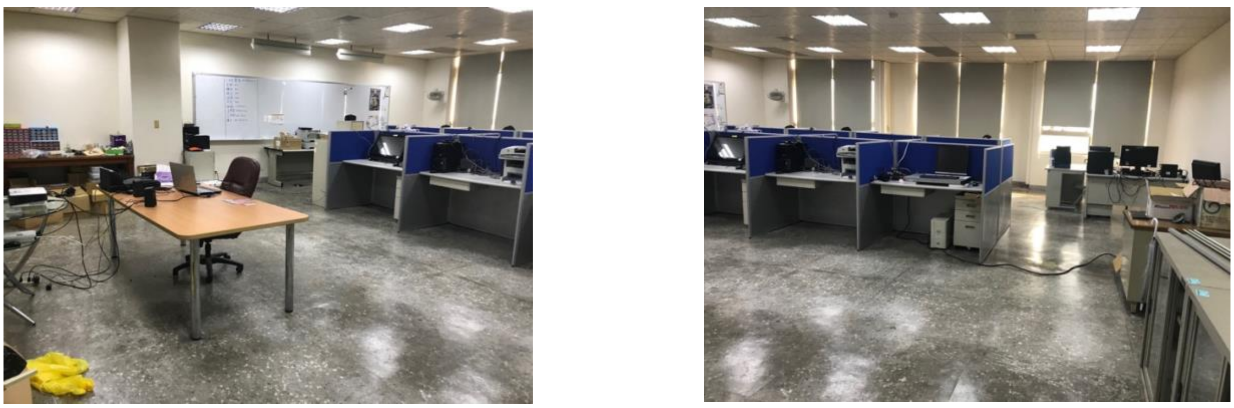

Fig. 2 Experimental Area 1 – real scene

The division situation shows in Fig. 3 and the upper left corner is set to the origin (0,0), moreover, the area is divided into 12 blocks and every block is composed of 9 tiles. Low-power Bluetooth transmitter Beacon is placed in four corners of the area with coordinates BLE1(0,0)、BLE2(3,0)、BLE3(3,4)、BLE4(0,4). The data format of fingerprint data collected from Beacon is (Block serial number, BLE1, BLE2, BLE3, BLE4).

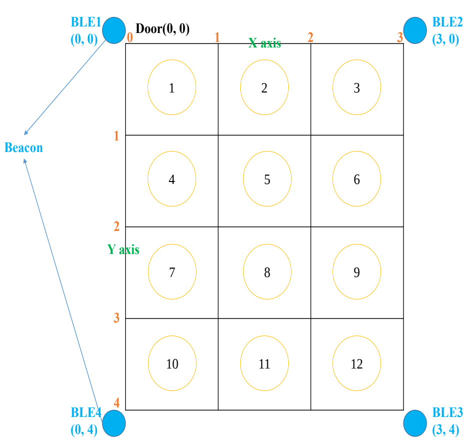

Fig. 3 Experimental area 1 divide into 12 blocks

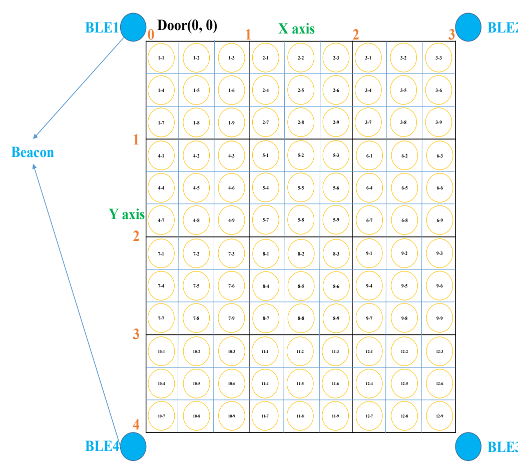

Fig. 4 Experimental area 1 divide into 108 blocks

In order to understand and test the relationship between the positioning accuracy and the density of the positioning signal, each block in Fig. 3 is partitioned into 9 sub-blocks which show in Fig. 4.

A2. Experimental Area 2

The experimental area 2 is the 7th floor corridor in Science Building at National Chung Hsing University and the range of experiment in this research shows in Fig. 5. In experimental area 2, four Beacons and two Beacons were used to simulate different signal deployment densities, and then analyze the signal from different densities.

Fig. 5 Experimental Area 2 – real scene

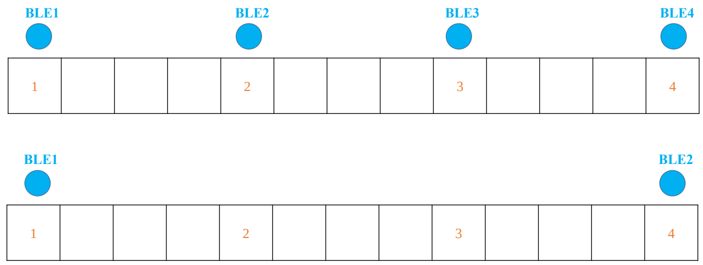

Fig. 6 The position of BLE and signal collection points

B. Collecting Stage

When the planning stage is completed, the Bluetooth signal RSSI send by iBeacon is collected in sequence to the different block of each area. After the data preprocessing and Kalman filter, the fingerprint data is stored into the database. To identify different iBeacons, the traditional method is to use of MAC and UUID, but this study can modify the Major and Minor through the APP which provided by the iBeacon company. This increases more flexibility for the definition of identification codes for different areas and different iBeacons.

C. Training Stage

If the classification target of an unknown case is a category variable, such as predicting "success" or "failure", we will call this prediction a "classification problem"; if the classification target is a numerical continuous variable, such as a prediction "score", "rise and fall", this is called "regression problem". Due to the positioning experiment of this study adopts the signal block classification, we use the classification prediction method to carry out the machine learning positioning application. In order to get the effect of comparative immediateness so we choose KNN, SVM and Random Forest three machine learning algorithms to compare the results with each other. Using the fingerprint database which is created in collect stage and training the prediction model by one of three machine learning algorithms for the subsequent prediction stage to complete the positioning application. The prediction model is classified by the RSSI feature fingerprint which is collected in different blocks.

D. Positioning Stage

The positioning process in this stage which shown in Fig. 7 is divided into two parts: signal collection and instant interpretation positioning. Both parts use the RSSI data collected by the Android operating system mobile device. First, collecting the RSSI of Bluetooth signal and preprocessing by mean filtering every 1,000 raw data is taken. The Kalman filter is used to further filter the signal, then find out the position by prediction model which is created in training stage.

IV. Results

A. Experimental equipment, environment and applications

Based on the method which proposed in Section III, we develop an Android application that is easy to collect and observe RSSI data. This application is designed in simple user interface and instantly shows the signal that collect from all Beacon devices. There is a special function in the application that can filter the signal from the Beacon devices which belong to this experiment through setting the identification number of Major and minor. We choose SQLite database to store the important information about Beacon's Block, Major, Minor and RSSI. It is important to note that the phones that implement in this application must support the BLE module, and the operating system must be at least Android 4.3 (API Level 18) or later to be compatible with this application. The model of the phone that we used is ASUS ZenFone 5 T00F A500CG and the operating system is Android 4.3. The Bluetooth signal transmitter we used is THLight USBeacon and it can transmit BLE broadcast signals in accordance with APPLE iBeacon. The application is developed in Android Studio 3.0.1 using JAVA and integrates with Android software development kit 1.8.0. The programs of three algorithms and RSSI signal analysis are developed in Eclipse 4.6.1 using JAVA and integrate with Java software development kit.

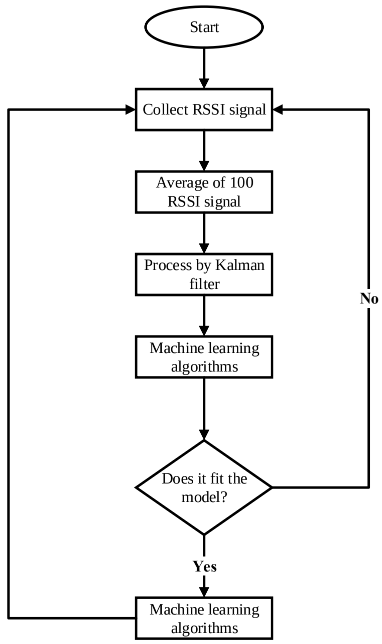

Fig. 7 The process of positioning stage

In experiment area 1, the Beacon devices are deployed at three different heights, 10 cm, 150 cm, and 250 cm from the ground. The height of the mobile phone which collects RSSI signal is about 150 cm. When the distance is different from Beacon, the RSSI of the three deployment heights is quite close. If the Beacon devices are deployed on the ground or on the wall, it is easy to interfere or block the signal due to environment or obstacles (the human body is also one of the possible obstacles) (A. Ozer and E. John, 2016), so we placed the Beacon devices near the ceiling in four corners as shown in Fig. 9. The experimental area is drawn in a smart phone program. When the user moves, there is a mark on the picture followed by the user to mark the user's location. In experiment area 2, we deployed the Beacon devices on the ceiling as shown in Fig. 10. After deploying the Beacon devices, in Fig. 11, the application which collects RSSI signal is used to pack the signal and send to computer node for signal analysis.

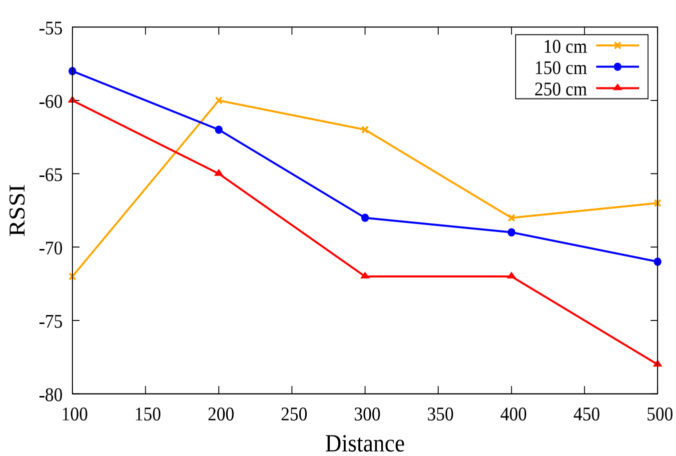

Fig. 8 The RSSI of different deployment heights

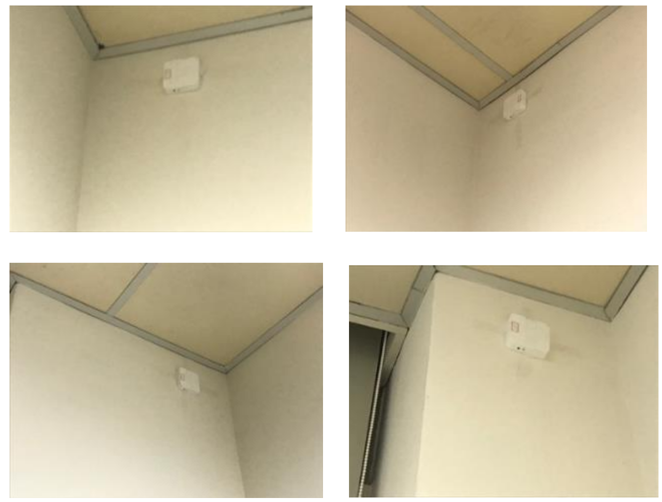

Fig. 9 Beacons deployed in experimental area 1

The application of positioning shows the indoor location of person who holds the mobile phone device. According to Fig. 12, we divide area into 12 blocks and there are 4 Beacon devices on the wall. A person takes a mobile phone device and walks around. At every position the mobile device gets the RSSI signal and block number of 4 Beacon devices. For example, in the format (1, -71, -62, -53, -77) that 1 represents the block 1; -71 represents the RSSI strength of Beacon 1; -62 for the RSSI strength of Beacon 2; -53 and -77 shows the strength of Beacon 3 and Beacon 4, respectively.

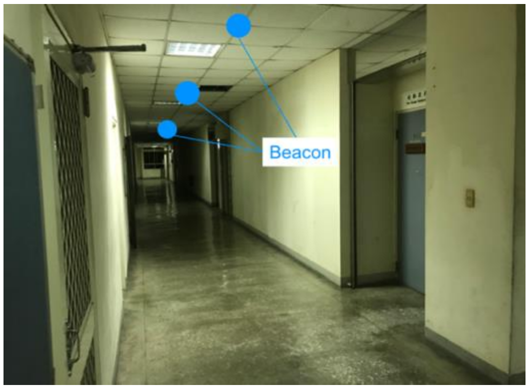

Fig. 10 Beacons deployed in experimental area 2

Fig. 11 The application of collecting RSSI signal

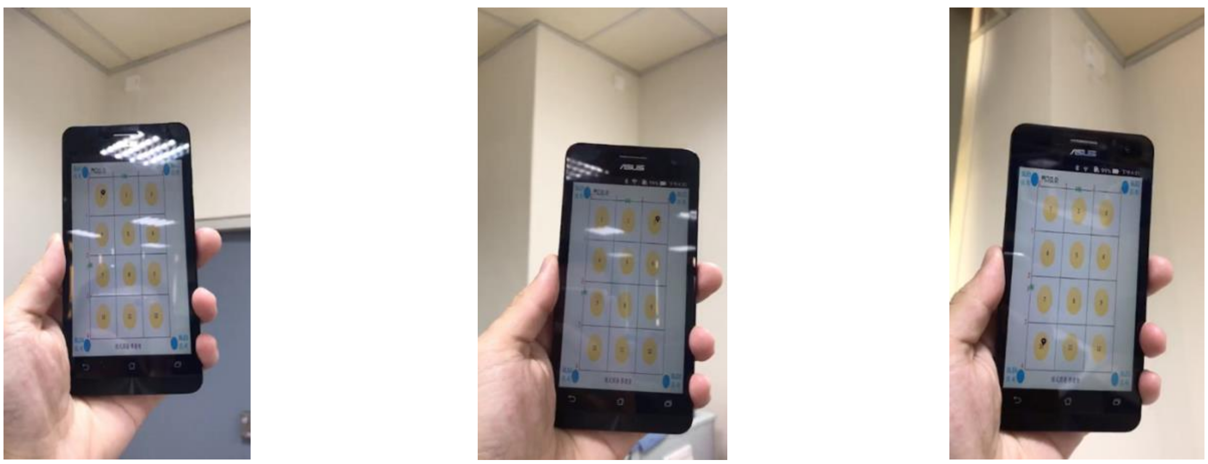

Fig. 12 The application of positioning

B. *RSSI collection and analysis*

Standing at the fixed point to collect the RSSI signal of the Beacon device, as shown in Fig. 13, the signal is unstable. We also measure the farthest distance to 35 meters between Beacon device and mobile phone, the signal is measured every 1 meter. During the process, the RSSI signal continuously oscillate and the farther away from Beacon device, the lower RSSI signal is received by mobile phone. Due to the signal status is unstable, several methods are implemented for signal preprocessing.

In Fig.14 we receive 100 signals at a distance of 1 meter and collect it from 1 meter to 20 meters. The median filter, mean filter, mode filter and Kalman filter are used for filtering analysis, moreover, the results of these RSSI signal are recorded.

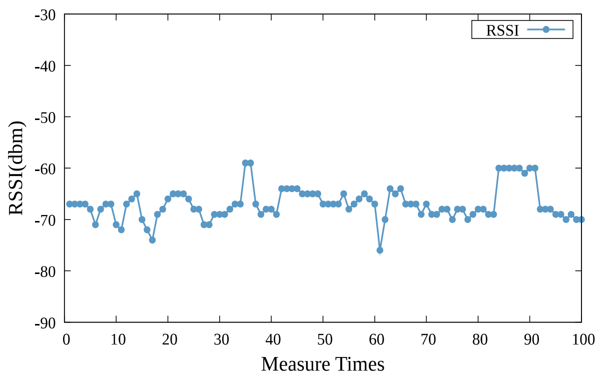

Fig. 13 Bluetooth signal oscillation

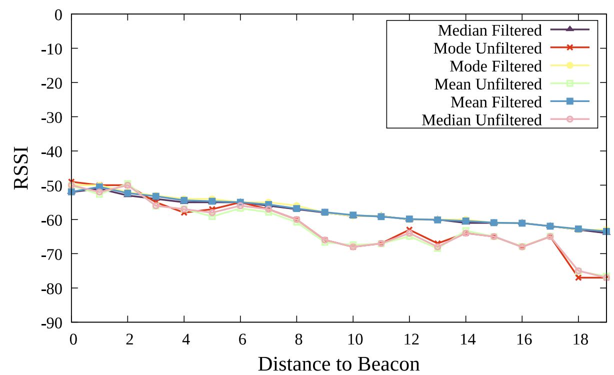

Fig. 14 RSSI results of different filters and distance

C. Comparison accuracy of machine learning algorithms

The experiment divides the experimental area 1 into 12 and 108 blocks to compare the accuracy. The results in Table I show that the more blocks we divide and the accuracy is lower. In Table II, the results of experimental area 2 show that the denser the Beacon devices are deployed, the lower accuracy we get. The site in Table II means signal collecting points.

Table I.
The accuracy of algorithms in experimental area 1

Number of blocks \Algorithms	KNN		SVM		Random Forest	
	Learning Accuracy	Time (s)	Learning Accuracy	Time (s)	Learning Accuracy	Time (s)
12 blocks	**97.83%**	< 0.1	**95.91%**	**0.18**	**97.75%**	**0.17**
108 blocks	**51.55 %**	< 0.1	**49.55 %**	**0.81**	**52.31 %**	**1.1**

Table II.
The accuracy of algorithms in experimental area 2

Number of Sites\ Algorithms	KNN		SVM		Random Forest	
	Learning Accuracy	Time (s)	Learning Accuracy	Time (s)	Learning Accuracy	Time (s)
4 Sites	**89%**	**< 0.01**	**89.75%**	**0.14**	**87.75%**	**0.3**
7 Sites	**83.7143%**	**< 0.01**	**82.8571%**	**0.04**	**82.7143%**	**0.13**
12 Sites	**70.6154**	**< 0.01**	**69%**	**0.11**	**70.3077%**	**0.17**

V. CONCLUSION AND DISCUSSION

Based on the Kalman filter, we put forward the method of pre-processing of Bluetooth signal data, and confirmed the density of different Beacon signal collection points through the experimental results, which has an impact on the training of machine learning algorithm to produce predictive model and positioning accuracy, and according to the results of this study. It is found that the higher the density of the Beacon signal collection, the accuracy of the positioning will decrease at any time. The results of this study showed that the signal collection density of indoor positioning was about 1 meter, and the accuracy was the best.

Three kinds of machine learning algorithms are used to verify the accuracy of the model prediction respectively. It is concluded that the accuracy of the KNN algorithm is the highest. The positioning accuracy is increased to 1 meter. The whole process is through database to train and generate predictive models. If these processing steps can be transplanted into the mobile device in the future, I believe that can also provide more real-time and rapid dynamic machine learning Prediction model and positioning function correction.

ACKNOWLEDGMENT

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