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A Location Tracking System using BLE Beacon Exploiting a Double-Gaussian Filter

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Abstract

In this paper, we propose indoor location tracking method using RSSI(Received Signal Strength Indicator) value received from BLE(Bluetooth Low Energy) beacon. Due to the influence of various external environmental factors, it is very difficult to improve the accuracy in indoor location tracking. In order to solve this problem, we propose a novel method of reducing the noise generated in the external environment by using a double Gaussian filter. In addition, the value of the RSSI signal generated in the BLE beacon is different for each device. In this study, we propose a method to allocate additional weights in order to compensate the intensity of signal generated in each device. This makes it possible to improve the accuracy of indoor location tracking using beacons. The experiment results show that the proposed method effectively decrease the RSSI deviation and increase location accuracy. In order to verify the usefulness of this study, we compared the Kalman filter algorithm which is widely used in signal processing. We further performed additional experiments for application area for indoor location service and find that the proposed scheme is useful for BLE-based indoor location service.

Keywords: Indoor localization, BLE, RSSI, Gaussian filter, Friis, Triangulation

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1. Introduction

Recently, with the development of computer technology and electronic components, IT technology is widely used in various fields. Especially, as the demand for location based services increases, researches for precisely tracking the location of users are actively underway. Basically, location tracking technology is widely used with GPS technology and indoor location tracking technology is being introduced in an environment where it is difficult to track GPS signals. Indoor location systems typically provide a way for a user to track a location where GPS signals are not available. Indoor location tracking techniques are emerging in various forms depending on mathematical algorithms, wireless technologies or hardware characteristics. Widely used indoor location tracking systems are based on technologies such as Infrared Badge, RFID [1], Ultrasound [2], UWB [3], and WIFI. Especially, various sensors (accelerometer, gyroscope, magnetometer, microphone or camera) are embedded in mobile phones, and indoor location tracking technology is developing centering on mobile phones. Smartphones are user-friendly tools that users carry around all the time, and they are used as a core device for indoor location tracking because they have built-in computer devices that can perform high-performance computations.

With the recent addition of BLE technology to smartphones, a new challenge has emerged in the field of indoor location tracking. The BLE technology improves existing Bluetooth technology, consumes less energy and can be used for a long time, and provides an approximate distance estimation using RSSI value. A BLE is recently developed wireless technology, which is widely used for various purposes because it is inexpensive, low-energy and easy to install. The most common use of this system is to generate events when a person who carries a BLE device is located within the Beacon's coverage. One of the well-known BLE services is iBeacon, which has proven to be an efficient indoor location system [4]. Although it is very popular and simple approach, this scheme only provides limited information whether the user with BLE device is within the coverage area of the BLE Beacon or not. In other words, it cannot calculate the exact location of a user. With an accurate location estimation, we can provide path guiding, safety control, and location-based information service. Functionally, Beacon is a communication device equipped with a low-power Bluetooth that sends its own ID and RSSI value. BLE scanner or Internet-enabled device receive that information and find the current location or try to connect the device [5]. However, there are limitations in RSSI value that are not accurate due to various problems. RSSI is very important to determine the location of device, but it is easily affected by environment. For example, various electromagnetic noise in the indoor environment, signal distortion due to the position of the indoor structure such as the wall and the ceiling occur. Even at a fixed location, RSSI values continuously varied as time goes [6, 7]. Using an inaccurate RSSI value for calculating the location significantly decreases accuracy of localization.

In this paper, we propose a system for indoor location tracking using BLE technology. In the proposed system, a BLE scanner that receives BLE signals is installed on the ceiling, and a beacon signal generated by a personal BLE device is analyzed to calculate the position of the user. To mitigate RSSI weakness, we propose a DGF (Double Gaussian Filter) algorithm consisting of a weight value derived from the RSSI quality, double Gaussian filtering method for stabilizing RSSI values, distance, and location. The key idea is to refine RSSI values by applying Gaussian filter to raw RSSI data from source and to calculate location using weigh values. To show the usefulness of the proposed system, we demonstrate the indoor location-tracking scheme for practical usage model. We configured multiple fixed areas, and if a user enters the area then the proposed system generates an event. With this approach, we can evaluate the behavior of the proposed system. In experiment, we conduct several tests and provide a comparative analysis by comparing with Kalman filter algorithm.

The remainder of this paper is organized as follows. Section 2 of this paper explains related studies about indoor location tracking and research results. In section 3, we present the detail of system design and implementation. We show the configuration of experiment and results of experiment in Section 4. Finally, we summarize the results and conclude this paper in Section 5.

2. Related Work

There are lots of research result for improving localization accuracy in indoor location tracking system. Various filters and weight algorithms are used to compute accurate RSSI and localization. To improve localization accuracy, Cheng and Shi [8, 9] propose a weight algorithms. The key idea of this paper is to add weigh values to each location results. Especially, they used an Anchor optimized modified weighted centroid localization algorithm based on RSSI. The algorithm optimize the anchor nodes according to the distance from the unknown node to the anchor nodes. The proposed system selects the nearest four anchors to localize and the reciprocal of the sum of measured distance was be taken as the weigh. Nick and Suarez [10, 11] suggest a filter algorithms that predict a current value based on previously measured values. Nick describes the localization of a passive UHF RFID tag via Extended Kalman Filter (EKF) and Unscented Kalman Filter (UKF) using the RSSI values. And they provide simulation results that UKF achieves higher localization accuracies than EKF. In this paper, Kalman filters recursively process input data which includes noise from each input data until it meets the current measured value. As a result, Kalman filter returns more accurate results when used continuously than those from moment-to-moment use. Kalman filter can divide predict and update part. Predict part assume current value by previous and measured value. Update part update current value which calculated from predict part. But Kalman filter has disadvantage that provide high accuracy when only the RSSI value is linear condition. Therefore, use the Extended and Unscented kalman filter that can improve the accuracy even if non-linear condition. Suarez presents the experimental validation of a filter and a predictor of availability of a service in the wireless terminal based on the RSSI [11]. They test the performance of the filter and the predictor that improves other filters and they show the proposed filter allows simplifying a lot of network algorithms and protocols.

Furthermore, Using Particle filter for accurate localization is presented in [12]. Particle filter shows better accuracy than Extended and Unscented Kalman Filter, because it close to Bayesian recursive filter estimation when enough sample data exist. However, if the sample data is not enough then its efficiency will decrease. Furthermore, it should be problem to calculate. Mean filter and Gaussian filter for get accurate RSSI values algorithm is presented in [13]. Mean Filter is get average value form both previous and current value. That average value will be current value. But characteristic of RSSI, use only average is hard to reduce RSSIs noise or error rate. Gaussian filter can calculate standard deviation from both previous and current value. Standard deviation value will help to reduce noise or error rate of RSSI. Because Gaussian filter make value to normal distribution by using standard deviation.

There exist many kind of distance measurement method [14]. They presented performance comparison of Free Space Friis Model, Flat Earth Model [15], and Linear Approximation Mode [16]. The Friis transmission equation is used in telecommunications engineering, and gives the power received by one antenna under idealized conditions given another antenna some distance away transmitting a known amount of power. A linear approximation is an approximation of a general function using a linear function. To calculate accurate distance, they have applied averaging and smoothing algorithm on the recorded RSSI values. As the experiment, they have successfully reduced the error rate of distance significantly.

Recently, there have been many research results to calculate the location [16, 17, 18]. They present various kind of triangulation method : TOA(Time Of Arrival), TDOA (Time Difference Of Arrival), AOA (Angle Of Arrival), RSSI(Received Signal Strength Indication). We briefly described the key idea of several triangulation method. In TODA systems for Wi-Fi or Bluetooth, the device sends signals to surrounding measuring units and records the time difference between received signals. AOA systems calculate the device position using goniometry. Here, the measuring units use directional antennas or antenna arrays to measure the angle of incoming signals sent by a device. Received signal strength indication utilizes radio propagation over a space. Accordingly, RSSI does not waste time connecting to other devices for searching locational data. This system is also unaffected by install location. Alternatively, least square estimation uses minimum values from the square of the difference between the approximate value and real value [19, 20]. From these choices, we have applied a fingerprinting method for location tracking, as presented by [21, 22, 23]. If this fingerprinting positioning system is its off-line phase, the location fingerprints are collected by dividing the space into rectangular grids, at which point multiple access points are fixed to collect the RSSI at each grid location. The vector obtained from the RSSI values at a point is called the location fingerprint of that point.

Several studies mentioned above show sufficient accuracy and efficiency in indoor location tracking using RSSI. However, RSSI-based location tracking requires large amounts of sample data for high accuracy. Some studies also use filter algorithms that require high computational overhead to improve accuracy. Furthermore, some studies also show unreliable accuracy with small sample data. In this paper, we propose a method to effectively use Gaussian filter with fast computation speed in order to solve various problems mentioned above. We also introduce a method for extracting a suitable sample from the history of RSSI data in order to accurately track the position with a small amount of samples.

3.1 Overview

In order to provide accurate location tracking service in indoor environment, this study assumes indoor environment such as nursing hospital. Nursing hospitals can periodically monitor what each patient is doing, analyzing patient activity information, and providing appropriate medical care for the patient. Nursing hospitals should be able to distinguish whether each patient is currently in the room, in the hallway, or in the lobby. Also, it should be able to analyze the activity information according to the position such as watching the TV in the lobby or exercising in the exercise equipment. In this way, it is possible to analyze what activity the patient was doing through analysis of the position of the patient in the indoor space. In this study, we propose an indoor location tracking technique that uses BLE beacon technology to accurately locate each patient in an indoor space such as a hospital. In particular, there are two main tasks to be solved in this study.

(1) It is possible to clearly distinguish the location of a patient in a large space, such as a living room or a hall. This makes it possible to make a guess based on the location of the patient in a large space.

(2) When a patient enters a dangerous area located in a specific area, the monitoring system determines the situation and provides a function to generate an event. For example, in a large room such as a living room, if there exists prohibited area for a patient then monitoring system have to generate an event when a patient approaches that area.

In this study, we want to provide accurate indoor location tracking service using BLE beacon. In order to analyze the position using the BLE function, two devices are required. The first is a BLE beacon scanner that receives and analyzes the beacon signal generated by the BLE client to determine where the client is located in the room. The second is a BLE client that generates a BLE beacon signal and can use a smartphone or smart watch with BLE functionality. In this study, we implemented a program to analyze and receive BLE beacon signals by installing a USB module with BLE on the Raspberry board to build a BLE scanner. The BLE client also uses an Android-based smartphone.

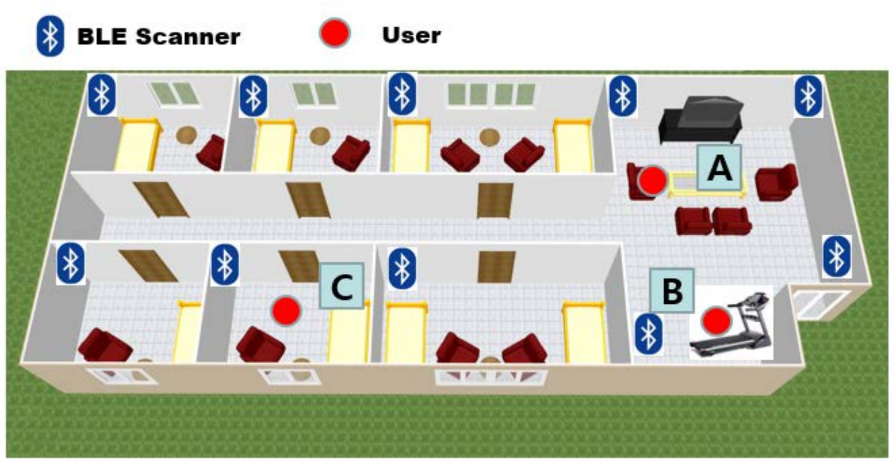


Fig. 1. Indoor loation tracking service example: nursing hospital for patient monitoring

As can be seen **Fig. 1**, we can see multiple BLE scanners in nursing hospital. For example, if a patient is in position (A) area then we can assume the patient is sitting on the couch and watching TV. Alternatively, if the patient is located in position (B), then the patient may assume that he or she is exercising on a running machine. If the patient is staying in the room at (C) position, the BLE beacon signal is continuously received and can be easily monitored.

However, despite the many advantages of using BLE, it is very difficult to accurately locate the indoor location because the error of the RSSI value received from the BLE beacon signal is very large. Therefore, the indoor location tracking method using RSSI value needs to be improved for accurate location tracking. In this paper, we propose a dual Gaussian filter method to reduce the error of RSSI value received from BLE scanner and to measure the exact position. We also show how to increase the position accuracy by weighting the RSSI value to obtain improved performance.

3.2 System design of location tracking system using DGF algorithm

Fig. 2 shows the overall operation sequence of the proposed system. The core components of the system are the BS (beacon scanner), the RSSI database, and the LBS system.

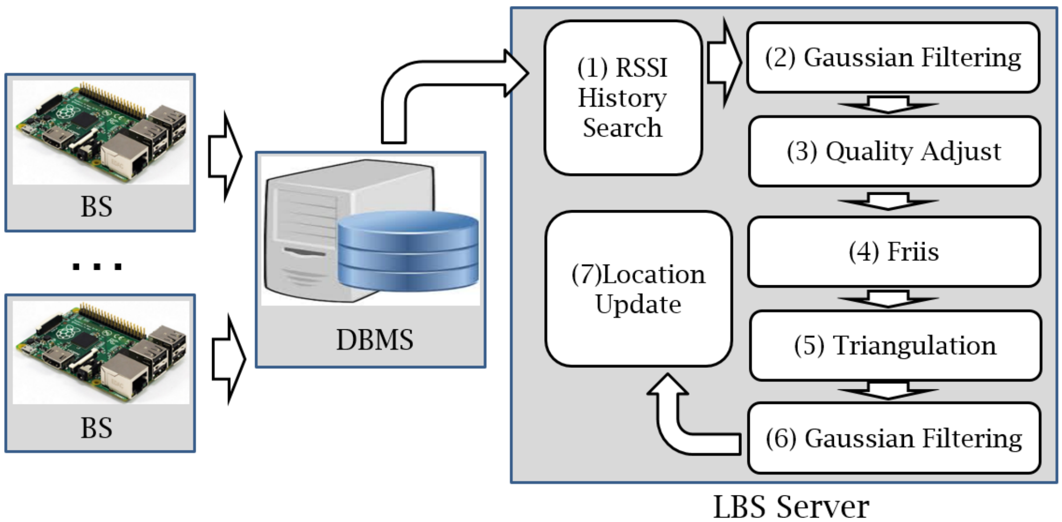


Fig. 2. Overall System processing sequences of the proposed system

The proposed system consists of multiple beacon scanners and beacon clients. The beacon scanner receives the signal generated by the beacon client, and stores the value in the database. The LBS server analyzes the RSSI value stored in the database and calculates the location of the beacon client. In this study, to achieve accurate indoor location tracking system, we implemented the system in three stages. The first step is to refine the received RSSI value. The second step is to generate the indoor position value through the distance calculation. Finally, the final indoor position is refined. The detailed operation performed on the LBS server is composed of 6 steps as follows.

(1) Searching RSSI history in the database

In the RSSI database, beacon information (mac address, received time, and RSSI value) received from each beacon client is continuously recorded. The LBS server retrieves the recently received RSSI value to track the location of each beacon client. At this time, information must be received from three or more beacon scanners in order to calculate the position through triangulation. Therefore, it is important to find an RSSI value satisfying these conditions in the RSSI database.

(2) Performing first step Gaussian filtering

As mentioned earlier, the RSSI value is heavily influenced by the surrounding environment and there is a lot of noise in the data. Therefore, it is necessary to refine the data to improve the reliability of the RSSI value. In this study, we perform a refinement process on initial data using Gaussian filter. The Gaussian filter has a very fast calculation time and has the advantage of using a standard deviation higher than the average value. A Gaussian filter modifies the input signal by convolution with a Gaussian function, which smooths the input values. The one-dimensional Gaussian filter has an impulse response given by equation (1).

$$g(x) = \sqrt{\frac{\alpha}{\pi}} \cdot e^{-\alpha \cdot x^2} \tag{1}$$

and can be expressed with the standard deviation as a parameter given by equation (2)

$$g(x) = \frac{1}{\sqrt{2\pi \cdot \sigma}} \cdot e^{\frac{-\chi^2}{2\alpha^2}} \tag{2}$$

Using this equation (2), we can obtain filtered results of observed RSSI values.

(3) Performing weight-based quality correction

In the initial RSSI data, there are other factors that reduce the reliability of data in addition to the errors due to noise occurring in the surrounding environment. For example, when receiving beacon client signals using different beacon scanners at the same location, an error occurs in the received RSSI value. Therefore, it is necessary to refine the differences in signal strength between beacon scanners. In this paper, we applied different weight value to each beacon scanner to remove the data error caused by the beacon scanner.

The main ideas are as follows. First, the degree of error is calculated by checking how much error is caused by the value measured by the beacon scanner. When a new RSSI value is received, the value is corrected in consideration of the error rate of the beacon scanner. For example, if the quality of the beacon is 100, it is assumed that there is no error, and 0 is assigned to the weight value. If the beacon quality is 80, the RSSI value is corrected by adding a weight value corresponding to 20% of the measured RSSI value. In this way, errors generated by the beacon scanner can be reduced.

(4) Distance measurement with Friis algorithm

In order to track the indoor location, the beacon client must be provided with a distance from three or more beacon scanners. It is typically used in the Friis algorithm to find the distance between each beacon scanner and beacon client. If you can get RSSI values between two devices, you can use the Friis algorithm to find the distance between the two devices. However, in order to obtain the exact distance between two devices, information such as power, frequency, and frequency wavelength is needed. The Friis transmission equation (3) gives the power received by one antenna under idealized conditions, when another antenna transmits a known amount of power at a given distance. The power received, Pr, can be expressed with the transmitting power Pt, wavelength λ, distance d, and antenna gains Gt, Gr.

$$\frac{P_r}{P_t} = G_t G_r \left(\frac{\lambda}{4\pi d} \right) \tag{3}$$

The antenna of the beacon scanner obtains *Gt* and *Gr* from the beacon client. These values are usually expressed in dB and free space. Generally, free-space path loss is the loss in signal strength of an electromagnetic wave, which would result from a line-of-sight path through free space, with no obstacles nearby to cause reflection or diffraction. Because of this advantage, Friis is often used to determine the distance between two devices in an area free from obstructions. In this paper, the proposed system is free from obstacles because the beacon scanner is installed on the ceiling. Therefore, there is no problem using Friis.

(5) Position estimation through triangulation

To estimate the position of the beacon scanner using triangulation, a distance value from at least three different beacon scanners to the beacon client is required. Using the selected three beacon scanners, position values are obtained through triangulation. In general, the triangulation process is calculated using the coordinates of three known points and the respective distance values. In this study, the location values of beacon scanners installed on the ceiling are already stored in the database. Therefore, the position of the beacon scanner can be calculated by the distance value from the beacon scanner calculated through Friis to the beacon client.

$$\begin{aligned} d_1^2 &= (x - x_1)^2 - (y - y_1)^2 \\ d_2^2 &= (x - x_2)^2 - (y - y_2)^2 \\ d_3^2 &= (x - x_3)^2 - (y - y_3)^2 \end{aligned} \tag{4}$$

In equation (4), where (x1, y1), (x2, y2), and (x3, y3) are coordinates of three known points, respectively, and (x, y) is the coordinate of the unknown location.

(6) Performing second step Gaussian filtering

Even if a Gaussian filter and a weight value are applied to the RSSI data collected from the beacon scanner, the error rate is not completely eliminated. If we look at the results of the triangulation, it may cause errors of several tens of centimeters to several tens of meters. In this study, the error value is reduced to a minimum by applying Gaussian filtering to the position values derived from triangulation. Thus, the proposed dual Gaussian filtering algorithm reduces the error rate of location tracking by applying Gaussian filtering in two steps.

3.3 Implementation details for the DGF algorithm

The DGF algorithm described above is refined by a quality control method using Gaussian filter and weight in order to reduce errors in the collection of raw data, and then the indoor position value is generated by Friis and triangulation. In order to reduce the error of the final position value, a second Gaussian filter is applied to correct the data to be generated within the standard deviation range. In the **Fig. 3**, the following pseudocode describes the detailed operation of the dual Gaussian filtering algorithm.

Algorithm 1 DGF Algorithm

Require: Input $RSSI$, RSSI values received by scanners

1: **for** each scanner SC received beacons signals **do**
2:     **for** mac, a MAC address of a beacons signal at s **do**
3:         $RSSIs \leftarrow$ a set of previous RSSI values from SC with mac
4:         **if** $RSSIs$ is enough to apply a Gaussisn filter **then**
5:             $G\_RSSI \leftarrow$ Gaussian($RSSI$, $RSSIs$)
6:         **else**
7:             $G\_RSSI \leftarrow RSSI$
8:         $W_G_RSSI \leftarrow$ApplyWeight(G_RSSI)
9:         $Dist_s^m \leftarrow$ Friis(W_G_RSSI)
10: **for** each MAC address mac of beacons **do**
11:     $D^m \leftarrow$ a set of $Dist_i^m$ for $1 \leq i \leq n$
12:     **if** $|D^m| \geq 3$ **then**
13:         $(x, y) \leftarrow$ Triangulation(D^m)
14:         $PLoc \leftarrow$ a set of previous coordinates (x, y) with mac
15:         $(x', y') \leftarrow$ Gaussian((x, y), $PLoc$)
16: **function** APPLYWEIGHT(G_RSSI)
17:     $Quality \leftarrow 2 \cdot (G\_RSSI + 100)$
18:     $Weight\_ST \leftarrow$ Weight strength based on $Quality$
19:     $result \leftarrow Quality / Weight\_ST + G\_RSSI$
20:     **return** $result$

Fig. 3. Pseudocode of the proposed DGF algorithm

- Line 1-2: It extracts meaningful value from data stored in database. That is, the LBS server continuously records information of all nearby beacon scanners and all beacon clients. This constantly generated information is used to find information from the same beacon scanner that received the signal from the same beacon client. At this time, signals generated from one beacon client can be tracked by receiving signals from three or more beacon scanners.
- Line 3: A set of previously stored RSSI data from the same beacon scanner that measures the same beacon client signal from the data stored in the database.

- Line 4-7: This code shows how to apply a Gaussian filter. RSSI is the currently measured input data. RSSIs are a collection of previously measured data. RSSIs are used to obtain the standard deviation of the previous data. If there is enough data to apply the Gaussian filter, it should be set to *true*. Otherwise, *false*.
- Line 8: This code adds the weight value and calls applyweight function in line 16. In line 17, the *Applyweight* function returns the quality of the *G_RSSI* value corrected by the Gaussian filter. In line 18, the algorithm assigns an error rate to the *Weight_ST* variable and a correction value that reduces the internal error of the beacon scanner. In line 19-20, *Quality / Weight_ST* is performed to obtain the correction value and added to *G_RSSI*, and the value is returned to *W_G_RSSI* of line 8. In this code, *W_G_RSSI* means RSSI values with weight policy and Gaussian filter.
- Line 9: This code applies the *W_G_RSSI* value calculated using the Gaussian filter and the weight value to the Friis formula to find the distance between the beacon scanner and the beacon client. Where *m* represents the mac address of the same beacon client and s represents the value of the same beacon scanner. That is, $Dist_s^m$ is a set of distance values between the current beacon scanner and the measured beacon client stored in the database.
- Line 10: This part searches only the *Dist* values that are the same as the mac address of the beacon client corresponding to the current input. This is done to find previous data of the device before performing triangulation.
- Line 11: In this part of the code, we add the *Dist* value with the mac address value of the same beacon client to the D^m set.
- Line 12: Triangulation is performed if the *Dist* value is more than 3.
- Line 13: Perform triangulation using the selected three distance values. Here, the position values of the respective scanners stored in the database are used together.
- Line 14: Store the position values of the previously measured beacon client in the *PLOC*. This is used to obtain the standard deviation of the previous data when applying a Gaussian filter at line 15.
- Line 15: Applies a Gaussian filter using the position value of the current beacon client and the previous position values. And calculates the filtered position value (x ', y').

4. Experiment and result

4.1 Experiment environment

For experiments, we used a Raspberry Pi Model B as a BLE scanner. The Raspberry Pi was equipped with a Broadcom BCM2835, 512MB RAM, and NEXT-104BT USB (Bluetooth 4.0). For each experiment, we collected RSSI values for different locations and executed the proposed procedure to calculate the location of the beacon. MATLAB (Mathworks, Natick, MA) was used to compare and analyze the results.

In order to show the usefulness of this study, various experiments were conducted in this study. In particular, we performed performance comparison with the existing Kalman filter. Kalman filters are used in many fields because of their high accuracy. Therefore, the Kalman filter and DGF are compared to compare the difference in accuracy and processing speed. The Kalman filter is an algorithm for predicting variation in the data using a Kalman measurement value that is calculated by averaging incremental values containing noise over time. Accordingly, the Kalman Filter has been used as a comparison to prove the efficacy of our proposed model.

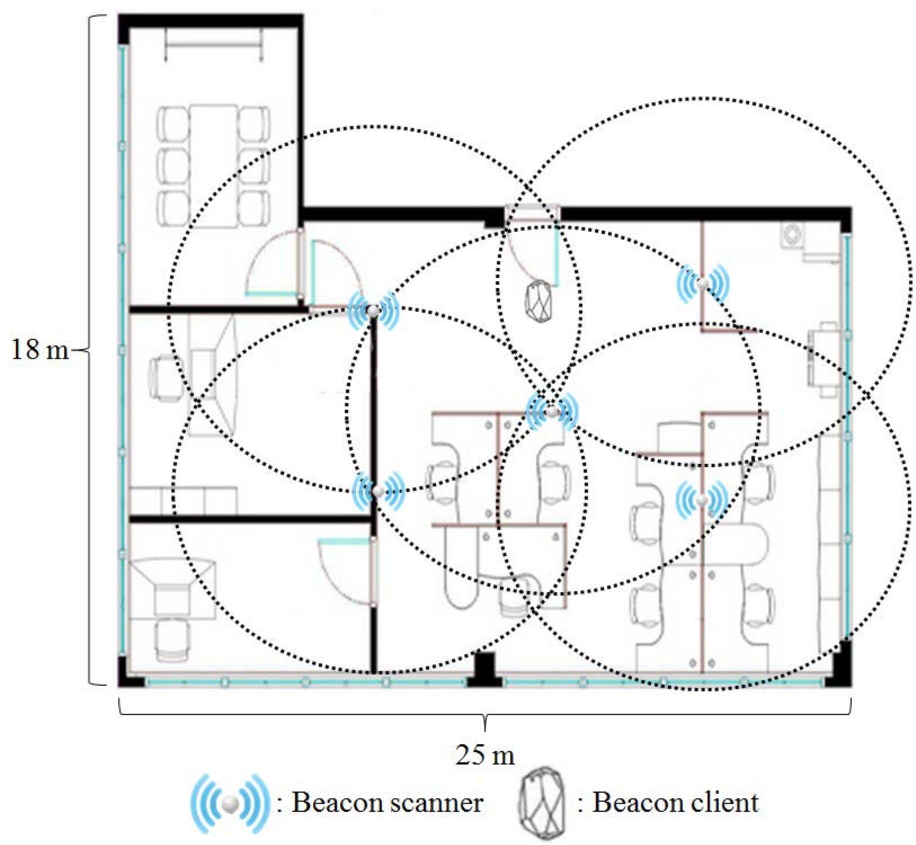


Fig. 4. Experiment environment setup

4.2 Experiment result using Gaussian filter and Weight

This experiment shows the result of applying Gaussian filter to the RSSI data received from the beacon client. We also show the experimental results when weight is applied to the result of the first Gaussian filtering.

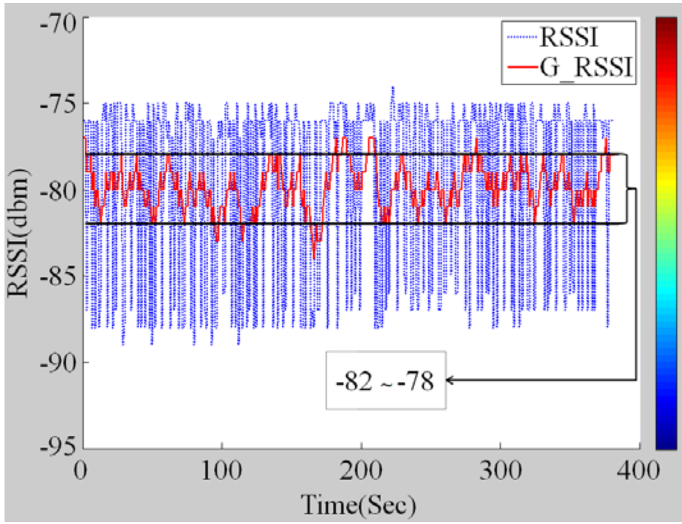


Fig. 5. Experimental results of RSSI values with Gaussian filter(from 7m distance)

Fig. 5 shows the change in RSSI signal between the beacon client and the beacon scanner in 5 minutes. The x-axis means the elapsed time and the y-axis means the RSSI signal values. The solid blue line represents the raw RSSI values and the thick red line indicates RSSI values with Gaussian filter(G_RSSI). The raw RSSI value shows a very large change in the range of -88 to -74, but it shows that the deviation of the value is relatively reduced when the Gaussian filter is applied. However, even if a Gaussian filter is applied to the RSSI, the deviation of the result value is large.

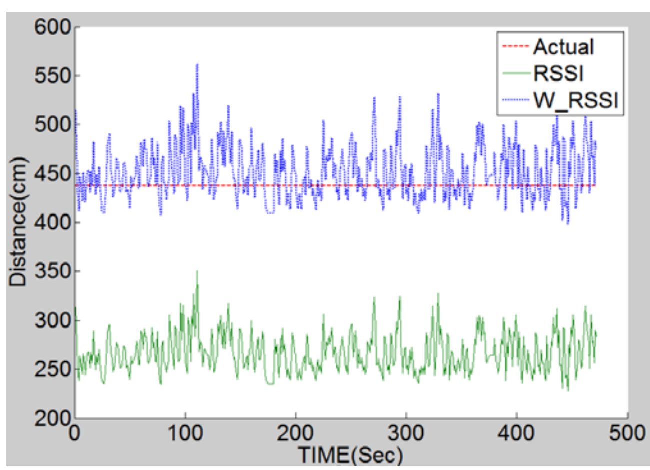


Fig. 6. Experiment result with weight values

Fig. 6 shows the effect of weight values. In this experiment, we experimented to adjust the weight value for the calibration of the beacon scanner. The distance between the beacon scanner and the beacon client was set at 440 cm. At this time, we show the experimental result of W_RSSI calculated by using the RSSI values with weight and RSSI values without weight. The experiment result with weight policy is very close to the actual distance. This experiment shows that the weight scheme can be effectively used to reduce the error of the beacon scanner.

4.3 Performance Comparison of Kalman Filter and DGF Algorithm

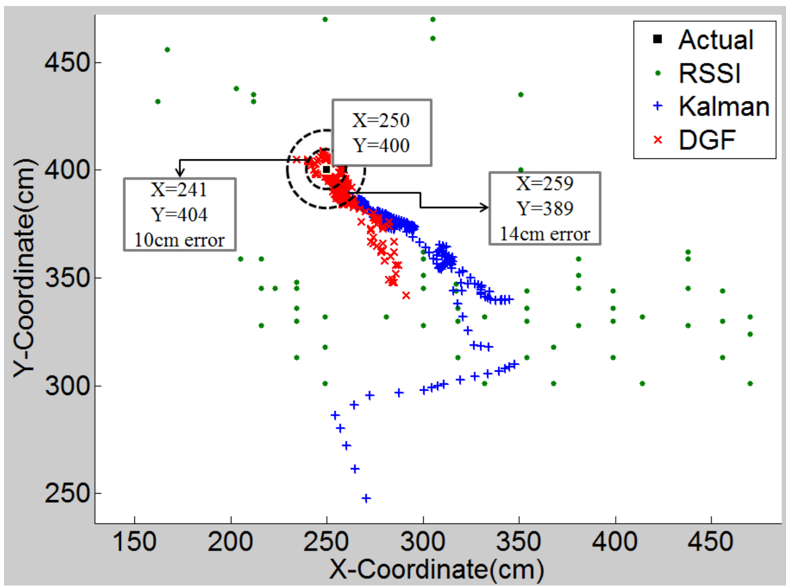
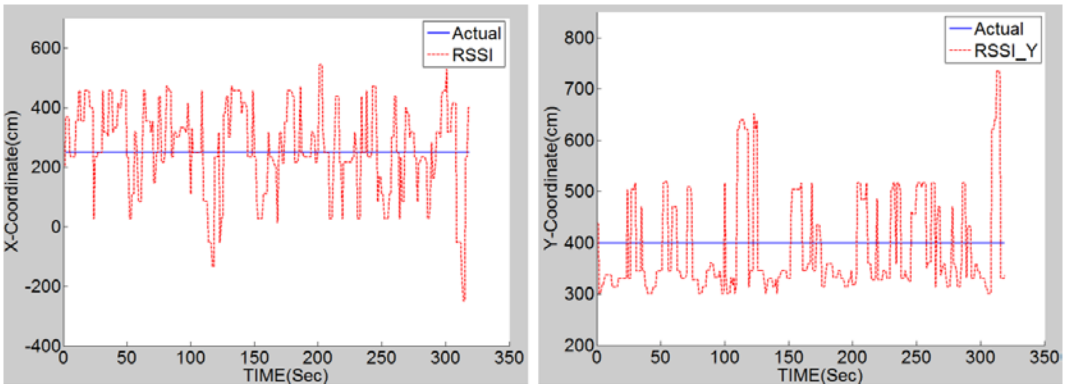
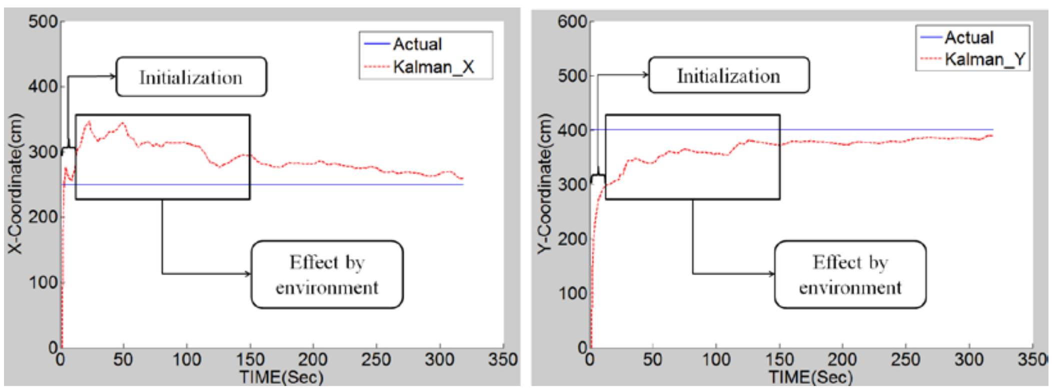


Fig. 7. Location tracking result of DGF and Kalman filter

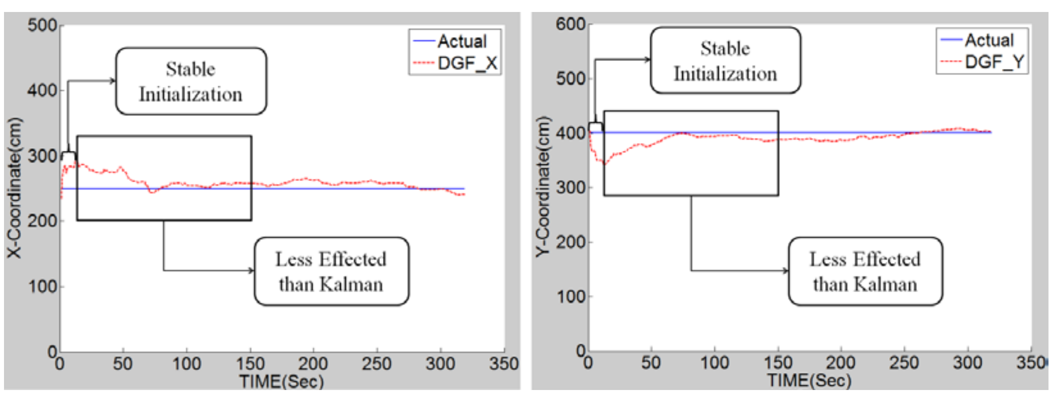
Fig. 7 shows the distribution of the input RSSI data, the predicted position through the Kalman filter, and the predicted location through the DGF algorithm. As can be seen from the graph, it can be seen how the actual position differs from the predicted position in each method. Experimental results show that the value of raw RSSI is widely distributed and very difficult to track. The Kalman filter shows an average error of 14 cm, but the distribution of data is spread widely. The proposed DGF algorithm shows the most accurate error of 10 cm. It can also be seen that the predicted position values are distributed within a certain range.



(a) coordinate distribution result for raw RSSI scheme



(b) coordinate distribution result for the Kalman filter scheme



(c) coordinate distribution result for the DGF scheme

Fig. 8. Coordinate distribution for each algorithm

Fig. 8 shows the coordinate distribution result for each algorithm. **Fig. 8(a)** shows the estimated x, y coordinate for raw RSSI data. With this result, it is difficult to estimate accurate location of beacon client because the distribution is scattered. **Fig. 8(b)** shows the experiment result of

Kalman filter. In this experiment, the initialization means the state before the received RSSI data is filtered, and the algorithm shows the result when the first filter is not applied. That means the initial value is not sufficient to obtain the standard deviation. And *the effect by environment* explains the effect when it is influenced by the environment. When the beacon scanner is initialized, error values occur instantaneously. This is because it contains RSSI values with high error rates reflected from the surrounding obstacles. As the number of filtered data increases, the error rate of the data gradually improves. **Fig. 8(c)** shows the x, y coordinates of the DGF. It can be seen that the DGF generates less error in the initialization step than the Kalman filter method, and it is strong against the noise generated in the external environment.

Table 1. Comparison of DGF and Kalman filter

Case	Avg_x	Avg_y	Mode_x	Mode_y	Time
Actual	250	400	250	400	N/A
RSSI	264	388	234	330	0.01
DGF	259	398	258	387	0.22
Kalman	288	363	280	378	0.86

Table 1 is a summary of the x, y coordinates of the RSSI, Kalman filter and DGF. Gaussian filters are known as very fast algorithms. It is important to verify the processing speed because DGF proposed in this study takes two Gaussian filtering operations and one weight processing time. Experimental results show that the DGF takes 0.22 seconds to predict the final position, but the Kalman filter takes 0.86 seconds. Therefore, in terms of the processing speed, the DGF algorithm is about four times faster than the Kalman filter method.

5. Conclusion

In this paper, we propose a DGF algorithm to enhance indoor location tracking accuracy using Gaussian filtering and weight scheme. In DGF algorithm, Gaussian filter is applied to the raw RSSI values to reduce errors and refining process for beacon scanner is performed using weight scheme. With this method, we can get distance values using Friis and estimated location using triangulation. Finally, second Gaussian filter is applied to the estimated location to minimize location errors. Our experimental results show that the DGF algorithm, which consists of a double Gaussian filter and weight method, helps to calculate accurate distances between a scanner and beacon. If more than three distance values exist, then the proposed system can calculate accurate localization. To prove the efficiency of these DGF algorithms, we compared the results with those from using a Kalman algorithm to ensure accuracy and reliability. DGF exhibited almost the same accuracy as that of the Kalman algorithm after initialization, but the DGF was four times faster than the Kalman algorithm. In experimental results, the DGF algorithm shows the usefulness of an effective indoor location tracking system based on BLE beacons using RSSI. This system uses less processing time than Kalman algorithms.

In the future, we will conduct additional experiments with many obstacles and environmental variation to ensure that the proposed system can provide accurate and effective result. Aside from proving the practicality and efficiency, we have a plan to expand the proposed algorithm to cooperate with other localization scheme such as Wifi, GPS and RFID.

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