Indoor Localization for Bluetooth Low Energy Using Wavelet and Smoothing Filter

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***Abstract*— This paper presents an investigation on the impact of the Bluetooth Low Energy (BLE) received signal strength indicator (RSSI) value for indoor localization in real line-of-sight (LOS) and dynamic non-LOS environments. Experimentation demonstrates that the RSSI value of BLE signals is unstable in indoor environments. The principle underlying this behavior is discussed in this paper. Two self-adaptive filters (smoothing filter and wavelet filter) are applied to stabilize and de-noise the RSSI sequence. We demonstrate that the stability of localization performance is enhanced by employing these filters. The standard deviation of the RSSI sequence is reduced from 4.6 meters to 0.8 meters, which means that a steady increase in the accuracy and stabilization of the localization is achieved.**

Keywords—Bluetooth low energy; RSSI; Indoor positioning; De-noise; Smoothing filter; Wavelet filter

I. INTRODUCTION

Many recent and future mobile applications in military and civilian facilities demand accurate estimates of the location of an item or person. Consequently, the mobile positioning service is becoming one of the key functions in mobile networks [1]. Currently, the Global Positioning System (GPS) and cellular networks are widely used to locate a user's position in outdoor environments [2]. However, satellite and mobile phone base station-based localization techniques require a LOS transmission channel and stops working in a non-LOS environment such as an indoor area [2]. Thus, many solutions and algorithms for indoor localization have been investigated and proposed during the last decade [3-5]. However, it is difficult to achieve an accurate, low-cost, and low-power indoor localization system.

Since the invention of Bluetooth low energy (BLE), smart mobile devices with Bluetooth 4 (Smart Bluetooth) access functions have grown in popularity. Indoor localization based on BLE technology has become an important research topic. Instead of using Wi-Fi routers, Bluetooth 4-based localization systems locate the position of a mobile device by receiving the received signal strength (RSS) from a low-energy Bluetooth beacon in an indoor area.

BLE devices have the advantages of lower power consumption, lower costs, and a smaller size compared with WiFi [6]. A 3V button battery could drive the latest BLE beacon for half a year. BLE beacons, with low cost and smaller size, could reduce the Bluetooth 4 beacons' deployment conditions. In addition, deploying more BLE beacons could dramatically increase the signal cover density with lower costs than Wi-Fi routers. Consequently, the latest BLE-based localization techniques could supply higher localization accuracy because of the higher signal cover density without significant additional expenditure.

RSSI-based indoor localization techniques still have certain limitations. The channel propagation performance between signal transmitters and receivers fluctuates dynamically [7]. The interference of the channel propagation is indeterminate, and this variation is unpredictable even in a LOS environment. Therefore, it is difficult to accurately estimate the distance between transmitters and receivers by directly applying the RSSI value.

In this paper, we focus on the positioning of mobile devices in indoor environments. Specifically, this paper analyses the working principle of the RSSI-based indoor positioning algorithms and the fluctuation factor of the RSSI signal for BLE. Two adaptive filters, wavelet and smoothing filters, are applied to remove the fluctuation phenomenon of the received signal. Finally, the triangulation-based algorithm we proposed previously [8] was applied to compare the performance between the original and processed signals.

II. RSSI-BASED ALGORITHM AND FILTER DESIGN

A. RSSI-based indoor position algorithm

$P\ (r)$ is the RSSI of the unknown position at the distance r between the receiver and transmitter.

$\mathrm{P}(r_0)$ is the received signal power of the position at the distance r0 between the receiver and transmitter. Normally, r0 is one meter.

$X\sigma$ is a Gaussian random variable caused by shadow fading.

n is the path loss coefficient with a range between two and six.

By applying the path loss model-based RSSI equation, a user's position can be calculated or measured if the coordinates of the transmitters are known in advance. Recently, RSSI-based indoor localization algorithms have two derivations: fingerprint and triangulation. RSSI fingerprint algorithms collect the features (RSS from the transmitter) of the local environment and then estimate the user coordinates by matching measurement results with the nearest a priori location fingerprints [9]. Triangulation-based algorithms estimate the target location by first measuring the distance between the transmitter and receiver and then calculating the target coordinates based on the properties of triangles. Compared to fingerprint algorithms, the advantages of triangulation-based algorithms are that, first,

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triangulation-based algorithms do not require a database to record the RSSI value for each coordinate in advance; and second, the record database cannot predict the feature variation of a local scene.

RSSI-based indoor localization techniques still have certain limitations. The features of channel propagation between signal transmitters and receivers fluctuate dramatically, and this variation dramatically increases in a complex indoor environment with multiple obstacles and reflections. Most of the current research on RSSI-based indoor positioning algorithms can work only in an ideal LOS environment, which is practically non-existent.

Furthermore, in a real environment, the status of user positions and the environment are dynamic and unpredictable; therefore, the sequence of the RSSI value is not a stationary process. In this situation, a Fourier transform-based filter cannot be used to clean the noise of a specific frequency because the spectrum of the RSSI value changes over time. .

B. *Employment of Filters*

As mentioned above, the Fourier transformation-based filter cannot be applied to de-noise the RSSI sequence at a specific frequency, as the spectrum of the RSSI value sequence changes over time [10]. In a real environment, the coordinates of the users are dynamic and unpredictable. Filters should adapt to spectral changes over time because the information on user behaviors must be retained during the process of filtering. In other words, self-adaptability is a basic property of the filter for stabilizing the RSSI sequence. In this paper, two different types of filter were applied to de-noise and stabilize the sequence of the RSSI value: smoothing and wavelet.

1) *Smoothing filter*

During the experiments in an indoor area, a user's position changes rather smoothly as a function of time. However, the RSSI noise has rapid, random changes in amplitude from point to point within the RSSI sequence. Therefore, it may be useful to reduce the noise through a process called smoothing [10].

By applying the smoothing filter, the RSSI values are modified and stabilized: RSSI values that are higher than the immediately adjacent points (normally caused by the shadow fading effect and the variations of the environment) are decreased, while the values that are lower than the adjacent points are increased. The shape of the RSSI sequence becomes smoother, and the step response to the value changes are slower. Because the user coordinates cannot change dramatically, as a human cannot teleport from place to place, the sequence of RSSI values can be assumed to be smooth. Therefore, the RSSI signal will not be distorted too much by smoothing, and the noise can be decreased. In this situation, a smoothing filter can be defined as a low-pass filter. The low-frequency components (RSSI sequence) in the spectrum can pass with little change while the high-frequency components (noise) are reduced. The basic three-point rectangular smoothing algorithm can be written as follows [10]:

$$S = \frac{S(i-1)+S(i)+S(i+1)}{3} \tag{2}$$

where

S is the smoothing result.

S(i) is the current RSSI value.

Appling the smoothing operation more than once, which means smoothing a smoothed signal and implementing a weighted framework, is a common solution to generating a longer and more complicated smoothing filter. Three smoothing filters, one pass, two pass and three pass, are shown in Figure 1. The width of those filters is 15 points. It is evident that the three pass smoothing filter is more stable than the one-pass filter, as the rapid noise is de-noised three times.

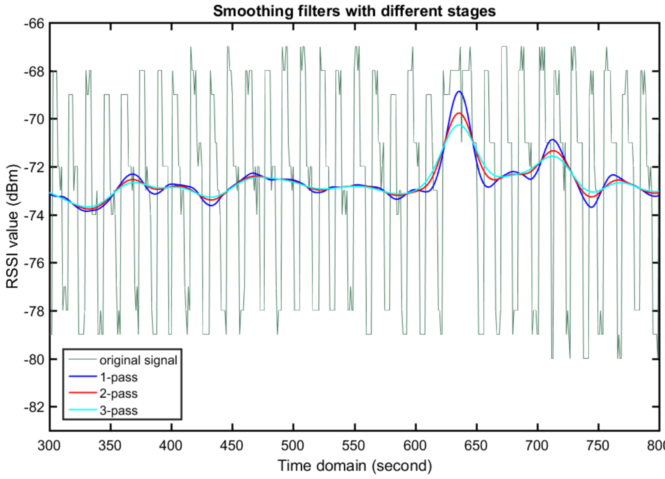

Figure 1. Smoothing filters with different stages

Increasing the width of the smoothing filter is another method of removing the noise efficiently. The RSSI signal can be stabilized by increasing the width of the smoothing filter, as the noises are evenly distributed in the filtered sequence. In Figure 2, the 30-point smoothing filter and the 15-point smoothing filter successfully de-noise the RSSI value. It is evident that the smoothness of the 30-point filter is better than the 15-point filter.

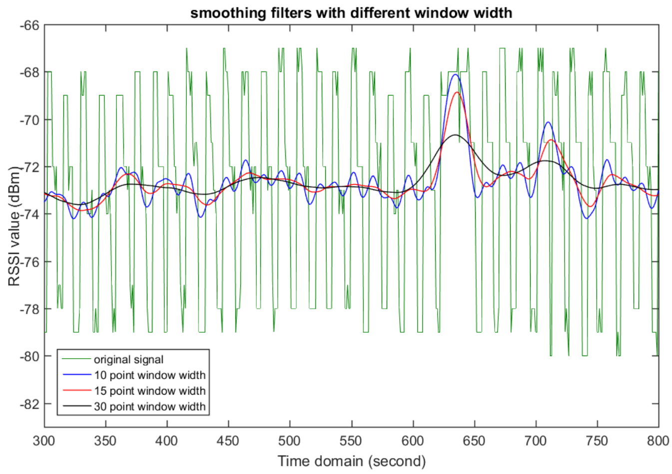

Figure 2. Smoothing filters with different window widths

The smoothing filter also has certain insufficiencies. First, the noise within the RSSI sequence is not truly removed. The fluctuating noise encircling the RSSI sequence does not mean that the average value of the noise is equal to the average power of the RSSI [10]. Because of the unpredictable shadow fading effect, the power of the RSSI sequence can be decreased (obstacles and the human body) or increased (signal reflection) by the environment. The distance calculated by the RSSI value will be inaccurate because the power of the noise is also merged into the RSSI sequence. The localization error caused by the smoothing filter cannot be ignored when the distance between the transmitter and receiver is more than five meters, according to equation 1. Second, the width of the window is limited by the BLE communication interval. Normally, to decrease the power consumption, the communication interval of BLE devices is 1 second each time in broadcast mode [11] (in debug mode, this frequency can be increased to 0.1 seconds each time). The filters with a width of more than 40 points are essentially useless in real life because the response of the localization algorithms is over delayed (more than 20 seconds). Third, a multiple-stage smoothing filter will increase the response time because of the weighted framework.

2) Wavelet filter

As mentioned above, the RSSI value sequence changes over time, and this changes the results in a dynamic spectrum. If the signal can be defined as a non-stationary process, then a correlation between the time and frequency domains must exist. Because of the theory that frequency resolution and time resolution cannot be acquired at the same time [10], a short-time Fourier transformation (STFT) still has certain limitations: a wider window can provide a good resolution of frequency but low time resolution, and a narrower-sized window provides a better time resolution but low resolution of frequency [10]. Wavelet analysis is similar to STFT. The wavelet transform breaks the signal into its wavelets with different frequencies and then scales and shifts versions of the "mother wavelet" [12].

By applying the wavelet transformation, temporal resolution and frequency resolution can be balanced: low-frequency components can be offered a high spectrum resolution with a wide window because the low-frequency signals are easy to identify in the spectrum; high-frequency components can be identified in a spectrum with a narrow window because of its high resolution in the time domain [13, 14].

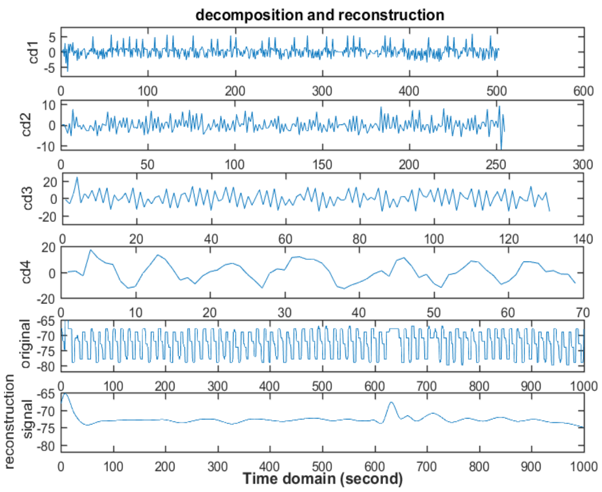

Figure 3. decomposition and reconstruction of wavelet filter

According to Figure 3, the RSSI sequence was decomposed at different frequencies (1/2 for cd1, 1/4 for cd2, 1/8 for cd3, and 1/16 for cd4). It can be seen from the original signal that a 1/15 Hz noise was exist. This noise was located between 1/8 and 1/16 Hz. By applying different levels of hard and soft thresholds on different scales (major on cd4), the rebuilt RSSI sequence was dramatically stabilized and the features of the users' behaviors were retained.

Wavelet filters also have certain limitations. First, the computation of wavelet filters is overloaded. Synchronously denoising a RSSI sequence has a high-level hardware requirement. Second, it is difficult to build a self-adaptive filter with an effective threshold, as the transport parameters in different environments are entirely different.

III. Experiemtal Results and Analysis

In this section, first, we present experimental results to demonstrate the performance of the smoothing and wavelet filter. Different parameters for the filters were employed to compare the performance of the filters in different situations. Second, filters were applied to modify the localization accuracy and stability through a simulation based on our proposed algorithm and experimental results.

In the experiment, a user held a mobile device to receive the signal from a BLE beacon on two occasions: at the beginning, the transmission environment can be defined as a real-life LOS environment without any obstacles. The user first kept stationary for two minutes, 3 meters away from the Bluetooth beacon. Then, the user moved 1 meter away (4 meters between the user and beacon) from the beacon and stopped for 2 minutes. Afterward, the user started to step toward the BLE beacon 1 meter away (3 meters between the user and beacon). This action was repeated in the route again until the eighth minute. At that time, the distance between user and beacon was 3 meters. However, two obstacles (two people) began to move randomly between the user and the BLE beacon. The sample rate during this period was once each second. The experimental RSSI sequence is shown in Figure 4.

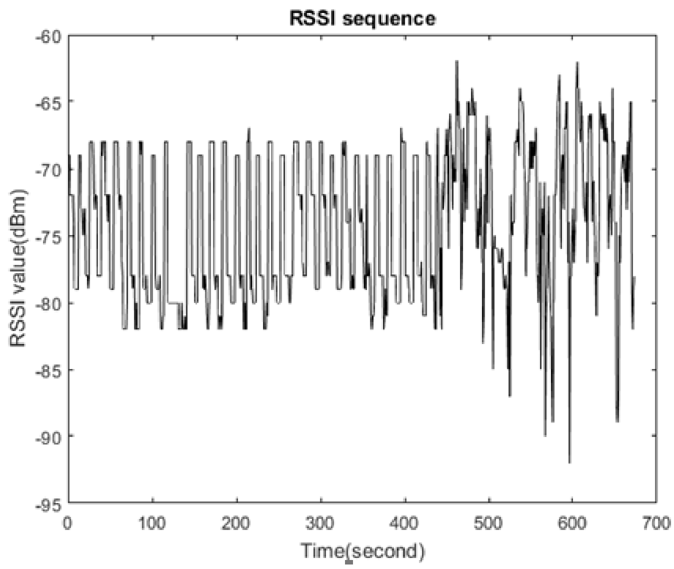

Figure 4. RSSI sequence without de-noising and stabilization

As shown in Figure 4, the RSSI values fluctuated within ±5dBm, which resulted in a ±1.5 meter error. During the LOS period, the sequence could not clearly indicate the difference between four meters and three meters. Furthermore, during the second stage, the RSSI sequence fluctuated dramatically, the P-Peak value was -62dBm to -92dBm, and the maximum localization error could reach 10 meters.

A. *Smoothing filter*

Smoothing filters were applied to de-noise the RSSI sequence with differently sized windows and stages. The stabilized results are shown in Figures 5 and 6:

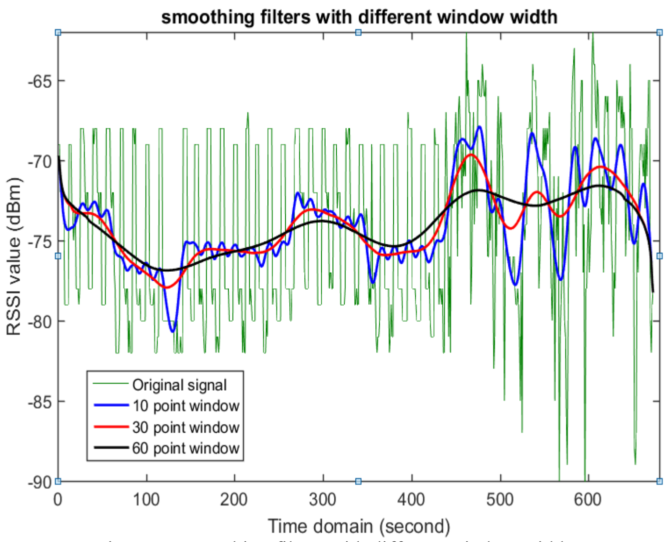

Figure 5. Smoothing filters with different window widths

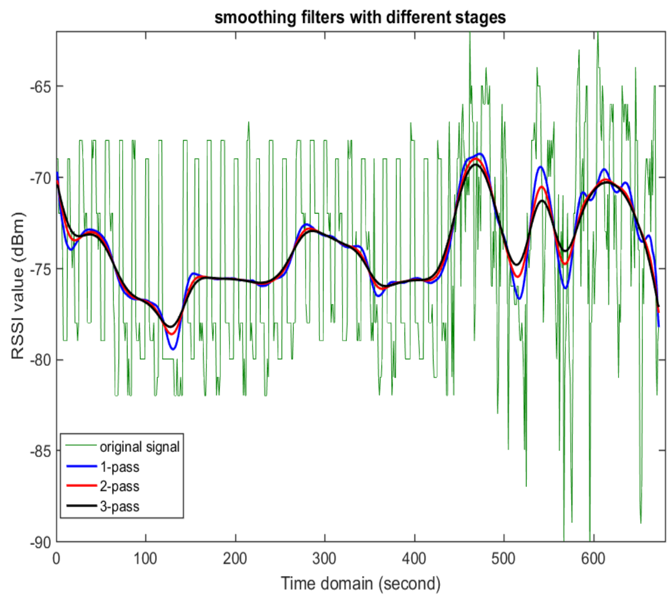

Figure 6.Smoothing filters with different stages

Shown in Figure 5, the RSSI values were de-noised by applying the three smoothing filters. The stability of the RSSI curve has a direct correlation with the window width of the smoothing filter. Otherwise, the localization and other useful information, such as fast-moving people, will be lost distinctly under the 65 point smoothing filter. This is due to the principle of the smoothing filter: the noise is not truly removed during the process. The fluctuation and errors are evenly dispersed to the desired signal. In addition to increasing the size of the window, the curve of the signal becomes more stable.

In Figure 6, the RSSI values were stabilized by employing the three smoothing filters in different stages. There is also a direct correlation between stability and the stage of the smoothing filter. The stability of the three-pass filter is better than that of the one-pass filter. However, the users' experience will be reduced by the weighted framework. According to the principle of the weighted framework, the response time of localization software will be seriously delayed because a high pass smoothing filter gives a very low weight value to the latest value.

B. *Wavelet filter*

Wavelet filters with different windows were applied to stabilize the RSSI value. This section will not discuss high-level decomposed wavelet filters and 2-D wavelet filters because of their very high level of computation. Several basic wavelet filters with different window sizes are shown in Figure 7.

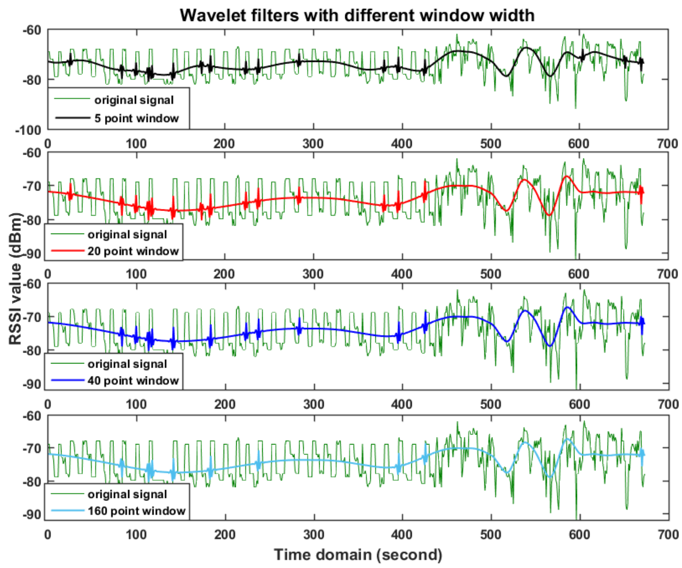

Figure 7. Wavelet filters with different window widths

It can be seen that the noise components are reduced slightly, while the window width increases. However, there are similar results regarding the signal curves between the five-point window and the 160-point window. De-noising the RSSI sequence by increasing the communication ratio and window width would be an ideal solution; however, it is not an actual solution when considering the power consumption in current mobile devices. A 180-point window with a one-second communication ratio means that the positions held in the past three minutes could affect the current position physically. Currently, because of the power consumption, the communication ratio does not satisfy the demand of localization services. Consequently, wavelet filters with a narrow window can be applied to de-noise the RSSI sequence; however, the potential of the wavelet filters is still limited by current hardware devices.

C. Comparison

Figure 8 shows a smoothing filter and a wavelet filter with a 20 point window. The distance between the mobile device and BLE beacon is three meters, and the experimental environment can be defined as a real LOS environment. The stage of the smoothing filter is one-pass. The following can be seen from Figure 5: first, both the smoothing filter and the wavelet filters show good performance in de-noising the RSSI sequence; second, the stability of the wavelet filter is smoother than the smoothing filter and the main feature points are reserved.

When applying the smoothing filter and the wavelet filter on our proposed weighted triangulation algorithm [8], the minimum error did not increase dramatically (only 0.2 meters). However, the stability of the algorithm can be increased because of the dramatic decrease in the standard deviation. The standard deviation of the RSSI sequence in Figure 5 decreased from 4.59 meters (three meters, 1.5-hour data collection, and one time/second communication ratio) to 0.7650 meters (smoothing filter) and 0.6879 meters (wavelet filter). The localization error was generally decreased by one meter.

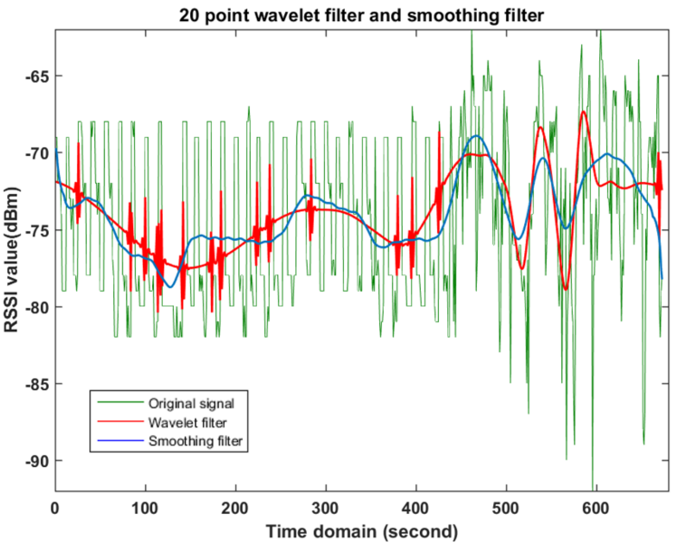

Figure 8. A comparison between smoothing filter and wavelet filter

IV. CONCLSUION

In this paper, we have discussed the principle of RSSI-based indoor positioning algorithms and the dynamic negative impact factors of the RSSI sequence caused by shadow fading and other influences such as moving people. To de-noise and stabilize the RSSI sequence, smoothing filters and wavelet filters were applied. The principle of the filters mentioned above were introduced and the de-noising performance were tested with different stages and parameters.

Smoothing filters are easy to employ because of their low computation complexity. The limitations of smoothing filters are that, first, the noise components could not be removed completely, as the average error is added into the RSSI sequence; second, the users' experience is affected by the response time because of the employment of multiple stages and the window width.

Wavelet filters could remove the noise efficiently and can be self-adaptive. However, the performance of wavelet filters is limited by hardware conditions including computation and power consumption. Experimental results under real LOS and non-LOS environments indicate that both smoothing filters and wavelet filters have demonstrated the ability to stabilize and denoise the curve of the RSSI sequence. The standard deviation of the localization error tested by our proposed algorithm [8] was decreased from around 4 meters to 0.8 meters according to the experimental results.

Future work will be directed toward improving the adaptability of the filters by integrating more thresholds to secure the stability when users move. An RSSI-based indoor localization algorithm that exploits RSSI curve filters will be built to achieve a mature indoor localization system.

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