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Performance Comparison of Various Smoothing Methods For Detection of Device-Free Target

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ABSTRACT

In the device-free localization systems, it is major issue how to detect a device-free target, which does not carry any assistant electronical devices. When a target crosses the communication links, the target causes the fluctuation of received signal strength (RSS) values at the receiver side. However, the performance of the detection scheme based on RSS tends to be degraded because of noises in indoor environments. In this paper, we present various smoothing methods to mitigate the effect of noises for enhanced performance of target detection. To compare the performance of various smoothing methods, we performed experiments with IEEE 802.15.4 ZigBee devices. According to the experimental results, it is shown that the Gaussian kernel smoothing, the weighted moving average smoothing, and the exponential moving average smoothing methods can provide more suitable performance than other methods in terms of mean square error, while the exponential moving average smoothing provides more suitable performance in terms of detection accuracy and detection temporal accuracy.

Key Words : Device-free, Detection, Time series signal analysis, Smoothing technique, Sensor networks

Ⅰ. Introduction

Recently, it has been addressed for commercial and military applications to detect a device-free target, which does not carry any assistant electronic devices in indoor environments. When a target crosses the communication links, the target causes the fluctuation of received signal strength (RSS) values at the receiver side. The communication link between transceivers naturally forms RSS sequence data in time domain, and the variation of RSS data sequences can reflect the status of the link. For example, if there is an object on the link of a pair of transceivers, the collected RSS sequence would exhibit a large attenuation likewise a valley pattern[1]. Therefore, the detection scheme based on RSS is commonly used because of its simplicity and low hard-ware costs. However, the performance of the detection scheme based on RSS tends to be degraded because of noises in indoor environments[2]. Thus, it needs to mitigate the environmental noises in the collected RSS data to clearly detect the presence of targets in the link.

Since the RSS data sequence of a pair of transceivers has a natural order property with time, it can be defined as temporal series in time domain. For statistical analysis of time series, various smoothing methods are introduced and used for many applications such as infectious disease forecasting[3], climate change[4], economic and

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finance aspects[5]. In terms of signal processing, smoothing methods are used to reduce experimental noise for obtaining important statistical properties of a temporal sequence.

In the detection of a device-free target, the environmental noise also can cause the attenuation of RSS data sequence and it causes the degradation of the detection performance. In order to mitigate the influence of noise as much as possible and obtain the time trend information, which is collected when a target crosses the link, more robustly, smoothing methods can be applied to obtain more effective and useful signal features from the collected RSS data sequences.

In this paper, therefore, we consider the detection problem of a device-free target crossing the link formed by a pair of transceivers, and present various smoothing methods for processing of the RSS time series data. To compare the performance of various smoothing methods, which are commonly used in various fields, we developed a detection system for a device-free target with IEEE 802.15.4 ZigBee devices and performed experiments to collect data. We also compared the performance of considered smoothing methods with experimental results.

The remainder of this paper is organized as follows. In section 2, various smoothing methods are briefly reviewed. In section 3, we present the developed detection system for a device-free target and discuss the data collection process. In section 4, the experiment results are provided and discussed. Finally, conclusions are drawn in section 5.

Ⅱ. Smoothing Methods

When the data is collected over time, it has a form of random variable. It is known that the smoothing technique reveals more clearly the underlying trend of the data by reducing the effect of random variable. In this study, we consider that a pair of transceivers forms an unobstructed communication link, and the RSS data sequence between a transmitter and a receiver can be collected over time as $X=(X_1,\ldots,X_i,\ldots,X_N)$, where X_i is the RSS at time i and N is the length of time series. Various smoothing methods can be classified into the moving average smoothing and the kernel smoothing, which are briefly reviewed as follows.

2.1 Moving Average Smoothing

Moving average smoothing technique is the most common and widely used time sequence smoothing method. The main idea is to utilize the weighted sum of the points within fixed subset as the smoothed value[6,7]. According to the weight distribution function of the data points in the subset, it can be divided into the simple moving average smoothing, the weighted moving average smoothing, and the exponential moving average smoothing.

2.1.1 Simple moving average smoothing (SMA)

The SMA method is relatively simple because it takes the equally weighted mean value of all points within a specified window as for the weight distribution function. It is expressed as follows:

$$\begin{aligned}\hat{X}_t &= \frac{1}{2m+1}(X_{t-m}+\ldots+X_{t-1}+X_t+\\ &\qquad X_{t+1}+\ldots+X_{t+m})\\ &= \frac{1}{2m+1}\sum_{i=-m}^{m}X_{t+i}\end{aligned} \tag{1}$$

where m is the half smoothing window width, i is the lag factor on time t. $\hat{X}_t$ is the smoothed RSS data at time t, X_t is the actual experimental RSS data at time t.

2.1.2 Weighted moving average smoothing (WMA)

The WMA method assigns more weight to the adjacent data at a given point in time, i.e., these adjacent time points are highly correlated with the current time value and can provide a higher confidence level to the current time value. In this way, it is possible to make these important neighbor values evident in the current RSS value[6]. It is expressed as follows:

$$\hat{X}_t = \frac{1}{2m+1}(a_{t-m}X_{t-m} + ... + a_{t-1}X_{t-1} + a_t X_t + a_{t+1}X_{t+1} + ... + a_{t+m}X_{t+m}) \text{ where } = \frac{1}{2m+1}\sum_{i=-m}^{m} a_{t+i}X_{t+i} \tag{2}$$

a_i is weight for ith-index. $\hat{X}_t$ is the smoothed data at time t.

2.1.3 Exponential moving average smoothing (EMA)

The EMA method assigns exponentially decreasing weights over time and takes all the past data into consideration. Different from the WMA, the weight for each older data point decreases exponentially in the EMA, so data will never reach to zero. When the time sequence of observations starts at time $t > 0$, the simplest form of the EMA is given as follows[7]:

$$\hat{X}_t = \alpha X_t + (1-\alpha)\hat{X}_{t-1} \tag{3}$$

where α is the smoothing factor $(0 < \alpha < 1)$[8]. α can be calculated by using the formula $\alpha = 2/(n+1)$[9]. In other words, the smoothed statistic $\hat{X}_t$ is a simple weighted average of the current observation X_t at time t and the previous smoothed statistic $\hat{X}_{t-1}$.

2.2 Kernel Smoothing

Kernel smoothing technique is a flexible method of nonparametric estimation without the need of sufficient prior data knowledge[10]. This technique is most appropriate when the dimension of the data, p, is low ($p < 3$), such as data visualization[11]. The kernel can be regarded as the weight function, and the weight function is inversely reflected to the distance between the observation and the estimated value[12]. Let $K_\lambda(X_0, X)$ be a kernel function at X_0 denoted as follows:

$$K_\lambda(X_0, X) = D\left(\frac{\| X - X_0 \|}{\lambda(X_0)}\right) \tag{4}$$

where $D(\bullet)$ is typically a positive real valued function, whose value is decreasing as the distance between the X and X_0 increases. $\| \bullet \|$ is Euclidean norm, $\lambda(X_0)$ is the kernel radius or window size. The well-known Nadaraya-Watson approach is usually adopted as follows[13]:

$$\hat{X}_t = \frac{\sum_{m=1}^{N} K_\lambda(X_t, X_m) X_t}{\sum_{m=1}^{N} K_\lambda(X_t, X_m)} \tag{5}$$

where X_t is observation value at time t, N is the number of desired observations. Some particular cases of kernel smoothers are described in the following subsections.

2.2.1 Gaussian kernel smoother (GKS)

The GKS is widely used kernel trick in many fields. This scheme is particularly beneficial when the data are sparse because it efficiently utilizes the entire data set to compute the value at every point. The Gaussian kernel in one-dimension (1D) at X_0 is defined as follows[12,14]:

$$K(X_0, X) = \exp\left(-\frac{\| X - X_0 \|^2}{2\sigma^2}\right) \tag{6}$$

where X denotes data within the kernel radius or span, σ^2 is the variation.

2.2.2 Nearest neighbor kernel smoothing (NNKS)

The NNKS method takes more confident belief from neighbors according to their distance to a given temporal point, which gives rather greater weight from closer neighbors[15]. One widely used approach to calculate mentioned weight function is according to the inverse of their time interval distance from a given point, and also Laplace smoothing operator is introduced to avoid division by zero as follows[16]:

$$K(X_0,i)=\begin{cases}\dfrac{1}{i+1}, & i<m \\ 0, & else\end{cases} \tag{7}$$

where i is the i-th closest neighbor of X_0, m is maximum number of neighbors among window.

Ⅲ. Developed Detection System

To compare the performance of various smoothing methods, we developed a detection system for a device-free target with IEEE 802.15.4 ZigBee devices and performed experiments. As for the detection system, XBee Pro S1 RF modules, which operate within the ISM 2.4 GHz frequency band, are used as the transceivers, and Arduino UNO platform is used to develop an integrated receiver and uploader. We also used an ethernet extension board for uploading data to the server. Experimental devices are shown in the Figure 1. We also developed our experiment data collection system. The whole data reception and uploading flow is shown in Figure 2.

The data transmission in the experiments is as follows: when the Arduino controls the XBee transmitter to send a signal, the Arduino receiver controls the XBee RF to receive the signal and uses the Arduino program to extract the signal strength value of the received signal. Then, the ethernet network expansion module uploads the RSS value to the sever through the router, and our sever adds a time tag to the data according to the reception time,

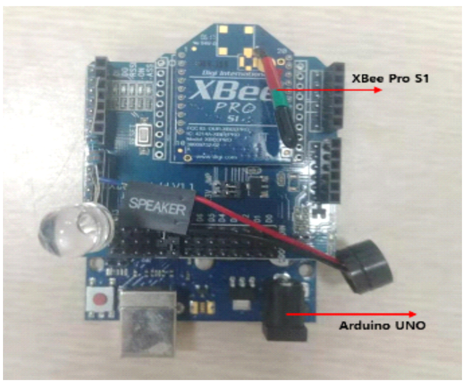

Fig. 1. Experiment devices

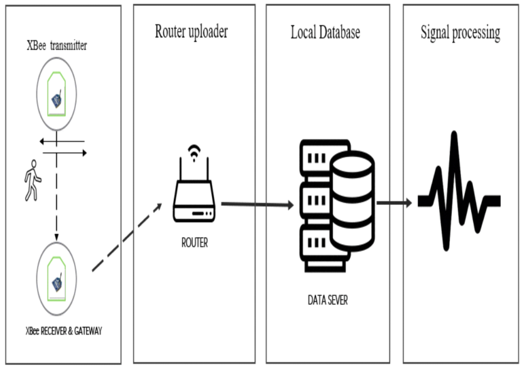

Fig. 2. Overview of data reception and uploading system

and finally the signal processing is done by using the data in the sever.

Experiments were performed at general building of our university as shown in Figures 3 and 4. The transceivers are placed one meter above the ground, one pedestrian moves across the line-of-sight link in a normal speed of walk about 1 m/s. The signal transmission time interval was 100ms along the 7.5 meters communication distance, i.e., 10 RSS values were recorded in one second. In the experiments, the target crossed the link 4 times continually.

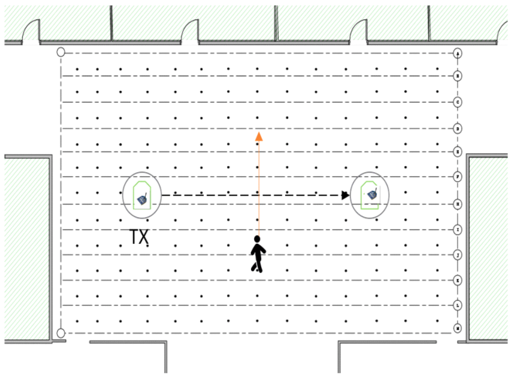

Fig. 3. Schematic of experiment field

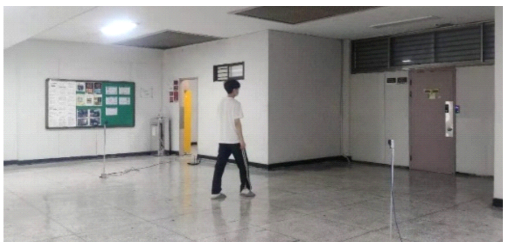

Fig. 4. Actual experiment scenario

Ⅳ. Experiment Results and Discussion

Considering the walking speed of the pedestrian and the signal transmission time interval, the two different window sizes, which are 5 and 10 respectively, are considered for each smoothing method. For a fair comparison, the same date is used for all the considered smoothing methods. Note that we adopted the absolute value of all the RSS in the experimental figures to give an intuitive visibility. Figures 5, 6, 7 are results of the moving average smoothing methods, while Figure 8, 9 are results of the kernel smoothing methods.

Figure 5 shows the results of the SMA method. As shown in the figure, both cases with different window size can detect the target well. It is worth to note that the waveform with window size 5 is sharper than the other case at the crossing moment. Figure 6 shows the results of the WMA method. By comparing with Figure 5, it is shown that the waveform of the WMA is sharper than that of the SMA at the crossing moment. Figure 7 shows the results of the EMA method. By comparing with Figure 6, it is shown that multiple peaks are around the crossing moment.

Figure 8 shows the results of the GKS method. By comparing with Figure 6, it is shown that the waveform of the GKS is similar to that of the WMA at the crossing moment. Figure 9 shows the results of the NNKS method. As shown in the figure, the waveforms of the NNKS is similar to

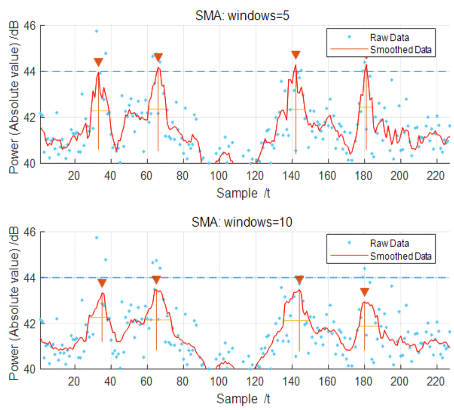

Fig. 5. Result with the SMA method

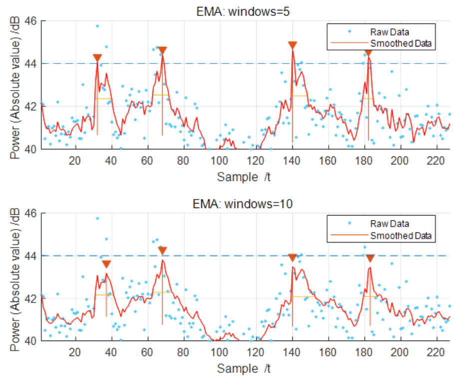

Fig. 6. Result with the EMA method

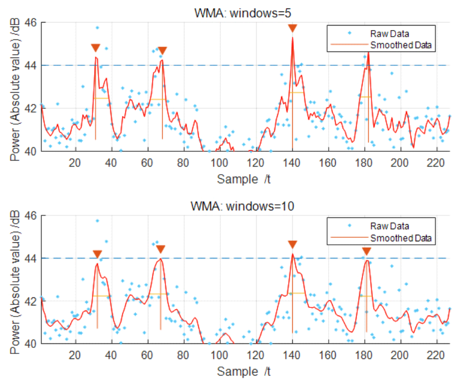

Fig. 7. Result with the WMA method

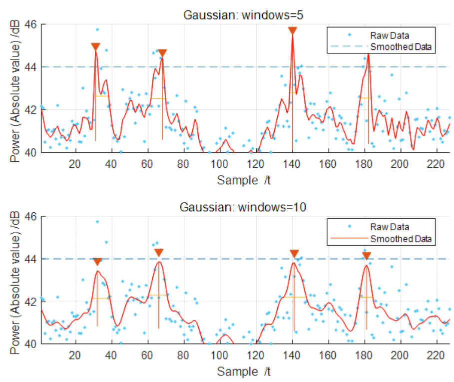

Fig. 8. Result with the GKS method

that of the GKS around the crossing moment.

To compare the accuracy and robustness level of all the smoothing methods, two different error criteria, which are the mean square error (MSE) and the mean absolute percentage error (MAPE), are used. The MSE is the average of the squared error

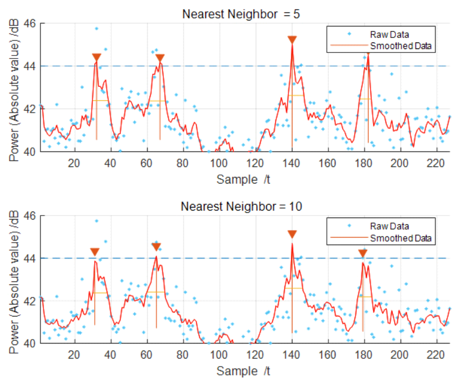

Fig. 9. Result with the NNKS method

sum between the smoothed value and the actual experimental data, and it can be expressed as follows[17]:

$$MSE = \frac{\sum_{i=1}^{N} \| X_i - \hat{X}_i \|_2}{N} \tag{8}$$

where $\hat{X}_i$ denotes the smoothed data at time i, while X_i is the actual experiment data, and N is the total number of RSS data. The MAPE is also known as the mean absolute percentage deviation. It gives us an indication on how much the average of absolute error of the smoothed value, compare to the actual experimental data. The MAPE is also good for removing the scale-dependent error and is expressed as follows[18]:

$$MAPE = \frac{\sum_{i=1}^{N} \left\| \frac{X_i - \hat{X}_i}{X_i} \right\|}{N} \times 100 \tag{9}$$

where $\hat{X}_i$ denotes the smoothed data at time t, while X_i is the actual experiment data, and N is the total number of RSS data.

Table 1 shows the performance of all the considered smoothing methods in terms of the two different error criteria. As shown in the table, the GKS, the WMA, and the EMA methods with S=5 can provide more suitable performance than other methods in terms of MSE, while the WMA, the EMA, and the NNKS methods with S=5 provide more suitable performance in terms of MAPE. Note that all the methods with S=5 are superior to those with S=10.

To compare the performance of various smoothing methods with the detection scheme based on RSS, we set a detection threshold for RSS value to determine the target detection. Since multiple RSS values over the threshold can be collected while the target is crossing, we specify that a group of multiple values exceeding threshold is considered as one successful detection. Based on the experimental data, we set the detection threshold as 44. For the evaluation of detection temporal accuracy, we considered the sample time of greatest peak. The sample time difference between the greatest peak of the raw data and the greatest peak of the smoothing methods is considered as detection temporal accuracy. Note that less difference indicates more accurate in detection temporal accuracy.

As shown in table 2, the detection accuracy for S=5 is superior to that of S=10 for all the methods.

Table 1. Error comparison for all the smoothing methods.

	MSE		MAPE	
	S=5	S=10	S=5	S=10
SMA	1.26	1.25	1.67	1.75
WMA	0.65	0.94	1.24	1.46
EMA	0.79	1.13	1.39	1.68
GKS	0.62	1.05	1.25	1.55
NNKS	0.75	0.84	1.29	1.40

*S: window size

Table 2. Comparison of detection and temporal accuracy.

	Detection Accuracy (detected count./total count)		Temporal Accuracy
	S=5	S=10	S=5
SMA	3/4	0/4	0.13s
WMA	4/4	1/4	0.17s
EMA	4/4	0/4	0.08s
GKS	4/4	1/4	0.20s
NNKS	3/4	2/4	0.15s

*S: window size

Although the detection accuracy drops dramatically for S=10, we can see a clear change of ups and downs as shown in the figures. We would like to remind that the detection threshold has a large impact on the detection accuracy, so here we only discuss the case of this experiment. It can be seen from the table that the smoothing method can provide better results for target detection under suitable window size and threshold. In temporal accuracy, the EMA has the smallest error, while the GKS method has the biggest error, 0.2s. However, it is worth to note that the detection time for various methods are within acceptable limits compared to the pedestrian crossing time.

Ⅴ. Conclusions

In this paper, we presented various smoothing methods to mitigate the effect of noises for enhanced performance of device-free target detection. To compare the performance of various smoothing methods, we developed a detection system for a device-free target with IEEE 802.15.4 ZigBee devices and performed experiments. According to the experimental results, it is shown that the GKS, the WMA, and the EMA methods can provide more suitable performance than other methods in terms of mean square error, while the EMA method provides more suitable performance in terms of detection accuracy and detection temporal accuracy.

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