Multi-threshold signal detection method based on wavelet transform*

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Abstract. Wavelet transform is a commonly used signal processing tool. In order to reduce the false alarm rate of the double-threshold detection method based on wavelet transform, a width threshold is proposed. The idea is that a true peak, after compression and re-reconstruction, will not only have longer ridges, but also have a longer width, but this is rarely the case from noise and pulsed peaks. The double-threshold detection algorithm and multi-threshold detection algorithm are compared by simulation. From the simulation results, the width threshold can effectively reduce the peak signal generated by the interference, thus verifying the necessity and effectiveness of adding the width threshold.

Keywords: Double-threshold · Width threshold · Multi-threshold.

1 Introduction

The EMG signal has non-stationary characteristics in physiological nature. When using the simple time domain method and the simple frequency domain method to analyze separately, the non-stationary characteristics are often simplified, and the EMG signal is regarded as a short-term stationary or time-invariant signal. The signal is analyzed, ignoring the associated information contained in the EMG signal over time [1]. However, this shortcoming can be overcome by using a time-frequency domain joint analysis method. In the detection of myoelectric signals, the main task is to determine the transient peak signal of muscle response, and the moment when the peak arrives is especially important. Although EMG signals come in a variety of shapes, they all contain transient peaks that can be used to improve detection performance by characteristics. As with the double-threshold detection algorithm used in [2], the detection performance is greatly improved compared to the simple time domain and frequency domain analysis methods. However, in production and life, due to the error of man-made and machine equipment itself, it is inevitable that there will be pulse interference in the signal, and this problem cannot be effectively solved by either single-

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threshold or double-threshold. Therefore, based on the double-threshold detection algorithm, the width threshold is added to form a multi-threshold detection algorithm.

2 Existing detection method

The traditional signal detection method is to process signals in the time domain and frequency domain, such as spectrum analysis and time domain averaging methods. Most of these methods are classified into single-threshold detection. Wavelet analysis theory, neural network, etc. are popular nowadays. Most of these methods also remove the noise signal by setting the threshold, especially the double threshold detection method in [2].

2.1 Single-threshold detection method

Multi-resolution decomposition of wavelet transforms on known signals. Thought is a special shape with a large value that is obtained at one or more resolution levels. Then, a local maximum above a certain threshold is selected as a possible peak signal to remain. This single-threshold method is relatively simple to operate, but its shortcoming is that the retained noise is too much, the false alarm rate is high, and the accuracy is poor. For production activities with high precision requirements, this single-threshold detection method obviously does not meet the requirements.

2.2 Double-threshold detection method

In the case of low SNR, the wavelet transform is also used to perform multi-resolution decomposition on the known signals, and the peak signals retained by the single-threshold detection method are combined between the signals reconstructed by different resolutions to identify the ridges. The length of the ridge is defined as the number of peaks at the same position between the signals reconstructed at each level of resolution. In order to increase the possible peaks that need to be processed in the ridge length threshold, the height threshold can be appropriately adjusted. However, lower thresholds also reduce accuracy, especially in low SNR signals. In order to improve the accuracy, and not to affect the number of possible peaks too much, the shorter length ridge is considered to be from noise [2].

Although the double-threshold algorithm already has a good detection effect [2], the interaction between the two thresholds also occurs in the case where one is a shorter ridge, but it is also a peak signal. The signal is filtered out and a false negative occurs. The other is that the pulse interference signal in the signal is retained as a peak signal and a false alarm occurs.

In order to solve such false negatives and false positives, especially for pulsed interference signals, we propose a third threshold, "width threshold", which is combined with a double-threshold detection method to form a multi-threshold detection method.

3 Modeling of EMG signals

A synthetic data simulating the EMG signal is given $x[k]$:

$$x[k] \overset{def}{=} \sum_{i=1}^{N_p} P[k - p_i] + \omega_\sigma[k] + \beta_n, n = 1, 2, \cdots, m \quad (1)$$

Here p_i is the moment when the *i-th* instantaneous peak signal is generated. N_p is the number of transient peaks produced in the signal. $\omega_\sigma[k]$ is a Gaussian white noise with variance σ^2. β_n is a random impulse interference generated by man or machine. r is sparsity, and its defined as the ratio of the samples without the instantaneous peak signal in the total sample. If the length of the instantaneous peak signal is M, then each data sample of length $M/(1 - r)$ contains a transient peak signal that is completely evenly averaged. So the entire length of the data $x[k]$ is $M/(1 - r) \cdot N_p$.

Since the signal is transient, the SNR is different from the traditional definition because the energy or power of the signal depends on the density of the signal: in a fixed time interval, if there are more signals, the energy or power will increase. Therefore, the concept of instantaneous average power is used to define the SNR:

$$SNR \overset{def}{=} \frac{P_{signal}}{P_{noise}} = \frac{\frac{1}{s_2 - s_1 + 1} \cdot \sum_{n=s_1}^{s_2} s[n]^2}{\sigma^2} \quad (2)$$

Here $[s_1, s_2]$ is the support interval of the instantaneous signal $s[n]$, σ^2 is the variance of Gaussian white noise. Power is the variance for Gaussian white noise.

For the pulsed interference signal β_n, since the moments that occur in practice are unpredictable, in order to better reflect the actual situation, we set the moments at which they appear to be random. Consider two situations here:

Case 1: When the position where the pulse signal appears coincides with the peak signal, in the overlapping position, due to the addition of energy, the chance of the position being larger is not missed.

Case 2: When a pulse signal appears between two peak signals, the most likely missed report.

Based on the above analysis, the main consideration is the case of adding pulse interference between two peak signals. Therefore, the original signal that needs to be processed can be generated by combining (1) with equation (2).

4 Decomposition of myoelectric signals

For the time-discrete signals given above, we use wavelet transform to reconstruct and reconstruct the signal. Since the noise in the original signal is assumed to be Gaussian white noise, the mean value of the noise is zero. Based on the above assumptions, we define the width of the peak as: the number of sample points that a peak contains from start to finish. The idea is that a true peak will have a longer width after compression and reconstruction, and this is rarely the case with noise-derived peaks. We set the peak width threshold in the secondary decomposition reconstructed signal, which can further remove the peak of the noise remaining in the double-threshold detection process, thereby reducing the false positive rate of the detection result.

The following describes the multi-threshold detection method.

4.1 Height threshold

The height threshold is selected as

$$\gamma_i = c \cdot max(Xr_i), i = 1, 2, \cdots, d \tag{3}$$

Here Xr_i represents the amplitude of the signal after the *i-th* decomposition and reconstruction, the amplitude and height in the signal are correlated, and the amplitude is measurable. It may be assumed that the height threshold and the amplitude of the signal are positively correlated, denoted as c. Then c is the "threshold coefficient" and d is the maximum number of decompositions. γ_i is the height threshold. There are different height thresholds for signals of different resolution levels.

4.2 Ridge threshold

In the case of low SNR, a high threshold preserved peak signal is combined between signals reconstructed at different resolutions to identify the ridge. The length of the ridge is defined as the number of peak positions between the reconstructed signals at the same position. The idea is that a true peak will have a longer ridge after compression and reconstruction, while the peak from noise does not. In order to increase the possible peaks that need to be processed in the ridge threshold, the width threshold can be appropriately adjusted. However, lower width thresholds also reduce accuracy, especially in low SNR signals. In order to improve the accuracy, and not to affect the number of possible peaks too much, the shorter length ridge is considered to be from noise [2].

The selection of the ridge threshold is affected by the number of decompositions, so the ridge threshold is defined:

$$l_{thres} \overset{def}{=} k_{ridge} \cdot d, k_{ridge} \in R^+ \tag{4}$$

Here k_{ridge} is the "threshold coefficient" and l_{ridge} is the ridge threshold. The peaks at those moments that do not exceed l_{ridge} are removed, and in the remaining ridges, each ridge corresponds to a peak signal. The position of the peak is estimated from the time at which the peak value of the ridge is decomposed and reconstructed.

4.3 Width threshold

After the screening of the height threshold and the ridge threshold, most of the peak signals are retained, but the false peak signals may be retained, resulting in a large false positive rate. To solve the problem, we take advantage of the width defined earlier. Defining the length of the peak signal as the number of sampling points in an instantaneous peak signal, denoted as L_f, and since the mean of Gaussian white noise is zero, in order to minimize the noise interference, we take the width threshold:

$$w_s = g \cdot L_f \tag{5}$$

Here g is the "threshold coefficient" and w_s is the width threshold. After many experiments, we consider setting the width threshold to the signal of the secondary decomposition reconstruction.

4.4 Additional condition

Due to the setting of the length threshold and the width threshold, we have to consider these situations.

The length of a true peak signal ridge should not exceed the ridge length threshold, l=l_{ridge}, a false alarm may occur. The width of a true peak signal just can't exceed the width threshold, $w < w_s$, which can also cause false negatives. In order to minimize the negative effects of increasing the ridge length threshold and the width threshold, we consider limiting the peak with ridge length and width. The idea here is to refer to the antagonism in physiology.

Under the setting of the ridge length threshold, we add the condition: when l=l_{ridge}, if the width $w > w_s$, then we think that the peak signal is a true peak. Under the setting of the width threshold, we add the condition: when $w < w_s$, if l=d, which means that the length of the ridge can reach the maximum, we think that the signal is true.

5 Simulation

The parameters are set as follows:

1) The number of peak signals N_p is set to 10;
2) The sampling rate is 2000Hz;
3) The peak value of the instantaneous peak signal is set to 100;
4) The sparsity r is set to 0.8;
5) The SNR is taken as 5.

The magnitude of the pulsed interference signal is set to 0.618 times the peak value of the instantaneous peak signal plus the maximum value in the noise signal. The double-threshold method and the multi-threshold method are subjected to 1000 consecutive experiments, and the results are as follows.

Table 1. Simulation results.

Both methods do not recognize pulse interference	119,139,160,213,222, 283,510,692,702,732
Noise is recognized as a peak in the double-threshold, but it is correctly identified in the multi-threshold	174,389,445,465,622
Peak signal is not recognized by either method	944,953,984
Double-threshold identification is correct, multiple-threshold are missing	639
Both methods recognize noise as a peak	268

The numbers indicate the order in successive 1000 experiments. It can be seen from the table that the multi-threshold method has only one negative effect compared to the double-threshold method. The 639-*th* experiment, the experimental results are as follows.

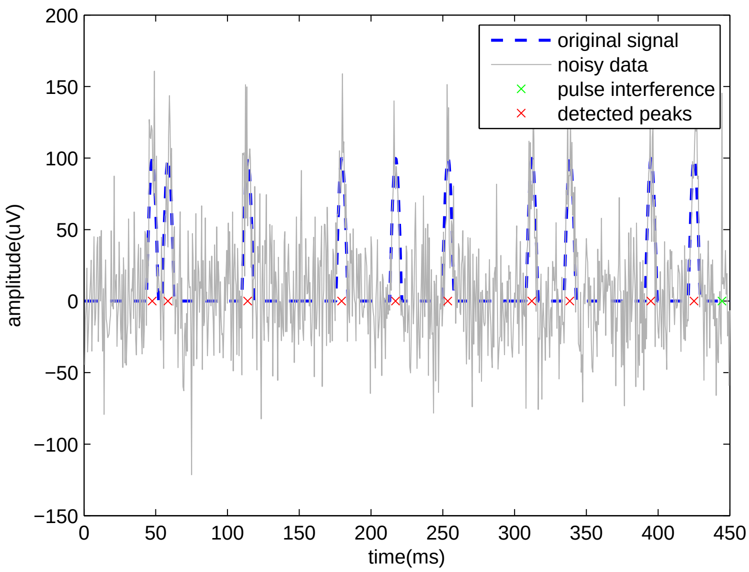

Fig. 1. Original signal diagram produced by the 639-*th* experiment.

The blue dotted line indicates the peak in the composite signal, the green x indicates the time at which the pulse interference is present, and the red x indicates the time at which the peak maximum value in the composite signal is located. It can be seen from Fig.2 that the moment of the pulse interference signal appears at about 440ms.

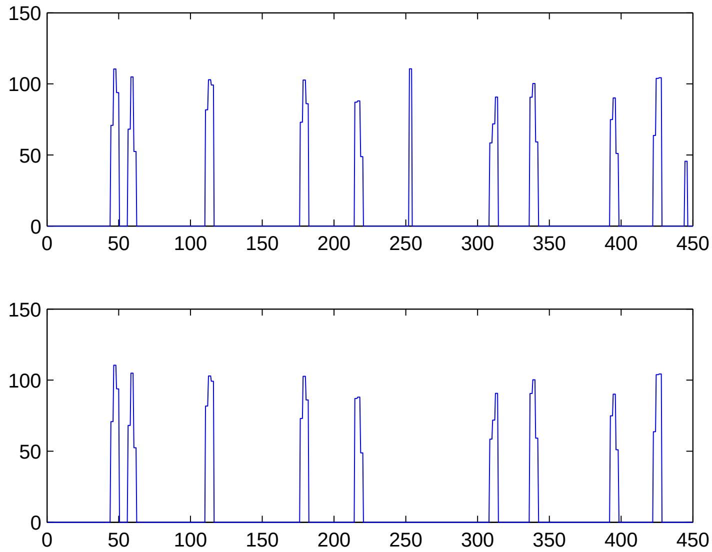

Fig. 2. Comparison of the width threshold before and after the second decomposition and reconstruction.

As can be seen from Figure 2, after the width threshold is set, possible peak signals around 250ms and 440ms are filtered out.

It can be seen from Fig.3 that the ridge length of the possible peak signal near 250ms is 4, and the ridge length of the possible peak signal near 440ms is 2.

In Fig.4, a circle indicates the position of the peak in the composite signal, a green $*$ indicates the position of the interference signal, and a red $*$ indicates the detection result. That is, the double-threshold method can correctly identify the position of the peak and filter the pulse interference signal.

As can be seen from Fig. 5, although the multi-threshold detection method filters out the pulse interference signal, it also filters out the true peak signal near 250ms. This is a negative impact of the multi-threshold approach, but its odds are only 0.1%.

In addition to the above results, there are 32 experiments in which the double-threshold method does not recognize pulse interference as a peak, but multiple-thresholds can identify the correct situation. Combined with the experimental results in Table 1, although the multi-threshold has a negative impact, it can be ignored compared to the benefits it brings. The double-threshold detection method has a peak signal detection accuracy of 94.5% in 1000 simulation experiments, and the multi-threshold detection method can achieve a correct rate of 98.5%.

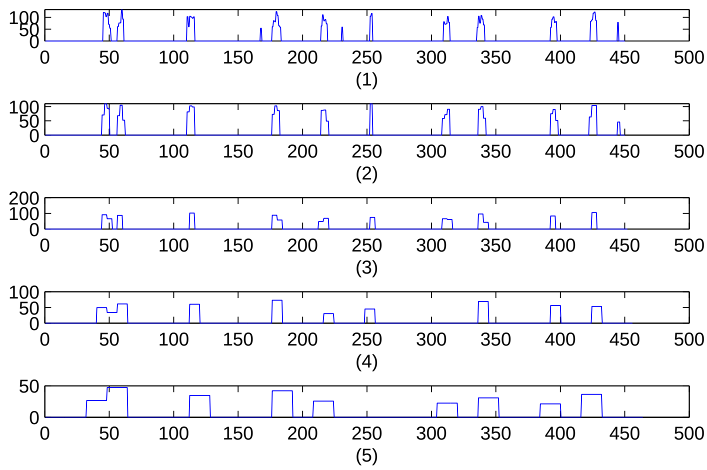

Fig. 3. Results of refactoring after five decompositions before setting the width threshold.

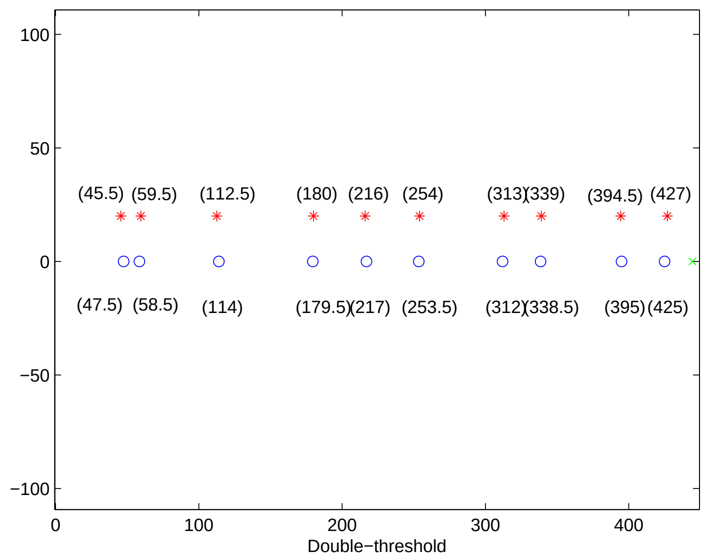

Fig. 4. Double-threshold test results.

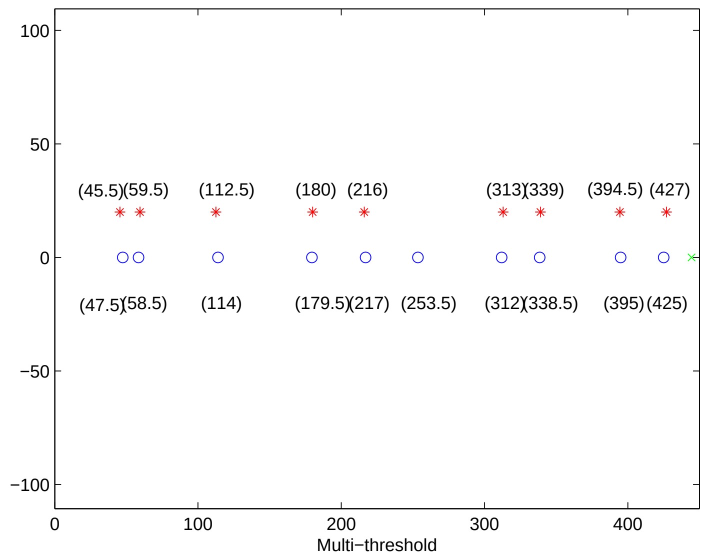

Fig. 5. Multi-threshold detection results.

6 Conclusion

In this paper, based on the wavelet transform double-threshold detection technique proposed in [2], the effect of reducing the false alarm rate is achieved by adding the width threshold, thus forming a multi-threshold detection algorithm. From the simulation results, the setting of the width threshold effective.

There are still many shortcomings in this method. First, the selection of thresholds in the multi-threshold method is to be selected through simulation experiments. In this paper, the number of experiments for threshold selection is small, and the threshold size is not optimal. Second, because of the particularity of the peak signal, the algorithm can only be used in the processing of signals containing peak shapes, which has certain limitations.

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A Please visit the link for simulation results.

https://github.com/pgmtbmg/JaysonY