Research on Modified Wavelet Threshold Denoising Algorithm Based around SEMG Signal

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Abstract: The surface electromyography (SEMG) signal of the lower limbs is collected by attaching electrodes to the surface of the muscles of the lower limbs, so it is non-invasive and simple to operate. Selected the threshold and the threshold function is very important when used the wavelet threshold denoising method to process some non-linear SEMG signals. But the traditional threshold is a fixed value, which is not conducive to the improvement of the denoising effect. Present paper discusses the previous wave threshold denoising means aiming at their shortcomings, to this end, an improved threshold method is proposed in present paper, which can change the threshold with the number of decomposition layers. In the meantime, the shortcomings of the previous threshold functions can be overcome by the modified threshold function. The SNR and MSE is selected as the parameters to evaluate the denoising performance and comparing the modified wavelet threshold denoising arithmetic with the traditional threshold arithmetic, the experiment results indicated that the denoising impact of the modified arithmetic is better than the previous arithmetic and it has certain practical value.

1. Introduction
The surface electromyography (SEMG) signal of the lower limbs is collected by attaching electrodes to the surface of the muscles of the lower limbs, so it is non-invasive and simple to operate. It is advanced relative to the movement state of the limbs [1]. So the movement intention of the human body can be reflected, and the system's operation delay in subsequent pattern recognition can also compensated by it.

The noise source of SEMG signal is complex, which including mainly the interference of irrelevant electrical signals in the body, the signal interference caused by the shaking of the limbs when collecting data, and the interference of electronic components. In the pre-processing part, the focus of research is how to extract useful signals from the original signals. Wavelet change has a good local time-frequency analysis capability, which can adjust the sampling length of diverse frequencies in the time-domain. Therefore, it is more suitable for processing non-stationary, fast-changing SEMG signals with a lot of detailed information than traditional filtering algorithms. At present, wavelet image denoising mainly uses wave transform mode maximum method, wave transform scale correlation means, and wave threshold denoising method for image denoising. In these methods, the computation amount of the wave threshold denoising method is smaller, it is easy to implement and has a wide range of applications.

Since the hard and soft threshold algorithm for the wave threshold denoising was proposed by Dono-ho [2]-[3], many scholars have made corresponding improvements to it. Some have proposed a
function combining the two methods; Some add adjustment factors to optimize the threshold function; Another adjust the threshold factor according to different sampling lengths [4]. These improved methods have played an improved role in signal processing and denoising.

Present paper proposes a modified method for the shortcomings of traditional thresholds and threshold functions. On the premise of retaining the merits of traditional threshold algorithms, a new modified wave threshold denoising means is proposed to improve its flexibility and continuity. The experiments show that this means possess better denoising result than previous wave threshold denoising methods, and more accurate SEMG signals can be extracted.

2. Previous wave threshold denoising

2.1. The theory of wave threshold denoising
After the noisy signal is disintegrated by wave transform, the useful signal parameter through wave change is larger than that the parameter of the noise signal. Set a threshold based on the characteristics of the signal after wave transform: If the amplitude of the parameter for wave transform is less than that threshold, it is considered that this is caused by noise, to set the wavelet coefficients to zero and to eliminate this part of the signal. If the amplitude of the parameter for wave transform is larger than or equal to that threshold, it is deemed to be generated by a useful signal and which will be retained. Then having disposed high-frequency coefficients and low-frequency coefficients are reconstructed through inverse wave transform, so that the noise is removed [5].

The specific steps of the wave threshold denoising means are as follows:

1. Using appropriate wave basis to perform wavelet transformation on the collected SEMG signal with noise, the wave decomposition coefficient $w_{j,k}$ of this signal is calculated.

2. Selecting the appropriate threshold and threshold function to calculate the wavelet decomposition coefficient $w_{j,k}$ of this signal, the estimated wave decomposition coefficient $f(w_{j,k})$ is obtained.

3. The signal is reconstructed by $f(w_{j,k})$ obtaining the SEMG signal after wavelet denoising.

In the process of wave threshold denoising, a suitable wave base should be selected to make changes. In the selection process, regularity, orthogonality, symmetry, similarity, vanishing moment, and support length should be thought over. The vanishing moment, support length and regularity are mutually restricted [6]. By comparing and analysing several commonly used wavelet bases such as Daubechies, Symmlets, Biorthogonal, Coiflets, and Harr, the final selection is Symmlets wavelet bases with orthogonality, approximate symmetry, and shorter support length so that the calculation time is shorter is used to collect the original EMG signal is processed by wavelet transform.

2.2. Selection of previous wave threshold
The traditional wave threshold selection means is classified into comprehensive threshold and part threshold. The comprehensive threshold is to use the same threshold for quantization to all wave coefficients. The part threshold is selected according to the probability and fuzzy membership. Common comprehensive thresholds include unified threshold, BayesShrink threshold, SureShrink threshold, and maximum and minimum thresholds. The most common unified threshold is based on the size or length of the normal deviation signal of the noise; The choice of BayesShrink threshold depend on the model assumption that the wave parameter of the noiseless image obeys the generalized Gaussian distribution.

Although the comprehensive threshold is convenient and simple to operate, there is a problem for threshold selection. If the threshold is lesser selected, the original signal will not be completely denoised and there will be residue, which will affect the subsequent analysis of signal feature extraction [7]. If the threshold is greater selected, some useful signals will also be eliminated. Therefore, the concept of part threshold was invented, which mainly determines the threshold based on a certain point or a certain part feature. It is more reasonable than the comprehensive threshold. But the calculation process of the part threshold will be complicated sometimes.
2.3. Traditional wavelet threshold function

(1) Hard threshold function

\[ f(w_{j,k}) = \begin{cases} w_{j,k} & |w_{j,k}| \geq \lambda \\ 0 & |w_{j,k}| < \lambda \end{cases} \]  

(1)

It can retain the characteristics of real signals such as spikes better. But its discontinuity at \( w_{j,k} = \pm \lambda \) will make the estimated wavelet coefficients have poor continuity. This will cause the signal to oscillate.

(2) Soft threshold function

\[ f(w_{j,k}) = \begin{cases} sgn(w_{j,k})(|w_{j,k}| - \lambda) & |w_{j,k}| \geq \lambda \\ 0 & |w_{j,k}| < \lambda \end{cases} \]  

(2)

The soft threshold method is a smoother denoising method, which has better continuity. But when the wave coefficient is greater, the signal curve after processing will be too smooth and distorted. There will be a fixed error between the wave coefficient and that estimated wave coefficient. This makes that the approximation between the original signal and the reconstructed signal is not good enough.

(3) Semi-soft threshold function

\[ f(w_{j,k}) = \begin{cases} w_{j,k} & |w_{j,k}| \leq \lambda \\ sgn(w_{j,k})\frac{|w_{j,k}| - \lambda}{\lambda_1 - \lambda_0} & \lambda_0 \leq |w_{j,k}| \leq \lambda_1 \\ 0 & |w_{j,k}| < \lambda \end{cases} \]  

(3)

The semi-soft threshold means improves the oscillation effect that is generated by the hard threshold function. At the same time, it can also effectively improve the phenomenon of definite differences when the soft threshold function processes wavelet transforms coefficients larger than the threshold. However, when the wave decomposition coefficient is between values \( \lambda_0 \) and \( \lambda_1 \), signal fluctuations will occur, which will affect the denoising effect.

(4) Soft and hard threshold compromise function

\[ f(w_{j,k}) = \begin{cases} sgn(w_{j,k})(|w_{j,k}| - a\lambda) & |w_{j,k}| \geq \lambda \\ 0 & |w_{j,k}| < \lambda \end{cases} \]  

(4)

This method combines the characteristics of the previous threshold function, and \( a \in [0,1] \). This method changes the function by adjusting the coefficient \( a \).

3. Improved wave threshold denoising

3.1. Selection of improved wave threshold

In the wave threshold function denoising means, the choice of threshold is very important. If the threshold is lesser, the signal still contains a lot of noise, which is not conducive to subsequent processing. This requires the threshold to be as large as possible within a reasonable range to attain the objective of removing more unpitched sound. If the selected threshold too great, it will cause the loss of useful signals. The traditional global threshold is a fixed value at different scales \( j \). It will not change as the count of wave decomposition layers changes. However, the SNR of different decomposition layers is different, and the wave coefficient in the noise will decrease by the count of wave decomposition layers increases. Therefore, as the count of decomposition layers increases, it is better to choose a smaller threshold appropriately [8]. In this way, while effectively removing more noise, more useful signals can be retained. By adding the variance of the decomposition layer noise to the threshold calculation formula, the threshold can be changed with the SNR. The introduction of the decomposition scale \( j \) can make the improved threshold adaptive and the denoising result is better. The threshold of the \( j \) decomposition layer can be expressed by the following formula:

\[ \sigma = \frac{\text{median}(w_{j,k})}{0.6745} \]  

(5)
\[ \lambda = \frac{\sigma(2 \log(N))^{1/2}}{j} \]  

(6)

In the formula, \( \sigma \) is the estimation value of the horizontal noise, and \( N \) is the extent of this signal.

3.2. Selection of modified wave threshold function

To surmount the limitations of the above FUNC, using a modified threshold FUNC to process the wave coefficients obtains the wave estimated coefficients in this paper. Now of the absolute value of the wave parameter before the change is lesser than that threshold (\( |w_{j,k}| < \lambda \)), the improved wave threshold FUNC is identical to the traditional threshold FUNC, which will make the all wave coefficients before the change to zero. Now of the absolute value of the wave parameter before the change is larger than the threshold (\( |w_{j,k}| \geq \lambda \)), the wave parameter will be shrunken. Its decay exponential term allows it to have approximation and continuity, allowing it to surmount the problem about deviation of the soft threshold FUNC. The previous threshold functions and improved threshold functions were shown in figure 1. The modified threshold FUNC curve is between the hard one and the soft one. It is a shrinkable approximation logarithmic threshold function. Its expression is as follows:

\[
f(w_{j,k}) = \begin{cases} 
(1 - \mu) \cdot w_{j,k} + \mu \cdot \text{sgn}(w_{j,k})(|w_{j,k}| - \lambda) & |w_{j,k}| \geq \lambda \\
0 & |w_{j,k}| < \lambda 
\end{cases}
\]

(7)

\[
\mu = \frac{\lambda}{|w_{j,k}| \cdot \exp\left(\frac{|w_{j,k}| - \lambda}{|w_{j,k}| + \lambda}\right)^{1/2}}
\]

(8)

Figure 1. The previous threshold function and modified threshold function

4. Simulation experiment

A piece of original SEMG signal shown in figure 2 is obtained through the acquisition device. Combining traditional threshold, improved threshold and their homologous function, and improved threshold method to construct wave denoising method. In order to test the effect of the improved threshold and the improved threshold function method, a simulation experiment was carried out with MATLAB2019a software. The traditional threshold is set by the method provided in the software toolbox Wavelet Toolbox. Call the relevant functions of the wavelet toolbox in MATLAB to process the original signal. Through comparison and analysis, the Symmlets wavelet base is finally used for decomposing the noisy with 4-layer wavelet. The SNR and MSD indicators are introduced to assess the denoising effects of each method. After denoising, the larger SNR of the signal is and the smaller the MSD, which indicate that more effective information is retained, noise is removed thoroughly, and there will be a better denoising effect.
Figure 2. Original SEMG signal of biceps femoris

Figure 3. The SEMG signal after wavelet denoising

Figure 2 and figure 3 are comparison diagrams of the original signal and the biceps femoris SEMG signal after denoising by traditional wavelet threshold. The horizontal axis is the time of the sampling point, and the vertical axis is the voltage value of the SEMG signal.

Table 1. The denoising effects of diverse thresholds and diverse threshold FUNC (SNR, MSD)

| Threshold          | Hard threshold FUNC | Soft threshold FUNC | Improved threshold FUNC |
|--------------------|---------------------|--------------------|------------------------|
| Traditional threshold | S/N=23.652          | S/N=21.762          | S/N=23.423             |
|                     | MSD=2.35            | MSD=2.91            | MSD=2.47               |
| Improvement threshold | S/N=26.713          | S/N=24.712          | S/N=27.136             |
|                     | MSD=1.67            | MSD=2.11            | MSD=1.51               |

The experimental effect in table 1 shows that the SEMG signal obtained by the denoising method combining the modified threshold and its FUNC has the highest SNR and the lowest MSD. The hard threshold FUNC has a better denoising result than the soft that, and the reconstructed SEMG signal has a higher SNR and a lower root mean square deviation. However, due to the continuity of the soft threshold function, the SEMG signal obtained after reconstruction is smoother. The SEMG signal obtained by the denoising method combining the modified threshold and the modified threshold function has the highest SNR and the lowest MSD. At the same time, this method can also obtain a smoother reconstructed signal. This characteristic is determined by the continuity of the modified threshold function.
5. Conclusions
Present paper discusses the previous wave threshold denoising means. A better threshold selection method has been proposed and the threshold function has been modified aiming at its shortcomings. The modified threshold is more flexible and can change with the count of wave decomposition layers. It overcomes the shortcomings of incomplete denoising and easy removal of useful signals due to the fixed threshold for traditional wavelet threshold. The new wave threshold function has continuity and overcomes the shortcomings of discontinuity in the hard one. In the meantime, the denoising signal obtained by it has a smaller deviation from the original signal. Comparing the new method with the traditional method by simulation experiment, the effect shows that the modified wave threshold denoising means is more effective than the previous threshold means, and that has certain application prospects.

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