Denoising of surface electromyogram based on complementary ensemble empirical mode decomposition and improved interval thresholding

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ABSTRACT
Surface electromyogram (sEMG) signals are physiological signals that are widely applied in certain fields. However, sEMG signals are frequently corrupted by noise, which can lead to catastrophic consequences. A novel scheme based on complementary ensemble empirical mode decomposition (CEEMD), improved interval thresholding (IT), and component correlation analysis is developed in this study to reduce noise contamination. To solve the problem of losing desired information from sEMG, an sEMG signal is first decomposed using CEEMD to obtain intrinsic mode functions (IMFs). Subsequently, IMFs are selected via component correlation analysis, which is a measure used to select relevant modes. Thus, each selected IMF is modified through improved IT. Finally, the sEMG signal is reconstructed using the processed and residual IMFs. Root-mean-square error (RMSE) and signal-to-noise ratio (SNR) are introduced as evaluation criteria for the sEMG signal from the standard database. With SNR varying from 1 dB to 25 dB, the proposed method increases SNR by at least 1 dB and reduces RMSE compared with stationary wavelet transform and other denoising algorithms based on empirical mode decomposition. Moreover, the proposed method is applied to hand motion recognition. Results show that the rate of the denoised sEMG signal is higher than that of the raw sEMG signal.

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I. INTRODUCTION
Surface electromyogram (sEMG) is a technique used to generate bioelectric signals that can reflect information related to muscle and body behavior.1 sEMG signals are extensively used in various fields, such as sports medicine, rehabilitation training, and mechanical control.2–4 In addition, sEMG signals are extremely weak, with magnitudes limited within the μV range. Moreover, sEMG signals are nonlinear, nonstationary, and distributed between 10 Hz and 500 Hz. However, these signals are vulnerable to corruption by noises due to their characteristics. Three types of noise occur: power line interference, white Gaussian noise, and baseline wandering.5 Therefore, denoising sEMG signals is a prerequisite6 for analyzing and applying sEMG information.

Previous studies have shown that the wavelet threshold denoising algorithm can be used to reduce noise in sEMG.6 Wavelet transform exhibits good local properties in the time and frequency domains. However, the wavelet base and the number of decomposition layers should be selected by an expert. Research shows that wavelet bases and decomposition layers exert considerable influences on the denoising result.6 To overcome the aforementioned drawbacks, wave atom transform has been proposed to replace wavelet transform.8 Wave atom transform is a novel multiscale decomposition method for analyzing signals corrupted by noise and uncertainty.8

The empirical mode decomposition (EMD) algorithm is used in denoising signals by overcoming the shortcomings of wavelet denoising.10–15 EMD can decompose a nonstationary signal into
intrinsic mode functions (IMFs), which present different time scales of the original signal. Wu and Huang proposed ensemble EMD (EEMD) because mode mixing in EEMD is a data-driven analysis algorithm that adds white noise to a noisy signal before the signal is decomposed. Simultaneously, EEMD considers noise contamination induced by residue. To resolve the aforementioned problem, Yeh et al. proposed a new noise-assisted analysis method, namely, complementary EEMD (CEEMD), in which white noises are added with a pair of opposite noises to the target signal. Experiments show that the improved method is better than the general denoising method and its application is convenient and flexible. Inspired by wavelet thresholding, Kopsinis and McLanaghan developed a novel EMD interval thresholding (IT) (i.e., EMD-IT) denoising method, and various signals were used to test this algorithm. In their method, a zero-crossing interval is regarded as a unit that presents thresholding performance. In this manner, the approach can overcome discontinuity.

The effective selection of relevant modes is a critical problem in EMD-based denoising methods. Yang proposed a new criterion, namely, similarity measure, for selecting relevant modes. However, similarity measure should be fitted to analyze stationary signals. Chen developed a correlation analysis algorithm for selecting representative modes for fault diagnosis. Inspired by the correlation analysis algorithm, we used component correlation analysis to select the most representative modes as relevant modes. In the current study, a novel method based on CEEMD, component correlation analysis, and improved IT was proposed to eliminate noise contamination in sEMG signals. To reduce the loss of desired information from sEMG, CEEMD was used to decompose raw signals into IMFs. Then, component correlation analysis was applied to calculate the correlation coefficients between the raw sEMG signals and each IMF to select relevant modes. Subsequently, the IMFs with large correlation coefficients were processed via improved IT. Finally, the signal was reconstructed using the processed IMFs and the unprocessed residual IMFs. For sEMG from the standard database, the proposed method achieved better denoising performance compared with those of EMD and EMD-IT. Previous experiments showed that noise-free signals would increase a system’s recognition rate.

In this regard, an application experiment on denoised sEMG signals was conducted to evaluate the performance of the proposed method.

The remainder of this paper is organized as follows: Sec. II presents the proposed method and reviews the basic theories of related algorithms. Section III conducts a case study to evaluate the proposed approach. Section IV applies the proposed method to an sEMG signal denoising experiment for motion recognition. Section V discusses and concludes the study.

II. METHODS

We propose a novel sEMG denoising method based on CEEMD, component correlation analysis, and improved IT. The flow diagram of the proposed approach is shown in Fig. 1, and the steps are as follows:

1. The raw sEMG signal is decomposed via CEEMD.
2. The correlation coefficients of each IMF and the original signal are calculated. Appropriate IMFs are selected using component correlation analysis.
3. The selected IMFs are modified through improved IT.
4. sEMG is reconstructed using the modified and unprocessed residual IMFs.

A. CEEMD

CEEMD is an improved method based on the EMD algorithm proposed by Huang. EMD decomposes signals into IMFs, where each IMF denotes a dynamic feature. An IMF must meet two requirements. (1) The numbers of maximum points and zero crossings (ZCs) for a time series should be equal to or different by a maximum of one. (2) The average of the upper and lower envelopes should be zero at any moment. Following the standard principle of EMD, an sEMG signal \( x(t) \) is decomposed as follows:

\[
x(t) = \sum_{i=1}^{n} \text{imf}_i(t) + \text{res}_n(t),
\]

where \( \text{imf}_i(t) \) is the \( i \)th IMF and \( \text{res}_n(t) \) is a RES that presents the trend of a signal.

If \( \text{res}_n(t) \) is regarded as the \( (n+1)th \) IMF, then Eq. (1) can be rewritten as follows:

\[
x(t) = \sum_{i=1}^{N} C_i(t),
\]

where \( C_i(t) \) is the \( i \)th IMF and \( N = n+1 \).

In EEMD, white noise is added to the original signal to overcome mode mixing. In CEEMD, white noises are added in pairs. Han and Mirko verified the advantages of CEEMD. For sEMG \( x(t) \), the CEEMD algorithm includes the following steps:

1. In CEEMD, pairs of white noises, which consist of a positive noise and a negative noise, are added to the original data to
generate two sets of ensemble IMFs
\[
\begin{bmatrix}
  x'_j(t) \\
  x''_j(t)
\end{bmatrix} = \begin{bmatrix}
  1 & 1 \\
  1 & -1
\end{bmatrix} \begin{bmatrix}
  x(t) \\
  N_i(t)
\end{bmatrix}, \quad j = 1, 2, \ldots, M,
\]
(3)

where \( x(t) \) denotes the original data, \( N_i(t) \) is the added white noise, \( x'_j \) is the sum of the original data with positive noise, \( x''_j \) is the sum of the original data with negative noise, and \( M \) is the number of trials.

(2) \( x'_j(t) \) and \( x''_j(t) \) are decomposed to obtain the \( i \)th IMF component \( C_{ij}(t) \) and \( C_{ij}(t) \) using EMD.

(3) The decomposition result, i.e., the \( i \)th IMF \( C_i(t) \), is obtained by averaging multiple components as follows:
\[
C_i(t) = \frac{1}{2M} \sum_{j=1}^{M} (C_{ij}(t) + C_{ij}(t)).
\]
(4)

Then, the signals decomposed with positive and negative noises will take positive and negative residues, respectively. Errors can be reduced based on the influence of the positive and negative residues.

B. Component correlation analysis

Component correlation analysis is used to examine the correlation between the original sEMG and IMFs. The IMFs with larger correlation coefficients than the reference correlation coefficient are selected. The correlation coefficient between sEMG \( x(t) \) and each IMF \( C_i(t) \) is calculated as follows:

(1) The covariance between \( x(t) \) and \( C_i(t) \) is calculated
\[
c_{xc}(i) = E[(x(t) - u_x)(C_i(t) - u_{C_i})]
\]
\[
= \lim_{T \to \infty} \frac{1}{T} \int_0^T [(x(t) - u_x)(C_i(t) - u_{C_i})]dt,
\]
(5)
where \( c_{xc}(i) \) represents the covariance of \( x(t) \) and \( C_i(t) \), \( u_x \) denotes the mean values of \( x(t) \), and \( u_{C_i} \) indicates the mean values of \( C_i(t) \).

(2) The correlation coefficient is calculated
\[
\rho_{xc}(i) = \frac{c_{xc}(i)}{\sigma_x \sigma_{C_i}}
\]
(6)
where \( \rho_{xc}(i) \) represents the correlation between \( x(t) \) and \( C_i(t) \) and \( \sigma_x \) and \( \sigma_{C_i} \) are the standard variances of \( x(t) \) and \( C_i(t) \), respectively.

(3) The reference correlation coefficient \( T \) is calculated.

The thresholding \( T \) can filter IMFs with small correlation coefficients. The thresholding \( T \) can be calculated as follows:
\[
T = \frac{1}{N} \sum_{i=1}^{N} \rho_{xc}(i).
\]
(7)
\( N \) is the number of IMFs. The \( i \)th IMF is selected when \( \rho_{xc}(i) > T \).

C. Improved IT

The wavelet thresholding denoising algorithm is effective in denoising noise in sEMG signals. The wavelet coefficients are modified when they are lower than the thresholding value. Stationary wavelet transform (SWT)-based denoising has been proven to derive good sEMG signals.\(^{30}\) Wavelet thresholding can be applied directly to EMD, but EMD direct thresholding (EMD-DT), whether hard or soft, can have catastrophic consequences.\(^{24}\)

IT is proposed to overcome the discontinuity of direct thresholding. We regard the samples from adjacent zero-crossing intervals as mode cells. In the interval \( Z_{(i)} = [x_{(i)}^c(x_{(i-1)}^c)] \) \( j = 1, 2, \ldots, N_i \), \( N_i \) is the sum zero-crossing number of the \( i \)th IMF, and \( x_{(i)}^c \) is the \( i \)th adjacent zero-crossing of the \( i \)th IMF. Hence, the method is translated into\(^{20}\)
\[
\tilde{C}_i(Z_{(i)}^c) = \begin{cases} 
C_i(Z_{(i)}^c) & \left| C_i(r_{(i)}^c) \right| > T_i \\
0 & \left| C_i(r_{(i)}^c) \right| \leq T_i
\end{cases}
\]
(8)
and
\[
\tilde{C}_i(Z_{(i)}^c) = \begin{cases} 
C_i(Z_{(i)}^c) & \left| C_i\left( e_{(i)}^c \right) \right| > T_i \\
0 & \left| C_i\left( e_{(i)}^c \right) \right| \leq T_i
\end{cases}
\]
(9)
for hard and soft thresholding, respectively. In the preceding formulas, \( C_i(r_{(i)}^c) \) represents the single extreme of the adjacent zero-crossing interval \( Z_{(i)}^c \), \( C_i(Z_{(i)}^c) \) denotes the sample amplitude from zero-crossing intervals \( Z_{(i)}^c \) to \( Z_{(i)}^c \), and \( \tilde{C}_i(Z_{(i)}^c) \) is the thresholded version of the \( i \)th IMF.

FIG. 2. (a) Clean sEMG signals (denoted as sEMG1) collected from the standard database. (b) Noisy sEMG signals.
A considerable difference exists between noise-only and noisy IMFs. The energy of IMF exhibits linear reduction in a semilog diagram. The energy of noise-only IMF can be calculated as follows:

$$E_i = \frac{E_0^2}{\beta^k}$$

where $E_i$ denotes the energy of the first IMF and the values of parameters $\beta$ and $k$ are set as 0.719 and 2.01, respectively.

Each IMF is corrupted by noise, thereby indicating that noise has a different energy in each IMF. Hence, thresholding is dependent on scaling and is a multiple of the universal thresholding of IMFs:

$$T_i = C\sqrt{\frac{E_i}{2 \ln N}}$$

where $C$ is a constant parameter. The best $C$ for CEEMD is 0.6–0.8. $C$ is 0.8–0.9 for translation invariant thresholding, as confirmed by our experiments. After the analysis, we set $C$ as 0.8.

The application of hard IT can have catastrophic consequences due to the discontinuity at the instant when $|C_i(r_i^j)| = T_i$. Certain effects cause the filtered reconstructed signal to oscillate randomly at the thresholding, which deteriorates the smoothness of the reconstructed signal. In contrast with hard IT, soft IT can reduce the effects of discontinuity. However, the constant deviation will decrease the signal-to-noise ratio (SNR) and increase the root-mean-square error (RMSE), thereby resulting in poor denoising performance.

The new threshold function established in this study can effectively compensate for the limitations of the hard and soft thresholding methods, which is defined as follows:

$$C_i(Z_j^i) = \begin{cases} C_i(Z_j^i)(1 - \frac{T_i}{|C_i(r_i^j)|})^{n} & |C_i(r_i^j)| > T_i \\ 0 & |C_i(r_i^j)| \leq T_i \end{cases}$$

where $n$ is a tunable parameter. $Z_j^i$ denotes the data of adjacent zero-crossing intervals. When $n$ is close to infinity, the improved IT is approximately hard IT. Similarly, the improved IT is soft IT when $n$ is set as 1. The function curve smoothens with a decrease in $n$. When the noisy signal contains numerous saltation points, the improved IT should be close to hard IT. Similarly, when the noisy signal is smooth, the improved IT should be close to soft IT. That is, the improved IT can exhibit the advantages of hard and soft IT. When an IMF represents a high-frequency component, a large $n$ is set to process this IMF.
TABLE I. Correlation coefficients between the original signal and each IMF.

<table>
<thead>
<tr>
<th>IMF component</th>
<th>Correlation coefficient</th>
<th>IMF component</th>
<th>Correlation coefficient</th>
</tr>
</thead>
<tbody>
<tr>
<td>IMF1</td>
<td>0.1749</td>
<td>IMF7</td>
<td>0.4183</td>
</tr>
<tr>
<td>IMF2</td>
<td>0.3550</td>
<td>IMF8</td>
<td>0.1675</td>
</tr>
<tr>
<td>IMF3</td>
<td>0.4172</td>
<td>IMF9</td>
<td>0.1160</td>
</tr>
<tr>
<td>IMF4</td>
<td>0.4681</td>
<td>IMF10</td>
<td>0.0017</td>
</tr>
<tr>
<td>IMF5</td>
<td>0.3602</td>
<td>IMF11</td>
<td>-0.0041</td>
</tr>
<tr>
<td>IMF6</td>
<td>0.4587</td>
<td>RES</td>
<td>0.0012</td>
</tr>
<tr>
<td>T</td>
<td>0.2161</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

D. Reconstruction of sEMG signal

The modified IMF is defined as \( \tilde{C}_i \), and the residual IMF is \( C_i \), where \( i \) is the order of IMFs. Hence, the sEMG signal \( \tilde{x}(t) \) is reconstructed as follows:

\[
\tilde{x}(t) = \sum_{q=1}^{m} \tilde{C}_i(q) + \sum_{p=1}^{N-m} C_i(p),
\]

where \( q \) is the number of modified IMFs and \( p \) is the number of IMFs. In residual IMFs with minimal noise energy, the first component, IMF1, is abandoned because the proportion of noise in IMF1 is considerable.

III. EXPERIMENT RESULTS

The clean signals (denoted as sEMG1 and sEMG2) were derived from the standard database with a sampling rate of 1000 Hz. White Gaussian noise was added to obtain a noisy sEMG signal. Figure 2 shows the clean and noisy sEMG (denoted as sEMG1) signals with 15 dB SNR.

A noisy sEMG signal \( x(t) \) is set as

\[
x(t) = s(t) + \delta n(t),
\]

where \( s(t) \) denotes the clean sEMG signal from the standard database, \( n(t) \) indicates white Gaussian noise, and \( \delta \) represents the scale factor of noise. The artificially noisy sEMG signals are quantified using the SNR levels, which vary from 1 dB to 25 dB to verify the performance of the proposed method.

The noisy signal (denoted as sEMG1) was decomposed via CEEMD. Figure 3 presents the result of 11 IMFs and RES.

FIG. 4. IMFs denoised through improved IT.
FIG. 5. Reconstructed and clean sEMG signals using different methods.

To further illustrate the selected IMFs, we obtained the thresholding using Eq. (7), where $T = 0.2161$. Table I reports the correlation coefficients between the noisy signal $x(t)$ and each IMF. The coefficients of IMFs 2, 3, 4, 5, 6, and 7 are higher than $T$. In addition, IMFs 2, 3, 4, 5, 6, and 7 are processed via improved IT. The results are presented in Fig. 4.

We used the EMD and EMD-IT methods in comparison with the proposed method. RMSE and SNR were introduced as evaluation

<table>
<thead>
<tr>
<th>SNR$_{in}$</th>
<th>EMD</th>
<th>SWT</th>
<th>EMD-DT</th>
<th>EMD-IT</th>
<th>Proposed method</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>[SNR$_{out}$ (dB)/RMSE]</td>
<td>[SNR$_{out}$ (dB)/RMSE]</td>
<td>[SNR$_{out}$ (dB)/RMSE]</td>
<td>[SNR$_{out}$ (dB)/RMSE]</td>
<td>[SNR$_{out}$ (dB)/RMSE]</td>
</tr>
<tr>
<td>1 dB</td>
<td>3.613/0.0535</td>
<td>4.276/0.0656</td>
<td>3.765/0.0762</td>
<td>3.988/0.0802</td>
<td>5.246/0.0746</td>
</tr>
<tr>
<td>5 dB</td>
<td>7.647/0.0265</td>
<td>8.995/0.0356</td>
<td>9.633/0.0452</td>
<td>14.321/0.0086</td>
<td></td>
</tr>
<tr>
<td>10 dB</td>
<td>12.858/0.0095</td>
<td>12.965/0.0070</td>
<td>15.865/0.0070</td>
<td>17.632/0.0043</td>
<td></td>
</tr>
<tr>
<td>15 dB</td>
<td>15.888/0.0067</td>
<td>17.423/0.0056</td>
<td>22.356/0.0032</td>
<td>25.124/0.0023</td>
<td></td>
</tr>
<tr>
<td>20 dB</td>
<td>21.231/0.0045</td>
<td>24.542/0.0025</td>
<td>28.795/0.0013</td>
<td>28.795/0.0013</td>
<td></td>
</tr>
<tr>
<td>25 dB</td>
<td>28.781/0.0015</td>
<td>24.542/0.0025</td>
<td>28.795/0.0013</td>
<td>28.795/0.0013</td>
<td></td>
</tr>
</tbody>
</table>
TABLE III. Comparison of the SNR\textsubscript{out} and RMSE of the denoised sEMG signal (sEMG2).

<table>
<thead>
<tr>
<th>SNR\textsubscript{in}</th>
<th>EMD (SNR\textsubscript{out} (dB)/RMSE)</th>
<th>SWT (SNR\textsubscript{out} (dB)/RMSE)</th>
<th>EMD-DT (SNR\textsubscript{out} (dB)/RMSE)</th>
<th>EMD-IT (SNR\textsubscript{out} (dB)/RMSE)</th>
<th>Proposed method (SNR\textsubscript{out} (dB)/RMSE)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 dB</td>
<td>3.864/0.0965</td>
<td>4.776/0.0885</td>
<td>4.765/0.0762</td>
<td>4.986/0.0802</td>
<td>5.793/0.0696</td>
</tr>
<tr>
<td>5 dB</td>
<td>7.421/0.0485</td>
<td>8.595/0.0311</td>
<td>8.395/0.0405</td>
<td>8.456/0.0373</td>
<td>9.986/0.0253</td>
</tr>
<tr>
<td>10 dB</td>
<td>12.967/0.0125</td>
<td>13.523/0.0113</td>
<td>13.786/0.0103</td>
<td>14.076/0.0099</td>
<td>15.541/0.0089</td>
</tr>
<tr>
<td>15 dB</td>
<td>17.097/0.0079</td>
<td>17.536/0.0060</td>
<td>16.385/0.0077</td>
<td>17.876/0.0065</td>
<td>18.976/0.0061</td>
</tr>
<tr>
<td>20 dB</td>
<td>22.576/0.0043</td>
<td><strong>24.750/0.0023</strong></td>
<td>23.565/0.0037</td>
<td>24.055/0.0029</td>
<td>24.542/0.0021</td>
</tr>
<tr>
<td>25 dB</td>
<td>25.567/0.0012</td>
<td>25.996/0.0011</td>
<td>25.372/0.0015</td>
<td>27.042/0.0061</td>
<td>26.005/0.0009</td>
</tr>
</tbody>
</table>

where \( x \) is the sEMG signal and \( \tilde{x} \) represents the denoised sEMG signal.

We used modified IMFs 2, 3, 4, 5, 6, and 7; the residual IMFs 8, 9, 10, and 11; and RES to reconstruct the sEMG signal using Eq. (13). Figure 5 presents the reconstructed sEMG and clean signals using different methods.

Tables II and III provide the denoising performance of the five methods with SNR\textsubscript{in} varying from 1 dB to 25 dB. The data before the brackets pertain to SNR\textsubscript{out}, whereas the remaining data denote RMSE. The denoising performance of all the methods remains stable throughout an increase in SNR\textsubscript{in}. However, the closer SNR\textsubscript{in} is to 25 dB, the worse the denoising performance of the EMD method. By contrast, the proposed method provides the best result compared with the other methods in nearly all the cases. Moreover, the RMSE of the proposed method is less than those of the other methods.

IV. APPLICATION EXPERIMENT OF sEMG SIGNAL DENOISING TO MOTION RECOGNITION

We verified the sEMG denoising method for motion recognition. The two sEMG channels were recorded from the flexor palmar and long palmar using a self-constructed signal acquisition system with a sampling frequency of 1000 Hz. As shown in Fig. 8, four motions of the upper limb, namely, hand open, hand close, wrist flexion, and wrist extension, were selected (Figs. 6 and 7).

Five features were extracted, namely, the integral of variance (VAR), Wilson amplitude (WAMP), zero crossing (ZC), mean frequency (MF), and energy of wavelet coefficient (EWT). The Gaussian kernel support vector machine (GK-SVM) was selected for classification.

Fig. 6. sEMG sensor placement.

Fig. 7. Four hand motions: (a) Hand open, (b) hand close, (c) wrist flexion, and (d) wrist extension.
TABLE IV. Recognition rates of raw and denoised sEMG signals (%).

<table>
<thead>
<tr>
<th>Motions</th>
<th>Raw sEMG</th>
<th>Denoised sEMG</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hand open</td>
<td>77.5</td>
<td>87.8</td>
</tr>
<tr>
<td>Hand close</td>
<td>76.2</td>
<td>85.6</td>
</tr>
<tr>
<td>Wrist flexion</td>
<td>78.5</td>
<td>87.9</td>
</tr>
<tr>
<td>Wrist extension</td>
<td>80.1</td>
<td>90.4</td>
</tr>
<tr>
<td>Average</td>
<td>78.1</td>
<td>87.9</td>
</tr>
</tbody>
</table>

The recognition results are presented in Table V. We observe that the direct application of raw sEMG has a negative effect. By contrast, the proposed method exhibits better performance in all the motions, particularly wrist extension. Moreover, the average accuracy rate of motion recognition was improved from 78.5% to 87.9% compared with the raw sEMG. The proposed method achieves better performance based on the aforementioned denoising result because it diminishes the noise component.32

V. DISCUSSIONS AND CONCLUSION

A CEEMD-based improved IT framework for denoising sEMG signals was presented and evaluated experimentally. As an extension of EMD, CEEMD adaptively separates nonlinear and nonstationary signals into several IMFs, which can represent different dynamic properties from various oscillation levels. CEEMD not only produces several more strictly band-restricted IMFs compared with EMD but also reduces the computational complexity of EEMD. Given that noise has different dynamic properties from useful components, noise can be removed easily from special band-restricted IMFs. To optimize the CEEMD-based framework, improved IT, which could adapt thresholding to specific IMFs, was proposed.

As shown in Fig. 5, the proposed method retains more useful information compared with the other methods. Furthermore, the comparison results of five different methods are presented in Tables II and III. Notably, the proposed method achieved better denoising performance at nearly all SNR levels. Evidently, the noise level influences the efficiency of the denoising methods. When SNR is high, the performance of the proposed method is unsatisfactory because noise distribution is dispersed in IMFs and the thresholding procedure is limited. To evaluate the denoising performance of the proposed method, we applied the method to motion recognition. The proposed method can considerably enhance recognition rates, as shown in Table IV. The analysis result can be valuable to many practical applications in which a clean sEMG signal is a prerequisite for applying sEMG.

We have demonstrated that the proposed method adopts a better denoising procedure, which improves denoising result. We propose a denoising framework for sEMG signals based on CEEMD, component correlation analysis, and improved IT. The process removes noise from noisy data via correlation coefficients and improved IT. We use CEEMD to decompose an sEMG signal into several IMFs. By performing component correlation analysis and improved IT on the identified IMFs, the denoised sEMG signal is reconstructed using the modified and residual IMFs. To demonstrate the effectiveness of the proposed method, we have conducted numerical experiments with different SNR values for the sEMG signal derived from the standard database. The result confirms that the proposed method exhibits better performance in terms of stability and continuity compared with EMD, SWT, EMD-DT, and EMD-IT. Finally, the proposed method is applied to motion recognition. The results show that the recognition rate of the denoised sEMG is higher than that of the raw sEMG.

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REFERENCES


