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Improved DTCWT-LMS and FastICA Based sEMG Signals Filtering

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Abstract

A novel design of dual-tree complex wavelet transform (DTCWT) and fastICA was proposed, aiming at the noise interference and aliasing between multi-channels sEMG signals. Firstly, DTCWT was utilized to decompose signals to different frequency band. Secondly, an improved LMS adaptive filter was designed for filtering sub band noise layer by layer. Finally, fastICA algorithm was introduced to separate crosstalk between channels. Some experiments were carried out to compare the proposed method with other algorithms, and the results showed that the algorithm proposed could filter noise effectively, keep better convergence especially in low signal-to-noise ratio and eliminate crosstalk more thoroughly by fastICA.

Keywords*: sEMG; dual-tree complex wavelet transform; subsection variable step size LMS; fastICA.*

1. Introduction

Surface electromyogram (sEMG) signals, recorded on the face of the skin, provides crucial information about the neuromuscular activity in muscle. Thus, sEMG signals can be used for the rehabilitation, prosthesis, sports training, ect [1-3]. But some problems need to be solved before the commercial applications. For one thing, sEMG signals are very weak, with an amplitude usually between 100~5000μV. Various noise such as artifacts and neuroelectrical excitement of non-measured muscles gathering at the skin-electrode could interface contaminate the signals[4], though high-precision measuring instruments are used. At the same time, the frequency spectrum collected by commonly used sensors ranges from 0 to 400Hz, and overlaps with several noise sources in the same low-frequency spectra. For another, multi-channel sEMG sensors are used widely for more information on different limb movements and there are much aliasing between multi-channels[5]. So it is necessary to design a specific filter to decrease such noise and represent the signal that matches better with the muscular function.

The adaptive interference cancellation is a very efficient method to solve the problem of the signal interference with overlapping spectra[6-7], especially for the interference in single or a kind of different narrow frequency band. The wavelet transform is a good method to divide the signals into different frequencies, and the wavelet transform-domain least mean square (WT-LMS) algorithm is proposed to reduce the common artifacts in nonstationary biological signals without removing significant information[8-10]. However, an important drawback of the wavelet transform is that, the distribution of energy between coefficients at different scales is very sensitive to the shifts in the input data[11-12].

In this study, an algorithm of complex wavelet transform-adaptive filter was proposed for filtering out noise and crosstalk between channels effectively. And a variable step size LMS was present. FastICA[13-14] as a separation method for multi-channel aliasing signals with no inhibitory effect on noise, was used to separate multi-channel sEMG signals. At last, denoising performance of dual tree complex discrete wavelet transfor-domain subsection variable step size LMS (DTCWT-SMVSS) proposed in this paper was compared with other algorithms. Experiments shown the satisfied results in sEMG signals test.

2. Background Matherials

2.1.s MVSS Algorithm

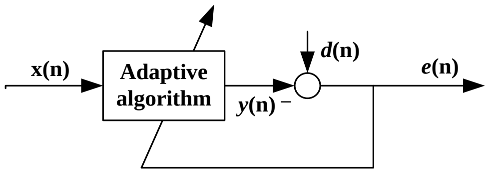


Figure 1. Structure of the Adaptive Filter

Figure 1 shows a typical adaptive filter, where $x(n)$, $d(n)$ and $e(n)$ are the references, corrupted and output error signals respectively. $d(n)$ is composed of the desired signal $s(n)$ and noise signal $v_0(n)$, which is additive and not correlated with $s(n)$. Likewise, $x(n)$ is uncorrelated with $s(n)$ and correlated with $v_0(n)$. So the output of the filter $y(n)$ is a close estimate of $v_0\,(n)$. Here, $w(n)$ is the filter coefficients.

Then the error signal is defined as

$$e(n) = d(n) - x(n)w^T(n) \tag{1}$$

and the $w(n)$ is updated as follow

$$w(n+1) = w(n) + \mu(n)e(n)x(n) \tag{2}$$

where $\mu(n)$ is the step size of the algorithm which controls the stability and the convergence rate. It is updated as follow[15]

$$p(n) = \beta p(n) + (1-\beta)e(n)e(n-1) \tag{3}$$

$$\mu(n+1) = \begin{cases} \mu_{\min} & \mu(n+1) < \mu_{\min} \\ \mu_{\max} & \mu(n+1) > \mu_{\max} \\ \lambda\mu(n) + \gamma p^2(n) & else \end{cases} \tag{4}$$

Where $p(n)$ is the mean time estimation of $e(n)e(n\text{-}1)$; β, $0<\beta<1$, is error forgetting factor; λ, $0<\lambda<1$, is step regulatory factor, which decides the step size at convergence, and γ, $\gamma>0$, decides the influence degree of step, controls the algorithm's imbalame and covergence speed, and.

2.2. Dual Tree Complex Wavelet Transform

The structure of DTCWT, giving real and imaginary parts of complex coefficients from primary and secondary tree respectively, is shown in Figure 2.

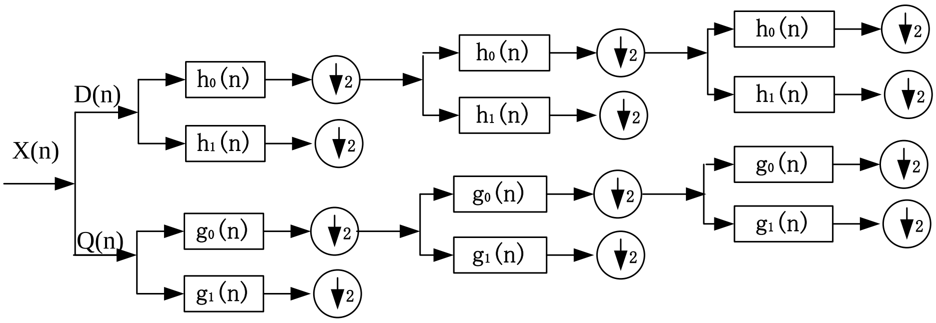


Figure 2. DT-CWT Filterbank

It consists of two DWT filter banks, and each pair of lowpass and highpass filters is imposed the half sample delay condition. This enables high directional selectivity and approximately shift-invariance[10]. h_0(n) and $g_0(n)$ are two low pass filters, and similarly, $h_1(n)$ and $g_1(n)$ are two high pass filters. They should satisfy that[11]

$$g_0(n)= h_0(n\text{-}0.5) \tag{5}$$

and

$$X(n) = D(n) + jQ(n) \tag{6}$$

where $D(n)$ is in-phase and $Q(n)$ is quadrature phase components of the siganl. They can also be represented in terms of the directienal signals as

$$\begin{aligned} D(n) &= \pm S_f(n) \pm H\left[S_r(n)\right] \\ Q(n) &= \pm H\left[S_f(n)\right] \pm S_r(n) \end{aligned} \tag{7}$$

where $S_f(n)$ and $S_r(n)$ represent forward and reverse signals respetively and H[] stands for the Hilbert transform. The information concerning on flow direction is encoded in the phase relationship between $D(n)$ and $Q(n)$.

2.3. FastICA algorithm

ICA is a statistical method for transforming an observed multidimensional random vector into components as statistically independent as possible[14]. As sEMG signal is Non-Gaussian signal and each channel is statistically independent, it satisfies the requirement of ICA completely.

$X = AS$ where $X = [x_1, x_2, \cdots, x_m]^T$ is a m- imensional aliasing signals, $S = [s_1, s_2, \cdots, s_n]^T$ is a zero-mean unknown independent signals, and A is a $m \times n$ reversible matrix.

The main goal of ICA is to find the matrix W such that Y=WZ ($Y = [y_1, y_2, \cdots, y_n]^T$ is an approximation signal of S and $Z = [z_1, z_2, \cdots, z_n]^T$ is the centralization and whitening result of X) becomes as independent as possible.

The concrete steps are

A. let $W = W / \sqrt{\|WCW^T\|}$ and $C = E\{zz^T\}$;

B. let $W = \frac{3}{2}W - \frac{1}{2}WCW^TW$;

C. repeat 2. until convergence.

3. DTCWT-SMVSS Algorithm for sEMG Filtering

3.1. Algorithm Structure

The corrupted $d(n)$ is the signals collected by skin-electrode interface, and consisted of the pure sEMG signal $s(n)$ and various noise signals $v_0(n)$. The reference $x(n)$ is the error of $d(n)$ reconstruction, which is connected with $v_0(n)$ and independent with $s(n)$. The ouptut of the whole algorithm is $\hat{s}(n)$, which is an optimal estimate of $s(n)$. The stucture of proposed DTCWT-SMVSS algorithm is shown in Figure 3.

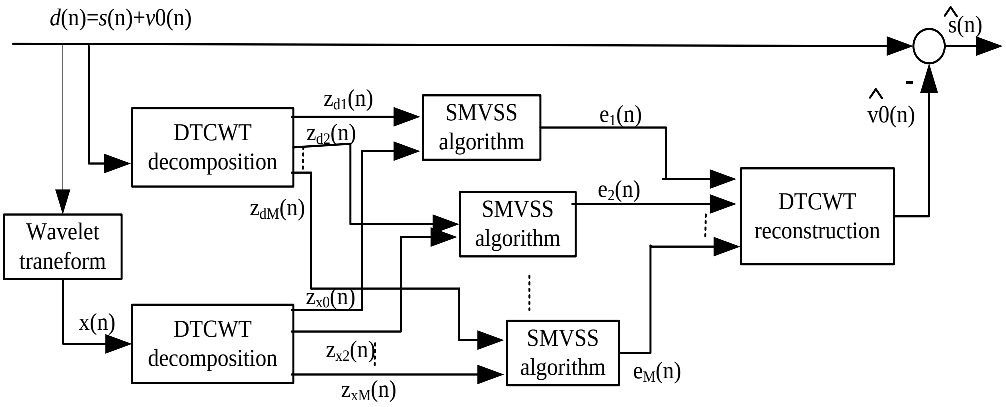


Figure 3. The Structure of Proposed DTCWT-SMVSS Algorithm

3.2. Signals Decomposition and Reconstruction

Although the frequencies of several noise overlap with that of the sEMG signals, by decomposing with the corrupted signals the noise spectral range is greatly narrowed in each packet, which is good for adaptive filter to get optimized step size.

Let

$$d(n) = [d(n), d(n-1), \cdots, d(n-N+1)]^T \tag{8}$$

and

$$x(n) = [x(n), x(n-1), \cdots, x(n-N+1)]^T \tag{9}$$

be the corruped and reference signal vector. For the first step, they should be decomposed respectively. As the DTCWT consists of a pair of DWT trees, each representing real and imaginary parts of the transform, and in both DWTs all the filters are real, so

$$z_{dj}(n) = \left[z_{dr}^{j}(n), z_{di}^{j}(n) \right] \tag{10}$$

$z_{dr}^{j}(n)$ is the real part of the decomposition result of d(n) in the j^{th} subfilter, $z_{di}^{j}(n)$ is the imaginary part, and the same to

$$z_{xj}(n) = \left[z_{xr}^{j}(n), z_{xi}^{j}(n) \right], \tag{11}$$

which is the decomposition result of $x(n)$ in the j^{th} subfilter. If the signals is decomposed L-band, the number of adptive filters is L.

For descripion clearly, let $z_x(n)$=[$z_{x1}(n)$, $z_{x2}(n)$,…, $z_{xL}(n)$]^T, $z_d(n)$=[$z_{d1}(n)$, $z_{d2}(n)$,…, $z_{dL}(n)$]^T, and $e(n)$=[$e_1(n)$, $e_2(n)$,…, $e_L(n)$]^T, then $z_{xi}(n)$, $z_{di}(n)$ and $e_i(n)$ are the reference, corrupted and output signal of the i^{th} subfilter(0<i<L), respectively. The output of DTCWT reconstruction is $\hat{v}_0(n)$, which is a close estimate of $v_0(n)$.

3.3. SMVSS Agorithm

The corrupted and noise signals result in that the frequency range of decomposed signals is in a very narrow band. The adaptive filter could have better filtering performance when the noise is of single or narrow frequency band. But it is difficult to find a perfect step size for every filter to get satisfied filtering effect, and there is a contradictory relation between convergence speed and steady performance.

Let $w_i(n)$ be the i^{th} subfilter coefficients, so the error signal is designed as $e_i(n) = z_{di}(n) - w_i^T(n) z_{xi}(n)$, and the updating equation for each subfilter is improved

$$w_i(n+1) = w_i(n) + \mu_i(n) e_i(n) z_{xi}(n), \tag{12}$$

$$p_{i1}(n+1) = \beta_1 p_{i1}(n) + (1-\beta_1)\left|e_i(n) e_i(n-1)\right|, \tag{13}$$

$$p_{i2}(n+1) = \beta_2 p_{i2}(n) + (1-\beta_2)\left|e_i(n) - e_i(n-1)\right|, \tag{14}$$

$$p_i(n+1) = \begin{cases} p_{i1}(n+1) & p_{i1}(n+1) > p_{i2}(n+1) \\ p_{i2}(n+1) & else \end{cases}, \tag{15}$$

$$\mu_i(n+1) = \alpha \mu_i(n) + \gamma p_i(n+1) \tag{16}$$

At the beginning of the algorithm or there is a break in the signal, a bigger $\mu_i(n)$ is needed for improving convergency rate. But $\left|e_i(n) e_i(n-1)\right|$ is smaller than $e_i(n)$ or $e_i(n-1)$, even though (1-β_i) is bigger, because $e_i(n)$ and $e_i(n-1)$ are both smaller than 1. But $\left|e_i(n) - e_i(n-1)\right|$ is bigger than $\left|e_i(n) e_i(n-1)\right|$ at that moment, so p_{i2}>p_{i1}, so the same to the other situation. When the signals is to be flatten, $e_i(n)$ is smaller, $\left|e_i(n) - e_i(n-1)\right|$ is smaller than $\left|e_i(n) e_i(n-1)\right|$.

4. Experimental Analysis

4.1. The Results of DTCWT-SMVSS Filtering

For verifying the efficiency of algorithm proposed in this paper and comparing the filter performance with other previous ones, we simulated a pure sEMG signal with gaussian white noise, and the results were evaluated by the signal to noise ratio (SNR) and similarity degree of waveforms (η). They are

$$SNR = 10\lg \frac{\sum_{i=1}^{N} s^2(i)}{\sum_{i=1}^{N}\left(s(i) - \hat{s}(i)\right)^2} \tag{17}$$

$$\eta = \frac{\sum_{i=1}^{N} s(i) * \hat{s}(i)}{\sqrt{\sum_{i=1}^{N} s^2(i) * \sum_{i=1}^{N} \hat{s}^2(i)}} \tag{18}$$

where $s(i)$ is original signal without noise, $\hat{s}(i)$ is the signal after being filted, N is signal length. So the bigger the SNR is, the better the filtering performance is. $\eta(-1 \le \eta \le 1)$, which -1 means the two waveforms in comparing are completely opposite; 0 means they are orthogonal; and 1 means they are same.

In the aspect of parameters optimization, DTCWT-SMVSS was at (L=6, β_1=0.8, β_2=0.85, α=0.3, γ=0.3), while with other algorithms, such as WT-LMS (L=6, μ=0.01), WT-SMVS (L=6, β=0.8, α=0.3, γ=0.3), and DTCWT-LMS (L=6, μ=0.05). The SNR and η were computed as proportion of noise changed, and the results were shown in Table 1.

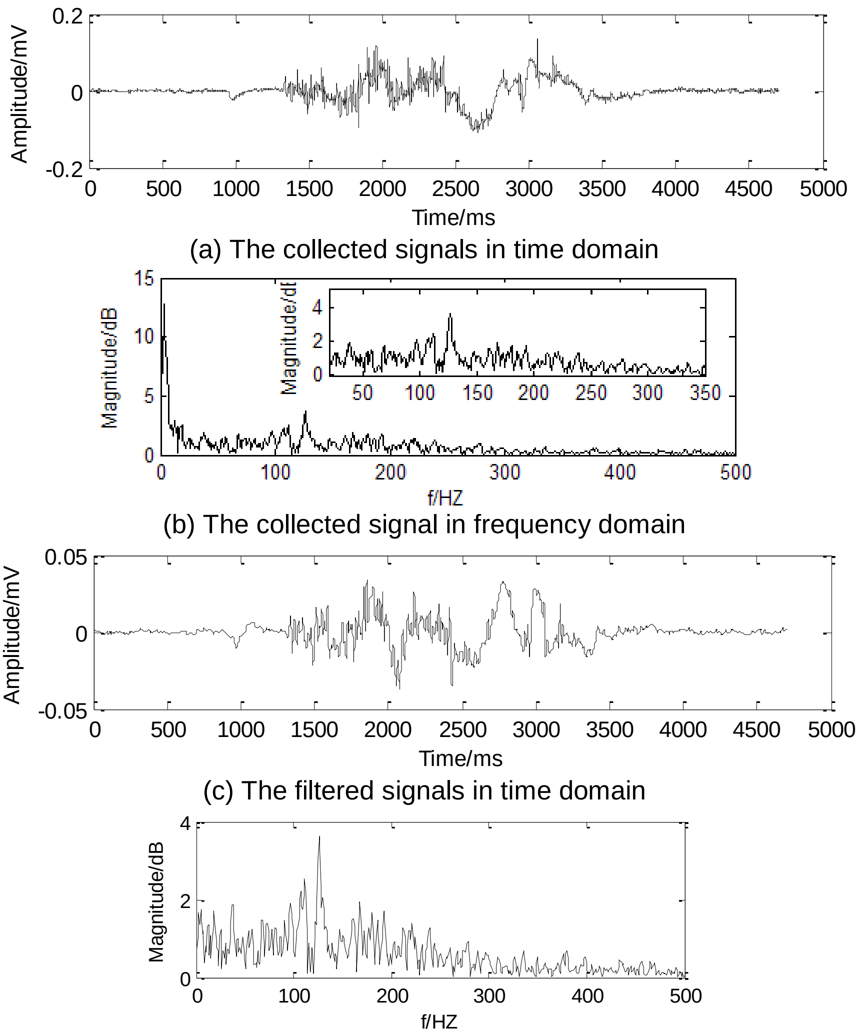
Table 1. The Comparison Result of Some Algorithms

SNR before filting		WT_ LMS	WT- SMVS	DTCWT_ LMS	DTCWT_ SMVS	DTCWT_ SMVSS
24.0320	SNR	13.3702	24.0501	32.4064	35.0928	47.7289
(0.3)	η	0.8587	0.9576	0.9803	0.9852	0.9958
10.3867	SNR	12.4301	10.4281	30.8340	24.1128	37.9520
(0.6)	η	0.8436	0.8587	0.9769	0.9571	0.9888
1.8337	SNR	12.9731	1.8719	27.4693	15.8505	28.9716
(0.9)	η	0.8533	0.7387	0.9677	0.9099	0.9731

From Table 1. it can be seen that, with the decreasing of SNR before filting, the proportion of noise increased, and the SNR and η decreased for all algorithms. But due to the condition that other parameters were always unvaried, the method proposed in this paper has best SNR and η for all the time with η>0.97, especially when noise was bigger. Also, WT-SMVS and DTCWT-SMVS were not suitable for sEMG signals, and the step μ depended on $\mu_{\min}$ for most time. So when the noise increased, the SNR decreased quickly. WT-LMS and DCTWT-LMS were computed the fasted, but it was difficult to find a good μ for them.

4.2. Actually Signal Experiments

To verify the effectiveness of the algorithm, many experiments have been conducted with the sEMG equipment of Thought Technology Ltd, and the sampling rate is 500Hz. Subjects were asked their consent prior to the experiment and to fill in a brief questionnaire concerning personal data, such as age, gender, height, weight, laterality and self-reported health status. The skin of the subjects was carefully cleaned with isoprogyl alcohol. Before the experiments, the subject stands naturally and relaxed without vigorous exercise. Four electrods were palpated on pronator teres, brachioradialis, biceps brachii and deltoid during the arm moved repeatedly. To ensure a consistent start and end position, repetition was alternated with a rest posture lasting approximately 1s.



(a) The collected signals in time domain

(b) The collected signal in frequency domain

(c) The filtered signals in time domain

(d) The filtered signal in frequency domain

Figure 5. The Filtering Results of Some Algorithms

A part of collected signal is shown in Figure 5. It can be seen that the artifacts was obvious in (a) and the low frequency interference was strong. After filtering the artifacts was removed and the noise was reduced greatly as shown in (c), the frequency spectrum of filtered signal is nearly the same as (b), which means that the frequency in main band was almost lossless after filtering.

4.2. FastICA Experiment Results

There are two uncertainties in ICA, namely the sequence of output vector, which means the corresponding relationship between signals and muscles could not be gotten, and the amplitude of output vector, which the real energy information of muscles movement could not be available.

Therefore the maximum correlation coefficient between the fastICA component and source signals was used in this paper. At the first stage, the STCWT-SMVSS was used to filter most noise. Then fastICA was used to separate multi-channel. Figure 6 is the collected multi-channel signals, and the channels from (a) to (d) are the signals of pronator teres, brachioradialis, biceps brachii and deltoid respectively. Figure 7 shows the corresponding fastICA results. The correlation coefficient between four channels sEMG signals is shown in Table 2.

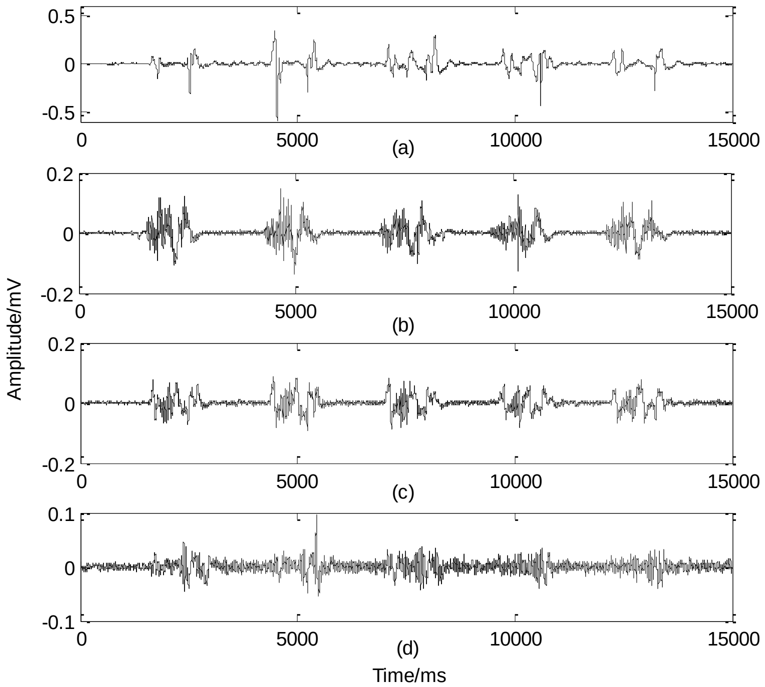


Figure 6. Collected Signals from Four Channels (from (a) to (d) are the Signals of Pronator Teres, Brachioradialis, Biceps Brachii and Deltoid Respectively)

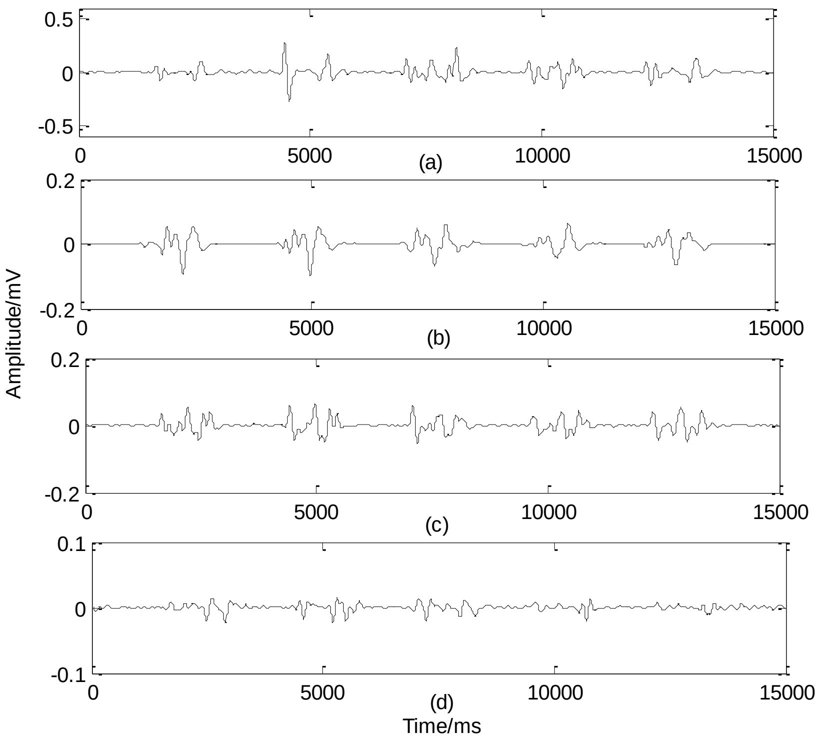


Figure 7. The Results of FastICA (from (a) to (d) are the Signals of Pronator teres, Brachioradialis, Biceps Brachii and Deltoid Respectively)

Table 2. The Correlation Coefficient between Four Channels sEMG Signals

	Before fastICA				After fastICA			
Cha.	a	b	c	d	a	b	c	d
a	1.000	-0.138	0.405	0.081	1	3.072e-15	1.053e-16	-8.067e-16
b	-0.138	1.000	-0.338	-0.132	3.072e-15	1	5.530e-16	-2.285e-15
c	0.405	-0.338	1.000	0.034	1.053e-16	5.530e-16	1	9.523e-16
d	0.081	-0.132	0.034	1.000		-8.067e-16	-2.285e-15	9.523e-16

From table2 it can be illustrated that, the crosstalks in collected signals between channel (a) and (c), (b) and (c), (c) and (d) were obvious, corresponding to the arm motion. After fastICA the correlation coefficients between any two channels approached to 0, meaning there was no crosstalk in each channel.

5. Conclusion

The basic premise for accurately analysis sEMG required noise and crosstalk filtered effectively in collected sEMG signals. A new method was proposed by combining DTCWT-- subsection variable step size LMS and fastICA. The experiments have shown that the method, DTCWT_SMVSS, was robust with white noise and work well even for the case of low SNR, and the crosstalk was eliminated more thoroughly by fastICA after filtering.

References

[1] M. Khezri and M. Jahed, “A Neuro-fuzzy Inference System for sEMG-based Identification of Hand Motion Commands”, IEEE Transactions on industrial electronics., vol. 5, no. 58, **(2011)**.
[2] L. A. Rivera and G. N. DeSouza, “Recognizing Hand Movements from a Single sEMG Sensor Using Guided under-Determined Source Signal Separation”, Proceedings of IEEE Internation Conference on Rehabilitation Robotics, , Zurich, Switzerland, **(2011)** June 29-July 1.
[3] S. Kwon, Y. Kim and J. Kim, “Movement Stability Snalysis of Surface Electromyography- Based Elbow Power Assistance”, IEEE Transactions on Biomedical Engineering, vol. 4,no. 61, **(2014)**.
[4] C. J. D. Luca, L. D. Gilmore, M. Kuznetsov and S. H. Roy, “Filtering the Surface EMG Signal: Movement Artifact and Baseline Noise Contamination. Journal of Biomechanics, vol. 43, **(2010)**.
[5] X. G. Xi, H.G. Zhu and Z.Z. Luo, “De-noising Method of the sEMG Based on EEMD and Second Generation Wavelet Transform”, Chinese Journal of Sensors and Actuators, vol. 11,no. 25, **(2012)**.
[6] X. Z. Fu, Z. Liu, S. L. Hu and Z. K. Liu, “Variable Step-size LMS Adaptive aAgorithm and its Application in Time Delay Estimation for Low SNR”, Journal of Central South University (Science and Technology).vol. 3, no. 43, **(2012)**.
[7] S. Attallath, “The Wavelet Transform-Domain LMS Adaptive Filter with Partial Subband-Coefficient Updating”, IEEE Transactions on Circuits and Systems- Ⅱ:Express Briefs., vol.1, no.53, **(2006)**.
[8] L. Smital, M. Víek, JiříKozumplík and I. Provazník, “Adaptive Wavelet Wiener Filtering of ECG Signals”, IEEE Transations on Biomedical Engineering, vol. 2, no. 60, **(2013)**.
[9] Z. Yang, G. Luo and Z. P. Fan, “Application of Wavelet Scalogram Threshold Algorithm in Electromyo-Graphy of Diaphragm Denoising”, Journal of Signal Processing, vol. 5, no. 29, **(2013)**.
[10] I.W. Selesnick, R. G.Baraniuk and N. G. Kingsbury, “The Dual-Tree Complex Wavelet Transform”, IEEE Signal Process, vol. 22, **(2005)**.
[11] G. Serbes and N. Aydin, “Symmetrical Modified Dual Tree Complex Eavelet Transform for Processing Quadrature Doppler Ultrasound Signals”, Proceedings of the 33rd Annual International Comference of the IEEE EMBS Boston, Boston,USA, **(2011)** August30-September 3.
[12] N.G. Kingsbury, “Complex Eavelets for Shift Invariant Analysis and Filtering of Signals”, Journal of Applied and Computational Harmonic Anslysis, vol. 3,no. 10, **(2001)**.
[13] A. Hyvärinen, “Fast and Robust Fixed Point Algorithms for Independent Component Analysis”, IEEE Transactions on Neural Network, vol. 2, no. 28, **(1999)**.
[14] X. R. Cao and R. Liu, “General Approach to Blind Source Separation”, IEEE Transactions on Signal Processing, vol. 3, no. 44, **(1996)**.
[15] T. Aboulnasr and K. Mayyas, “A Robust Variable Step-size LMS Algorithm: Analysis and Simulation”, IEEE Trans on Signal Processing, vol. 3,no. 45, **(1997)**.

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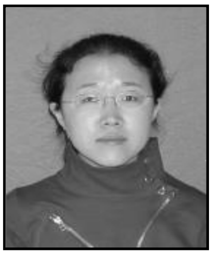

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