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Wavelet Transform and Independent Component Analysis Application to Multi-channel SEMG Processing

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***Abstract*—Multi-channel Surface Electromyography (SEMG) always interfere each other while being acquired, which would distort the source SEMG feature. The new method of SEMG processing is put forwarded to eliminate the signal interference between multi-channel SEMG by combining the wavelet transform with the independent component analysis (ICA). In this method, some noise is removed from the raw SEMG first which are reconstructed again for the observed signals of ICA. Then, the observed signals are separated blindly by using Infomax algorithm. Finally, this paper induces correlation coefficient to judge the consistency of the outputs in ICA with the source SEMG. The experimental results indicate that this method is an effective way to separate multi-channel SEMG.**

I. INTRODUCTION

SURFACE electromyography (SEMG) signal is biological electricity signal associated with intramuscular activity, which contains plenty body movements information [1]. At present, SEMG signals have been widely applied in clinical diagnosis, bioelectricity feedback, sports training and other domain, especially in the control of artificial limb movements [2].

In the application to the bionic control of artificial limb, it is indispensable to collect multi-channel SEMG signals recorded on the skin surface of forearm muscle by multi electrodes. In the process of SEMG signal collection, different channel signal often interferes each other, so that the signal each electrode obtained is a different combination of their own source signals. Thus, each channel SEMG signal can not reflect their own underlying feature, which brings inconvenience to the bionic control of artificial limb, even makes a wrong result. This appearance is inevitable in the process of signal collection, and the signal interference can not be easily cancelled by normal de-noising method because of their overlapping spectra in many frequency range. However, Independent Component Analysis (ICA) is an effective way to separate such multi-channel signals blindly [5].

ICA is a signal processing technique originating from the field of blind source separation which recovers “source” from several observed mixtures without prior knowledge about the mixture. ICA has been widely used in many fields such as biomedical signal processing, speech processing and communication. At present, Infomax algorithm which is presented by Linsker [3] is one of the most effective and conventional algorithms. In this paper, Infomax algorithm will be discussed to separate multi-channel SEMG signals in detail.

II. METHODS AND PRINCIPLES

A. ICA Mathematical Model

The implementation of ICA decomposition is shown as Fig.1.

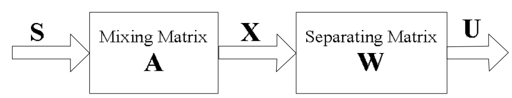


Fig. 1 ICA mathematical model

Seen from Fig.1, the signal mixing model can be defined as follows

$$X = AS \tag{1}$$

Where, $S = [s_1, s_2, \cdots, s_N]^{\mathrm{T}}$ are the source signals that can not be directly observed, and $X = [x_1, x_2, \cdots, x_M]^{\mathrm{T}}$ are the observed signals. These observed signals are obtained at the output of a set of sensors, where each sensor receives a linear combination of source signals which are statistical independency in every disperse time. Then, the ICA mathematical model is below [4] [5]

$$X = AS = \sum_{j=1}^{N} a_j s_j + n(i) \tag{2}$$

Where $A = [a_1, a_2, \cdots, a_N]$ represents a $M \times N$ unknown mixing matrix, in order to facilitate the analysis, here makes $M = N$. $n(i)$ denotes noise which is neglected frequently in the model, because ICA is impossible to remove noise from source signals. Thereby, the mathematical model ICA often adopted is

$$X = AS = \sum_{j=1}^{N} a_j s_j \ . \tag{3}$$

Before applying ICA to signals, it is better to preprocess the signals with a whitening method. After this preprocessing with a linear transformation of the observed signals, the means of signals are zero the variances are one. The implementation of ICA is seeking for a separating matrix W to make $U(U=WX)$ be the optimal approach to S without prior knowledge about A and S .

B. Wavelet Decomposing and Reconstruction

SEMG signal is a nonlinear and non-stationary random signal, which is extremely weak and easily contaminated by noise from power, measuring instrument, and electromagnetic signals. Seen from equation (3), ICA algorithm is a non-noisy model. Before applying ICA to signals, it is better to remove these noise. So, this paper tries to use the theory of wavelet decomposing and reconstruction which is based on multiresolution analysis of wavelet transform to resolve the problem. The theory of wavelet transform related in this paper can refer to Ref. [6].

With the wavelet multiresolution analysis, the amplitude of useful signal increases as scales increase, whereas the wavelet coefficients of the noise weaken rapidly as scales increase. Thus, the energy of SEMG noise concentrates in small scales. In order to remain the effective ingredient of SEMG signal to its limit, the wavelet coefficients in the big scales were remained, and the wavelet coefficients in the small scales such as 1-scale and 2-scale were de-noised by soft-thresholding method, then a new SEMG signal is reconstructed again with these wavelet coefficients. Do it in this way, not only remains the information of SEMG source signal but also removes the noise, which brings convenience to the following ICA. Now, the arithmetic to wavelet decomposing which is presented by Mallat is given as below [6].

$$\begin{aligned} c_{j,k} &= \sum_m h(m-2k)c_{j-1,k} \\ d_{j,k} &= \sum_m g(m-2k)d_{j-1,k} \end{aligned} \tag{4}$$

Where, $c_{j,k}$, $d_{j,k}$ indicates scale coefficient and wavelet coefficient respectively in j scale space, $h(n)$ and $g(n)$ is filter coefficient. Thus, the arithmetic to wavelet reconstruction of Mallat as the formula (5) shows [6].

$$c_{j-1,m} = \sum_k c_{j,k}h(m-2k) + \sum_k d_{j,k}g(m-2k) \tag{5}$$

Fig. 2 shows a raw SEMG signal with 5-scale wavelet transform. Where, x_0 is SEMG signal collected, and $x_0{}'$ is a new signal reconstructed from the wavelet coefficient of 1 to 2 scale which de-noised by soft threshold first and the wavelet coefficient of 3-scale to 5-scale.

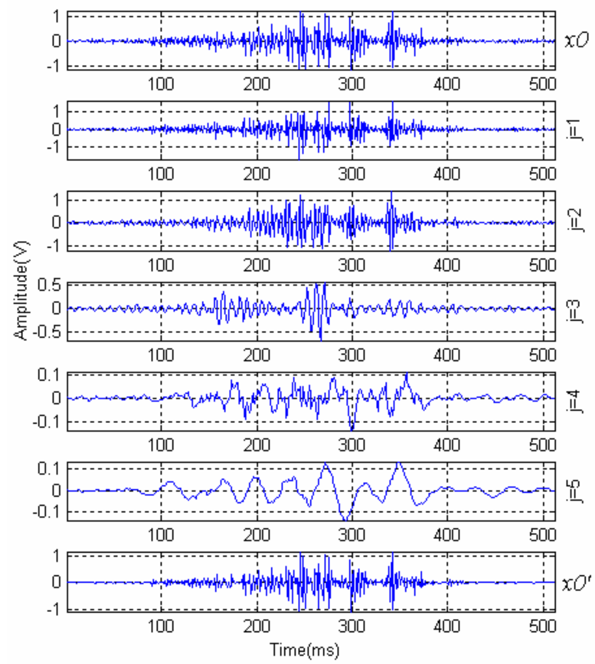


Fig. 2 Wavelet decomposing of SEMG

C. Infomax Algorithm

Infomax algorithm [3] which based on information theory is an adaptive learning of neural networks method, and algorithm structure shows as Fig. 3.

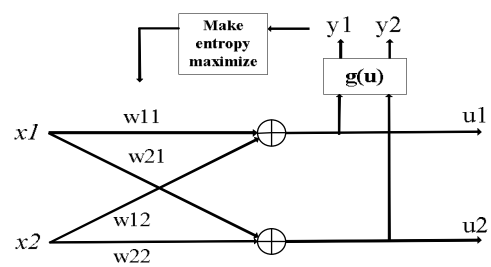


Fig. 3 Infomax algorithm structure

As information theory defines, the mutual information between input X and output Y is given as below

$$I(Y,X) = H(Y) - H(Y \mid X). \tag{6}$$

Where, $H(Y)$ denotes output entropy, and $H(Y \mid X)$ denotes conditional entropy which presents the entropy but not coming from the input. Take noise for instance, $Y=\psi(X)+n$, then, $H(Y \mid X)=H(n)$. Mutual information is often positive, so minimum of mutual information equivalent to maximum of output entropy. Entropy defines as follows

$$H(Y) = -E\{\ln P_Y(Y)\} = -\int_{-\infty}^{\infty} P_Y(Y)\ln P_Y(Y)dY \tag{7}$$

Where $P_Y(Y)$ is probability density function of Y . Moreover $Y=g(U)$, $g(\bullet)$ is a nonlinearly monotonic function. Then,

$$P_Y(Y)=\frac{P_X(X)}{|J|} \tag{8}$$

Where J denotes Jacobian determinant of separating matrix.

$$J=\det\begin{bmatrix}\frac{\partial y_1}{\partial x_1}\cdots\frac{\partial y_1}{\partial x_N}\\ \vdots \\ \frac{\partial y_N}{\partial x_1}\cdots\frac{\partial y_N}{\partial x_N}\end{bmatrix}=(\det W)\prod_{i=1}^{N}\frac{\partial y_i}{\partial u_i} \tag{9}$$

Here, $g(\bullet)$ choices sigmoid function. As $y_i=\frac{1}{1+\exp(-u_i)}$, we can transform equation (9) as follows

$$J=(\det W)\prod_{i=1}^{N}y_i(1-y_i) \tag{10}$$

Then we can get $H(Y)$ from equation (8) and (7)

$$H(Y)=E[\ln|J|]-E[\ln P_X(X)] \tag{11}$$

As equation (11) shows, $H(Y)$ varies as $E[\ln|J|]$ when X is known, i.e. $H(Y)$ varies as W. So, we can get ΔW from equation (8) and (7).

$$\Delta W\propto\frac{\partial H}{\partial W}=\frac{\partial}{\partial W}\ln|J|=\frac{\partial}{\partial W}\ln|\det W|+\frac{\partial}{\partial W}\ln\prod_{i=1}^{N}y_i(1-y_i) \tag{12}$$

W is developed in row i : $W=\sum_j w_{ij}A_{ij}$, A_{ij} is algebraic cofactor corresponded to element. Because of $\frac{\partial}{\partial w_{ij}}\ln|\det W|=\frac{A_{ij}}{\det W}$, then

$$\frac{\partial}{\partial W}\ln|\det W|=\frac{(W^*)^{\mathrm{T}}}{\det W}=\left[W^{\mathrm{T}}\right]^{-1}. \tag{13}$$

Where, W^* is adjoint of W.

We can transform the second polynomial of equation (12) and get follow equation

$$\frac{\partial}{\partial W}\ln\prod_{i=1}^{N}y_i(1-y_i)=(1-2Y)X^{\mathrm{T}}. \tag{14}$$

Sum up:

$$\Delta W\propto\left[W^{\mathrm{T}}\right]^{-1}+(1-2Y)X^{\mathrm{T}}. \tag{15}$$

Then we get the iterative algorithm to get the separating matrix W,

$$W_{k+1}=W_k+\Delta W_k. \tag{16}$$

We can train the neural network based on equation (16) until it finally comes to the convergence, and obtain the separating matrix W.

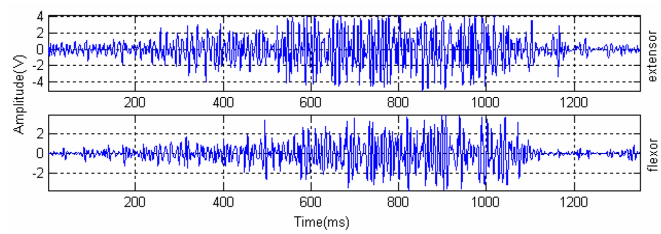
III. Experimental Results and Analysis

The experiment system is composed of SEMG signal preprocessing instrument, National Instruments data gathering card 6024E and Labview system. Before experiment, we chose a pair of SEMG collection electrodes and adhere them to the suitable positions of extensor and flexor of twist of healthy testees respectively. SEMG signals are amplified and filtered with a band of 10-500 HZ, and then transformed into digital signals at sampling frequency of 1 KHZ.

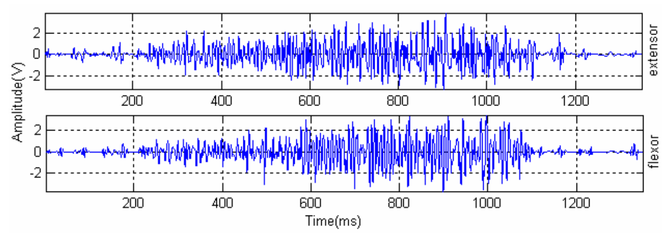
In order to facilitate the comparison, we make the experiment and analysis when extensor and flexor in the different muscle state.

A. The Experiment of Extensor and Flexor Contraction

SEMG signals are recorded from extensor and flexor under holding a fist, then cut off 1350 samples which include this action to rebuild observed signals. In Fig.4, (a) shows a pair of observed signals under holding a fist, (b) shows tow components separated by Infomax algorithm of ICA.



(a)

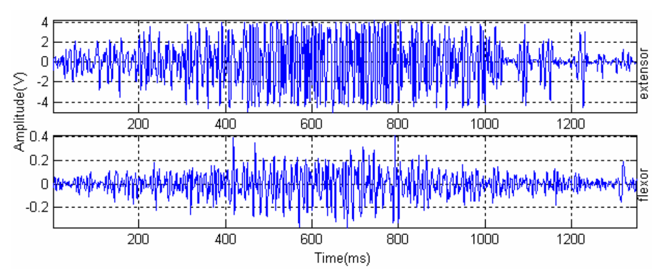


(b)

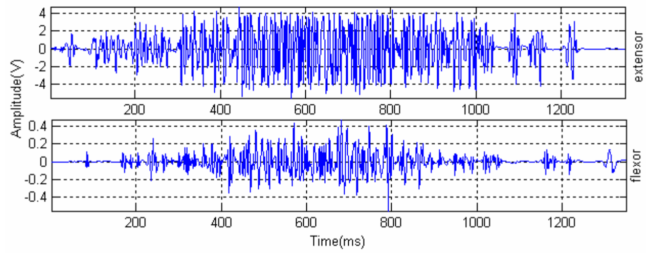
Fig. 4 (a) A pair of observed signals under holding a fist
(b) Tow components of ICA

B. The Experiment of Extensor Contraction but Flexor Relaxation

SEMG signals are recorded from extensor and flexor under extending twist, then cut off 1350 samples which include this action to rebuild observed signals. In Fig.5, (a) shows a pair of observed signals of under extending twist, (b) shows tow components separated by Infomax algorithm of ICA.



(a)

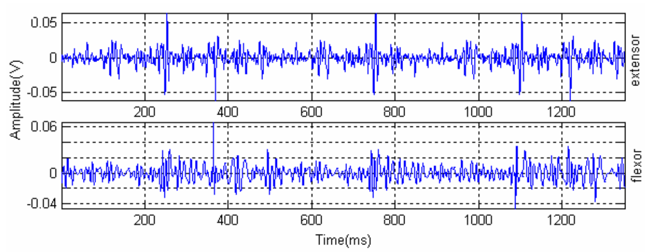


(b)

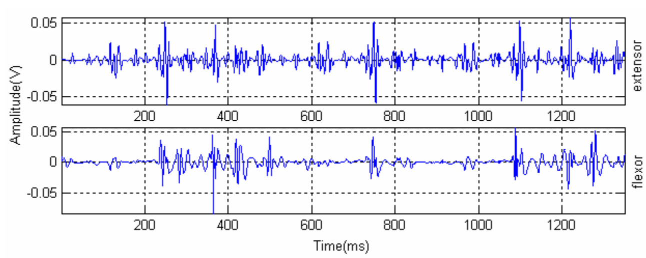
Fig. 5 (a) A pair of observed signals under extending twist
(b) Tow components of ICA

C. The Experiment of Extensor and Flexor Relaxation

SEMG signals are recorded from extensor and flexor under static posture of relaxant forearm, then cut off 1350 samples randomly to rebuild observed signals. In Fig.6, (a) shows a pair of observed signals of under relaxant forearm, (b) shows tow components separated by Infomax algorithm of ICA.



(a)



(b)

Fig. 6 (a) A pair of observed signals under relaxant forearm
(b) Tow components of ICA

In order to judge the consistency of the outputs in ICA with the source signals and the degree of signal interference removing between these pairs of observed signals, cross-correlation coefficient of signal vector and matrix vector are induced in this paper.

TABLE I
THE CROSS-CORRELATION COEFFICIENT OF SIGNAL VECTOR

Signal process / Muscle state	Observed signal	After wavelet transform	Output in ICA
extensor and flexor contraction	0.0665	0.0658	0.0007
extensor contraction but flexor relaxation	0.0393	0.0407	0.0012
extensor and flexor relaxation	0.0038	0.0034	0.0002

The cross-correlation coefficients of signal vectors which observed directly or processed by wavelet transform or separated by Infomax algorithm of ICA when extensor and flexor in different state are listed in the TABLE I. Seen from the table, the cross-correlation coefficient of signal vector is nearly not changed after processed by wavelet transform, whereas, the cross-correlation coefficient decreases in a great degree after separating by ICA. Thus, we can know wavelet transform can not remove multi-channel SEMG signals interference, whereas ICA is an effective way to eliminate such ingredient.

TABLE II
THE CROSS-CORRELATION COEFFICIENT OF MATRIX VECTOR

Extensor and flexor contraction		Extensor contraction but flexor relaxation		Extensor and flexor relaxation	
	$\hat{B}(1)$ $\hat{B}(2)$		$\hat{B}(1)$ $\hat{B}(2)$		$\hat{B}(1)$ $\hat{B}(2)$
$B(1)$	**0.9763** 0.0489	$B(1)$	**0.9970** 0.1848	$B(1)$	**0.9890** 0.1349
$B(2)$	0.1802 **0.9822**	$B(2)$	0.2907 **0.9481**	$B(2)$	0.0033 **0.9882**

The cross-correlation coefficients of matrix vectors when extensor and flexor in different state are listed in the TABLE II. Where, B is inverse matrix of W, i.e. $B = W^{-1}$. $\hat{B}$ is inverse matrix of $\hat{W}$, $\hat{W}$ is separating matrix of new pair observed signals which consisted of regularly spaced differences of original observed signals. The cross-correlation coefficient of B and $\hat{B}$ reflect the self correlating degree of output in ICA and source signal, i.e. the degree of output in ICA approach to the source signal. In Ref. [7], known from the conclusion of judgment on consistency of outputs in ICA with source signals, the component of ICA is consistent with the corresponding source signal when the maximum cross-correlation coefficient of matrix vector not less than 0.95; and that the maximum cross-correlation coefficient should not be less than 0.8 to ensure the separation accuracy. So, the independent component of ICA showed in Fig.4 (b) and Fig.5 (b) and Fig.6 (b) are the source signals corresponding to each observed signals.

Moreover, observed from TABLE I, we can find that the cross-correlation coefficient of observed signal is correlated with the degree of muscle state. The larger the SEMG amplitude is, the more interfered ingredient is.

IV. Conclusion

Multi-channel SEMG signals always interfere each other while being acquired, which would distort the source signal feature, moreover, the existence of noise makes signal model more complex, which brings inconvenience to the analysis of SEMG signal. So, it has great significance to separate source signal from the raw SEMG signal collected from each electrode. The method discussed in this paper combines the wavelet transform with the ICA. By using the noise filtering function of wavelet transform, some noise is removed from the raw SEMG signals first which would form the input of ICA. So the defect that ICA algorithm at present is impossible to remove noise from source signals can be overcomed effectively. In order to judge the efficiency of this method, we make experiment and analysis when extensor and flexor in different muscle state. And, the cross-correlation coefficients of signal vector and matrix vector are induced to verify the effect of ICA separating. The experimental results indicate that this method is an effective way to process multi-channel SEMG signals. Besides, this method offers an excellent value for blind separating of multi biomedical signals.

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