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Cortico-Muscular Coherence Enhancement via Coherent Wavelet Enhanced Independent Component Analysis

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Abstract—Functional coupling between the motor cortex and muscle activity is usually detected and characterized using the spectral method of cortico-muscular coherence (CMC) between surface electromyogram (sEMG) and electroencephalogram (EEG) recorded synchronously under motor control task. However, CMC is often weak and not easily detectable in all individuals. One of the reasons for the low levels of CMC is the presence of noise and components unrelated to the considered tasks in recorded sEMG and EEG signals. In this paper we propose a method for enhancing relative levels of sEMG components coherent with synchronous EEG signals via a variant of Wavelet Independent Component Analysis combined with a novel component selection algorithm. The effectiveness of the proposed algorithm is demonstrated using data collected in neurophysiological experiments.

Index Terms—Cortico-muscular coherence, sEMG, wavelet decomposition, ICA, enhancement.

I. INTRODUCTION

As one of the primary methods for quantifying functional coupling between the motor cortex and the periphery, the spectral method of cortico-muscular coherence (CMC) has been used extensively [1]–[5]. However, CMC is often very weak and even some healthy subjects do not express CMC above significance threshold. There are two known factors that could weaken CMC, one of which is the misalignment between EEG and sEMG signals due to the time delay between synchronized processes in the muscle and the cortex. The other factor is the presence of noise and components unrelated to the considered activity in both EEG and sEMG [6], [7]. Since CMC reveals protocols of cortico-muscular interactions, providing information that is important for understanding mechanisms of movement control, and how they are disrupted in movement disorders [8]–[10], it is of great importance to be able to enhance levels of CMC. In our recent work we addressed the issue of misalignment between EEG and sEMG signals via the methodology of Cortico-Muscular Coherence with Time Delay [7], whilst in this study we focus on increasing the relative level of relevant components in the mixture of signals collected by sEMG.

The method we propose for the enhancement of relevant components of sEMG is based on the concept of Wavelet Independent Component Analysis, which has been proposed previously in the context of artifact rejection from EEG signals [11]–[15]. In this study we propose to apply independent

component analysis (ICA) to low-channel count sEMG signals and select components from the mixture using a greedy algorithm that aims to maximize the coherence between the resynthesized sEMG signal and EEG. The method is applied to data collected in a neurophysiological experiment and compared in terms of its effectiveness in enhancing cortico-muscular coherence to a denoising algorithm based on wavelet expansion thresholding [16], commonly used for noise removal in biological signal processing. The results demonstrate that the proposed method based on wavelet ICA achieves much more pronounced cortico-muscular coherence enhancement, achieving up to 73% relative increase in CMC levels.

The paper is organized as follows. In Section II we describe models and methods used, including a model of cortico-muscular interactions, denoising based on wavelet expansion thresholding and the proposed method of coherence enhancement. Experimental results are presented in Section III, and conclusions are drawn in Section IV.

II. METHODS

A. Simplified Model of sEMG

In movement control, a cortical excitation signal x_0 is transmitted to the controlled muscle via multiple paths, each of which has a different delay and attenuation. The control signal received by the muscle, y_0 , thus has the form

$$y_0(t) = \sum_{i=1}^{N_x} b_i x_0(t - D_i) \quad (1)$$

where b_i and D_i are attenuation and delay, respectively, of an individual path. For signals of small amplitude this linear model is a good approximation of the propagation system. The corresponding surface electromyogram $y(t)$ is a mixture of $y_0(t)$ with noise and various other events unrelated to the considered task, which all combined constitute a signal $n_y(t)$ that we will refer to as noise. The sEMG signal thus has the form $y(t) = y_0(t) + n_y(t)$. Analogously, a synchronously recorded EEG signal $x(t)$ is a mixture of the muscle-control event $x_0(t)$ and a component $n_x(t)$ that is a combination of noise and other cortical events and artifacts, $x(t) = x_0(t) + n_x(t)$. The coherence between the sEMG and EEG signals at a frequency ω can be shown to have the form

$$C_{xy}(\omega) = \frac{|B(\omega)|^2 S_{x_0 x_0}^2(\omega)}{(S_{x_0 x_0}(\omega) + S_{n_x n_x}(\omega)) (|B(\omega)|^2 S_{x_0 x_0}(\omega) + S_{n_y n_y}(\omega))}, \quad (2)$$

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where $S_{x_0x_0}(\omega)$, $S_{n_xn_x}(\omega)$, $S_{n_y n_y}(\omega)$ are power spectral densities of $x_0(t)$, $n_x(t)$, and $n_y(t)$, and $B(\omega)$ is the frequency response of the propagation channel in (1). It can be observed that in the absence of the noise components n_x and n_y the coherence is equal to one, however, if the components x_0 and y_0 , involved in cortico-muscular interaction, are weak compared to the noise, the coherence is very low.

B. Wavelet Threshold Denoising

Wavelet threshold denoising (WTD) is one of standard techniques for denoising of biological signals, and will be considered in this study as a reference method. The method first involves finding a wavelet expansion of a signal, followed by thresholding of expansion coefficients. The thresholding effectively removes some of the noise from wavelet coefficients, and then the signal is synthesized from the denoised coefficients. In this study soft thresholding is used which is specified by the following function

$$\eta_T(c) = \text{sgn}(c)(|c| - T)_+, \quad (3)$$

where T is the threshold [16].

The WTD technique is capable of removing some background noise and some Gaussian white noise from sEMG. However, it may not be effective in removing some artifacts with high energy concentrating in narrow band frequency bands, as well as some of the signals unrelated to the control process of interest.

C. Coherent Wavelet Enhanced Independent Component Analysis (COWICA)

Independent component analysis (ICA) is a technique for separating independent source signals $s_i(t)$, $i = 1, \dots, n$ from their linear mixtures $x_j(t)$, $j = 1, \dots, m$ which can be described as

$$X(t) = AS(t), \quad (4)$$

where $X(t) = [x_1(t), x_2(t), \dots, x_m(t)]'$, $S(t) = [s_1(t), s_2(t), \dots, s_n(t)]'$ and A is an $m \times n$ mixing matrix. The process amounts to finding the inverse matrix A^{-1} by making the demixed components of $S(t)$ maximally independent. In order to have the mixing matrix A of full rank for its inverse to exist, the number of observed mixtures m , must be at least as large as the number of estimated components n . Hence, when there are no sufficiently many channels to provide redundancy needed for accurate source estimation, ICA might not be able to separate the sources.

In data collection for CMC analysis, in order to minimize health-care costs, it is important to acquire signals using a small number of channels. To overcome the limitations imposed on ICA in the context of low-channel data acquisition, inspired by previous work on Wavelet Independent Component Analysis [11]–[15], we investigate applying wavelet decomposition prior to ICA to generate wavelet components (WCs) for increasing the effective number of mixtures [12]. In order to increase the number of components as much as possible, all wavelet expansion components up to a certain scale are used as the input to ICA.

In the context of CMC enhancement, a subset of separated components $s_i(t)$ is then recombined, aiming to reconstruct a version of sEMG which contains a higher relative level of the component $y_0(t)$ which is the response to the cortical activity $x_0(t)$. For that purpose we propose a greedy algorithm which involves three steps. First, in the mixture in (4) the independent component $s_1(t)$ is replaced by the zero signal. Note that mixture signals $x_j(t)$ are wavelet expansion components of sEMG signals. Surface EMG signals are then reconstructed from components $x_j(t)$ obtained when $s_1(t)$ is removed and CMC is calculated with such sEMG. If this removal of $s_1(t)$ increases the coherence, then $s_1(t)$ is kept at zero, otherwise it is restored. The process is then repeated for all other components $s_i(t)$. We will refer to this coherence enhancement method as Coherent Wavelet Enhanced Independent Component Analysis (COWICA).

The coherence between EEG and sEMG, which are non-stationary processes, was estimated in this study in the short-time Fourier domain [17], [18]. In particular, the time-varying power spectral and cross-spectral densities were estimated by averaging the short-time Fourier transform (STFT) magnitude spectra over different epochs: $\hat{S}_{xx}(t, \omega) = \frac{1}{L} \sum_{l=1}^L |X_l(t, \omega)|^2$, and analogously for $\hat{S}_{yy}(t, \omega)$ and cross spectral density $\hat{S}_{xy}$, where L is the number of epochs, and $X_l(t, \omega)$ is the STFT of $x(t)$ at observation window centered around time instant t . The coherence between $x(t)$ and $y(t)$ is then estimated as $C_{xy}(t, \omega) = |\hat{S}_{xy}(t, \omega)|^2 / (\hat{S}_{xx}(t, \omega) \hat{S}_{yy}(t, \omega))$. Coherence above the 95% confidence limit (CL) is defined to be significant, where $CL_{(a\%)} = 1 - (1 - \frac{\alpha}{100})^{\frac{1}{(L-1)}}$ and α is set to 95 [19].

III. RESULTS

A. Experiment

Five healthy subjects were asked to perform a simple motor task with their dominant hand holding a plastic ruler in a key grip parallel to and above the table surface. The sensation that their grip on the ruler may be lost was given by pulses of lateral displacement generated by an electromechanical tapper at defined times. The subjects were asked to maintain the position of the ruler by holding it gently against the stylus of the tapper. Surface EMG was recorded using pairs of adhesive electrodes placed 5cm apart over the belly (active electrode) and tendon (inactive electrode) of first dorsal interosseous (FDI) and flexor pollicis brevis (FPB) of the dominant hand. EEG was recorded from the scalp overlying the contralateral motor cortex. EEG and sEMG were sampled at 1024 Hz and amplified and bandpass filtered (0.5 - 100 Hz for EEG; 5 - 500 Hz for EMG). The stimulus delivered 1.1 second after the start of the data collection period of a single trail which lasted 5 seconds. In order that subjects could not anticipate the arrival of the next stimulus, the stimuli were delivered at pseudorandom intervals varying between 5.6 s and 8.4 s (mean 7s). A short rest was between blocks, each of which contains 25 corresponding data epochs. Up to 8 blocks of data (200 epochs) were collected for each

Fig. 1. CMC plots obtained with Hanning window of length $W = 125$ ms and shifts of 9.8 ms between consecutive windows. CMC values below the 95% confidence limit are set to zero. (a) Original CMC between EEG and sEMG. (b) CMC between EEG and sEMG after denoising performed by applying WDT with *sym8* wavelet at 4 scales. (c) CMC between EEG and denoised sEMG after applying COWICA with *db7* wavelet at 7 scales.

TABLE I
INCREASE OF CMC ACHIEVED BY COWICA AND WDT

Subject	Coherence increase of Peak 1 (%)					Coherence increase of Peak 2 (%)				
	by WDT	by COWICA				by WDT	by COWICA			
		<i>db1</i>	<i>db4</i>	<i>db7</i>	<i>db10</i>		<i>db1</i>	<i>db4</i>	<i>db7</i>	<i>db10</i>
B	7.11	19.43	25.97	29.02	27.75	3.69	18.81	8.19	12.32	8.85
J	4.61	28.64	19.87	22.04	19.51	5.30	21.02	24.70	27.79	32.54
K	4.15	7.22	6.20	11.91	5.50	8.99	36.71	30.47	33.76	37.29
L	12.42	25.14	17.78	11.76	22.80	5.51	15.55	35.11	17.88	38.74
N	6.96	46.18	33.18	30.92	30.32	3.27	73.48	60.96	65.82	56.49

subject [20]. The power line noise was removed by a digital notch filter.

B. Coherence Estimation

The coherence between EEG and sEMG was estimated via the STFT using Hanning window of length $W = 125$

ms (128 samples) with shifts $\Delta t = 9.8$ ms (10 samples) that provided the most suitable time-frequency resolution [7]. Denoising and time-frequency analysis were done to the complete signals to investigate the overall increase of CMC. The increase in coherence at two prominent coherence peaks, referred to as Peak 1 (appears between 1.5 s and 2.5 s) and Peak 2 (appears between 2.5 s and 3.5 s) [7] are estimated and provided as an illustration of the effectiveness of considered methods. We were focused on the CMC enhancement of prominent peaks instead of the averaged increase of CMC of the whole period because the motor cortex and the periphery might not exhibit synchronous behavior all the time.

C. Noise Suppression for Coherence Enhancement

Both WDT and the wavelet decomposition step of COWICA, were performed using *Daubechies*, *Symlets* and *Coiflet* wavelet families. Since the sampling rate used was 1024 Hz, and α (8 to 13 Hz), β (13 to 36 Hz) and γ (36 to 85 Hz) frequency bands have different functions in sensory-motor integration, in order to approximate this frequency resolution we used 7 scales of the wavelet transform. However, for the WDT, the most effective number of scales depends on the particular signal. We report results for the number of octaves which achieved the highest coherence increase. Note that in the case of WDT both EEG and sEMG are denoised, whereas in the case of COWICA only sEMG was enhanced.

An example of CMC enhancement of Subject B after WDT and COWICA is shown in Fig. 1(b) and Fig. 1(c), respectively, in comparison with the original CMC shown in Fig. 1(a). We can observe from these figures that both methods increase CMC especially where it exhibits strong synchronization, but COWICA improves CMC markedly whilst WDT practically does not achieve pronounced enhancement. Moreover, after applying COWICA, significant coherence appears even where it could not be observed in both pre-stimulus period (0 s to 1 s) and post-stimulus period (1.5 s to 5 s).

Next we compare COWICA to WDT in terms of the increase of CMC at specific coherence peaks. Table I shows relative increase in the level of CMC at two prominent peaks in the post-stimulus period. It can be observed that CMC is increased substantially by applying COWICA, however WDT does not improve coherence considerably. Note that in Table I for WDT we present the best results of those achieved with different wavelets and number of scales of the wavelet transform. Results obtained by using COWICA are shown for Daubechies wavelets '*db1*', '*db4*', '*db7*' and '*db10*' and 7 scales of the wavelet transform. Comparable results were obtained with other wavelet families.

IV. CONCLUSION

This study proposed a method for enhancing corticomuscular coherence inspired by Wavelet Independent Component Analysis. We reconstructed sEMG with the independent components in the wavelet transform domain which contributed to the coherence between monitored cortex and muscle activities. These components were selected via a

novel algorithm which is designed specifically to increase coherence levels. Using physiological data, we illustrated the potential of the proposed method to increase CMC levels in a comparative assessment along with wavelet threshold denoising (WTD). A particularly appealing feature of the method is in that it is effective even when only two channels of sEMG are used.

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