Cross-Frequency Information Transfer from EEG to EMG in Grasping*

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Abstract— **This paper presents an investigation into the cortico-muscular relationship during a grasping task by evaluating the information transfer between EEG and EMG signals. Information transfer was computed via a non-linear model-free measure, transfer entropy (TE). To examine the cross-frequency interaction, TEs were computed after the times series were decomposed into various frequency ranges via wavelet transform. Our results demonstrate the capability of TE to capture the direct interaction between EEG and EMG. In addition, the cross-frequency analysis revealed instantaneous decrease in information transfer from EEG to the high frequency component of EMG (100-200Hz) during the onset of movement.**

I. Introduction

Electroencephalogram (EEG) and electromyogram (EMG) have been widely studied in the cortical control of movement [1], [2]. For example, EEG and EMG of motor execution have been explored by means of oscillatory rhythms [3], connectivity [4], and recruitment patterns [2]. In particular, frequency specific changes in both EEG and EMG have been shown to occur during motor tasks, with EEG studies showing consistent results for task related synchronization and desynchronization. For instance, in the primary motor cortex, particularly at electrodes C3 and C4, desynchronization in the mu rhythm (9-12Hz) and synchronization in the beta rhythm (16-31Hz) have been observed. A range of studies have also investigated relationships in the time-frequency domain allowing changes in frequency powers across the duration of a task to be revealed [1].

While a number of research studies into EEG and EMG have been conducted independently of each other the number of studies investigating both simultaneously is limited. Grosse et al. [5] have reviewed the frequency relationships within motor areas of the central nervous system and EMG. Specifically, they highlight the importance of synchronization in the beta (15-30Hz) and low gamma (30-60Hz) EEG frequency ranges with muscle activity. It has also been shown that EMG envelopes can be reconstructed from EEG current sources for delta EEG (below 4Hz), suggesting that low frequency EEG possesses relevant information about the activation of muscles [6].

Many of these studies still have some constraints to their analysis such as linear dependency, limited frequency ranges or problems with volume conduction. Also, as EEG and EMG signals are in different frequency ranges, we have observed a lack of methods to discuss the plausible cross frequency interaction. Commonly the primary measure of frequency relationships has been linear coherence [5], however, more recently Transfer Entropy (TE) has been used as an alternative approach to measuring connectivity [4]. TE is a non-parametric measure of the amount of information transfered between two random processes [7]. Like its counterpart Granger causality (GC), TE quantifies the increase in the predictivity of the state of a signal. Yet, it is TE's non-parametric and non-linear characteristics that make it more favorable to general application to neural signal analysis.

In this paper, two aspects of information transfer from the brain to the muscles controlling the hand during a grasping task were studied. First, we measured the information transfer from EEG to EMG using TE. Second extending upon previous studies which explore frequency relations between EEG and EMG this study is perhaps the first investigation of the cross frequency interaction between EEG and EMG signals. Highlighting the applicability of TE to reaveal the cross frequency interaction between two types of bio-signal. To achieve this, signals were decomposed into several frequency ranges via continuous wavelet transformation and the TE value of different combinations was evaluated.

II. Method

A. Experimental Design and Data Collection

In this study, subjects were asked to grasp a ball and relax alternately according to audio instructions. Each subject grasped the ball for 3s after hearing a high pitch beep. Then, a low pitch sound instructed them to relax their hand for around 3-5s. Each session consisted of 25 trials and a 2 minute break. The whole experiment contained five sessions, giving a total of 125 trials. After placing the EMG electrodes, the subject's arm remained stationary and rested on the arm of the chair. The ball was suspended just above the subjects palm when he/she was resting or not holding the ball. The choice of the ball size depended on the subject hand size, a tennis ball for bigger hands or a squash ball for smaller hands.

Twelve right-handed subjects participated in this experiment. All the participants have no history of neurological or psychological disorder. Participants gave informed consent to the experimental procedure, which was approved by the ethics committee at the City University of Hong Kong. EEG and EMG signals were recorded simultaneously using an Active Two System (Biosemi, Inc.) with Ag/AgCl electrodes and sampling rate of 2048Hz. 64-channel EEG was placed according to the international 10/20 system. EMG signals were acquired using four pairs of individual lead electrodes placed above the extensor digitorum, flexor digitorum, abductor pollicis longus and flexor pollicis longus.

B. Data Analysis

1) Signal preprocessing: We examined the EMG signals of only the flexor pollicis longus which controls the thumb flexion. For this study, we selected 8 subjects all with activation-to-relax ratio larger than 10dB [8],

$$\frac{EMG_{activation}}{EMG_{relax}} = 20\log_{10}\left(\frac{A_{hold}}{A_{relax}}\right) \tag{1}$$

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where A are the amplitudes of the EMG during the baseline relaxed period and at the peak hold time during the grasp respectively.

We focused on seven EEG channels, including F3, F4, Fz (frontal region), Pz (parietal region), C3 (left motor region), C4 (right motor region), and Cz (center region), which have previously been shown to have strong associations with motor tasks [3]. The EEG and EMG signals were band-passed to 1-100Hz and 10-200Hz respectively using a Kaiser window FIR filter. An FIR notch filter was also applied at 50, 100 and 150Hz to remove powerline noise and harmonics. Then, EEG and EMG were downsampled to 500Hz and was segmented based on the detection of grasping onset time.

2) Wavelet decomposition: The continuous wavelet transform (CWT)

$$X_{\omega}(a,b) = |a|^{-1/2} \int dt x(t) \psi^{*}(\frac{t-b}{b}) \tag{2}$$

where a the scaling, b is the translation and ω is the frequency was applied using a Morlet wavelet

$$\psi_{\omega}(t) = \pi^{-1/4} e^{j\omega t} e^{-t^2/2} \tag{3}$$

to decompose the signal into different frequency ranges [9]. The EEG signal was decomposed with four central frequencies $f_0 = 6$, 12, 24 and 48Hz which correspond to the centers of the θ, α, β and γ bands. Whereas the EMG was decomposed with $f_0 = 30$, 70 and 145Hz corresponding to 'low', 'middle' and 'high' frequency bands [2].

3) Transfer Entropy: A model-free method, transfer entropy (TE) [4], [7], was applied to evaluate the information transfer between brain regions and muscles using TRENTOOL [10]. TE is derived from mutual information (MI) but related to transferred information rather than the shared information. Defining two time series $X = x_t$ and $Y = y_t$, the transition probabilities satisfy the Markov condition if Y is independent of the history of X

$$p(y_{t+u}|\boldsymbol{y_t^{d_y}}, \boldsymbol{x_t^{d_x}}) = p(y_{t+u}|\boldsymbol{y_t^{d_y}}) \tag{4}$$

where $\boldsymbol{y_t^{d_y}} = (y_t, y_{t-\tau}, ..., y_t - (d-1)\tau)$ is the delay embedded vector of y_t with embedding dimension d and delay τ [4], and $\boldsymbol{x_t^{d_x}}$ is the corresponding delay embedded vector for x_t. The Kullback-Leibler divergence of the probability distributions is defined the transfer entropy from X to Y, denoted as $TE(X \rightarrow Y)$

$$TE(X \rightarrow Y) = \sum p(y_{t+u}|\boldsymbol{y_t^{d_y}}, \boldsymbol{x_t^{d_x}}) \log \frac{p(y_{t+u}|\boldsymbol{y_t^{d_y}}, \boldsymbol{x_t^{d_x}})}{p(y_{t+u}|\boldsymbol{y_t^{d_y}})} \tag{5}$$

Equation (5) can also be rewritten as the sum of Shannon entropies as follows

$$\begin{aligned} TE(X \rightarrow Y) =& H(\boldsymbol{y_t^{d_y}}, \boldsymbol{x_t^{d_x}}) - H(y_{t+u}, \boldsymbol{y_t^{d_y}}) \\ &+ H(y_{t+u}, \boldsymbol{y_t^{d_y}}) - H(\boldsymbol{y_t^{d_y}}) \end{aligned} \tag{6}$$

Time series TE values were computed from 1s epochs with 0.2s step size using k-nearest neighbor (with $k = 4$ [11]). The embedding parameters (τ and d) were optimized by Ragwitz criterion. Statistical significance at each step was computed by comparing with the baseline during the relaxed period.

III. Result

A. Information Transfer in the Overall Signal

1) Lag in TE: We first considered the overall signals containing the entire frequency content. In order to determine the maximum change in TE in relation to the relaxed baseline, we considered a range of time lags (u) between the EMG and each of the EEG channels shown in Fig. 1. It indicates the TE series between EEG and EMG with respect to different lags (u). Observing the maximum TE, we identified the time lag in information transfer from different EEG channels to the flexor pollicis longus ($u_{C3} =$ 30ms; $u_{Pz} =$ 20ms; $u_{F4} =$ 10ms; and $u_{Cz} =$ 30ms). As initial studies indicated most significant results for $u_{C3} =$ 30ms (results for other subjects not shown) this value was selected for the preliminary study.

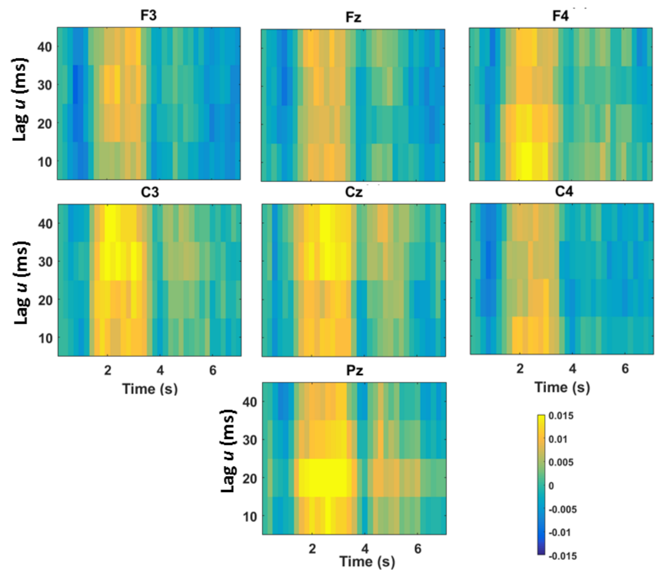

Fig. 1: Transfer Entropy from EEG to EMG with respect to different lag u (y-axis) in the grasping task of Subject #1.

2) TE from EEG to EMG: Each trial consisted of a relaxed period (baseline), onset of movement, a period of holding the grasp and then the release of the grasp as shown in Fig. 2. All TE values were calculated and then compared with the baseline, so positive TE implies an increase in information transfer relative to the relaxed stage before activation, and vice versa. With the increase in the EMG activity at the onset of the grasp, there was a drop in TE across all the EEG channels. During the holding phase, TE increased further and remained steady fluctuating around the same level. Then, TE dropped to negative values with the release of the ball, which indicated a decrease in information transfer relative to the baseline. Finally, returning to zero at the baseline.

Comparing the results across subjects, Fig. 3 constantly shows a negative TE during grasping and a positive TE while holding. While background information transfer from brain to muscle was observed at all times even without the grasp, part of the information transfer is suppressed at the movement transition times, both onset and release. When the muscle is contracting in a static condition, the amount of information being transferred is greater than during the relax stage.

B. Information Transfer Across Different Frequency Bands

1) Signal Decomposition: EEG and EMG were decomposed via CWT with Morlet window and central frequencies f_0 specified according to Table. I and II. The resulting wavelet coefficients and spectrum are shown in Fig. 4 and 5. The EEG was decomposed into the four traditional EEG bands: theta, alpha, beta and gamma.

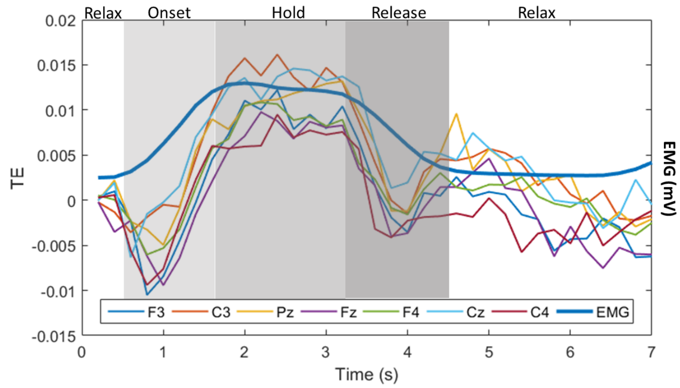

Fig. 2: Average EMG of all the trials of one subject and 7 channels of EEG TE value. Each trial was divided into four stages: relax, onset, hold and release.

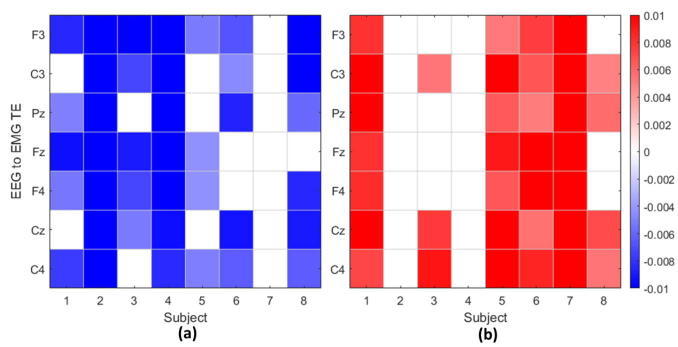

Fig. 3: Statistically significant TE values from different EEG channels (row) to EMG for each subject (column) ($p < 0.05$) during (a) onset of grasp, and (b) object hold.

The EMG signal was separated in low (LF), middle (MF) and high (HF) frequency band as shown in Table I and II.

TABLE I: EEG decomposition

EEG		$f_0(Hz)$	Range (Hz)
Theta	θ	6	$4-8$
Alpha	α	12	$8-16$
Beta	β	24	$16-32$
Gamma	γ	48	$32-64$

TABLE II: EMG decomposition

EMG		$f_0(Hz)$	Range (Hz)
Low Frequency	LF	30	15-50
Middle Frequency	MF	70	50-100
High Frequency	HF	145	100-200

2) Cross-Frequency TE: After decomposing the signals, TE of each decomposed EEG-EMG pair was evaluated. From Fig. 6, we observe that the frequency specific EEG to EMG TE has the greatest similarity to the overall TE, shown on Fig. 2, for the HF EMG. Both the LF and MF EMG TEs show less clear results across all of the EEG frequency. Table. III, shows the correlation between original TE and the frequency-specific EEG TE to the HF EMG. The correlation analysis shows that only some frequency bands of EEG channels to HF EMG ($100-200$Hz) have similarity with the original TE. During the holding stage, the magnitude of the TE from different EEG frequency bands to HF EMG, shown in Fig. 7, is much lower than the significant positive TE observed from the original EEG in Fig. 3. However, at the onset and the end of the grasp, the TE from alpha, beta and gamma bands of EEG to HF EMG all decreased as shown in Fig. 8.

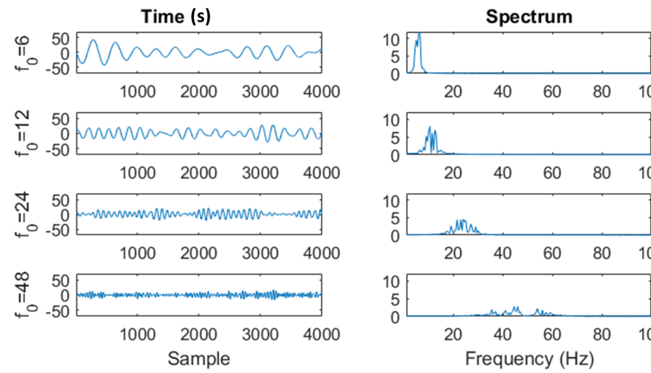

Fig. 4: Decomposed EEG time series and corresponding spectra with central frequency 6, 12, 24 and 48Hz using CWT with Morlet window.

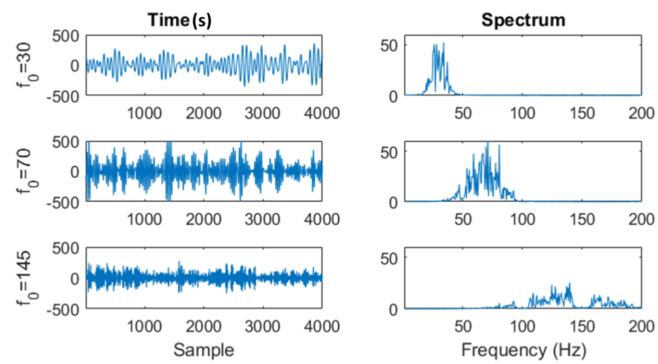

Fig. 5: Decomposed EMG time series and corresponding spectra with central frequency 30, 70 and 145Hz using CWT with Morlet window.

TABLE III: Correlation of original TE from all EEG and frequency-specific TE to HF EMG

EEG	F3	C3	Pz	Fz	F4	Cz	C4;
θ	0.28	0.29	0.46	-0.01	0.33	0.14	0.19
α	0.69	0.60	0.61	0.51	0.46	0.49	0.57
β	0.33	0.54	0.44	0.43	0.49	0.43	0.57
γ	0.56	0.67	0.76	0.42	0.56	0.56	0.49

IV. Conclusion

Previous studies for EEG and EMG have focused on frequency responses in individual frequency bands. In this study, we extended upon this to consider cross frequency relationship. We have used transfer entropy to evaluate the information flow from the brain to a muscle during grasping. At the transition stages of the movement, the information transfer from EEG to EMG decreased. We have then observed a significant positive TE, which indicates the increase in information transfer from the brain to the muscle during the holding of an object. However, as it is known that EEG and EMG fall into very different frequency ranges (EEG: below 100Hz; EMG: below 200Hz), we have therefore also investigated frequency specific information transfer by evaluating the cross-frequency transfer entropy. We have identified consistent drops in TE from

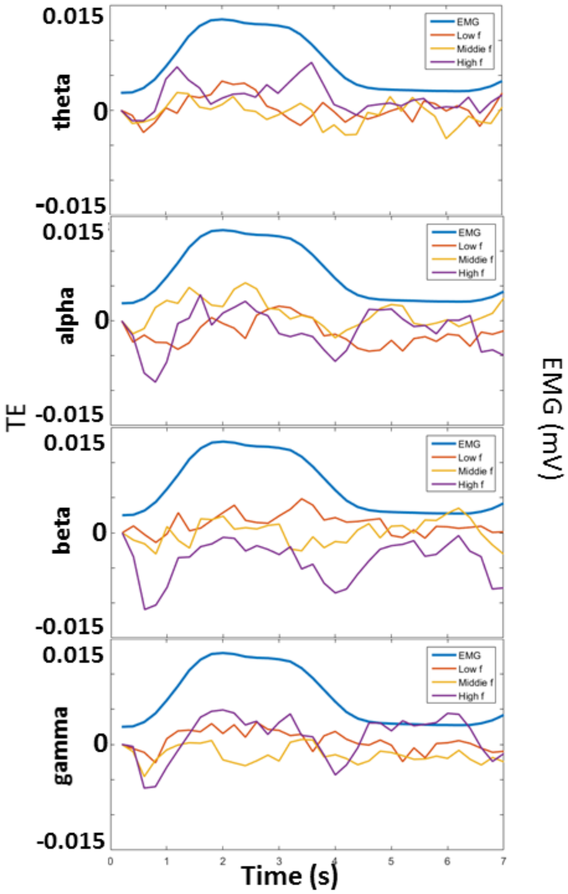

Fig. 6: Average cross-frequency TE from C3 of Subject 1. At the onset of grasping, TEs to HF EMG from the alpha, beta and gamma bands of EEG dropped.

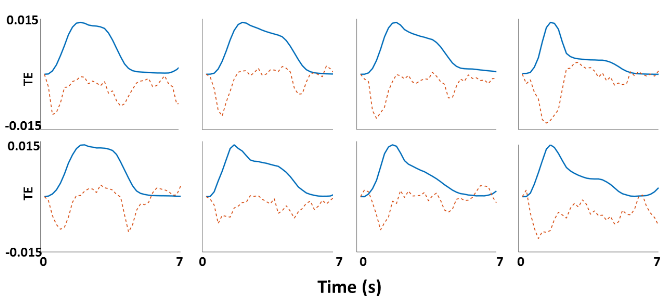

Fig. 7: Red doted line: Example TE from C3 beta to HF EMG for 8 subjects. Blue solid line is the corresponding EMG enveople.

EEG rhythms in the alpha, beta, and gamma bands to EMG between 100-200Hz at both the onset and the end of each grasp movement. This allows us to consider into the relationship between signals from different frequency ranges of physiological time series data, while going beyond the limitations of the more commonly used coherence measurements.

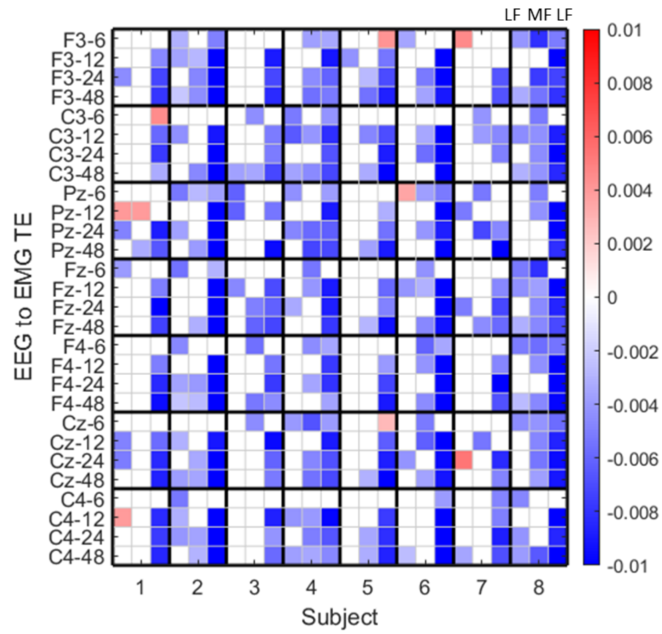

Fig. 8: The statistically significant ($p < 0.05$) TE from different frequency EEG bands to frequency-specific EMG during onset of grasping for the 8 subjects.

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