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Information Transfer Index-A Promising Measure of the Corticomusclar Interaction*

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ABSTRACT

It is generally believed that a major cause of motor dysfunction is the impairment in neural network that controls movement. But little is known about the underlying mechanisms of the impairment in cortical control or in the neural connections between cortex and muscle that lead to the loss of motor ability. So understanding the functional connection between motor cortex and effector muscle is of utmost importance. Previous study mostly relied on cross-correlation, coherence functions or model based approaches such as Granger causality or dynamic causal modeling. In this work the information transfer index (ITI) was introduced to describe the information flows between motor cortex and muscle. Based on the information entropy the ITI can detect both linear and nonlinear interaction between two signals and thus represent a very comprehensive way to define the causality strength. The applicability of ITI is investigated based on simulations and electroencephalogram (EEG), surface electromyography (sEMG) recordings in a simple motor task.

Keywords: Information Theory; Information Transfer Index; Corticomuscular Interaction

1. Introduction

The relationship and interdependence between simultaneously recorded neurophysiological signals, give insights into the function of the systems that produce them. Since Conway discovered that oscillations at beta band (15 - 30 HZ) in the magnetoencephalogram (MEG) in humans are coherent with the surface electromyogram (sEMG) in 1995 [1]. Many researches have been done focusing on the functional relationship between neurons in the sensorimotor cortex and motor units in the effector muscle. To assess the interdependence between EEG and EMG, cross-correlation or coherence functions have been extensively used which can provide information on the linear correlation between two signals [2]. Coherence has been highly successful as a methodology for assessing functional coupling in neurosciences. Previous study has shown that increased corticomuscular coherence can improve motor performance during steady-state motor output [3] indicating that coherence may promote effective corticomuscular interaction. Studies have also revealed changes in coherence in some pathological conditions, such as stroke [4]. The methods give useful information in the study of corticomuscular interaction, but it has the intrinsic limitation that they are linear methods, although neural connectivity may be nonlinear. Thus linear methods are insufficient for the study of complex neurophysiological data. Furthermore, they cannot give the direction of information flow. To better understand the underlying mechanism and functional relevance of the sensorimotor neural network, it is important to know the direction of the information flow between EEG and EMG [5]. In view of detecting coupling direction, directed coherence was proposed based on Granger causality methods [6]. But this is also a linear method. A potential new method should be nonlinear naturally leading to the application of information theoretic techniques. Information theoretic tools, such as entropy, address the issue of linearity and so far have numerous applications in neuroscience. First attempts to measure the relationship between two random variables were based on mutual information (MI), which can be interpreted as the amount of uncertainty about one signal that can be reduced by observation of another. MI is based on probability distributions and is sensitive to second and all higher order correlations. But conventional MI can not account for the direction of information flow, because it is a symmetric measure. Seung-Hyun Jin addressed this issue by defining the time-delayed mutual information (TDMI), which adds a time delay in one of the variables

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[7]. Still it is based on static probability distribution thus didn't accounting for system dynamics. Transfer entropy was proposed by Thomas Schreiber which is on the basis of transition (dynamic) probabilities computation [8]. Many researches have found it a model-free measure of effective connectivity for the neurosciences [9]. Gourevitch used transfer entropy to detect the information flow between auditory cortical neurons [10]. The main advantage of this measure is that it is nonlinear and dynamic; furthermore it has directional sense to define information transfer.

The author has proposed the concept of information transfer index (ITI) based on joint complexity entropy for studies on mechanical fault diagnosis [11]. Taking advantages of transition (dynamic) probabilities in describing dynamic information interaction process, modification is made to the original definition of ITI. In this paper the modified ITI based on transition probabilities has been introduced and used to describe the information transfer of different coupling models and experimental data.

2. Method

2.1. Calculation of Information Transfer Index

Let *X* and *Y* be two signals recorded from two associated systems, the original ITI is defined as:

$$ITI_{x\to y}=\frac{H_c\left(X\right)+H_c\left(Y\right)-H_c\left(X,Y\right)}{H_c\left(X\right)}\in[0,1] \qquad (1)$$

where $H_c\left(X\right)$, $H_c\left(Y\right)$ are the complexity entropy of signal *X* and Y, $H_c\left(X,Y\right)$ is their joint complexity entropy. This calculation can describe the amount of information in *X* that shared by *Y*. Though it isn't accounting for system dynamics and it cannot discriminate against common history and input signals. Taking advantages of transition probabilities, the new definition is based on the concept that if the future of a signal *Y* is better predicted with the observation of the past and present of a signal *X*, then it is believed that there is information transmitted from *X* to *Y*. To quantify the influence of *X* on the system *Y*, the modified ITI is calculated as:

$$ITI_{x\to y}=\frac{H\left(y_{t+u}\mid y_t^n\right)-H\left(y_{t+u}\mid x_t^m,y_t^n\right)}{H\left(y_{t+u}\mid y_t^n\right)}\in[0,1] \qquad (2)$$

where $H\left(y_{t+u}\mid y_t^n\right)$ is the entropy of the process *Y* conditional on its past. The ITI indicates the directed information interactions by measuring the uncertainty reduction via conditional entropy. It quantifies how much the past of a process *X* influence the transition probabilities of another process *Y*. We are interested in the deviation from the following generalized Markov condition.

$$H\left(y_{t+u}\mid y_t^n\right)=H\left(y_{t+u}\mid x_t^m,y_t^n\right) \qquad (3)$$

where $x_t^m=\left(x_t,\cdots,x_{t-m+1}\right)$, $y_t^m=\left(y_t,\cdots,y_{t-m+1}\right)$. When the transition probabilities or dynamics of *Y* are independent of the past of *X*, (3) is fully satisfied, and we infer an absence of directed interaction from *X* to *Y*. Other way there is information flow from *X* to *Y*. ITI naturally incorporates directional and dynamical information, because it is inherently asymmetric and based on transition probabilities.

Sensible causality hypotheses are formulated in terms of the underlying systems rather than on the signals being actually measured. To overcome this problem reconstructing the full state space of a dynamical system from the observed signals is needed. In this work, we use delay-coordinates to create a set of vectors in a higher dimensional space according to (4) to map our scalar time series into trajectories in a state space of high dimension.

$$x_t^d=\left(x\left(t\right),x\left(t-\tau\right),x\left(t-2\tau\right),\ldots,x\left(t-\left(d-1\right)\tau\right)\right) \qquad (4)$$

2.2. Parameter Selection

This procedure depends on two parameters, the dimension d and the delay τ of the embedding. The two parameters considerably affect the outcome of the ITI estimates. For instance, a low value of d can not sufficiently unfold the state space of a system. On the other hand, a too large dimensionality may lower the estimation accuracy and significantly enlarges the computing time. A popular option is to take the delay embedding τ as the auto-correlation decay time of the signal. To determine the embedding dimension, the Cao criterion offers an algorithm based on false neighbors computation [12].

3. Simulation and EEG Experiment

3.1. Simulation Data

To test the ability of ITI to detect the direction of information flow and identify the relationship between two time series. We used four different models, *i.e*. independent, linear, quadratic and threshold models.

1) The first test case we used two independent time series *X* and *Y* generated by the following processes.

$$x_t=\sum_{i=1}^{10}a_i x_{t-i}+\sigma u_t \qquad (5)$$

$$y_{1t}=\sum_{i=1}^{10}a_i y_{t-i}+\sigma v_t \qquad (6)$$

where the coefficients a_i and b_i are drawn from a normalized Gaussian distribution, u_t and v_t are independent Gaussian noise of unit variance.

2) The second test case consisted in simulating a linear causal interaction between the two systems. We

added to the internal dynamics of Y a term related to the past dynamics of X and γ

$$y_{2t} = (1-\gamma)\sum_{i=1}^{10} b_i y_{t-i} + \gamma x_{t-\delta} + \sigma v_t \quad (7)$$

3) The third test case consisted in generating two quadratically coupled processes.

$$y_{3t} = (1-\gamma)\sum_{i=1}^{10} b_i y_{t-i} + \gamma x_{t-\delta}^2 + \sigma v_t \quad (8)$$

4) The last pair of time series is mediated by the threshold function reflecting the effective connectivity of special relevance in neuroscience applications.

$$y_{4t} = (1-\gamma)\sum_{i=1}^{10} b_i y_{t-i} + \gamma \frac{1}{1+\exp(b_1 + b_2 x_{t-\delta})} + \sigma v_t \quad (9)$$

3.2. EEG Experiment

Our experiments were preformed on 12 volunteers (mean age 22 years ± 3 years). During the experiments the subject performed knee flexion and extension. Scalp EEG and sEMG were recorded. Bipolar sEMG was recorded from quadriceps femoris and gastrocnemius (**Figure 1**). Recording diameter of each electrode was 8 mm and center-to-center interelectrode distance was 2 cm. A reference electrode was placed on the skin overlying the tibial tuberosity. The EMG signals were amplified (1000); band-pass filtered (1 Hz - 500 Hz). Scalp EEG signals referenced to the common linked electrodes at the earlobes were recorded simultaneously during the task and were amplified (1000); band-pass filtered (0.3 Hz - 75 Hz).

We cut the trials into 10 s segments and manually discarded the segments trials contaminated with eye-blinks and sensor jumps. Signals from C3 and C4, which represents the sensorimotor cortex were selected for further investigation. Then functional relationship between motor cortex and muscle was analyzed from EEG, sEMG electrode pairs using the algorithm to compute information transfer index as described above.

4. Result

4.1. Simulation Studies

1) Detection of information interactions for different coupling models (**Figure 2**). ITI correctly detected effective connectivity ($X \rightarrow Y$) for all three simulated coupling types (linear, threshold, quadratic) 30 trials were used to compute statistics. No false positives, *i.e*. significant results for the direction $Y \rightarrow X$, were observed. For these analysis we used a coupling constant γ of 0.5 a delay time u of 20 samples prediction time u of 21 samples.

2) ITI calculated as a function of coupling strength. The statistical evaluation shows that the ITI calculated via a range of coupling strength γ from 0 - 1 reliably reflect the different coupling strength (**Figure 3**) for all three investigated coupling models (linear, threshold, quadratic). For these analyses, we used a delay time u of 20 samples prediction time u of 21 samples.

3) Detection of interaction delay. 30 trials from the quadratically coupled model, the coupling strength γ was chosen as 0.5, the interaction delay δ was set to 25 samples and prediction time u was scanned from 1 to 50 samples (**Figure 4**).

Figure 1. EEG recorded together with EMG during the task.

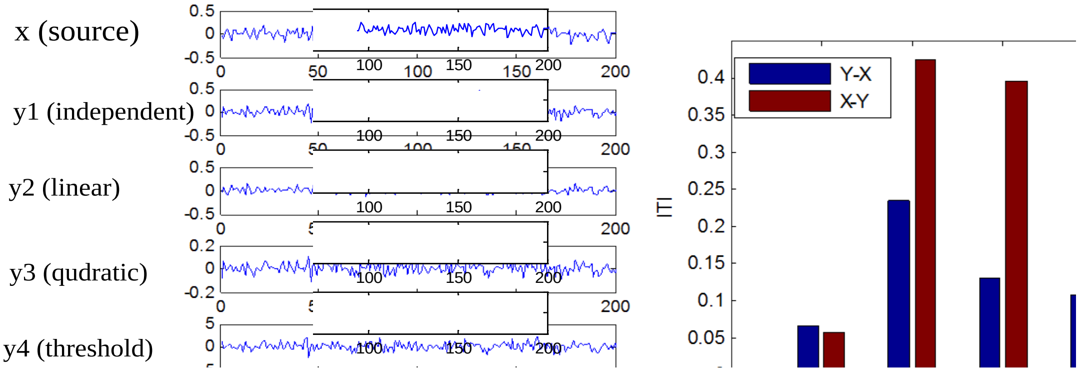

Figure 2. Averaged ITI calculated from different test models. Coupling strength γ = 0.5; delay time δ = 20; prediction time u = 21.

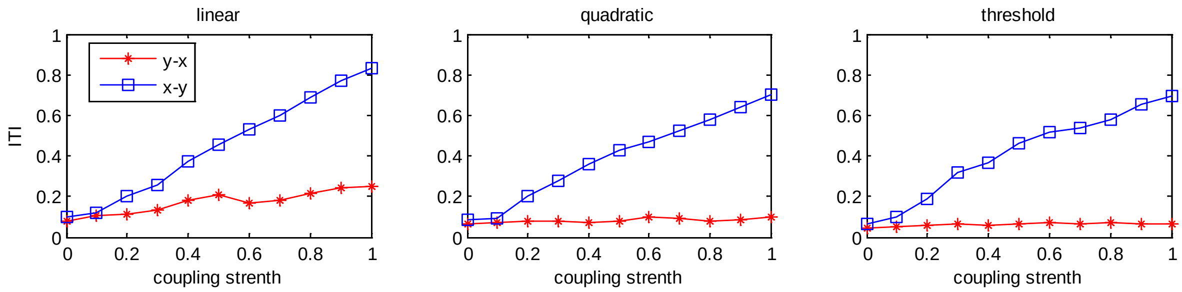

Figure 3. Averaged ITI calculated as a function of coupling strength from the three different coupling models. Coupling strength was set from 0 to1.

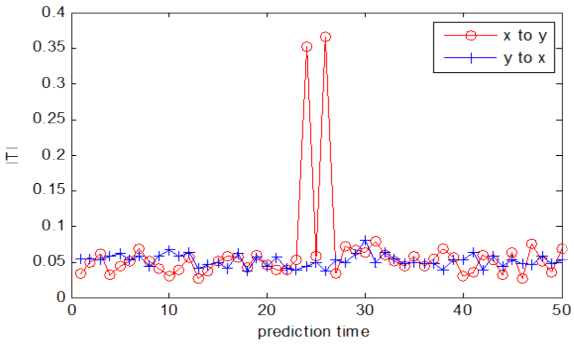

Figure 4. ITI calculated as a function of prediction time from a quadratically coupled model, the coupling strength γ was chosen as 0.5, the interaction delay δ was set to 25 samples and prediction time was scanned u from 1 to 50 samples.

4.2. ITI between EEG and EMG

As expected, ITI during the movement was significantly higher than the non-moved period (**Figure 5**). **Figure 6** shows the ITIs calculated in different frequency bands (beta band and gamma band). The information is not only travels from cortex to muscle but also back from muscle to cortex. The descending flow is expected as the motor command and the other way contains the sensory feedback which may allow the cortex to measure the states of the limb.

5. Conclusions

In this study, we introduced the information transfer index as a model-free and nonlinear method to detect information flow between two time series. The ability to detect linear and nonlinear information flow was tested on simulated data generated from different models, that is, independent, linear, threshold and quadratic models. The result shows that our method reliably detects the causal relationship between two time series correctly. And the ITI shows the ability of reflecting the coupling delay and strength. In conclusion, information transfer index or ITI has promising features that should make it useful for studies on corticomusclar interaction.

The next step of this work is to investigate information transmission mechanism in sensorimotor system in pa-

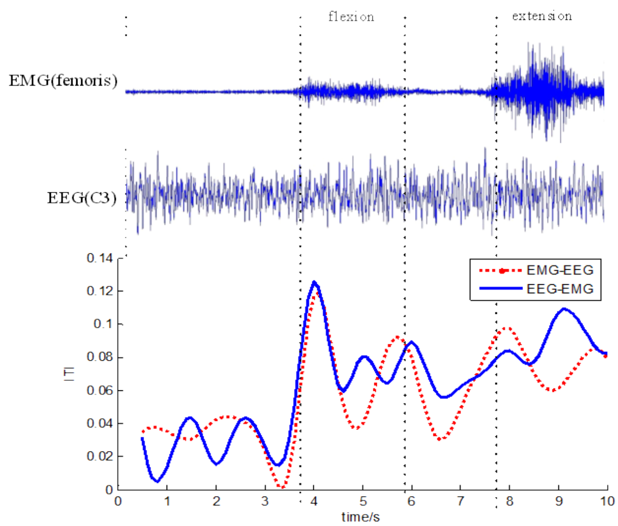

Figure 5. A segment of simultaneously recorded EEG sEMG pair and ITI calculated between them.

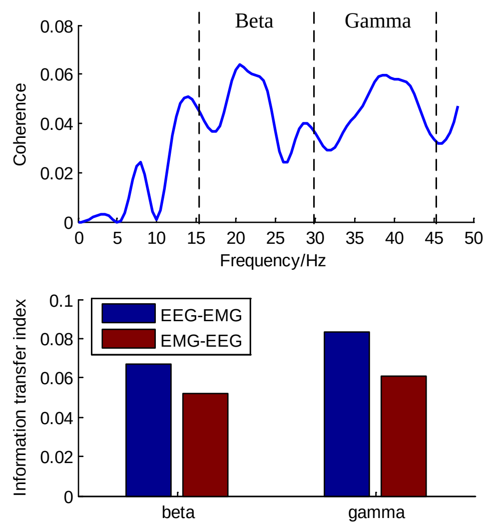

Figure 6. The upper graph presents the coherence between the EEG and sEMG, and the below are the ITIs calculated in different frequency.

tients with various neurological disorders such as stroke, peripheral nerve injury. This method will be a helpful addition in evaluating the integrity and functionality neural circuits.

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