

1st Perspectives on Oscillation Control

Introduction

Transfer Entropy

$$TE_{X \rightarrow Y} = MI(Y^{+t}; (X^{-t} | Y^{-t})) \quad \text{eq. (1)}$$

Causal Mutual Information

$$\begin{aligned} CaMI_{X \rightarrow Y} &= MI(X^{-t}; (Y^{+t}, Y^{-t})) \\ &= MI(X; Y) + TE_{X \rightarrow Y} \end{aligned} \quad \text{eq. (2)}$$

Directionality Index

$$\begin{aligned} DI &= TE_{X \rightarrow Y} - TE_{Y \rightarrow X} \\ &= CaMI_{X \rightarrow Y} - CaMI_{Y \rightarrow X} \end{aligned} \quad \text{eq. (3)}$$

Objective: infer how the activity from one cortical region affects another by analysing their EEG signals.

Context: This has been previously done in [1] using correlation measures to build the adjacency matrix expressing the functional connections. Here, we will advance this work by adopting instead causality measures from information theory which are more robust against nonlinear systems.

Theoretical background: The causality identification method proposed by Granger [2] is only valid for linear(izable) systems, which is not the case at work. However, its principles can be translated to information theory, with Transfer Entropy [3] (eq. 2) being a valid measure for Granger-causality-like tests. Alternatively, one can calculate the Causal Mutual Information [4] (eq. 2), *i.e.* the sum of transfer entropy and mutual information. From this, we determine the net transfer entropy (Directionality Index, eq. (3)), which informs the arrow of causation.

Applications and tools: These tools have been successfully used to infer neuron networks from data [5]. Moreover, we will apply a computational framework that makes clever usage of the repetition of the same stimulus during the experiment [6].

Results and Discussions

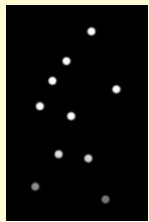


Figure 1: frame from the visual stimulus (video)

Experiment: The experiment consists of a volunteer observing a sequence of 30 videos, 30s each, contain points representing a human figure standing still, or walking (Fig. 1). The cortical response from the visual stimuli was recorded by a clinical EEG, with 19 electrodes arranged in 10:20 system, 500Hz sampling, available at IPq-HC/USP. The data was pre-processed using artefact rejection (filtering, ICA) routines of EEGLAB [7].

Results: We analyse the β -wave (12.5-30Hz) from the signals, as it relates to complex cognitive tasks. This component has autocorrelation decaying to zero at $\tau = 16\text{ms}$. For symbolic encoding, a total of 8 marginal partitions were chosen for each variable (electrode), at positions such that the same number of points reside in each interval. The symbolic length was selected as $L=1$ both for the past and the future sequences. From this, the resulting net transfer entropy (*Directionality Index*) is given below (Fig. 2). The threshold found for its value to express a link was 0.003 bits, following methodology of [5].

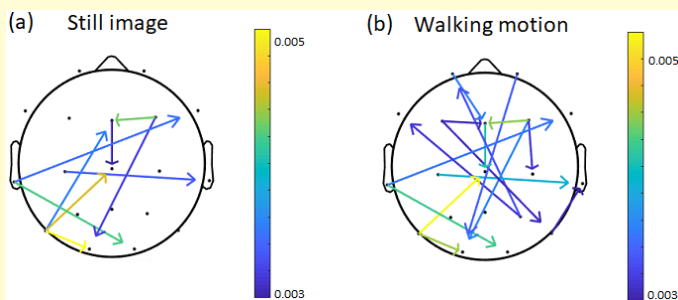


Figure 2: Comparison of the directionality index links formed from the EEG signals of different cortical areas when the volunteer observed the still image of the human figure or the video with the walking motion. Although both share many common links, The walking motion present additional features, particularly pointing to frontal areas. Directionality index values expressed in bits.

Conclusions/Remarks

Using the net transfer entropy (*Directionality Index*) it is possible to identify functional connectivity from EEG data and distinguish the response of a static visual stimulus from a response of a stimulus expressing a motion. The case of the moving stimulus maintains most of the links of the static image case, but also adds connections, particularly to and from the frontal areas, which were previously not observed at the selected threshold.

This experiment will now be applied to volunteers with Parkinson disease currently under Deep Brain Stimulation (DBS) treatment, so enabling comparative analysis of the conditions DBS 'on' and DBS 'off'. With such experiment, we intend to clarify the impact of the DBS treatment on the cortical associations, more specifically regarding visual-motor tasks.

References

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