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Multi-set canonical correlation analysis in action-observation (mirror neuron) study

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Abstract: We used simultaneous functional near infrared spectroscopy along with electroencephalography to investigate mirror neuron network in human brain. We applied multi-set canonical correlation analysis in order to analyze the integrated, totally different in nature, datasets.

1. Introduction

Recent developments in neuroimaging techniques have provided us with different sources of information on brain functions leading to deeper understanding of cognitive processing. Electroencephalography (EEG) is a neuroimaging technique to capture electrical changes associated with neural activities [1]. On the other hand, functional near infrared spectroscopy (fNIRS) is a non-invasive neuroimaging modality that measures hemodynamic response of the brain [2]. The combined EEG-fNIRS system has the advantage of EEG excellent temporal resolution and fNIRS good spatial resolution.

Although multimodal datasets would provide us specific facets of neural or functional brain activities, the analysis of multimodal datasets is inherently a challenging problem since neural response of the brain may not instantaneously be related to the brain hemodynamic response [3, 4]. EEG recordings have shown brain neural activities occur in msec, whereas this takes up to 5 sec for hemodynamic response of the brain to appear. Therefore, EEG sampling frequency is around kHz while fNIRS sampling rate is in the ranges of 10 Hz. Here We take into account the multi-variability of the two datasets using canonical correlation analysis (CCA), since it finds linear transformations that are maximally correlated.

We utilized such a system to study mirror neuron network (MNN) [5]. MNN is a network of motor and somatosensory brain regions though to link self-action to other-action. Mirror Neurons fire when both action execution and observation of a particular action (e.g., reaching for and grasping banana). MNN is associated with the development of sophisticated social behaviors that emerge in typical human infants (e.g., complex imitation, shared emotion) [6].

1. Materials and methods

1.1. Experiment design and participants

We designed our experiment after [7] mentioned in their comprehensive review on MNN. Our paradigm consisted of action observation, action execution. We processed the data from 11 typical adults. All participants gave written, informed consent prior to the experiment.

1.2. Data acquisition

We recorded EEG and fNIRS data simultaneously. EEG data were collected via EGI Geodesic Sensor Nets. We placed 128 EEG channel cap with 24 fNIRS on the subject's head. FNIRS were captured by Hitachi ETG-4000 system. We used our specific cap designed to cover the most sensorimotor areas.

2. Data processing

EEG and fNIRS datasets were preprocessed through standard pipelines. Please see [8] for details on EEG preprocessing procedure. fNIRS data went through PCA motion artifact correct along with bandpass filter with cut off frequencies of 0.001 and 0.1.

2.1. Multi-set Canonical correlation analysis (mCCA)

To explore the relationship between sets of multi-dimensional variables, the coordinate system in which the variables are described is crucial. Even a strong correlation between two sets of variables may not be visible if an inappropriate coordinate system is used [9]. CCA draws relations between two sets when the sample size is relatively small in relation to the number of features, or when the two sets exhibit non-linear relations [10]. It finds the coordinate system (basis vectors) in which the projections of each set onto these coordinates are maximized (Fig. 1) [11]. mCCA is the extended version of CCA developed for more than two datasets [12-14].

2.2. *Generative model for data fusion*

We considered the generative model proposed in [15] to solve data integration problem. In such a model, we assumed fNIRS dataset contains spatial information on region of interest at different sampling time is a mixture of spatial components and their corresponding mixing vectors. EEG data matrix also contains temporal components and their mixing vectors. Therefore, CCA decomposes the integrated datasets such that the correlation in trial to trial variations across modalities and the correlation within modalities, across all subjects, are maximized. The generative model [13] can be expressed as: $X_K = A_K C_K$ for $k = 1, \dots, 2N$, where $X_K \in \mathbb{R}^{T \times V_K}$, $A_K \in \mathbb{R}^{T \times D}$, $C_K \in \mathbb{R}^{D \times V_K}$ is the number of spatial regions/timestamps in fNIRS/EEG X_K datasets. T is the number of instances (timepoints) in X_K and D is the *min(rank* (X_K)). Using least squares approximation, we can estimate A matrices as the canonical variates obtained by mCCA and then reconstruct brain neural activities : $\widehat{C_K} = (A_K^T A_K)^{-1} A_K^T X_K$, for $k = 1, \dots, 2N$. Figure 1 shows the summary of this process. The reconstructed brain activities (hemodynamic response, fNIRS data, in our case) is depicting brain activities in one neuroimaging modality considering highly correlated covariations of the other modality.

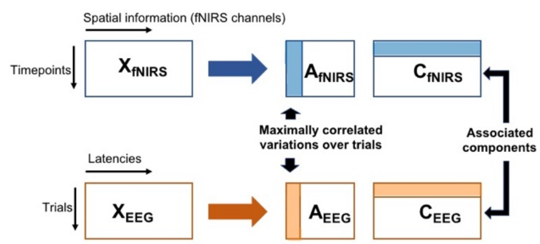

Figure 1. generative model for fNIRS and EEG data fusion [15].

3. Results

Figure 2 shows our preliminary results from applying CCA on EEG and fNIRS execution and observation conditions on C3 region which corresponds to somatosensory motor area. Here we expect to see less activation in the EEG dataset and more activity in the fNIRS recordings. From the picture, the EEG channels 24, 19, 21 and 22 have the most correlation during execution, while channels specified by green are less correlated. This make sense since the premotor cortex should have the most activity during task execution.

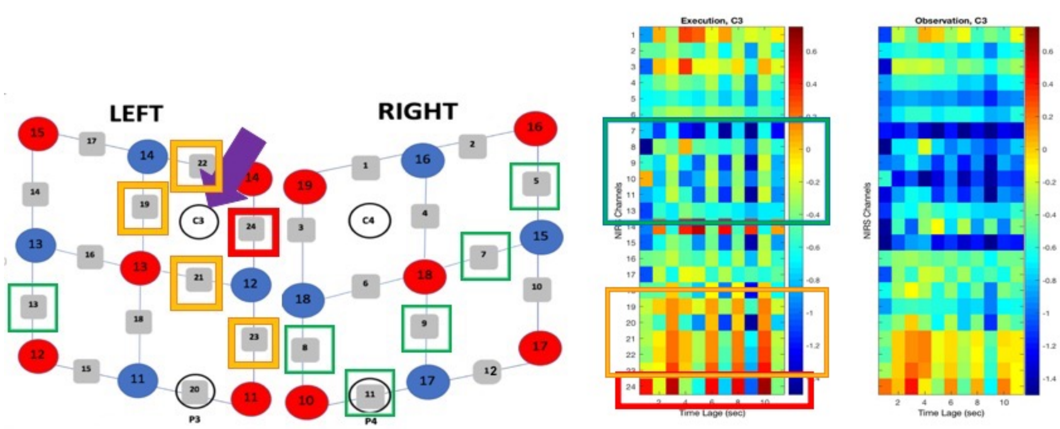

Figure 2. fNIRS channel layout on the left and reconstructed fNIRS activity considering covariations with EEG dataset on the right. Red and orange squares indicate high correlation while green squares indicate low correlation.

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