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How to validate similarity in linear transform models of event-related potentials between experimental conditions?

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HIGHLIGHTS

- Linear transform models (LTMs) of ERP data are investigated.
- Using ICA, relative mapping coefficients (RMC) in LTMs are defined.
- Using RMCs of an ERP, similarity in LTMs between conditions is examined.

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ABSTRACT

Background: It is well-known that data of event-related potentials (ERPs) conform to the linear transform model (LTM). For group-level ERP data processing using principal/independent component analysis (PCA/ICA), ERP data of different experimental conditions and different participants are often concatenated. It is theoretically assumed that different experimental conditions and different participants possess the same LTM. However, how to validate the assumption has been seldom reported in terms of signal processing methods.
New method: When ICA decomposition is globally optimized for ERP data of one stimulus, we gain the ratio between two coefficients mapping a source in brain to two points along the scalp. Based on such a ratio, we defined a relative mapping coefficient (RMC). If RMCs between two conditions for an ERP are not significantly different in practice, mapping coefficients of this ERP between the two conditions are statistically identical.
Results: We examined whether the same LTM of ERP data could be applied for two different stimulus types of fearful and happy facial expressions. They were used in an ignore oddball paradigm in adult human participants. We found no significant difference in LTMs (based on ICASSO) of N170 responses to the fearful and the happy faces in terms of RMCs of N170.
Comparison with existing method(s): We found no methods for straightforward comparison.
Conclusions: The proposed RMC in light of ICA decomposition is an effective approach for validating the similarity of LTMs of ERPs between experimental conditions. This is very fundamental to apply group-level PCA/ICA to process ERP data.

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1. Introduction

EEG data are modeled as the linear transform model (LTM) under the EEG frequency range (Makeig et al., 1996, 1997, 1999). In this model, the data collected along the scalp are the mixtures of sources which are of electrical brain activity, and a mixing/mapping matrix connects the sources and the mixtures. The coefficients of the matrix contain mapping coefficients between sources in brain and points along the scalp. In an experiment to elicit event-related

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potentials (ERPs), EEG data processing methods are often applied to estimate ERPs' components in light of the LTM model (Luck, 2005; Sanei and Chambers, 2007).

As an advanced signal processing method, independent component analysis (ICA) conforming to a LTM has been successfully applied to separate scalp EEG data into sources of ERPs (Makeig et al., 1996; Vigario and Oja, 2008). It has been performed on the EEG data of a single trial (Cong et al., 2010; Iyer and Zouridakis, 2007), the concatenated EEG data of a number of single trials (Delorme and Makeig, 2004; Eichele et al., 2011), and the averaged EEG data over many single trials (Cong et al., 2011b; Makeig et al., 1997). In this study, we focus on the data processing for the averaged EEG data.

For example, in a passive oddball paradigm to elicit ERPs using pictures of human faces as stimuli, the happy and the fearful expressions have been applied as infrequently presented 'deviant' stimuli among natural 'standard' faces (Astikainen et al., 2013; Astikainen and Hietanen, 2009). Then, for a participant's averaged EEG data, the LTM regarding an electrode site for two deviants reads

$$x_{m,h,l}(t) = a_{m,1,h,l}S_{1,h,l}(t) + \cdots + a_{m,n,h,l}S_{n,h,l}(t) + \cdots + a_{m,N(l),h,l}S_{N(l),h,l}(t) + v_{m,h,l}(t)$$

$$x_{m,f,l}(t) = a_{m,1,f,l}S_{1,f,l}(t) + \cdots + a_{m,n,f,l}S_{n,f,l}(t) + \cdots + a_{m,N(l),f,l}S_{N(l),f,l}(t) + v_{m,h,l}(t)$$

where 'h' denotes the deviant of the happy expression, and 'f' represents the deviant of the fearful expression, 'l' is the index for a participant, 'n' symbolizes the number of the source, $N(l)$ is the number of all sources for the participant #l, and 'm' is the number of the electrode. For the lth participant under the deviant of the happy expression, $x_{m,h,l}(t)$ denotes the averaged EEG data, $S_{n,h,l}(t)$ represents the nth source of electrical brain activity, and $a_{m,n,h,l}$ is the mapping coefficient for $S_{n,h,l}(t)$ to the point where the electrode #m is placed, and $m \in [1, M]$, $n \in [1, N(l)]$, $n \in [1, N(l)]$, and $l \in [1, L]$, M is the number of all electrodes, and L is the number of all participants. It should be noted that $a_{m,n,h,l}$ depends on the properties of the volume conductor in brain of the participant #l, the location of the nth source in brain, and the measurement point along the scalp (Makeig et al., 1999).

For the averaged EEG data, group ICA is often applied with the concatenation of ERP data of different experimental conditions (Kalyakin et al., 2009, 2008) or/and different participants (Kovacevic and McIntosh, 2007; Vakorin et al., 2010). Using group ICA, only one set of independent components and an unmixing matrix are estimated (Eichele et al., 2011). Such an approach does inherently assume that the LTMs of different experimental conditions or/and different participants are theoretical identical (Cong et al., 2013b). This means the mapping coefficients of a source keep identical across different experimental conditions or/and participants, i.e., $a_{m,n,h,l} = a_{m,n,f,l}$, or/and $a_{m,n,h,l_1} = a_{m,n,h,l_2}$, $\forall l_i \in [1, L]$, $i = 1, 2$, $l_1 \neq l_2$, and the orders of sources remain the same along different experimental conditions or/and participants (Cong et al., 2013b). They are indeed the general hypotheses in the electrical fields of the brain (Nunez and Srinivasan, 2005). However, within the knowledge of the present authors, we have not found any previous study to straightforwardly validate these hypotheses in terms of signal processing methods despite that ICA (Eichele et al., 2011), principal component analysis (PCA) (Dien, 2012; Lohvansuu et al., 2013) and tensor decomposition (Cong et al., 2013c) have utilized such assumption. This motivates us to formulate a signal processing approach for validating the hypotheses.

In this study, we develop an ICA-based procedure to examine the similarity in LTMs of an ERP, N170, between two stimulus types (fearful faces vs happy faces) in the example mentioned above.

2. Method

2.1. Data description

Twenty two healthy adult volunteers were recruited by a newspaper advertisement (18 females, age range 30–58 years, mean 46.1 years) to take part in the experiment for data collection. All participants were right-handed and reported to have normal or corrected-to-normal vision. An informed written consent was obtained from each participant. The experiment was undertaken in accordance with the Declaration of Helsinki, and the ethical committee of the University of Jyväskylä approved the research protocol.

In order to elicit ERPs, pictures of emotionally expressive faces were presented to the participants. The stimuli were neutral, fearful and happy faces of four different actors from the series 'Pictures of Facial Affect' (Ekman and Friesen, 1976). The stimuli were presented in a passive oddball condition: the pictures of neutral facial expressions served as a repeated standard stimulus (probability = 0.8) and the pictures of the happy and fearful expressions (probability = 0.1 for each) as rarely presented deviant stimuli. During the recordings, the participants sat in a chair, and were instructed to pay no attention to the visual stimuli but instead focused on a radio play presented via loud speakers. At least two standards were presented between randomly presented consecutive deviants. The stimulus duration was 200 ms, and the stimulus onset asynchrony was 700 ms. Such a paradigm elicited a so called N170 response which is sensitive for faces and enhanced for emotional faces compared to neutral faces (Astikainen et al., 2013; Astikainen and Hietanen, 2009).

EEG data were collected with 14 electrodes including Fz, F3, F4, Cz, C3, C4, Pz, P3, P4, P7, P8, Oz, O1 and O2 according to the international 10–20 system through Brain Vision Recorder software (Brain Products GmbH, Munich, Germany). An average reference was used. Bipolar electrodes were placed above and below the left eye and lateral to the left and right orbit to measure the eye movements and blinks. Data were digitally on-line filtered from 0.1 to 100 Hz. The sampling frequency was 1000 Hz. Data were first offline preprocessed with Brain Vision Analyzer software (Brain Products GmbH, Munich, Germany). Continuous data were segmented (from 200 ms pre-stimulus period to 500 ms after the stimulus onset) and the baseline was corrected against 200 ms pre-stimulus interval. Segments with amplitude values beyond the range between −100 and 100 μV in any recording channel, including the electrooculogram channel, were rejected. The number of kept trials for the averaging was about 100 per deviant type.

After the data preprocessing, the remaining trials were averaged to produce the ERP waveforms, i.e., the averaged EEG data.

2.2. Procedure of ICA to estimate peak amplitude of an ERP

After the conventional ERP data processing, the peak amplitude of an ERP is often measured from the averaged EEG for the further statistical analysis. As shown in the Introduction, the averaged EEG data are still mixtures of many brain sources. Using ICA, the averaged EEG data can be spatially filtered to theoretically produce the sole waveform of one brain source in the electrode field (Cong et al., 2013a, 2011c, 2011d).

2.2.1. Complete ICA procedure as a spatial filter

When sensor noise is omitted or included in the LTM (Cong et al., 2014), the LTM associating the EEG data ($\mathbf{x}$) along the scalp and the electrical sources ($\mathbf{s}$) in brain can be expressed as

$$\mathbf{x} = \mathbf{A}\mathbf{s} \quad (1)$$

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