NeuroImage 90 (2014) 128–139

Contents lists available at ScienceDirect

NeuroImage

journal homepage: www.elsevier.com/locate/ynimg

Decoding spatial attention by using cortical currents estimated from electroencephalography with near-infrared spectroscopy prior information

Hiroshi Morioka [a,b], Atsunori Kanemura [a,1], Satoshi Morimoto [a], Taku Yoshioka [a], Shigeyuki Oba [b], Motoaki Kawanabe [a], Shin Ishii [a,b,*]

[a] *ATR Neural Information Analysis Laboratories, Kyoto 619-0288, Japan*
[b] *Graduate School of Informatics, Kyoto University, Kyoto 611-0011, Japan*

ARTICLE INFO

Article history:
Accepted 18 December 2013
Available online 27 December 2013

Keywords:
Brain–machine interface (BMI)
Variational Bayesian Multimodal EncephaloGraphy (VBMEG)
Electroencephalography (EEG)
Near-infrared spectroscopy (NIRS)
NIRS–EEG simultaneous measurement
Spatial attention

ABSTRACT

For practical brain–machine interfaces (BMIs), electroencephalography (EEG) and near-infrared spectroscopy (NIRS) are the only current methods that are non-invasive and available in non-laboratory environments. However, the use of EEG and NIRS involves certain inherent problems. EEG signals are generally a mixture of neural activity from broad areas, some of which may not be related to the task targeted by BMI, hence impairing BMI performance. NIRS has an inherent time delay as it measures blood flow, which therefore detracts from practical real-time BMI utility. To try to improve real environment EEG–NIRS-based BMIs, we propose here a novel methodology in which the subjects' mental states are decoded from cortical currents estimated from EEG, with the help of information from NIRS. Using a Variational Bayesian Multimodal EncephaloGraphy (VBMEG) methodology, we incorporated a novel form of NIRS-based prior to capture event related desynchronization from isolated current sources on the cortical surface. Then, we applied a Bayesian logistic regression technique to decode subjects' mental states from further sparsified current sources. Applying our methodology to a spatial attention task, we found our EEG–NIRS-based decoder exhibited significant performance improvement over decoding methods based on EEG sensor signals alone. The advancement of our methodology, decoding from current sources sparsely isolated on the cortex, was also supported by neuroscientific considerations; intraparietal sulcus, a region known to be involved in spatial attention, was a key responsible region in our task. These results suggest that our methodology is not only a practical option for EEG–NIRS-based BMI applications, but also a potential tool to investigate brain activity in non-laboratory and naturalistic environments.

Introduction

It is of major importance to develop new ways of neural decoding based on non-invasive and portable measurements such as electroencephalography (EEG) and near-infrared spectroscopy (NIRS), since these are the only methods that are currently applicable in non-laboratory environments and suitable for practical real-world brain–machine interface (BMI) applications. BMI has attracted much attention in biomedical engineering fields for its usefulness in assisting disabled people and enhancing people's lifestyle (Iturrate et al., 2009; Rebsamen et al., 2010; Tanaka et al., 2005; Wolpaw and Wolpaw, 2012). There exist several technologies for measuring brain activities of humans, in particular, non-invasive ones are preferred due to their longevity and safety; e.g., EEG, NIRS, magnetoencephalography (MEG), and functional magnetic resonance imaging (fMRI). Although MEG and fMRI's higher spatial/temporal resolution has led to success in existing decoding studies (Chan et al., 2011; Kamitani and Tong, 2005; Waldert et al., 2008), they lack the portability of EEG and NIRS, in which the body does not need to be fixed. However, EEG and NIRS methodologies lack the decoding methodologies that can match the performance of fMRI and MEG methods.

EEG measures the voltage fluctuations on the scalp, which result from ionic current flows within a large number of neurons (i.e. volume conduction effect); therefore, EEG signals are comprised of a mixture of signals originating from different cortical areas (Wolters et al., 2006). The contamination of electrical measurements originating from regions not related to the task targeted by the BMI can deteriorate the BMI performance. On the other hand, NIRS has inherent time delays as it measures blood flow caused by neural metabolism, which greatly hinders real-time BMI. Source current localization, which is to reconstruct cortical currents based on measurements outside the scalp, has a potential to address these issues in EEG–NIRS-based BMIs working in real environments.

* Corresponding author at: 2-2-2 Hikaridai, Seika Town, Kyoto 619-0288, Japan. Fax: +81 774 95 1259.
E-mail address: ishii@i.kyoto-u.ac.jp (S. Ishii).
[1] Now with ISIR, Osaka University, Osaka 567-0047, Japan.

1053-8119/$ – see front matter © 2013 Elsevier Inc. All rights reserved.
http://dx.doi.org/10.1016/j.neuroimage.2013.12.035

Indeed, decoding from cortical currents has several advantages (Toda et al., 2011). First, EEG sensor signals are mapped onto currents on the cortex, each of which possesses information specific to a particular cortical region, thus avoiding the volume conduction effect. In addition, artifacts evoked by, e.g., eye movements can be eliminated by incorporating extra dipoles during the source current estimation (Morishige et al., 2009). By estimating cortical currents and separating task-relevant brain activities, improvement in BMI performance can be expected. Second, we may be able to obtain brain activities with higher spatial resolution by assuming a large number of cortical current dipoles compared to that of EEG sensors. Third, a large body of neuroscientific knowledge can be used for validating the reconstructed cortical activities and hence BMI decoders based on them. Cortical currents invoked by performing a task can be analyzed based on the function of active brain regions. Since activity in a specific brain region would induce both cortical current and blood flow, we can compare the task-relevant cortical current sources and the fMRI-based neural correlates involved in the same task. Despite such advantages, cortical source current estimation is an ill-posed inverse problem because many different source configurations can generate the same EEG observations (Grech et al., 2008; Michel et al., 2004). Therefore, some prior assumptions are required to obtain a unique solution; e.g., L1-norm minimization method (Uutela et al., 1999), L2-norm minimization method (Wang et al., 1992), LORETTA (Pascual-Marqui et al., 1994), and the Wiener filter or Bayesian inference (Dale et al., 2000; Kajihara et al., 2004; Phillips et al., 2002; Schmidt et al., 1999) which resolved the ill-posedness by using fMRI data as prior information on the source current variance. More recently, Variational Bayesian Multimodal EncephaloGraphy (VBMEG) (Sato et al., 2004; Yoshioka et al., 2008) has been proposed to incorporate the prior information as a hierarchical prior: the blood-flow information from fMRI is substituted into the parameter specifying the probability distribution of the current variance rather than the variance itself, and the variance is estimated through the variational Bayesian estimation procedure. This constitutes placing a soft constraint on the variance, and thus is robust to the vulnerability of inaccuracies in prior information.

The simultaneous use of NIRS measurement is a promising solution for real-environment BMI as it can reduce the ill-posedness of the EEG source current estimation and estimate reasonable activation patterns. NIRS measures the concentration changes of oxygenated and deoxygenated hemoglobins (oxyHb and deoxyHb, respectively) in the superficial layers of the cortex (Villringer et al., 1993). Thus, NIRS can detect active, nonactive, and deactive cortical regions via blood flow caused by neural activities that also induce EEG signals. Aihara et al. (2012) showed that, by applying VBMEG to EEG measurement during a finger tapping task, cortical currents could be estimated better by incorporating NIRS prior than solely from EEG, though EEG and NIRS were measured by different but similar tasks.

Training a BMI classifier using relatively few data has an issue in the machine learning side. The estimated current dipoles on the cortical surface are high-dimensional in general, having more degrees of freedom as compared to the number of available data points, thus causing an overfitting problem (Hastie et al., 2009; Kriegeskorte et al., 2009). It is therefore important to reduce the dimensionality by selecting in a sparse manner current dipoles that are relevant to the task of interest. Sparse logistic regression (SLR; Yamashita et al., 2008) estimates the weight parameters of logistic regression with the automatic relevance determination (ARD) hierarchical prior via Bayesian inference, and can automatically and sparsely select informative features for decoding (BMI classification) (Miyawaki et al., 2008; Shibata et al., 2011). Thus, by using SLR for decoding after the cortical current estimation, we can effectively select the current dipoles having region-specific information related to the task.

Spatial attention is often used as a task for BMI because it is natural in real environments and justifiable from existing neuroscience/BMI studies. Because BMI users may not be able to move their eyes, covert spatial attention is a standard and natural way to decode the direction of intended control. In particular, it would be convenient to control objects in the visual domain such as a cursor on a computer screen. Recent studies have reported that subjects' covertly attended direction could be decoded from brain activities even in a single trial. For instance, (Kelly et al., 2005a, 2005b) showed that shifts in covert spatial attention between the left and right visual hemifields can be decoded from EEG's alpha-desynchronization in the posterior sites contralateral to the attended hemifield; the average accuracy for off-line decoding was 73% (Kelly et al., 2005b) and for on-line decoding was 62% (Kelly et al., 2005a).[2] This finding has been followed by an MEG study (Van Gerven et al., 2009) with a reported off-line decoding accuracy of 61% on average, and an fMRI study Andersson et al. (2011) in real-time with an accuracy above 90%.

In this study, we propose a novel methodology for decoding covert spatial attention from cortical currents estimated from EEG with NIRS prior information with an SLR classifier. Structural MRI data are also used to provide accurate head models. This is the first study applying cortical current estimation from EEG with NIRS prior information to BMI decoding. We introduce a novel form of Bayesian prior to capture event related desynchronization (i.e., modulations in frequency power) which is a well-known phenomenon during many tasks involving higher-order functions including spatial attention. A major advantage of our new procedure is that it can examine activation patterns on the cortex in light of existing neuroscientific knowledge. Such verification would also imply the possibility that the EEG–NIRS-based decoding technique contributes to studies of brain functions in non-laboratory and naturalistic conditions.

Method

Subjects

Experiments were conducted on eight right-handed males between 20 to 40 years of age (mean: 24.6, SD: 6.4) who had normal or corrected-to-normal vision. All subjects gave written informed consent for the experimental procedures, which had been approved by the ATR Human Subject Review Committee.

Experimental setup

The subjects were seated in a comfortable chair 1 m away from a 19-inch display for visual presentation. A white cross was displayed at the center of the display as a fixation point. Visual stimuli of left and right bars were centered at an eccentricity of 8°. The size of the bars was 1.3°. The head position of the subject was fixed by chin and forehead supports. A keyboard for response was placed in front of the subject. This experiment was conducted in a dark room.

Task for subjects

We used a spatial attention task in which subjects attend to the left or right following instruction by the visual stimulus. This task was modified from Tootell et al. (1998). Fig. 1A shows the time course of epochs in a block. One block consisted of two epochs: Attention (8 s) and Control (4 s). One experiment consisted of 8 sessions, and each session consisted of 24 blocks.

In the Attention epoch, two white flashing bars were presented repeatedly in a rapid stream until the end of the epoch. These flashing bars were presented for 100 ms followed by an inter-stimulus interval (600–800 ms) where no bar was presented. At each appearance, the orientations of each bar were selected randomly with equal probability

[2] This percentage was not directly reported in Kelly et al. (2005b); however we calculated their average accuracy by dividing the number of correct selections by the sum of the correct and incorrect selections (not including inconclusive trials), which are shown in Table 1 of their article.