Journal of Neuroscience Methods 253 (2015) 18–27

Contents lists available at ScienceDirect

Journal of Neuroscience Methods

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

Basic neuroscience

A novel approach to identify time-frequency oscillatory features in electrocortical signals

Huibin Jia[1], Weiwei Peng*,[1], Li Hu*

Key Laboratory of Cognition and Personality (Ministry of Education) and Faculty of Psychology, Southwest University, Chongqing 400715, China

HIGHLIGHTS

- A novel approach was proposed to optimally identify oscillatory features.
- Time-frequency oscillatory features were identified based on their spatial distributions.
- The novel approach was validated using both simulated and real electrocortical datasets.
- The novel approach can help explore the precise functions of oscillatory activities.

ARTICLE INFO

Article history:
Received 18 February 2015
Received in revised form 27 April 2015
Accepted 26 May 2015
Available online 6 June 2015

Keywords:
Time-frequency analysis
Topographic segmentation analysis
Scalp topography
Event-related synchronization/desynchronization (ERS/ERD)
Time-frequency oscillatory features

ABSTRACT

Background: Sensory, motor, and cognitive events could not only evoke phase-locked event-related potentials in ongoing electrocortical signals, but also induce non-phase-locked changes of oscillatory activities. These oscillatory activities, whose functional significances differ greatly according to their temporal, spectral, and spatial characteristics, are commonly detected when single-trial signals are transformed into time-frequency distributions (TFDs). Parameters characterizing oscillatory activities are normally measured from multi-channel TFDs within a time-frequency region-of-interest (TF-ROI), pre-defined using a hypothesis-driven or data-driven approach. However, both approaches could ignore the possibility that the pre-defined TF-ROI contains several spatially/functionally distinct oscillatory activities.
New method: We proposed a novel approach based on topographic segmentation analysis to optimally and automatically identify detailed time-frequency features. This approach, which could effectively exploit the spatial information of oscillatory activities, has been validated in both simulation and real electrocortical studies.
Results: Simulation study showed that the proposed approach could successfully identify noise-contaminated time-frequency features if their signal-to-noise ratio was relatively high. Real electrocortical study demonstrated that several time-frequency features with distinct scalp distributions and evident neurophysiological functions were identified when the same analysis was applied on stimulus-elicited TFDs.
Comparison with existing methods: Unlike traditional approaches, the proposed approach could provide an optimal identification of detailed time-frequency features by making use of their distinct spatial distributions.
Conclusions: Our findings illustrated the validity and usefulness of the presented approach in isolating detailed time-frequency features, thus having wide applications in cognitive neuroscience to provide a precise assessment of the functional significance of oscillatory activities

---

Abbreviations: CWT, continuous wavelet transform; EEG, electroencephalography; ERPs, event-related potentials; ERD, event-related desynchronization; ERS, event-related synchronization; FDR, false discovery rate; LMM, linear mixed model; RT, reaction time; SNR, signal-to-noise ratio; TFDs, time-frequency distributions; TF-ROIs, time-frequency region-of-interests.

* Corresponding authors. Tel.: +86 18084053555; fax: +86 23 68252983.
E-mail addresses: ww.peng0923@gmail.com (W. Peng), huli@swu.edu.cn (L. Hu).

[1] Equal contribution.

http://dx.doi.org/10.1016/j.jneumeth.2015.05.026
0165-0270/

1. Introduction

Brief sensory, motor, and cognitive events could elicit a number of transient changes in the ongoing electrocortical signals, including event-related potentials (ERPs), event-related synchronization and desynchronization (ERS and ERD) (Mouraux and Iannetti, 2008). While ERPs are time-locked and phase-locked to the presentation of stimuli, ERS/ERD reflects time-locked and non-phase-locked power modulations of ongoing electrocortical oscillations (Pfurtscheller and Aranibar, 1977; Pfurtscheller and Lopes da Silva, 1999). These modulations are characterized by either transient increase (ERS) or decrease (ERD) of oscillatory power, whose functional significance differs greatly according to their temporal, spectral, and spatial characteristics (Ohara et al., 2004). For example, ERD in the alpha band (8–12 Hz) has been hypothesized to reflect cortical activation (Mouraux et al., 2003; Yordanova et al., 2001), and ERS in the gamma band (30–100 Hz) has been suggested to play a crucial role in cortical integration and perception (Fries, 2009; Martinovic and Busch, 2011). Therefore, ERS/ERD is popularly used as an effective biological index to discriminate neurological disorders and monitor psychometric measures (Gross et al., 2007; Ploner et al., 2006b).

To estimate ERS/ERD, time-frequency decomposition algorithms (e.g., short-time Fourier transform and continuous wavelet transform [CWT]) are normally adopted to transform single-trial electrocortical responses to time-frequency distributions (TFDs) (Zhang et al., 2012). The obtained TFDs are suggested to express stimulus-elicited changes in oscillatory power (e.g., ERS/ERD), relative to a pre-stimulus reference interval (Grandchamp and Delorme, 2011). This time-frequency baseline correction has been demonstrated to be optimally achieved using the subtraction approach (i.e., subtracting the average of the pre-stimulus interval from each post-stimulus time-frequency point), which avoids the positive bias introduced by the percentage approach (i.e., dividing the post-stimulus values obtained at each frequency with the subtraction approach by the average of the pre-stimulus values at that frequency) (Hu et al., 2014b).

To investigate the functional significance of ERS/ERD by assessing their relationship with various experimental measures (e.g., reaction time and sensory perception), a region-of-interest in the time-frequency domain (TF-ROI) is normally required to be defined prior to measuring the ERS/ERD activities (Hu et al., 2013; Valentini et al., 2013). The TF-ROI was popularly defined using two different approaches: hypothesis-driven and data-driven approaches. The hypothesis-driven approach manually defined the time and frequency limits for each TF-ROI based on the findings of previous studies (Hu et al., 2014a; Peng et al., 2012). In contrast, the data-driven approach defined the boundary of TF-ROI by isolating the region that was modulated by some experimental manipulations, i.e., based on the output of statistical comparison (Tang et al., 2013; Zhang et al., 2012). However, both hypothesis-driven and data-driven approaches ignored two important facts. First, ERS/ERD of nearby time-frequency points may vary markedly in spatial distribution, which indicated that the adjacent ERS/ERD activities could be generated from distinct neural populations and capture different functional significance (Hu et al., 2013). Second, the TF-ROI, especially defined using data-driven approach, may be too large to represent one region containing single oscillatory response. In other words, the defined TF-ROI may contain several spatially/functionally distinct oscillatory responses. Therefore, the availability of a novel approach that could optimally and automatically define TF-ROIs based on the spatial and functional similarity of oscillatory responses is highly in demanding.

Recently, topographic segmentation analysis has gained its popularity to define brain microstates of electrocortical signals, each of which is characterized by a fixed spatial distribution and a distinct functional state of the brain (Koenig et al., 2002; Van de Ville et al., 2010). In principle, brain microstates are isolated based on the similarity of scalp distributions of electrocortical responses (Murray et al., 2008a). Based on the same principle, the topographic segmentation analysis could be potentially advanced to define TF-ROIs by separating oscillatory responses in the time-frequency domain into spatially and functionally distinct features, which is the aim of the present study. The validity and usefulness of the proposed approach were demonstrated using both simulated and real electrocortical datasets.

2. Material and methods

2.1. Subjects

Resting electroencephalography (EEG) data were collected from 38 healthy right-handed volunteers (21 females) aged 21 ± 1.9 years (mean ± SD, range: 19–25 years), and event-related EEG data were collected from 18 healthy right-handed volunteers (9 females) aged 22 ± 2.5 years (mean ± SD, range: 19–29 years). All subjects gave their written informed consent and were paid for their participation. The local ethics committee approved the experimental procedures. Both datasets were already published in our previous studies (resting EEG: Peng et al., 2014; event-related EEG: Hu et al., 2013).

2.2. Experimental procedures

To collect resting EEG data, each subject was required to seat on a comfortable chair in a silent, temperature-controlled room, and were instructed to keep relaxed and eyes open for at least 5 min.

To collect event-related EEG data, each subject was stimulated with nociceptive pulses using an oddball paradigm. Nociceptive stimuli were delivered to either the medial or the lateral side of subject's left hand dorsum. Nociceptive stimuli were constant-current square electrical pulses with 0.5 ms duration, delivered through a stainless steel concentric bipolar needle electrode consisting of a needle cathode (length: 0.1 mm; diameter: 0.2 mm) surrounded by a cylindrical anode (diameter: 1.4 mm) (Inui et al., 2002; Inui et al., 2006). The stimulus intensity was twice of individual perceptual threshold, which was previously proved to be able to preferentially activate the Aδ nociceptive fibers without coactivation of the fast-conducting Aβ fibers (Mouraux et al., 2010).

Nociceptive stimuli were delivered in 2 blocks. In one block, target (rare stimuli: 20%) and non-target (frequent stimuli: 80%) stimuli were respectively delivered to the medial and lateral sides of subject's left hand dorsum. In the other block, the delivered sites of target and non-target stimuli were reversed. The order of blocks was counterbalanced across subjects. Each block consisted of 200 stimuli, including 40 target stimuli and 160 non-target stimuli, and inter-stimulus intervals were randomly varied between 2500 and 3000 ms. Subjects were required to respond as fast and accurately as possible to the predefined target stimuli by pressing the response button upon their detection of the targets using the right index finger, and the reaction times (RTs) were recorded.

2.3. EEG recording

Both resting and event-related EEG data were recorded using a 64-channel Brain Products system (pass band: 0.01–100 Hz; sampling rate: 1000 Hz for resting EEG and 500 Hz for event-related EEG; physical reference channel: nose for resting EEG and left mastoid for event-related EEG) with a standard EEG cap based on the extended 10–20 system. All channel impedances were kept lower than 10 kΩ. To monitor ocular movements and eye blinks,