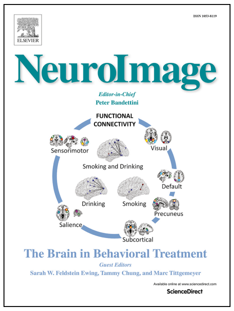

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Modeling Brain Dynamic State Changes with Adaptive Mixture Independent Component Analysis

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Abstract

There is a growing interest in neuroscience in assessing the continuous, endogenous, and nonstationary dynamics of brain network activity supporting the fluidity of human cognition and behavior. This non-stationarity may involve ever-changing formation and dissolution of active cortical sources and brain networks. However, unsupervised approaches to identify and model these changes in brain dynamics as continuous transitions between quasi-stable brain states using unlabeled, noninvasive recordings of brain activity have been limited. This study explores the use of adaptive mixture independent component analysis (AMICA) to model multichannel electroencephalographic (EEG) data with a set of ICA models, each of which decomposes an adaptively learned portion of the data into statistically independent sources. We first show that AMICA can segment simulated quasi-stationary EEG data and accurately identify ground-truth sources and source model transitions. Next, we demonstrate that AMICA decomposition, applied to 6-13 channel scalp recordings from the CAP Sleep Database, can characterize sleep stage dynamics, allowing 75% accuracy in identifying transitions between six sleep stages without use of EEG power spectra. Finally, applied to 30-channel data from subjects in a driving simulator, AMICA identifies models that account for EEG during faster and slower response to driving challenges, respectively. We show changes in relative probabilities of these models allow effective prediction of subject response speed and moment-by-moment characterization of state changes within single trials. AMICA thus provides a generic unsupervised approach to identifying and modeling changes in EEG dynamics. Applied to continuous, unlabeled multichannel data, AMICA may likely be used to detect and study any changes in cognitive states.

Keywords: Electroencephalography (EEG), brain states, non-stationarity, independent component analysis (ICA), adaptive mixture ICA (AMICA), unsupervised learning, sleep staging, drowsiness detection

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1. Introduction

An expanding focus in neuroscience has been on endogenous temporal dynamics of neural network activity that gives rise to fluidity and rapid adaptability in cognition and behavior. A growing body of evidence suggests that these temporal dynamics may arise from continual formation and dissolution of interacting cortical and allied subcortical source activities in large-scale brain regions whose joint electrical activities can be described as dynamic systems featuring continuous transitions between intermittently stable states (Chu et al., 2012; Betzel et al., 2012).The temporal dynamics and network topology of these "brain states" can be identified using functional neuroimaging techniques including invasive electrophysiological recordings, functional MRI (fMRI), magnetoencephalography (MEG), and electroencephalography (EEG) (Freyer et al., 2009; Chu et al., 2012). Among noninvasive modalities, EEG provides a more direct measurement of brain activity with millisecond resolution that, because of the low weight and bulk of its sensors, is appropriate for studying fast-changing brain states in real-world environments.

Earlier methods applied nonparametric statistical approaches that used EEG power spectral density, autocorrelation function, and entropy measures (Natarajan et al., 2004) to detect change points allowing segmentation of EEG into piecewise stationary processes (Kaplan et al., 2001). Microstate analysis (see Khanna et al. (2015) for a review) takes the spatial distribution of electrodes into account and attempts to define quasi-stable "microstates" in terms of unique electric potential patterns across the multichannel EEG scalp electrode montage during behavioral states or resting states (Lehmann et al., 1987; Van de Ville et al., 2010). The global functional connectivity approach (Chu et al., 2012; Betzel et al., 2012) measures inter-electrode channel signal synchrony to attempt to characterize brain states as stable functional networks. However, both the microstate and global connectivity models analyze scalp electrode signals that in themselves are highly correlated through common volume conduction and summation at the electrodes of potentials arising from brain and also non-brain sources (eye movements, ECG, etc.). The results of both methods have few or no interpretable connections to particular brain source activities that underlie the observed scalp phenomena. Hidden Markov Models (HMM) form another family of generative models with a rigorous temporal structure used to measure nonstationary functional connectivity. Such models have been

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