Journal of Neuroscience Methods 249 (2015) 41–49

Contents lists available at ScienceDirect

Journal of Neuroscience Methods

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

Computational Neuroscience

Motor imagery classification via combinatory decomposition of ERP and ERSP using sparse nonnegative matrix factorization

Na Lu[a,*], Tao Yin[b]

[a] State Key Laboratory for Manufacturing Systems Engineering, Systems Engineering Institute, Xi'an Jiaotong University, Xi'an, Shaanxi, China
[b] Vision Microsystems Co., Ltd, Shanghai, China

HIGHLIGHTS

- MALS-NMF allows for negative entry while preserving the pure addition of components.
- Sparsity constraint has been incorporated into MALS-NMF.
- The knowledge obtained by MALS-NMF on ERP and ERSP have been combined.

ARTICLE INFO

Article history:
Received 21 October 2014
Received in revised form 26 March 2015
Accepted 27 March 2015
Available online 3 April 2015

Keywords:
Motor imagery
Classification
Event related potential
Nonnegative matrix factorization
Brain computer interface

ABSTRACT

Background: Brain activities could be measured by devices like EEG, MEG, MRI etc. in terms of electric or magnetic signal, which could provide information from three domains, i.e., time, frequency and space. Combinatory analysis of these features could definitely help to improve the classification performance on brain activities. NMF (nonnegative matrix factorization) has been widely applied in pattern extraction tasks (e.g., face recognition, gene data analysis) which could provide physically meaningful explanation of the data. However, brain signals also take negative values, so only spectral feature has been employed in existing NMF studies for brain computer interface. In addition, sparsity is an intrinsic characteristic of electric signals.
New method: To incorporate sparsity constraint and enable analysis of time domain feature using NMF, a new solution for motor imagery classification is developed, which combinatorially analyzes the ERP (event related potential, time domain) and ERSP (event related spectral perturbation, frequency domain) features via a modified mixed alternating least square based NMF method (MALS-NMF for short).
Results: Extensive experiments have verified the effectivity the proposed method. The results also showed that imposing sparsity constraint on the coefficient matrix in ERP factorization and basis matrix in ERSP factorization could better improve the algorithm performance.
Comparison with existing methods: Comparisons with other eight representative methods have further verified the superiority of the proposed method.
Conclusions: The MALS-NMF method is an effective solution for motor imagery classification and has shed some new light into the field of brain dynamics pattern analysis.

1. Introduction

To explore the brain dynamics under different mental task is of essential importance to understand the brain functional mechanism and develop techniques to assist people with disabilities (Wolpaw, 2007; Cuiwei et al., 1995). EEG (electroencephalogram) is a widely used non-invasive technique measuring the electrical signal of the brain activities. The recorded brain signals present characteristics like very high dimension, non-linear, non-stationary and low signal to noise ratio, which bring challenges to the existing signal analysis methods (Wolpaw et al., 2002). In recent years, the analysis methods for brain dynamics, especially the classification methods have attracted increasing attention of researchers from different fields like bioengineering, computer science, and cognitive science (Stewart et al., 2014; Heung-Il and Seong-Whan, 2013; Li et al., 2013).

More specifically, within the BCI (brain computer interface) field, a wealth of studies has been conducted to mine the brain response patterns related to different mental activities. As the most popular technique in BCI, EEG records the voltage variation along

* Corresponding author. Tel.: +86 153 88608981; fax: +86 029 82665487.
E-mail address: lvna2009@mail.xjtu.edu.cn (N. Lu).

http://dx.doi.org/10.1016/j.jneumeth.2015.03.031
0165-0270/

time by multiple electrodes deployed over the skull. With respect to different mental tasks, the variation pattern of the EEG signal reveals distinct characteristics temporally and spatially. Many methods have been developed or employed to uncover the featured patterns buried in the EEG data, such as common spatial pattern (CSP) (Haiping et al., 2010; Kai Keng et al., 2008), independent component analysis (ICA) (Makeig et al., 2004; Makeig and Onton, 2009), principle component analysis (PCA), and time-frequency methods like Fourier analysis (Makeig, 1993), Hilbert-Huang transform (HHT) (Wu et al., 2011) and wavelets (Ting et al., 2008). All these methods aim at finding a basis composed of few intrinsic vectors (components), and the linear combination of which could accurately or approximately represent the samples. NMF has attracted increasing attention in recent decades due to its physically interpretable representation as pure parts addition (Lee and Seung, 1999; Hoyer, 2004). Some previous research has tried to address the classification problem of brain signals, especially the motor imagery, using NMF (Lee et al., 2006, 2010; Lee and Choi, 2009). However, NMF requires the raw data to be nonnegative, which is obviously not the case for electric signal. The existing papers on EEG classification using NMF mainly employ spectral features, like PSD (power spectral density), Wavelet parameters and so on, to analyze the data, which thus only consider the frequency domain information (Lee et al., 2006, 2010; Lee and Choi, 2009; Liu et al., 2004). However, to combine time domain and frequency domain features could high possibly benefit the classification algorithm, as suggested in Makeig et al. (2004).

ERP (event related potential) is a widely used time domain feature for motor imagery classification, the average of which captures the fluctuation mode of the brain response to specific motor imagery. However, it has been indicated in Makeig (1993) that the ERP cannot fully reveal the characteristic of the brain response to the external stimuli. On the other hand, the frequency domain knowledge also only carries certain aspect of the information conveyed by the data. ERSP (event related spectral perturbation) measures the change against the baseline power and could deliver information that is not revealed by ERP (Makeig et al., 2004). Therefore, combining ERP and ERSP is a promising solution for better performance in motor imagery classification.

In addition, a critical and intrinsic property of electric signal is sparsity, including the brain signal. The thriving technologies like sparse coding (Olshausen and Field, 1996), compressive sensing (Candes et al., 2006; Candes and Tao, 2005), have constructed the basis and validated the effectivity of sparse representation. There is good reason to believe that a small number of intrinsic patterns exist for specific motion related sensorimotor rhythms (SMRs) which could be combined to represent the recorded EEG sequence. Therefore, introducing sparse representation of EEG signals into the analysis of brain dynamics could help to figure out the intrinsic pattern structure of the brain activities. We also notice that some efforts have been made to incorporate sparsity considerations into the BCI research (Wang et al., 2012; Younghak et al., 2012).

Based on the above considerations, a new solution for brain dynamics (motor imagery) classification is developed in this paper. A modified MALS-NMF method is proposed first, which has incorporated the sparsity constraint and eliminated the nonnegativity constraint on the basis matrix in NMF. The ERP and ERSP features are then combinatorially decomposed by MALS-NMF, and the results of which are used to train a SVM classifier based on one-versus-rest strategy. Extensive experiments have verified the superiority of the proposed method.

It is worthwhile to highlight the several contributions of the proposed method here:

1. Different from the existing application of NMF method in brain signal analysis which only works in the frequency domain, the proposed MALS-NMF method allows for negative entries while preserving the pure addition manner of components (nonnegative coefficient matrix), which has thus enabled analysis in both time and frequency domain, and laid basis for uncovering the intrinsic brain response patterns.
2. Sparsity constraint has been incorporated into the MALS-NMF, which is an essential characteristic of the brain signal in question.
3. The knowledge obtained by MALS-NMF on ERP and ERSP have been combined for the motor imagery classification task, which is verified to have superior performance through extensive experiments. The discovered patterns have also shown promise in understanding the intrinsic patterns of brain activities.

The rest of the paper is organized as follows: Section 2 discussed the related researches. The MALS-NMF method and the overall solution are described in Section 3. Experiments and comparisons are given in Section 4. Section 5 forms conclusion.

2. Related research

NMF is one of the matrix factorization methods that has attracted much attention of researchers in recent years (Lee and Seung, 1999; Deng et al., 2011; Ding et al., 2010). One unique property of NMF is that it imposes nonnegativity constraint on both decomposed matrices, which could result in physically meaningful part representation due to its pure addition manner.

Many NMF variants have been developed in the past decade, and here we only describe several representative studies due to the space limit. Ding et al. (2010) developed two variants of NMF, called Semi-NMF and convex NMF. The former one allows negative entries in the decomposed matrices and thus compromises the nonnegativity constraint; the latter one forces the basis vectors to be a convex combination of data points, which introduces sparsity into the algorithm implicitly. However, there is not a combination of the two variants. Li et al. (2001) recognized that the basis learnt by the original NMF are not necessarily localized, and thus may not be well separated parts. They proposed the local nonnegative matrix factorization (LNMF) method by introducing sparsity and redundancy constraints to obtain a minimum number of basis vectors to achieve better locality. However, these constraints are not sufficient for the algorithm to produce non-overlapping parts. E.g., for face images, the locality level is determined by how well the faces are aligned in the training samples. The sparsity constraint in Hoyer (2004) shares same property with that of LNMF. Cai et al. (Wu et al., 2011) proposed a graph regularized nonnegative matrix factorization (GNMF), which constructs an affinity graph to introduce the inter-sample geometric similarity as a closeness constraint on the sample representations. A constrained nonnegative matrix factorization (CNMF) was developed by Liu et al. (Haifeng et al., 2012) with the label information as a hard constraint, which leads to a merged representation of samples from the same class. However, one assumption of CNMF is that two samples from the same class must have the same representation using the bases obtained after decomposition, which may not be practical given the fact, e.g., the face images of the same person can be very different under different conditions like different view angles. Kim and Park (2007) developed a sparse NMF based on ALS, which has been modified to form the MALS-NMF in this paper by allowing for negative basis matrix. More specifically, for brain signal analysis, some variants of NMF such as GNMF (group NMF) (Lee and Choi, 2009), semi-supervised NMF (Lee et al., 2010) etc. have been developed. Among which, GNMF is specially designed for multiple subjects analysis which maximizes the inter-subject difference and minimizes the intra-subject distinction. The semi-supervised NMF incorporates the known labels of samples into the matrix factorization problem