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Multichannel EEG Brain Activity Pattern Analysis in Time-Frequency Domain with Nonnegative Matrix Factorization Support

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Abstract. A novel approach combining a time-frequency representation of brain activity in form of recorded EEG signals together with nonnegative matrix factorization (NMF) post-processing section in brain computer interface (BCI) training paradigm is presented. Such a combination of two emerging signal analysis techniques enables us to find and enhance very small oscillations related to presented visual stimuli. Presented results confirm validity of the chosen approach.

Keywords: EEG, time-frequency signal analysis, brain computer interface, empirical mode decomposition, nonnegative matrix factorization, EEG analysis.

1. Introduction

It is of much interest recently to utilize electrical brain activity to control devices or computers in form of brain computer interfaces (BCI). In this paper we propose a new method for extraction of features and analysis/enhancement of EEG brain patterns. In the first stage we perform analysis in the time-frequency domain using empirical mode decomposition (EMD) technique. Since the obtained intrinsic mode functions (IMF) are still highly redundant and superimposed, in the second stage we apply nonnegative matrix factorization (NMF) to perform model reduction and extract hidden nonnegative factors. Such a two-stage approach lets us properly find very weak oscillation patterns in very noisy EEG signals. Those oscillation patterns represent subjects' visual responses (so called steady state visual evoked potentials – SSVEP) to visual stimuli presented in

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form of flashing patterns. Standard signal processing techniques are usually not able to extract those tiny oscillations due to a very low signal to noise ratio.

2. EEG Preprocessing

At the EEG preprocessing level we utilize a single channel method EMD [1], which is a new technique gaining recent attention in form of applications in the area of neurophysiological signal processing [2]. EMD generally utilizes empirical knowledge of oscillations embedded in time series. It decomposes a signal into intrinsic modes in order to represent them as a superposition of components with well defined instantaneous frequencies - IMF, which should approximately obey the requirements of: (i) completeness; (ii) orthogonality; (iii) locality; (iv) adaptiveness. To obtain an IMF it is necessary to remove local riding waves and asymmetries, which are estimated from local envelope of minima and maxima of the waveform. In the next step the IMF functions are transformed into Hilbert spectra domain to visualize their time-frequency representations in form of ridges, which are plotted in form of very sharp tracks on spectrograms as illustrated in Figure 1(b), where also the whole process of EEG signal decomposition into IMF components is presented in details. Such redundant representations can be further decomposed from obtained spectral images with utilization of nonnegative matrix factorization (NMF) methods as explained in the next section.

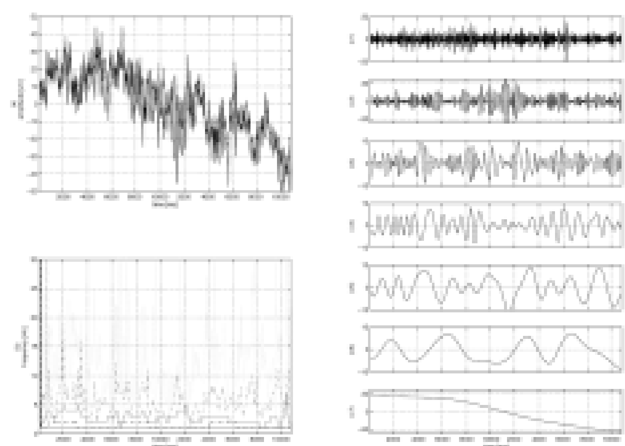

Fig. 1. Example of typical EEG signal with local trend and corresponding EMD decomposition and its Huang-Hilbert spectrogram. An original recording of EEG signal is presented in upper left panel (a), while obtained IMF components are plotted in form of nine panels on the right side (c). IMF components are sorted starting from highest subbands (marked c1) till the low frequency probably amplifier drift, which is usually rejected as noise. Time-frequency image of all IMFs is depicted in lower-left panel (b).

3. Nonnegative Matrix Factorization

Nonnegative Matrix Factorization (NMF) is an emerging method with a wide spectrum of applications, e.g. in data analysis, spectrometry, language modelling, signal and image processing, or neurophysiology. The aim of NMF is to find the following matrix decomposition of the observed data: $\mathbf{Y} = \mathbf{AX}$, where $\mathbf{Y} \in \Re^{I \times K}$, $\mathbf{A} \in \Re_+^{I \times R}$, $\mathbf{X} \in \Re_+^{R \times K}$, $\Re_+$ is the nonnegative orthant (subspace) with appropriate dimensions, I is the number of observations, K is the number of samples, and R is the number of lateral (hidden) components. Depending on the application, the components $\mathbf{A}$ and $\mathbf{X}$ have different physical meaning and interpretation. In our approach, $\mathbf{X}$ is a matrix whose each row represents the traced IMF, but $\mathbf{A}$ is a mixing matrix of the true sub-spectra. Typically, NMF is achieved with alternating minimization of specific cost functions, such as the squared Euclidean distance or Kullback-Leibler divergence [3]. In our applications, we have used a more generalized alpha-divergence that is more robust to different distributions of interferences in data [3]. The function has been minimized with a projected alternating second-order algorithm (see details in [4]), which is usually more robust than traditional Lee-Seung NMF algorithms [3-6]. Additionally, we have also applied the multilayer technique [5] to get a substantial improvement in the performance. The obtained preliminary results are very promising – see Figure 2. NMF works in our application quite efficiently, probably because the signal representations in a time-frequency domain are very sparse and redundant.

4. Results and Conclusions

We presented a new method which combines brain activity analysis from recorded EEG signals in BCI paradigm setting. EEG signals were first analysed in single channels to find amplitude and frequency modulated IMF components. Such novel analysis approach enables us to find better and novel representations in comparison to contemporary techniques. The IMF components further represented in form of Hilbert spectra formed very sparse time-frequency representations which were further decomposed and reduced with the modified NMF algorithms. Time-frequency images in Figure 2 illustrate the power of the presented approach. We were able to successfully extract the first and second harmonic components (corresponding to flashing frequency of 10 Hz) representing our subjects' attentional choices of flashing patterns.

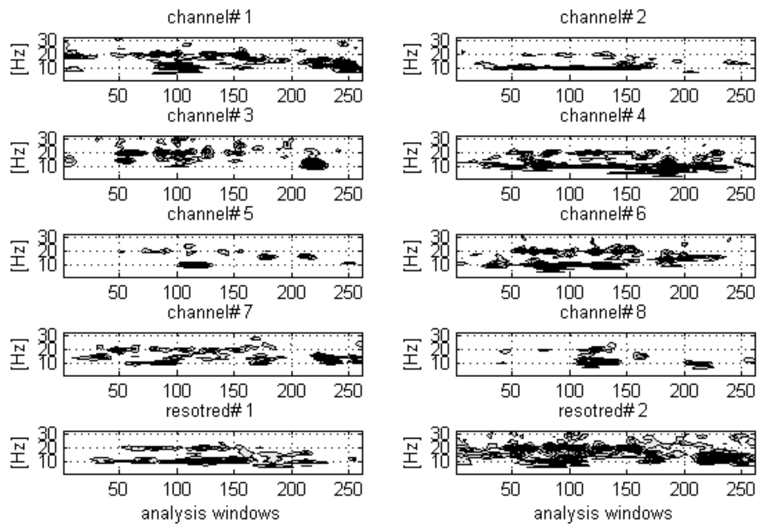

Fig.2. Example of eight originals traces of IMF functions (channel# 1-8) after EMD and depicted as time-frequency images for subject focusing attention on flashing pattern. The estimated two hidden nonnegative components (restored#1 and 2) after applying NMF in two bottom panels. Spectrogram "restored# 1" presents the searched SSVEP signal of 10 Hz, in the time window 25-225 s, while noise was separated into "restored# 2" nonnegative component.

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