Combining EMD with ICA to analyze combined EEG-fMRI Data

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Abstract

Within a combined EEG-fMRI study of contour integration, we analyze responses to Gabor stimuli with a combined Empirical Mode Decomposition and an Independent Component Analysis. Generaly, responses to different stimuli are very similar thus hard to differentiate. EMD and ICA are used intermingled and not simply in a sequential way. This novel combination helps to suppress redundant modes resulting from an application of ensemble EMD alone. The simulation results show an improved mode separation quality. Hence, the proposed method is an efficient data analysis tool to clearly reveal differences between similar response signals and activity distributions.

1 Introduction

It had been already noted by early Gestalt psychologists that the human visual system tends to group local stimulus elements into global wholes. Such grouping is often based on simple rules such as similarity, proximity, or good continuation of the local elements [3]. One special instance of perceptual grouping is contour integration where local parts of Gabor elements are re-integrated into a continuous contour line. Contour integration is typically tested with a stimulus paradigm where arrays of Gabor patches are presented to the subjects (see Fig.1). In 1998, N.E. Huang et al. [4] invented a heuristic tool for complex, non-stationary signal analysis named Empirical Mode Decomposition (EMD). Soon afterwards, EMD has been extended to Ensemble EMD [8], a noise-assisted variant to suppress mode mixing, as well as to multi-dimensional EMD (MEEMD) [6], [9] including complex-valued data sets [7]. EEMD/MEEMD cannot guarantee completeness and orthogonality, and may produce redundant components which affect the accuracy of the decompositions. Combining Independent Component Analysis (ICA) with EEMD [5] allows to overcome some of the above limitations. But MEEMD-ICA cannot reveal small differences between closely similar signals. The aim of this paper is to introduce a new way to combine EEMD with ICA which allows to fully suppress redundant signal components in different IMFs. Eventually, the non-stationary signal or image can be decomposed and distinguished accurately, yielding a much better decomposition and feature extraction performances.

2 Methods

2.1 EEMD/MEEMD

EMD was developed from the assumption that from any signal locally simple oscillations can be extracted. The resulting component signals are called Intrinsic Mode Functions (IMF). Such IMFs are obtained from the signal by means of a sifting algorithm resulting locally in pure oscillations with zero mean. Amplitude and frequency of the IMFs may change over time. Furthermore, IMFs are ordered according to their frequency content. In contrary with wavelets, EMD is a data driven algorithm that decomposes the signal without prior knowledge.

The decomposition of an image, for example an fMRI brain slice, starts by applying EEMD to each column $X_{*n} \equiv \mathbf{x}_n$ of the $M \times N$ - dimensional data matrix $\mathbf{X}$, where M denotes the number of samples and N gives the dimension of the data vectors. The 1D-EEMD decomposition of the n-th column becomes

$$\mathbf{x}_n := X_{*,n} = \sum_{j=1}^{J} C_{*,n}^{(j)} \tag{1}$$

where the column vector $C_{*,n}^{(J)}$ represents the residuum of the n-th column vector of the data matrix. This finally results in J component matrices, each one containing the j-th component of every column $\mathbf{x}_n, n = 1, \ldots, N$ of the data matrix $\mathbf{X}$.

$$\mathbf{C}^{(j)} \quad = \quad [\mathbf{c}_1^{(j)}\ \mathbf{c}_2^{(j)}\ \cdots\ \mathbf{c}_N^{(j)}] = [C_{*,1}^{(j)}\ C_{*,2}^{(j)}\ \cdots\ C_{*,N}^{(j)}] \tag{2}$$

Next one applies an EEMD to each row of eqn. 2 yielding

$$C_{m,*}^{(j)} \quad = \quad \left(c_{m,1}^{(j)} c_{m,2}^{(j)} \cdots c_{m,N}^{(j)}\right) = \sum_{k=1}^{K} \left(h_{m,1}^{(j,k)} h_{m,2}^{(j,k)} \cdots h_{m,N}^{(j,k)}\right) = \sum_{k=1}^{K} H_{m,*}^{(j,k)} \tag{3}$$

where $c_{m,n}^{(j)} = \sum_{k=1}^{K} h_{m,n}^{(j,k)}$ represents the decomposition of the rows of matrix $\mathbf{C}^{(j)}$. These components $h_{m,n}^{(j,k)}$ can be arranged into a matrix $\mathbf{H}^{(j,k)}$ according to

$$\mathbf{H}^{(j,k)} = \begin{bmatrix} h_{1,1}^{(j,k)} & h_{1,2}^{(j,k)} & \cdots & h_{1,N}^{(j,k)} \\ h_{2,1}^{(j,k)} & h_{2,2}^{(j,k)} & \cdots & h_{2,N}^{(j,k)} \\ \vdots & \vdots & \cdots & \vdots \\ h_{M,1}^{(j,k)} & h_{M,2}^{(j,k)} & \cdots & h_{M,N}^{(j,k)} \end{bmatrix} \tag{4}$$

The resulting component matrices have to be summed to obtain

$$\mathbf{C}^{(j)} = \sum_{k=1}^{K} \mathbf{H}^{(j,k)}. \tag{5}$$

Finally this yields the following decomposition of the original data matrix $\mathbf{X}$

$$\mathbf{X} = \sum_{j=1}^{J} \mathbf{C}^{(j)} = \sum_{j=1}^{J} \sum_{k=1}^{K} \mathbf{H}^{(j,k)} \tag{6}$$

where each element is given by

$$x_{m,n} = \sum_{j=1}^{J} \sum_{k=1}^{K} h_{m,n}^{(j,k)} \tag{7}$$

To yield meaningful results, components $h_{m,n}^{(j,k)}$ with comparable scales, i. e. similar spatial frequencies of their textures, should finally be combined [9] according to comparable minimal scale combination principle(CMSC). In practice, for two-dimensional data sets this implies that the components of each row, which represent a common horizontal scale, and the components of each column, which represent a common vertical scale, should be summed up [9].

Hence, the CMSC - principle leads to BIMFs given by

$$\mathbf{S}^{(k')} = \sum_{k=1}^{K} \mathbf{H}^{(k,k')} + \sum_{j=k'+1}^{J} \mathbf{H}^{(k',j)} \tag{8}$$

which thus yields a decomposition of the original data matrix $\mathbf{X}$ into BIMFs according to

$$\mathbf{X} = \sum_{k'=1}^{K} \mathbf{S}^{(k')} \tag{9}$$

where $\mathbf{S}^{(K)}$ represents the non-oscillating residuum. The extracted BIMFs can be considered features of the data set which, according to the CMSC - principle, reveal local textures with characteristic spatial frequencies which help to discriminate the functional images under study.

2.2 ICA

Independent component analysis(ICA) aims to find a linear representation of data based on maximally non-Gassian components which renders them statistically independent. Consider M statistically independent sources $\mathbf{H} = \{\mathbf{h}_1, \mathbf{h}_2, ..., \mathbf{h}_M\}$ and M sensor signals $\mathbf{X} = \{\mathbf{x}_1, \mathbf{x}_2, ..., \mathbf{x}_M\}$. The goal of ICA is to find a de-mixing matrix which recovers the hidden components H underlying the observations X . The different $\mathbf{y}_m$ are estimates of the latent variables $\mathbf{h}_m$ according to the following model

$$\mathbf{y}_m = \mathbf{W}\mathbf{x}_m = \mathbf{W}\mathbf{A}\mathbf{h}_m \qquad \text{with } \mathbf{W}\mathbf{A} = \mathbf{P}\mathbf{D}. \tag{10}$$

where W denotes the demixing matrix, P represents a permutation matrix and D a scaling matrix. Examples of common ICA implementations are the *JADE* algorithm [2] and the *INFOMAX* algorithm [1].

2.3 Proposed Method

As mentioned above, a combination of EEMD/MEEMD with ICA yields a signal decomposition free of redundant remnants of other components in any extracted IMF. The newly proposed methods works as follows:

1. Decompose the measured signal or image $\mathbf{X}$ with EEMD and BEEMD resulting in IMFs or BIMFs which are ordered according to their frequency content.

2. Initialize $i = 1$ and $j = 1$; where $i, j = 1.....K$ and K represents the number of extracted modes.
3. Choose a pair of IMFs, IMF_i and $IMF_{j \neq i}$, and feed it into an ICA algorithm. After decomposing the IMFs with ICA, we obtain two independent components IC_i and IC_j, respectively.
4. If $i > j$, choose the IC with higher frequency according to their Hilbert - Huang Transform [4]. Otherwise, choose the IC with the lower frequency.
5. Replace IMF_i with the selected IC.
6. Increase j by one and repeat the steps above until $j = K$. This results in a new Intrinsic Mode Component (IMC).
7. Increase i by one and repeat steps 3 to 6 until $i = K$.
8. This procedure yields IMCs/BIMCs which neither fulfill the conditions for an IMF or a BIMF nor an IC.

3 Simulation

In order to demonstrate the performance of the proposed method, one EEG signal and a slice of the related fMRI image collected during a contour integration task is selected. Such signals are illustrated for both stimuli, *contour* and *non-contour* (see Fig. 1). The EEG signals and related fMRI images, as shown in Fig. 1, are decomposed by EEMD in case of EEG signals, and by BEEMD in case of fMRI images. Eight IMFs are extracted from the EEG signals (but only three are shown), and six IMFs are obtained from each fMRI image. The resulting components are shown in Fig. 2. As can be seen from the original signals, exhibited in Fig.1, no noticeable differences between the recorded signals, following contour and non-contour stimuli, can be detected. Even from the IMFs and BIMFs, obtained from an EEMD/BEEMD decomposition (shown in the top row of Fig.2) no characteristic difference can be noticed. A similar result is obtained if, after decomposing the recorded signals with EEMD/BEEMD, an ICA is applied to the IMFs/BIMFs directly (see Fig. 2, middle row). This is due to incomplete signal decompositions by these methods which leave remnants of one components in others, causing some redundancy in the different components. Such redundancies load a large subjectivity onto any diagnosis based on these methods. In contrast, the IMCs/BIMCs extracted by our proposed method, can overcome this limitation and yields clearly different characteristics corresponding to both stimuli. This can be seen clearly from the bottom row of Fig. 2. As a cross-check, we can obtain ICs identical to the ones shown in Fig. 2, middle row, if we apply ICA to the IMCs/BIMCs obtained from our method. This corroborates that no information loss has occurred during the analysis.

4 Discussion and Conclusion

In real applications, stimulus responses would most likely not be identical under different conditions. Rather some response asymmetries are to be expected. Because response differences are small, they become submerged in the background of the extracted modes. Hence, such differences cannot be classified simply by visual inspection of the responses. We even demonstrated that such small differences cannot be revealed by plain EEMD/BEEMD or a sequential combination of EEMD with ICA. The reason is some partial mode mixing which appears in noise-assisted ensemble EMD. Our proposed method is able to do so because it helps to suppress remnants of other modes interfering in any of the extracted modes. This

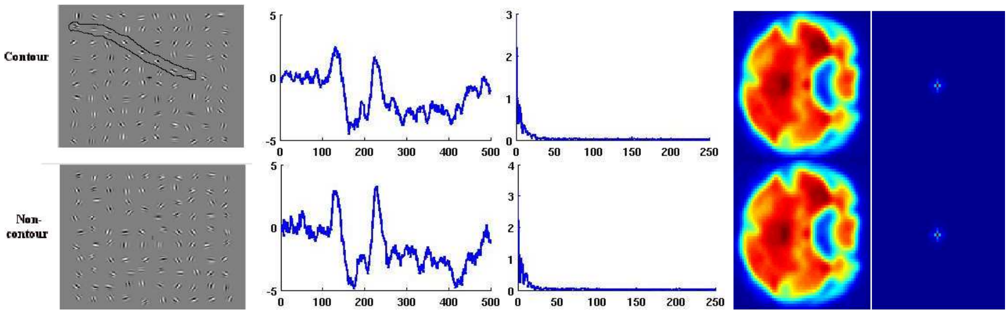

Figure 1: *Left:* contour and non-contour stimuli. *Middle:* EEG signals and their corresponding Fourier spectra. *Right:* stimulus-related fMRI images and their spatial frequency spectra.

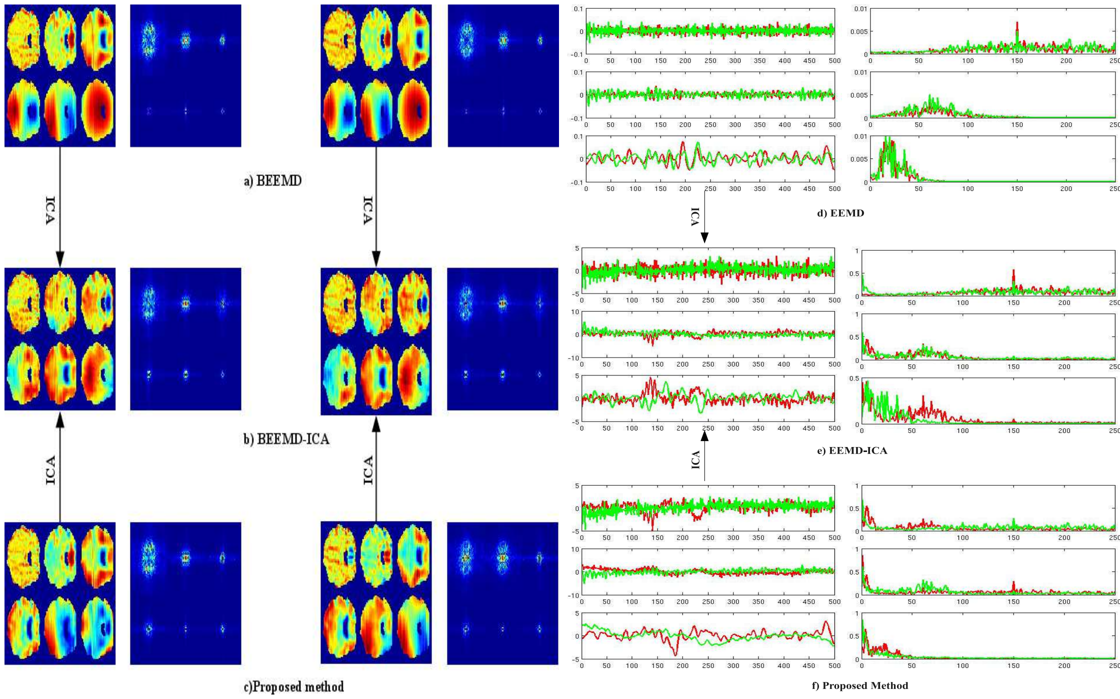

Figure 2: fMRI activity distributions and EEG recordings in response to contour (column 1 and column 3, red line) and non-contour (column 2 and column 3, green line) stimuli. *Top:* BIMFs and related IMFs extracted with BEEMD and EEMD from fMRI and EEG recordings. *Middle:* ICs resulting from an ICA applied to BIMFs and related IMFs obtained from original data sets directly. *Bottom:* BIMCs and related IMCs extracted with our proposed method. For fMRI images, modes are sorted from left to right and from top to bottom according to their spatial frequency content. For EEG time series, the three interesting modes are shown together with their corresponding Fourier spectra.

results in clean modes with no interferences from other modes and thus improves the separation quality considerably. The results showed that the proposed method can be applied to efficiently extract features from biomedical signals and images. This is especially important if different response classes need to be differentiated.

Response classification of our proposed method has been evaluated against competing methods like applying BEEMD to the raw data sets or applying BEEMD and ICA sequentially. The study comprised 18 subjects where a combined EEG-fMRI analysis has been performed within a contour integration task with contour and non-contour Gabor stimuli. As classifier, a Support Vector Machine (SVM) using the Leave One Out Cross Validation (LOOCV) technique has been employed . Dimension reduction has been achieved by projecting the extracted modes onto principal components and using the projections as input to the classifier. A Student t-test was used to select informative features and the parameters of the classifier were optimized by using a grid search approach. The values between square brackets in Table 1 show the number of selected features for an optimal performance and the first column indicates the mode.

Table 1: Comparison of statistical measures (Accuracy, Specificity and Sensitivity) obtained with different techniques evaluating corresponding classification results.

	BEEMD			BEEMD-ICA			Proposed Method		
♯	Acc	Spec	Sens	Acc	Spec	Sens	Acc	Spec	Sens
1	0.81[7]	0.84	0.79	**0.84[34]**	**0.80**	**0.89**	**0.92[35]**	**0.89**	**0.94**
2	0.82[4]	0.84	0.79	0.68[1,30]	0.68	0.68	0.63[1]	0.58	0.68
3	**0.89[2,11]**	**0.89**	**0.89**	0.79[23]	0.79	0.79	0.71[32]	0.78	0.63
4	0.84[3]	0.84	0.84	0.63[22]	0.68	0.57	0.84[3]	0.84	0.84
5	0.84[29]	0.89	0.79	0.66[18]	0.63	0.68	0.74[29]	0.74	0.74
6	0.79[26]	0.74	0.84	0.76[29]	0.84	0.69	0.71[21]	0.68	0.74

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