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High Order Differential Covariance based Source Separation of Monkey's fMRI Data

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Abstract

Blind source separation is a statistical technique in which an observed mixed data is decomposed in source signals and mixing channel. In BSS normally no, or little knowledge about the mixing channel is available a priori. In this work a higher order differential Covariance based source separation technique is used to separate the physiological sources blindly from Monkey's fMRI data. Proposed covariance based technique is applied first applied to simulated data and then on Monkey's data. Results are compared with other conventional BSS algorithms. Proposed algorithm outperforms conventional BSS algorithms in terms of quality and computational complexity.

Keywords: Medical image processing, BSS algorithm, fMRI data source separation

Introduction

Functional Magnetic Resonance Imaging (fMRI) is a well known brain functionality measuring technique which depends on blood oxygen level dependent (BOLD) signal [1]. Before the development of fMRI, positron Emission Tomography (EPET) and Single Photon Emission Computed tomography (SPECT) were used for measuring the brain functionality which were invasive techniques [2]. However, due to non invasiveness fMRI is considered as the best technique which is now extensively used not only for clinical purposes but also for research [3]. In fMRI data acquisition experiment, subject (patient) is asked to perform some activity repeatedly in cycles. Due to the experimental task, relevant brain neuron responsible for the activity become active and thus uses more oxygen. This oxygen is supplied in the blood. Due to the oxygenated blood magnetic properties of the activated voxels changes and thus there is a change in the BOLD signal. fMRI scanner acquire BOLD signal continuously from all brain voxels. fMRI data is in the form of hundreds of images corrupted by Rician noise, and due to which it suffers from low SNR [4]. Due to this low SNR it is not possible to see activated voxel s in the data by bare eye. Therefore, some statistical techniques are used for processing the data. First step of fMRI data analysis is to de-noise the data from Rician noise which is a challenging noise from de-noising point of view [5].

Next step is to extract activated brain voxels using some statistical technique. These techniques may be divided broadly in model driven and data driven approaches. In model driven approaches, fMRI experimental paradigm is required to be known before hand. The most well known model driven approach is Statistical parametric Mapping [6]. Hypothesis testing in SPM is done using General Linear Model (GLM) for data and hemo-dynamic response model. Other model driven approaches include Time frequency analysis [7], Canonical correlation analysis (CCA) [8] etc. In case of CCA experimental model is correlated with the fMRI data patterns and decision about activated regions is made on the basis of strong correlation between data and experimentalmodel. However, in case of time frequency analysis activated regions are distinguished from the non activated regions on the assumption that their spectra's are different.

On the other hand data driven approaches do not depend on the experimental model and fMRI mixed data sources are extracted using some Blind Source Separation (BSS) technique. These include principal Component Analysis (PCA) [9], Independent Component analysis (ICA) [10], Non-negative Matrix Factorization NMF [11] and matrix Factorization (MF)[12] etc. In PCA, fMRI mixed data is transformed in to another coordinate in which vectors with greater variance are termed as principal components. In case of ICA, sources of activated voxels are extracted from the mixed data using different flavors of ICA provided that they are independent. In NMF, sources are separated with the constraint that data and source components are non-negative while the constraint of non-negativity is relaxed in case of MF.

In this work Monkeys fMRI data is processed using a covariance based BSS technique. For checking the validity of the algorithm simulated data is first processed using covariance based technique. Afterwards actual monky's fMRI data is processed and the results are compared with other conventional BSS algorithms.

BSS Model with Different Solutions

This section describes few conventional blind source separation techniques followed by the covariance based algorithm. Before going to these algorithms, it is necessary to review the BSS model.

Consider the observation matrix $\boldsymbol{O}$ of dimension *mxn*. This observation matrix consists of sources and corresponding mixing matrix of dimension *kxn* and *mxk* respectively. This model can be described mathematically as under [13].

$$\boldsymbol{O} = [\boldsymbol{M}][\boldsymbol{S}] \qquad (1)$$

Where $\boldsymbol{M}$ is the mixing matrix and $\boldsymbol{S}$ is the source matrix, both are unknown. The task is to find $\boldsymbol{M}$ and $\boldsymbol{S}$ blindly using any blind source separation algorithm such that

$$\boldsymbol{S} = [\boldsymbol{A}][\boldsymbol{X}] \qquad (2)$$

Here $\boldsymbol{A}$ is the un-mixing matrix which needs to be find out. There exist a large number of solutions to BSS problem using different approaches.

We will first discuss joint diagonalization algorithm (JD) [14, which uses covariance matrix of observed data for source separation. In this scheme cost function, which is based on the covariance of observation matrix is maximized for finding the un-mixing matrix iteratively.

$$f(A) = off(A^T R_O A) \qquad (3)$$

In equation (3) $\boldsymbol{R_O}$ is the covariance matrix of fMRI observed data and is given by $\boldsymbol{R_O} = \boldsymbol{E}[\boldsymbol{O}\boldsymbol{O}^T]$.

Update equation for finding $\boldsymbol{A}$ is given as [14]

$$\boldsymbol{A}(n+1) = \boldsymbol{A}(n) - \alpha(AR_OA^T - I)^3 \qquad (4)$$

Where $\boldsymbol{A}(n)$ **and** $\boldsymbol{A}(n+1)$ are old and updated values of un-mixing matrix.

Independent component analysis is one of the best solution for BSS problem which is used extensively in different fields [16]. ICA has different flavors of cost functions which are based on kurtosis, negentropy, infomax etc. Here we are just discussing the infomax model which is as under [16].

$$h(\boldsymbol{S}) = E[\textstyle\sum_{i=1}^{m} \ln p_s(s_i)] + ln|\boldsymbol{A}| \qquad (5)$$

After some manipulation ICA infomax is given as under [16].

$$\boldsymbol{A}(n+1) = \boldsymbol{A}(n) + \boldsymbol{\nabla}(h) \qquad (6)$$

$$\boldsymbol{\nabla}(h) = \boldsymbol{A}^{-T} - 2tanh(\boldsymbol{AO})\boldsymbol{O}^T \qquad (7)$$

where $h(S)$, $p_s(s_i)$, and $|U|$ are entropy, pdf and determinant respectively.

Proposed third order differential covariance based BSS solution:

Starting from equation (1) which shows the BSS model, let us take covariance of both sides

$$E[\boldsymbol{O}\boldsymbol{O}^T] = E[\boldsymbol{A}\boldsymbol{S}\boldsymbol{S}^T\boldsymbol{A}^T]^T \qquad (8)$$

Mathematically these covariance of observed data and mixing matrix multiplied by source matrix should be equal. Which can be written as $\boldsymbol{R_O} = \boldsymbol{R_{AS}}$ and ultimately $\boldsymbol{R_O} - \boldsymbol{R_{AS}} = \boldsymbol{0}$. This fact can be used to form the cost function of differential covariance based [17].

$$\boldsymbol{f}(\boldsymbol{A}) = \boldsymbol{R_O} - \boldsymbol{R_{AS}} \qquad (9)$$

By taking the third order cumulant of this cost function, faster convergence can be achieved. This is due to the fact that high order cumulant make the cost function steeper and thus even small steps in the iterative update equation make the convergence faster.

$$\boldsymbol{f}(\boldsymbol{A}) = [\boldsymbol{R_O} - \boldsymbol{R_{AS}}]^3 \qquad (10)$$

Now update equation for un-mixing matrix using the steepest decent algorithm can be written as

$$\boldsymbol{A}(n+1) = \boldsymbol{A}(n) - \frac{\partial f(A)}{\partial A} \qquad (11)$$

$$\boldsymbol{A}(n+1) = \boldsymbol{A}(n) - 3(\boldsymbol{R_O} - \boldsymbol{R_{AS}})^2\boldsymbol{A}^T \qquad (12)$$

It should be noted that in all these methods data is first centered and then white.

Data:

To validate the performance of the proposed algorithm, it is first applied to simulated data.

This data consists of four sources which are linearly mixed by a known mixing matrix. Observed mixture consists of eight sources. This mixture is processed by the proposed algorithm and also by the conventional approaches which are discussed here for blind source separation.

Another data set which is of actual monkeys fMRI data is taken from on line resource MAPAWAMO project and which is online available at http://cogsys.imm.dtu.dk/toolbox/ica/.

This data was taken by showing visual stimulations to monkeys for equal rest and activity periods.

Simulation and Results Discussion

As discussed in the previous section, simulated data is normally required for testing the validity of any proposed algorithm generally and specifically in case of fMRI. In this work general simulated data is used as a first data set, which consists of our sources. Observed data consists of eight sources which are formed by the linear combination of the basic sources. Sources are shown in first row of Fig. 1 while observed sources are shown in second and third row of Figure 1. This data is processed by Joint diagonalization algorithm and modified infomax ICA [16] algorithm, the results of extracted sources is shown in row 2 and row 3 of Figure 2. Sources are also extracted by the proposed high order differential covariance algorithm with result shown in Row 4 of Figure 3. It can be even visually seen that the results of the proposed method are superior since it has one to one correspondence with the actual sources of row 1 Figure 2. Table 1 shows the correlation results and execution time of all these algorithms for this simulated data. Execution time of JD is very short but the results are not up to the mark. On the other hand execution time ICA infomax and proposed algorithm are almost same, but the performance of the proposed algorithm is superior.

Since it is now clear that proposed algorithm performs best for BSS problem source separation. Therefore it is now applied to Monkeys fMRI data. This monkey fMRI data consists of 80 images, four of which are shown in Figure 3. Sources and time courses are extracted from Monkeys fMRI data using JD, ICA Infomax and proposed algorithm and the results are shown in Fig. 4,5,6 respectively. Last image and corresponding time course is the activity image and time course is corresponding model of the fMRI experiment.

Conclusion

In this work a higher order differential covariance based source separation technique is proposed. This technique is based on the fact that the contrast function can be made more steeper by taking its high order cumulant and since faster convergence can be achieved. The proposed algorithm was tested on simulated general data and the applied to actual fMRI monkey data. The results are also compared with JD and ICA infomax for comparison. Results show that the proposed algorithm converges fast and extract sources with good quality.

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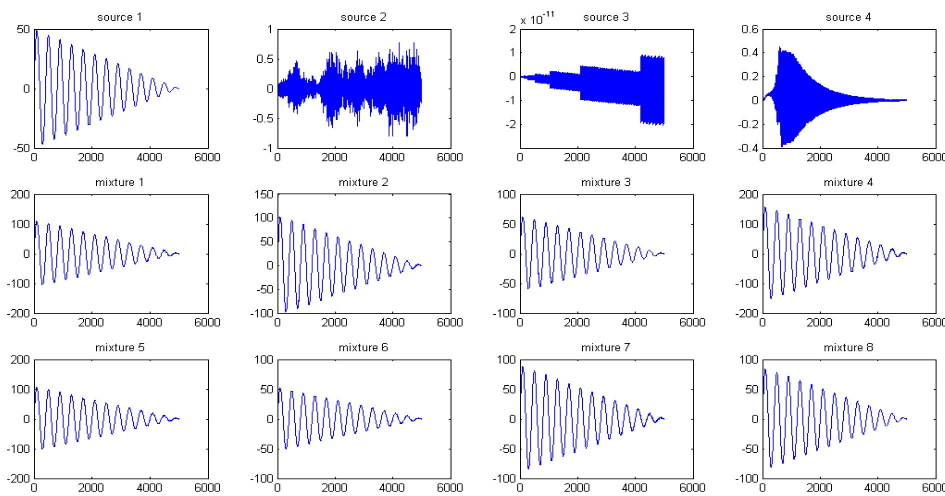

Figure 1. Simulated sources (first row) and mixtures (second and third row)

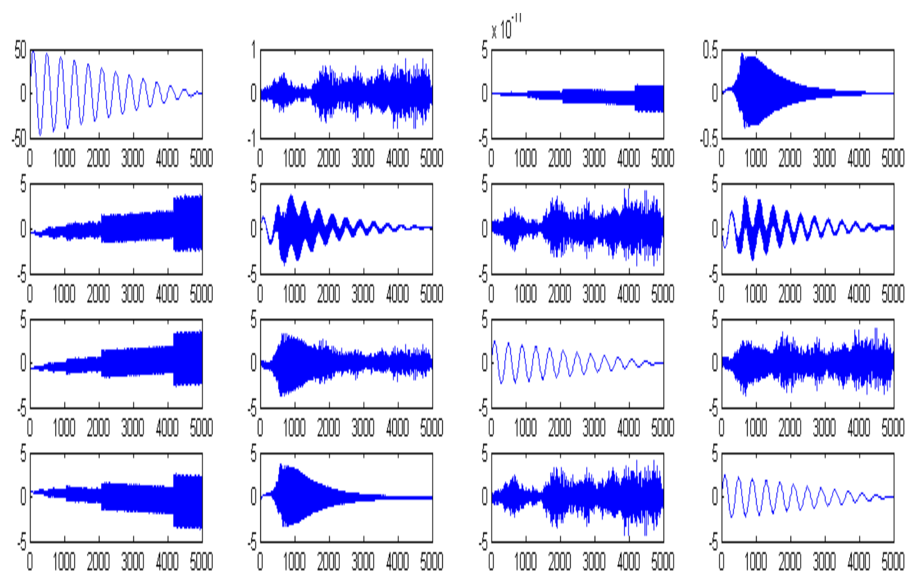

Figure 2. Sources extracted by JD (second row), by ICA infomax (third row) and proposed high order diff cov based algorithm (fourth row)

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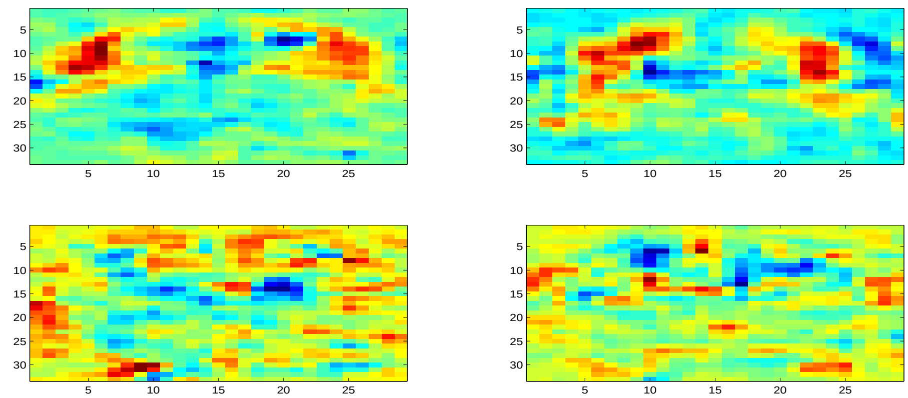

Figure.3 Four sample images of Monkeys fMRI

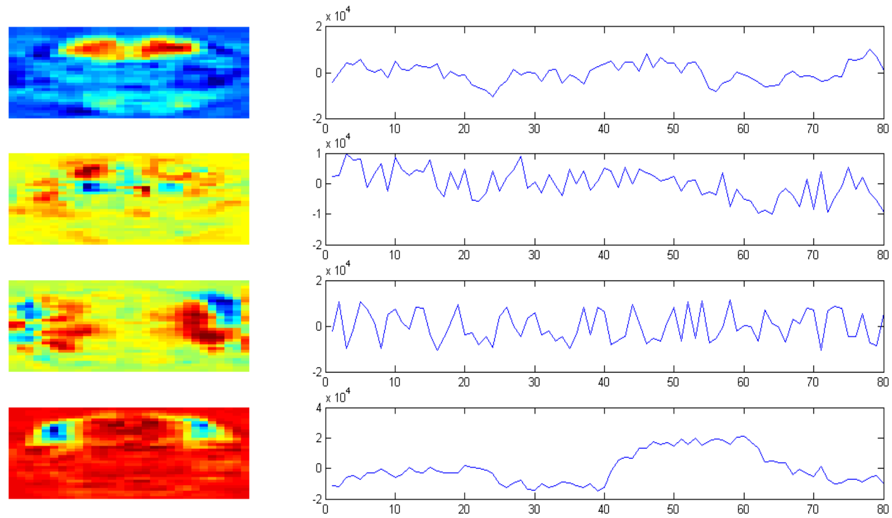

Figure 4. Extracted sources by JD Algorithm

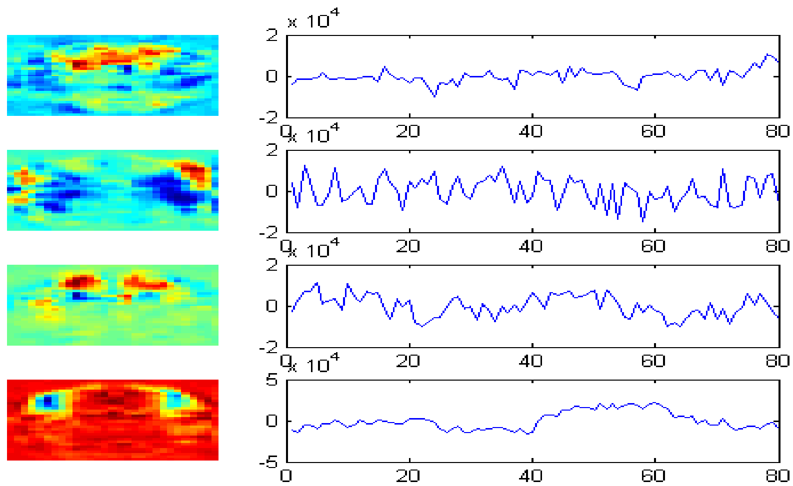

Figure 5. extracted sources by modified infomax ICA algorithm

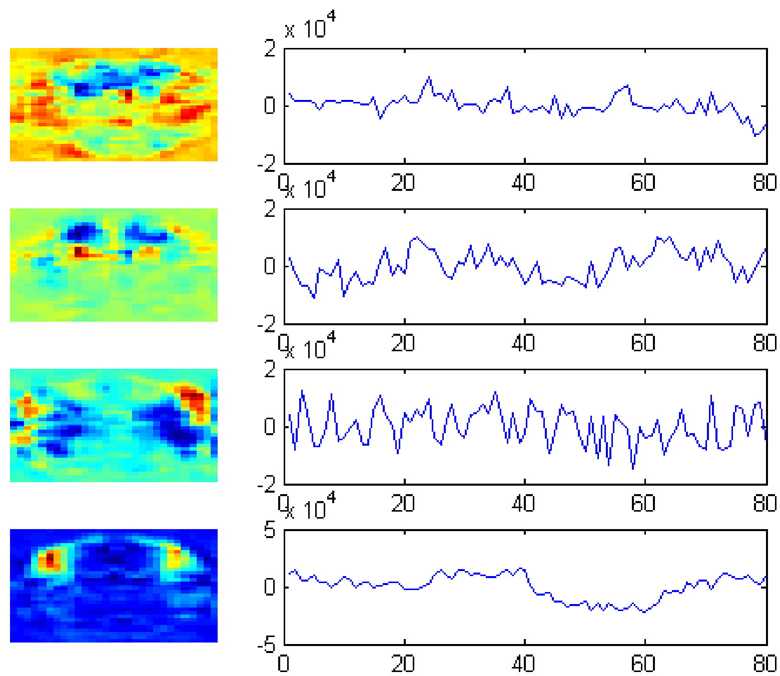

Figure 6 Extracted sources by Proposed differential Covariance based algorithm

Table. 1 Correlation and execution time of conventional and proposed algorithm for simulated data

Algorithm (Time sec)	S1	S2	S3	S4
JD (0.8)	0.84	0.89	0.99	0.89
ICA(1.00)	1.00	0.95	0.99	0.95
COV based (1.2)	1.00	0.99	0.99	0.99