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Covariance based BSS Algorithm for Functional Magnetic Resonance Imaging (fMRI) data Source Separation

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Abstract

Functional Magnetic Resonance Imaging (fMRI) is a measuring technique used for brain functionality. Observed fMRI data is generally a mixture of hidden sources and corresponding time courses. Different blind source separation (BSS) techniques are used for extracting these hidden sources and time courses. In this work a differential covariance based blind source separation technique is proposed which relies on the difference of covariance of observed data and covariance of sources and mixing matrix. Performance of the proposed method is evaluated on the synthetic fMRI data. Finally comparison of ontained results is done with joint Diagonalization (JD) and Algorithm for multiple unknown source extraction (AMUSE). Comparision results shows that the proposed algoritham is better in terms of time and quality of extracted sources and time courses.

Keywords: Functional magnetic resonance imaging (fMRI), covariance based source separation, blind source separation.

Introduction

Due to the rapid growth of computing and information technology, it is now widely used in the field of helath[1,2], agriculture[3], media and mass communicdation[4] etc. In health, electro medical equipments and processing of medical data like,x-rays, ultrasound and Electrocardiography (ECG), MRI and fMRI are the hottest areas in which computer and information sciences are playing their roles.

fMRI is a brain functionality measuring technique used for clinical and research purposes. Since fMRI is non-invasive in nature, therefore, this technique is preferred by its predecessors i.e. Positron Emission Tomography (PET), Single Photon Emission Computed Tomography (SPECT)[5] etc. While performing the fMRI experiment, patients/subjects follow the experimental paradigm. The experimental paradigm may consists of a number of cycles of activity and non-activity. Voxels related to activity becomes active and thus utilize more oxygenated blood which changes the magnetic properties thus causing change in blood oxygen level dependent (BOLD) signal[5]. BOLD signal is recorded for each voxel against time for axial, coronal and sagittal slices. This highly complicated data suffers from low SNR due to Rician noise which is signal dependent and is a very challenging noise to remove [6]. Different Rician noise removal techniques exist in the literature and are used before the processing of fMRI data[7,8]. Furthermore, there exist other sources of activity like respiratory system, cardiac system, head moments and other artifacts. To separate all these sources of activity different blind source separation techniques are used. These algorithms may broadly be divided in two main categories, in which one soley depends on the experimental paradigm[9] while the other one does not require any knowledge abou the experimental cycles of activity and non-activity. Model based techniques include statistical parametric mapping (SPM)[10], correlation analysis [11] and time frequency analysis [12]. In time frequency analysis activation based voxels are extracted from the observed mixed data using the assumption that spectra,s of experimentally activated regions, physiologically activated regions and non-activated regions are different and thus can be distinguished. In case of correlation analysis time series of each voxel is correlated with the experimental paradigm and decision about activity and non-activity is made. However, in case of SPM t-test and f-test are performed and the results are mapped on a statistical map.

On the other hand analysis methods based on data driven approaches consists of Independent Component Analysis (ICA)[13], Principal Component Analysis (PCA)[14], Non-negative matrix factorization (NFM)[15] etc. In PCA approach, fMRI data is transformed such that vectors with large variances are considered as the principal components. Since these vectors are less than the actual dimension of the data, therefore, this technique is also used for data reduction. In case of NMF, fMRI data is decomposed into sources and time courses using the well known NMF technique[16]. In all blind source separation techniques, well known and well established technique with promising results is the ICA algorithm[14]. In ICA data is decomposed into sources and time curses with the assumption that sources of activity and non-activity are independent. Different cost functions are used for ICA including Kurtosis, Infomax etc. There are other techniques used for BSS problem like Algorithm for multiple unknown source extraction (AMUSE), Joint Diagonalization (JD) etc.

In this work we are using higher order differential covariance based BSS which is based on JD and is related to simple differential covariance based BSS algorithm [authors previous unpublished work].

Model of BSS problem with different solutions

Let the observed data matrix is D having dimension kxm comprising of a linear combination of time course matrix T of dimension kxn and source matrix S of dimension nxm such that

$$D = [T][S] \tag{1}$$

BSS goal is to find out the un-mixing matrix U such that

$$S = UD \tag{2}$$

Where $U = T^{-1}$ and $U^T U = I$.

Generally in ICA algorithms data is first made zero mean and then white so that search space for the un-mixing matrix become small and the algorithm converge faster[18]. Another step normally done before processing fMRI data is the dimension reduction step using SVD or PCA. This data is now ready to be processed by ICA. Two well known flavors of ICA will be discussed here i.e. kurtosis and infomax.

Since the kurtosis measure for checking the Gaussianity of sources which is non zero and hence it is maximized.

$$f(U) = E[S]^4 - 3[E[S]^2]^2 \tag{3}$$

$$f(U) = E[UD]^4 - 3[E[UD]^2]^2 \tag{4}$$

The goal is to find the un-mixing matrix, which can be find out iteratively using a fourth order cumulant of the given contrast function.

$$U(n+1) = U(n) + [UD]^4 D^T \tag{5}$$

Here $U(n)$ and $U(n+1)$ are the old and new values of un-mixing matrix as obtained by the high order simple fixed point iteration method.

In case of infomax the cost function is given as under[19].

$$h(\boldsymbol{S}) = E[\sum_{i=1}^{m} \ln \mathrm{p_s}(\boldsymbol{s}_i)] + ln|\boldsymbol{U}| \tag{6}$$

Here $h(S)$ represents the entropy, $p_s(s_i)$ represents the pdf, and $|U|$ represents the determinant of un-mixing matrix U. After performing certain manipulation update equation for un-mixing matrix is written as

$$U(n+1) = U(n) + \nabla(h) \quad \text{Where}$$

$$\nabla(h) = U^{-T} - 2tanh(UD)D^T \tag{7}$$

Another well known technique for BSS problem is the joint diagonalization in which un-mixing matrix $\boldsymbol{U}$ is find out by maximizing a cost function which is dependent on the auto covariance of the observation matrix and is given as

$$f(U) = off(U^T R_D U) \tag{8}$$

Where $R_D = E[DD^T]$.

Now using the above cost function, update equation for un-mixing matrix can be written as

$$U(n+1) = U(n) - \alpha(UR_D U\text{^}T - I)^3 \tag{9}$$

Where $U(n+1)$ and $U(n)$ are new and old values of the un-mixing matrix while α is the update rate and is less than one.

AMUSE is another BSS technique which is based on covariance and SVD of the observed data matrix. Source vector s is extracted using

$$S = CDV \tag{10}$$

Where C represents singular values and V represents diag of the inverse of C. Further details of the algorithm can be found in greater detail in Tong L., Soon V.C., Huang Y.F. and Liu R.[20].

Proposed differential Covariance based BSS algorithm

Consider equation (1), which shows observed data to be the linear combination of time series and source matrix. To extract these unknown sources here we use a cost function which is the differential covariance of observed data matrix and transpose of time series and source matrix.

$$E[DD^T] = E[USS^T U^T]^T \tag{11}$$

Or it can be written as $R_D = R_{US}$ where R_D, R_{US} is the covariance matrix of left and right hand side of equation (1) respectively. Ideally difference of both covariances should be zero to hold equation (11).

Therefore a cost function which is based on these covariance matrices can be written as

$$f(U) = R_D - R_{US} \tag{12}$$

For finding an un-mixing matrix this cost function can be used in fixed point or in steepest descent algorithm.

$$U(n+1) = U(n) - \mu(R_D - R_{US}) \tag{13}$$

Here again μ is the update rate. This cost function is already proposed by the author in our unpublished work. To proceeds further, higher order/exponential of the cost function shown in equation (12) can be used for quick convergence. Tested cost function in this work is given as under

$$f(U) = exp(R_D - R_{US}) \tag{14}$$

The corresponding update equation for un-mixing matrix can be written as

$$U(n+1) = U(n) - \mu(exp(R_D - R_{US})) \tag{15}$$

Update un-mixing matrix equation (15) is more fast and accurate as compared to equation (13).

fMRI simulated data set

To validate and test the proposed algorithm it is necessary to apply it to simulated data for which the ground truth is available and in case of satisfied results, it is used on actual fMRI data. In this article synthetic fMRI data is processed by the proposed scheme for source separation. This data is freely available on the internet http://mlsp.umbc.edu/simulated_fmri_data.html . This data was first created by Correa, Nicolle, Tülay Adalı, and Vince D. Calhoun[19] for testing their algorithm. The data consist of eight sources of activity, physiological activity, artifacts etc as shown in figure-1. These sources are mixed using the corresponding time courses and thus an observed mixed data is developed which consists 100 images. Four sample images are shown in figure-2.

Simulation Results

Mixed sources of synthetic fMRI data are processed by JD and AMUSE along with the proposed differential covariance algorithm. The resultant sources and corresponding time series are displayed in figure-3,4,5 respectively. In figure-3 it is quite clear that extracted sources and time courses are not similar to figure-1 even visually. Similarly figure-4 also do not have one to one correspondence with figure-1 as well. However, figure-5 which shows extracted sources and time courses by the differential covariance algorithm shows a greater resemblance with the actual sources and time courses of figure-1. Table-1 shows the correlation analysis of actual sources/time courses with the extracted sources/time courses by different methods.

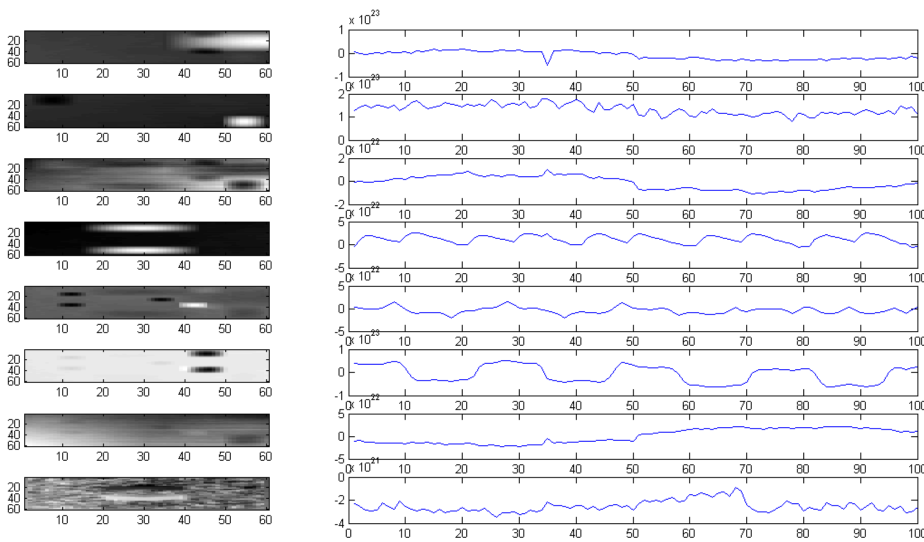

Figure-1
simulated fMRI sources and corresponding time courses

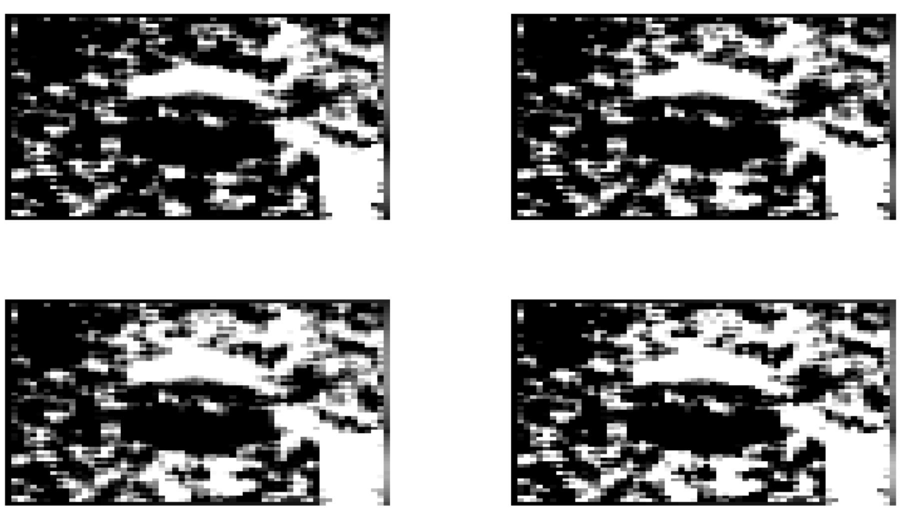

Figure-2
Four sample fMRI mixed images

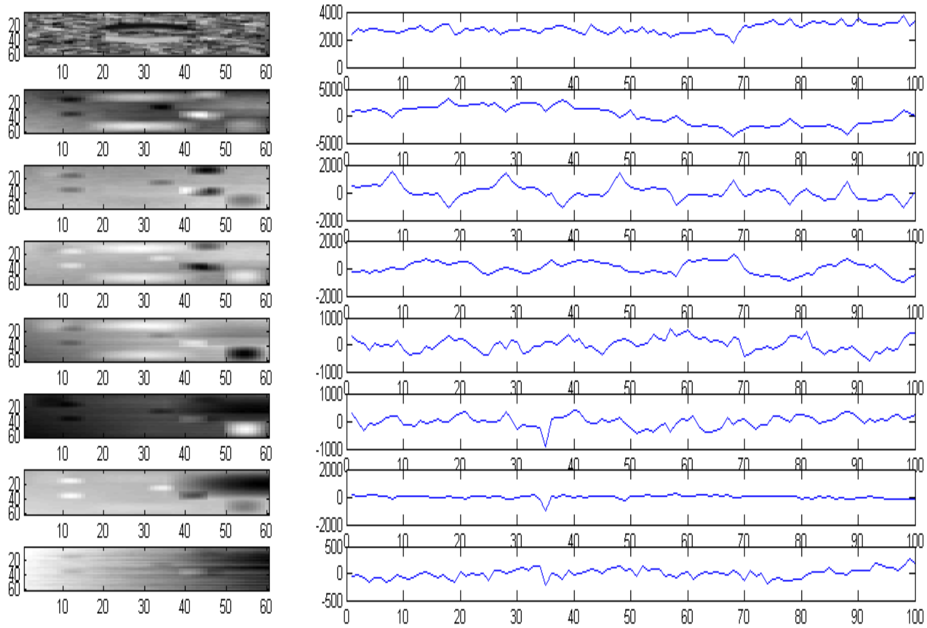

Figure-3
Extracted sources by AMUSE algorithm

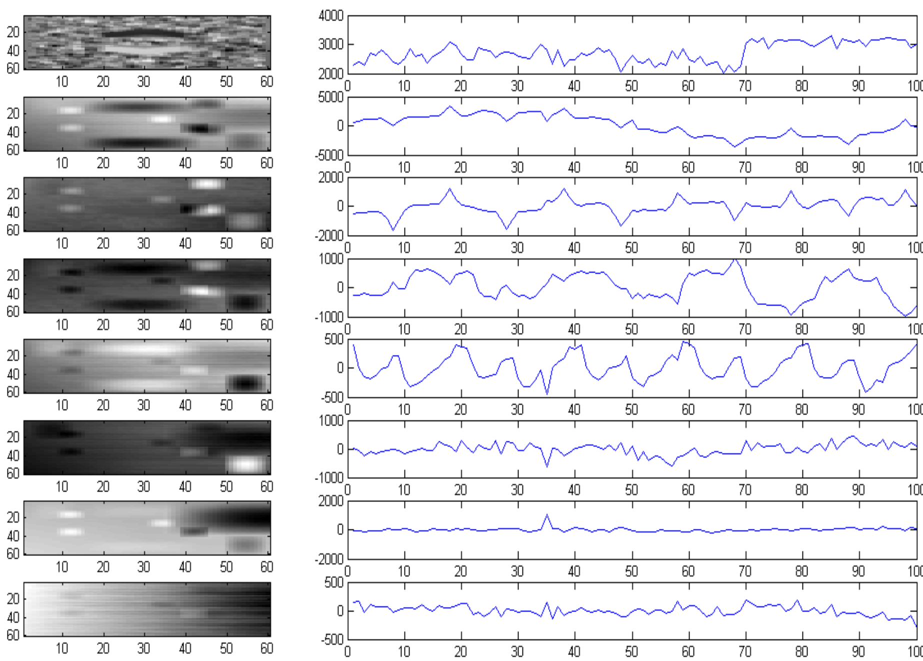

Figure-4
Simulated fMRI sources by JD algorithm

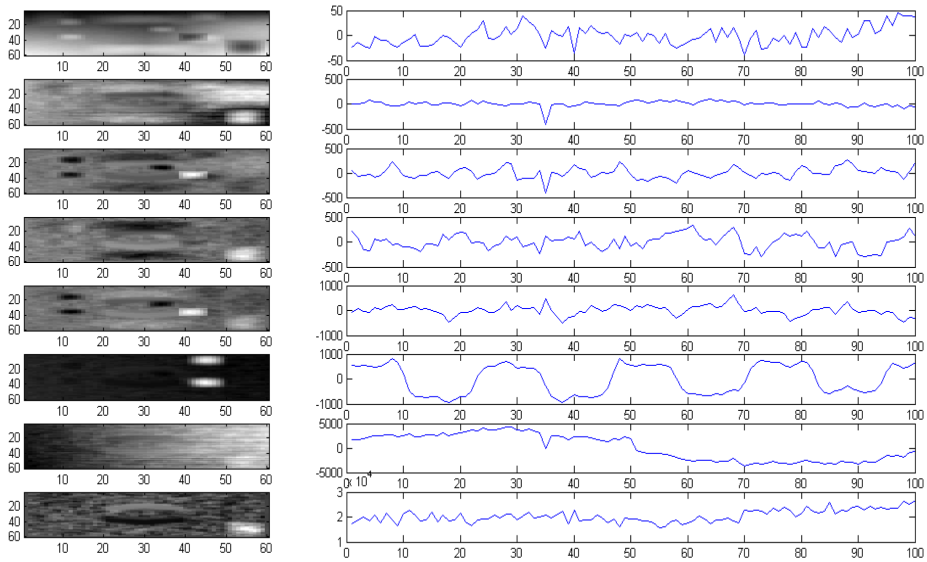

Figure-5
Simulated fMRI sources by proposed differential covariance based algorithm

Table-1
Correlation results of extracted sources/time courses (S/T) with actual sources/time courses

Sources /Time courses (Time)	S1/T1	S2/T2	S3/T3	S4/T4	S5/T5	S6/T6	S7/T7	S8/T8	Average
Conv JAD (1 sec)	0.69/0.87	0.27/0.34	0.97/0.39	0.97/0.87	0.82/0.24	0.47/0.10	0.45/0.25	0.84/0.84	0.68/0.48
AMUSE (1.2 sec)	0.68/0.86	0.48/0.83	0.98/0.40	0.92/0.67	0.85/0.19	0.44/0.19	0.56/0.35	0.90/0.67	0.58/0.41
Proposed exp cov: based algorithm (1 sec)	0.95/0.97	0.72/0.73	0.98/0.98	0.80/0.94	0.86/0.76	0.78/0.75	0.90/0.97	0.80/0.92	0.68/0.70

Conclusion

In this work a higher order differential covariance based BSS algorithm is proposed. The idea relies on the on the fact that the covariance of the observed data and the extracted sources and mixing matrix must be same. The proposed algorithm is applied to simulated fMRI data and the results are compared visually with the ground truth and using correlation. Visual and correlation results show that the proposed method performed well. The proposed algorithm is also suggested to be applied to other similar BSS problem.

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