A Modified JadeR for Signal Separation under Gaussian Noise

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Abstract -*A Modified version of Joint Approximation Diagonalization Estimation of Real Signals algorithm (JADER) is proposed to enhance efficiency and speed of Blind Signal Separation (BSS). MJADER based on the mixture's dimensions minimization step, where the cumulant matrices have been estimated using a reduced-dimension observed mixture. The approach (M-JADER) is based on a threshold step, it is easy to implement, computationally efficient and faster than standard JADER about 50% where it has less running time. The comparison done under tow types of niose(semi-white Gaussian noise and Uniform noise).*

Keywords: Joint Approximation Diagonalization, JadeR, Blind Source Separation, BSS.

1 Introduction

Consider a situation in which a number of sources emitting signals which are interfering with one another, familiar situations in which this occurs a crowded room with many people speaking at the same time, interfering electromagnetic waves from mobile phones or crosstalk from brain waves originating from different areas of the brain. In each of these situations, the mixed signals are often incomprehensible and it is of interest to separate the individual signals. This is the goal of Blind Source Separation (BSS), it is a well-known and well-studied field in the adaptive signal processing and machine learning.

The problem is to recover original and unknown sources from a set of mixtures recorded in an unknown environment. The term blind refers to the fact that both the sources and the mixing environment are unknown[1].

This approach initially leads to what is known as independent component analysis (ICA), In ICA the general idea is to separate the signals, assuming that the original underlying source signals are mutually independently distributed. Due to the field’s relatively young age, the distinction between BSS and ICA is not fully clear. Today ICA is used in many different applications, e.g. medical signal analysis, sound separation, image processing, dimension reduction, coding and text analysis. The proposed algorithm separate the mixture of speech signals of two independent sources using many simple computational

Steps and with less running time. JadeR algorithm was proposed by [2, 3] it is based on a joint diagnolization principle. Its algorithm performs slowly when the length of the original sources to be separated very long. JADER algorithm sometimes couldn’t separate the speech signals efficiently.

The next section discusses the BSS problem in briefly.

2 BSS problem

A classic problem in BSS is the cocktail party problem. The objective is to sample a mixture of spoken voices, with a given number of microphones the observations, and then separate each voice into a separate speaker channel the sources.

BSS can be described by Equation(1) [4, 5]

$$X(i) = A\,S(i) \qquad (1)$$

Where X is the mixture, A is the mixing matrix and S is the source signal to be extracted.

Matrices A and S are unknown so BSS techniques have been used to solve this problem in order to extract source signals S without any information about A and S matrices.

$$S(i) = A^{-1}\,X(i) \qquad \textbf{(2)}$$

The next section illustrates the preprocessing steps that simplify the separation process.

3 Preprocessing steps

Before examining specific ICA algorithms, it is instructive to discuss preprocessing steps that are generally carried out before ICA.

3.1 Centering

This process makes the average of data X over all samples equal to zero by subtracting its mean vector $\mu = E\{x\}$, this step will simplify applying of ICA techniques

Eq.**(3)** Represents the centering process, where X_c centered data, X is observed data and μ mean vector.

$$X_c = X - \mu \qquad \textbf{(3)}$$

3.2 Whitening

Another step in the preprocessing stage is a whitening. The zero mean x_c vector. This step consists of some linearly transforming the observation vector to make its components uncorrelated and have unit variance.

For whitening using **(4)**, where W_x is the whitening matrix, V is an eigenvector of M and D is diagonal matrix of M.

$$W_x = \boldsymbol{V}\boldsymbol{D}^{-1/2}\boldsymbol{V}^T\, \boldsymbol{x} \qquad \textbf{(4)}$$

The next section illustrates the BSS techniques of Standard JADER and modified JADER algorithms.

4 Efficient BSS Techniques

4.1 Standard JADER Algorithm.

JADER is a BSS technique depend on the fourth cumulant of observed data. It using the joint diagnolization algorithm that extracts the unitary matrix that diagonalizes the cumulant matrices. In particular with cumulant, which can be viewed as the generalization of the mean (first-order auto-cumulant) and the variance (second-order auto-cumulant) to orders higher than 2. In the Jade algorithm, for each observed signal, the cumulant of the signals with themselves (auto-cumulant), as well as the cumulant of all combinations of signals (cross-cumulant), are calculated, and are placed in a fourth order tensor, of dimensions $n\,n\,n\,n$ (where n is the number of PCA loadings of equal variances in Pw, and therefore the number of ICs to be calculated). If the signal vectors are independent, their fourth-order cross-cumulant will be zero and their auto-cumulants maxima. The Jade algorithm uses fourth order statistical cumulants to calculate its cost function, which is a measure of signal independence, and repeatedly rotates the set of un-separated signals to minimize the cost and maximize independence. It is aims to minimize the cross correlation and maximize the auto correlation[2].

JadeR algorithm Steps can be described as follows [3, 6]:

1- Computing the 4th order cumulant matrix of the whitened signals by storing the most significant eigenvectors on a cumulant matrix.

2- Apply Joint diagonalization on the output of step 2 by unitary matrix U`.

3- Finally, estimate an inverse of A to recover the original signals.

4.2 The proposed technique M-JADER algorithm

The modified algorithm has been introduced, its steps can be described as follow:

1- Reduce the observed mixture dimension by thresholding the absolute difference between mixture rows using a threshold T as follows.

$$M(i) = \{X(:,i) | d(i) > T\} \qquad \textbf{(5)}$$

Where

$$d(i) = |X(1,i) - X(2,i)|, i = 0,1,\cdots,N \qquad (6)$$

2- Preprocessing the minimized data using preprocessing steps.

3- Calculate the fourth order cumulant matrices of the whitened signals.

4- Compute eigenvector V of cumulant matrices.

5- Multiply V^T by the whitening matrix W_x

$$Q = V^T \times W_x \qquad \textbf{(7)}$$

6- The result matrix Q is the un-mixing matrix, the source signals can be computed by **(8)** where S is the source signals, Q is un-mixing matrix and X is the mixture.

$$S = Q \times X \qquad (8)$$

5 Experimental results

In this section, some experimental results were proposed to demonstrate the effectiveness of the proposed idea. Separation of mixtures of speech signals has been performed using Matlab 2016a environment under different degrees of white Gaussian noise. Gaussian noise was produced using Matlab function (wgn) with different Signal to Noise Ratio (SNR_{dB}) (-50 to 50). The performances of the proposed algorithm were also compared with the standard JADER algorithm.

The next subsection discusses the common performance metrics briefly [7].

5.1 Performance Metrics:

Correlation coefficient vs. SNR_{dB} used as a performance metric to inspect the ability difference between the original JADER and MJADER to separate two of speech signals.

1- Correlation Coefficient

Can be defined as a statistic used to measure the degree or strength relationship between two variables. Correlation coefficients have been computed by

$$p(x_1 \,, s_1) = \frac{E(x_1 s_1) - E(x_1)E(s_1)}{\sigma_{x_1}\sigma_{s_1}} \qquad (9)$$

2- Signal to Noise Ratio (SNR)

The signal-to-noise ratio (SNR_{dB}) is well defined and understood in electrical engineering and communications, The SNR is defined as signal power divided by noise power[8].

It is can be computed as follows:

$$Snr = \frac{p_s}{p_n} \qquad (10)$$

$$SNR_{dB} = 10 \cdot \log_{10}(Snr) \qquad (11)$$

5.2 Simulation

The separation simulated using two independent signals for two humans (man and woman)as shown in Fig 1 , these signals are mixed linearly, the mixtures shown in Fig 2.

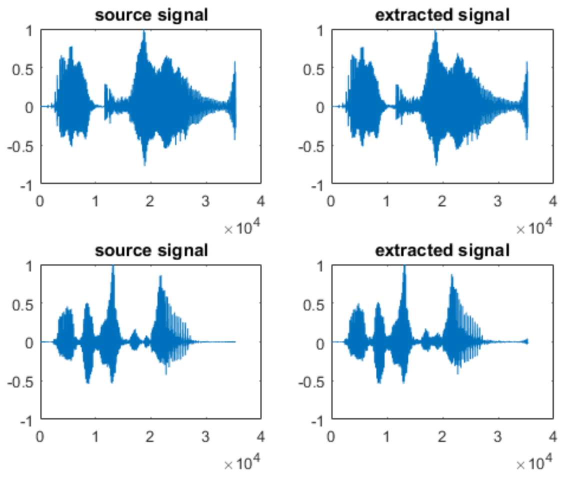

Fig 1 Two speech signals separated using M-JADER

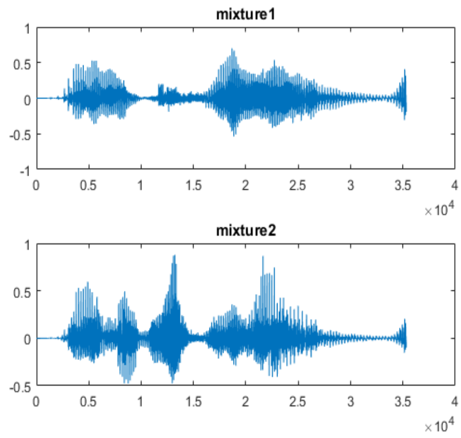

Fig 2 The mixtures

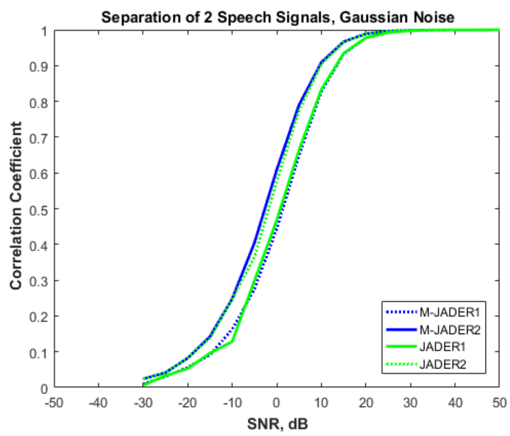

Fig 3 correlation coefficient vs. SNR for separation under Gaussian noise and positive mixing matrix

Fig 3 correlation coefficient vs. SNR between the source signals and extracted signals, which separated using JADER and M-JADER algorithm. It is clear to see that the proposed technique has the highest correlation coefficient and has less running time comparing with JADER as shown in Table 1

Table 1 runing time comparison between M-JADER and JADER

Iteration	JADER/ seconds	M-JADER/seconds
1	0.019401	0.009211
2	0.019534	0.010473
3	0.020562	0.009018

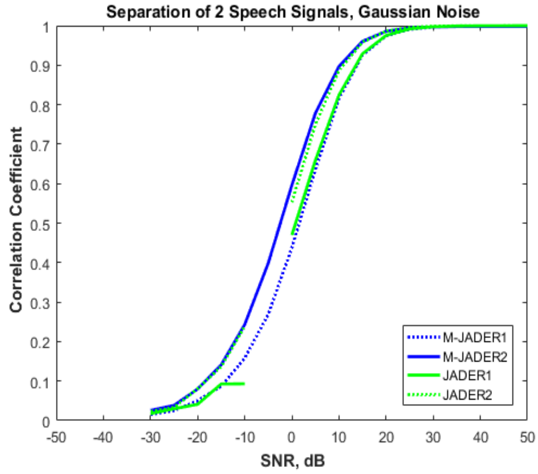

Fig 4 correlation coefficient vs. SNR for separation under Gaussian noise and negative mixing matrix

When the mixing matrix has negative values JADER algorithm became unstable. As shown in ***Fig 4*** *and* ***Fig 5***.

Table 2 JADER and MJADER comparison using SNR vs.correlation coefficients

SNR	JADER	MJADER
-15	NaN	0.139928
-10	0.241208	0.246161
-5	NaN	0.40406
0	0.598905	0.610821
5	0.776101	0.791866
10	0.905486	0.911021
15	0.965964	0.967206

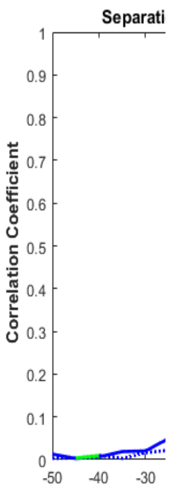

Fig 5: Correlation coefficient vs. SNR for separation speech signals under Gaussian noise and two negative values mixing matrix

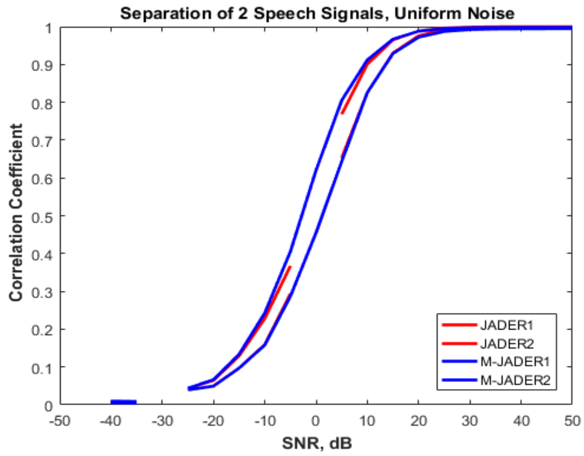

Fig 6 Correlation coefficient vs. SNR for separation speech signals under Uniform noise and two negative values mixing matrix

5.3 Comparison with FastICA algorithm

FastICA algorithm

It is one of the most popular algorithms for independent component analysis (ICA), it is de-mixing a set of statistically independent sources that mixed linearly.

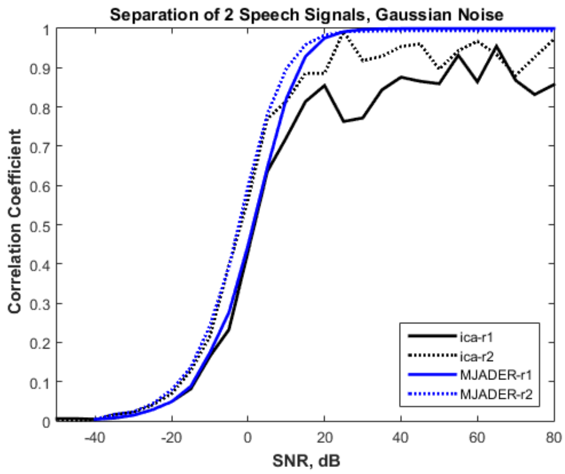

Fig 7 correlation coefficients vs.SNR of comparison MJADER with FastICA

Future tests will include mixed signals over long-range communication systems [9, 10] or short-range systems as in [11].

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6 Conclusions

A modification for the signal separation algorithm JadeR has been proposed. The modification is based on reducing the dimensionality of signals via selecting values based on a threshold. Good experimental results have been obtained with higher correlation values between the original signals and extracted signals. The proposed (M-JADER) is faster than original JADER with reduced computations.

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