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Performance evaluation of Blind Signal Separation method using advanced MUK algorithm

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Abstract: *Blind source separation (BSS) has raised interest in various fields of research, as testified by the wide literature. This paper present a quadratic programming algorithm for fast blind source separation. The transmitted signal is subjected to Additive white Gaussian noise. The received signals are, hence, corrupted by inter-user interference (IUI), and considered as the outputs of a linear (MIMO) memory-less system. A number of independent and identically distributed signals that are transmitted simultaneously through a linear instantaneous mixing channel will be separated blindly. We focus on a straightforward blind constrained criterion stemming, and we derive an adaptive algorithm for blind source separation. This work also shows that by applying source orthogonalization through successive processing, the quadratic programming approach can be applied efficiently. Moreover, our approach has lower computational complexity. Simulation has been done using MATLAB R2012a.*

Keywords*: Blind signal separation, quadratic programming, generalized eigen value problem, multiuser kurtosis (MUK) algorithm.*

1. INTRODUCTION

Blind signal separation, also known as blind source separation, is the separation of a set of source signals from a set of mixed signals, without the aid of information (or with very little information) about the source signals or the mixing process. In the classical noiseless and instantaneous BSS model *K* independent sources (denoted by a vector *x)* are linearly mixed by an unknown square matrix *A*[1]. The goal is to separate the sources from the measured mixture:

$$y=Ax \quad \textbf{(1)}$$

Possibly by estimating the mixing matrix and inverting it, using only *N* measurements of *y* and without any knowledge about the sources and their distributions, nor the mixing *A* [2]. In the specification of the model, we assume that the signals have no time structure (i.e. the samples of *y* are IID (independent and identically distributed)). This assumption is used for performance analysis, and for development of some of the algorithms. Yet, the algorithms still work, possibly with reduced performance, if a time relation exists.

The problem is sometimes termed independent component analysis (ICA) [3]. The point of view of ICA is a little different from BSS. ICA takes the input data and attempts to decompose it into independent components. It doesn't necessarily assume that the data was created in this manner. For example, ICA may be used for feature-extraction in sound and image signals, in which the BSS model doesn't necessarily hold. For practical purposes the ICA and the BSS problems are the same one (because ICA methods use the same source-mixing model as BSS) [4], [5]. Since the chief difficulty is the problem of it's under determination, methods for blind source separation generally seek to narrow the set of possible solutions in a way that is unlikely to exclude the desired solution. In one approach, exemplified by principal and independent component analysis, one seeks source signals that are minimally correlated or maximally independent in a probabilistic or information-theoretic sense [3], [4]. A second approach, exemplified by nonnegative matrix factorization, is to impose structural constraints on the source signals. These structural constraints may be derived from a generative model of the signal, but are more commonly heuristics justified by good empirical performance [9]. A common theme in the second approach is to impose some kind of low-complexity constraint on the signal, such as sparsity in some basis for the signal space. This approach can be particularly effective if one requires not the whole signal, but merely its most salient features [9].

There are different methods of blind signal separation [9]:

- Principal components analysis
- Singular value decomposition
- Independent component analysis
- Dependent component analysis
- Non-negative matrix factorization
- Low-complexity coding and decoding
- Stationary subspace analysis
- Common spatial pattern

ISSN 2320-6802

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2. LITERATURE REVIEW

2.1 MUK Algorithm [2]:

W' (k+1) = W(k) + μ sign (K_a)Y*v(k) Z (k).............(2)

Where,

Z(k) = [$|z_1(k)|^2 z_1(k) \dots |z_p(k)|^2 z_p(k)$] ....(3)

Equation……………………

$$W_j\ (k+1)=\frac{W_j'(k+1)-\sum_{l=1}^{j-1}(W_l^H(k+1)(W_j'(k+1))(W_l\ (k+1))}{||W_j'(k+1)-\sum_{l=1}^{j-1}(W_l^H(k+1)(W_j'(k+1))(W_l\ (k+1))}$$

....................(4)

TABLE 1

MUK ALGORITHM [2]

1. k=0 : initialize W(0)= W_0
2. for k > 0
3. obtain W' (k+1) from (2)
4. obtain W_1 (k+1)= W_1'(k+1)/ $||W_1'$(k+1)||
5. for j = 2 : p
6. compute W_j (k+1) from (4)
7. Go to 5
8. W(k+1) = [W_1 (k+1)…….. W_p (k+1)]
9. Go to 2

2.2 Principal component analysis [7]

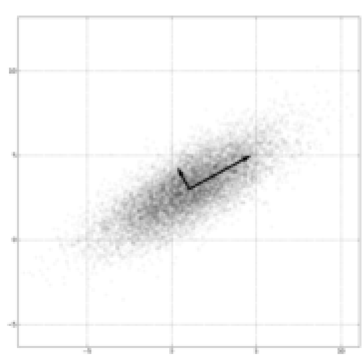

Figure 1: PCA of a multivariate Gaussian distribution [7]

Principal component analysis (PCA) has been called one of the most valuable results from applied linear algebra. PCA is used abundantly in all forms of analysis - from neuroscience to computer graphics because it is a simple, non-parametric method of extracting relevant information from confusing data sets. With minimal additional effort PCA provides a roadmap for how to reduce a complex data set to a lower dimension to reveal the sometimes hidden, simplified dynamics that often underlie it. PCA of a multivariate Gaussian distribution centered at (1, 3) with a standard deviation of 3 in roughly the (0.878, 0.478) direction and of 1 in the orthogonal direction. The vectors shown (figure 1) are the eigenvectors of the covariance matrix scaled by the square root of the corresponding eigenvalue, and shifted so their tails are at the mean.

Principal component analysis (PCA) is a statistical procedure that uses an orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables called principal components. The number of principal components is less than or equal to the number of original variables. This transformation is defined in such a way that the first principal component has the largest possible variance (that is, accounts for as much of the variability in the data as possible), and each succeeding component in turn has the highest variance possible under the constraint that it is orthogonal to (i.e., uncorrelated with) the preceding components. Principal components are guaranteed to be independent if the data set is jointly normally distributed [4], [5]. Now, consider a small example showing the characteristics of the eigenvectors. Some artificial data has been generated, which is illustrated in the Figure 2The small dots are the points in the data set. Sample mean and sample covariance matrix can easily be calculated from the data. Eigenvectors and eigen values can be calculated from the covariance matrix. The directions of eigenvectors are drawn in the Figure as lines [7]. The first eigenvector having the largest eigen value points to the direction of largest variance (right and upwards) whereas the second eigenvector is orthogonal to the first one (pointing to left and upwards).

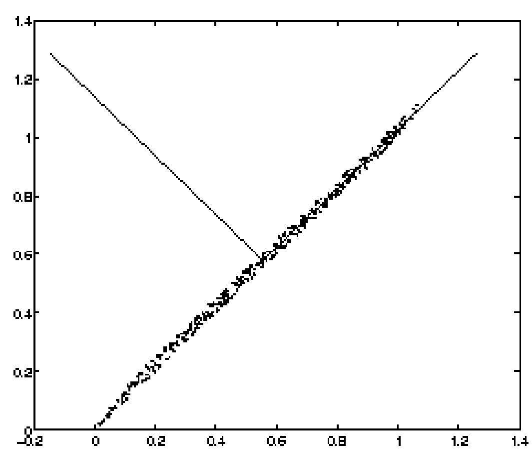

Figure 2: Eigenvectors of the artificially created data

In this example the first eigen value corresponding to the first eigenvector is λ_1=0.1737 while the other eigen value is λ_2=0.0001. By comparing the values of eigen values to the total sum of eigen values, we can get an idea how much of the energy is concentrated along the particular eigenvector. In this case, the first eigenvector contains almost all the energy. The data could be well

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approximated with a one-dimensional representation [7]. Sometimes it is desirable to investigate the behavior of the system under small changes. Assume that this system, or phenomenon is constrained to an *n*-dimensional manifold and can be approximated with a linear manifold. Suppose one has a small change along one of the coordinate axes in the original coordinate system [7]. If the data from the phenomenon is concentrated in a subspace, we can project this small change $\delta_x$to the approximate subspace built with PCA by projecting $\delta_x$on all the basis vectors in the linear subspace by

$\delta_y = A_k \, \delta_x$………………………..(5)

Where the matrix A_k has the K first eigenvectors as rows. Subspace has then a dimension of K. $\delta_y$represents the change caused by the original small change. This can be transformed back with a change of basis by taking a linear combination of the basis vectors by

$\delta_x = A_k^T \, \delta_y$……………………….(6)

Then, we get the typical change in the real-world coordinate system caused by a small change $\delta_x$by assuming that the phenomenon constrains the system to have values in the limited subspace only.

2.3 Constellation Diagram:

A constellation diagram is a representation of a signal modulated by a digital modulation scheme such as quadrature amplitude modulation or phase-shift keying. It displays the signal as a two-dimensional scatter diagram in the complex plane at symbol sampling instants [8]. In a more abstract sense, it represents the possible symbols that may be selected by a given modulation scheme as points in the complex plane. Measured constellation diagrams can be used to recognize the type of interference and distortion in a signal [8].

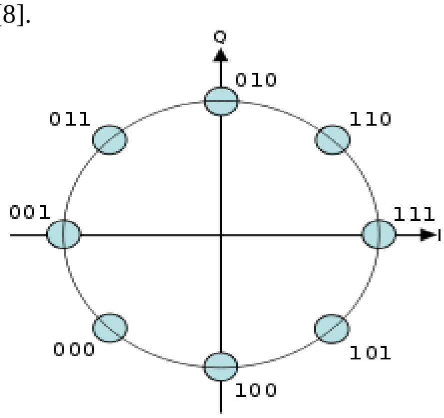

Figure 3: A constellation diagram for Gray encoded 8-PSK.

As the symbols are represented as complex numbers in figure 3, they can be visualized as points on the complex plane. The real and imaginary axes are often called the *in phase*, or I-axis, and the *quadrature*, or Q-axis, respectively. Plotting several symbols in a scatter diagram produces the constellation diagram. The points on a constellation diagram are called *constellation points*. They are a set of *modulation symbols* which comprise the *modulation alphabet*.

3. Quadrature phase-shift keying (QPSK)

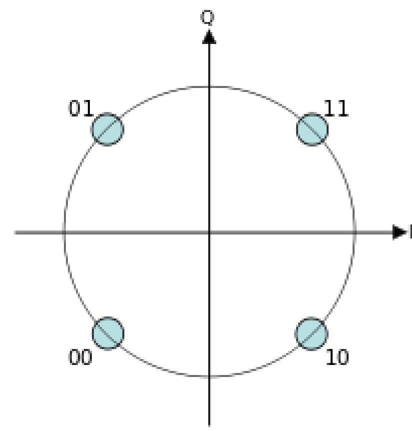

Figure 4: Constellation diagram for QPSK with Gray coding.

Adjacent symbols only differs by one bit with each other. Sometimes this is known as *quadriphase PSK*, 4-PSK, or 4-QAM. (Although the root concepts of QPSK and 4-QAM are different, the resulting modulated radio waves are exactly the same.) QPSK uses four points (figure 4) on the constellation diagram, equi-spaced around a circle [8]. With four phases, QPSK can encode two bits per symbol, shown in the diagram with Gray coding to minimize the bit error rate (BER) sometimes misperceived as twice the BER of BPSK [8].

4. NEW PROPOSED SCHEME

We have used the methodology:

1. Initialization of input parameters i.e. PSK constellation, number of samples, number of transmitters, number of receivers, noise variance.
2. Creation of Random symbols (QPSK symbols) according to number of samples and transmitters.
3. Mapping of random symbols on constellation.
4. Creation of Random Channel Matrix depending on number of transmitter and receivers.
5. Computation of received samples by putting mapped symbols on channel matrix.
6. Creation and addition of white Gaussian noise.

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7. Addition of Additive White Gaussian Noise to the signal to be received.
8. Perform principal component analysis on noisy received signal.
   - Compression of received noisy signal.
   - Perform Eigen value decomposition on compressed signal.
   - Sort the Eigen values in the decreasing order.
   - Keep the largest Eigen values.
   - Keep the largest Eigen vectors.
   - Extraction of whitened data from received noisy signal.
9. Application of multiuser Kurtosis maximization algorithm through a stochastic-gradient update on whitened data.
10. Application cat Unitary Constraint (Gram-Schmidt orthogonalization).
11. Estimation of source and channel depending upon Eigen values, Eigen vectors matrices and orthogonalized data.
12. Display of constellation mapped data for all the received data and extracted data.

Further work is targeted toward the extension of the technique to convolutive mixing channels, non-stationary environments, and the quantitative analysis of the steady-state behaviour of the algorithm in the presence of noise.

5. CONCLUSIONS AND FUTURE WORK

All the simulation has been implemented in MATLB R2008a using generalized tool box and wireless communication toolbox. After initialization of input parameters i.e. PSK constellation, number of samples, number of transmitters, number of receivers, noise variance, creation of Random Channel Matrix depending on number of transmitter and receivers has been done. Then, Additive White Gaussian Noise is added to the signal to be received. Principal component analysis is performed on noisy received signal. Multiuser Kurtosis maximisation algorithm is then applied through a stochastic-gradient update on whitened data. Then, source and channel have been estimated depending upon Eigen values, Eigen vectors matrices and orthogonal data. Figure 5, 6 and 7 shows the received signal constellation from all three receivers. Figure 8 and 9 shows the extracted signal constellation from received signal for both transmitters. Both figures show that algorithm has selected good coefficients from received symbols.

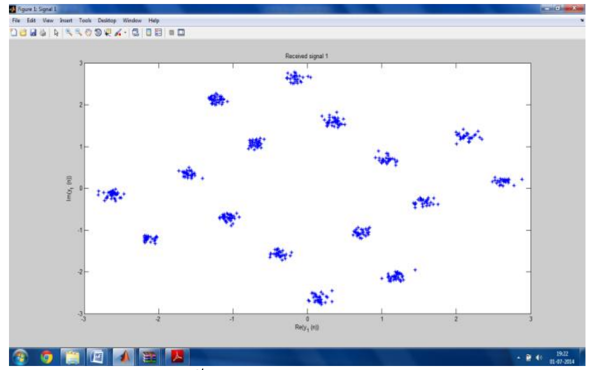

Figure 5: 1st receiver signal constellations

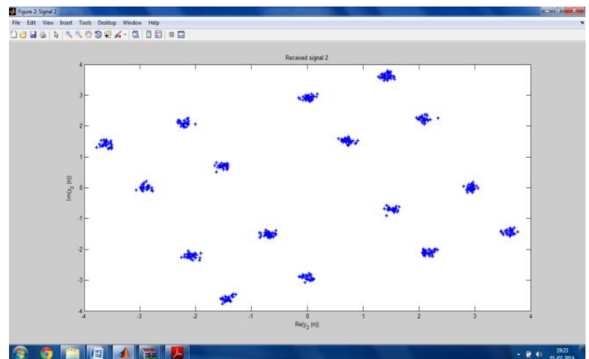

Figure 6; 2nd receiver signal constellations

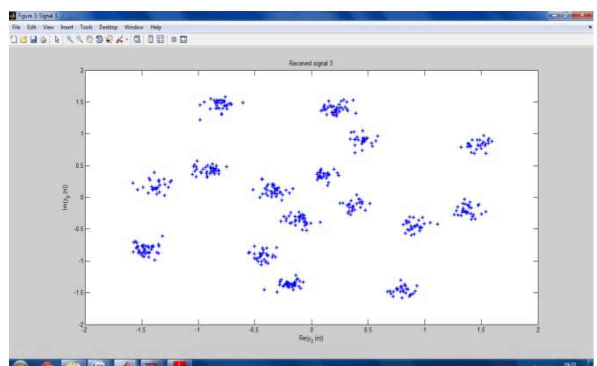

Figure 7: 3rd receiver signal constellations

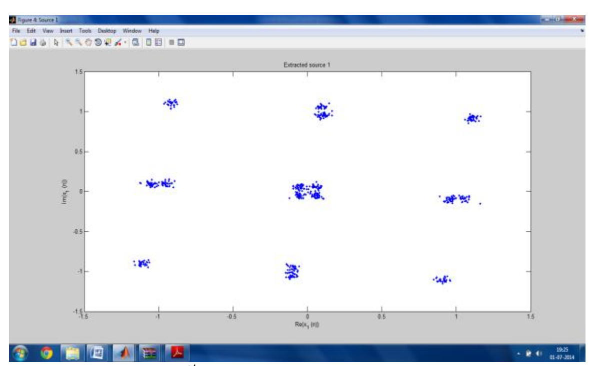

Figure 8: 1st Extracted signal constellations

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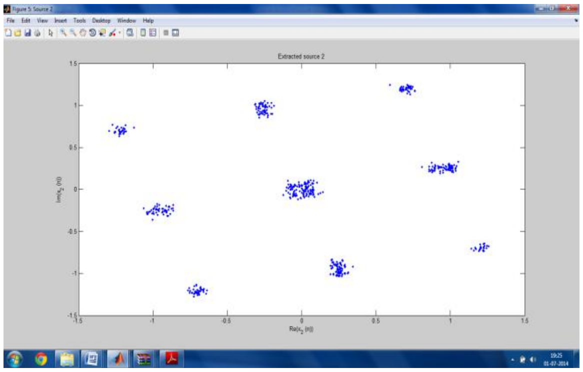

Figure 9: 2nd Extracted signal constellations

In this paper, we have studied the problem of unsupervised or blind source separation of independent and identically distributed sources. Based on a set of necessary and sufficient conditions for the correct retrieval of all the sources, we use MUK (multiuser kurtosis adaptive) algorithm for the blind source separation of immediate mixtures. Due to MUK constrained optimization criterion, the algorithm combines at each iteration, a stochastic gradient update with a Gram–Schmidt orthogonalization that projects the updated parameters to the whiteness constraints. Main feature of the Gram–Schmidt component of the algorithm is that it results in the algorithm's updating procedure having a deflation structure, which turns out to be key in its convergence behaviour. More specifically, an analysis of the stationary points of the MUK algorithm reveals its absence of undesired stationary points, making it globally convergent to settings that recover (in the absence of noise and up to scalar phase and permutation ambiguities) all the input signals perfectly. This result holds for any number of input signals. The good performance of the algorithm was demonstrated through extensive computer simulations, where its global convergence was confirmed, together with its robustness to the sources' distance from Gaussianity, the non-perfect received signal prewhitening, and the presence of additive white Gaussian noise. Based on this behaviour, it is our belief that the MUK algorithm is a powerful technique that can be used in a number of blind source separation applications. Further work is targeted toward the extension of the technique to convolutive mixing channels, non-stationary environments, and the quantitative analysis of the steady-state behaviour of the algorithm in the presence of noise.

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