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A Case Study on Independent Vector Analysis for Convolutive Mixed Audio Signal

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Abstract— **Convolutive mixtures of signals are common in acoustic environment and are difficult to separate. Independent vector analysis (IVA) presents a uniform probabilistic framework to separate convolutive mixtures of acoustic signals using , which is based on the frequency components originating from the same source and is capable of preventing permutation disorder. Independent vector analysis (IVA), an extension of Independent component analysis (ICA) from univariate components to multivariate components, that provides an efficient framework for avoiding the permutation problem and scaling in blind source separation (BSS). IVA utilizes both the statistical independence among multivariate signals and the statistical inner dependency of each multivariate signal. This project is made to overcome the problems such as Scaling and Permutation Ambiguity.**

Index Terms— **Blind Source separation, Independent component Analysis (ICA), Independent Vector Analysis(IVA) ,Cocktail party problem.**

I. Introduction

Blind source separation (BSS) is a technique for estimating individual source components from their mixtures at multiple sensors [1-2]. It is called blind because we don't use any other information of the mixtures. Blind source separation, is the separation of a set of source components from a set of mixed signals, without the aid of information (or with very little information) about the source signals or the mixing process. There are different methods for blind source separation like principal component analysis, independent component analysis, and Fast Independent component analysis is a computational method for separating a multivariate signal into additive sub components supposing the mutual statistical independence of the non-Gaussian source signals. The problem of blind source separation (BSS) received considerable research interest over the last decade due to potential applications in various areas including digital communications, speech enhancement, geophysical data processing, data mining and medical imaging. The problem of BSS is the "cocktail party problem", where a number of people are talking simultaneously in a room and one is trying to follow one of the discussions. Another example to show the use of source separation is a parliament house with a large number of people in it. Each person might speak a different or the same language at the same time. Hence it is difficult to listen to the one actually speaking. Similarly in general we use a an two sources (speaker) and two sensors (microphone), where the microphone receives the both source S1 and S2.This problem is known as "cocktail party problem". The various methods used for separation of speech and voice signals are PCA [3], ICA [4], FAST ICA [5], wavelet based ICA and so on. ICA is one of the widely used methods for Blind source separation which uses the statistical properties of the components like gaussianity, kurtosis and so on. Independent component analysis is a well-known algorithmic method that can solve the blind source separation (BSS) problem efficiently. The underlying assumption of ICA is that the observations are linear mixtures of hidden sources which are statistically independent and thus the sources can be separated by maximizing the independence of the outputs. Separation of convoluted mixtures has been tackled in the frequency (or time-frequency) domain, where the mixing process is bin-wise. ICA is blind to permute, the bin-wise separation results in permutation disorder across the bins and thus prevents correct signal reconstruction. This is called the Permutation Problem and has been fixed by computing the direction of arrival of the frequency components or the cross correlation of their magnitudes or by smoothing the filter. On the other hand, a multivariate extension of ICA called independent vector analysis (IVA) exploits [6-15] the dependency among the frequency components such that the permutation problem can be avoided.

II. Methodology

A. Principal Component Analysis

PCA is a way of identifying the underlying geometry in data and expressing them in such a way as to highlight their similarities and differences. It is a simple method of extracting relevant information from mixed signals found in many fields of computer graphics, audio signal processing and biomedical field. The main advantage of PCA is that it reduces the a high dimensional complex data set to a lower dimension without much loss of information and to reveal the hidden underlying data.PCA can be termed as a linear transformation method which can express the data as a linear combination of its basis vectors.

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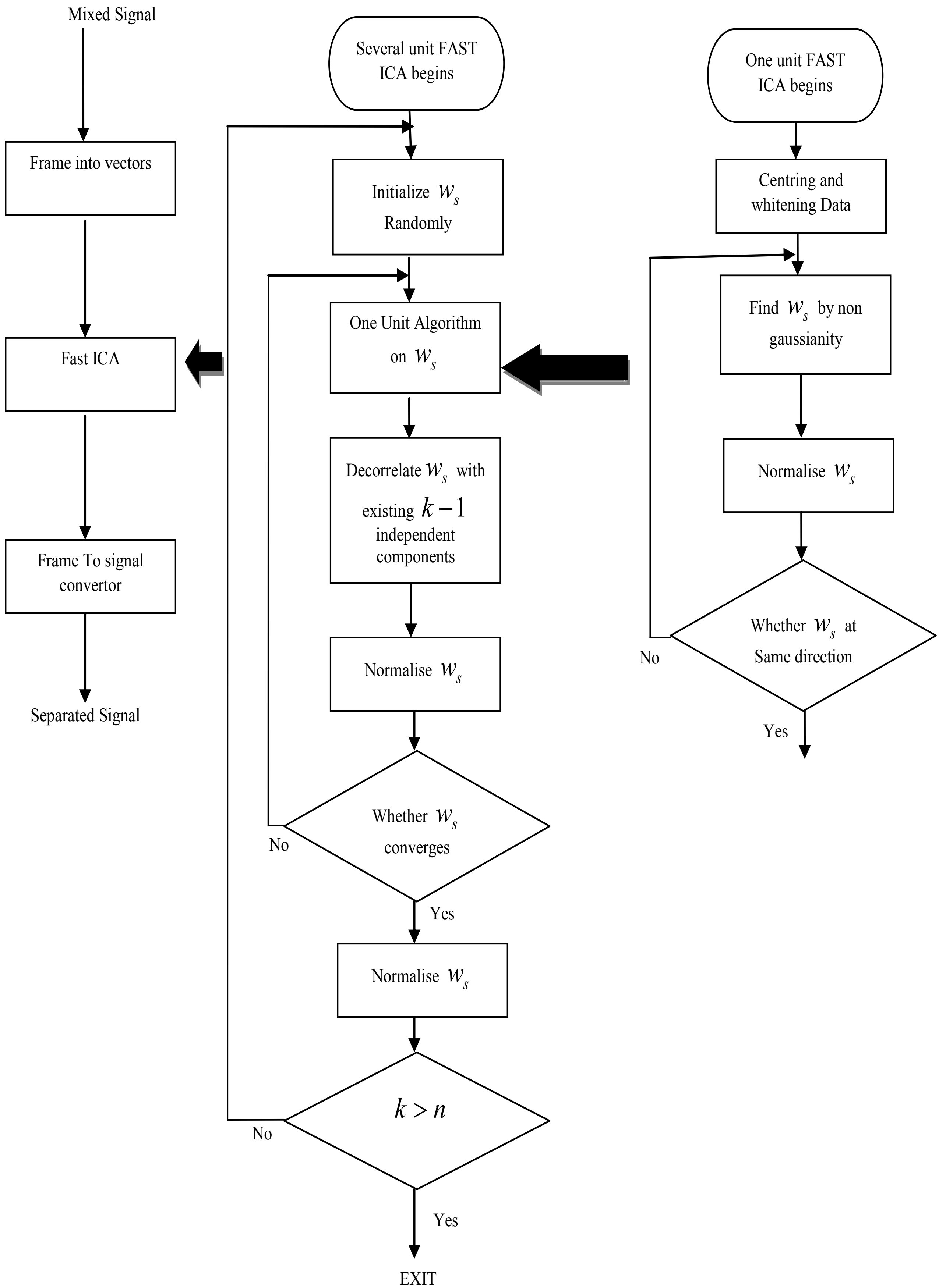

Figure 1.Flowchart for Independent Vector Analysis (IVA)

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Let X and Y be m×n matrices related by a linear transformation D. X is the original observed data set and Y is the representation of that data set

$$Y = D.X \tag{1}$$

The above Equation (1) represents a change of basis. D is matrixes that transforms X into Y .The rows of D, are a set of new vectors for expressing the columns of X .The covariance matrix of the input data X is given by

$$S_x = \left(\frac{1}{n-1}\right)\left[XX^T\right]$$

(2)

S_x is square and symmetric matrix and n represents the number of samples. The covariance matrix describes the relationships between pairs of measurements thus the redundancy is removed when covariance between separate measurements become negligible. The PCA is based on the following assumptions that the dimensionality of data can be efficiently reduced by linear transformation and the most information is contained in those directions where input data variance is maximized. The main drawback of PCA is that the way of encoding second order dependencies is done by finding the directions of maximal variance. PCA decorrelates the input data but it doesn't address the higher order dependencies. PCA uses a second order method to reconstruct the signal in the mean square sense. The data are represented in an orthonormal basis in the PCA that are determined by the second order statistics (covariance's) of the input data. Such a representation is needed for Gaussian data but non-Gaussian data contain a lot of additional information in its higher order statistics. Thus PCA fails to detect sources and is not suitable for non-Gaussian distribution.

B. Independent component Analysis(ICA)

Independent component analysis is a technique that solves the Blind source separation problems. Independent component analysis (ICA) is a computational method for separating a multivariate signal into additive sub components where the sub components are non-Gaussian signals and they are statistically independent from each other. ICA is a special case of blind source separation. When the statistical independence assumption is correct, separation of a mixed signal is better. ICA finds the Independent components (ICs) by maximizing the statistical independence of the estimated components. The methods of independence for ICA are Minimization of mutual information and Maximization of non-Gaussianity. The Minimization-of-Mutual information ICA algorithms use measures like Divergence and maximum entropy. The non-Gaussianity family of ICA algorithms uses kurtosis and negentropy. In ICA pre-processing steps are usually carried out before the ICA .Preprocessing is the centering and whitening of data. Centering is the process where centered by subtracting the observed vector x mean vector m=E$\{x\}$, thus the centered data is

$$x_c = x - m \tag{3}$$

Whitening involves the transforming of the observed vector such that its components are uncorrelated and have unit variance. Let the whitened data satisfies the following equation

$$E\{x_w x_w^T\} = I$$

(4)

The main drawbacks of ICA are magnitude and scaling ambiguity and permutation ambiguity. The scaling problem is one where the separated signal has very high amplitude than the input source signal. The permutation ambiguity is another major problem considers two sources 1 and 2 are mixed, then we get source 2 separated from source 1 and source 1 separated from source 2.

FastICA is a fixed point ICA algorithm that uses the higher order statistics for the recovery of mixed sources. Fast ICA can estimate independent components one by one (deflation approach) or simultaneously (symmetric approach). Fast ICA uses simple estimates of Negentropy based on the maximum entropy principle. The fixed point algorithm is based on the mutual information that is shown below

$$I(s) = \int f_s(s) \log \frac{f_s\ (s)}{\pi f_{si}(s_i\ )} ds$$

(5)

The one-unit algorithm to estimates one of the independent components. To estimate several independent components, the one-unit FastICA algorithm is made to run for several units with weight vectors $w_1, .. w_n$. After every iteration the outputs are decorrelated to prevent different vectors converging to same maxima.The basic method of FastICA algorithm is as follows:

1. Take a random initial vector $w(0)$ and divide it by its norm. Let $k = 1$.
2. Let $w(k) = E\{z[z^T w(k-1)]^3\} - 3w(k-1).$
3. Divide $w(k)$ by its norm.
4. If $\left|w^T(k)w(k-1)\right|$ is not close enough to 1, let $k = k+1$, and go back to step(2) otherwise the algorithm is convergent and outputs $w(k)$. The final weight vector $w(k)$ given by the algorithm equals one of the columns of the demixing matrix B .The weight vector $w(k)$ separates one of the non-Gaussian source signals in the sense that $w(k)^T x(t)$,where t = 1,2,…….equals one of the source signals. The problem of permutation ambiguity is overcome in Fast ICA ,but the Scaling problem exists and also is computationally expensive

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C. Independent Vector Analysis(IVA)

Independent vector analysis (IVA) is an extension of independent component analysis (ICA) from univariate components to multivariate components that, provides an efficient framework for avoiding the permutation problem in blind source separation (BSS). IVA utilizes both the statistical independence among multivariate signals and the statistical inner dependency of each multivariate signal. An element-wise notation is used, where the $M \times K$ observation x_{ik} is assumed to be given as a scaled sum of $L \times K$ latent sources s_{jk}.

$$X_{ik} = \sum_{j=1}^{L} a_{ik} s_{jk} \qquad (6)$$

Where $i = 1,\ldots,M$; $j = 1,\ldots,L$; i=1,…,M and $k = 1,..,K$. M denotes the number of mixtures, L the number of sources and K the number of different dimensions. To make the model simpler, a vector-matrix notation is used. The vector-matrix is shown below

$$X_{:1} = X_{::1} S_{:1} \quad , \quad X_{:2} = X_{::2} S_{:2} \quad ,\ldots, \quad X_{:k} = X_{::k} S_{:k}$$
(7)

Solving the permutation problem is not the only advantage of the IVA model. Another problem where the ICA model fails but the IVA model manages to get a correct solution is when it is applied to Gaussian sources or when the mixing matrix is very close to the singular matrix

III. RESULT AND DISCUSSION

In this section the performance measure of the separated source signal is calculated using. Signal to Interface Ratio (SIR) values are measured for the performance measurement. The Signal to Interface Ratio (SIR) in decibels is calculated from the formula

$$SIR(dB) = 10 \log_{10} \frac{\sum_{t=1}^{T} \|s_t\|^2}{\sum_{t=1}^{T} \|m_t - s_t\|^2} \qquad (8)$$

Where $s_{1,\ldots.}s_t$ represents the separated source signal and $m_{1,\ldots.}m_t$ represents the mixed source signal. The mixing model is mainly classified into instantaneous mix and convolutive mix. The instantaneous mixing is mixing of the Source signals without any delay. The convolutive mixing is mixing of the source signals with some delay that is the echoes. The echoes can be formed by adding the minimal and maximum delayed source signals. The minimal delayed of source 1 and maximum delay of source 2 is added to the original source signal 1. Similarly the minimal delayed of source 2 and maximum delay of source 2 is added to the original source signal 2. Thus the echoes or the delayed signal may be obtained. Here convolutive mixing is taken and the algorithm is applied for separation of input source signals. Here the convolutive mixing coefficient is $a_1 = [.9$ $.3\ .2]$, $a_2 = [.02\ .04\ .09]$, $a_3 = [.04\ .03\ .09]$, $a_4 = [.9\ .6$ $.4]$. PCA is a classical method, it is not a type of Blind Source Separation .It uses some prior knowledge information to separate the mixed source signal .It is done in the time domain. There are two types of PCA such as Correlation and Covariance type .The mostly Covariance type is used that result in better separation .But till scaling and permutation problem occurs. ICA is made for the convolutive mixed source signal and the input source signal is separated. It is a blind source separation type and overcomes the BSS problem such as cocktail problem. But till the scaling and permutation problem exists. So the output is partially separated.

The Fast ICA is a fixed point ICA that is used for recovery of mixed sources using higher order statistics. The problem of permutation ambiguity is overcome in Fast ICA, but the Scaling problem exists and also is computationally expensive. The IVA is modified from Fast ICA where the framing of signal into vectors is done on the input and signal to frame convertor on the output of Fast ICA vectors. It provides an efficient framework for avoiding the well-known permutation problem in blind source separation (BSS).The problem in ICA such as Scaling and Permutation problem is overcome and the separation is better than the above methods.

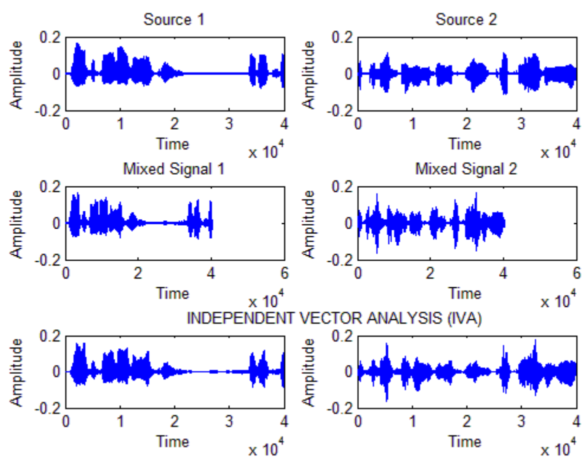

Figure 2. Separated Source signal using IVA for Male and Female voice

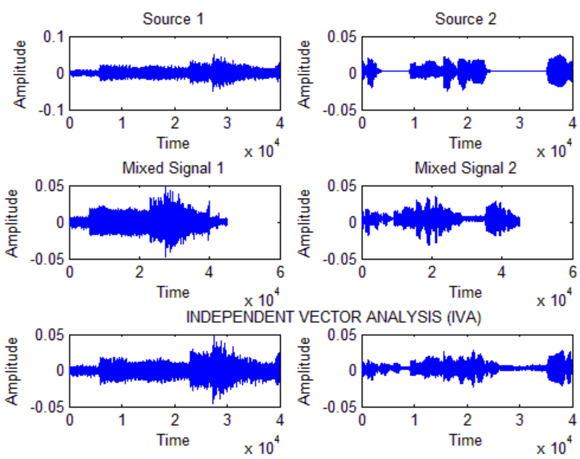

Figure 3. Separated Source signal using IVA for Flute and Guitar Instruments

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The above Fig 2 and 3shows the two input source signals and the separated signal using an IVA. The Fig 2 shows the Male and Female voice as input source signals and the 500 number of delays are added to convolutive mix and finally the separated mixed signal. Similarly the Fig 3 shows the flute and guitar instruments as inputs and an 5000 number of delayed signal is added in the mix.

The Table 1 below shows the SIR (dB) for separated signals using the Independent Vector Analysis. The comparison is made for different combination of Input source signals are tabulated in the table. The two different types of Delayed made on the convolutive mixing. The number of delayed samples is made for 500 and 5000 delayed samples. The different sources such combination of instrumental music, male and female voice, speech and music signals are taken.

Sl. No	**Mixed Sources**	**SIR(*dB*) For different number of delayed samples**	
		500 samples	**5000 samples**
1	Flute	4.479448	8.401513
	Guitar	5.761189	7.32028
2	Female Voice1	3.718067	4.107076
	Female Voice 2	3.615761	3.592756
3	Male Voice 1	16.28960	13.852716
	Male Voice 2	20.423667	19.912981
4	Male Voice	13.729470	10.55130
	Female Voice	8.841416	5.749122
5	Male Voice	9.225518	12.736208
	Flute	11.974098	16.337240
6	Female Voice	4.078863	7.035170
	Flute	5.618877	6.853886
7	Reading Letters	9.128376	10.157706
	Flute	6.318136	3.952418
8	Reading Letters	8.385399	11.357187
	Male Voice	6.318136	12.875657
9	Reading Letters	7.284327	10.775984
	Female Voice	6.544961	6.026585
10	Reading Letters	7.619039	11.565392
	Female Song	11.657142	13.585137
11	Hindi Reading	5.44912	9.563131
	Female Song	8.728828	13.16883
12	Hindi Reading	6.54814	13.837470
	Music	4.68421	8.841416
13	Music 1	15.85612	18.473944
	Music 2	9.58662	11.684232

IV. CONCLUSION

In this paper the different combinations of input source signals are taken and IVA is applied for separation of mixed signal and their Signal to Interference (dB) is calculated. The problem in previous methods such as Scaling and Permutation ambiguity is overcome by IVA.

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