ICA based Blind Source Separation in Voice Applications

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Abstract— Independent component analysis ICA technique for blind source separation is computationally proficient, and has an area of interest to researchers for many practical applications in various fields of science and engineering. This paper attempts to cover the basic concepts involved in the technical review of the ICA and its applications. BSS exploits the prior knowledge of nature and structure of hidden sources such as sparseness, noise, Gaussianity and statistical independence. Independent Component Analysis and Blind Source Separation refer to the problem of recovering statistically independent signals from a linear mixture. In this paper, ICA method in voice applications is presented. We studied two algorithms, Bell and Sejnowski Infomax algorithm and Hyvarinen Fastica algorithm.

Keywords— Gaussianity, Statistical Independence, BSS, ICA, Infomax, Fastica.

I. INTRODUCTION

The issue of source separation is an inductive inference problem. There are not enough details to consider the solution, so one must use any available details to infer the most potential solution [1]. The aim is to procedure these observations in such a way that the original source signals can be extracted by the adaptable system [1].The problem of Blind source separation (BSS) has received considerable attention recently because of its significant potential applications comprising over a variety of diverse professions like sonar and radar signal processing, telecommunications, array signal processing, wireless communication, biomedical signal processing, speech and image processing [2][8].

First of all, Blind Source separation BSS problem is described in this paper. BSS model is briefly discussed in section II. Then, the Independent Component analysis problem, which is most widely used technique of Blind source separation, is introduced. General description of approach to achieve separation of voice signals through ICA and underlying assumptions of ICA are discussed in section III. Two different algorithms of ICA are discussed in section IV and V. In last portion we presented extracted voice signals, implemented in Matlab. Voice signals in GUI are also shown. Section VI discusses the conclusion of the paper.

II. BLIND SOURCE SEPARATION

The purpose in a primary BSS problem is to draw out unknown source signals that are mutually independent from the observed signals obtained from the sensor. The separating process becomes essential as the sources are combined by an unknown medium and lastly the combined signals are provided by the sensor. Generally, the observations are obtained at the output of a set of sensors, each sensor getting a different combination of the source signals [6]. The phrase 'blind' stresses the fact that the mixing structure is unidentified [2]. Many different techniques have been attempted by several scientists using neurological systems, artificial learning, higher order statistics and adaptive noise cancellation, each claiming various levels of success [8].

A. Blind Source Separation Model

Basic block diagram of BSS is shown in figure 1. The source data is mixed with a mixing matrix A to produce x(n), which will serve as senor data. Optimized Algorithms like ICA or SVD act on this senor data to produce separating matrix W from which replica of original signal y (n) can be extracted [2] [10].

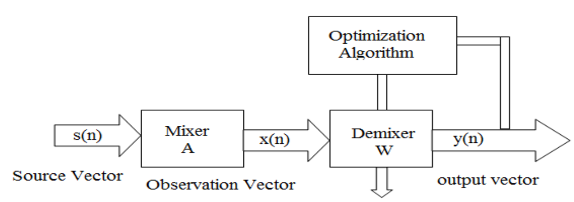


Fig.1 Basic Model of BSS

First of all, we consider the linear instantaneous model that is common in BSS [11].

$$\mathbf{x}=\mathbf{A}s \qquad (1)$$

Where,
A= Mixing matrix $(m \times n)$
s= Source vector $(n \times 1)$
x= Observation vector $(m \times 1)$

Solution to the Blind Source Separation depends upon issues like [2] [10]:

- Mixing process is time invariant or time varying,
- Mixture is linear or non-linear,
- Mixing process is convolutive or non-convolutive,
- Senor is noisy or noise-less and
- Relation between number of sources (n) and number of measurements (m).

Let us suppose N source vectors [10]

$$S(t) = (S_1(t) \dots S_N(t))^T \qquad (2)$$

And the observed signals are by

$$X(t) = (X_1(t) \dots X_M(t))^T \qquad (3)$$

So,

$$X(t) = AS(t) + \mathbf{n}(t) \qquad (4)$$

The goal is to estimate the sources S and the mixing matrix A. Here, $\mathbf{n}(t) = (n_1(t) \dots n_M(t))^T$ is a vector of additive noise [10] [11]. The original sources are recovered by finding W, which is theoretically equal to the inverse of A, i.e., $W=A^{-1}$, so that y is as close as possible to s [2].

$$\mathbf{y=Wx} \qquad (5)$$

This is a simplified model which ignores any time delay in recording [1].

III. INDEPENDENT COMPONENT ANALYSIS (ICA)

The most common assumption is that source signals are statistical independent. The techniques based on this assumption are known as Independent Component Analysis methods. These are statistical techniques of decomposing complex information set into individual parts [5].

BSS by ICA (Independent Component Analysis) has obtained much interest due to its potential applications on signal processing, exclusively in speech enhancements techniques [4]. ICA represents a mathematical design whereby the noticed multivariate data, generally given as a large database of samples, are believed to be linear or nonlinear mixtures of some unidentified latent variables [3].

The generalize ICA network is shown in fig.2.

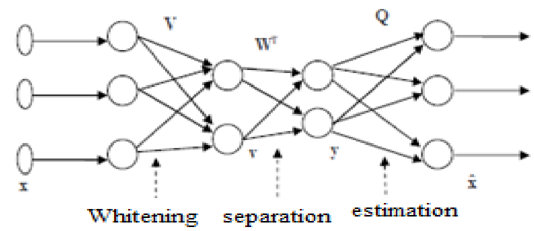


Fig.2 The ICA Network

A. ICA Assumptions

- Sources being considered must be statistically independent [1].
- Independent components have non-Gaussian distribution.
- Mixing Matrix is invertible.

Satisfying these three cases, it is possible to estimate the independent components module some mystery trivial. Clearly, these assumptions are not very restrictive and as a result, we have only very little information on the sources and the mixing process itself [1] [7].

B. Preprocessing

In the next section, we discussed about specific algorithm, but before we discuss these preprocessing steps. That helps for better understanding and easier programming.

1) *Centering:* The primary and necessary preprocessing is to centre x, i.e. deduct its mean vector $m = E\{x\}$ so as to create x a zero-mean varying. What this means is that zero-mean. We obtain centered observation vector as:

$$x_c = x - m \qquad (6)$$

2) *Whitening:* Another phase which is very useful in exercise is to whiten the observation vector. This implies that before use of the ICA criteria (and after centering), we convert the noticed vector x linearly so that we acquire a new vector which is white-colored, i.e. its elements are uncorrelated and their differences equivalent unity [1] [7]. In other terms, the covariance matrix of $\tilde{x}$ is similar to the identity matrix:

$$E\{\tilde{x}\tilde{x}^T\} = I \qquad (7)$$

One well-known means for whitening is to use the eigen-value decomposition (EVD) of the covariance matrix $E\{\mathbf{xx}^T\} = \mathbf{EDE}^T$, where $\mathbf{E}$ is the orthogonal matrix of eigenvectors of $E\{\mathbf{xx}^T\}$ and $\mathbf{D}$ is the diagonal matrix of its eigen values, $\mathbf{D}$= diag ($d1$... dn).

IV. FASTICA ALGORITHM

Aapo Hyvarinen has introduced a family of algorithms, which are grouped under the name of "fixed-point algorithms". Members of this family are used primarily by the algorithmic approach and on the other by the contrast function, distinguished. The key to all variants is independent components found by maximizing the negentropy of each mixture. Fixed FastICA algorithm is used for the recovery of higher statistics independent sources [1] [8].

Adaptive algorithms based on stochastic gradient descent may be problematic when used in an environment where there is no need adaptation. Such is the case in practical matters, in many cases. The long of encountering, and in fact depends primarily on the choice of the order of learning. As a remedy to this problem is to make use of the repetition of the algorithm [2]. In the algorithm for the fixed point, namely, the FastICA, and then makes use of the kurtosis. The algorithm FastICA uses a simple system, highly efficient iteration of the output end of the country to find a specific function of the biased vector [1] [2] [8] [13].

There are two main algorithmic approaches in Fixed Point algorithm. The symmetric approach uses a modified update rule for the simultaneous separation of all independent components, while the focus of deflation updated columns individually; find the independent components one after another.

FastICA ICS can be recognized individually (deflation approach), or both (symmetric approach) [8].

The basic form of the FastICA algorithm is as follows. Choose an initial weight vector w.

$$\mathrm{w}^+ = E\{\mathrm{x}g(\mathrm{w}^T\mathrm{x})\} - E\{g'(\mathrm{w}^T\mathrm{x})\}\mathrm{w} \quad (8)$$

$$\mathrm{w} = \mathrm{w}^+/\|\mathrm{w}^+\| \quad (9)$$

First note that the maxima of the approximation of the negentropy of $\mathbf{w}^T\mathbf{x}$ are obtained at certain optima of $E\{G(\mathbf{w}^T\mathbf{x})\}$. According to the Kuhn-Tucker conditions, the optima of $E\{G(\mathbf{w}^T\mathbf{x})\}$ under the constraint $E\{(\mathbf{w}^T\mathbf{x})^2\} = \|\mathbf{w}\|^2 = 1$ are obtained at points where [1] [8]:

$$E\{xg(w^T x)\} - \pi\beta = 0 \quad (10)$$

FastICA uses following non-linear parameters to apply.

$$g(y) = \begin{cases} y^3 \\ \tanh(y) \end{cases} \quad (11)$$

The freedom of choice is, except that the algorithms smoothly with tanh nonlinearity of separation cannot over-Gaussian signals. Otherwise it will be dedicated to another, namely the cubic nonlinearity, however, is a more stable platform for linearity tanh [1].

If algorithm has three mixtures and it have to separate three voice signals from it then within a second it gives the separated voice signals which sounds like original.

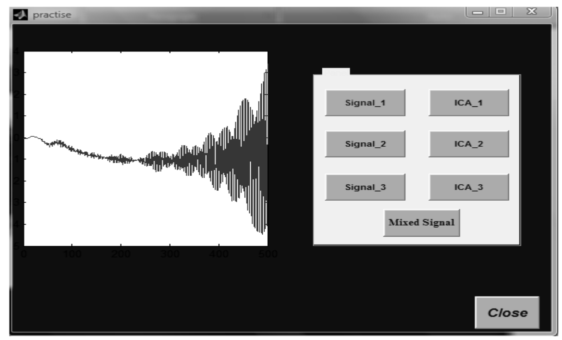


Fig.3 Separated_ _Signal

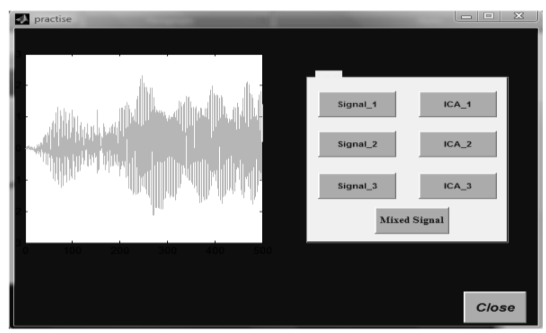


Fig.4 Separated_ _Signal

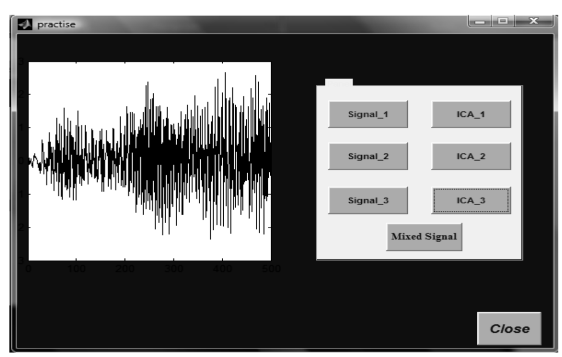
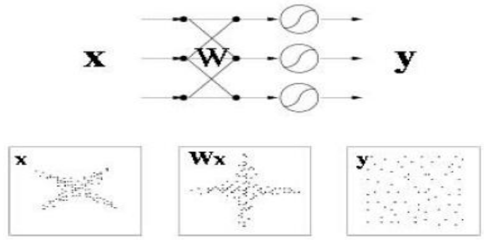


Fig.5 Separated_ _Signal

The above results are the three separated voice signals which are similar to the original voice signals.

V. INFOMAX ALGORITHM

In infomax algorithm we maximize entropy and use high Kurtosis for separating the signals from there mixtures. Starting with maximizing entropy it gives independent signals after nonlinear transformation, as shown below[14]



Where X is the mixture signal and when it is operated with unmixing matrix it gives y which is our independent signal. Entropy of X is estimated as[15]

$$\mathrm{H(X)} = -\frac{1}{N}\sum_{t=1}^{N} \ln(\mathrm{px})X^{t} \qquad (12)$$

Kurtosis is the name of name given to the fourth-order cumulant of a random variable, It is actually measure of nongaussaniaty[16]. The kurtosis of y is defined as

$$\mathrm{Kurt(y)=E\{y^4\}-3(E\{y^2\})^2} \qquad (13)$$

As the number of mixture signals increases, the probability of recovering the independent and nongaussian signals decreases.

By implementing these equations in matlab we can separate our independent and nongaussian signals. The two audio signals, gong and splat which are available in Matlab, are loaded then we mix them and try to recover the original signal from these mixtures. Order of recovering original signal doesn't matter because algorithm is blind to original signals. As the numbers of iterations are increased we get more accurate results but processing time also increases. The simulation results are shown below

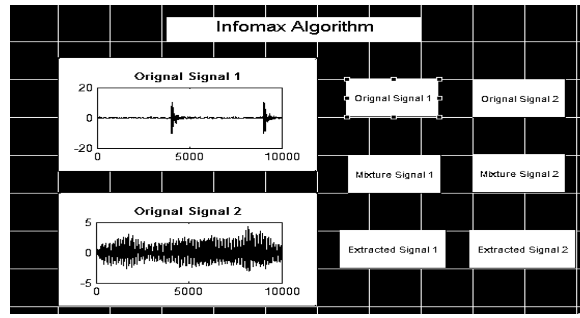


Fig.6 Original_ _Signal

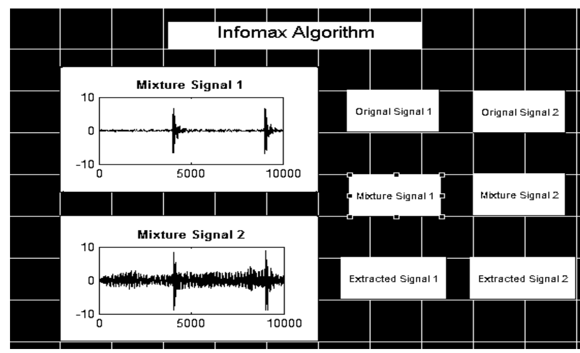


Fig.7 Mixture_ _Signal

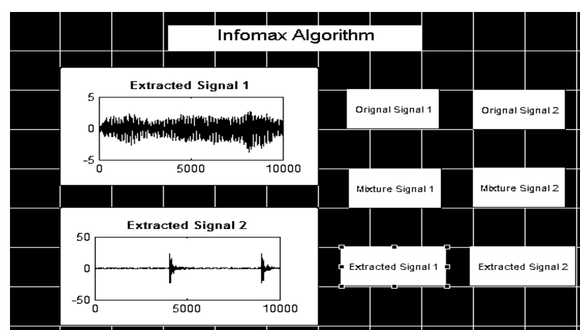


Fig.8 Extracted_ _Signal

Same number of mixture signals (shown in fig.7) are taken as the voice signals to be separated. The result shows that extracted voice signals (shown in fig.8) are similar to that of original voice signals which are shown in fig.6.

VI. Conclusion

This paper discussed two algorithms that both of these algorithms have advantages of their own in terms of speed and accuracy. InfoMax algorithm take more time but it gives more accurate results in comparison to Fast ICA but Fast ICA becomes more attention taking when we talk about speed because it take less time to give results than InfoMax. So we can use these algorithms for separating voice signals according to our requirements.

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