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INDEPENDENT COMPONENT ANALYSIS BASED ON BLIND SOURCE SEPARATION BY USING MARKOVIAN AND INVERTIBLE FILTER MODEL

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ABSTRACT

In this process blind sources are analyzed independently and the independent component analysis separates the underlying sources from the given mixture. Before to this process many more methods are used for blind sources they have non-Gaussian and sample dependences, this method can exploit both properties jointly. This proposed system uses mutual information rate that is used to analysis and derivation of algorithms. In this process, two types of source models are used for entropy rate estimation they are Markovian and another one is invertible filter model that gives the general independent component analysis (ICA). Under the Markovian source model, the entropy rate equals the difference between two joint entropies. Under the invertible filter source model, the source is generated by an invertible filter that is driven independently and identically distributed random process, the entropy rate of the source equals the entropy of the driving process under some constraints. The proposed Fast ICA algorithm is presented for Entropy estimation by using MATLAB2009 Software.

Keywords: independent component analysis (ICA), blind source separation (BSS), markovian model, invertible filter model, entropy estimation, mutual information rate.

INTRODUCTION

Blind source separation [11] is a well researched area. One key advantage of ICA is that the microphone location and speaker locations do not need to be known in advance. Consequently the restriction on sensor placement is less critical as compare to the beam forming techniques.ICA is a well-known method of finding latent structure from data. ICA is a statistical process that expresses a set of multi dimensional observations as a combination of unknown latent variables. These latent variables are called sources or independent components and they are assumed to be statistically independent of each other. ICA has been one of the most attractive solutions for the BSS problem because it yields a useful decomposition with two simple ambiguities, scaling and permutation ambiguity.

Blind source separation

Blind techniques such as blind source separation [6] have become popular in the signal processing and machine learning community. One of the central tools for this problem is ICA. This technique, a set of original source signals are retrieved from mixtures based on the assumption of their mutual statistical independence. Blind source separation is also known as Blind signal separation, is a problem to separate independent sources given in a mixed signal where the mixing process is unknown. To extract each source from the mixed signals specified technique are used. Even if the mixing process is unknown, it can separate the sources if they are independent to each other.

Independent Component Analysis

The data model for independent component analysis [11] is estimated by formulating an objective function and then minimizing or maximizing it. Such a function is often called cost function or objective function. The optimization of the contrast function enables the estimation of the independent components. The ICA method [10] combines the choice of an objective function and an optimization algorithm. The statistical properties like consistency, asymptotic variance, and robustness of the ICA technique depend on the choice of the objective function and the algorithmic properties like convergence speed, memory requirements, and numerical stability depend on the optimization algorithm. The contrast function in some way or other is a measure of independence. In this section different measures of independence is discussed which is frequently used as contrast functions for ICA. The independent component analysis algorithm allows two source signals to be separated from two mixed signals using statistical principles of sample dependence and non gaussianity.

That the ICA separation of mixed signals gives very good results are based on two assumptions and three effects of mixing source signals. Two assumptions:

- The source signals are independent of each other.
- The values in each source signal have non-gaussian distributions.

Three effects of mixing source signals:

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- Independence: As per assumption 1, the source

- signals are independent; however, their signal mixtures are not. This is because the signal mixtures share the same source signals.
- *Normality*: The distribution of a sum of independent random variables tends towards a gaussian distribution. Loosely speaking, a sum of two independent random variables usually has a distribution that is closer to gaussian than any of the two original variables. Consider the value of each signal as the random variable.
- *Complexity*: The temporal complexity of any signal mixture is greater than that of its simplest constituent source signal.

Those principles contribute to the basic establishment of ICA. To extract signals from a set of mixtures are independent like sources signals, or have non-gaussian histograms like source signals, or have low complexity like source signals.

EXISTING SYSTEM

ICA can estimate a de-mixing matrix and separate signals under the assumption of statistical independence among the source signals. Most of the ICA algorithms [4] exploit one of the following two properties: non-Gaussianity (higher-order statistics) or sample dependency. There are numerous applications where not only one set of observations but multiple data sets, which have some dependence among them, need to be jointly analyzed. The Markovian assumption helped to improve separation performance by taking into account the temporal autocorrelation of the sources. Nevertheless, this method suffers from a high computational cost, which is due to a cumbersome nonparametric estimation of the score functions and to slow convergence of the gradient algorithm used for solving the estimating equations.

Maximum likelihood algorithm

Maximum-likelihood estimation [14], [15] is a method of estimating the parameters of a statistical model. These process is to presents a new maximum likelihood method for blindly separating linear instantaneous source mixtures, where sources are assumed to be mutually independent, Markovian and possibly non stationary. The proposed approach extends previous works, by using two approaches based on blocking and kernel smoothing, respectively. In Maximum Likelihood (ML) BSS approach, sources were modeled as q-th order stationary Markovian process. The Markovian assumption helped to improve separation performance by taking into account the temporal autocorrelation of the sources. Nevertheless, this method suffers from a high computational cost, which is due to a cumbersome nonparametric estimation of the score functions and to slow convergence of the gradient algorithm used for solving the estimating equations. Moreover, it is based on the source stationarity assumption, which is obviously unrealistic for most real signals. Starting from this idea, In this letter an ML Markovian method, where to exploit possible source non stationarity by adapting two approaches based on blocking and kernel smoothing. This method can take into account higher-order non-stationarities, contrary to most classical non stationary BSS algorithms.

Joint approximate diagonalization of Eigen matrices (JADE)

Approximate joint diagonalization of a set of matrices is an essential tool in many blind source separation (BSS) algorithms. The measure of the attained diagonalization of the set is the weighted least-squares (WLS) criterion. The most well-known algorithms are restricted to finding an orthogonal diagonalized matrix, relying on a whitening phase for the non orthogonal terms. Often, such an approach implies unbalanced weighting, that will result in degraded performance. This paper, an iterative alternating-directions algorithm is proposed for minimizing the [3] WLS criterion with respect to a general diagonalizing matrix. The standard application of JADE requires a pre-whitening phase, followed by orthogonal joint diagonalization of the transformed matrices using an extended Jacobi Algorithm.

PROPOSED SYSTEM

The proposed system, for the estimation of entropy rate is the most difficult process and main problem since it requires the joint distribution of the whole process commonly. To solve this problem two different source models for entropy rate estimation are used for that effective models to process entropy rate. The two models are one Markovian source model and another one is invertible filter source model [1], [7]. The Markovian source model is fully deter-mined by the joint distribution; an algorithm using a multivariate generalized Gaussian distribution (MGGD) as the source prior. The entropy rate minimization via multi-variate generalized Gaussian distribution (ERM-MG) is used. The invertible filter source model is fully determined by the filter and the probability density function (PDF) of the innovation. These two algorithms entropy rate minimization via AR driven by GGD process (ERM-ARG) and entropy rate bound minimization via AR source (ERBM -AR), respectively. To introduce the entropy rate bound minimization (ERBM), [5] which was called full BSS (FBSS). By comparing three algorithms that assume invertible filter source model, we discuss how the performance of ICA methods is affected by modeling, and show the gain in performance obtained by using a flexible model. Results are observed by listening to the output voice signals through headphone. The resultant voice signals are very clear.

Modules descriptions

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1. Multiple Audio Inputs
2. Mixing Audio Sources
3. ICA analysis
4. Markovian Model
5. Entropy Rate Estimation

Multiple audio inputs

Audio is sound within the acoustic range available to humans. An audio frequency (AF) is an electrical alternating current within the 20 to 20,000 hertz (cycles per second) range that can be used to produce acoustic sound to humans. In computers, audio is the sound system that can be added to a computer. Audio card contains a special built-in processor and memory for processing audio files and sending them to speakers in the computer. An audio file in which captured sound that can be played back. Sound is a naturally analog signal that are converted to digital signals by the audio card, using a microchip generally called an analog-to-digital converter (ADC).Some sound is played, the digital signals are sent to the speakers where they are converted back to analog signals that generate variety of sound. Audio files are usually compressed for storage or faster transmission. The files are in Wave file format is assumed. In order to receive sound in real-time for a multimedia effect, listening to music, or to take part in an audio or video conference, sound must be processed as streaming sound. Multiple audio inputs is nothing but take one or more audio inputs is known as multiple audio inputs.

Mixing audio sources

In sound recording, audio mixing or mix down is the process by which multiple recorded sounds are combined into one or more channels, for 2-channel stereo. In mixing process, the source signals level, frequency content, dynamics, and panoramic position are manipulated and effects such as reverb may be added. In order to produce a mix that is more appealing to listeners. Audio mixing is done in studios for the purpose of creating an album or single. The mixing stage often follows a multi track recording. This process is carried out by a mixing engineer, sometimes it is used by the musical producer, or even the artist, who mixes the recorded material. After mixing, a mastering they prepares the final product for reproduction on a CD, for radio.

ICA analysis

Independent component analysis is a computational method for separating a multi variate signal into additive sub components. These underlying latent variables are called sources or independent components and they are assumed to be statistically independent of each other. The ICA model is

$$X = AS$$

Where A *is* unknown mixing matrix. Consider *x* and *S* as random, where the matrix *X* has observations *x* as its columns and similarly the matrix *S* has latent variable vectors *s* as its columns. The mixing matrix *A* is constant for all observations. If both the original sources *S* and the way the sources were mixed are all unknown, and only mixed signals or mixtures *X* can be measured and observed, then the estimation of *A* and *S* is known as blind source separation (BSS) problem.

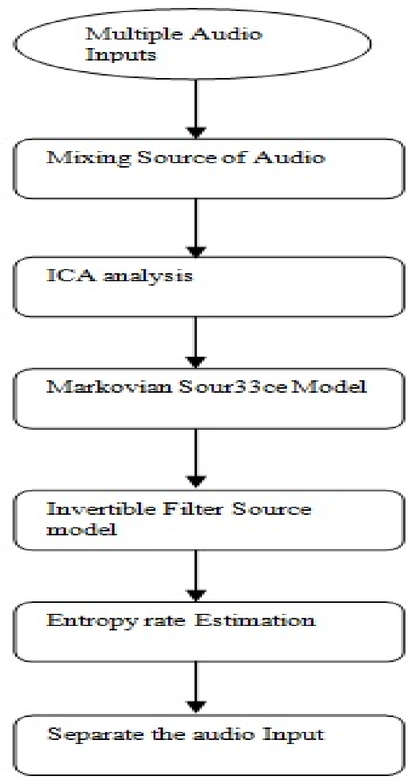

Figure-1. Architectural design.

Fast ICA algorithm

The Fast ICA or fixed-point algorithm is one of the most successful algorithms for linear independent component analysis in terms of accuracy and computational complexity. The algorithm is based on a fixed-point iteration scheme maximizing non-Gaussianity as a measure of statistical independence. When Fast ICA is used with symmetric de-correlation, it is essentially equivalent to a Newton method for maximum likelihood estimation. There are two varieties of the Fast ICA algorithm: the deflation, or one-unit algorithm, and the symmetric algorithm.

Whitened signal

The whitened signal model is a noise whitening module works similarly to automatic filter that can enhances low level spectral components and attenuates the high level. Another source model assumes that signal is generated by an invertible filter driven by an i.i.d. process. The whitening filter can be non causal, and the filter order. The filter coefficients for each whitening filter can be

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different, but the filter orders are assumed to be the same for simplicity. To scale the whitening filter such that the input and output will have equal entropy, which means the entropy rate of equals the entropy. By assuming the signal is generated by an invertible filter, we can derive the cost function, update rule, and the CRLB.

Markovian model

An algorithm using a multivariate generalized Gaussian distribution as the source prior.

Entropy rate minimization: Multivariate generalized Gaussian distribution model (ERM-MG)

The general form for Markovian source separation, To derive an algorithm based on markovian source model. The MGGD provides a flexible tool for data modeling and simulation. Hence, to derive the score function and update rule.

Invertible filter model

The Invertible Filter Model [1] is fully determined by the filter and probability density function of the innovation.

Entropy rate minimization: Auto Regressive Generalized Gaussian Distribution source model (ERM-ARG)

An effective model for the invertible filter model to follow an AR model driven by GGD innovation process. Source separation can be achieved using entropy rate minimization via auto regression driven by generalized Gaussian process (ERM-ARG) [1], and the algorithm approaches the Cramer-Rao lower bound (CRLB) effectively when the sources follow the model. Another effective Markovian source model is AR model driven by a GGD innovation process. For this model, to derive the cost function, update rule, and CRLB.

Entropy Rate Minimization: Auto Regressive model (ERM-AR)

The algorithm with parameter models can attain optimum performance in ML sense when the source distribution matches the model exactly.AR is the flexible model.

Entropy Rate Bound Minimization (ERBM)

In addition to using a flexible model on the density of the driving process ERBM [5] is desirable to have a flexible model on the whitening filter. It also provide desirable performance for the variety of source since it uses a flexible model for both the filter and PDF of the driving process.

Entropy estimation

Entropy is the quantitative measure of disorder in the system [4]. The entropy rate of data source means the average number of bits per symbol needed to encode it.

SIMULATION AND EXPERIMENTAL RESULT

The voice signal has been plotted for our visual reference. The below subplot show the orginal voice signal of input voice 1 and input voice 2. And also the histogram plot of the original voice also shown in this Figure-2.

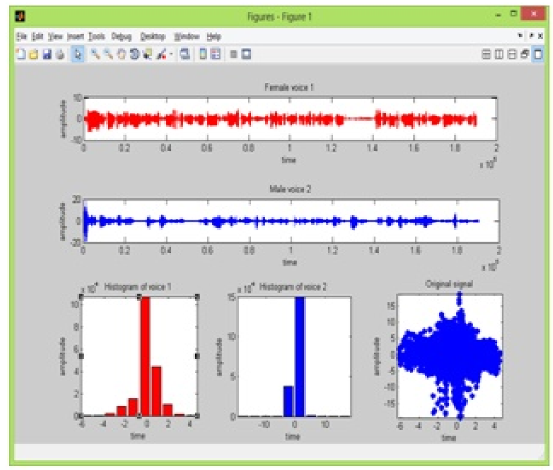

Figure-2. Plotting of two voice signal.

The further process of this method is mixing the unique voice data inputs. That will be shown in the below Figure-3.The mixing process is done by two way that also shown in the subplot.

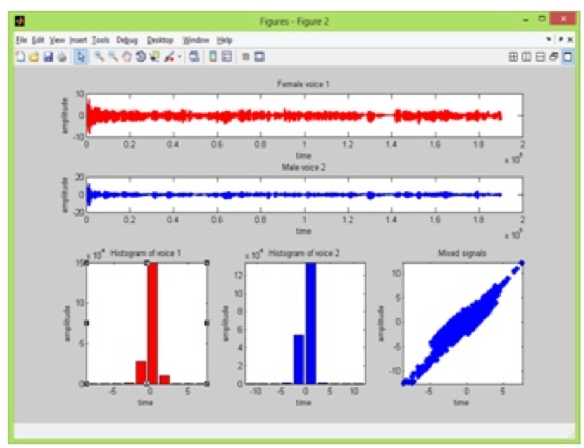

Figure-3. Mixing of voice sources.

The whitened signal model is nothing but noise whitening module works similarly to the automatic filter that enhances low level spectral components and attenuates high level ones. Additionally, de-emphasis is applied after whitening(high frequencies are attenuated), so that spectrum of processed signal is similar to the spectrum of speech signal(which has low energy in high frequency range). Whitening and de-emphasis enhance the quality o the speech signal. This module is especially useful if constant " whistiling" is present in the recording.

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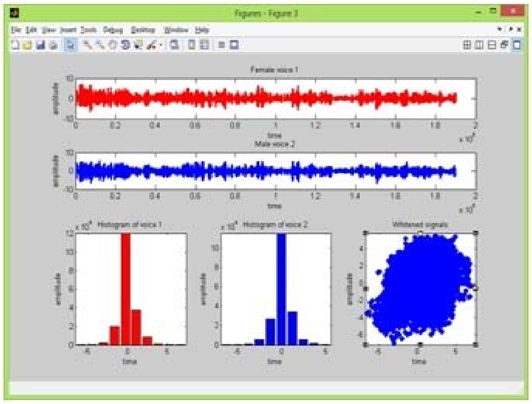

Figure-4. Whitened signals.

This subplot shows the separation of audio input 1 and audio input 2.

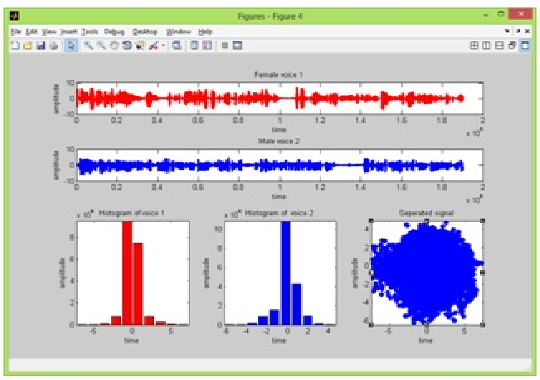

Figure-5. Separation of the audio.

The invertible filter model for blind source separation that shown in the Figure 6. that process fully based on scramble.It interfere with the sound so that the message can only be understood by someone with special equipment.

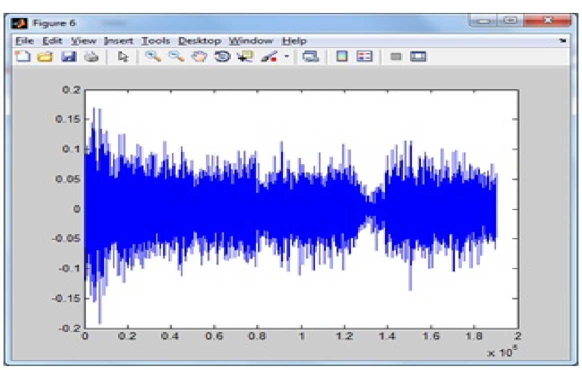

Figure-6 Invertible filter model

These routines scramble an audio file by moving around short, overlapping windows within a local window. They can be used to create new versions of existing recordings that preserve the spectral content over longer time scales, but remove structure at shorter timescales is shown in Figure-7.

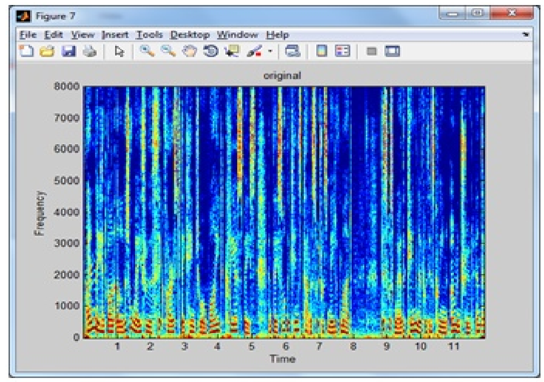

Figure-7. Time-domain scrambling.

The algorithm is closely related to the maximum likelihood approach based on entropy rate minimization but uses a simpler contrast function that can be accurately and efficiently estimated using nearest-neighbor distances. The advantages of the new algorithm are highlighted using simulations and real electroencephalographic data.

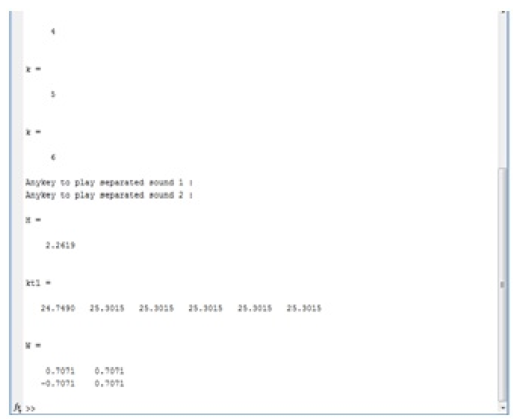

Figure-8. Entropy estimation.

Table-1. The parameters used in ouput for calculation

K	Fast ICA calculation for voice signal.
W	Whitened signal calculation.
H	Entropy Estimation.

CONCLUSIONS

To exploit both non-Gaussianity and sample dependency diversities, the mutual information rate are proposed as the cost function and to discuss two types of approaches, based on whether the source is Markovian or generated by an invertible filter, to estimate the entropy rate and present the general update rule, and performance

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analysis for each source model assumption. Four algorithms are introduced. ERM-MG is based on the Markovian source assumption, and ERM-ARG, ERBM-AR, and ERBM are based on the invertible filter assumption. To compare the performances of these algorithms using simulated data, and demonstrate the effectiveness on real world data. Thus the entropy of the voice signal is minimized by considering the mutual information rate.

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