PERFORMANCE ANALYSIS OF SUB AND SUPER-GAUSSIAN BLIND AUDIO SOURCE **SEPARATION**

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Abstract - The audio source separation in blind mixing environment plays a key role in various application such as humanoids, human machine interaction etc . In this work various quality measure have been discussed and a separation quality evaluation method BSS_Eval has been demonstrated. This work also includes separation quality analysis of blind mixture in sub-Gaussian and super-Gaussian mixing scenario. Experimental result reflects that all separated signals having positive kurtosis, which ensures super-Gaussian nature of separated components and SIR value of separated independent components is 19.64% higher for super-Gaussian mixing in comparison of sub-Gaussian mixing.

Kewyords- Blind source separation, Independent Component Analysis, Kurtosis, Gaussian.

INTRODUCTION L

Separation of Audio source from the mixture of audio signals using a set of Algorithms is referred to as Blind Audio Source Separation. The "cocktail party problem", where a lot of people are talking simultaneously can be described as the need why we need to separate the source signal from the received mixed audio signal [1]. To understand the voice of a particular person the desired voice needs to be separated from the other unwanted voices.

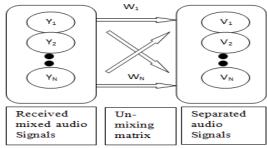


Figure 1 Separation Mechanism

In Figure 1, the source separation mechanism is explained where a set of mixed audio signals Y= $[Y_1, Y_2, \dots, Y_N]$ are separated using a weighted matrix $W = [W_1, W_2, \dots, W_N]$ and the separated audio signals $V = [V_1, V_2, \dots, V_N]$ are collected at the output.

BASS using Independent Component Analysis (ICA) has a great potential nowadays in fields like Telecommunications, Acoustics, medical and Image Signal Processing [2,3]. This algorithm separates source signals from the mixed audio signals. The assumptions followed for the technique are that at a given instant the value of the source is a random variable and each source is statistically independent. The ICA works when number of sensors is equal to number of input signals. From the figure it is explanatory that if a mixing matrix A of size N X N is being used for the mixing process and Matrix W being used for the un-mixing process then the source signal can be derived back by the equation: (1)

V(t)=W.Y(t)=W.A.X(t)

where X(t) is the input signal.

The Central Limit Theorem states that the tendency of a sum of independent signals, under specific conditions rises towards being Gaussian distribution [4]. These linearly combined signals can be separated by transforming them to be Non Gaussian. Non Gaussianity of a signal can be measured using various measuring tools. The most prominent tool used is the Kurtosis value. Based on this value the Gaussianity of the signal can be defined. Kurtosis value is zero, negative and positive for Gaussian, Sub-Gaussian and Super Gaussian respectively. ICA estimation utilizes the principle of Non Gaussianity.

This work describes certain quality measures of separated audio signals from an audio mixture comprising of Sub-Gaussian and Super-Gaussian signals. The work also compares the impact of BASS using various algorithms with the ICA algorithm. The concept of Non-Gaussianity and Negentropy is first described in Section II. In Section III, the background of Blind Separation and Independent Component Analysis is described along with the quality measures of source separation. In Section IV, the result analysis of the separation is discussed. Finally in section V we discuss the conclusion of the experiments held with ICA separation technique.

II. CONCEPT OF NON-GAUSSIANITY AND NEGENTROPY

The Probability Distribution Function of mixed signals is Gaussian in nature while source signals are Non Gaussian in nature. A linear combination of number of independent signals is called a Gaussian signal. Separating the independent sources from a Gaussian signal is carried by transforming the signal into non-Gaussian signal.

A. SUPER AND SUB GAUSSIAN SIGNALS:

Non Gaussian signals are The Probability Distribution Functions of super and sub-Gaussian signals are shown in the figure 2 and figure 3 respectively.

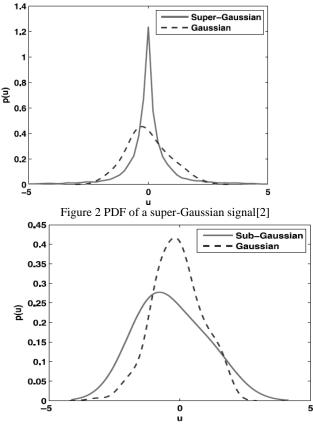


Figure 3 PDF of a sub-Gaussian Signal [2]

The dotted lines in the Figure 2 and Figure 3 plot the distribution of Gaussian signals. From the Figure 2 it is clear that the peak of the distribution of a super-Gaussian signal is higher than that of a Gaussian signal. While in Figure 3 it is evident that the sub-Gaussian signals have a wide distribution.

B. KURTOSIS

Kurtosis is referred to as the fourth order moment about the mean. For a signal z the Kurtosis value is calculated from the equation: $Kurt(z) = E[z^4] - 3(E[z^2])$ (2)

where E is the expectation operator. For a normalized variable the variance is equal to 1. If z is a normalized then the variance will be equal to 1 or it can be said that $E[z^2]=1$. Equation 2 can now be simplified to:

$$Lurt(z) = E[z^4]-3$$
 (3)

If z variable is having a positive kurtosis then the variable tends to have a super-Gaussian distribution and if having a negative kurtosis the variable tends to have a sub-Gaussian distribution. For a Gaussian signal the kurtosis value is zero. Super-Gaussian signals are also called the Platy Kurtotic signals while the Sub-Gaussian signals are called Lepto Kurtotic signals.

C. NEGENTROPY

Negentropy is another well known method to measure Non-Gaussianity. The concept of Negentropy is based on the Information Theory. The maximum the entropy of the signal, the more uniform the signal will be [4]. For a discrete random variable C the entropy H is defined as:

$$H(C) = -\sum_{i} P(C = c_i) ln \ P(C = c_i)$$
(4)

where c_i is the value of random variable. After the generalisation of the Equation 4 we reach the entropy for continuous random variable.

$$H(C) = -\int P_C(c)lnP(c)dc$$
(5)

The Negentropy of varaiable C would be:

$$J(C) = H(C_g) - H(C) \tag{6}$$

 C_g is the Gaussian random variable with the same covariance as C. For calculating the Negentropy one must calculate the Probability distribution function of the variable first.

III BASS AND INDEPENDENT COMPONENT ANALYSIS

BASS using ICA is a statistical technique that linear combinations statistically represents of independent component variables from the mixed multidimensional random variables [5]. ICA is being used in many applications such as image processing which is an important task for video surveillance, traffic management and medical imaging [6,7]. The principle behind ICA is independence and non-Gaussianity. By independence it means that two sources at a given instant cannot have a value that is related to each other and these values are a random variable. The number of sensors will be equal to the number of sources [8]. Suppose a hall having N audio sources and N audio recorders at separated locations. Each audio recorder receives a mixture of audio signals, mixing matrix being A of size N X N.

After going through the mixing process the received signal Y is given by:

These received mixed audio signals are now separated using the weighted matrix W of size N X N.

After going through the separating process the separated signal V is given by:

$$Y = \begin{cases} W_{11}.A_{11}.X_{11} & W_{12}.A_{12}.X_{12}..W_{1N}.A_{1N}.X_{1N} \\ W_{21}.A_{21}.X_{21} & W_{22}.A_{22}.X_{22}..W_{2N}.A_{2N}.X_{2N} \\ \dots & \dots & \dots \\ W_{N1}.A_{N1}.X_{N1} & W_{N2}.A_{N2}.X_{N2}..W_{NN}.A_{NN}.X_{NN} \end{cases}$$
(10)

Preprocessing methods are used to speed up the separation process. The statistical tool is used to remove the second order correlation by pre-whitening the observation vector Y. The weight matrix comprises of two matrices, the second order pre-whitening matrix W_{pw} and W_i matrix, the un-mixing matrix found by various inverse techniques. The complete W matrix is then represented as:

$$W = W_{pw}.W_i$$
(11)

ICA techniques are being used in many applications nowadays, the image processing and compressing being the prominent one [9]. There are various ICA techniques used for audio separation. The FastICA techniques employ Symmetric and Deflationary arithmetic approaches for ICA implementations. The statistics employed for this fixed point ICA are of higher order[2]. The negentropy estimates are used to extract the independent components. Sources having non-Gaussian distributions follow the JADE algorithm. The algorithm works on the JADE principle of diagonalization of cumulated matrices. After the preprocessing and further reduction the cumulated matrix is diagonalized with an orthogonal transformation [10].

Performing the BASS and ICA both, the SONS algorithm is based on the time delays, the number of time windows and the size of each window [11].

The quality of Source separation is evaluated by different quality measures; Signal to interference ration (SIR), Signal to distortion Ratio (SDR), Signal to Artefacts ratio (SAR) and Signal to Noise ratio (SNR). Number of learning epochs for convergence of algorithm can also be considered as a quality measure.

SIR is a very essential parameter for the measurement of quality of separation is blind scenario. The mathematical definition of SIR is as follows;

SIR is the measure of Source to Interference ratio. As the name suggests it checks the quality of the separation based upon the interferences the source suffers while mixing and other activities. The equation of the SIR is defined as:

$$SIR = 10\log_{10} \frac{\left\|s_{signal}\right\|^2}{\left\|e_{interf}\right\|^2}$$
(11)

 S_{signal} is the separated signal.

e_{interf} is the error term due to interference.

Some times in blind audio source separation signal to interference ratio is also recommended.SDR is the measure of Source to Distortion ratio. Like SIR, SDR also measures the quality of the separated source signal. The error terms induced due to interference(e_{interf}), noise(e_{noise}) and artifacts(e_{artif}) are also taken into consideration while calculating SDR. The value of SDR is calculated as:

$$SDR = 10\log_{10} \frac{\left\|s_{signal}\right\|^2}{\left\|e_{interf} + e_{noise} + e_{artif}\right\|^2}$$
(12)

In MATLAB the quality of source separation in case of blind mixture can be evaluated by BSS EVAL. BSS_EVAL is a performance measurement toolbox developed specially for the Blind Source Separation [12]. This toolbox works in a framework where the source signals alongwith the interferences and noises are available for comparison. The toolbox is downloadable http://www.irisa.fr/metiss/bss eval/ from and is distributed under the GNU General Public License for MATLAB[®]. This toolbox follows a set of instructions for attaining a certain result. Functions like bss_crit and bss decomp gain are available quality for measurements.

IV RESULT ANALYSIS

To evaluate the quality of separation in case of sub-Gaussian and super-Gaussian mixture, Four signal's were taken and mixed by a random sub and super-Gaussian mixing environment and signals were separated by sub-Gaussian and super-Gaussian ICA approaches and resultant sub and super-Gaussian probability distribution function of separated signal are shown is Figure 4 and 5 respectively.

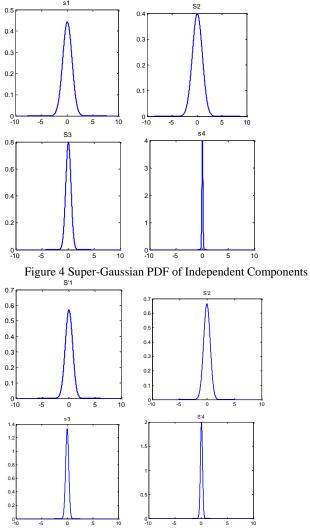


Figure 5 Sub-Gaussian PDF of Independent Components

Figure 4 and 5 shows the PDF of the separated signals in sub-Gaussian and super-Gaussian mixing environment. Figure represents that kurtosis value can't be negative in any case, hence after separation all separated source depicts super-Gaussian nature.

Table 1. consist of quality parameters (SIR value) of separated signals in both mixing environment by three different ICA algorithms Fast-ICA, JADE and SONS.

| Super-Gaussian | | | | Sub Gaussian | | |
|----------------|---------|-------|-------|--------------|-------|-------|
| | FastICA | JADE | SONS | FastICA | JADE | SONS |
| SIR(S'1) | 25.62 | 20.42 | 18.41 | 21.3 | 16.24 | 13.36 |
| SIR(S'2) | 23.28 | 19.92 | 19.33 | 20.24 | 15.38 | 11.89 |
| SIR(S'3) | 24.38 | 19.21 | 19.84 | 19.84 | 15.44 | 12.23 |
| SIR(S'4) | 23.22 | 20.01 | 20.23 | 19.26 | 14.8 | 11.67 |
| SIR(AV) | 24.12 | 19.89 | 19.45 | 20.16 | 15.46 | 12.28 |

Table 1 SIR values of separated signals in sub and super Gaussian mixing environment.

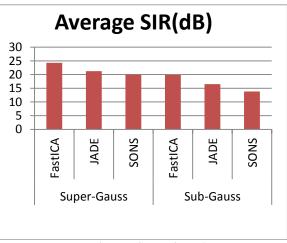


Figure 6 Comparison chart

Comparison chart depicts that SIR value increases sub-Gaussian mixing environment to super-Gaussian mixing environment by 4 to 5 dB.

V CONCLUSION

Quality measurement for various mixing environment is very essential for evaluation of any blind source separation. In this works sub-Gaussian and super-Gaussian mixing models has been discussed alongwith various quality measurement parameters as; SIR, SNR, SDR and SAR. Experiment has been performed for source separation from mixed signals in sub and superGaussian mixing environment. Some important findings are that the separated signal is always super-Gaussian and SIR value increases from 20.16 dB to 24.12 dB from sub-Gaussian to super-Gaussian.

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