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COMPARATIVE ANALYSIS OF TIME DOMAIN AND FREQUENCY DOMAIN BLIND AUDIO SOURCE SEPARATION TECHNIQUES

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ABSTRACT

This paper introduced comparative analysis of blind audio source separation techniques in time domain, frequency domain. In time domain analysis modified convex divergence method and ICA decomposition techniques are considered and in frequency domain Inter-frequency Correlation with Microphone Diversity techniques are considered. To perform this analysis a critically determined system consists of three audio sources and three microphones are considered. Frequency domain analysis can be implemented for over determined mixture also, in that it extracts principle component to form a determined mixture. Simulations are performed on a closed room recording samples and convergence speed and complexity is compared. Result reflects that divergence based ICA overshadows the other competitors in terms of convergence speed and proved as a better audio source separation technique in blind scenario.

I. INTRODUCTION

The objective of Blind Audio Source Separation (BASS) is intended to separate multiple independent audio sources from an ill-informed mixing environment [1]. The general mixing model can be formulated as follows [2];

$$M(t) = A(t) \otimes s(t) + \psi(t) \qquad (1)$$

For the sake of simplicity ideal mixing environment can be considered by ignoring the role of noise components. The model for source separation mathematically formulated as;

$$\hat{S}(t) = W(t) \otimes M(t) \qquad (2)$$

Where:

't is the sample index and mathematical operation is matrix convolution.

Most of the frequency domain blind source separation algorithms uses weight overlap and add method or STFT (short time Fourier transform) method for finding the coefficient of an equivalent filter, so that independent sources can be separated. Frequency domain approach needed long duration of recordings to make conclusion [3]. Frequency domain source separation approaches encounter two major problems; First the frequency domain ICA suffers with permutation ambiguity in order of output. To counter that a wise criteria considered in various algorithms as, if the component of a signal in frequency bin 'p' arrives at the output 'k' , then respective component of same signal in bin'p+1' should also arrive in output 'k'. If this condition proves false, then algorithm needs to apply since beginning and result considered as mixed.

Second problem is, there is no information about magnitude of every frequency bin. If we assume perfect separation and ignore permutation ambiguity issue, the magnitude still needs to be scaled by a constant in each frequency bin. To achieve that an addition filter needs to be applied at output, which further increases the complexicity of frequency domain techniques? Principle of minimal distortion [4] is a typical cure of this problem, which rectifies any probable need of additional filtering at the output of the unmixing ICA algorithms. Frequency domain algorithms also encounters bad bin problem when mixing system is over-determined.

In time-domain techniques the convolution model derived into an instantaneous form by incorporating matrices or data vectors and the convolutive process is simply transformed into a matrix multiplication technique. Matrices are defined from available signal data captured by microphones and treated as observation space. Generally a matrix is defined so that its rows contain the time-lagged copies of signals received from microphones. The objective of time domain ICA decomposition is to find out subspace that corresponds to separated signals [5]. The observation space can be decomposed completely or partially [6]. In complete decomposition the original signals are represented as "n" independent subspaces covering the entire observation space. In partial decomposition signals are considered as one dimensional subspace

In this work a comparative analysis has been performed over three algorithms, on frequency domain algorithm Inter-frequency correlation with microphone diversity (ICMD) [7] and two time domain first one modified convex divergence and second one is time domain subspace decomposition method. Rest of the paper organized as follows; section II consist of two time domain algorithms, section III explains ICMD algorithm, simulation results and comparative analysis is being performed in section IV. Finally, section V consists of final conclusion.

II. TIME DOMAIN ALGORITHMS

NC-ICA is convex divergence based algorithm; it is modified version of existing convex divergence ICA [8]. This algorithm is intended to determine estimate the unmixing weight matrix by introducing divergence based unsupervised learning mechanism for weight updation. For ensuring non-Gaussianity positive kurtosis value fixed as stopping criterion of algorithm. The modified divergence equation is as follows;

$$D_{NC}(x,y,\alpha) = \iint \{\lambda f(p(x,y)) + (1-\lambda) f(p(x)p(y)) - f(\lambda p(x,y) + (1-\lambda)p(x)p(y))\}dxdy$$

$$= \iint \{\frac{\alpha^2}{1-\alpha^4}\left[\frac{1+\alpha}{2} + \frac{1-\alpha}{2} p(x,y) - (p(x,y))^{1-\alpha/2}\right]$$

$$+ (\frac{\alpha^3}{1-\alpha^4})\left[\frac{1+\alpha}{2} + \frac{1-\alpha}{2} p(x)p(y) - (p(x)p(y)^{1-\alpha/2}\right]$$

$$-\frac{\alpha}{1-\alpha^2}\{\left[\frac{1+\alpha}{2} + \frac{1-\alpha}{2}\left(\frac{\alpha}{1+\alpha^2} p(x,y) + \frac{1-\alpha+\alpha^2}{1+\alpha^2} p(x)p(y)\right)\right] - [\frac{\alpha}{1+\alpha^2} p(x,y) + \frac{1-\alpha+\alpha^2}{1+\alpha^2} p(x)p(y)]^{1-\alpha/2}\}\}dxdy$$

(3)

Where;

$$\lambda = \frac{\alpha}{1+\alpha^2}$$

α is convexity parameter

p(x,y) and p(y,x) are joint probability and p(x)

and p(y) are marginal probabilities.

In this algorithm first data needs to pre-processed by centring and whitening, then input data matrix applied into algorithm for weight updation, Scaled natural gradient [9] learning method is adopted

$$W^{(t+1)} = W^{(t)} - \eta \frac{c^{(t)}}{d^{(t)}} \frac{\partial D_{NC}(\chi, W^{(t)}, \alpha)}{\partial W^{(t)}} W^{(t)T} W^{(t)} \tag{4}$$

Once algorithms stops after fulfilling the stopping criteria. Weight needs to normalise and centre removal performed. And obtained estimated weight matrix applied as per equation (2) for estimation of source signals.

Second time domain algorithm is complete ICA decomposition of observation space. In this algorithms first, it is assumed that M samples of simultaneously recorded from array of microphones are yi(n) y2(n). . . .. . ym(n). And a matrix is created by delaying each recorded sample by l. Matrix Y is created

$$Y = \left\{ \begin{array}{ccc} \text{'y1[l].} & \cdots & \text{y1[M]} \\ \text{'y1[l-1]} & \cdots & \text{y1[M-1]} \\ \vdots & & \vdots \\ \text{'y1[1]} & \cdots & \text{y1[M-l+1]} \\ \text{'y2[l]} & \cdots & \text{y2[M]} \\ \vdots & & \vdots \\ \text{'yn[1]} & \cdots & \text{yn[M-l+1]} \end{array} \right\}$$

Figure 1 Decomposition Matrix

The ICA technique for separating audio sources from mixed signal can be classified on the foundation of whether; they are performing complete or partial decomposition of available observation data space.

Apply above mentioned ICA algorithm to determine independent components. After determine the independent clustering technique is applied to evaluate a cluster on the basis of similarity criterion. Once respective cluster is formed reconstruction process is applied to determine independent sources.

III. FREQUENCY DOMAIN APPROACH

In frequency domain source separation technique author used ICMD techniques. In this method assuming the P number of unknown sources, at each frequency only P microphones are fed to ICA algorithm to form output. By this technique, we uses cascaded ICA initialization technique to check output permutation ambiguity.

Similar to all frequency domain algorithms, the input from all recording microphones are first needs to transform from time domain to frequency domain using short time Fourier transform. Assuming that the number of sources P is known and we considered here critically determined system. Mazur and Mertin's α- algorithms

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[10] is "on observation based, the false alignment generally takes position where performance of separation is poor", In result of that, the output at one frequency bin could match with more than one bins output. Hence mapping is not possible.

Let us consider Rxy(n-1, n) as a normalized cross-correlation sample matrix of the amplitudes of unmixing signals in consecutive bins. Let's assume the vector of output signals

$$Xn(t)= [Xn(1,t). . . . . .Xn(P,t)]T \qquad [5]$$

Where, Xn(P,t) is the p^{th} output in the bin 'n' at the sample time 't'. Now the standard deviation of Xn(t) can be estimated over time period 'T'. The normalized signal can be written as;

$$u_n(t) = x_n(t) / \hat{\sigma}x, n(p) \qquad [6]$$

When the resulting output signal in both bins are obtained well separated and the same permutation holds in both the cases , then cross-correlation will diagonally dominant. If there is permutation changes occur at output then process needs to repeat again. All corresponding bins are detected and combine as per microphone diversity and separated sources are obtained.

IV. SIMULATIONS AND RESULT DISCUSSIONS

To evaluate and compare performance of techniques discussed in prior section; three audio sources have been taken, there were one male voice sample, one female voice sample and one recording of musical instrument. For the sake of uniformity 20000 sample are taken of each audio source signal shown in figure 2. Mixing environment is created by matrix convolution of source signals with a randomly generated matrix. Mixed sources are shown in figure. 3

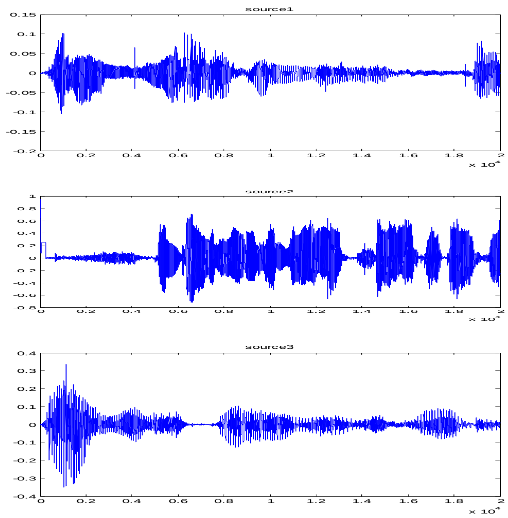

Figure 2 Source Audio Signals

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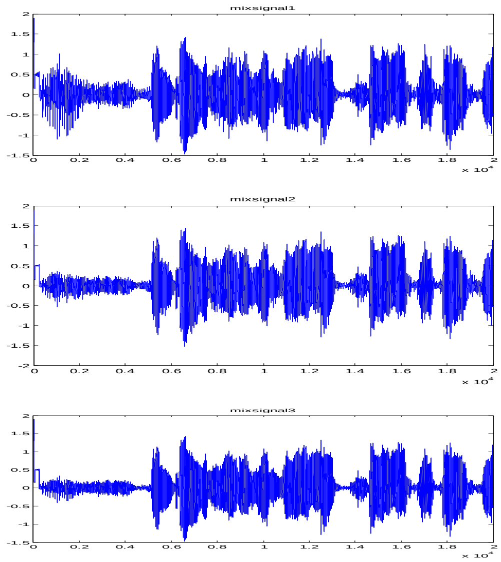

Figure 3 Mixed Signals 1,2,3

First modified convex divergence algorithm is applied where, convexity parameter are assumed as -1, results are shown in figure 4. In this SIR values are 28.3, 31.2 , 33.1 dB respectively and execution time on AMD, 2.4 GHz processor is 12 Seconds.

Second algorithm used is time domain subspace decomposition, in which k-mean clustering is used over mixture of data and cluster results are shown in figure 5. In this techniques SIR values were 26.6, 29.2, 30.2 dB respectively, and it takes execution time 16 second on same processor.

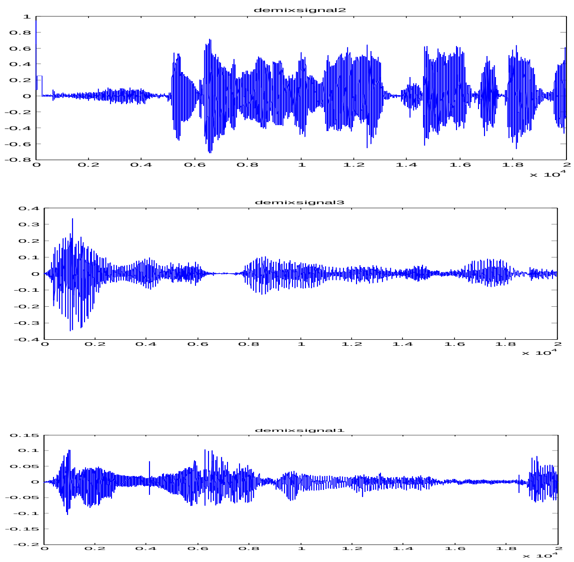

Figure 4 Estimated Signals by NC-ICA De-Mixed Signal 1,2,3

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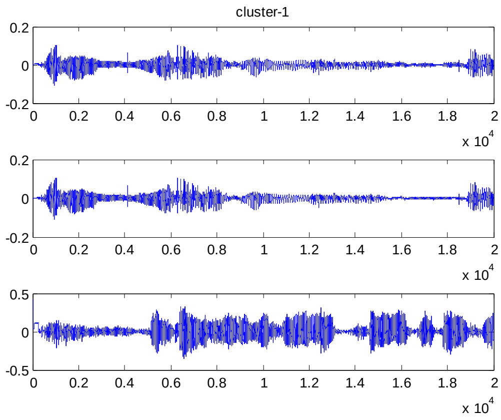
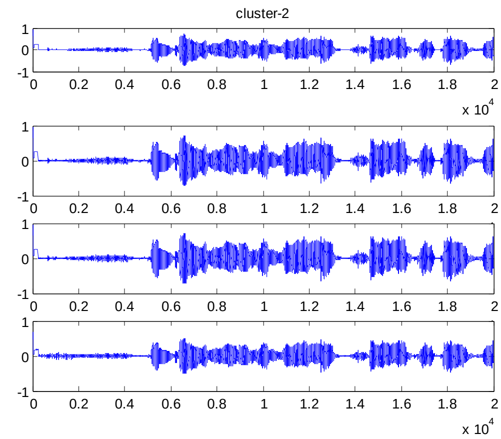
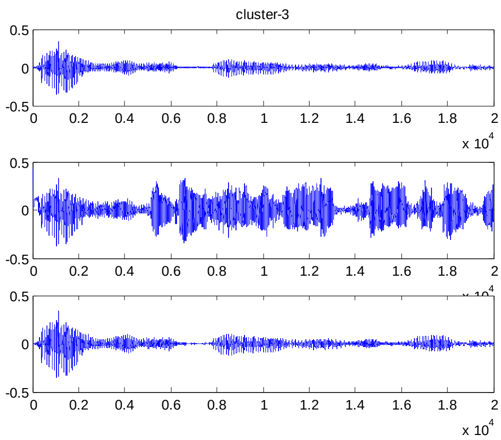


(a) Cluster of Source -1



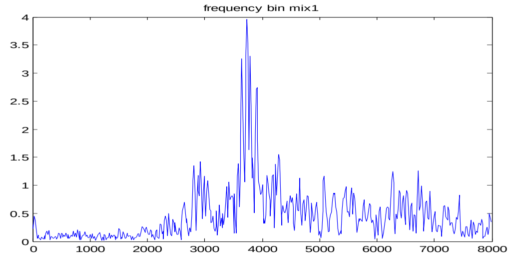
(b) Cluster of Source -2



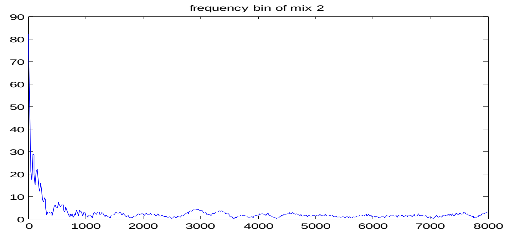
(c) Cluster of Source- 3

Figure 5 Clustering Process

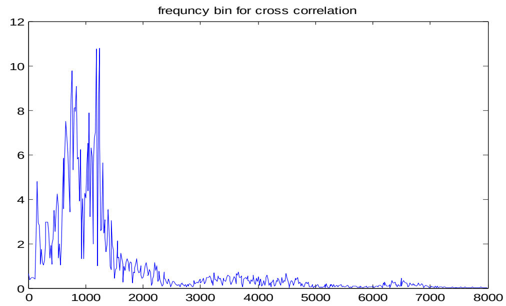
In third approach frequency domain techniques are used where various frequency bins are identified and ICMD technique is applied. Some of the frequency bins are shown in figure 6 . Results reflects that microphone diversity techniques suits well for real mixing environment, in artificial mixing environment performance is inferior in comparison of time domain algorithms . It takes more time for separation, 22 seconds in this experiment on same setup.



(a) Frequency bins of mixture 1



(b) Frequency bin of mixture 2



(C) Frequency bin for Rxy

Figure 6 Frequency bins

Some more results were obtained but due to space limitation key results are shown Results reflects that , the modified convex divergence based algorithm converges faster than other two competitor and also gives good quality of separation. Here any straight comment could not be made on frequency domain algorithms as ICMD is better suited for real experimental arrangements.

V. CONCLUSION

In this paper a comparative analysis being performed over two time domain algorithm and one frequency domain algorithms. Results are evident that various source separation techniques provide better speed and separation quality in case of audio source separation. The modified divergence based algorithms exhibits better performance for specific value of convexity parameter. The clustering and decomposition techniques of observation subspace also offers better performance. In this experiment the performance of frequency domain algorithm was inferior somewhere but its not true always. ICMD could exhibit a quality performance in a real mixing environment. This is a matter of future discussion.

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