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Evaluation of ICA Enhanced with DCT Compressed Mixing of Audio Signals

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Abstract: *In bury Audio environs with distributed microphones, Independent Component Analysis (ICA) can be applied to recuperate signals from an intermixture of signals and noise. This paper presents the evaluation of the performance of ICA enhanced with DCT Compression. Compressive Sensing demonstrates an approach for data acquisition below Nyquist rate ie, a small number of compressive measurements of original signals can be adequate for demand recovery. In fact, here ICA depress the signal mixtures into lower domain, in consequence of that it possess lower computational complexity.*
Keywords - *Audio Signals, Compressive Sensing, DCT, Independent Component Analysis (ICA).*

I. INTRODUCTION

Blind Audio Separation problems can be trace to causes by the dissociation of audio signals from the mixture incur from the distributed microphones, capturing the auditory scene. One of the felicitous approach to simplify the current problem is Independent Component Analysis (ICA). Compressive Sensing (CS) is a novel frame work for signal acquisition that has attracted growing interest in the signal processing field. Traditional signal acquisition is based on the sampling theorem, which shows that the sampling rate must be greater than twice the maximum frequency component of the signal. When the signal frequency increases, the sampling rate becomes faster and faster, which presents a huge challenge to sampling device as well as in data storage and transfer. In these cases CS provides an anticipate solution.

The main contribution of this paper lies in demonstrating an efficient compressive sampling of data through DCT compression, which possess lower memory and high speed and separation of signals through ICA method. By using the properties of the DCT, we can treat the audio signals as sparse in frequency domain. On the other hand, CS has been traditionally used to acquire and compress certain sparse signals. The use of DCT and CS to obtain an efficient representation of audio signals, especially when they are sparse in frequency domain.

The underlying algorithm for solving the problem consists of two procedures: 1) the reconstruction of mixing signals via DCT compressed sensing method and 2) blind mixing matrix estimation through ICA method. First step recovers the mixing signal from the observed compressive measurements, and second step estimates the mixing matrix from the mixtures estimated in the first step.

II. PRELIMINARIES

A. BSS using ICA

Consider the signals are assumed to be independent of each other. The mixing process of source signals in BSS problem can be sorted into several models.

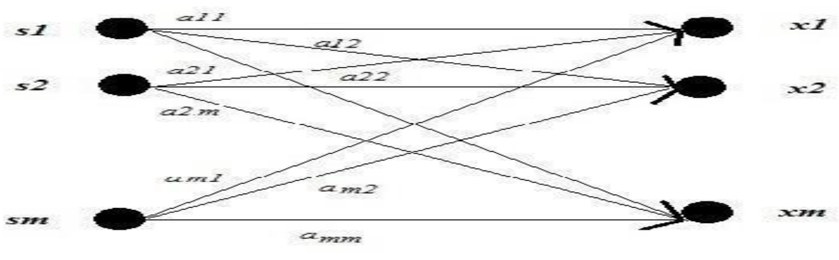

Fig 1. Instantaneous linear mixture model.

For example, convolved mixture model, the instantaneous linear mixture model, or the nonlinear mixture model etc. In this paper, only considering the instantaneous linear mixture model as shown in fig 1. The mixing process can be denoted by,

= (1)

Where = [1, 2, 3, … ,] denotes the signals of sources with samples at discrete time sequences = 1,2, … , and

11 ⋯ 1
= [⋮ ⋱ ⋮]
1 ⋯

A is known as the mixing matrix and = [1, 2, … ,] represents linear mixtures.

For example, imagine that you are in a room where two people speaking simultaneously. You have two microphones, which you hold in different locations. The microphones give you two recorded time signals, which we could denote by 1( ) and 2( ) , with 1 and 2 the amplitudes, and the time index. Each of these recorded signal is weighted sum of the speech signals emitted by the two speakers, which we denote by 1( ) and 2( ) . Then we can explain this as a linear equation:

1( ) = 11 1 + 12 2 (1.1)
2( ) = 21 1 + 22 2 (1.2)

Where 11, 12, 21, and 22 are some parameters that depend on the distances of the microphones from the speakers. This is called cocktail-party problem. In BSS problems, there is no idea about the mixing matrix or how the mixing process are done.

One of the approach to solving this problem would be to use some information on the statistical properties of the signals ( ) to estimate the . Actually, it turns out that it is enough to assume that 1( ) and 2( ), at each time instant , are statistically independent. The recently developed technique of Independent Component Analysis, or ICA, can be used to estimate the based on their independence, which allow us to separate the two original signal sources 1( ) and 2( ) from their mixtures 1( ) and 2( ) .In ICA the task is to find out the original signals from the mixture , which can be find out by

= (2)

= $^{-1}$ (3)

ICA is very closely related to Blind Source Separation. A source means here an original signal, i.e., independent component. Blind means that we have no or very little, on the mixing matrix, and make little assumptions on the source signals. ICA is one method, perhaps most widely used, for performing Blind Source Separation.

B. Compressive Sensing using DCT

Compressive Sensing theory pointed that high dimensional signals, which allow a sparse representation by a suitable basis, can be recover from previously considered incomplete linear measurements. To state the CS problem mathematically, take = ( ) $_{=1}$ ∈ be the signal. For prior information, assume that itself is sparse, i.e. it has very few non-zero coefficient in the sense that

$\| \|_0$ = #{ : ≠ 0}

Is small or there exist an orthonormal basis φ such that = φ with being sparse. Further, let be an × matrix, which is typically called sensing matrix. Also assume < and does not possess any zero columns.

Then the problem can be formulated as, recover from the knowledge of

= (4)

Or recover from the knowledge of

= φ (5)

In this paper compressive recovery is performed using DCT. Since DCT have the properties like Decorrelation and Energy compaction. The main advantage of signal transformation is the removal of redundancy between neighboring values. This leads to uncorrelated transform coefficients which can be encoded independently. Efficiency of a transformation scheme can be directly gauged by its ability to pack input data into as few coefficients as possible. This allows the quantizer to discard coefficients with relatively small amplitudes without introducing distortion in the reconstructed signal. DCT exhibit excellent energy compaction for highly correlated signals.

III. PROPOSED FRAMEWORK

The proposed framework shown in Fig.2. Which starts from the signal mixing, which then followed by DCT compression, so that we obtain the sparse representations of mixed signals. Then by using these sparse signal we performs the ICA, so that compressively sensed measurements are taken for performing ICA. From there we can reduce the memory space, time consuming etc. Finally the original signals are recovered by performing DCT decompression technique.

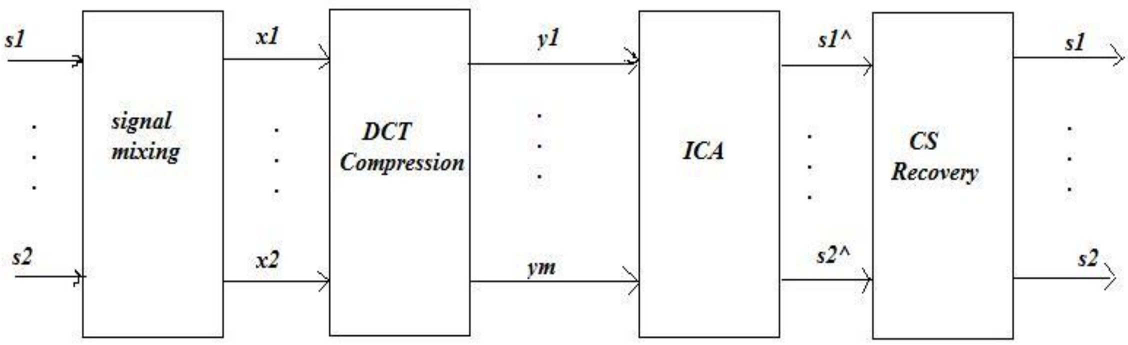

Fig 2. Framework of the proposed work

A. Theory of ICA

ICA is one of the most popular method in BSS field. When using ICA problems, the source signals must satisfy two important properties: That is, all the source signals are independent to each other and one of the signals is Gaussian. To define the concept of independence, consider two random variables y1 and y2. Basically, the variables y1 and y2 are said to be independent if the information on the value of y1 does not give any information on the value of y2, and vice versa [6]. Basically, signals 1( ), 2( ), . . . , ( ) are considered to be independent if information on the value of ( ) does not give any information on the value of ( ) for ≠ .And the Central Limit Theorem, which is a classical result in probability theory, tells that the distribution of a sum of independent random variables tends toward a Gaussian distribution, under certain conditions. Thus, a sum of two independent random variables usually has a distribution that is closer to Gaussian than any of the two original random variables. The mixture of two independent gaussian signals is also a Gaussian signal whose probability density function only contains the second order statistical property, without higher order properties. Thus, if more than one signal is Gaussian, the signals cannot be separated by ICA methods.

Before finding the gaussianity we have to prove the signals are uncorrelated. Because all independent signals are uncorrelated. Or before performing ICA algorithms we have to do some preprocessing steps to prove uncorrelatedness. So we perform the Principal Component Analysis (PCA). PCA can be perform by using two operations one is centering and the other is whitening. The most basic and necessary pre-processing is "center" by subtract its mean vector = { } so as to make a zero-mean variable. That is, = − . Another useful pre-processing strategy in ICA is whiten the observation vector . This means that before the application of the ICA algorithm (and after centering), we transform the observed vector linearly so that we obtain a new vector which is white, i.e. its components are uncorrelated and their variances equal unity. In other words, the covariance matrix of equals the identity matrix: { } = .

To perform ICA we have to prove the signals are non-gaussian. There different measures for non-gaussianity. Here use the method Kurtosis. The normalized kurtosis of a signal is denoted as follows [7]:

$$(\ ) = \frac{\{\ ^4\}}{(\ \{\ ^2\})^2} - 3 \qquad (6)$$

Where $\{\ ^2\}$ is second order moment and $\{\ ^4\}$ is the fourth order moment. When $(\ ) = 0$, the signal is Gaussian else it is non-gaussian.

After pre-processing steps signals are treated for ICA, to extract independent components. The basic steps of Fast ICA using kurtosis maximization, is as follows:

1. Take a random initial vector (0) and normalize the vector. Let k=1.
2. Update ( ) = [× ((− 1))] − 3 (− 1)
3. Normalize ( )
4. If | ( ) (− 1)| is not close to 1, let k=k+1, and go back to step 2.Otherwise the algorithm converges and outputs ( )

B. DCT Compression and decompression

In DCT Compression the compression operation is performed by elements are sorted in their matrix form and find the DCT components and their indices. Discrete Cosine Transform can be used for speech compression because of its high correlation in adjacent coefficient. We can reconstruct a sequence very accurately from very few DCT coefficients. This property of DCT helps in effective reduction of data. DCT of 1-D sequence ( ) of length N is given by,

$$(\ ) = \left[\frac{2}{\ }\right]^{1/2} \sum_{=0}^{-1} (\ ) \left[\frac{(2\ +1)\prod}{2}\right] \qquad (7)$$

Where, m=0, 1,.. N-1

The elements are arranged in the descending order, after that the threshold is decided. After the coefficients are received from the transform, thresholding is done. Very few DCT coefficient represent 99% of signal energy, thresholding is calculated and the coefficient below the threshold is discarded that means it reduces the size of the signal which results in compression. Hence reducing the size of the signal which results in compression. The data is converted back into original form by using decompression technique. The decompression is performed by IDCT operation and zeros are inserted in place of the removed coefficients. Now convert the signal back to its vector form. Thus the signal is reconstructed. The inverse DCT is,

$$(\ ) = \left[\frac{2}{\ }\right]^{1/2} \sum_{=0}^{-1} (\ ) \left[\frac{(2\ +1)\prod}{2}\right] \qquad (8)$$

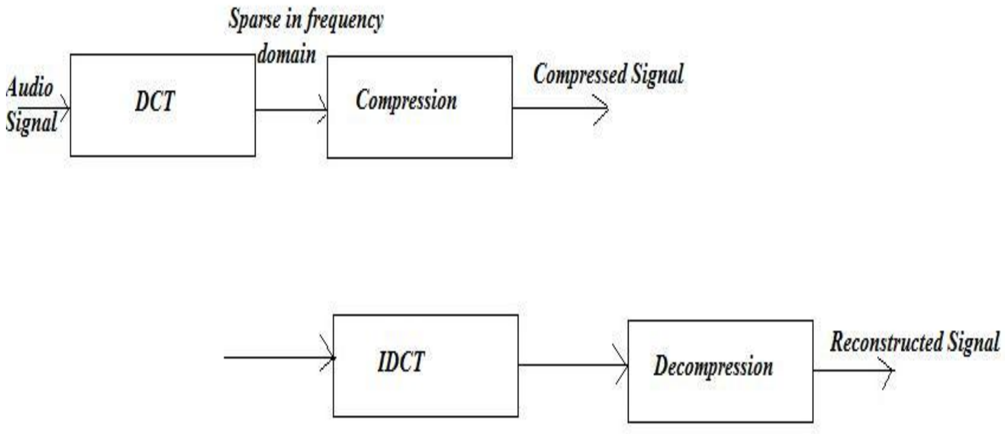

Fig.3. Block diagram of DCT Compression

IV. SIMULATION RESULTS

Fig.4 shows the MATLAB simulated plot of ICA without applying DCT compression. The simulation process includes inputting two audio signals and the two mixtures are generated by instantaneous linear mixing process. The input signal can be any of the audio signal such as speech, music etc. For the analysis the audio signals are chosen with 10000 samples. Generate random gaussian signals using the “randn ()” function.Then finding uncorrelatedness by performing PCA. Centering is performed by subtracting its mean vector and whitening is performed using Eigen value decomposition. Finally the signals will get separated from the mixtures by performing Fast ICA algorithm using kurtosis and the separate signals will obtain. The plot of ICA includes the audio signals that are inputted, and the mixed signals that we obtained, the signals that are obtained after performing PCA and finally the independent components that we obtain after performing Fast ICA.

Evaluation of ICA enhanced with DCT Compressed mixing of Audio signals

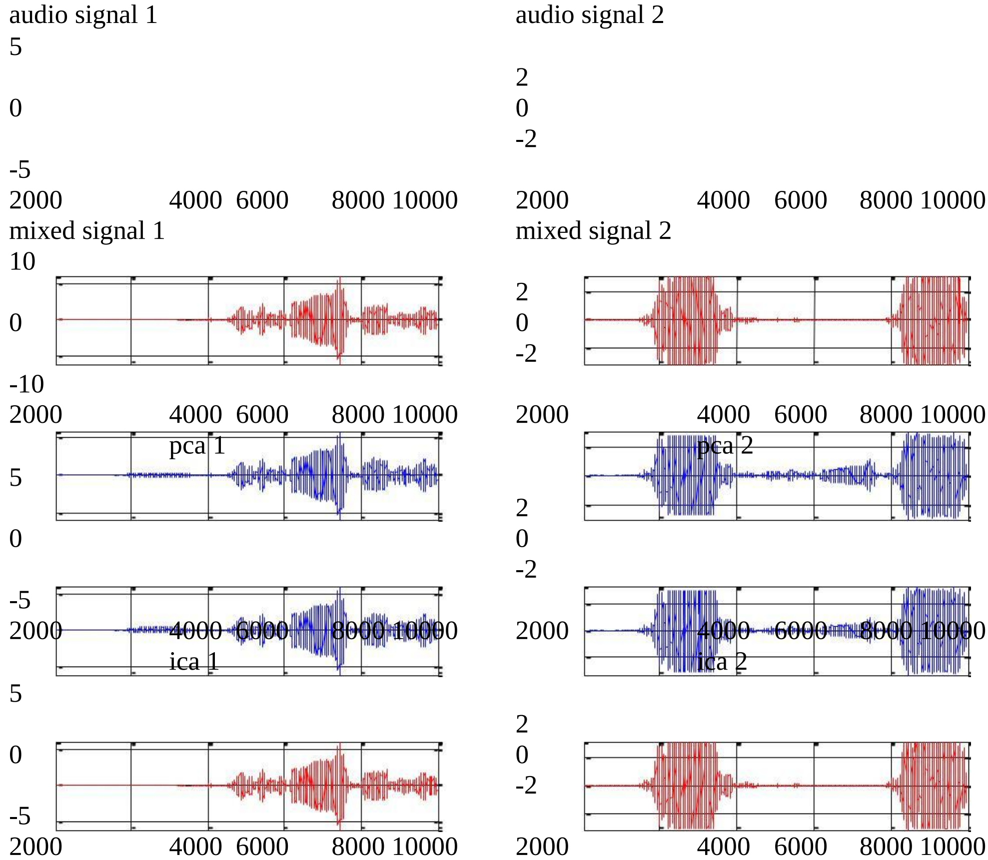

Fig.4. ICA without DCT Compression

Fig.5 shows the ICA with DCT Compression, the mixtures are compressed so that the blind mixtures are applied to lower domain. Here, we present the use of DCT to preprocess the audio in order to obtain a sparse representation of the signal in the frequency domain. After that compression is performed by thresholding. Compression factor can be calculated by the ratio of the length of original signal to the compressed signal. Then PCA is performed compressively. That is to perform the Preprocessing steps such as Centering and whitening we use the sparse signals. From that all ICA applying to lower domain. The simulation result includes the audio signals that are inputted, mixtures that we obtained, compressed PCA, compressed ICA and the reconstructed signals from the compressed signals.

signal 1 mix1 dct of mix1
5 10
20
0 0 0
-20
-5 -10
5000 10000 5000 10000 5000 10000
signal 2 mix2 dct of mix2
2 5 20
0 0 0
-2 -5 -20

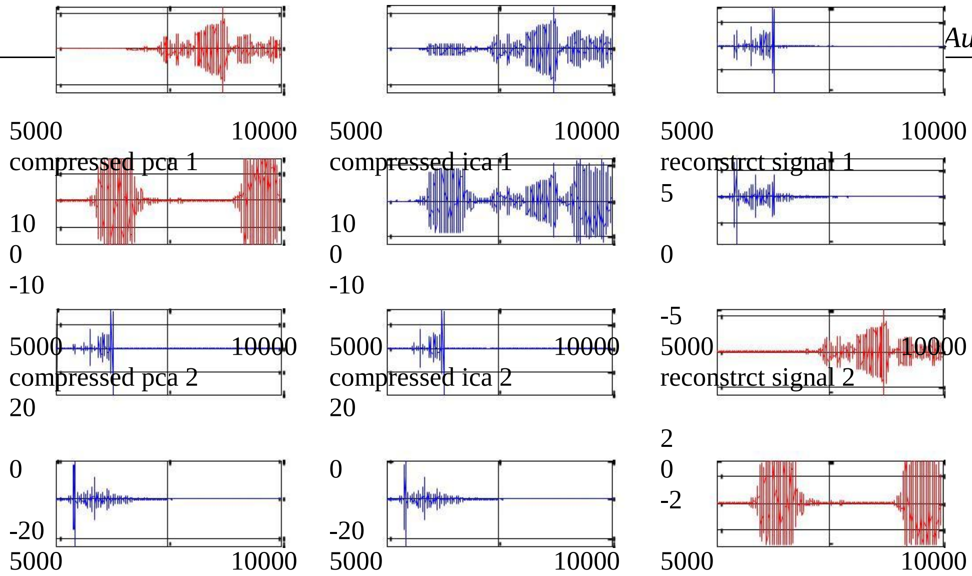

Fig.5. ICA with DCT Compression.

V. CONCLUSION

As a conclusion, Compressive Sensing is has the capability to produce a signal in compressive form, which other than usual sampling theorem store only sparse components. This paper has proposed an efficient implementation of DCT, as a method to obtain a sparse audio signal representation, and the application of the compressive sampling algorithm to this sparse signal. Which has the ability to pack input data into as few coefficients as possible. This allows the quantizer to discard coefficients with relatively small amplitude without introducing audio distortion in the reconstructed signal.

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