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Separation of Indian classical seven tune signal from musical instrumental mixed signal using PCA/ICA based Fast-ICA method

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Abstract

Suppression of voice or instrumental from musical composed signal is very useful in many applications to understand the real frequency range of individual sigal, such as lyrics recognition modification of amplitude, and music information retrieval. Audio source separation problems can be identified successfully by using Independent Component Analysis. In this paper, we examine the source separation problem using the general framework of Principal Component Analysis (PCA)/Independent Component Analysis (ICA) based Fast-ICA. For the greatest part of the analysis, the sinusoidal signal is taken as reference signal and added with different harmonics to generate the classical Indian music seven tune such as SA-RE-GA-MA-PA-DHA-NI-SA. Firstly, we explore the generation of music scene of classical music tune which is modeled as instantaneous mixtures of the auditory objects, to establish the basic tools for the analysis of the research work. Secondly the case of real instrument recording has been modeled as mixtures of the audit objects such as bass, drum and guitar. The signal is sampled at a frequency of 44100Hz as per the compact disc quality. Then the signal has been passed through the low filter to have desired frequency analysis. A novel PCA-ICA based Fast-ICA framework is introduced to separate the classical signal from the signal mixture. Quantitative result shows the system performance and the source separation task successfully.

Keywords:

ICA-PCA;
Music Signal Separation;
Blind source separation;
Speech signal;
Fast-ICA.

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1. Introduction

Extracting source signals present in a complex signal mixture is a difficult problem in signal processing with applications throughout the vicinity of engineering problem. In such cases, it is necessary to separate the acoustic signals through technical means arises .This is a well-known example called "cocktail party problem," in which the aim is to recover the voices of individuals simultaneously from the recording room [1]. It is observed in different cases that very little information about the source signals is known. Without details regarding the source, choosing of the signals is done in a blind way, and thus this kind of

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problem was entitled Blind Source Separation [2]. The most common assumptions made are statistical independence of the sources and one condition is that at most one of the components is Gaussian The Blind Source Separation issue was solved by one of the best result oriented algorithm is the Independent Components Analysis .

The problem of the Blind Source Separation of the sources of signal is reduced at finding a linear representation for which the components are independent from the statistic point of view. Statistical parameters of the sources are used as a criterion in Independent Component Analysis (ICA) for solving the problem.[17]. To recover the data matrix, the sources and coefficients provided by ICA multiplied together, which is similar to the decomposition of matrix obtained through principal component analysis (PCA) [3].ICA is used in many application domains [4, 5], in neuroimaging, in which the goal is to decompose electroencephalographic (EEG) data in temporally independent sources [6] and functional magnetic resonance imaging (fMRI) data into spatially independent brain networks [7]. A model proposed by Woods et al. [12] which is mixed ICA/PCA in which the sources of Gaussian uses cross-validation for determining the number of components but computational burden is more. The Fast ICA [15] is the algorithm which can separate signal sources from the combined audio and instrument signals using positive and negative kurtosis statistical parameters.

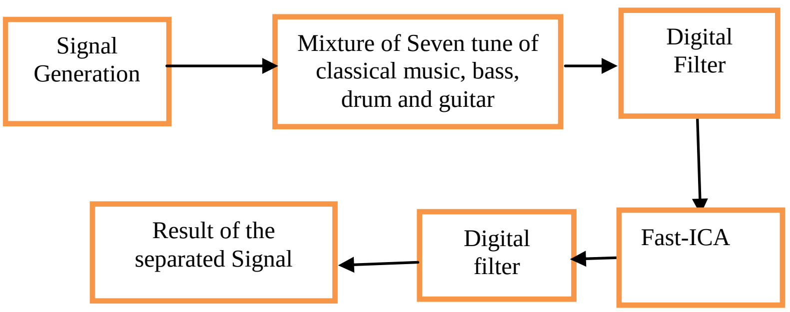
In this paper, we describe a new algorithm for mixed ICA/PCA which allows to take advantage of the speed and flexibility of Fast ICA. So it is found Fast ICA is much faster than mixed ICA/PCA method. We demonstrate the utility of Fast ICA [15, 16] for signal mixtures consisting of sources of music and mixture of unknown composition of musical lyrics and experimented the performance of the existed algorithm on simulated mixtures of classical music signal and audio musical instrument signals.

The paper is organized as follows: In Section 2, we state the generation of signal from the fundamental harmonics of sinusoidal signal and a brief introduction on PCA/ICA and Fast ICA. In Section 3, we describe our approach of generation and separation of signal resaults and Section 4 presents Conclusions.s followed by reference and

2. Research Method

In this paper, the complex signal mixture of audio and instrument sigalns have been decomposed in to a small set of independent source signals using Independent component analysis (ICA) is a popular algorithm used by researchers [18]. The signal mixture contains both nongaussian and Gaussian sources, the ICA is not capable enough to recover the Gaussian sources and the estimate of the nongaussian sources will be affected. Therefore, it is required to use mixed ICA/PCA methods which can separate Gaussian and nongaussian sources from the complex signal mixture of audio and instrument signals.

2.1 Block diagram of the proposed research work:



2.2 Independent Component Analysis Model:

Independent component analysis [15, 16] is defined as a given a set of observation of some random variable

$x_1(t), x_2(t).........x_n(t)$ Where t represents the time, assuming they are generated by linear mix of group of independent components $s_1(t), s_2(t).........s_n(t)$ where

$$x_1(t) = a_{11}s_1(t) + a_{12}s_2(t) + ... + a_{1n}s_n(t)$$
$$x_1(t) = a_{11}s_1(t) + a_{12}s_2(t) + ... + a_{1n}s_n(t)$$

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$$x_n(t) = a_{n1}s_1(t) + a_{n2}s_2(t) + ... + a_{nn}s_n(t)$$

Or we can write in a matrix format as

$$X = AS \quad (1)$$

Where A is the mixed coefficient matrix. When the mixed matrix and source signal X , we need to find a separable matrix $W = A^{-1}$,so as to realize the isolation of S from X , namely

$$Y = A^{-1}X \quad (2)$$

In the analysis of mixed signal S represents different signals such as audio signal, and the instrument generated signals such as drum, guitar and bass. A Presents the way in which the independent signals mix. Using Fast ICA, Y can be found out as estimate of the source signal S .

2.3 Fast-ICA

Fast-ICA [15, 16] is actually a kind of fixed point iterative scheme used to look for the maximum non-gaussianity of $A^{-1}X$. Before the extraction of independent component, we need to find a criterion to measure the gaussianity of the separated signals. The criterion used to measure the gaussianity of signal includes kurtosis and negative entropy. For separation of signals, we have choosen negative entropy as the criterion to measure the gaussianity of the separation signal.

The Negative entropy is defined as:

$$J(y) = H(y_{gauss}) - H(y) \quad (3)$$

$where\ H(y) = -\int p_y(\eta)\log p_y(\eta)d\eta$ Defined as the comentropy of random variable y, and y_{gauss} is Gaussian random vector. In information theory the entropy can be used as a kind of metrices to measure non-gaussianity.

So, the negative entropy often uses an approximation as

$$J(y) \propto [E\{G(y)\} - E\{G(y_{gauss})\}]^2 \quad (4)$$

Where $G(\cdot)$ is a nonlinear and non-quadratic function, which can be choosed according to experience means calculating mean $E(\cdot)$. So, we can use negative entropy maximization as the criterion of independence.

Based on the central limit theorem, to maximize nongaussianity means to maximize $J(y)$. When non-gaussianity reached maximum value, the separation of independent component analysis has been completed. To maximize $J(y)$ means to maximize $E\{G(y)\}$ which is equal to $E\{G(w^T x)\}$ and on the basis of Newton's iterative formula

$$x_{n+1} = x_n - \left[f(x_n) \big/ f^{'}(x_n) \right] \quad where \quad n = 0,1,2......$$

We get the iterative formula of Fast-ICA algorithm as below

$$w_i(t+1) = E\{x \cdot g(w_i^T \cdot x)\} - E\{x \cdot g^{'}(w_i(t)^T \cdot x)\}w_i(t) \quad (5)$$

$$w_i^* = w_i(t+1) \big/ \|w_i(t+1)\| \quad (6)$$

Where the gaussian $g(x) = x\exp\left(-x^2 \big/ 2\right)$

In the above formula , w_i^* means the process to normalize the result of every step of the iteration. This process should be repeated until it is convergent, then the independent component could be extracted.

2.4 Signal generation by considering music signal:

In speech signal processing approach we have experimented how a sinusoidal signal with increased harmonic frequency behaves as music tune, mixing of real time speech signal, instrument generated signal and separation of individual signals using Fast ICA (Independent component analysis).

- In the first phase we have generated the seven tune of Indian classical music **sa-re-ga-ma-pa-da-ni and sa-ni-da-pa-ma-ga-re-sa** by taking a sinusoidal signal with increased harmonics.
- In the second phase, the seven tune, according to the number of samples of seven tune filtered by the digital filter.
- In the third phase, the sound of bass, drum and guitar has been mixed with the original signal and an instrumental song has been generated which can be heard in real time. The signal has been separated by existing Fast-ICA Method.

Generation of Indian classical music sa-re-ga-ma-pa-da-ni and sa-ni-da-pa-ma-ga-re-sa using MATLAB.

```
Voice=audioread ('satyasis.wav');
Bass=audioread ('bass.wav');
Drums=audioread ('drums.wav');
Guitar=audioread ('guitar.wav');
Fs=44100;
t=0:1/Fs: 2; %Time to plot
f1=440; f2=2*f1; f3=3*f1; f4=4*f1; f5=5*f1; f6=6*f1; f7=7*f1; f8=8*f1;
A1to A8=0.1to 0.8;
y1=A1*sin (2*pi*f1*t); %Fundamental harmonic signal
 y2=A2*sin (2*pi*f2*t);
y3=A3*sin (2*pi*f3*t);
y4=A4*sin (2*pi*f4*t);
y5=A5*sin (2*pi*f5*t);
y6=A6*sin (2*pi*f6*t);
y7=A7*sin (2*pi*f7*t);
y8=A8*sin (2*pi*f8*t);
pp1= [1.5*y1 2*y2 3*y3 4*y4 5*y5 6*y6 7*y7 8*y8 9*y8 7*y7 6*y6 5*y5 4*y4 3*y3 2*y2 y1];
```

The signal generated with a sampling frequency of 44100Hz, which is the audio record frequency. The complete music signal generated at the centurion university, Bhubaneswar, Odisha, India signal processing lab of electronics and communication engineering department. For the purpose of signal analysis using ICA and Fast ICA, the complex signal has been generated by using MATLAB R2016 Software. The sources of the signal separation has been accomplished by using ICA and Fast-ICA method.

3. Results and Analysis

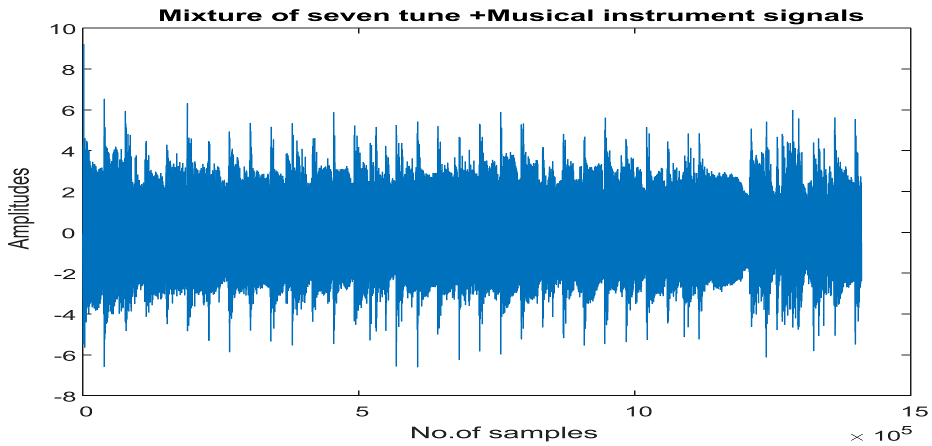

Figure-1: Mixture of seventune signal and other musical instrument signal

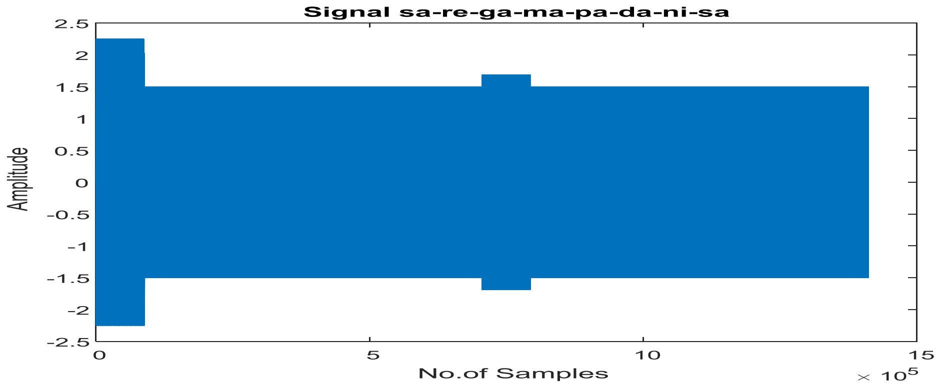

Figure-2: Generation of seventune classical music signal

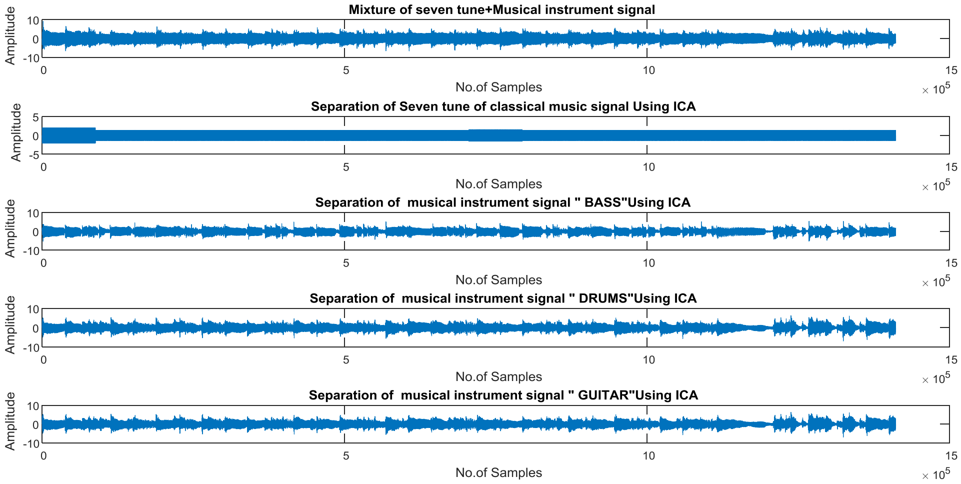

Figure-3: Separation of musical instrument signals and seven tune signal using ICA

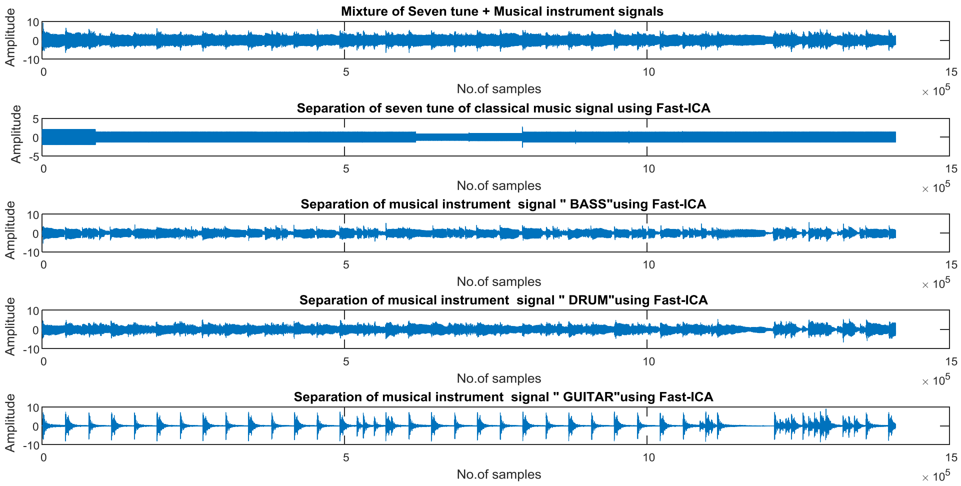

Figure-4: Separation of musical instrument signals and seven tune signal using Fast-ICA

Table 1. The summary of the percentage separation and computational time taken by algorithm

Type of signal	Frequency in Hz	Sampling frequency in Hz	No.of samples	Correct separation by ICA in percentage	Correct separation by Fast-ICA in percentage	Time taken by ICA	Time taken by Fast ICA
Seven Sur	440	44100	1411216	94.23	99.38	51.43567 1 sec	24.75675 1sec
Bass	440	44100	1411216	94.45	99.85		
Drum	440	44100	1411216	95.12	99.94		
Guitar	440	44100	1411216	95.45	99.97		

Form the Table-1 it is found that the computational time taken by Fast-ICA is much more lesser in comparison with the ICA method. From the figure -4 it is observed that the Fast-ICA method is separating the signals with clarity and perfection. It is shown in the figure that all the beats are correctly identified and separated, which is not seen perfectly in the figure-3.

Figure -1 and figure -2 are the generations of seven tune and the mixed signal which are generated with asampling frequency of 44100 Hz.

4. Conclusion

In this paper, Independent component analysis (ICA) and Fast ICAalgorithm are used for decomposing complex audio and instrument generated signal mixtures into independent source signals. It is found that in some cases of signal mixture both nongaussian and Gaussian sources are present. Therefore, we introduce a new method for mixed ICA/PCA which we call Mixed ICA/PCA through Fast ICA to separate mixtures of Gaussian and nongaussian sources. It is found found that the signal separation is better in case of Fast ICA algorithm which van be observed from the table.This paper follows a new method of generation of classical music signal sa-re-ga-ma-pa-da-ni and its reverse and mixed with different musical instrument signals to generate a musical instrumental song. The method of blind source separation method PCA/ICA based Fast-ICA algorithm has been applied to separate the siganls. The Fast-ICA algorithm based on negative entropy used to separate the signals and identify the different frequency and amplitude of the signals. In the Fast-ICA algorithm, we have taken negative entropy, and used the method of symmetrical orthogonalization for separation of multiple independent components. The Simulation results shows that, the Fast ICA method can accurately detect the source signal, with less computional time which is mentioned in the table in comparison to the ICA method.

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