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A COMPARATIVE STUDY OF BLIND SOURCE SEPARATION BASED ON PCA AND ICA

[1]Mohammed Safwan, [2]Deepak S G, [3]Ashish A B, [4]Hemanth B R, [5]Prashantha H S
[5]Professor, Dept. of Electronics and Communication Engineering
[1,2,3,4] Undergraduate Student, Dept. of Electronics and Communication Engineering
Nitte Meenakshi Institute of Technology, Bangalore, India

Abstract: Blind source separation (BSS) consists of the extraction of individual signals from their mixture using no prior knowledge about their nature. Here, we address the blind separation of audio sources by means of Principal component analysis (PCA) and Independent Component Analysis (ICA), which is a popular method for BSS using the assumption that the original sources are mutually independent. PCA and ICA algorithm working for mixed signals is studied and depicted in this paper.

Index Terms – source separation, PCA, ICA

1. Introduction

Frogs are among the most vocal animal and generally communicates using sounds to convey warnings, attract mates and defend their territories against the opponent. The sound produced by frogs can be used as a species identifier. Each species has a unique call that holds sufficient individual information thus making it feasible for a human to detect their existence in a particular area. The species identification based on vocalization is considered valuable for biological research and environmental monitoring application. Frogs usually interact acoustically in large social aggregations, comprising hundreds of males making large breeding choruses at the potential breeding site. Thus, the high noise levels and temporally overlapping sound signals within frog choruses interfere with the ability of listeners to detect, recognize, and discriminate among vocalizations. For several applications, such as automatic sound recognition, it is essential to separate the target source sounds from the complex acoustic environment as pre-processing steps, before it can be used as an input to the system to increase the performance. In recent years, sound separation has received much attention in the research of signal processing fields and one common method is Blind Source Separation (BSS). BSS is the procedure of estimating the original sources from signal mixtures. A typical example of BSS cases is the well-known ‘cocktail party problem’. The cocktail party problem is a phenomenon of being able to focus on a specific human voice while filtering out other voices or background noise. Many methods for BSS have been proposed, which aim at providing a solution to the cocktail party problem. Some of the widely used techniques for solving BSS include Independent Component Analysis (ICA) and Principle Component Analysis (PCA). The ICA-based separation technique is among the dominant successful BSS techniques. ICA’s has diverse applications including speech-music separation, speech separation, power system analysis, face recognition and biomedical signal analysis. FastICA, Infomax, and JADE are several different algorithms available to compute the independent component. The fast-fixed point algorithm (FastICA) is the most popular due to its fast convergence and good separation. While ICA exploits higher-order statistics of the data, PCA only considers the second-order statistics to solve the BSS problem. ICA on the other hand has been proved to produce good results in addressing monaural separation problems, multichannel source separation, source separation in automatic speech recognition and music analysis. This paper proposes to compare the differences and performances of the ICA and PCA techniques in the context of music-vocal-noise separation.

2. Methodology

2.1. ICA approach for source separation

ICA is a statistical analysis method of Blind Source Separation. The term blind is used here because there is no explicit knowledge of source signals or the mixing systems besides the mixtures. ICA is formulated by which the independent original signals are extracted from the mixtures at multiple sensors. Imagine a room with two persons and two sensors (i.e. microphone) for recording. When these two persons speak at the same time, each sensor will register a particular linear combination of the two signals. From Fig. 1, if the two original signals denoted by S_1 and S_2, then the linear combination of their mixtures, X_1 and X_2 can be expressed mathematically as:

$$X_1 = A_{11}S_1 + A_{12}S_2 \quad \dots (1)$$

$$X_2 = A_{21}S_1 + A_{22}S_2 \quad \dots (2)$$

where A_{11}, A_{12}, A_{21} and A_{22} represent the mixing matrix that generates X from S. The ICA aims to recover the original signals S only from the signal observations X without specific prior information about the sources and the mixing system. By using the vector-matrix notation, the mixing process from equation (1) and (2) can be modelled as

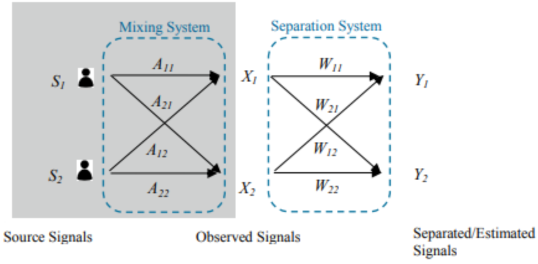

Fig. 1: Basic BSS

$X = AS$ … (3)

where X, S are random vectors and A is the matrix of parameters. The model in equation (3) is known as independent component analysis or ICA model. This ICA model is a generative model that describes the computation of source signals or independent components, S by estimating the mixing matrix A from the known random vector X. After determining A, demixing matrix, WW denoted by $W = A^{-1}$ is computed. Then, the estimated sources can simply be recovered as $S = WX$ (where SS is the real independent component) by maximizing the non-gaussianity to achieve the independence of sources.

2.1.1. Data pre-processing for ICA

Before applying specific ICA algorithm on the signals, it is imperative to execute some pre-processing to the observed data in order to reduce the complexity of ICA algorithm implementations. Common pre-processing often involves signal centering and whitening. Centering is achieved simply by subtracting the mean, $E(x)$ of the signal from each reading of that signal. This to ensure x has a zero-mean variable. By taking expectation on both sides of $X = AS$, implies that S is zero mean as well. Once the mixing matrix A is estimated with the centered data, we can obtain the actual estimates of the independent components. Whitening has the advantage of halving the number of parameters to be estimated. Instead of having to estimate the n^2 elements of the original matrix A, we only need to estimate the new orthogonal mixing matrix. By data whitening, the computational complexity of ICA is reduced and leads to a high probability of achieving a successful signal recovery.

2.1.2. FastICA algorithms

The FastICA algorithm is based on a fixed-point iteration scheme for finding a maximum of the non-gaussianity of $w^T x$. The resulting FastICA learning rule finds a direction, i.e., a unit vector w such that the projection $w^T x$ maximizes non-gaussianity. In this approach, it is assumed that the data is pre-processed by centering and whitening as discussed in the preceding section. The whole FastICA process is decomposed into samples; the following equation represents a one-unit FastICA algorithm for each data sample after the whitening process.

1. Initialize weight vector, w (e.g. random)
2. Iterate: $w^+ = E\{x\alpha(w^T x)\} - E\{\alpha'(w^T x)\}\, w$
3. Divide w^+ by its norm, $w = w^+ / \|w^+\|$
4. If not converge, go back to step 2.

Where w is a column-vector of unmixing matrix. w^+ is a temporary variable used to calculate w. α' is the derivative of α and $E(.)$ is the expected value (mean). In this work, the FastICA algorithm is applied to mixture of vocal, music and noise signals. A random mixing matrix was specified to mix the sound source signals. The mixtures are the pre-processed to recover the estimated sources Fig. 2 presents a flowchart of FastICA.

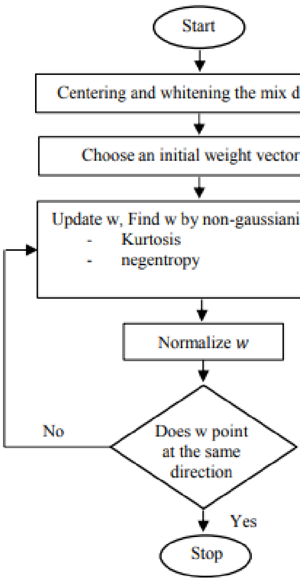

Fig. 2: Flowchart of Fast-ICA

2.2. PCA approach for source separation

PCA was originally developed by Karl Person in 1901 which is then commonly used for signal processing for separating linear combination of signals. PCA is a method that is used to reduce number of linear dimensional from multi-directional data in the maximum variance. It simplifies statistical problem by composing sample characteristic, where the similar elements or elements with highest variance are determined. The main steps of the PCA algorithm are presented in the following:

1. Centering input signal.
2. Calculation of eigenvectors and eigenvalues of covariance matrix by using singular-value decomposition (SVD). It is used to produce diagonal matrices, S that has same dimension as input signal, X and nonnegative diagonal element, as well as unitary matrices U and V, such that $X=U * S * V'$.
3. Compute principal component such that $Z_{pca} = S * V'$.

3. Simulation and Separation Results

The FastICA and PCA is implemented using python 3.8.5. The packages included are sklearn, scipy (version 1.7.1), numpy (version 1.21.3) and librosa (version 0.8.1). The bellow figure shows the representation of the signals taken as input, mixed and processed signals. It gives the proper result of comparison of output signal with input signal. The input signal taken for algorithm implementation is the vocal, music and random generated white Gaussian noise.

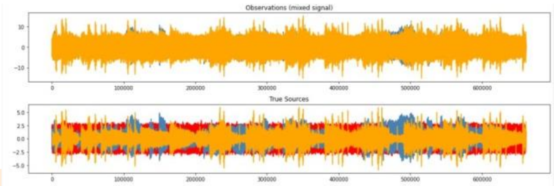

Fig. 3: Representation of observed mixed signals and true source signals

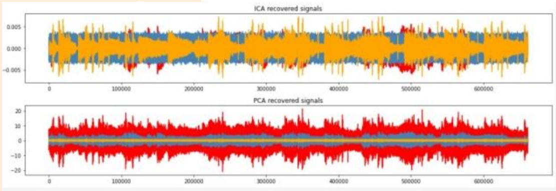

Fig. 4: Representation of recovered signals FastICA and PCA respectively

4. Conclusion

We have presented a comparison of blind source separation using FastICA and PCA methods on three set mixtures various sounds. Visually, the simulation shows that FastICA is better than PCA for estimating the original source signals from the mixtures. However, from the objective evaluation result, it shows that FastICA gives the best value compared to PCA. PCA has the lowest performance and this confirms that PCA is not preferable for sound separation problem. From the experiment, we reach a conclusion that FastICA works well compared to PCA as it provides more clear output and perceptually more relevant to sound separation.

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