

Separation of a Sound from Number of Sounds Using BSS Algorithm

R Suganya¹, C Selvi², T.Kowsalya³

P.G. Students, Muthayammal Engineering College, Rasipuram, India¹

Associate Professor, Muthayammal Engineering College, Rasipuram, India²

Professor Head, Muthayammal Engineering College, Rasipuram, India³

ABSTRACT: Tracking of a particular sound from number of sounds in an environment is a difficult process. Blind Source separation (BSS) aims at estimating a set of source signals. The separation is said blind as we don't know the mixture parameters and we try to estimate the sources by only knowing the observations. BSS is very up to date at present in signal processing because of the great number of applications for instance in acoustics, in telecommunications, neurobiology and in astrophysics. Recently a number of adaptive learning algorithms have been proposed for blind source separation. Operation is based on Principal component analysis.

KEYWORDS: Blind Source Separation algorithm, Adaptive, Principal Component Analysis.

I. INTRODUCTION

During the past decades, much attention has been given to the separation of mixed sources, in particular for the blind case where both the sources and the mixing process are unknown and only recordings of the mixtures are available. In several situations it is desirable to recover all sources from the recorded mixtures, or at least to segregate a particular source. Furthermore, it may be useful to identify the mixing process itself to reveal information about the physical mixing system.

Blind source separation is a problem of recovering a number of original stochastic independent from a number of mixtures. Principal component analysis (PCA) is a statistical procedure that uses an orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables called principal components. The number of principal components is less than or equal to the number of original variables. This transformation is defined in such a way that the first principal component has the largest possible variance and each succeeding component in turn has the highest variance possible under the constraint that it is orthogonal to the preceding components. The principal components are orthogonal because they are the eigenvectors of the covariance matrix, which is symmetric. PCA is sensitive to the relative scaling of the original variables.

PCA is the simplest of the true eigenvector-based multivariate analyses. Often, its operation can be thought of as revealing the internal structure of the data in a way that best explains the variance in the data. If a multivariate dataset is visualised as a set of coordinates in a high-dimensional data space, PCA can supply the user with a lower-dimensional picture, a projection or shadow of this object when viewed from its most informative viewpoint. This is done by using only the first few principal components so that the dimensionality of the transformed data is reduced.

II. MIXING MODEL

The convolutive model introduces the following relation between the m th mixed signal, the original source signals, and some additive sensor noise $V_m(t)$:

$$X_m(t) = \sum_{n=1}^k \sum_{k=0}^{k-1} a_{mnk} s_n(t-k) + v_m(t)$$

In matrix form, the convolutive model can be written as:

$$X(t) = \sum_{k=0}^{k-1} A_k S(t-k) + v(t)$$

Where A_k is an $M \times N$ matrix which contains the k th filter coefficients. $V(t)$ is the $M \times 1$ noise vector. In the z domain the convolutive mixture can be written as:

International Journal of Innovative Research in Science, Engineering and Technology

(An ISO 3297: 2007 Certified Organization)

Vol. 4, Special Issue 6, May 2015

$$X(z) / A(z)S(z) + V(z)$$

Where $A(z)$ is a matrix with FIR polynomials in each entry. This model is known as the *instantaneous* or delayless or linear mixture model.

Instantaneous Mixing Model: Assuming that all the signals arrive at the sensors at the same time without being filtered, the convolutive mixture model (2) simplifies to $x(t) / As(t) + v(t)$.

Here, A/A_0 is an $M \times N$ matrix containing the mixing coefficients. Many algorithms have been developed to solve the instantaneous mixture problem.

Delayed Sources: Assuming a reverberation-free environment with propagation delays the mixing model can be simplified to

$$\sum_{n=1}^N a_{mn} s_n(t - k_{mn}) + v_m(t)$$

where k_{mn} is the propagation delay between source n and sensor m .

If only one of the sources was different from zero, then all x^t 's would be proportional to a^j and all data points in mixture space would be aligned along the direction of this basis vector.

$$X^t = \sum_{n=1}^N a^j s^j \text{ for } t/1, 2, \dots, T$$

When the sources are sparse, smaller coefficients are more likely and thus, for a given data point t , if one of the sources is significantly larger, the remaining ones are likely to be close to zero. Thus, the density of data in mixture space, besides decreasing with the distance from the origin, shows a clear tendency to cluster along the directions of the basis vectors a^j 's. Estimating the mixing matrix, then, consists of finding the directions of maximum data density. For $M/2$, a simple and useful representation of mixture space is a scatter plot of the data that shows x_2^t against x_1^t for every data point t .

Mixed sound separation: Figure displays the tasks that are carried out by the sink. Estimate the directions of arrival (DOA) of unknown signals that are received from each sensor node. Our observations indicate that the proposed CBSS method exhibits better separation performance as the DOA difference increases. Based on such findings, the system is designed to select the sensor node with the maximum average DOA difference, and the separated signals that correspond to this sensor node are utilized to perform sound verification. Figure 2 illustrates an example of the DOA difference with respect to each sensor node. In this example, mixed signals received by sensor node 3 are chosen to perform sound separation verification

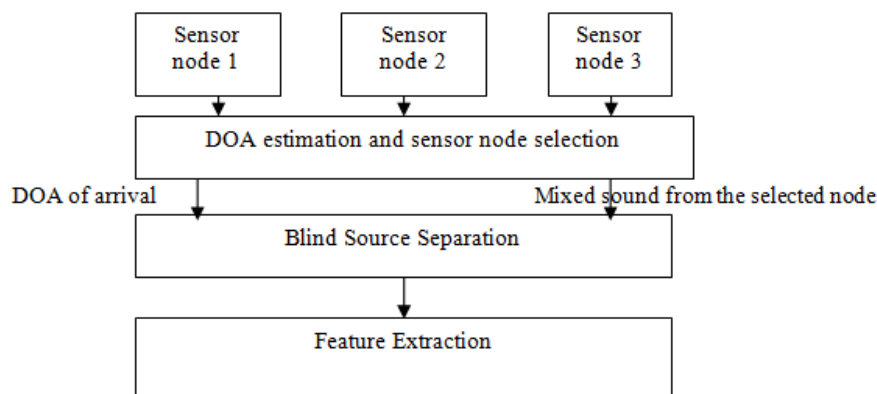


Fig. 1. Mixed sound separation

International Journal of Innovative Research in Science, Engineering and Technology

(An ISO 3297: 2007 Certified Organization)

Vol. 4, Special Issue 6, May 2015

III. SOUND VERIFICATION

Dynamic testing verifies the execution flow of software e.g. decision paths, inputs and outputs. It describes the methodology and explains the application of this testing philosophy according to the dimensions of type (functional and structural) and granularity. Dynamic testing involves the creation of test-cases and test-vectors and execution of the software against these tests. It also includes a summary of various statistics compiled on the effectiveness of dynamic testing.

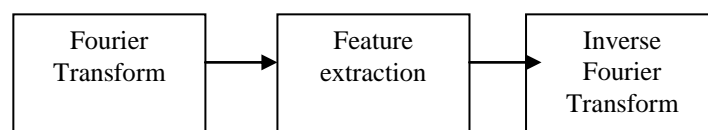


Fig. 2. Sound Verification

IV. EXPERIMENTAL RESULTS

In this paper we have taken five input signals with various parameters. Here they are mixed in the ratio of 1:2. These input signals are differentiated by different colours. Final resultant graph is the mixture of all the above input signals and their mixed ratio separated by different colts is plotted between their MMSE and numbers of bins have been used.

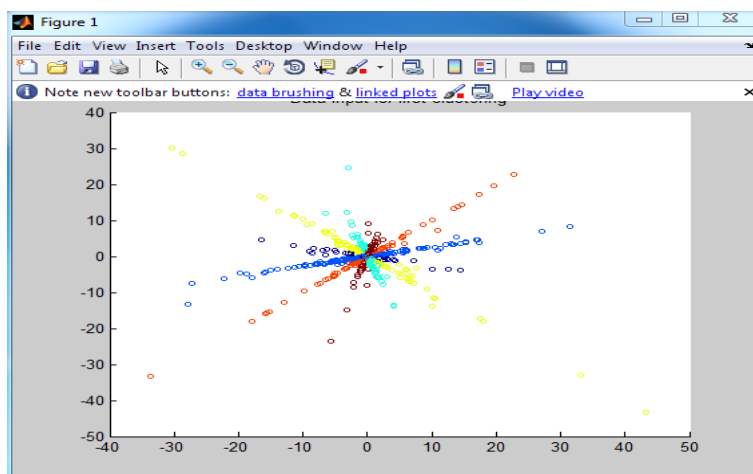


Fig. 3. Input 1

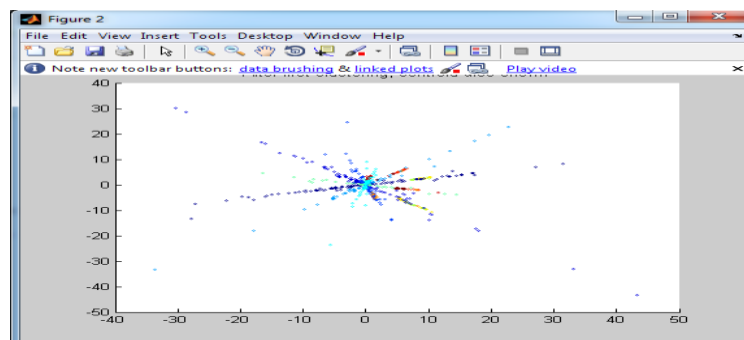


Fig. 4. Input 2

International Journal of Innovative Research in Science, Engineering and Technology

(An ISO 3297: 2007 Certified Organization)

Vol. 4, Special Issue 6, May 2015

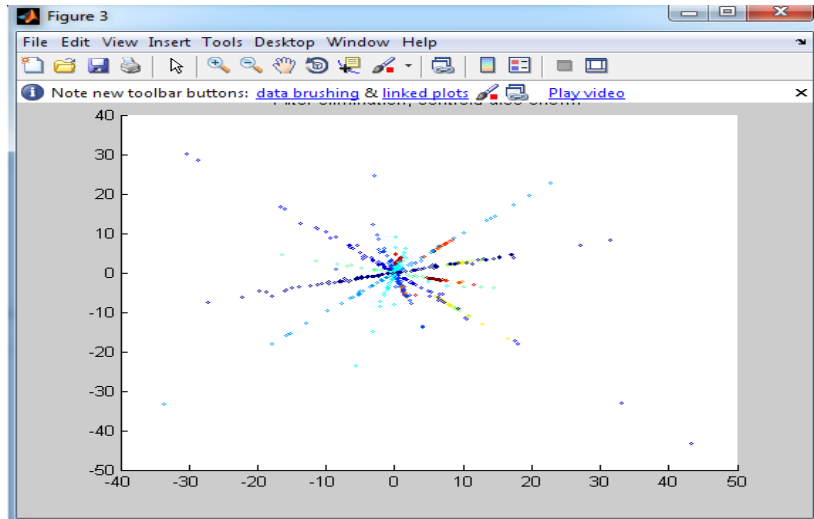


Fig. 5. Input 3

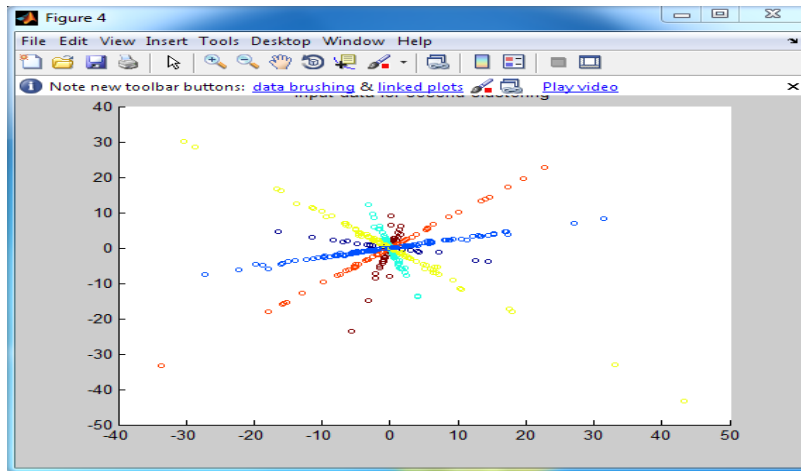


Fig. 6. Input 4

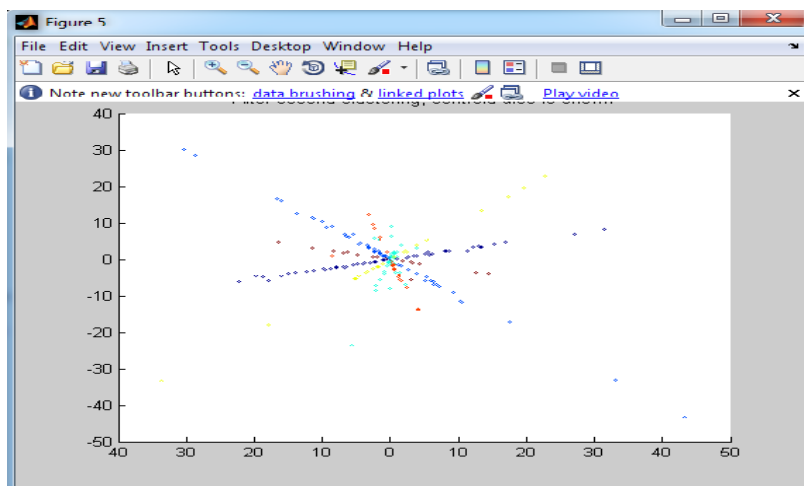


Fig. 7. Input 5

International Journal of Innovative Research in Science, Engineering and Technology

(An ISO 3297: 2007 Certified Organization)

Vol. 4, Special Issue 6, May 2015

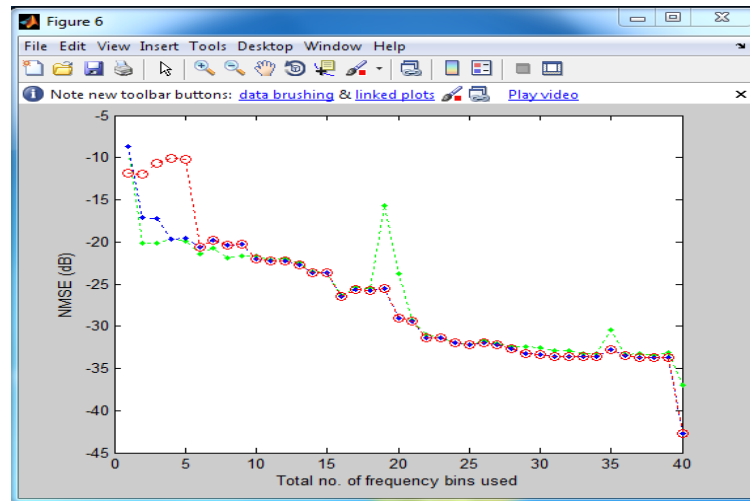


Fig. 8. Resultant figure

V. CONCLUSION

In this paper we separated a wanted signal from a group of mixed signals. it is done by blind source separation algorithm. This improves the sound verification performance.

REFERENCES

- [1] R. C. Luo and O. Chen, "Mobile sensor node deployment and asynchronous power management for wireless sensor networks," *IEEE Trans. Ind. Electron.*, vol. 59, no. 5, pp. 2377–2385, May 2012.
- [2] D. R. Raymond, R. C. Marchany, M. I. Brownfield, and S. F. Midkiff, "Effects of denial-of-sleep attacks on wireless sensor MAC protocols," *IEEE Trans. Veh. Technol.*, vol. 58, no. 1, pp. 367–380, Jan. 2009.
- [3] M. Peng, Y. Xiao, and P. P. Wang, "Error analysis and kernel density approach of scheduling sleeping nodes in cluster-based wireless sensor networks," *IEEE Trans. Veh. Technol.*, vol. 58, no. 9, pp. 5105–5114, Nov. 2009.
- [4] B. Zhang, R. Simon, and H. Aydin, "Harvesting-aware energy management for time-critical wireless sensor networks with joint voltage and modulation scaling," *IEEE Trans. Ind. Inf.*, vol. 9, no. 1, pp. 514–526, Feb. 2013.
- [5] C. Caione, D. Brunelli, and L. Benini, "Distributed compressive sampling for lifetime optimization in dense wireless sensor networks," *IEEE Trans. Ind. Inf.*, vol. 8, no. 1, pp. 30–40, Feb. 2012.
- [6] P. T. A. Quang and D.-S. Kim, "Enhancing real-time delivery of gradient routing for industrial wireless sensor networks," *IEEE Trans. Ind. Inf.*, vol. 8, no. 1, pp. 61–68, Feb. 2012.
- [7] T. M. Chiwewe and G. P. Hancke, "A distributed topology control technique for low interference and energy efficiency in wireless sensor networks," *IEEE Trans. Ind. Inf.*, vol. 8, no. 1, pp. 11–19, Feb. 2012.
- [8] V. C. Gungor and G. P. Hancke, "Industrial wireless sensor networks: Challenges, design principles, technical approaches," *IEEE Trans. Ind. Electron.*, vol. 56, no. 10, pp. 4258–4265, Oct. 2009.
- [9] F. Talantzis, A. Pnevmatikakis, and A. G. Constantinides, "Audio-visual active speaker tracking in cluttered indoor environments," *IEEE Trans. Syst., Man, Cybern. B, Cybern.*, vol. 39, no. 1, pp. 799–807, Jun. 2008.
- [10] J. Nishimura and T. Kuroda, "Versatile recognition using Haar-like feature and cascaded classifier," *IEEE Sensors J.*, vol. 10, no. 5, pp. 942–951, May 2010.
- [11] T. Kowsalya and Dr. S. Palaniswami (2014) 'A Clock Control Strategy Based clustering Method For Peak Power And Rms Current Reduction' in *Journal of Theoretical and Applied Information Technology* Vol. 63 No.2 © 2005 - 2014 JATIT & LLSISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195 459
- [12] T. Kowsalya and Dr. S. Palaniswami (2012) 'Decoupled SRAM Cell with Bit Line Decoupled Current Mode Sense Amplifier' Published in *European journal of Scientific Research* in volume 84 issue 2 Aug 2012