Comparative analysis of Kurtosis and Negentropy principles for music elements separation using Independent Component Analysis



Rithesh Kumar R¹ and Mohanaprasad K¹, ¹ VIT University, Vellore, India

rithesh.kumar7493@gmail.com



Output- Piano

SIR: -3.95 dB

SIR: -6.16 dB

tar and make high think here the able and blood the second

Output- Piano

Objective:

Individual music separation from a mixture of music was obtained using Independent Component Analysis (ICA), which works on the principle of maximizing the non-Gaussianity. Here two methods namely Kurtosis and Negentropy are used to maximize the non-Gaussianity of the mixed music signal. Using signal to interference ratio (SIR), performance are compared and was found that ICA using Negentropy gives better separation with more number of sources.

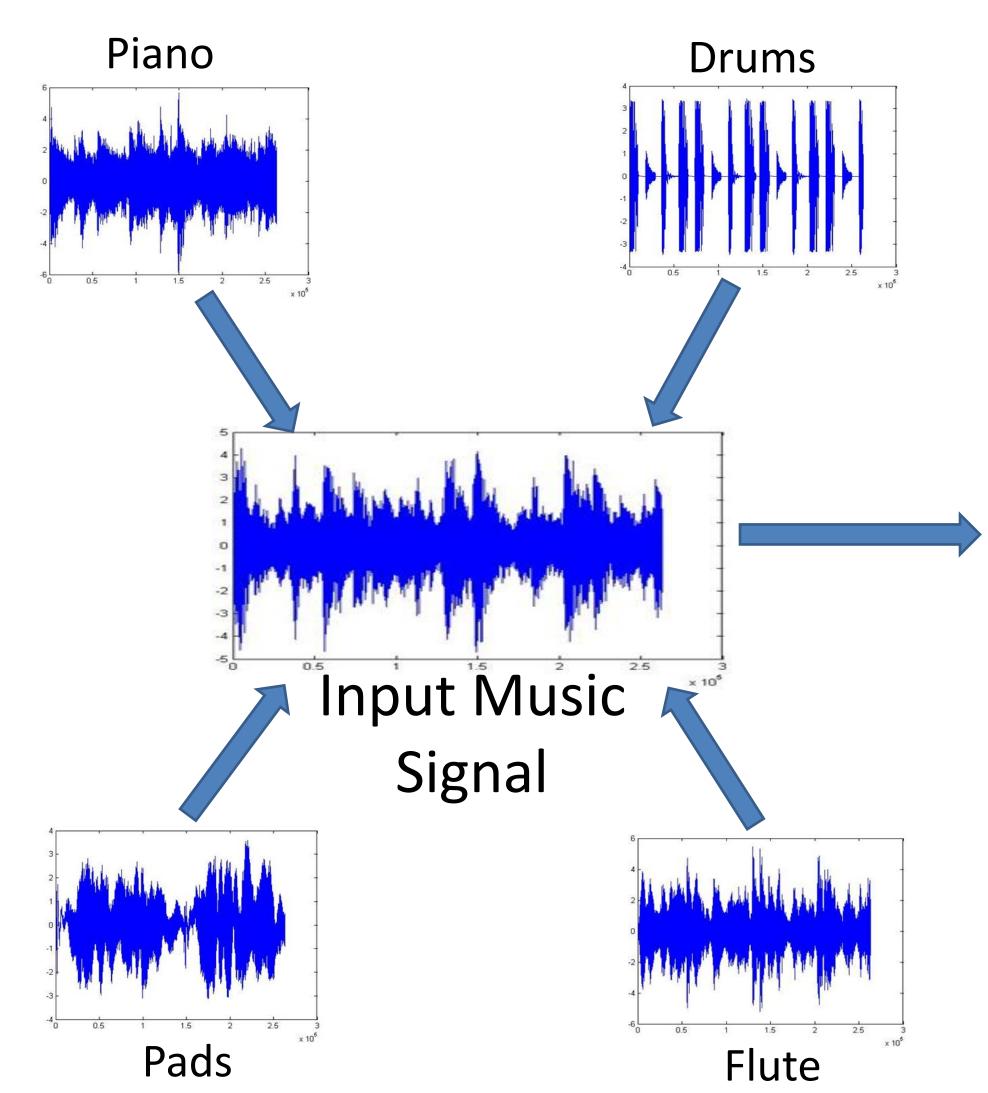
Methodology

A piece of music created with piano, pad, drum and flute elements was chosen.

They were sampled at a sampling frequency of 44100 Hz with a period of 7 seconds. The original signals of those components are shown in figure. They represents a random mixture of the individual independent components. Now to separate the mixture ICA algorithm is 2. used.

The generalized algorithm for ICA is as follows:

- 1. Centralize the data (i.e) X=X-E[X]
 This step is carried out to make the mean of the signal zero.
- 2. Whitening: This is to make the signals uncorrelated
- 3. Finding the maximized non-Gaussian points.



Whitening- Singular Value Decomposition (SVD) Uncorrelation is achieved by making the variance

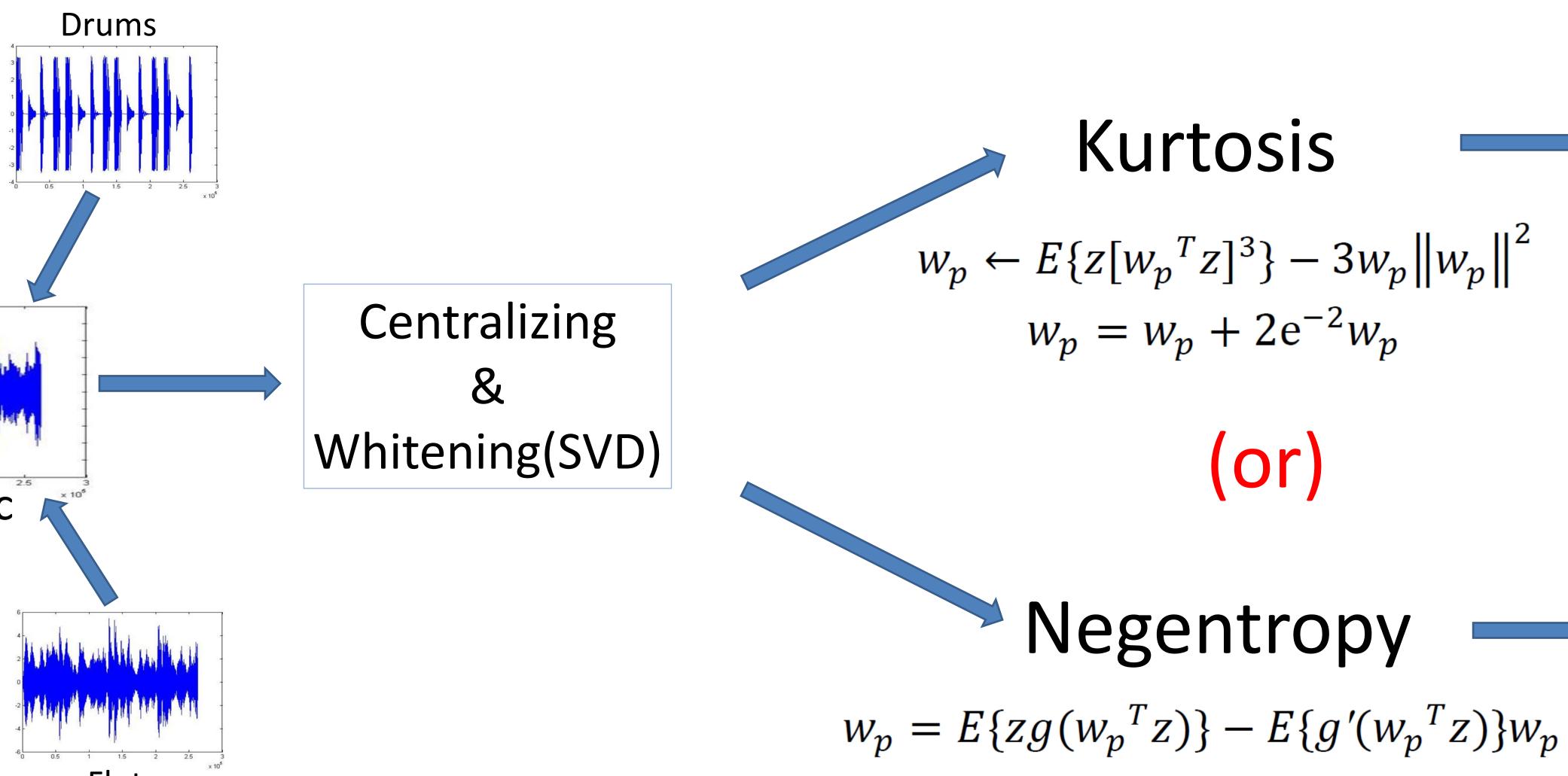
Uncorrelation is achieved by making the variance as unity and co-variance as identity by the following steps

- 1. Obtain covariance matrix of the centered data
- 2. Using SVD method, obtain Eigen vector corresponding to the lowest Eigen value of the covariance matrix.
- 3. Whitening is achieved by multiplying the Eigen vector (from step2) with centered data.

Maximization of Non Gaussianity:

The non-Gaussianity is measured based on two parameters.

- 1. By maximizing Kurtosis.
- 2. By maximizing Negentropy.



Results:

	SIR (dB)						
No. of sources	Kurtosis	Negentropy					
2	-4.2380	-9.3205					
3	-5.8434	-3.4968					
4	-5.4540	-2.6590					

Conclusions:

Through numerous iterations and analysis, it is understood that both Kurtosis and Negentropy gradients are efficient in separating the sources from the music mixture. When there are more number of sources (elements), Negentropy gives a better result, while the converse is true for Kurtosis.

The average SIR values obtained for all the cases considered is -3.95 dB for Kurtosis and -6.16 dB for negentropy. Kurtosis method is a lot simpler and much more efficient. However, for a complex multi element mixture, the negentropy method proves to be more capable.

Future Work:

To separate sources from a live music recording.

Acknowledgement:

Our sincerest gratitude to VIT University for their support.

References

[1]Aapo Hyvtirinen,		JuhaKarhunen,				Erkkioja:	
IndependentCo	mponent Analysis.	John	Wiley	&	Sons,	Inc.,	New
York, (2001).							

independent component analysis. IEEE trans. Neural Network 10(3), 626-634 (1999)

[3] Dan Kalman: A Singular Valuable Decomposition: The SVD of Matrix. Lecture document, The American Universit Washington(2002)

[4] Clifford G D: Singular Value Decomposition & Independent Component Analysis. J. Biomed. Signal and Image Proce. Spring, 1-

[5] P. Comon: Independent component analysis—a new concept. Signal Processing, 36:287–314 (1994)

[6] Bell AJ, Sejnowski T J: An information-maximization approach to blind separation and blind deconvolution. Neural Computation, 7(6):1129-1159(1995).

[7] Toch B, Lowe D, Saad D: Watermarking of audio signals using

ICA. In Third InternationalConference on Web Delivering of Music, 8, 71-74(2003).

[8] Barros A. Mansour A. Ohnishi N: Adaptive blind elimination of

[8] Barros A, Mansour A, Ohnishi N: Adaptive blind elimination of artifacts in ECG

signals. In Proceedings of I and ANN (1998).

[9] Makeig S, Bell A J, Jung T P, Sejnowski T J: Independent component analysis of electroencephalographic data. In Touretzky DS, Mozer MC, Hasselmo ME (eds.), Advances in Neural Information Processing Systems, volume 8. The MIT Press, 145-151(1996).

[10] Mohanaprasad K, Arulmozhivarman P: Comparison of Independent Component Analysis techniques for Acoustic Echo Cancellation during double talk scenario. Australian Journal of Basics and applied Sciences, 7(4), 108-113(2013).

[11] Hyv arinen A. Sparse code shrinkage: Denoising of nongaussian data by maximum likelihood estimation. Neural Computation 11(7):1739-1768(1999).