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Comparative Evaluation Of PCA And ICA Focussing On Blind Separation Of Noisy Speech Signals

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Abstract: Statistical analysis of *Blind source separation* problem has remained the main focus of mathematician and Engineers for the past two decades in diverse fields of science. The popular data mining technique of principle component analysis and fast revolutionary method of independent component analysis (ICA) has been deployed here as a solution to the above mentioned problem. Our contribution outlines the performance of these two statistical analysis tools in the case of super-gaussian linear noisy speech signal mixtures. Speech signals were mixed in the presence of noise and then these artificial noisy speech data were separated using the eigen-value decomposition algorithm of PCA and a novel algorithm of ICA based on the mathematical model of PCA and ICA. The quality of separated speech signals were comparatively evaluated using the SNR of each signal. All the visual and analytical results suggest that ICA retrieve all the independent components more faithfully than PCA in our noisy speech signals scenario.

Keyword: BSS, ICA, PCA, super-Gaussian, SNR.

1. INTRODUCTION

We start with a common application of *blind source separation* (BSS) problem which is termed as cocktail party effect. Among a certain number of voice sources present in a party, the ability to distinguish and focus on a specific source is the cocktail party effect. If there are microphones installed in the same room and the *number* of microphones is the same as the *number* of sources, then the recorded sounds of these microphones are observation mixtures of the source signals.

BSS is a wide-ranging method of finding the original source signals from the given linearly produced observation mixture signals with a very little or no knowledge of what are the sources and how they were mixed (Comon, 1994). We only know that the mixture is instantaneously created using linear addition of source waveforms and the original signals are independent statistically of each other *(Bell, 1995)*, (Theis., 2002).

There are many applications of this method in various fields of science especially biomedical sciences, financial analysis of data, extraction of features, speech and image recognition and design of its hardware for disable persons (Jung, 2001), *(Sarela, 2000)*, (Chalhoun 2001) Electrocardiogram (ECG), Electroencephalogram (EEG) and Magneto encephalography (MEG) are generally measured biomedical signals from clinical instruments, however these measured signals are mixtures of key activity signals plus unknown noise signals which are insignificant eye movements, muscle noise and instrument power noise. This problem can be easily solved by statistical methods of BSS.

Another good application area of this method is to separate the one signal from the intrusive other signals in CDMA.

Use of BSS methods for financial data analysis for hidden factors determination is also a good practice in business management. In business there are seasonal variations and factors due to holidays and annual variations. Also factors like price changes which have a abrupt effect on the consumer purchasing power can be thought as independent from each other. Therefore they can be estimated using BSS algorithms.

We are using this method for the most common application of speech signals scenario which is termed as cocktail party effect (Arons, 1992) (Stone 2004) Using statistical approach to this problem needs a transformation mechanism. There are a number of such linear transformation methods among which PCA and ICA are of most interest among researcher these days.

Use of PCA for the above mentioned problem of BSS has been carried out in different shapes by researchers from time to time. A noise reduction algorithm using PCA and a consistent underlying parameters estimation for speech signals is investigated in the work of Amin Haji Abholhassani (Moor, 1993). There are ECG applications where PCA algorithms

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have been useful, including, ST-T segment study for the discovery of myocardial ischemia, data compression, pulling out of atrial fibrillatory effect for comprehensive classification of atrial fibrillation, (Francisco Castells1*, 2007).

Similarly ICA has been widely used and quite a few algorithms has been designed and tested for the BSS problem. Estimation of independent component using ICA approach of minimization of mutual information, maximization of non-Gaussianity, projection pursuit and maximum likelihood is developed and deployed in many fields of science (Oja, 2000). It has found eminent position in the field of biomedical treatment and diagnosis process (R.Sarela, 2000).

In this research work we have compared the two methods of PCA & ICA for the task of separation of noisy speech signals mixture. For this purpose PCA algorithm of Eigen-value decomposition and ICA algorithm of fast ICA is used and then the output estimated components has been tested for speech quality and its noise reduction level. A matlab program for the SNR ratio of input and output signals has been developed. The output of this program shows that for realistic blind source separation ICA is more authentic and faithful than the PCA.

The rest of the paper is prepared as follows: section two provides the conceptual and mathematical background of PCA and ICA. It also explains the algorithms applied here for estimation of components. Section 3 includes the simulation results of the mixtures produce in matlab. And section 4 is the conclusion of the paper.

2. MATERIAL AND METHODS

Proposed model

To further explain the details of each statistical method let us define a linear PCA and ICA model on the basis of speech signals data as depicted in equation(1)

$$Y = Bs + n \text{---------- (1)}$$

The linear mixture Y is observed variables and the latent's variables s and mixing matrix B both are unknown. n is the noise added to the mixture.

Here columns of B are ICA bases vectors. We assume that the mean of Y $E\{Y\} = 0$ and covariance of Y is $C_y = E\{yy^t\}$. PCA finds an orthogonal square matrix W the rows of which are eigenvectors of the covariance matrix and we project our data onto this new set of axis which we discover statistically by using the measure of variance and leads to a set of orthogonal axis and so the signals are decorelated in a second order sense (Oja, 2000). This process is known as Eigen value decomposition in which we try to transform the mixture Y linearly such that the variances in the covariance matrix becomes equal to unity and the covariance's are equal to zero(Cardoso., 1998). So the covariance matrix,

$$C_y = E\{yy^t\} = I \text{.....(2)}$$

The blind source separation by ICA is an iterative process where a certain neuron is updated according to certain conditions and at the end we get a demixing matrix for example W which is the inverse of the mixing matrix B in equation(1) and the result is an estimation of the independent sources as $X = BY = s$. The condition is set according to a certain base which is Non-gaussianity in our case. If the sources probability distribution is not Gaussian we cannot estimate them at all. For Gaussian independent components the mixing matrix B in equation (1) is not identifiable. This was the main reason of late starting the ICA research because the scientist of classical probability theory assumes that the random variables are Gaussian distributed.

The Central Limit Theorem tells us that the probability distribution of summation of independent random variables are more Gaussian, thus, a sum of independent random variables generally has a distribution that is more Gaussian with respect to other random variables. ICA used this theorem in reverse order as if the sum of two or more random variables is Gaussian distributed then each of them will be non-gaussian in nature.

We need a demixing vector W which increases the Non-gaussianity of Y or give us the direction in which the Non-guassianity increases. If we maximize the Non-gaussianity, we will get the independent components eventually.

There are methods which can be used to measure nongaussianity like KURTOSIS (A. Hyv¨arinen, 2001) but it has drawbacks of outliers (Huber, 1985). So we use a simple modified version of NEGENTROPY or negative ENTROPY because it's easy and feasible to approximate (Cover, 1991),

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

Where Y_{gauss} is a gassian random variable of the same coviariance matrix as Y.

The approximation of NEGENTROPY based on maximum entropy can be generalized as:

$$J(y) = [E\{G(y)\} - E\{G(V)\}]^2 \text{ ……. (4)}$$

Here G is any non-quadratic function (Oja, 2000) and V is a Gaussian variable of zero mean and unit variance. Now we need an algorithm which maximizes this contrast function. For this purpose we have used a simple modified version according to our application of fixed point iterative algorithm which was invented by Hyvarinen and Oja (Hyv¨arinen., 1991). According to the inventor of fastICA algorithm, here are some choices that has proved to be very precise and robust for estimating the nongaussianity of a random variable

$$G_1(u) = \left({}^{1}/_{a_1}\right)\log(\cos(ha_1u)) \text{……. (5)}$$

$$G_2(u) = -exp\left(-{}^{u^2}/_{2}\right) \text{…… (6)}$$

Where $1 \leq a_1 \leq 2$

The equation in (4) is also known as CONTRAST function. The mixture matrix is first centered and then whitened by using the EVD techniques of PCA for first and second order moment dependencies (Huber, 1985). The PCA performs whitening of the data and dimensionality reduction.

In ICA analysis the popular algorithm of FASTICA is used which is fixed point iteration scheme for maximizing the nongaussianity of mixture signal (Stone. 2004)

There are two approaches of ICA estimation

(1) Deflation approach
(2) symmetric approach

The deflation approach which is a means of orthogonalizing the inputs that calculates the independent components one by one based on a Gram-Schmidt-like decorrelation (Douglas., 2003).

In many cases the implementation of sequential orthognalization e.g. deflationary approach is not suitable (Jolliffe., 2002). In symmetric approach no vectors is preferred over other and all of them are calculated symmetrically.

The output estimated components has been tested for speech quality and its noise reduction level. A matlab program for the SNR ratio of input and output signals has been developed.

3. RESULTS AND DISCUSSION

The experimental results of the PCA and ICA model for blind separation of linear noisy speech mixture can be explained by some simulation examples.

The simulation environment was made as follows:

First the speech mixtures of 2 to 6 speech sources was made artificially in matlab and the noise were added as an extra source to each mixture as white Gaussian noise. All the source signals from 26 different sources were made available to the simulation environment as (.wav) files. These wave files were all downloaded from a web source named as http://www.wavsource.com/. It was made sure that all these files are of same size. They are all of same bit resolution set to 16 bits and of same sampling frequency set to 8000Hz.

These source files were randomly picked by a matlab script in a group of 2,3,4,5 and 6 signals and normalized so that the data of each signal is adjusted and aligned with respect to its standard deviation.

These mixtures of source signals were analyzed by eigen value decomposition algorithms of PCA for estimation of principle components and finally derivation of source components in terms of these principle components. Also these mixtures of noisy speech signals were passed through fixed point fastICA algorithm proposed by Aapo Hayvarinen Hyv" arinen 2001) for estimation of independent components. The contrast function as given in equation (7) and (8) below were based on the entropy and negentropy of the independent components so that the more nongaussian the components becomes, its negentropy increases and its entropy decreases.

$$g_1(u) = \tanh(a_1u) \text{……(7)}$$

$$g_2(u) = uexp\left(-{}^{u^2}/_{2}\right) \text{…….(8)}$$

We present here some of many simulation results where we have recovered the source signals from their various mixtures using the algorithm of PCA and then the deflation fixed point algorithm of ICA. Using symmetric approach has the same effect as the deflation in our case.

The full dimension eigen-value decomposition for PCA is presented in Fig 2 for two recovered signals and the estimated independent components for ICA of the same source signals are depicted in Fig 3.

The **Fig. 1-4** shows the original source signals for comparing purposes.

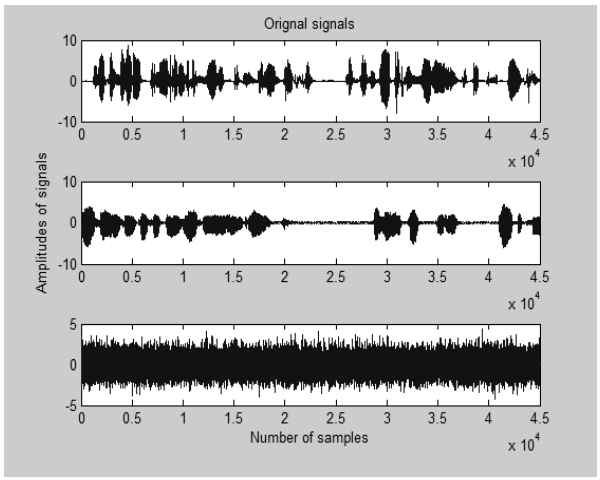


Figure 1 ***Original sources before mixing***

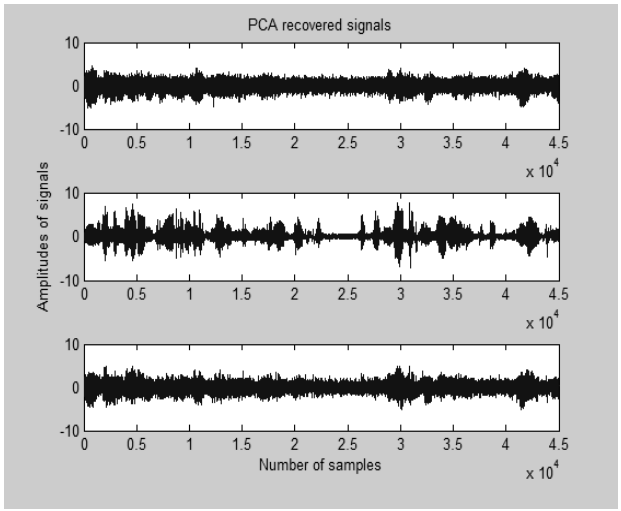


Figure 2 ***Recovered signals using PCA***

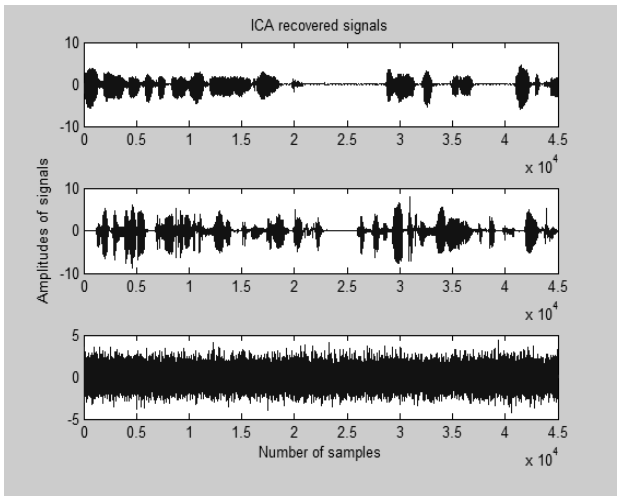


Figure 3 ***Recovered signals using ICA***

Now if we compare the two **Figures 2** and **3 with 1**, it is easily conceivable that the 1st signal of **Figure 3** matches with that 2nd signal of Figure 1. Also the 2nd signal waveform of Figure 3 matches with that of 1st signal waveform very much. On the other hand the PCA recovered signals of Figure 2 are not even matching to any of the original signal waveforms in Figure 1.

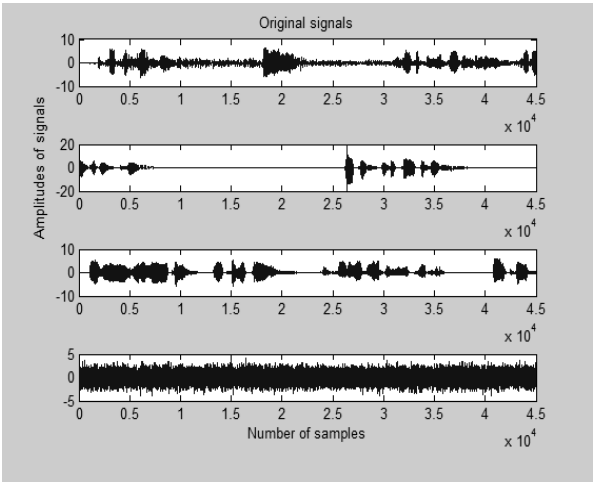


Figure 4 three original source signals before mixing

Similar is the case when we mixed three signals and tried to separate them by PCA and then ICA. ICA separated waveforms of **Fig. 4,6** agreed with the original signal waveforms of figure 4 up to a high level than the PCA separated signal waveforms.

From the above graphical results and many other simulated environments it can be easily concluded that due to strong algorithm of ICA and its underlying principles, ICA can betterly recover the source speech signals waveform than the PCA.

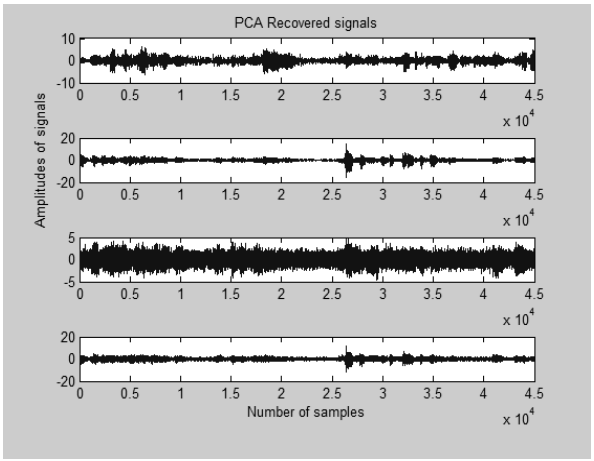


Figure 5 Three recovered signals using PCA

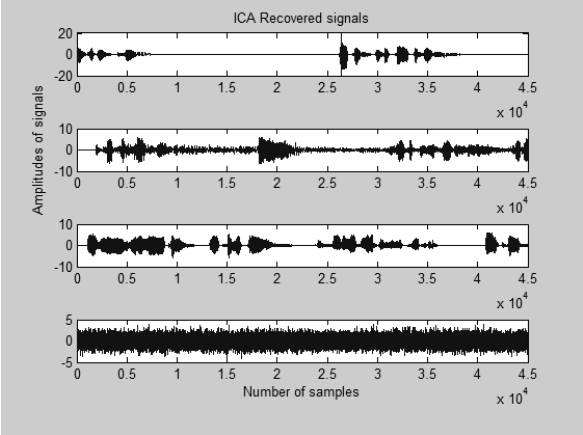


Figure 6 ***Three recovered signals using ICA***

For the calculation of speech signals quality signal to noise ratio is a powerful tool for comparison purposes. It calculates the quality of the enhanced version of separated speech signal quantitatively.

A matlab program was written to compute the SNR of the input file and the output file. The separated speech waveforms were analyzed for its quality by calculating the overall and segmented SNR of each signal by comparing it with the clean waveform of source signal waveform. First we calculate the input SNR by comparing the mixture signal with the clean file and then find the output SNR by comparing the PCA and ICA recovered signals with that of clean waveforms. Finally the delta SNR is computed by subtracting input SNR from the output.

Table1-4 shows the results of computed overall and segmented SNR for various mixture of speech signals. **Table 1** shows the computed input and delta SNR for a mixture of two signals.

Table 1 Input and delta SNR values for mixture of two signals

S.No.	Overall SNR_i	Seg SNR_i	Overall ΔSNR	Seg ΔSNR
FOR PCA				
1	-18.6755	-9.9912	7.3447	0.8045
2	-18.6755	-9.9912	7.3552	0.7825
FOR ICA				
1	-18.6755	-9.9912	10.9151	0.8811
2	-18.6755	-9.9912	8.2604	1.8401

Table 2 Input and delta SNR value for mixture of three signal

S.No.	Overall SNR_i	Seg SNR_i	Overall ΔSNR	Seg ΔSNR
For PCA				
1	-21.6972	-9.9559	8.3578	-0.0259
2	-21.6972	-9.9559	7.7935	0.08
3	-21.6972	-9.9559	9.0419	0.4901
For ICA				
1	-21.6972	-9.9559	12.2503	6.1568
2	-21.6972	-9.9559	10.1331	0.0408
3	-21.6972	-9.9559	7.762	0.1118

Table 3 Input and delta SNR value for mixture of four signals

S.No.	Overall SNR_i	Seg SNR_i	Overall ΔSNR	Seg ΔSNR
For PCA				
	-11.5876	-9.7755	1.5228	1.0203
	-11.5876	-9.7755	1.5032	1.1208
	-11.5876	-9.7755	1.3354	0.8849
	-11.5876	-9.7755	2.931	1.9823
For ICA				
	-11.5876	-9.7755	3.2729	2.0487
	-11.5876	-9.7755	2.6433	2.6929
	-11.5876	-9.7755	0.4459	0.7262
	-11.5876	-9.7755	-0.0839	0.2544

Similarly **Table 2, 3** and 4 shows the computed overall and segmented input and delta SNR values for a mixtures of 3,4 and 5 signals. By observing and comparing the overall and segmented delta SNR values of both PCA and ICA recovered signals. We can see that for each mixture the ICA delta SNR values are higher than the PCA by some factor. It means that the ICA due to its powerful algorithm is better suited for the task of blind separation of noisy speech signals.

4. CONCLUSION

PCA encode second order dependencies by rotating the axis of the data in the maximum covariance direction. It decorrelates the underlying components but does not deal with high degree dependencies. ICA is general method that separates the high degree dependencies as well as second order.

Table 4 Input and delta SNR value for mixture of five signals

S.No.	Overall SNR_i	Seg SNR_i	Overall ΔSNR	Seg ΔSNR
For PCA				
1	-20.3418	-10	9.2508	1.1926
2	-20.3418	-10	8.1165	0.6111
3	-20.3418	-10	9.4179	0.8794
4	-20.3418	-10	8.4616	0.4715
5	-20.3418	-10	8.8989	0.9104
For ICA				
1	-20.3418	-10	9.6098	2.285
2	-20.3418	-10	9.7982	3.0112
3	-20.3418	-10	9.1693	2.9503
4	-20.3418	-10	9.6222	0.4185
5	-20.3418	-10	9.0204	2.3192

ICA does not limit the axes of the data to orthogonal as PCA but it rather tries to place them in the direction of maximal of independencies of the data. Although PCA and ICA both shares some common features for example they both have the objective of producing generative models where an unsupervised learning algorithm is used still they both produce quite different results.

The super Gaussian nature of noisy speech is interesting because the observations of it represent a linear mixture of interesting events. ICA obtains all the information contains in the high order statistics by transforming the PCA ill-posed problem of decorrelated decompositions intowell-posed problem of independent decompositions. In other words if we believe that the hidden variables are statistically independent the ICA techniques for realistic blind source separation is more authentic and faithful than the PCA.

REFRENCES:

Arons. (1992). A review of the cocktail party effect. Journal of the America Voice I/O Society,12 , 35-50.

Bell, S. (1995). An information maximization approach to blind separation and blind deconvolution. Neural Comp,7 , 1129-1159.

Calhoun, V. T. (2001). spatial and temporal independent component analysis MRIdata with two task related waveforms. Proc.Intl.Soc.Mag,Reson.Med.9, 24-35.

Cardoso., J. (1998). Blind signal separation: Statisticalprinciples. Proceedings of IEEE conference on ciruit and systems,86, pp. 2009-2025.

Comon, P. (1994). Independent component analysis, A new concept? Signal Processing , 3 (36), 287-314.

Cover, T. M. (1991). Elements of Information Theory. John Wiley and sons.pp.425-475

Douglas., S. C. (2003). Blind source separation and independent component analysis: A crossroads of tools and ideas. 4th International Symposium on Independent component analysis and blind signal separation (ICA2003), 1-10. Nara, Japan.

Francisco, P. L. (2007). Principal Component Analysis in ECG Signal Processing. EURASIP Journal on Advances in Signal Processing , 225-234.

Huber, P. (1985). Projection pursuit. T. The Annals of Statistics,13(2) , 435-475.

Hyv¨arinen, J. K. (2000). Independent Component Analysis. In J.K.A. Hyv¨arinen, Independent Component Analysis 411-430. John Wiley Sons, 2001.

Hyv¨arinen., A. (1991). Beyond independent components. In Proc. Int. Conf on Articial Neural Networks,, (pp. 809–814). Edinburg, UK.

Jolliffe., I. T. (2002). Principal Component Analysis. In I. T. Jolliffe., Principal Component Analysis. NY: Springer-Verlag.pp.1214-1252

Jung, T. -P.-W. (2001). Imaging brain dynamics using independent component analysis. Proc. IEEE Transaction on signal processing 89,7, (pp. 1107-1122).

Moor. (1993). The singular value decomposition and laong and short spaces of noisy matrices. IEEE transaction on signals processing, 41, pp. 2826-2838.

Oja, A. H. (2000). Independent Component Analysis: Algorithms and Applications. Neural Networks, 13(4-5) ,411-430.

Papoulis., A. (1984). Probability, random variables and stochastic processes. (2nd Edition ed.). McGraw-Hill.pp. 425-455

Pekar, J. C. (2001). "Spatial and temporal independent component analysis of fMRI data with two task-related waveforms. ”Proc. Intl. Soc. Mag. Reson. Med. 9 , pp.24-45.

Sarela, J. V. (2000). Independent Component approaches to the analysis of EEG and MEG recordings. IEEE Trans. Biomed Eng.47 ,pp. 589-593.

Stone. (2004). Independent Component analysis. MIT press pp. 1214-1245.

Theis., F. (2002). Mathematics in Independent Component Analysis. Lagos Verlag. Transaction on signal processing. pp. 2510-2545

Vigário, R. S. (2000). Independent component approaches to the analysis of EEG and MEG recordings. IEEE Trans. Biomed. Eng. 47 , 589-593.