Study of ICA Algorithms for Separation of Speech Signals

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Abstract

The speech data can be Gaussian or non-Gaussian or both. If the data is Gaussian then the extraction and processing of speech data becomes computationally less complex. Due to this reason many existing techniques like factor analysis, Principle Component analysis, Gabor wavelets etc. assume the data to be Gaussian and processing involves only second order moments such as mean and variance. But if the data is non-Gaussian, then the extraction and processing of speech data becomes computationally more complex as it involves higher order moments like kurtosis and a new measure of non-Gaussianity known as negentropy. In this paper a recently developed technique, known as Independent Component Analysis, is applied to speech signal data and detailed analysis is done for step wise output of the algorithm. In the context of adaptive Neural Network, ICA method tries to train the non-Gaussianity instead of assuming the data to be Gaussian.
Keywords: Non Gaussuanity, ICA, Whitening, Dewhitening, Symmetric orthogonalization Deflationary orthogonalization

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I. INTRODUCTION

The other method for obtaining the features such as edges and textures, which is being used here is the ICA - a technique which uses higher order statistics of the given data. ICA has become increasingly popular in recent years because of its simplicity. These filters are similar to Gabor filters, but seen to be richer in the sense that their frequency response may be more complex. Inspite of this ICA is preferred for nongaussian data. ICA is a method for finding underlying factors or components from multivariate statistical data. ICA is different from the other existing methods as it looks for components that are both statistically independent and non-gaussian. It is a techniques to separate linearly mixed sources i.e Given a linear mixture of statistical independent sources, ICA recovers these source components by producing a mixing matrix, i.e Given X=AS, ICA, recovers s by producing A. Where X is known mixed signal, A is unknown mixing matrix an S is the source matrix.

Before actually applying ICA technique, preprocessing of the given data is done. The first step is to perform Principle Component Analysis (PCA). It gives the direction in which maximum data lies. It also provides the number of sources mixed; as during the analysis it was observed that number of PCA considered over threshold value of 1e-7 is equal to the number of speech signals mixed. The second step is to whiten or sphere the data. This means that we remove any correlation in the data and observed data is forced to be uncorrelated. As whitening makes the data to have unit variance with zero mean and zero correlation, then applying ICA means only to rotate this representation back to the original axis space. By rotating the axis and minimizing Gaussianity, ICA is able to recover the original sources which are statistical independent and non- Gaussian.

One of the simple and intuitive principle for estimating the model of ICA is based on maximization of non-gaussianity. Non-gaussianity is actually of paramount importance in ICA estimation. Without non gaussianity the estimation is not possible at all. Therefore it is not surprising that non gaussianity could be used as a leading principle in ICA estimation. The present research work mainly deals with the above algorithm studied from the reference and applied to different applications.

II. MEASURES OF NON-GAUSSIANITY

A. *Kurtosis*

To use non-gaussianity in ICA, one must have aquantitative measure of non-Gaussianity of random variable. In literature it has been proved that High order contrast function can be used for ICA. The classical measure of nongaussianity is kurtosis or the fourth order cumulant.

Hence the kurtosis is simply a normalized version of the fourth moment as for the gaussian case the fourth moment is equal to and hence kurt (y) =0. Thus for Gaussian variable kurtosis is zero but for most nongaussian random variable it is non-zero.

As the constraint is that the variance of y is equal to l. Geometrically, this means that vector q is constrained to be the unit circle on the 2-D plane. The optimization problem is now to find the maxima of the function on the unit circle. Let for simplicity assume that kurtosis is equal to 1. It is obvious (Delfasse and Loubaton, 1995) that the maxima are at the points when exactly one of the element vectors of q is zero and the other non-zero, because of the unit circle constraint the non-zero element must be equal to 1 or –1. But these points are exactly the ones when y equals one of the independent components S, and therefore the problem has been solved.

B. Negentropy

Negentropy is another very important measure of nongaussianity. To obtain a measure of non-gaussianity that is zero for a gaussian variable and always non negative for a random variable, a slightly modified version of the definition of differential entropy called negentropy can be used. Negentropy J is defined as

$$J(y) = H\,(Y_{gauss}) - H\,(y)$$

Where gauss Y is a gaussian random variable of the same covariance matrix as y. As the gaussian variable has the largest entropy among all the random variables, the negentropy for the random variables will always be positive and it is zero if and only if it is a gaussian variable. Moreover, the negentropy has an additional property that it is invariant for invertible transformation.

But the estimation of negentropy is difficult, as it would require an estimate of the pdf. Therefore in practice negentropy is approximated by using higher order moments.

Again the random variable y is assumed to be standardized i.e. zero mean and unit variance In order to increase the robustness another approach is to generalize the higher order cumulant approximation. So that it uses expectations of general non-quadratic functions. As a simple case, consider any two non-quadratic functions G1 and G2 so that G1 is odd and G2 is even and the following approximation is obtained.

The non-quadratic function G should be chosen such that it does not grow too fast. It will help to obtain more robust estimator. In literature the following choices of G have proved very useful –For the present research work, the first two non-linearities have been used. Thus this approximation gives a very good compromise between the properties of two classic nongaussianity measures – Kurtosis and negentropy. They are conceptually simple, fast to compute and robust. And therefore can be used as objective function in ICA method.

III. ESTIMATION OF INDEPENDENT COMPONENTS

In practice more than one independent component are required by running the algorithm, many times and using different initial points. The key to extending the method of maximum non gaussianity to estimate more independent component is based on the fact that the vectors corresponding to different independent components are orthogonal in the whitened space. Thus, to estimate several independent components, the algorithm has to be run several times with vectors w1,….wn, and to prevent different vectors from converging to the same maxima, vectors W must be Orthogonalized after every iteration. The following two methods are used for achieving decorrelation.[4]

A. Deflationary Orthogonalization

A simple way of orthogonalization is deflationary orthogonalization using Gram-Schmidt method. In this the independent components are estimated one by one. The orthogonalization used is

B. Symmetric Orthogonalization

In certain applications, it may be desirable to use a symmetric decorrelation, in which no vectors are privileged over others. This means that the vectors wi are not estimated one by one; instead they are estimated in parallel. The deflationary method has a drawback that the estimation errors in the first vectors are cumulated in the subsequent one by the orthogonalization. This drawback can be overcome by Symmetric orthogonalization; another advantage is that it computes all the ICs in parallel.
Symmetric orthogonalization is done by first doing the iterative step of one unit algorithm one every vector wi in parallel and afterwards orthogonalizing all the wi by symmetric method given as

IV. A FAST FIXED POINT ALGORITHM USING

A. Negentropy

The use of kurtosis can lead to a much faster method for maximizing negentropy as compared to the present day gradient methods. It is introduced as fixed point algorithm in the literature, by Appo Hyvarien and E.Ojha, for 1-D signals.

This algorithm finds a direction for a unit vector W such that the projection WTZ maximizes non-gaussianity. Non gaussianity is measured by the approximation of negentropy J(WTZ) , where the variance of WTZ must be constrained to unity. For whitened data this is equivalent to constraining the norm of W to be unity. FastICA is based on a fixed point iteration scheme for finding a maximum of the non gaussianity of WTZ. It can be derived as an approximative Newton iteration. The FastICA algorithm using negentropy combines the superior algorithmic properties resulting from the fixed point iteration with the preferable statistical properties due to negentropy. The FastICA algorithm stated by Aapo Hyvarinen and E.Oja was modified because during the course of the work it was observed that if the PCA is done first and then whitening, then the not only the computational complexity reduces but it greatly reduces the time taken by the algorithm to converges, especially for the speech data [1,2]. The application of ICA was extended to the different set of mixed speech signals. In this section the speech signals are considered to be the sources.

The algorithm was implemented for mixed speech signals separation, assuming that the mixing matrix was random. Hence every time the algorithm was run it was found that the mixed speech signal coefficient was different.
The algorithm was applied to many different sets of mixed speech signals. Out of which the results for one set of mixed speech signals is shown, for Deflationary approach with tanh(y) as nonlinearity and Symmetrical approach with tanh(y) as nonlinearity.

V. CONCLUSIONS

As the deflationary approach is finding out the ICA one by one definitely the number of iteration required for the convergence of ICA algorithm will be more for deflationary approach as compared to the symmetric approach. Whitening is difficult if the number of speech signals mixed is increased and hence the chance of getting the overlapped speech signals also increases. But still speech signals are audable which proves that ICA is stronger than whitening.

Depending of dewhitening matrix the speech signals are obtained. If the maximum number of dewhiteneing coefficient lies in second and/or fourth quadrant, then original speech signals is retrieved otherwise speech signals retrieved is negative.

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