The International Journal Of Engineering And Science (IJES)
|| Volume || 3 || Issue || 8 || Pages || 45-50 || 2014 ||
ISSN (e): 2319 – 1813 ISSN (p): 2319 – 1805

Single Channel Speech De-noising Using Kernel Independent Component Analysis (KICA)

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ABSTRACT
In this paper, a single channel speech De-noising algorithm is proposed by adding a noisy signal to the observed signal for single channel De-noising using independent component analysis and further the signals are separated. We illustrate Simulation result gives us better De-noising using ICA.

Keywords – *Independent component analysis, Framing, de-framing, Blind source separation.*

Date of Submission: 26 July 2014 — Date of Publication: 10 August 2014

I. INTRODUCTION

Speech communication plays an important role in communication system. But, in practice speech signals are distorted by background such as train noise, car noise, etc. De-noising of speech signals plays an important role to increase the quality and intelligibility of received speech signals.[7] In the past few decades number of speech de-noising methods has been proposed. Most of the methods work on multi channel speech de-noising where one of the channels is taken as primary input and others as a reference noisy signal. But, in practice for speech communication system only one channel is available, example mobile, hearing aid, tele - conferencing etc, thus single channel speech De-noising becomes a challenging task. Our work tends towards development of single channel speech enhancement.

There are various methods of speech de-noising like spectral subtraction based on estimation of noise, wavelet transform based on soft threshold parameters, etc [1] In this paper we are proposing speech de-noising method based on kernel ICA (Independent Component Analysis). ICA basically is a blind separation of statistically independent sources, assuming the linear mixing of the sources at the sensors. Normally ICA works on the multi-channel signals but here we are suppose to work on a single channel to perform the operation of ICA it is quite challenging one with a single channel to perform on ICA.

It is possible to transform one dimensional time series signal to multi dimensional time series by using a delay embedding technique. So that single channel can be converted to multi channel signal to perform ICA often. This transform of delay embedding technique produces non-linearity. ICA is a linear transformation technique so to overcome this non-linearity we introduce kernel tricks. Kernel tricks are used for mapping non-linear input space to linear feature space.

This paper is arranged as follows:-

Section 1- covers introduction to need of speech de-noising. Section 2- is the review of ICA (Independent Component Analysis). Section 3- is brief detailed information about kernel independent component analysis. Section 4- covers the proposed methodology of our paper. Section 5- gives us the simulation results and finally Section 6- is the conclusion of our paper.

II. REVIEW OF ICA

The problem of Blind Source separation boils down to finding a linear representation were components are statistically independent. ICA is recently invented method in which the goal is to find a linear representation of non-Gaussian data so that the components are statistically independent as possible. ICA differs from other method that it looks for the components that are both statistically independent and non-Gaussian.[2].

The basic ICA model, consist of mixed signals where $x(t)$ can be expressed as

$$x(t) = As(t)......... .(1)$$

Where A is unknown mixing matrix, and $s(t)$ represents source signals which are assumed to be statistically independent. ICA model describes that how the observed mixture signals $x(t)$ are generated by a process that uses the mixing matrix A to mix the source signals $s(t)$.

B.S.S of signal can be achieved by finding a de-mixing matrix W as shown in Figure 1.

$$\hat{s}(t) = Wx(t)......... .(2)$$

Signal $\hat{s}(t)$ is the estimation of source signals $s(t)$.

The recovered signals $\hat{s}(t)$ are almost equal to that of original signals $s(t)$ if $W = A^{-1}$ and $\hat{s}(t)$ are called as independent components.

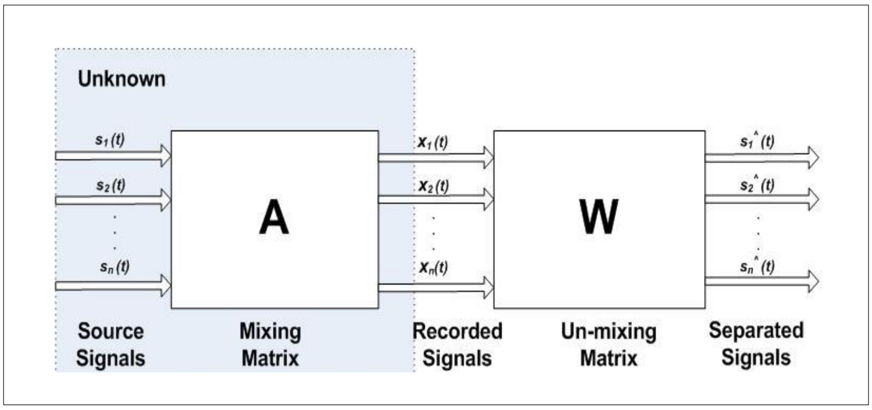

Figure 1:- Blind source separation (BSS) block diagram. $s(t)$ are the sources. $x(t)$ are the recordings, $\hat{s}(t)$ are the estimated sources A is mixing matrix and W is un-mixing matrix.

Before performing ICA some assumptions has to be considered.

III. STATISTICAL INDEPENDENCE

Defined in terms of probability density of the signals. Consider the joint probability density function (pdf) of $s1$ and $s2$ be P($s1$,$s2$). Let the marginal pdf of $s1$ and $s2$ be denoted by P1($s1$) andP$p2$($s2$) respectively. $s1$ and $s2$ are said to be independent if and only if the joint pdf can be expressed as;

$$P_{s1,s2}(s1, s2) = P1_{(s1)}P2(_{s2}) .... (3)$$

1. Un-correlatedness and Independence

s1 and s2 are un-correlatedness if their covariance C(*s1,s2) is zero.*

$$\begin{aligned} C(s1, s2) &= E\{(s1-ms1)(s2-ms2)\} \\ &= E\{s1s2-s1ms2-s2ms1+ms1ms2\} \\ &= E\{s1s2\}-E\{s1\}E\{s2\} \\ &= 0 \quad \ldots \ldots\ldots\ldots\ldots\ldots\ldots.. (4) \end{aligned}$$

Where $ms1$ is mean of the signal. Hence independent variables are always uncorrelated. But inverse is not true.

2. Non-Gaussianity

Central limit theorem states, that the sum of two independent signals usually has a distribution that is closer to Gaussian than distribution of two original signals. Thus, Gaussian is linear combination of many independent signals. To separate the signals again from their mixtures can be done by making linear signal transformation as non- Gaussian. Non-gaussianity is done when the data is centered (zero mean) and has variance equal to 1.

3. The sources being considered are statistically independent

Statistically independence is the feature that enables estimation of the independent components from the observations.

4. The independent components have non-Gaussian distribution

The second assumption is necessary because of the close link between Gaussianity and independence. It is impossible to separate Gaussian sources using the ICA framework because the sum of two or more Gaussian random variable is itself Gaussian.

5. The mixing matrix is invertible.

The third assumption is if the mixing matrix is not revertible then clearly the un-mixing matrix we seek to estimate does not even exist. If these three assumptions are satisfied, then it is possible to estimate the independent components.

Pre-processing technique:-

Before examining specific ICA algorithms, it is instructive to discuss preprocessing steps that are generally carried out before ICA.

1. Centering

A simple preprocessing steps that is commonly performed is to 'center' the observation vector x by subtracting its mean vector $m = E\{x\}$.

$$x_C = x - m \text{ ……………….. (5)}$$

This step simplifies ICA algorithms by allowing us to assume a zero mean. Once the un-mixing matrix has been estimated using the centered data, we can obtain the actual estimates of the independent components as follows:

$$\hat{s}(t) = A^{-1}(x_c + m) \text{ ………. (6)}$$

From this point onwards, all the observed vectors will be assumed centered. The mixing matrix, on the other hand, remains the same after this preprocessing so we can always do this without affecting the estimation of the mixing matrix.

2. Whitening

Another useful preprocessing strategy in ICA is to first whiten the observed variables. This means that before the application of the ICA algorithm (and after centering), we transform the observed vector x **linearly** so that we obtain a new vector $\hat{x}$, which is white i.e. its components are uncorrelated and their variances equal to unity.

I. KERNEL INDEPENDENT COMPONENT ANALYSIS

Kernel ICA (KICA) algorithm which can process the non-linear transformation is a method of combining KPCA with ICA. The basic idea of the KICA is to use the linear independent component analysis to deal with the sample data which is mapped to a high dimension feature space by using nonlinear characteristics. Kernel function confirms to Mercer condition. The idea of the KPCA is to use the linear principle component analysis to deal with the sample data which is mapped to a high dimension feature space by using a nonlinear mapping transformation.

Most commonly used kernel functions are:-

1. Radial Basics Gaussian Function as expressed in equation (7) produce infinite dimension in feature space

$$k(x, x') = \exp\left(-\frac{\|x - x'\|^2}{2\sigma^2}\right) \ldots\ldots\ldots\ldots\ldots (7)$$

And simplest

2. Polynomial Kernel Function as expressed in equation (8) having finite dimensions

$$k(x, y) = ((x.y) + c)^2 \ldots\ldots\ldots\ldots \ldots\ldots\ldots\ldots \ldots..(8)$$

II. PROPOSED METHODOLOGY

The proposed method for de-noising of single channel speech signal is shown in the Fig. no 2.

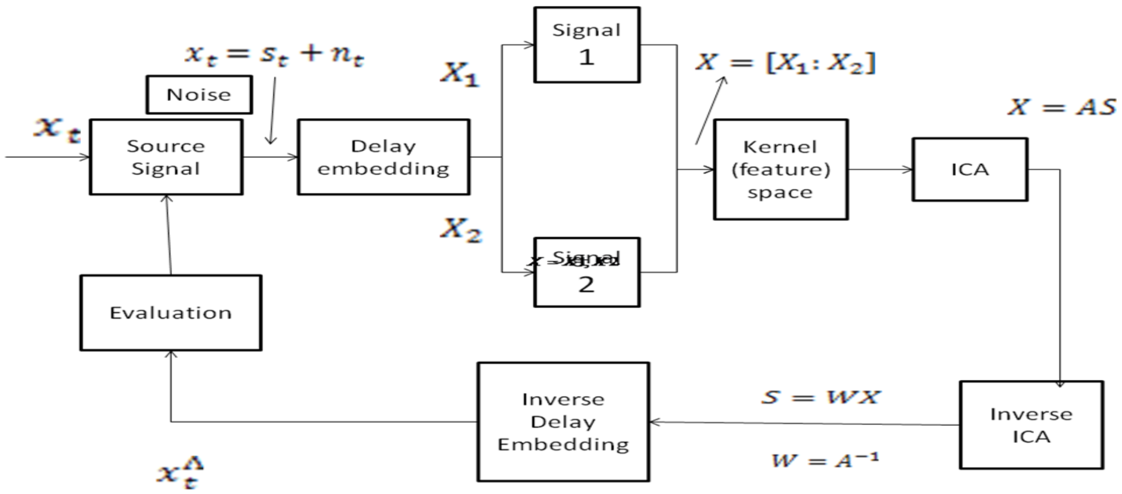

Figure 2- Principal Block Diagram of the ICA algorithm.

Assume that $x(t)$ is input speech having clean speech $s(t)$ and additive noise $n(t)$. Therefore the input signal would be presented as

$$x(t) = s(t) + n(t) \ldots\ldots\ldots \ldots\ldots\ldots\ldots ..(9)$$

$x(t)$ Consist of N observation obtain by windowing $x(t)$ having hamming window. Now we transfer one dimensional signal to multi dimensional by using Delay embedding.[3].

$$X = [x_1 \quad x_2 \quad . \quad . \quad x_M]^T \ldots\ldots\ldots (10)$$

Can be expressed as

$$X = \begin{bmatrix} x_1 & x_2 & . & x_N \\ x_2 & x_3 & . & x_{N+1} \\ . & . & . & . \\ x_D & x_{D+1} & . & x_K \end{bmatrix} \ldots\ldots\ldots\ldots (11)$$

$$X = D \times N \ldots\ldots\ldots \ldots\ldots\ldots \ldots\ldots\ldots \ldots\ldots\ldots .(12)$$

And

$$K = D + N - 1$$

Where D is the dimension and N is the number of observations.

IV. SIMULATION RESULTS

We perform a simulation to confirm the windowing and de-windowing concept practically. A speech signal in .wav format is taken as input signal (i.e. sp01.wav) with the help of windowing and de-windowing i.e. (framing and de-framing) is done on that speech signal of its over-sampled signaled and again the original speech signal is been obtained. Fig 3 shows the results of framing, de-framing, windowing and de-windowing.

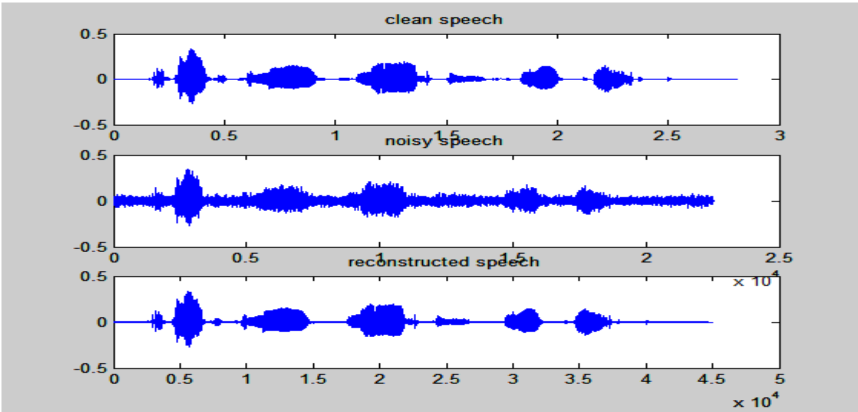

Figure 3 Simulation results.

III. CONCLUSION

In this paper, a single channel speech de-noising which is based on ICA is proposed to reconstruct original speech from noisy speech. Up to certain length of the speech a framing and de-framing is done to again get back the original single channel speech.

ACKNOWLEDGEMENTS

I am grateful to the department of Electronics and Communication Engineering for giving a lot of freedom, encouragement and guidance. I am also thankful to the Technical Staff of the DSP Laboratory, CCOEW, Pune for helping me during the experimental work.

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