International Journal of Scientific Engineering and Research (IJSER)
www.ijser.in
ISSN (Online): 2347-3878, Impact Factor (2014): 3.05

Acoustic Echo Canceller with Blind Source Separation

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Abstract: ***Acoustic echo cancellation (AEC) aim to suppress the echo picked up by the micro phone in a hand free communication system. There are so many techniques which are used for removing of acoustic echo from original speech signal. We propose to apply a independent component analysis (ICA) technique for separation of near end signal for echoes. Proposed method can be regarded as a optimal coupling of linear echo canceller, multi channel source separation and non linear echo canceller under a proposed blind source separation technique.***

Keywords: BSS, ICA, ECHO Canceller

1. Introduction

Echo is the repetition of a waveform due to reflection from points where characteristics of medium through which wave propagate changes. Echo signal are expressed as delayed and distorted version of sound which is reflected back to source of sound[1]. The acoustic echo canceller system is used in hand free system to reduce the undesired echoes which come due to loudspeaker and microphone coupling. There are two types of echoes in communication system.

1. **Acoustic Echo**
2. **Hybrid Echoes**

IJSER15265

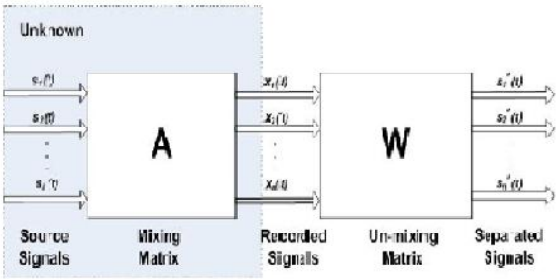
In this paper we will discuss acoustic echoes with BSS. In BSS the word blind source separation refers to fact that we do not know how signal are mixed or how they are generated. We are estimating the original source signal without knowing the parameter of mixing or filtering process. There is no guarantee that estimated or extracted signal have exactly the same waveform as ||Double talk detection is a typical problem that is deeply concerned in AEC implementation to detect the situation in which both sides talk simultaneously. During the double talk period, the residual error increases due to local speech so that the AEC stability bound decreases and the algorithm may start to diverge [3].

ICA is essentially a method for extracting individual signal from mixture. In this paper independent component analysis is introduced as a widely used technique for solving blind source separation (BSS) problem. Independent component analysis (ICA) is a recently developed method in which the goal is to find a linear representation of nongaussian data so that the components are statistically independent, or as independent as possible [4].

2. Blind Source Separation (BSS)

BSS is a technique in which I have a no. of sources emitting signal which are interfering with another situation in a crowded room with many people speaking at the same time. Interfering the electromagnetic wave from mobile phones or cross talk from brainwave originating from different area of the brain. In each of their situations of mixed signal are often incomprehensible and it is of interest to separate the individual signal. This is the goal of blind source separation.. ICA the general idea is to separate the signal. Assuming the original underlying source signal are mutually independently distributed and uncorrelated the signal for higher order moment and produce a non orthogonal basis. ICA is very closely related to the method called blind source separation (BSS) or blind signal separation. A “source” means here an original signal, i.e. independent component, like the speaker. “Blind” we no very little, if anything, on the make little assumptions on the source ethod, perhaps the most widely used, for ce separation.

Block Diagram of BSS



3. Objective

Blind source separation is one of foremost used technique in this era, with its application in variety of sectors. The aim of this technique is to separate the mixed signal which are new to world. Fast ICA algorithm for linear independent analysis in term of accuracy and complexity. Fast ICA algorithm is neural means parallel and distributive.ICA is the extension of PCA.PCA is used as preprocessing step of ICA technique. The main objective is Convergence speed of Fast ICA algorithm is superior from other.

4. Fast ICA Algorithm

1) Let Preprocess the data
2) Before the Fast ICA algorithm can be applied, the input vector data xX should be centered and whitened.

a) Centering the data

The input data **X** is centered by computing the mean of each component of **X** and subtracting that mean. This has the effect of making each component have zero mean. Thus:

$\mathbf{X \leftarrow X\text{-}E\{X\}}$

b) Whitening the data

Whitening the data involves linearly transforming the data so that the new components are uncorrelated and have variance one. If $\tilde{\mathbf{X}}$ is the whitened data, then the covariance of the whitened data is the identity matrix:

$\mathbf{E\{XX^T\}=I}$

This can be done using Eigen value decomposition of the covariance matrix of the data: $\mathbf{E\{XX^T\}=EDE^T}$ where E is the matrix of eigenvectors and D is the diagonal matrix of eigenvalues. Once eigenvalue decomposition is done, the whitened data is:

$\mathbf{X \leftarrow ED^{-1/2}E^TX}$

3) Single component extraction

The iterative algorithm finds the direction for the weight vector **W** maximizing the non-Gaussianity of the projection $\mathbf{W^TX}$ for the data X. The function is the derivative of a nonquadratic nonlinearity function f(u).

Randomize the initial weight vector **W**, Let $\mathbf{W^+ \leftarrow E\{X_g(W^TX)^T\}\text{-}E\{g'(W^T)\}}$where means averaging over all column-vectors of matrix X.

Let $\mathbf{W \leftarrow W^+/||W^+||}$

If not converged, go back to 2

4) Multiple Component Extraction

The single unit iterative algorithm only estimates one of the independent components, to estimate more the algorithm must repeated, and the projection vectors decorrelated. Although Hyvärinen provides several ways of decorrelating results, the simplest multiple unit algorithms follows. 1 indicates a column vector of 1's with dimension M.

5. Algorithm

Input: C Number of desired components
Input: $\mathbf{X \epsilon R^{N*M}}$ Matrix, where each column represents an N-dimensional sample, where C<N
Output: $\mathbf{W \epsilon R^{C*N}}$ Un-mixing matrix where each row projects X onto into independent component.
Output: $\mathbf{S \epsilon R^{C*M}}$ Independent components matrix, with M columns representing a sample with C dimensions.

For in 1 to c:
$\mathbf{W_P}$ ← Random vector of length N
while $\mathbf{W_P}$ changes
$\mathbf{W_P \leftarrow 1/M\{Xg(W_P^TX)\}}$
$\mathbf{W_P \leftarrow W_P\text{-}\sum W_P^TW_JW_J}$
$\mathbf{W_P \leftarrow W_P/||W_P||}$

6. Properties

[1] The convergence is cubic (or at least quadratic), under the assumption of the ICA data model. This is in contrast to ordinary ICA algorithms based on (stochastic) gradient descent methods, where the convergence is only linear. This means a very fast convergence, as has been confirmed by simulations and experiments on real data.
[2] Contrary to gradient-based algorithms, there are no steps size parameters to choose. This means that the algorithm is easy to use.
[3] The algorithm finds directly independent components of (practically) any non-Gaussian distribution using any nonlinearity g. This is in contrast to many algorithms, where some estimate of the probability distribution function has to be first available, and the nonlinearity must be chosen accordingly.
[4] The performance of the method can be optimized by choosing a suitable nonlinearity g. In particular, one can obtain algorithms that are robust and/or of minimum.

7. Conclusion and Future Work

Blind source separation using independent component analysis is a difficult task when based on the signal. There are many approaches in BSS technique to estimate the signals but FAST ICA ALGORITHM is better because of its accuracy and convergence speed. Example of real world, in CDMA system information sequence of different users remain statistical independent and PN sequence of different users keep uncorrelated each other. So ICA helps to achieve blind estimation of information sequence and PN sequence. Application of ICA is in different areas such as telecommunication, biomedical signal processing, audio processing and image processing etc.

If you are using Word, use either the Microsoft Equation Editor or the MathType add-on (http://www.mathtype.com) for equations in your paper (Insert | Object | Create New | Microsoft Equation or MathType Equation). “Float over text” should not be selected.

Number equations consecutively with equation numbers in parentheses flush with the right margin, as in (1). First use the equation editor to create the equation. Then select the “Equation” markup style. Press the tab key and write the equation number in parentheses.

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