Asian Journal of Applied Science and Technology (AJAST)
(Open Access Quarterly International Journal) Volume 2, Issue 2, Pages 926-932, April-June 2018

Reckoning of Pristine Signal and Meliorating Algorithm Constancy by Overcoming Ambiguity

P.Venkateswari[1] and Mrs. M. Navaneetha Velammal[2]

[1]PG Scholar, [2]Associate Professor
[1,2]Francis Xavier Engineering College, Tirunelveli, Tamilnadu, India.

Article Received: 27 January 2018 *Article Accepted: 23 February 2018* *Article Published: 25 May 2018*

ABSTRACT

Reckoning pristine signal and meliorating algorithm constancy by overcoming various ambiguities. The pristine signal is need to be reckoned because it might get convolutively mixed. Here the pristine signals are reckoned through internal measures only, without having any prior knowledge about mixing process or pristine components and hence it is called to be Blind Source Separation. Using Reproducing Kernel Hilbert Space based Independent Component Analysis (ICA) statistically independent vectors are reckoned. The existing algorithm uses Fast ICA algorithm, however it has some limitation such as lack in computation time and high computation load and there is a need of some other algorithm to limit the required matches. In order to improve the quality and computation speed of the separated speech, a permutation algorithm based on Dynamic Time Warping (DTW) with Reproducing Kernel Hilbert Space (RKHS) algorithm is proposed. Using Linear Predictive Cepstrum Coefficient, feature parameters can be extracted. The nearby frequency bins might have high similar features which leads to permutation ambiguity thereby DTW is used to compare them and generate an adjusting matrix by which algorithm's constancy get meliorated. The score value is used for reckoning the quality level by adapting Perceptual Estimation of Speech Quality.

Keywords: Blind Source Separation, Reproducing Kernel Hilbert Space, Linear Predictive Cepstrum Coefficient, Dynamic time warping, Perceptual Estimation of Speech Quality.

1. INTRODUCTION

1.1 Need of Blind Source Separation

Blind Source Separation (G.D. Clifford 2008) finds application in various domain like speech signal enhancement, speech signal processing, image denoising. The problem considered here is the cocktail party problem. It was first defined by Colin Cherry in 1953, considering trouble of perceiving speech in a noisy environment.

1.2 Independent Component Analysis

Independent Component Analysis is one of the beneficial approaches for the cocktail party problem (Yoel Ainhoren 2008). ICA analyzes each of the components independently to estimate independent source signals. The idea is to separate original signal from convolutively mixed signal (Madhab Pal 2013). The pristine signal might get convolutively mixed by noise, reverberation and interference (Ma. Guadalupe Lopez P 2011). Here it is given as

A = WS

A→ Represents mixed Signal

W→ Represents Instantaneous mixing matrix

S→ Represents Pristine Signal.

The instantaneous mixing matrix is obtained by generating random matrix (Madhab Pal 2013) and multiplying it with the transpose of each of the input signal. Using ICA the unmixing matrix (Kostas Kokkinakis, 2008) is reckoned. It is represented as

B = ZA

B→ Represents Reckoned Signal

Z→ Represents unmixing matrix

A→ Represents mixed Signal

Here the unmixing matrix is obtained by using RKHS which makes use of canonical correlation which is used to calculate higher order dependencies between the signals. In this, Linear Predictive Cepstrum Coefficient is employed to find the coefficients of the autoregressive model (Madhab Pal 2013) that is used to minimize the difference between the pristine and reckoned values of the signal. These reckoned signals will experience two types of ambiguities such as scaling and permutation which gets overcome by performing scaling compensation and adapting Dynamic Time Warping technology

2. PROBLEM DESCRIPTION AND PREVIOUS WORK

2.1 Second-order technique fails

In previous ICA's, signals are supposed to be non-Gaussian probability distribution. The modified ICA can use either Gaussian or non-Gaussian probability distributed signals because most signals in our daily life are in Gaussian distribution. ICA can be employed on time domain or frequency domain but in time domain high computation and parameter adjustments are required at the deconvolutive filter that will lead to practical limitations, so perform ICA on frequency domain. The Fast ICA (Aws Al-Qaisi 2015) algorithm has some limitation such as lack in computation time and high computation load (Kostas Kokkinakis 2008) and there is a need of some other algorithm to limit the required matches. BSS involves minimization of mutual information but second order technique fails to reduce the redundancy between the mutual information, so for redundancy reduction higher order statistics should be taken into account. The idea is estimation of cumulants and polyspectra. But it is computationally difficult and it might result in inaccurate results when cumulants higher than fourth order are ignored. The Taylor series expansions based on these nonlinearities yield higher-order terms. But it does not guarantee that the higher-order statistics yielded by the nonlinearities are related to the calculation of statistical dependency.

2.2 Methods to solve the Permutation problem

The first approach is by taking correlation between envelopes of signals from adjacent frequency bins (Asano et al., 2003), but this approach fails because in above discussed approach only some envelope information can be extracted to match and some detailed information might be ignored. Another method is reckoning Direction of Arrival of signals to overcome the permutation ambiguity (Ikram and Morgan, 2002), but this method requires the sources to be far apart from the microphones. This DOA can estimate the source's direction from the separation matrix, but at low frequencies the direction of sources cannot be reckoned (Sawada et al., 2004).

3. PROPOSED METHOD

3.1 Reproducing Kernel Hilbert Space

Reproducing Kernel Hilbert Space can be applied for reckoning unmixing matrix and the source signals. RKHS makes use of contrast functions in canonical correlation by which higher order statistics can be calculated and it removes the redundancy existing between the information. This unmixing matrix will maximize the statistical independency of the reckoned original sources. The Inverse Short Time Fourier Transform is used with reckoned signal to reconstruct the pristine time-domain signals.

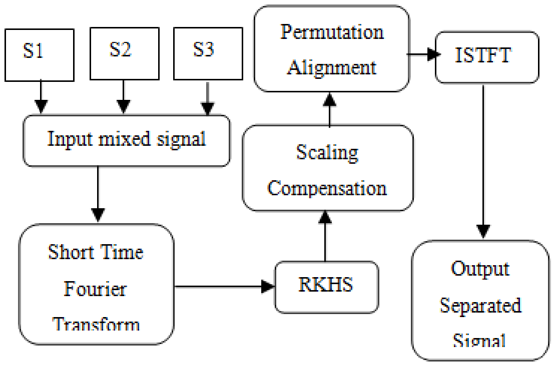

Fig3.1 Block diagram of Proposed System

ISTFT-Inverse Short Time Fourier Transform

3.2 Frame blocking and windowing

Frame blocking method is employed to extract the feature parameters. Each of the frames is windowed to minimize the discontinuities of the signal at both the ends of frame. The windowing process can be expressed as follows:

$$\hat{J}(f_k, \tau) = J(f_k, \tau)\omega(n)$$

Where $\hat{J}(f_k, \tau)$ denotes the windowed independent components in the k^{th} frequency bin, and $\omega(n)$ denotes Hamming window.

3.3 Linear Predictive Coding Coefficient (LPCC)

The feature extraction is used to represent speech signal into a finite number of measures of signal. Each feature represents the spectrum of speech signal in a windowed frame. The coefficients taken from auto regressive model minimizes the difference between reckoned and pristine value. LPC analysis is an effective method to estimate the parameters of speech signals. Cepstral analysis is the process of finding the Cepstrum of a speech sequence. Cepstral coefficients can be reckoned from the LPC via a set of recursive procedure. The Cepstral coefficients obtained in this way are called Linear Predictive Cepstral Coefficients (LPCC). Thereby the resulting speech signals are linear combination of the previous p samples. Therefore, the speech production model can also be defined as linear prediction model or the autoregressive model.

3.4 Dynamic Time Warping (DTW)

Dynamic Time Warping is used for reckoning of distance between two time series. A time series is a list of samples taken from a pristine signal and they are ordered by the time at which their corresponding samples were obtained. The matching distance can be used between two time series to resample one of them followed by making comparison in sample-by-sample. The drawback here is, that it does not produce intuitive results because the compared samples may not correspond well. The DTW algorithm removes this discrepancy by reckoning the optimal alignments between the sample points in the two time series. The algorithm is called "time warping" because it warps the axes of the two time series in such a way that the corresponding samples will appear at same location on a common time axis.

3.5 Perceptual Estimation of Speech Quality (PESQ)

Quality evaluation for speech processing is important in the field of BSS when speech signal is taken into account, which has been growing in the recent years. For convolutive BSS, the quality of algorithms is reckoned using signal-to-interference ratio but it requires the knowledge of mixing conditions. It is found to be difficult to determine the signal-to-interference ratio in an real time environment. So Perceptual Estimation of Speech Quality is adapted. In PESQ, both the reference signal REF and degraded signal DEG will be sampled at f_k Hz. It can measure both NB-PESQ (narrowband PESQ measure) as well as WB-PESQ (wideband PESQ measure). It supports both modes through the MODE parameter. Using the score value PESQ can be determined.

4. SIMULATED RESULTS

Step1:

Initially three input signals were given and spectrogram representation is given in x-y axis as Time Vs Amplitude

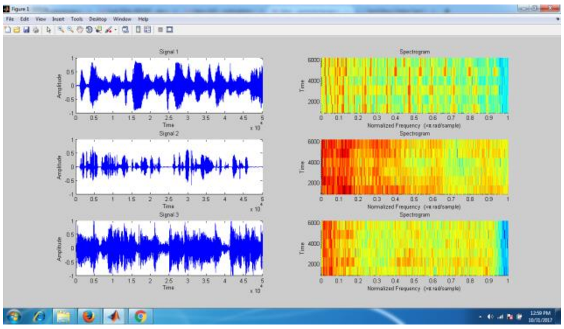

Fig 4.1 Input signals gets read and their spectrogram representation

The input signal is taken at range <1x5121 double>, no clipping is done at this range to obtain full fidelity of the signal. If the signal exceeds the range then audio is clipped at '-1' to '+1'

Step2:

The three input signals were mixed and their spectrogram representation in x-y axis as follows

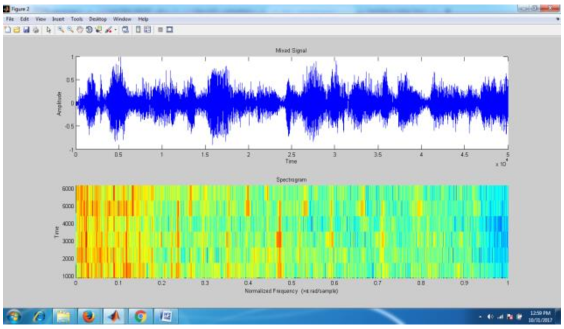

Fig 4.2 Mixed input signal

The mixing value range is at ‘3x50000double’. The mixing signal obtained by generating random matrix from the given input signal and multiplying it with the transpose of each input signal.

Step3:

Here the three mixed signal gets separated. Using RKHS the higher order feature parameters are extracted and ambiguity gets overcome by DTW.

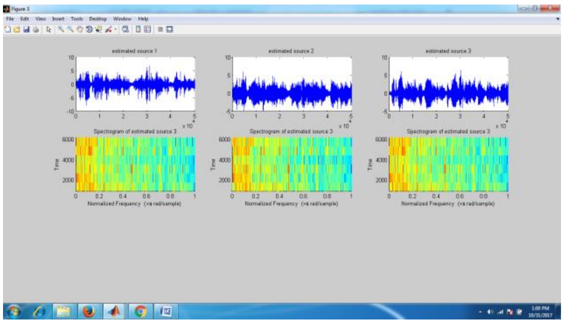

Fig4.3 Separation of target signal from the mixed signal

Step4:

Here the PESQ was estimated for the original and the estimated signal. The PESQ is obtained by taking the score value. The score value is estimated for all the three signals.

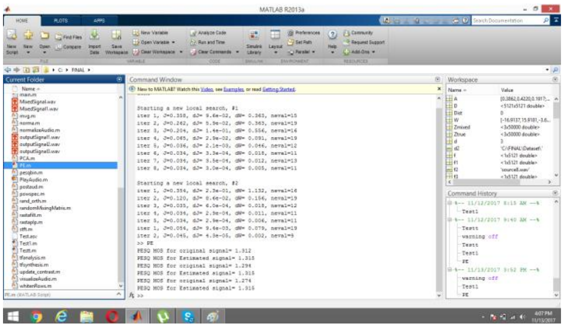

Fig4.4 Perceptual Estimation of Speech Quality

5. CONCLUSION

Blind Source Separation is performed by using Reproductive Kernel Hilbert Space which makes use of contrast function on canonical correlation, by which higher order statistics can be reckoned. The feature parameters are extracted using Linear Predictive Cepstral Coefficient (LPCC). During estimation of pristine signal, there arises permutation ambiguity problem which gets overcome by adapting Dynamic Time Warping. Quality of signal estimated by PESQ which makes use of score values.

ACKNOWLEDGEMENT

This work was supported in part by Department of Science & Technology (DST), FIST Program at Francis Xavier Engineering College, Tirunelveli, Tamilnadu, India.

REFERENCES

[1] Asano F, Ikeda S, Ogawa M, 2003. Combined approach of array processing and independent component analysis for blind separation of acoustic signals. Speech Audio Process., IEEE.

[2] N. Muthukumaran and R. Ravi, 'Hardware Implementation of Architecture Techniques for Fast Efficient loss less Image Compression System', Wireless Personal Communications, Volume. 90, No. 3, pp. 1291-1315, October 2016.

[3] Kattepur .A.K, Lie .J.P, Sattar F. High fidelity blind source separation of speech signals.,17th European Signal Processing Conference (EUSIPCO 2009)

[4] N. Muthukumaran and R. Ravi, 'The Performance Analysis of Fast Efficient Lossless Satellite Image Compression and Decompression for Wavelet Based Algorithm', Wireless Personal Communications, Volume. 81, No. 2, pp. 839-859, March 2015.

[5] Jaun S. Calderon Piedras, Alvaro D Orjuela - Canon, David A. Sanabria – Quiroga. Blind Source Separation from Single channel Audio Recording using ICA algorithms Image, Signal Processing and Artificial Vision on Symposium 2014

[6] N. Muthukumaran and R. Ravi, 'VLSI Implementations of Compressive Image Acquisition using Block Based Compression Algorithm', The International Arab Journal of Information Technology, vol. 12, no. 4, pp. 333-339, July 2015.

[7] Clifford. G.D -Blind Source Separation: Principal & Independent Component Analysis Biomedical Signal and Image Processing Spring 2008

[8] N. Muthukumaran and R. Ravi, 'Simulation Based VLSI Implementation of Fast Efficient Lossless Image Compression System using Simplified Adjusted Binary Code & Golumb Rice Code', World Academy of Science, Engineering and Technology, Volume. 8, No. 9, pp.1603-1606, 2014.

[9] M. Ruban Kingston, N. Muthukumaran, R. Ravi, 'A Novel Scheme of CMOS VCO Design with reduce number of Transistors using 180nm CAD Tool', International Journal of Applied Engineering Research, Volume. 10, No. 14, pp. 11934-11938, 2015.

[10] R. Sudhashree, N. Muthukumaran, 'Analysis of Low Complexity Memory Footprint Reduction for Delay and Area Efficient Realization of 2D FIR Filter', International Journal of Applied Engineering Research, Vol. 10, No. 20, pp. 16101-16105, 2015.

[11] N. Muthukumaran and R. Ravi, 'Design and analysis of VLSI based FELICS Algorithm for lossless Image Compression', International Journal of Advanced Research in Technology, Vol. 2, No. 3, pp. 115-119, March 2012.

[12] B. Manoj Kumar and N. Muthukumaran, 'Design of Low power high Speed CASCADED Double Tail Comparator', International Journal of Advanced Research in Biology Engineering Science and Technology, Vol. 2, No. 4, pp.18-22, June 2016.

[13] N. Muthukumaran, 'Analyzing Throughput of MANET with Reduced Packet Loss', Wireless Personal Communications, Vol. 97, No. 1, pp. 565-578, November 2017.

[14] P. Venkateswari, E. Jebitha Steffy, Dr. N. Muthukumaran, 'License Plate cognizance by Ocular Character Perception', International Research Journal of Engineering and Technology, Vol. 5, No. 2, pp. 536-542, February 2018.

[15] N. Muthukumaran, Mrs R.Sonya, Dr. Rajashekhara and V. Chitra, 'Computation of Optimum ATC Using Generator Participation Factor in Deregulated System', International Journal of Advanced Research Trends in Engineering and Technology, Vol. 4, No. 1, pp. 8-11, January 2017.

[16] Ms. A. Aruna, Ms.Y.Bibisha Mol, Ms.G.Delcy, Dr. N. Muthukumaran, 'Arduino Powered Obstacles Avoidance for Visually Impaired Person', Asian Journal of Applied Science and Technology, Vol. 2, No. 2, pp. 101-106, April 2018.

[17] Mrs. S. Murine Sharmili, Dr. N. Muthukumaran, 'Performance Analysis of Elevation & Building Contours Image using K-Mean Clustering with Mathematical Morphology and SVM', Asian Journal of Applied Science and Technology, Vol. 2, No. 2, pp. 80-85, April 2018.

[18] J. Keziah, N. Muthukumaran, 'Design of K Band Transmitting Antenna for Harbor Surveillance Radar Application', International Journal on Applications in Electrical and Electronics Engineering, Vol. 2, No. 5, pp. 16-20, May 2016.

[19] B. Renuka, B. Sivaranjani, A. Maha Lakshmi, Dr. N. Muthukumaran, 'Automatic Enemy Detecting Defense Robot by using Face Detection Technique', Asian Journal of Applied Science and Technology, Vol. 2, No. 2, pp. 495-501, April 2018.

[20] Ms. Mary Varsha Peter, Ms. V. Priya, Ms. H. Petchammal, Dr. N. Muthukumaran, 'Finger Print Based Smart Voting System', Asian Journal of Applied Science and Technology, Vol. 2, No. 2, pp. 357-361, April 2018.

[21] N. Muthukumaran and R. Ravi, 'Quad Tree Decomposition based Analysis of Compressed Image Data Communication for Lossy and Lossless using WSN', World Academy of Science, Engineering and Technology, Volume. 8, No. 9, pp. 1543-1549, 2014.

[22] Aws Al-Qaisi -Blind Source Separation of Mixed Noisy Audio Signals Using an Improved Fast ICA-Journal of Applied Sciences ©2015