Comparison of Independent Component Analysis techniques for Acoustic Echo Cancellation during Double Talk scenario.

Mohanaprasad Kothandaraman
VIT University

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Comparison of Independent Component Analysis techniques for Acoustic Echo Cancellation during Double Talk scenario

[1]Mohanaprasad Kothandaraman, [2]Dr.Arulmozhivarman Pachaiyappan,

[1,2]School of Electronics Engineering, VIT University, Vellore, Tamil Nadu, India 632002.

Abstract: To cancel the acoustic echo present in various communication environments, adaptive filters are used. But this fails during double talk situation. Independent component analysis (ICA) can cancel echo effectively without the need of double talk detectors by separating far-end speech and near-end speech signals. This paper has implemented one of the ICA techniques – Maximization of nongaussianity using kurtosis with the help of gradient and Fast ICA algorithm. The result shows that Gradient algorithm produce improvement of 5 dB in Echo return loss enhancement (ERLE) compared to Fast ICA algorithm. Similarly the execution time is less in Fast ICA compared to Gradient algorithm.

Key words: ICA (Independent Component Analysis), Fast ICA, Gradient, Kurtosis, ERLE (Echo Return Loss Enhancement),

INTRODUCTION

In Hands free conversation undesired acoustic echo is a major problem. This echo occurs due to continuous coupling between microphone and loud speaker, which reduces the quality of speech. To cancel this echo, a variety of adaptive algorithm has been found and implemented (B. Widrow and M.E. Hoff, 1960; S. Haykin, 2002, p.230). These algorithms work well only in single talk situation, (i.e.) either the far end speaker or the near end speaker will be active at particular time. In the case of double talk situation, these algorithms fail to find the echo path and hence the echo is not cancelled completely. Solution was found to rectify this problem that is by slowing down or freezing the adaptation. Hence many researchers focused on the double talk detector algorithm (J. Benesty, *et al*, 2000; H. Bunchner, *et al*, 2006; T. Vanwatershoot, *et al*, 2007)

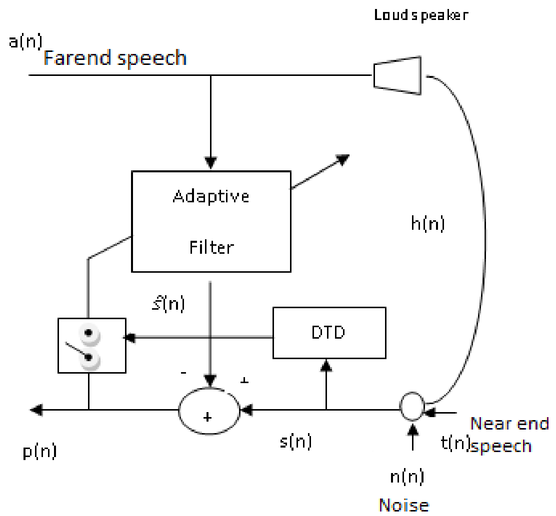

Fig. 1: The Echo canceller circuits with double talk detection.

In figure.1 where a(n) is a far-end speech signal, t(n) is a near-end speech signal, n(n) is a background noise signal, s(n) is a received microphone signal, ŝ(n) a estimated echo path signal, h(n) is a acoustic echo path and p(n) is a error signal and it is given by a equation

$$p(n) = s(n) - \hat{s}(n) \tag{1}$$

Which depicts when double talk is detected by the DTD (Double Talk Detector), it turns off the filter co-efficient updation of the adaptive filter and vice-versa (T.S. Wada and B-H. Juang, 2008). But this method does

Corresponding Author: Dr.P.Arulmozhivarman, School of Electronics Engineering, VIT University, Vellore, Tamil Nadu, India 632002.
Tel: 09443311373, E-mail: parulmozhivarman@vit.ac.in

not solve the problem completely. To improve the efficiency of acoustic echo canceller during double talk the proposed method uses Blind signal separation (BSS) or Independent Component analysis (ICA) (A. Hyvärinen, *et al*, 2001) . This method is suggested because without the use of double talk detector and adaptive filter, echo can be cancelled effectively.

ICA is a method for finding underlying factors or components from multidimensional statistical data. It differs from other methods by looking its components as statistically independent and non –Gaussian. ICA is applied in speech-processing, array processing, medical data and finance. There are four ICA estimation principles they are (i) Non linear de-correlation, (ii) Maximization of nongaussianity, (iii) Maximum likely-hood ratio and (iv) Minimization of mutual information. Maximization of non-gaussianity has two techniques they are a) Kurtosis and b) Negentropy. In this paper Maximization of non-gaussianity is implemented by using kurtosis through gradient and Fast ICA algorithms.

MATERIALS AND METHODS

Independent Component Analysis:

Definition:

The basics ICA model is shown in figure 2 and ICA definition is given as

$$X = A * S \tag{2}$$

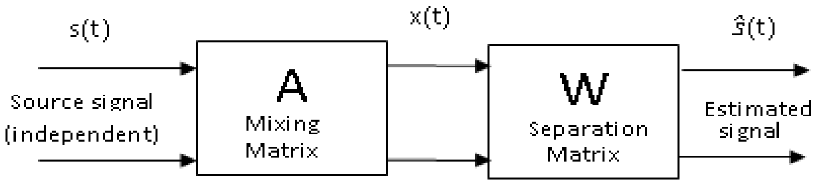

Fig. 2: ICA model

Where, X is the linear combination of mixing matrix and source signal. A is unknown mixing matrix and S is source signal assumed to be mutually independent (s_1, s_2 ...s_n) (Ganesh R. Naik and Dinesh K. Kumar, 2011). The source signal is estimated by using separation matrix $W = A^{-1}$ is given by

$$S = A^{-1} * X \quad \text{(OR)} \quad S = W * X \tag{3}$$

'W' cannot be determined exactly because matrix A is unknown, yet it can be determined by adaptively calculating the W vectors and setting up a cost function which maximizes the nongaussianity by using kurtosis and negentropy.

ICA by Maximization of nongaussianity:

Maximization of nongaussianity is the simplest ICA estimation principle (Tahir Ahmad and Mahdi Ghanbari, 2011). The components of nongaussian are independent; this is given by central limit theorem which is defined as the distribution of a sum of independent random variable tends towards a Gaussian distribution. This is illustrated in the figure 3.

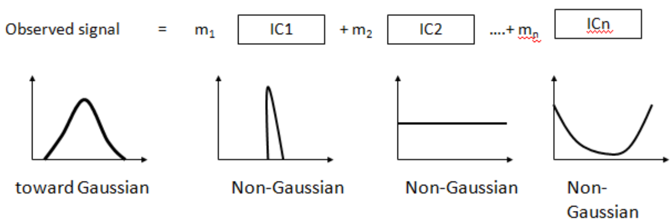

Fig. 3: Central Limit Theorem

Kurtosis:

Measurement of Nongaussianity of random variable for ICA is kurtosis. Kurtosis is the fourth order cumulant and it is given by

$$Kurt(Y) = E\{(X-\mu)^4\} - 3(E\{(X-\mu)\}\}^2 \quad (4)$$

Where μ is the mean. The equation [4] can also be modified as

$$Kurt(Y) = E\{Y^4\} - 3(E\{Y^2\})^2 \quad (5)$$

Since y assumed to unit variance, the equation [5] can be simplified further more as

$$Kurt(Y) = E\{Y^4\} - 3 \quad (6)$$

This modified equation is the normalized version of the fourth order moment. $E\{Y^4\}$

The result can be interpreted as

Kurtosis > 0 for super Gaussian (Lepto kurtosis)
Kurtosis = 0 for Gaussian (normal kurtosis)
Kurtosis < 0 for Sub-Gaussian (Platy kurtosis).
This is shown in figure 4.

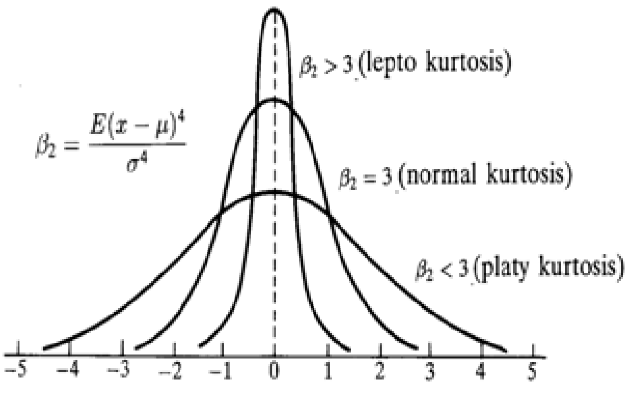

Fig. 4: Types of kurtosis

The results conclude that kurtosis is 0 for Gaussian random variables and non-zero for non-Gaussian random variables.

ICA formulation for Echo Cancellation:

Acoustic echo cancellation problem has been address by the researcher (T.S. Wada and B-H. Juang, 2009) through ICA based Maximum likelihood estimation. Here we focussed on echo cancellation using kurtosis with gradient and fast ICA implementation. Echo is a delayed version of far-end speech signal and a weighted sum of echo components a(n-m), m= 0,1..M-1, and it is given by equation

$$h(n) = \sum_{m=0}^{M-1} q_0^T a(n-m) \quad (7)$$

q_0 is the room impulse response

Microphone signal s(n) is a sum of near end speech signal t(n) and echo h(n) is given by

$$s(n) = h(n) + t(n) \quad (8)$$

a(n) is assumed to be a zero mean input signal. Near-end speech signal is assumed to be zero mean and statistically independent with the system input a(n). Formulated linear model for ICA is given by

$$\begin{bmatrix} a(n) \\ s(n) \end{bmatrix} = \begin{bmatrix} I & 0 \\ q_0^T & 1 \end{bmatrix} \begin{bmatrix} a(n) \\ t(n) \end{bmatrix} \tag{9}$$

Where I denotes the identity matrix. With the help of above model t(n) is separated by using

$$\begin{bmatrix} a(n) \\ \hat{t}(n) \end{bmatrix} = \hat{Q} \begin{bmatrix} a(n) \\ s(n) \end{bmatrix} \tag{10}$$

$$\hat{Q} = \begin{bmatrix} I & 0 \\ \hat{q}_t & p \end{bmatrix} \tag{11}$$

Where $\hat{q}^t = [\hat{q}_0, \hat{q}_1, ...\hat{q}_{m-1}]^t$

$$\hat{t}(n) = \hat{q}^t a(n) + ps(n) \tag{12}$$

Where p is nonzero scalar quantity which is set to 1, a(n) and $\hat{t}(n)$are as independent as possible.

Ica Algorithms:

Gradient Algorithm using Kurtosis:

Modified gradient algorithm using kurtosis is as follows

The steps involved for solving ICA problem, we need to perform pre-processing of the observed data using whitening process

1. Centre the data to make its mean zero

$$X = \hat{X} - m_X \tag{13}$$

2. Whiten the observed data X to give Z = VX assume X is zero mean, where $V = D^{-1/2}E^T$ is a whitening matrix. D & E is the Eigen value & Eigen vector matrix of covariance matrix of X,

i.e. $E[XX^T] = EDE^T$ (14)

Finally Z is given as follow $Z = VX = D^{-1/2}E^T X$ (15)

3. Choose the initial random mixing matrix W and orthogonalize it.
4. Compute direction in which absolute value of kurtosis of $Y = W^T Z$ is increasing.
5. Let L=1 Take a random initial vector W(0) of norm 1.
6. Let $W(L) = W(L-1) + \alpha(L) * sign(Kurt(W(L-1)^T Z)) * E[Z(W(L-1)^T Z)^3]$ (16)
7. Orthogonalize using $W(L) = W(L) / \|W(L)\|$ (17)
8. If $|W(L)^T W(L-1)|$ is not close enough to 1 then L= L+1 and go back to step 6 otherwise output is the vector W(L).(i.e.) Move the vector W in that direction

Fast ICA Algorithm using Kurtosis:

Modified Fast ICA algorithm using kurtosis is as follows

1. Centre the data to make its mean zero

$$X = \hat{X} - m_X \tag{18}$$

2. Whiten the observed data X to give Z = VX assume X is zero mean, where $V = D^{-1/2}E^T$ is a whitening matrix. D & E is the Eigen value & Eigen vector matrix of covariance matrix of X,

i.e. $E[XX^T] = EDE^T$ (19)

Finally Z is given as follow $Z = VX = D^{-1/2}E^T X$ (20)

3. Choose m, no of ICAs to estimate and set counter L=1
4. Choose an initial guess of unit norm of W_L (randomly)
5. Let $W_L = E\{Z[W_L^T Z]^3\} - 3W_L\|W_L\|^2$ (21)
6. Do deflation de-correlation using

$$W_L = W_L - \sum_{j=1}^{L-1}(W_L^T W_L)W_L$$

(22)

7. Orthogonalize using $W(L) = W(L)/\|W(L)\|$ (23)
8. If W_L has not converged $|\langle W_L^{K+1}, W_L^K\rangle| \neq 1$, goto step 5
9. Set L=L+1, if $L \leq m$ go back to step 4.

RESULTS AND DISCUSSIONS

Simulation Process:

Acoustic Echo with double talk scenario, a set of recorded speech signals are taken from Harvard University data base and the acoustic echo cancellation studies using ICA techniques are demonstrated using Matlab. In this recorded signal male voice is used as far-end speech signal and female voice is used as near-end speech signal. These two signals were observed for 20 sec in which for 10 sec these two signals were active at the same time. This is considered to be microphone signal and this moment is taken as double talk situation. Then a random matrix is multiplied with the microphone signal. The resultant is applied as input to the gradient kurtosis and fast ICA algorithm. The reduction of echo from the above process can be found by using Echo Return Loss Enhancement (ERLE) and Correlation coefficient.

ERLE in dB can be calculated using the given equation

$$ERLE = 10\log_{10} E[s(n)^2]/E[p(n)^2] \tag{24}$$

Where s(n) is the received echo in the microphone signal and p(n) is the echo residue after cancellation. The literature review showed that, if ERLE is between 30-40 db then echo cancellation is optimum. Higher value of ERLE higher the cancellation of echo.

Correlation coefficient can be calculated using the equation

$$Corrcoef(X,Y) = Co\text{var}iance(X,Y)/\sqrt{Co\text{var}iance(X,X)Co\text{var}iance(Y,Y)} \tag{25}$$

When the correlation coefficient reaches 1 then the two signals are highly correlated. When the value of correlation coefficient reaches nearly zero then there is no correlation between the two signals.

Result for kurtosis maximization using gradient and Fast ICA method:

Table 1: shows the performance comparison of Acoustic echo cancellation under double talk situation addressed using gradient and Fast ICA Kurtosis method.

Echo signal with Double talk Condition	Kurtosis using Gradient					Kurtosis using Fast ICA				
	ERLE (in dB)	Correlation Coefficient		Execution time	No of iteration	ERLE (in dB)	Correlation Coefficient		Execution time	No of iteration
		Input	Output				Input	Output		
	30-35	0.86	0.002	16 seconds	12	28-30	0.86	0.0037	0.6-0.7 seconds	7

From the above table we observed that Fast ICA provides better computation time compared with gradient ICA with minimum no of iteration. At the same time gradient ICA provides best ERLE compared with Fast ICA.

Conclusion:

This paper clearly shows that there is a 5 db increase in ERLE in gradient based ICA when compared with Fast ICA. In Fast ICA the Convergence speed is very higher than gradient ICA. Furthermore similar comparison can be performed using other ICA techniques.

REFERENCES

Benesty, J., D.R. Morgan and J.H. Cho, 2000. “A new class of doubletalk detectors based on cross-correlation,” IEEE Trans. Speech Audio Process., 8(3): 168-172.

Buchner, H., J. Benesty, T. Gansler and W. Kellermann, 2006. “Robust extended multidelay filter and double-talk detector for acoustic echo cancellation,” IEEE Trans. Audio, Speech, Lang. Process., 14(5): 1633-1644.

Ganesh, R., Naik and Dinesh K. Kumar, 2011. An overview of independent component analysis and its application, Informatica., pp: 63-81.

Haykin, S., 2002. Adaptive Filter Theory, 4th ed. Upper Saddle River, NJ: Prentice-Hall, chapter-5.

Hyvärinen, A., J. Karhunen and E. Oja, 2001. Independent Component Analysis. New York: Wiley, pp: 165-202.

Tahir Ahmad and Mahdi Ghanbari, 2011. “A Review of Independent Component Analysis (ICA) Based on Kurtosis Contrast Function” Australian Journal of Basic and Applied Sciences, 5(9): 1747-1755 ISSN 1991-8178.

Van Waterschoot, T., G. Rombouts, P. Verhoeve and M. Moonen, 2007. “Double-talk-robust prediction error identification algorithms for acoustic echo cancellation,” IEEE Trans. Signal Process., 55(3): 846-858.

Wada, S., and B.-H. Juang, 2009. “Acoustic echo cancellation based on independent component analysis and integrated residual echo enhancement” in Proc. IEEE WASPAA, Oct. pp: 205-208.

Wada, S., and B.-H. Juang, 2012. “Enhancement of Residual Echo for Robust Acoustic Echo Cancellation” in IEEE Trans. Audio, Speech and Language processing. pp: 175-180.

Wada, T.S., and B - H. Juang, 2008. “Towards robust acoustic echo cancellation during double-talk and near-end background noise via enhancement of residual echo” in *Proc.* IEEE ICASSP, pp: 253-256.

Widrow, B. and M.E. Hoff Tr., 1960. “Adaptive switching circuits,” in *IRE Wescon Conv.Rec*., pp: 96-104.

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