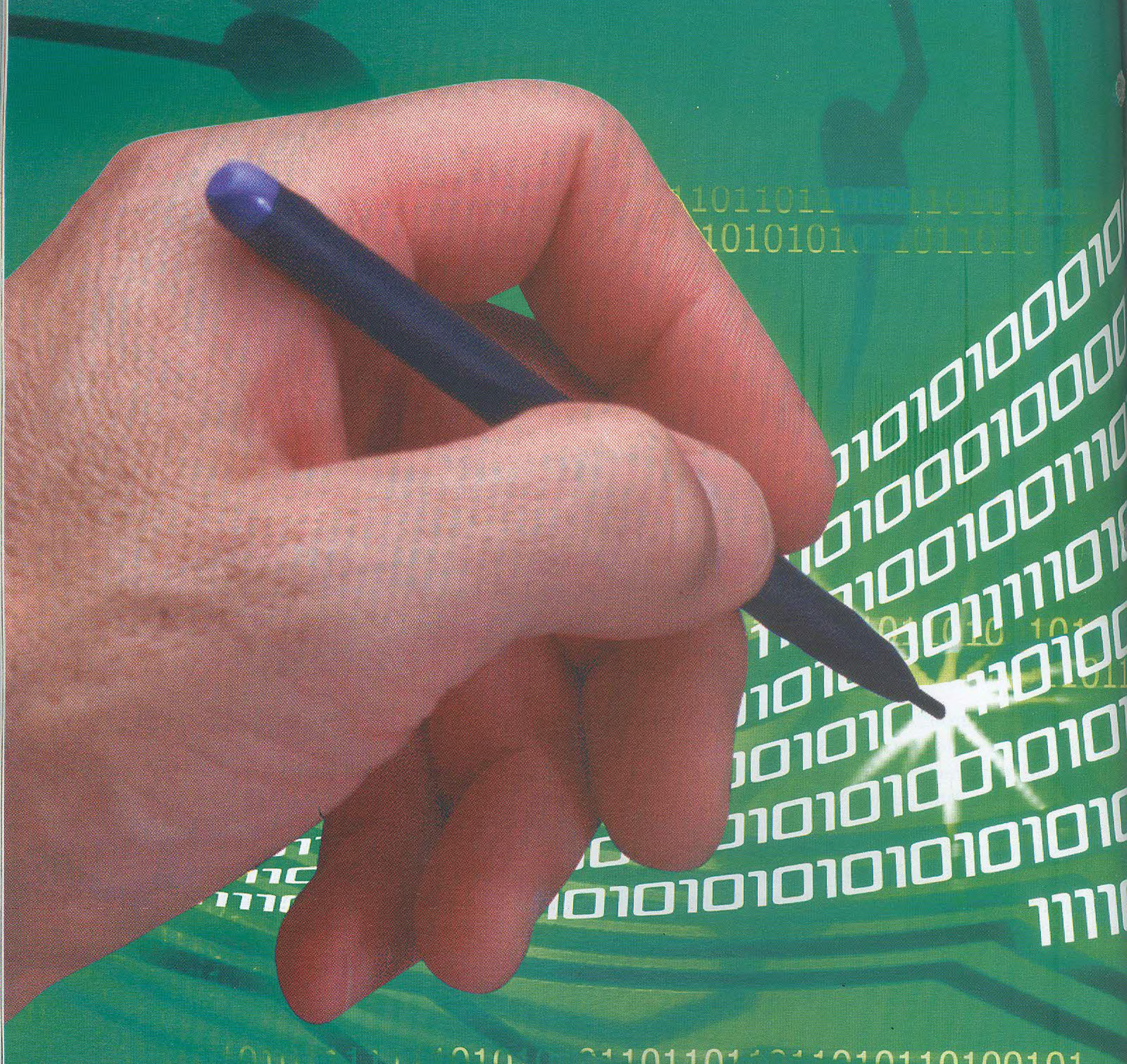
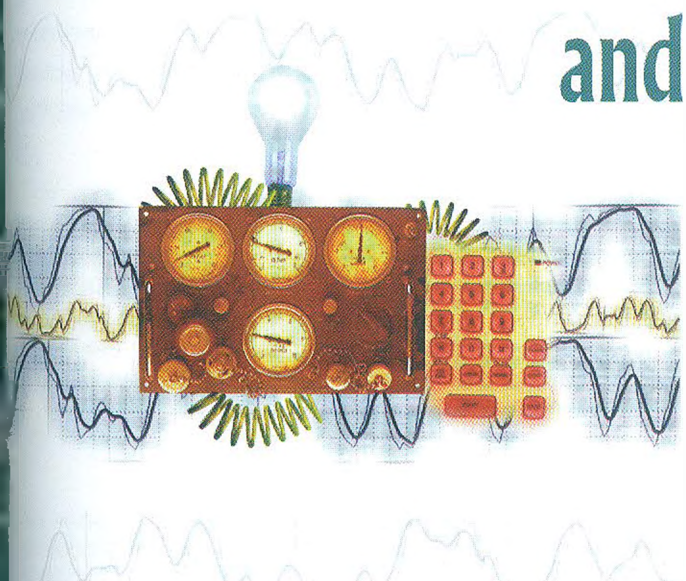
Nonlinear
Blind Source Separation



Using Cross power spectral density and Cross Correlation

ABSTRACT

Blind source separation (BSS) is an emerging technique, which enables the extraction of target speech from observed mixed speeches. BSS algorithms are based on restoring the statistical independence of the source signals. This paper is concerned with blind source separation of convolutive mixtures of acoustic signals, especially speech in which the source signals are instantaneously mixed in unknown nonlinear processes. A statistical and computational technique, called independent component analysis (ICA), used for BSS, is examined by achieving maximum entropy at the output end, also cross power spectral density and cross correlation coefficient of observed unmixed signal and source signal is check to conform the received signal is the original signal. Effectiveness of the proposed method is validated in BSS of male and female voice signals gets signal to interference ratio 8.75 with the proposed algorithm, 7.03 and 5.12 with algorithm based on Mutual Information and non-causal FIR filter. This paper synthesizes proposed algorithm on Field Programmable Gate Array (FPGA) - Xilinx VIRTEX V1000E that executes at the maximum frequency of 12.288 MHz. The performance comparisons between the proposed and another two ICA-related FPGA implementations [4][5], show that the proposed FPGA implementation has potential in performing complicated algorithms on large volume data sets.



Mrs. Sangeeta Nakhate, Dr. R. P. Singh, Dr. A. Somkuwar

INTRODUCTION

While transmission of data in the information technology it is difficult to recognize the original data due to interference of other signals having same spectrum, for that purpose separation of unknown (blind) signal is necessary, same thing is applicable for voice communication (like in cell phone online chat etc.) where Speech recognition is the fundamental need, but with existing systems for source separation based on Filters, the recognition rate drops rapidly when more than one person is speaking or there is background noise . The problem of separation of blind sources from their convolutive mixture has received much attention due to number of applications in Information Technology, Communication and medical signal processing. Blind Source separation (BSS) is the problem of estimating unobserved signal from their mixture. Various criteria have been proposed for blind source separation like independent component analysis [1], mutual information minimization [6], Second-order statistical approaches, Recursive algorithms with low computational complexity have also been presented by using the natural gradient method and the fast fixed-point algorithm. In novel proposed ICA based algorithm for blind source separation adaptation is made towards the extraction of statistically independent sources by maximizing entropy.

Blind source separation (BSS) is an approach for estimating source signals s_n using only the information of mixed signals x_n observed at each input channel. Typical examples of such source signals include mixtures of simultaneous speech signals that have been picked up by several microphones, brain waves recorded by multiple sensors, and interfering radio signals arriving at a mobile station.

Independent component analysis (ICA) is a statistical method that was originally introduced in the context of neural network modeling. Recently, this method has been used for the BSS of sounds, fMRI and EEG signals of biomedical applications, wireless communication signals, images, and other applications. ICA thus became an exciting new topic in the fields of signal processing, artificial neural networks, advanced statistics, information theory, and various application fields. Very general statistical properties are used in ICA theory, namely information on statistical independence. In a source separation problem, the source signals are the "independent components" of the data set. In brief, BSS poses the problem of finding a linear representation in which the components are mutually independent. ICA consists of estimating both the unmixing matrix W and sources s_n, when we only have the observed signals x_n. The unmixing matrix W is determined so that one output contains as much information on the data as possible.

In recent years, advances in Very Large-Scale Integrated Circuit (VLSI) technology have allowed designers to implement large complex designs on Application-Specific Integrated Circuits (ASICs) with millions of transistors. Field Programmable Gate Arrays (FPGAs) that is a programmable device in the ASIC family has been honored the best selection for fast design implementation. In this paper, we implement proposed algorithm on an FPGA of Xilinx VIRTEX V1000E (which contains 1 million logic gates) executes at the maximum frequency of 12.288 MHz. The performance comparisons between the proposed and another two ICA-related FPGA implementations show that the proposed FPGA implementation has potential in performing complicated algorithms on large volume data sets. More details are given in section III.

II. PROPOSED ICA BASED ALGORITHM FOR BLIND SOURCE SEPARATION

Proposed Algorithm attempts to separate unknown signal $s(t)= [\ s_1(t),\ s_2(t),\ ---\ s_n(t)\ ]$, Where $s_1(t)$ to $s_n(t)$ are n statistically independent signals are recorded with the help of n separated microphones. Let's take $x_1(t), x_2(t), --- x_n(t)$ are signals observed at the microphone, can be written as.

$x(t)=As(t)$, Where $s(t)$ is the vector of sources at instant t, A is the mixing matrix and $x(t)$ is the observed signal.

$u(t)=Wx(t)$
Where W is unknown matrix have to find out
WA=PD
Where P is permutation matrix and D is diagonal matrix.
Thus we can write the recovered signal

$$u(t)= \frac{PD}{A} . x(t)$$

The number of microphones and the number of sources are the same as n. The measured mixed signals at the nth microphone at τ^{th} sampling time may be represented as

$$x_n(\tau)= s_n(\tau) + \sum_{m \neq n}^{N} \sum_{t=0}^{T-1} Anm[d]\ S_m[\tau-d] \tag{1}$$

Where n=1,2,.....N.

$$u(\tau)=x_n(\tau) + \sum_{m \neq n}^{N} \sum_{t=0}^{T-1} Wnm[d]\ u_m[\tau-d] \tag{2}$$

$s_n(\tau)$ denotes the n^{th} source signal at τ^{th} sampling time and Anm[d] is the convolutive mixing coefficient m^{th} source to n^{th} microphone with d^{th} time delays for multipath reverberation. T is the number of longer time delay for convolutive mixing filter Wnm(d) is unmixing coefficient from m^{th} source to n^{th} microphone with d^{th} time delays.

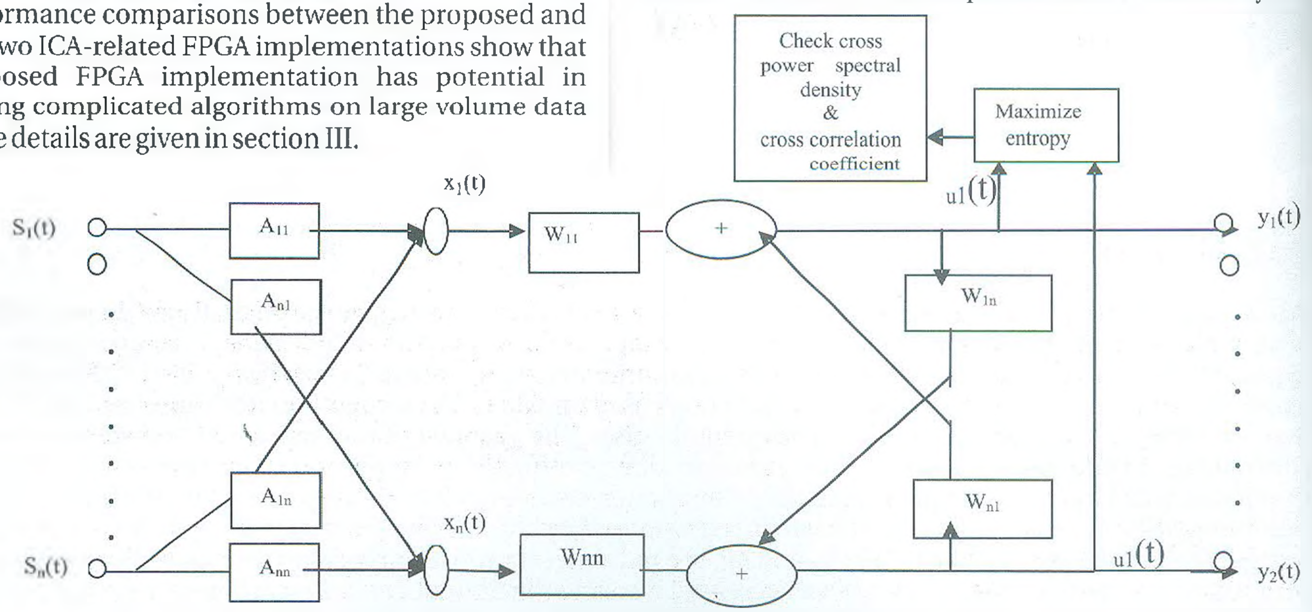


Fig .1 Network structure for blind source separation

The proposed algorithm estimates the unknown mixing coefficients from mixed signals $x_n(t)$. The proposed algorithm estimates the unknown mixing coefficients from mixed signals $x_n(t)$. The proposed algorithm based on ICA in which the adaptation is made towards the extraction of statistically independent sources by maximizing entropy at the output end. The cross power spectral density and cross correlation coefficient of observed unmixed signal and source signal is check to conform the received signal is the original signal.

(a) Maximum Entropy Spectral Estimation

The power spectrum of a stationary signal is defined as the fourier transform of autocorrelation sequence.

$$P_{xx}(f) = \sum_{n=-\infty}^{\infty} r_{xx}(m)\, e^{-2\Pi fm} \qquad (3)$$

Equation (3) requires the autocorrelation $r_{xx}(m)$ for lag m in the range of $\pm\infty$, but in practice an estimate of the autocorrelation is available only for the value of m in a finite ranges of say ±p. In general there are an infinite number of different correltion sequences that have the same values in the range $|m| \leq p$ as the measured values.

The maximum entropy estimate is based on the principle that the estimate of the autocorrelation sequence must correspond to most random signal whose correlation values in the range of $|m| \leq p$ coincide with measured values.

The randomness of the entropy of a signal is defined as

$$H[P_{xx}(f)] = \int_{-1/2}^{1/2} \ln P_{xx}(f)\, df \qquad (4)$$

To obtain the maximum entropy correlation estimate, differentiate equation (4) with respect to the unknown values of correlation coefficients and set the derivatives to zero.

$$\partial H[P_{xx}(f)] / \partial r_{xx}(m) = \int_{-1/2}^{1/2} [\partial \ln P_{xx}(f) / \partial r_{xx}(m)]\, df = 0 \qquad (5)$$

For of $|m| > p$

For the derivative of the logarithm of the power spectrum with respect to the autocorrelation value we can be written as

$$\partial \ln[P_{xx}(f)] / \partial r_{xx}(m) = p_{xx}^{-1}(f)\, e^{-2\Pi fm} \qquad (6)$$

substituting equation (6) in equation (4)

$$p_{xx}^{-1}(f) = \sum_{m=-\infty}^{\infty} C(m)\, e^{-2\Pi fm} \qquad (7)$$

Where C(m) is autocorrelation sequence.

$$\text{Where}C(m) = \int_{-1/2}^{1/2} p_{xx}^{-1}(f)\, e^{2\Pi fm}\, df \qquad (8)$$

From equation (7) and (8) $C(m)=0$ for $|m|>p$
Maximum entropy power soectrum is given by

$$\hat{P}_{xx}(f) = 1 / \sum_{m=p}^{p} C(m)\, e^{-2\Pi fm} \qquad (9)$$

Since the denominator polynomial in equation (9) is symmetric, it follows that for every zero of this polynomial situated at radius r, there is a zero at radius 1/r, Hence this symmetric polynomial can be factorised and expressed.

$$\sum_{m=-p}^{p} C(m)\, u^{-m} = 1/\sigma^2\, W(u) W(u^{-1}) \qquad (10)$$

Where $1/\sigma^2$ is a gain term and W(u) is a polynomial of order q defined as

$$W(u) = 1 + W_{11} u^{-1} + W_{12} u^{-2} + \text{--------} + W_{1q} u^{-q}$$

$$\hat{P}_{xx}^{ME}(f) = \sigma^2 / \; W(u) W(u^{-1}) \qquad (11)$$

Equation (11) shows that the maximum entropy power spectrum estimate is the power spectrum of a an autoregressive model which is obtained by maximising the entropy of the power spectrum with respect to unknown autocorrelation values.

$$\text{Change in weight } \Delta W \;\alpha\; \partial \hat{P}_{xx}^{ME}(f) / \partial W$$

We can write change in weight for p=2

$$\Delta W_{nm} = \eta\, \xi\, [u_n^{-1}(\tau) + W_{mm}\, u_n^{-1}(\tau)\, u_n^{-2}(\tau - d)]$$

$$\text{Where } \xi = 1/\{\, 1 + W_{nn}\, u_n^{-1}(\tau) + W_{nm}\, u_m^{-2}(\tau-d) + [\, W_{mn} + W_{nm} W_{mn}\, u_m^{2}(\tau-d)]\, u_n(\tau) + [\, W_{mm} + W_{nn} W_{mm}\, u_n^{-1}(\tau)\,]\, u_m^{2}(\tau-d)\,]$$

(b) **Check for Cross-Correlation and Cross Covariance**

Cross-Correlation of two random signal observed at the microphone, $x_n(\tau)$ and observed signal $u_n(\tau)$ can be written as signals

$$\gamma_{xu} = \sum_{n=1}^{N} \gamma x_n\, u_n(\tau) \qquad (12)$$

Cross-Covariance is checked by the function

$$C_{xu}(\tau_1\tau_2) = \gamma_{xu}(\tau_1\tau_2) - \sum_{n=1}^{N} \mu_{xn}(\tau)\ \mu_{un}(\tau) \qquad (13)$$

Where $\mu_{xn}(\tau)$ and $\mu_{un}(\tau)$ are mean of signal $x_n(\tau)$ and $u_n(\tau)$ respectively

Power spectral density of signal $x_n(\tau)$ is given as

$$\gamma x_n x_n(\tau) = \int_{-1/2}^{1/2} p_{xnxn}^{?1}(f) e^{2\pi fm}\ df$$

For the same frequency power spectral density of signal $u_n(?)$ is find out with the function

$$\gamma u_n u_n(\tau) = \int_{-1/2}^{1/2} p_{unun}^{-1}(f) e^{2\pi fm}$$

df approximately equal to maximum value of $\gamma x_n x_n(\tau)$.

Then $y_n(t) = 1/(1 - e^{-un(\tau)})$ will be exactly equal to $s_n(t)$.

III. FPGA IMPLEMENTATION OF PROPOSED ALGORITHM

The neural network is composed with repetition of simple core operation, for this reason we have implemented a high performance system using parallelism. However in practical applications for memory-intensive ICA algorithm, parallelism is limited by bandwidth. Therefore we incorporate a processor and memory in a basic BSS module shown in fig (2)

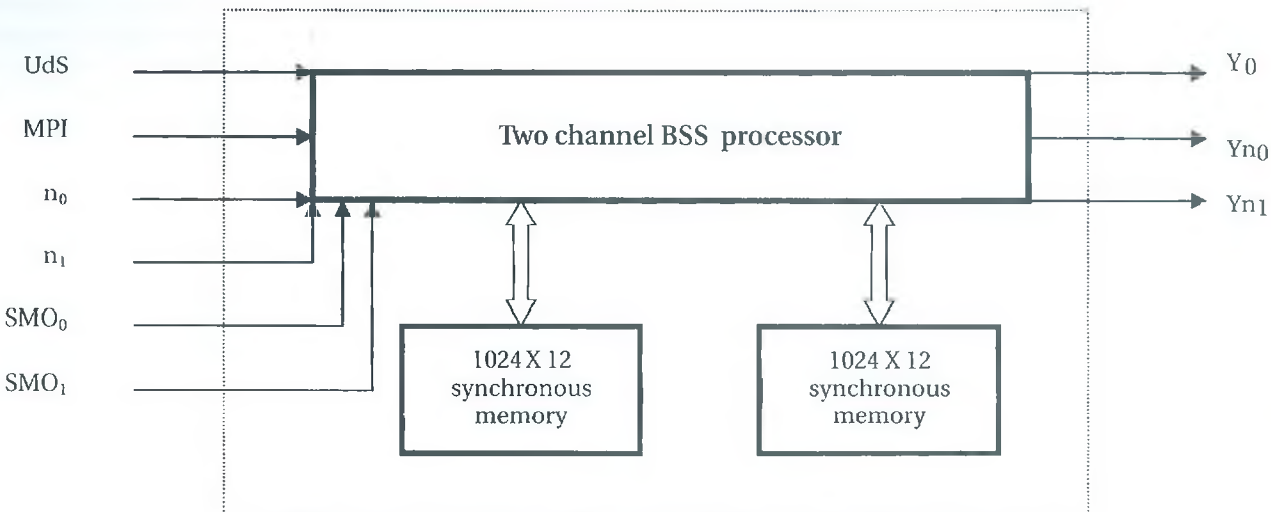


Fig. (2) input and output configuration of bss & anc module

UdS, MPI, n_0, n_1, SMO_0, SMO_1, Y_0, Yn_0 and Yn_1sdenotes update signal, many modules microphone input, noise-reference inputs, output of sub module, deconvoluted and oldest noise data respectively. Each module has its own memory for noise data and weight coefficients for easy multimodule system implementation. Specifications of module are summarized in table I

Table I
Hardware specification of BSS module

Memory size	Noise Weight	1024 X 12 bits= 12268 bits 1024 X 30 bits= 30720 bits
Memory Bandwidth	Noise Weight	noise source X time delay X sampling freq. 2 X 512 X 12000 = 12.288 MHz noise source X time delay X (memory operation memory module) X sampling freq. 2 X 512 X (2/2) X 12000 = 12.288 MHz
Core speed		12.288 MHz

By incorporating many modules, one can design more powerful chips for BSS applications. Updates controls the direction of the learning is unique for each microphone channel. Extended systems with more channels by accumulating the Yo of submodules that have the same Update and connecting to the SMO of the master module. Yn_0 is useful for the extension of time delays by connecting the Yn_0 to the n_0 of hierarchically upper module. Fig. (3) shows two channels High performance system using parallelism for BSS with 500 time delays.

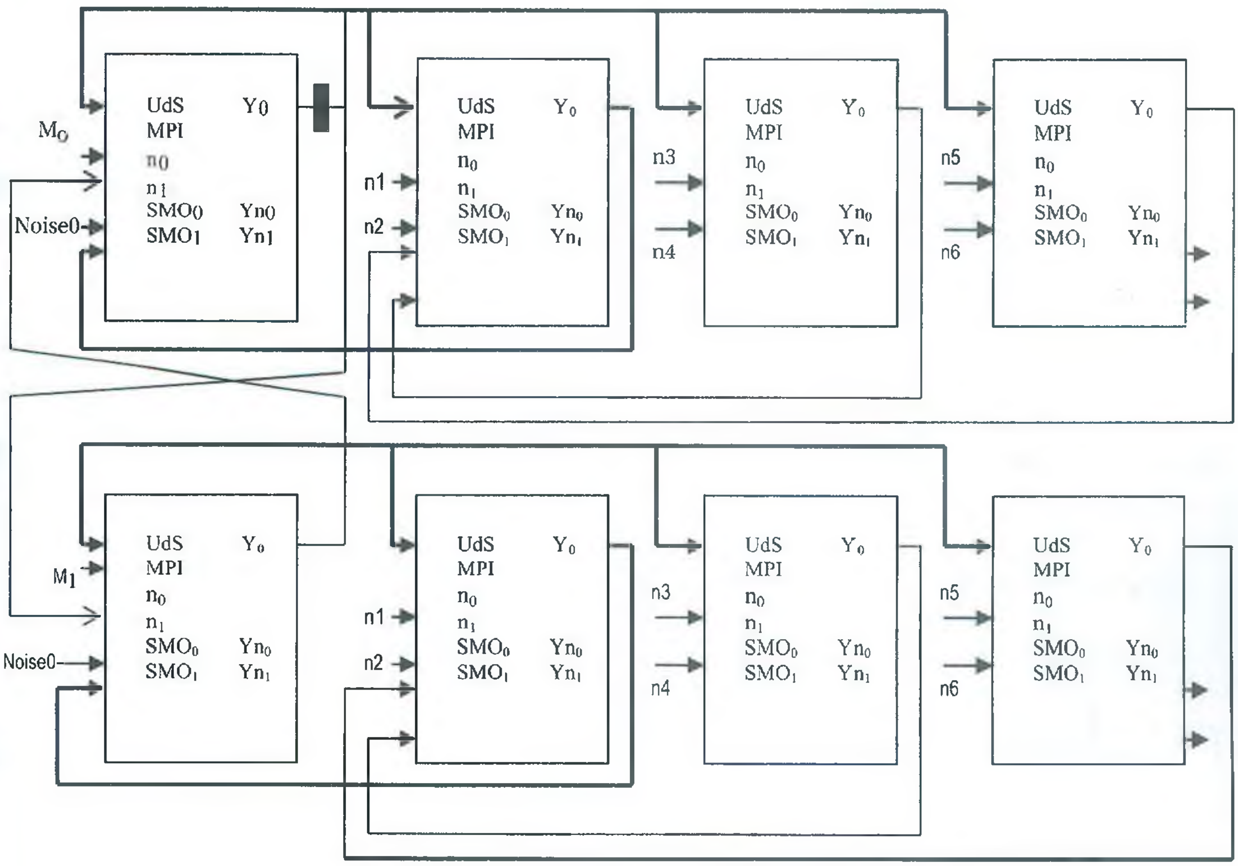


Fig. (3) High performance system using parallelism

IV. EXPERIMENTAL RESULTS AND COMPARISON

Actual voices as source signals $s_1(t)$ and $s_2(t)$ are male and female voices respectively are taken. The unknown nonlinear mixture structure is specified as

A1 =

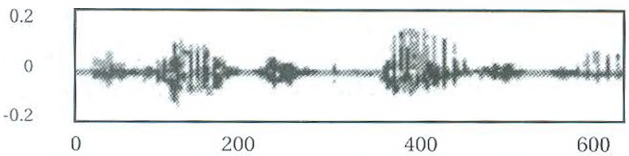
$$\begin{bmatrix} 0.6 & 0.4 \\ 0.5 & 0.7 \end{bmatrix}$$

A2 =

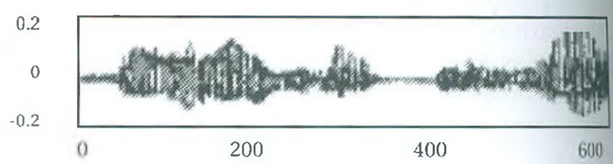
$$\begin{bmatrix} 0.7 & 0.4 \\ 0.5 & 0.7 \end{bmatrix}$$

In the iterative procedure following parameters have been setup as
The number of samples taken: 12000
The order of polynomial: $q = 5$
The weight of criterion: $\sigma = 0.5$
Initial value of weights: $W_{max} = 0.5$
Final value of weight: $W_{min} = 0.1$

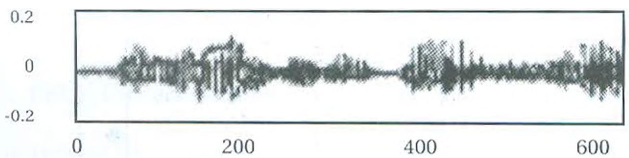
the results of the nonlinear blind source separation using proposed algorithm from the mixtures of male and female voices is shown in figure (4) and (5).



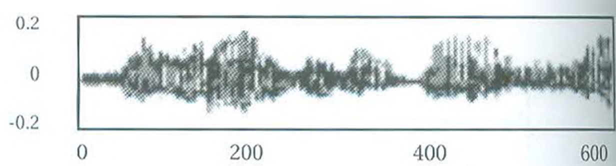
(a) male voice s_1 signal



(b) female and s_2 signal

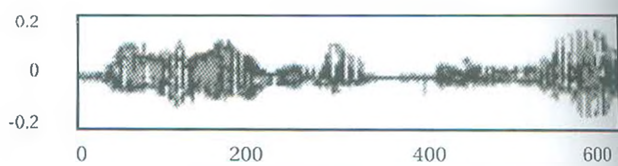


(c) the observed signal x_1



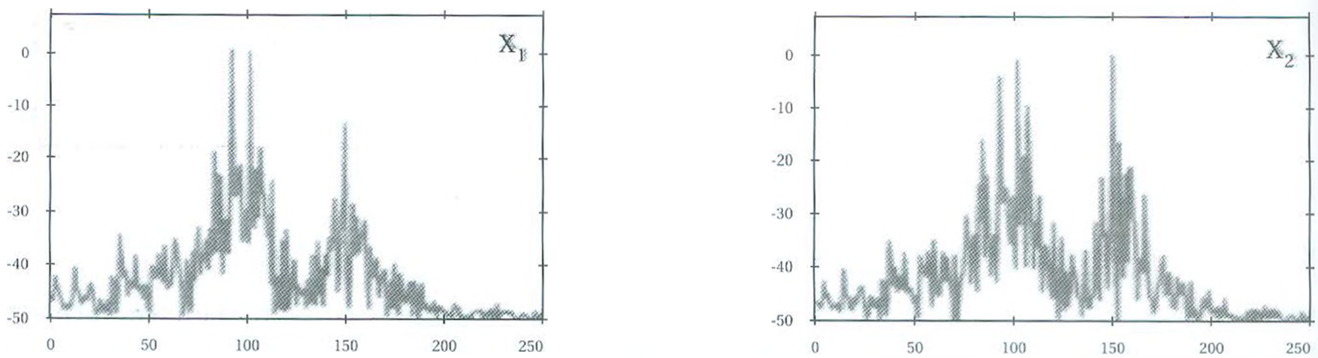
(d) observed signal x_2

(e) reconstructed voice signal y_1

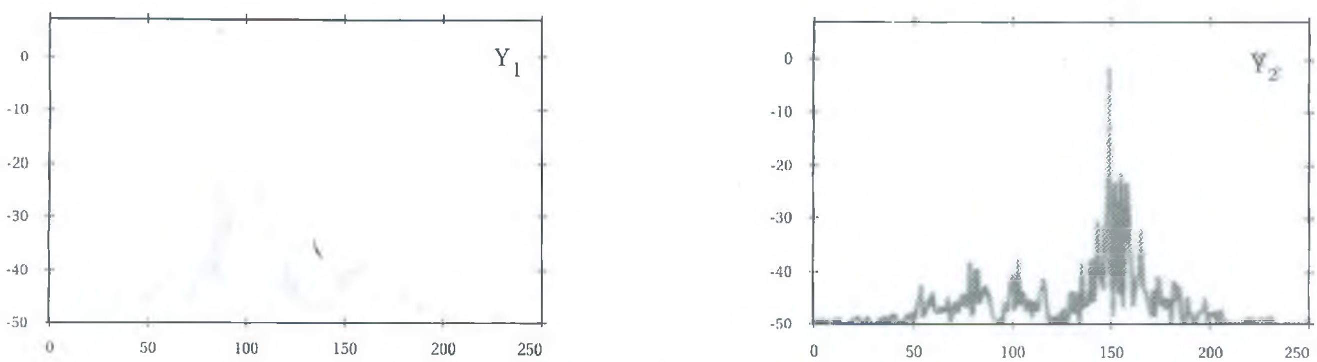


(f) reconstructed voice signal y_2

Fig. 4



(a) Spectrum of observed signals x_1 and x_2



(b) Spectrum of output signals. y_1 and y_2

Fig. 5

Table II gives the comparison between adaptive parameters used in the iteration procedure of Mutual Information Based Separation Algorithm and proposed algorithm.

Table II

Methods for BSS	Adaptive Parameters				
	Number of samples	q	σ	W_{max}	W_{min}
Mutual Information Based Separation Algorithm	8192	5	0.5	0.9	0.4
Proposed algorithm	12000	5	0.5	0.5	0.1

Table III shows Correlation Coefficients between reconstructed signals (Y_1, Y_2) and original source signals (s_1, s_2) and intermediate signals (x_1,x_2)

Table III

	Mutual Information Based Separation Algorithm				Proposed algorithm			
	s_1	s_2	x_1	x_2	s_1	s_2	x_1	x_2
y_1	0.987	-0.026	0.589	0.536	0.996	-0.017	0.453	0.476
y_2	0.037	0.992	0.826	0.860	-0.013	0.998	0.893	0.899

Signal to interference ratio observed with a noncausal FIR filters is 5.12, with Mutual Information Based Separation Algorithm is 7.03 and with proposed algorithm is 8.75.

V. CONCLUSION

We have presented the new blind source separation algorithm for extraction of original signal from a nonlinear mixture structure which is compared with the algorithm based on mutual information. Although the order of the polynomial which has been found out in the proposed algorithm and weight criterion is taken same that is 5 and 0.5 respectively as in the Mutual Information Based Separation Algorithm, less iteration are required. The final value of weight calculate is $W_{min} = 0.1$ while making adaptation towards the extraction of statistically independent sources by maximizing entropy; Cross power spectral density and cross correlation coefficient of observed unmixed signal and source signal is check to conform the received signal is the original signal which provides better signal to interference ratio i.e., 8.75 with the proposed algorithm than 7.03 and 5.12 with algorithm based on Mutual Information and non-causal FIR filter respectively. This paper also discussed the FPGA implementation for the proposed algorithm which provides a fast hardware implementation solution.

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