GRADIENT ASCENT INDEPENDENT COMPONENT ANALYSIS ALGORITHM FOR TELECOMMUNICATION SIGNALS

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ABSTRACT

Independent Component Analysis (ICA) algorithm is normallused for un-mixing and feature extraction of the fixed input block lengths. In case of varying block lengths re-adjustment of the maximum number of iterations and the step size parameter is required. In this paper, we introduced an Adaptive Step size Gradient Ascent ICA (AS-GAICA) technique for varying block length that can also controls the maximum number of iterations adaptively. The performance of the proposed technique is compared with Fast-ICA and Optimum Block Adaptation ICA (OBAICA) for telecommunication signals. Simulation results show that the proposed scheme outperforms the Fast-ICA and OBAICA algorithms.

KEYWORDS: *Independent Component Analysis, Gradient Ascent Fast-ICA, OBAICA*

INTRODUCTION

ICA is a signal processing mechanism used for separation of the mixed received signals[1,2]. It is widely used in various engineering disciplines like multidimensional data processing[3], wireless communication[8], speech processing[9,10], biomedical signal processing[11,12], vibration analysis[13] and machinery fault diagnoses[14]. In all these applications multidimensional mixed data is first recorded and then processed through ICA algorithms. This technique got a lot of attention due to its easy mathematical modeling and widespread application in practical scenarios, due to the fact that the recorded signals through sensors from any physical process are always the mixtures of signals coming from the physical systems or processes under observation[4]. The ICA algorithms require very less statistical information of the data as compared to many other statistical signal processing techniques[5] like kalman filter, least mean square, and recursive least square algorithm. In case for ICA to process mixed signals it is assumed that the signals are generated from non-Gaussian distribution having statistical independence. Moreover, the source signals become more Guassian after miximg as compared to the source signals that are non-Gaussian in nature[6].

There are various techniques of ICA such as complexity pursuit, maximum likelihood estimation, Infomax and projection pursuit[7] and has been widely studied in literature. Aapo Hyvarinen presented the fast fixed point algorithm for ICA in[15], and defined criteria for selection of the contrast functions. In[16] the infomax algorithm is extended and used for the separation of mixed super and sub Guassian signals. In[17], an efficient ICA (EFICA) algorithm is proposed, that can process non-stationary signals, while the unknown number of signals separation is discussed in[18]. An Optimum ICA based algorithm is presented in[19] for separation of short messages from multiple users. An ICA based procedure for the un-mixing of time varying communication signals is presented in[21]. Blind Signal Separation (BSS) for diminishing step size gradient ascent algorithm of ICA based on entropy maximization is presented in[22]. Mixed communication signals received on the same carrier can be separated with prediction of symbol error rate using BSS with a Time-Varying Mixing Matrix[23]. In[24], the authors addressed the problem of time varying multiple input multiple output (MIMO) channel estimation and tracking with Kalman filter for Alamouti scheme using the BSS technique.

Different gradient based ICA techniques are presented in the literature. In[27] an adaptive step size gradient based ICA technique is proposed applicable in un-mixing of fixed block length signals. A modified gradient based ICA and gradient ascent ICA algorithms are shown in[28] and[29] respectively.

In this paper, an adaptive step size GAICA (AS-GAICA) algorithm is proposed for dynamic block lengths. To the best of our knowledge the adaptive step size adjustment for dynamic input block lengths is not discussed in any research article for GAICA algorithm. This technique also

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adjusts the maximum number of iterations according to the input data block lengths. There are different situations where the dynamic blocks are received during handover in the mobile telecommunication system. Similarly in a speech processing system the length of the last recorded block may be different while in wireless sensor networks (WSNs) the events occurring in the sensing field are random thus the received block lengths will be different for different types of the detected events in the field. The performance of the AS-GAICA is compared with the Fast-ICA and the OBAICA algorithms for fixed and time varying wireless channels. Standard deviation of the error signal (Estd) and Signal to Interference Ratio (SIR) were taken as performance evaluation parameters. In this case the error signal is taken as the difference of the source and reconstructed signals.

Rest of the paper is organized in four sections, with section 2 describing the problem formulation, notation and assumptions; section 3 gives the details of AS-GACIA while the results are discussed in section 4. The paper is concluded in the last section.

Problem Formulation

This section describes the notations, assumptions and some mathematical background for the easy understanding and discussion of the rest of the paper.

Mathematical notations (.)', and $(.)^T$ are used for derivative and transpose respectively. Matrices are represented by capital bold font and vectors by small bold font.

Assumptions used in this paper are; (i) The source signals must be statistically independent, (ii) The source signals must have non-Gaussian distributions, (iii) Mixing matrix will be square.

Problem Formulation

In this research work a MIMO system with m number of transmit and receive antennas is considered. The transmitted signals are $\boldsymbol{s}_1, \boldsymbol{s}_2, \ldots, \boldsymbol{s}_m$, where $\boldsymbol{s}_m=[s_{11}, s_{12}, \ldots, s_{mL}]$,while the received signal is the mixed version of the input signals and denoted as $\boldsymbol{x}_1, \boldsymbol{x}_2, \ldots, \boldsymbol{x}_m$ as given in the system model, shown in Fig.1. The mixed received signals are processed and un-mixed using ICA algorithm into $\boldsymbol{y}_1, \boldsymbol{y}_2, \ldots, \boldsymbol{y}_m$ un-mixed signals. The recorded mixed data can be represented as

$$X = AS \quad (1)$$

Where $\boldsymbol{X}$ is the mixed data matrix, $\boldsymbol{A}$ is the mixing matrix and $\boldsymbol{S}$ contains the independent source signals. Equation (1) can also be represented as follows,

$$\begin{bmatrix} x_{11} & x_{12} & \cdot & \cdot & x_{1L} \\ x_{21} & x_{22} & \cdot & \cdot & x_{2L} \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ x_{m1} & x_{m2} & \cdot & \cdot & x_{mL} \end{bmatrix} = \begin{bmatrix} a_{11} & a_{12} & \cdot & \cdot & a_{1m} \\ a_{21} & a_{22} & \cdot & \cdot & a_{2m} \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ a_{m1} & a_{m2} & \cdot & \cdot & a_{mm} \end{bmatrix} \begin{bmatrix} s_{11} & s_{12} & \cdot & \cdot & s_{1L} \\ s_{21} & s_{22} & \cdot & \cdot & s_{2L} \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ s_{m1} & s_{m2} & \cdot & \cdot & s_{mL} \end{bmatrix} \quad (2$$

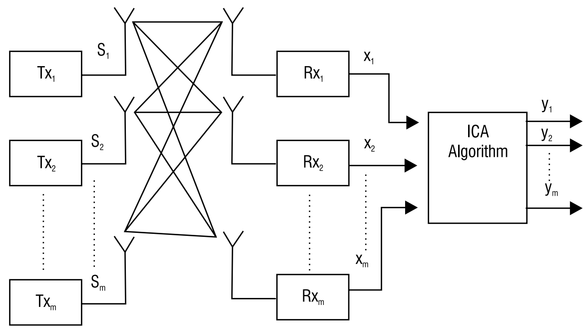

Figure 1: Block diagram of ICA system model

For equal number of the transmitted and source signals we can calculate inverse of the matrix $\boldsymbol{A}$, called the un-mixing matrix to recover the transmitted un-mixed signals as given in the following equation. Where $\boldsymbol{W}$ denotes the unmixing matrix.

$$Y = WX \quad (3)$$

The ICA algorithms are used for estimating the un-mixing matrix for separation of the mixed signals.

AS-GAICA algorithm

GAICA is a variation of the ICA algorithm and its convergence depends on the size of the step and the number of iterations. In case of variable block size these parameters need to be re-adjusted as in GAICA the accuracy of the un-mixing matrix depends on proper selection of the step size parameter and the number of iterations required for convergence. For this purpose a technique of adjusting these parameters is developed in this paper.

It can be proved that the total entropy of the un-mixed signals is greater than that of the unmixed signals. The source signals s_m having cdf u and pdf . Now entropy of the resultant signals can be calculated as

$$h(Y) = E[\sum_{i=0}^{m-1} \ln u'(y_i)] + \ln|W| \tag{4}$$

Entropy of the estimated source signal is given on equation (4). Actually the original source signals are not available. We have only the received mixed signals. The probability density function is known. Equation (4) selects $\boldsymbol{W}$ which maximizes the entropy of the estimated source signals. The gradient of entropy from equation (4) can be written as

$$\frac{\partial h(Y)}{\partial w_{ip}} = E[\sum_{i=1}^{m} \frac{\partial \ln u'(y_i)}{\partial w_{ip}}] + \frac{\partial \ln|W|}{\partial w_{ip}} \tag{5}$$

Where i=1, 2, …,m, and p=1, 2, …, m. Equation (5) becomes,

$$\frac{\partial h(Y)}{\partial w_{ip}} = [W^{-T}] + E[\sum_{i=1}^{m} \frac{u''(\boldsymbol{y}_i)}{u'(\boldsymbol{y}_i)} x_i] \tag{6}$$

$$\nabla h = E[\boldsymbol{\psi}(\boldsymbol{y})\boldsymbol{x}^T] + \boldsymbol{W}^{-T} \tag{7}$$

Where, $\boldsymbol{\nabla h} = \frac{\partial h(\boldsymbol{Y})}{\partial \boldsymbol{W}}$ and. $\boldsymbol{\psi}(y) = \frac{u''(y_i)}{u'(y_i)}$ Now the general form of the update rule becomes as follows

$$\boldsymbol{W}_{j+1} = \boldsymbol{W}_j + \eta \nabla \boldsymbol{h} \tag{8}$$

Where j represents the current iteration number, and η is the step size and the convergence of the algorithm depends on proper selection of these parameters. Combining equation (7) and (8) we get,

$$\boldsymbol{W}_{j+1} = \boldsymbol{W}_j + \eta\{E[\psi(\boldsymbol{y})\boldsymbol{x}^T] + \boldsymbol{W}^{-T}\} \tag{9}$$

Now we need the pdf of the source signals in Equation (9), where in most of the practical scenarios we have supper-Gaussian signals[25,26] with cdf *tanh* function[25], as given below

$$u(y) = \tanh(y) \tag{10}$$

The first and second derivatives of equation (9) can be calculated as

$$u'(y) = 1 - \tanh^2(y) \tag{11}$$

$$u''(y) = -2\tanh(y)u'(y) \tag{12}$$

$\psi(y) = \frac{u''(y_i)}{u'(y_i)}$, can be calculated as

$$\psi(y) = \frac{-2\tanh(y)u'(y)}{1-\tanh^2(y)} = -2\tanh(y) \tag{13}$$

Thus equation (9) will become as

$$\boldsymbol{W}_{j+1} = \boldsymbol{W}_j + \eta(\boldsymbol{W}^{-T} - 2E\{\tanh(\boldsymbol{y})[\boldsymbol{x}]^T\} \tag{14}$$

The dynamic input data blocks require re-adjustment of the step size and maximum numbers of iterations are required for convergence. The maximum number of iterations can be modeled as follows

$$Iter. = \mu\Gamma\rho \tag{15}$$

Where μ is a scaling constant, Iter. represents the number of maximum iterations, ρ and Γ are defined as follows

$$\Gamma = \sqrt{L} \tag{16}$$

$$\rho = \log_{10}(L) \tag{17}$$

The step size parameter can be written as

$$\eta = \rho^2 / \Gamma \tag{18}$$

The graphical interpretation of the equations (18) and (15) are shown in Figs. 2 and 3, showing changes in the step size and the number of iterations according to the dynamic input data blocks lengths. The block length ranges from 100 to 10,000.

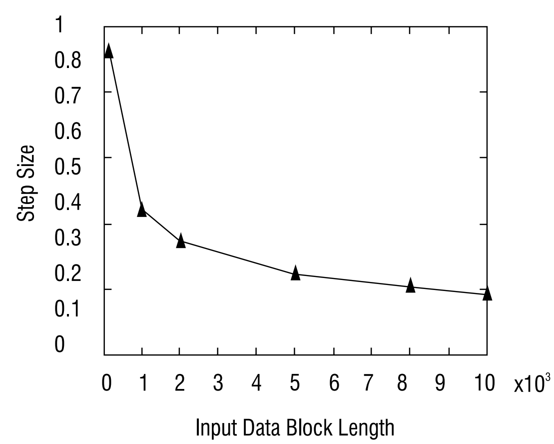

Figure 2: Input data block lengths versus step size

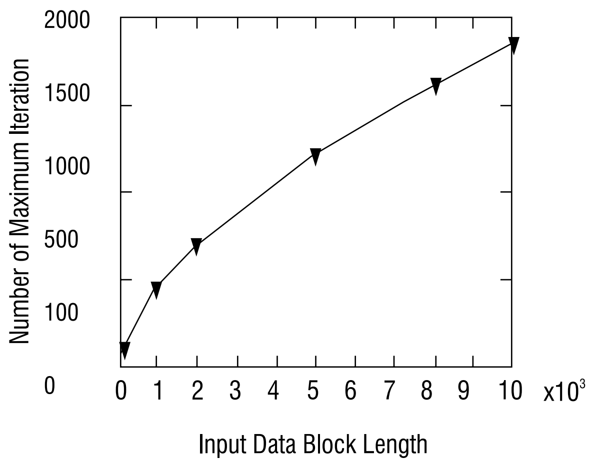

Figure 3: Input data block lengths versus maximum number of iterations

The minimum and maximum limits of step sizes can be represented as follows

$$2\log_{10}(L_{\min})/\sqrt{L_{min}} \geq \eta \geq 2\log_{10}(L_{\max})/\sqrt{L_{max}}$$

Where $\eta_{\min} = 2\log_{10}(L_{\max})/\sqrt{L_{\max}}$,

and $\eta_{\max} = 2\log_{10}(L_{\min})/\sqrt{L_{\min}}$.

The above equations show that the step size parameter changes according to the input data block. The minimum and the maximum values of the step size depend on the input data block. At a block length of 100, 1000 and 10,000 the step size is 0.92, 0.44 and 0.184 respectively.

Combining equations (18), with equation (14) gives the updated equation

$$\boldsymbol{W}_{j+1} = \boldsymbol{W}_j + (\rho^2/\Gamma)(\boldsymbol{W}^{-T} - 2E\{\tanh(\boldsymbol{w}^T\boldsymbol{x})[\boldsymbol{x}]^T\}) \tag{19}$$

Puttingin $R=W^{-T} - 2E\{Tanh(w^Tx)\ [x]^T\}$equation (19)

$$\boldsymbol{W}_{j+1} = \boldsymbol{W}_j + (\rho^2/\Gamma)\boldsymbol{R} \tag{20}$$

The proposed scheme has superior performance for varying block lengths. The block lengths range from 100 to 10,000 with a step size variations ranges from 0.92 to 0.184.

Convergence Enhancement of the AS-GAICA algorithm

The AS-GAICA algorithm selects the appropriate value of the step size and the maximum number of iterations and produces the good quality results (as shown in Results and Discussion section) for dynamic block lengths. The convergence speed is slow in term of defined number of iterations (as shown in Results and Discussion section). We proposed a technique to increase the convergence speed of the algorithm. This technique is explained as below,

After receiving a data block of length L, the step size and maximum iterations can be calculated from equations (18) and (15). The algorithm to further refine these parameters is as follow,

$$\eta_j = F_j.\eta \tag{21}$$

Where

$$F_j = \frac{iter._j}{\sqrt{iter_j}} \tag{22}$$

The updated value of the step size can be calculated using equations (21) and (22). From this step size the number of iterations can be calculated as

$$iter._j = \frac{\mu\rho^3}{\eta_j} \tag{23}$$

The change in the maximum number of iterations can be calculated as

$$\Delta iter._j = iter. - iter._j \tag{24}$$

Summing up the changes in the maximum number of iterations for all j gives

$$iter.' = \sum_j \Delta iter. \tag{25}$$

Now if, then go back to and calculate the step size as follows,

$$\eta_{j-1} = \frac{\mu\rho^3}{iter._{j-1}} \tag{26}$$

RESULTS AND DISCUSSION

Performance of the AS-GAICA is demonstrated by using two BPSK modulated signals with equal carrier frequencies and symbol error rates using Additive White Gaussian Noise (AWGN) channel. The performance measures are standard deviation of the error signal (Estd) and signal to interference ratio (SIR). Two performance evaluation criterions were used for the evaluation of the algorithm. Where, error signal is the difference of the estimated output of the algorithm and actual source signal, as shown in the following equation

The SIR in dB can be defined as follows

In this equation the block length is represented by *L*, original signal by ***s***(n), and un-mixed signal by ***y***(n).

Simulation setup 1: Performance comparison of the GAICA and AS-GAICA algorithms

In this simulation setup, the performance of the GAICA and AS-GAICA algorithms for two BPSK modulated signals is evaluated. The simulation results are shown in Fig. 4, and 5, where Fig. 4 gives results for different data block lengths versus Estd, and Fig. 5 gives the number of iterations versus Estd. From these figures it can be observed that the proposed scheme has superior performance.

Figure 6 shows the performance of the algorithms for different input SNRs ranging from -3dB to 10dB and block size of 3000 samples. Here the AS-GAICA has superior performance as compared to GAICA.

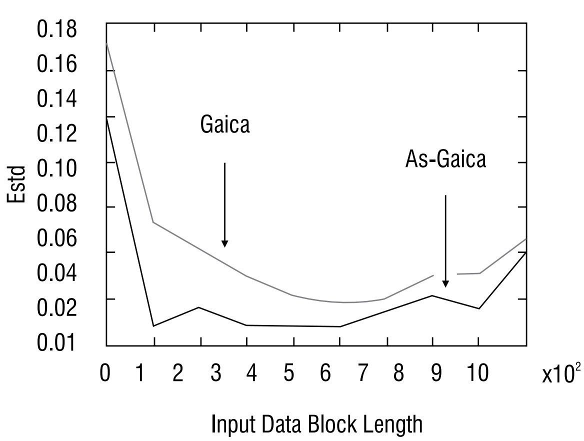

Figure 4: Input data block length versus standard deviation of the error signal

The convergence characteristics of both the algorithms are given in Fig. 7 and 8 for input data blocks of 10,000, 8000 and 4000 samples. The algorithm converges if magnitude of entropy gradient becomes zero. From these figures it can be observed that the AS-GAICA algorithm converges for all the three data blocks while simple GAICA fails for big block sizes.

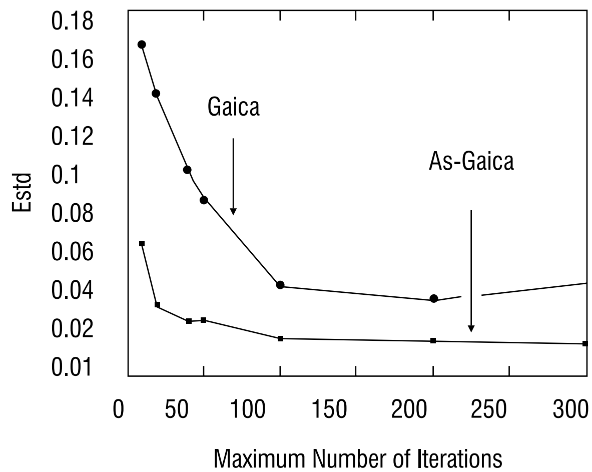

Figure 5: Maximum number of iterations versus standard deviation of the error signal

To complete the discussion, the performance of both the algorithms were also evaluated for two speech signals s_1 and s_2, as shown in Fig. 9. The source signals, the mixture signals and the estimated reconstructed speech signals are shown in Fig. 10 in frequency domain. In the figure showing the source signals, signal-1 is shown in blue and signal-2 is shown in green. The reconstructed signals are shown after applying the AS-GAICA algorithm, here the green graph corresponds to the reconstructed signal-1 and the blue graph show

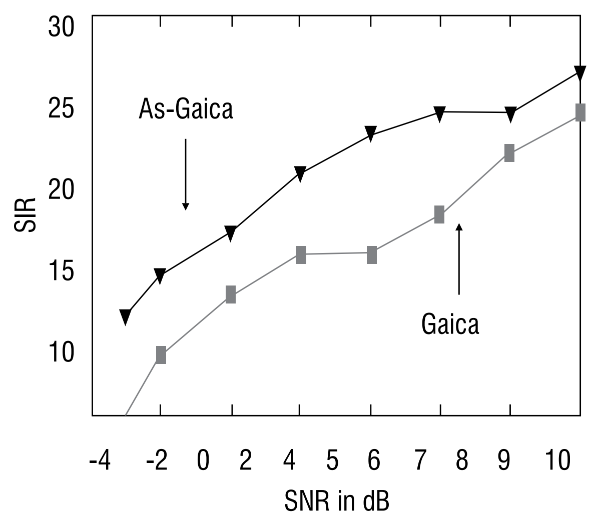

Figure 6: SNR versus SIR in dB for the GAICA and AS-GAICA algorithms

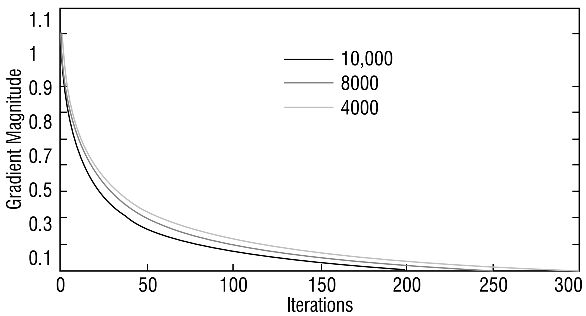

Figure 7: Convergence characteristics of AS-GAICA algorithm for different size of input data block

reconstructed signal-2 . The Estd for different input data blocks are summarized in Table 3 for GAICA and AS-GAICA algorithms, which shows that the proposed scheme outperforms the former.

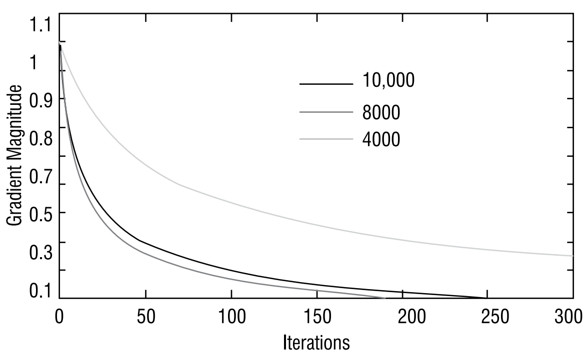

Figure 8: Convergence characteristics of GAICA algorithm for different sizes of input data blocks

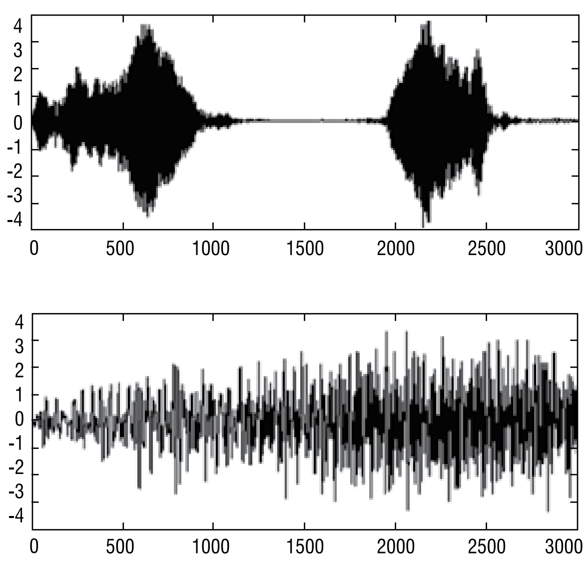

Figure 9: Two speech signals in time domain

Simulation setup 2:

In this simulation setup, the performance of

Table 3: Error standard deviations at different data block lengths

S. No.	Data points	Estd (GAICA)	Estd (ASGAI-CA)
1	10,000	0.0659	0.0600
2	9000	0.0507	0.0454
3	8000	0.0500	0.0404
4	7000	0.0395	0.0337
5	6000	0.0382	0.0283
6	5000	0.0411	0.0283
7	4000	0.0504	0.0298
8	3000	0.0616	0.0361
9	2000	0.0741	0.0287
10	1000	0.1519	0.1195

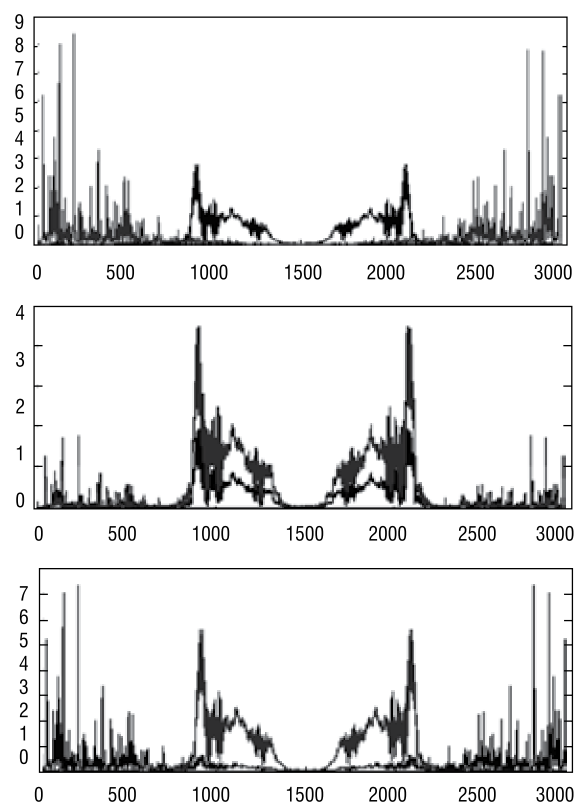

Figure 10: Frequency domain representation of source, mixed and reconstructed signals

AS-GAICA, Fast-ICA, and OBAICA algorithms for BPSK modulated signals are discussed. Different simulations performed are given below,

In first simulation setup BPSK signals were considered with different block sizes and a constant mixing matrix within the processing block of data. After applying the Fast-ICA, OBAICA and AS-GAICA algorithms the results are shown in Fig. 11 in term of SIR giving superior resultsfor AS-GAICA.

Secondly time varying case is considered. In this case time varying mixing is used within the processing data block. Results are shown in Table 4. From these results one can observe that performance of the AS-GAICA is superior as compared to Fast-ICA and OBAICA algorithms.

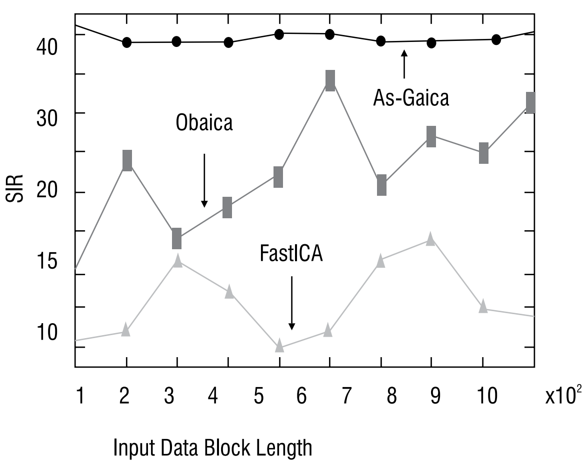

Figure. 11: SIR versus different data block length of BPSK signal when mixing matrix is constant

Table 4: Performance Comparison of AS-GAICA, Fast-ICA, and OBAICA in term of SIR.

Algorithm	SIR
AS-GAICA	36
Fast-ICA	18
OBAICA	15

CONCLUSION

The paper discussed a variation of ICA called AS-GAICA with the properties of automatic step size adaptation and number of iterations adjustment. This technique adjusts the step size and number of iterations according to the input data blocks lengths. The performance of the AS-GAICA and GAICA is compared for telecommunication BPSK modulated signals and speech signals for different input SNRs ranging from -3dB to 10dB. The performance of the AS-GAICA was also compared with fast-ICA and OBAICA for fixed and time varying channels. In all these simulations the AS-GAICA outperformed the rest of algorithms.

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