An Improved FCAICA Approach for EEG Artifact Removal

M. Jayasanthi[1] and NJR.Muniraj[2]

[1]Karpagam College Of Engineering, Tamilnadu, India.
[2]Tejaa shakthi Institute Of Technology for Women, Tamilnadu, India.

(Received: 14 February 2015; accepted: 29 April 2015)

An important problem in brain signal processing is the presence of noise and artifacts in neural recordings A systematic method of recognition, identification and artifact removal of Electroencephalography (EEG) waves is essential to reduce the probability of misinterpretation of brain waves and to limit its consequences. Electrophysiological signals produced by eye movement, eye blinks, head movement and muscle noise are typical causes of artifacts. So this paper mainly concentrates on removal of these artifacts from the recorded data using Independent component analysis (ICA) approach. ICA is a statistical method to extract independent source signals from the multivariate data. This paper uses orthogonal property of matrices to reduce the number of calculations and complexity of the 2-channel ICA algorithm. Using this property, the artifacts are removed with reduced area and power consumption. Simulation is also carried out for 9-channel EEG using Fast Confluence Adaptive ICA (FCAICA) algorithm. High convergence speed is also achieved by this adaptive method. Signal to Interference Ratio (SIR) is improved using IEEE single precision floating-point arithmetic.

Key words: Contrast function optimization; Convergence speed; EEG Artifact Removal; Independent component analysis.

Biomedical signals such as EEG (Electroencephalogram), ECG (Electrocardiogram) measured by clinical sensors are contaminated by artifacts and other noises e.g. muscle noise, instrumental power noise etc[1]. EEG recordings are mandatory for finding the mental wellbeing which is increasingly becoming one of the most important aspects in healthcare arena. EEG recording is a long standing procedure for recording the electrical activity generated by populations of neurons of the cerebral cortex. One of the many technical challenges of using EEG-based monitoring systems is the contamination due to EEG artifacts that includes muscle noise, eye activity, blink artifacts, head movement and instrumental noises such as line noise, electronic interference etc. Major artifacts can come from a variety of sources including cardiac rhythm, outside sources and even neural processes other than the one of interest, this way affecting the clinical interpretation of traces. During EEG acquisition phase, contamination and distortion are introduced in the recorded data by eye movements and eye blinks. Both of these environmental factors produce large electrical potentials around the eyes, called ocular artifacts (OAs). An eye blink produces signal with amplitudes ten times more than that of the EEG signal. Eye movements are recorded during EEG acquisition, even when the subjects are posed to close their eyes. Due to the presence of both of these Ocular artifacts, it is difficult to differentiate between normal and abnormal brain activity[2]. Artifact rejection is thus a key analysis for both visual inspection and digital processing of EEG. In this paper, FCAICA algorithm presented in[3] is improved in terms of convergence speed and proposed for EEG artifact rejection.

* To whom all correspondence should be addressed.
E-mail: mjayasanthi@yahoo.co.in

In recent years, many methods have been developed to solve the problem of EEG artifact rejection. The most widely used methods for attenuating the ocular artifacts are based on time-domain[4] or frequency-domain[5] techniques. Ting *et al*. developed a semi-automated algorithm to separate the multichannel EEG into source components by estimating the correlation matrices of the data[6]. Principal component analysis (PCA) technique was used to eliminate artifacts from the recorded EEG signals[7]. As, sometimes the OAs are smaller in amplitude with respect to the EEG, PCA cannot remove the artifacts from EEG absolutely. Later, independent component analysis (ICA) approach based on blind source separation was proposed to obtain components that are approximately independent[8,9].Then, automatic EEG artifact removal methods are proposed based on regression analysis for reducing Electro-oculogram (EOG) artifacts[10] and based on weighted support vector machine. The advantages are demonstrated with real-life EEG recordings and comparisons are made with several benchmark methods[11]. The performance of AMUSE, SOBI, Infomax, and JADE algorithms is assessed to separate myogenic activity from EEG during sleep[12]. James and Gibson applied constrained-ICA (cICA) technique for automatic artifact extraction in EEG and MEG[13]. Another automatic procedure of Blind Source Separation (BSS) based on logical rules related to spectral and topographical information is introduced in order to identify the components related to ocular interference by Barbanoj *et al*[14]. Implementation of ICA algorithms is not successful for real-time applications such as essential features extraction for brain computer interface (BCI)[15,16]. In order to realize the real-time signal processing, the ICA algorithms are implemented in VLSI Technology which further speeds up the computations involving vector and matrix manipulations. Fixed-point VLSI architecture was proposed for 2-Dimensional Kurtosis optimization based FastICA with reduced and optimized arithmetic units[17]. Due to the computational complexities and convergence rates, ICA consumes much more time for high density applications like hyperspectral images. So Parallel ICA (pICA) was developed to provide an optimal parallelism background with potentially faster and real-time solution[18]. ICA algorithm is designed with modularity concept for FPGA implementation[19] and then with systolic architecture[20]. A mixed-signal VLSI system was developed to separate and localize mixtures of traveling wave sources. It operates on spatial and temporal differences in the acoustic field at extremely small aperture[21]. FPGA implementation of 32-channel convolutive ICA chip was demonstrated with real world signals[22]. Pipelined FastICA, which can process the real time sequential mixed signal, was also developed for FPGA implementation[23].Various analog VLSI implementations of ICA algorithm also available. As digital implementation offers the flexibility of reconfigurable ICA, they are most common in signal processing.

This paper presents an improved FCAICA technique for 2-channels and also presents Multichannel FCAICA for EEG artifact rejection. The algorithm is developed with reduced algorithmic complexity and implemented in VLSI. The developed algorithm has been applied to EEG mixtures. The commonly used Fast ICA algorithm is also developed for comparison . With the intention of real-time ICA processing in VLSI, to improve the precision[24] and to speed up the computations, the ICA algorithms are written in hand coding HDL code in floating point arithmetic.

This paper is organized as follows. Section 2 describes the background of ICA. Section 3 explains improved FCAICA algorithm and Section 4 demonstrates the simulation, synthesis and backend analysis results. Finally, conclusions are drawn in Section 5.

ICA Background

ICA is a signal processing technique used for extraction of independent sources from their mixtures.EEG mixtures are separated into their individual components by looking for independent time-varying signals within these mixtures. Before applying these mixtures to ICA block, preprocessing is done on these signals to reduce the process complexity. The original source signal $S=(S_1,S_2,\ldots\ldots S_N)$ and observed mixture $M=(M_1,M_2\ldots M_N)$ are related by the expression (1)

$$M = XS \quad \text{... (1)}$$

where N is the number of sources/ mixtures and X is a full rank matrix that is called mixing matrix. Under the assumptions of independency of EEG sources, ICA is performed to solve the problem by finding inverse matrix. The

Inverse linear transformation matrix W, which is the inverse of mixing matrix X is then used in estimation of sources(Sest) as in (2)

Sest = WM =S ...(2)

i.e when a mixed signal(M) is multiplied with inverse of mixing matrix , estimate of the original signal (Sest) can be found .

Fig 1 shows the overall framework of EEG processing system with proposed ICA algorithm.EEG signal is first acquired from the human using brainwave sensors. The acquired signal contains artifacts like ocular artifacts, ECG artifacts, muscle noise etc. The power line noise can be removed with filters during preprocessing and then the preprocessed EEG is sent for Digitization. The digitized EEG data is sent to ICA block where the required features or EEG components are extracted.

Improved ICA algorithm

The algorithm presented in this paper, performs adaptive optimization of kurtosis based contrast function using improved FCAICA algorithm to find the independent components. The main aim of this algorithm development is to improve the convergence performance of the algorithm , to reduce the resources used and to improve the operating frequency. The convergence speed of the algorithm is improved by reducing the number of iterations. The adaptive optimization unit of the FCAICA algorithm presented in[3], updates the weight values based on the kurtosis function. The adaptive optimization unit contains a subtractor and a comparator unit that requires fewer resources when evaluated with conventional ICA methods. In this algorithm, initial weight vectors to estimate the demixing matrix W in (2), are assumed as w_i's. This algorithm computes new weights from the initial weights in an adaptive manner based on the fitness function's absolute value.

Contrast function

The effectiveness of EEG extraction depends on the contrast function optimization. The basic idea behind the ICA algorithm is Central limit theorem which states that, the sum of even two sources or random variables which are independent and distributed identically is more Gaussian than its original form. Hence non-gaussianity is a measure of independence. For the given EEG data x, the fourth order moment in kurtosis is specified in (3).

$$\mathrm{kurt}(x) = E\{x^4\} - 3(E\{x^2\})^2 \quad ...(3)$$

where $E\{\ \}$ is the statistical expectation operator. If signal is Gaussian, the fourth moment $E\{X^4\}$ equals to $3(E\{X^2\})^2$ and hence kurtosis is zero. For normalized x,variance is unity and so the kurtosis is simply given by (4).

$$\mathrm{kurt}(x) = E\{x^4\}-3 \quad ...(4)$$

Kurtosis value is non-zero for non-gaussian random variables or signals. The weight vector is updated in ICA by the learning rule with

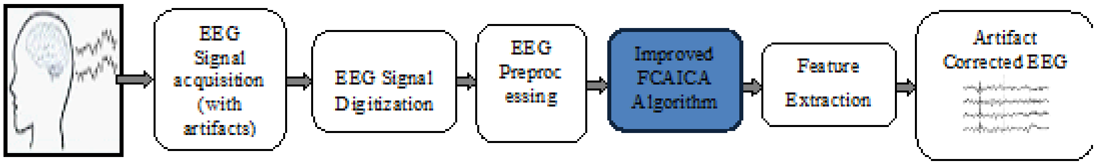

Fig. 1. Proposed algorithm with Overall Framework

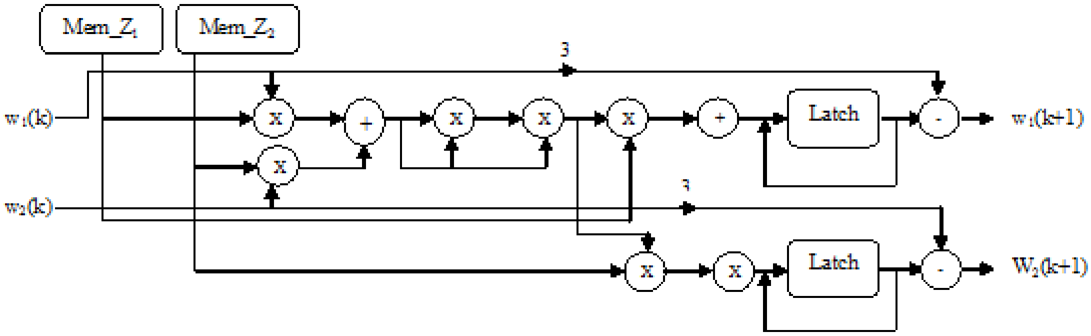

Fig. 2. Architecture for finding w(k+1) of FCAICA algorithm

nonlinear function $g(x)=x^3$

$$w_{newi}(k+1) \leftarrow E\{Z.(w(k)Z^{T})\} - 3w(k) \qquad ...(5)$$

This is used in the main iteration of the proposed algorithm for weight updation. The Fig 2 shows the architecture of iteration process defined in (5) for 2 sources.

Prposed ICA Algorithm for 2 units

Having obtained the low complexity EEG signal, this algorithm finds the columns of unmixing matrix to extract the signal without artifacts. Weights are updated continuously in an iterative and adaptive manner till convergence is achieved. Once convergence is achieved, the corresponding weight vectors are the columns of demixing matrix.i.e this process gets evaluated to w1= [w_{11} w_{12}]. The detailed steps are given below.

1) Create a weight matrix W by assuming Y sub matrices or column vectors where Y defines the size of the search space .

2) Calculate the norm of each vector and divide by corresponding norms

$$Norm_w = \sqrt{(w_1 w_1 + w_2 w_2)}$$

3) Find the updated weight vector Wnew for all the weights in W using

$$w_{newi}(k+1) \leftarrow E\{Z(w(k)Z^{T})^{3}\} - 3w_i(k)$$

4) Determine the fitness cost fi of all weights : fi= wi(k+1)-wi(k)

5) For k from 1 to M vectors, store the lowest obtainable fitness value as reference vector and test for convergence.

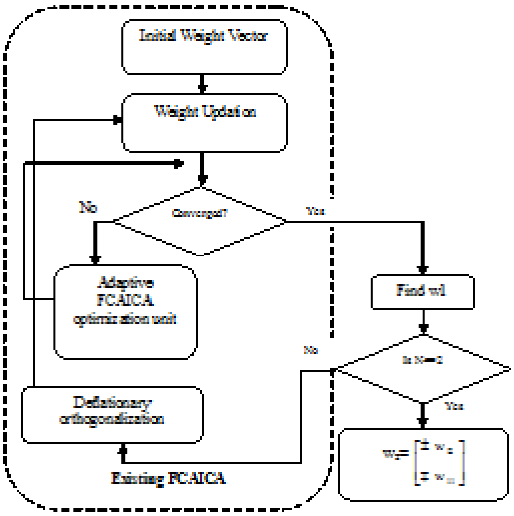

Fig. 3. Improved FCAICA -Architecture

If fi (k)< fi (k+1) then refi(k)= fi (k);

If convergence is achieved, the corresponding vector is one of the columns of demixing matrix. If it is not converged go to the next step.

6) If refi (k) is positive, reduce the weight vector by an amount of C.

7) For negative value of refi (k), increment the weight vector by an amount of C. Where C is a random nonnegative floating point number between '0' and '1'.

8) Repeat from step 3 until both vectors point at same direction or until convergence is achieved.

If the convergence is accomplished, the best fitness vector is selected for a column (w1) of demixing matrix B where B= [w1 w2]. To find the second independent component or the second column [w2] of B, orthogonal property of matrix is used. Since estimated columns of demixing matrix W are mutually orthonormal, only one vector is possible, which is orthonormal to w_1. So without any loss of generality w_2 is found from w1

$$w_2 = \begin{bmatrix} \pm w_{12} \\ \mp w_{11} \end{bmatrix} \qquad ...(6)$$

This w1 and w_2 are then used to find the estimate of source signals. This one-step method of finding the w2 removes the iterations needed while number of sources to be extracted is two. While finding more than two independent components, deflationary othogonalization should be made to ensure that the same independent components are not estimated more than once. The detailed flow and steps to be followed are given in Fig 3.

Deflationary Orthogonalization for more than two independent components

While finding more than two independent components, deflationary orthogonalization is done to prevent that the algorithm estimates the same independent component more than once.

$$Wp \Leftarrow Wp \quad (Wp^{T} Wj)Wj \qquad ...(7)$$

This is done after every iteration step by subtracting the projections of all previously estimated vectors from the current estimate before normalization as in (7)

Improved FCAICA -Architecture

Proposed area efficient and cost-effective architecture for 2 channel and multichannel

FCAICA is shown in Fig. 3. The signals acquired from the brain consist of EEG waves with artifacts. The architecture for removal of these artifacts mainly comprises iteration unit. In FCAICA, initially assumed weights are updated after normalization. Then convergence is checked through the convergence checking unit. On satisfying the convergence threshold or reaching the maximum iteration, the iteration process is terminated and the data are sent for independent component extraction. Otherwise FCAICA adaptive optimization unit checks the fitness parameter for having a positive or negative value. If the difference value is positive, then a non-negative floating point number is subtracted from the assumed weight vector to get new weight.

If the difference value is negative, then a nonnegative floating point number is added to the assumed weight vector to get new weight. This iteration process is repeated until convergence is reached or maximum iteration limit is reached. The resulting weight vectors form one column of the demixing matrix (W).The demixing matrix is multiplied with the mixture input to get estimates of the source signal (Sest).

In improved FCAICA method, on achieving the convergence, the corresponding weight vectors are taken as one of the columns of demixing matrix (W). The second column of the demixing matrix is found by using orthogonal property of matrices. Without performing any iterative process or weight vector assumption and updation, the second column is easily found. For the case of more than two channels, orthogonalization should be performed to ensure that, same components are not estimated again and again.So, in this improved method, the reduction in area and improvement in convergence speed is achieved in 2-channel ICA by eliminating the orthoganolization and using orthonormality property of matrices.

RESULTS AND DISCUSSION

Simulation results of EEG

The simulation is carried out for the EEG mixtures acquired with 2-channel as well as 9 channels. Fig 4(a) and Fig 4(b) show the raw EEG with artifacts acquired from the sensors and their estimated components respectively.

Convergence Analysis

The convergence analysis is done with the simulation results obtained from NCsim Tool v10. Convergence speed represents the time taken for each of the column weight vectors corresponding to independent components to be estimated. It is achieved when a vector w(k) and its updated vector w(k+1) are pointing in the same direction. The FCAICA takes 11 iterations and 18 iterations to extract two EEG components. The improved FCAICA takes 11 iterations to extract 1st EEG component and no iteration is needed for

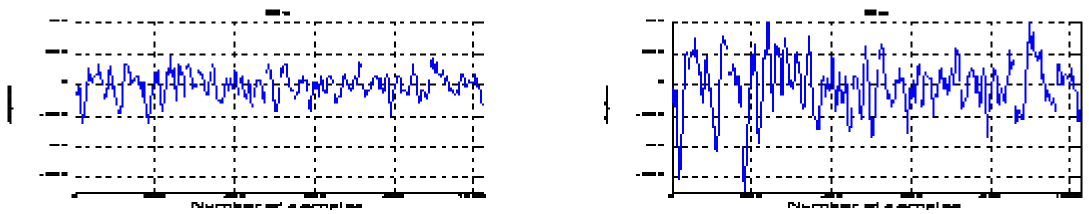

Fig. 4(a). EEG with artifacts obtained from 2-channel

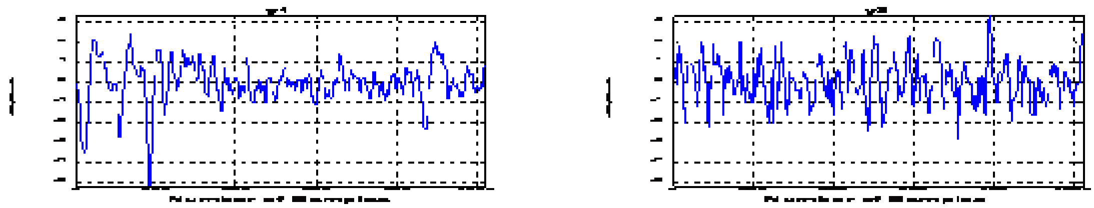

Fig. 4(b). Artifacts removed EEG using Improved FCAICA finding the 2nd EEG component. The Table 1 shows the number of iterations needed for extraction of 2 EEG components by different algorithms.

SIR Analysis

Signal to Interference Ratio of (SIR) of 2-channel EEG estimation and 9-channel EEG estimation is shown in Fig 6(a) and Fig 6(b) respectively. The SIR of Extracted EEG components range from 0 to 30dB with mean value 8.65dB.This is fine enough to acquire the quality of the original EEG sources. The practice of using floating point arithmetic operations significantly improve the SIR of EEG waves.

Table 2 gives the SIR values obtained with floating point and fixed point arithmetic. These values show that Floating point FCAICA and Improved Floating point FCAICA provide better result compared to fixed point implementation.

Algorithm for extraction of EEG components is written in VHDL and simulation is performed using NCSim tool. The physical design process that involves Floorplanning, Placement, Routing and Post route simulation are carried out with "RTL Compiler" and "Encounter" tools after successful completion of the synthesis process. Fig 7 provides implementation results of proposed 2-channel ICA obtained from the Cadence Tool 10.1 in comparison with Fast ICA and FCAICA. It

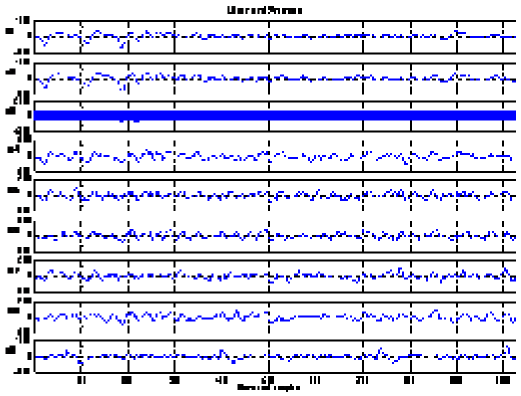

Fig. 5(a). 9-Channel EEG with artifacts

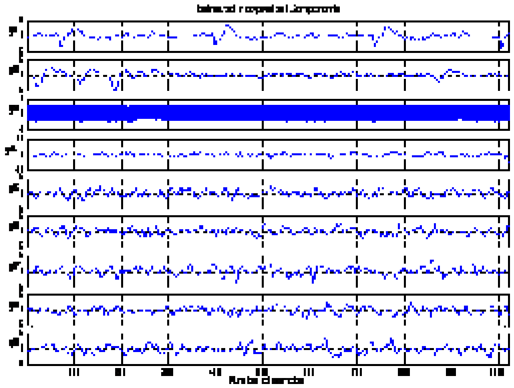

Fig. 5(b). EEG without artifacts (Corrected by FCA ICA)

Table 1. Convergence performance

Number of Iterations Taken to extract EEG	Fast ICA	FCAICA	Improved FCAICA
Component 1	18	11	11
Component 2	11	11	Nil

Table 2. Comparison of SIR of ICA algorithms

Mean SIR(dB)	FCA ICA (Fixed point)	FCAICA (Floating point)	Improved FCAI CA (Floating point)
	8.04	10.25	10.68

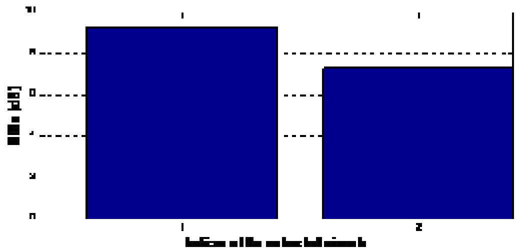

Fig. 6(a). SIR of 2-channel Estimated EEG signal

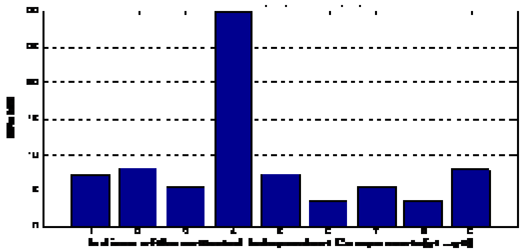

Fig. 6(b). SIR of Estimated EEG signal for 9-channels

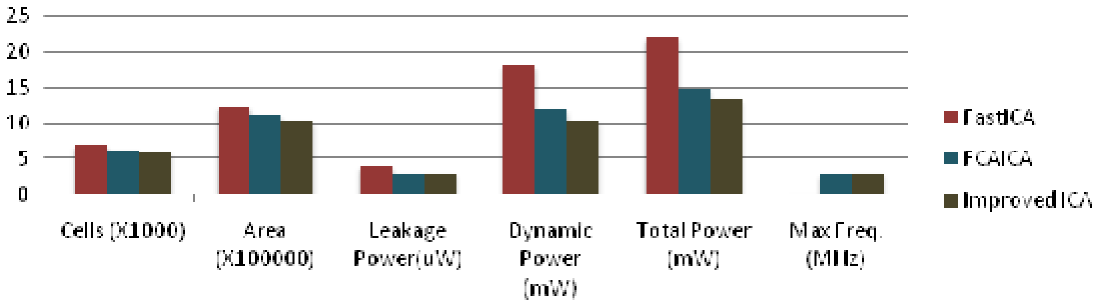

Fig. 7. Comparison of Design parameters of ICA algorithms obtained from Cadence Tool

provides the information about the resources used and power consumption. Investigation of the Figure 7 shows that the maximum operating frequency has been improved in proposed method .It is 192 KHz, 2.89 MHz, 3.12 MHz for FastICA, FCAICA and Improved FCAICA respectively. Power and area is also reduced compared to floating point Fast ICA implementation. An improvement of 7.48% and 10.23% is achieved over FCAICA in terms of area and power respectively.

CONCLUSION

In this paper, an improved time-domain approach to extract the EEG components from the added artifacts is presented. This approach is validated with simulation processes. Algorithms are synthesized and GDSII file is created by using Cadence Tool. Use of modularity, hierarchy, orthonormality of matrices and optimized floating point arithmetic units simplify the design, reduce the power .The power is also reduced by eliminating the iteration process while finding 2nd independent component in 2-channel ICA. The usage of optimization algorithm improves the convergence speed and enables finding the optimal solution. Floating point manipulations increase precision and SIR of the signal. The limitation of this system is that, it occupies more hardware when compared to its fixed point implementation. This is not a concern when the quality of the EEG extraction is prime important. Further research includes the application of the proposed method for other signals, such as ECG, fMRI and Spread spectrum signals.

REFERENCES

1. P. Berg and M. Scherg. A multiple source approach to the correction of eye artifacts. *Electroencephalogr. Clin. Neurophysiol*, 1994; **90**: 229–241.

2. Hong Peng, Bin Hu, Qiuxia Shi, Martyn Ratcliffe, Qinglin Zhao, Yanbing Qi, and Guoping Gao. Removal of Ocular Artifacts in EEG—An Improved Approach Combining DWT and ANC for Portable Applications.*IEEE Journal Of Biomedical And Health Informatics*, 2013; **17**(3)

3. Jayasanthi Ranjith.NJR.Muniraj,A Novel Floating Point Fast Confluence Adaptive Independent Component Analysis for Signal Processing Applications. *Advances in Signal Processing*, 2013; **1**(3): 37-43.

4]. G Gratton, M. G. Coles, and E. Donchin.A new method for off-line removal of ocular artifact. *Electroencephalogr. Clin.Neurophysiol*, 1983; **55**(4): 468–484.

5. J. C. Woestengurg, M. N. Verbaten, and J. L. Slangen. The removal of the eye movement artifact from the EEG by regression analysis in the frequency domain. *Biological Psychol.*, 1983; **16**: 127–147.

6. C. Q. Chang, F. H. Chan, K. H. Ting, and P. C. Fung.Automatic correction of artifact from single-trial event-related potentials by blind source separation using second order statistics only. *Med. Eng. Phys.*,2006; **28**(8):780–794.

7. T. D. Lagerlund, F. W. Sharbrough, and N. E. Busacker..Spatial filtering of multichannel electroencephalographic recordings through principal component analysis by singular value decomposition. *Clin. Neurophysiol.*, 1997; **14**(1):73–82.

8. S. Hu, M. Stead, and G. AWorrell.Automatic identification and removal of scalp reference signal for intracranial EEGs based on

independent component analysis.*IEEE Trans. Biomed. Eng.*, 2007; **54**(9):1560– 1572.

9. R. Vigario, J. Sarela, V. Jousmaki, M. Hamalainen, and E. Oja, Independent component approach to the analysis of EEG and MEG recordings. *IEEE Trans. Biomed. Eng.*,2000; **47**(5): 589–593.
10. D. Zimmermann, R. Scherer, R. Leeb, G. Pfurtscheller, A. Schlgl, and C. Keinrath.A fully automated correction method of EOG artifacts in EEG recordings. *Clin. Neurophysiol. 2007;* **118**(1): 98–104.
11. C. J. Ong, E. P. Wilder-Smith, X. P. Li, S. Y. Shao, and K. Q. Shen. Automatic EEG artifact removal: A weighted support vector machine approach with error correction. *IEEE Trans. Biomed. Eng.*, 2008; **56**: 336–344.
12. J. L. Cantero, M. Crespo-Garcia, and M. Atienza..Muscle artifact removal from human sleep EEG by using Independent component analysis. *Ann. Biomed. Eng.,2008;* **36**(3):467–475.
13. C. J. James and O. J. Gibson.Temporally constrained ICA: An application to artifact rejection in electromagnetic brain signal analysis. *IEEE Trans. Biomed. Eng.*,2003; **50**:1108–1116.
14. M. J. Barbanoj, S. Romero, and M. A. Maanas.A comparative study of automatic techniques for ocular artifact reduction in spontaneous EEG signals based on clinical target variables: A simulation case. *Comput. Biol Med.*2008*;* **38**(3): 348–360.
15. B. J. Culpepper and R. M. Keller.Enabling computer decisions based on EEG input. *IEEE Trans. Neural Syst. Rehabil. Eng.* 2003; **11**(4):354–360.
16. L. Tian, D. Erdogmus, A. Adami, M. Pavel, and S. Mathan..Salient EEG channel selection in brain computer interfaces by mutual information maximization. *Proc. IEEE Annu. Int. Conf. Eng. Med. Biol. Soc*, 2005; 7064–7067.
17. Acharyya, A., K. Maharatna, S. Jinhong, B.M. Al-Hashimi and S.R. Gunn. Hardware Efficient Fixed-Point VLSI Architecture for 2D Kurtotic FastICA. *Proceedings of the European Conference on 19th IEEE European Circuit Theory and Design*,2009; 165-168.

DOI: 10.1109/ECCTD.2009.5274943

18. Hongtao, D. and H. Qi. A Reconfigurable FPGA system for parallel independent component analysis. *EURASIP J. Embedded Syst.*, 2006; **1**(1). DOI: 10.1155/ES/2006/23025
19. Celik,A.,M.Stanacevic and C. Gert.Gradient Flow Independent Component Analysis in Micropower VLSI.,2005; . http://machinelearning.wustl.edu/mlpapers/paper_files/NIPS2005_865.pdf
20. Jeong, Y.K. and H.J. Jang. Adaptive parallel computation for blind source separation with systolic architecture. *Intelli. Inf. Management*, 2005; : 46-52. DOI: 10.4236/iim.2010.21006
21. Hongtao, D., H. Qi and X. Wang. Comparative Study of VLSI Solutions to Independent Component Analysis, *IEEE Trans. Industrial Electronics,* 2005; **54**: 548-558. DOI: 10.1109/TIE.2006.885491
22. Kim, C.M., HM. Park, T. Kim, Y.K. Choi and S.Y. Lee. FPGA implementation of ICA algorithm for blind signal separation and adaptive noise canceling. *IEEE Trans. Neural Netw*.2006; **14**: 1038-1046.
23. Kuo-Kai Shyu, Ming-Huan Lee, Yu-Te Wu, and Po-Lei Lee. Implementation of Pipelined FastICA on FPGA for Real-Time Blind Source Separation. *IEEE Trans. On Neural Networks,* 2008; **19**(6); PMID18541497
24. Dinesh, P., N. Das and A. Routray. Implementation of Fast-ICA: A Performance Based Comparison Between Floating Point and Fixed Point DSP Platform. *Measurement Sci. Rev.*, 2011; **11**: 119-128.