AENSI Journals

Australian Journal of Basic and Applied Sciences

ISSN:1991-8178

Journal home page: www.ajbasweb.com

A Review on Algorithms for Descriptive Components Extraction from Biomedical Signals and Images

[1]R. BalaSaranya, [1]K. Adalarasu, [2]T. AravindKrishna, [3]M. Jagannath

[1]Department of Electronics & Communication Engineering, PSNA College of Engineering & Technology, Dindigul, Tamilnadu, India
[2]Director, Centre for Research in Business Data Logic and Analysis, Coimbatore, India
[3]Associate Professor, School of Electronics Engineering, VIT University, Chennai, Tamilnadu, India

ARTICLE INFO

Article history:
Received 19 August 2014
Received in revised form
19 September 2014
Accepted 29 November 2014
Available online 15 December 2014

Keywords:
Biomedical Signals and Images, Principal Components Analysis (PCA), Independent Components Analysis (ICA), Blind Source Separation (BSS).

ABSTRACT

Source separation problems in digital signal processing are those which are used to separate useful signal from a mix of signals of interest, other signals and noise. The typical example of a source separation problem is the cocktail party problem, where many number of peoples are talking simultaneously in a room and a listener is trying to follow one of the discussions. The human brain can separate the voices of different people (source separation) using neurons in the auditory region. But source separation using digital signals is difficult task with the available techniques. Several approaches have been proposed for solving this issue but most of the techniques are still in development stages. Some of the successfully tested approaches are principal components analysis (PCA) and independent components analysis (ICA). Both the approaches work well when there are no delays or echoes present. Blind source separation algorithm has been widely noticed that there are many possible applications like analyzing biomedical signals and images. This article discusses the recent development of component separation algorithms used in the field of biomedical signal and image processing.

To Cite This Article: R. BalaSaranya, K. Adalarasu, T. AravindKrishna, M. Jagannath., A Review on Algorithms for Descriptive Components Extraction from Biomedical Signals and Images. ***Aust. J. Basic & Appl. Sci.,*** *8(18): 565-571, 2014*

INTRODUCTION

Component separation is an important task in many signal processing applications. Here, enough information is not available to deduce solution, so one must use any available information to infer the most probable solution. The aim of component separation is to process these observations in such a way that the original source signals are extracted by adaptive systems. Blind source separation (BSS) has raised much interest in the signal processing community. Its aim is to recover original sources (original signals) from their mixture of signals (measured signals). The term “blind” here is used because neither the original signals nor the mixing system are known. BSS has a multitude of interesting applications in telecommunication, speech recognition, medical signal processing and others.

Independent component analysis (ICA) and principal component analysis (PCA) in source separation have many practical applications such as, machine fault detection, seismic monitoring, reflection canceling, finding hidden factors in financial data, text document analysis, radio communications, audio signal processing, image processing, data mining, time series forecasting, defect detection in patterned display surfaces, bio medical signal processing etc. Each component can be represented by a linear combination of the original variables. Such a representation captures the essential structure of the data in many applications such as feature extraction, signal separation etc. The various linear transformation methods include brain source separation, principal component analysis, factor analysis and projection pursuit and independent component analysis.

This article discusses the recent developments in component separation algorithms as applicable to the biomedical signal and image processing.

Methods:

Principal Component Analysis:

Artificial Neural Network (ANN) is the tool that is mostly used in medical diagnosis systems because of its powerful prediction characteristics. These models with high computational complexity can only be run on

Corresponding Author: Dr. K. Adalarasu, Professor, Department of Electronics and Communication Engineering, PSNA College of Engineering and Technology, Dindigul, Tamilnadu, India.
E-mail: adalbiotech@gmail.com

expensive processors. To enable the implementation of ANN models on mobile and cheap devices, the features of Electrocardiography (ECG) signal, which are applied to ANN inputs, should be reduced. This approach enables the implementation of a simple ANN architecture. In this the features of ECG signal are reduced dramatically using PCA while keeping the error of the ANN learning rate at an acceptable level such as 5%. As a result, a simple Matlab ANN model, which consists of eight inputs, a hidden layer with two neurons and one output neuron, is implemented in FPGA by using IEE 754 32 bits floating-point numerical representation (Danisman *et al*., 2009).

Sigurdsson and Ulfarsson (2010) used principal component analysis (PCA) technique for dimensionality reduction in simulated data and real fMRI data. PCA has also proven to be useful in functional magnetic resonance imaging (fMRI) research where it is used to decompose the fMRI data into components which can be associated with biological processes. PCA is derived from a maximum likelihood framework. A first order roughness penalty term is added to the log-likelihood function which is then maximized for the parameters of interest with expectation maximization (EM) algorithm.

Bowers *et al*. (2010) design an algorithm for analyzing changes in ECG morphology based on principal component analysis (PCA) in a surrogate respiratory signal from single-lead ECGs signals. The respiratory-induced variability of ECG features such as P waves, QRS complexes, and T waves are described by PCA. ECG and breathing signals were recorded for twenty subjects under controlled breathing for 180 seconds at 4, 6, 8, 10, 12, and 14 breaths per minute and normal breathing conditions. Respiration was derived from the ECG using three methods; PCA-based techniques, RR intervals and QRS amplitudes of ECG. ECG-derived respiration was compared to the recorded breathing signal by magnitude squared coherence and cross-correlation. Based on the overall analysis the top ranking algorithm for both coherence and correlation was the PCA algorithm when applied to QRS complexes. The value of Coherence and correlation were significantly larger for this algorithm than the RR algorithm ($p<0.05$ and $p<0.0001$, respectively) and amplitude algorithm. PCA provides a novel algorithm for analysis of both respiratory and non-respiratory related beat-to-beat changes in different ECG features.

Dorado *et al*. (2012) proposed a PCA algorithm to derive a respiratory signal from ECGs and it is a proven method for analysis of heart beats. An improved ECG-derived respiration (EDR) algorithm based on kernel PCA (kPCA) was applied. kPCA can be seen as a generalization of PCA where non-linearities in the data are taken into account by nonlinear mapping of the data by using a kernel function, into a higher dimensional space in which PCA is carried out. The comparison of several kernels suggests that a radial basis function (RBF) kernel performs best when deriving EDR signals. Further improvement is carried out by tuning the parameter that represents the variance of the RBF kernel. The performance of kPCA is assessed by comparing the EDR signals to a reference respiratory signal, using the correlation and the magnitude squared coherence coefficients. On comparing the coefficients of the tuned EDR signals using kPCA to the EDR signals obtained using PCA various statistically significant differences are found in the correlation and coherence coefficients. Thus kPCA performs well than PCA in the extraction of a respiratory signal from the single-lead ECGs.

Smitha and Vinod (2013) proposed a portable low complexity emotion detector using PCA. Many autistic children have impairment in understanding other people's emotions which hinder their interpersonal communication. A real-time portable emotion detection system will aid such children to interact with the external world easily by them to understand facial emotions during their face to face communication. The Eigen values are obtained using power-deflation iteration method and the proposed architecture optimizes the required number of selective Eigen values called as Eigen range rather than finding all the Eigen values and vectors. The proposed emotion recognizer architecture is implemented on Virtex 7 XC7VX330T FFG1761-3 FPGA and achieved 82.3% detection accuracy for a word length of 8 bits.

Feng Luan *et al*. (2013) proposed a novel noise suppression method based on robust principal component analysis (rPCA) technique, applied to the estimation of bio-electromagnetic field in source space. Noise suppression in MEG measurement is particularly challenging issue because it is difficult to remove the noise and preserve the information components in the MEG data. This method gives a constrained optimization of MEG electromagnetic domain transformations such that the matrix of transformed MEG measurement can be decomposed as the sum of a sparse matrix of noise and a low-rank matrix of de-noised data. Resultant of these techniques showed significant improvement of the MEG feature parameter accuracy.

Geva *et al*. (2014) developed brain computer interface applications for both healthy and clinical populations. To detect target images within a rapid serial visual presentation (RSVP, 10 Hz) of images from 5 different object categories based on single-trial brain responses. The goal was to detect distinctive spatio-temporal brain patterns within a set of event related responses and introduced a novel classification algorithm such as the spatially weighted FLD-PCA (SWFP). FLD-PCA is based on a two-step linear classification of event-related responses, using fisher linear discriminant (FLD) classifier and PCA for dimensionality reduction. As a benchmark algorithm hierarchical discriminant component Analysis (HDCA) is considered and also the modified version of HDCA is hierarchical discriminant principal component analysis algorithm (HDPCA). By comparing the classification accuracies of three algorithms (FLD-PCA, HDCA and HDPCA), whereas HDPCA significantly increases classification accuracies compared to the HDCA. Presenting several repetitions of the same image exemplars improve accuracy, and thus may be important in cases where high accuracy is crucial.

Independent Component Analysis:

Jeong-Won Jeong *et al*. (2001) proposed a mixture density ICA for functional magnetic resonance imaging (fMRI) and EEG data to localize the independent sources for alpha activity. In the basic and extended versions of ICA, nonlinearity functions are fixed to have specific forms such as supergaussian or subgaussian. In the propose technique they utilized ICA with mixture density model so that any assumption about the source density is not required. A better separation is possible by matching flexible parametric nonlinearity to any kind of density of sources. Study results concluded that mixture density ICA provides better separation by matching flexible parametric nonlinearity to any kind of density of sources.

Standard implementations of ICA are restrictive due to the square mixing assumption. For signal recordings which have large numbers of channels, the large number of resulting extracted sources makes the subsequent analysis laborious and highly subjective. These types of issues occur in neuro-physiological analysis where there is strong apriori information about the signals being sought. Temporally constrained ICA (cICA) can extract signals that are statistically independent, which are constrained to be similar to some reference signal which can incorporate such apriori information (James and Gibson, 2003). This method is explained using synthetic dataset and on a number of artifactual waveforms identified in multichannel recordings of EEG and MEG. cICA repeatedly converges to the desired component within a few iterations and subjective analysis shows the waveforms to be the expected morphologies with realistic spatial distributions. The cICA can be one of the better tools to EM brain signal analysis, with an initial application in automating artifact extraction in EEG and MEG.

Using blind source separation (BSS) the fetal electrocardiogram (fECG) was extracted from maternal cutaneous electrode recordings. From this perspective, the problem reduces to the estimation of independent sources of fetal cardiac bioelectric activity. BSS method based on higher-order statistics is contrasted with a significant classical technique for fECG extraction. In this the Pearson-ICA algorithm and BELL's (Bell and Sejnowski, 1995) algorithm for BSS are used for fECG extraction (Sargam and Sahambi, 2004). They were applied to multichannel ECG recording obtained from a pregnant woman. For robustness, two scenarios, i.e., (a) different amplitude ratios of simulated maternal and fetal ECG and (b) different values of additive white Gaussian noise were investigated. It was observed that if the ratio of the amplitude of maternal to fECG is 10:1 with an input SNR of 2 dB, both algorithms were able to extract the fECG. The signal-to-error (SER) ratios of the extracted maternal and fECG were around 3 dB and 1 dB, respectively. The outcome of this study demonstrates that the more robust performance of Pearson-ICA and Bell's algorithm is an important biomedical application.

Vandun and Wouters (2007) proposed an algorithm for the detection of auditory steady-state responses (ASSR) for reliable hearing threshold estimation at audiometric frequencies. The duration of ASSR measurement can be long, which is unpractical for wide scale clinical application. ICA use is to improve the ASSR detection in recorded single-channel as well as multi-channel electroencephalogram (EEG) data. ICA applied on single-channel and multi-channel recordings yields a significantly better performance than the clinically used single-channel reference technique for data obtained at intensities above hearing threshold. For single-channel measurements, 23 % of time reduction was achieved for a single subject. For multi-channel EEG measurements there is a significant measurement time reduction possible of 52% for 48-sweep measurements compared to the single-channel reference technique. This study result concludes that ICA is able to reduce measurement duration significantly.

Surface electromyogram (sEMG) was a source signal for the identification of isometric hand gesture. sEMG is a measure of the electrical activity of the muscles and a measure of the strength of muscle contraction. sEMG may be a good measure of the actions and gestures but this is unable to identify small variations in the muscle activity, especially when there are number of simultaneous active muscles (Nalik, Kumar and Weghoron, 2007). ICA is a statistics based source separation technique and they decompose the sEMG signal to identify the small variations in muscle activity. Temporal de-correlation source separation (tDSEP) is one type of the ICA algorithm, based on the simultaneous diagonalisation of several time-delayed correlation matrices. The tDSEP uses the property that the cross correlation functions vanish for mutually independent signals and are based on the second order statistics. The temporal de-correlation method provides better performance for physiological signal analysis such as sEMG, EEG etc.

A constrained genetic algorithm optimization based ICA overcomes the long standing permutation ambiguity and recovers the independent components in a fixed order which is dependent on the statistical characteristics of the signals to be estimated. The constrained GA based ICA has also been compared with the most popular fast ICA algorithm (Acharya and Panda, 2007).

Wei-Chung huang (2008) used an independent component analysis (ICA) technique with information maximization (Infomax). The proposed technique was applied into 4-channel one-line EEG signal separation

Australian Journal of Basic and Applied Sciences, 8(18) December 2014, Pages: 565-571

and implemented on FPGA with a fixed-point number representation. As experimental results show the proposed design is 56 times faster than soft performance, and the correlation coefficient between absolute value and off-line processing is 80%. Finally, live demonstration is implemented in the DE2 FPGA board, and the design had 16,605 logic elements. Both ICA and support vector machines techniques were used to extract EOG features from the forehead EOG signals. The performance of the techniques was evaluated using the correlation coefficients between the forehead EOG signals and the traditional EOG signals. In this support vector machine classifier was trained by 2000 randomly selected samples, half EOG and half EMG and its classification accuracy is over 90% (Hao-Yu Cai *et al*., 2011). fICA can be used as valuable pre-processing technique such as cross talk removal, artifact reduction etc., and improve the quality of the original bio-sensors recordings (Nalik and Hung, 2013).

Blind Source Separation:

Farook *et al*. (2004) proposed an algorithm to monitor fetal ECG (fECG) signal which has interference with maternal ECG (mECG). The fetal heart is very small and thus the electrical current it generates is much lower than that of the mother. Adaptive filtering technique can be used to remove or suppress the maternal ECG and extracted fECG. Blind source separation (BSS) algorithm can be used to separate fECG from mECG effectively. BSS of independent signals from a mix of signals is a common problem in many real world multi-sensor applications. However, the algorithm requires high computation and hence a real-time implementation using software is either not practical or is expensive. The low-cost fPGA (field programmable gate array) hardware architecture for the realization of a real-time BSS in the application of fECG signal separation has been implemented.

Field programmable gate array (FPGA) is used to implement the information-maximization (Infomax) algorithm of BSS with a fixed-point number representation. A system design of the Infomax BSS algorithm in the case of 2 inputs and 2 outputs is presented by using the Quartus II, the DSP builder and the Simulink. Compared with ASIC design, FPGA implementation has many advantages such as short development time, convenient design platforms and low cost (Qiuhua *et al*., 2005).

The fetal electrocardiogram (fECG) provides clinically significant information concerning the electrophysiological state of a fetus. The fECG was extracted from abdominal composite signals. This method consists of the cancellation of the mother's ECG and blind source separation with the reference signal (BSSR). The cancellation of the mother's ECG component was performed by subtracting the linear combination of mutually orthogonal projections of the heart vector (Sato *et al*., 2007). The BSSR is a fixed-point algorithm, the Lagrange function which includes the higher order cross-correlation between the extracted signal and the reference signal as the cost term rather than a constraint. In practical application, this techniques use to extract the P and T waves in addition to the R wave. The reliability and accuracy of this method is confirmed by comparing the extracted signals with the directly recorded ECG. The gestational age-dependency of the physiological parameters of the extracted fECG also coincided well with that of the magneto-cardiogram, which is a proven method for clinical applications.

Rieta *et al*. (2005) proposed BSS as one of the most effective techniques for the atrial activity (AA) extraction in supra-ventricular tachyarrhythmia episodes like atrial fibrillation (AF). The proposed techniques include wavelet transform de-noising and natural gradient algorithm for the BSS system. This helps improve the extraction quality with low computational load. Synthetic signals have been used to test this technique in different noisy cases. A higher cross-correlation coefficient (between the extracted signal and the original ones) is obtained in sparse sequential separation which is found to exceed the correlation obtained using standalone BSS method.

Koch *et al*. (2014) presented a method for smart auscultation by proposing a novel blind recovery of the original cardiac and respiratory sounds from a single observation mixture in the framework of non-negative matrix factorization (NMF). The method learns the spectra of mixed signals in unsupervised or semi-supervised fashion depending upon the applications. A modified NMF technique is proposed which enforces the spectral structure of the target sources in mixture factorization, resulting in good separation of target sources even in the presence of non-stationary noise. Moreover, data is processed in small batches which 1) enables mitigation of the spectral variations in mixing sources and 2) reduces computational complexity. The analytical work is verified through simulations using synthetic as well as actual clinical data collected from different subjects in different clinical sittings. This smart auscultation method demonstrates excellent results even in noisy clinical environments.

Mu rhythm in electroencephalogram (EEG) signal is used for studies concerning motor activity. Mu rhythm is more activated in the central region of the brain and raw EEG is contaminated with artifacts. The application of blind source separation (BSS) alone is insufficient to extract the mu rhythm component. A two stage approach was used to extract the mu rhythm component; first stage uses second-order blind identification (SOBI) with stationary wavelet transform (SWT) to automatically remove the artifacts. In the second stage, SOBI is applied again to find the mu rhythm component and compared with independent component analysis with discrete wavelet transform (ICA-DWT) as well as SOBI-DWT, ICA-SWT, and regression technique for artifacts removal in a simulated EEG data. This study concluded that SOBI-SWT artifact removal enhances the extraction of the mu rhythm component (Raveendran *et al*., 2009).

To removal of electrooculography (EOG) signals that strongly appear in frontal electrodes of EEG signal use multivariate extension of empirical mode decomposition (EMD) model, also called MEMD. MEMD decomposes a multichannel signal into a set of intrinsic mode functions (IMF), and the number of IMFs is identical among the channels (Tanaka *et al*., 2012).

RESULTS AND DISCUSSION

Principal Component Analysis:

Bower *et al*. (2010) showed that PCA provides a novel algorithm for analysis of both respiratory and non-respiratory related beat-to-beat changes in different ECG features. Smitha *et al*., (2013) showed that this algorithm provides a real-time portable emotion detection system which aid many autistic children who have impairment in understanding other people's emotions which hinder their interpersonal communication. This system helps them to interact with the external world easily and understand facial emotions during their face to face communication. Feng Luan *et al*. (2013) showed that robust PCA provides very high accuracy in noise suppression during MEG measurement which is a very challenging task because it is very difficult to remove the noise and preserve the information components in the MEG data. PCA can also be used for implementing artificial neural network (ANN) architectures. Danisman *et al*. (2009) used PCA for reducing the features of ECG signal and designed ANN architecture. High dimensionality reduction can be achieved by using PCA in fMRI data by Sigurdsson *et al*., (2010). Dorado *et al*. (2012) derived respiratory signal from ECGs and proved that kernel PCA is the well performing algorithm for the analysis of heart beats. Geva *et al*. (2014) used hierarchical discriminant PCA (HDPCA) to detect target images within a rapid serial visual presentation and proved that this algorithm provides very high accuracy.

Independent Component Analysis:

Singh *et al*. (2001) showed that mixture density ICA provides better separation by matching flexible parametric nonlinearity to any kind of density of sources. Constrained ICA (cICA) algorithm can be one of the best tools for EM brain signal analysis, with an initial application in automating artifact extraction in EEG and MEG (James and Gibson, 2003). Vandun and Wouters (2007) results concludes that ICA is able to detect auditory steady-state responses (ASSR) for reliable hearing threshold estimation at audiometric frequencies. In this they achieved significant time reduction for both single channel and multi-channel signal recordings. The temporal de-correlation method provides better performance for analysing physiological signal analysis such as sEMG, EEG etc.

Nalik *et al*. (2007) concluded that TDSEP provides high accuracy in the detection of small variation in the muscle activity. Acharya and Panda (2007) concluded that constrained genetic algorithm optimization based on ICA overcomes the long standing permutation ambiguity and recovers the independent components in a fixed order. Wei-Chung huang (2008) used ICA technique with information maximization (Infomax) algorithm in on-line EEG signal separation. They concluded that this system provides faster design and very good correlation.

Brain Source Separation:

Parmar and Sahambi (2004) demonstrated that Pearson-ICA and Bell's algorithm have important biomedical applications. Using blind source separation (BSS) the fetal electrocardiogram (FECG) was extracted from maternal cutaneous electrode recordings. In this they proved that SNR value of the extracted signal is very low.

Farook *et al*. (2004) result shows that it provides high accuracy in monitoring fECG signal which is one of the challenging tasks. Infomax algorithm of BSS with a fixed point number representation in FPGA implementation provides short development time and lower cost (Qiuhua *et al*., 2005). Sato *et al*. (2007) proposed the blind source separation with the reference signal (BSSR) which provides reliability and accuracy in signal separation and compared the performance with ultrasonic measurement. Rieta *et al*. (2005) proved that BSS is an effective method for extracting atrial activity (AA) and this system provides fast and easy implementation in real time systems. Raveendran *et al*. (2009) showed that second-order blind identification (SOBI) with stationary wavelet transform (SWT) of artifact removal enhances the extraction of the mu rhythm component. Tanaka *et al*. (2012) developed an EOG removal algorithm which is higher accuracy and can be used for neuro engineering applications.

Conclusion:

This article illustrates how various component separation algorithms can be used in health care such as diagnosis of diseases, extracting important features of physiological signals such as EEG, ECG, EMG etc, and medical imaging. Commonly component separation algorithms are used in various practical applications such as machine fault detection, seismic monitoring, reflection canceling, finding hidden factors in financial data, text document analysis, radio communications, audio signal processing, image processing, data mining, time series forecasting, defect detection in patterned display surfaces, bio medical signal processing etc. This article provides know how about component separation algorithm and various techniques involved in analyzing the features, achieving very high accuracy of separation and exploring for future applications.

REFERENCES

Acharya, D.P., G. Panda, Y.V.S. Lakshmi, 2007. Constrained genetic algorithm based independent component analysis. IEEE Congress on Evolutionary Computation, pp: 2443-2449.

Alpert, G.F., R. Manor, A.B. Spanier, L.Y. Deouell, A.B. Geva, 2014. Spatiotemporal representations of rapid visual target detection-A single-trail EEG classification algorithm. IEEE Transaction on Biomedical Engineering, 61(8): 2290-2303.

Bell, A.J., T.J. Sejnowski, 1995, A non-linear information maximization algorithm that performs blind separation. Advances in Neural Information Processing Systems, MIT Press, Cambridge.

Castells, F., J.J. Rieta, J. Millet, V. Zarzoso, 2005. Spatiotemporal blind source separation approach to atrial activity estimation in atrial tachyarrhythmias. IEEE Transactions on Biomedical Engineering, 52(2): 258-267.

Chareonsak, C., S. Farook, Yu Wei, Xiong Bing, 2004. Design of FPGA hardware for a real-time blind source separation of fetal ECG signals. IEEE International Workshop on Biomedical Circuits and Systems, pp: S2/4-13-16.

Feng Luan, Jong-Ho Choi, Hyun-kyo Jung, 2013. RPCA-based noise suppression in MEG measurement improving Bio-Electromagnetic source Estimation. IEEE transactions on Magnetics, 49(5): 1585-1588.

Hao-Yu Cai, Jai-Xin Ma, Li-Chen Shi, Bao-Liang Lu, 2011. A novel method for EOG feature extraction from the forehead. IEEE International Conference on Engineering in Medicine and Biology Society, pp: 3075-3078.

James, C.J., O.J. Gibson, 2003. Temporally constrained ICA: an application to artifact rejection in electromagnetic brain signal analysis. IEEE Transaction on Biomedical Engineering, 50(9): 1108-1116.

Jeong-Won Jeong, Tae-Seong Kim, M. Singh, 2001. Independent component analysis with mixture density model and its application to localize the brain alpha activity in fMRI and EEG. IEEE Symposium Conference Record on Nuclear Science, 4: 1897-1901.

Langley P, E.J. Bowers, A. Murray, 2009. Principal Component Analysis as a tool for analyzing beat-to-beat changes in ECG features-Application to ECG-derived respiration. IEEE Transaction on Biomedical Engineering, 57(4): 821-829.

Molla, M.K.I., T. Tanaka, T.M. Rutkowski, 2012. Multivariate EMD based approach to EOG artifacts separation from EEG. IEEE International Conference on Acoustics Speech and Signal Processing (ICASSP), pp:653-656.

Naik, G.R., Yina Guo, Hung Nguyen, 2013. A new approach to improve the quality of biosensor signals using fast independent component analysis: Feasibility study using EMG recordings. Engineering in Medicine and Biology Society (EMBC), pp: 1927-1929.

Nalik, G.R., D.K. Kumar, H. Weghorn, 2007. Performance comparison of ICA algorithms for isometric hand gesture identification using surface EMG. Intelligent Sensors, Sensor Networks and Information, pp: 613-618.

Ozdemir, A.T., K. Danisman, M.H. Asyali, 2009. FPGA based arrhythmia classifier. Biomedical Engineering Meeting, pp:1-4.

Parmar Sargam, D., J.S. Sahami, 2004. A comparative survey on removal of MECG artifacts from FECC using ICA algorithms. Intelligent Sensing and Information Processing, pp: 88-91.

Sato, M., Y. Kimura, S. Chida, T. Ito, N. Katayama, K. Okamura, M. Nakao, 2007. A novel extraction method of fetel ECG from the composite abdominal signal. IEEE transactions on Biomedical Engineering, 54(1): 49-58.

Shah, G., P. Koch, C. Papadias, 2014. On the blind recovery of cardiac and respiratory sounds. IEEE Journal of Biomedical and Health Informatics, 99: 1.

Siew-Cheok Ng, P., Raveendran, 2009. Enhanced µ Rhythm extraction using blind source separation and wavelet transform. IEEE Transactions on Biomedical Engineering, 56(8): 2024-2034.

Sigurdsson, J., M.O. Ulfarson, 2010. Smooth noisy PCA using a 1^{st} order roughness penalty, Machine Learning for Signal Processing. IEEE International workshop, pp: 325-330.

Smitha, K.G., A.P. Vinod, 2013. Low complexity FPGA implementation of emotion detection for autistic children. Medical Information and Communication Technology (ISMICT), 103-107.

Australian Journal of Basic and Applied Sciences, 8(18) December 2014, Pages: 565-571

Van Dun, B., J. Wouters, Moonen, 2007. Improving Auditory Steady-State Response Detection using independent component analysis on multichannel EEG data. IEEE Transactions on Biomedical Engineering, 54(7): 1220-1230.

Wei-Chung Huang, Shao-Hang Hung, Jen-Feng Chung, Meng-Hsiu Chang, Lan-Da Van, Chin-Teng Lin, 2008. FPGA implementation of 4-channel ICA for on-line EEG signal separation. International Conference on Biomedical Circuits and systems, pp: 65-68.

Widjaja, D., C. Varon, A.C. Dorado, J.A.K. Suykens, S. Van Huffel, 2012. Application of kernel principal component analysis for single-lead-ECG-derived respiration. IEEE transaction on Biomedical Engineering, 59(4): 1169-1176.

Zhongfeng Li, Qiuhua Lin, 2005. FPGA implementation of Infomaxx BSS algorithm with fixed point number representation. IEEE International Conference on Neural Network and Brain, 2: 889-892.