Survey on EEG Signal Processing Methods

Research · January 2014

2 authors:

T. V. Prasad
Godavari Institute of Engineering and Technology

Rajyalakshmi Tvk
Vasireddy Venkatadri Institute of Technology

Volume 4, Issue 1, January 2014 ISSN: 2277 128X
International Journal of Advanced Research in Computer Science and Software Engineering
Research Paper
Available online at: www.ijarcsse.com

Survey on EEG Signal Processing Methods

M. Rajya Lakshmi*
Ph. D Scholar
Dept. of Computer Sc. & Engg
K. L. University
Guntur, AP, India

Dr. T. V. Prasad
Former Dean of Computing Sciences
Dept. of Computer Sc. & Engg
Visvodaya Technical Academy
Kavali, AP, India

Dr. V. Chandra Prakash
Professor
Dept. of Computer Sc. & Engg
K. L. University
Guntur, AP, India

Abstract: Brain Computer-Interfacing is a methodology that provides a way for communication with the outside environment using the brain thoughts. The success of this methodology depends on the selection of methods to process the brain signals in each phase. This paper aimed at addressing the various methodologies required to be adapted in each phase of brain signal processing. Prior to this survey, previous surveys have been listed various methods, some experimental results and compared them. This paper shows clear and easy interpretation of each method and their advantages and disadvantages including the signal acquisition, signal enhancement, feature extraction and, signal classification.

Keywords: Brain Computer-Interface, Signal Processing, Feature Extraction, EEG signals, brain thoughts.

I. Introduction

Brain Computer Interface is a process that makes use of the brain's output path way for conveying the commands and messages to the external world [1]. There are basically two types of BCI systems. They are Invasive BCI and Non-Invasive BCI. Most of the Asian countries prefer to the essence of Non-invasive BCI systems due to their affordability and flexibility in capturing the signals from the brain [2]. A BCI system is composed of four phases. They are Signal Acquisition, Signal Pre-Processing, Signal Classification and, Computer Interaction [3].

II. Signal Acquisition

The acquisition of brain signals is accomplished by using various non-invasive methods like Electro Encephalography (EEG), functional Magnetic Resonance Imaging (fMRI), Near Infra-Red Spectroscopy (NIRS) and, Magneto Encephalography (MEG).

A. *EEG*

EEG was recorded on animal brain in 1875 by Richard Caton. It was first recorded on human brain by Hans Berger in 1929 [4]. EEG is the most used signal acquisition method because of the high temporal resolution, safety, and ease of use. 10-20 standard electrodes placement is used in EEG signal acquisition. EEG has low spatial resolution and is non-stationary in nature. EEG signals are susceptible to artefacts caused by eye blinks, eye movements, heartbeat, muscular activities and the power line interferences [5].

B. *fMRI*

The fMRI technology in general is used in clinical laboratories. fMRI makes use of the level of haemoglobin and is known as Blood Oxygenation Level Dependent (BOLD). More set up cost is required. It has high temporal and spatial resolution. Time delay occurs in data acquisition process [6].

C. *NIRS*

The NIRS technology has low temporal resolution and this may even hinder the transformation rates. To improve the transmission rates, NIRS is combined with the EEG and it forms Hybrid BCI. NIRS also uses BOLD to estimate the classification accuracies. It is inexpensive but shows very low performance than EEG based- BCI [7].

D. *MEG*

Using the MEG technology the magnetic signals that are generated by electrical activities are captured. This methodology provides wider frequency range and excellent spatiotemporal resolution but requires expensive and heavy sized equipment. Table I shows comparison of various signal acquisition methods used in Non-invasive BCI systems. In Fig. 1, the above non-invasive acquisitions are shown [8].

III. Signal Pre-Processing

After signal acquisition phase, signals are to be pre-processed. Signal pre-processing is also called as Signal Enhancement. In general, the acquired brain signals are contaminated by noise and artefacts. The artefacts are eye blinks, eye movements (EOG), heart beat (ECG). In addition to these, muscular movements and power line interferences are also mingled with brain signals [9]. Artefact removal can be done using Common Average Referencing (CAR), Surface Laplacian (SL), Independent Component Analysis (ICA), Common Spatial Patterns (CSP), Principal Component Analysis (PCA), Single Value Decomposition (SVD), Common Spatio-Spatial Patterns (CSSP), Frequency

Normalization (Freq-Norm), Local Averaging Technique (LAT), Robust Kalman Filtering, Common Spatial Subspace Decomposition (CSSD) etc. The most frequently used methods are ICA, CAR, SL, PCA, CSP and Adaptive Filtering [10].

A) EEG B) fMRI C) NIRS D) MEG

Fig. 1: Signal acquisition Methodologies

TABLE I
COMPARISON OF SIGNAL ACQUISITION METHODS USED IN NON-INVASIVE BCI SYSTEMS

S. No	Method	Signals captured	Advantages	Disadvantages
1	EEG	Electrical Signals on brain Scalp	• High Temporal resolution • Safe and easy technique	• Susceptible to EOG signals, ECG signals, muscular activities and power line interference • Low spatial resolution • Non stationary signal
2	fMRI	Metabolic signals using BOLD response	• High temporal and spatial resolution	• Set up cost is more • Delay in data acquisition process
3	NIRS	Metabolic signals using BOLD response	• High spatial resolution • Inexpensive • Portable	• Low temporal resolution • Hinder transformation rates • Less performance
4	MEG	Magnetic Signals generated by electrical activities	• Wider frequency range • Excellent spatio-temporal resolution	• Needs bulky setup • Expensive experimental setup

A. *ICA*

ICA was first applied to EEG by Makeig et al. in 1996 [11]. ICA separates the artefacts from the EEG signals into independent components based on the characteristics of the data without relying on the reference channels. The data in the recorded trails, each channel data and the frontal data are also preserved during the ICA artefact removal [12]. The ICA algorithm decomposes the multi-channel EEG data into temporal independent and spatial-fixed components. It is computationally efficient. ICA shows high performance when the size of the data to decompose is large [13]. ICA requires more computations to decompose signals [12] [14]. EEGLAB supports various types of ICA algorithms (nearly 20 algorithms) and most used algorithms are Joint Approximate Decomposition of Eigen matrices (JADE), fixed point ICA, Infomax [15].

B. *CAR*

This method removes the noise by subtracting the common activity from the position of interest. The common activity can be the noise present in the EEG signal [16]. The referencing methods are used to improve the Signal-to-Noise Ratio (SNR). The presence of the artefacts yields low SNR in EEG signals. In CAR method the removal of mean of all electrodes from all the electrodes results in noise free signals. The results in [17] show that CAR outperforms all referencing methods and shows best classification accuracy results. Finite sample density and incomplete head coverage of EEG electrode arrays cause problems in calculating the averages in referencing methods [18].

C. *SL*

An estimate of current density entering or leaving the scalp through the skull is referred to as the Surface Laplacian of the skull. It only considers the outer shape of the volume conductor and does not require any details of volume conduction [19]. Ocular movements can be efficiently eliminated during the signal acquisition. For large artefacts ranging from 50µV (>50µV) visual inspection is needed and by considering shape of the artefacts the gradients of activities are obtained [20]. Hjorth method offers good framework for theoretical explorations. SL is robust against artefacts generated at uncovered regions by the electrode cap and it solves the electrode reference problem [21]. SL is a way of viewing the EEG data with high spatial resolution. SL is sensitive to the choice of spline parameters during spline interpolation [18]. As SL is sensitive to artefacts, care has to be taken during the artefact removal [20].

D. *PCA*

PCA was invented in 1901 by Karl Pearson and later developed independently by Harold Hotelling in 1930 [22]. The PCA transforms the correlated vectors into linearly uncorrelated vectors. These uncorrelated vectors are called as "Principal Components" [22][23]. This is a classical method of Second Order Statistics. It depends on decomposition of covariance matrix. PCA helps in reduction of feature dimensions. Ranking will be done by using PCA based on the variability of the signal properties. This ranking helps in classification of the data. The application of PCA in a BCI system yields best classification results [24]. The PCA is well but it is not as well as ICA [25].

TABLE II
COMPARISON OF SIGNAL ENHANCEMENT METHODS

S. No	Method	Advantages	Disadvantages
1	ICA	• Computationally efficient. • Shows High performance for large sized data. • Decomposes signals into temporal independent and spatial fixed components	• Can't be applicable for under determined cases • Requires more computations for decomposition.
2	CAR	• Outperforms all the reference methods • Yields improved SNR	• Finite sample density and incomplete head coverage cause problems in calculating averages
3	SL	• Robust against the artefacts generated at regions that are not covered by electrode cap. • It solves electrode reference problem	• Sensitive to artefacts • Sensitive to spline patterns
4	PCA	• Helps in reduction of feature dimensions • Ranking will be done and helps in classification of data	• Not well as ICA.
5	CSP	• Doesn't require *a priori* selection of sub specific bands and knowledge of these bands	• Requires use of many electrodes • Change in position of electrode may affect classification accuracies.
6	Adaptive Filtering	• Ability to modify the signal features according to signals being analyzed • Works well for the signals and artefacts with overlapping spectra nature	

E. *CSP*

CSP was first presented by Koles and it can detect abnormal EEG activity [26]. CSP performs transformation of EEG signal into a variance matrix that maximally discriminates between different classes [27]. CSP uses spatial filtering and with spatial information it detects the patterns in EEG. CSP does not require *a-priori* selection of subject specific frequency bands and knowledge of these bands and requires use of many electrodes. It is sensitive to artefacts and electrode positions [27] [28]. During the training process the identical electrode positions is to be maintained to capture the same signals. The increase in accuracies may obsolete because of the change in electrode positions [29] [30].

F. *Adaptive Filtering*

Adaptive filters have the ability to modify signal properties according to the specific characteristics of the signals being analyzed. Noise removal using filters removes noise along with important information. If the signal and noise are overlapping then filters will remove the signal of interest. This problem can be overcome by the adaptive filters. Adaptive interference cancellation is a very efficient method to solve the problem of signals and interferences with overlapping spectra. By using the least mean square algorithm (LMS) the artefacts from EEG signal can be efficiently removed. With the use of LMS algorithm optimization of mean square error is achieved [31]. In [32] for the removal of artefacts a new algorithm for the adaptive filters was proposed and it is named as Recursive Least-Squares (RLS) algorithm and it has proved that the artefacts in the ECG signals are removed and a considerable improvement has observed in the SNR of ECG signal.

Table II shows the comparison of mostly used signal pre-processing methods with their processing, advantages and disadvantages.

IV. FEATURE EXTRACTION

After obtaining the noise-free signals from the signal enhancement phase, essential features from the brain signals were extracted. For feature extraction from EEG signals use methods like Adaptive Auto Regressive parameters (AAR), bilinear AAR, multivariate AAR, Fast Fourier Transformations (FFT), PCA, ICA, Genetic Algorithms (GA), Wavelet Transformations (WT), Wavelet Packet Decomposition (WPD) [10] [33-39]. Among these ICA, PCA, WT, AR, WPD, FFT are mostly used.

A. *ICA*

ICA can also be used as a feature extraction method. ICA forms the components that are independent to each other. From the components essential features were extracted using ICA. An important application of ICA is Blind Source Separation. This helps in identifying the independent signals and also noise separation from brain signals. Blind Source Separation (BSS) of acoustic signals are referred to as Cocktail party problem means separation of a no. of independent components from a set of un-controlling records [33].

B. *PCA*

PCA is s a pre-processing technique as well as a feature extraction method. It is a powerful tool for analyzing and for dimension reduction of data without loss of information [34]. Using PCA the information present at all the time series multi channel is extracted as principal components. By eliminating the artefacts and by forming the principal components PCA reduces the dimensions of signals [35].

C. *WT*

Wavelet Transformation was formulated by Grossman and Morlet gave in 1984 [36] and is used for feature extraction. In [37] Scott et.al proposed a method to perform the feature extraction with the B-Spline parameters. This function can act as low pass filter as well as high pass filter and with these filtering characteristics it stood as B-spline clients. By using multi resolution analysis filter coefficients can be obtained.

D. *AR*

AR method is used for feature extraction in time domain analysis. By using shorter duration of data records this method yields better frequency resolution and reduces the spectral loss problems. It is the most frequently used method for non stationary signals such as EEG where parameters are supplied to the model. The difficulty lies in establishing the parameter model property. Various auto regressive methods are employed in feature extraction of EEG signals and are Bilinear AAR, Adaptive AR parameters (AAR), multivariate AAR (MVAAR). Of these methods, MVAAR exhibits best performance by considering Meta parameters that are common to a feature extraction method and achieves a classification accuracy of 83% [38] [39].

E. *WPD*

WPD can extract features in both time and frequency domain with the coefficients mean of WT. Initial features are taken as the power at special subsets and the separabilities were measured by using Fisher's criterion. In Fisher's criterion, the coefficients with higher separability were considered effective and formed as final vector. It divides the original signal into two subspaces based on frequency. Wavelet packet tree shows the decomposition of low frequency wavelets. The results of Ting et. al [40] shows that WPD yields better performance results and it is superior to AR model. It shows good performance in the extraction process of non-stationary signals like EEG [40].

F. *FT*

FT was identified by Joseph Fourier in 19th century [36]. It extracts the signal features by transforming the signals from time domain to frequency domain. It works well for stationary signals and, linear random processes. It cannot measure both the time and frequency. With prior assumptions some of FT techniques may exhibit better performance in other cases [38]. In this frequency analysis the signals are divided into one-second windows overlapping a half second window. This half second overlaps results in large amount of data for the training of the classifier that forms classes. This frequency based analysis is named as Discrete Fourier Transformation (DFT) and also termed as Power Spectral Density (PSD) [41].

In Table III various feature extraction methods are compared and their advantages, disadvantages are presented.

V. CLASSIFICATION

After feature extraction the signals are classified into various classes using various classifiers. Different types of classifiers include linear classifiers, Artificial Neural Networks (ANN) based classifiers, nonlinear Bayesian classifiers and, nearest neighbour classifiers [42]. Of these classifiers linear classifiers and non linear Bayesian classifiers are mostly used in BCI design.

A. *Linear Classifiers*

Linear classifiers use the linear functions to classify signals into classes. The most frequently used linear classifiers are Linear Discriminant Analysis (LDA) and Support Vector Machine (SVM) [43].

1) *LDA:* LDA creates models of the Probability density function respectively [44]. LDA is simple to use and has very low computational requirements. It provides good results. For non-Gaussian distributions LDA may not preserve the complex structure in the data. LDA fails if the discriminatory function is not in mean but in the variance of the data [45].

2) *SVM:* SVM is a linear classifier that is used by most of the BCI applications. SVM was developed by Vapnik and was driven by statistical learning theory following the principle of structural risk minimization [46]. SVM finds a hyper plane to separate the data sets. It separates data sets with clear gap that is as wide as possible to classify them into their relevant category. The hyper plane maximizes the margin that is the distance between the hyper plane and the nearest points from each class that are called as support vectors [47][48]. The objective of this method is to provide good generalization by maximizing the performance of machine while minimizing the complexity of learned model [44]. In [47] by using a kernel-based SVM approach a mean classification accuracy of 87% was obtained. SVM has more performance and has high computational complexity [45].

TABLE III
COMPARISON OF FEATURE EXTRACTION METHODS

S. No	Method	Advantages	Disadvantages
1	ICA	• Computationally efficient. • Shows High performance for large sized data. • Decomposes signals into temporal independent and spatial fixed components	• Can't be applicable for under determined cases • Requires more computations for decomposition.
2	PCA	• A powerful tool for analyzing and for reducing the dimensionality of data without important loss of information	• Assumes data is linear and continuous. • For complicated manifold PCA fails to process data.
3	WT	• Capable to analyze signal with discontinuities through variable window size. • It can analyze signals both in time and frequency domains. • Can extract energy, distance or clusters etc.	• Lacking of specific methodology to apply WT to the pervasive noise. • Performance limited by Heisenberg Uncertainty.
4	AR	• Requires only shorter duration of data records. • Reduces spectral loss problems and gives better frequency resolution.	• Difficulties exist in establishing the model properties for EEG signals • Not applicable to non stationary signal.
5	WPD	• Can analyze the non stationary signals.	• Increased computation time.
6	FFT	• Powerful method of frequency analysis.	• Applicable only to stationary signals and linear random processes. • Suffers from large noise sensitivity. • Poor time localization makes it not suitable to all kinds of applications.

B. *ANN*

ANNs are non linear classifiers composed of large number of interconnected elements called neurons. Each neuron in ANN simulates the biological neuron and is capable of performing simple computational tasks. The most frequently used neural network is the Multi Layer Perceptron Neural Network (MLPNN) in which, the network is arranged into three layers viz., input layer, hidden layer and output layer. The advantage of MLPNN is that its fast operation, ease of implementation and requiring small training sets. The no. of inputs denotes the no. of features selected and, no. of outputs denotes the no. of classes formed. The complexity of an ANN is estimated by the no. of neurons in the hidden layer of it. The large the no. of neurons in hidden layer the more the complexity, less no. of neurons in hidden layer causes classification errors. No specific criterion was defined for making this decision in hidden layer. By using trial and error method the no. of neurons has to be decided [44] [49].

C. *NBC*

NBCs produce non linear decision boundaries. They are generative in nature and enabled to perform more efficient rejection of uncertain samples than discriminative classifiers. Bayesian Classifiers assign a feature vector to its class with highest probability. Using Bayes' rule a *posteriori* probability of a feature vector is computed. Hidden Markov Model is a non linear Bayesian classifier and is a dynamic classifier. This classifier is suitable for the classification of time series. These are not as widespread as Linear Classifiers and NNs in the field of BCI applications [50].

D. *NNC*

NNCs assign a feature vector to a class based on its nearest neighbours. If the feature vector is from the training set then it is named as k-Nearest Neighbour (k-NN) classifiers. k-NN is a non parametric method, it predicts objects values or class memberships based on the k-closest training examples in the feature space. It assigns the label of a test sample with the majority label of its k-nearest neighbours from the training set. k-NN is very simple to understand, transparent, easy to implement, and debug [50].

In Table IV, comparison of various signal classification methods was given.

TABLE IV
COMPARISON OF SIGNAL CLASSIFICATION METHODS

S. No	Method	Advantages	Disadvantages
1	LDA	• It has low computational requirements • Simple to use. • It provides good results.	• It fails when the discriminatory function not in mean but in variance of the features. • For non-Gaussian distributions it may not

S. No	Method	Advantages	Disadvantages
			preserve the complex structures.
2	SVM	• It provides good generalization. • Performance is more than other linear classifier.	• Has high computational complexity.
3	ANN	• Ease of use and implementation. • Robust in nature. • Simple computations are involved. • Small training set requirements are required.	• Difficult to build. • Performance depends on the number of neurons in hidden layer.
4	NBC	• Requires only small amount of training data to estimate parameters. • Only variance of class variables is to be computed and no need to compute the entire covariance matrix.	• Fails to produce a good estimate for the correct class probabilities.
5	k-NN	• Very simple to understand. • Easy to implement and debug.	• Poor runtime performance if training set is large. • Sensitive to irrelevant and redundant features. • On difficult classification tasks out performed by other classification methods.

VI. CONCLUSION

A clear representation of various signal processing methods used in each level of BCI signal processing is presented in this paper. The results of this survey give a way to select methods required for processing signals. And it also discusses the methods that are not suitable, while describing the following phases of EEG/ BCI signal processing: 1) Signal Acquisition 2) Signal Enhancement 3) Feature Extraction and 4) Signal Classification. This information may give guidance on finding the best method in accomplishing relevant experiments. Work on implementation of above methods in a hybrid methodology is underway.

With the use of various methods of processing, researchers have developed models for animating objects, identifying human emotions, thought based games. With the adequate knowledge of these new and efficient methods with mingled characteristics to always attain better performances can be developed. These new methods may drive to a new era of BCI applications including the thought based operating system, finding the intensity of human emotion, detecting the gender of human based on thoughts, automation of house hold appliance usage based on thoughts etc.

REFERENCES

[1] Jonathan R. Wolpaw, Niels Birbaumer, Dennis J. McFarland, Gert Pfurtscheller, Theresa M. Vaughan, “Brain–computer interfaces for communication and control”, Clinical Neurophysiology 2002.

[2] M. RajyaLakshmi, T. Kameswara Rao, Dr. T. V. Prasad, “Exploration of Recent Advances in The Field of Brain Computer Interface”, IOSR J. of Computer Engg., Vol.8, Issue 2, 2012.

[3] T. Kameswara Rao, M. Rajya Lakshmi, Dr. T. V. Prasad, “An Exploration of Brain Computer Interface and Its Recent Trends”, Int. J. of Advanced Research in Artificial Intelligence, Vol. 1, Issue 8, 2012.

[4] Jonathan R.Wolpaw , Niels Birbaumer, William J.Heetderks, Dennis J.McFarland, P. Hunter Peckham, Gerwin Schalk, Emanuel Donchin, Louis A. Quatrano, Charles J. Robinson, and Theresa M. Vaughan, Brain–Computer Interface Technology: A Review of the First International Meeting, IEEE Trans. on Rehabilitation Engg, Vol. 8, No. 2, 2000

[5] Leigh R. Hochberg and John P. Donoghue, “Sensors for Brain-Computer Interfaces”, IEEE Engineering in Medicine and Biology Magazine. Sep/Oct 2006.

[6] Anders Eklunda, Mats Andersson, Hans Knutsson, fMRI Analysis on the GPU Possibilities and Challenges, Computer Methods and Programs in Biomedicine, 2012.

[7] Siamac Fazli , Jan Mehnert, Jens Steinbrink, Gabriel Curio, Arno Villringer, Klaus-Robert Müller, Benjamin Blankertz, Enhanced performance by a hybrid NIRS–EEG brain computer interface, Neuro Image 59 , 2012 519–529.

[8] Aruna Tyagi and Vijay Nehra, Brain–computer interface: a thought translation device turning fantasy into reality, Int. J. Biomedical Engg. and Tech., Vol. 11, No. 2, 2013.

[9] M. Teplan, Fundamentals of EEG Measurement, Measurement Sc. Rev., Vol. 2, Section 2, 2002.

[10] Ali Bashashati, Mehrdad, Fatourechi, Rabab K Ward and Gary E Birch, A survey of signal processing algorithms in brain–computer interfaces based on electrical brain signals, J. of Neural Engg., Vol. 4, 2007.

[11] Arnaud Delorme, Scott Makeig, EEGLAB: an open source toolbox for analysis of single-trial EEG dynamics including independent component analysis, J. of Neuroscience Methods, Vol. 134, 2004.

[12] A. Srinivasulu, M. Sreenath Reddy, Artifacts Removing From EEG Signals by ICA Algorithms, IOSR J. of Electrical and Electronics Engg., Vol. 2, Issue 4, Sep-Oct. 2012.

[13] T.P. Jung, S. Makeig and C. Humphries, Extended ICA Removes Artefacts from Electroencephalographic Recording, Advances in Neural Inf. Processing Systems, Cambridge, Vol. 10, 1998.

[14] S. Araki, H. Sawada, R. Mukai and S. Makino, A novel blind source separation method with observation vector clustering, Proc. of IWAENC2005, 2005.

[15] Antara Bhattacharya, Dr. N. G. Bawane, S. M. Nirkhi, Brain Computer Interface Using EEG Signals, and Available at: http://www.schalklab.org/sites/default/files/misc/Abrain-computer interface using electrocorticographic signals in humans.pdf.

[16] Josep Mouriño, José del R. Millán, Febo Cincotti, Silvia Chiappa, Raimon Jané, Fabio Babiloni, Spatial Filtering in the Training Process of A Brain Computer Interface, IEEE Engg. in Medicine and Biology Soc., Oct 2001.

[17] Mohammed J. Alhaddad, Common Average Reference (CAR) Improves P300 Speller, Int. J. of Engg. and Tech., Vol. 2 No. 3, 2012.

[18] Thomas C Ferree and Ramesh Srinivasan, Theory and Calculation of the Scalp Surface Laplacian, Electrical Geodesics, Inc., August 24, 2000.

[19] Siyi Deng, William Winter, Samuel Thorpe, Ramesh Srinivasan, EEG Surface Laplacian using realistic head geometry, Int. J. of Bioelectromagnetism, Vol. 13, No. 4, pp. 173-177, 2011.

[20] C. Tandonnet, B. Burle, T. Hasbroucq, F. Vidal, Spatial Enhancement of EEG traces by Surface Laplacian Estimation: Comparison between Local and Global Methods, Clinical Neurophysiology 116 (2005) 18–24.

[21] Claudio G. Carvalhaes, Patrick Suppes, A Spline Framework for Estimating the EEG Surface Laplacian Using the Euclidean Metric, Neural Computation 23, 2010.

[22] Principal Component Analysis, available at http://en.wikipedia.org/wiki/Principal_component_analysis.

[23] Feng Gu, Julie Greensmith, Robert Oates and Uwe Aickelin, PCA 4 DCA: The Application Of Principal Component Analysis To The Dendritic Cell Algorithm, In 9th Annual Workshop on Computational Intell. (UKCI), 7-9 Sept, 2009.

[24] Tomas Zeman, BSS - Preprocessing Steps for Separation Improvement, May 2000, Available at http://noel.feld.cvut.cz/vyu/prj-czs-asi/zeman/pca.pdf

[25] Bruce A. Draper, Kyungim Baek, Marian Stewart Bartlett, J. Ross Beveridge, Recognizing Faces with PCA and ICA, Computer Vision and Image Understanding 91, 2003, available at www.ComputerScienceWeb.com.

[26] Dieter Devlaminck, BartWyns, Moritz Grosse-Wentrup,Georges Otte, and Patrick Santens, Multisubject Learning for Common Spatial Patterns in Motor-Imagery BCI, Computational Intell. and Neuroscience Volume 2011.

[27] Fabien Lotte and Cuntai Guan, Regularizing Common Spatial Patterns to Improve BCI Designs: Unified Theory and New Algorithms, IEEE Trans. On Biomedical Engg., Vol. 58, No. 2, 2011.

[28] Guger C, Ramoser H and Pfurtscheller G, Real-time EEG analysis with subject-specific spatial patterns for a brain–computer interface (BCI), IEEE Trans. Rehabil. Eng, 2000.

[29] Pfurtscheller G, Neuper C, Guger C, Harkam W, Ramoser H, Schlogl A, Obermaier B and Pregenzer M, Current trends in graz brain–computer interface (BCI) research, IEEE Trans. Rehabil. Eng. 8, 2000.

[30] Ramoser H, Muller-Gerking J and Pfurtscheller G, Optimal spatial filtering of single trial EEG during imagined hand movement,IEEE Trans. Rehabil. Engg., 2000.

[31] A Garcés Correa , E Laciar , H D Patiño , M E Valentinuzzi, Artifact removal from EEG signals using adaptive filters in cascade, 16th Argentine Bioengineering Cong. and the 5th Conf. of Clinical Engg., IOP Publishing J. of Physics: Conf. Series 90 (2007).

[32] Chinmay Chandrakar, M.K. Kowar, De-noising ECG Signals Using Adaptive Filter Algorithm, Int. J. of Soft Computing and Engg. (IJSCE), Vol. 2, Issue 1, 2012.

[33] D. A. Torse, R. R. Maggavi, S. A. Pujari, Nonlinear Blind Source Separation for EEG Signal Pre-processing in Brain-Computer Interface System for Epilepsy, Int. J. of Comp. Applications, Vol. 50, No.14, 2012.

[34] Mbeledogu. N. N, Odoh. M. and Umeh. M. N, Stock Feature Extraction Using Principal Component Analysis, 2012 Int. Conf. on Computer Tech. and Sc., IPCSIT vol. 47 (2012).

[35] Ales Prochazka, Martina Mudrova, Oldrich Vysata, Robert Hava, and Carmen Paz Suarez Araujo, Multi-Channel EEG Signal Segmentation AND Feature Extraction, Intelligent Engineering Systems (INES), 2010.

[36] Ioana Adam, Complex Wavelet Transform: application to de-noising, Ph. D Thesis, Politehnica University Of Timisoara Université de Rennes 1, available at http://www.tc.etc.upt.ro/docs/cercetare/teze_doctorat/tezaFiroiu.pdf

[37] Anna Caterina Merzagora, Scott Bunce, Meltem Izzetoglu and Banu Onaral, Wavelet analysis for EEG feature extraction in deception detection, Proceedings of the 28th IEEE EMBS Annual Int. Conf. New York City, USA, 2006.

[38] Ali S. AlMejrad, Human Emotions Detection using Brain Wave Signals: A Challenging, European Journal of Scientific Research, Vol.44 No.4, 2010.

[39] Patrick Ofner, Gernot R. Muller-Putz, Christa Neuper and Clemens Brunner, Comparison of Feature Extraction Methods for Brain-Computer Interfaces, Proc. of the 5th Int. BCI Conf. 2011, Graz, Austria.

[40] Wu Ting a, Yan Guo-zheng , Yang Bang-hua , Sun Hong, EEG feature extraction based on wavelet packet decomposition for brain computer interface , Aug 2007.

[41] Marcin Kołodziej, Andrzej Majkowski, Remigiusz J. Rak, Linear discriminant analysis as EEG features reduction technique for brain-computer interfaces, Przegląd Elektrotechniczny (Electrical Review), R. 88 NR 3a/2012.

[42] Abdul- Bary Raouf Suleiman, Toka Abdul-Hameed Fatehi, Features Extraction Techniques of EEG Signal For BCI Applications, Comp. and Inf. Engg. Dept. College of Electronics Engg., University of Mosul, Mosul, Iraq,2011.

[43] F Lotte, M Congedo, A L_ecuyer, F Lamarche and B Arnaldi, A Review of Classification Algorithms for EEG-based Brain-Computer Interfaces, J. of Neural Engg., Vol 4, 2007.

[44] Deon Garrett, David A. Peterson, Charles W. Anderson, and Michael H. Thaut, Comparison of Linear, Nonlinear, and Feature Selection Methods for EEG Signal Classification, IEEE Trans. on Neural Systems And Rehabilitation Engg., Vol. 11, No. 2, June 2003.

[45] Senthilmurugan.M, Latha.M and Dr.Malmurugan.N, Classification in EEG-Based Brain Computer Interfaces Using Inverse Model, Int. J.of Computer Theory and Engg., Vol. 3, No. 2, April 2011.

[46] Abdolreza. Asadi Ghanbari, Ali Broumandnia, Hamidreza Navidi, Ali.Ahmadi, Brain Computer Interface with Genetic Algorithm, Int. J. of Inf. and Comm. Tech. Research, Vol. 2 No. 1, January 2012.

[47] Alexandre Barachant, St´ephane Bonnet, Marco Congedo and Christian Jutten, BCI signal classification using a Riemannian-based kernel, Proc. of the European Symp. on Artificial Neural Networks, Computational Intell. and Machine Learning (ESANN 2012). Bruges (Belgium), 25-27 April 2012, i6doc.com publ.

[48] P. K. Padhy,Avinash Kumar, Vivek Chandra, Kalyan Rao Thumula and A. Kumar, Feature Extraction and Classification of Brain Signal, World Acad. of Sc., Engg. and Tech. 55 2011.

[49] Mahmut HEKIM, ANN-based classification of EEG signals using the average power based on rectangle approximation window, Przegląd Elektrotechniczny (Electrical Review), R. 88 NR 8/2012 211.

[50] Fabien Lotte, Study of Electroencephalographic Signal Processing and Classification Techniques towards the use of Brain-Co–mputer Interfaces in Virtual Reality Applications, Docteur De L'institut National Des Sciences Appliquées De Rennes Mention Informatique, Jan 2009 (Ph D).

* * * * *