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A Survey on Artifacts Detection Techniques for Electro-Encephalography (EEG) Signals

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Abstract

The EEG signals are the prime sources to diagnose and manipulate Epilepsy, state of coma and numerous studies. The EEG signals in the active brains constitute various body activities controlled or out of human consciousness. There exist considerable researches that focus to minimize the artifact values in the EEG domain. This paper is the evaluation of detection methods to study their efficiency and constraints of experimental limitations.

Keywords*: EEG, EOG, HEOG, VEOG, Brain, Artifacts*

1. Introduction

Human Brain could be scaled as the most intricate systems existing. Brain supports enormous activities that co-operate with surroundings to produce best possible efforts. Certain brain diseases like Alzheimer's a neuro-degenerative disease that could be identified only by brain signal processing [4]. The study of brain in terms of mathematical model is a complex approach. Many methods of brain activity recognition are available such as Gabor Transform, Wavelet Transform, Deterministic Chaos, Wavelet Entropy *etc.*, [5].

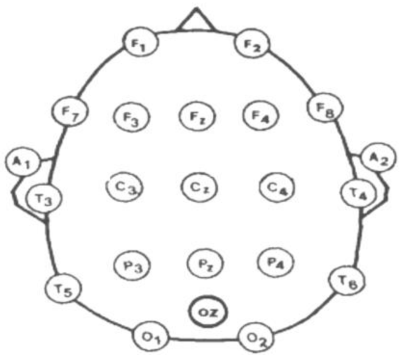

Figure 1. 10-20 System of Montage of Electrodes. Notation: F - frontal, C - central, P -parietal, T - temporal, O - occipital and A - earlobereference Modified from Reilly, 1993 [21]

The electrodes of impedance < 5000 are placed at different ends over scalp for measurement of EEG values. The electric potential is the difference among the active pair of electrodes (bipolar recordings) or passive electrodes (monopolar recordings) also known as base values. Figure 1 illustrates the rough architecture of EEG recordings.

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Electroencephalography allows the processing of brain signals to investigate the internal functionality and look for abnormalities based on pre-defined protocols (methods) [1]. The measure of brain activities are the potential difference of two fixed points in scalp. Electroencephalogram or EEG is the non-invasive measure of the electrical signals (Figure 2) in brain [2].For the research and medical purposes brain activity signals are differentiated on basis of signal's frequency [3]. These frequency bands exist only for the purpose of nomenclature and are sourced by rhythmic activity in brain. The free available EEGLAB can extract the frequency by employing spectral methods (For *ex.*, Welch). A tabular form of EEG signal's frequency to compare is shown in Table 1 [22].

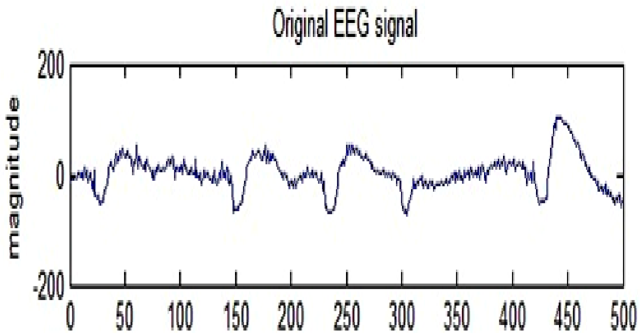

Figure 2. The EEG Signal

Table 1. Rhythmic Activity Signals Frequency Band Comparison

Band	Frequency (Hz)	Location
Delta	2-4	Adults
Theta	4-8	Hand Tasks
Alpha	8-13	Posterior Regions
Beta	13-35	Low-Amplitude Waves
Gamma	35+	Somatosensory cortex
Mu	8-12	Sensorimotor cortex

The correlation among brain and muscles activity is high on the interest of researchers in biomedical engineering. The primary reason of interest lies on the fact that muscles activities (Electromyogram, study of muscle activity) are the function of brain signals and identification of specific process in brain related to this is a subject of integrated focus and modified concern [6-10]. Measurement of resting potential that is generated by electric dipole created with difference in potential across negative and positive cornea is called Electrooculography [12-14]. For the programming of third party applications such as wheel chair movement [11] these signals are essential but are considered as artifacts in EEG signals.

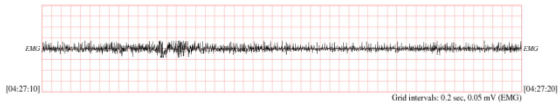

Figure 3. EMG Signal Graph Representation at Grid Interval = 0.2 sec and 0.05 mV for Duration of 10 Seconds [source: physionet.org]

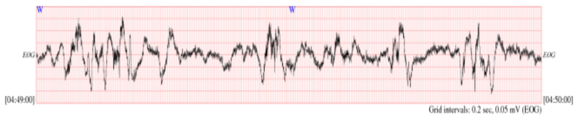

Figure 4. EOG Signal Graph Representation at Grid Interval = 0.2 Sec and 0.05 mV for Duration of 1 Minute [source: physionet.org]

Artifacts

The brain is a complex organ simulating almost all the activities of body. The EEG signals recorded from the scalp of brain thus are not pure brain impulses and are the composition of various artifact intended activities such as Eye movement, muscle reflection, electrode location, setup impedance etc. The constitution of signals resulted by all such features are termed as artifacts. The physiological artifacts caused by the bioelectrical signals consisting of heartbeat, muscle activity and eye blinks are primary sources of low frequency artifacts [15, 18]. These artifacts if rendered unprocessed could be mistaken as the original EEG reading [16].

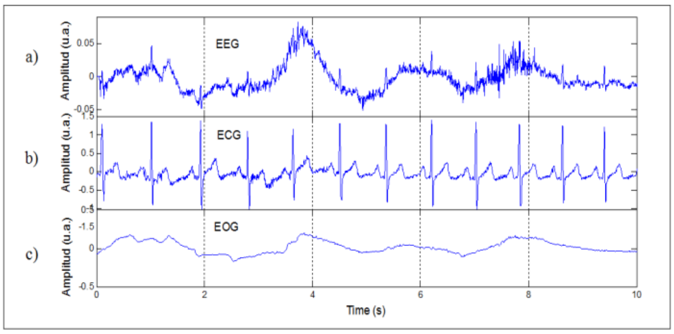

Figure 5. a) EEG Signals with Artifacts Caused by b) ECG Signals and C) EMG Signals [25]

The electrodes or the acquisition system are influenced by fluorescent lights and wires that inherit the values of EEG signals distributed in several channels of EEG [17]. The line frequency interfaces could be considered as original EEG values of the range 50-60 Hz. Eye movements create the artifacts of < 4 Hz but with high propagation. These artifacts are measured by EOG signals whose waveforms are the function of eye movement. EOG measures the dipole and mix with EEG as they spread over scalp [19]. EEG signals are heavily affected by the Cardiac Activity as they posses high electrical energy [15]. The crest values compliment with EEG signals. A detail of bioelectrical signals analysis could be studied in details following the research work of Rangaraj M. Rangayyan [20]. The author summed the discussion of action potential, Electroneurogram (ENG), Electromyogram (EMG), Electrocardiogram (ECG), Electroencephalogram (EEG), Event-related Potentials (ERP), Electrogastrogram (EGG), Phonocardiogram (PCG), Carotid Pulse (CP), Speech Signals, Vibromyogram (VMG), Vibroarthogram (VAG) and Signals from Catheter-tip- sensors.

Electrooculography (EOG)& Electromyography (EMG)

The EOG signals are nothing but the minute potential difference across the cornea and retina [23]. These signals could be traced by placing electrodes on foreheads. In EEG signals the microvolt potential difference of EOG signals cause a considerable noise. Three mechanisms for the eye voltage generation are reviewed in [28]:

- Dipole Movement of Cornea Retina: A dipole is created due to positive charge of cornea and inverse charge in retina .When eye moves from its starting position then dipole is detected with small change. Electrodes are placed on scalp to capture the change which is stored as the dipole, and because of neuro-potentials the electric field fluctuates [29].
- Retinal Dipole Movement: This is a measure of dipole at the retinal location and considered small effects at cornea [30]. Author also focuses on this classification requirement because eye-movement also introduces significant electric signals in addition with eye blinks while recordings of EEG.
- Eyelid Movement: Even some electric field is also introduced because of Eyelids movement in the absence of eye movements [31].

Not much research on the mathematical representation of EOG artifacts was found in EEG signals except that authors of [24] agreed with Elbert et al, 1985 on horizontal, vertical and radical EOG fractions:

$$Y(t,ch) = S(t,ch) + [EOG1(t), EOG2(t), EOG3(t)] \, . [b_1(ch), b_2(ch), b_3(ch)]^T \tag{1}$$

Here,
$Y(t,ch)$ = Record of value of Channel
ch = Channel
t =Time
S = Original Signal (pure nature)
$EOG123$ = Noise source U by horizontal, vertical and radical fractions of EOG
$b(ch)$ = EOG artifacts weight at EEG channel
T = Transpose of matrix.

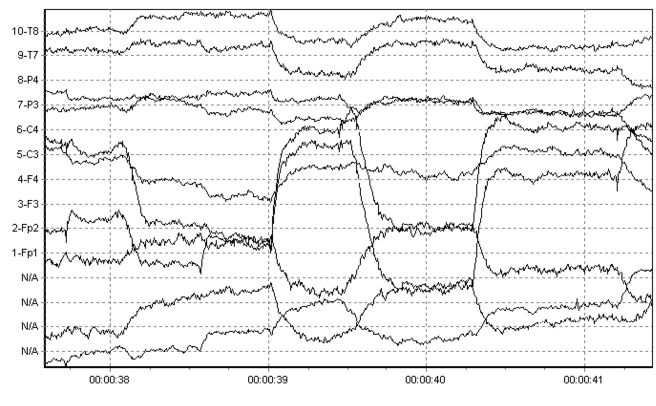

Figure 6. EOG Artifacts [source: Wikipedia.org]

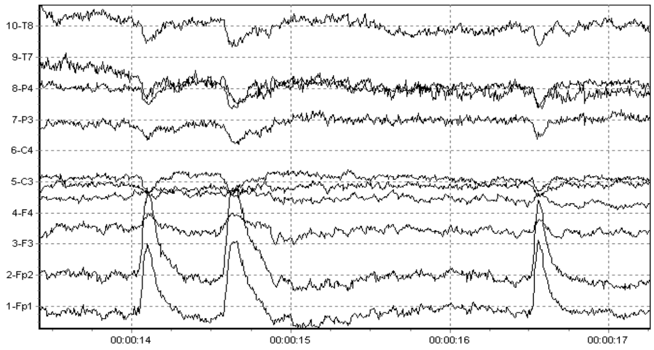

Figure 7. Blink Artifacts [source: Wikipedia.org]

EMG signals are the collective actions of body muscles. EMG artifacts share same frequency range as of EOG signals but the research in this segment is minimal. Most of the concern is directed in the mitigation and reduction of EMG signals rather than analysis. Enormous scale of research can be viewed for removal of eye and muscle artifacts. Many researchers propose the pre-processing of signals to limit the properties of original signal. The filtered signals holds high percentage of pure EEG signals yet no method claims for 100% efficiency.

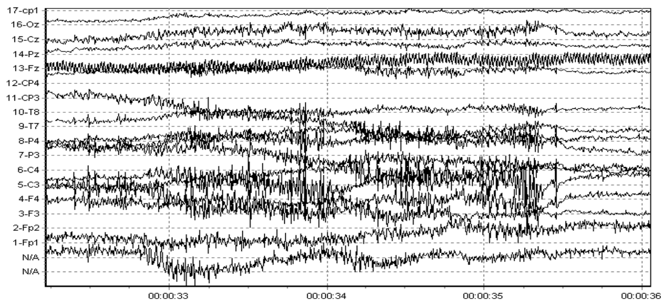

Figure 8. EMG Artifacts [source: Wikipedia.org]

2. Mitigation Practices of Artifacts

To minimize the artifact components from brain signals, a considerable amount of research is already done so far. Initial stages of artifact detection were upgraded with automated algorithms that could separate the unwanted peaks from signals of consideration. This paper embarks three dominant methods for its survey that were employed in numerous applications of brain signals. Comparative Analysis of linear methods like Regression Method, blind source separation methods like Component Analysis (PCA and ICA), Wavelet Decomposition and Empirical Mode Detection are studied to architect the structure of this survey.

Linear Regression Analysis

Regression methods are classified as the time domain and frequency domain regression for correction of EOG signals. The time domain method compares the voltage at every single time point irrespective of the frequency. An estimate of EOG presence in EEG signals is considered in mathematical model and its parameters are defined in auto regression manner estimated by Ordinary Least Square (OLS) method [32-35]. Minimization of mean square error is the function of estimation for parameter selection performed and is performed given by trials, electrodes and segments of trials. The coefficient (β) for estimation of EOG in EEG determines the amount of artifacts signals in EEG readings [28]. The EMG signals in real holds similar properties as of EOG signals (for ex. Frequency, amplitude) hence the nature of artifacts for both EOG and EMG co-relates each other.

$$\beta = \frac{(X_1 - \bar{X}_1)(Y_1 - \bar{Y}_1) + (X_2 - \bar{X}_2)(Y_2 - \bar{Y}_2) + \cdots + (X_n - \bar{X}_n)(Y_n - \bar{Y}_n)}{\sum (X_i - \bar{X}_i)^n} \tag{2}$$

Where,
$\beta =$ Estimated EOG present in EEG analysis
$x =$ EOG signal
$y =$ EEG signal
$n =$ Number of Iterations
The above equation is for n number of iterations. For single EOG artifact the above expression can be reduced to:

$$\beta = \frac{\sum (X_i - \bar{X}_i)(Y_i - \bar{Y}_i)}{\sum (X_i - \bar{X}_i)^2} \tag{3}$$

The estimated EEG is the function of measured EEG, propagation coefficient, EOG and a constant that defines the baseline effect of EOG over EEG.

$$EEG(t) = EEG(m) - (\beta . EOG) - C \; and$$
$$C = \bar{X}_i - (\bar{Y}_i . B) \tag{4}$$

$EEG(t) =$ Estimated EEG
$EEG(m) =$ Measured EEG
$\beta =$ Parameter co-efficient defined in eq. 2
$C =$ Constant

The equation as the representation of matrix (for n number of iterations) is written as [32]:

$$Y = X\theta + E \tag{5}$$

Here,

$$Y = [y(1)y(2) \ldots y(m)]$$
$$X = [x^T(1)x^T(2) \ldots x^T(m)]$$
$$\beta = [\beta_1\beta_2 \ldots \beta_m]$$
$$E = [e(1)e(2) \ldots e(m)]$$

The value of β is updated in the next iteration. The values of Y and X evolve with value this value till the updated β is convergent. OLS corrects EEG value according to last β value.

The frequency domain analysis on five 256-sampled EEG and EOG channels is researched by [32]. The Fast Fourier Transformation of every epoch was carried out for signals. The transmittance coefficient for maximum and minimum powers of EOG is:

$$A(\mu) = \frac{\sum (EEG(\mu)_m EOG^*(\mu)_m) - \sum (EEG(\mu)_n EOG^*(\mu)_n)}{\sum (EOG(\mu)_m EOG^*(\mu)_m)} \tag{6}$$

Where,
$A(\mu) =$ Transmission Coefficient
$EEG(\mu)_m =$ Maximum Power of EEG
$EEG(\mu)_n =$ Minimum Power of EEG
$EOG^*(\mu)_m =$ Conjugated Complex of Maximum Power of EOG
$EOG^*(\mu)_n =$ Conjugated Complex of Minimum Power of EOG

The Regression methods and Principle Component Analysis were overruled by [26] due to their limitations. Authors argued serious contamination by blinks and saccades as there exists difference in transfer functions of EOG-to-EEG. Regression methods subtract the relevant EEG signals along with artifacts. In absence of standard regressing channel the method stands unreliable.

Component Analysis

Blind Source Separation techniques are commonly employed approaches for detection of true and false components in a mixture of signals and images [36]. The method considers true physical sources and parameters of mixing system that could be incorporated in meaningful code and blind signal decomposition. Here, two BSS methods are discussed that were researched by numerous people as a solution of artifacts detection in brain signals.

- Principle Component Analysis

The PCA algorithm is defined as, "A linear projection that transforms multivariate data into a set of linearly independent variables. The successive components (orthogonal to previous component) tend to minimize reconstruction error. The objective function is [36]:

$$J(U,V) = \min_{U,V} \|X - UV\|^2$$
$$= \sum_{i=1}^{n} (x_i - Uv_i)^2 \tag{7}$$

Where,
$U = (u_1, u_2, \dots, u_k)$ First k projection vectors
$V = (v_1, v_2, \dots, v_k)$ Dataset after projection of artifacts

$$U^T U = I_k$$
$$V = U^T X$$

PCA holds good for reduction of muscle artifacts but performs poor in eye blink category. Lagerlund et al. [39] proved the inefficiency of PCA for same amplitudes of artifacts and EEG signals as the assumption of orthogonality in both does not hold true.

Lins *et al.*, [37] optimized PCA for eye signals artifacts separation from multichannel EEG. He compared the performance of Regression analysis and PCA based on spatio-temporal dipole module [38] and found the performance of PCA better. However, in case of comparable amplitudes, the separation technique could not perform on given standards [39]. Normally a considerable amount of research in terms of PCA for artifacts is not available may be the reason that a more generalized version of PCA *i.e.*, independent components is available simultaneously. In a separate comparative study of PCA and ICA [40-43], ICA tends to perform better separation outputs when the input source is noisy.

- Independent Component Analysis

One of the conventional and efficient approaches for detection is Independent Component Analysis. Many researchers integrated properties of ICA to upgrade method for better performance. The positive feature that popularized this method is its ability to cope with diverse artifacts such as eye blink, muscle and electrical (caused due to impedance of electrodes). ICA belongs to the blind source separation category that differentiates the EEG waveforms with maximal independence against each other [27]. A specific pattern in the ICA components are found for eye blinks and muscle activities. In EEG signals these artifacts overlap with original source signal and thus ICA tends to distinguish and measure the overlapping projection.

ICA exploits higher-order statistical dependencies among data and discovers a generative model for the observed multidimensional data. In the ICA model, observed data variables are assumed to be linear mixtures of some unknown independent sources (independent components).A mixing system is also assumed to be unknown. Independent components are assumed to be non-Gaussian and mutually statistically independent. ICA can be applied to feature extraction from data patterns representing time series, images or other media.

The ICA model assumes that the observed sensory signals x_i are given as thepattern vectors$X = [x_1, x_2, \cdots, x_n]^T \in R^n$. The sample of observed patternsis given as a set of N pattern vectors$T = \{x_1, x_2, \cdots, x_n\}$that can be representedas a $n \times N$ data set matrix $X = [x_1, x_2, \cdots, x_n] \in R^{n \times N}$ which containspatterns as its columns. The ICA model for the element $x_i$is given as linearmixtures of m source independent variables s_j

$$x_i = \sum_{j=1}^{m} h_{ij} s_j, \quad i = 1, 2, \ldots, n$$

Where,x_i is observed variable, s_j is the independent component (source signals)and h_{ij} are mixing coefficients. The independent source variables constitutethe source vector (source pattern) vectors $s = [s_1, s_2, \cdots, s_n]^T \in R^m$. Hence, the ICAmodel can be presented in the matrix form

$$\mathrm{x} = Hs$$

Where $H \in R^{n \times m}$ is $n \times m$ unknown mixing matrix where row vector $h_i = [h_{i1}, h_{i2}, \cdots, h_{im}]$ represents mixing coefficients for observed signalx_i. Denotingby h_{ci} columns of matrix H we can write

$$\mathrm{x} = \sum_{i=1}^{m} h_{ci}, s_i$$

The purpose of ICA is to estimate both the mixing matrix H and the sources(independent components) s using sets of observed vectors x.The ICA model for the set of N patterns x, represented as columns in matrixX, can be given as, $X = HS$ Where $S = [s_1, s_2, \cdots, s_n]$ is the m × N matrix which columns correspond toindependent component vectors $s_i = [s_{i1}, s_{i2}, \cdots, s_{im}]^T$ discovered from theobservation vector xi. Once the mixing matrix H has been estimated, we cancompute its inverse $B = H^{-1}$, and then the independent component for theobservation vector x can be computed by $s = B\mathrm{x}$. The extracted independent components s_i are as independent as possible, evaluatedby an information-theoretic cost criterion such as minimum Kulback-Leiblerdivergence kurtosis, negenropy.

- *Pre-processing*

Usually ICA is preceded by preprocessing, including centering and whitening.

Centering

Centering of x is the process of subtracting its mean vector $\mu = E\{x\}$ from x:

$$x = x - E\{x\}$$

Whitening (sphering)

The second frequent preprocessing step in ICA is de-correlating (and possiblydimensionality reducing), called whitening. In whitening the sensor signalvector x is transformed using formula

$$y = W\mathrm{x}, \quad so\ E\{yy^T\} = I_l,$$

Where $y \in R^l$, is the $l - dimensional\,(l \cdot n)$ whitened vector, and W is $l \times n$ whitening matrix. The purpose of whitening is to transform the observed vectorx linearly so that we obtain a new vector y (which is white) which elementsare uncorrelated and their variances are equal to unity. Whitening allows alsodimensionality reduction, by projecting of x onto first l eigenvectors of the covariancematrix of x.

Whitening is usually realized using the Eigen-value decomposition (EVD) of thecovariance matrix $E\{yy^T\} \in R^{n \times N}$ of observed vector x

$$R_{\mathrm{xx}} = E\{\mathrm{xx}^T\} = E_{\mathrm{x}} \Lambda_{\mathrm{x}}^{1/2} \Lambda_{\mathrm{x}}^{1/2} E_{\mathrm{x}}^T$$

Here, $E\mathrm{x} \in R^{n \times n}$ is the orthogonal matrix of Eigenvectors of $R_{\mathrm{xx}} = E\{\mathrm{xx}^T\}$ and Λ is the diagonal matrix of its eigenvalues

$$\Lambda_{\mathrm{x}} = diag(\lambda_1, \lambda_2, \ldots, \lambda_n)$$

With positive eigenvalues $\lambda_1 \geq \lambda_2 \geq .. \geq \lambda_n \geq 0$,the whitening matrix can becomputed as

$$W = \Lambda_{\mathrm{x}}^{-1/2} E_{\mathrm{x}}^{T}$$

And consequently the whitening operation can be realized using formula

$$y = \Lambda_{\mathrm{x}}^{-1/2} E_{\mathrm{x}}^{T} \mathrm{x} = \mathrm{Wx}$$

Recalling that, $x = Hs$, we can find from the above equation that

$$y = \Lambda_{\mathrm{x}}^{-1/2} E_{\mathrm{x}}^{T} \quad Hs = H_{\omega} s$$

We can see that whitening transforms the original mixing matrix H into a newone, H_{ω}

$$H_{\omega} = \Lambda_{\mathrm{x}}^{-1/2} E_{\mathrm{x}}^{T} \quad H$$

Whitening makes it possible to reduce the dimensionality of the whitened vector,by projecting observed vector into first $l\,(l \leq n)$ eigenvectors corresponding tofirst l eigenvalues $\lambda_1, \lambda_2, .., \lambda_l$, of the covariance matrix, E_{x}. Then, the resultingdimension of the matrixWis, $l \times n$ and there is reduction of the size of observedtransformed vector y from $n$to$l$.

Output vector of whitening process can be considered as an input to ICA algorithm.The whitened observation vector y is an input to un-mixing (separation)operation

$$s = By$$

Where, B is an original un-mixing matrix.An approximation (reconstruction) of the original observed vector x can becomputed as,

$$\tilde{x} = Bs \text{ ,Where,} B = W_{\omega}^{-1}.$$

For the set of N patterns x forming as columns the matrix X We can providethe following ICA model

$$X = B\,S$$

Where $S = [s_1, s_2, \cdots, s_n]$ is the $m \times N$ matrix which columns correspond toindependent component vectors $s_i = [s_{i1}, s_{i2}, \cdots, s_{im}]^T$ discovered from theobservation vector, x_i .Consequently we can find the set S of corresponding independentcomponent vectors as

$$S = B^{-1} X.$$

- Generalized Morphological Component Analysis

In GMCA, each of the *m*sources $\{S_1{:}, \ldots, S_m{:}\}$ is assumed to be sparse in an overcompletedictionary.

Romero *et al.*, [44] performed a independent study on various filtering algorithms to different montages of simulated EEG and EOG signals. The results stated about the effectiveness of ICA (BSS) methods in detection of eye signals even in case when EOG was absent or the signal length was constrained. Delorme *et al.*, [44] found 10-20% increase in performance for almost every ICA algorithm when collectively applied with pre-processing.

Wavelet Transform

Along with the muscular and ocular interferencesin brain signals, the electroencephalogram signals are often received with considerable noise content. The BSS and regression methods in this case, filter the true signals only on a partial basis [50]. Wavelet denoising is decomposition of signals in terms of discrete wavelet transform so as to obtain few wavelet coefficients with high absolute values with invariant noise energy [51].

For a signal with mixed noise

$$x(k) = c(k) + n(k)$$

The wavelet transform is generated as

$$w_x = w_c + w_n$$

Where,

$c =$ Noise free content

n = Noise source
x = Source Signal

Denoising is separation of wavelet coefficients based on a threshold. However, as the coefficients are invariant in case of lower frequencies, the consideration is scaled to estimation of threshold δ, among trough and crest of wavelet coefficients [50]. Donoho [52] proposed wavelet shrinkage to mimic Gaussian noise by localizing information of deterministic signal in limited number of wavelet coefficients [53].

$$C_{j,k} = \sum_{t \in Z} x(t) g_{j,k}(t)$$

Where,
$C_{j,k}$ = Wavelet Coefficients
$g_{j,k}(t)$ = Scaling function

In the soft thresholding method [53] wavelets coefficients are replaced to set them in range of $[-\delta, \delta]$ to zero and others are shrunk in absolute value. Donoho calculated δ as:

$$\delta = \sqrt{2\log(M)\bar{\sigma}^2}$$

Where,
$\bar{\sigma}^2$ = Estimation of noise variance σ^2 and

$$\bar{\sigma}^2 = median\left(\left|C_{j,k}\right|\right)/0.6745$$

The pseudo code for transformation of wavelet signals could be summed as:

1. Performing the elimination of outliner
2. Introduction of wavelet transformation to input signal $x(t)$
3. Implementation of thresholding to output of statement 2
4. Generation of denoised signals through inverse wavelet transformation

3. Results

The experiments on linear regression has been mentioned by ZahmeetSakaff [48] which is based on five models of regression analysis. Input data is considered as EEG source full of artifacts shown in (Figure 8(a)) and all the methods were introduced and results are compared (sub sections of Figure 8). The author discussed for both positive and negative epoch (Figure 9), and concluded that quadratic regression model performed better compared to rest of techniques.

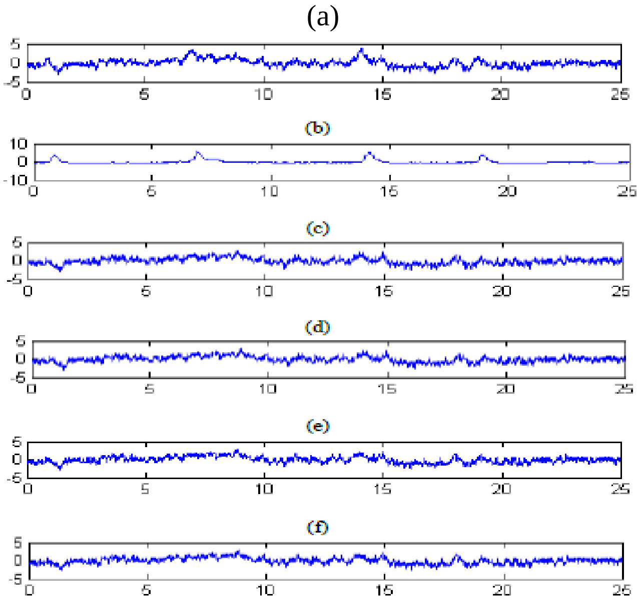

Figure 8: Regression Analysis Method for Removal of Artifacts in Electroencephalography Signals with Positive Epochs

Figure 8 shows the Regression Analysis Method for Removal of Artifacts in Electroencephalography Signals with Positive Epochs (a) Recording of EEG before Artifacts Removal (b) EOG with Artifacts (c) Schlogl *et al*. Linear Method for Artifact Rejection (d) Standard Linear Regression Model for Rejection of Artifacts (e) Quadratic Regression Model for Artifacts Rejection (f) Artifacts Rejection by Cubic Regression Model.

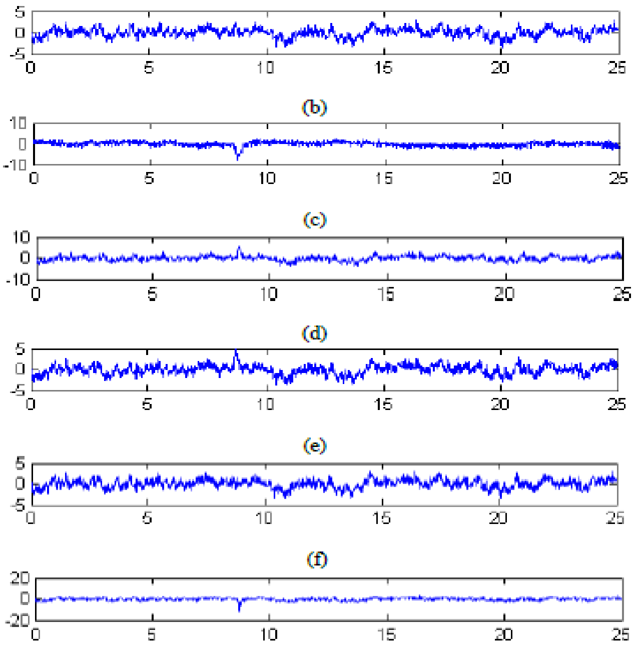

Figure 9. Shows the Regression Analysis Method for Removal of Artifacts in Electroencephalography Signals with Negative Epochs

Figure 9 shows the Regression analysis method for removal of artifacts in Electroencephalography signals with negative epochs having (a) Recorded EEG with artifacts from source (b) EOG with artifacts (c) artifact rejection by linear method (d) Artifacts rejection by Standard Linear Regression Model (e) Artifacts rejection by Quadratic regression model (f) Artifacts Rejection by Cubic non-linear Regression model.

Romero *et al*. [47] considered artifacts minimization algorithm for PCA and FASTICA and presented a tabular comparison of percentage error in spectral variables. The absolute value of errors are estimated and relative index of alpha, beta, theta and delta are calculated from both EEG source having artifacts and corrected EEG source.

Table 1. Percentage Error in Spectral Variables

Spectral Variables	PCA	FASTICA
Total Power	23.93	48.61
Abs. delta	38.99	77.77
Rel. Delta	22.9	17.08
Abs. theta	23.82	43.62
Rel. theta	10.21	11.76
Abs. Alpha	24.49	35.57
Rel. Alpha	12.61	11.46
Abs. beta	26.67	48.33
Rel. beta	16.68	12.01
Mean of Variables	22.03	33.02

According to his studies the non-correlated ocular artifacts were witnessed only in range of theta and delta bands. For absolute powers the errors were similar for Regression and ICA. For high absolute alpha power errors Regression and PCA clipped much cerebral activity than any other method applied.

T. P Jung [26] compared the performance of PCA and ICA on a 5 sec source recording of EEG.

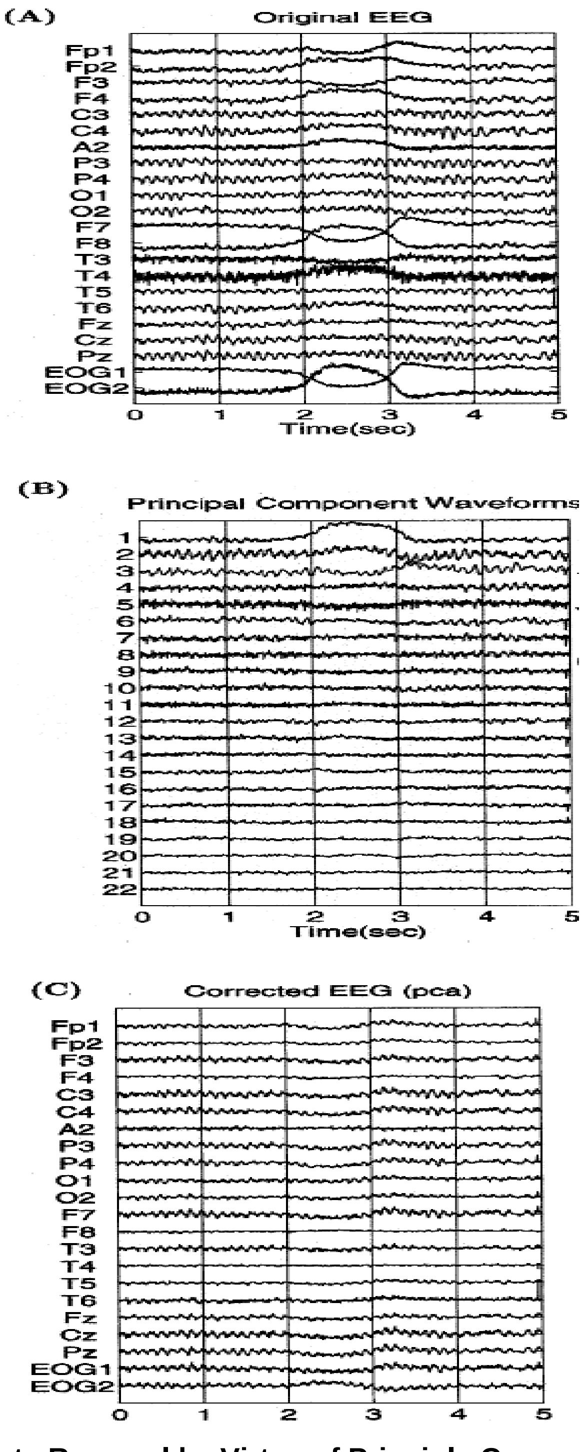

Figure 10. Artifacts Removal by Virtue of Principle Components (a) Original 5s EEG Epoch Signal (b) Principle Component Waveforms for 5 Selected Components (c) Epoch Correction of Artifacts by Implementation of PCA

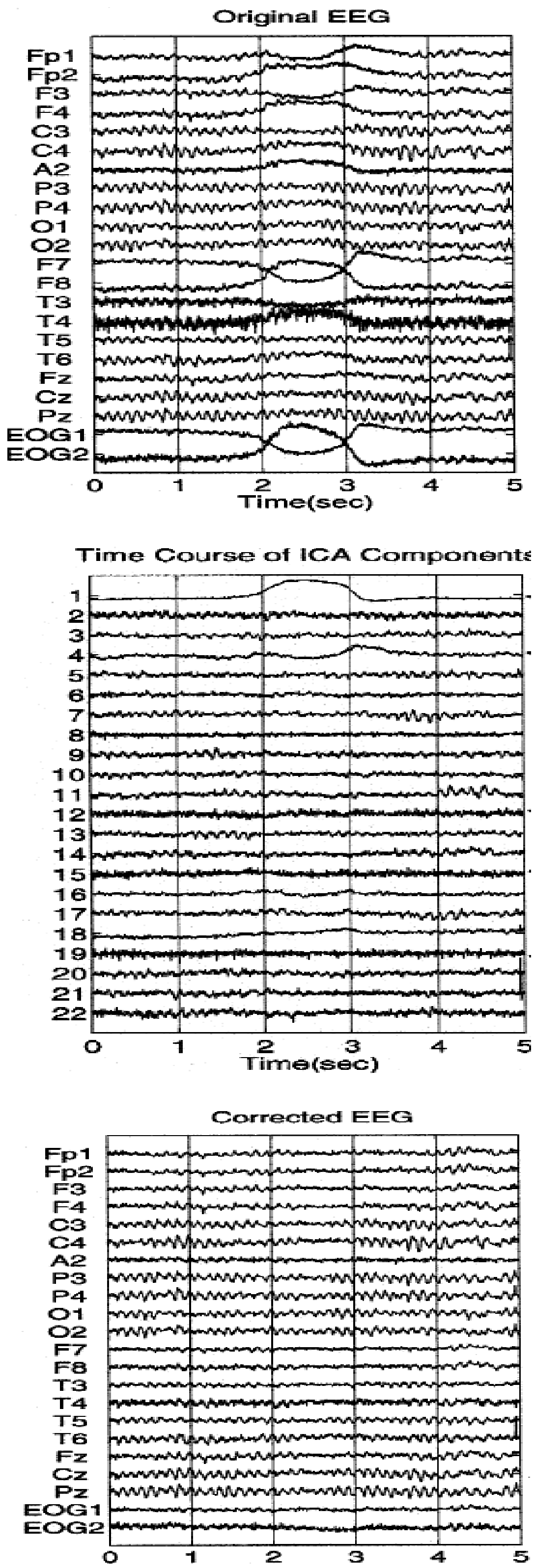

Figure 11. Artifacts Removal by Virtue of Independent Components (a) Original 5s EEG Epoch Signal (b) Independent Component Waveforms for 5 Selected Components (c) Epoch Correction of Artifacts by Implementation of ICA

The ICA tends to filter artifacts into separate components. Forward to identification of independent components, the non-artifactual components are projected back so that rows representing individual components set back to zero. The INFOMAX algorithm for separation of independent components performs in better manner in comparison with FAST ICA and second order blind inference [49].

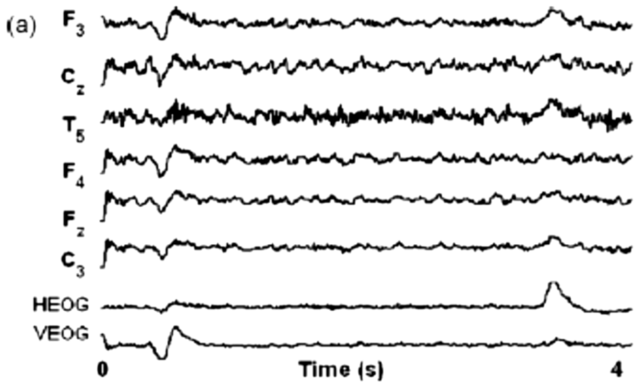

Figure 12. A Typical 4-s EEG Signal

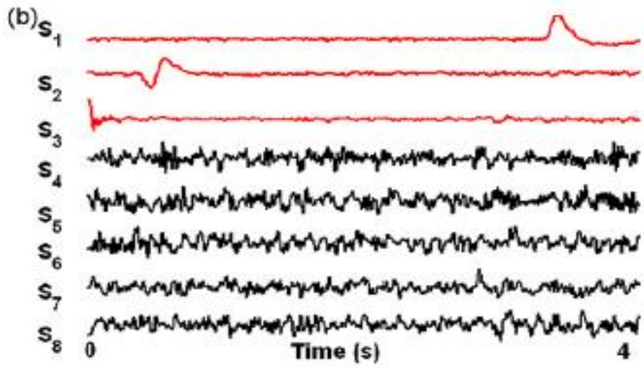

Figure 12. Corresponding Independent Sources by Extended INFOMAX Algorithm

LeilaFallah [46] used wavelet for decomposition in which a blinking artifact signal was decomposed in tree form with 2 categories in 6 signals. For frequency range of 0-1.4 Hz bior3.3 wavelet was applied for decomposition in level six approximations

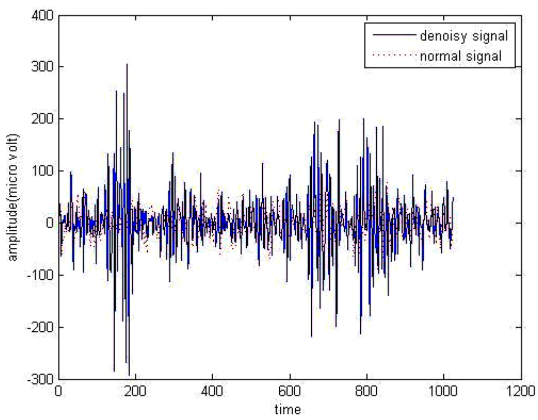

Figure 13. Artifact Denoising Using Wavelets

[54] introduced the effective collaboration of Independent components and Wavelet based independent components analysis. Authors identified ICA to be effective method but supplementary noise is added with signals whereas WICA is practical design that reproduce control signals (Figure 14).

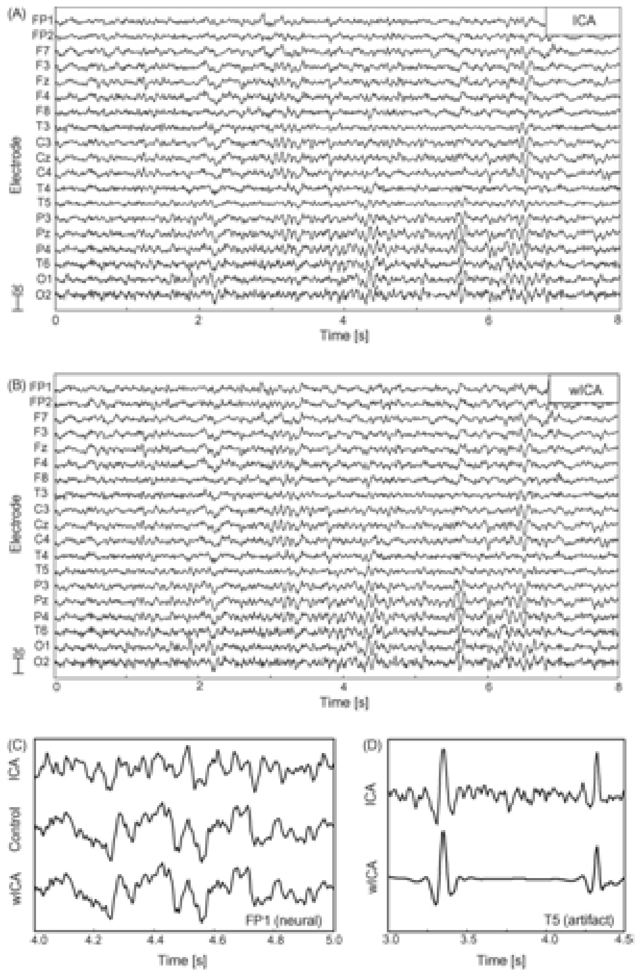

Figure 14. ICA and WICA based Method for Artifacts Suppression (a) Ocular and Heartbeat Artifacts Reduction by ICA (b) Ocular and Heartbeat Artifacts Reduction by WICA (c) At FPI Electrode the Error Free Signals in Zoomed View (d) Estimation of Heart Beat artifacts

4. Conclusion

The artifacts for brain signal is discussed by numerous researchers but before wavelet denoising the noise in brain signals was under studied factor. The signals were cleaned up to a good extent yet the noise factor is supposed to be concentrated. The detection algorithms in this survey were quantitatively studied by various researchers and have applications in diverse applications. However, in brain signals artifact reduction scenario, the performance scale of single algorithm is unreliable. The regression analysis technique clips the necessary epochs of true signals hence in case of ocular artifacts that possess low amplitudes the true signals get distorted. The Principle Components was devised by some researchers but the parallel presence of more generalized version (ICA) over ruled the possibilities of PCA for this segment. The introduction of noise in brain signals by ICA as supplement is undesirable hence the wavelet was scaled that practically generates the true source signals.

In future we would configure the benefits of ICA with Double Density Wavelet transform, considering the advantages of DDWT over DWT. Double density approximates DWT that ease closer spacing among wavelet transforms over same scale.

References

[1] S. K. Gurumurthy, V. S. Mahit and R. Ghosh, “Analysis and simulation of brain signal data by EEG signal processing technique using MATLAB”, International Journal of Engineering and Technology (IJET), **(2013)**.

[2] J.-R. Duann, T.-P. Jung, S. Makeig, “Brain Signal Analysis”, http://sccn.ucsd.edu/~duann/papers/duann-brainsig _ draft2.pdf.

[3] S. Blanco, *et al.*, "Time-frequency analysis of electroencephalogram series", Physical Review E, vol. 51, no. 3, **(1995)**, pp. 2624.

[4] J. Dauwels, F. Vialatte, and A. Cichocki, “Diagnosis of Alzheimer’s disease from EEGSignals: Where Are We Standing?” http://www.dauwels.com/Papers/AD_Review.pdf.

[5] R. Q. Quiroga, “Quantitative analysis of EEG signals:Time-frequency methods and Chaos theory”, aus Buenos Aires, Argentinien, Lubeck, Institute of Physiology - Medical University Lubec, **(1998)**.

[6] H. Valentova and J. Havlik, “Initial Analysis of the EEG Signal Processing Methods for Studying Correlations between Muscle and Brain Activity”, Department of Circuit Theory, http://amber.feld.cvut.cz/bmeg/wp-content/uploads/2012/03/Valentova-ITBAM-2010.pdf.

[7] R. Bortel and P. Sovka, “EEG–EMG Coherence Enhancement Signal Processing”, vol. 86, **(2006)**, pp. 1737-1751.

[8] S. Salenius, R. Salmelin, C. Neuper, G. Pfurtscheller and R. Hari, “Human Cortical40 Hz rhytm is Closely Related to EMG Rhythmicity”, Neuroscience Letters, vol. 213, no. 2, **(1996)**, pp. 75– 78.

[9] Tuncel, D. A. Dizibuyuk, and M. K. Kiymik. “Time Frequency Based Coherence Analysis between EEG and EMG Activities in Fatigue Duration”, Journal of Medical Systems, vol. 34, no. 2, **(2010)**, pp. 131-138.

[10] S. Salenius, K. Portin, M. Kajola, R. Salmelin and R. Hari, “Cortical Control of Human Moto neuron firing During Isometric contraction”, Journal of Neuro physiology, vol. 77, no. 6, **(1997)**, pp. 3401-3405.

[11] N. M. M. Noor and S. Ahmad, “Analysis of Different Level of EOG Signal from Eye Movement for Wheelchair Control”, Department of Mechatronics, Kuliyyah of Engineering, IIUM, Gombak, Malaysia.

[12] R. Barea, L. Boquete, M. Mazo and E.Lopez, “System for Assisted Mobility Using Eye Movements Based on Electrooculography”, IEEE Transactions on Neural Systems and Rehabilation Engineering, vol 10, no. 4, **(2002)**, pp. 209-218.

[13] R. Barea, L. Boquete, M. Mazo, E. Lopez, and L. Bergasa, “Electrooculographic guidance of a wheelchair using eye movements codification”, The International Journal of Robotics Research, vol. 22, no. 10, **(2002)**, pp. 641 – 652.

[14] S. Yathunanthan, L. U. R. Chandrasena, A. Umakanthan, ,V. Vasuki and S. R. Munasinghe, “Controlling a Wheelchair by Use of EOG Signal”, ICIAFS 2008: Proceedings of International Conference on Information and Automation for Sustainability, **(2008)**; Colombo, Sri Lanka.

[15] L. Sornmo and P. Laguna,“Bioelectrical signal processing” in cardiac and neurological applications (1st ed.), ELSEIVER, ISBN 0-12-437552-9, USA, 2005.

[16] Y.L.Wang, J.H. Liu and Y.C. Liu, “Automatic Removal of Ocular Artifacts from Electroencephalogram Using Hilbert-Huang Transform”, The 2nd International Conference on Bioinformatics and Biomedical Engineering, ICBBE, **(2008)**; Shanghai, China.

[17] S. Sanei and J. Chambers, “EEG Signal Processing (1st ed.)”, Jhon Wiley & Sons, **(2007)**.

[18] A. Crespel, P. Gélisse, M. Bureau and P. Genton, “Atlas of Electroencephalography (1st ed)”, vol. 1 & 2, Libbey Eurotext, **(2005)**.

[19] L. Vigon,, Saatchi, M.R., Mayhew, J.E.W. and Fernandes, R. , “Quantitative evaluation of techniques for ocular artifact filtering of EEG waveforms”, IEE Processing Science Meas. Technology, vol. 147 no. 5, **(2000)**, pp. 219-228.

[20] R. M. Rangayyan, “Biomedical Signal Analysis” A case study approach, R856, R36. IEEE Engineering in Medicine, **(2002)**.

[21] E. Reilly, E. Niedermeyer and F.H. Lopes da Silva, “EEG Recording and Operation of the Apparatus”, Electroencephalography: Basic Principles, Clinical Applications and Related Fields, 3rd ed., **(1993)**, pp. 104-124.

[22] D. Garrett, D. A. Peterson, C. W. Anderson and M. H. Thaut, “Comparison of Linear, Nonlinear, and Feature SelectionMethods for EEG Signal Classification”, IEEE Transactions on Neural Systems and Rehabilitation Engineering, vol. 11, no. 2, **(2003)**.

[23] L. Cruz, “Mathematical Model for Biomedical Systems&Their Engineering Analogy”, http://intelsath.com /downloads/pdfeyeboard/eyeboard.pdf.

[24] A. Schlogl, C. Keinrath, D. Zimmermann, R. Scherer, R. Leeb and G. Pfurtscheller, “A fully automated correction method of EOG artifacts in EEG recordings”, Clinical Neurophysiology , vol. 1, no.18, **(2007)**, pp. 98–104.
[25] M. A. G. Correa and E. L. Leber, “Noise Removal from EEG Signals in Polisomnographic Records Applying Adaptive Filters in Cascade”, **(2011)**.
[26] T.-P. Jung, S. Makeig, C. Humphries, T.-W. Lee, M. J. Mckeown, V. Iragui, and T. J. Sejnowski, “Removing electroencephalographic artifactsby blind source separation”, Psychophysiology, vol. 37, **(2000)**, pp. 163–178.
[27] A. Delorme, T. Sejnowski, and S. Makeig, “Enhanced Detection of Artifacts in EEG Data Using Higher-Order Statistics and Independent Component Analysis” Neuroimage , vol. 34, no. 4, **(2007)**, pp. 1443–1449.
[28] R. J. Croft and R. J. Barry, “Removal of Ocular Artifacts from the EEG: A Review”, Neurophysiol Clinical, vol. 30 ,pp. 5-19, **(2000)**.
[29] C.H.M. Brunia, J. Mocks, M. V. D. Berg-Lenssen, “Correcting Ocular Artifacts- A Comparison of Several Methods”, J. Psychophysiol, vol 3, **(1989)**, pp. 1-50.
[30] P. Berg, “The Residual after Correcting Event-Related Potentials for Blink Artifacts” Psychophysiology , Vol 23, Pp no 354-64, 1986.
[31] P. Berg and M. Scherg, “Dipole Models of Eye-Movements and Blinks”, Electroencephalogr Clin Neurophysiol, vol. 79, **(1991)**, pp. 36-44.
[32] D.V. Moretti, F. Babiloni, F. Carducci, F. Cincotti, E. Remondini, P.M. Rossini,S. Salinari, C. Babiloni, “Computerized processing of EEG–EOG–EMG artifacts for multi centric studies in EEG oscillations and event-related potentials” International Journal of Psychophysiology, vol. 47, pp. 199–216, **(2003)**.
[33] R. Verleger, T. Gasser and J. Mocks, “Correction of EOG artifacts in event related potentials of the EEG: aspects of reliability and validity”, Psychophysiology, vol. 19, **(1982)**, pp. 472–480.
[34] G. Gratton, M.G.H. Coles and E. Donchin, “A new method for the off-line removal of ocular artifact” , Electroencephalogr. Clin. Neurophysiol, vol. 55, **(1983)**, pp. 468–484.
[35] B.W. Jerwis, M.J. Nichols, E.M. Allen, N.R.Hudson and T.E. Johnson, “The assessment of two methods for removing eye movement artifact from the EEG”, Electroencephalogr.Clin. Neurophysiol ,vol. 61, **(1985)**, pp. no. 444–452.
[36] A. S. Cichocki, "Blind source separation: new tools for extraction of source signals and denoising", Defense and Security, International Society for Optics and Photonics, **(2005)**.
[37] O.G. Lins, T.W. Picton, P. Berg and M. Scherg, “Ocular Artifacts in Recording EEG and Event-related Potentials II: Source dipoles and SourceComponents”, Brain Topography, vol. 6, no. 1, **(1993)**, pp. 65-78.
[38] P. Berg and M. Scherg, “Dipole models of eye activity and its applicationto the removal of eye artifacts from the EEG ad MEG”, Clin. Physiol Meas., vol. 12, **(1991)**, pp. 49-54.
[39] T.D. Lagerlund, F.W. Sharbrough and N.E. Busacker, “Spatial Filtering of Multichannel Electroencephalographic Recordings through Principal Component Analysis by Singular Value Decomposition”, J. Clin. Neuro physiology, vol. 14, no. 1, **(1997)**, pp. 73-82.
[40] K. Delac, M. Grgic and S. Grgic, "Independent comparative study of PCA, ICA, and LDA on the FERET data set", International Journal of Imaging Systems and Technology, vol. 15, no. 5, pp. 52-260, **(2005)**.
[41] B. A. Draper, *et al*., "Recognizing faces with PCA and ICA." Computer vision and image understanding ,vol. 91, no. 1, **(2003)**, pp. 115-137.
[42] A. Selinger and D. A. Socolinsky, “Appearance-based facial recognition using visible and thermal imagery: a comparative study”, Equinox Corp NY, **(2006)**.
[43] R. Mutihac and M. M. V. Hulle, "PCA and ICA neural implementations for source separation-a comparative study", Neural Networks, (2003), Proceedings of the International Joint Conference, vol. 1, IEEE, **(2003)**.
[44] S. Romero, M.A. Ma˜nanas, M.J. Barbanoj, “A comparative study of automatic techniques for ocular artifact reduction in spontaneous EEG signals based on clinical target variables: a simulation case”, Comput Bio Med , vol. 38, **(2008)**, pp. 348–60.
[45] A. Delorme, T.J. Sejnowski and S. Makeig, “Enhanced detection of artifacts in EEG datausing higher-order statistics and independent component analysis”, NeuroImage, vol 34, **(2007)**, pp. 1443–9.
[46] L. F. Araghi, “A New Method for Artifact Removing in EEG Signals", Proceedings of the international Multiconference of Engineers and Computer Scientists, **(2010)**.
[47] S. Romero, A. M. Mañanas and M. J. Barbanoj, "A comparative study of automatic techniques for ocular artifact reduction in spontaneous EEG signals based on clinical target variables: a simulation case", Computers in biology and medicine, vol. 38, no. 3, **(2008)**, pp. 348-360.
[48] Z. Sakkaff and A. Nanayakkara, "Removal of ocular artifacts from EEG signals in brain computer interface", Proceedings of the Technical Sessions, vol. 24, **(2008)**.
[49] H. Ghandeharion and A. Erfanian, "A Fully Automatic Ocular Artifact Suppression From EEG Data Using Higher Order Statistics: Improved Performance by Wavelet Analysis", Medical engineering & physics, vol. 32, no. 7, **(2010)**, pp. 720-729.

[50] R.-V. Rebeca, *et al*., "Ocular Artifacts Removal in Scalp EEG: Combining ICA and Wavelet Denoising", 5th International Conference on Physics in Signal and Image Processing, **(2007)**.
[51] L. V, Birgale and M. Kokare, "Iris Recognition Using Discrete Wavelet Transform", Digital Image Processing, 2009 International Conference on. IEEE, **(2009)**.
[52] D. L. Donoho, I.M. Johnstone, G. Kerkyacharian, and D. Picardi, “Wavelet Shrinkage: Asymptopia?”, J. R. Stat. Soc. B, vol. 57, **(1995)**, pp. 301-369.
[53] U. E. Emir, *et al*., "Wavelet denoising vs. ICA denoising for functional optical imaging", Neural Engineering”, 2003 Conference Proceedings First International IEEE EMBS Conference on. IEEE, **(2003)**.
[54] N. P. Castellanos and V. A. Makaro, "Recovering EEG Brain Signals: Artifact Suppression with Wavelet Enhanced Independent Component Analysis", Journal of neuroscience methods, vol. 158, no. 2, **(2006)**, pp. 300-312.

