Methods for the elimination of ocular artefacts from EEG

John William Carey Medithe* and
Usha Rani Nelakuditi

Department of Electronics and Communications Engineering,
Vignan's Foundation for Science, Technology
and Research University,
Guntur, Andhra Pradesh, India
Email: careymedithe@gmail.com
Email: usharani.nsai@gmail.com
*Corresponding author

Abstract: Electroencephalogram (EEG) is a significant medical imaging tool which reflects the electrical activity of the brain due to firing of the neurons in brain. These EEG potentials will be in an order of microvolt, which is low in amplitude are prone to contamination of artefacts from other human organs like eye, muscle, heart, etc. The overlapping of the artefacts on normal EEG may affect the physician's interpretation of EEG, finally leading to wrong diagnosis. Among the all the artefacts contaminating into the EEG signal Ocular Artefact (OA) is the dominant artefact. This is because the OA caused by the eye is very much nearer to the psyche. This paper gives the perspective of various methods used to filter the ocular artefacts. The benefits and drawbacks of each method are also presented. Outcomes of respective methods when the EEG signal applied are simulated using EEGLAB Toolbox for MATLAB and NI LabVIEW.

Keywords: EEG; electroencephalogram; ICA; ocular artefacts; PCA; wavelet decomposition.

Reference to this paper should be made as follows: Medithe, J.W.C. and Nelakuditi, U.R. (2018) 'Methods for the elimination of ocular artefacts from EEG', *Int. J. Biomedical Engineering and Technology*, Vol. 28, No. 2, pp.147–159.

Biographical notes: John William Carey Medithe received the BTech in Electronics and Communication Engineering from Jawaharlal Nehru Technological University, Kakinada, India, in 2012 and ME in Communication Systems from Andhra University, Visakhapatnam, India, in 2014. Since 2015, he has been with the Vignan's Foundation for Science, Technology and Research University, where he is currently working towards the PhD degree at the Image Processing and Machine Vision Research Centre. He is awarded with the UGC JRF Fellowship Award in 2016, in recognition of his academic background and the impact of his research plan. His research interests include signal processing, biomedical circuits and communication systems.

Usha Rani Nelakuditi received the Doctoral degree (PhD) in a field of Medical Imaging from Jawaharlal Nehru Technological University, Ananthapur, India, in 2013. She has published more than 30 research articles in various reputed journals and international conferences. She was the principal investigator for three government funded research projects from various

funding agencies like AICTE and DST, Govt. of India. She was being as a Head of the Electronics and Communications Engineering department since 2013 in Vignan's Foundation for Science, Technology and Research University. Her areas of research include biomedical signal and image processing, VLSI and instrumentation and automation.

1 Introduction

The electroencephalogram is a prescribed means to measure and record the electrical activity of the brain (Homan et al., 1987; Singh and Bansal, 2014). Human brain consists of about 100 billion numbers of neurons. These neurons are specialised to transmit nerve impulses. The electric potential over the scalp induced due to the firing of neurons. These firings of neurons are acquired and interpreted as the voltage responses with respect to time. In general, there are other bio-electric potentials developed in the human body, other than brain electric potential like ECG, EOG, EMG, etc., gets superimposed onto the true electrical potential of the brain. Overlaying, other bio-potentials over the brain electric potential, makes true EEG signal as a contaminated EEG signal. The other undesired electrical potentials which are contaminating into the true EEG signal are to be considered as the artefact with respect to the brain electrical activity. The episode of artefacts can be caused in many sources from the side of patient, environment and equipment used for recording of EEG. In examining and study of the artefacts of all the artefacts, the electrical activity caused by the Ocular organ in the human physical structure is treated as chief artefact. The Ocular potential which is contaminating into the true EEG signal creates misinterpretation in the EEG analysis. The Ocular artefact can be occurred as an episode when there is any movement done by Ocular organ. The potential which is exited near and around the ocular region due to the movements of the Ocular region is recorded as EOG (Medithe and Nelakuditi, 2016). The Frontal and Front polar electrodes of EEG acquisition system are very much prone to the contamination of EOG artefact into the true EEG signal.

1.1 Acquisition of EEG

To acquire EEG signal in the reliable and protected approach and to have better analysis and interpretation, International Federation of Clinical Neurophysiology (IFCN) gives standards for the acquisition of EEG signal to study brain electrical activity. The American Clinical Neurophysiology Society has suggested minimum 21 electrodes for the acquisition of EEG forms a standard system called International 10-20 to acquire basic electrical activity in every lobe of the brain (Homan et al., 1987; Shoran et al., 2015). 10-20 resembles the percentage of the distance between the electrodes. It also gives the positioning of the electrodes located over the scalp. The left hemisphere of the brain bears odd numbered electrodes, while the even numbered electrode placed over the right hemisphere of the psyche. EEG signal acquired from the differential gain of the two nearby electrodes forms a channel called as the bipolar montage. Electrodes with common reference to all electrodes forms as an individual channel called as referential montage, which are placed on the scalp. Here, electrode acts as a transducer which output can be acquired as a voltage response over a point of time. Midline electrodes are marked as ‘Z’, while other points marked as Frontal (F), central (c), Front polar (Fp), Parietal (P), Occipital (O), Temporal (T) and Occipital (O) shown in Figure 1. Increase in number of the electrodes gives accurate location of the seizures and other specific information about artefacts involved. The experimental analysis is done using EEGLAB Toolbox for MATLAB, on a 32-channel EEG data set. The 32-channel location data set is shown in Figure 2.

Figure 1 The 10-20 international system for the acquisition of EEG and minimum requirement of electrodes recommended by the American Clinical Neurophysiology Society (Nicolas-Alonso and Gomez-Gil, 2012)

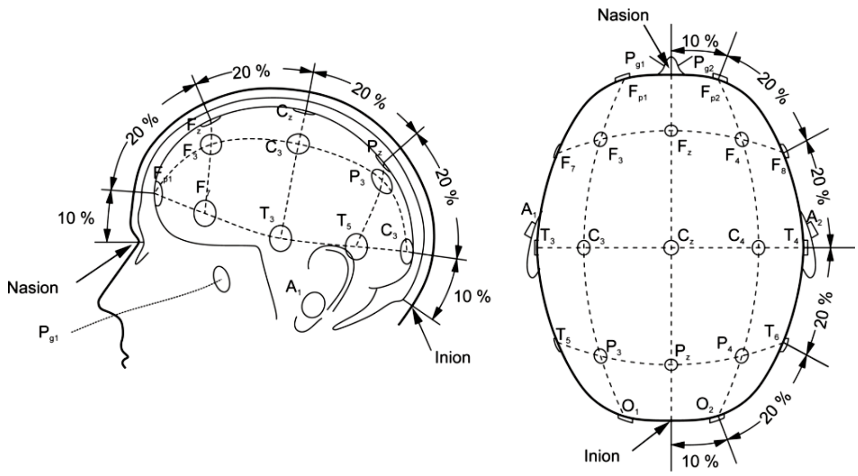


Figure 2 Channel location of the 32-channel EEG data set to perform ocular artefact rejection

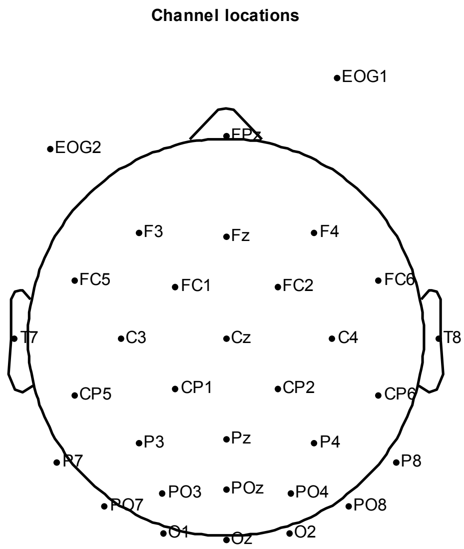
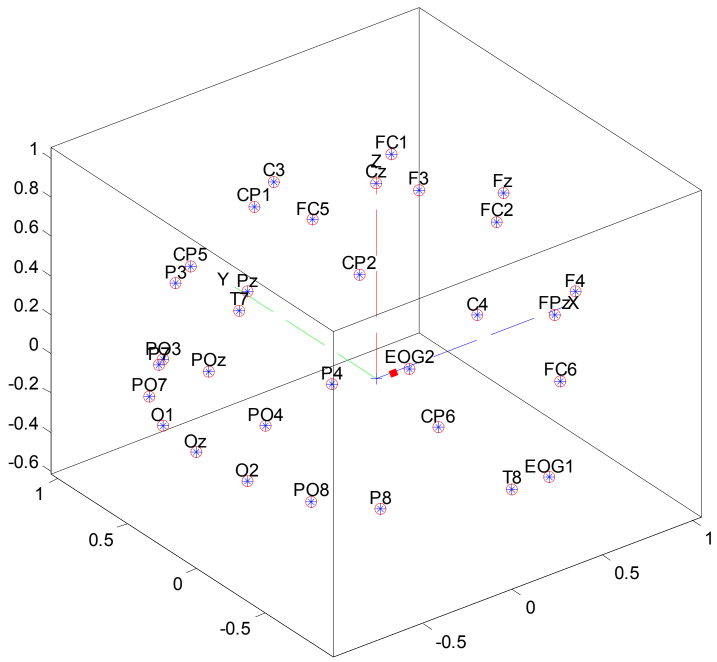


Figure 3 3-dimensional representation of the 32-channel data set locations (see online version for colours)



1.2 Ocular artefacts (OA)

These undesired artefacts occur as an episode when the ocular potential is superimposed on the true electrical activity developed in the brain. This ocular potential can be differentiated and explicated by the type of the movement done by the subject's eye and even by the blink of an optic. The electrodes which are ranged nearer to the Ocular region like Frontal (F) and Front polar (Fp) are the electrodes that are mostly affected with Ocular artefact. It is to be considered that the eye acts as a dipole where the retina is more negatively charged than the cornea. The potential difference between the cornea and retina is around 100 mV (Croft and Barry, 2000a; Berg and Scherg, 1991a; Gasser et al., 1985; Berg and Scherg, 1991b; Bansal et al., 2015).

1.2.1 Ocular artefacts by the movements of an eye

As the eyeball acts a dipole, it is observed that Ocular artefact potential is induced by the cornea onto the nearest electrode of the ocular region when the eyeball moves vertically upwards (Croft and Barry, 2000a). The charge of the retina gets induced onto the electrodes when the eyeball moves downwards. In the case of horizontal movements of an eye, the potential varies from the left and right of the hemisphere. The odd electrodes get more induced when eyeball turns to the left. Right-side movement of eye ball induces potential on even numbered electrodes.

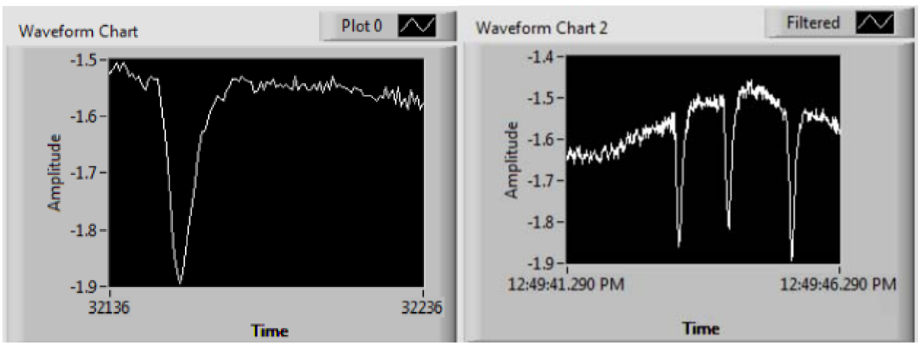
1.2.2 Ocular artefacts by the eye blink

This artefact comes as an unexpected and an involuntary episode of open and closure of an eyelid. In this blink episode lid of an eye acts as a sliding electrode or as a link that connects the scalp to the positively charged cornea (Croft and Barry, 2000c; Berg and Scherg, 1991b; Gasser et al., 1985).

When the lid of an eye slide over the eyeball where the cornea is positively charged, then lid of an eye pick up the Ocular potential from cornea and superimpose onto the nearby Frontal electrode where electrode turns out to be more positive consequences as an eye blink ocular artefact.

The ocular artefacts are recognisable up to a certain extent. Horizontal, vertical and radial eye movements produce square-shaped EOG waveforms, while eye blinks produce spike-like waves (Kandaswamy et al., 2005). This undesired ocular potential get overlaid onto the EEG signal and makes physician to face difficulty in the analysis and interpretation of brain electrical activity. The episode of eye blink contaminating into frontal EEG electrode is shown in Figure 4.

Figure 4 (a) The continuous blink artefact episodes acquired from the front electrode using NI LabVIEW interface, (b) filtered output using advanced signal processing tool kit



(a) (b)

2 Ocular artefacts elimination methods

There are many methods suggested in the literature to remove Ocular artefacts from the transcriptions of the EEG. Few elementary methods are reported to eliminate these artefacts and grounds for their Merits and Demerits are also put forward.

2.1 Eye fixation method

Although, Ocular artefacts are contaminating into the EEG when subject performs any movements of the eyeball or when the occurrence of an eye blink voluntarily or involuntarily. In order to get rid of the impact of EOG on the true EEG signal, subject is asked close eyes intentionally to control the apparent motions of the optic. But, this type of intentional fixation is not possible with some subjects like children, mentally ill people who cannot understand the pedagogy of a general practitioner. Owing to intentional closure of the eye, the alpha activity in the Occipital region may be increased because of the lack of visual source and Contingent Negative Variation (CNV) also effected on practising this method (Croft and Barry, 2000c; Hillyard and Galambos, 1970; Kandaswamy et al., 2005).

2.2 EOG rejection

This is a basic algorithm which is founded on preliminary detection of the artefact by visual examination. If the voltage (amplitude) of an EEG signal has typically in order of 50 microvolt, subsequently the signal fraction which is having more amplitude than 50 microvolt treat as an artefact and that segment is detached (Croft and Barry, 2000a; Kandaswamy et al., 2005).

Figure 5 The selection of EEG episode to perform rejection operation (see online version for colours)

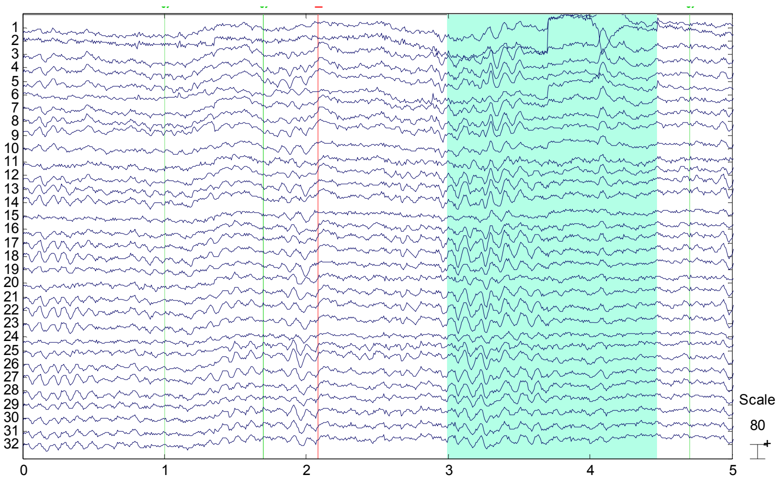
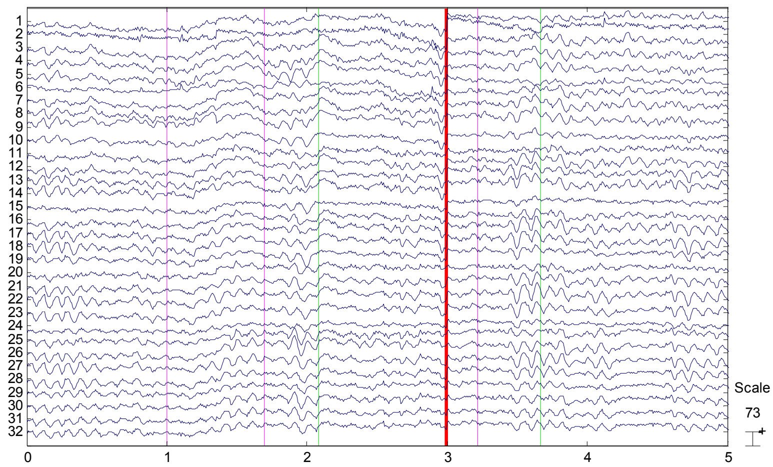


Figure 6 The resultant EEG signal after rejection of selected episode (see online version for colours)



In this setting, if the artefact exists in EEG signal in less than 50 microvolt can't be removed. Here, as the artefact overlaid electrode has more potential than usual, it is assumed that the artefact contaminated signal would be greater than normal EEG signal. But, rejection of segment of signal contaminated with artefacts usually outcome in a loss of brain electrical information. For instance, here, in Figure 2 the selected region is handled as an artefact and rejected using EEGLAB Toolbox for MATLAB and the resultant EEG recording is presented in Figures 5 and 6.

2.3 Regression

This method is a statistical analysis to estimate the relations between variables. Good reference channel EOG is required to subtract Ocular content from the uncontaminated EEG signal (Croft and Barry, 2000a). In this study, the amount of EOG contamination of the true EEG signal can be known the Regression coefficient *B*. Regression can be processed and analysed in both time and frequency Domain (Croft and Barry, 2000c; Hillyard and Galambos, 1970).

2.3.1 Time domain regression

For every instant of the time and without considering frequency, time domain regression gives the amount of EOG on the true EEG signal. In equation (1) true EEG due to the brain activity $x_{tr}(t)$, Measured EEG $x(t)$, Ocular artefact from eye into EEG $e_0(t)$, Regression Coefficient represented as *B*, *Y*-intercept of the Regression Equation *C* at the time interval *i* (Croft and Barry, 2000a; Kandaswamy et al., 2005).

$$x(t) = x_{tr}(t) + B.e_0(t) + C \quad (1)$$

$$B = \frac{\sum\left(x_i - \overline{x_i}\right)\left(y_i - \overline{y_i}\right)}{\sum\left(x_i - \overline{x_i}\right)^2} \quad (2)$$

$$C = \overline{x_i} - \left(y_i - B\right) \quad (3)$$

2.3.2 Frequency domain regression

Eye produces different voltages with different frequencies for every movement of an eye. The signal is divided into different lower frequencies using Fourier transform. Now, for different frequencies in the frequency domain the Regression coefficient *B* is calculated (Croft and Barry, 2000a; Woestenburg et al., 1983; Croft and Barry, 2000b; Kandaswamy et al., 2005).

2.4 Aligned artefact average (AAA) and revised AAA (RAAA) methods

This algorithm slightly differs and more precise than preceding technique, there for every instant of time the Coefficient *B* is calculated and same in the case for different frequencies. Here, averages aligned on the movement of the eye are used to calculate the regression coefficient *B*. In Revised AAA, Saccade and blink artefact can be corrected by using B as the same set. Appropriate use of horizontal, vertical and Radial EOG channels is needed (Croft and Barry, 2000a; Croft and Barry, 2000c; Kandaswamy et al., 2005).

2.5 Blind source separation method

It is a statistical method for the analysis of non-uniform signals like EEG signal. It can be employed for the separation of signal into its principal components using Eigenvalue decomposition or singular value decomposition. Independent components can also be obtained using blind source separation method which has efficiency to identify the artefact which is underlying in brain electrical activity.

2.5.1 Principal component analysis (PCA)

On the whole, it translates possible correlated variables into smaller uncorrelated variables called principal components by singular value decomposition. Here, EEG signals are collected, when the subject performs some episodes using Ocular organ like movements done by eye and blinks. This algorithm, PCA, will give the central components for the movements of an eye and for eye blinks. These elements can be taken out by the plain inversion computation. The precision of this method depends on the accessibility of precise inverse solutions for EEG and EOG. PCA bears with a prime drawback that it cannot separate eye artefacts completely from brain signals, when both artefact and brain signal have similar amplitudes (Jung et al., 2000; Tatjana et al., 2002; Shengkun and Sridhar, 2011).

2.5.2 Independent component analysis (ICA)

As EEG signal faces the artefact contamination problem, these artefact components can be separated from contaminated EEG using Blind Source Separation (BSS) algorithm to obtain components that are separate and independent (Makeig et al., 1996; Jung et al., 2000; Kandaswamy et al., 2005). Four assumptions made to have a good severance of the contaminated signal into individual components. These individual components can be achieved when these assumptions are taken into the consideration: (i) source signals are statistically independent, (ii) signals considered as linear mixtures of source, (iii) propagation delays are negligible, and (iv) number of measured signals are similar to the number of source signals. Fourth assumption is debatable, as the number of statistically independent brain electrical signals contributory to the EEG signal is not known (Kandaswamy et al., 2005). But, first three assumptions are contented. The cocktail problem exhibiting by the mixing model and its separation by Unmixing model is shown in Figure 7 (Journée, 2008).

a. Mixing model

Here, considering the two signals $s_1(t)$ and $s_2(t)$ forms a linear mixture matrix A as $\begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}$ the resultant mixed signals stated as $x_1(t)$ and $x_2(t)$. The vector equation for mixing model is given in equation (4), where X and S are vectors containing components such as $x_1(t)$, $x_2(t)$ and $s_1(t)$, $s_2(t)$.

$$X = A \times S \tag{4}$$

b. Unmixing model

Separation of artefacts from a contaminated EEG signal components $x_1(t)$ and $x_2(t)$ as an independent components done by blind source separation algorithm. The equation for Unmixing model can be written as equation (5), where $z_1(t)$ and $z_2(t)$ are separated components.

$$Z = W^T \times X \tag{5}$$

Here, W^T extends facility to carry out blind source separation of linear mixtures (Journée, 2008). The identification and rejection of an EOG contaminated independent components is a critical task. Component rejection from the EEG recording is shown in Figure 8, where red waveform indicates separation of components from EEG recordings.

Figure 7 The cocktail (mixing of two signals) problem, Unmixing model (see online version for colours)

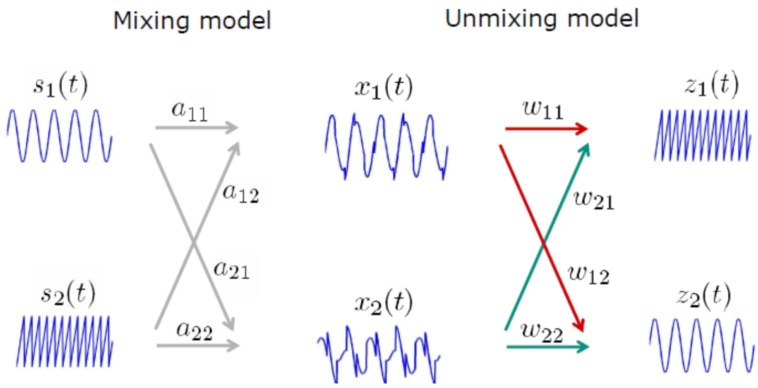
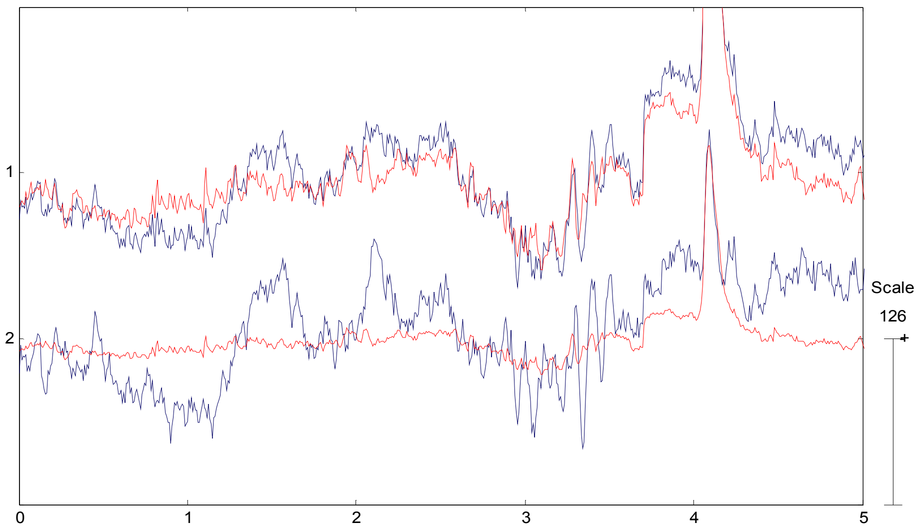


Figure 8 Separation of independent components from EEG recordings using EEGLAB toolbox for MATLAB (see online version for colours)



2.6 Wavelet analysis

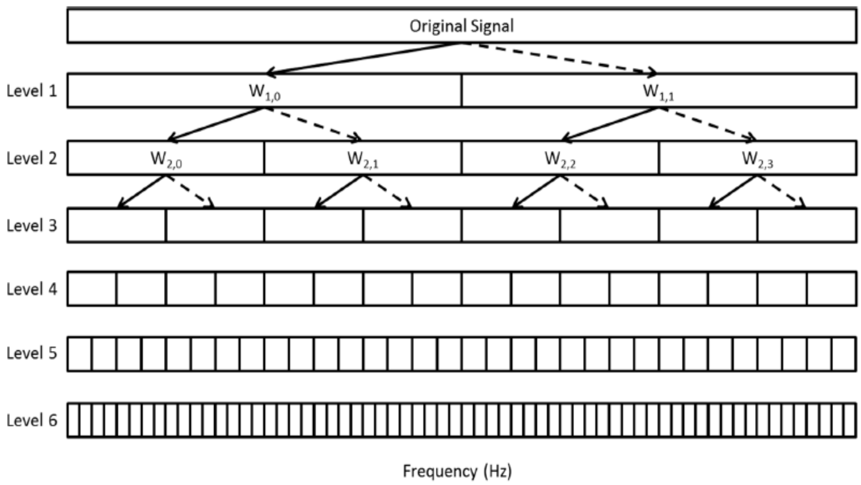
This signal processing technique algorithm has great possibility to remove the artefacts from the EEG signal, even when the artefact is underlying in the true EEG signal and this method is proficient in elimination of lower frequency Ocular artefact and preserving the brain signal simultaneously. Wavelet Transform divides an artefact contaminated signal into minor segments with different individual frequency. This algorithm is dominant in representing multi-resolution and non-stationary signals like EEG, where the frequency of the signal is not same all over. Multi-resolution is another vital property exhibit by the Wavelet decomposition, fits its window with different frequencies which play an essential role in separating artefacts in these bio-potential signals. Dilating and translating the mother wavelet results entire family of the each respective wavelet, given in equation (6).

$$\phi(x)_{(a,b)} = \frac{1}{\sqrt{a}}\phi\left[\frac{x-b}{a}\right] \tag{6}$$

where a and b are scale and shift parameter. Discreet Wavelet Transform (DWT) is obtained by filtering the EEG signal using the multiple series of digital filters at multiple scales. Changing the resolution of a signal using subsampling can be called as scaling operation. Nevertheless, for the uncontaminated EEG the threshold limit is to be calculated, which is a drawback to this method (Tatjana et al., 2002; Kandaswamy et al., 2005; Khan and Farooq, 2015). The six-level wavelet decomposition is shown in Figure 9 (Lee et al., 2014). Here, the original signal is transformed into individual frequency component $W_{j,n}$ and where solid line represents detailed coefficients and the dotted line represents scaling coefficients.

Here, entire artefact contaminated EEG signals is divided into individual frequencies as wavelet exhibits multi-resolution and non-stationary properties. Now, artefacts can be removed by assuming a proper threshold value which rejects artefacts.

Figure 9 Six-level wavelet decomposition of EEG signal



Wavelet algorithm is more precise in analysing the non-stationary signals than Fourier analysis. The Fourier transform is also a powerful tool to analyse EEG signal in giving information regarding the frequency content of the signal. However, a Fourier transform does not give information about the time at which a particular frequency has occurred in the signal. Hence, it is not desirable to study non-stationary signal like EEG. To overcome this problem, Short-Time Fourier Transform (STFT) was introduced. Even though STFT has the ability to provide time information, multi-resolution is not possible. Hence, wavelet is the paramount approach in dealing with EEG signal which exhibits multi-resolution and non-stationary characteristics.

3 Summary

All the methods described in the above section have been summarised in Table 1. Each method has been simulated and practised in MATLAB with EEGLAB tool kit and National Instruments LabVIEW with advanced signal processing tool kits. Methods to remove the ocular artefacts are stated and merits and demerits are consolidated in Table 1.

Table 1 Methods to remove ocular artefacts in EEG, merits and demerits

Method	*Demerits*	*Merits*
Eye fixation method	Owing to lack of vision, alpha activity increases	Major ocular artefact can be detached
EOG rejection	There is a serious loss of brain information	Visibly noticeable artefact can be removed
AAA and RAAA	The use of horizontal, vertical and radial EOG channels is needed	Accurate than regression
PCA	Correction of artefact can't be done when artefact and brain signal exhibit similar amplitude	Major components can be separated easily
ICA	Visual inspection and identification of independent components which is component to be removed	Major components can be separated easily
Wavelet transform	Identifying the scaling parameters is a critical task	Artefact at multi-scales can be identified

4 Conclusions

Elimination of the Ocular artefacts from EEG signal is exigent task. Methods for the removal of ocular artefacts from the contaminated EEG signal has been reviewed and simulated. Although ICA and wavelet analysis have demerits in analysing EEG signal, these are the most practical artefact removal methods for the detection and separation of Ocular artefacts from the artefact contaminated EEG. Elimination of artefacts can also be accomplished using Adaptive filtering, Artificial Neural Networks and other soft computing techniques. Practising two or more methods simultaneously or individually can be done to have a better signal analysis.

References

Bansal, D., Mahajan, R., Roy, S., Rathee, D. and Singh, S. (2015) 'Real-time man-machine interface and control using deliberate eye blink', *International Journal of Biomedical Engineering and Technology*, Vol. 18, No. 4, pp.370–384.

Berg, P. and Scherg, M. (1991a) 'Dipole models of eye movements and blinks', *Electroencephalography and Clinical Neurophysiology*, Vol. 79, No. 1, pp.36–44.

Berg, P. and Scherg, M. (1991b) 'Dipole modelling of eye activity and its application to the removal of eye artefacts from the EEG and MEG', *Clinical Physics and Physiological Measurement*, Vol. 12, pp.49–54.

Croft, R. and Barry, R. (2000a) 'Removal of ocular artifact from the EEG: a review', *Neurophysiologie Clinique/Clinical Neurophysiology*, Vol. 30, No. 1, pp.5–19.

Croft, R. and Barry, R. (2000b) 'EOG correction: which regression should we use?', *Psychophysiology*, Vol. 37, No. 1, pp.123–125.

Croft, R. and Barry, R. (2000c) 'EOG correction of blinks with saccade coefficients: a test and revision of the aligned-artefact average solution', *Clinical Neurophysiology*, Vol. 111, No. 3, pp.444–451.

Gasser, T., Sroka, L. and Möcks, J. (1985) 'The transfer of EOG activity into the EEG for eyes open and closed', *Electroencephalography and Clinical Neurophysiology*, Vol. 61, No. 2, pp.181–193.

Hillyard, S. and Galambos, R. (1970) 'Eye movement artifact in the CNV', *Electroencephalography and Clinical Neurophysiology*, Vol. 28, No. 2, pp.173–182.

Homan, R., Herman, J. and Purdy, P. (1987) 'Cerebral location of international 10–20 system electrode placement', *Electroencephalography and Clinical Neurophysiology*, Vol. 66, No. 4, pp.376–382.

Journée, M. (2008) *Independent Component Analysis*. Available online at: http://perso.uclouvain.be/pa.absil/Grenoble2008/Grenoble_Matlab_project.pdf

Jung, T., Makeig, S., Humphries, C., Lee, T., McKeown, M., Iragui, V. and Sejnowski, T. (2000) 'Removing electroencephalographic artifacts by blind source separation', *Psychophysiology*, Vol. 37, No. 2, pp.163–178.

Kandaswamy, A., Krishnaveni, V., Jayaraman, S., Malmurugan, N. and Ramadoss, K. (2005) 'Removal of ocular artifacts from EEG – a survey', *IETE Journal of Research*, Vol. 51, No. 2, pp.121–130.

Khan, Y.U. and Farooq, O. (2015) 'Wavelet-based multi-class discrimination of EEG for seizure detection', *International Journal of Biomedical Engineering and Technology*, Vol. 19, No. 3, pp.266–278.

Lee, B., Lee, B. and Chung, W. (2014) 'Mobile healthcare for automatic driving sleep-onset detection using wavelet-based EEG and respiration signals', *Sensors*, Vol. 14, No. 10, pp.17915–17936.

Makeig, S., Bell, A.J., Jung, T-P. and Sejnowski, T.J. (1996) 'Independent component analysis of electroencephalographic data', *Advances in Neural Information Processing Systems*, Vol. 8, pp.145–151.

Medithe, J.W.C. and Nelakuditi, U.R. (2016) 'Study on the impact of light on human physiology and electroencephalogram', *Journal of Biomimetics, Biomaterials and Biomedical Engineering*, Vol. 28, pp.36–43.

Nicolas-Alonso, F.L. and Gomez-Gil, J. (2012) 'Brain computer interfaces, a review', *Sensors*, Vol. 12, No. 2, pp.1211–1279.

Shoran, M., Kumar, S. and Chawla, S. (2015) 'Methods of denoising of electroencephalogram signal: a review', *International Journal of Biomedical Engineering and Technology*, Vol. 18, No. 4, pp.385–395.

Shengkun, X. and Sridhar, K. (2011) 'Signal classification via multi-scale PCA and empirical classification methods', *International Journal of Mechatronics and Automation*, Vol. 1, Nos. 3/4, pp.213–223.

Singh, S. and Bansal, D. (2014) 'Design and development of BCI for online acquisition, monitoring and digital processing of EEG waveforms', *International Journal of Biomedical Engineering and Technology*, Vol. 16, No. 4, pp.359–373.

Tatjana, Z., Bibian, S., Guy, A.D., Huzmezan, M. and Ries, C. (2002) 'Wavelet based de-noising technique for ocular artifact correction of the electroencephalogram', *Proceedings of the Second Joint EMBS/BMES Conference*, Vol. 1, pp.7803–7612.

Woestenburg, J.C., Verbaten, M. and Slangen, J. (1983) 'The removal of the eye-movement artifact from the EEG by regression analysis in the frequency domain', *Biological Psychology*, Vol. 16, Nos. 1–2, pp.127–147.