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Review of State of Art in Electrooculogram Artifact Removal from Electroencephalogram Signals

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Abstract: Electroencephalogram (EEG) is a time varying brain electrical activity, highly sensitive and gives a coarse view of neural activity. It has been used to study cognitive processes and the physiology of the brain. EEG recordings are distorted by physiological and non- physiological signals causing problems to the clinicians, neuropsychologist and researchers for analysis, interpretation and diagnosis. Artifacts, compromise investigation by masking effects of interest or diminish specificity by masquerading as a neurogenic effect. Advances in signal processing have brought significant improvement in removal of these artifacts from the recorded EEG. The possible ocular artifacts are of great significance and concern as they contaminate the signal to a larger extent. The objective of this paper is to present a detailed survey of the published literature of various techniques for the removal of the various artifacts, especially artifact due to movement of eyes. An evaluation of various detection, rejection and removal techniques is elaborated, with the emphasis on the principles of the various methods, followed by the relative advantages and disadvantages of each.

Keywords: Artifacts, Electroencephalogram, Electro-oculogram (EOG), Independent Component Analysis (ICA), Wavelets.

INTRODUCTION

Electroencephalogram is the recording of spontaneous activity of brain in terms of electrical potential along the scalp produced by the large number of interconnection of neurons. It is an important non-invasive tool for diagnosing, monitoring the brain activity depicting a view of neural activity to study cognitive processes and the physiology of the brain. EEG has capability to reflect all the activity of the brain, so it has been found to be a very powerful tool in the field of neurology and clinical neurophysiology [1]. The analysis of biomedical signals is not continuous, homogeneous and regular; rather, it is heterogeneous and irregular, often even chaotic [2]. Computer analysis of EEG signals using precise signal processing techniques is necessary and highly useful as traditional detection or prediction methods including visual and manual scanning of EEG are very tedious, time consuming and may be inaccurate.

EEG is measured using electrodes and conductive material placed at the scalp in accordance with "10-20" International Standard system The periodic activity manifests itself in the form of rhythms having bands of frequency range of 0.5 to 100 Hz and with 10 to 100 μV range of amplitudes of voltage The individual bands are discriminated on the basis of the frequency ranges as Delta (δ), Theta (θ), Alpha (α), Beta (β) and Gamma (γ) [3]. Beta waves are detectable over the parietal and frontal lobes and are present in alert or anxious state with frequency range varying from 13 Hz to 30 Hz. The alpha waves can be measured from the occipital region in posterior regions of head in an awaken person when the eyes are closed and the person is relaxed falling in range of 8 – 13 Hz. The theta waves (4-7Hz) are obtained from children and adults during drowsiness and sleep. The delta waves having frequency of below 3Hz are detectable in infants and deep sleeping stage in adults.

This review paper is an exhaustive survey to classify various techniques and methods available to deal with the artifact removal from EEG signals. It lays stress over the artifacts removal, especially artifacts due to eyes movement, their detection and elimination to get true EEG which can serve as an important benchmark for useful EEG analysis. Section 2 introduces Artifacts; Section 3 provides a discussion on various physiological artifacts. In Section 4 various EOG removal techniques are elaborated and in Section5 the conclusion of the study is given.

Artifacts

The signals obtained from the scalp are highly contaminated with various unwanted signals, produced by events extraneous to the biological event of interest. The presence of artifacts introduce spikes which can be confused with neurological rhythms, making the EEG signals analysis biased and difficult leading to wrong conclusions [4]. The various kind of physiological and extra physiological artifacts which prominently affect true EEG are Instrumental artifacts; generated by the use of an instrument powered from the mains power supply, Analysis artifact; that arise in the course of processing the signal and Biological artifacts; signals arising from different part of body[5]. The original EEG signal acquired as per International Standard , affected by various artifacts is depicted in Fig 1.

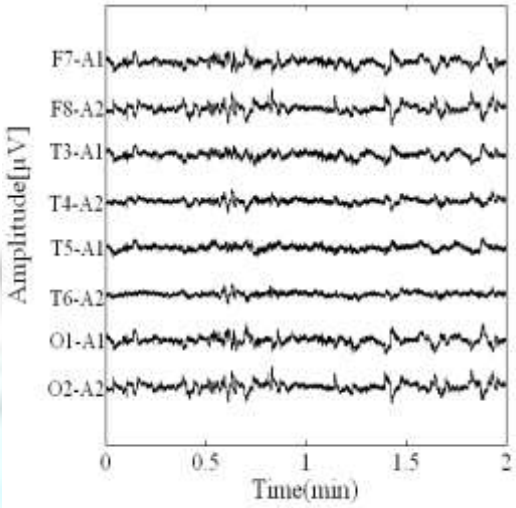

Figure 1: Observed EEG recording mixed with artifacts

EEG amplifiers are equipped with notch filters that suppress signals in a narrow band around the mains frequency (50 or 60 Hz power supply signals). If there is main power supply interference still visible in the signal after activating the notch filter; it may be due to high electrode impedance. The analysis artifacts can be controlled with advanced signal processing techniques, for example, round-off errors due to the quantization of signal samples can be made non-effective by setting the large number of discrete amplitude levels in the quantizer [6].

The other major artifacts dealing with physiological signals are the signals generated from heart, muscles, and eyes, head movement, sweating and breathing. A major issue of concern in analysis of EEG is the detection and elimination of artifacts leaving underlying background signals due to brain activity intact. Recognition and elimination of the artifacts in real – time recordings is a complex task, but essential to the development of practical systems. The artifacts compromise sensitivity of main signal as they are confounded with statistical contrasts. The removal of the artifact becomes essential as the preprocessing step for any type of EEG analysis.

A. Artifact Rejection

The simplest method of dealing with artifacts is to eliminate epoch in which artifact activity is detected. A critical step in the rejection technique is the identification of these epochs and setting the criterion of identification of epochs to avoid “false alarms”. Rejection is often combined with manual avoidance refraining the subject to move the eyes or to blink during measurement which introduces an additional task for the subjects, which may interfere with the brain processes and result in certain changes in EEG signal. It is observed that "refraining-from-blinking" instructions lead to changes in the amplitude of some evoked potentials (Nl and P3) as postulated by Verleger [7]. In addition, the frequency of blinks varies widely among subjects and conditions, and there is a problem for subjects to "keep their eyes focused" (that is no movement of eyes) making this method ineffective for dealing with the artifacts.

B. Artifact Elimination

The different methods available for reducing and removal of artifacts are application of spatial filters [8], blind source separation [9], and linear regression models, in time as well as frequency domain. In 2003, Durka *et al.* [10] have used a simple but effective technique for discriminating a “good” EEG and artifacts by optimizing the threshold limits to mark an epoch as an artifact. The optimized parameters are directly related to the signal’s energy distribution, in the frequency or time domain. The details of these methods are covered in Section 4.

Physiological Artifacts

Electromyogenic **(***EMG)* artifact results due to activities of muscles at rest and while contraction of frontal and temporal muscles (clenching of jaw muscles). These artifacts pose a risk to validity for proper investigation of EEG signals. The various techniques available in literature for the removal of EMG artifacts are filters, adaptive filters, blind source separation, Independent Component Analysis (ICA) [11]. Authors in [12] have used higher order statistical property, kurtosis, the 4^{th} cumulant of data to make a clear distinction between non-artifact and artifact signal, and rejecting the later one.In 2010, Gao et al. [13] have used Canonical Correlation Analysis (CCA) technique using correlation threshold to remove the EMG artifacts automatically, without eliminating the signal of interest.

Electrocardiogram (*ECG*) artifacts occur when the relatively high cardiac electrical field affects the surface potentials on the scalp, especially at the terminals which are on the frontal lobe because the amplitude is high enough to confound the EEG signals at those points. ECG artifacts constitute a serious problem for the automatic interpretation and analysis of brain activity signals. In 1984, Fortgens and Bruin [14] have proposed the algorithm to remove artifacts from EEG by subtracting the weighted artifact of source signals of ECG, computed by applying a variance minimization criterion function. Nakamura and Shibasaki [15] and Schlögl et al. [16], investigated the use of Ensemble Average Subtraction method to correct ECG artifacts. Sahul et al. [17], introduced artifact cancellation by adaptive filtering (AF) using an ECG channel reference. However, these methods use reference ECG signal, it requires consecutive R-waves of separate ECG channels to eliminate artifacts from EEG signal [18].

In 2000, ICA based artifact reduction method was proposed by Everson and Roberts [19] for the artifact removal. In 2008, Devuyst et al. [20] have based their research on a modification of the ICA algorithm using a single-channel EEG and ECG. Their approach gave promising results as compared to earlier proposed techniques. Dewan et al. [21] have performed the separation of ECG artifact from EEG in the absence of separate ECG recordings using adaptive thresholding method along with clustering technique to detect R –peaks.

The origin of ocular artifact *EOG (Electrooculargram)* is eye activity which has significant detrimental effect on EEG signals. When human eye blinks or moves, an electric field is created which can be 10 times larger in amplitude than electrical signals originating from cerebral cortex and lasts for up to 400 ms [22]. Since eye movements are difficult to suppress over the period of EEG recording, almost all the EEG recordings get contaminated with EOG artifacts. EOG has been attributed to the fact that the eyeball acts as a dipole, where external surface of the cornea (at the front of the eye) is positively charged with respect to the posterior surface of the retina (at the back of the eye). Therefore, each eyeball acts like a battery and generates an electric field, which interferes with the surface recording of the electrical activity of the brain, at particular electrode locations. A simplified model of the electric dipole within the eyeball is given by Berg *et al.* [23] in 1991. The direction of the dipole is aligned with the line of sight and the size of the dipole is determined by the amount of light hitting the retina in the back of the eye. EOG contamination is prominent only in the frontal EEG channels [24] because of eye's proximity to the brain. The propagation of the EOG artifact from the eyes to the rest of the scalp locations is practically instantaneous [25]. Vertical eye movements will influence midline electrodes much more than lateral movements. Figure 2 depicts the EEG signal affected by the signals due to the movement of eyes with the two major spikes representing the blink of eyes.

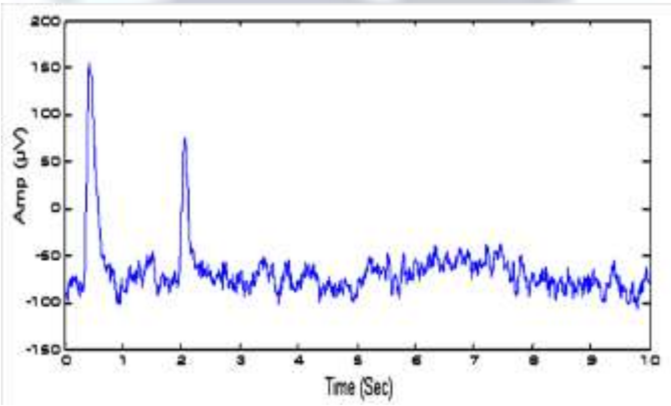

Figure 2: EEG mixed with EOG

Various factors related to EOG are considered by researchers extensively. A problem with most of these methods is the difficulty of modeling the complex anatomy and conductivity properties of the eye region. [26-27]

EOG Removal technique

As the artifacts have overlapping spectra with signal of interest, they have to be removed such that the useful information is not lost. Main techniques employed for the removal of ocular artifacts are as follows.

A. Regression Techniques

A number of regression-based techniques have been proposed for OA (Ocular Artifact) removal, where the observed EEG signal can be expressed by [28]

$$OEEGi\ (t) = kvi\ VEOG\ (t) + khi\ HEOG\ (t) + EEGi\ (t) \quad (1)$$

where, OEEGi(t) is the observed EEG signal and VEOG(t) and HEOG(t) are the vertical and horizontal components of the EOG at time and EEG(t) is the true uncontaminated signal to be found at that instant. The scaling coefficients kvi and khi are determined to obtain true EEG signal, using dedicated electrodes near the eyes. The various methods employed to compute these scaling coefficients, categorize the various regression techniques. Regression methods were introduced by Quilter et al. [29] and subsequently modified by Verleger et al. [30]. In all the regression-based approaches, calibration trials are conducted to determine the scaling factors between the EOG channels and each of the EEG channels [31], EOG components in the EEG recording are then estimated using these coefficients in the 'correction phase' and EOG correction is carried out either in the time or in the frequency domain. Gratton et al. [32] in 1989 have proposed a time domain regression method in which the scaling factors are computed separately for each epoch and averaged. They have further expanded the technique to include correction of both vertical and horizontal artifacts by means of a multiple regression method. In 1998, Gratton further modified the technique by providing separate propagation factors for blinks and saccades [33].

Frequency domain techniques [34] are based on the assumption that the scaling factors depicting the propagation of the EOG vary with the frequency of the EOG activity. Since the scaling factors vary with frequency, there is a possibility of accounting for differences between eyes blink and eye movement effects. These techniques can deal better with slow drifts in potential during prolonged recording epochs, which are often a cause of inaccuracies in the correction of ocular artifacts with time domain methods. In 1991, Kenemans et al. [35] have compared the two regression techniques with two data sets and the transfer from EOG to EEG was checked for frequency-independence (constant gain) or frequency-dependency.

Regression-based methods are capable of reducing ocular artifacts provided that there are good reference EOG channels and the regression coefficients. The main limitation being the requirement of reference EOG channels during the measurement of EEG. The rigorous comparison between the two types of regression techniques and component based techniques is done by Wallstrom et al. [28] and Schlögl et al. [36] on real and simulated data of varying epoch length.

B. Filtering Techniques

Conventional filtering techniques cannot be applied to eliminate artifacts as EEG signal and artifacts have overlapping spectra. Whereas, adaptive filters having the capability of modifying their properties, are preferred for interference cancellation. In 2002, Nicole and Berg [37] describe the basic principle of artifact correction by spatial filtering and focus on the pre selection approach, which is fast enough to be applied while paging through the segments of a digital EEG recording. Adaptive filtering technique involves usage of filters, preferably FIR to remove the extra signals by adjusting the filter coefficients adaptively. The coefficients are varied in accordance to the optimization of error signal between the observed and desired signals. In 2009 algorithm proposed by Jones et al. [38] involves minimizing the error optimally. The choice of algorithm employed determines the efficiency and cost of the filters. In accordance with Fig 3, in equation 2, s(n) is the primary signal picked up by the electrode. This is a mixture of true signal x(n) with noise signal v(n).

$$s(n) = x(n) + v(n) \quad (2)$$

Two reference signals, $r_v(n)$ and $r_h(n)$ uncorrelated correspond to vertical EOG component (vEOG) and horizontal EOG component (hEOG) respectively. Equation 3 gives the error signal e(n), the difference between primary signal s(n) and reference signals r(n). $r_v'(n)$ and $r_h'(n)$ are filtered reference signals, filtered through adaptive filter having impulse response as $h_v(n)$ and $h_h(n)$. Thus,

$$e\ (n) = s(n) - r_v'(n) - r_h'(n) \quad (3)$$

The square error expectation is taken as

$$E\ [e^2\ (n)] = E\ [(s(n) - rv'(n) - rh'(n))^2]$$

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$$= E\,[(x(n)^2] + E[(v(n) - rv'(n) - rh'(n))^2] \quad (4)$$

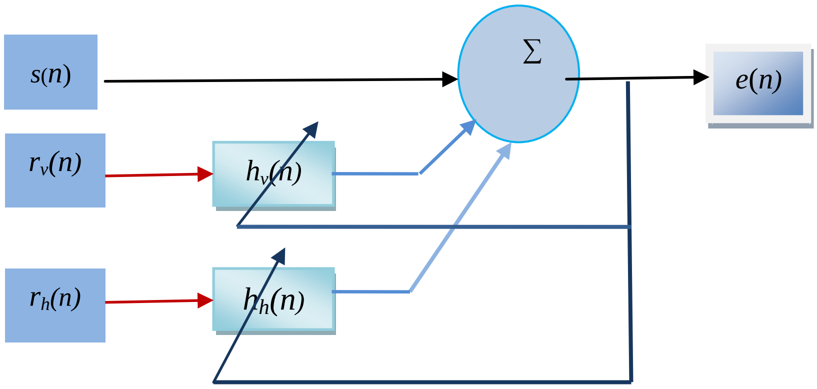

Figure 3: Adaptive filter with two reference channels and two filters with adjustable coefficients [39].

The concept of adaptive filter for EOG removal started with only one reference signal. The modification in filtering technique was given by He et al. [40] in 2004, by separately recording vertical EOG and horizontal EOG signals as two reference inputs as shown in Figure 3.

The most common method used in adaptive filtering is Least Mean Square (LMS) algorithm and Recursive Least Square (RLS) algorithm for minimizing expectancy of error. In 2010, Arezki et al.[41] have used LMS with computational complexity using step size to control the rate of adaption. Correa et al. in 2007 [42] used three adaptive filters in cascade to cancel line interference, ECG and EOG artifacts present in EEG records. Using the same concept as He, they modified it by using three filters for three different artifacts, using steepest descent algorithm for optimization.

A difficulty in this work is the determination of filter order and convergence factor. In nutshell, the implementation of adaptive filtering is simple and fast, and the results can be obtained without requiring complex calculations but require additional sensors to provide reference signals, and a negative spike appears in the background of EEG just at the moment of EOG spike. Another filtering technique which does not involve any reference signal and is totally based on statistical approach is Wiener filtering [43] and based on probabilistically estimation approach is Bayesian filtering [44].

C. Blind Source Separation (BSS)

This method is based on multivariate statistical analysis techniques such as Principal Component Analysis (PCA) and ICA. In 1993, Lins et al. [45] and Lagerlund et al. [46] used PCA-based methods to decompose the artifacts contaminating EEG signal into artifact components and brain activity components and reconstruct the EEG by eliminating the artifact components. PCA decomposes the signals into uncorrelated components that are spatially orthogonal. As shown by Te-Won Lee [47] PCA does not effectively segregate each source such as brain, cardiac, and eye movement generators, into a separate component. PCA cannot completely separate eye artifacts from brain signals especially when they both have comparable amplitudes [48].

ICA is an extension of PCA in which the components are assumed to be mutually statistically independent instead of merely uncorrelated. ICA algorithms are superior to PCA, in removing a wide variety of artifacts from the EEG, even in the case of comparable amplitudes. However, the ICA components lack the important variance maximization property possessed by the PCA components [49].

Makeig *et al.* [50] in 1996 reported the first application of ICA for EEG data analysis by using the algorithm of Bell and Sejnowski [51] proposed in 1995. ICA uses BSS technique in which multichannel signal (recorded EEG signal) is decomposed into independent components or sources. It involves formation of a matrix and projection of a set of components onto another set of so called independent component.

The K simultaneously recorded EEG signals at time *t* are given by

$$X(t) = \{x_1(t), x_2(t) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\, x_K(t)\}$$

These are the linear mixture of the unknown independent source signals S (t) and artifacts of neural origin.

$$S(t) = \{s1(t), s2(t) \ldots\ldots\ldots\ldots\ldots sn(t)\}$$

Assuming an unknown matrix A, a mixing matrix of size proportional to the product of number of electrodes and number of independent sources, the ICA algorithm is depicted in Figure 4 and the expression can be represented as

$$X(t) = \mathbf{A}\, S(t) \tag{5}$$

Estimating mixing matrix (A) which is a function of geometry of the sources and conductivity properties of scalp and skull and calculating independent sources (S) from X, such that X = **A**S best approximates the independent sources S. Once A is determined, its inverse gives the separating matrix (W), from which S can be determined giving the independent source signals (Equation 6, 7).

$$S(t) = \mathbf{A}^{-1} X(t) \tag{6}$$

$$S(t) = \mathbf{W}\, X(t) \tag{7}$$

$$\mathbf{W} \text{ (separating matrix)} = \mathbf{A}^{-1}$$

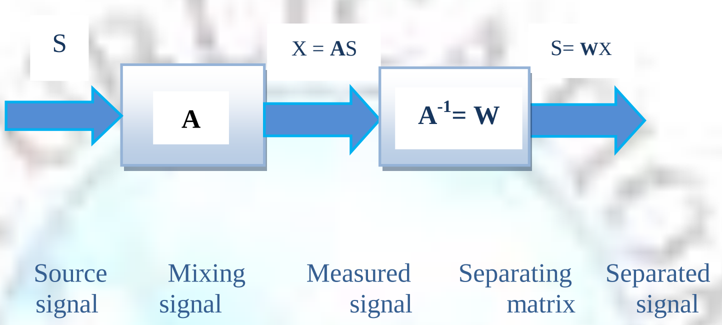

Figure 4: Schematic illustration of mathematical model of ICA

The objective is to maximize the statistical independence of the outputs and once S is known the components that account for artifacts can be removed. Thus, it is an effective way enabling direct access to the underlying brain functioning by finding the independent sources of neural activity in the brain. A modification in ICA proposed in 1997 by Hyvärinen and Oja [52], was Fast ICA which attempts to separate underlying components from a given set of mixed measurement channels based on their "non-Gaussianity". The algorithm works on maximizing the non-Gaussianity of components by their Kurtosis (the 4^{th} order cumulant given to a random variable) or negentropy.

Joint Approximate Diagonalization of Eigen (JADE) matrix is another BSS algorithm which effectively diagnolizes the fourth order cumulant to separate the estimated sources and observed sources [53]. In 2004, Joyce et al. [54] proposed an automatic method for the removal of eye movement and blink artifacts from the EEG using the second-order Statistics-based Blind Source Identification (SOBI) algorithm. In 2010, Dong *et al*. [55] used JADE method for removing ocular artifacts for both eye blinks and saccades and concluded that it is an effective tool for multichannel EEG recordings.

In 2005, Krishnaveni *et al*. [56] have done an extensive comparison of the entire present ICA algorithm like MS-ICA, SHIBBS(Shifted Block Blind Separation), Kernel-ICA, JADE and RADICAL(Robust, Accurate, Direct ICA) for removal of ocular artifacts from EEG and assessed them in terms of quantitative analysis by using a reliable Mutual Information Estimator. The results show that RADICAL algorithm performs best at separating the source signals from the observed EEG signals. ICA is a non-parameteric algorithm having advantage over other methods, in that no a prior information is required, thus reducing number of sensors and cost and complexities [57].

D. Soft Computing Techniques

Nonlinear analysis using Neural Networks, Support Vector Machines (SVM) and Wavelets, have been a powerful approach for preprocessing the signal by removing the unwanted signals. Neural networks provide a well-established framework for pattern recognition and classification problems whenever there is a difference in the patterns of EEG and artifacts. Segments of the EEG signal is translated into meaningful feature vectors and classified into true signals and artifacts with the help of a neural network classifier. To train ANN, features from artifacts are used and then test sets are used to remove the artifacts with good approximation [58].

In 2008, Suresh and Puttampada [59] have presented noise cancellation and signal enhancement using sophisticated real time neural networks algorithm, Real Time Recurrent Learning (RTRL). This technique combines adaptive noise canceller and signal enhancer in for removing the artifact signal without clipping the original. RTRL algorithm is employed for training the neural network that converges faster with a lower mean square error of the order 0.000001. A hybrid soft computing technique, Adaptive Neuro-Fuzzy Inference System (ANFIS) is proposed by S.Kezi *et al*. [60] to estimate the interference and to separate the artifacts from EEG signal. The comparison with neural network and the conventional adaptive filter using least mean square algorithm shows that neuro fuzzy yields the better results.

Wavelets have become a popular choice for analyzing non-stationary signals, as it provides an optimal resolution both in time and frequency domains, without requiring signal stationarity. Wavelet analysis provides flexible control over the resolution in time, space and scale making them a preferable choice for the removal of ocular artifacts from EEG signal and analyzing non-stationary signals.

The wavelet transform of the affected EEG signal gives the wavelet coefficients which are actually the correlation coefficients between the EEG and the mother wavelet. The coefficients generated differentiate between the actual EEG and artifact, after setting of proper threshold limit, which may be empirically selected, context based, adaptive or non-adaptive, chosen optimally so as to differentiate between the signal of interest and artifacts [61]. These coefficients once removed, true signal is regenerated from the remaining coefficients, giving the artifact free signal. Figure 5 illustrates the basic scheme of wavelet decomposition; discrete time signal Cj+1 enters the analysis bank and is filtered by the filters h0(n) and h1(n) (low-pass and a high-pass filter respectively) which separate the frequency content of the input signal in frequency bands of equal width. The output of the filters contains half the frequency content, but an equal amount of samples as the input signal. Generalizing, a generic signal can be decomposed into a sum of orthogonal signals; a family of short oscillatory trains of various durations and frequency content, the so called mother wavelet

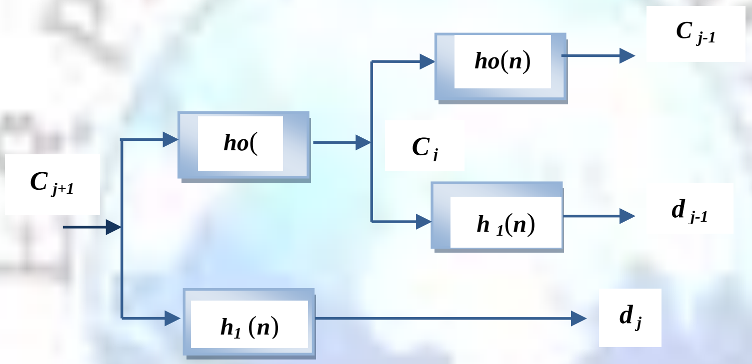

Figure 5: Wavelet Decomposition Scheme

In 2006, Krishnaveni *et al*. [62] using both the concepts of ICA and wavelets for artifact suppression and elimination, preserved spectral and coherence of neural activity. The method is not optimum as it is applied only to the frontal and frontal polar channels. In 2011, Babu *et al*. [63] proposed method using adaptive filter with Fast RLS algorithm and wavelet transform to remove artifacts. This technique not only improves the quality of EEG signal but also increases the PSNR (Peak Signal to Noise Ratio) value and decreases the elapsed time in comparison to RLS algorithm. Giuseppina Inuso *et al*. [64] have used a hybrid technique, combining wavelet analysis, Kurtosis and Renyi's entropy for investigation of the brain activity. They have exploited the peculiarities of EEG to optimize EEG artifact detection and used the wavelet concept for multi-resolution analysis and higher order statistics methods to identify the epochs affected by artifacts. Support Vector Machines (SVM) has been introduced into eye blink artifact removal by Shoker et al. [65]. SOBI (Second Order Blind Identification) algorithm is used in this method to separate the EEG recordings into independent sources, and the selected eye blink artifact components together with remaining non-eye blink components are used to train SVM classifier. SVMs are trained with artifact data recorded and SVM classification is utilized for the identification of the artifact component [66]. Undoubtedly, the training step in this method is complex, involving a lot of eye blink and non-eye blink artifact-independent components to train SVM classifier, but classification accuracy is quiet high. it is possible to implement an online-automated artifact removal technique on the basis of BSS/ICA and SVMs.

Conclusion

The electroencephalogram has been the most utilized signal to assess brain functions owing to its excellent time resolution. It has long been a key tool in epilepsy diagnosis and sleep disorders, but there are still many challenges in the analysis of the brain signals. Brain activity and its signal processing play a vital role in neurology, neuroscience, and neural engineering. All the potential topics for future research, especially for Brain Computer Interface (BCI), artifact removal are the main preprocessing step. The above examined techniques required by the EEG research community for artifact removal, and making the signal suitable for further analysis are amongst the most commonly used. No single method is the best method, and every technique has its own pros and cons as evident in comparison Table 2. So, in future customized algorithm, taking the best from each method, are likely to develop enhancing the existing method's performances and accuracy. With the advanced signal processing techniques, the computational complexities and cost will significantly drop, making these methods implementation for different brain imaging modalities, compression and visualization of brain signals easier and effective.

Table 1: Comparison between the various techniques used for artifacts removal from EEG signal

METHODS	FEATURES	TECHNIQUE USED	LIMITATIONS
Time Domain Regression	Simple, less costly, requires reference channels and predetermined calibration trials, automatic, can operate on single channel.	Iterative methods for computing scaling factors using reference signals and calibration.	Cannot deal with prolonged recorded epochs, incapable of performing real time processing less sensitive to high frequencies EEG contamination of the EOG.
Frequency Doman Regression	Higher Computational cost, require procedures for preprocessing and calibration, time consuming, deal better with slow drift in potentials.	Scaling factors vary with frequency of EOG activity, scaling factors calculated accordingly.	Less sensitive to inaccuracies due to slow drift in potentials, a priori input is required.
Adaptive Filter s	Real time removal of EOG, adaptable, flexible, does not require calibration trials. Bidirectional contamination effect taken care of, adaptable for long period of recordings.	Usage of adaptive filters, by varying the weights of the filters adaptively	A negative spike appears in the background EEG at the moment of EOG spike, erroneous results when the neurological phenomenon of interest and the EMG, ECG or EOG artifacts overlap or lie in the same frequency band as of EEG.
Independent Component Analysis	No a priori user input is required, accurately identify the time courses of activation and scalp topographies, can operate in non-linear domains.	Blind Source Separation, Independence of cortex (source) and observed signals.	Number of sources are limited to number of electrodes, based on statistical analysis of data, automatic artifact removal is difficult.
Soft Computing	Wavelet transforms are suitable for real-time application, Artificial Neural Networks are good enough for solving complex classification problems, SVM for efficient classification.	Adaptive methods of classification, feature recognition using Neural Networks, Support Vector Machine, Wavelets.	Selection of the threshold functions and limits and selection of mother wavelet. Large data set of Input parameters and training set required.

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