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Review on Latest Multichannel EEG Acquisition and Artifact Filtering Methods

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ABSTRACT
Electroencephalographic (EEG) signal records the electrical activity of the neurons near the scalp within the brain. Significant artifacts are introduced in the recording of EEG signals which leads to unreliable results. EEG paves the way for diagnosis of many neurological disorders and other abnormalities in the human body. The main aim of research is to get clean EEG signal with enhanced accuracy for proper diagnosis. Extensive research has been conducted in this area with different techniques. This paper reviews some of the important artifact removal techniques for performance enhancement.

General Terms
Biomedical Signal Processing

Keywords
EEG, Artifacts, EOG, EMG, ECG, EMA, Adaptive Filtering.

1. INTRODUCTION
Electroencephalographic (EEG) signal records the electrical activity of the neurons near the scalp within the brain [1]. Both physiological and pathological information could be obtained from EEG signal. The study of EEG signal has its applications in diagnosis and treatment of brain diseases, neuroscience, and cognitive science [2-3], Such as: psychogenic non-epileptic seizures [13, 24] syncope, sub-cortical movement disorders, migraine variants, catatonia, adjunct test of brain death, etc. Saeid Sanei & J.A.Chamers, *et al.* Cardiff University UK (2007) discussed that, EEGs cover up the way for diagnosis of many neurological disorders and other abnormalities in the human body. The acquired EEG signals from a human (and also from animals) may, for example, be used for examination of the different clinical problems.

The variety of clinical problems confirms the rich potential for EEG analysis and motivates the need for sophisticated signal processing techniques to aid the clinician in their analysis. The brain rhythms will next be described, which are expected to be measured within EEG. Letian Wang, *et al.* Delft University, UK (2009) discussed that, EEG signals can be typically described in terms of rhythmic activity and transients. The rhythmic activity is divided into bands of frequency. Certain mental states can be reflected in these frequency bands. The different frequency bands are delta (0 to 4 Hz), theta (4-7 Hz), alpha (8-13Hz), beta (13-30 Hz), gamma (30-100Hz).

The review is planned as follows. In section 2 different methods of EEG measurements/acquisition are studied. In section 3 various types of artifacts introduced at the time of measuring of EEG signals are studied. In section 4 the important research aspects for removal of artifacts are studied. Different algorithms used for removal of artifacts are referred. In section 5 the observations concerned to different schemes for artifact removal are discussed. Finally review is concluded in section 6

2. EEG ACQUISITION/MEASURING
The invasive EEG method is only functional when the doctors cannot identify the disease using the noninvasive technique. It means that noninvasive technique has many application and widely acceptable by the patient. Noninvasive EEG recording method does not require the doctor plug the electrodes which will be dangerous to the patient's brain .The EEG signal could be acquired by placement of the electrodes on the outside of scalp [4-6]. Occasionally the conductive gel is used to get better signal to noise ratio (SNR)

For Acquisition and preprocessing of brain signals experimental setup used which consists of 27 Ag/AgCl electrodes at positions of the extended international 10-20 system [5]. Brain activity was measured with The EEG acquisition scheme discussed in [4-5] could provide a wireless bridge connecting electrodes on the surface of scalp and EEG analysis using algorithms in the computer. The prototype for both 8 and 16 channels EEG is designed.

There is a great demand for technologies that enable neuroscientists and clinicians to monitor the synchronized activity of large numbers of neurons in the brain [8]. Multi electrode neural recordings are becoming regular practice in basic neuroscience research, and knowledge gained from these studies is enabling medical and neuroprosthetic applications .Recent advances in MEMS technology have formed small (less than 4 mm in any dimension) arrays of microelectrodes consisting of as many as 100 recording sites. It reports that, fully integrated amplifier is developed and tested for recording of biological signals.

A viable, low cost Electroencephalogram (EEG) signal acquisition device consisting of only 3 electrodes which collects and records the signals in the desktop computer using DSP Processor DS-1104 is described. The main considerations while making such a device are simplicity, ease of use and applicability [22].

Various techniques regarding the different arrangements for EEG acquisition and sensors to be used for measurements are discussed [23]. All such techniques used for the acquisition of EEG signal with the help of various sensors available such as wet and dry electrodes, wireless EEG system etc**.** Another scheme of data acquirement and real-time signal analysis system for monitoring multichannel EEG signal is presented. This system consists of: non-invasive EEG electrodes, DC filters, 50Hz band stop filters, differential amplifiers, instrumentation amplifiers, analog to digital converters, serial port communication modules and MATLAB based signal analysis. The filter design will be introduced in point to point communication between EEG front end and PC [25].

3. ARTIFACTS IN EEG SIGNALS

While measuring the EEG, all of the signals are not contributed by the electrical activity of the brain. Many potential changes seen in the EEG may be from other sources [6, 9]. These changes are called artifacts and their sources may be the equipment or muscles, etc. which represents the unwanted signal in EEG.

Artifacts are undesired signals that can introduce significant changes in neurological signals and ultimately affect the neurological phenomenon Fatourechi et al. 2007. Some types of artifacts will decrease or increase alpha power which leads to errors in the alpha wave measurement. There are different types of artifacts. They are mainly categorized into physiological and non physiological types.

3.1 Physiological Artifacts

3.1.1 Ocular artifacts (OA)

Ocular artifacts are caused by eye movements, such as blinking eyes and rolling eyeballs. In the frequency domain, ocular artifacts boost the power of EEG signals from 2Hz to 20 Hz. Unluckily, alpha waves fall in the range of 8Hz to 12Hz. Hence, the presence of ocular artifacts in EEG signals will cause unreliable detection of alpha power [26-27, 29-30, 38].

3.1.2 Muscle artifacts (MA/EMG)

Like the brain, muscles also generate electrical signals. These signals are picked up by EEG electrodes and become muscle artifacts. MA look like fast oscillations.EEG signals disturbed by MA have larger amplitudes than normal EEG signals. Human beings have large number of muscles all over their bodies. The muscle movement that happens near electrodes, such as teeth squeezing, will have huge impact on the power spectrum of EEG signals. Usually, presence of MA in EEG signals will increase the power of EEG signals in the frequency band from roughly 20Hz to 50Hz [31,34,36,38].

3.1.3 ECG artifacts

ECG artifacts are quite common and can be mistaken for spike activity. Because of this, modern EEG acquisition usually includes a one-channel ECG from the extremities. This also allows the EEG to recognize cardiac arrhythmias that are an important differential diagnosis to syncope or other episodic/attack disorders [26, 34, 38].

3.2 Non Physiological Artifacts

3.2.1 Electrodes movement artifacts (EMA)

This type of artifacts is caused by the contact changes between electrodes and the skin of the subject. If the subject moves his head, the electrodes on the headphone will have relative movement on the skin of the subject. This causes the changes of conduction between electrodes and skin which disturbs the recording of EEG signals. Electrodes movements may occur with different speed and in different directions, so the shape of electrodes movement artifacts varies a lot. In the frequency domain, Alpha wave measurement and detection will seriously be influenced by the electrodes movement artifacts [17, 28].

3.2.2 Electrical Interference

EEG data can be contaminated by a strong signal of AC power which occurs during data transferring, from EEG electrodes to the recording device. The frequency of artifact is either 50 Hz or 60 Hz, depending on the location. This power line interference may easily contaminate the electrode with loose connection [22]. It can further be affected by electromagnetic radiation emitted from the electrical appliances and nearby electrical cables.

4. ARTIFACT REMOVAL/FILTERING METHODS

4.1 Adaptive Filtering

Adaptive filtering scheme is discussed for different types of artifacts removal [26, 28, 37, 38].

Artifacts in EEG (electroencephalogram) records are caused by various factors, like line interference, EOG (electrooculogram) and ECG (electrocardiogram). These noise sources increase the difficulty in analyzing the EEG and to obtaining clinical information. Three adaptive filters in cascade based on a least mean squares (LMS) algorithm are used. The first one eliminates line interference, the second adaptive filter removes the ECG artifacts and the last one cancels EOG spikes. A difficulty found in this work was the determination of L (filter order) and μ (convergence factor) [26].

The most motivated is the reduction of artifacts due to body movements. Therefore, a motion artifact reduction (MAR) method that consists of combination of a band-pass filters and multi-channel adaptive filtering (AF), suitable for real-time MAR is devised. This method was capable of substantially reducing artifacts produced by head movements [28].

ICA is used in combination with RLS filtering to remove ocular artifacts [37]. For ECG and EMG artifacts removal real time recurrent learning algorithm is used RTRL (Real Time Recurrent Learning) algorithm is implemented which is the most recent and sophisticated real time neural networks algorithm. The technique used in an algorithm is the combination of adaptive noise canceller and adaptive signal enhancer [38]

4.2 Blind Source Separation

Blind source Separation method is used for different types of artifacts removal [32, 36].

Zhang Chaozhu et al.uses stone algorithm for removing ocular artifact from EEG signal. Blind Source Separation (BSS) is popular technique in signal processing. Stone’s method is to use two different linear filters which process the same set sources, first uses to remove the EOG artifact in EEG signals; it is also a new field for the stone algorithm application. This is compared with two classical algorithms to determine the superiority of the proposed algorithm [32].

For removal of EOG and EMG artifacts, Second Order Blind Identification (SOBI) algorithm is applied. However, the disadvantage of SOBI is that it cannot give the information about the order of sources. Thus identification procedures of artifacts are further needed [36].

4.3 Transform Based Methods

Transform based methods are used for different types of artifacts removal [27, 30, 33, 39, 40]. Discussion here focuses on EOG artifact removal

V.Krishnaveni et al. proposes the scheme of ocular artifacts removal using Wavelet Transform. It automatically identifies slow varying OA zones and applies wavelet based adaptive thresholding method only to the recognized OA zones, which avoids the removal of background EEG information. Adaptive thresholding applied only to the OA zone does not influence the low frequency components in the non-OA zones and also preserves the shape of the EEG signal in non-artifact zones which is of very much importance in clinical diagnosis [27].

A new model to remove ocular artifacts (OA) from electroencephalograms (EEGs) is presented using DWT [40]. The model is based on discrete wavelet transform and adaptive noise cancellation (ANC). The result of the new model shows improved results with respect to the recovery of true EEG signals which has a better tracking performance [30].

DWT and adaptive predictor filter (APF) is used for removal of ocular artifacts. The results exhibit that the proposed method achieved a lower MSE and higher correlation between the original and corrected EEG [33].

Hybrid algorithm to remove OA from single channel EEG data is discussed which comprises of algebraic method based OA detection, followed by DWT decomposition based ocular artifact removal. DWT is chosen over SWT mainly for its quicker operational speed.DWT is applied to only OA zone rather than entire signal. It shows efficacy of an algorithm [39].

4.4 Empirical Mode Decomposition

Empirical mode decomposition techniques are also used for different types of artifacts removal [29, 31].

The adaptive filtering and EMD approach is used for eye blink artifact removal. The performance index of this experiment is the correlation coefficient between bands of clean EEG and filtered EEG, which indicate that, this method outperforms the high pass filtering for removal of blink corruption from EEG signal. The results showed that novel method based denoising compared with Butterworth high pass filtering gives improved results on blink-contaminated EEG [29].

The EMG artifacts are removed using MEMD method. Firstly, the EEG signals were decomposed by the MEMD into multiple multivariate intrinsic mode functions (MIMFs) with diverse frequency bands. Then the power spectra were calculated for each MIMF by with Welch method. Because the power spectrum of EEG and EMG were focused on different frequency ranges, the MIMFs which included the EMG artifacts could be removed. Finally, the clean EEG could be reconstructed by the remaining MIMFs [31].

4.5 Combination Methods

For filtering of various types of artifacts combination methods are efficiently used [30, 34, 35, 37, 38, 41]. The model discussed is based on discrete wavelet transformation (DWT) and adaptive noise cancellation (ANC). The first step of model is to use DWT. The second step is the selection of a threshold and its application to the three lowest level coefficients to derive new wavelet coefficients. Using those new coefficients, the OA signal is reconstructed. It shows that ANC has less processing overheads than ICA [30].

A novel method based on ANFIS-DE (Adaptive Neuro Fuzzy Inference System tuned by Differential Evolution algorithm) to estimate the artifacts and to extract the EEG signal from contaminated EEG signal is discussed. Differential Evolution (DE) algorithm is used to find the optimum design parameters of ANFIS to achieve improved performance and quicker convergence with simple structure [34].

ECG artifact removal using Pan Tomkins algorithm along with linear regression is presented. It uses a robust method for the automated elimination of cardiac intervention from EEGs by identifying QRS peaks in the ECG without assuming periodicity [35].

The scheme for removal of ocular artifacts using ICA-RLS algorithm is also used. The details are discussed earlier [37]. The Real time recurrent learning algorithm is used for ECG AND EMG artifacts removal. It is the combination of Adaptive noise canceller and adaptive signal enhancer.MSE obtained is very low and promising [38]. NLMS-DWT based eye blink removal method is also presented. This method gives a better result compared to the ICA method [41].

5. DISCUSSION

It is observed that, till now in the literature review so many approaches for EEG artifacts filtering methods were discussed viz. Adaptive filtering scheme [26, 28, 37, 38], Blind source Separation scheme [32, 36], Transform based methods [27, 30, 33, 39, 40], Empirical mode decomposition techniques [29, 31] and combination methods [30, 34, 35, 37, 38, 41].These methods are suggested by worldwide researchers for getting clean EEG signal for proper diagnosis.

The technique discussed using adaptive filtering takes care of most of artifacts for removal which reduces most of the common artifacts. The coefficient's adaptation in three independent filters is simpler and faster than their adaptation in a single filter. An intricacy in selection of filter order and convergence factor is crucial [26].

Ocular artifacts are removed using wavelet transform but other artifacts are not considered. The proposed method minimizes the amplitude of the ocular artifact, while preserving the magnitude and phase of the high frequency background EEG activity using SURE algorithm [27]. Motion artifacts and eye blink artifacts are considered for removal using adaptive filtering and EMD approach. This method combines the band-pass and adaptive filtering to cope with the limitations of the reference ETI signal [28].

DWT method is used for ocular artifact removal. With respect to other methods in this area, it is able to provide better attenuation levels for common types of OAs present in EEG signals. This performance does produce some processing overhead with respect to these alternative methods [30].

EMG artifacts are removed using EMD approach. Three models [WPT and ICA], [DWT and ANC], and [DWT and APF] are introduced. The method DWT and adaptive prediction techniques achieve enhanced performance when compared to the other two methods [33].

6. CONCLUSION

Plenty of research work is going on in this area to get more accuracy but still it is a challenging task for all the researchers in the world to achieve quality and quantity EEG signal for diagnostic purpose. To summarize, in above review different modes of acquisition of EEG signal and artifact removal methods are reviewed. Several issues are to be addressed before choosing the proper alternative approach. The number of channels, computational cost, execution time and accuracy are among the major issues that contribute to the selected methods. In general, the accuracy and robustness of the algorithm will increase at the cost of computational complexity of the method used.

It is examined that different artifact removal methods are having certain advantages and limitations also. It is the thrust area of research. Hence there is a great scope to increase the accuracy for better performance. Therefore it is proposed that an effective technique may be developed which is based on proper combination technique. ICA algorithm may be considered first e.g. which may be combined with WT, STFT or adaptive thresholding WT. Otherwise any other suitable combination may be developed which will achieve better results to get clean EEG signal qualitatively and quantitatively.

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