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Artifacts analysis in EEG signal

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ABSTRACT

The EEG (Electroencephalogram) signal indicates the electrical activity of the brain. They are highly random in nature and may contain useful information about the brain state. However, it is very difficult to get useful information from these signals directly in the time domain just by observing them. They are basically non-linear and non-stationary in nature.In this paper, we describe a method for analysis and identification of Electroencephalography (EEG)Hence, important features can be extracted for the diagnosis of different diseases using advanced signal processing techniques. Linear, Frequency domain, time - frequency and non-linear techniques like correlation dimension (CD), largest Lyapunov exponent (LLE), Hurst exponent (H), different entropies, and fractal dimension(FD), Higher Order Spectra (HOS), phase space plots and recurrence plots are discussed in detail using a typical normal EEG signal.

I INTRODUCTION

Human Brain controls and coordinates internal and external behavior of the human body. Brain signals can be acquired by using modalities such as, PET, CT, MRI, fMRI, MEG have been used for acquiring images and signals of the brain. Electroencephalography (EEG) is one of the modality for analyzing the brain signals where signals are acquired with respect to the electric potentials generated from the cerebral cortex. EEG signals are categorized by five types based on frequency. Delta wave frequency range is 0.1-4 Hz and it is the slowest brain wave activity found in infants and adults with sleep stage. Theta wave lies in the frequency 4-8 Hz which is found during deep relaxed state and meditation. Alpha wave falls in the range of 8-13 Hz mostly found in adults who are awake but relaxed. Beta wave lies in the range of 13-30 Hz and concerned with active thinking. A frequency of 30-100 Hz belongs to Gamma wave which integrates the combination of two senses

II EEG ARTIFACTS

Artifacts are the unwanted noise or some disturbance caused while recording the brain signals. Artifacts are the signals which are not originated from the cerebral cortex. Has been divided into two types: Physiological and Non-Physiological. Physiological artifacts arise from the patient by moving the head, sweating, Eye blinks, and Eyeball

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rotation, Non-Physiological artifacts occurred due to the external faults like electrode failure, power supply, and ventilation. Ocular artifacts are similar in frequency of EEG signals and it is difficult to identify.

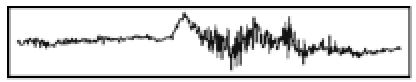
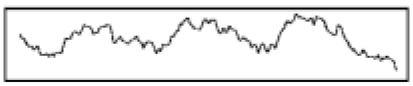


Figure 1 a) Eye Blink b) Muscle Contradiction



c) Heart pulse d) Eye Movement

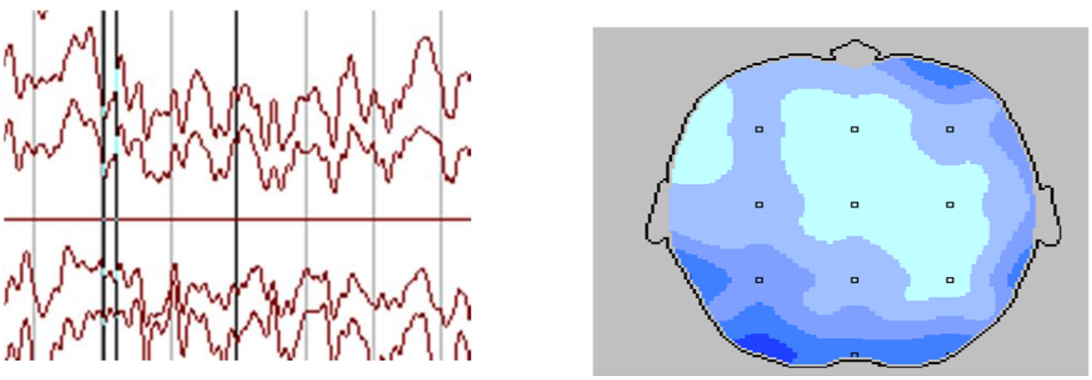


Figure 2. Artifact due to movement of Eye boll in EEG signal

III METHODS

In this research methodology discussfour different methods for detecting trials containing artifacts:

1. Extreme values. First, we used standard thresholding of potential values. Here, data trials were labeled as artifactual if the absolute value of any data point in the trial exceeded a fixed threshold. This method is currently the most widely used artifact detection method in the EEG community. It is most effective for detecting gross eye blinks or eye movement artifacts.

2. Linear trends. Marked linear trends at one electrode typically indicate transient recording-induced current drifts. To detect such events, we measured the goodness of fit of EEG activity to an oblique straight line within a sliding time window. We then either marked or not the data trial depending on the minimum slope of this straight line and its goodness to fit (in terms of r2).

3. Data Improbability.Most artifacts have "unusual" time courses, e.g., they appear as transient, 'odd', or unexpected events, and may be so identified by the outlying values of their statistics relative to normal brain activity. We tested the use of the joint-probability of the observed distribution of data values and the kurtosis of the data value distribution for detecting such artifacts. To estimate the relative probability of each trial from the data, we first computed the observed probability density function (*De*) of data values over all trials for each electrode *e* (over 4165 equally spaced bins, giving a total of 20285 values per channel or component activity). Each data sample point was thus associated with a probability.

4. *Spectral pattern.*Finally, some EEG artifacts have specific activity and scalp topographies that are more easily identifiable in the frequency domain. For instance, temporal muscle activations typically induce relatively strong 20-60 Hz activity at temporal electrodes, while saccadic eye blinks produce unusually strong (1-3 Hz) low frequency activity at frontal electrodes. To detect these artifacts, we computed the Slepianmultitaper spectrum (Thomson, 1982) for each single trial and each single channel, using Matlab*pmtm*function defaults (4 orthogonal tapers; FFT length of 256 data points for each data epoch). The main advantage of using multi-taper over standard spectral methods is that, for rhythmic activity in the data, the signal/noise ratio may be lower (Thomson, 1982). To reveal deviations from baseline, we then subtracted the epoch mean spectrum for each channel, and finally applied maximum thresholding to the resulting trial spectral estimate.

To test and optimize the artifact detection process, we used event-related EEG data from a 'Go/Nogo' visual categorization task (Delorme et al., 2004). EEG was recorded at a 1000 Hz sampling rate using a 32-electrode scalp montage with all channels referenced to the vertex electrode (Cz). The montage did not include specific eye artifact channels, but did include channels for electrodes located above the eyes (FPz; FP1, FP2). Responses to target and non-target stimuli presented about every 2 seconds were recorded for each subject. Data epochs were extracted surrounding each stimulus, extending from 100 before to 600 ms after stimulus onsets. The mean value in the pre-stimulus baseline (-100 to 0ms) was subtracted from each individual epoch. Data were then pruned of noticeable eye and muscle artifacts by careful visual inspection (AD), resulting in 119 "clean" data epochs.

In the test data depicted above, each data channel could only have one type of artifact, excepting the first two artifact types (eye and muscles), which projected with varying strengths to all the electrodes. We took care that the randomly selected channels for each artifact type differed from each other and did not coincide with channels where the two first topographical artifacts had maximum amplitude. Since our goal was to test the sensitivity of each method for detecting artifacts, we varied simulated artifact amplitude to find the smallest artifacts that each method could detect. Artifacts at the smallest amplitude level (-50 dB) were so small that none of the methods were able to detect them. For each artifact type, amplitude was gradually increased from -50 dB to 0 dB. To compute signal to noise ratio (SNR; i.e. Artifact to background brain EEG signal ratio), we divided the spectrum of each type of artifact (not mixed yet with data) at each frequency by the data spectrum at the same frequency. We then found the frequency with the largest SNR and converted it to dB scale (10*log10 (SNR)). Prior to computing SNR for the first two (topographic) artifacts, we scaled their amplitudes by the highest channel gain in the applied scalp map.

ARTIFACT DETECTION AND REMOVAL METHODS

Electroencephalography signals are generated from the cerebral cortex and some influences can lead to disturbing signal referred as artifacts. Manual artifact identification is time consuming. Automatic identification and removal method will be fast but sometimes the data loss occurred. Hence an efficient algorithm for artifact detection plays an important role in EEG signal processing.

Principal Component Analysis (PCA)

Principal Component Analysis is widely used technique for dimensionality reduction. PCA is a suitable method for identifying the high dimensional data and by reducing the dimension of the data without losing any information. It will be implemented using Single Value Decomposition (SVD) for calculating the orthogonal basis of the signal. PCA can express the EEG signals using a linear order combination of basic vector.

Support Vector Machine (SVM)

SVM is used to train the data for removing artifact from EEG signals. SVM classifiers can be trained with three classes: EMG artifact, EOG artifact and Clean EEG. For Component separation, Infomax and Amuse algorithms can be used. Features will be extracted using three sets such as component location, spectral information and time series information. These features are given to SVM classifier with RBF kernel which classifies EOG and EMG artifact from EEG signals.

Singular Value Decomposition (SVD)

Singular valued decomposition (SVD) is applied in many applications which is mainly for extracting a periodic component from noisy signals. Let X be the real m X n matrix with rank k. It exists with U and V, $X=U\Sigma VT$, where U is the left singular matrix, V is the right singular matrix, VT is the transpose of V and Σ is the uniquely defined matrix. Consider, y (t) = x (t) +e (t) where x (t) is the periodic waveform, e (t) is the noise. SVD gives less performance for lower amplitude artifact signals.

Regression Based Methods

Regression method is the most widely used for ocular artifact removal. It works on either time domain or frequency domain which depends on the reference channel (EOG). Some regression based methods are Adaptive Filter, ARMAX Modeling Wavelet Transform discussed as follows;

Adaptive Filter is one of the methods to remove the ocular artifact [6]. Reference channel (EOG) is given as one of the input and EEG signals contaminated with ocular artifact are given to the Adaptive filter. The coefficients are adjusted to having the optimized signal whereas the coefficients are calculated using Recursive Least Square (RLS) algorithm. Adaptive Filter produces the optimized original signal by subtracting EOG from EEG with ocular artifact. ARMAX Modeling method is to find the clean EEG from EEG with Ocular artifact. ARMAX uses the linear subtraction method. This method subtracts the EOG signal from the EOG artifact mixed EEG signal.

INDEPENDENT COMPONENT ANALYSIS

ICA is a tool commonly used to separate artifacts from EEG signals and also recovering the independent sources of signals. ICA algorithm efficiently performs source separation of EEG signals from other non-brain signals like neck, muscle, eye movements, eye blinks, Cardio activities and other noises. Preprocessing phase ofICA includes centering, whitening and dimension reduction to reduce the complexity of the problem. Whitening and dimensionality reduction can be performed using Principal Component Analysis (PCA) or Single Value Decomposition (SVD).

Infomax Algorithm

This algorithm blindly separates independent signals from mixtures [1]. The component distribution function can be determined using parametric approach. The extended version of informax gives the independent sources either using super Gaussian or Sub Gaussian distribution. EEGLAB toolboxes have the function, runica for separating components using Infomax algorithm.

IV CONCLUSION

Electroencephalography is one of the modality to determine the disorders and to identify the activity on a particular location. EEG signals are contaminated with artifacts and can be identified and removed using various methods. ICA is one of the widely used methods and also having high accuracy for artifact detection and removal.

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