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Classification of Denoising Techniques for EEG Signals: A Review

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Abstract

EEG (Electroencephalogram) signals contain the electrical activity of the brain. During the recording are observing the brain signals contains the neuron movements in brain. In real time EEG signal processing the source separation is major problem encountered many ways in biomedical signal processing, because the signal contain very low amplitude in terms of µV so the signals that are very easily contaminated by various types of interferences that are also called as artifacts. EEG signal is very difficult to identify or retrieve the original information because the signals directly associated in time domain. The signals are basically non-linear and non stationary in nature. However the importance of signal separation is used to diagnose brain related issues such as Narcolepsy, Sleep apnea syndrome, Insomnia and Parasomnia it becomes necessary to make these signals free from noise for proper analysis and detection of the diseases. Nowadays, there are several noise removal techniques employed to reduce the artifacts in EEG signals. In this manner we deeply discussed in this paper like ICA, PCA, AR, Wavelet and filtering techniques. Various methods of denoising are studied and considering advantages and disadvantages of all the methods it is concluded that the nonlinear filtering technique is best for artifacts removal.

Keywords - Artifact, EEG, PCA, ICA, AR, Wavelet Transform.

I. INTRODUCTION

Electroencephalography signal (EEG) is observed are recording of impulsive electrical activity of the neuron over a certain period of time [1] the communication between the nervous and neurons using electrical system. The movement of neurons carrying the information are process the information by changing the current in each cells. These activities changing the currents generate electric and magnetic fields that can be observed from the electrodes on the scalp. The observed signals from each electrode are amplified, denoising and then visualized or recorded as the Electroencephalogram (EEG) it means the movement of neurons writing out the electrical activity of the brain. EEG signal analysis contains entire information about overall activity of the millions of neurons in the brain.

Brain is the most significant organs of humans, for controlling the entire body system like coordination of human muscles and nerves. The analysis of EEG signal is commonly used to study the difficulty of human brain. The EEG is used to evaluate the different brain disorders and it can be used evaluate people are normal are abnormal associated with brain. The analysis of continuous EEG signals is very difficult. Different types of EEG waves are categorized by the frequency namely Alpha waves (7.5-14 Hz), Beta waves (14-40 Hz), Gamma waves (above 40 Hz), Theta waves (4-7.5 Hz), Delta waves (0.5-4 Hz) [2].All the waves represents different mental states of the patient.

EEG signals contain very low amplitude (µV) and they can be easily contaminated by interferences [3][4]. The noise can be internal or can be generated from the external. The interferences in the EEG signals are called the artifacts, and the artifacts must to be removed from the original signal for the appropriate analysis of the EEG signals. There are various types of interferences occur in the EEG signals during observation are the power line interferences, baseline movement, EMG interferences and so on [5]. We must remove these kinds of interferences from the original EEG signal for appropriate processing and analysis of the diseases related to brain.

Thus the various techniques of artifact removal in a real time EEG signal have become a well active research topic in signal processing, engineering and neuroscience [6-7]. The structure for artifact removal using multi-channel EEG signals is Independent Component Analysis (ICA) [8]. ICA defines a great statistical model for the observed multivariate data, which is basically nature in linear and non-stationary for some unknown latent variables. The mixing system is also unknown. There are two major assumptions in applying ICA to EEG signals. First, the ICA component projections are summed linearly at scalp electrodes. Second, the time course of EEG activity and artifacts are statically independent. ICA has a limitation of the number of separable signal sources, up to N sources from N electrodes. However, EEG signals are generated by numerous synapses, so the number of electrodes is actually much fewer than sources. This problem is called under-determined and it is known to be essentially difficult to solve using linear filtering including ICA.

II. ARTIFACTS

EEG signals contains a artifacts amid the watching are recording, the signs will show up amid the EEG record which won't originate from the brain. The greater part of the ancient rarities in the EEG signals show up amid the signal recording because of a few routes, for example, electrodes misplacement, body condition, electrodes impedance, and so forth. There is additionally a finding of physiological antiques, that is, bioelectrical signals from different parts of the body (heart and muscle action, eye squint and eyeball development) that are enlisted in the EEG. The ancient rarities fundamentally characterized into Powerline noises and Baseline noises. The powerline noises in EEG signals, are often contaminated with the 50 or 60 Hz line frequency interference from electrode wires, light fluorescents and different types of equipment's which are caught by the electrodes and procurement framework. The start of light of fluorescents for the most part causes manufactured spikes in the EEG. They are conveyed in a few channels of EEG and can commit an error in the investigation of the record [9]. In other hand the baseline noises contact mismatch of the electrodes and perspiration of the patient under the electrodes may affect the electrode impedance which causes low frequency artifacts. Baseline drift may now and then be caused by varieties in temperature and predisposition in the instrumentation and amplifiers also. This sort of artifacts is undesired and should be evacuated before any further signal handling, for appropriate examination and show of the EEG signal.

III. EEG SIGNAL DENOISING TECHNIQUES

There are several methods employed to denoising the EEG signals that can be implemented for removal of noise offered in the EEG signals are discussed below.

A. PCA Based Denoising.

Principal component analysis (PCA) connected with an arrangement of numerical process that changes various possible related factors into fewer uncorrelated factors called central segments [10]. The main essential segment reports for as a great part of the variability in the possible information, and each consequent segment reports for however much of the extraordinary changeability as could be expected. PCA are ensured to be independent only if the informational index is together normally conveyed. PCA is delicate to the relative scaling of the first variables. Depending upon the field of utilization, it is additionally named the discrete Karhunen–Loève change (KLT), the Hotelling transform or proper orthogonal decay (POD).

The essential thought in PCA is to find the parts $s_1, s_2,\dots ,s_n$ with the goal that they clarify the greatest measure of variance possible by n linearly transformed segments. PCA can be characterized in an instinctive way utilizing a recursive detailing. Characterize the heading of the main principal component, say w_1, by

$$w_1 = \arg\max_{\|w\|=1} E\{(w^T x)\} \quad (1)$$

where w_1 is of a similar measurement m as the random information vector x. (Every one of the vectors is represented in column vectors). In this way the principal component is the projection on the course in which the variance of the projection is amplified. Having decided the first k-1 principal components, the k-th principal components is resolved as the principal components of the lingering:

$$w_k = \arg\max_{\|w\|=1} E\{[w^T (x - \sum_{i=1}^{k-1} w_i w_i^T x)]^2\} \quad (2)$$

The principal components are then given by $s_i = w_i^T x$. In practice, the calculation of the wi can be basically refined utilizing the (example) covariance matrix $E\{xx^T\} = C$. The wi are the eigenvectors of C that relate to the n biggest eigenvalues of C. The essential objective in PCA is to lessen the measurement of the information. Along these lines one for the most part picks n << m. In reality, it can be demonstrated that the description given by PCA is an ideal direct measurement reduction method in the mean-square sense. Such a decrease in measurement has vital advantages. To begin with, the computational overhead of the resulting preparing stages is lessened. Second, clamor might be decreased, as the information not contained in the n first segments might be generally because of commotion. Third, a projection into a subspace of a low measurement, for instance two, is helpful for picturing the information. PCA is scientifically characterized as an orthogonal linear transformation that changes the information to another coordinate framework with the end goal that the best variance by any projection of the information comes to lie on the primary coordinate, the second most prominent variance on the second coordinate, and so on [11-12].

B.ICA Based Denoising

Another important approach for denoising the EEG signal is the ICA method of denoising. An ICA based denoising method has been developed by Hyvarinen and his Coworkers [13-14] . The basic motivation behind this method is that the ICA components of many signals are often very sparse so that one can remove noises in the ICA domain. The ICA model assumes a linear mixing model x= AS, where x is a random vector of observed signals, A is a square matrix of constant parameters, and s is a random vector of statistically independent source signals. Each component of s is a source signal. Note that the restriction of A being square matrix is not theoretically necessary and is imposed only to simplify the presentation. Also in the mixing model we do not assume any distributions for the independent components. Suppose we have n observed signals xi where i= 1,,2….n from mixing m source signals yi, where, i=1,2,…….m we want to find such a transformation Matrix W that for a given number of dimensions d Y'=W*X, where Y' is a dx1 vector. The transformed variable yi is considered the component explaining the essential structure of the observed data. These components should contain as much as possible information of the observed data [15]. ICA usually carries all the information in a single component and most of the times this component carries non- artefactual information which may lead to information loss. Also ICA performance depends on the dataset size. Another limitation which arose in this method is that the signals can be analyzed only in time domain not in the frequency domain as the artifacts in EEG have a typical frequency range and are overlapped with the spectrum of the EEG data this becomes one of the disadvantage of this method [16].

The FastICA Algorithm

Adaptive algorithms based on stochastic gradient descent might be risky when utilized as a part of an environment where no adjustment is required. This is the situation in numerous handy situations. The convergence is frequently moderate, and depends significantly on the decision of the learning rate sequences. As a solution for this issue, one can utilize cluster calculations in light of fixed-point iteration [17-18]. A fixed-point calculation, named FastICA, was presented utilizing kurtosis, and the FastICA calculation was summed up for general difference capacities. For sphered information, the one-unit FastICA calculation has the accompanying structure:

$$w(k) = E\{x_g(w(k-1)^T x)\}\ E\{g'(w(k-1)^T x)\}\ w(k-1) \quad (3)$$

where the weight vector w is also normalized to unit standard after each iteration, and the function g is the derivative of the function G utilized as a part of the general differentiation work is given in below equation

$$J_G(y) = |E_y\{G(y)\} - E_v\{G(v)\}|^p \quad (4)$$

The desires are assessed, in practice, utilizing test midpoints over a sufficiently vast specimen of the information. Units utilizing this FastICA calculation would then be able to be joined, similarly as on account of neural learning rules, into frameworks that gauge a few free parts. Such frameworks may either evaluate the autonomous segment one-by-one utilizing progressive decorrelation, or they may appraise all the free segments in parallel, with symmetric decorrelation [19]. The FastICA algorithm is neural in that it is parallel and distributed, but it is not adaptive. Instead of using every data point immediately for learning, FastICA utilizes test midpoints processed over bigger examples of the information. The convergence rate of the xed-point calculations is plainly better than those of the more neural calculations. Accelerate factors in the range from 10 to 100 are normally watched [20]. When FastICA is utilized with symmetric decorrelation, it is basically comparable to a Newton technique for greatest probability estimation.

C. AR Based Denoising

The non-parametric strategies experience the spectral leakage effects of windowing. Spectral leakage masks weak signal components. A parametric control power spectrum estimation technique beats the issue of spectral leakage and gives better frequency resolution. These strategies expect the signal to be a stationary random process. This procedure can be displayed as the output of a filter with repetitive white noise input. The filter parameters are obtained from the signal. There are distinctive approaches to get these parameters. The techniques are characterized depending upon the presence of poles in the z-domain. On the off chance that there are no poles, at that point it is MA (moving average) Model. If there are poles present and every one of the zeros are situated at the origin, at that point it is an AR (auto recursive) demonstrate. A model having poles and zeros naturally appropriated in the z-poles is called ARMA (auto recursive moving average) [21-22]. The EEG signs of typical, epileptic and alcoholic were dissected utilizing power spectra densities utilizing Fast Fourier Transforms (FFT) by Welch technique, auto recursive (AR) Yule-Walker and Burg's strategy. They have utilized initial three pinnacle power and pinnacle frequencies of the power range for the investigation [23].

Among the three parametric strategies, AR technique is broadly utilized for the investigation. Burg's AR technique is examined below. Burg technique depends on limiting forward and in reverse expectation errors while fulfilling the Levinson-Durbin recursion [24-25]. In this technique as opposed to computing autocorrelation work, reflection coefficients are assessed directly. The essential favorable conditions of this technique are settling firmly divided sinusoids in signals with low noise levels, and evaluating short information records, in cause where the AR power spectral density estimates are near the excepted value [26]. Burg Method varies from Yule-Walker Method in the way the PSD, $\underset{xx}{P_{BU}}(f)$, is acquired, as appeared in the accompanying condition:

$$\underset{xx}{P_{BU}}(f) = \frac{e^{\wedge}p}{|1 + \sum_{l=1}^{p} a^{\wedge}{}_p(l)e^{-2jfl}|^2} \quad (5)$$

Where e^p denotes the total least square error and it is the sum of the forward and backward prediction errors.

$$e^{\wedge}{}_{f,p}(n) = x(n) + \sum_{i=1}^{p} a^{\wedge}{}_{p,i}x(n-i), n = p+1,....,U \quad (6)$$

$$e^{\wedge}{}_{b,p}(n) = x(n-p) + \sum_{i=1}^{p} a^{\wedge *}{}_{p,i}\, x(n-p+i), n = p+1,....,U \quad (7)$$

For both, Burg and Yule Yule-Walkar, the model order was chosen as the one that minimizes the akaike information criterion (AIC) figure of merit.

$$AIC(p) = N.\ln(\lambda^{\wedge 2}) + 2p \quad (8)$$

where N is the number of information test samples and $\lambda^{\wedge 2}$ is the assessed white noise variance. To decrease computational complexity, we accepted as ideal the estimation of p that satisfied the AIC basis in the initial two epochs. The most essential parts of the AR technique is the choice of the order p.

D. Short Time Fourier Transform (STFT)

Fourier Transform is not suitable for analyzing non-stationary signals. A signal of finite length is expressed as the sum of frequency components of infinite duration. It fails to provide the exact location of an 'event' along the time scale in the frequency domain. In STFT, the signal is divided into small segments and the signal within this segment is assumed to be stationary. For this purpose, a window function, whose width is equal to the segment of the signal is chosen. The definition of the STFT is:

$$STFT^{(w)}{}_x(t,f) = \int_{-\infty}^{\infty} [x(t).w^*(t-t')].e^{-j2\pi f t}dt \quad (9)$$

where,

x(t) is the signal and w(t) is the window function and * is the complex conjugate.

The drawback of STFT is the finite length window. The narrow window offers better time resolution and poor frequency resolution. And wider window results in good frequency resolution and poor time resolution. These wide windows may violate the condition of stationarity. Hence, the resolution is a problem in STFT and it can be resolved using wavelet transform [27].

E.WAVELET Based Denoising.

The term 'wavelet' refers to an oscillatory vanishing wave with time-limited extend, which has the ability to describe the time-frequency plane, with atoms of different time supports Generally, wavelets are purposefully crafted to have specific properties that make them useful for signal processing. Wavelets are a mathematical tool that can be used to extract information from many kinds of data, including audio signals and images. Mathematically, the wavelet is a function of zero average, having the energy concentrated in time.

$$\int_{-\infty}^{\infty} \phi(t)dt = 0(1) \quad (10)$$

In order to be more flexible in extracting time and frequency information's, a family of wavelets can be constructed from a function (t), also known as the 'Mother Wavelet', which is confined in a finite interval. 'Daughter Wavelets', are then formed by translation with a factor u and dilation with a scale parameter s:

$$s : \phi u, s(t) = (1/\sqrt{s}) * \phi(t)(t-u)/s \quad (11)$$

In wavelet denoising we decompose the signals in to high frequency components and low frequency components using the thresholding method and apply wavelet transform to the low frequency components.

Wavelet change replaces the sinusoidal waves of Fourier transform by interpretations and expansions of a window function called 'wavelet'. There are two types of wavelets transform (i) discrete wavelet transform (DWT) (ii) continuous wavelet transform (CWT). DWT gives adequate data both to examination and combination of the first signal, with a significant reduction in the computation time. The channels of various cutoff frequencies can be utilized to analyze the signal at various scales. The signal is gone through a progression of high pass channels to dissect the high frequencies, and it is gone through a progression of low pass filter to investigate the low frequencies. It is generally utilized for pressure and compression and noise reduction. This strategy can be utilized to remove alpha, beta, theta and gamma frequencies of the EEG. 'Wavelet' is a rush of limited term and limited vitality, which is associated with the signal to get the wavelet coefficients. The mother wavelet is a reference wavelet, whose coefficients are assessed for the whole scope of enlargement and interpretation factors [28-29]. The mother wavelet is moved persistently along the time scale for assessing the arrangement of coefficients at all moments of time. In the following stage, the wavelet is enlarged for an alternate width and normalized to contain a same amount of energy from the mother wavelet. This procedure is repeated for the whole signal. Consequently CWT is processed by changing the size of the investigation window, moving the window in time, increasing by the signal, and coordinating over all circumstances. This procedure produces wavelet coefficients that are elements of scale and position. The wavelet coefficients are appeared as pixel intensity, in a two dimensional plane with y-axis representing to the expansion of the wavelet, and the x-axis, its interpretation. Consequently the wavelet change plot (scalogram) is a 2D shading design portraying the area of the 'event' happening in the time scale. The EEG signals were decayed into recurrence sub groups utilizing discrete wavelet change and later sustained to the neural system for order into epileptic or typical signal [30]. These CWT coefficients can be utilized as highlights to recognize the specific sickness.

F. Linear Filtering.

Linear filtering is helpful for removing artifacts located in certain frequency bands that do not cover with those of the neurological marvels of intrigue. For instance, low-pass filtering can be utilized to remove EMG artifacts and high-pass filtering can be utilized to remove EOG artifacts. Linear filtering was usually utilized as a part of early clinical investigations to remove artifacts in EEG signals. Adaptive filter depend on the enhancement hypothesis and they have the ability of modifying their properties as per listed features of the signals being analyzed in this structure of adaptive filter. There is an original signal d(n) and an noise signal x(n). The linear filter H(z) produces a output y(n), which is subtracted from d(n) to compute the error e(n).[31] The goal of a adaptive filter is to change (adjust) the coefficients of the linear filter, and subsequently its frequency response, to produce a signal like the noise occurrence in the signal to be filtered. The adaptive process includes minimization of a cost work, which is utilized to decide the filter coefficients. At first, the adaptive filter changes its coefficients to limit the squared error between its outputs and an original signal. In stationary conditions, the filter should merge to the Wiener solution. On the other hand, in non-stationary conditions, the coefficients will change with time, according to the signal variation, thus converging to an optimum filter [32-33]. In an adaptive filter, there are basically two processes:

1. A filtering process, in which an output signal is the response of a digital filter. Usually, FIR filters are used in this process because they are linear, simple and stable.

2. An adaptive process, in which the transfer function H(z) is adjusted according to an optimizing algorithm. The adaptation is directed by the error signal between the primary signal and the filter output..

IV. Conclusion

EEG signals can be utilized as a valid indicator, which enables us to watch mental states and diseases identified with the brain. The EEG signal is exceptionally subjective and can be considered as a disordered signal. The impact of different physiological occasions on the EEG signal has been discussed. Various signal analysis techniques time domain, frequency domain, linear and nonlinear systems are also discussed. The linear and frequency domain are not exceptionally successful in the investigation of the physiological signs. The signals were denoised utilizing PCA, ICA, AR, Wavelet strategy and linear filtering. It is realized that signals with higher PSNR and SNR and low MSE are less noise signals. By taking a various evaluation parameters like MSE, PSNR, SNR computed by different authors it is concluded that linear filtering method gave the best denoising result with its multiresolution capacities in time and frequency domain analysis for large amplitude and less configuration. Wavelet change investigations the signals in both time and frequency domain and furthermore motions with low noise amplitudes can be removed from the signals by choosing the best wavelet to decompose the signal in small amplitude. ICA technique depended on the blind source separation and it could analyze the signals just in time domain the frequency components of the signal along these lines could not be analyzed. In PCA strategy the correlated values are changed in to uncorrelated smaller values called the principal component for signal denoising. The PCA and ICA can analyze the signal just in time domain and also PCA technique relies upon the extent of informational size of the signal which is to be denoised.

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