Canvassing Various Techniques for Removal of Biological Artifact in EEG

Ashish Raj, Akanksha Deo, Manoj Kumar Bandil

Abstract*— *EEG is an important tool for diagnosis, monitoring and managing various nervous disorder .It is a neurophysiologic measurement of the electric activity of bioelectric potential of brain. The electrical activity of brain changes in accordance with various parameters inside & outside environment. To study human physiology with respect to EEG, bioelelectric potential of brains is recorded with help of electrodes. These raw signals are firstly processed with help of mathematical tools in order to make them more and more informative. The informative signal thus calculated from recording is known as ERP (event related potential). These ERP data are very specific and it changes with every physiological & biological change in human body. The analysis of ERP has got a wide range of clinical importance. It serves as a base for diagnosis and detection of various diseases. ERP are also helpful in designing various emotion sensor interfaces.

But there are certain artifacts which are present in raw EEG recording. These artifacts make the ERP contaminated and it introduces inconsistency in the output. Thus it is necessary to eliminate these artifacts from the EEG. The ERP generated from artifacts free EEG are most suitable for versatile researches and efficient diagnosis. The clinical information thus obtained is of considerable importance in identifying different pathologies. Artifacts in EEG signals arise due to two types of factors; Biological factors and External factors. The Biological factors are caused by EOG (Elecro-oculogram), ECG (Electrocardiogram), EMG (Electromyogram) and Respiratory (PNG).The External factors are caused due to line-interference, leads and electrodes. These noises have an adverse effect on EEG signals and act as a hindrance to obtain clear cut information from EEG signals. This is a paper scrutinizing different methods for removing artifacts with illustrating characteristics of a good informative EEG signal

Index Terms*— *EEG; EMG; ECG; ocular artifacts; muscular artifacts; spike detection; Wavelet transform; Neural network.

I. INTRODUCTION

Electroencephalogram is most important tool to measure the electrical activity of brain to distinguish between seizure and non-seizure states To record the EEG signals surface electrodes are placed on the scalp of patient with the help of gel to increase the conductivity of scalp surface. After recording the EEG signals, these signals are sent to an amplifier to increase its magnitude since EEG signals are voltages of low magnitude .Amplification of low voltages make the analysis easy. The output of the recording comes in the form of waveform which is nothing but oscillations of current.EEG can be recorded simply in two ways-with stimulus and without stimulus. The EEG recorded without internal or external stimulus is called spontaneous EEG while it is called Event Related Potential (ERP) when recorded with internal or external stimulus.

When these brain potentials are synchronized, it indicates the normal state of brain but when there is some abnormality in brain electrical potential, it indicates mental disorder. Event-related potentials are patterned voltage changes embedded in the ongoing EEG that reflect a process in response to a particular event (e.g., visual or auditory stimuli).ERPs are measured from the same “raw data” (i.e., scalp electrical activity over time and space) as EEG. ERP reflects sensory, motor, and/or cognitive events in the brain. It reflects synchronous post-synaptic potentials of large neuronal populations engaged in information processing. Signal averaging is most common method of extracting the signal. EEG is sampled for ~1 second after each stimulus presentation & averaged together across like stimuli. The time-locked signal emerges in which noise averages to zero.[1] We have to extract time locked activity by averaging these raw data.EEG signals are basically stimulus related processing whereas the noise are tonic background activity related to ongoing process(level of arousal..etc).There is a severe problem of signal to noise in EEG data .Since EEG is of the order of ± 50 micro volts. But ERP are on order of 2- 20 micro volts. We often want to detect difference of 1-2 microvolt thus precision is the important prerequisite in analysis of ERP.

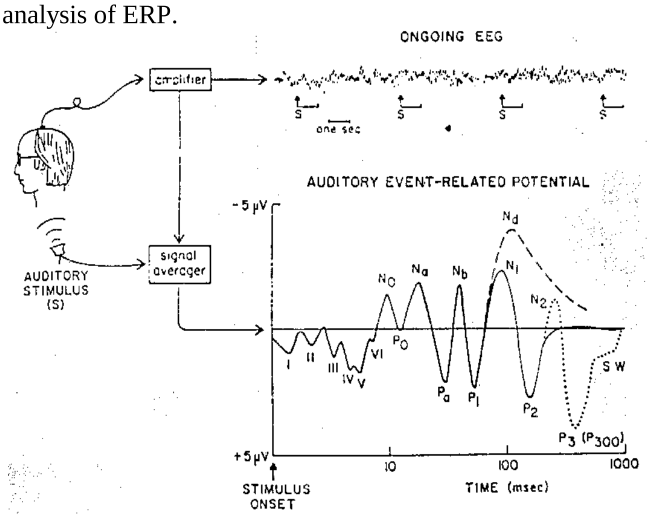

Figure 1.Generation of ERP from raw EEG signal

Signal and noise (in each epoch) sum linearly together to produce the recorded waveform for each epoch (not some peculiar interaction). The evoked signal wave shape attributable solely to the stimulus is the same for each presentation.

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The noise contributions can be considered to constitute statistically independent samples of a random process.

A large number of researches present a wide variety of methods for identifying and removing artifacts in the EEG. These methods may operate in either a fully automatic or semi-automatic manner. It can be applied either for one or more than one types of artifacts. Artifacts are identified over a wide range of different features which comprises properties of the artifact as diverse as their time series topology, their spectral template, and their statistical properties of either uni- or multivariate EEG. The efficacy of artifact identification and removal methods may be evaluated in a number of ways. Frequently, visual inspection of the time series of the EEG is presented as sufficient evidence for the efficacy of the removal method. Therefore there should be an analytic definition of clean EEG. This could fulfil the purpose for a more rigorous evaluation of artifact removal methods. Currently artifact removal studies define their success in different ways. Thus, some defines success as the number of artifacts detected minus non-detected artifacts, divided by the total number of artifacts, while some defines success by measures of sensitivity and specificity with regards changes in artifactual and non-artifactual EEG components. A metric for testing how clean an EEG epoch is would allow rigorous comparisons between these studies to be made. For example, artifact removal methods could be evaluated by looking at the change in the EEG cleanliness metric before and after use of the method. Thresholds are trained on the data to optimally identify clean epochs via differential evolution (DE). Finally, the optimal thresholds are presented and an algorithm is discussed for identifying clean EEG epochs. [2]

In a clinical diagnosis, artifacts are rejected by visual examination of recording. There are simple criteria for artifact recognition, which can help in the search of an appropriate online cleaning technique. Some simple criteria, for a corrupted EEG signal, are as follows:-

i. High amplitude of delta wave (0.5-4 Hz) in channels Fp1 and Fp2.
ii. Similarity of signals in channels Fp1 and Fp2.
iii. Rapid decline of delta wave posterior (the amplitude of delta wave in Fp1 and Fp2 is much higher than in other channels).

II. PARADIGM OF METHODOLOGIES

2.1 Avoidance of Artifacts

Avoidance of artifacts is the best suitable step to be taken to eliminate the problem occurring due to them. Major artifacts which occur during recording data are caused by blinking of eyes and movement of eyeballs. As it is very difficult for the person under observation to control these self initiated activities throughout the recording of data still by giving proper instructions to the person under observation these artifacts can be avoided up to great extent .Since if person under observation is asked to strictly control the eye blinking & eyeball movement, the person has to concentrate more on this so that it enhances the amplitude some evoked potential. So that even by instructing the person to control these natural activities, complete avoidance of these artifacts is not possible. For this, other methods of artifacts rejection are used.

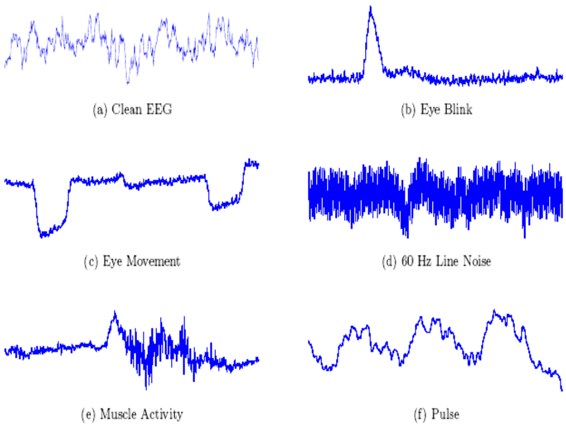

Figure 2.Various artifacts present in EEG signals

2.2 Rejection of Artifacts

Even by avoiding the occurrence of artifacts some of the artifacts still remain in the recording. So the next step to avoid the problem created due to presence of these artifacts is to reject them .Artifacts rejection refers to the process of rejecting the trials affected by artifacts. It is the only single way to deal with the recording of brain signal affected by various artifacts.

This process comprises mainly of two methods-manual artifact rejection and automatic artifact rejection.

2.2.1 Manual Artifacts Rejection –

Manual rejection of artifacts in EEG is done by the EEG experts by visual inspection. The experts by visual inspection analyze the portion affected by artifacts in the EEG recording and remove them. As it is done by visual inspection of EEG expert, no computational techniques are involved in manual rejection method. Major disadvantage of artifacts rejection by manual artifact rejection technique is the excessive manual labour involve in it. The problem becomes even more severe when the analysis has to be done on more than one individual or when the very de se data has to be processed.

2.2.2 Automatic Artifacts Rejection-

Rejection technique for artifacts involving automatic process is based on previously set values of potentials occurring during recordings. Values for two types of signals can be pre set, first is (EMG) signals and second is EEG signals. If the EOG signals are present in the form of artifacts along with EEG signals then in such case to reject these artifacts by automatic rejection method some values are previously set for these signals .However, if in recorded data values of EOG (EMG) signals exceeds this previously set values, the system automatically identifies it as artifacts. Same procedure is followed for EEG signal. This is useful when in recording data EOG (EMG) signals are absent. Some previously set values are assigned for EEG signals, if these values exceed the previously set values then the system automatically consider them as artifacts.

2.3 Removal of Artifacts-

Even after avoiding and rejecting the artifacts if there still remain some artifacts which goes unidentified then there must be methods for removal of these artifacts from the recorded data to get the clean EEG.

Common methods involved for removal of artifacts are discussed as follows.

2.3.1 Subtraction Method –

The artifacts in the recording of EEG signals are assumed to be caused by blinking of eyelids, movement of eyeballs (EOG), and movement of muscle in any body parts (EMG), heartbeats (ECG) etc. These artifacts are mixed with EEG signals recording. If these signals are recorded separately and by applying proper weights if these signals are subtracted from the original EEG data recording then as a result of this process only clean EEG will remain and all other artifacts will get removed.

2.3.2 Linear Combination & Regression Method –

It is assumed that EEG data recording is the linear combination of clean EEG and artifacts. Regression using the EOG channel was attempted in the time and frequency domain. [3]

$$eeg\ (t) = EEG\ (t) - \sum \beta_g\ eog\ (t-g) \qquad \text{(i)}$$

Where eeg (t) and eog (t - g) are the recorded EEG and EOG information at times (t) and (t –g), respectively. EEG (t) represents the uncorrupted EEG at time t, and β measures the effect of the EOG on EEG (t) at time (t – g) and g ranges from 0 to T. Two correction procedures based on regression in the time domain were studied. Each procedure uses the following linear model to approximate the relationship between the observed EOG, the observed EEG and the true unobserved EEG, where by 'true' EEG; we mean the signal that would have been recorded in the absence of ocular artifacts.

2.3.3 Blind Source Separation Method -

Blind source separation method involves two methods such as Principal Component Analysis (PCA) and Independent Component Analysis (ICA). After deleting the artifacts from the original EEG by BSS method, the clean EEG can be reconstructed without artifacts. Blind source separation (BSS) is the technique used to separate independent signals from a set of mixed signals without any prior knowledge of the signals. The source signals $s(t)=[s_1(t),s_2(t),\ldots,s_m(t)]^T$ are to be estimated from the observed signals $x(t)=[x_1(t),x_2(t),\ldots,x_m(t)]^T$. The system is modelled as x(t) = As(t), where the mixing matrix, A, represents unknown observations. The most simple and widely used assumption in EEG processing is the linear instantaneous mixing: source signals reach the sensors simultaneous. [4].The noisy mixture in this case is written as.

$$X = AS + N \qquad \text{(ii)}$$

Where X is the matrix of the mixed signals (x_i) corresponds to a row of X, *i.e.*, a sensor signal), A is the unknown non-singular mixing matrix, S is the matrix of independent sources (s_i corresponds to a source), N is an additive noise matrix. The motive of BSS is to calculate a linear transformation B of the sensor signals X that makes the outputs as independent as possible.

$$Y = BX = BAS + BN \qquad \text{(iii)}$$

Where Y is the estimation of the sources S. We assume here that the number of sources is equal to the number of sensors *Q*. In this case, $A\ \mathcal{E}\ R^{QXQ}$ and the ideal separation is obtained when $B = A^{-1}$ and, Y is an estimate of noise in S.

BSS algorithms look for a matrix B such as the product BA is a permuted diagonal and scaled matrix. Thus, original sources can be recovered except for their order (permutation) and their amplitude (scale). The estimated sources Y will be permuted and normalized to standard deviation of unity.

2.3.4 Principal Component Analysis-

The mathematical technique in PCA is Eigen analysis. We solve for the Eigen values and Eigen vectors of a square symmetric matrix with sums of squares and cross products. The eigenvector related with the largest Eigen value has the same direction as the first principal component. The eigenvector associated with the second largest Eigen value determines the direction of the second principal component. The sum of the Eigen values equals the trace of the square matrix and the maximum number of eigenvectors equals the number of rows (or columns) of this matrix.

The overall algorithm can be illustrated as follows-

i. Read the EEG signal, EOG signal and get noisy EEG signal.
ii. Split the EEG data into vectors of certain length and covariance matrix of the vectors.
iii. Calculate eigen values and eigen vectors of the above data on covariance matrix.
iv. For each eigen vector low pass filtering is done using a filter of cut off frequency 50 Hz and the energy of filtered data is calculated.
v. The energy calculated corresponding to eigen value is compared with a threshold. If this energy is greater than that of threshold then mark these for reconstruction else discard the vector.
vi. We reconstruct only on those Eigen vectors which are marked for reconstruction. Finally MSE and PSNR are calculated for noisy and filtered EEG signals Principal component analysis method has been considered to be able to remove ocular artifacts but not completely provides the clean EEG. Problem occurs with PCA method when eye movements and other sources of artifacts such as ECG, EMG etc have almost same amplitudes.

2.3.5 Independent Component Analysis –

An EEG signal contaminated with artifacts consist of true signal S(t) along with artifacts ε(t) and can be represented by the relation as

$$C\ (t) = S\ (t) + \varepsilon\ (t) \qquad \text{(iv)}$$

Independent component analysis has been successfully employed to eliminate e(t) from the true EEG signals. Blind Source separation had given a method principal component analysis and independent component analysis is just advancement to it. Important criteria to be fulfilled for successful implementation of ICA is as follows-

i. The number of sources should be equal to number of sensors applied;
ii. The mixing medium should be linear with negligible propagation delay;
iii. The source should be independent.

ICA starts assuming that K simultaneously recorded EEG signals $X(t) = \{x_1(t) \ldots x_K(t)\}$ are linear mixtures of ($N \leq K$) a priori unknown independent components (sources) $S(t) = \{s_1(t), \ldots, s_N(t)\}$ including artifactual and of the neural origin.[5]

$$X(t) = MS(t), \qquad \text{(v)}$$

Where M is the unknown mixing matrix defining weights at which each source is present in the EEG signals recorded at the scalp. Topography scalp maps of the components provide additional information on the localization of the sources.

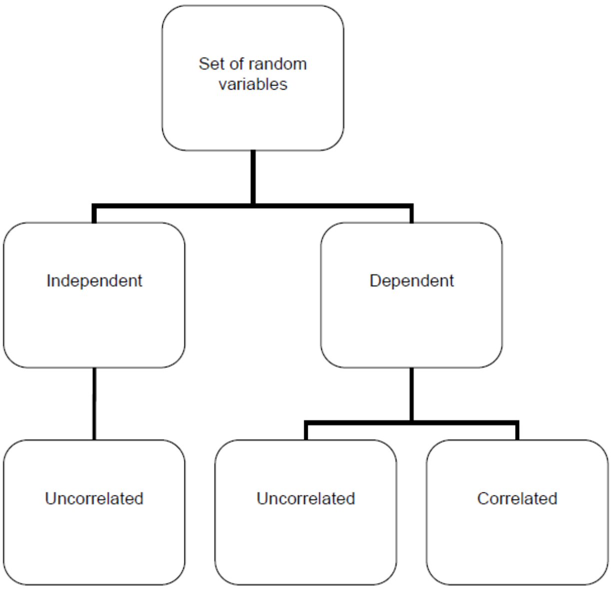

Figure 3.Independence and Correlation

The aim of ICA is to estimate both $S(t)$ and M from $X(t)$. Once the algorithm has been applied we analyze the temporal structure and topography of the components $S(t)$ (e.g. the ocular artifacts mainly project to frontal sites) and identify among them those components that account for artifacts. Then we set the identified artifactual components to zero, $S_{artf}(t) = 0$, obtaining a new component matrix $\hat{S}(t)$ where the artifactual sources have been rejected. Finally, we reconstruct ICA-corrected EEG signals.

$$\hat{X}(t) = M\hat{S}(t). \qquad \text{(vi)}$$

Obtained this way the new data set $\hat{X}(t)$ represents the ICA estimation of the original, artifact free data.

2.3.6 Wavelet Transform –

Wavelet Transform is a mathematical compression technique. Unlike Fourier Transform it is applied on time varying signals (Fourier Transform is applied on stationary signals).

$$\Psi_{j,k}(t) = 2^{j/2}\Psi(2^j - k) \qquad \text{(vii)}$$

The Discrete Wavelet Transform (DWT) means, choosing subsets of the scales j and positions k of the mother wavelet $\psi(t)$.Choosing scales and positions are based on powers of two, which are called dyadic scales and positions (j and k are integers).Equation shows that, it is possible to build a wavelet for any function by dilating a function on $\psi(t)$ with a coefficient 2j, and translating the resulting function on a grid whose interval is proportional to 2–j. Contracted (compressed) versions of the wavelet function match the high-frequency components, while dilated (stretched) versions match the low frequency components. By correlating the original signal with wavelet functions of different sizes, the details of the signal can be obtained at several scales. These correlations with the different wavelet functions can be arranged in a hierarchical scheme called multi-resolution decomposition. Many researchers developed real-valued extensions to the standard DWT such as SWT (Stationary Wavelet Transform). The key point is that it gives a better approximation than the discrete wavelet transforms (DWT) since, it is redundant, linear and shift invariant [6].These properties provide the SWT to be realized using a recursive algorithm.[6]

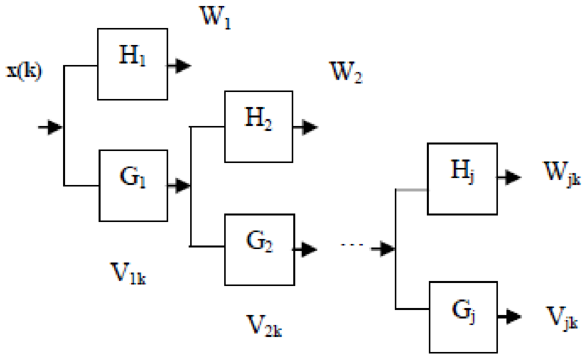

Figure 4.Computation of the SWT of a signal x (k)

In given figure 4. $W_{j,k}$ and $V_{j,k}$ are called the detail and the approximation coefficients of the SWT. The filters H_j and G_j are the standard low pass and high pass wavelet filters, respectively. While performing analysis using wavelet transform technique, it is noticed that the larger coefficients get generated from the area which is more affected due to the presence of artifacts (noise). The data having very low affected due to presence of artifacts produces small coefficients compared to the noisy zones. A predefined limit is decided foe the values of these coefficient between clean EEG coefficients and the coefficients due to artifacts (noise). After the successful identification of artifacts affected area, it is eliminated by applying proper techniques. In this way, clean EEG is obtained with the use of wavelet transform techniques.

2.3.7 Liner Filtering –

Filtering of EEG signals follows a process that employs use of a filter. From the study so far done, it is concluded that low pass filter is useful in removing artifacts caused by eye blinking, eye blinking (EOG). But in case if EEG signals and artifacts caused by EOG, EMG are in the state of overlap, the filter is not able to remove the artifacts all alone. If it does so, a part of clean EEG can also be removed which is undesirable.

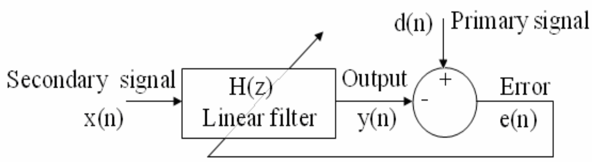

Figure 5. Signal processing with adaptive linear Filters

Figure 5 illustrates the structure of an adaptive filter. There is a primary signal d(n) and a secondary signal x(n). The linear filter H(z) produces an output y(n), which is subtracted from d(n) to compute an error e(n).

The objective of an adaptive filter is to change (adapt) the coefficients of the linear filter, and hence its frequency response, to generate a signal similar to the noise present in the signal to be filtered. The adaptive process involves minimization of a cost function, which is used to determine the filter coefficients. By and large, the adaptive filter adjusts its coefficients to minimize the squared error between its output and a primary signal. In stationary conditions, the filter should converge to the Wiener solution. Conversely, in non-stationary circumstances, the coefficients will change with time, according to the signal variation, thus converging to an optimum filter [7].

In an adaptive filter, there are basically two processes:

i. 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 simple and stable.
ii. 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. The most used optimizing criterion is the least mean square (LMS) algorithm.

2.3.8 Artificial Neural Network –

Use of artificial network for artifacts removal is one of the finest methods. The properties of ANN such as massive parallel structure, high degree of interconnection capabilities of high speed computations, non linear mapping and self organization makes it best candidate for prediction and compression problem. Basically for higher efficiency neural networks are accompanied with pre-processing of EEG signals on wavelet transform .The EEG signal is sampled and reconstructed on basis of wavelet transform and a neural network based predictor is introduced in them. Fig.6 shows the basic network for neural network based analysis and synthesis.

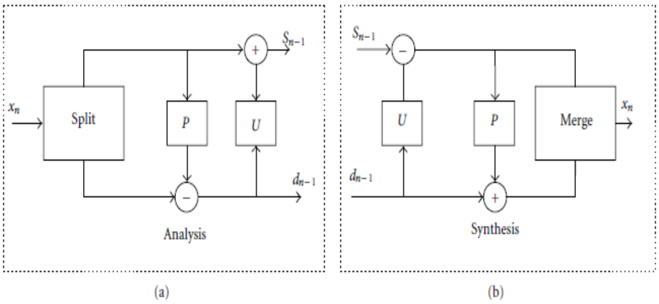

Figure 6.Neural network based analysis and synthesis

The introduction of ANN brought new possibilities in development of adaptive methods of structures recognition and solving complex classification problems which can be related to their ability to learn a certain mapping from the set of the realization examples. However performance of ANNs depends heavily on input parameters. We will apply ANNs for artifact recognition testing their performance for different input parameter sets.

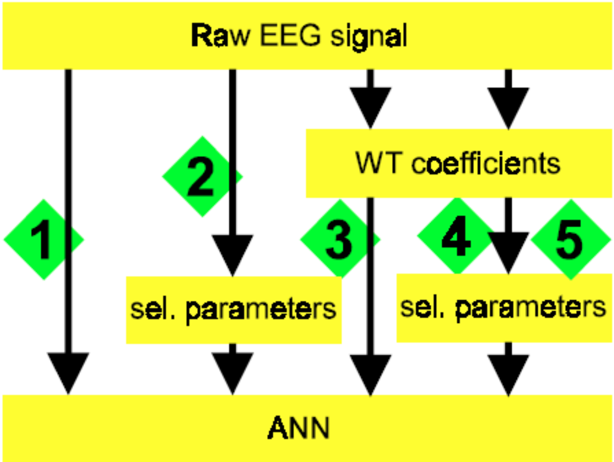

Figure 7.Five ways of pre-processing of the input EEG signal

III CONCLUSIONS

EEG signals involve enormous set of informations about the function of brain. We have discussed various methods to obtain clean EEG signals by removing artifacts so that efficient informative ERP is generated.

ICA method could be used in situations, where large number of noises needs to be distinguished, but it lags for real time application like on line Brain Computer Interface (BCI). ICA performs best for correcting imaging artifacts

Wavelet transforms are applied for on line application, but the critical parameter is the selection of the threshold function.

Linear filtering is best when; the frequency of noises does not interfere or overlap with each other but optimal parameters of the Kalman filter must be estimated, which is relatively easy in the case of simulations because we know a priori the EEG without artifacts. In the case of experimental data, it may be difficult to find optimal filter parameters and the results should be affected by this imprecision. Alternatively, the PCA approach offers a relative robustness.

Artificial Neural Networks (ANNs) is an emerging and adaptive method of structure recognition and solving complex artifact removal problems and predictive systems with help of different learning and training algorithms. We can conclude that for ANN application in the time series classification pre-processing should include frequency information about the signal. In many other applications power spectra calculated from Fourier transform are applied. We can recommend wavelet transform as more efficient and faster method, providing both - time and frequency characteristics of signal and thus offering universal pre-processing. [8] Lossless compression techniques are also designed with help of combination of wavelet transform accompanied with a neural network predictor.

REFERENCES

1. ERP lecture, Dr .John J. Curtin, University of Wisconsin-Madison.
2. Ian Daly, Floriana Pichiorri, Josef Faller, Vera Kaiser, Alex Krielinger, Reinhold Scherer and Gernot M¨uller-Putz,” What does clean EEG look like”,EMBC 2012.

3. James N. Knight Department of Computer Science Colorado State University Fort Collins, Fall 2003,"Signal Fraction Analysis and Artifact Removal."
4. R. Romo Vázquez, H. Vélez-Pérez , R. Ranta , V. Louis Dorr , D. Maquin , L. Maillard," Blind source separation, wavelet denoising and discriminant analysis for EEG artefacts and noise cancelling", Biomedical Signal Processing and Control volume-7.
5. Janett Walters-Williams & Yan Li" Performance Comparison of Known ICA Algorithms to a Wavelet-ICA Merger".
6. G.geetha, Dr.S.N.Geethalakshm," EEG De-noising using SURE Thresholding based on Wavelet Transforms", International Journal of Computer Applications, Volume 24– No.6, June 2011
7. A Garcés Correa, E Laciar, H D Patiño, M E Valentinuzzi," Artifact removal from EEG signals using adaptive filters in cascade". 16th Argentine Bioengineering Congress and the 5th Conference of Clinical Engineering.
8. Rafal Ksiezyk, Katarzyna Blinowska, Piotr Durka," Neural Networks with Wavelet Preprocessing in EEG Artifact Recognition"

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