Reduction of Ocular Artifacts in EEG using DWT and LMS-KALMAN Filtering

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Abstract - *A novel model to reduction of ocular artifacts (OA) from electroencephalograms is obtained. The new model is based on discrete wavelet transformation (DWT) and adaptive predictor filter (APF) based on AAR (LMS-Kalman filtering) model. Using simulated & measured data, the model accuracy is compared with the accuracy of existing method APF based on AAR (RLS-Kalman filtering) model. A mainly novel aspects of the new model is the use of DWTs to build an OA reference signal, using the last three lowest frequency wavelet coefficients of the electroencephalograms. The results show that the new model shows an better performance with respect to the improvement of original EEG signals and as well as a better tracking performance when compared to existing method. For the reason that the novel model needed only single channel sources & it is well suitable for use in portable environments where constraints with respect to acceptable wearable sensor attachments usually dictate single channel devices.*

Key Words: **EEG, Ocular Artifacts, DWT, LMS, KALMAN Filtering.**

1. INTRODUCTION

ELECTROENCEPHALOGRAM (EEG) signals have a long history of utilization as a noninvasive methodology in the estimation of mind capacity. Late decades have created a vast group of archived examination and numerous reports tending to the estimation of emotional wellness conditions utilizing EEG signals got from physiological parameters. EEG is a critical and generally noninvasive testing system which empowers the catch [using electrode situated on the scalp] of exceptionally valuable data identifying with the diverse physiological conditions of the cerebrum. But, EEG signals are exceptionally contaminated with different artifacts both from the subject and from the hardware obstructions. along with the numerous contaminations, artifacts ocular noise is a very important signal, called *ocular artifacts* (OA); for instance, a solitary squint of an eye produces signal amplitudes in overabundance of 10 times of the surrounding EEG signal. Eye developments will likewise be recorded amid EEG accumulation, notwithstanding when the subjects are requested that maintain their eyes shut and still. Subsequently, it's important to build up a proficient and compelling strategy to accomplish antiquity evacuation.

A variety of systems have been utilized at this office to amend OA in EEG signals in light of different suppositions about the relationship between the EEG signals and the ancient rarities. Be that as it may, the greater parts of these routines are offline. With a specific end goal to oblige online applications, much research has concentrated widely on nonlinear filtering and eye tracking methods such as nonlinear filtering (which includes adaptive filters), statistical models (e.g., ARMAX) and Artificial Neural Networks (ANNs). A case of adaptive filtering for online OA evacuation of the system connected independently recorded vertical and horizontal EOG signals as two reference inputs and was actualized by a recursive minimum squares calculation to track the non-stationary bit of the EOG signals. We can portrays a methodology utilizing a fast eye following with a novel online calculation (to evacuate both eye development and blink artifacts) to empower the time's extraction "course" of a flicker from eye tracker pictures. On the other hand, the two systems are reliant on having admittance to one or all the more relapsing (EOG) channels and were unsuited to lightweight compact hardware. The general subtraction technique (ARMAX) which does not oblige any relapsing channels; this methodology depends on the suspicion that the deliberate EEG is depicted as a straight blend of foundation EEG flags and defiling visual antiques. As of late, various half and half de-noising methodologies have been proposed; for instance, an online system for expelling visual antiquities from EEG signals produced from a solitary channel EEG gadget utilizing the *Singular Spectrum Analysis* and the *Singular Value Decomposition* strategy.

Moreover, Electroencephalographic (EEG) information is generally utilized as a bio-signal for the recognizable proof of distinctive mental states in the human brain. EEG signals can be caught by moderately inexpensive equipment and acquisition techniques are non- invasive and not excessively confounded. On the negative side, EEG signals are described by low SNR and non-stationary attributes, which makes the preparing of such flags for the extraction of valuable data a testing undertaking. At the point when a man performs particular occasions, for example, prompted symbolism errands, left-hand or right-hand developments, envisioned engine assignments and sound-related undertakings, comparing varieties in the individual's qualities EEG signal occur. These are commonly recognized by event-related potentials (ERP). For instance, event-related potentials connected with true and imagined motor undertakings display recurrence particular attributes: a diminishing in EEG band force happens on the contra-lateral side, a wonder called Event-Related De-synchronization (ERD), took after some time later by an increment in band power on the ipsi-parallel side, known as Event-Related Synchronization (ERS). Thus the discovery and distinguishing proof of ERD and ERS marvels would empower the order of mental movement. Such methods can discover helpful application in *brain-computer interface* (BCI) frameworks where EEG information is measured from the cerebrum and handled by a PC to, for instance, distinguish and classify real or imagined left and right-hand movements for the implementation of valuable errands.

2 METHODOLOGY

In this segment we exhibit an itemized discourse of the model(s) and technique of the undertaking.
The recorded EEG signs are contaminated by the artifacts. The eye and mind exercises have physiologically separate sources; consequently this sullying is thought to be an added substance clamor inside of the EEG signal. A general model for EOG contamination can be depicted by

$$y(n) = x(n) + F(r);$$

Where : y(n) and x(n) are the examples of the recorded & true EEG. Saparately, **F** is an unknown transfer function & **r** speaks to the source EOG.

2.1 A Model Based on DWT and APF

1) Signal Decomposition and OAs Zone Detection Using WT:

Wavelet Transform (WT) is an imperative frequency based tool for extracting both time and frequency space data of non-stationary signals, for example, EEG. WT can give adaptable control over the determination with which events are localized in time, space and scale. OAs are mostly focused on the low frequency band, accordingly DWT is utilized to build the OA in the frequency domain or decompose the EEG signals and detect OA zones. DWT is given by,

$$WTx(j,k) = \int x(t)\ \Psi^*_{j,k}(t)\ dt;$$

$$\Psi^*j,k\ (t) = 2j/2\ \Psi\ (2jt\text{-}k);$$

Where, j & k are integers; Ψ(t) is the "mother" wavelet capacity which produces the arrangement of development capacities with whole number files the scales (j) and (k) positions .
The range of frequency of EEG signal is 0Hz-64Hz, while OA happen inside of the extent 0Hz-16Hz. Multi-scale DWT decomposition is utilized to extract the low frequency parts and the non-stationary time series is then disintegrated into a few rough stationary time arrangement; this takes into consideration customary anticipating systems to precisely foresee the genuine wave state of the decomposition signals.

In this proposed model utilized the **Daubechies 7** (5 layers) wavelet is chosen as the "mother" wavelet capacity to deteriorate the crude EEG signals into high and low level coefficients which are then reproduced into a variety of frequency parts. In this way, it is just important to transform the low frequency signals relating to the OA. This methodology enormously enhances the de-noising precision as well as maintains a strategic distance from the evacuation of superfluous foundation EEG data.
In the event that an EOG modification procedure is applied to the whole length of the EEG signal, it prompts impressive loss of valuable background EEG action because of signal modifications in the non-OA zones. Consequently there is a requirement for automated recognition of artifact zones. A few techniques have been attempted to to automatically identify the artifact zones. In this technique taking into account DWT as proposed and received to identify the OAs zones of the low-frequency components decomposed from the contaminated EEG.

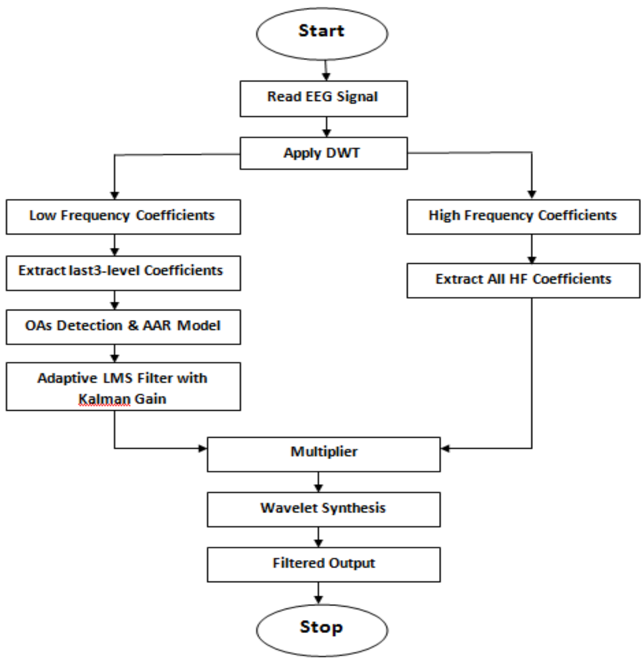

Fig-1: Proposed System.

2) Signal Prediction:

A variety of studies have been produced as for the anticipating of EEG time arrangement. We apply AAR models and an APF to enhance forecast. The APF utilizes a adaptive filter to assess the future estimations of a signals in view of past qualities. The difference between the adaptive prediction and other AAR model estimation routines is that the previous obliges less preparing and henceforth can be utilized continuously. As the signal is non-stationary, the AAR parameters are permitted to vary in time.

This is described by the expressions,

$$Y_k = a_{1,k} y_k + a_{2,k} y_{k-1} + \dots\dots\dots + a_{p,k} y_{k-p} + x_k$$

$= A_k Y_{k-1} + X_k$; $(X = N\{0, \sigma_X^2 (K)\}$

Where X is a zero-mean-Gaussian-noise process with varience σ_X^2. If k is typically an integer and depicts discrete equidistant time focuses. The time in sec is $t = k/f0 = k * \Delta T$ with the sampling rate and the sampling interval ΔT. p is the model order and $a_{i,k}$ is the time- varying AR model parameters. In resulting segments it will be demonstrated how the time differing AR parameters can be evaluated in a versatile way. For this situation, the parameters are called AAR parameters. All AAR estimation algorithms have in common estimate of the one-step prediction error (e) as

$e_k = y_k - \hat{y}_k$: $(\hat{y}_k = A_k Y_{k-1})$;

MSE = 1/N

There are several AAR estimation algorithms that can be used as predictors, such as the *Least-Mean-Squares* (LMS) approach, the *Recursive-Least-Squares* (RLS) approach, *Recursive AR* (RAR) techniques, as well as ***Kalman Filtering*** (KF).

In considering tracking performance, AAR parameters are estimated with KF as for the iteration from k-1 to k. The update equations of KF for an AAR model can be summarized by the set of equations:

$Q_k = Y^T_{k-1} * A_{k-1} * Y_{k-1} + V_k$;

$K_k = A_{k-1} * Y_{k-1} \mid Q_k$;

$\hat{a}_k = \hat{a}_{k-1} + K_k^T * e_k$;

$X_k = A_{k-1} - K_k * Y_{k-1}^T * A_{k-1}$;

$A_k = X_k + W_k$;

e_k is the one step prediction error, v_k is the variance of the innovation process, k_k is the Kalman Gain. A_{k-1} & X_k are the a-priori and the a posteriori state error correlation matrix.

3. RESULTS AND DISCUSSION

In this project, presented a novel model that combines DWT and APF based AAR (DWT and Kalman gain) techniques to eliminate the OAs in contaminated EEG signals. We have demonstrated the efficiency of the new model by using the model to process simulated and standard EEG data. The new model is able to eliminate OAs in the low-frequency band even when their frequency is overlapping with that of the EEG signal. Using simulated data, have demonstrated the superior performance of new model using various parameters that relate to efficiency and accuracy, and although not totally statistically comprehensive, the analysis is sufficient to support claims. The standard real EEG data also provide good corroboration with respect to real life data. In this new model, DWT was applied to a contaminated EEG signal to obtain wavelet coefficients; this is the first step of the model. 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. Because the preliminary results suggested that the OAs mainly lie in the low-frequency band, this allows the OAs signal to be used as a reference signal without loss of generality. Using this reference signal, AAR based on an LMS-Kalman filtering is used to remove the OAs from the true EEG. There are several *advantages* to using APF with adaptive filtering over conventional methods:

1) Deriving the reference signal from the original single channel EEG is simple and enables efficient computation, and also avoids the collection of synchronous ocular reference signals. Hence, the design facilitates the use of lightweight portable equipment.

2) Dynamic tuning of the APF filter's coefficients with respect to eye movements and eye blinks enables the removal of the OAs effectively while retaining the true EEG information. As the APF filter adaptively adjustments its coefficients based on an LMS- Kalman filtering algorithm, it is much more flexible than filters with static coefficients.

3) Good performance with respect to signal tracking. The APF filter does not corrupt clean EEG areas without OAs, so the intrinsic components of the EEG record are well preserved.

3.1 Simulation Results

The mean squared error (MSE) is defined as,

$$MSE = E\{|x - \hat{x}|^2\}$$

Peak SNR is one of the quantitative measures for signal quality evaluation. Peak SNR is based on Mean Square Error,

$$PSNR = 10\log_{10}(255^2/_{MSE})$$

Where MSE is the Mean Square Error.

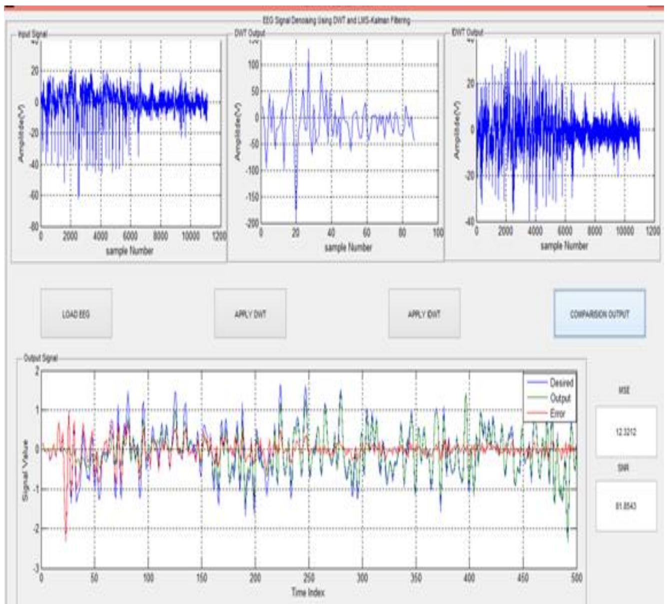

Fig-2: Simulation Output

	MSE	PSNR
PROPOSED METHOD	12.3212	81.854

Table-1: Proposed System Output

4. CONCLUSIONS

Thus, the new model using DWT and APF based AAR models (LMS-Kalman Filtering) techniques to reduction of ocular artifacts in contaminated EEG signals. The above work of new approach enables the removal of OA in the OA zones and the simultaneous retention of the waveform of the signals in non-OA zones. Also, the system achieves enhanced performance when compared to the existing system in terms of effectiveness and speed of execution. The use of APF methods to recover real EEG by predicting EEG signal amplitudes in OA zones. The benefit of the adaptive prediction technique lies in the fact that it allows the description of a signal by means of model coefficients and parameters characterizing the basic rhythms.

There are several **features** that require further investigation:

• EEG signals have very complex pseudo-random nature. Several linear and nonlinear prediction techniques can be used to predict the EEG signal in the short-term. But, the duration of prediction needs to be increased to improve efficiency. Efforts should be directed towards addressing long-term EEG signals.
• In spite of AAR modeling having been successfully used by several investigators for EEG signal analysis, a parametric method is only efficient within relatively restricted parameter ranges.
• In future studies, use additional statistical methods to prove this model.

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