An Adaptive method to remove ocular artifacts from EEG signals using Wavelet Transform

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Abstract: This paper presents an adaptive filtering method for removing ocular artifacts in the electroencephalogram (EEG) records. The major concern in analyzing EEG signals is the presence of ocular artifacts in EEG records caused due to various factors. It has become necessary to design specific filters to remove the artifacts in EEG records. In this method, we propose an adaptive filtering method, which makes use of RLS (Recursive Least Square) algorithm for removing ocular artifacts from EEG recordings through wavelet transform.

Key words: EEG, ocular artifacts, recursive algorithm, stationary wavelet transform

INTRODUCTION

The statistical analysis of electrical recordings of the brain activity by an electroencephalogram is a major problem in neuroscience. Eye artifacts have been recognized to be one of the major contaminants in EEG recordings. A common problem faced during the clinical recording of the EEG signal are the eye-blinks and movement of the eye balls that produce ocular artifacts. One way of dealing with this problem is to provide subjects with a fixation point and to instruct them to make no eye movements or blinks. The effective filtering of these ocular artifacts is extremely difficult owing to the fact that their frequency spread (1 Hz–50 Hz) is observed to be overlapping with that of the EEG. A number of methods have been proposed in recent years for correcting ocular artifacts in EEG signals based on various assumptions about the relationship between the EOG signals and the artifacts. However, most of these methods are non-adaptive. In early work on eye artifact correction, the transfer function from EOG to EEG is assumed to be linear and time-invariant. Croft [2] reviews a number of methods of dealing with ocular artifact in the EEG, focusing on the relative merits of a variety of EOG correction procedures. Garces Correa [3] proposed a cascade of three adaptive filters based on a Least Mean Squares (LMS) algorithm to reduce the common artifacts present in EEG signals without removing significant information embedded in these records. Wavelet analysis provides flexible control over the resolution with which neuro-electric components and events are localized in time, space and scale. Samar [7] describes the basic concepts of wavelet analysis and other applications. An example of an EEG mixed with EOG is illustrated in Figure 1.

![Fig. 1: EEG mixed with EOG](image)

Recently, Stationary Wavelet Transform (SWT) of the corrupted EEG signal has been used to de-noise it. In this paper we present an adaptive filtering technique for de-noising of these ocular artifacts using Symlet (sym3) wavelets.

Wavelets for analyzing EEG signals: In statistical settings usually we are more concerned with discretely sampled, rather than continuous functions. Wavelet transform [1,9] has emerged as one of the superior technique in analyzing non-stationary signals like EEG. Its capability in transforming a time domain signal into time and frequency localization helps to understand the behavior of a signal better.
The Discrete Wavelet Transform (DWT) means choosing subsets of the scales \( j \) and positions \( k \) of the mother wavelet \( \psi(t) \).

\[
\psi_{j,k}(t) = 2^j \psi(2^j t - k)
\]  

Choosing scales and positions are based on powers of two, which are called dyadic scales and positions (\( j \) and \( k \) are integers). Equation (1) shows that it is possible to build a wavelet for any function by dilating a function \( \psi(t) \) with a coefficient \( 2^j \), 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. Then, 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. The multi-resolution decomposition algorithm separates the signal into “details” at different scales and a coarser representation of the signal named “approximation”.

The basic DWT algorithm can be modified to give a SWT that no longer depends on the choice of origin. As a consequence of the sub sampling operations in the pyramidal algorithm, the DWT does not preserve translation invariance. This means that a translation of the original signal does not necessarily imply a translation of the corresponding wavelet coefficients. The SWT has been introduced in order to preserve this property. Instead of sub sampling, the SWT utilizes recursively dilated filters in order to halve the bandwidth from one level to another. This decomposition scheme is shown in figure 2.

![Wavelet decomposition scheme](image)

**Fig. 2: Wavelet decomposition scheme**

**Adaptive Filtering:** Adaptive algorithms play a very important role in many diverse applications such as communications, acoustics, speech, radar, sonar, seismology, and biomedical engineering. Adaptive algorithms such as LMS, recursive LS or exponentially weighted LS can be used to update the coefficients of the adaptive filter. Among the most well-known adaptive filters are the recursive least-squares (RLS) and fast RLS (FRLS) algorithms. The latter is a computationally less complex version of the former. Even though the RLS is not as widely used in practice as the least-mean-square (LMS) algorithm, it has a very significant theoretical interest since it belongs to the Kalman filters family. The convergence rate, the misalignment, and the numerical stability of adaptive algorithms depend on the condition number of the input signal covariance matrix. The higher the condition number, the slower the convergence rate and/or less stable is the algorithm. Thus, there is an interest in computing the condition number in order to monitor the behavior of adaptive filters.

The idea behind RLS filters is to minimize a cost function \( C \) by appropriately selecting the filter coefficients \( w_n \) and updating the filter as new data arrives. The error signal \( e(n) \) and desired signal \( d(n) \) are defined in the negative feedback diagram (figure 3) below:

![Structure of an adaptive filter](image)

**Fig. 3: Structure of an adaptive filter**

In RLS algorithm there are two variables involved in the recursions (those with time index \( n-1 \)) : \( w(n-1), P_{n-1} \). RLS algorithm has higher computational requirement than LMS, but behaves much better in terms of steady state MSE and transient time.

**RLS algorithm:**
1. Initialize \( w(0) = 0, P_0 = \delta I \)
2. For each time instant, \( n = 1, \ldots, N \)
\[
2.1 \quad w(n) = w(n-1) + P(n)u(n) (d(n) - w^T(n-1)u(n))
\]
\[
2.2 \quad P(n) = \frac{1}{\lambda + u(n)^T R(n-1) u(n)} R(n-1) - R(n-1) u(n) u(n)^T R(n-1)
\]

**MATERIAL AND METHOD**

The EEG recordings are contaminated by EOG signal. The EOG signal is a non-cortical activity. The method proposed in this paper involves the following steps:

1. **Preprocessing:**
   - Bandpass filtering
   - notch filter

2. **Feature Extraction:**
   - Power spectral density
   - Time domain analysis

3. **Classification:**
   - Support Vector Machine (SVM)
   - Neural Network

4. **Post-processing:**
   - lung sound segmentation
   - background noise reduction

5. **Validation:**
   - Cross-validation
   - Sensitivity, specificity, accuracy

6. **Result:**
   - Comparisons with existing methods
   - Performance evaluation

The proposed method provides a robust solution for the problem of EOG signal identification in EEG recordings, which is crucial for the development of advanced bioelectronic devices and medical applications.
(i) To apply Stationary Wavelet Transform to the contaminated EEG and reference EOG with Symlet (sym3) as the basis function and decomposes up to eight levels.

(ii) To apply adaptive filter with RLS algorithm, in which the output signal is subtracted from the corrupted EEG signal to produce the artifact free EEG signal.

(iii) To apply wavelet reconstruction procedure to reconstruct the EEG signal to produce the artifact free EEG signal.

RESULTS AND DISCUSSION

EEG data with ocular artifacts are taken from \(^7\) for testing the proposed method. The data is sampled at a rate of 128 samples per second. The effect of ocular artifacts will be dominant in the Frontal and Fronto-polar channels like FP1, FP2, F7 and F8. Figure 4 shows the EOG signal used as reference signal \(x(n)\) and the corrupted version of EEG as primary signal \(d(n)\) with eight level wavelet decomposition.

![Approximation coefficient plot](image1)

![Detail coefficient plot](image2)

Fig. 4: (a) 'Approximation coefficient' plot

Fig. 4: (b) 'Detail coefficient' plot

The reference EOG signal and the corrupted EEG were acquired simultaneously in polysomnographic studies. EEG, EOG records belonged to five records and were downloaded from the MIT-BIH polysomnographic Database-Physiobank \(^4\). For testing purposes, in case no real records were available, artificially generated signals are quite acceptable.

The filter \(H(z)\) adapts the amplitude and phase of EEG+EOG to attenuate the EOG artifacts. The output signal \(\hat{d}(n)\) is subtracted from the EEG contaminated with EOG artifacts, to give the result as the signal \(e(n)\), which is the EEG signal free of EOG. Adaptive filter based on RLS algorithm with wavelet decomposition were described in order to cancel EOG artifacts. Advantage of adaptive filter over conventional ones include preservation of components intrinsic to the EEG record. Besides, they can adapt their coefficients to variations in heart frequency, abrupt changes in the line frequency or modifications due to eye movements. Note that in the output signal there are no low frequencies, so indicating that the EOG was actually removed. This is shown in figure 5.

A difficulty found in this work was the determination of \(L\) (filter order) and \(\mu\) (convergence factor). These parameters are very important; \(L\),
because it leads to appropriate filtering, and $\mu$, to get adequate adaptation. If $\mu$ is too big, the filter becomes unstable, and if it is too small, the adaptation may turn out too slow. Several tests were carried out to determine the optimum value for these parameters. The order $L$ of $H(z)$ was 4 and the convergence rate was 0.3. In all cases, artifacts were adequately attenuated, without removing significant useful information.

Figure 6 shows the power spectra of the contaminated EEG (EEG + EOG) and the corrected EEG. From this figure, it is shown that the power of the spectral components have been retained. The frequency correlation between the noisy EEG and EOG is shown in figure 7. This shows how close both the signals are in terms of the shape.

**Fig. 5:** EEG with artifact and corrected EEG

**Fig. 6:** Power spectrum plot

**Fig. 7:** Frequency correlation plot
**Conclusion:** Our proposed method using adaptive filter with RLS algorithm through wavelet transform reduces the artifacts in EEG. We conclude that adaptive cancellation with help of wavelet decomposition can be considered to be a preprocessed work and is an efficient processing technique for improving the quality of EEG signals in biomedical analysis.

**REFERENCES**