CHAPTER IV

REMOVAL OF OCULAR ARTIFACTS FROM EEG SIGNALS USING ADAPTIVE FILTER THROUGH WAVELET TRANSFORM WITH LMS ALGORITHM *

4.1 Introduction

In this chapter, an adaptive filter with Least Mean Square (LMS) algorithm is proposed to remove ocular artifacts in the EEG signal using EOG signal as a reference signal. In recent years, a growing field of research in “adaptive systems” has resulted in a variety of adaptive automations whose characteristics, in limited ways, resemble certain characteristics of living systems and biological adaptive processes. An adaptive automation is a system whose structure is adjustable in such a way that its performance improves through contact with its environment.

In signal processing, the function of a filter is to remove unwanted parts of the signal, such as random noise, or to extract useful parts of the signal, such as the components lying within a certain frequency range. There are two main kinds of filters, analog and digital.

* Content of this chapter with the title Removal of artifacts from EEG signals using adaptive filter through wavelet transform has been published in IEEE International Conference Proceedings on Signal Processing, Beijing, China, October 2008, 2138 – 2141.
They are quite different in their physical makeup and in the way they work. The chief objective of digital filtering is to change the spectral information contained in an input signal \( x_i \) to produce an enhanced output signal \( y_i \), either in the time or frequency domain. Earlier, especially in the medical field, signal processing was done mostly in the continuous or analog time domain. While, in analog filters, the active component count and size, termination impedance matching and lossy reactive elements are important, digital filters are concerned with word length, rounding errors, and occasionally processing delays. Digital filtering may be carried out off-line or in real time. The common forms of filters are either direct, cascade or parallel.

Wavelet analysis provides flexible control over the resolution with which neuro-electric components and events are localized in time, space and scale. Many researchers have been contributing adaptive filter with or without using LMS algorithm for removing ocular artifacts in EEG signal. In this chapter, adaptive filter with wavelet transform approach is considered.

4.2 Motivation for using Adaptive Filter

In an adaptive filter, there are basically two processes:

(i) A filtering process is a process, in which an output signal is the response of a digital filter. Usually, Finite Impulse Response (FIR) filters are used in this process, because they are simple and stable.

(ii) An adaptive process is a 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. This algorithm is an application scheme widely used in practice due to its simplicity.

The objective of an adaptive filter is to change the coefficients of the linear filter, and hence, its frequency response, to generate a signal similar to the noise present in the signal, has to be filtered. The adaptive process involves minimization of a cost function, which is used to determine the filter coefficients. The adaptive filter adjusts its coefficients to minimize the squared error between its output and a primary signal. In case of non-stationary circumstances, the coefficients will change with time, according to the signal variation, thus, converging to an optimum filter. The use of adaptive filters, which have the capability of modifying their properties according to selected features of the signals are being analyzed. Figure 4.1 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 \( e(n) \).

![Figure 4.1 Structure of an Adaptive Filter](image)
Adaptive filtering is one of the most efficient methods for removal of ocular artifacts which can be applied in real time. In conventional adaptive filtering, the primary input is measured EEG and the reference input is EOG. The adaptive interference cancellation is a very efficient method to solve the problem when signals and interferences have overlapping spectra. From the figure 4.1, it is clear that the input d(n) is the EEG corrupted with artifacts (EEG+EOG). The reference signal x(n) is an original EOG (without artifact). The output of H(z) is y(n), which is an estimation of the original EOG. This signal y(n) is subtracted from the corrupted d(n) to produce the error e(n), which is the EEG without artifacts. In this chapter, it is assumed that the corrupted signal d(n) is composed of the desired s(n) and noise n(n), which is additive and not correlated with s(n). Likewise, the reference signal x(n) is uncorrelated with s(n) and correlated with n(n). The reference x(n) feeds the filter to produce an output y(n) that is, a close estimate of n(n).

4.3 Related Literature Review

Boudet et al. [9] presented a global artifact removal method corresponding to an evolution of the AFOP method (Adaptive Filtering by Optimal Projection) in order to improve its stability. Benkherrat et al. [7] used a variable step size adaptive algorithm (VSSLMS) to eliminate the artifacts in real time, where both EEG and EOG signals were recorded simultaneously. The efficiency of this technique is comparing EEG before and after filtering using cross-correlation function. He et al. [33] studied the accuracy of the adaptive filtering method quantitatively using simulated data and compared it with the accuracy of the time domain regression. In conventional adaptive filtering, the primary
input is measured EEG and the reference inputs are vertical EOG and horizontal EOG signals. Kavitha et al. [48] proposed an adaptive filtering approach which includes radial EOG signal as a third reference input and analyzed the performance of the algorithm.

Recently, ARMAX modeling of EEG signal method assumes that the recorded EEG signal is a combination of EOG artifacts and the background EEG. Then, the background EEG is estimated via estimation of ARMAX parameters. Parisa Shooshtari et al. [69] investigated the efficiency of each method for the removal of EOG artifacts. Filligoi et al. [27] described an off-line procedure based on stochastic parameter identification and filtering. Two adaptive algorithms (time varying and exponentially weighted) based on the $H^\infty$ principles are proposed by Puthusserypady and Ratnarajah [74] for the minimization of EOG artifacts from corrupted electroencephalographic signals. Selvan and Srinivasan [88] proposed an efficient technique that combines two popular adaptive filtering techniques, namely, adaptive noise cancellation and adaptive signal enhancement, in a single recurrent neural network for the adaptive removal of ocular artifacts from EEG. The problem of real-time ocular or eye artifact correction is addressed by Weiziu Du et al. [113], based on the framework of the general adaptive interference canceller, wherein the EOG signals are used as the reference signal. Mehrkanoon et al. [60] proposed an adaptive filtering method to remove these artifacts from EEG signals. Ping He et al. [72] proposed an adaptive filtering method for removing ocular artifacts from EEG recordings.
Garces Correa et al. [29] proposed a cascade of three adaptive filters based on a Least Mean Square (LMS) algorithm. The first filter eliminates line interference, the second adaptive filter removes the ECG artifacts and the last one cancels EOG spikes. Each stage uses a finite impulse response (FIR) filter, which adjusts its coefficients to produce an output similar to the artifacts present in the EEG. Instead of a cascade of three adaptive filters, the proposed method involves only one adaptive filter with LMS algorithm. The performance of the proposed method, compared with Garces Correa’s [29] work, gives better results with less complexity.

4.4 Mathematical Background

The Least Mean Square (LMS) Algorithm, introduced by Widrow and Hoff in 1959 [114] is an adaptive algorithm, which uses a gradient-based method of steepest descent. LMS algorithm uses the estimates of the gradient vector from the available data. LMS incorporates an iterative procedure that makes successive corrections to the weight vector in the direction of the negative of the gradient vector which eventually leads to the minimum mean square error. Compared to other algorithms, LMS algorithm is relatively simple as, it does not require neither correlation function calculation nor the matrix inversions.

4.4.1 LMS Algorithm formulation

From the method of steepest descent, the weight vector equation is given by

\[ w(n+1) = w(n) + \mu \left[ -\nabla \left( E\{e^2(n)\} \right) \right] \]  

(4.1)
where $\mu$ is the step-size parameter and controls the convergence characteristics of the LMS algorithm; $e^2(n)$ is the mean square error between the output $y(n)$ and the reference signal $x(n)$ which is given by,

$$e^2(n) = [ d(n) - w^T x(n) ]^2 \quad (4.2)$$

The gradient vector in the above weight update equation can be computed as

$$\nabla_w \left( E\{e^2(n)\} \right) = -2P + 2Rw(n) \quad (4.3)$$

In the method of steepest descent, the biggest problem is the computation involved in finding the values $P$ and $R$ matrices in real time. The LMS algorithm, on the other hand, simplifies this by using the instantaneous values of covariance matrices $P$ and $R$ instead of their actual values, that is,

$$R(n) = x(n) x^T(n) \quad (4.4)$$
$$P(n) = d(n) x(n) \quad (4.5)$$

Therefore, the weight update can be given by the following equation,

$$w(n+1) = w(n) + \mu x(n) \left[ d(n) - x^T(n) w(n) \right]$$
$$= w(n) + \mu x(n) e(n) \quad (4.6)$$

The LMS algorithm is initiated with an arbitrary value $w(0)$ for the weight vector at $n = 0$. The successive corrections of the weight vector eventually leads to the minimum value of the mean squared error. Therefore, the LMS algorithm can be summarized in the following equations;
4.4.2 Convergence and Stability of the LMS algorithm

The LMS algorithm with some initial arbitrary value for the weight vector will be converging and obtain stability for

\[ 0 < \mu < \frac{1}{\lambda_{\text{max}}} \]  

(4.10)

where, \( \lambda_{\text{max}} \) is the largest eigenvalue of the correlation matrix \( R \). The convergence of the algorithm is inversely proportional to the eigenvalue spread of the correlation matrix \( R \). When the eigen values of \( R \) are widespread, convergence is slow. If \( \mu \) is chosen to be very small, then the algorithm converges very slowly and if \( \mu \) is too big, the filter becomes unstable. The LMS algorithm is implemented for any practical system without squaring, averaging or differentiation and is elegant in its simplicity and efficiency.

4.5 Methodology

Artifacts in EEG (electroencephalogram) records are caused by various factors, like line interference, EOG (electro-oculogram) and ECG (electrocardiogram). These noise sources increase the difficulty in analyzing the EEG and in obtaining clinical information. For this reason, it is necessary to design specific filters to decrease such artifacts in EEG records.
In order to use the LMS algorithm, first, a filter order is determined and then a good step-size. This is done by finding the autocorrelation of the reference signal and the cross-correlation between the reference and primary signals. The given signal contains 1280 samples. In the reduced levels of signals, the number of samples are very less. In this chapter, adaptive filter is applied to reduce the noise in EEG signals. Using the wavelet transform, \( d(n) \) and \( x(n) \) are changed into reduced levels, where the values of wavelet coefficient is less. The value that is got from the convolution of reduced level \( x(n) \) and coefficient in the filter is taken as \( y(n) \). With this, when the reduced level \( d(n) \) samples are subtracted, the output is \( e(n) \). Here, the stability of the filter depends upon the reduced level of squared value of \( e(n) \).

Again, the value of \( e(n) \) is convoluted with the coefficient of filter, and this value is subtracted from \( d(n) \) and the value of \( e(n) \) is checked. This method is done so many times to reduce the value of \( e(n) \).

The proposed algorithm is based on single adaptive filter instead of three filters, and it involves the following steps:

- Stationary wavelet transform is applied to the contaminated EEG and reference EOG with Symlet (sym3) as the basis function and decomposed up to eight levels.
- Adaptive filter with LMS algorithm is applied, in which, the output signal is subtracted from the corrupted EEG signal.
Wavelet reconstruction procedure is applied to reconstruct the EEG signal to produce the artifact free EEG signal.

4.6 Results and Discussion

EEG data with ocular artifacts are taken for testing the proposed method. The data is sampled at a rate of 128 samples per second. Figure 4.2 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.

![Reference EOG](image1)

Figure 4.2 (a) Reference EOG

![Corrupted EEG](image2)

Figure 4.2 (b) Corrupted EEG
The effect of ocular artifacts is dominant in the Frontal and Fronto-polar channels like FP1, FP2, F7 and F8. Hence, it is sufficient to apply the algorithm to these channels. The filter $H(z)$ adapts the amplitude and phase of EEG+EOG to attenuate the EOG artifacts. The output signal $y(n)$ is subtracted from the EEG contaminated with EOG artifacts, to give error signal $e(n)$, which is the EOG free of EEG signal. Adaptive filter, based on LMS algorithm with wavelet decomposition, is applied in order to cancel EOG artifacts. The advantage of adaptive filter over conventional methods is the preservation of components intrinsic to the EEG record. In the output signal, no low frequencies were noted to indicate that the EOG was actually removed.

A difficulty found in this work was the determination of $N$ (filter order) and $\mu$ (convergence factor). These parameters are very important, because, the filter order $N$, leads to appropriate filtering, and the convergence factor, $\mu$, to get adequate adaptation. Several tests were carried out to determine the optimum value for these parameters. The order $N$ of $H(z)$ is 128 and the convergence rate is 0.3. Therefore, artifacts were adequately attenuated without removing significant useful information. In the output signal, there are no low frequencies, indicating that, the EOG was actually removed. This is shown in figure 4.3
Figure 4.4 shows the power spectra of the contaminated EEG (EEG + EOG) and the corrected EEG. From this figure, it is shown that the powers of the spectral components have been retained.

Figure 4.3 EEG with artifact and Corrected EEG

Figure 4.4 Power Spectral Density Plot

85
The frequency correlation between the noisy EEG and EOG is shown in figure 4.5. This shows how close both the signals are in terms of shape.

![Figure 4.5 Frequency correlation between noisy data and de-noised data](image)

Table 4.1 summarizes the suppression ratio of various channels of the primary signal before and after filtering.

<table>
<thead>
<tr>
<th>Channels</th>
<th>FP₁</th>
<th>FP₂</th>
<th>F₃</th>
<th>F₄</th>
<th>F₇</th>
</tr>
</thead>
<tbody>
<tr>
<td>%</td>
<td>71.99</td>
<td>72.14</td>
<td>47.40</td>
<td>3.26</td>
<td>3.01</td>
</tr>
</tbody>
</table>

Table 4.1. Suppression Ratio (dB)
4.7 Conclusion

Removal of ocular artifacts using adaptive filter with LMS algorithm through wavelet transform is proposed in this chapter to achieve better performance. Many researchers used adaptive filter LMS algorithm, adaptive filters in cascade with LMS algorithm, etc. In this chapter, adaptive filter with LMS algorithm through wavelet transform and instead of adaptive filters in cascade, based on LMS algorithm, one adaptive filter using wavelet transform with LMS algorithm is applied. The LMS algorithm simplifies the computation by estimating the gradient from instantaneous values of correlation matrix of the tap inputs and the cross-correlation vector between the desired response and the tap weights, by which the error signal is minimized. The adaptive cancellation with the help of wavelet decomposition is a preprocessed work and is an efficient processing technique for improving the quality of EEG signals in biomedical analysis.