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Artifact removal from EEG signals using adaptive filters in cascade

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Artifact removal from EEG signals using adaptive filters in cascade

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Abstract. 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 to obtaining clinical information. For this reason, it is necessary to design specific filters to decrease such artifacts in EEG records. In this paper, a cascade of three adaptive filters based on a least mean squares (LMS) algorithm is proposed. The first one 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. The proposed cascade adaptive filter was tested in five real EEG records acquired in polysomnographic studies. In all cases, line-frequency, ECG and EOG artifacts were attenuated. It is concluded that the proposed filter reduces the common artifacts present in EEG signals without removing significant information embedded in these records.

1. Introduction

EEG records carry information about abnormalities or responses to certain stimuli in the human brain. Some of the characteristics of these signals are the frequency and the morphology of their waves. These components are in the order of just a few up to 200 μV, and their frequency content differs among the different neurological rhythms, as the alpha, beta, delta and theta rhythms [1].

Such rhythms are analyzed by physicians in order to detect neural disorders and cerebral pathologies [2]. However, these rhythms are generally mixed with other biological signals, for example alpha is commonly mixed with the EOG (electro-oculogram). In this case, opening, closing or movements of the eyes produce artifacts in the EEG. Other artifact sources are the ECG (electrocardiogram), EMG (electromyogram) and the power line interference (50 or 60 Hz) [3]. An example of an EEG mixed with ECG and corrupted with line interference is illustrated in Figure 1.

Due to the presence of artifacts, it is difficult to analyze the EEG, for they introduce spikes which can be confused with neurological rhythms. Thus, noise and undesirable signals must be eliminated or attenuated from the EEG to ensure a correct analysis and diagnosis.

In this work, we propose a cascade of adaptive filters in order to remove some frequent artifacts in EEG signals. The aim of these filters is to cancel ECG, EOG and line interference.

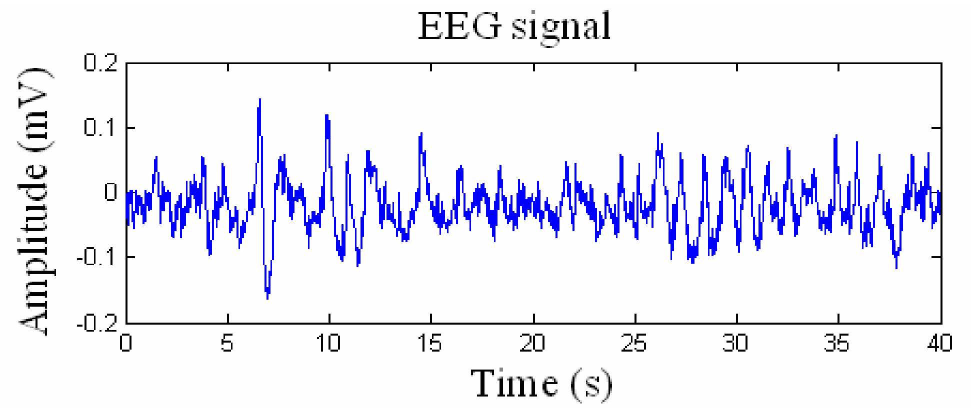

Figure 1. Example of a real EEG recording mixed with ECG and corrupted with line interference.

2. Methodology

2.1. Adaptive Filtering.

Conventional filtering cannot be applied to eliminate those types of artifacts because EEG signal and artifacts have overlapping spectra.

Herein, we propose the use of adaptive filters, which are based on the optimization theory. Adaptive filters have the capability of modifying their properties according to selected features of the signals being analyzed. Figure 2 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)*.

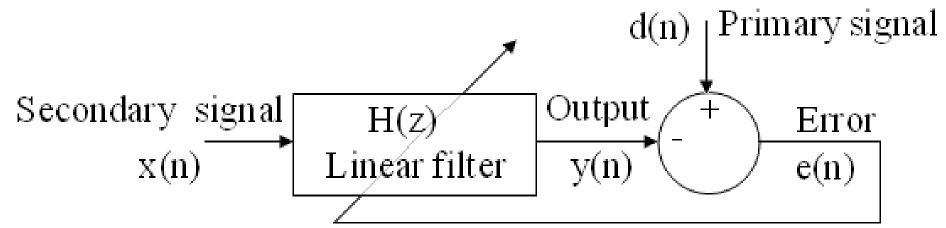

Figure 2. Structure of an adaptive filter.

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 [4].

In an adaptive filter, there are basically two processes:

-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.

-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*.

The structure of the FIR can be represented as,

$$y(n) = \sum_{k=0}^{L} w_k x(n-k) \tag{1}$$

where L is the order of the filter, *x(n)* is the secondary input signal, w_k are the filter coefficients and *y(n)* is the filter output.

The error signal *e(n)* is defined as the difference between the primary signal *d(n)* and the filter output *y(n),* that is,

$$e(n) = d(n) - y(n) \tag{2}$$

where

$$e(n) = d(n) - \sum_{k=0}^{L} w_k x(n-k) \tag{3}$$

The squared error is,

$$e^2(n) = d^2(n) - 2d(n)\sum_{k=0}^{L} w_k x(n-k) + \left[\sum_{k=0}^{L} w_k x(n-k)\right]^2 \tag{4}$$

The squared error expectation for N samples is given by

$$\zeta = E\left[e^2(n)\right] = \sum_{k=0}^{N} e^2(n) \tag{5}$$

$$\zeta = \sum_{n=1}^{N}\left[d^2(n)\right] - 2\sum_{k=0}^{L} w_k r_{dx}(n) + \sum_{k=0}^{L}\sum_{l=0}^{L} w_k w_l r_{xx}(k-l) \tag{6}$$

where $r_{dx}(n)$ and $r_{xx}(n)$ are, respectively, the cross-correlation function between the primary and secondary input signals, and the autocorrelation function of the secondary input, that is

$$r_{dx}(n) = \sum_{n=1}^{N} d(n)x(n-k) \tag{7}$$

$$r_{xx}(n) = \sum_{n=1}^{N} x(n)x(n-k) \tag{8}$$

The objective of the adaptation process is to minimize the squared error, which describes a performance surface. To get this goal there are different optimization techniques. In this work, we used the method of steepest descent [5]. With this, it is possible to calculate the filter coefficient vector for each iteration *k* having information about the previous coefficients and gradient, multiplied by a constant, that is,

$$w_k(n+1) = w_k(n) + \mu\left(-\nabla_k\right) \tag{9}$$

where μ is a coefficient that controls the rate of adaptation.

The gradient is defined as,

$$\nabla_k = \frac{\partial\left\{e^2(n)\right\}}{\partial w_k(n)} \tag{10}$$

Substituting (10) in (9) leads to

$$w_k(n+1) = w_k(n) - \mu \frac{\partial\left\{e^2(n)\right\}}{\partial w_k(n)} \tag{11}$$

Deriving with respect to w_k and replacing leads to,

$$w_k(n+1) = w_k(n) - 2\mu e(n)\frac{\partial\left\{e(n)\right\}}{\partial w_k(n)} \tag{12}$$

$$w_k(n+1) = w_k(n) - 2\ \ \mu\ \ e(n)\frac{\partial\left\{d(n) - \sum_{k=0}^{L} w_k x(n-k)\right\}}{\partial w_k(n)} \tag{13}$$

Since *d(n)* and *x(n)* are independent with respect to w_k , then

$$w_k(n+1) = w_k(n) - 2\ \mu\ e(n)x(n-k) \tag{14}$$

Equation (14) is the final description of the algorithm to compute the filter coefficients as function of the signal error *e(n)* and the reference input signal *x(n)*. The coefficient μ is a constant that must be chosen for quick adaptation without losing stability. The filter is stable if μ satisfies the following condition,

$$0 < \mu < 1 / (10.L.P_{xx}) \tag{15}$$

where L is the filter order and P_{xx} is the power of the input signal computed as,

$$P_{xx} \approx \frac{1}{M+1}\sum_{n=0}^{M-1} x^2(n) \tag{16}$$

2.2. Cancellation of Artifacts

The adaptive interference cancellation is a very efficient method to solve the problem when signals and interferences have overlapping spectra. This method has been used, among other applications, in external electroenterogram records [6] and in impedance cardiography [7]. Other applications in biomedical signals are, for example, removal of maternal ECG in fetal ECG records [8], detection of ventricular fibrillation and tachycardia [9], and cancellation of heart sound interference in tracheal sounds [10].

The basic adaptive noise canceller scheme is the same as that illustrated in Figure 2, where the primary signal is called “corrupted signal” and the secondary is called “reference signal”.

In this scheme, it is assumed that the corrupted signal *d(n)* is composed of the desired *s(n)* and noise $n_0(n)$, which is additive and not correlated with *s(n)*. Likewise, the reference *x(n)* is uncorrelated with *s(n)* and correlated with $n_0(n)$. The reference *x(n)* feeds the filter to produce an output *y(n)* that is a close estimate of $n_0(n)$ [9].

To accomplish the objectives of this project, we arranged a cascade of three adaptive filters (Figure 3). The input $d_1(n)$ in the first stage is the EEG corrupted with artifacts (EEG + line-frequency + ECG + EOG). The reference $x_1(n)$ in the first stage is a sine function generated with 50 or 60 Hz, depending on the line type. Tests were carried out to determine the optimum values of L and μ. The order L of $H_1(z)$, $H_2(z)$ and $H_3(z)$ was 128 and the coefficient convergence rates μ_1, μ_2 and μ_3 were 0.001. The output of $H_1(z)$ is $y_1(n)$, which is an estimation of the line artifact present in the EEG. This signal $y_1(n)$ is subtracted from the corrupted $d_1(n)$ to produce the error $e_1(n)$, which is the EEG without line-interference. The $e_1(n)$ error is forwarded as the corrupted input signal $d_2(n)$ to the second stage. The reference input $x_2(n)$ of the second stage can be either a real or artificial ECG. The output of $H_2(z)$ is $y_2(n)$, representing a good estimate of the ECG artifact present in the EEG record. Signal $y_2(n)$ is subtracted from $d_2(n)$; its result produces error $e_2(n)$. Thus, we have obtained the EEG without line and ECG interference. Then, $e_2(n)$ enters into the third stage as the signal $d_3(n)$. The reference input $x_3(n)$ of filter $H_3(z)$ is also a real or artificial EOG and its output is $y_3(n)$, which is a replica of the EOG artifact present in the EEG record. Such $y_3(n)$, subtracted from $d_3(n)$, gives error $e_3(n)$. It is the final output of the cascade filter, that is, the EEG without artifacts.

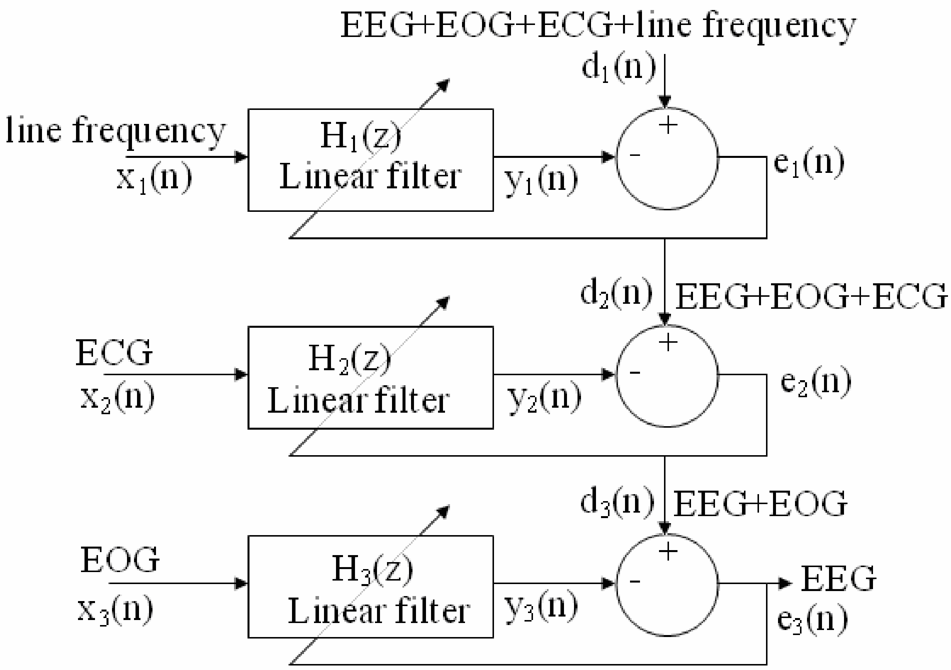

Figure 3. Adaptive filters cascade. The input signal is the corrupted EEG. The three references are line-frequency, ECG, and EOG. The output $e_3(n)$ represents the final output, which estimates the EEG record without artifacts.

The reference signals ECG and EOG and the corrupted EEG were acquired simultaneously in polysomnographic studies. EEG, ECG and EOG records belonged to five adult patients and were downloaded from the *MIT-BIH Polysomnographic Databas-Physiobank* [11]. For testing purposes, in case no real records were available, artificially generated signals are quite acceptable.

3. RESULTS

Five EEG records were filtered with the proposed adaptive cascade filter. As we mentioned above, the first stage attenuates the line-frequency artifact. The $H_1(z)$ filter adapts the amplitude and the phase of the artificial sinusoidal signal $x_1(n)$ (50 or 60 Hz) in order to have as output a replica, $y_1(n)$, of the line-frequency artifact present in the EEG. Figure 4 illustrates the power spectra of: (a) the original EEG with the 50 Hz interference, and (b) the first stage output $e_1(n)$. Note in the last one that this component is attenuated in $e_1(n)$ and there are not modifications in the EEG original spectrum in other frequencies.

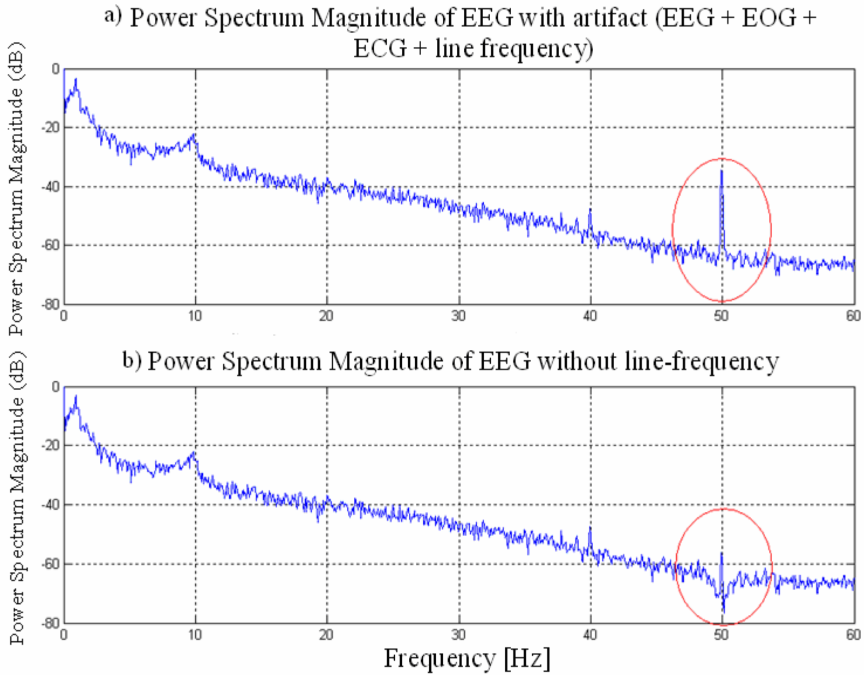

Figure 4. a) Power Spectrum Magnitude (PSM) of original EEG with artifacts. b) PSM of first stage output $e_1(n)$, where the 50 Hz component is attenuated.

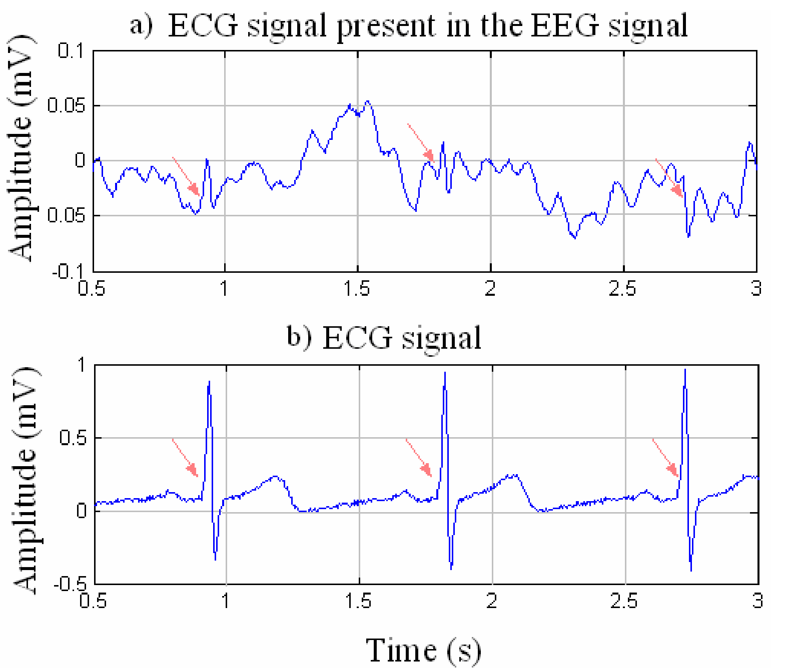

Figure 5 Example of an EEG record contaminated with ECG artifacts. a) EEG record with QRS complexes as false spikes. b) Real ECG signal acquired simultaneously from the same patient.

After 50 Hz filtering, the EEG is forwarded to the second stage in order to remove ECG artifacts. Figures 5 and 6 show the same examples of EEG's contaminated with ECG. It can be observed that QRS complexes are present in the EEG at the same instants that they appear in the ECG signal. The QRS amplitudes in the ECG are of the order of mV's, but in the external EEG they were reduced. These artifacts in the EEG records could be clinically misleading.

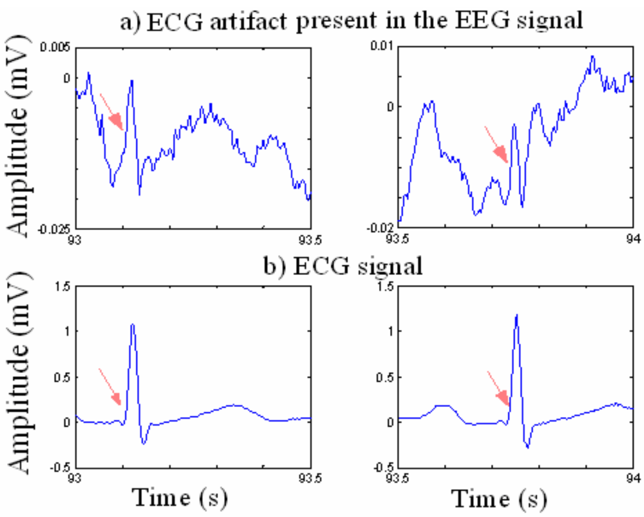

Figure 6. Examples of temporal segments of an EEG record contaminated with ECG artifact. a) EEG record, b) Beat morphologies registerd in ECG signal. Note the presence and morphology similarity of QRS complexes in the EEG record.

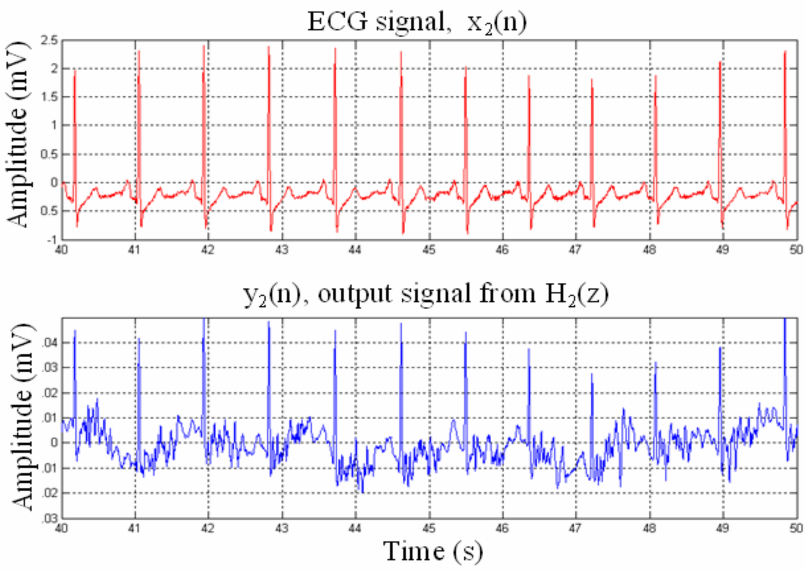

Figure 7. Input and output of $H_2(z)$ filter. a) ECG signal used as reference signal $x_2(n)$ of the second stage. b) The $H_2(z)$ filter output $y_2(n)$ is an estimation of the ECG artifacts present in the EEG.

Fig. 8 shows the ECG signal used as reference input $x_2(n)$ and the $H_2(z)$ filter output signal $y_2(n)$ of the second stage of the cascade adaptive filter. In this case, the filter $H_2(z)$ adapts the amplitude and phase of the ECG to attenuate the ECG artifacts.

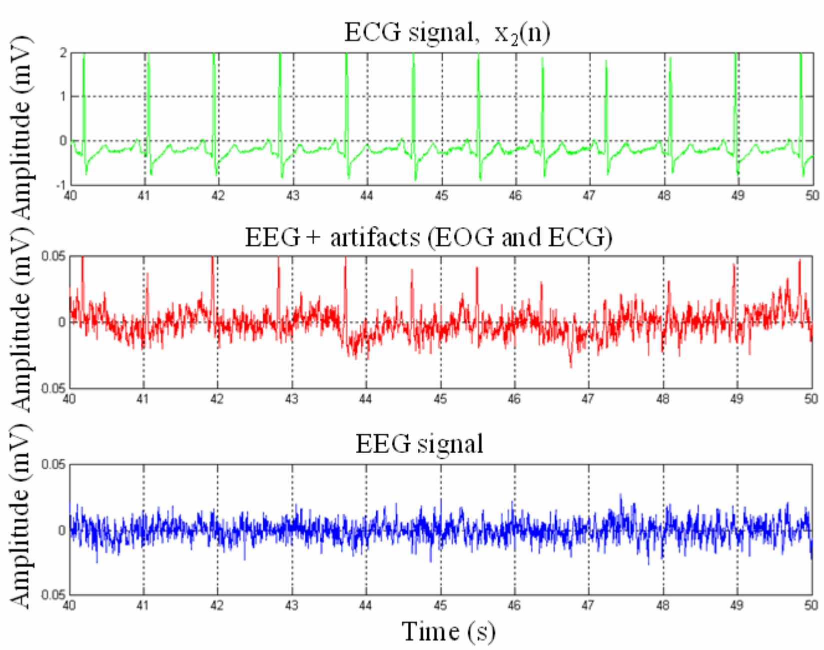

Figure 8. ECG artifact cancellation. a) Real ECG; b) EEG record contaminated with ECG artifacts; c) Output signal from the second stage of adaptive filter; note that the QRS complexes are eliminated.

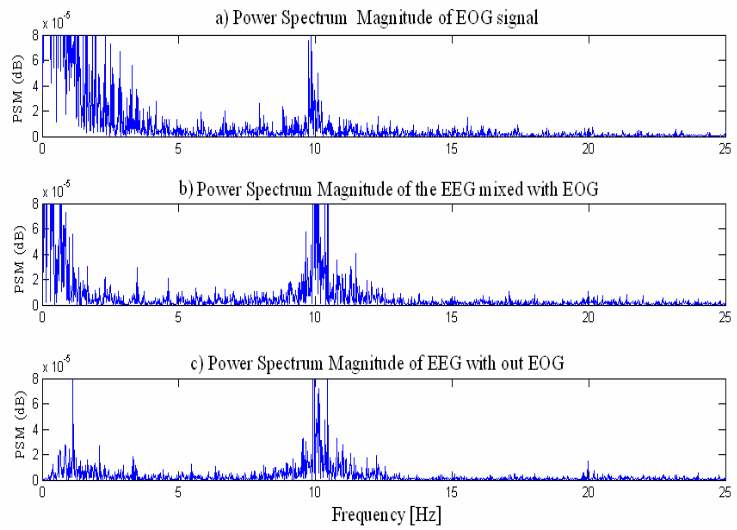

Figure 9. EOG artifact cancellation in the frequency domain. a) Power Spectrum Magnitude (PSM) of Real EOG; b) PSM of EEG mixed with EOG artifacts; c) PSM of the final EEG. Note that the latter does not have the low frequencies of the EOG.

Figure 8 illustrates the ECG artifact cancellation for the same EEG record shown in Figure 7. In its upper row (Fig. 9a), the ECG has been plotted (same $x_2(n)$ as in Fig. 8). The EEG mixed with the ECG ($d_2(n)$ in the adaptive filter cascade) is illustrated in Figure 8b. The output signal $y_2(n)$ (shown in Fig. 8b) is subtracted from the EEG contaminated with ECG artifacts, to give as result the signal $e_2(n)$, which is the EEG free of QRS complexes (Fig. 9 c).

After 50 Hz and ECG filtering, the EEG is forwarded to the third stage in order to remove EOG artifacts. Figure 9 shows the power spectrum of the EOG signal, $x_3(n)$ (Fig. 10a), the EEG mixed only with EOG, $d_3(n)$ (Fig. 10b) and the output adaptive cascade filter, $e_3(n)$ (Fig. 10c). Note that in the output signal there are no low frequencies, so indicating that the EOG was actually removed.

Table I summarizes the details for each EEG analyzed, i.e., the attenuation percentages of the components of maximum energy of line interference, ECG and EOG present in the EEG. These percentages were calculated comparing the value of the component of maximum energy of the reference signals present in the EEG records before and after filtering. In Table II the mean and the standard deviation of the previous percentages are displayed.

Table I. Attenuation of component of maximum energy (%).

Patient	***1***	***2***	***3***	***4***	***5***
Component of 50Hz	99,85	99,66	96,45	98,83	97,14
Component of maximum energy of ECG	53,16	38,52	44,41	7,87	4,07
Component of maximum energy of EOG	37,85	71,33	52,83	42,12	83,14

Table II. Statistical results (%).

Patient	**Mean**	**St. Des.**
Component of 50Hz	98,38	15,22
Component of maximum energy of ECG	29,60	22,05
Component of maximum energy of EOG	57,45	19,32

4. DISCUSSION AND CONCLUSIONS

Three adaptive filters in cascade, based on LMS algorithm, were described in order to cancel common artifacts (line interference, ECG and EOG) present in EEG records.

The advantages of using a cascade of three filters instead of filtering the three signals with a single adaptive filter are among others,

a) The coefficient's adaptation in three independent filters is simpler and faster than their adaptation in a single filter.

b) At each stage output, the error signals $e_i(n)$, EEG with one of the three attenuated artifacts are present; such separation (by artifact) may be useful in some applications where such output might be enough.

Advantages of adaptive filters 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 (caused, say, by ignition of electric devices) or modifications due to eye movements.

A difficulty found in this work was the determination of L (filter order) and μ (convergence factor). These parameters are very important; L, because it leads to appropriate filtering, and μ, to get adequate adaptation. If μ 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.

Results show that the proposed filter attenuates, on the average, 98.3% of the line frequency interference; 29.6% of the maximum energy component of the ECG ($\cong$15 Hz), and 55.8% the EOG component of maximum energy ($\cong$0.5 Hz). Apparently, the ECG and EOG components were attenuated in smaller proportion than the 50Hz, however, this probably takes place because their respective spectra overlap (reason for which adaptive filtering was used instead of a classic technique).

In some patients, the ECG attenuation was minimal (see Table I, line two, columns 5 and 6); once more the cause can be explained by spectra overlapping.

In all cases, artifacts were adequately attenuated, without removing significant useful information. We conclude that adaptive cancellation is an efficient processing technique for improving the quality of EEG signals in biomedical analysis.

Acknowledgments

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