Removal of Peak and Spike Noise in EEG Signals Based on the Analytic Signal Magnitude

Umberto Melia, Francesc Clariá, Montserrat Vallverdú, Pere Caminal

Abstract-Peak and spike artifacts in time series represent a serious problem for signal analysis especially in biomedical field. From the last decades, different techniques have been used for their removal mainly based on adaptive filters. This work presents a new approach for removing peak and spike artifacts based on the analytic signal envelope, filtered with a low-pass filter. The proposed algorithm was tested on electroencephalogram signals containing peak and spike artifacts. Results showed that this method permitted to remove the peak and spike artifacts preserving both high correlation (ρ >0.9) and spectral coherence ($\overline{C(f)}$ >0.85) with the original signal.

I. INTRODUCTION

In general, there are several disturbances that could contaminate the electroencephalogram (EEG) signal such as changes associated to cerebral activity that should be removed from the recordings before further analysis. A band-pass filter is adequate only when the true signal has all frequency content between the cutoff frequencies. This is usually not the case for general biomedical signal processing. In fact, a band-pass filter, in the characteristic EEG frequency band, is commonly used for eliminating EMG and power line noise but it is not enough for others, such as certain peak and spike noise. Also the heart electrical activity present throughout the body is often displayed as artifact component in EEG signals, since the electrodes used to measure EEG signals are sensitive to it [1].

The recorded EEG for the evaluation of epileptic seizures can present artifact and short-time high-amplitude events that mask the quasi-periodic structure of the seizures [2]. Different filter designs mainly based on adaptive algorithms with linear and nonlinear structures have been developed for artifact removal [3, 4]. Common problems faced during the clinical recording of the EEG signal are the eye blinks and movements of the eye balls that produce electrical activity on the scalp

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that interferes with the EEG. To correct or remove ocular artifacts from EEG, many regression-based techniques have been proposed [5-9]. They require calibration trials in order to determine the transfer coefficients between the EOG channels and each of the EEG channels for estimating the EOG component and subtracting it from the signal. Also independent component analysis (ICA) has been proposed [10] to separate the EOG signals from the EEG signals. This method, used to remove multiple types of artifacts simultaneously [11], requires off-line analysis and processing of data collected from a sufficiently large number of channels, and its success largely depends on correct identification of the noise components. Croft et al. [12] reviewed a number of methods of dealing with ocular artifact in the EEG, focusing on the relative merits of a variety of EOG correction procedures. He et al. [13] described a noise cancellation method based on adaptive filtering to remove ocular artifacts from EEG without calibration trials. This can be implemented on-line using EOG signal as reference.

Interferences can mask relevant features in the EEG and consequently must be removed [14]. To improve the approach to this problem, our work describes a new method for removing peak and spike artifacts from EEG signals. This method, that permits to make the components of signal amplitude and frequency independent, is based on analytic signal. This procedure has been tested on an EEG data set and compared with the performance of an adaptive filter. The methods previously described normally require multichannel recordings or a reference signal for the extraction and elimination of the noise. This issue presents a filter methodology that can be applied on a single channel record and without using any reference signal.

II. MATERIALS AND METHODOLOGY

A. The Hilbert Transform and the Analytic Signal

Let x(t) be a real-valued finite energy signal defined over the temporal interval $-\infty < t < \infty$, its Hilbert transform is defined as [15]

$$\hat{x}(t) = \frac{1}{\pi t} * x(t) = \frac{1}{\pi} \int_{-\infty}^{\infty} x(t) \frac{1}{t - \tau} d\tau$$
(1)

In the frequency domain, the result is obtained by multiplying the spectrum of the x(t) by j (+90°) for negative frequencies and -j (-90°) for positive frequencies. The time domain result can be obtained performing an inverse Fourier transform. Therefore, the Hilbert transform of the original function x(t) represents its harmonic conjugate [16].

Considering the concept of analytic signal of a real signal x(t), it can be written as

 $y(t) = x(t) + j\hat{x}(t) = m(t)\cos(\phi(t)) + j m(t)\sin(\phi(t))$ (2) In this way, the signal x(t) can be expressed as the product of two signals:

$$x(t) = m(t)\cos(\phi(t))$$
(3)

and the instantaneous phase as

$$\phi(t) = 2\pi f_0 t + z(t) \tag{4}$$

being z (t) a zero mean signal. The signal $x(t) = m(t) \cos(2\pi f_0 t + z(t))$ can be considered as a signal modulated both in frequency and amplitude. Consequently, the interest is to estimate the contribution that each component provides to the total x(t) signal bandwidth.

B. Frequency Component Contribution

In general, an angular modulation $x_f(t)$ with modulator $\phi(t)$, which represents a pass band signal centered at f_0 Hz, can be expressed as

$$x_f(t) = Re\{e^{j\phi(t)}\} = Re\{e^{j2\pi f_0 t}e^{jz(t)}\}$$
(5)

Taking the term $e^{jz(t)}$ and its series expansion $1 + jz(t) - \frac{1}{2!}z^2(t) - j\frac{1}{3!}z^3(t) + ...$ then $x_f(t)$ can be written as $x_f(t) = Re\left\{e^{j2\pi f_0 t}\left(1 + jz(t) - \frac{1}{2!}z^2(t) - j\frac{1}{3!}z^3(t) + ...\right)\right\}$ and its Fourier transform is the sum of the Fourier transforms of the infinite terms. Each of them has a frequency bandwidth centered in f_0 and with the size of the bandwidth of signal z(t) multiplied by the order of the term.

This shows that the spectrum of the frequency component $x_f(t) = \cos(\phi(t))$ is spread, representing a band pass signal and contributing to x(t) essentially at high frequencies.

C. Amplitude Component Contribution

The amplitude component m(t) is always positive and therefore represents a low pass signal. Its amplitude spectrum M(f) is not zero at zero frequency.

It is interesting to find a bound for the bandwidth *B* of the signal m(t) using the low pass spectrum M(f). The bandwidth *B*, defined at the cutoff frequency where $\frac{M(0)}{\sqrt{2}}$ is satisfied, depends on the absolute value of the derivative maximum $\left|\left(\frac{dm(t)}{dt}\right)_{max}\right|$ and the M(0). Fig. 1 will help to introduce the development of the next formulas, showing schematically the spectrum of a low pass signal.

Taking the absolute value of the derivative in the expression $m(t) = \int_{-\infty}^{\infty} M(f) e^{j2\pi ft} df$, the next expressions are deduced



Figure 1. Spectrum of low pass signal

$$\left|\frac{dm(t)}{dt}\right| = \left|\frac{d}{dt}\left(\int_{-\infty}^{\infty} M(f)e^{j2\pi ft}df\right)\right| \ge \left|\frac{d}{dt}\left(\int_{-B}^{B} M(f)e^{j2\pi ft}df\right)\right| \quad (6)$$
$$= \left|\frac{d}{dt}\left(\frac{M(0)}{\sqrt{2}}2Bsinc(2Bt)\right)\right|$$

then

$$\left|\frac{dm(t)}{dt}\right| \ge \left|\frac{M(0)}{\sqrt{2}} \left(\frac{2B\pi t \cos(2B\pi t) - \sin(2B\pi t)}{\pi t^2}\right)\right| \tag{7}$$

The maximum slope occurs at the first zero of the *sinc* function (t=1/(2B)). Therefore, if for any *t* the first member of the equation (7) is greater than or equal to the second member, then for a particular time *t* it will also be fulfilled. If this time is t = 1/(2B) for which the second member of the equation (7) takes the highest value, then equation (7) can be written as

$$\left|\frac{dm(t)}{dt}\right|_{max} \ge \left|-\frac{M(0)}{\sqrt{2}}4B^2\right| \tag{8}$$

The expression (8) shows that the absolute value of the maximum slope of m(t) is always greater than or equal to the constant obtained as function of B and M(0). Consequently, the equation can be written as

$$B \le \sqrt{\left(\frac{dm(t)}{dt}\right)_{max} \frac{\sqrt{2}}{4M(0)}} \tag{9}$$

providing a bound for the bandwidth (in Hz) of the component amplitude.

D. Description of the Filter Algorithm

The proposed algorithm implements a filter based on analytic signal envelope (ASEF) that reduces the amplitude of peaks or spikes in the EEG signals. It is based on filtering the envelope m(t) of a signal x(t) with a low pass filter with a very small pass band *B*.

The main steps of the filter algorithm for a signal x(t) are:

- Calculation of the analytic signal y(t) of x(t)
- Calculation of the envelope m(t) and the instantaneous phase $\phi(t)$
- Filtering of m(t) with a FIR filter of high order obtaining m_{filt}(t)

Multiplication of the filtered envelope m_{filt}(t) and the cosφ(t) in order to obtain the final filtered signal x_{filt}(t) (10)

 $x_{filt}(t) = m_{filt}(t) \cos\phi(t)$ (10)

E. Bandwidth of Low Pass Filter for EEG Signals

Considering a subset of 10 EEG signals corrupted by peak noise obtained from *www.physionet.org* [17]. After the calculation of M(0), for different values of slope, the bandwidth for the envelope was estimated. The derivative maximum bound of this EEG signal $\left(\frac{dm(t)}{dt}\right)_{max}$, the bound of the bandwidth *B* obtained from (9) are calculated for segments of the signals with and without peaks.

F. Evaluation of ASEF Filter

In order to test the proposed method, ASEF filter and normalized least mean squares (NLMS) adaptive filter [18] were applied to an EEG signal data set [17] and their performances compared. The NLMS adaptive filter characteristics were 300th order with step size of 0.1, no leakage and using a segment of EEG without peaks as reference signal. The correlation coefficient ρ between the original signal x(t) and $x_{filt}(t)$ and also the mean value of the coherence function $\overline{C(f)}$ [19] were calculated.

III. RESULTS

Table I shows the results of calculations of the bound of the bandwidth *B*. As it can be noted, the mean value of *B* for signals with peaks is B = 0.10284 Hz. The mean value of *B* for signals without peaks is B = 0.05547 Hz and it could represent the filter bandwidth to eliminate theoretically all the peaks. Normalizing the bandwidth *B* by the *B* of signals with peaks, the *B* of the signal without peaks is 54% of the total bandwidth. Then, a bandwidth of $B \le 0.0625$ Hz, that represents a maximum of the 60% of the total bandwidth, can be an acceptable value. This bound permits to preserve low amplitude peaks with physiological meaning.

The ASEF filter reduces the amplitude of the peak and spike noise (EEG movement artifacts), without changing the frequency components $(cos\phi(t))$ of the original signal.

Fig. 2 shows the envelope m(t) of an EEG signal [17] and its low pass filtered envelope $m_{filt}(t)$. As it can be seen in Figs. 3a and 3b, the filtered signal $x_{filt}(t)$ shows a reduction of the



Figure 2. Envelope m(t) (in pink) and $m_{filt}(t)$ (in yellow).

TABLE I	CALCULATION OF BANDWIDTH	VALUE

Signal with peaks $(dm(t))$			Signal without peaks $(dm(t))$		
<i>M</i> (0)	$\left(\frac{dm(t)}{dt}\right)_{max}$	В	<i>M</i> (0)	$\left(\frac{dm(t)}{dt}\right)_{max}$	В
0.91921	0.05313	0.12021	0.61271	0.00914	0.06107
1.04768	0.05284	0.11229	0.67573	0.00788	0.05400
1.06069	0.05188	0.11058	0.57646	0.00617	0.05174
1.06450	0.04912	0.10741	0.86802	0.00935	0.05189
0.90594	0.06563	0.13458	0.56150	0.00714	0.05640
1.29673	0.04986	0.09805	0.68448	0.00837	0.05530
1.05291	0.05073	0.10975	0.51947	0.00634	0.05524
0.92341	0.05088	0.11736	0.60698	0.00750	0.05559
1.13671	0.05245	0.10741	0.56466	0.00713	0.05620
1.10913	0.05722	0.11357	0.62281	0.00816	0.05725
	(dm(t))	1 5 0			

Values of M(0), $\left(\frac{um(t)}{dt}\right)_{max}$ and B for segments of signals with and without peaks.

peaks amplitude compared with the original signal x(t), but without affecting the position of the zero crossings (Fig. 3b). The correlation coefficient and mean value of the coherence function were $\rho = 0.955$ and $\overline{C(f)} = 0.896$, respectively.



Figure 3. A signal x(t) with peaks (in blue) and the filtered signal $x_{filt}(t)$ (in red).



Figure 4. A signal x(t) with peaks (in blue) and the filtered signal $x_{filt}(t)$ (in red).

Figs. 4a and 4b show the same signal x(t) that in Figs 3a and 3b but filtered with a NLMS adaptive filter. It can be noted that even the peaks are removed the $x_{filt}(t)$ presents evident changes in the segment without noise respect to the original signal. The correlation coefficient and mean value of the coherence function were $\rho = 0.548$ and $\overline{C(f)} = 0.258$, respectively.

IV. CONCLUSIONS AND DISCUSSIONS

A new algorithm for removing peak and spike noise from EEG is presented in this paper. This is based on filtering the analytic signal envelope. This algorithm preserves all information contained in the original signal phase, changing only the bandwidth of the envelope. It was tested on an EEG data set and compared with adaptive filters. A methodology to study the bandwidth of the envelope of signals with and without noise was designed. This has allowed a cutoff frequency of the low pass filter, used to filter the envelope, to be defined. Results showed that the cutoff frequency $B \le 0.0625$ Hz was able to remove all peak and spike noise from the EEG, but preserving the physiological information. Correlation coefficient calculated when ASEF filter is used for the EEG data set was $\rho > 0.9$ and the mean value of the coherence function $\overline{C(f)} > 0.85$.

An important aspect of the designed filter was that reference signal and multichannel recording are not needed. This is advantageous when it is necessary to minimize the number of channels of the recording. The results have shown the capability of the proposed filter ASEF in reducing the noise, preserving the frequency information and the position of zero crossings.

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