Denoising Simulated EEG Signals: A Comparative Study of EMD, Wavelet Transform and Kalman Filter

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Abstract— **Electrooculographic (EOG) artefact is one of the most common contaminations of Electroencephalographic (EEG) recordings. The corruption of EEG characteristics from Blinking Artefacts (BAs) affects the results of EEG signal processing methods and also impairs the visual analysis of EEGs. In this paper, our scope was a comparative analysis of the performance of three standard denoising methods like continuous Empirical Mode Decomposition (EMD), Discrete Wavelet Transform (DWT) and Kalman Filter (KF). In order to evaluate the performance of EMD, DWT and KF of noise reduction and to express the quality of the denoised EEG, we calculate several indexes such as the Signal-to-Noise Ratio (SNR). All the results obtained from noise simulated EEG data show that WT achieved the greatest SNR difference and also the mode mixing issue of EMD affected this method's performance.**

I. Introduction

Electroencephalogram (EEG) is a noninvasive measurement of the brain's electrical activity obtained using several electrodes placed on the scalp. Over the last decades and under an increasing medical demand, EEG became an important diagnostic tool for monitoring and managing dysfunctions and various neurological disorders of the human brain.

One of the most tempting problems in biomedical signal processing is the extraction of high resolution EEG from contaminated recordings. An increasing number of denoising techniques have been proposed for solving this problem [1].

It is still a challenge to get qualitative or quantitative EEG analysis because of various noise sources that make the denoising process extremely difficult [1].

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Electromyographic (EMG), electrodermal response, eye blinks, eye movements, and respiratory are the most common biologically noise sources that generate EEG artefacts [2].

EOG artefacts are one of the main problems of EEG analysis, since EEG recordings are usually contaminated from eye movements and Blinking Artefacts (BAs) which are impossible to prevent. It is essential to estimate EOG accurately, in order to subtract it from the contaminated EEG. The difficulty of achieving this is due to the high amplitude and the low frequency components of the EOG that overlap the frequencies of EEG [2].

Kalman Filter (KF) is not a recently implemented method and it has been employed for EOG detection [3], correction [4] and BA removal [5] with promising results.

Wavelets were introduced in early 90s with numerous applications in EEG processing. EEG is a non-stationary signal and several studies, using wavelet adaptive thresholding algorithms, have been applied in order to identify and remove EOG [6]. Also, wavelets have been used as a method for detecting epileptic spikes [7] and denoising Electrocardiographic (ECG) [8].

The Empirical Mode Decomposition (EMD) was introduced as a data driven method for decomposing the signal in components called Intrinsic Mode Functions (IMFs). EMD is a modern adaptive method for detecting and separating the EOG artefacts from EEG signals, with several modifications [9] and combinations with other methods [10].

In this work, the performance of these three methods EMD, WT and KF is quantitatively compared in removing EOG artefacts with different amplitudes from simulated EEG. In order to obtain the denoising results we apply the classic EMD [11], the KF with some modifications [5] and the Discrete Wavelet Transform (DWT) [12, 13].

The efficiency of EMD, WT and KF in rejecting the EOG artefacts was evaluated by calculating several metrics. The results were compared between the contaminated and original signals and between EOG clean and original signals.

II. Methods

A. Database Construction

In this paper, simulated EEG signals were generated by an algorithm described before [9]. Every signal contains 10000 samples with a sampling frequency 2kHz.

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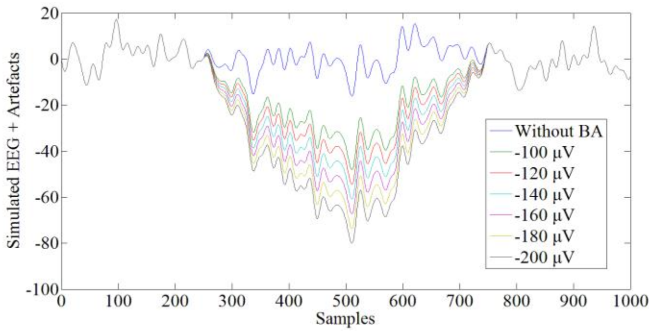

Fig. 1. Comparison of the EEG segment that contains one BA with amplitudes of -100μV, -120μV, -140μV, -160μV, -180μV and -200μV.

Artificial BAs were added every 1000 samples with amplitude that ranges from -100μV to -200μV with a -20μV step. The algorithm was adjustable in several parameters such as frames, epochs, sampling rate and noise amplitude. For every trial 32 channels were produced. The selection of the length of each signal is defined by the product of total epochs and frames which is fixed to 1000 samples containing one BA.

B. EMD

According to the principle of separation of scales, Empirical Mode Decomposition (EMD) reveals the various inherent oscillations tendencies in a given discrete signal $x(t)$. Each oscillation is represented by a function, called IMF, by means of a decomposition process called sifting algorithm. IMFs satisfy the following equations:

$$N_c - 1 \le N_e \le N_c + 1 \tag{1}$$

$$\frac{\left|e_{\max}(t) + e_{\min}(t)\right|}{2} = 0,\ \ t \in [0, T] \tag{2}$$

,where N_e is the number of exrema and N_c is the number of zero crossings in (1). Also, $e_{\max}$ and $e_{\min}$ represent the upper and lower envelopes respectively. Thus, the equation of signal $x(t)$ is configured as:

$$x(t) = \sum_{k=1}^{n} imf_k(t) + r(t),\ \ t \in [0, T] \tag{3}$$

,where $r(t)$ is the residual of EMD output.

Furthermore, EMD generates IMFs, in decreasing frequency order by selecting the highest frequency oscillation that is retained in the signal and extracting each IMF that has lower frequency oscillations than this.

Since, the BA lies in the low frequencies (< 4 Hz) [x], the IMFs that appear in this band are rejected. Thus, the filtered signal is the sum of the remaining IMFs and more specifically, only the first three IMFs were kept [9].

C. Discrete Wavelet Transform (DWT)

Wavelet is a “small wave” with short duration and an average value of zero. A y function sufficiently regular and localized, which is called “Mother Wavelet” (MW) is needed in order to decompose a signal. MW could be chosen from a numerous set of basis functions, which are usually non-symmetrical with a finite period.

DWT is a fast linear transformation that results in detecting specific signal transitions localized in time and frequency. The wavelet function $y(t)$, with scale a, shifting parameter b and t as the independent variable that represents time, is defined as [14]:

$$y_{a,b}(t) = \frac{y\left(\dfrac{t-b}{a}\right)}{\sqrt{a}} \tag{4}$$

By choosing a and b based on the powers of two (dyadic scales and positions) and defining k as the discrete representation of time, the decomposition of the signal becomes more precise [14]:

$$y_{m,n}(k) = 2^{-\frac{m}{2}}\, y\left(2^{-m}k - n\right)\ \ m, n \in \mathbb{Z} \tag{5}$$

Then the DWT for a given function $f(k)$ is [14]:

$$DWT(m,n) = 2^{-\frac{m}{2}} \cdot \sum_{k=-\infty}^{\infty} f(k) \cdot y\left(2^{-m} \cdot k - n\right) \tag{6}$$

DWT is as one of the most applied techniques in analyzing non-stationary signals like EEG [6, 7].

In this paper, we applied the DWT to eliminate EOG artefacts using Daubechies (db6) as a basis function with 9 decomposition levels. The number of details that were selected, optimized the performance of WT in EOG rejection. The sum of the selected details is the denoised signal, without the BAs.

D. Kalman Filter

KF is the appropriate estimator for linear dynamic systems in which noise is an inseparable factor. Any information about the system can be provided and be processed along with each measurement. Since it is an optimal recursive algorithm for signal processing, it uses past and present observations to execute estimations.

In its original formulation, KF aims at estimating the state $X \in \mathbb{R}^n$ of a discrete-time controlled process, described by a linear stochastic differential equation of the form:

$$X_k = AX_{k-1} + Bu_{k-1} + Cw_{k-1} \tag{7}$$

and the measured signal is described by the equation:

$$z_k = HX_k + v_k \quad (8)$$

,where the random variables w_k and v_k represent the system noise and measuring, respectively, which will be assumed uncorrelated with time (white noise) and with each other. The $n \times n$ matrix A relates the previous situation in discrete time $k-1$ to the current state of system at time k. The $n \times 1$ table B, relates the control input u to the state of System X and finally the $m \times n$ matrix H correlates the measurement z_k with system state X.

In this paper, the KF is applied to the simulated EEG in order to remove the BAs. The following equation describes the relation between the signals, where $EEG_c(t)$ is the contaminated EEG, $EEG_t(t)$ is the true EEG and $EOG(t)$ is the signal that the BA:

$$EEG_c(t) = EEG_t(t) + EOG(t) \quad (9)$$

III. Results

In order to quantitatively compare the three methods for different amplitudes of the BA, various performance measures were implemented. These measures were Normalized Root Mean Squared Error (NRMSE), Percent Root Mean Square Difference (PRD), Pearson product-moment correlation coefficient (R) and Signal-to-Noise Ratio (SNR). The equation that was used for the SNR calculation was the following:

$$SNR_{dB} = 20\log_{10}\left(\frac{\|EEG_c(t)\|}{\|EEG_c(t) - EEG_d(t)\|}\right) \quad (10)$$

,where $EEG_c(t)$ is the clean signal and $EEG_d(t)$ the denoised signal.

It has to be mentioned that for the KF, which is a model-based method, the clean EEG was known and used for determining the state-space equations. On the other hand the Wavelet Transform and the EMD are model-free methods.

EMD achieved the worst results in the simulation. Using EMD, the average drop in SNR_{dB} retaining the first 4 IMFs instead of the first 3 is almost 10dB and 0.7dB if we retain only the first 2. The choice of retaining 3 IMFs as a BA rejection EMD works well with a tendency to surpass KF, for a BA amplitude less than 140 μV, but still worse than the other two methods. For BA amplitude greater than the previous threshold, the SNR_{dB} drops from an average of 15dB to less than 14dB. This occurs mainly because of the major drawback of EMD called "mode mixing" [15], which in one of its aspects is the simultaneous presence of widely separate frequencies in the same IMF.

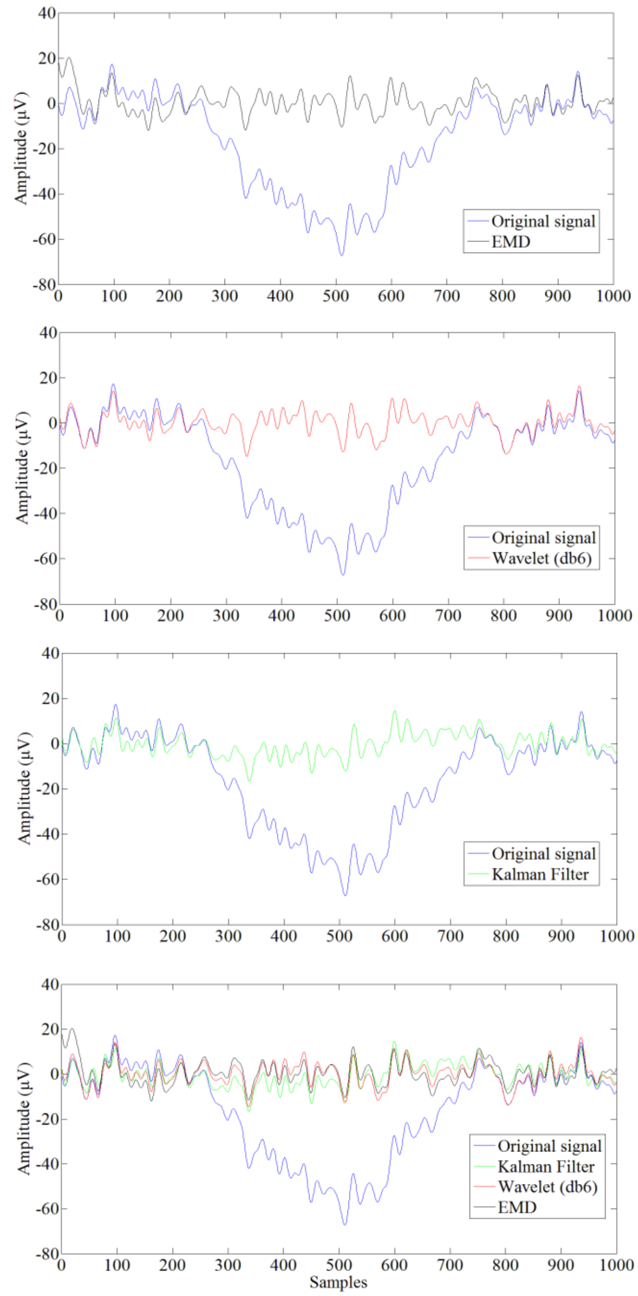

Fig. 2. Comparison of the Original Signal and the resulted signal of (a) EMD, (b) Wavelet (db6), (c) Kalman Filter and (d) all of the previous methods.

The basis function db6 was used after testing various basis functions and achieving the best results according to SNR differences. Concerning the specific choice of the basis functions for the DWT, our simulations led to the conclusion that this selection significantly affects the denoising performance.

KF achieved satisfactory results in respect with BA rejection independent of the BA amplitude. Unlike the other two methods KF is a model-based methods which an important disadvantage especially when the clean signal or the reference is not known.

TABLE I

AVERAGE ERROR MEASURES COMPARISON OF THE CONTAMINATED REGIONS FOR THE THREE METHODS

Measures	Before BAs Rejection	EMD		WT (db6)		KF	
		After BAs Rejection	Difference of the measures	After BAs Rejection	Difference of the measures	After BAs Rejection	Difference of the measures
NRMSE	0,185199	0,009824	-0,175375 (-94.69%)	0,003671	-0,181528 (-98.01%)	0,017073	-0,168126 (-90.781%)
PRD(%)	403,535724	80,010396	-323,525328%	79,884308%	-323,651416%	62,829967%	-340,705757%
R	0,377690	0,651936	0,274247(+72.59%)	0,601542	0,223853 (+59.268%)	0,789858	0,412168 (+109.128%)
SNR(dB)	-11,881587	2,073193	13,954780	6,896687	18,778274	4,063847	15,945433

IV. CONCLUSION

EEG processing and analysis require accurate information, which can be extracted from non-invasive EEG recordings. Usually, EEG signals are contaminated by various artefacts and thus noise reduction this is not an easy procedure.

Previous investigations in this research area showed that decomposition methods like WT and EMD, and estimating methods like KF are efficient approaches for the extraction of BAs from a contaminated EEG signal.

In this work WT, EMD and KF were successfully used in removing EOG BA in EEG. According to the SNR differences before and after the BA rejections, WT has a slight but clear advantage and has a minimum signal distortion as compared with the other two methods as demonstrated as “Fig.3.”.

The promising results achieved in this work indicate that these three methods outcome in significant improvement in artefact elimination.

Future work includes the comparison of these methods in detecting EOG artefacts inside simulated and real EEG signals. The effects of the decomposition levels of EMD and WT, and the selection of the basis function of WT in the quantity and the quality of EOG reduction will be explored.

This series of simulations also present the important need of using the newer variations of EMD like Ensemble Empirical Mode Decomposition (EEMD) which greatly reduces mode mixing [15]. Modified KFs will also be implemented in order to achieve better results in EOG rejection.

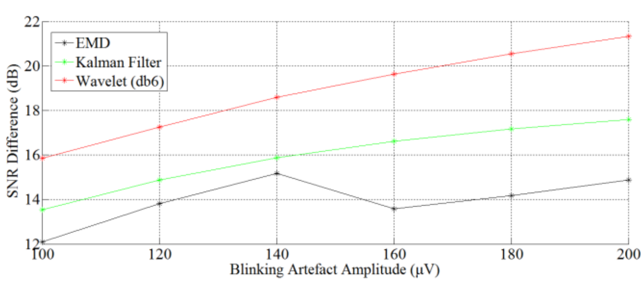

Fig. 3. SNR difference perfomance comparison of the EMD, Kalman Filter and Wavelet for the selected BA amplitudes.

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