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Research Article

Preprocessing of Electrical Activity in the Brain

G. Chekhmane* and R. Benali[2]

Department of Biomedical Engineering, University of Tlemcen, Algeria
***Corresponding author:** ghezalachekhmane@gmail.com

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Abstract. Electroencephalography (EEG) is the most effective tool to diagnosis of epileptic diseases. It provides a signal indicated the electrical activity of the brain, which is contaminated by different sources of artefacts and noises. This paper presents a method for removing ocular (EOG) and muscular (EMG) artefacts in the EEG records. The threshold denoising method based on the stationary wavelet transform (SWT) was used to remove these artifacts. The main objective is to improve the quality of the signal in terms of performance like signal to noise ratio (SNR), correlation coefficient (CC), mean squared error (MSE) and distortion coefficients (THD). As results, different types of thresholding and mother wavelets were in consideration and it was revealed that Daubechies along with the soft thresholding technique and four level of decomposition are better for a higher SNR and correlation coefficient thus decreasing the mean squared error and distortion factor so, these results improve the validity of the proposed technique.

Keywords. Electroencephalography (EEG); Artefacts and noises; Wavelet; Threshold; Signal to noise ratio (SNR)

Mathematics Subject Classification (2020). 65T60, 60H50

1. Introduction

Epilepsy is the most common neurological disease and affects more than 1% of population in the world. This pathology is characterized by the chronic manifestation of seizures as a result of synchronous dysfunction of a large number of neurons. The diagnosis of epilepsy is based on EEG exploration. It is a non-invasive medical technique was invented by German Hans Berger in 1924. It consists in placing electrodes (8-21) on the patient's scalp according to an international standard system (10/20), and connected to an acquisition system for an average duration of 20 minutes. The EEG is used to record in real time, a signal that represents the potential difference between two electrodes. In general, we can distinguish the appearance of five main brain rhythms (Delta, Theta, Alpha, Beta and Gamma) [7].

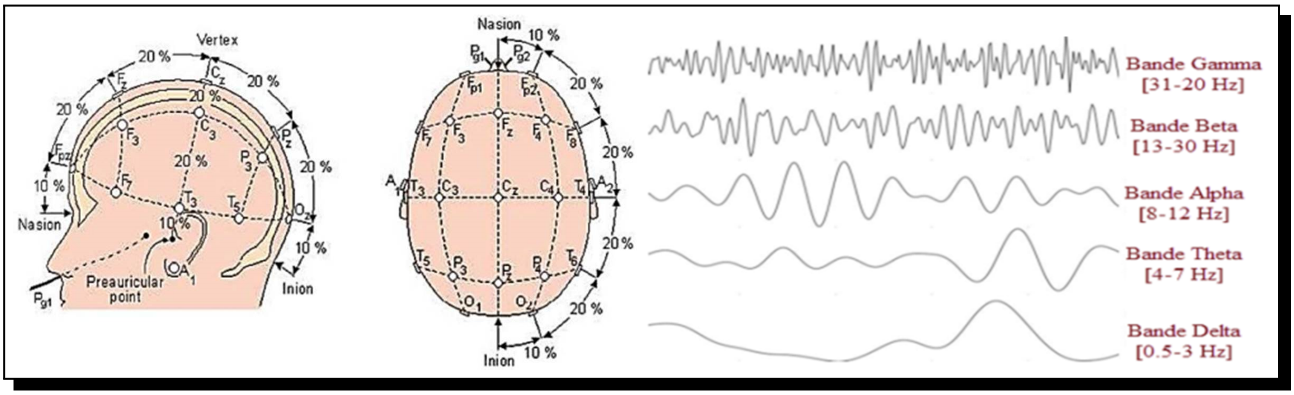

Figure 1. The international standard system 10/20 and brain waves in EEG

The EEG signal can be contaminated with unwanted interferences that one which to decrease or eliminate are artefacts and noises, due to muscle and eye movement as well as the resistivity of the EEG propagation medium. In the research [7], the second part is intended to use the threshold denoising method based on the stationary wavelet transform (SWT) applied on the database of the University of Bonn, then performance evaluation are analyzed finally.

2. Raw EEG Signal

However, the major disadvantage of this technique is the disturbances caused during the acquisition of EEG which are artefacts and noise. In which brain activity is always the target of destructive interference and which is present in practically all recordings. These unwanted artefacts mask the generated signals and complicate the interpretation of the data leading to a bad decision. Artefacts present in EEG signals can be derived from a variety of sources which are subdivided into two broad categories physiological artefacts are those caused by the biological activity of the user of the system. They come in the form of electrical potentials generated by the beating of the heart (ECG), movement of the eyes (EOG) and activation of muscles (EMG). As for non-physiological artefacts, they are present everywhere in the recordings and are linked to the locations of the electrodes as well as to the acquisition system and the environment in which it operates. On the other hand, any signal that does not contain or provide information about the system and that is not identified as artefacts is considered noises [1]. The most classic of measurement noises are related to the instrumentation used during recordings (electrodes, electrical wires, etc.) and to the environment [11].

3. Stationary Wavelet Transform

There is a particular type of invariable time-frequency transform, which is invariant: The stationary wavelet transform (SWT), while allowing the use of masks in the time-frequency plane. SWT is an improved technique of the wavelet transform which also uses the sampling method at each level of signal decomposition or its general principle is to describe the signal in the time-scale domain and then the reconstruction of the signals through coefficients.

The SWT has been used in several applications such as detection and denoising. The SWT on its decomposition uses the top sample method applied to its filtering process.

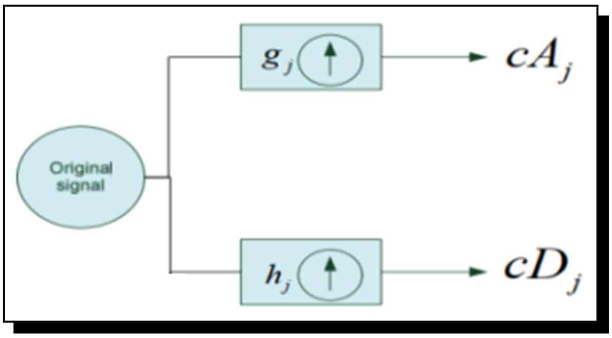

Figure 2. The DWT and SWT in one-level of decomposition

The approximation is produced by convolving the original signal with a low pass filter (g_j). On the other hand, the detail is derived from the convolution with an up-sampling high-pass filter (h_j) to build the coefficient. The decomposition of SWT can be calculated by:

$$cA_{j,k}^{SWT} = \sum_n cA_{j-1,k+2^j(n)}^{SWT} g(n), \tag{3.1}$$

$$cD_{j,k}^{SWT} = \sum_n cD_{j-1,k+2^j(n)}^{SWT} h(n), \tag{3.2}$$

where

$cA_{j,k}^{SWT}$: approximation coefficients of SWT,

$cD_{j,k}^{SWT}$: details coefficients of SWT,

j and k is the number of decomposition level and position, $g(n)$ and $h(n)$ are respectively low pass filter and high pass filter [4].

The major advantage of this method due to its time invariance (unlike the discrete wavelet transform (DWT) where the low pass and high pass filters are down sampled by 2 from one scale to another). SWT does not include this down sampling mechanism, so it is a redundant transform. The redundancy of the SWT makes it possible to better characterize the times of occurrence of phenomena, and to have better reproducibility of the transforms between successive events [8] and it has better sampling rates in the low frequency bands.

4. Algorithm

The wavelet denoising technique is used to eliminate the unwanted signal. The threshold denoising method was initially proposed by Donoho in 1995. The block diagram based on the wavelet transform is illustrated in Figure 3. It is carried out in three stages:

(1) The application of the stationary wavelet transform (SWT) to the signal affected by noise.

(2) Threshold estimation and thresholding of wavelet coefficients. The filtering of the coefficients thus obtained, in accordance with a certain criterion.

(3) The calculation of the inverse transform, from the coefficients from the previous step.

Therefore, this technique exploits the effect that the noises are represented by the set of low amplitude wavelet coefficients while most of the useful signal energy is concentrated in the few high amplitude coefficients. The noisy signal can therefore be filtered by setting the weak coefficients to zero following a thresholding operation and by applying an inverse wavelet transformation. These methods assume that the noise is concentrated in the details (often in the first details). The performance of these techniques is better and their strength lies in their simplicity of application and their efficiency. Several problems are encountered when filtering by wavelet decomposition, including:

4.1 Thresholding Method

Indeed, several techniques have been developed to estimate the threshold from which the wavelet coefficients will be considered as significant (useful signal) or insignificant (noise) coefficients. Donoho used two types of thresholding functions: hard thresholding and soft thresholding.

a. Hard Thresholding

Hard thresholding is more categorical than soft thresholding because a given coefficient is considered either as totally representing pure noise and therefore to be eliminated, or as a coefficient representing a portion of the signal therefore to be preserved. Function of hard thresholding $Th(x)$ applied to x is given by:

$$T_h(x) = \begin{cases} 0, & |x| < T, \\ x, & |x| > T, \end{cases} \tag{4.1}$$

where T represents the threshold value.

b. Soft Thresholding

Soft thresholding consists of eliminating any coefficient below the threshold and subtracting this threshold from the other coefficients. Let an arbitrary vector be the soft thresholding function $Ts(x)$ applied on x is given by:

$$T_s(x) = \begin{cases} \sin g(x)(x - |T|), & |x| \geq T, \\ 0, & |x| < T. \end{cases} \tag{4.2}$$

Threshold T for the coefficients of the wavelet transforms is:

$$T = \sigma\sqrt{2\log(N)}. \tag{4.3}$$

N: the number of samples. σ: the standard deviation.

$$\sigma = \frac{\text{median}(|d_i|)}{0.6745}. \tag{4.4}$$

d_i: represents the coefficients of the details obtained at level i.

4.2 Mother Wavelet Families

In reality, there is not a well-defined criterion for the choice of the mother wavelet and this choice greatly depends on the nature of the application and differs from application to another. Several works have been done in order to be able to mount the most suitable mother wavelet for filtering the EEG signal found by the wavelet family Daubechies, Symlet, Coiflet and Haar.

Signal to Noise Ratio (SNR)

SNR is an indicator of the quality of the transmission of information. SNR is defined as the ratio of signal power to noise power, often expressed in decibels. For high SNR value indicates high performance.

$$\text{SNR(indb)} = 10\log_{10}\left[\frac{\text{Original signal}^2}{(\text{Original signal} - \text{Reconstructed signal})^2}\right]. \tag{4.5}$$

Mean Square Error (MSE)

MSE is a measure of the quality of an estimator characterizing its precisionis. It is the average squared error between the original signal and the reconstructed signal.

$$\text{MSE} = \frac{(\text{Original signal} - \text{Reconsrected signal})^2}{\text{lentgh of original signal}}. \tag{4.6}$$

Correlation Coefficient (CC)

The correlation coefficient is the specific degree of quality measure that quantifies the strength of the linear relationship between the original signal and the filtered signal. The best correlation coefficient is close to one (corr > 0.95). The coefficient is noted CC in a correlation report.

$$\text{CC} = \frac{\text{cov}(\text{EEG}, \text{EEG}')}{\text{var}(\text{EEG}) \cdot \text{var}(\text{EEG}')}. \tag{4.7}$$

where cov: covariance, var: variance, EEG: signal after filtering, EEG: original signal.

Distortion Coefficient (THD)

THD measures the linearity of signal processing by comparing the output signal to an input signal.

$$\text{distortion factor}(THD) = \sqrt{\frac{\sum_{n=2}^{n} V_h^2}{V_1^2}} \times 100\% \tag{4.8}$$

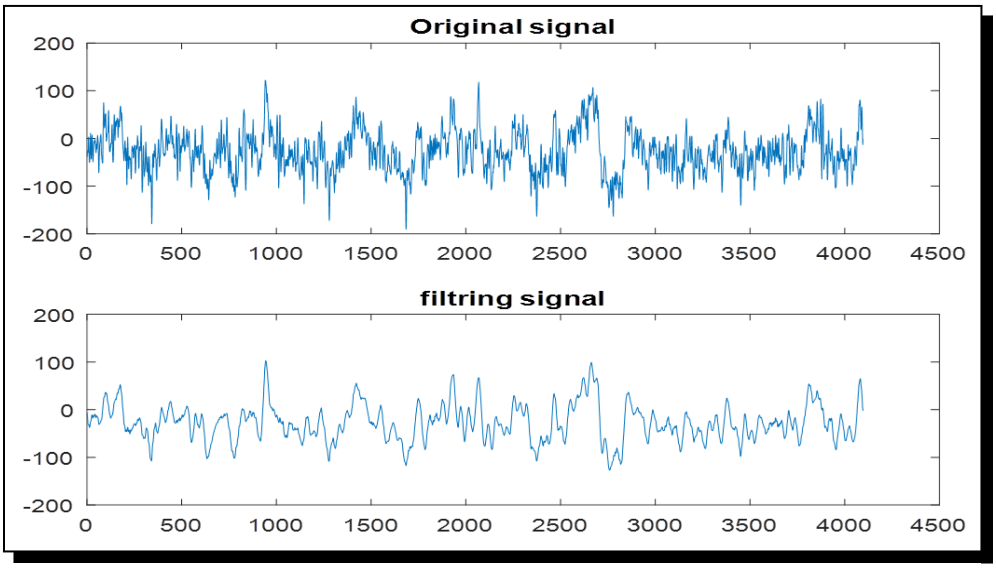

Figure 3. Wavelet denoising process

5. Results and Discussion

In this work, we presented a new approach to determine the optimal decomposition level and the best mother wavelet in EEG for denoising operation by applying the soft thresholding method.

SWT is applied to remove EMG and EOG artifacts from the EEG signal. We use ANDRZEJAK database obtained at the Department of Epileptology in Bonn, Germany. The data consists of five sets (denoted A through E), each containing a single channel of 100 segments with a duration of 23.6 s. Sets A (eyes open) and B (eyes closed) collected from five healthy volunteers. Sets C, D and E come from five patients for pre-surgical diagnosis of the intracranial EEG archive. Set D was recorded in the epileptogenic zone, and set C was recorded from the formation of the hippocampus in the opposite hemisphere of the brain. Sets C and D only contain activity during seizure-free intervals, while set E contains only seizure activity [3].

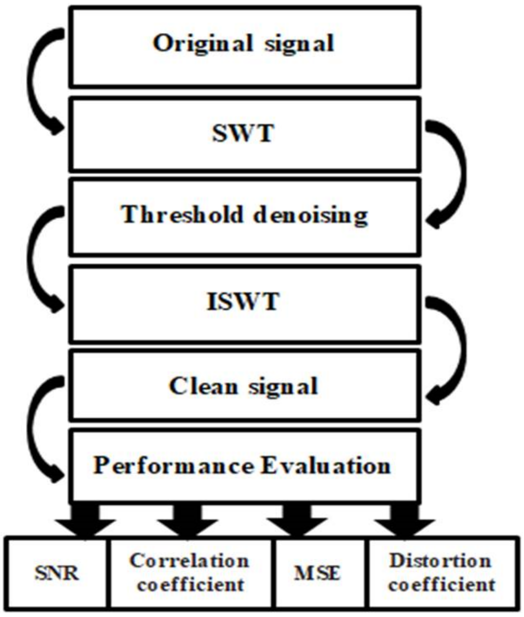

Figure 4. Result of the denoising normal EEG signal

This method is based on the term of performance by implementation of parameters quote before. The optimal level and the best wavelet function can be determined in Table 1.

Table 1. Different parameters at 3 and 4 level of decomposition by wavelet families

	Performance evaluation with 3 level				**Performance evaluation with 4 level**			
Wavelets	**MSE**	**SNR**	**THD**	**CC**	**MSE**	**SNR**	**THD**	**CC**
Db1	0.1855	1.3530	3.2913	0.4696	0.4801	7.1483	2.4776	0.6887
Db2	0.4767	1.4332	3.5347	0.4821	0.4052	11.1445	3.5347	0.8786
Db3	0.6925	1.4248	2.2051	0.4686	0.1066	10.1058	2.3574	0.8171
Db4	0.0789	1.5247	2.1280	0.4892	**0.0702**	**13.0199**	**1.8269**	**0.9131**
Db6	0.0921	1.4281	2.2363	0.4761	0.8294	12.3959	3.1134	0.8981
Db8	0.7147	1.3013	3.1165	0.4623	0.0814	12.2701	3.0189	0.8946
Db10	0.2523	1.3926	3.1155	0.4640	0.9166	11.4081	1.9839	0.8688
Sym2	0.1871	1.4767	3.1001	0.4784	0.0733	11.1445	2.1273	0.8786
Coif1	0.2514	1.4671	2.4218	0.4785	0.0800	8.9255	2.4218	0.7564
Haar	0.2285	1.4226	3.0063	0.4755	0.0816	7.1483	3.0063	0.6887

In most of the EEG signals, we have found that at 4 level of decomposition is better and the wavelet Daubechies 4 'db4' has a higher SNR and CC than other wavelet families, and a minimum MSE and THD, which means our method is efficient. In addition, the proposed method can provide high quality and give us information that is not delivered by other methods. It is shown that our approach is able to denoising the EEG signal.

Table 2. Comparison of authors' works

Authors	Methods	Wavelet functions & decomposition level	MSE	SNR
Ruimei *et al*. [6]	Improved threshold	Coif4-4 levels	0.2657	9.747
Mamun *et al*. [10]	DWT threshold denoising	Normal: Db8 Epileptic: dmey -4 levels	RMS 26.32 (Normal) 255.83 (Epileptic)	/
Daud *et al*. [2]	SWT and Butterworth band pass filter	Db3 -5 levels	2.43	PSNR 44.30-45.12
Kaur *et al*. [9]	DWT threshold denoising	Haar & bioorthogonal 1/1 -4 levels	0.725	2.304
Sharma [5]	DWT & SWT	Haar (SNR) Coif4 (NMSE)	NMSE -8.82 ±3.16	2.37± 0.82
This work	SWT threshold denoising	Db4 -4 levels	0.0702	13.0199

RMS: root mean square error, NMSE: normalized MSE, PSNR: peak SNR

6. Conclusion

The use of the wavelet denoising method is a theoretically powerful method, we find that at 4 level of decomposition is better and the wavelet Daubechies 4 'db4' has a higher SNR and correlation coefficient than other wavelet families, and a minimum mean squared error (MSE). In future research, we intend to generalize our algorithm to determine the most suitable parameters for real-time signals. Also, we aim to develop a hardware implementation to run the proposed algorithm.

Competing Interests

The authors declare that they have no competing interests.

Authors' Contributions

All the authors contributed significantly in writing this article. The authors read and approved the final manuscript.

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