Data Science Modeling for EEG Signal Filtering Using Wavelet Transforms

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***Abstract*—Modeling and constraint satisfaction applications had been considered aiming at diminishing the manual labor during the wavelet signal filtering. Electroencephalogram (EEG) signals are easily affected by various noise sources. The noise can be electrode noise or can be generated from the body itself. The noises in the EEG signals are called artifacts and these artifacts are needed to be removed from the original EEG signals for the proper analysis of the signals. This work presents denoising algorithm based on the combination of wavelet transform (WT), threshold processing and inverse wavelet transform. The proposed algorithm is tested using real EEG signals. To improve its efficiency, different modeling and data preprocessing methods had been applied.**

Keywords: Wavelet Transform, Denoising of EEG Signals, Intelligent System, Data Science, Constraints, Puzzle Methods

I. Introduction

The considered research aims to unify and improve the medical applications of signal filtering using wavelet transforms. The denoising stage could be implemented by using artificial neural networks and deep learning methods (ANNs) but even in this case the process is time and cost consuming and it does not adapt to unknown denoising problems like dynamic body and external noise occurrence, the change of the reasons for the noise, and so on.

Electroencephalogram (EEG) signal is often contaminated by electrocardiogram (ECG), electromyography (EMG) and eye blinking, which are physiologic sources of noise [1]. Also, EEG signal includes line interference and electrode noise. Analyzing depth of anesthesia using corrupted EEG signals may result in an incorrect result. Most of the contaminated signal comes from the eye ball movement and blinking which is known as electrooculogram (EOG) and electromyogram (EMG) signals from the muscles [2]. Therefore, it is necessary to filter the noise from EEG signal. The major noise source of EEG signal is EOG. It is because of the movement of the eye ball causes an electric field around the eye and affected the electric field of the scalp. This electric field could contaminate neurons potential of the brain and as a result EEG signal is contaminated. EOG is considered as a signal with high amplitude and low frequency. This signal is usually affected the lower band of EEG signal. Also, the EOG signal could increase the power of low frequency band [3].

There are many techniques to remove the artifacts from EEG signal, such as adaptive filter, frequency domain regression technique, Wiener filter technique, FIR filter, independent component analysis, and wavelet transform. However, each technique has its own ability to remove one particular artifact. For instance, the popular technique to remove the EOG artifact is adaptive filter. Kumar has used the adaptive filter technique combined with wavelet to remove the EOG [4]. On the other hand, the most popular technique to filter EMG artifact from the EEG signal is discrete wavelet transform [5, 6]. Furthermore, in order to remove the EMG signal from the EEG signal, Lanlan used the db4 wavelet and decomposed it using 8 layers [7]. The result shows that the wavelet is more effective to remove the noise from the EEG signal. However, this technique works only in removing the EMG signal from the EEG signal. Different to the method used by [7], Araghi used the bior3.3 discrete wavelet transform and decomposed it using six layers to remove the artifact from the EEG signal [8]. In contrast, Palendeng et al. explain that the wavelet transform technique which is combined with adaptive least mean square able to remove the EMG artifact as well as other artifact in low frequency [9]. Filtering the EEG signal is essential before analyzing it. Removing artifact from the EEG signal would reduce the error in calculations. In this paper, wavelet transform is proposed to remove the artifact from the EEG signal. The method is using WT because of its time invariance and it has better sampling rates in the low frequency bands. Also, WT could improve power of the wavelet transform

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and effectively eliminates noise in signal denoising. It has good ability in filtering the noise and retains the information. The main challenge in using wavelet transform is to select the most optimum mother wavelet for the given tasks, as different mother wavelet applied on to the same signal may produce different results. The selection of a mother wavelet function is an important step because studies have yet to provide specific mother wavelet basis functions that cater to all EEG channels. Four mother wavelets basis functions from families were investigated. This paper reviews on the mother wavelet selection methods and EEG signal denoising by using artificial neural networks and deep learning methods.

The remaining of the current paper is organized as follows: In Section 2, a set of logically-based constraint satisfaction methods had been considered. In Section 3, we comment wavelet transform. In Section 4, we present wavelet denoising algorithm. In section 5, we discuss experimental results. Finally, in Section 6, we present the conclusions.

II. Deep Knowledge Modeling and its Applications

Wavelet transform is a powerful method to analyze different signals. This type of research presents the time – scale information of the signal. Deep modeling and data preprocessing may significantly improve its applications and diminish the manual work. One of the problems in Data Science concerning deep modeling problems is related to the selection of data in order to process them more efficiently. Same methods could be used for data analysis and correction. These issues are directly related to the methods for deep modeling of data and knowledge, without which the application cycle for logical and statistical data processing in order to extract hidden patterns cannot be built. Different types of non-classical logics or machine learning methods are used for this purpose [10-13]. Classical selection tools include both various statistical applications and applications of non-classical logics (descriptive logics etc.). There are many studies for solving crossword puzzles [14-17], but in them the problems are solved in a probabilistic way, by chance, by using random numbers and combinations, which is not effective. This paper proposes to increase efficiency by using logically-oriented modeling tools. To solve the problem, it is proposed to use three groups of non-classical constraints described in connection with the research of the puzzle method together with the system of classical constraints [18]. A closed area is formed aiming at focus attention of a software agent to certain data, including M and N (Figure 1).

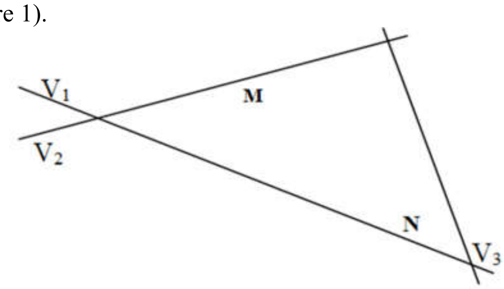

Figure 1. A system of linear constraints with focus on objects M and N

The specified area contains the required data for objects denoted by M and N. The closed area contains much less data, but they still may be too large. Aiming at better efficiency, it is proposed to use three more groups of constraints: binding, pointing and crossword groups. Binding constraints model situations where the solution is close to the center of the binding area, in other words, the farther from the center the less likely it is to find the desired solution. There are several types of binding constraints in this group. For example, binding may be unconditional or conditional, it may invalidate the linearity or other properties of other types of constraints intersecting the domain. In Fig. 2, the binding constraints are represented by the lines {B, D} intersecting the plane of the required solution G_1.

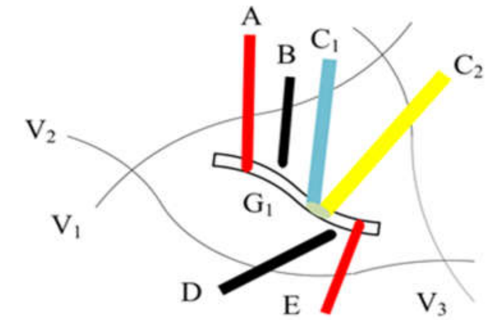

Figure 2. A system of nonlinear constraints and the three groups of logically-based constraints

Together with the binding constraints of Fig. 2, it is convenient to use the pointing (indicating) constraints {A, E} in order to determine not only the area, but also the direction of the search. The group of pointing constraints can be considered as a generalization of the classical systems of goal, target or fitness functions. In contrast, pointing constraints can change the direction of the search depending on the accumulated data or the knowledge (circumstances), in other words, the logic of data and based on them events can be followed. For example, if there is information that there is a pain, the data on his coordinates are probably no longer up to date. In this case, the direction has prognostic significance and the exact result is in doubt until the proof is found.

The last third group of constraints are those of the crossword puzzle: $\{C_1, C_2\}$ from Fig. 2. Unlike {A, E}, they reveal not only the direction, but also parts of the desired solution (of the goal). The purpose of their application is to solve the problem G_1 when only some parts of the solution $\{C_1, C_2\}$ are known. For this purpose, combinations of other types of constraints are most often used, the relationships between $\{C_1, C_2\}$, etc. are studied. $\{C_1, C_2\}$ belongs to G1 but is only the subset of the desired solution. Many algorithms may be investigated how to calculate the other, unknown parts of the goal, and how to estimate their fitness to the solution of the problem. As a whole, the quoted problem is how to make links from the known set $\{C_1, C_2\}$ from the example to the unknown knowledge, how to use the pointing and other constraints aiming to diminish the set of possible solutions. No matter what is the application algorithm, its goal is to produce a set of knowledge which is the most appropriate to $\{C_1, C_2\}$. The considered descriptions do not have a purpose to comprise all possible methods and applications, but to consider a synthetic view of the field as a whole.

III. Wavelet Transform

Wavelet transform is a powerful method to analyze the signal. This method could present the time – scale information of the signal. Frequency and time information of the signal can be obtained using this method. Wavelet is able to perform a different time and scale resolution, so the user could choose which particular signal they want. The other advantage of the wavelet is capable to localize the area of larger signals. Wavelet analysis aims to deal with time varying modes. It is more robust in non-stationary signal analysis. EEG signal is one of the non-stationary signals because this signal is varying in time. The benefit of wavelet analysis is capable to disclose information contain of the signals. The disclose information of the signal are trends, breakdown points, discontinuities and self-similarity [19]. In addition, wavelet is able to filter the signal as well as classify the signal.

Unlike the Fourier transform, the continuous wavelet transform provides an opportunity to construct a time-frequency representation of the spectrum of the studied signal, which achieves a very good localization at both time and frequency. Wavelet transform presents the best time resolution for low-frequency and high-frequency components, thus overcoming the shortage of short Fourier transform (STFT) to determine one-time frequency. Time-frequency representation of the signal is shown in Fig. 3 [20].

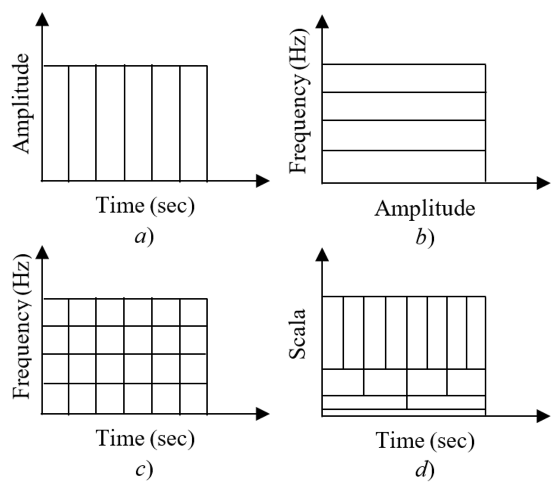

Figure 3. a) Window with time-amplitude separation of the signal, b) frequency-amplitude spectral window obtained by Fourier transform, c) frequency-time signal distribution obtained with STFT, d) window technique with wavelet transform

The width of the window varies with the wavelet transform, which is one of the most important features of the wavelet transform. In the wavelet analysis, it is essential to pay attention to the scaling function and the type of mother wave. There is a wide variety of family waves that have proven to be particularly useful in signal processing. In practice, various wavelets are used in the decomposition of signals such as waves of Symlets, Daubechies, Fejer-Korovkin, Coiflets, and others (Fig. 4) [20, 21]. Wavelets are determined by: a scaling filter, a scaling function, or a wavelet function (mother wavelet). Wavelet function $\psi(t)$ is a zero-average function [20].

$$\int_{-\infty}^{\infty} \psi(t)dt = 0 \tag{1}$$

Wavelets of a particular family $\psi_{a,b}(t)$ are determined by the function $\psi(t)$ (mother wave) and the scaling function $\varphi(t)$ (father wave) in the time domain. They are scaled and translated copies of the mother wave $\psi(t)$, which is usually a fast damping or a finite wave vibration.

The Continuous Wavelet Transform (CWT) of a function $f(t)$ can be represented as follows:

$$Wf(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} f(t)\bar{\psi}\left(\frac{t-b}{a}\right) dt \tag{2}$$

Where a and b are the parameters of the scale and the position or the mother wave is scaled by a factor a and translated by coefficient b. By appropriately selecting the parameters a and b of the waveform, the function can be separated as low- and high-frequency signal components and analyze its local features.

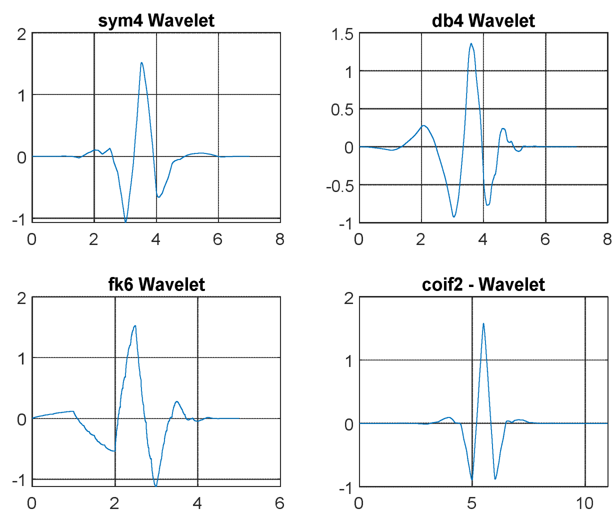

Figure 4. Mother wavelet functions used for denoising of EEG signal

IV. Wavelet Denoising Algorithm

The wavelet denoising algorithm will be applied to filter the signal. The denoising algorithm includes three major stages:

1. Decompose the signal from the original signal to different level composition by using a wavelet transform;

2. Threshold the signal based on the boundary of the noise;

3. Reconstruct the signal by using the reverse wavelet transform.

The block diagram of the algorithm is shown in Figure 5.

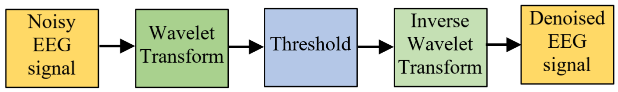

Figure 5. Block diagram of an interval-dependent threshold method

The denoising algorithm is applied to eliminate the noise from the useful signal [20] if the received signal consists of a useful and noisy constituent, as given in the equation:

$$y(\mathrm{t}) = x(\mathrm{t}) + \varepsilon(\mathrm{t}) \tag{3}$$

The analysis of $y(\mathrm{t})$ is equal to the sum of the analyses of signal $x(\mathrm{t})$ and the noise $\varepsilon(\mathrm{t})$.

The basis of this technique is the use of threshold functions with different forms, on the basis of which the limitation of the detailing coefficients is carried out. By setting a threshold value it is possible to “cut” the signal value below this threshold, it can significantly reduce the noise and shrink the signal. The threshold functions discussed in this paper and most commonly used in modern filtering algorithms have been represented in Figure 6 [20, 22]. The choice of threshold values for wavelet transform is a very important task. If the threshold value is too large or too small, the signal may not be detected accurately.

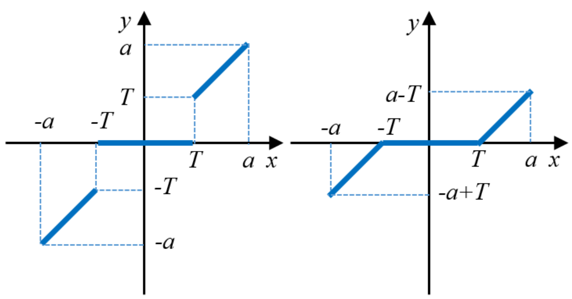

Figure 6. Threshold functions for processing the conversion coefficients: a) a hard threshold function; b) a soft threshold function

The hard threshold (Figure 6a) is described by equation [20]:

$$\mathrm{y(x)} = \begin{cases} x & if\ |x| \geq T \\ 0 & if\ |x| < T \end{cases} \tag{4}$$

The T-dimension can occupy values discussed below in the paper as x and y: the input and output coefficients of the wave transform.

Figure 6b shows the soft threshold function (soft threshold estimate), which is given by the expression [20]:

$$\mathrm{y(x)} = \begin{cases} sgn(x)(|x| - T) & if\ |x| \geq T \\ 0 & if\ |x| < T \end{cases} \tag{5}$$

The function $sgn(x)$ specifies the sign of the x coefficient.

$$sgn(x) = \begin{cases} 1,\ if\ x > 0 \\ 0,\ if\ x = 0 \\ -1,\ if\ x < 0 \end{cases} \tag{6}$$

The main difference between the soft threshold and the hard threshold is that the first (the soft threshold function) does not contain a jump at the point determined by the threshold value T. In other words, the soft function of the threshold, unlike the hard threshold, is continuous. Due to this circumstance, in the case of soft threshold processing, better signal processing is obtained near the break point. It should be noted that the reduction of the values of decomposition coefficients in the threshold value, in the case of a mute threshold processing, as a whole, for a large number of signals has a negative impact on the final evaluation of the quality of the recovered signal. Therefore, in general, as shown experimentally, better in terms of the numerical assessment of the quality of the recovered signal is the hard threshold estimate. In the case of soft threshold processing, the digital evaluation of the quality of the recovered signal is close to the latter in the case of hard threshold processing and it is necessary to select an appropriate threshold value T.

The denoising algorithm can be summarized by the following pseudo code:

1. Initialize noisy EEG signal (EEG_noise);
2. Wavelet function selection $\psi(t)$;
3. W_EEG_Signals = WT ($\psi(t)$, EEG_noise);
4. EEG_Denoise_Signals = THRESH (W_EEG_Signals);
5. EEG_Out_Signals = IWT (EEG_Denoise_Signals).

V. Experimental Results

To investigate the proposed denoising algorithm in this paper, the real EEG signal from healthy person was used. The EEG signal includes physiologic signals from the person and electrode noise. Part of the recording EEG signal is shown in Figure 7. Wavelet transform is proposed to remove the artifact from the EEG signal. In most cases, optimal mother wavelet functions are selected on the basis of the compatibility with the EEG signal characteristics to be analyzed. Accurate mother wavelet selection not only helps retain the original signal, but also enhances the frequency spectrum of the denoised signal.

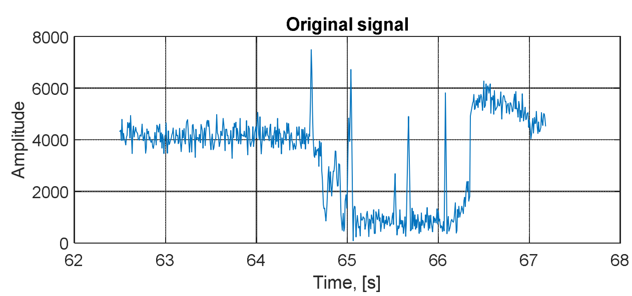

Figure 7. Original and denoised EEG signals

By using proposed algorithm and using wavelets Symlets (sim4), Daubechies (db4), Fejer-Korovkin (kf6), Coiflets (coif2), we obtained the result in Figures 8 and 9. The result shows that this algorithm is able to remove noise from the EEG signal effectively. The applied wavelet denoising algorithms are with threshold processing using thresholds, soft (Figure 8) and hard (Figure 9).

An important point in EEG signal processing via wavelet is the selection of a suitable mother wavelet and decomposition level to reduce the artifacts that contaminate EEG signals. The best selection of the wavelet function from the wavelet families helps conserve the decomposed EEG signal and obtain optimal reconstructed signals.

Using ANOVA, we determined the mother wavelet functions with the most significant differences to maximize their cross-correlation with the EEG signals. Statistical analysis was performed through ANOVAs in SPSS 22.

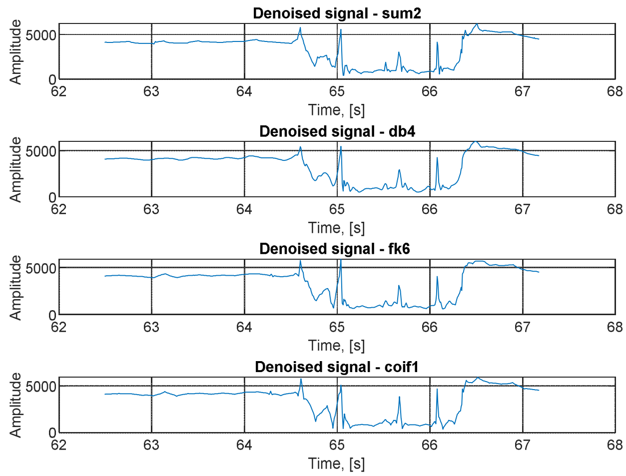

Figure 8. Denoised EEG signal by soft threshold

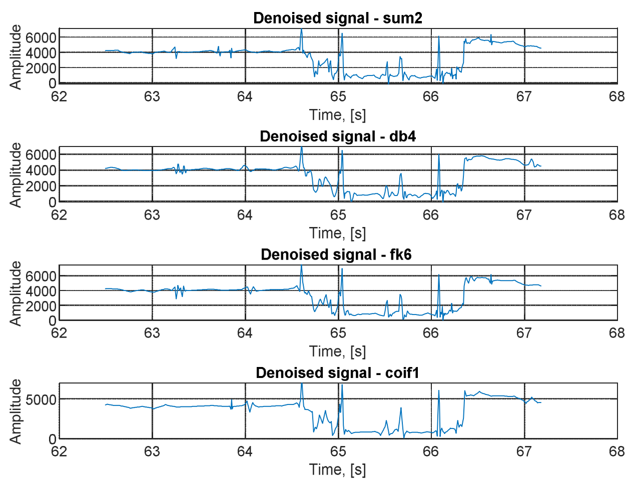

Figure 9. Denoised EEG signal by hard threshold

The significant differences among the four types of filtering and both types of threshold processing as dependent variable were evaluated. Post-hoc comparison was performed through Scheffe test. The significance was set at $p < 0.05$ [22, 23].

In our case, the best results were obtained using mother wavelet “db4” and hart threshold. Therefore, the most compatible mother wavelet with the EEG signals should be selected to achieve wavelet denoising, decomposition, reconstruction, and good feature extraction. The cross-correlation coefficients of EEG signals are shown in Table 1. The highest cross-correlation coefficient was obtained at mother wavelet “db4” and hart threshold. The results show that the choice of the wavelet function, as well as the type of threshold are essential for the denoising of the EEG signal. To optimize the selection process, this article proposes an intelligent upgrade for modeling and preprocessing EEG signals using a library of wavelets and a plurality of thresholds to denoise the EEG signal. For this purpose, Binding and Pointing are used as constraints for post-processing of the obtained wavelet results.

TABLE I. Cross-correlation of EEG signals

Name of wavelet	Type of threshold	
	Soft	Hard
sym4	0.9552	0.9606
db4	0.9566	0.9684
kf6	0.9572	0.9607
coif2	0.9569	0.9605

The default threshold value from the library control system is pointed to hard, and the set of wavelets is pointed to the four cases from Fig. 9. The usage of the pointing constraints aims to avoid the expensive and time consuming deep learning or other analogical procedures. This does not mean that the pointed values will be set in all cases. The values are shifted via system inquiries on different fault events or manually. The considered set of faults includes grip liquid contact problems, necessary adjustments and so on. The events including skin tremors, external noise, and work in rapidly changing environments will influence the defeat or adjustment of the pointed values. Hence, the control of wavelet/threshold values is realized in a data-driven manner without the usage of ANNs, probabilistic or possibilistic means. The system improvement procedures are based on the analysis of the answers to typical questions: WHY the outcome is so different when using wavelets from the library in the region 65-66s in Fig. 9, WHEN the reason leading to error occurrence will be revealed and eliminated, HOW the wavelet application influences the analysis of weak brain signals, etc. In this case, the research goes into ontological direction from [17].

The automatic answers to the considered questions are still out of scope of the considered research, but their appearance in the system log files makes the system more versatile and data-driven.

The focus of the system is binded to finding very small error signal values. The comparison in time segment around the middle of [63s,64s] in Fig. 9 sets the binding to db4 and fk6, but around 64s the binding is changed to the other two wavelets from the set. The general question WHAT is the reason (meaning) for this shift could help us improve the denoising procedures and keep the negligibly small signals in the focus.

The binding aims to eliminate the repeating error patterns caused by eyeball movements, etc. The irregular error events are more difficult to be revealed and in this case the above mentioned manual procedures had been applied. The binding of repeating error signal events helps for the revealing of other analogical errors like double eye blinking etc. The binding constraint analysis helps to reveal repeating patterns in the outcome EEG signals produced by pulse or other reasons. The reasons raise new questions WHY, WHAT, WHEN earlier described in this section.

The binding and pointing constraints allow us to model and process both interconnected EEG and error signals in a more universal way where the connections and larger parameter changes stay in the focus. Also, binding constraints are frequently applied to defeat different features, among them: how to make linear constraints slightly nonlinear in certain regions. A research on the transition of classical constraints into a system of ontologies is in progress. The application of the binding and pointing constraints helps us to reveal different hidden interconnections between signals or parts of a signal. Their analysis will all possible means leads to significant improvements.

VI. Conclusion

Different types of noise and artifacts contaminate EEG signals. In this paper, wavelet transform is proposed to remove the artifact from the EEG signal. The method is using wavelet transform because effectively eliminates noise and retains the information. In this study, the compatibility of four mother wavelet basis functions from the Daubechies, Symlets, Fejer-Korovkin, and Coiflets families were selected and subjected to analysis. Using ANOVA, we determined the mother wavelet and the type of threshold which maximize the cross-correlation with the EEG signals. From the obtained results we can conclude that the choice of mother wavelet is a complex process and the denoising stage could be implemented by using artificial neural networks and deep learning methods (ANNs).

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