**Data Science Modeling and Constraint-Based Data Selection for EEG Signals Denoising Using Wavelet Transforms**

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**Abstract—** This work presents basic information about Electroencephalogram (EEG) signals, their processing and application in practice. Modeling and constraint satisfaction cases have been considered aiming at diminishing the manual labor during the wavelet signal filtering and fitting to medical applications. The 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 have been applied. In case when there is a need of constraint shift/modification/elimination, new types of constraints are considered and applied.

**Keywords:** Wavelet Transform, Denoising of EEG Signals, Intelligent System, Data Science, Data Selection, Constraint Satisfaction, Puzzle Methods

**1. 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. In these conditions original deep modeling applications have been elaborated and considered, they are naturally combinable with classical constraint satisfaction cases. Deep modeling methods are fit to describe and gradually sustain different thinking and reasoning processes. They are effective in conditions when the logical reasoning is rather constrained and the machine learning using ANN couldn’t be widely applied because of the lack of proof explanations. It is considered that both classical and nonclassical logical operators may be applied in one scheme. On the other hand, the effectiveness of data selection and data processing significantly increases.

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]. Furthermore, in order to remove the EMG signal from the EEG signal, Lanlan used the db4 wavelet and decomposed it using 8 layers [6]. 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 [6], Araghi used the bior3.3 discrete wavelet transform and decomposed it using six layers to remove the artifact from the EEG signal [7]. 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 [8]. 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 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 chapter is organized as follows: In Section 2, a deep knowledge modeling and its puzzle methods applications had been considered. In Section 3 we comment a Electroencephalography applications. In Section 4, we discuss EEG signal denoising algorithm using wavelet transform. In Section 5, we present analysis of variance (ANOVA). In section 6, we discuss experimental results. Finally, in Section 7, we present the conclusions.

**2. 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 versatility and applications, and diminish the manual work much of which is hidden behind the perfect mathematically described apparatus. 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. Such 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, data-driven approaches and/or machine learning methods are used for this purpose [9-11]. 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 [12-16], but in most of 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. They are considered in connection with the research of the Puzzle method using the system of classical constraints [17]. The goal is to form a closed area is formed aiming at focus attention of a software agent to certain data including two objects M and N (Figure 1).

V1

V2

V3

M

N

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 than in the standard case but still it may be too large to explore. If the data selection process is enough effective, the focusing process/area closure helps to reveal a new information concerning data, metadata, knowledge and/or metaknowledge for objects M and N, for example: ’it follows from M that N is true’ or ‘there is a significant relation between M and N’. Some disadvantages: the constraint satisfaction is a rather static process. The set of constraints cannot be modified during the solving process. On the other hand, what is the constraint in the application sense? If this is a line/curve drawn on a surface, it should be enough to notice it to prevent crossing it. And what is its functionality? When the crossing itself is harmful not just to the intruder but only to the others, in many cases the violation will be a fact. Many other application problems arise. Below are the proposed solutions to the problems.

The constraint satisfaction solution should take in the account *why* does the constraint appear, *when* it could disappear, *how* does it apply, etc. Aiming at the data selection flexibility, new metaknowledge forms have been elaborated concerning logical-based control of the constraint application process.

First of all, the number of the linear constraints may be less than 3 depending on the selected set of goals. Then, one and the same constraint may be treated differently depending on the current conditions.

Denote the object M is a city museum area rounded by ancient city walls with a visitor entrance, service entrance and a hidden tunnel beneath the walls. Let the population P of individuals A,B,C,D,I ϵ P consists of individuals A and B with some ordinary and many hidden secret intelligence functions, a museum guardian C, a set of ordinary visitors D and an intruder I disguised as a tourist. Every individual can reveal a place on the wall where one can jump out outside the constraints (museum walls) but cannot return. Hence the constraint role could be broken only in one direction and this could be done only in an illegal manner. On the other hand, the individuals A, B, C could penetrate through the set of constraints legally through the service entrance, and all considered individuals could go through the constraints via the official entrance. The intruder appeared at the site M because of a gathered information that something peculiar happens. Could the drawing attention event be described using the standard set of objective or fitness functions? In general case this is possible. A generalized case is described below, it supports a more deep and effective modeling.

Let only A has means to use the hidden tunnel. Every such usage could attract the attention of I. Also I could conclude its existence analyzing the distribution of external guarding devices, and other collateral information. As a result I will reveal the most possible location of the tunnel entrance. This is modeled as a binding region with the maximum probability value in the centre. The usage of visual surveillance/drones/satellite information constantly or temporary extends the guarded region outside the walls. The described toy problem case aims to reveal the need of an introduction of new, logical-based types of constraints.

Aiming at better deep modeling, it is proposed to use three non classical groups of constraints: binding, pointing and crossword constraints. Binding constraints model situations where the solution is/was not far or close to the center of the binding area. A case is best investigated wren 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. It is explored that the binding process may be unconditional or conditional, it may invalidate the linearity/range/the region of the usage and/or other properties of other constraints intersecting the binding domain. In Fig. 2 the binding constraints are represented by the lines {B, D} intersecting the surface containing the required/searched solution G1.

V1

V2

V3

A

B

C1

C2

D

E

G1

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

Together with the binding constraints of Figure 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 group of constraints is the crossword one depicted by {C1, C2} from Figure 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 G1 when only some parts of the solution {C1, C2} are known. For this purpose, combinations of other types of constraints are most often used, the relationships between {C1, C2}, etc. are studied. {C1, C2} 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 {C1, C2} 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 {C1, C2}. 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.

In EEG applications the pointing examples frequently concern the points in the centers of the binding areas where the signals were successfully obtained. The binding examples also concern best signal processing practice, good medical practice and so on. In the latter case little changes are possible: some binding models naturally support fuzzy and neuro-fuzzy applications. The pointing constraints are used for description and maximization of the effectiveness of specific brain-computer interface features and communications to other medical devices. Not only the good practice but also bad practice examples could be described using pointing and/or binding constraints. The proposed novel groups of constraints are not purposed to change the signal processing schemes.

**3. Electroencephalography (EEG) applications**

***3.1 Electroencephalography***

Electroencephalography (EEG) measures the electrical activity generated by the brain using electrodes placed on the scalp [18]. EEG (popularly known as *brain waves)* measures the sum of the post-synaptic potentials generated by thousands of neurons having the same radial orientation with respect to the scalp (Figure 3).



Figure 3. Example of EEG signal for a healthy subject (time is displayed in seconds).

Signals recorded by EEG have a very weak amplitude, in the order of some microvolts. It is thus necessary to strongly amplify these signals before digitizing and processing them. Typically, EEG signals measurements are performed using a number of electrodes which varies from 1 to about 256, these electrodes being generally attached using an elastic cap. The contact between the electrodes and the skin is generally enhanced by the use of a conductive gel or paste. This makes the electrode montage procedure a generally tedious and lengthy operation. Electrodes are generally placed and named according to a standard model, namely, the 10-20 international system (Figure 4). This system has been initially designed for 19 electrodes, however, extended versions have been proposed in order to deal with a larger number of electrodes. EEG signals are composed of different oscillations named “rhythms”. These rhythms have distinct properties in terms of spatial and spectral localization. The normally used terms for EEG frequency bands whose sample is shown in Figure 5.

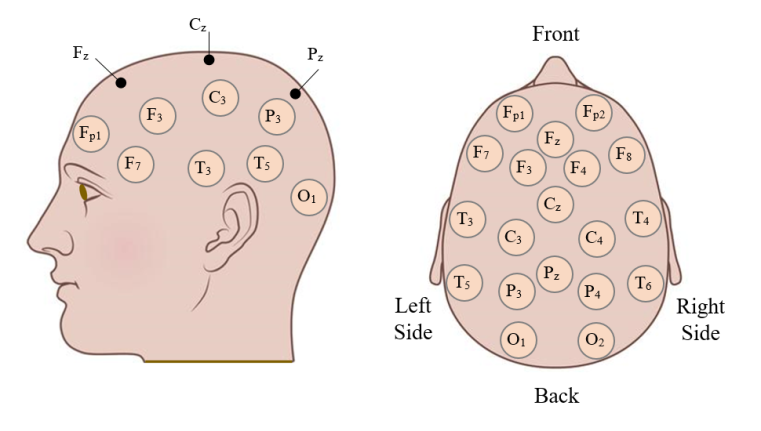


Figure 4. Positions and names of the 10-20 international system electrodes.



Figure 5. Five major brain waves distinguished by their different frequency ranges.

• **Delta rhythm:** This is a slow rhythm (0.5-4 Hz), with a relatively large amplitude, which is mainly found in adults during a deep sleep. Delta waves occur during meditation in a state of deep sleep or coma. Abnormal delta activity may occur with the person, has learning disabilities or have difficulties maintaining conscious awareness (such as in cases of brain injuries).

• **Theta rhythm:** This a slightly faster rhythm (4-7 Hz), observed mainly during drowsiness and in young children. Theta waves are involved in sleep or daydreaming. This brain wave can indicate intuition or automatic tasks.

• **Alpha rhythm:** These are oscillations, located in the 7-13 Hz frequency band, which appear mainly in the posterior regions of the head (occipital lobe) when the subject has closed eyes or is in a relaxation state. Alpha waves connect the gap between our conscious thinking and subconscious mind. It helps us to calm down or it promotes a feeling of relaxation.

• **Beta rhythm:** This is a relatively fast rhythm, belonging approximately to the 13-30 Hz frequency band. It is a rhythm which is observed in awaken and conscious persons. This rhythm is also affected by the performance of movements, in the motor areas. Beta waves are active in a waking state. This frequency is visible in logical-analytical reasoning. In their activity, we focus on a problem solving.

• **Gamma rhythm:** This rhythm concerns mainly frequencies above 30 Hz. This rhythm is sometimes defined has having a maximal frequency around 80 Hz or 100 Hz. It is associated to various cognitive and motor functions. Gamma waves are important for learning, memory and information processing.

***3.2. Signal and data processing of EEG***

Due to very low in amplitude, EEG signals are prone to artifacts and noise [19]. The noise can be electrode noise or can be generated from the body itself. These various types of noises that can contaminate the signals during recordings are the electrode noise, baseline movement, EMG disturbance, eye movements, eye blinks and sometimes ECG disturbance. The noises in the EEG signals are called the artifacts and these artifacts are needed to be removed from the original signal as noise/artifacts makes analysis and further processing of the EEG signals difficult.

The signal and data processing of EEG could be gathered into a single and more general, higher level component, which could be denoted as “EEG processing”. This component is a key element in the design of a processing algorithm as it aims at transforming the input brain signals into a command for a given application. As such, the “EEG processing” component can be seen as the preprocessing, feature extraction and classification of EEG signals (figure 6).

Signal Analysis & Feature extraction

Preprocessing

Signal processing

Data processing

Data clustering & Classification

Multi-channel EEG Collection

Figure 6. Signal and data processing of EEG signals

It is important to note that the boundaries between the “preprocessing”, “Signal analysis & feature extraction” and “Data clustering & classification” components are not hard boundaries, and these boundaries may even appear as fuzzy. Thus, the preprocessing and feature extraction components are sometimes merged into a single algorithm, whereas the classification algorithm can be missing or reduced to its simplest form, i.e., a decision threshold on the feature values. However, it is interesting to distinguish these components, as they have different inputs and outputs as well as different goals.

*3.2.1 Preprocessing*

Once the data have been acquired, they are generally preprocessed in order to clean (de-noise) the signals and/or to enhance relevant information embedded in these signals [20]. Indeed, EEG signals are known to be very noisy, as they can be easily affected by the electrical activity of the eyes (EOG: ElectroOcculoGram) or of the muscles (EMG: ElectroMyoGram), e.g., face or jaw muscles. These muscle artifacts are especially annoying as they have an amplitude which is much larger than the one of EEG signals. As such, it appears as difficult to remove these artifacts without accidentaly removing relevant information embedded in these EEG signals. Moreover, it is interesting to remove the background brain activity which is not related to the neurophysiological signals of interest. Overall, the preprocessing step can be defined as a method which transforms a set of signals into a new set of signals which are supposedly denoised. In other words, the preprocessing step aims at increasing the signal-tonoise ratio of the input signals.

In order to perform this preprocessing, various spatio-spectro-temporal filters are used [21, 22]. These filters can be simple frequency filters or more advanced filters such as independant component analysis [23] or common spatial patterns [24].

*3.2.2. Signal analysis and feature extraction*

Measuring brain activity through EEG leads to the acquisition of a large amount of data. Indeed, EEG signals are generally recorded with a number of electrodes varying from 1 to 256 and with a sampling frequency varying from 100 Hz to 1000 Hz. In order to obtain the best possible performances, it is necessary to work with a smaller number of values which describe some relevant properties of the signals. These values are known as “features”. Such features can be, for instance, the power of the EEG signals in different frequency bands. Features are generally aggregated into a vector known as “feature vector”. Thus, feature extraction can be defined as an operation which transforms one or several signals into a feature vector. Identifying and extracting good features from signals is a crucial step in Signal analysis and feature extraction. Indeed, if the features extracted from EEG are not relevant and do not describe well the neurophysiological signals employed, the classification algorithm which will use such features will have trouble identifying the class of these features, i.e., the mental state of the user. Consequently, the correct recognition rates of mental states will be very low, which will make the use of the interface not convenient or even impossible for the user. Thus, even if it is sometimes possible to use raw signals as the input of the classification algorithm, it is recommended to select and extract good features in order to maximize the performances of the system by making easier the task of the subsequent classification algorithm. According to some researchers, it seems that the choice of a good preprocessing and feature extraction method have more impact on the final performances than the choice of a good classification algorithm [25].

In the following we focus on different features extracted from EEG signals for emotion detection. These techniques can be divided in three main groups, which are: 1) the methods that exploit the temporal information embedded in the signals [26], 2) the methods that exploit the frequential information [27] and 3) hybrid methods, based on time-frequency representations, which exploit both the temporal and frequential information [28].

*a) Time domain features*

These features are extracted from the signal in its original domain. First of all, the statistical properties of the signal such as mean, standard deviation, maximum, minimum, difference of maximum and minimum, median, mode and power are mostly used. Another feature is entropy, which is the symbol of scattering data [29]. Also, Hjorth in 1970 [30], introduced some features called activity, mobility and complexity, which are then used by researchers for EEG emotion detection [31]. Other common features in time domain include fractal dimension [32], non-stationary index [33], Higher Order Crossings [34].

*b) Frequency domain features*

Presentation of a signal in frequency domain is possible by using Fourier transform. The mostly used algorithm to compute Discrete Fourier Transform (DFT) is Fast Fourier Transform (FFT). The most popular feature in the context of emotion recognition from EEG is power in different frequency bands [35]. It is assumed that the signal is stationary for the duration of a trial. Different frequency bands are found by wavelet transform. The frequency bands of EEG signals slightly vary in different studies. The extracted features from the resulting representation of the signal in frequency domain are: average power (mean) of frequency bands [36], and relative minimum, maximum, and variance. Additionally, the ratio of mean band powers is calculated for each channel. A set of frequency domain features has been introduced by Hosseini and et al. in [37] which is called higher order spectra.

*c) Time frequency domain features*

If a signal is non-stationary, time-frequency methods can provide additional information by considering dynamical changes. In this category we can mention the features extracted by applying the wavelet transform to the signal [38]. Also, Hilbert- Huang spectrum of intrinsic mode functions is used [39].

***3.2.3. Classification***

After feature extraction, the extracted features should be classified for identifying neurophysiological signalsby using an appropriate classification algorithm. Classification is achieved using algorithms known as “classifiers”. Classifiers are able to learn how to identify the class of a feature vector, thanks to training sets. These sets are composed of feature vectors labeled with their class of belonging.

These classifiers can be divided into several categories which are: linear analysis, nonlinear analysis, adaptive algorithms, clustering and fuzzy techniques, and neural networks [18, 20, 40].

***3.3. Applications of EEG***

Applying appropriate signal processing of brain signals and evaluation of some of the parameters of the signals, it is possible to solve a wide range of tasks. Some applications of EEG signals are used to assess various emotional and physiological states of a person such as whether he is healthy or sick, happy or unhappy, calm or anxious and many others. It is possible to assess many other conditions, such as whether he has consumed alcohol or not, whether he has used GSM or not, and others. EEG devices can provide valuable information about human mental health states, thoughts, and imagination [20]. Electroencephalography can be used for various applications. Below is a list of the three most common applications of EEG technology:

**Neuroscience and Clinical Applications**

Neuroscience attempts to understand the functionality of the nervous system. It allows clinical or non-clinical researchers to get an idea about how the brain acts when humans experience different emotional states and how the brain works in various mental states. Researchers have applied EEG devices in their studies in the below fields. Most generally, psychological studies utilize EEG to study the brain processes underlying attention, learning, and memory. How do we perceive the world? How do our expectations shape the way we see our surroundings?

Whenever brain processes are impaired, deficits in behavioral, attentional and cognitive processing can be observed. Clinical and psychiatric fields use EEG to evaluate the patients’ cognitive states, determine lesion sites, and classify symptoms.

Also, EEG is heavily used to evaluate the effect of medical and psychological treatment. More and more therapies utilize virtual reality technology and record EEG data to monitor how the patients’ brains improve over time.

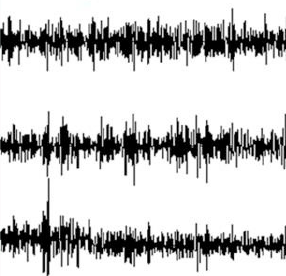
Real-time EEG signals can be used to provide immediate information about brain-wave activities. EEG data have been applied for diagnosing and predicting many abnormal brain diseases and cognitive impairments, as Epilepsy; Parkinson’s Disease; Memory problems like Alzheimer’s; Language impairments such as Dyslexia; Attention Deficit Hyperactivity Disorder; Seizures; Schizophrenia; Autism in adults and children; Sleep disorders and insomnia; Anxiety; Post-traumatic stress disorder; Huntington’s disease; Multiple sclerosis diagnosis; Amyotrophic lateral sclerosis; Traumatic brain injury; Coma; Level of consciousness and Neurosurgery [41-45].

Raw data

Signal and data processing

Applications



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Neuroscience and Clinical Applications

Brain-Computer Interface

Human Factors and Custom Solutions

Figure 7.Applications of EEG signals

Neuroscience can also be applied to understanding human emotion in VR with/without the ability to touch the environment by displaying various types of media, such as: Real world or VR pictures; Images of nature and city environments; TV advertisements; Auditory stimuli; Multimedia, along with memory recall and dreams [46-48]. Cognitive neuroscience is studding Measuring cognitive load; Detecting differences between brain wave activity during suicidal and non-suicidal states. Understanding brain activity during insight (insight is a moment where a human understands how to solve a puzzle or gains knowledge); Analyzing brain workload during decision making or learning a new task; Studying sleep pattern [49, 50].

Behavioral neuroscience is studding Changing the workplace light and measuring brain alertness status; Measuring drowsiness or sleep detection for drivers and pilots; Measuring mental workload of deaf children exposed to a noisy environment during a word recognition task; Determining surgeon stress level while performing surgery; Identifying and reducing stress level; Environmental Psychology. Neurophysiology is studding Measuring changes in brain after drinking alcohol; Detecting fatigue, GSM talking [51-53].

**Brain-Computer Interfaces (BCI):**

BCIs, sometimes called brain–machine interfaces (BMIs), are one of the most common applications of EEG. BCIs use real-time EEG data to control and direct mechanical and electronic devices.

BCI devices are commonly used as a human–machine interface to help individuals with mild to severe motor disabilities, including those who are not able to communicate with others. This can help paralyzed patients steer their wheelchairs or move a cursor on a screen. The most common BCI applications are aimed at people with disabilities or motor activity impairment also control of mechatronic devices by control of mobile phone apps using eyewinks; directing electrical wheelchair movement; control of artificial body part such as prosthetic hand or arm; controlling a robot using body gestures; speech recognition system for people with speech disability; mouse cursor control using imagined hand movement; controlling a video game or virtual reality (VR) environment using body gesture and eye movement; controlling of robotic body parts, robot, drone and vehicle. Monitoring and controlling sensors inside of smart houses [54, 55].

**Human Factors and Custom Solutions:**

Originating from Psychology, the field of Human Factors focuses on workplace optimization; both with respect to tools and interfaces as well as social interaction. In this area, EEG research is used to identify brain processes related to specific personality traits such as intro-/extroversion or social anxiety. Additionally, brain processes can provide information about individuals’ differences. Recently, cognitive and emotional brain status has been utilized for biometrics, meaning EEG data are used to identify people.

Some research attempts to understand customers’ preferences and expectations regarding a specific product and their reaction to TV advertising by analyzing EEG signals. In the field of neuromarketing, economists use EEG research to detect brain processes that drive consumer decisions, brain areas that are active when we purchase a product/service, and mental states that the respective person is in when exploring physical or virtual stores.

Some customized EEG solutions are Sport, fitness and meditation: Monitoring health status and boosting quality of life using brain activity during exercise and listening to music. Measuring the reading ability of students; Measuring confusion level during online lectures or concentration level and cognitive workload when students are trying to solve a math puzzle with the aim of designing intelligent tutor systems (ITS); Real-time brain visualization, which can have educational, training, or entertainment applications [56, 57].

The processing and analysis of EEG signals and their subsequent application requires in-depth knowledge in the field of signal and data processing. There is a wide variety of algorithms for processing EEG signals as well as methods for assessing and recognizing human mental activity, but there is still no unified algorithm to be used in practice and to give results with a high probability of recognizing mental activity. This requires the use of intelligent decision-making systems and adaptive replacement and tuning of the algorithms used. In this article, we consider only one exemplary task in EEG signal processing. Our goal is to offer an intelligent solution to the problem of denoising of EEG signal by using Wavelet transform. The problems in solving this task are, choice of mother wavelet, decomposition level and threshold. The selection of these parameters will be made through the application of statistical analysis using the ANOVA method. To automate this process, the article proposes the use of deep modeling and the use of intelligent decision-making systems to configure the best algorithm.

**4.** **EEG Signal Denoising Using Wavelets**

**4.1. Wavelet transform**

Wavelet transform is a powerful method to analyze the EEG signals. This method could present the time – scale information of the signal. 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. Recently, WT has been extensively used with non-stationary signals because WT shown powerful in removal several EEG artifact noises, which can be corrupted the original EEG signal during recording time, such as eye blinking noise, eye movement noise, muscles activity noise, power line noise, and electromyogram noise [58]. 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 [59]. In addition, wavelet is able to filter the signal as well as classify the signal. 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 (Figure 8) [58, 60]. WT can be classified into two categories: continuous wavelet transform (CWT) and discrete wavelet transform (DWT).



Figure 8. Mother wavelet functions used for denoising of EEG signal

The CWT performs a multiresolution analysis by contraction and dilatation of the wavelet functions. The discrete wavelet transform (DWT) uses filter banks for the construction of the multiresolution time-frequency plane. The time-frequency resolution problem is caused by the Heisenberg uncertainty principle and exists regardless of the used analysis technique. By using an approach called multiresolution analysis it is possible to analyze a signal at different frequencies with different resolutions. A filter bank consists of filters which separate a signal into frequency bands. An example of a three channel filter bank is shown in Figure 9. A discrete time signal enters the analysis bank and is filtered by a low-pass filter and a high-pass filter which separate the frequency content of the input signal in frequency bands of equal width. The output of the filters each contain half the frequency content, but an equal amount of samples as the input signal. The two outputs together contain the same frequency content as the input signal, however the amount of data is doubled. Therefore downsampling by a factor two, denoted by , is applied to the outputs of the filters in the analysis bank. The DWT decomposes a signal into different frequency bands by passing it through two quadrature mirror filters via a finite impulse response, where is a high-pass filter and is a low-pass filter. is related to the scaling function, whereas is related to the mother WT.

Using Mallat’s fast algorithms [61] the gradual decomposition of the original signal become:

(1)

(2)

The signal convolves with when this signal acts as an LPF; otherwise, this signal acts as an HPF and convolves with . The result transforms the original signal into two sub-bands and . is the approximation component that represents low-resolution components; is the detail decomposition component that describes high-resolution components [59, 60].

Signal

Detail D3

Approximation A3

Detail D2

Detail D1

2

LPF1

HPF1

2

2

LPF2

HPF2

2

2

LPF3

HPF3

2

Figure 9. Discrete wavelet decomposition tree

Reconstruction of the original signal (Inverse Wavelet Transform) is possible using the synthesis filter bank, where the signals are upsampled and passed through a low-pass and a high-pass filters. The filters in the synthesis bank are based on the filters in the analysis bank. The outputs of the filters in the synthesis bank are summed, leading to the reconstructed signal.

# **4.2. 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: In this phase, the original EEG signal will be divided into several levels based on the decomposition level value. At each level, the EEG signal will decompose into two parts namely Approximation coefficients (cA), and Detail coefficients (cD). The detail coefficients will process using high-pass filter and approximation coefficients will continue decompose for next level. Figure 10 shows the decomposition process using DWT for three decomposition level. The first two parameters of WT which are wavelet function name or mother wavelet function (Ф) and Decomposition level (L) must be selected in this phase.

2. Threshold the signal based on the boundary of the noise: In this phase, the thresholding type (β), thresholding selection method (λ), and wavelet rescaling approach (ρ) must be determined for each level according to the coefficients noise level in the corrupted EEG signal.

3. Reconstruct the signal by using the reverse wavelet transform. In this phase, the EEG denoised signal is reconstructed using Inverse Discrete Wavelet Transform (IDWT). Figure 10 shows the signal reconstruction process for three decomposition level.

Threshold

Reconstruction

Level 3

Level 2

Level 1

A3

D3

A2

D2

A1

D1

EEG Denoised signal

Decomposition

Level 2

Level 3

cA3

cD3

cA2

cD2

Noisy EEG signal

Level 1

cA1

cD1

mother wavelet

Figure 10. Wavelet Denoising Algorithm

The denoising algorithm is applied to eliminate the noise from the useful signal [58] if the received signal consists of a useful and noisy constituent, as given in the equation:

(3)

The analysis of is equal to the sum of the analyses of signal and the noise .

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 11 [62]. 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.

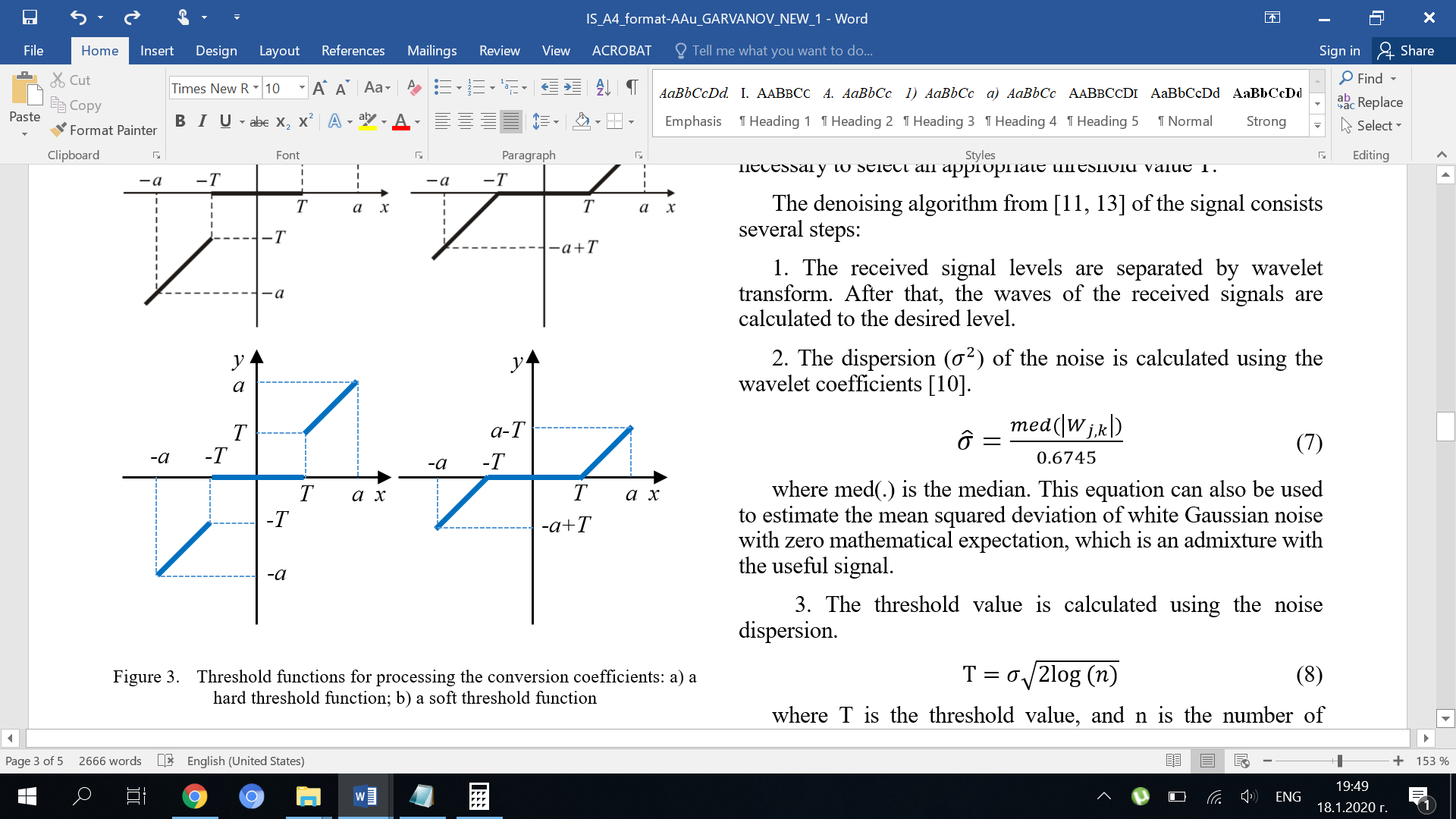


Figure 11. Threshold functions for processing the conversion coefficients: а) a hard threshold function; b) a soft threshold function

The hard threshold (Figure 11а) is described by equation [61]:

(4)

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

Figure 11b shows the soft threshold function (soft threshold estimate), which is given by the expression [62]:

(5)

The function specifies the sign of the coefficient.

(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 . 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 .

Wavelet selection, as well as wavelet decomposition level, and selected threshold can be made by applying statistical analysis using the ANOVA method.

**5. Analysis of variance (ANOVA)**

There are two types of variables in the ANOVA (Analysis-Of-Variance): independent and dependent variables. Independent variables or factors are used to group the data. They have two, three or any finite number of levels. One-Way ANOVA assumes the presence of one independent variable (factor) with two or more levels. The dependent variable sets the differentiating feature by which the groups (samples) are compared. Changes in the dependent variable are, or are assumed to be, a consequence of changes in the independent variable, which is why it is often called the result variable. In the univariate analysis, the simultaneous independent effects (so-called “main effects”) and interactions of two or more independent variables on the dependent variable are evaluated by a generalized statistical procedure.

ANOVA is used to test hypotheses, whether several means are equal. This technique is an extension of the t-test for independent samples, making it possible to determine not only the differences between the mean values, but also which exact mean values ​​differ from the others. There are two types of tests to compare means: a priori contrasts and post hoc tests. Contrasts are tests performed before the experiment, and post hoc tests are performed after the experiment. The trends between categories can also be tested.

The values of the factor (discrete independent variable) should be integers and the dependent variable must be quantitative (interval level of measurement). Each group is an independent random sample of the normal population. The analysis of variance is resistant to deviations from normality, although the data should be symmetrical. The groups should come from populations with equal variances. To test this hypothesis, the Levene test for dispersion homogeneity is applied.

Therefore, the logic of the analysis of variance is based on the decomposition of the total variance of the variable (deviation of all values ​​from their total mean) into two important components: intergroup variance – the deviations of group means from the total mean and intragroup variance – the individual deviations of the values from the mean within a given category (group). ANOVA uses the statistic F as the ratio of between and within group variances. The stronger the effect of the factor value, the greater the differences between the intergroup variance and the intragroup variance (the value of F will be great).

**6. 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 12. 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 12. 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 13 and 14. 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 13) and hard (Figure 14).

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 13. Denoised EEG signal by soft threshold



Figure 14. 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 [63].

In our case, the best results were obtained using mother wavelet “sym4” 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 “sym4” 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.

1. Cross-correlation of EEG signals

|  |  |  |
| --- | --- | --- |
| Name of wavelet | Type of threshold | |
| Soft | Hard |
| sym4 | 0.868 | 0.885 |
| db4 | 0.869 | 0.882 |
| kf6 | 0.869 | 0.883 |
| coif2 | 0.868 | 0.882 |

The default threshold value from the control system is pointed to hard, and the set of wavelets is pointed to the considered four cases from Figure 14. The usage of the pointing constraints aims to avoid the expensive and time consuming deep learning or 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 or probabilistic means. The system gradual improvement procedures are based on the analysis of the answers to typical questions, among them: WHY the outcome is so different when using wavelets from the library in the region 81-82s in Figure 14, WHEN the reason leading to error occurrence is planned to be revealed and eliminated, HOW the wavelet application influences the analysis of weakest brain signals, and so on. In this case, the research goes into ontological direction described in the book chapter [17].

The automatic answers to the quoted 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. It gives opportunity to make more effective the existing manual work.

The binding process aims to eliminate the repeating error patterns caused by eyeball movements, and different non expected processes. The rare/irregular error events are more difficult to be revealed. In this case the above mentioned manual signal processing preparation procedures had been applied. This is avoided in the considered constraint modeling application. The binding of repeating error signal events helps to reveal analogical errors like double eye blinking etc. The binding constraint analysis emphasizes repeating patterns in the outcome EEG signals produced by pulse or other reasons. The analysis of the reasons raises new questions WHY, WHAT, WHEN earlier described in this section and points to the new unknown knowledge groups which should be linked to the existing knowledge base and experience.

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. For example, we may point to some knowledge or dataset as peculiar/odd that later return to analyze it. Also, binding constraints are frequently applied to defeat different features, among them: how to make linear constraints slightly nonlinear in binding or certain pointed regions. A research on the transition of classical constraint sets into a system of ontologies is in progress. The mutual application of binding and pointing constraints helps us to reveal different hidden interconnections between signals or parts of a signal. Their analysis with all possible means leads to significant improvements.

**7. Conclusions**

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). Examples are considered of new constraint applications from binding and/or pointing groups. Their usage doesn’t change the considered signal processing schemes but makes them more effective and the modeling tools mode deep and universal.

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