DENOISING ELECTROENCEPHALOGRAM (EEG) SIGNALS OF DEAF ADULTS WITH NO EARLY INTERVENTION USING HYBRID Β-HILL CLIMBING ALGORITHM(HBHC) AND WAVELET TRANSFORM(WT)

Shirly G[1], Jerritta S[2*]

[1]School of Engineering, Department of Electronics & Communication Engineering, Vels Institute of Science, Technology and Advanced Studies (VISTAS) and National Institute of Speech & Hearing(NISH), India

[2]School of Engineering, Department of Electronics & Communication Engineering, Vels Institute of Science, Technology and Advanced Studies (VISTAS), India

*Corresponding Author: sn.jerritta@gmail.com

Abstract

When dedicated neural structures in the brain that rely on auditory input fail to remember to transmit impulses to remedy the failure of the language processing location of the brain at the age of 17+, a method must be devised. Participants were non early intervened deaf and hard of hearing undergraduates. All of them use Indian Sign Language. Their language skill is dismal and their incidental learning was affected. Electroencephalogram (EEG) is vital in detecting brain activity. Electrical activity reported is often polluted with artifacts which affect the exploration of EEG signals. There are several approaches available to remove artifacts. This study concentrates on muscular artifacts during finger spelling of words and used hybridization between β-hill climbing algorithm and wavelet transform (WT). β-hill climbing is proposed to find optimal wavelet parameters for EEG signal denoising. Performance was calculated by statistical parameters mean square error (MSE), mean absolute error (MAE), peak signal-to-noise ratio (PSNR), signal to noise ratio (SNR), and percentage root mean square difference (PRD). The study proves that ‘db4’ wavelet function gives the better performance than the other wavelet function or hybrid filters.

1) **Keywords**: electroencephalogram, hybrid filter, statistical parameters, artifacts, deaf adults

1. Introduction

The first three years of life are the crucial time of brain development, but it persists during early childhood and adolescence [1]. First language acquisition should happen during this critical age for first language acquisition [2]. After this critical period, the acquisition of grammar is difficult and is never fully achieved for most. Learning, behaviour, and health are all built on the foundation of flexible or plastic neural circuits. They become inflexible over time. Language acquisition does not favour adults over children. Deaf teens, on average, perform many grade equivalents lower than their peers in high school at the mean level of reading comprehension, according to numerous studies [3]. Language is a core intellectual ability. It is supported by complex neural and psychological mechanisms. In the first few years of life, the brain develops rapidly.

A complex neural network develops in the brain during the early acquisition of the first language. Event-related potential (ERP) constitutes a millisecond-by-millisecond record of neural information processing [4]. It is evoked by an external or internal event [5]. To

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understand how a deaf person reads, ERPs can be recorded, which respond to specific aspects of language. Comprehension can be tested analytically.

Electroencephalography (EEG) denotes the electrical activity of the brain. It represents the voltage fluctuations resulting from ionic current flows within the neurons of the brain [6][7] which are measured with electrodes on the scalp [8]. EEG is an easy and non-invasive [9] electrical pulse measurement tool. It detects the electrical field produced by the joint activity of millions of cortical neurons that can be detected on the scalp [10][11]. EEG enables to explore what occurs in one's brain while they are performing a cognitive task, such as language comprehension [12]. EEG signals are a mixture of signals from two separate sources [13]: 1) features which are of neural-cerebral activity, and 2) artifacts, which are of non-cerebral origins. Artifacts are to be detected, which is a problem faced by researchers [14]. Studies suggest that EEG is a legitimate method for exploring various aspects of language processing [15].

During recording time, there are several artifacts noises can corrupt the original EEG signal such as eye blink, eye movements, muscles activity, and interference of electronic devices signals [16]. Therefore, the EEG signal should be processed to reduce these noises. There are several techniques for EEG noises removal such as filtering, adaptive thresholding, and other method. Recently, wavelet transform (WT) shown a powerful performance with nonstationary signal denoising such as ECG and EEG [17][18].

Kalaivani et al in [19] proposed wavelet transform to processing the EEG signal. The authors used WT for EEG signal denoising where used db8 as mother wavelet function, used number 8 for decomposition EEG signal. Finally, the authors classified the EEG signal based on the extracted features which are extracted from the signals after processed using wavelet transform.

PinkiKumari et al in [6] suggested of using WT for EEG signal denoising, where the authors used db4 as a mother wavelet function, 5 levels for signal decomposition. Moreover, the authors tested their method using EEG dataset [20].

Noor Al-Qazzaz et al in [17] presented a comparative study to efficient mother wavelet functions which can provide the high signal characteristics for optimally EEG channel. The authors tested 45 different functions which are taken from Daubechies, Symlets, and Coiflets. Finally, sym9 shown the efficient results for all the brain regions.

In this paper, the authors propose the β-hill climbing algorithm and the optimal WT parameters (βHCWT) for EEG signal denoising. Selecting WT parameters is a challenging task that is usually performed based on empirical evidence or experience. The optimal wavelet parameters for EEG signal denoising are obtained by checking the minimum mean square error (MSE) between the original and denoised EEG signals. The proposed hybrid method was also evaluated using five criteria which are: SNR, MSE, MAE, PSNR and PRD. Finally, βHCWT is compared with WT [6] and the effect of β-hill climbing on WT performance is detected. The study proves that 'db4' wavelet function gives the better performance than the other wavelet function or hybrid filters.

Wavelet Transform

Wavelet Transform (WT) is a common and powerful tool for signal representing in time-frequency domain. WT was successfully used with non-stationary signals such as ECG and EEG where WT was applied for signal compression, feature selection, and signal [21][22]. WT can be classified into two categories: continuous wavelet transform (CWT) and discrete wavelet transform (DWT)[23]. In this paper DWT has been utilized for signal decomposition and inverse DWT used for signal reconstruction.

Recently, WT has been extensively used with non-stationary signals because WT is shown to be powerful in removal several EEG artifact noises, which can corrupt the original EEG signal during recording time, such as eye blinking noise, eye movement noise, muscles activity noise, power line noise, and EMG noise[24][25].

WT represents signals in the time-frequency domain and uses five parameters to obtain a smooth signal, including i) wavelet function name or mother wavelet function (Φ), ii) Decomposition level (L), iii) thresholding type (β), v) thresholding selection method (λ), and iv) wavelet rescaling approach (ρ), with each parameter having several types or values as shown in Table 1.

Table 1

Wavelet parameter range

Wavelet parameters	**Range**
Mother wavelet (Φ)	**Daubechies** (db2..db45), **Symlet** (sym1..45), **Coiflet** (coif1..coif5), and **Biorthogonal** (bior1.1..bior3.9)
Decomposition level (***L***)	5
Thresholding type (β)	soft and hard
Selection method (λ)	Heursure, Rigrsure, Sqtwolog, and Minimax
Rescaling approach (ρ)	sln, one, and mln

Signal Denoising

Discrete wavelet transform (DWT)

The DWT restricts the wavelet basis function's a and b to discrete points, resulting in the discretization of scale and displacement, as well as the discrete wavelet basis function which is,

$$\psi_{j,k}(t) = 2^{-\frac{i}{2}\psi(2^{-j}t-k)}$$

where $j \in Z, k \in Z$, the DWT is

$$WT_x(j.k) = \int x(t)\psi^*_{j,k}(t)dt$$

Low-pass filters (LPF) and high-pass filters (HPF) are used to filter the input EEG signal X(n) (HPF). The approximation coefficients (CA) of LPF are low-frequency components of the input signal, while the detail coefficients (CD) of HPF are high-frequency components of the input signal as shown in Figure 1 which illustrates the process of wavelet decomposition by taking four-layer wavelet decomposition as an example. At the end of the decomposition levels, the cutoff frequency is found.

The signal denoising process involves three phases which are signal decomposition using DWT, apply thresholding, and signal reconstruction iDWT. These three phases are described as bellow.

Signal decomposition: 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 (A), and Detail coefficients (D). The detail coefficients will process using high-pass filter and approximation coefficients will continue decompose for next level. Figure 1 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 (Φ) and Decomposition level (L) must be selected in this phase.

Apply Thresholding: 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.

Signal Reconstruction: In this phase, the EEG denoised signal is reconstructed using Inverse Discrete Wavelet Transform (iDWT). Figure 1 shows the signal reconstruction process for four decomposition level.

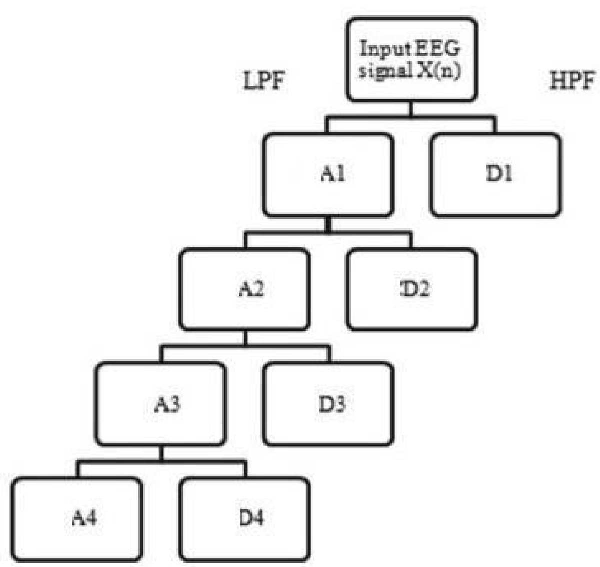

Figure 1. Four layer wavelet decomposition. A-Approximate and D-Detail coefficients are marked.

β-hill climbing algorithm

Hill climbing is a simple trajectory-based method which is an iterative approach that starts with an arbitrary solution to a problem and then continues the search by means of trying a trajectory in the problem space to find a better solution. If the previous step produced a better solution, an incremental change will continue to find a new solution. This process is repeated until the solution can no longer be improved. The problem with hill climbing algorithm is that only uphill movements are accepted, which leads to getting easily stuck in the local optima [3]. Several extensions have been proposed to overcome this problem. The most recent extension is proposed by Al-Betar in 2016 called β-hill climbing [3], wherein a single stochastic operator is adapted in hill climbing to strike an efficient balance in both exploration and exploitation during the search. The β-hill climbing has successful achieved good results in many global problems such as sudoku problem, signal processing, and feature selection [1,5,9]. In this paper, the authors proposes the β-hill climbing algorithm as an optimization technique to find the optimal wavelet parameters for EEG signal denoising.

Hybrid *β*-hill climbing algorithm wavelet transform (*βHWT)*

In this paper, the *β*-hill climbing algorithm is hybridized with WT and checked to solve the EEG signal denoising problem. The *β*-hill climbing algorithm initially locates the optimal wavelet parameters that will minimize the MSE between the original and denoised signals. Afterward, the WT uses the optimal parameters to solve the EEG signal denoising problem. Selecting the best combination of wavelet parameters is a challenging task because the optimal wavelet denoising parameters are not determined by applying a certain technique but rather by referring to experience or empirical evidence. The proposed hybrid method involves three phases.

In the first phase (**Initialization**), several parameters for the EEG denoising problem are initialized in three steps.

- First, the input EEG signal x(n) is read.
- Second, the noise for the input EEG signal x(n), the wavelet denoising parameters (Φ, L, β, λ, ρ), and the β-hill climbing parameters are initialized. Notice that, the original EEG signal database was corrupted using three different noise types which are standard White Gaussian noise, Power Line noise, EMG noise.
- Third, the MSE, MAE, SNR, PSNR and PRD for the noisy EEG signal are computed according to equations: (1) to (5) defined later in this paper.

In the second phase, the *β*-hill climbing algorithm is applied to search the EEG signal space for the optimal wavelet parameters that can obtain the minimum MSE.

The third phase involves the ***Decomposition*** of the EEG signal by using discrete wavelet transform (DWT), ***Thresholding*** based on the noise level coefficients, and ***Reconstruction*** of the denoising signal via inverse DWT (iDWT).

2. Aim of study

The aim of the study is to find an effective technique for clearing ocular artifact (eye blink), muscular artifact (finger spelling of words), and electrode pop artifact from the EEG, and thus to find the optimum solution for denoising the EEG of deaf individuals who have not received early intervention.

3. Methodology

EEG Data Acquisition

Participants were undergraduate students in a college with programs exclusively for deaf and hard of hearing. All of them use Indian Sign Language [unified sign language which is getting established under ISLRTC, Government of India.] Until recently the deaf and hard of hearing used regional sign languages [26]. The participants had no early intervention, hence their language skill is dismal as their incidental learning was affected. When dedicated neural structures in the brain that rely on auditory input fail to remember to transmit impulses to remedy the failure of the language processing location of the brain at the age of 17+, a method must be devised [27]. There is a dearth of literature on brain wave analysis for comprehension of such candidates. The deaf and hard of hearing use a lot of body movements while they read a sentence. This is because they tend to sign the sentence for better comprehension. This also bring in artifacts.

A purposive sample of 10 students randomly selected from of a batch of 50 (n=10, sex= M/F, age= 18 to 30). The inclusion criteria were candidates, with no disability other than congenital profound hearing loss, candidates with no early intervention. The audiologists determined the severity of deafness. The tests performed were tympanometry and acoustic reflex measurement (Tymp), Auditory Brainstem Evoked Response Audiometry (BERA), Otoacoustic emission (OAE), and Pure tone Audiometry (PTA). Goodmann classified the severity of hearing impairment [28] as shown in Table 2. It indicates that severe hearing loss ranges between 70 to 90 dBHL and profound hearing loss ranges from 91 dBHL.

Table 2. Classification of severity of hearing impairment

Classification	PTA range in dBHL
Normal hearing	-10 to 15
Slight hearing loss	16 to 25
Mild hearing loss	26 to 45
Moderate hearing loss	46 to 55

Moderately severe hearing loss	56 to 70
Severe hearing loss	71 to 90
Profound hearing loss	91 and above

Exclusion criteria was students with a history of neurological and psychiatric disorders, with disability other than congenital profound hearing loss and underwent early intervention. EEG recording for participants was recorded in the college. A senior EEG technician, with fourtyyears experience in recording EEG waves was made available to record EEG. Informed consent approved by the ethical committee for their participation was collected from all participants prior to EEG recording. The recording was done after college hours or on holidays. EEG data was acquired from ten participants using Clarity Brain Tech device. 18 electrodes were fixed on the scalp following 10-20 system International standard while the participants were reading and comprehending seven stories displayed in a Laptop. Web based application was developed to provide stimuli to the brain. Uniformity of comprehension material was maintained for all participants with seven narrations from English text book of class-2 of NCERT which has comprehension questions under “Reading is fun”. The stories were presented in the following seven modes. One story each in English text, English text with visuals, Malayalam text, Malayalam text with visuals, Total communication with English speech, Total communication with Malayalam speech and Indian Sign Language. After each story they had to answer 3 or 4 questions.

The participants were requested to try to avoid/restrict movements like swallowing, blinking, head and facial muscle contractions during recordings. But as the recording time was 30 to 45 minutes, several physical and eye movements were recorded along with cerebral activity.

Figure 2. EEG Acquisition Setup. Clarity BrainTech device was used to acquire EEG signals.

MATLAB R2018b toolbox is used for these and the performance were computed using the equations [29] from 1- 5 as follows,

Formula and computations for various filters

1. Mean Square Error(MSE)

MSE is a quantitative parameter used in determining signal quality and fidelity, particularly in signal processing [30]. The goal of a signal fidelity calculation is to compare the original signal with the reproduced signal by assigning a numerical score that represents the degree of similarity / fidelity or, alternatively, the level of inaccuracy / distortion. As shown in the following equation, the MSE value is expressed as

$$MSE = \sum_{i=1}^{N} \quad (X(i) - filtered\ signal(i))^2 \text{(1)}$$

Where, $X(i)$ is the amplitude of the input EEG signal with artifact and $filtered\ signal(i)$ is amplitude of artifact eliminated signal using filters, N is the number of signals samples [30]. The MSE value is normally converted to the PSNR value in order to assess the image quality of the decibel value.

2. Peak Signal To Noise Ratio(PSNR)

PSNR is also a quantitative parameter that is used, especially in signal processing, to evaluate signal quality and fidelity.

The PSNR is expressed as $PSNR = 20 * log_{10}\left(\frac{Max(X)}{\sqrt{MSE}}\right)$ (2)

3. Noise Power

As follows, the noise power is evaluated

$$Pn = \sum_{i=1}^{N} \quad [X(i)^2 - X(i)\ denoised\ signal^2\ ] \qquad (3)$$

4. Percentage Root Mean Square Difference(PRD)

By point-wise comparison with the original results, the PRD indicates reconstruction fidelity.

$$PRD = 100 * \sqrt{\frac{\sum_{i=1}^{N} \quad [X(i) - X(i) denoised\ signal]^2}{\sum_{i=1}^{N} \quad [X(i)]^2}} \qquad (4)$$

5. Mean Absolute Error (MAE)

MAE calculates the average size of the errors in a series of forecasts without taking into account their trajectory.

$$MAE = \frac{1}{n}\sum_{j=1}^{n} \quad |Xi - Xt| \qquad (5)$$

Table 3
Wavelet parameters

Noise	Muscular/finger spelling				
	Φ	**L**	**β**	**λ**	**ρ**
WG	db4	5	soft	Rigrsure	Sln
PL	db4	5	soft	Rigrsure	One
EMG	db4	5	soft	Rigrsure	One

[WG- White Gaussian noise, PL-Power Line noise, EMG- EMG noise, Mother wavelet (Φ), Decomposition level (L), Thresholding type (β), Selection method (λ), Rescaling approach (ρ)]

Mother wavelet db4 and sym4 used for wavelet transform.

4. Results

It is noted from the parameters that standard WT outperformed hybrid WT. WT is a powerful tool that represents the signal based on the correlation between the translation and dilation of the mother wavelet Daubechies and Symlet wavelet functions are used here. Mean square error (MSE), Percentage Root Mean Square Difference (PRD), Mean absolute error (MAE), Peak signal to noise ratio (PSNR), and Noise power are used to evaluate denoising. The study group's neural correlation will be developed by extracting significant characteristics from the denoised data.

For evaluating the performance of the proposed hybrid method (βhcwt) five criteria have been used which are: Signal-to-NoiseRation (SNR), SNR improvement Mean Square Error (MSE), Root Mean Square Error (RMSE), and percentage root mean square difference (PRD). Table 1. Wavelet Parameters Range Wavelet parameters Range Mother wavelet (Φ) Daubechies (db2..db45), Symlet (sym1..45), Coiflet (coif1..coif5), and Biorthogonal (bior1.1..bior3.9) Decomposition level (L) 5 Thresholding type (β) soft and hard Selection method (λ) Heursure, Rigrsure, Sqtwolog, and Minimax Rescaling approach (ρ) sln, one, and mln As well as, the original EEG signal was corrupted using three different noises which are (Power line noise (PLN), Electromyogram (EMG), and White Gaussian Noise (WGN)) [31][32]. The formulas of these noises are describing in equations (2,3, and 4) respectively. These noises represents the artifacts which will corrupt the original EEG signal during the recording time such as eye blink noise, eye movement noise, electro signal distortion..etc.

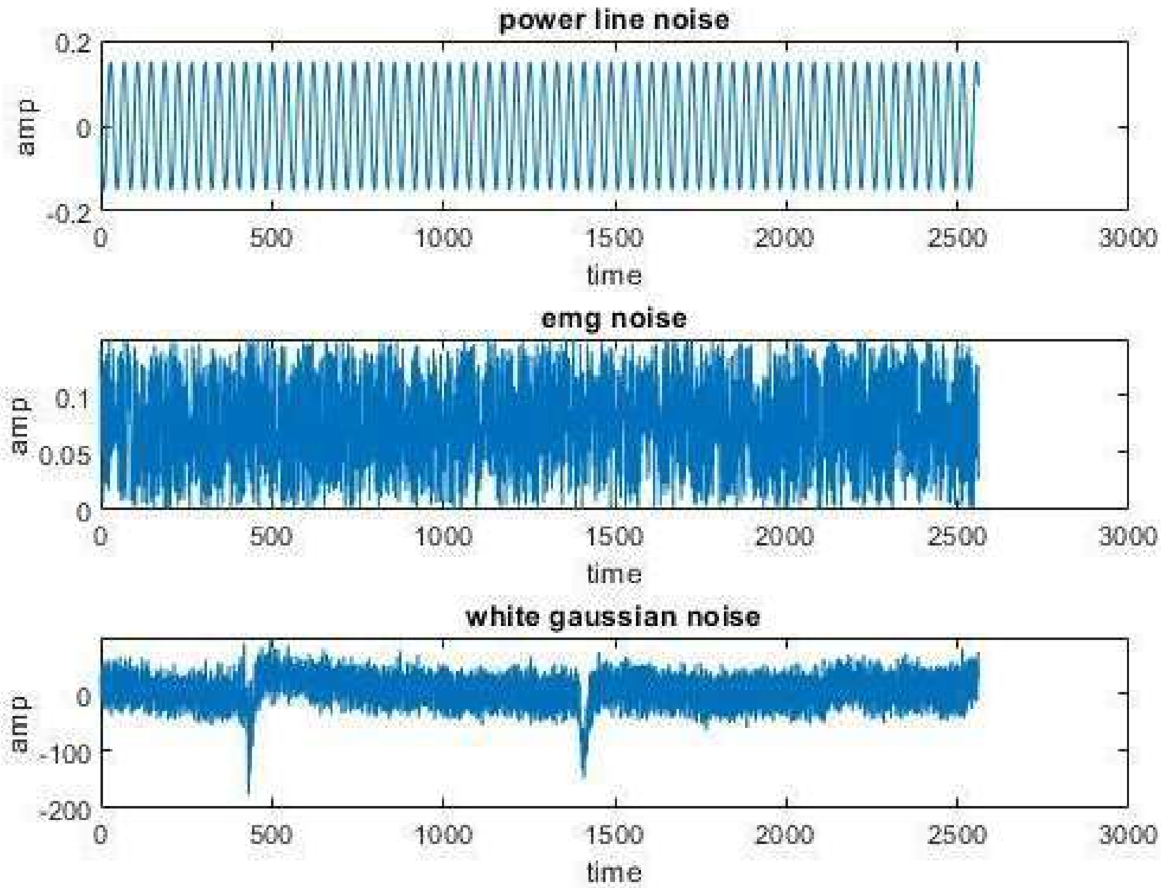

Figure 3.Three different noise types. Standard White Gaussian noise, Power Line noise, EMG noise.

Figure 4. Raw EEG. Muscular Artifact while finger spelling of English words using Indian Sign Language

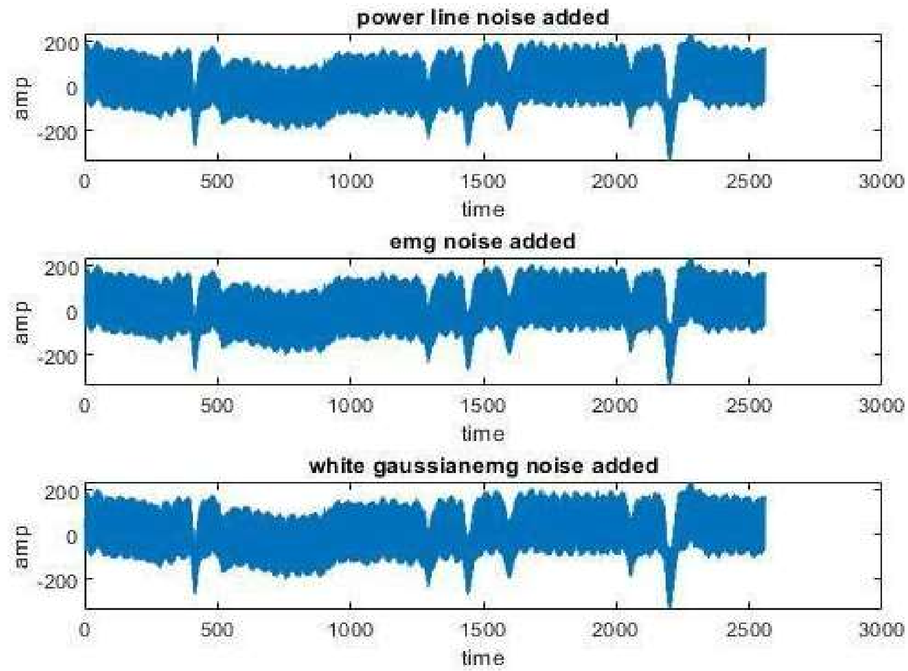

Figure 5. Raw EEG signal. Corrupted using Standard White Gaussian noise, Power Line noise, EMG noise.

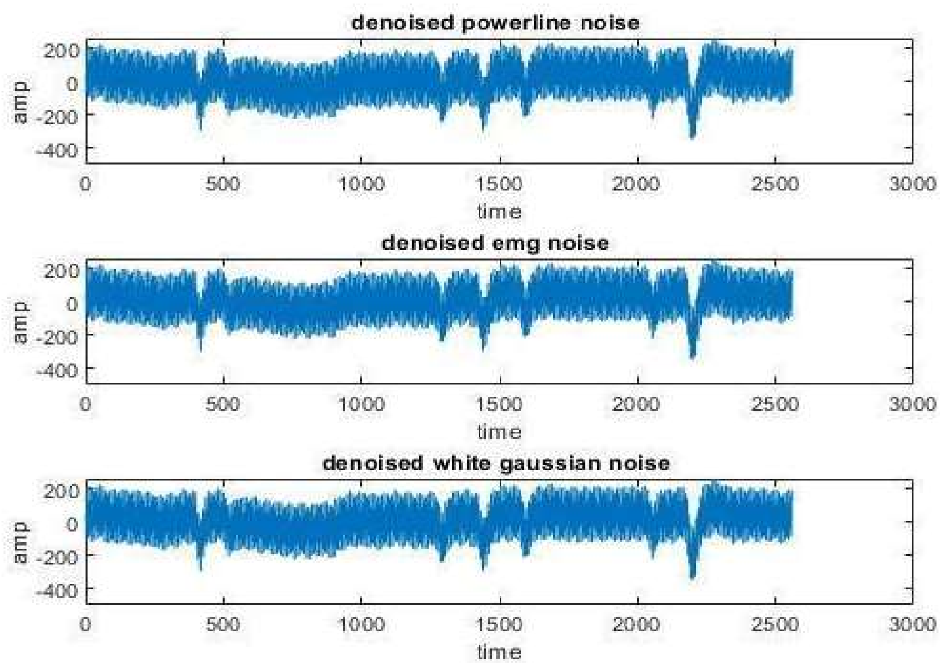

Figure 6.Denoised EEG signals. White noises removed

Table 4

Parameters of Hill climbing when White Gaussian Noise used

MSE	MAE	SNR	PRD	PSNR
0.000139862	10.20586168	0.712394238	0.011826329	78.36752227
6.05E-07	2.673402553	-0.79721190	0.000777919	93.77698412
0.000131059	6.723854876	5.407034785	0.011448097	73.47320947
2.50E-05	13.0232497	6.484986225	0.004999064	86.52834342
0.000146795	14.10838918	2.878710454	0.012115905	50.37408293
4.16E-06	1.408122131	0.543483166	0.002040028	84.17755541
4.95E-07	1.968782297	-0.25486079	0.000703229	103.1444974
6.39E-06	9.807270029	5.450833286	0.002528832	95.85959382
3.21E-05	11.1121564	2.552749668	0.005663895	82.32233103
3.91E-05	6.52163408	1.140972352	0.006253768	85.66078931
7.59E-06	8.657724968	5.522142648	0.002754415	60.74183916
2.02E-05	1.951317926	0.415276799	0.004488958	80.21224528
1.30E-05	3.209158399	-8.14410119	0.00360359	74.8858913
3.01E-06	12.68278858	4.773228091	0.001735847	87.46544846
2.07E-05	11.07764244	5.924599383	0.004546324	92.37602857
0.00015408	8.511127683	4.661355987	0.012412883	75.38900407
4.31E-05	9.746575031	4.716789982	0.006562812	82.74305138
2.69E-05	8.54164786	6.173443563	0.005187523	76.33037697

Table 5
Parameters of Hill Climbing when Power Line Noise used

MSE	MAE	SNR	PRD	PSNR
4.98E-05	10.20740136	0.718374304	0.007056387	82.85287352
6.41E-07	2.669990593	-0.78638590	0.00080088	93.52432524
1.91E-05	6.723392383	5.407904026	0.004368661	81.84090747
6.04E-05	13.0220162	6.487443655	0.007771539	82.69597679
5.97E-05	14.10793905	2.880061341	0.007723507	54.28490941
1.01E-06	1.407862858	0.565649903	0.001003968	90.33587798
1.59E-06	1.966173302	-0.24448431	0.001260746	98.07387528
2.77E-05	9.807818598	5.456742877	0.005261821	89.49527143
3.70E-05	11.11288379	2.554653116	0.006085774	81.69831819
1.54E-05	6.520459334	1.150608605	0.003919227	89.71961764
2.56E-06	8.6590219	5.524716877	0.001600511	65.45725006
4.99E-07	1.950087277	0.444858892	0.00070628	96.2756134
1.40E-06	3.212194435	-8.11658592	0.001183468	84.5574662
2.77E-06	12.68455519	4.777271661	0.001663316	87.83618407
1.47E-05	11.07642869	5.924284636	0.003832237	93.86018929
4.22E-05	8.509290347	4.664358907	0.006496699	81.01260209

2.75E-05	9.74661353	4.720882129	0.005244662	84.69050026
2.61E-05	8.544749894	6.174900523	0.005108745	76.46329438

Table 6
Hill Climbing when EMG Noise used

MSE	**MAE**	**SNR**	**PRD**	**PSNR**
0.00687582	10.20870731	0.714220102	0.082920564	61.45127659
0.005634499	2.671593062	-0.798668719	0.075063297	54.08711923
0.006437308	6.721889139	5.407723817	0.080232838	56.5608321
0.004636607	13.02190422	6.485782606	0.068092638	63.84411414
0.006986901	14.10723836	2.877215803	0.083587683	33.59835406
0.005908712	1.406481809	0.537081604	0.076868145	52.65535078
0.005565672	1.968702372	-0.24458108	0.074603431	62.6312515
0.004984693	9.807066344	5.455587817	0.070602356	66.94160923
0.006715794	11.11451839	2.55191687	0.081949951	59.11366048
0.005176076	6.520406661	1.147295366	0.07194495	64.4436186
0.006000778	8.65842671	5.522453892	0.077464688	31.76034958
0.005648709	1.949543797	0.438397441	0.075157896	55.73566433
0.00593634	3.210221566	-8.12252182	0.077047645	48.28541252
0.005505768	12.68403979	4.775540061	0.074200861	54.84749823
0.0051886	11.0764233	5.923432179	0.07203194	68.37873387
0.006783314	8.509604117	4.664049065	0.082360876	58.95203808
0.004987116	9.747343838	4.717119284	0.070619515	62.10635561
0.006556614	8.543997518	6.174164038	0.080972921	52.46278218

Table 7
Wavelet transform using function Daubechies

MSE	**MAE**	**SNR**	**PRD**	**PSNR**
3.26E-06	10.73266228	0.731404042	0.001804244	94.69861514
4.35E-08	2.804086915	-0.75984403	0.000208503	105.2134113
1.27E-06	7.129304069	5.409122791	0.001126435	93.6137529
3.85E-06	13.88500919	6.485961956	0.001961577	94.65400794
4.40E-06	14.99519441	2.903789383	0.002096802	65.61005111
5.72E-08	1.432285569	0.642327932	0.000239224	102.7941708
9.51E-08	2.05005264	-0.21414896	0.000308449	110.3027639
1.98E-06	10.64735735	5.4586121	0.001405659	100.9603908
1.86E-06	11.94846386	2.538727576	0.001361999	94.70109713
8.38E-07	6.816958413	1.182972521	0.000915537	102.350107

2.08E-07	9.188140082	5.543208381	0.000455741	76.36805615
1.06E-08	2.26861241	0.360098085	0.00010317	112.9840918
1.39E-07	3.336131198	-7.97872619	0.000372952	94.58753394
3.59E-07	13.56035156	4.779292741	0.00059898	96.70743651
5.03E-07	11.66406226	5.936046369	0.000709292	108.5127356
2.43E-06	8.963692638	4.688010705	0.001557537	93.4176915
1.61E-06	10.43403588	4.718836053	0.001269537	97.0119438
1.83E-06	9.091365139	6.179919287	0.001352693	88.00559086

Table 8
Wavelet transform using function Symlets

MSE	MAE	SNR	PRD	PSNR
5.07E-05	10.20802015	0.714739976	0.007119422	82.775627
5.44E-07	2.670908595	-0.79499094	0.000737845	94.23636794
1.96E-05	6.722253872	5.407790939	0.004431696	81.71647577
5.94E-05	13.02161321	6.485931865	0.007708504	82.76671501
6.06E-05	14.10759026	2.877192538	0.007786541	54.21430804
1.14E-06	1.40454824	0.54246607	0.001067003	89.80696533
1.43E-06	1.965796082	-0.24845495	0.001197711	98.51938422
2.70E-05	9.806665516	5.455331085	0.005198786	89.59995348
3.78E-05	11.113018	2.551283299	0.006148809	81.60881498
1.49E-05	6.520042783	1.14638483	0.003856192	89.86045233
2.77E-06	8.657968024	5.522939663	0.001663546	65.12172874
4.14E-07	1.94882381	0.444647921	0.000643246	97.08761846
1.55E-06	3.209596154	-8.12287977	0.001246503	84.10673237
2.56E-06	12.68448872	4.775107025	0.001600281	88.17175278
1.42E-05	11.07626608	5.923501871	0.003769202	94.00424751
4.30E-05	8.509892785	4.664389602	0.006559734	80.92873285
2.68E-05	9.746572836	4.717449137	0.005181627	84.79552688
2.67E-05	8.543920414	6.17487536	0.005171779	76.35677856

5. Discussions

In this section the results of hybrid method (βhcwt) and WT for EEG signal denoising are discussed. We find that db4 is the efficient mother wavelet function for EEG denoising as noted by Kumari and team [33]. The parameters of the methods studied are shown in Tables 4 to 8. The results showed that the db4 has successfully achieved the efficient EEG signal denoising for all criteria for Power Line Noise (PLN) and White Gaussian Noise (WGN).

6. Conclusion

This study proposes a new hybrid method for denoising EEG signals that combines the β-hill climbing algorithm with WT. The proposed method can be considered a preprocessing tool for analyzing and classifying tasks with non-stationary signals, such as EEG signals. WT has five main parameters, with each parameter having different values. Selecting the suitable WT parameters is a challenging task that is usually performed based on empirical evidence or experience.

This paper compared a hybrid method between β-hill climbing algorithm and wavelet transform (βhcwt) and WT for EEG signal denoising. The task of β-hill climbing algorithm is to find the optimal wavelet parameters for EEG signal denoising that can obtain the minimum mean square error (MSE) between the original and denoised EEG signals. The proposed hybrid method was also evaluated using five criteria which are: SNR, SNR improvement, MSE, RMSE, and PRD. Finally, βhcwt compares with WT without βhc to present the effect of β-hill climbing on WT performance. The db4 method demonstrated an outstanding noise removal performance for non-stationary signals.

El-Dahshan used a hybrid of the genetic algorithm and WT for denoising biological signals, in which the genetic algorithm was applied to find the best set of wavelet parameters.

Srivastava et al. in proposed a signal denoising method that involved selecting the number of decomposition levels, adopting a new approach for estimating the thresholding value, adopting positive and negative thresholding values based on the wavelet coefficients, denoising in the approximation part, and adjusting the noise thresholding level.

Nguyen et al. used a method where the original signal was corrupted with white Gaussian noise (WGN) and different SNR input noise levels. This method, which performance was evaluated based on mean squared error (MSE) and SNR, successfully removed white Gaussian noise from the signal.

The above techniques have been adopted with an attempt to achieve a high SNR, which corresponds to a low noise level in the output signal. However, two factors, namely, high SNR and low percentage root mean square difference (PRD), must be also considered to guarantee an efficient system. An increase in SNR indicates the smooth denoising of signals, while a decrease in PRD indicates the efficient denoising of the original EEG signal.

7. Compliance of Ethical Standards

Conflicts of Interest

The authors declare that they have no conflict of interest

Ethical Consideration

Ethical approval was obtained from the Ethics Committee Board of KarpagaVinayaga Institute of Medical Science and Research Centre, Chennai regarding the protocol and data acquisition procedure prior to performing the experiments.

Ethical Approval ID

IEC Ref.No:KIMS/MIS/2018/1

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