Denoising Semi-simulated EEG Signal Contaminated Ocular Noise using Various Wavelet Filters

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Abstract—**Denoising is crucial in electroencephalography (EEG) processing to remove undesired components contaminated in a signal. Wavelet filters are a powerful and robust denoising approach to eliminate the noises in EEG. However, a broad number of wavelet families and decomposition levels confused the selection of the optimal and most appropriate wavelet filter. Therefore, this study aims to determine the optimal wavelet filter based on the signal-to-noise ratio (SNR) for EEG denoising. This work used the semi-simulated EEG signal contaminated with ocular noise as the observed signal. The wavelet filter with various wavelet families that is Haar, Daubechies (db), Symlets (sym), coiflets (coif), Discrete Meyer (dmey), Fejer-Korovkin (fk), biorthogonal (bior), and Reverse Biorthogonal (rbior) from decomposition level 1 to 8 were applied. A MATLAB wavelet toolbox with a soft thresholding method was used to denoise the desired signal. The result showed that the highest SNR value was 63.0172 dB. The highest SNR indicated that the filter had a high ability to remove the noises in EEG signals. Therefore, this work suggested that the haar, db1, bior1.1, and rbior1.1 of the mother wavelet at decomposition level 8 were the most efficient for removing the ocular noise.**

Keywords—brain signal, electroencephalography, ocular noise, wavelet family, decomposition level, filtration

I. INTRODUCTION

Brain research involves studying structures and functions of the human nervous system and brain. This allows people to understand the biological basis of behavior, memory, learning, consciousness, and perception. The involvement of brain imaging modalities such as EEG, computerized tomography, functional magnetic resonance imaging, magnetoencephalography, functional near-infrared spectroscopy, and positron emission tomography is required to accommodate the brain research purpose. However, the brain signal or image acquired from this modality is usually contaminated with external and internal disturbances. Therefore, an efficient approach to removing the noise is essential to avoid misinterpretation of the original information. Latest, there is various denoising approach available for processing the noisy signal, for example, empirical mode decompositions [1], blind source separation [2], regression and combination [3], Fourier transform [4], and wavelet transforms [5]. Among them, the wavelet transform is considered one of the robust methods for processing the non-stationary brain signal characteristics. Furthermore, besides filtration, the wavelet transform can also be applied for features extraction because of its properties suitable for processing the continuous, discrete, and continuous-discrete time data [6]. However, since the main goal of this work is focusing on EEG denoising, thus, the following section only discuss on this topic.

The limitation of using the wavelet transform method in EEG denoising is the selection of the appropriate criteria of wavelet family and decomposition level [7]. The performance of wavelet transform in removing the noises depends on the choice of the mother wavelet and decomposition level. Unsuitable selection of wavelet properties may lead to non-proper noise removal and loss of important information. There are no standard wavelet properties for applying in EEG denoising until now. Most of the studies randomly chose any type of them to save time [8]. The main reason could be the large variety of mother wavelet and decomposition levels, limiting the researcher from performing each. Therefore, a quantitative comparison of denoising performance using various wavelets is required to provide a standard guideline for scientists and researchers to process the EEG signals. This recent work investigates the most suitable wavelets for EEG denoising based on the signal-to-noise ratio (SNR) parameter.

II. ELECTROENCEPHALOGRAPHY

EEG is widely used for clinical and research purposes to record and measure brain signals. From measurement, the brain functions, abnormalities, neurophysiological dynamics, and brain disorders can be diagnosed. The EEG is a portable, safe and high temporal resolution modality, affordable price, and short acquisition time [9]. The recorded EEG signal is acquired from the voltage difference between the active and reference electrodes over time. The electrodes are used as a medium to detect the tiny electrical charges that come from brain cells activities. The EEG has a small amplitude of about –100 to +100 μV, making it easily corrupted with noises [10]. The noise is an undesired component or signal that the brain does not generate. These noises must be removed by the denoising process to maintain the important information. Two

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common types of noises are always contaminated in EEG signals: biological and technical noises [11].

Biological noises come from physiological processes in the human body such as muscle movement, eye movement and blink, cardiac rhythms, respiration, and perspiration. Meanwhile, technical noise originates from electrode popping, cable movement, electromagnetic interferences, and electrical devices. The technical noises can usually be controlled by taking extra precautions during data acquisition. However, biological noises are almost impossible to avoid because they involve involuntary human actions.

Among them, most noise is generated from eye movements and blinks, also known as electrooculography (EOG) noise [12]. The changes in the resting potential of the retina during eyes activities cause an interruption in EEG measurements. The EOG noise can be detected in low-frequency components of 10 Hz with amplitude up to 1 mV. Therefore, the noises in EEG signals need to be removed to avoid misinterpretation of actual information. Before this, the Fourier transform (FT) filter is commonly used in filtration EEG noises. However, it found that the FT is not the best way to remove non-stationary and time-frequency domain signals because causing to information loss [13]. Therefore, the wavelet transform-based filter was introduced to overcome FT filters' limitations.

III. Wavelet Filters

Morlet and Grossman proposed the wavelet method in the 20th century based on oscillatory function. The usage of wavelets in signal denoising was initially introduced by Donoho and Johnstone. Theoretically, the wavelet method refers to the linear transformation with the mathematical technique that decomposes the input signal into detail coefficients (cD[k]) and approximation coefficients (cA[k]) [14]. The detail coefficients represent the high-frequency coefficients, whereas the approximation coefficients are low-frequency coefficients. Equation (1) and (2) represents the wavelet decomposition for input signal [6].

$$D[k] = \sum_{j=-\infty}^{\infty} s[j]h[2k-j], \tag{1}$$

$$A[k] = \sum_{j=-\infty}^{\infty} s[i]g[2k-j], \tag{2}$$

where j is the sampling data point, k is the number of sampling data, $s[j]$ is the discrete radar signal with noise, $h[2k-j]$ is the high pass filter, and $g[2k-j]$ is the low pass filter that depends on mother wavelet function.

The output of wavelets depends on shifting and scaling factors of a single wavelet function (mother wavelet) [7]. A few types of mother wavelet can be applied in signal denoising, such as haar, db, sym, coif, dmey, fk, bior, and rbior. Each of them had different properties, which strongly influenced the denoising performance of input signals. Wavelet filter band is a cascaded arrangement of filters such as bandpass filter, low-pass filter, and high-pass filter connected by sampling operators for getting the desired decomposition and recomposition of the signal from a spectrum perspective [14]. The sampling can be composed of up-samplers/expanders or down-samplers/decimators. Through wavelet filtration, the noises in the signal can be removed and preserve important information. Besides, these filters also allow the wavelet to extract the required components or frequencies from input signals. Fig. 1 illustrates the wavelet filter bank applied in the denoising process.

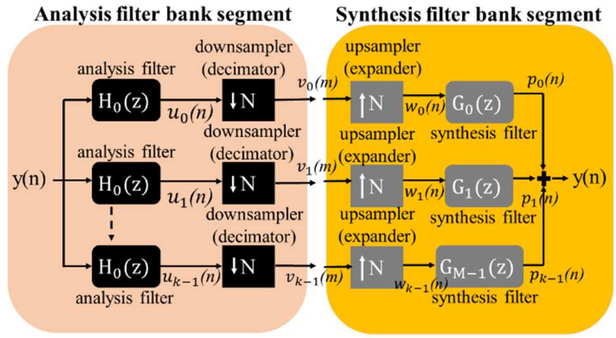

Fig. 1. Wavelet filter bank composed of the analysis filter bank and synthesis filter bank segments

The analysis and synthesis filter banks may consist of either low-pass or high-pass filters [14]. These filters will pass specific frequencies components of the input signal y(n). The output from the synthesis filter is summed to the expected output, and the frequency-response matches with the analysis filter. The down-sampler represents the frequency downsampling of the input signal by a factor of N. The N^{th} samples will retain in a given sequence. In contrast, the up-sampler upsamples the signal by a factor of N. It performs by adding zeros at every n^{th} level in the input signal sequences [6], [14]. The usage of wavelet filter banks for the denoising process should consider the specific properties of the input signal and wavelet function to achieve the desired outputs.

IV. Methodology

A. Semi-simulated EEG dataset

The dataset used in this work is downloaded from the Mendeley Data website [15]. The clean or noise-free EEG signal is obtained from the experimental study before being manually contaminated with EOG noise. This semi-simulated signal is inspired by the model proposed by Elbert et al., [16]. The EEG signal was acquired from healthy subjects during the eyes-closed session using 19 electrodes based on the 10–20 International System. However, only the Fp1 channel from one subject is selected for data filtration to reduce the execution time in our work. The EEG signal has sampling frequency of 200 Hz and filtered with bandpass filter at 0.5–40 Hz and notch filter at 50 Hz. The duration of EEG acquisition was 30 s. The acquired EEG signal was carefully inspected to avoid any contamination with technical and biological noises. Meanwhile, the EOG signal was acquired from the same subject during eyes opened state. There are six electrodes used where four of them attached below and above of the left eye and another two on the outer canthi of each eye. This technique produces two bipolar signals, vertical-EOG (VEOG), representing the upper minus lower EOG electrode measurements, and horizontal-EOG (HEOG) refers to left minus right EOG measurements. The recorded EOG was filtered with bandpass at 0.5–5 Hz. Thus, to generate the semi-simulated EEG dataset, the contamination model introduced by Klados et al., and Yong et al., [15], [17] follows as represented in Equation (3):

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$$Noisy\_EEG = EEG + VEOG + HEOG \quad (3)$$

B. Filtration Method

The noisy EEG signal was filtered using a wavelet toolbox in MATLAB R2021b. Eight types of wavelet function or mother wavelet: haar, db, sym, coif, dmey, fk, bior, and rbior, were chosen as evaluation for denoising performance. In addition, the decomposition level was selected from level 1 to level 8. The criteria of the selected wavelet filter as summarized in Table 1.

TABLE I. TYPES OF CHOSEN WAVELET FILTER FOR FILTRATION EEG CONTAMINATED OCULAR NOISE

Mother Wavelet	Classes	Decomposition Level
Haar	Haar	1, 2, 3, 4,5, 6, 7, 8
Daubhecies	db1, db2, db3, db4, db5, db6, db7, db8, db9, db10	
Symlets	Sym2, Sym3, Sym4, Sym5, Sym6, Sym7, Sym8	
Coiflets	Coif1, Coif2, Coif3, Coif4, Coif5	
Discrete Meyer	dmey	
Fejer-Korovkin	fk4, fk6, fk8, fk14, fk18, fk22	
Biorthogonal	bior1.1, bior1.3, bior1.5, bior2.2,bior2.4, bior2.6, bior2.8, bior3.1, bior3.3, bior3.5, bior3.7, bior3.9, bior4.4, bior5.5, bior6.8	
Reverse Biorthogonal	rbior1.1, rbior1.3, rbior1.5, rbior2.2,rbior2.4, rbior2.6, rbior2.8, rbior3.1, rbior3.3, rbior3.5, rbior3.7, rbior3.9, rbior4.4, rbior5.5, rbior6.8	

Fig. 2 shows the flow of the denoising process using the wavelet filter toolbox. The stationary wavelet transform (SWT) is typically used to remove the signal noise in wavelet denoising. There are three standard wavelet classes: SWT, discrete wavelet transform (DWT), and continuous wavelet transform (CWT). However, the SWT is the most preferable for denoising because it has time-invariant properties and better time resolution [18]. Therefore, it is crucial to preserve the actual time of signal during denoising to avoid loss of signal information.

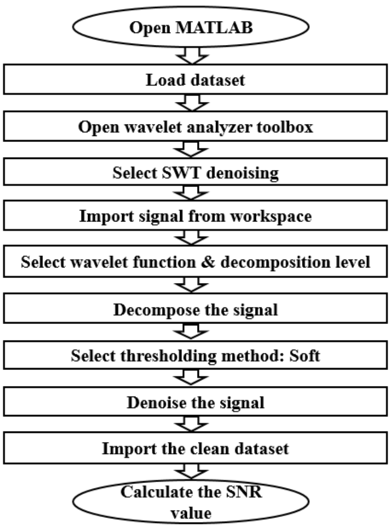

Fig. 2. Denoising flow of EEG contaminated ocular noise using wavelet analyzer toolbox

Three main steps involve in denoising the ocular noise contaminates in EEG signals. First, the signal will decompose based on the selected decomposition level and split into two sections through low-pass and high-pass filters of SWT. Then, the approximation and details components were generated at different frequency resolutions, as visualized in Fig. 3. Next, the soft thresholding method was executed to eliminate the EOG noise. Finally, the clean EEG signal was generated with the same length as the input EEG signal due to the time-invariance property of the SWT filter.

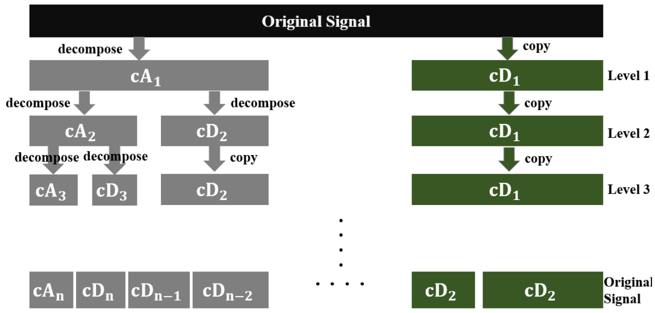

Fig. 3. Example of decomposition process at level 3 using wavelet filter

The denoising performance of the EEG signal was evaluated based on SNR value. The larger the SNR value, the better the noise reduction effect. The SNR was determined as in Equation (4):

$$SNR = 20log_{10}\frac{Voltage_{EEG\ signal}}{Voltage_{noise}} \quad (4)$$

V. RESULTS AND DISCUSSIONS

Table II shows the SNR value of various wavelet filters for denoising the noisy EEG signal. Based on the result, it showed that increasing decomposition level led to an increase in SNR value. Therefore, it indicated that more EOG noise had been removed with the increase of decomposition level. This trend can be seen for all of the executed wavelet filters. The range of SNR for decomposition level 1 was around 1.2293 dB–17.5003 dB, whereas the decomposition level 8 was about 61.7065 dB–63.0172 dB. The percentage increment from decomposition level 1 to level 8 was higher than 100%. However, there was an issue at decomposition level 3 and level 4, where the decrement was found for almost wavelet filters. It can be seen that the SNR for db3–db10 was decreased from decomposition level 3 to level 4. The others also facing this problem at certain functions, which were the Sym3, Sym4, Sym5, Sym6, Sym7, Sym8, Coif2, Coif3, Coif4, Coif5, dmey, fk6, fk8, fk14, fk18, fk22, bior1.5, bior2.4, bior2.6, bior2.8, bior3.3, bior3.5, bior3.7, bior3.9, bior4.4, bior5.5, bior6.8, rbior1.5, rbior2.4, rbior2.6, rbior2.8, rbior3.3, rbior3.5, rbior3.7, rbior3.9, rbior4.4, rbior5.5 and rbior6.8 showed decrement of SNR from decomposition level 3 to level 4. Increasing wavelet functions led to the decrement of SNR values for almost decomposition level. For example, the SNR of the Daubechies function from db1 to db10 at decomposition level 1 was reduced from 17.5003 dB to 6.9814 dB. A similar trend was also found for Symlets, Coiflets, fk, biorthogonal, and reverse biorthogonal functions.

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TABLE II. DENOISING PERFORMANCE OF SEMI-SIMULATED EEG SIGNAL CONTAMINATED OCULAR NOISE FOR VARIOUS WAVELET FILTERS

Wavelet functions	Signal-to-noise ratio (dB)							
	Decomposition levels							
	1	2	3	4	5	6	7	8
Haar								
-	17.5003	28.0018	34.2759	39.4770	47.4519	54.0880	57.8468	63.0172
Daubechies								
db1	17.5003	28.0018	34.2759	39.4770	47.4519	54.0880	57.8468	63.0172
db2	15.0835	26.2544	32.2073	33.7203	44.1889	52.9197	55.8249	62.6782
db3	12.0942	25.3560	32.0070	31.8331	42.6974	52.6250	55.2128	62.6341
db4	10.9837	24.9961	32.0233	31.3033	41.7150	52.3942	54.8703	62.6066
db5	10.0559	24.7217	32.0034	31.1479	40.7678	52.2952	54.6941	62.6042
db6	9.2131	24.4916	31.9613	31.0969	39.9808	52.2528	54.5939	62.6086
db7	9.1439	24.4073	31.9558	31.1198	39.2922	52.1803	54.5359	62.6012
db8	9.1849	24.3489	31.9444	31.1402	36.6807	52.0966	54.4957	62.6204
db9	7.9674	24.0894	31.8408	31.0578	37.9927	52.0650	54.5267	62.6476
db10	6.9814	23.8914	31.7561	30.9927	37.3966	52.0221	54.4642	62.6346
Symlets								
Sym2	15.0835	26.2544	32.2073	33.7203	44.1889	52.9197	55.8249	62.6782
Sym3	12.0942	25.3560	32.0070	31.8331	42.6974	52.6250	55.2128	62.6341
Sym4	10.5655	24.9220	31.9917	31.2696	41.6380	52.4719	54.8761	62.6089
Sym5	9.3925	24.6024	31.9519	31.0911	40.7490	52.3656	54.7468	62.6253
Sym6	8.4133	24.3551	31.9032	31.0324	39.9580	52.2500	54.6197	62.6188
Sym7	8.1200	24.2353	31.8835	31.0398	39.2524	52.0588	54.4741	62.5912
Sym8	6.9068	23.9875	31.7955	30.9767	38.5739	52.1068	54.5364	62.6364
Coiflets								
Coif1	14.8732	26.1820	32.1936	33.5596	44.0589	52.8988	55.8952	62.7315
Coif2	9.9278	24.7745	31.9531	31.1996	41.3867	52.4360	54.8385	62.6120
Coif3	7.6909	24.2061	31.8520	30.9926	39.6030	52.2132	54.6303	62.6361
Coif4	6.4068	23.8763	31.7477	30.9463	38.1344	52.0755	54.5461	62.6500
Coif5	5.4195	23.6335	31.6370	30.8863	36.8651	51.9931	54.4072	62.6213
Discrete Meyer								
-	9.3324	22.2238	30.6809	30.2851	28.2821	51.8878	54.4795	62.8605
Fejer-Korovkin								
fk4	15.6929	26.9975	33.2300	37.1251	46.0667	53.0978	56.1110	62.4662
fk6	11.3296	25.2006	32.1350	31.5176	42.2230	52.5867	55.0177	62.6213
fk8	9.6675	24.6215	32.0500	31.3235	40.5191	52.2660	54.6720	62.6173
fk14	5.6027	23.5307	31.5805	30.9059	35.3650	51.8650	54.4370	62.6385
fk18	3.0719	23.0644	31.2103	30.6619	32.3404	51.9092	54.5490	62.7329
fk22	1.2293	22.7789	30.9017	30.5329	29.5637	51.9246	54.5851	62.8504
Biorthogonal								
bior1.1	15.5003	28.0018	34.2759	39.4770	47.4519	54.0880	57.8468	63.0172
bior1.3	14.4494	26.0883	32.1248	33.6514	43.9419	51.7112	54.8842	62.2639
bior1.5	13.3291	25.6611	32.1565	31.9886	42.3467	51.0862	53.9696	62.1272
bior2.2	12.9042	25.6916	31.9258	33.4835	44.1185	52.9075	55.9173	62.7202
bior2.4	11.6705	25.2705	31.9707	31.7978	42.6875	52.6755	55.2228	62.5932
bior2.6	11.1098	25.0386	32.0452	31.3285	41.6574	52.4427	54.8681	62.6040
bior2.8	10.8469	24.8914	32.0801	31.2340	40.7960	52.2752	54.6680	62.5938
bior3.1	2.9994	23.1248	30.7932	32.5565	43.8574	52.7000	55.8639	62.6958
bior3.3	6.0195	24.1451	31.4816	31.3044	42.5503	52.5785	55.1784	62.6195
bior3.5	6.0313	24.2057	31.6796	30.9290	41.5374	52.5894	54.9655	62.6457
bior3.7	6.0246	24.1021	31.7405	30.8573	40.6728	52.5019	54.8124	62.6519
bior3.9	6.0632	24.0207	31.7646	30.8791	39.9031	52.2735	54.6108	62.6156
bior4.4	8.1160	24.4952	31.8038	31.0646	41.5773	52.4648	54.8660	62.6048
bior5.5	6.2952	24.1314	31.7520	30.8696	40.6750	52.3278	54.7295	62.6184
bior6.8	6.4550	23.9908	31.7824	30.9279	39.2058	52.1896	54.6214	62.6493
Reverse Biorthogonal								
rbior1.1	17.5003	28.0018	34.2759	39.4770	47.4519	54.0880	57.8468	63.0172
rbior1.3	10.2804	25.1441	31.6610	33.2619	44.0539	52.8685	55.7414	62.6404
rbior1.5	6.9025	24.4439	31.5944	31.4118	42.5788	52.5780	55.1787	62.6196
rbior2.2	16.7777	26.7393	32.4516	33.9248	44.2505	52.9422	55.9765	62.7473
rbior2.4	12.2604	25.3978	32.0299	31.8582	42.7068	52.6280	55.2151	62.6350
rbior2.6	9.5529	24.7345	31.9087	31.1791	41.6158	52.4625	54.8695	62.6062
rbior2.8	7.5172	24.3027	31.8243	30.9500	40.7061	52.3354	54.6874	62.6015
rbior3.1	16.5086	26.7230	32.4564	33.9337	39.8103	49.0067	53.4036	61.7065
rbior3.3	12.9163	25.5500	32.1018	31.9318	42.1853	50.7847	54.0834	62.1586
rbior3.5	11.7803	25.1650	32.0997	31.3866	41.6881	52.4499	54.8582	62.5668
rbior3.7	10.7435	24.8613	32.0654	31.2171	40.8188	52.3436	54.6932	62.6038
rbior3.9	9.3204	24.5085	31.9682	31.1044	40.0240	52.2598	54.5912	62.6028
rbior4.4	11.6707	25.1542	32.0969	31.3846	41.6827	52.4827	54.8849	62.6125
rbior5.5	11.1151	24.9443	32.1031	31.2593	40.8240	52.3824	54.7300	62.6186
rbior6.8	7.9221	24.2046	31.8708	31.0258	39.2448	52.1696	54.5488	62.6205

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This shows that the decomposition levels 3 and 4 do not efficient for removing ocular noise for almost wavelet functions. A higher decomposition than level 4 is required to eliminate the noises effectively. Each wavelet function or mother wavelet has a different influence in denoising performance. In comparison for Daubhecies function, the highest SNR was found in db1 at decomposition level 8 of 63.0172 dB, and the lowest SNR was 6.9814 dB at db10 of decomposition level 1. A similar trend was also found for other functions where the highest SNR was found at decomposition level 8 and the lowest at decomposition level 1. The highest SNR for Haar was 63.0172 dB, Sym2 was 62.6782 dB, Coif1 was 62.7315 dB, dmey was 62.8605 dB, fk22 was 62.8504, bior1.1 was 63.0172 dB, and rbior1.1 was 63.0172 dB (Fig. 4 and Fig. 5).

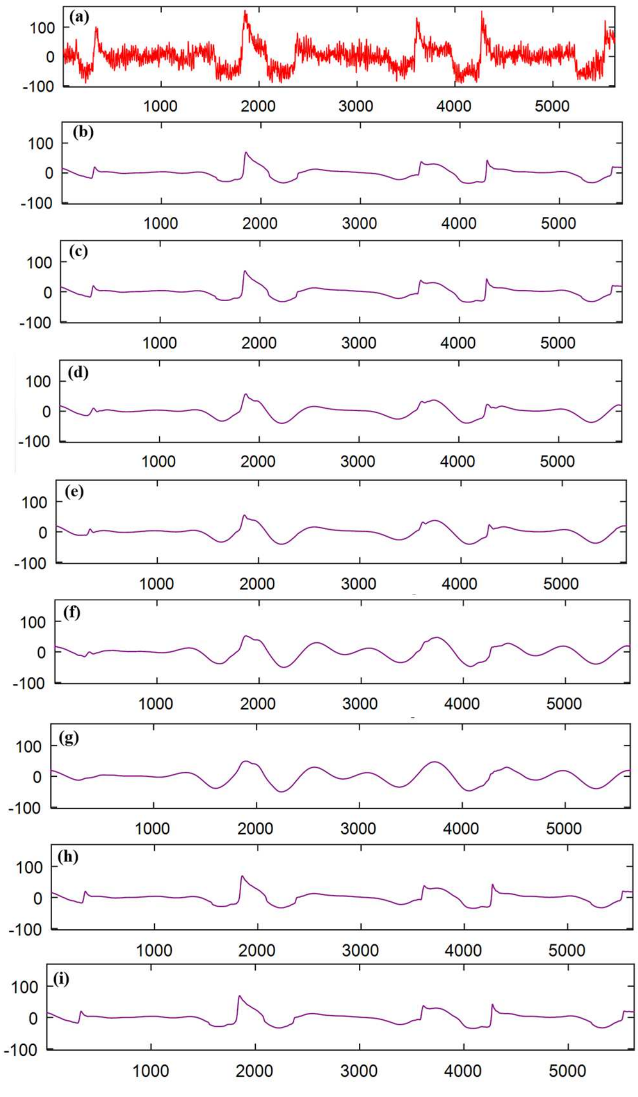

Fig. 4. EEG signals: (a) contaminated with ocular noise, (b) Haar filter, (c) db1 filter, (d) Sym2 filter, (e) Coif 1 filter, (f) dmey filter, (g) fk22 filter, (h) bior1.1 filter, and (i) rbior1.1 filter

The denoising performance of the Haar function is similar to db1 because they have similar characteristics [19]. Therefore, the highest SNR obtained from this work was 63.0172 dB. It is important to achieve the highest SNR value because it indicates that more noise had been removed from the EEG signal [20], [21]. Meanwhile, lower SNR revealed low noise elimination from EEG signal.

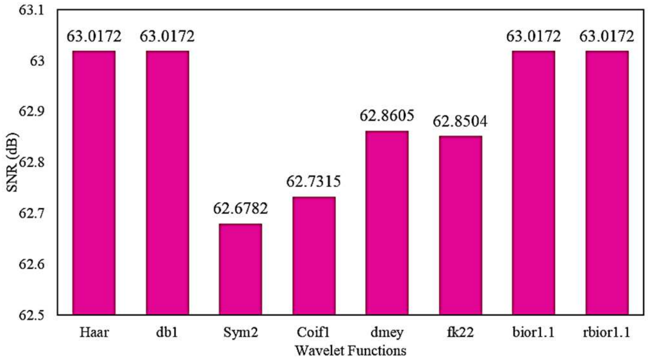

Fig. 5. The highest SNR for each wavelet function found at decomposition level 8

The low wavelet function showed better denoising performance than the high wavelet function. This may be caused by different characteristics of the mother wavelet that give various denoising performances [22], [23]. Therefore, choosing suitable wavelet types function and decomposition level is crucial for efficiently removing the noise. In this work, the haar, db1, bior1.1, and rbior1.1 at decomposition level 8 were the best for denoising the ocular noise in EEG signal that produces a similar SNR value (63.0172 dB). Meanwhile, the most inappropriate wavelet filter was from decomposition level 1 for all the wavelet filters because giving the lowest SNR, which believes the ocular noise does not correctly remove from the EEG signal. Besides, it seems that starting from decomposition level 6, more increment of SNR was observed. This may be due to wavelet filters begin to remove more EOG noise from EEG signals. Thus, it suggests that the researcher should apply the wavelet filter with a decomposition level higher than 5 to achieve optimum noise removal.

In this preliminary work, the best and optimal wavelet filter was chosen based on SNR value without visualizing their influence on EEG signal before and after denoising. It could be that decomposition level 8 is the best when referring to the SNR value. However, this level may have removed some of the important EEG signals. Therefore, further studies require the signal visualization and comparison between the denoise EEG signal and original EEG signal also should be included. The other limitations of this work are the selected wavelet filter was suitable for removing the ocular noise. As known, other types of noises might be contaminated in EEG signal during the acquisition stage. Thus, the raw EEG dataset should be included in the analysis to determine the wavelet's ability to remove other noise types. Other than that, in future works, the hard thresholding method also needs to be applied to evaluate the denoising performance compared to the soft thresholding method. Throughout this work, the reader will gain some knowledge on the process of selecting an optimal wavelet filter. Besides, the findings also aid the researcher in choosing the best wavelet filter for removing the ocular noise in EEG signal.

VI. Conclusion

The purpose of this work is to determine the efficient wavelet filter for removing EOG noise contaminated in EEG signal. The EOG noise was selected because it is the most common presence in the EEG signal and is hard to handle. The main reason is that it is a spontaneous action by a human.

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The best way to remove EOG noise is through filtration. The wavelet method is among the best to filter the undesired components through the frequencies decomposition technique. This recent work selected eight types of mother wavelet and eight decomposition levels to evaluate the denoising performance. The SNR is used as the main criterion to determine the best performance. In filtration, the soft thresholding method was chosen to remove the EOG noise. The findings showed that different wavelet filters provide different influences on denoising performance that may cause by the properties of wavelet function itself. The best filter should have a high SNR value, which indicates that high noise had been removed from the original signal. In this work, the haar, db1, bior1.1, and rbior1.1 at decomposition 8 gave the highest SNR value of 63.0172 dB. Thus, it suggested that these wavelet filters are optimal for removing the EOG noise. However, there are still limitations in this work, such as broad the wavelet filter setting, type of noisy dataset, and method in analyzing the denoising process, which requires further improvement.

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References

[1] N. Salankar, P. Mishra, and L. Garg, “Emotion recognition from EEG signals using empirical mode decomposition and second-order difference plot,” Biomed. Signal Process. Control, vol. 65, pp. 1-13, 2021.

[2] F. Cong, Blind Source Separation, EEG Signal Processing and Feature Extraction, Springer: Singapore, 2019.

[3] J. Witteveen, P. Pradhapan, and V. Mihajlovic, “Comparison of a pragmatic and regression approach for wearable EEG signal quality assessment,” IEEE J. Biomed. Heal. Informatics, vol. 24, pp. 735-746, 2020.

[4] X. Xiao and Y. Fang, “Motor imagery EEG signal recognition using deep convolution neural network,” vol. 15, pp. 1-11, 2021.

[5] M. Al-kadi and M. Marufuzzaman, “Effectiveness of wavelet denoising on electroencephalogram signals,” J. Appl. Res. Technol., vol. 11, pp. 156-160, 2013.

[6] S. Garg and R. Narvey, “Denoising and feature extraction of EEG signal using wavelet transform,” Psychology, vol. 5, pp. 1249-1253, 2013.

[7] F. Kharbat, S. Nashwan, and S. Ashraf, “General model for best feature extraction of EEG using discrete wavelet transform wavelet family and differential evolution,” Int. J. Distributed. Sen. Netw., vol. 16, pp. 1-21, 2020.

[8] B. K. Kumar, “Denoising of EEG signal using wavelets and SIMULINK techniques,” vol. 8, pp. 418-422, 2019.

[9] M. Soufineyestani, D. Dowling, and A. Khan, “Electroencephalography (EEG) technology applications and available devices,” Applied Sciences (Switzerland). vol. 10, pp. 1-23, 2020.

[10] A. Biasiucci, B. Franceschiello, and M. M. Murray, “Electroencephalography,” Current Biology. vol. 29, pp. 80-85, 2019.

[11] G. R. Muller-Putz, “Electroencephalography,” Handbook of Clinical Neurology, vol. 168, pp. 249-262, 2020.

[12] I. Daly, “Removal of physiological artifacts from simultaneous EEG and fMRI recordings,” Clin. Neurophysiol., vol. 132, pp. 2371-2383, 2021.

[13] A. S. Al-Fahoum and A. A. Al-Fraihat, “Methods of EEG signal features extraction using linear analysis in frequency and time-frequency domains,” ISRN Neurosci., pp. 1-7, 2014.

[14] T. Alotaiby, F. E. A. El-Samie, S. A. Alshebeili, and I. Ahmad, “A review of channel selection algorithms for EEG signal processing,” EURASIP J. Adv. Signal Process., vol. 66, pp. 1-21, 2015.

[15] K. Manousos and B. Panagiotis, “A semi-simulated EEG/EOG dataset for the comparison of EOG artifact rejection techniques,” Mendeley Data, vol. V4, 2019.

[16] T. Elbert, L. W. B. Rockstroh, and N. Birbaumer, “Removal of ocular artifacts from the EEG-A biophysical approach to the EOG,” Electroencephalogr. Clin. Neurophysiol., vol. 60, pp. 455–463, 1985.

[17] X. Yong, M. Fatourechi, R. Ward, and G. Birch, “Automatic artefact removal in a self-paced hybrid brain- computer interface system,” J. Neuroengineering Rehabil., vol. 50, pp. 1-20, 2012.

[18] S. H. Wang, Y. D. Zhang, Z. Dong, and P. Phillips, Wavelet Families and Variants, Springer: Singapore, 2018.

[19] I. Sharif and S. Khare, “Comparative analysis of Haar and Daubechies wavelet for hyper spectral imageclassification,” Int. Arch. Photogram. Rem. Sens. Spati. Inf. Scie, pp. 937-941, 2014.

[20] Z. A. A. Alyasseri and A. Member, “EEG signals denoising using optimal wavelet transform hybridized with efficient metaheuristic methods,” IEEE Access, vol. 8, pp. 10584-10605, 2020.

[21] C. Kaur, A. Bisht, P. Singh, and G. Joshi, “EEG Signal denoising using hybrid approach of variational mode decomposition and wavelets for depression,” Biomed. Signal Process. Control, vol. 65, pp. 1-10, 2020.

[22] S. T. George, D. Raveena, J. Dolly, and S. Radha, “Artifact cleaning of motor imagery EEG by statistical features extraction using wavelet families,” Int. J. Circuit Theory App., vol. 48, pp. 1-23, 2020.

[23] I. Aliyu and C. G. Lim, “Selection of optimal wavelet features for epileptic EEG signal classification with LSTM,” Neural Comput. Appl., pp. 1-21, 2021.

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