FPGA-IMPLEMENTATION OF WAVELET-BASED DENOISING TECHNIQUE TO REMOVE OCULAR ARTIFACT FROM SINGLE- CHANNEL EEG SIGNAL

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ABSTRACT

This paper presents the real-time implementation on FPGA of the wavelet-based denoising technique to remove the ocular artifact from the signal-channel EEG signal. The advantage of this method over conventional methods is that there is no need for the recording of the electrooculogram (EOG) signal itself. This approach papers both for eye blinks and eye movements. Discrete Wavelet Transform (DWT) is selected end the hard-thresholding is applied to the wavelet coefficients using the Statistical Threshold (ST) estimated in interested bands. This real-time architecture presents two characteristics: 1) quantization of the filter coefficients and the elimination of the multiplier to reduce the hard cost, and 2) symmetrical extension of the signal boundary to full reconstruction while the data volume is invariable. Experimental results show that proposed architecture efficiently removes the ocular artifact from EEG signal.

KEYWORDS

Wavelet transform, EEG, ocular artefact, hard-thresholding, denoising

1. INTRODUCTION

Electroencephalogram (EEG) is the recording of the brain's neuronal activity by placing electrodes on the scalp [1]. The EEG remains most of cerebral information that has been utilized in many medical diagnosis and therapies including epilepsy, sleep disorder, and so on [2]. However, EEG records are often corrupted by different types of artifacts that lead to the requirement of the use of complex methods for identification and to an increase in the difficulty in analysing the clinical information. Therefore, artifact removal is very necessary. Those artifact sources are usually divided into two categories: extra physiologic, such as power-line interference and electrodes noise, and physiologic, such as eye, muscle, and cardiac activities. The former artifact can often be removed by traditional filtering techniques, but removal of the latter artifact requires careful attention due to the fact that it can be within the same frequency range of the EEG signal [3]. Compared with other physiologic artifacts, the ocular artifact is the most significant, so a real-time ocular artifact removal technique is our aim.

Ocular artifact is caused by eye movements and eye blinks during the EEG recording and have frequency ranges of 0–7 Hz and 8-13 Hz, respectively. But sometimes, vertical eye movement

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artifacts seem to produce a rise in the higher frequencies [4]. Therefore, we applied threshold denoising in bands with frequency between 0-16Hz. The widely used methods for ocular artifact removal from EEG signal are based on the time domain and frequency domain like Principal Component Analysis (PCA) [5] and the Independent Component Analysis (ICA) [6], which are also shown to be efficiently to remove ocular artifact, but they rely on multiple channel data. Fourier transform (FT) [7] and short-time Fourier transform (STFT) [8] have already been applied for signal analysing but they are also suffering from shortcomings when handling non-stationary and non-deterministic EEG signal. From the variety of approaches available, the Wavelet transform (WT) was found to be the most effective time-frequency domain analysis method to deal with EEG signal, because WT provides accurate frequency information at low frequencies and accurate time information at high frequencies, and this property is matched with biomedical applications [9].

In this paper, we implement the wavelet-based denoising algorithm to real-time removal the ocular artifact from the single-channel EEG signal and verify hardware designs on Xilinx FPGA.

2. WAVELET-BASED DENOISING

2.1. Discrete Wavelet Transform

The continuous wavelet transform (CWT) of a signal $x(\tau)$ is defined as the correlation between $x(\tau)$ and the basis function $\psi_{(\alpha,\beta)}(\tau)$ as follows:

$$\mathrm{CWT}_{(\alpha,\beta)}=\int_{-\infty}^{+\infty}\chi(\tau)\,\psi^{*}_{(\alpha,\beta)}(\tau)\,d\tau \tag{1}$$

Where (*) denotes the complex conjugate and $\psi_{(\alpha,\beta)}(\tau)$ are obtained by performing dilations and shifting of the mother wavelet $\psi(\tau)$.

$$\psi_{(\alpha,\beta)}=1/\sqrt{\alpha}\psi(\tau-\beta/\alpha) \tag{2}$$

Where α, β is called the scale factor and the time translation factor. The scale factor to approximate different frequencies by compression or stretching, the time translation factor enables the wavelet traverse the signal. A large value of scale parameters represents analysis of low-frequency components of the signal. On the other hand, a small value of this parameters represents analysis of high-frequency components of the signal.

Because of the continuous values of α and β, he CWT has a lot of redundancy in computation, which is not what we want. When α, β is selects as discrete numbers that defined on the basis of power of two as follows:

$$\alpha_\lambda=2^\lambda \tag{3}$$

$$\beta_{\lambda,\kappa}=2^\lambda k,\ \ \lambda, k\in Z \tag{4}$$

Then DWT is obtained and defined as follows:

$$DWT_{(\lambda,k)}=2^{-\lambda/2}\int_{-\infty}^{+\infty}\chi(\tau)\,\psi^{*}\left(2^{-\lambda}\tau-k\right)d\tau \quad (5)$$

When α is selects as (3), but β is still continuous values, then stationary wavelet transform (SWT) is obtained.

$$SWT_{(\lambda,\kappa)}=2^{-\lambda/2}\int_{-\infty}^{+\infty}\chi(\tau)\,\psi^{*}\left(2^{-\lambda}\tau-2^{-\lambda}\kappa\right)d\tau \quad (6)$$

Compare (1), (2), (5) and (6), DWT with orthogonal wavelet is considered non-redundant and highly efficient wavelet transform to obtain discrete wavelet representation of signals, it requires less computational resources than others wavelet transform for real-time analysis. Therefore, in this paper, we choose DWT, which is a good choice for single-channel hardware implementation.

2.2. Discrete Wavelet Transform

Mallat algorithm [10] is usually used to compute the DWT, it can speed up the calculation of DWT. This algorithm is based on a pair of low-pass (H) and high-pass (G) filters, named quadrature mirror filters (QMF), their relationship as follows:

$$G(n)=(-1)^{k}H(N-n-1). \quad (7)$$

Where N is the number of filter coefficients.

These filters are constructed from the wavelet function ψ(τ) and scaling function φ(τ), their relationship as follows:

$$\varphi(\tau)=\sqrt{2}\sum_{\kappa}H(k)\varphi(2\tau-k). \quad (8)$$

$$\psi(\tau)=\sqrt{2}\sum_{\kappa}G(k)\psi(2\tau-k). \quad (9)$$

The outputs of the high-pass filters corresponds to the high frequency components of the signal, called details components $d_\lambda(k)$ and the outputs of the low-pass filters corresponds to the low frequency components of signal, called approximations components $a_\lambda(k)$. Using the $d_\lambda(k)$ and $a_\lambda(k)$ can fully reconstruct original signal, this process is called the inverse discrete wavelet transform (IDWT).

The IDWT used a pair of low-pass $(\tilde{H})$ filters and high-pass filters $\tilde{G}$ to reconstruction. The decomposition and reconstruction filters are related to each other as follows:

$$\tilde{H}=H(N-n-1) \quad (10)$$

$$\tilde{G}=G(N-n-1) \quad (11)$$

There, four filters have the same absolute value, but sign and position are different from each other.

2.3. Threshold and Thresholding Function

The wavelet-based denoising technique are usually based on the Donoho algorithm [11] that consists to apply a thresholding function to the wavelet coefficients at different scales. The main idea of this algorithm is to compared the wavelet coefficients with the preset threshold.

Hard thresholding function as follows:

$$\omega = \begin{cases} \omega & |\omega| \geq T \\ 0 & |\omega| < T \end{cases} \tag{12}$$

Soft thresholding function as follows:

$$\omega = \begin{cases} \mathrm{sgn}(\omega)(|\omega| - T) & |\omega| \geq T \\ 0 & |\omega| < T \end{cases} \tag{13}$$

Where ω is the wavelet coefficients, T is the preset threshold.

A coiflet 3 wavelet (coif3) filter has been chosen, since the shape of its mother wavelet resembles the shape of the eye blink artifact [4]. According to [3], [12], the statistical threshold T with hard thresholding function would be better, T as follows:

$$T = 1.5\sigma(Hk)$$

Where σ (Hk) is standard deviation of detail coefficients at the k level.

2.4. Performance Metrics

Signal to artifact ratio (SAR), signal to noise ratio (SNR) and root mean square error (NMSE) are used in this paper to evaluate denoising performance [3], [13]. SAR, SNR and NMSE as follows:

$$\mathrm{SAR}{=}10\log(\sigma(\chi)/\sigma(\chi - \tilde{\chi})). \tag{15}$$

$$\mathrm{SNR}{=}10\log(\textstyle\sum_{\lambda=1}^{k} \chi(\lambda)^2 / \sum_{\lambda=1}^{\kappa} (\chi(\lambda) - \tilde{\chi}(\lambda))^2 \tag{16}$$

$$\mathrm{RMSE}{=}\sqrt{\textstyle\sum_{\lambda=1}^{\kappa} (\chi(\lambda) - \tilde{\chi}(\lambda))^2 / k} \tag{17}$$

Where χ is original signal, $\tilde{\chi}$ is denoising signal, and k is the length of χ.

3. IMPLEMENTATION AND ANALYSE

In order to implement the method of using DWT to remove the ocular artifact with Mallat algorithm and Donoho algorithm on hardware, we need quantization of the filter coefficients and overcome boundary effects. There, pipeline technique and symmetrical-extendsion technique are used to solving filters implement and avoid boundary effects.

3.1. EEG Data Source

The EEG data is used in this paper are taken from the BCI Competition 2008 Graz data set B, was publicly available [14]. This database consists of EEG data from 9 subjects, recorded the real EEG signal and electrooculogram (EOG) signal. All of data were recorded with a sampling frequency of 250 Hz, and they were through a band-pass filter between 0.5 Hz and 100 Hz, and a notch filter at 50 Hz to filter power-line noise.

The eye and brain activities have physiologically separate sources, it makes them independent [15], and can be represented as follows:

$$EEG_{rec} = EEG_{true} + k \cdot \mathrm{EOG} \tag{18}$$

Where k represents the propagation factor. According to [18], we can consider EEGtrue is clean EEG signal, and EEGtest is contaminated EEG signal by ocular artifact. We used EEGtest as we need for this paper. In this paper, k=1.

3.2. Implementation Architecture

The proposed architecture consists of three parts: decomposition, denoising and reconstruction. That is based on the Mallat algorithm and Donoho algorithm described in the previous mentioned. As shown in Figure 1, for acceptable computational complexity and obtain the frequency range of interest, the contaminated EEG decomposition five level, the correspond frequency down to up almost in 0-4 Hz, 4-8 Hz, 8-16 Hz, 16-32 Hz, 32-64 Hz and 64-128 Hz.

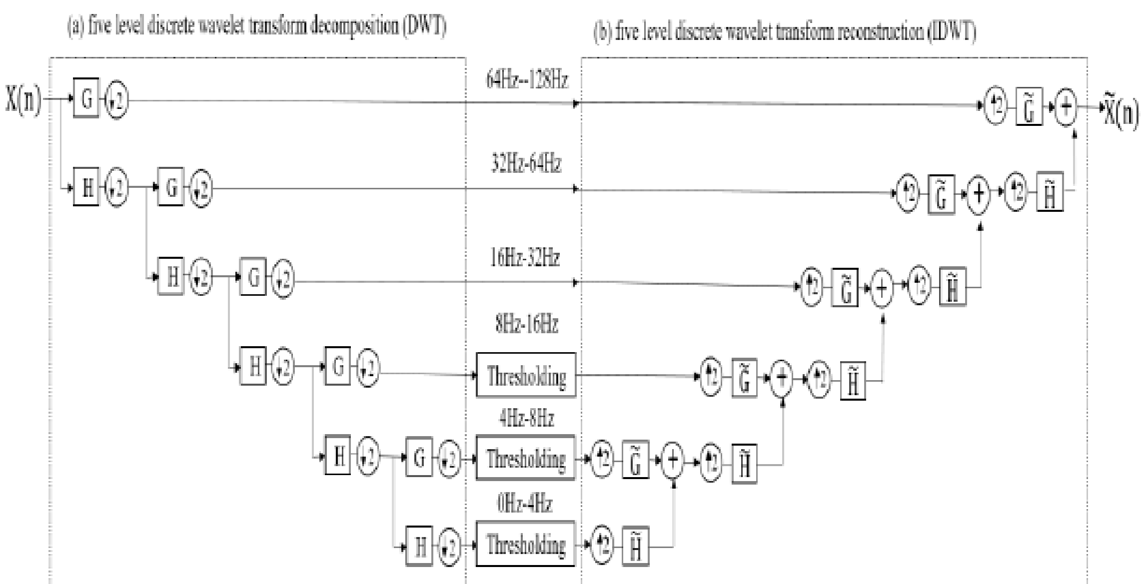

Figure 1. Real-time denoising architecture based on wavelet transform

When a sequence x(n) coming, x(n) is decompose by DWT into detail components and approximation components, and double sampling. Then only the approximations components are continue divided into two part as before. The last two level include one approximations component and two detail components are denoising by hard thresholding to get the new wavelet coefficients. When the decomposition and denoising are done, insert one zero between each sample. Then used the new wavelet coefficients to reconstruction the sequence, the process is just the opposite of the decomposition.

3.3. Filters Coefficients

In order to implement the DWT filters on hardware, the filters coefficients should be quantified that is enlarges the filter coefficients and then take the integer par. In this paper, 32 times, 64 times, 128 times and 256 times are applied to test EEG signal, the reconstruction results show that enlarge 256 times can bring minimum error that we can allowed, as shown in the Figure 2 (a), (b), (c), (d). Obviously the higher times error will be lower, but it will lead to greater hardware cost.

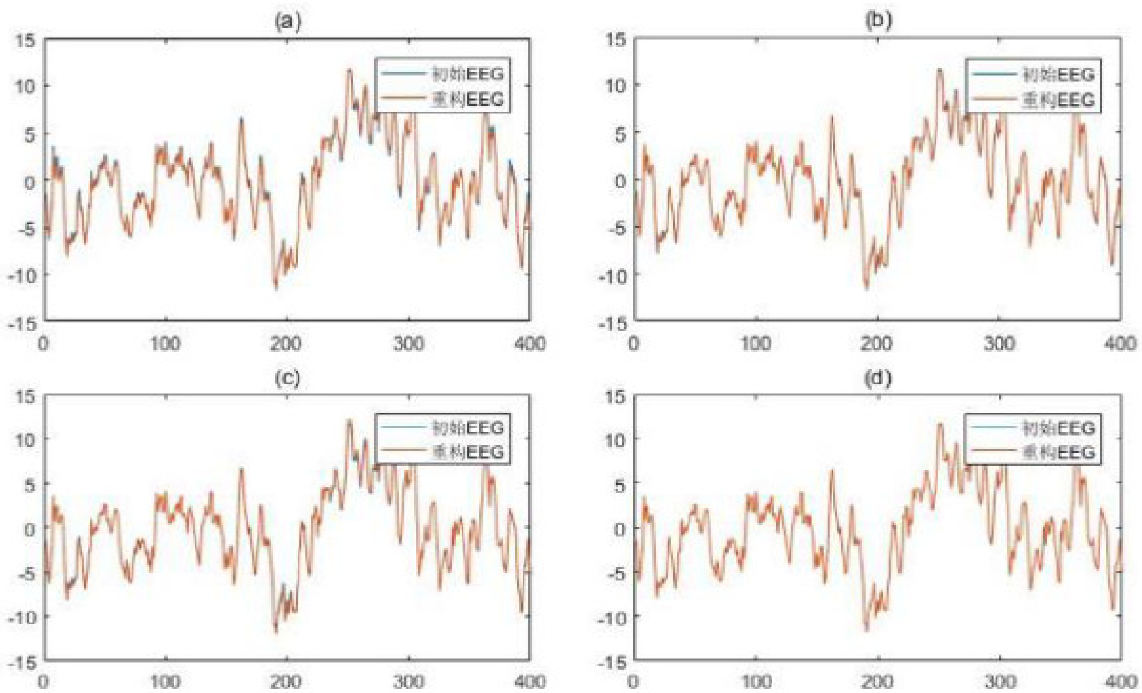

Figure 2. EEG reconstruction results with different quantification

Then used the power of two to represent the coefficients after expand 256 times, taking coefficients about colif3 filters (H) for example, as shown in the Table 1.

According to this characteristic, we applied shift-adder replaces the multiplier to implement no multiplier FIR filter, and take account of quantification, four coefficients are going to zero, so that only fourteen coefficients are useful data, four level pipeline can complete the addition. Because of the DWT filters features, just like the previous analysis four kinds of filters (H, G, $\tilde{H}$,$\tilde{G}$) can be used this structure ,as shown in Figure 3.

3.4. Boundary Effect

DWT is assuming that the data is infinite, but in practice, the data is often limited, so overcome boundary effect is necessary. According to the DWT algorithm, it is a convolution process. So when used filters to replace convolution to deal with limited data will bring boundary effects, especially the filter length is longer. There are usually three ways to extend the boundary: zero-extension, cycle-extension and symmetrical-extension.

Zero-extension is used zero instead of data which beyond the boundary, it's advantage is simple, but will lead to distortion duo to mutation. Cycle-extension is periodization of the original signal, it will increase a lot of computation. Symmetrical-extension only used boundary data, and can be fully reconstruction without adding data.

To avoid the boundary effect, in this paper choose extend seventeen boundary data that symmetric with the original boundary data before data through decomposition filters. Then select valid data to reconstruction enable the data volume is invariable, this equivalent to reducing the amount of reconstruction computation, it is important for hardware implementation. Due to the five-level is the same architecture to one-level, so there take one-level denoising based on DWT-IDWT with coif3 wavelet for example, as shown in Figure 4. Where L is the length of the data in the corresponding position, the original data length set 32, and the outputs data is select last 32 data from 49. Experiments show that it can be fully reconstructed. So in the five-level architecture, when data enter into second level, the data is not 49 but 32, following level is the same as this. Finally, a lot of computation is reduced.

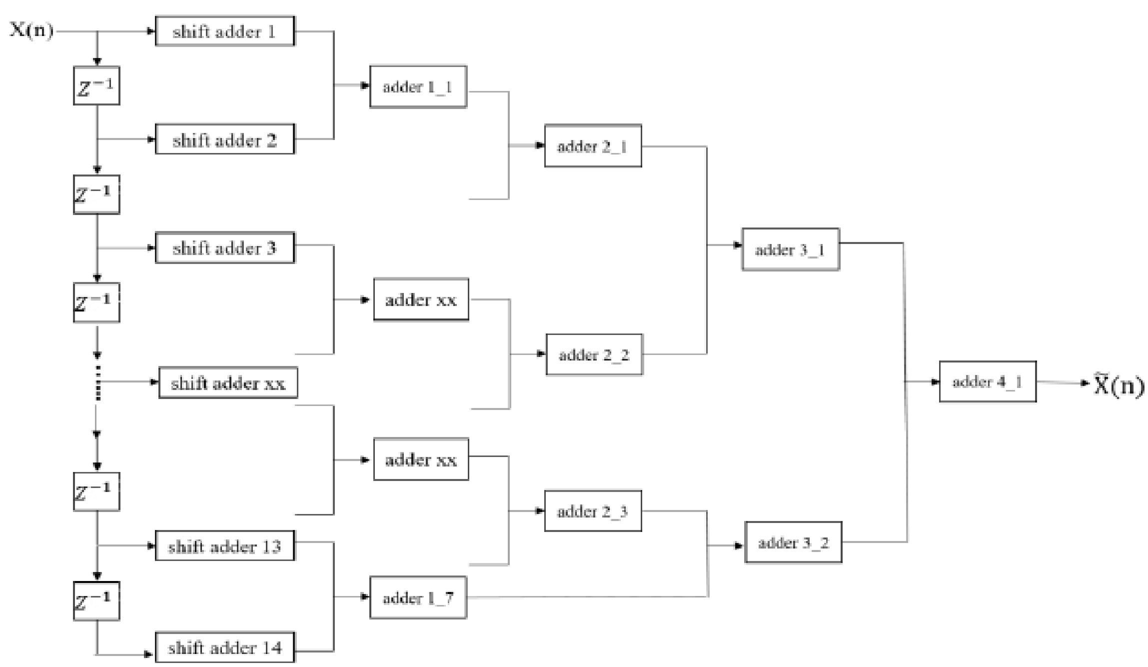

Figure 3. Shift adder and four level pipeline addition structure used to implement filters

Table 1 Filter coefficients (H) of coif3 wavelet

Coefficients(H)	Original	Trunc	Power of two
1	0.00379351286	1	2^0
2	0.00778259642	2	2^1
3	-0.02345269614	-6	-2^2-2^1
4	0.06577191128	-17	2^4-2^0
5	0.06112339000	16	2^4
6	0.40517690240	104	$2^7-2^4-2^3$
7	-0.79377722262	-203	$-2^8+2^6-2^3-2^1-2^0$
8	0.42848347637	110	$2^7-2^4-2^0$
9	0.07179982161	18	2^4+2^1
10	-0.08230192710	-21	$-2^4-2^2-2^0$
11	-0.03455502757	-9	-2^3-2^0
12	0.01588054486	4	2^2
13	0.00900797613	2	2^1
14	-0.00257451768	-1	-2^0
15	-0.00111751877	0	0
16	0.00046621696	0	0
17	0.00007098330	0	0
18	-0.00003459977	0	0

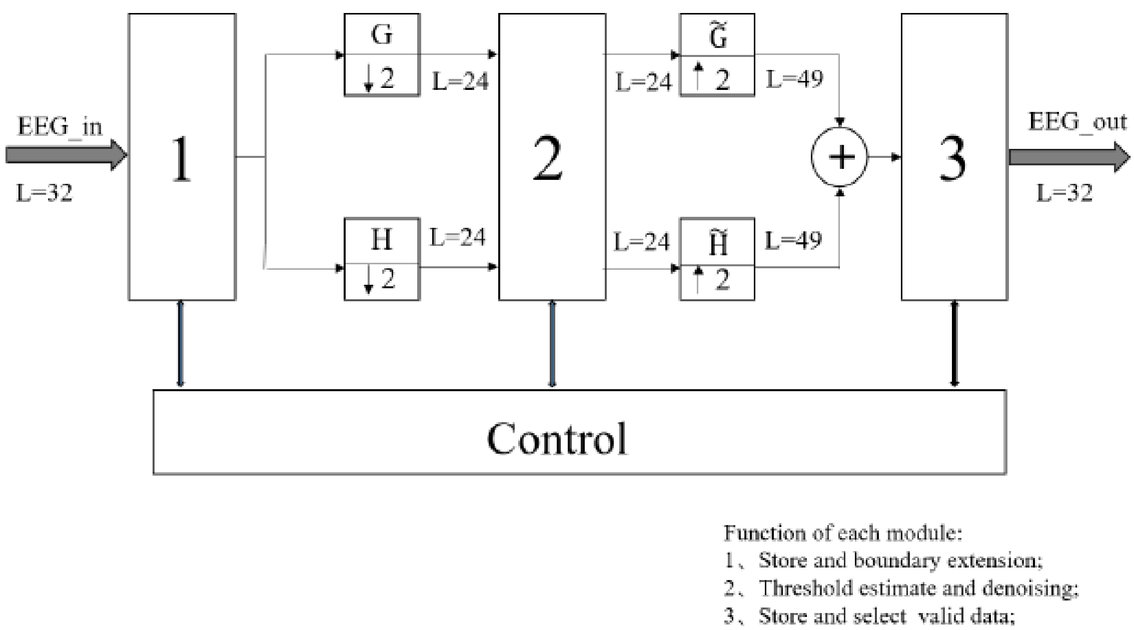

Figure 4. FPGA architecture for one-level denoising based on DWT-IDWT with coif3 wavelet

3.5. FPGA Results

We used previous EEG database to obtain EEG test data by formula (18) for this paper. In this paper, SAR, SNR and RMSE to be counted before and after denoising, shown in Table 2. The results shown that SNR have big improvement. The greater value of SAR, is considered to the more artifact is removed, and the smaller value of RMSE is considered to before and after artifact denoising the error is smaller, which means that the useful signal is retained as far as possible. In Figure 5, it also shows that the ocular artifact is effective removal from EEG signal. Besides, we can find the ocular artifact maximum frequency is over 13Hz, it fits with what we said before.

Table 2. Indication of EEG before and after denoising

Indication	Before	After	Difference Value
SNR	-51.53	1.28	53.21
SAR	-25.96	-9.98	15.98
RMSE	53.32	51.92	-1.4

4. CONCLUSIONS

In this paper, a real-time removal of the ocular artifact from signal-channel EEG signal based on discrete wavelet transform was implemented on FPGA. In addition to considering hardware cost in the implementation, boundary effects are also take into account. The method what we adopted to remove ocular artifact shows effective, and reduced a lot of computation.

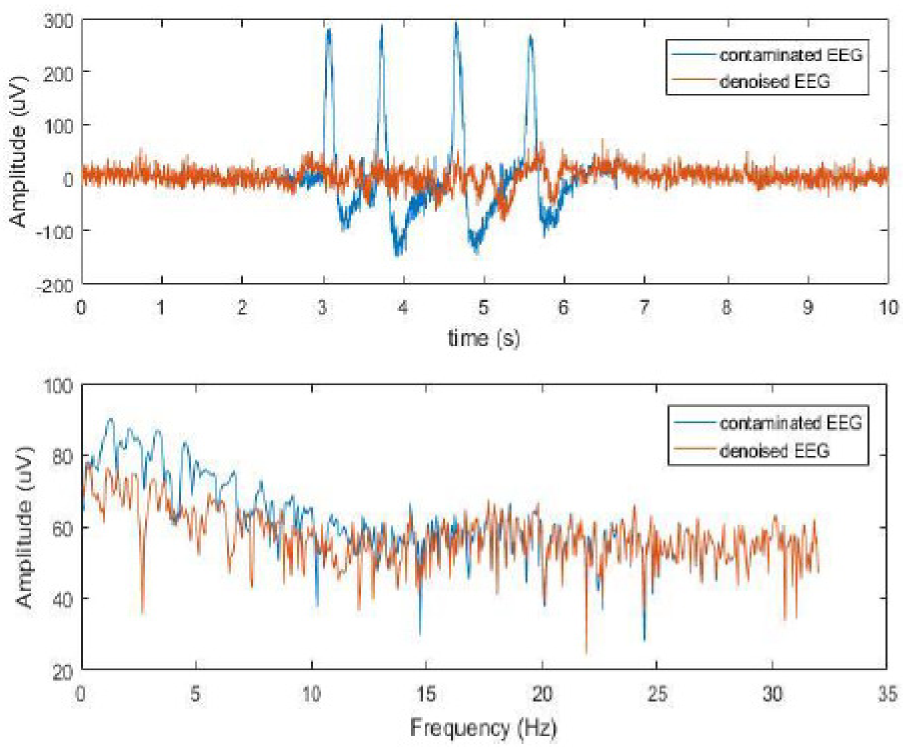

Figure 5. Compare of EEG before and after denoising

In the future, we will apply this denoising structure in the Brain Machine Interface (BCI) system to compare the effects about feature extraction and classifications for EEG signal before and after denoising.

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