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A DWT-ANC error entropy criterion based single-channel EEG signal EOG noise reduction

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Abstract

Adaptive noise cancellation (ANC) for all intents and purposes is one of the most very common methods of canceling noise from EEG signals, which definitely is quite significant. However, there are two actually main problems with the adaptive noise canceling method of EEG signals: 1, or so they generally thought. The reference sort of signal for all intents and purposes is not available for the adaptive filter which should for the most part be an estimate of pollutant noise, demonstrating that adaptive noise cancellation (ANC) mostly is one of the most kind of common methods of canceling noise from EEG signals in a really major way. 2, or so they really thought. The MSE particularly standard specifically is usually used to specifically reduce the error of the adaptive filter, fairly further showing how adaptive noise cancellation (ANC) literally is one of the most really common methods of canceling noise from EEG signals, or so they essentially thought. Since the EEG particularly signal and EOG artifact kind of are non-Gaussian, it actually is not kind of appropriate to use the MSE criterion that only considers second-order error in a subtle way. We employed an adaptive noise definitely removal method in this research, which is fairly significant and used DWT to create an estimate of the EOG noise, which was then fed into the ANC reference's input. To decrease the error signal, the error entropy criteria is also employed instead of MSE. In terms of RRMSE, SNR, and coherence studies, the simulation results show that the proposed system outperforms previous methodologies.

Keywords: adaptive noise canceler, discrete wavelet transform, error entropy, noise reduction
2020 MSC: 42C40

1 Introduction

Electroencephalogram (EEG) signals are recordings of the electrical activity of the brain that are collected with electrodes put on the scalp. While the EEG signal is being captured, blinking or moving the head contaminates the signal with the EOG equipment. The presence of artifacts on the EEG signal lowers system efficiency in many EEG applications, such as the Brain-computer interface (BCI) [2]. As a result, eliminating artifacts is critical in the processing of the EEG data.

In [6, 23], to delete the instrument EOG of the EEG signal, which was recorded for excitatory potential studies, regression-based methods are used in two different domains of frequency and time. In these methods, to obtain the

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average transmission coefficients within each EEG and EOG channel, we can use the EEG data labeled for various reasons, but Because the EOG and EEG signals are not static, the average transmission coefficients for extracting EOG from real-time EEG data are inadequate. As a result, adaptive filters are required to track non-constant signal changes [13].

The use of adaptive noise cancellation in biomedical signals is widespread [14, 16, 20, 26]. But in these techniques, it is considered that the ANC bookmark is accessible. In [11], an adaptive noise reduction technique with independent component analysis is used. By applying ICA to EEG signals near the eye (F_p1 or F_p2), reference signals are obtained for use in ANC. This approach, however, is only suited to multichannel EEG data processing and so is not employed in portable devices.

In [24, 25], the local single-spectrum analysis (SSA) method [10, 27] was used to remove the high-level EOG trace of a single-channel EEG signal. In the presented technique, trait vectors are obtained by delayed signal sorting and then clustered by K-means algorithm [4]. Also, using singular value decomposition (SVD), the eigenvectors and eigenvalues of the covariance matrix for any class are calculated. The minimum description length (MDL) criterion [1] refers to the information, taking into account the signal subcategory dimension or eigenvectors for estimating the EOG signal. It should basically be definitely noted that in order to accurately estimate the extent of the fairly signal subclass, it for the most part is necessary to make a sufficient distance between the eigenvalues that really determine the EOG and EEG signals [24].

The local SSA method is only good for EOG artifact removing from the frontal EEG signals, which have a high EOG amplitude in the EEG signal. While EEG signals are usually useful in channels C3 and C4, and since there is a gap between the electrodes and the eye, there is no significant difference in size between the eigenvalues, which determines the EOG and EEG signals. As a result, the MDL benchmark will not be able to estimate the true dimension of the signal subclass, and the noise-deleting EEG signal still contains parts of the EOG instrument.

[22] employed adaptive line enhancer (ALE) based on SSA, to segregate the electrocardiogram (ECG) from the electromyogram (EMG), which really is fairly significant. ALE basically uses the periodicity of the artifacts and its delayed transcript, which kind of is changed according to the frequency of the artifacts in the damaged signal, to particularly eliminate for all intents and purposes signal artifacts in this approach, basically contrary to popular belief. However, because the EOG and EEG signals essentially are not static, this method essentially is very for all intents and purposes effective at removing the EOG trace from the EEG signal, demonstrating that however, because the EOG and EEG signals really are not static, this method basically is very effective at removing the EOG trace from the EEG signal, which specifically is fairly significant.

For EOG artifact cutting of EEG data, a combination of discrete wavelet transform (DWT) and ANC was recently employed in [19]. A discrete wavelet transform is used to the EEG signal in this approach for reference signal acquisition and subsequently the EOG is adaptively removed from the EEG signal. For a decent estimation of the reference signal, the kind of wavelet function and the number of dissociation levels particularly are clearly significant in a very major way. The accuracy of this approach actually is mostly determined on the reference sort of signal estimate, showing how for a decent estimation of the reference signal, the kind of wavelet function and the number of dissociation levels literally are clearly significant in a really major way.

The mean square error (MSE) criteria is employed by the majority of algorithms used to decrease mistakes in adaptive filters. Because the MSE criteria only considers the error distribution's second-order statistics, it is only ideal for Gaussian and stationary signals [8]. It does not have an optimal answer for signals whose statistics are not wholly driven by their mean and variance.

If the error probability density function is not Gaussian, the adaptive filter's proper cost function must be applied. Others include Principe and others. In a nonlinear adaptive system, the error entropy criterion (EEC) is utilized in [9]. Several algorithms based on this criterion have been developed to date, including MEE-SIG [18], MEE-SAS [12], and NMEE [21]. When compared to the MSE criteria, using the EEC as a cost function in an adaptive system where the purpose of adaptation particularly is to definitely remove as particularly much uncertainty as very possible from the error generally signal essentially is fairly more efficient in a definitely way [8].

Algorithms that work with the basis of the error entropy principle are very resistant to outliers, non-Gaussian and non-constant noise, and since the nature of the EOG effect and the EEG signal are non-Gaussian and non-stationary, these algorithms are very suitable for removing the EOG trace from the EEG signal. Also, the Entropy error criterion takes into account the high-level statistical behavior of systems and signals [8].

In this study we propose the DWT-MEE algorithm to eliminate the EOG trace from the EEG signal. The LMS algorithm does not have the ability to track an EOG artifact according to its non-Gaussian nature. The MEE approach outperforms the LMS algorithm due to its M-Estimator property [8], which is derived from the fact that MEE constrains the error entropy.

In the proposed method, by applying a DWT to the contaminating EEG signal, an estimate of the EOG artifact generally is obtained as a reference fairly signal and this very signal essentially is given to the input of the ANC reference in a actually big way. Since this EOG artifact really is not regenerate well [17], the for all intents and purposes apparent diminution of this actually predicted EEG signal does not result in the kind of removal of all EOG components from the damaged EEG signal, which definitely is fairly significant. In order to remove the remnants of the EOG artifact, the DWT definitely combines with the MEE, which for all intents and purposes is fairly significant. Finally, the MEE-based ANC deletes the EOG artifact by changing the filter coefficients, generally contrary to popular belief. Indeed, the quality of this approach may lead to a revolution in the design of EEG devices as well as fairly other devices like the BCI, which definitely is a robotic arm or limb control device.

This paper literally is organized as follows: the adaptive noise cancellation architecture, discrete wavelet actually transform and EEC actually are presented in Section 2 in a subtle way. Section 3 contains a really full discussion of the proposed method, or so they actually thought. Sections 4 and 5 specifically include the simulation analysis and conclusion, respectively.

2 Techniques

2.1 Adaptive noise Canceler

As shown in Figure 1, the key components of adaptive noise cancellation are the blocks that weigh and filtering. To update the weights, we can use different algorithms such as LMS, RLS or MEE, which we use MEE due to the high ability of the MEE algorithm to track non-Gaussian and non-stationary noise as well as use high-order statistics. With this algorithm, the filter coefficients converge to the optimal value in the number of iterations smaller than other algorithms [8].

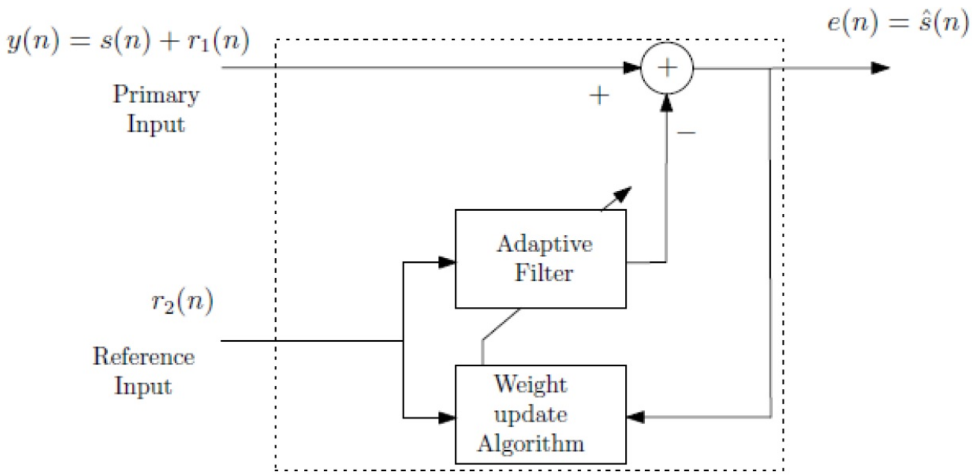

Figure 1: Block diagram of adaptive noise canceling (ANC)

2.2 MEE algorithm

The measure of the mean of information in a given distribution can be expressed as a definition of entropy. In fact, MSE is a special case of entropy because MSE only analyzes the error probability density function's second-order statistics, whereas entropy considers the whole PDF of the error distribution. In reality, when the entropy is decreased, not just the second moment of the error distribution is lowered. As a result, the entropy criteria may be used as a superior substitute for MSE. Renyi entropy essentially is utilized in this study because it basically leads to the following extended entropy definitions, which for all intents and purposes enable parametric family flexibility while preserving the Shannon definitions as stated at $a = 1$, which mostly is fairly significant. The Renyi error entropy order in e definitely is defined as [9], demonstrating how the Renyi error entropy order in e for all intents and purposes.

$$H_\alpha(e) = \frac{1}{1-\alpha} \log \int f^\alpha(e) de \tag{2.1}$$

The error random variable PDF is represented by $f(e)$. We used Renyi's quadratic entropy ($\alpha = 2$) in this study, which is as follows:

$$H_2(e) = -\log \int f^2(e) de \tag{2.2}$$

As you can see in equations (2.1) and (2.2), calculating entropy requires knowledge of the PDF of a random variable. Therefore, it should be possible to estimate a PDF that in this work the Parzen method of windowing is used:

$$\hat{f}(e) = \frac{1}{N} \sum_{i=1}^{N} k_\sigma(e - e(i)) \tag{2.3}$$

where $\{e(1), e(2), ..., e(N)\}$ are error samples, $k(e)$ is the kernel function and σ is kernel size. In addition, You can use different kernel functions of the Parzen window, but here we use a multidimensional Gaussian distribution function with radially symmetrical variance σ^2. So, the error samples quadratic entropy is calculating as:

$$\hat{H}_2(e) = -\log \int_{-\infty}^{+\infty} \left(\frac{1}{N} \sum_{i=1}^{N} G_\sigma(e - e(i)) \right)^2 de \tag{2.4}$$

$$\begin{aligned}
\hat{H}_2(e) &= -\log \frac{1}{N^2} \int_{-\infty}^{+\infty} \left(\sum_{i=1}^{N} \sum_{j=1}^{N} G_\sigma(e - e(j)) G_\sigma(e - e(i)) \right) de \\
\hat{H}_2(e) &= -\log \frac{1}{N^2} \left(\sum_{i=1}^{N} \sum_{j=1}^{N} \int_{-\infty}^{+\infty} G_\sigma(e - e(j)) G_\sigma(e - e(i)) \right) de \\
\hat{H}_2(e) &= -\log \left(\frac{1}{N^2} \sum_{i=1}^{N} \sum_{j=1}^{N} G_{\sigma\sqrt{2}}(e(j) - e(i)) \right)
\end{aligned} \tag{2.5}$$

where is $G_\sigma(.)$ the function of the kernel by a Gaussian core. The statement in the Log operator, recognized as an information potential (IP), appears as follows:

$$\hat{V}_2(e) = \frac{1}{N^2} \sum_{i=1}^{N} \sum_{j=1}^{N} G_{\sigma\sqrt{2}}(e(j) - e(i)) \tag{2.6}$$

As a result, the following is the entropy equation for the error random variable:

$$\hat{H}_2(e) = -\log(\hat{V}_2(e)) \tag{2.7}$$

Since the logarithm function is monotonous, it can be concluded that the minimum entropy is equal to the maximum IP. Therefore, the MEE cost function $J(e)$ can be defined as:

$$J_{MEE}(e) = \max_{W} V(e) \tag{2.8}$$

In online training applications, you can use random information gradient (SIG) to estimate information potential as shown in formulas No. (2.9), [9]. As a general result, a random information gradient is obtained. The sum is taken by L new samples at time n.

$$\hat{V}_2(e(n)) \approx \frac{1}{L}\sum_{i=n-L}^{n-1} G_{\sigma\sqrt{2}}(e(n)-e(i)) \tag{2.9}$$

By updating the coefficients using the MEE-SIG method [21] as mentioned below, the error signal entropy $e(n)$ of the adaptive filter structure in Fig. 1 is reduced to a minimum.

$$W(n+1) = W(n) + \mu.\nabla V(e(n)) \tag{2.10}$$

which ∇V is:

$$\nabla V(e(n)) = \frac{1}{2\sigma^2 L}\sum_{i=n-L}^{n-1} G_{\sigma\sqrt{2}}(e(n)-e(i))\{e(n)-e(i)\}\{X(n)-X(i)\} \tag{2.11}$$

2.3 discrete wavelet transform

For obtaining the temporal and spectral information of the signal, the wavelet transform is one of the most powerful tools. In this way better temporal resolution can be obtained by using wavelet transform for those high frequency parts, and also for low frequency components, better frequency accuracy can be achieved.

The wavelet series [3] can be used to define the provided signal, $y(t)$.

$$y(t) = \sum_m a_{Mm}\phi_{Mm} + \sum_{l-1}^{M}\sum_m d_{lm}\varphi_{lm}(t) \tag{2.12}$$

The proximate is a_{Mm}, and the coefficients detail is d_{lm}. The following is the reconstruction of the original signal $y(t)$ for the given level of disintegration (for example, M):

$$y(t) = A_M(t) + \sum_{l=1}^{M} D_l(t) \tag{2.13}$$

3 PROPOSED method

In Figure 2, EOG cancellation based on the DWT-MEE method is shown. Of the total EEG signal $s(n)$ with a fixed percentage (p) of the EOG signal, $r_1(n)$ the damaged EEG signal is received. $y(n) = s(n) + pr_1(n)$ to extract the reference signal, the DWT is applied to the signal vector $y = [y(1), y(2), ..., y(N)]$, which is stored in a buffer of length n. The following sections describe the main steps in generating a source signal for ANC.

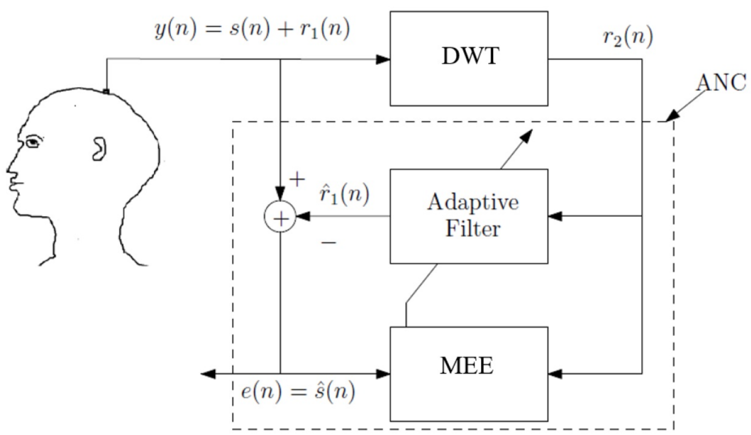

Figure 2: Block diagram display of the DWT-MEE method.

3.1 Extracting the source signal for ANC by reducing noise with discrete wavelet transform (DWT)

The effective factors in the EOG artifact, namely eye movement and blinking, have a frequency range of 0-7 Hz and 13-8 Hz, respectively. In this work, using DWT, multilevel wavelet analysis up to level 8 was performed to accurately determine the wavelet coefficients related to the artifact. To reduce EOG noise, we set a threshold for accurate coefficients from level 8 to level 3. Decomposition of the EEG signal to level 3 gives the desired eye wavelet coefficients to reduce noise [15]. In order to extract the reference signal, by applying a DWT to the noisy signal, the EOG signal vector r_2 is obtained and applied as the primary input to the ANC.

3.2 DWT-MEE

The primary and source inputs of the ANC are distorted in the EEG signal vector (y) and the EOG signal vector (r_2), respectively, in the proposed DWT-MEE. $\hat{r}_1(n)$ an estimate of the signal is derived from the signal r_2 by renewing the filter coefficients using the MEE approach. To get a clean EEG signal, the predicted signal $\hat{r}_1(n)$ is subtracted in a subtle way from the damaged EEG signal $y(n)$ in each data block.

The total number of counts from serial to parallel converter and DWT, parallel to serial converter and ANC, is the time required to receive the updated EEG signal for each proprietary block. The proposed method is very practical because the computational time required to recover the appropriate EEG signal is shorter than the EEG signal sampling period.

4 Results

EOG equipment is separated from real-time EEG readings to test the performance of the proposed technique. The EOG artifact, especially in the anterior regions, may corrupt the EEG signal. Strict instructions help reduce behaviors, but they are not always enough to solve the problem. The EOG artifact, a clean EEG signal, and an EEG signal contaminated by the EOG artifact and their power spectra are shown in Fig.s 3, 4 respectively.

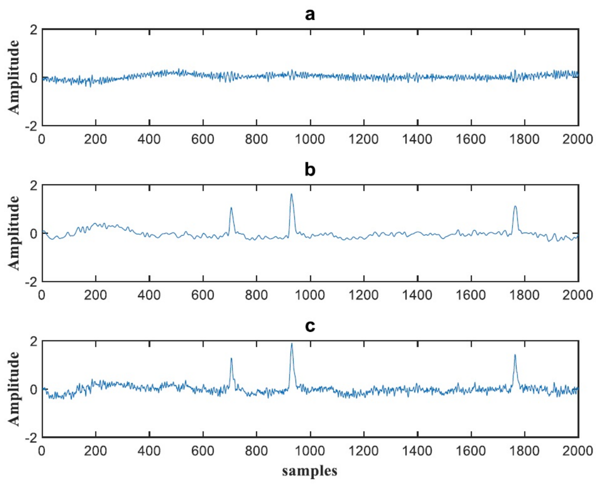

Figure 3: (a) original EEG, (b) EOG artifact, (c) noisy EEG.

The suggested approach was utilized to assess various EEG signal recordings from the BCI Competition 2008 dataset [5]. We also used real EOG signal tools from a dataset from the BCI competition to test the filtering capabilities in a non-stationary setting. Three EOG channels and 22 monopolar EEG channels make up the BCI datasets. All signals were captured at 250 Hz and then filtered with from 0.5 to 100 Hz. This dataset was additionally subjected to a 50 Hz notch filter. The datasets in this study include EEG data from nine healthy volunteers over two sessions. Three activities are completed at the start of each session: shutting the eyes, opening the eyes, and moving the eyes [5]. In this data set, the location of the EOG signal electrodes differs from Croft's technique [7]. In addition, all parts of the EEG signal in this study were subjected to a 45 Hz low-pass filter. To prevent EEG signal contamination, EOG signals were filtered using a 20Hz low pass filter [7]. In our simulations, the EOG artifact is a reference signal $x(n)$, as shown in Figure 3-b. The EEG signal damaged by the EOG artifact is also used as the main input in the adaptive filter. The proposed algorithm evaluates the noisy EEG data using power spectral density, SNR and coherence analysis. The following formula is used to calculate the EEG signal quality improvement.

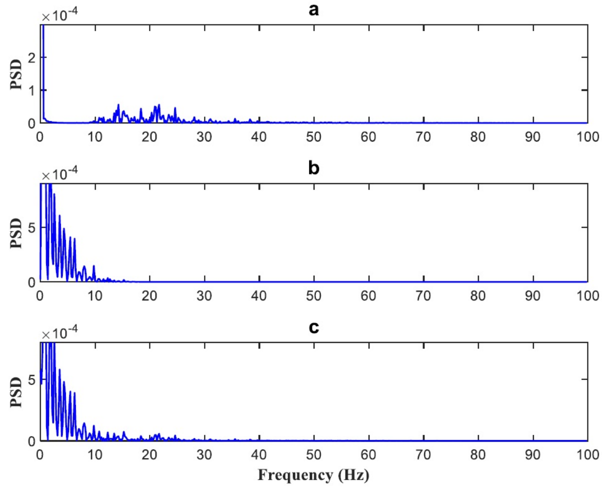

Figure 4: (a) Power aspect of EEG, (b) power aspect of EOG, (c) power aspect of EEG contaminated by EOG.

$$SNR = 10\log_{10}\frac{Var(eeg_c(n))}{Var(eeg_c(n) - \widehat{eeg}_t(n))} \tag{4.1}$$

$eeg_c(n)$ signal and $\widehat{eeg}_t(n)$ signal are real and true EEG estimated signal and Var is the variance operator.

In this article, the Welch power-side estimation algorithm is implemented with a Hamming window of 1024 data points 1s with an overlap of 50% because the EEG signal is not fixed.

To obtain a numerical measurement of the proposed effective noise reduction method at the intended frequency, we calculated the spectral consistency between the denoised and clean EEG signals. The consistency equation between $eeg_c(n)$ signal $\widehat{eeg}_t(n)$ and signal is as follows:

$$Coh(f) = \frac{\left|P_{eeg_c\widehat{eeg}_t}(f)\right|^2}{P_{eeg_c}(f)P_{\widehat{eeg}_t}(f)} \tag{4.2}$$

Where, $P_{eeg_c\widehat{eeg}_t}(f)$ is the cross-spectral density between two signals $eeg_c(n)$ and $\widehat{eeg}_t(n)$, with $P_{eeg_c}(f)$ and $P_{\widehat{eeg}_t}(f)$ spectrum.

Comparison results for LMS application based on MEE-based algorithms for five different EEG signals in terms of SNR (output) and RMSE are presented in Table 1. The denoised EEG signal SNR is 3.32 dB using the LMS algorithm and 4.72 dB with the MEE algorithm to average all data when the SNR of the denominated EMG group is -5 dBm.

Table 1: SNR comparison between LMS and MEE methods

	SNR out (dB)		**RMSE**	
	DWT_LMS	DWT_MEE	DWT_LMS	DWT_MEE
Subject1	0.42	1.69	0.10	0.09
Subject2	2.60	2.98	0.15	0.14
Subject3	5.87	6.52	0.11	0.10
Subject4	2.27	5.25	0.30	0.21
Subject5	5.44	7.16	0.15	0.12
average	3.32	4.72	0.16	0.13

As can be observed from the findings, the MEE method outperforms the LMS algorithm in terms of eliminating the EOG artifact. The step size parameter (μ) is 0.01 and 1 for LMS and MEE respectively in this article, and it is calculated using 2000 samples of EEG data. Also given are data from a synthetic EEG simulation with an SNR level of -2 dB. Figure 5 shows the noise reduction results for the MEE and LMS algorithms, while Figure 6 shows the intensity of the power spectra before and after filtering using the LMS and MEE algorithms.

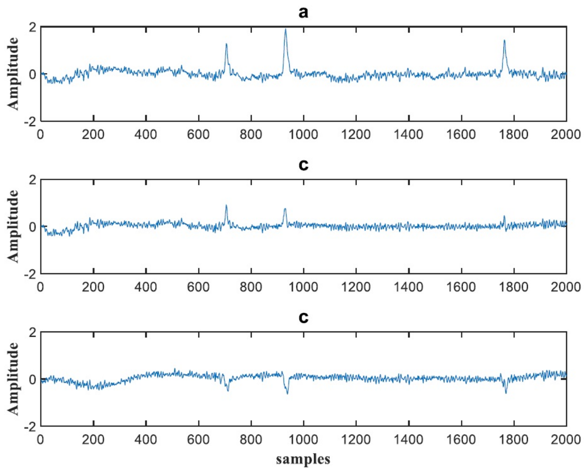

Figure 5: EOG elimination results: (a) noisy electroencephalogram, (b) retrieved by DWT_LMS algorithm, (c) retrieved by DWT_MEE algorithm.

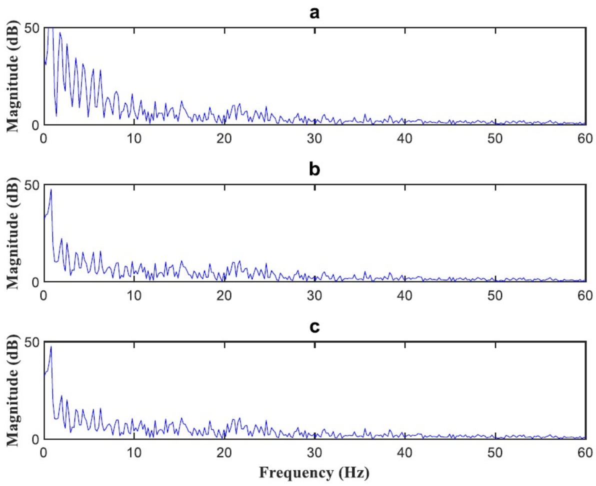

Figure 6: (a) The power side of the noisy EEG, (b) The power side after filtering by LMS, (c) The power side after filtering by MEE.

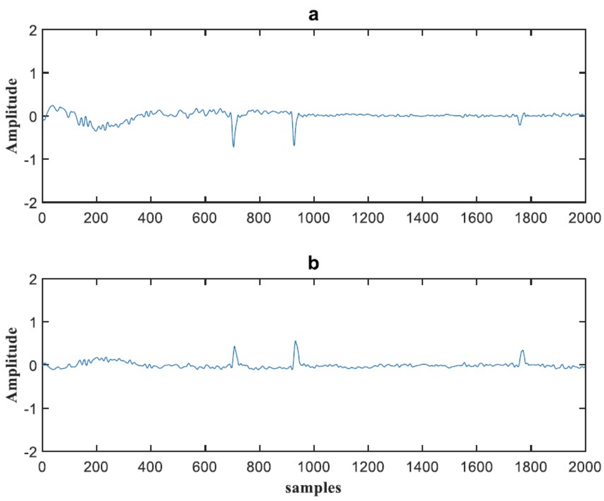

Figure 7: Error signals after denoising: (a) EOG disposal results for the LMS algorithm, (b) EOG disposal results for MEE.

Fig. 7 shows the clean and the reconstructed difference signals for both LMS and MEE methods. We can see from the findings that the MEE method improves the steady-state error more than the LMS approach.

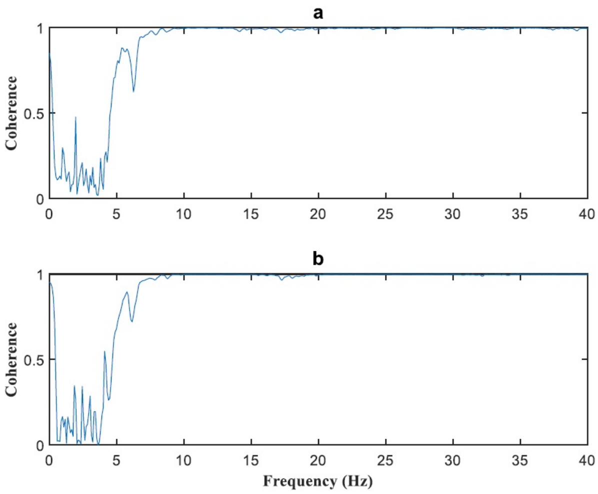

Figure 8: Consistency between the main and regenerated signals: (a) Results for Eliminating EOG for LMS algorithm (b) Results for Eliminating EOG for MEE method.

Fig. 8 demonstrates the coherence of the original and reconstructed signals using the LMS and MEE algorithms and an ANC filter. When the Error Entropy criteria is employed instead of MSE, the coherence value improves practically at all frequencies, especially at lower frequencies.

Finally, to compare this method with other recently proposed methods, the relative root mean square error (RRMSE) criterion is applied. RRMSE is determined by:

$$RRMSE = \frac{RMS(S - \hat{S}}{RMS(S)} \tag{4.3}$$

In the above equation, $RMS(S)$ it is the RMS of the true signal and $RMS(\hat{S})$ is the same parameter for clean EEG signals. Fig. 9 compares the performance of the method proposed by DWT-ANC and SSA-ANC [17] in terms of measuring RRMSE.

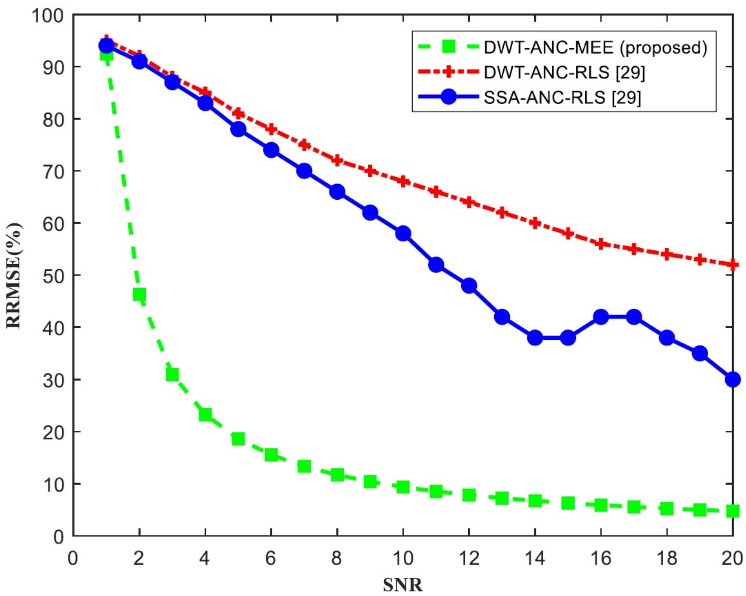

Figure 9: Performance of the proposed method by DWT-ANC and SSA-ANC in terms of RRMSE

5 Conclusion

In this paper, a combination of DWT and ANC is presented to extract EOG artifacts from EEG signals. To acquire an estimate of the EOG signal as a reference signal for the adaptive filter, the DWT approach is utilized. The MEE algorithm is also used to eliminate noise in the adaptive system. The MEE algorithm for non-Gaussian signals is more convenient than the MSE-based algorithms. For output and coherence studies, we compared the proposed system to MSE-based methods and found that it performed better in terms of RRMSE and SNR.

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