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Comparison Among the Artifact Removing Algorithms for the Suppression of Artifact from EEG

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Abstract—It is very important to eliminate artifacts from electroencephalogram (EEG) to analyze EEG accurately. Artifacts integrated with the EEG signal at the time of recording and cant be removed at the begging stage. Ocular artifact is most noticeable artifact in EEG. The filtering approach is most common method to reject eyeblink artifacts from EEG signals where the signal is decomposed to separate artifactual from neural signals. In this paper we compare recently developed data adaptive filtering methods (discrete wavelet transform (DWT), stationary wavelet transform (SWT), and lifting wavelet transform (LWT)) that are appropriate for the taking out of periodic activity. The ability of the method has been evaluated to remove eye blink artifacts by means of two performance metrics signal to artifact ratio (SAR) and mean square error (MSE). It is found that all examined methods considerably reduce the ocular artifacts. Compared to the effect of SAR and MSE of the three filtering method, it is concluded that LWT algorithm is the best artifact removing algorithm for de-noising EEG signals.

Index Terms—EEG, artifact rejection, eye blink artifact, discrete wavelet transform, stationary wavelet transform, lifting wavelet transform;

1 INTRODUCTION

THE important pre-processing stage for most EEG analysis is the elimination of undesirable artifacts from the electroencephalogram (EEG). These unwanted signals come from eye blink, eye movement and muscle movement, the heart beat or outer sources. In this study, we considered only eye blink artifacts removal. These are usually caused by ocular activity near the head, such as eye blinking or eye movement, and are denoted by low-frequency action (below 20 Hz) [1].

Up to now, there are many methods proposed for removing the eye blink artifacts like: Auto-Regression based method (AR) [2,3], Adaptive Filters [4,5], Principal Component Analysis (PCA) [6], and Wavelet Transform (WT) [7]. The EEG signal denoising is done using wavelet transform according to following three processes- firstly, disintegrate the signal into a number of levels, secondly, threshold the detail coefficients and thirdly, reconstruction of the signal from the filtered characterization. The sources of interest will be decomposed on

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the basis of wavelet [8] for removing artifact using WT method.

To preserve the leading coefficients, different forms of thresoldings are used in DWT [8, 9, 10]. The DWT also remains an exciting tool for EEG processing on its own [11, 12, 13, 14]. The DWT technique is not capable to remove entirely ECG like artifacts in EMG signal [16]. Hence, some other artifact removing techniques like ICA [15] usually merged with the DWT.

The wavelet transform technique has been used to remove artifact from non-stationary neural signals. This technique is also a very powerful tool to recognize unusual changes due to artifacts [17]. Although the DWT is not translation invariant, it is the simplest technique compared to continuous wavelet transforms. Due to the translation problem, the small signal variation causes the large changes in the wavelet coefficients [18, 19].

The stationary wavelet transform (SWT) algorithm can solve the translation invariant problem of DWT. In this technique, no down sampling of data is necessary. However, the algorithm has redundant information problem and it is slower than DWT.

The two-channel filter bank is used in DWT iteratively. The filter bank can also be used in polyphase lifting scheme. The lifting wavelet transform produces the DWT like coefficients. The wavelet transform filter bank can be decomposed into the lifting scheme [20, 21]. To rebuild ECG signals the db4 lifting wavelet is used [22].

In paper [26], lifting-based discrete wavelet transform is used to remove artifacts from EEG signals using db4 wavelet. In this paper, lifting wavelet transform (LWT)approach is presented to distinguish low frequency artifacts from contaminated EEG. Using wavelet transform, the signal is fragmented into many subbands. Each sub-band is thresholded and again each subband is added together to obtain the clean signal. Also, this paper aims to show the comparison when EEG signal is filtered with lifting wavelet transform (LWT) and stationary subspace analysis (SSA). The comparative study presented that LWT approach is more effective to obtain the EEG signals after eliminating the contaminated artifacts.

This paper compares different wavelet decompositiontechniques. Specifically, a comparative research of discrete wavelet transform, stationary wavelet transform and lifting wavelet transform with db4 wavelet is presented for removing ocular artifact from only selected channel of EEG data. Furthermore, we present and evaluate the methods ability to remove ocular artifacts by means of two performance metrics.

The remaining parts of the paper are organized as- the algorithms used in the paper (DWT, SWT and LWT) are described in part II, the experimental result and discussion of the artificially contaminated EEG data and performance metrics are explained in part III, and finally part IV gives a brief conclusion to the paper.

2 Methods

2.1 Discrete Wavelet Transform (DWT)

The discrete wavelet transform creates a binary tree. The left part of the tree characterizes lower frequency band and right part characterizes the higher frequency band. In this algorithm, only the left part is decomposed. The DWT filter decomposes seven decomposition levels from the EEG signals. The sampling frequency of the original EEG is related to the frequency band

$[f_m \ /2, f_m \ ]$. If fs is the sampling frequency and L is the level of decomposition then the frequency band will be $f_m = f_s/2L$. The decomposition technique, wavelet transform (WT) observes the signal at various resolution levels and different translations in time by bandpass filtering [24]. The WT decomposes signals into two coefficients detail and approximate. The coefficients comprise subband signals. The analyzed EEG signal can be denoted as:

$$s(t) = \sum_{b=1}^{L} q_b(t) + q_{L+1}(t) \tag{1}$$

where, q_b and q_{b+1} are the b^{th} and $(L+1)^{th}$ subbands corresponding to the detail and approximate coefficients respectively.

To remove low frequency noise from EEG signal, a noise assisted WT technique is used. The DWT based filtering method of EEG is presented in Fig. 1. In this method, the contaminated EEG signal is decomposed into seven levels and the decomposed subband is demonstrated in Fig. 2. In Fig. 2, the first row represents contaminated EEG and the rest of the rows are decomposed subbands. After completion of the decomposition process, the signal is characterized as:

$$\tilde{s}(t) = \sum_{b=1}^{L+1} q_b(t) \tag{2}$$

where, $\bar{s}(t) \approx s(t)$. In this method the clean EEG signal is easily achieved from contaminated EEG by applying DWT. Then the clean EEG is evaluated by the same evaluation parameter used in others filter that are mentioned later. The db4 mother wavelet is chosen for those filters. The lower frequency subbands are summed up to calculate the lower frequency EEG signal.

$$\hat{s}(t) = \sum_{b=1}^{D} C_b(t) \tag{3}$$

where, C_b (t) is the b^{th} subband of the EEG channel, D is the index of subbands. The subbands contain lower frequency EEG band [25]. The whole process is summarized in Fig. 1.

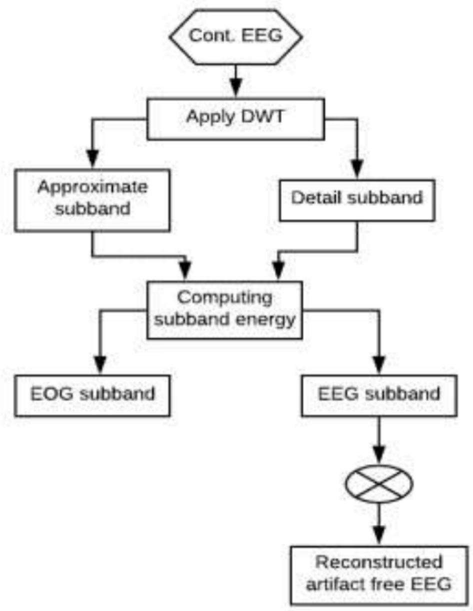

Fig. 1: Schematic diagram of discrete wavelet transform approach for the removal of artifact.

2.2 Stationary Wavelet Transform (SWT)

The SWT is calculated same as DWT but down-sampling and up-sampling blocks are not present. Stationary wavelet transform is also called un-decimated DWT, i.e. the decimators after filters are not applied. Since there is no down-sampling, it does not lose any time information and have shift invariance property. Because of over-sampling, it has very good time resolution at low frequencies and hence it produces smoother results in low frequency bands.

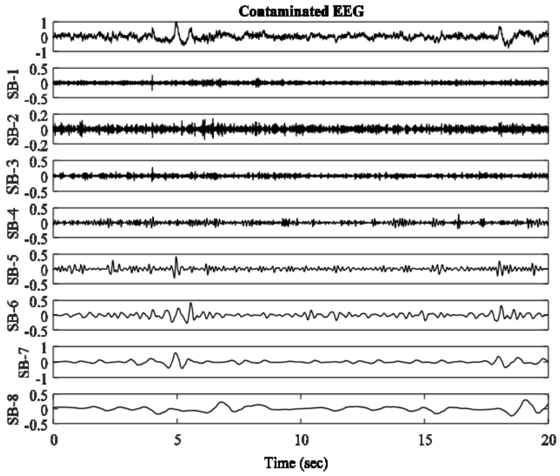

Fig. 2: Representation of subbands of contaminated EEG using DWT method.

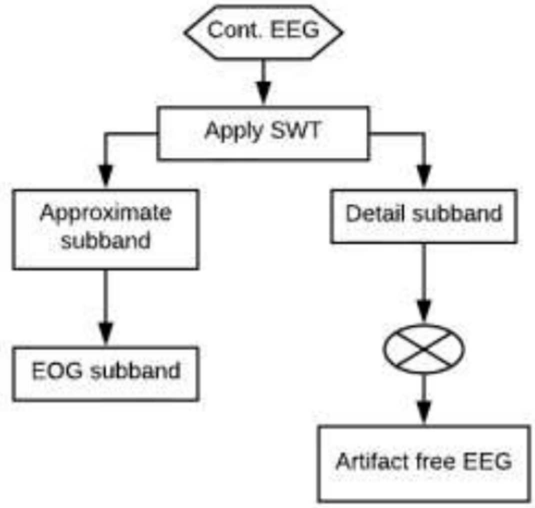

Fig. 3: Schematic diagram of stationary wavelet transform approach for artifact removal.

It also does not suffer with aliasing because no down-sampling is done at any stage. Filtering operation differentiates SWT from DWT algorithms. In SWT, after decomposition the length of approximate and detail sequence remains same as the original signal. The SWT algorithm up samples the filter coefficient by a factor of $2^(j-1)$ after finding the coefficients at $j^(th)$ level [23]. The reconstruction filter is level dependent. Between each filter coefficients $2^(j-1)$ zeros are inserted. This process ends after recovering the original signal. In this way, the approximate and detail coefficients that represents lower and higher order band respectively are produced. These coefficients represent the correlation among artifactual signal and the wavelet function. The higher correlation indicates larger coefficient values of artifactual components. On the other hand, for the actual neural activities small coefficients are produced. In this paper, the swt function of MATLAB and db4 mother wavelet is used to remove artifact using SWT. The decomposition is done up to seventh level (shows in Fig. 4) and the algorithm which act as a filter bank is

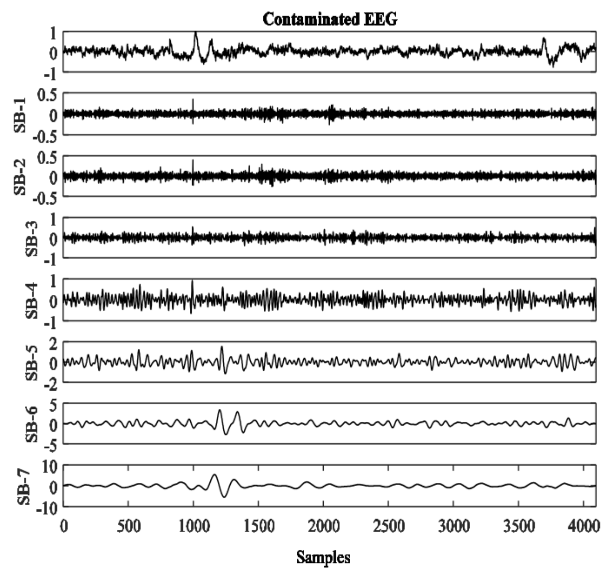

Fig. 4: The subband decomposition of contaminated EEG using SWT method.

shown in Fig. 3.

Since better separation of signal and noise depends on the wavelet basis, the mother wavelet, the shrinkage rule and the noise level rescaling are significant to the design of a noise removal technique [8].

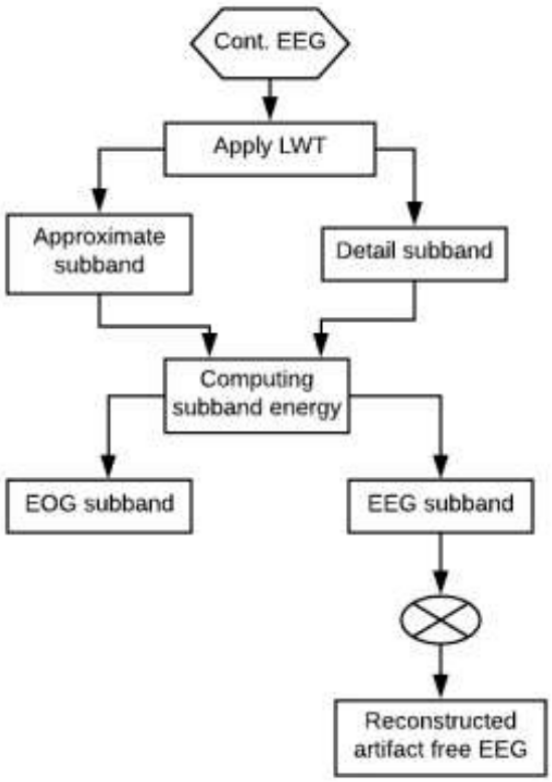

Fig. 5: Schematic diagram of lifting wavelet transform approach for artifact removal.

2.3 Lifting Wavelet Transform (LWT)

In paper [26], lifting wavelet transform is used to remove EOG instead of usual wavelet transform which perfectly extract neural signals from artifact mixed EEG components. It is very responsible tool for extracting useful neural signals. It performs wavelet decompositions with lifting scheme. The multiphase form of the DWT system with additional zero-padding mode is reduced in LWT in the absence of extra-coefficients. Whereas wavelet transform can be executed in spatial or time domain, the LWT scheme does not depend on Fourier transform. The computation cost of LWT is noticeably lower than those of traditional wavelet transform. The block representation of lifting wavelet transform for removing artifacts is represented in Fig. 5. The LWT method is also implemented in MATLAB for removing artifacts.

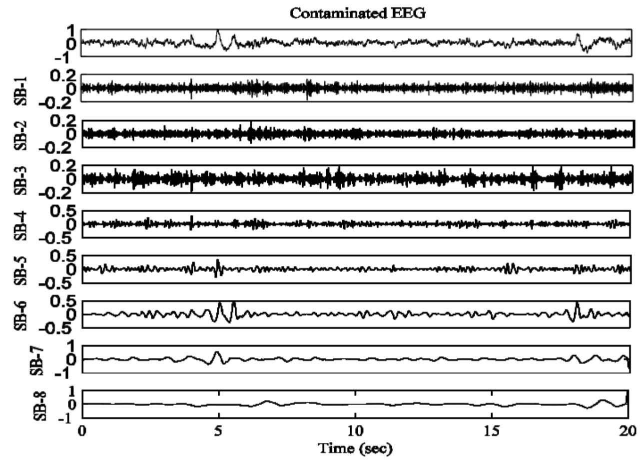

Fig. 6: The subband decomposition of contaminated EEG using LWT method.

The basic steps in lifting operations are: split, predict, update and normalization [26]. In this study, a noise aided LWT based method is applied here to reduce the low frequency and high amplitude noise from recorded EEG. The contaminated EEG signal is decomposed using LWT which is plotted in Fig. 6. After subband decomposition, the reconstructed signal is calculated as

$$\tilde{s}(t) = \sum_{b=1}^{L+1} q_b(t) \tag{4}$$

where, $\bar{s}(t) \approx X(t)$. The LWT based filtering method of EEG signal is presented in Fig. 5. In this Fig., the clean EEG signal is easily achieved from contaminated EEG by applying LWT and thresholding. The db4 mother wavelet is choosing for this filter. The thresholding is applied according to Fig. 8. As a reference channel, the fractional Gaussian noise (fGn) is used here. The subband decomposition of fGn is shown in Fig. 7. In LWT, the lower frequency EEG signal can be estimated by adding up to the lower order subbands as:

$$\hat{s}(t) = \sum_{b=1}^{D} C_b(t) \tag{5}$$

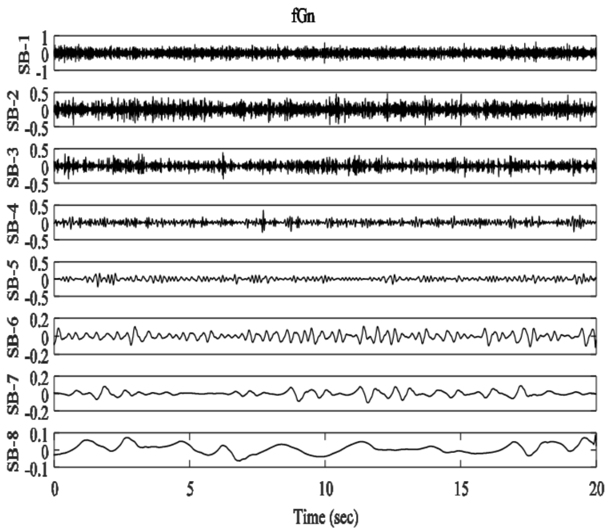

Fig. 7: The structure of subband decomposition of fGn using LWT.

where, C_b (t) is the b_{th} subband of the EEG signal. Here, D is the critical (threshold) subband index and the subbands indices 1,2,3,....,D are accountable for relatively lower frequency EEG element.

It is a well-recognized wavelet transform of a 1-D signal and inverts the transform to demonstrate perfect reconstruction. The reconstructed signal of DWT, SWT and LWT method and the reconstruction error are presented in Fig. 9. From this Fig, it is apparent that LWT methods perfectly reconstructed the EEG signal. The reconstruction error of LWT is lower than other two methods.

3 Result and Discussion

In this section, the LWT based method is tested with the artificially corrupted EEG signal and after that the signal is comprised with DWT and SWT. For comparison purposes, the time series contaminated EEG data is decomposed

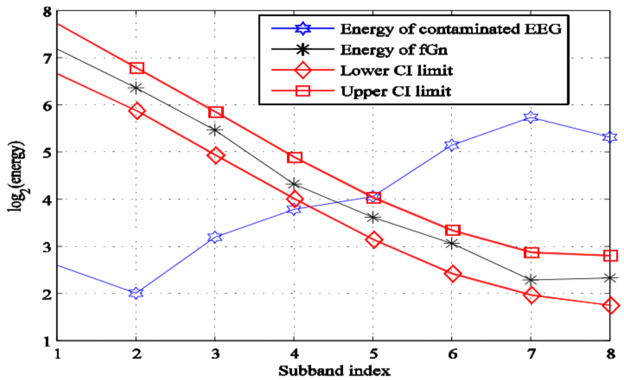

Fig. 8: The subband of contaminated EEG is selected using adaptive threshold based on the subband energy of fGn in LWT method.

into multiple subbands using DWT, SWT and LWT which are presented in Fig. 2, Fig. 4 and Fig. 6 respectively.

The potential multiresolution decomposition approach, DWT, SWT and LWT which are analyzing a non-stationary signal like EEG. In this study,db4 is used with 7 level decomposition. It is another approach for EOG artifact reduction. To get artifact free EEG, the DWT, SWT and LWT based filters are used. In DWT, SWT and LWT, the contaminated EEG signal and a reference signal fGn are decomposed up to level 7 using db4 mother wavelet. After decomposition, we got 8 subbands for DWT and LWT whereas SWT decomposes seven subbands that are illustrated in Fig. 2, Fig. 6 and Fig. 4 respectively.

The algorithm for DWT and LWT methods are same for artifact removing. So, here we discussed only LWT. To get the threshold subband index D from recorded signal, the whole process is following: 1) The target EEG signal is decomposed along with the reference signal fGn (in Fig. 7.) upto finite subbands using wavelet method. 2) The subband energy of fGn and its corresponding 95% confidence interval

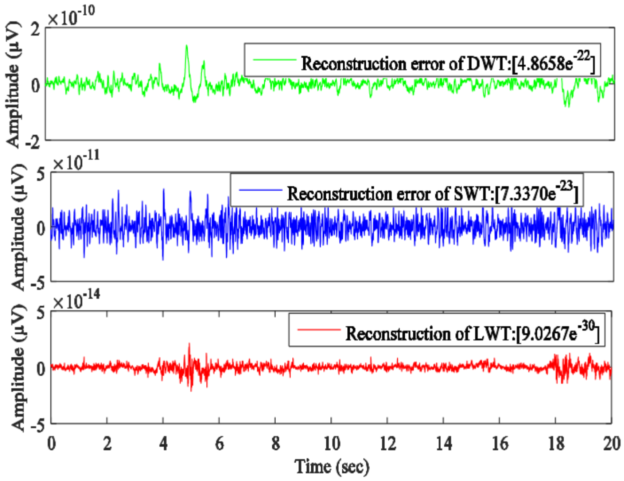

Fig. 9: Reconstruction error of contaminated EEG using DWT (Top), using SWT (Middle), using LWT (Bottom).

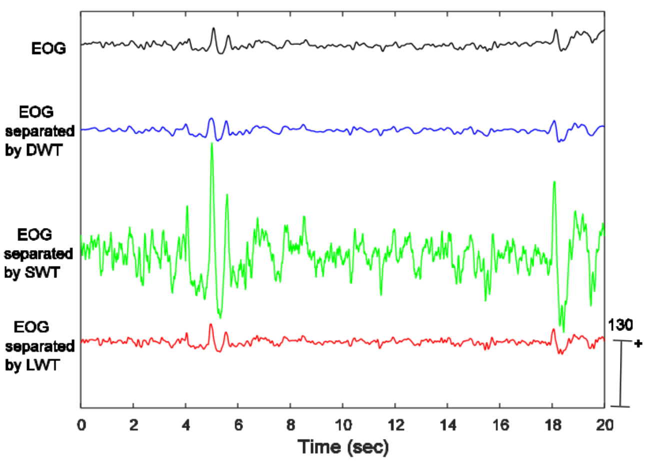

Fig. 10: Illustration of the EOG which contaminated the EEG and compared it with other EOG separated by different three methods in time domain.

(CI) is calculated. 3) The subband energy of EOG mixed neural signal is also computed. It is found that the lower order subband energy exceed the upper limit of CI derived from step 2 and the exceeding band is the n th subband. The targeted in th (in Fig. 8, n = 5) subband is the beginning index to get EOG signal. 4) Using Eq. (4), the artifact free EEG signal is separated by adding the subband beggining from 1 to D th subband of neural signal. Based on the subband energy, the thresholded subband is selected which is illustrated in Fig. 6. Using Eq. (5), the pure EEG is separated after computing the threshold subband. The subband decomposition of recorded electroencephalography data and fractional Gaussian noise are shown in Fig. 6 and Fig. 7 respectively.

From Fig. 8, it is easily seen that the 5 th subband exceed the upper bound of confidence interval. So, the 5 th band is the first subband index, where there are presented 8 subbands. The 5 th subband coefficient is the starting point of lower frequency components. The electro-oculogram is separated by summing the subband coefficients 5 to 8. By subtracting electro-oculogram from raw electroenceph-alography, we get the purified electroencephalography that reflects the actual neural activities. The electro- oculogram suppression results for a single channel of recorded electroencephalography are illustrated in Fig. 10. in which the separated electro-oculogram for DWT, SWT and LWT are presented in the second, third and fourth rows respectively. From Fig. 10, it is found that the extracted EOG using SWT method contains more original information whereas the DWT and LWT methods have cancelled out the artifacts. The underlying EEG data arelow frequency, high amplitude neural data may be lost using SWT artifact correction method. In order to remove the artifact and reduce data loss DWT and LWT methods are used.

Fig. 11. depicts the contaminated EEG and clean EEG for the three methods. From this Fig., it is observed that the LWT baesd method is best for reducing the EOG from contaminated EEG without cutting the information and assist to get clean EEG. The pure EEG does not show

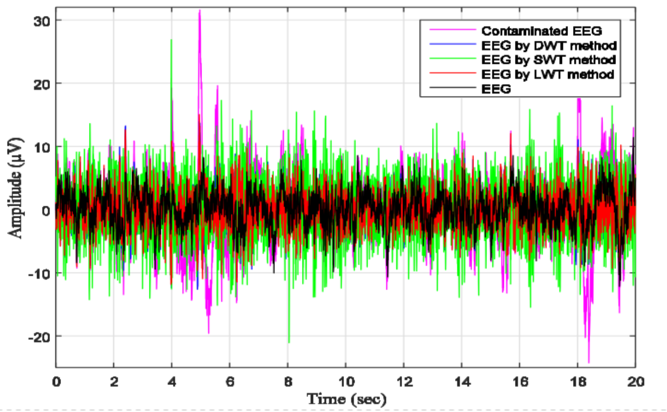

Fig. 11: Overall experimental comparison of EOG mixed EEG signal and artifact free EEG signals from different artifact removing approach in time domain.

any large EOG. As a result, the purified EEG signal is found as completely artifact free in LWT method.

3.1 Performance Metrics

Signal to artifact ratio (SAR) and mean square error (MSE) parameters have been used to measure the effectiveness of LWT method to remove the ocular artifacts from EEG signal successfully.

Signal to artifact ratio (SAR):

The metrics signal to artifact ratio (SAR) [27, 28] is commonly found comparing the energy of the signal and the energy of the artifact. The following equation expresses the ratio given below:

$$SAR_{dB_{contaminated\_EEG}} = 20log10 \frac{rms[x(t)]}{rms\left[s(t) - \hat{s}(t)\right]}$$

Here, $x(t)$ is the clean EEG signal. The symbol $s(t)$ stands for noisy EEG signal, $\bar{s}(t)$ is the clean EEG signal and N for the signal length or the number of samples.

Mean square error (MSE):

The MSE is used to find out the similarity between two signals, i.e. the original signal and artifact free signal [29].

$$MSE = \frac{1}{N}\sum_{i-1}^{N}[s_i(t) - \hat{s}_i(t)]^2$$

Here, s_i(t) stands for contaminated EEG, $\bar{s}_i$ (t) estimates signal de-noised by DWT, SWT and LWT, N for the signal length or the number of samples. And the lower is the MSE value, the better is the method for the artifact removing.

TABLE 1: A comparative summary of the discrete wavelet transform, stationary wavelet transform and lifting wavelet transform for contaminated EEG data.

No.	Methods	SAR in dB	MSE
1	DWT [18]	-4.6864	23.76
2	SWT [23]	-9.3077	68.77
3	LWT [26]	-4.7059	10.19

TABLE I shows the comparison results of the SAR and MSE values from DWT, SWT and LWT methods, respectively. The table shows that the DWT and LWT based technique yields the same SAR (lower the SAR value able to clean more artifact) result than stationary wavelet transform. The SAR value is -9.3077dB for stationary wavelet transform while for LWT filter it is -4.7059 dB. The lifting wavelet transform shows lower MSE value compared to the discrete wavelet transform and stationary wavelet transform. Depending on the MSE and SAR values, it is observed that the lifting wavelet transform filter with db4 mother wavelet is able to filter out more noise compare to discrete wavelet transform and stationary wavelet transform.

4 Conclusion

It is known that the EEG signal is mostly affected by eyeblink artifact. In the present study, we have demonostrated and compared the effectiveness of different wavelet based methods for removal of eye blink artifact from EEG signal. We adopted threshold effectively to denoise EEG signal. In this study, three different artifact removing techniques have been presented to determine their effects in removing the artifact. The DWT, SWT and LWT methods have been implemented successfully to remove eyeblink artifacts from contaminated signal. It is considered that the EOG signal has trend of the recorded neural signals. The target EOG signal is detected from recorded signal based on the subband energy of the reference fractional Gaussian noise (fGn) signals using target filter. The MSE and SAR is a popular parameter to determine the quality of signal after filtering. The DWT and LWT filter able to remove electrooculography artifacts while the SWT methods do not able to remove all of artifacts. For real-time experiment, fast algorithms are required. It is identified that DWT and LWT required lower computational cost compared with SWT for online processing. The SWT method can be used on that application where computational complexity is not essential. The lifting wavelet transform is better in removing the noise while preserving neuronal signals compare to other two artifact removing algorithms according to performance metrics. Our upcoming research information include hardware execution with a wearable embedded scheme for ocular artifact removal method for EEG channel, real-time eye blink artifact reduction, feature finding, and motor imagery categorizing to monitor based brain involvement in natural condition.

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