EPILEPSY SEIZURE DETECTION USING WAVELET BASED BY ARTIFACT REDUCTION

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ABSTRACT
This paper presents a method to remove artifacts from scalp EEG recordings to diagnosis/ detect seizure in epilepsy patients. Epilepsy is a neurological disorder in which the nerves in the brain communicate abnormally with each other. The proposed algorithm is based on stationary wavelet transform and takes the spectral band of seizure activities into account to remove artifacts in seizures. The features of EEG signal responsile for the detection of seizures from non seizure epochs have been found to be easily distinguishable after artifacts are removed and consequently the false alarms in seizure detection are reduced.

KEYWORDS: Artifact, Scalbp EEG, Epilepsy, Seizure detection, Stationary Wavele Transform

INTRODUCTION

Epilepsy is a neurological disorder in which the nerves in the brain communicate abnormally with each other. The occurrence of seizure is uncertain which is the cause of disability associated with epilepsy [1]. To reduce this uncertainty of epilepsy, a recording system that provides early as well as accurate seizure detection with immediate warning.. One way to achieve that is to use the long-term EEG recording to detect the characteristics of EEG waveforms during seizures. The prolonged EEG recording is not only can increase the chance of detecting seizure, but it is also useful in the diagnosis of non-epileptic paroxysmal disorders compared to a routine EEG. Unfortunately, EEG recordings are contaminated by different forms of artifacts such as artifacts due to pop-up, motio artifacts, ocular artifacts and EMG artifacts from muscle activity that reduces the accuracy of recorded EEG signal. Thus, in order to correctly diagnosis the epilepsy, it is extremely important to remove such artifacts, prior to seizure detection.

The proposed algorithm is based on the stationary wavelet transform (SWT) that takes the spectral band of seizure activities into account to separate artifacts from seizures. The reason of choosing wavelet transform over other methods (e.g. BSS, EMD, Adaptive Filtering, etc.) is its ability to decompose single-channel EEG data into different frequency band. In addition, the choice of SWT over discrete wavelet transform (DWT) is the factor that SWT is translational invariant since it involves up sampling of the filter coefficients instead of down sampling unlike in DWT[27]. The proposed method is evaluate for EEG data where data consist of epileptic seizures and artifacts. The algorithms remove artifacts as much as possible without distorting the signal of interest.

PROPOSED METHODOLOGY

BLOCK DIAGRAM

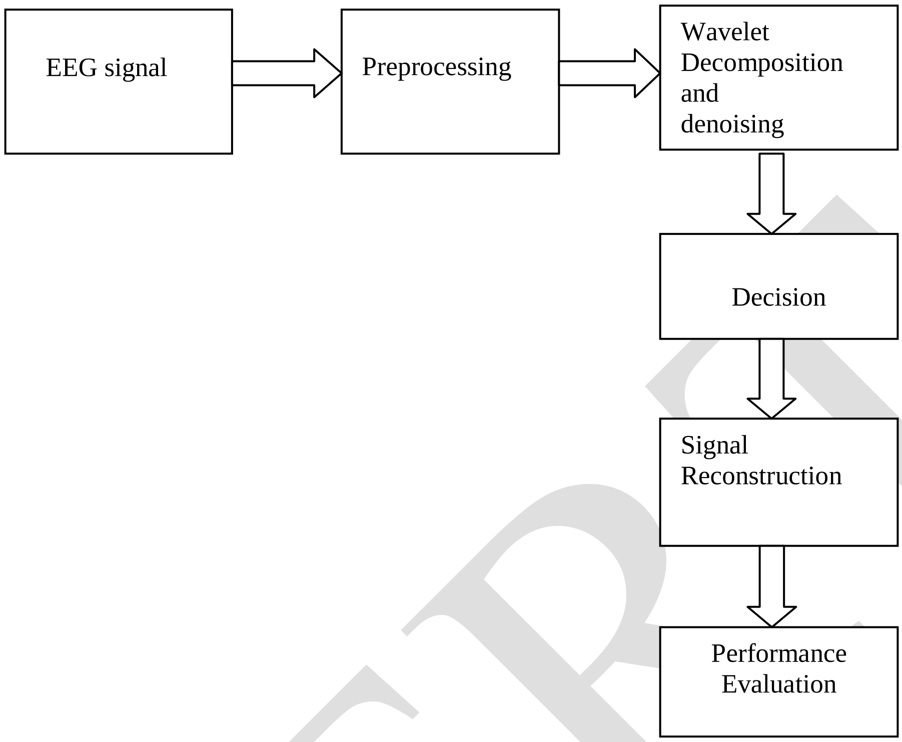

Fig 1: Block Diagram of diagnose and remove the artifacts from the seizure waveform

PROCEDURE:
The Facial Feature Extraction as shown in the block diagram is as follows;

1) EEG signal: The input signal is taken.
2) Preprocessing: In this stage preprocessing on signal is done. First of we segment an input signal then we apply high pass filter to pass the high frequencies. After that we calculate universal threshold of the signal.
3) Wavelet decomposition and denoising: Here We decompose the signal upto Two level. By using the denoising term, we refer to removing artifactual components from neural signals in the wavelet domain whether it is high-frequency or low-frequency artifacts by applying thresholding the detail coefficient after wavelet. decomposition.
4) Decision:In this stage we decide whether the epoch is artifactual or seizure is made.
5) Performance evaluation: The performance of the proposed algorithm has been evaluated in terms of amount of artifact reduction as well as amount of distortion that brings into the signal of interest, specially to the seizure events.

A. EEG SIGNAL
This stage generates a reference seizure epoch of length from an available seizure type specific seizure database. For example, the neonatal seizure events can be simulated from a free online database or patients databse from hospital.

B. PREPROCESSING
In the preprocessing we assume that the power line interference of 50/60 Hz and the baseline of raw EEG have been already removed to this preprocessing stage. In the preprocessing first of we segment an input image then we apply high pass filter to pass the high frequencies(above 0.5 Hz upto 30 Hz). After that we calculate universal threshold of the signal. The signal is firstly divided into non-overlapping epochs. The

choice of epoch duration plays an important role in both of artifact removal and amount of distortion in the signal(i.e. seizure events). let xraw(n) denote the sampled raw EEG signal which is sampled at fs Hz where n is the discrete-time index. Then, the jth epoch is given by

$$xj = \begin{pmatrix} \text{xraw}(jN-1) \\ \text{xraw}(jN-2) \\ \\ \text{xraw}(jN-N) \end{pmatrix}$$

C.WAVELET DECOMPOSITION AND DENOISING

We decompose the signal upto 2 level. By using the denoising term, we refer to removing artifactual components from neural signals in the wavelet domain whether it is high-frequency or low-frequency artifactsby applying thresholding the detail coefficient after wavelet decomposition.The stationary wavelet transform is performed on the epochs {xj}j>1 with level-2 decomposition by Haar wavelet transform

D. DECISION

In this stage we decide whether the epoch is artifactual or seizure is made. We choose two levels of threshold: one is upper limit T_{high} and the other one is lower limit T_{low}. Hence three conditions arise which results in three decisions: if it is high likelyhood to be a seizure, then denoising is not performed on that epoch; if it is in between seizure and artifacts, then we carefully denoise the epoch and finally if it is least likely to be seizure then we fully denoise that epoch.

E. RECONSTRUCTION

In the final stage of reconstruction, based on the decision stage, we apply inverse SWT to reconstruct the EEG epochs. Thus a new sequence of reconstructed data is obtained.

F. PERFORMANCE EVALUATION

The performance of the proposed algorithm has been evaluated in terms of amount of artifact reduction as well as amount of distortion that brings into the signal of interest, specially to the seizure events. several efficiency metrics have been calculated in time as well as in spectral domain to quantify such evaluation. From the input EEG signal we have calculate following parameters: Fs

1) ΔSNR: The SNR is defined as the ratio of signal power to the noise power. The ΔSNR is the difference in SNR before and after artifact Removal

$$\Delta SNR = 10\, log_{10}\left(\frac{\sigma^2_{x_{ref}}}{\sigma^2_{e_{br}}}\right) - 10\, log_{10}\left(\frac{\sigma^2_{x_{ref}}}{\sigma^2_{e_{ar}}}\right)$$

Where , $\sigma^2_{x_{ref}}$, $\sigma^2_{e_{br}}$, $\sigma^2_{x_{ref}}$, $\sigma^2_{e_{ar}}$ be the variance of reference signal, error signal before and after artifact removal respectively.

2) P_{dis}: The spectral distortion P_{dis} is calculated as follows:

$$P_{dis} = \frac{\sum_{F=1}^{Fs/2}\left(P_{rec}(f)\right)^2}{\sum_{F=1}^{Fs/2}\left(P_{ref}(f)\right)^2}$$

Where $P_{rec}(f)$ and $P_{ref}(f)$ the power spectral densities of reference signal and reconstructed signal respectively

3)ΔCor: The correlation computes a measure of similarity of two signals as they are shifted by one another. In order to calculate the improvement in correlation ΔCor due to artifact removal, the following equation is used,

$$\Delta\mathrm{Cor}(\%) = \frac{c_{rec} - c_{art}}{c_{art}} \times 100$$

4) RMSE: The root mean square error is calculated as follows:

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{n=1}^{N}[e_{ar}(n)]^2}.$$

5) $\mathrm{SNR}_{\mathrm{art}}$: Here we considered artifact as a signal and reference neural signal as a noise to calculate Artifact SNR

$$\mathrm{SNR}_{\mathrm{art}} = 10\, log_{10}\left(\frac{\sigma_{ebr}^2}{\sigma_{xref}^2}\right)$$

RESULT AND DISCUSSION

STEP 1: Take any input signal which is decomposed into low frequency signal and high frequency signal upto 2 level decomposition. Which is shown in below:

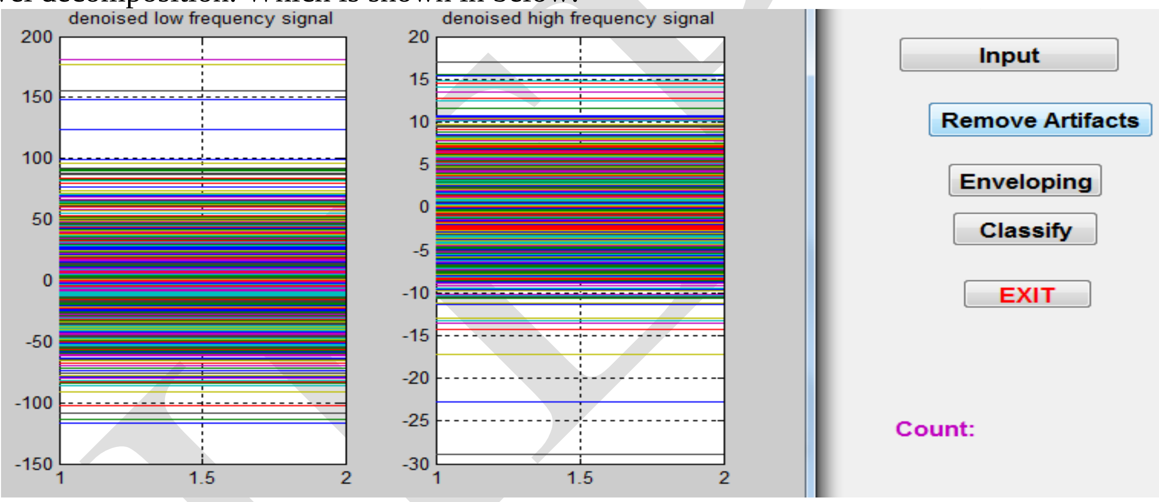

Figure 2.1: Decomposition of signal into low frequency signal and high frequency signal

STEP 2: The low frequency signal and high frequency signal are filtered using butterworth filter. Which is shown in below:

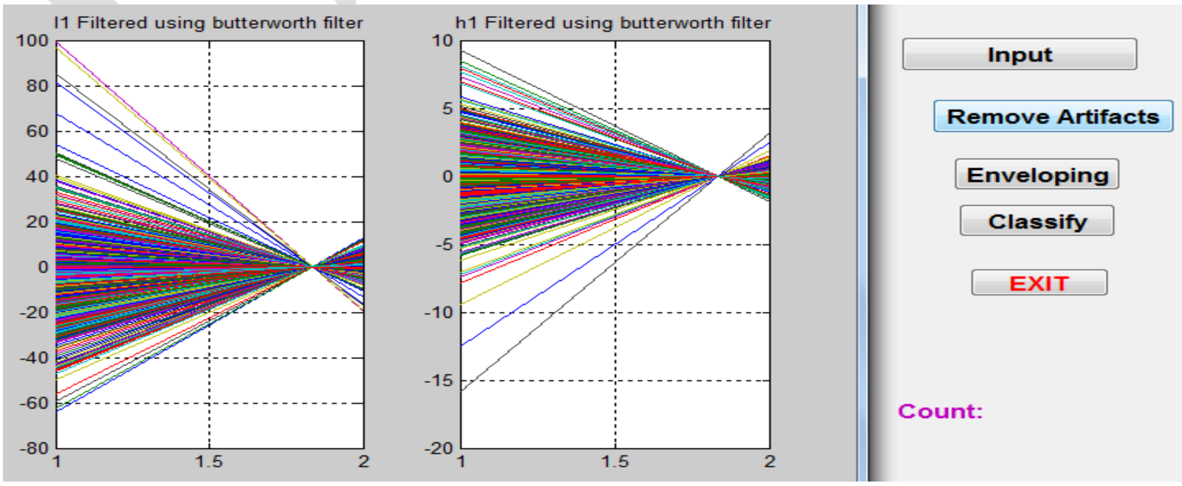

Figure 2.2: The low frequency signal and high frequency signal are filtered using butterworth filter

STEP 3: Artifacts are removed from non Seizure epoch and then signal is Reconstructed

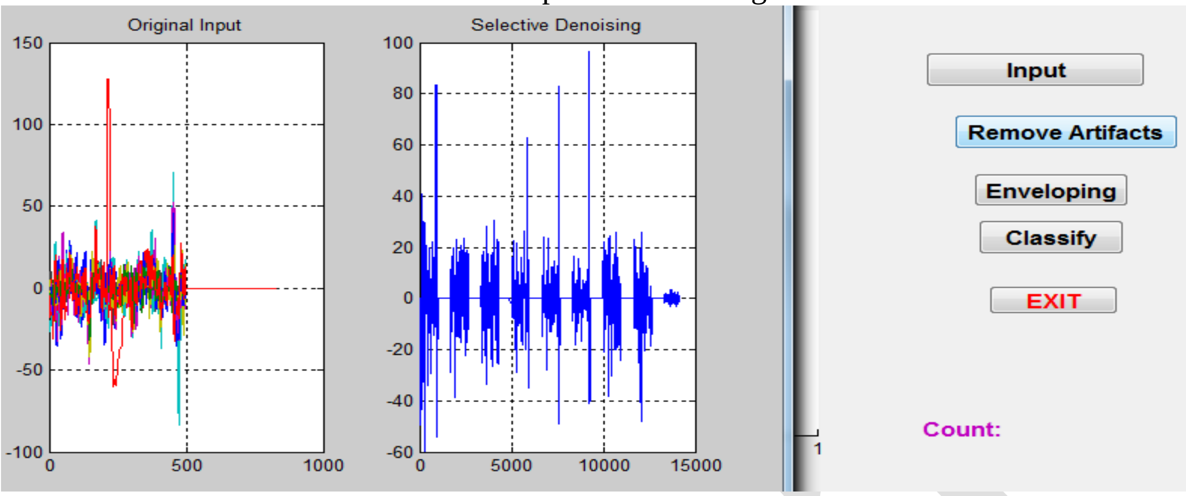

Figure 2.3: Reconstructed Signal

STEP 4: finally we classify of Whether signal is Seizure or Healthy

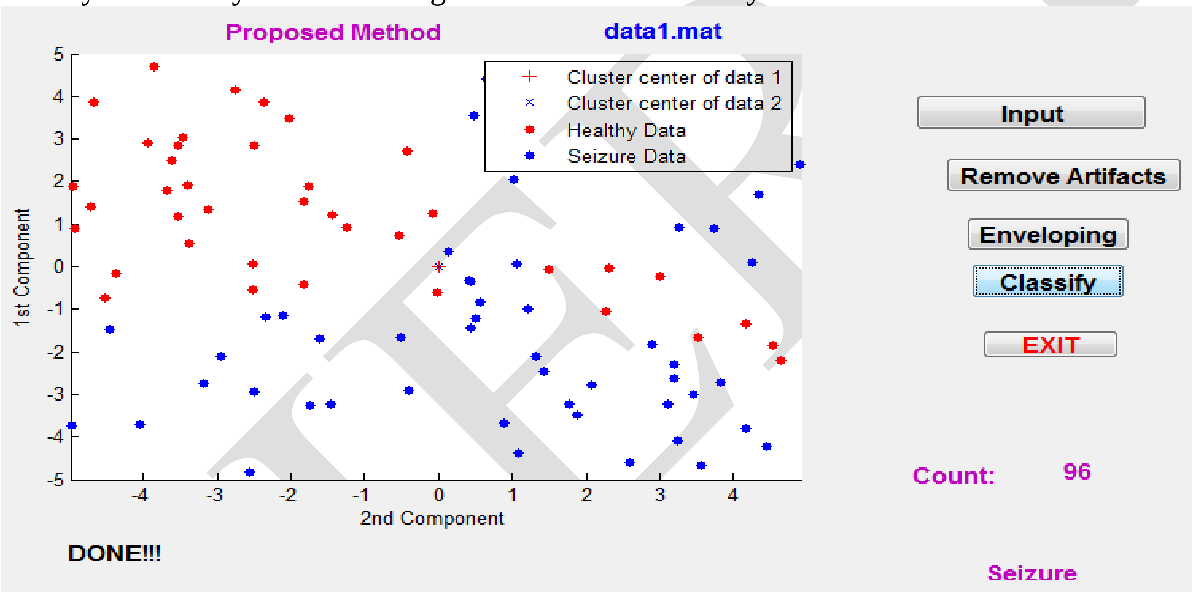

Figure 2.4: Classification of Signal whether it is Seizure or Healthy signal

The Table No.1 and Table No.2 shows the Parameter analysis and Impact of Artifact removal on detection Of seizure

Table 1:Parameter Analysis

Patient No. .	SNR	P_{dis}	ΔCor	RMSE	SNR_{art}
1	10.15	-10.19	1	9.63	11.90
2	5.54	-5.87	1	16.88	8.09
3	10.45	-10.48	1	31.07	10.90
4	10.45	-10.48	1	31.07	10.90
5	7.75	-8.36	1	24.49	.44

Table No.2 Impact of Artifact removal on detection of seizure

Patient No.	Ground Truth	Detected Output
1	Seizure	Seizure
2	Seizure	Seizure
3	Healthy	Healthy
4	Healthy	Healthy
5	Seizure	Seizure

CONCLUSION

The purpose of this research was to develop an artifact removal method in order to make the seizure analysis process easier for the clinicians and also to improve the performance of the available automated seizure detection algorithm.

REFERENCE

1) R. S. Fisher, B. G. Vickrey, P. Gibson, B. Hermann, P. Penovich,A. Scherer, and S. Walker, *"The impact of epilepsy from the patients perspective i. descriptions and subjective perceptions," Epilepsy Research, vol. 41, no. 1, pp. 39 – 51, 2000.*

2) S. F. S. O. Regan and W. Marnane, "*Automatic detection of eeg artefacts arising from head movements using eeg and gyroscope signals," Medical Engineering and Physics, vol. 35, pp. 867–874, 2013.*

3) A. Bertrand, V. Mihajlovic, B. Grundlehner, C. Van Hoof, and M. Moonen, *"Motion artifact reduction in eeg recordings using multi-channel contact impedance measurements," in Biomedical Circuits and Systems Conference (BioCAS), 2013 IEEE, Oct 2013, pp. 258–261.*

4) A. Bertrand, V. Mihajlovic, B. Grundlehner, C. Van Hoof, and M. Moonen, *"Motion artifact reduction in eeg recordings using multi-channel contact impedance measurements," in Biomedical Circuits and Systems Conference (BioCAS), 2013 IEEE, Oct 2013, pp. 258–261.*

5) J. T. Gwin, K. Gramann, S. Makeig, and D. P. Ferris, *"Removal of movement artifact from high-density eeg recorded during walking and running," Journal of Neurophysiology, vol. 103, no. 6, pp. 3526–3534, 2010. 4*

6) X. Yong, M. Fatourechi, R. Ward, and G. Birch, "*Automatic artefact removal in a self-paced hybrid brain- computer interface system," Journal of NeuroEngineering and Rehabilitation, vol. 9, no. 1, p. 50*

7) K. Sweeney, T. Ward, and S. McLoone, "*Artifact removal in physiological signals x2014;practices and possibilities," Information Technology in Biomedicine, IEEE Transactions on, vol. 16, no. 3, pp. 488–500, May 2012.*

8) B. Noureddin, P. Lawrence, and G. Birch, "*Online removal of eye movement and blink eeg artifacts using a high-speed eye tracker," Biomedical Engineering, IEEE Transactions on, vol. 59, no. 8, pp. 2103–2110, Aug 2012.*

9) P. He, G. Wilson, and C. Russell, "*Removal of ocular artifacts from electro-encephalogram by adaptive filtering," Medical and Biological Engineering and Computing, vol. 42, no. 3, pp. 407–412, 2004. [Online]. Available: http://dx.doi.org/10.1007/BF02344717*

10) C. Guerrero-Mosquera and A. Navia-Vazquez, "*Automatic removal of ocular artefacts using adaptive filtering and independent component analysis for electroencephalogram data," Signal Processing, IET, vol. 6, no. 2, pp. 99–106, April 2012.*

11) W.-Y. Hsu, C.-H. Lin, H.-J. Hsu, P.-H. Chen, and I.-R. Chen, "*Waveletbased envelope features with automatic {EOG} artifact removal: Application to single-trial EEG data," Expert Systems with Applications, vol. 39, no. 3, pp. 2743 – 2749, 2012.*

12) B. S. Raghavendra and D. N. Dutt, "*Wavelet enhanced cca for minimization of ocular and muscle artifacts in eeg," vol. 5, no. 9, pp. 846 –851, 2011.*

13) S. Puthusserypady and T. Ratnarajah, "*Hinfin; adaptive filters for eye blink artifact minimization from electroencephalogram," Signal Processing Letters, IEEE, vol. 12, no. 12, pp. 816–819, Dec 2005.*

14) A. Schlgl, C. Keinrath, D. Zimmermann, R. Scherer, R. Leeb, and G. Pfurtscheller, *"A fully automated correction method of EOG artifacts in EEG recordings," Clinical Neurophysiology, vol. 118, no. 1, pp. 98 – 104, 2007.*

15) S. Puthusserypady and T. Ratnarajah, *"Robust adaptive techniques for minimization of EOG artefacts from EEG signals," Signal Processing, vol. 86, no. 9, pp. 2351 – 2363, 2006, special Section: Signal Processing in UWB Communications.*

16) A. Flexer, H. Bauer, J. Pripfl, and G. Dorffner, "*Using ICA for removal of ocular artifacts in EEG recorded from blind subjects," Neural Networks, vol. 18, no. 7, pp. 998 – 1005, 2005.*

17) N. P. Castellanos and V. A. Makarov, "*Recovering EEG brain signals: Artifact suppression with wavelet enhanced independent component analysis," Journal of Neuroscience Methods, vol. 158, no. 2, pp. 300 – 312, 2006.*

18) C. Zhao and T. Qiu, "*An automatic ocular artifacts removal method based on wavelet-enhanced canonical correlation analysis," in Engineering in Medicine and Biology Society,EMBC, 2011 Annual International Conference of the IEEE, 2011, pp. 4191–4194.*

19) K. Sweeney. PhD Thesis, *National University of Ireland Maynooth, 2013*.

20) M. Zima, P. Tichavsk, K. Paul, and V. Krajca, "*Robust removal of short-duration artifacts in long neonatal EEG recordings using wavelet enhanced ICA and adaptive combining of tentative reconstructions," Physiological Measurement, vol. 33, no. 8, p. N39, 2012.*

21) H. Guo and C. Burrus, "*Convolution using the undecimated discrete wavelet transform," in Acoustics, Speech, and Signal Processing, 1996. ICASSP-96. Conference Proceedings., 1996 IEEE International Conference on, vol. 3, 1996, pp. 1291–1294 vol. 3.*

22) C. Guerrero-Mosquera and A. Navia-Va zquez, "*Automatic removalof ocular artefacts using adaptive filtering and independent component analysis for electroencephalogram data," Signal Processing, IET, vol. 6, no. 2, pp. 99–106, 2012.*

23) Z. Wang, P. Xu, T. Liu, Y. Tian, X. Lei, and D. Yao, *"Robust removal of ocular artifacts by combining independent component analysis and system identification," Biomedical Signal Processing and Control, vol. 10, pp. 250–259, 2014.*

24) M. K. I. Molla, M. R. Islam, T. Tanaka, and T. M. Rutkowski, "*Artifact suppression from EEG signals using data adaptive time domain filtering," Neurocomputing, vol. 97, no. 0, pp. 297 – 308, 2012.*

25) M. K. I. Molla, M. R. Islam, T. Tanaka, and T. M. Rutkowski, "*Artifact suppression from EEG signals using data adaptive time domain filtering," Neurocomputing, vol. 97, no. 0, pp. 297 – 308, 2012.*

26) M. Zima, P. Tichavsk, K. Paul, and V. Krajca, *"Robust removal of short-duration artifacts in long neonatal EEG recordings using waveletenhanced ICA and adaptive combining of tentative reconstructions," Physiological Measurement, vol. 33, no. 8, p. N39, 2012.*

27) H. Guo and C. Burrus, "*Convolution using the undecimated discrete wavelet transform," in Acoustics, Speech, and Signal Processing, 1996. ICASSP-96. Conference Proceedings., 1996 IEEE International Conference on, vol. 3, 1996, pp. 1291–1294 vol. 3.*