Ian McNulty, Shiva Maleki Varnosfaderani, Omar Makke, Nabil J. Sarhan, Eishi Asano, Aimee Luat, and Mohammad Alhawari. Analysis of Artifacts Removal Techniques in EEG Signals for Energy-Constrained Devices. In Proceedings of the IEEE International Midwest Symposium on Circuits and Systems (MWSCAS), August 2021. DOI: 10.1109/MWSCAS47672.2021.9531909.

Analysis of Artifacts Removal Techniques in EEG Signals for Energy-Constrained Devices

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***Abstract*—This paper analyzes and evaluates various denoising techniques, including Wavelet Transform and Moving Average Filter methods for removing ocular and motion artifacts from EEG signals. The performance of each technique is benchmarked in terms of signal-to-noise ratio (SNR) and normalized mean squared error (NMSE) on available EEG databases, including Bonn and Motion-Artifact Contaminated EEG databases. Simulation results show that the Wavelet Transform using the SURE Shrink algorithm with the hard thresholding rule has the best performance for removing ocular artifacts in intracranial EEG. In contrast, the Wavelet Transform using the universal threshold shrinkage rule with hard thresholding is the preferred method for removing motion artifacts in scalp EEGs. This study is an essential step toward more advanced work to achieve real-time, and low-cost denoising methods for energy-constrained devices.**

***Index Terms*—EEG, motion artifacts, moving average, SURE shrink, universal threshold, iEEG, scalp EEG, wavelet transform.**

I. Introduction

Electroencephalography (EEG) is an electrophysiological monitoring method, which records the neural activities of the brain. EEG is a useful tool to diagnose various brain disorders, including epilepsy and Parkinson's diseases [1]. Many commercial products, including wearables, are used to acquire EEG signals [2], [3], but signal quality could be deteriorated by undesired artifacts, which can be grouped into two main categories: *extrinsic* and *intrinsic* [4]. The extrinsic artifacts include environmental noise and instrumental error, such as faulty electrodes and line noise [5]. This type of noise can be mitigated by applying precise recording procedures. The intrinsic artifacts are caused by human activities, including ocular, cardiac, and motion artifacts [5]–[7].

The topic of artifact removal is an open research problem, where the denoising technique should be selected based on the application and signal type [5]. For example, scalp EEG (sEEG) is mainly affected by motion artifacts [8], while intracranial EEG (iEEG) is mostly sensitive to ocular and cardiac artifacts [9]. Figure 1 shows the frequency ranges of the EEG signals. As depicted in the figure, ocular and motion artifacts are the most challenging to remove since their frequency band lies within the EEG frequency band. In particular, ocular artifacts tend to have high-amplitude waveform, making it easier to detect and remove [5].

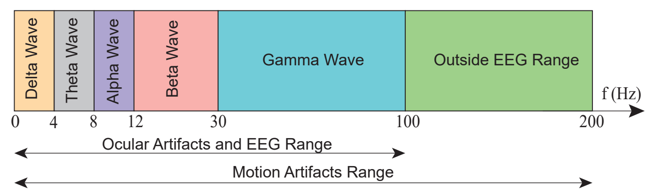

Fig. 1. The frequency range for EEG signals and various artifacts.

TABLE I
COMPARING VARIOUS DENOISING METHODS

Method Name	Pros	Cons
Wavelet Transform [10]	• Low computational complexity • Highly customizable • Capable of real-time processing	• Signal could be removed if overlaps with noise
Blind Source Separation [11]	• Can separate signal and noise	• Not efficient on single-channel EEGs • High computational complexity • Not capable of real-time processing
Empirical Mode Decomposition [12]	• Data-driven technique • Low computational complexity • Capable of real-time processing	• Sensitive to noise
Moving Average Filter [13]	• Low computational complexity • Capable of real-time processing	• No effective in removing certain types of noise

Various techniques are reported in the literature to remove artifacts and noise from EEG, as shown in Table I, including Wavelet Transform (WT), Blind Source Separation (BSS), Empirical Mode Decomposition (EMD), and Moving Average Filter [10]–[19]. Each technique is suitable for a particular

This work was supported by Richard Barber Interdisciplinary Research Program. Ian McNulty and Shiva Maleki Varnosfaderani contributed equally to this work. (Corresponding author: Mohammad Alhawari.)

application based on the given requirements. For example, BSS effectively separates the noise from the signal, but it requires high computational power. EMD is a data-driven approach that is sensitive to noise. Moving average filter removes the noise based on a time-domain filter; however, it is not effective in removing certain noise types such as motion artifacts. WT promises a real-time, low-computational, and high customizable method that is more suited for energy-constrained applications such as wearable devices.

In this paper, we analyze and evaluate various denoising approaches for removing artifacts and noise from sEEGs and iEEGs. The objective is to provide researchers and practitioners with benchmarks for various denoising techniques applied on two available databases. Five denoising techniques are analyzed and simulated using MATLAB, including the moving average method and multiple methods based on the WT: autocorrelation threshold, SURE Shrink algorithm, universal threshold, and statistical threshold. Both the Bonn (iEEG signals) and Motion-Artifact Contaminated EEG (sEEG signals) databases are employed. The analyzed metrics include signal-to-noise ratio (SNR), and normalized mean square error (NMSE).

The remainder of the paper is organized as follows. The details of the databases are presented in Section II. In Section III, evaluation metrics based on SNR and NMSE are explained along with simulation results. Finally, conclusions are drawn.

II. Background Information and Related Work

A. Datasets

Two databases are used: Motion-Artifact Contaminated EEG [16] and Bonn databases [17]. The first is a sEEG, collected from 6 different healthy subjects consisting of 4 experiments for each one, in 24 trials, and a sampling rate of 2048 Hz. Two electrodes are placed 20 mm apart, where one electrode is used to record the sEEG with a 1-minute motion artifact in every 2 minutes of recording, and the second electrode is used to record the ground truth sEEG [16]. The Bonn database consists of 5 folders of single-channel sEEG and iEEG segments, where each folder consists of 100 samples recorded at 173.61 Hz for 23.6-second segments. Folders Z and O include sEEG segments, which do not contain artifacts, while folders F, N, and S consists of iEEG segments that are mainly contaminated with ocular artifacts. To evaluate the performance of different methods in removing ocular artifacts, folders F, N, and S are selected.

B. Denoising Techniques

1) Wavelet Transform: WT is used to decompose a time-domain signal into the time-frequency domain with varying levels of accuracy in the frequency domain [10]. The components of the original signal obtained from the WT are known as wavelet coefficients. The original signal can be reconstructed by a linear combination of the extracted Wavelet coefficients, which can be extracted based on a mother Wavelet and a desired level of decomposition. The selection of the mother Wavelet is related to the shape of the signal being analyzed. In this paper, the Daubechies-4 mother Wavelet is selected due to its similar shape to interictal spikes in EEG signals [20].

The selection of the decomposition level depends on how fine-scale the analysis must be and how much computational complexity can be afforded. In this paper, the signal is decomposed to 7 and 11 levels of decomposition for Bonn and Motion-Artifact Contaminated EEG databases, respectively. The WT can be defined as the inner product of the signal X_n with the scaled and time-shifted Wavelet $\psi_{x_n}[m]$ [4]. In particular, the WT is given by

$$W_{x_n}(a,b) = < x_n, \psi_{a,b} >, \tag{1}$$

where a and b are the scale and shift parameters, respectively, x_n is the input signal, and ψ is the scaled and shifted version of the mother Wavelet.

Two broad classes of WT can be used for denoising signals: *WT with Autocorrelation Threshold* and *WT with Shrinkage Rules*. Once this set of Wavelet coefficients is obtained, the WT with Autocorrelation Threshold method calculates the autocorrelation at lag level 1 for each coefficient. If the autocorrelation of any coefficient is greater than a specific value, the entire coefficient is removed from the set of Wavelet coefficients before creating the denoised output signal [15]. WT with Shrinkage Rules denoises a given signal by reducing the values in the signal on a sample-to-sample basis. Specifically, the important part of the EEG is preserved while the coefficients for the other parts are simply thrown away. Shrinkage Rules must be coupled with a thresholding rule to decide on the samples with the value below, above, or at a specified threshold value. The Shrinkage Rules can be *soft thresholding* or *hard thresholding*, where both reduce samples whose absolute values fall below or reach the threshold value to 0; however, they differ in handling values above the threshold. Hard thresholding keeps these values unchanged, whereas soft thresholding shrinks the values towards zero.

One of the following three alternatives algorithms of WT with Shrinkage Rules can be used:

- *SURE Shrink Algorithm*: The extracted Wavelet coefficients are denoised according to the threshold value calculated by running an algorithm based on *Stein's Unbiased Risk Estimate* (SURE) [7]. This threshold is obtained by calculating Stein's Unbiased Estimate of Risk for each sample in the signal and using the minimum value calculated as the thresholding value.
- *Universal Threshold* (UT): The threshold value, K, is determined by

$$K = \sqrt{2logN} \times \sigma, \tag{2}$$

$$\sigma^2 = median(\frac{|C_a|}{0.6745}),\ \forall a = 1, 2, ..., j, \tag{3}$$

  where σ is the standard deviation, σ^2 is the variance, N is the number of data to be processed, $|C_a|$ is the absolute values of the Wavelet coefficients vector for the j levels of decomposition, and 0.6745 is the constant value for Gaussian noise [18].
- *Statistical Threshold* (ST): The threshold, T, for the Wavelet coefficients vector is given by

$$T = 1.5 \times std(C_a),\ \forall a = 1, 2, ..., j, \tag{4}$$

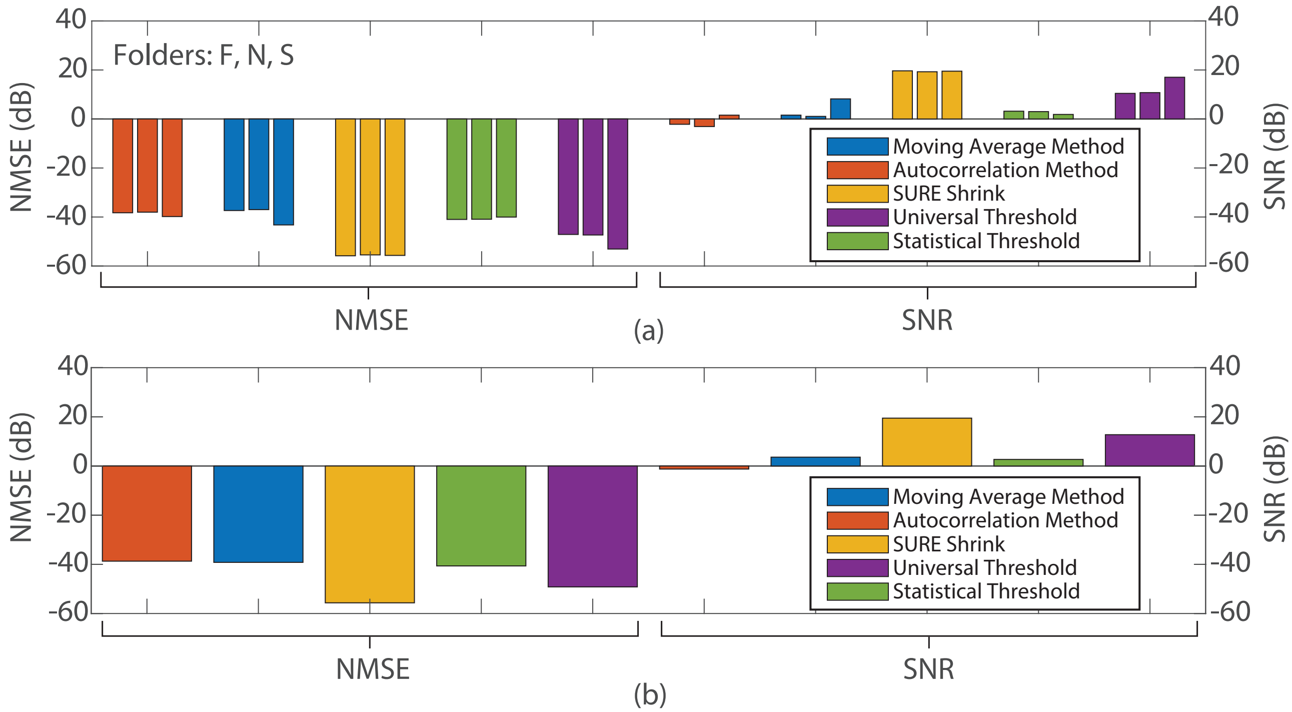

Fig. 2. Comparing various methods over All trials of the Bonn EEG database (Hard Thresholding when applicable). (a) Average NMSE and SNR for each folder. (b) Average NMSE and SNR for all the folders.

where $std(C_a)$ is the standard deviation of the Wavelet coefficient vector for the j levels of decomposition [18].

2) Moving Average Filter: A moving average filter is used in this work to remove the noise from the EEG databases. The implemented moving average filter uses a cascaded moving average algorithm to create a finite-impulse response filter (FIR). The filter has two stages: an I-point moving average overlapping with a J-point moving average filter [13].

III. Evaluation Methodology, Results and Analysis

This section presents the metrics used to investigate the denoising methods and simulation results in MATLAB for artifacts removal techniques on the EEG databases.

A. Efficacy Metrics

We compare the denoising techniques in terms of two major metrics: SNR and NMSE. SNR can be expressed as a ratio of the power of the signal to the power of the noise, which can be defined by

$$SNR = 10\log_{10}\frac{\sigma_{\hat{x}}^2}{\sigma_e^2}, \tag{5}$$

where $\sigma_{\hat{x}}^2$ is the variance of the denoised signal and σ_e^2 is the variance of the error signal. A positive SNR indicates that the power of the signal is larger than the power of the noise, which suggests an effective denoising method. On the other hand, a negative SNR indicates larger noise than the signal, which suggests a poor performance of the denoising technique. By contrast, NMSE is defined by

$$NMSE = 10\log_{10}\frac{\Sigma_{m=1}^{M}\left(x_n[m]-\hat{x}_n[m]\right)^2}{\Sigma_{m=1}^{M}\left(x_n[m]\right)^2}, \tag{6}$$

where $x_n[m]$ is the original contaminated EEG signal, and $\hat{x}_n[m]$ is the denoised EEG signal [7], [13]. As indicated in Equation 6, the smaller the error, $(x_n[m]-\hat{x}_n[m])$, the larger negative values of NMSE in decibels, and thus better performance of the denoising techniques.

B. Overall Results under the Bonn Database

Figure 2 compares the moving average method (as implemented in [19]), autocorrelation method (as implemented in [16]), and the three Shrinkage Rules, which include SURE Shrink, universal thresholding (UT), and statistical threshold (ST) for the Bonn database in terms of SNR and NMSE. Figure 2a shows average NMSE and SNR for each folder (F, N, S), and Figure 2b averages NMSE and SNR for all the folders. All Shrinkage Rules methods here employ hard thresholding. Note that this thresholding pertains only to the WT with Shrinkage rule methods since the moving average filter and WT with autocorrelation methods do not make use of a thresholding rule. As shown in Figure 2b, the WT with SURE Shrink using hard thresholding performs the best in both average SNR and NMSE. The SURE Shrink method reduces the high amplitude of the ocular artifact while preserving the original EEG signal. The results agree with the reported work in the literature when using SURE Shrink [21] and WT denoising methods [21], [5], [18]. The WT with autocorrelation performs the worst in terms of average SNR, due to the nature of the method, which caused removing the original signal in the denoising process.

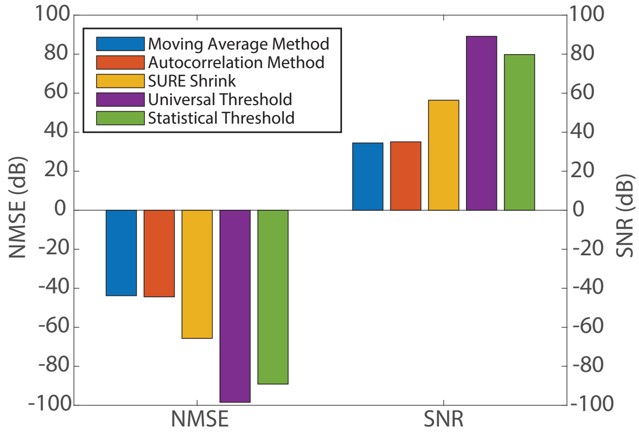

Fig. 3. Comparing various methods over all trials of the Motion-Artifact Contaminated database (Hard Thresholding when applicable).

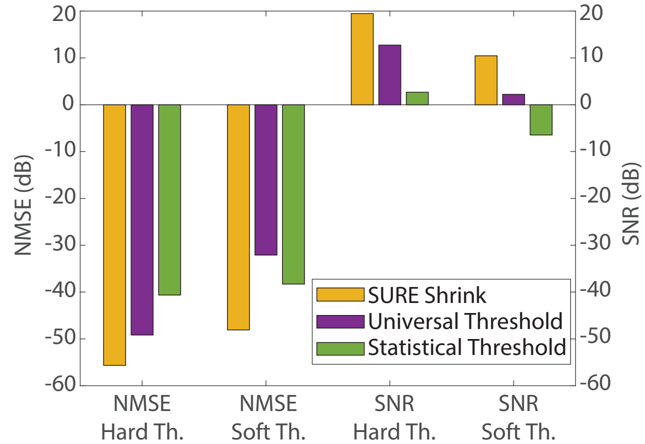

Fig. 4. Comparing Shrinkage Rules methods over all trials of all the folders of the Bonn EEG database (Hard and Soft Thresholding).

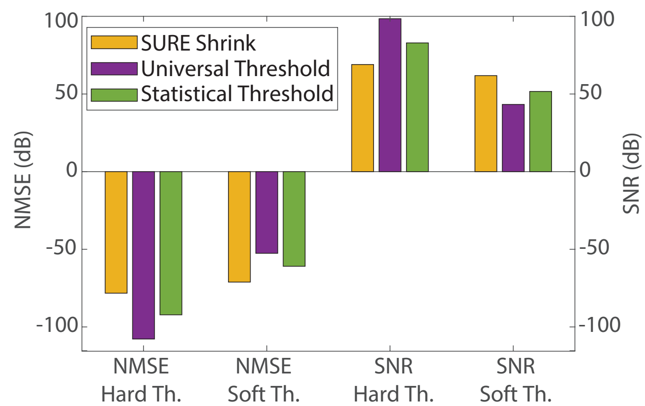

Fig. 5. Comparing Shrinkage Rules methods over all trials of the Motion Artifact Contaminated database (Hard and Soft Thresholding).

C. Overall Results under the Motion-Artifact Contaminated Database

Figure 3 shows the comparative results under the Motion Artifact Contaminated database in terms of SNR and NMSE. Once again, all Shrinkage Rules methods here employ hard thresholding. As depicted in Figure 3, the three shrinkage rules methods perform better than other techniques due to their data-driven specific approach to denoising. They remove more specific pieces of noise than other methods due to their sample-to-sample process, and thus maintaining the original signal. The universal threshold using hard thresholding performs the best since it takes into account the variance of the original signal, where motion artifacts have a large amount of variance in terms of amplitude and frequency range. The moving average filter and WT with autocorrelation threshold perform similarly for the worst denoising methods. This is partially due to the moving average filter not removing enough noise and primarily focusing on simply detrending the signal in time-domain. WT with autocorrelation performs worse than others primarily due to the lack of specificity in removing the noise, i.e., it removes parts of the original signal.

D. Analysis of Shrinkage Rules

Let us now compare the effectiveness of Shrinkage Rules methods and analyze the impact of thresholding, hard versus soft thresholding. As shown in Figure 4 and 5, the use of the soft thresholding tends to decrease average SNR and increase average NMSE after denoising for each method when tested on both databases. This is due to soft thresholding reducing parts of the signal that fall above the noise threshold whereas the hard thresholding rule leaves them and only removes or reduces values that fall below the threshold value. In particular, the average SNR obtained by the statistical threshold using soft thresholding has negative values in the Bonn database, suggesting that the method does not remove the noise but rather removes the original signal.

IV. Discussion on Computational Complexity of Denoising Techniques

WT has lower complexity and power consumption compared to other techniques, and can achieve real-time operation with low cost, which is useful for energy-constrained applications [5], [7]. The most expensive method is the WT with SURE Shrink due to the complexity of the SURE algorithm [7], while the WT with autocorrelation has the least computational complexity. In addition, WT with the universal threshold and WT with the statistical threshold require similar computational power due to relatively simple implementation and the similarities in how both threshold values are computed. Overall, for WT-based methods, the limiting factor in computational complexity is the wavelet transform itself due to the complexity of some mother wavelets, such as the Daubechies family, and higher decomposition levels. To reduce the computational complexity and the power consumption of WT-based methods, a lower level of decomposition can be used, such as level 5 or level 6, with a simple mother wavelet such as the Haar mother wavelet. The moving average filter method has variable computational complexity due to the variable window size, but the power consumption should not vary significantly.

V. Conclusion

This paper has evaluated various denoising techniques for removing the artifacts from iEEG and sEEG signals. Simulation results showed that the WT with universal threshold using hard thresholding performs the best in removing motion artifacts and denoising of sEEGs. For iEEG denoising and removing ocular artifacts, WT with SURE Shrink using hard thresholding is preferred. The detailed results and analysis are of great importance to researchers and practitioners in EEG systems and to achieve real-time, low-power, and low-cost denoising methods for energy-constrained devices.

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