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## Artifact Removal from EEG using Spatially Constrained Independent Component Analysis and Wavelet Denoising with Otsu's Thresholding Technique

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### Abstract

This paper presents a novel technique for removing the artifacts from the ElectroEncephaloGram (EEG) signals. EEG signals are influenced by different characteristics, like line interference, EOG (electro-oculogram) and ECG (electrocardiogram). The elimination of artifact from scalp EEGs is of substantial significance for both the automated and visual examination of underlying brainwave actions. These noise sources increase the difficulty in analyzing the EEG and obtaining clinical information related to pathology. Hence it is crucial to design a procedure to decrease such artifacts in EEG records. This paper uses Spatially-Constrained Independent Component Analysis (SCICA) to separate the Independent Components (ICs) from the initial EEG signal. As the next step, Wavelet Denoising (WD) is applied to extract the brain activity from purged artifacts, and finally the artifacts are projected back and subtracted from EEG signals to get clean EEG data. Here, thresholding plays an important role in delineating the artifacts and hence a better thresholding technique called Otsu', thresholding is applied. Experimental results show that the proposed technique results in better removal of artifacts.

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*Keywords:* Artifact Removal; ElectroEncephaloGram (EEG); Wavelet Denoising; Spatially-Constrained Independent Component Analysis (SCICA);

### 1. Introduction

Human brain possesses rich spatiotemporal dynamics because of its complicated nature. Electroencephalography (EEG) provides a direct determination of cortical behaviour with millisecond temporal resolution when compared to other techniques. Electroencephalogram (EEG) is multivariate

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time series data measured using multiple sensors positioned on scalp that imitates electrical potential produced by behaviours of brain and is a record of the electrical potentials created by the cerebral cortex nerve cells. There are two categories of EEG, based on where the signal is obtained in the head: scalp or intracranial. Scalp EEG being the main focus of the research, uses small metal discs, also called as electrodes, which are kept on the scalp with good mechanical and electrical touch. Intracranial EEG is obtained by special electrodes placed in the brain during a surgery. The electrodes should be of low impedance, in order to record the exact voltage of the brain neuron. The variations in the voltage difference among electrodes are sensed and amplified before being transmitted to a computer program. EEG offers a continuous graphic display of varying voltage with time.

However, the captured EEG [4-7] includes artifacts in the waveforms. Several researches have been conducted to remove the artifacts in the EEG signal and various techniques are resulted due to this research. This paper proposes a new technique for removing the artifacts [8, 9] from the EEG signal which uses Spatially-Constrained ICA (SCICA) [12, 13] and wavelet denoising techniques. Threshold plays an important role in separating the artifacts from the non artifact EEG [17]. Otsu's Threshold is been adopted as the thresholding method in this paper. This method assumes that EEG contains two classes namely, artifact and non artifact signal and then it calculates the optimum threshold separating those two classes.

## 2. Related Work

Shao *et al.*, [1, 2] proposed an automatic EEG Artifact removal which uses a Weighted Support Vector Machine approach with error correction. An automatic electroencephalogram (EEG) [15- 16] artifact removal method is presented in this paper. Compared to past methods, it has two unique features: 1) a weighted version of support vector machine formulation that handles the inherent unbalanced nature of component classification and 2) the ability to accommodate structural information typically found in component classification. The advantages of the proposed method are demonstrated on real-life EEG recordings with comparisons made to several benchmark methods. Results show that the proposed method is preferable than the other methods in the context of artifact removal by achieving a better tradeoff between removing artifacts and preserving inherent brain activities. Qualitative evaluation of the reconstructed EEG epochs also demonstrates that after artifact removal inherent brain activities are largely preserved.

Kavitha *et al.*, [3] suggested a modified ocular artifact removal technique from EEG [10, 11] by adaptive filtering. Electroencephalogram (EEG) is the reflection of brain activity and is widely used in clinical diagnoses and biomedical researches. EEG signals recorded from the scalp contain many artifacts that make its interpretation and analysis very difficult. One major source of artifacts is from eye movements that generate the Electrooculogram (EOG). Many applications of EEG such as Brain Computer Interface (BCI) needs real time processing of EEG [14]. Adaptive filtering is one of the most efficient methods for removal of ocular artifacts which can be applied in real time. In conventional adaptive filtering, the primary input is the measured EEG and the reference inputs are vertical EOG (VEOG) and horizontal EOG (HEOG) signals. In this paper, an adaptive filtering approach is proposed which includes radial EOG (REOG) signal as a third reference input. The analysis based on the performance of adaptive algorithms using two reference inputs i.e. VEOG and HEOG and that with three reference inputs i.e. VEOG, HEOG and REOG, it is found that the proposed 3 reference method gives more accurate results than the existing two reference method.

### 3. Methodology

The architecture of the proposed method for pre-processing of EEG data is presented in figure 1. As represented, EEG data implicated is generated based on ICA model as

$$x(t) = As(t) + v(t) \quad (1)$$

where  $x(t) = [x_1(t), x_2(t), \dots, x_M(t)]^T$  which is a linear mixture of  $N$  sources  $s(t) = [s_1(t), s_2(t), \dots, s_N(t)]^T$ ,  $A$  is  $M \times N$  mixing matrix, and  $v(t) = [v_1(t), v_2(t), \dots, v_M(t)]^T$  is nothing but the additive noise at the EEG sensors. Here the number of sources is represented as  $N$  and the waveforms are represented as  $s_i(t)$ , and mixing matrix  $A$  are all unknown. In order to make the problem simple, the square mixing problem is considered, i.e.,  $M = N$ . The source signals  $s_i(t)$  can be regarded as being created from various brain regions and artifacts. These artifacts mask the brain activity data, and are dangerous for further examination and processing. Thus it is especially vital to process EEG data  $x(t)$  so that contribution of artifacts is separated, without damaging the brain-activity data, and is the key focus of the technique provided by the author. As represented in figure 1, the proposed technique consists of following key process:

- Preprocessing with the help of existing filtering.
- Use SCICA to obtain SC-ICs representing artifacts in EEG data.
- Use Wavelet Denoising (WD) to separate any brain activity leaked to these artifact ICs.
- The extracted artifact-only signals are projected back, and subtracted from, EEG data to get clean EEG for further examination and processing.

The purpose of conventional filtering is to process raw EEG data  $x(t)$  to eliminate 50 Hz line noise, baseline values, artifacts which dwell in very low frequencies and high frequency sensor noise  $v(t)$ , and this phase may include mixture of different existing notch, lowpass, and/or highpass filters.

#### 3.1 Spatially-Constrained ICA (SCICA)

The main process in the proposed technique is the application of SCICA to obtain artifact ICs from filtered and baseline corrected EEG data  $y(t)$ . Description of SCICA is portrayed in detail. The key intention is to depict a Spatial Constraint (SC) on the mixing matrix  $A$  to symbolize specific prior knowledge or prior assumptions concerning the spatial topography of some source sensor projections, i.e., the SC operates on chosen columns of  $A$  and is enforced with reference to a set of predetermined constraint sensor projections, represented by  $A_c$ . Thus, the spatially constrained mixing matrix consists of two kinds of columns

$$A = [A_c, A_u] \quad (2)$$

Where  $\tilde{A}_c \approx A_c$  are columns which are regarded as constraint, and  $A_u$  otherwise regarded as unconstrained columns. Based on the usage, the predetermined sensor projections could be gathered by manual choice of sources extracted from a previous information segment with the help of existing ICA technique or derived from the predictions of some mathematical model of the signal obtaining procedure under examination. Based upon the confidence level regarding the accuracy of the constraint topographies  $A_c$ , and the level to which constrained columns  $\tilde{A}_c$  may diverge from reference  $A_c$ , there are three kinds of constraints: 1) hard constraints representing fixed column, 2) soft constraints permitting divergence within a small angular threshold  $\alpha$ , and 3) weak constraints that only afford an initial approximation for

otherwise unconstrained assessment. The spatially-constrained-FastICA (SCFastICA) technique is the one categorized under soft SCs.

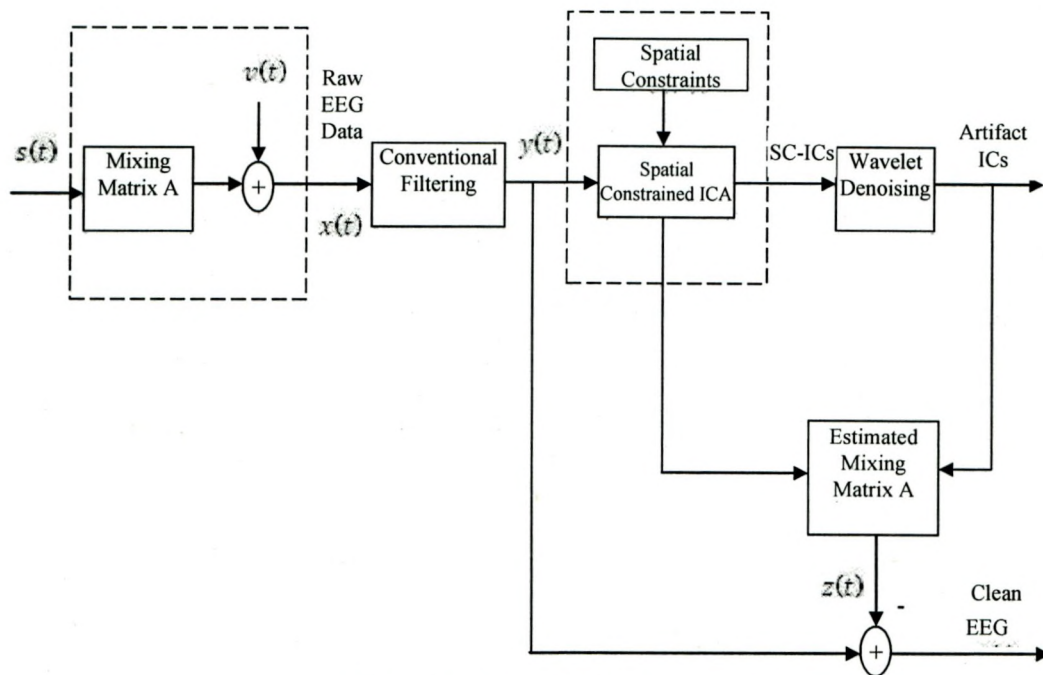


Fig 1: Overall Process of Artifact Removal

The SCFastICA technique aims to maximize the statistical independence of the unconstrained sources and at the same time reducing the divergence among the spatially constrained source sensor projections and their corresponding reference topographies. A deflationary technique is implemented to take out only desired components, and therefore the output of the SCFastICA technique is SC-ICs (which are artifact signals in our case), and an estimate of corresponding mixing matrix. This results in fast computational time, as compared with if all ICs are extracted.

### 3.2 Wavelet Denoising (WD) of SC-ICs

It is significant mentioning that SC-ICs determined by SCFastICA are expected to correspond to artifacts only; on the other hand, some brain action might escape to these gathered signals. The purpose of conventional filtering is to process raw EEG data  $x(t)$  to eliminate 50 Hz line noise, baseline values, artifacts inhabiting very low frequencies and high frequency sensor noise  $v(t)$ , and this phase may include mixture of different existing notch, lowpass, and/or highpass filters. As artifacts have a frequency overlap with the brain signals, conventional filtering technique cannot be utilized, and therefore this paper focuses on using Wavelet Denoising to take away any brain activity from gathered SC-ICs.

The Discrete Wavelet Transform (DWT) examines a finite length time domain signal by breaking up the initial domain in two phases: the detail and approximation data. The approximation domain is sequentially decomposed into detail and approximation domains. The basic principle is that the decomposition of a noisy signal on a wavelet basis (by DWT) have the property to “concentrate” the informative signal in few wavelet coefficients having large absolute values without altering the noise random distribution. After performing these operations, the noise coefficients have minimum values, inversely to the informative signal (normal or pathologic neural activity and artifacts). Consequently, denoising can be attained by thresholding the wavelet coefficients using Otsu’s thresholding method. The implementation is as follows:

- Choosing the value of the threshold using Otsu’s Thresholding Method
- Then DWT is performed to the SC-IC signal to obtain details and approximations
- Threshold the detailed components obtained in the previous step
- Finally inverse DWT is utilized to obtain only the artifact signal

### 3.3 Otsu’s Thresholding Method

A signal consists of  $N$  values with levels from 1 to  $L$ . The number of values with gray level  $i$  is represented by  $f_i$ , giving a probability of level  $i$  in the given signal is

$$P_i = \frac{f_i}{N} \quad (3)$$

In the case of bi-level thresholding, the values are separated into two classes,  $C_1$  with levels  $[1, \dots, t]$  and  $C_2$  with levels  $[t+1, \dots, L]$ . Then, the level probability distributions for the two classes are

$$C_1: P_i / w_1(t), \dots, P_t / w_1(t) \text{ and}$$

$$C_2: P_{t+1} / w_2(t), P_{t+2} / w_2(t), \dots, P_L / w_2(t)$$

where

$$w_1(t) = \sum_{i=1}^t P_i \quad (4)$$

and

$$w_2(t) = \sum_{i=t+1}^L P_i \quad (5)$$

Also, the means for classes  $C_1$  and  $C_2$  are

$$\mu_1 = \sum_{i=1}^t i p_i / w_1(t) \quad (6)$$

And

$$\mu_2 = \sum_{i=t+1}^L i p_i / w_2(t) \quad (7)$$

Let  $\mu_T$  be the mean intensity for the whole values. It is easy to show that

$$w_1 \mu_1 + w_2 \mu_2 = \mu_T \quad (8)$$

$$w_1 + w_2 = 1 \quad (9)$$

Using discriminant analysis, Otsu defined the between-class variance of the thresholded data

$$\sigma_E^2 = w_1 (\mu_1 - \mu_T)^2 + w_2 (\mu_2 - \mu_T)^2 \quad (10)$$

For bi-level thresholding, Otsu verified that the optimal threshold  $t^*$  is selected so that the between-class variance  $\sigma_E^2$  is maximized; that is,

$$t^* = \text{ArgMax}\{\sigma_E^2(t)\} \quad (11)$$

$$1 \leq t < L$$

The previous formula can be easily extended to multilevel thresholding of a signal. Assuming that there are  $M-1$  thresholds,  $\{t_1, t_2, \dots, t_{M-1}\}$ , which separates the original image into  $M$  classes:  $C_1$  for  $[1, \dots, t_1]$ ,  $C_2$  for  $[t_1+1, \dots, t_2]$ , ...,  $C_i$  for  $[t_{i-1}+1, \dots, t_i]$ , ..., and  $C_M$  for  $[t_{M-1}+1, \dots, L]$ , the optimal thresholds  $\{t_1^*, t_2^*, \dots, t_{M-1}^*\}$  are chosen by maximizing  $\sigma_E^2$  as follows:

$$\{t_1^*, t_2^*, \dots, t_{M-1}^*\} = \text{ArgMax}\{\sigma_E^2(t_1^-, t_2^-, \dots, t_{M-1}^-)\} \quad (12)$$

$$1 \leq t_1 < \dots < t_{M-1} < L$$

where

$$\sigma_E^2 = \sum_{K=1}^M w_K (\mu_K - \mu_T)^2 \quad (13)$$

With

$$w_K = \sum_{i \in C_K} p_i \quad (14)$$

$$\mu_K = \sum_{i \in C_K} i p_i / w_K \quad (15)$$

The  $w_K$  in equation (12) is regarded as the zeroth-order cumulative moment of the  $k$ th class  $C_k$ , and the numerator in equation (15) is regarded as the first-order cumulative moment of the  $k$ th class  $C_k$ ; that is,

$$\mu_K = \sum_{i \in C_K} i p_i \quad (16)$$

Once "clean" artifacts are obtained, these are projected back to EEG sensors with the help of mixing matrix  $A$  obtained by SCFastICA, and artifacts in the EEG data are obtained, as represented by  $z(t)$  in figure 1. At last, the clean EEG data  $\hat{x}(t)$  is obtained by subtracting artifacts  $z(t)$  from EEG data  $y(t)$ .

#### I. 4. EXPERIMENTAL RESULTS

This section presents the evaluation of the proposed artifact removal technique. Initially, EEG signals are captured with occurrence of artifacts. The captured EEG signal is shown in figure 2(a) and 3(a).

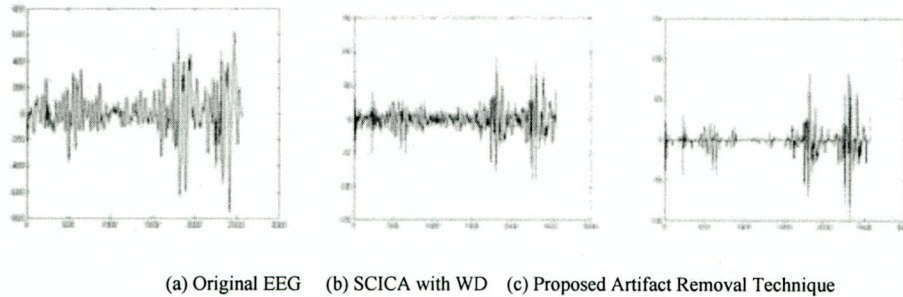


Figure 2: Results Obtained for Artifact Removal with a Sample Signal 1

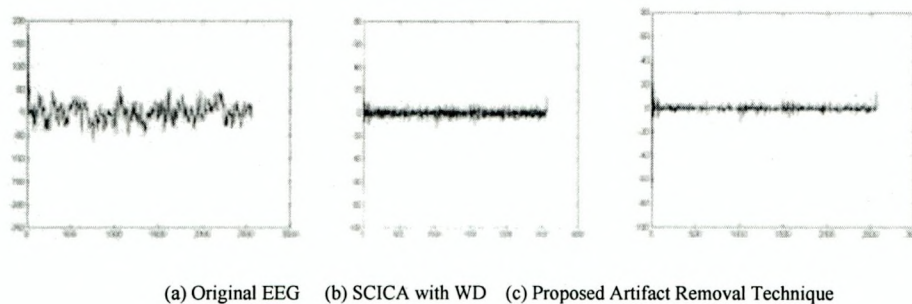


Figure 2: Results Obtained for Artifact Removal with a Sample Signal 2

The results obtained are depicted in figure 2 and figure 3. The signal resulted after the usage of wavelet filtering and Spatially-Constrained ICA is shown in figure 2(b) and 3(b). Final signal obtained by using the otsu's thresholding technique is shown in figure 2(c) and 3(c). From the figures, it can be observed that the proposed artifact removal technique results in better removal of artifacts when compared to the existing technique. This will help in improving the performance of the further processing with this obtained EEG signal.

#### 5. Conclusion

This paper focuses on removing the artifacts from ElectroEncephaloGram (EEG) signals. Artifact removal is an important process before analyzing the EEG signal for prediction of any pathological diseases. Various researchers have focused on this process and developed their own technique for artifact removal. This paper intends on developing a new technique to remove the artifact from EEG. The proposed approach uses Spatially-Constrained Independent Component Analysis (SCICA) to separate the exact Independent Components (ICs) from the initial EEG signal. Then, Wavelet Denoising is applied to extract the brain activities from purged artifacts, and finally project back the

artifacts to be subtracted from EEG signals to get clean EEG data. The thresholding technique used in this paper is otsu's thresholding. Experimental evaluation suggests that the proposed approach results in better removal of artifact when compared to the existing techniques.

## References

- [1] Shi-Yun Shao, Kai-Quan Shen, Chong Jin Ong, Wilder-Smith, E and Xiao-Ping Li, "Automatic EEG Artifact Removal: A Weighted Support Vector Machine Approach with Error Correction", *IEEE Transactions on Biomedical Engineering*, Vol. 56, 2009, Pp. 336-344.
- [2] Shi-Yun Shao, Kai-Quan Shen, Chong-Jin Ong, Xiao-Ping Li and Wilder-Smith, E.P.V, "Automatic identification and removal of artifacts in EEG using a probabilistic multi-class SVM approach with error correction", *IEEE International Conference on Systems, Man and Cybernetics*, 2008, Pp. 1134-1139.
- [3] Kavitha, P.T, Lau, C.T and Premkumar, A.B., "Modified ocular artifact removal technique from EEG by adaptive filtering", *International Conference on Information, Communications & Signal Processing*, 2007, Pp. 1-5.
- [4] Kyung Hwan Kim, Hyo Woon Yoon and Hyun Wook Park, "Improved algorithm for ballistocardiac artifact removal from EEG simultaneously recorded with fMRI", *26th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, Vol.1, 2004, Pp. 936-939.
- [5] P. LeVan, E. Urrestarrazu, and J. Gotman, "A system for automatic artifact removal in ictal scalp EEG based on independent component analysis and Bayesian classification", *Clinical Neurophysiology*, Vol. 117, No.4, 2006, pp. 912- 927.
- [6] R.J. Croft and R.J. Barry, "Removal of ocular artifact from the EEG: a review" , *Clinical Neurophysiology*, Vol. 30, No.1, 2000, pp. 5 – 19.
- [7] CA.Joyce, IF.Gorodnitsky, M.Kutas, "Automatic removal of eye movement and blink artifacts from EEG data using blind component separation" , *Phychophysiology.*, Vol. 41, No.2, 2004, pp.313- 325.
- [8] V. Krishnaveni, S. Jayaraman, S. Aravind, V. Hariharasudhan, K. Ramadoss, "Automatic identification and Removal of ocular artifacts from EEG using Wavelet transform " , *Measurement Science Review*, Vol. 6, No.4, 2006 pp.45-57.
- [9] V. Krishnaveni, S. Jayaraman, N. Malmurugan, A. Kandasamy, D. Ramadoss, "Non adaptive thresholding methods for correcting ocular artifacts in EEG" , *Academic Open Internet Journal*, Vol.13, 2004.
- [10] Shlomit Yuval-Greenberg, Orr Tomer, Alon S. Keren, Israel Nelken and Leon Y. Deouell, "Transient Induced Gamma-Band Response in EEG as a Manifestation of Miniature Saccades", *Neuron*, Vol.58, No.3, 2008, pp.429- 441.
- [11] S. Verobyov and A. Cichocki. "Blind noise reduction of multisensory signals using ICA and subspace filtering, with application to EEG analysis". *Biological Cybernetics*, 86:293-303, 2002.
- [12] M. Potter, N. Gadhok, and W. Kinsner. "Separation performance of ICA on simulated EEG and ECG signals contaminated by noise". *Canadian Journal of Electrical and Computer Engineering*, 27(3):123-127, July 2002.
- [13] S. Choi, A. Cichocki, H. Park, S. Lee, blind Source "Separation and Independent Component Analysis : A Review", *Neural Information Processing – Letters and Reviews*, Vol. 6, no. 1, January 2005.
- [14] A. Cichocki, Shun-ichi Amari, "Adaptative blind Signal and Image Processing Learning Algorithms and Applications", John Wiley & Sons, Ltd, 2002.
- [15] Sutherland, M.T., and Tang A.C. " Blind source separation can recover systematically distributed neuronal sources from "resting" EEG", *Proceedings of the Second International Symposium on Communications, Control, and Signal Processing (ISCCSP 2006)*, Marrakech, Morocco, March 13-15.
- [16] Joep J. M. Kierkels, Geert J. M. Van Botel, and Leo L. M. Vogten. "A Model-Based Objective Evaluation of Eye Movement Correction in EEG Recordings", *IEEE Transactions on biomedical engineering*, vol. 53, No. 2, February 2006.
- [17] Muhammad Tahir Akhtar and Christopher J. James, "Focal Artifact Removal from Ongoing EEG – A Hybrid Approach Based on Spatially-Constrained ICA and Wavelet De-noising", *Annual International Conference of the IEEE EMBS Minneapolis*, 2009, Pp. 4027-4030.
- [18] N.P. Castellanos and V.A. Makarov, "Recovering EEG brain signals: Artifact suppression with wavelet enhanced independent component analysis," *J. Neuroscience Methods*, vol. 158, 2006, pp. 300–312.