

Automated Classification and Removal of EEG Artifacts with SVM and Wavelet-ICA

C.Y. Sai, N. Mokhtar, H. Arof, P. Cumming and M. Iwahashi

Abstract—Brain electrical activity recordings by electroencephalography (EEG) are often contaminated with signal artifacts. Procedures for automated removal of EEG artifacts are frequently sought for clinical diagnostics and brain computer interface (BCI) applications. In recent years, a combination of independent component analysis (ICA) and discrete wavelet transform (DWT) has been introduced as standard technique for EEG artifact removal. However, in performing the wavelet-ICA procedure, visual inspection or arbitrary thresholding may be required for identifying artifactual components in the EEG signal. We now propose a novel approach for identifying artifactual components separated by wavelet-ICA using a pre-trained support vector machine (SVM). Our method presents a robust and extendable system that enables fully automated identification and removal of artifacts from EEG signals, without applying any arbitrary thresholding. Using test data contaminated by eye blink artifacts, we show that our method performed better in identifying artifactual components than did existing thresholding methods. Furthermore, wavelet-ICA in conjunction with SVM successfully removed target artifacts, while largely retaining the EEG source signals of interest. We propose a set of features including kurtosis, variance, Shannon's entropy and range of amplitude as training and test data of SVM to identify eye blink artifacts in EEG signals. This combinatorial method is also extendable to accommodate multiple types of artifacts present in multi-channel EEG. We envision future research to explore other descriptive features corresponding to other types of artifactual components.

Index Terms—Artifact Removal, Blind Source Separation, Electroencephalography (EEG), Wavelet Multiresolution Analysis (WMA), Independent Component Analysis (ICA), Support Vector Machine (SVM), Brain Computer Interface (BCI)

I. INTRODUCTION

THE ELECTROENCEPHALOGRAM (EEG) is the recording of electrical activity of the cerebral cortex through electrodes,

that are usually placed on the scalp. The EEG technique is widely used for the clinical diagnosis of epilepsy and sleep disorders. Today, the EEG is also attracting increasing interest in brain computer interface (BCI) applications. However, in practical settings the EEG signals are often contaminated by both biological and environmental artifacts [1-3]. Biological artifacts are signals arising from non-cerebral sources in the human body, such as cardiac, ocular or muscles activity. On the other hand, environmental artifacts originate from outside of the human body, due to electrode movement or interference from external devices such as power main or electric motor. Together, biological and environmental artifacts degrade EEG signals, thereby obstructing clinical diagnosis or BCI applications by distorting the observed power spectrum.

Conventional methods to remove EEG artifacts employ linear filters or regressions, in relation to the time of occurrence or the frequency range of target artifacts [4, 5]. However, filtering in either the time or frequency domains incurs substantial loss of observed cerebral activity because of the inherent spectral overlap between neurological activity and signal artifacts [6, 7]. Wavelet based multiresolution analysis using a discrete wavelet transform (DWT) is shown to be more effective in removing target artifacts, while better preserving the structure of the true EEG signal in both time and frequency domains [8, 9]. On the other hand, independent component analysis (ICA) is proven useful to isolate target artifacts into a separated independent component (IC) using blind source separation [3, 10]. In recent years, artifact removal using a combination of wavelet and ICA methods has shown promising results in practical applications [1, 11].

Applying the joint method of wavelet-ICA for artifact removal can necessitate visual inspection of the EEG recording, or make it necessary to apply a manually-defined or arbitrary threshold to identify and isolate the artifactual component from the EEG signals [1, 12]. The defined threshold may fail to capture target artifacts close to the arbitrarily defined boundary of the EEG signals. Additionally, using a manually-defined threshold to identify signal artifacts may also increase the false detection rate. Furthermore, depending on the particular dataset being assessed, the calculated thresholding value may not be appropriate to distinguish multiple target artifacts in cases of noisy signals recorded at multiple channels, as is frequently observed in the case for inherently noisy multi-channel EEG.

In this paper, we present a novel combination of methods comprising wavelet-ICA and support vector machine (SVM) for robust and generalizable removal of EEG signal artifacts.

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We introduce an improved method to identify artifactual components using SVM with selected training and test features. Combined use of wavelet multiresolution analysis (WMA) and ICA allow the removal of the artifactual components with minimal distortion to the cerebral signals of interest. After presenting our methods, we test the system on recorded EEG data and publicly available data from EEGLAB [13], and conclude with a discussion of the extendibility of new hybrid method for multiple artifacts removal.

II. METHODS

A. Wavelet Multiresolution Analysis

WMA incorporates the steps of DWT and inverse DWT. The initial DWT consists of sequential application of low- and high-pass filters to decompose a discrete signal into multiple wavelet components, as shown in Figure 1. Here, $x[n]$ represents a channel of EEG signal passed through a low pass filter, $g[n]$ and a high pass filter, $h[n]$ simultaneously. This process is repeated until each channel of the EEG signal is decomposed into n levels of wavelet details, i.e. $D_1(t), D_2(t), \dots, D_n(t)$ and a mother wavelet $A_n(t)$.

Inverse DWT is applied in a similar but reversed sequence by recombining the wavelet details and mother wavelet into a single channel, $x'[n]$. In practical use of WMA, only the wavelet details and mother wavelet corresponding to the frequency range of interest are retained.

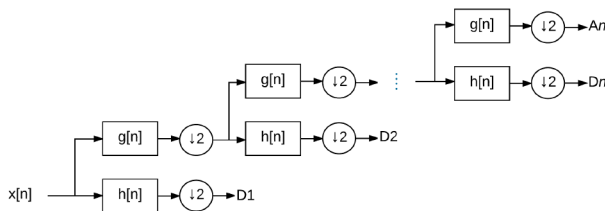


Fig. 1. Block diagram of DWT of a signal, $x[n]$. The annotation $\downarrow 2$ denotes reduction of the signal by a factor of 2, i.e. two-fold down-sampling.

B. Independent Component Analysis

ICA model describes multivariate signals in terms of a mixing of source components [14], by making the general assumption that multivariate signals, \mathbf{x} are separable into their statistically independent and non-Gaussian source components, \mathbf{s} . This approach has been widely applied in EEG signal processing to separate EEG artifacts [3, 15], with the requirement that several assumptions are met:

- 1) The multivariate signals consist of cerebral and artifactual sources that are linearly mixed and statistically independent.
- 2) The number of observed signals is greater than or equal to the number of source components.
- 3) At most one source component is Gaussian, and
- 4) The propagation delay of artifactual sources through the scalp is negligible.

The source components are synonymous with independent components (ICs). The relationship between a recorded signal and its source components is described by the equation

$$\mathbf{x} = \mathbf{A}\mathbf{s}. \quad (1)$$

In equation (1), \mathbf{A} is the unknown mixing matrix [14] which is

to be estimated by using the ICA algorithms [16-18]. Then, the inverse of matrix \mathbf{A} can be computed as the estimated un-mixing matrix, \mathbf{W} . Finally, the source components, \mathbf{s} are revealed by using the equation

$$\mathbf{s} = \mathbf{W}\mathbf{x}. \quad (2)$$

The reconstruction of source components into the multivariate signals is known as inverse ICA, which is accomplished by multiplying the inverse of the estimated mixing matrix, \mathbf{W}^{-1} with the source components, \mathbf{s} .

C. Support Vector Machine

SVM is a widely used classifier utilizing the method of supervised machine learning [19]. The goal of SVM is to construct an optimal hyperplane using training data that separate two or more datasets for classification in the test data [2]. The optimal hyperplane is constructed in order to obtain the maximal margin from the nearest samples of different datasets, known as the support vectors. In cases where the datasets are not linearly separable in the original finite dimensional space, the data can be re-mapped into a sufficiently higher dimensional space. This mapping is conducted by using a defined kernel function, $k(x, y)$, which presumably ensures an easier separation of the datasets. The hyperplane defined in the higher dimensional space can be viewed as a non-linear separating hyperplane in the original finite dimensional space. Thus, this approach is also known as a non-linear SVM.

III. PROPOSED METHOD

This paper proposed a hybrid method for automatic identification and removal of artifactual components in EEG signal, without any need to apply an arbitrary threshold in identifying the artifactual components. In brief, our hybrid method applies a combination of wavelet-ICA with pre-trained SVM to assist in classification of artifactual ICs. Figure 2 shows the block diagram of the complete system, which is implemented in the LabVIEW platform for its robustness in real time applications.

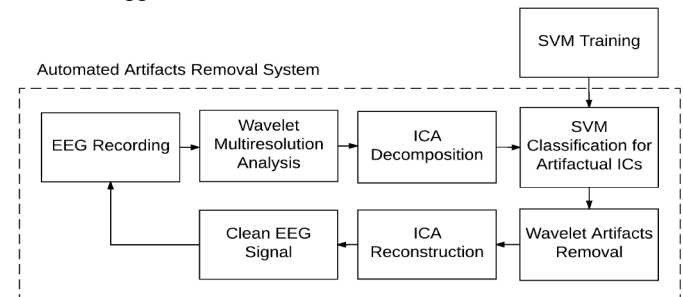


Fig. 2. Block diagram of the proposed artifacts removal system using wavelet-ICA and pre-trained SVM for artifactual components identification.

A. EEG recording

EEG acquisition equipment g.USBamp (g.tec, Austria) was used to acquire EEG signals from 11 healthy volunteers, who had given informed consent to participate in a protocol approved by local ethics committee (University Malaya Medical Centre Ethical Clearance: 20156-1404). The subjects are instructed to maintain a natural upright sitting position with eyes open for up to 30 minutes. EEG signals with eye blink

artifacts are recorded following involuntary eye blink activities. The electrodes were placed as specified by the 10-20 system. A total of 16 electrodes corresponding to channels FP1, FP2, F3, Fz, F4, T7, C3, Cz, C4, T8, P3, Pz, P4, O1, Oz, and O2 were used in this study. In our procedure, the ground electrode is set at FPz, and the reference point fixed at the left earlobe (A1). The scalp impedance of the recording is kept below 5 k Ω . The recordings were conducted with a sampling rate of 256 Hz. A notch filter of 50 Hz (Butterworth, order 4) and band pass filter of 0.5 to 100 Hz (Butterworth, order 8) was applied by default during the recording, whereupon the signal was separated into five-second epochs for further processing.

B. Procedure for Wavelet Multiresolution Analysis

WMA was first applied to the EEG recording in order to exclude all but the frequency bands of interest. Each channel of the recorded signal is decomposed by DWT to 8 levels using a mother wavelet of db8 [9]. By default, WMA deletes details at levels D1 and D2, corresponding to the frequency range of 32 to 128 Hz, and also the mother wavelet A8, corresponding to the frequency range of 0 to 0.5 Hz. As such, WMA retains relevant details of D8 to D3, corresponding to the frequency range of interest for EEG signal, i.e. 0.5 to 32 Hz. The wavelet details represent the traditional frequency bands of EEG signals defined as delta (0.5 to 4 Hz), theta (4 to 8 Hz), alpha (8 to 16 Hz) and beta (16 to 32 Hz) bands respectively [20]. WMA filtered most of the artifacts out of the frequency range of interest, notable high frequency noise (>32 Hz), and linear trend movement at extremely low frequency (<0.5 Hz).

C. ICA Decomposition

After preliminary filtering of the EEG signal by WMA, the processed signal is decomposed into ICs by using the matrix-pencil algorithm [18] with default parameters as implemented in LabVIEW. The number of ICs is constrained to be less than or equal to the number of channels of the EEG signal. We selected the matrix-pencil algorithm over alternates such as fastICA or the Infomax algorithm due to its superior performance in application for non-stationary signals [14, 18]. Additionally, the matrix-pencil algorithm based on second-order statistics also requires less computational load than algorithms based on higher-order statistics.

D. SVM Training and Classification

The decomposed ICs are evaluated by a pre-trained SVM to determine whether the ICs contain any artifactual component. The SVM is trained using features of selected sample ICs that contain the target artifactual components, which are in the present case eye blink artifacts (indeed, the eye blink artifact is one of the most common artifacts in EEG signals). The SVM is trained using training data of 5,000 ICs containing 2,500 ICs with eye blink artifacts and randomly selected 2,500 non-artifactual ICs, extracted from 10 participating subjects and labelled by visual inspection [21]. The classification is conducted on EEG recordings from an untrained subject and on public data. Parameters of SVM are selected as a linear kernel with soft margin constant, $C = 10$, determined by using 5-fold cross validation. We also propose the use of variance, kurtosis,

Shannon's entropy and range of amplitude as the most salient descriptive features to distinguish ICs contaminated by eye blink artifacts. We selected these features as the eye blink artifact has significantly higher amplitude in the proposed features compared to an uncontaminated EEG signal. We note that the selection of these features is not only useful for isolation of the eye blink artifact, but should also serve for other artifactual components such as those arising from electromyogram (EMG) signals. Indeed, this selection of features and training data of SVM should allow the system to identify multiple target artifactual components present in an EEG recording using a multi-class SVM, although this would be a matter for further study. Once an IC is identified as containing artifactual component, it is sent for further processing by the wavelet artifact removal model.

A separated validation algorithm is applied to validate the ICs that are classified as constituting an artifactual component. In this algorithm, we calculate the absolute value of each proposed features from the identified artifactual ICs, and compared this value with the other uncontaminated ICs. If the artifactual ICs' value exceed by a factor of at least three times the common mean value [22], then it can properly be considered as containing a significant artifactual component, and its features can be incorporated in the training of SVM for future classification. This procedure of updating the training data ensures that the system is adaptive to future data.

E. Wavelet Artifact Removal

Wavelet artifact removal is applied to the ICs identified by SVM as constituting artifactual components. The ICs are again decomposed by DWT and the wavelet components with a coefficient exceeding the universal value for wavelet denoise is deemed to be purely artifactual, and is thus removed [1, 12, 15]. The universal value, K for wavelet denoise is calculated as

$$K = \sqrt{2 \log N} \sigma, \quad (3)$$

where N is the length of the data to be processed and

$$\sigma^2 = \text{median}(|W(j, k)| / 0.6745) \quad (4)$$

represents the magnitude of neuronal wide band signal. In equation (4), $|W(j, k)|$ represents the absolute value of the wavelet coefficient, with constant 0.6745 accounting for the Gaussian noise. The selection and calculation for the universal value is discussed in detail in [9, 23].

F. Wavelet and ICA reconstruction

After the removal of artifacts, the remaining wavelet components are reconstructed into ICs by inverse DWT. Finally, inverse ICA is applied to reconstruct the filtered ICs into clean EEG signals with artifacts removed.

IV. RESULTS

We tested the proposed system on untrained EEG data recorded in our laboratory, and made further validation of the system's robustness and generalizability by quantitative analysis against a publicly available EEG dataset from EEGLAB [13]. The proposed system achieved satisfactory results in removing artifactual components while retaining cerebral activities of interest.

A. Test using recorded EEG signal

The procedure for EEG signal recording is as described in Section III. The recorded signal is first passed through WMA to retain only the frequency bands of interest. The raw 16-channel EEG signal and the signal remaining after passage through WMA are shown in Figure 3(a) and 3(b) respectively. We note that most of the artifacts lying outside of the frequency bands of interest are efficiently removed without distortion to the time and frequency resolution of the EEG signal.

However, some of the artifactual components overlapping the frequency resolution of the EEG signal were not removed. In particular, we note that the eye blink artifacts tended to remain in the 2 and 5 second segments of the five-second epoch. ICA is applied to the 16-channel signal in Figure 3(b) to decompose the signal into its estimated statistically independent and non-Gaussian ICs. The resulting 16 ICs decomposed by ICA using the matrix-pencil algorithm are shown in Figure 4. By visual inspection, we note that the first IC contains the eye blink artifacts. The values of the kurtosis, variance, Shannon's entropy and range of each IC are shown in Figure 5. IC1 has outlier value in each of the features proposed to separate eye blink artifacts from cerebral activities.

We find it pertinent that it is also possible to automatically identify IC1 as containing an artifactual component by arbitrarily setting a thresholding value anywhere between the amplitude of features of IC1 and other ICs. However, this

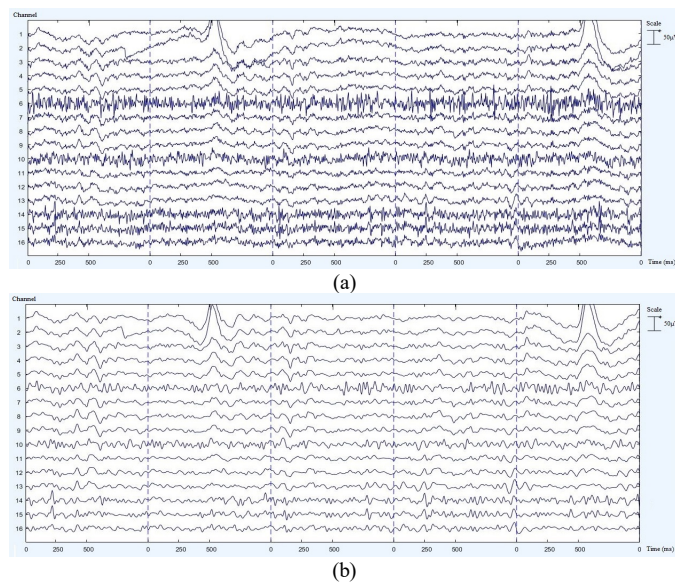


Fig. 3. The raw 16-channel EEG signal is shown in (a) and the signal after a pre-processing step using WMA is shown in (b). This step is conducted to retain only the frequency bands of interest (0.5 to 32 Hz). This pre-processing also eases ICA decomposition at later stages in the signal processing.

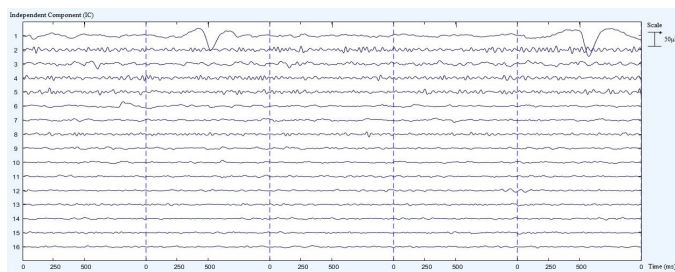


Fig. 4. Decomposed 16 ICs from EEG signal using ICA.

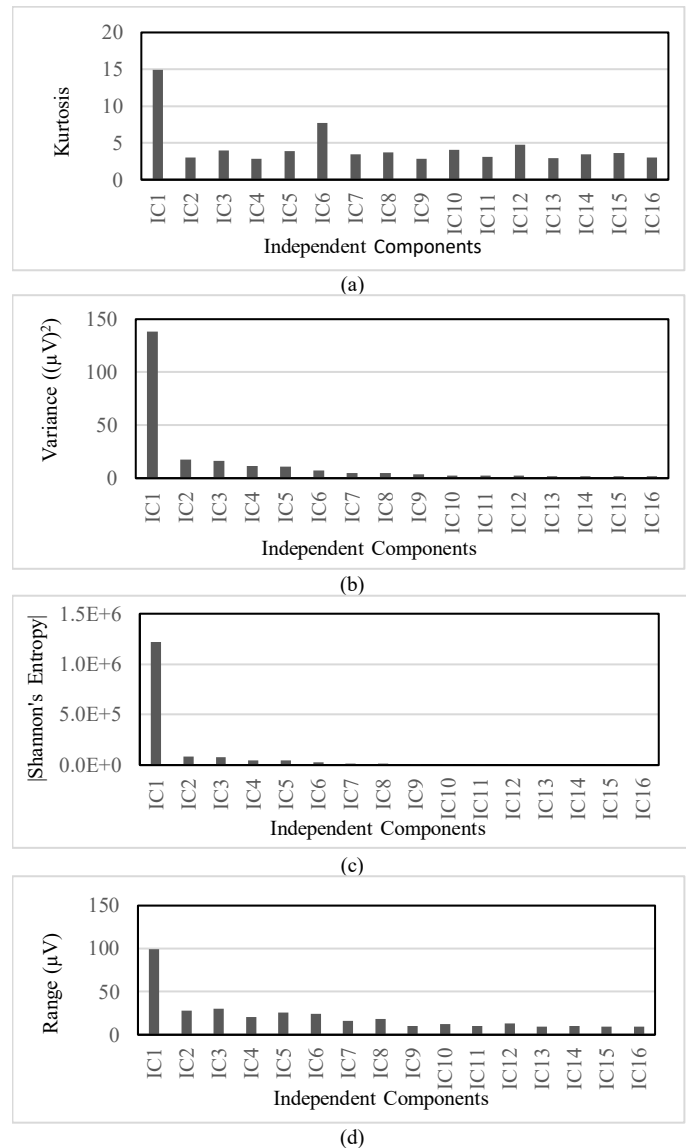


Fig. 5. Selected features that differentiate IC1, which contain eye blink artifacts, from the other ICs. The four descriptive features presented are (a) kurtosis, (b) variance, (c) absolute value of Shannon's entropy and (d) range of amplitude.

variant approach is often rigid and unsuitable to be applied for sporadic and non-stationary signal such as the case of EEG. The arbitrarily defined threshold may fail to detect the artifactual component or inadvertently introduced false detection near the boundary of the thresholding value. In contrast, our method used a SVM trained with the target artifactual component classified that IC1 indeed containing an artifactual component. Then, IC1 is further validated by the criterion of having key features with absolute value at least three times the common mean. The identified features of the first IC are included in the training dataset for future classification of eye blink artifact.

To filter the artifactual components in IC1, wavelet artifact removal is applied to IC1 to isolate the wavelet components with coefficient that exceeded the universal value, as defined in Section III. This method effectively removed the eye blink artifact identified in IC1, while minimizing the risk of inadvertently removing cerebral activities of interest that present in IC1. The final reconstructed clean EEG signal is shown in Figure 6.

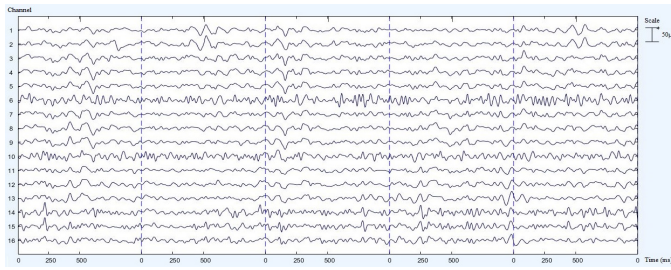


Fig. 6. Filtered 16-channel “clean” EEG signal.

B. Performance evaluation with dataset from EEGLAB

To validate further the robustness and generalizability of the proposed system, we conducted a test resembling that described in part A, but using a publicly available dataset from EEGLAB. We also provide the quantitative analysis to serve as potential benchmark for future research. This dataset is a recording of 32 channels [13], thus serving to investigate the extendibility of our system to an EEG recording of higher spatial resolution. As with our own data, the EEG signal was resampled at 256 Hz and divided into five-second epochs for further processing. An epoch of the original signal and the corresponding filtered result is shown in Figures 7(a) and 7(b) respectively. We see that, as with the 16-channel recording, the artifactual components (attributed to eye blink and lateral eye movement) are effectively removed, while cerebral activities of interest within the frequency bands of the EEG signal are well retained.

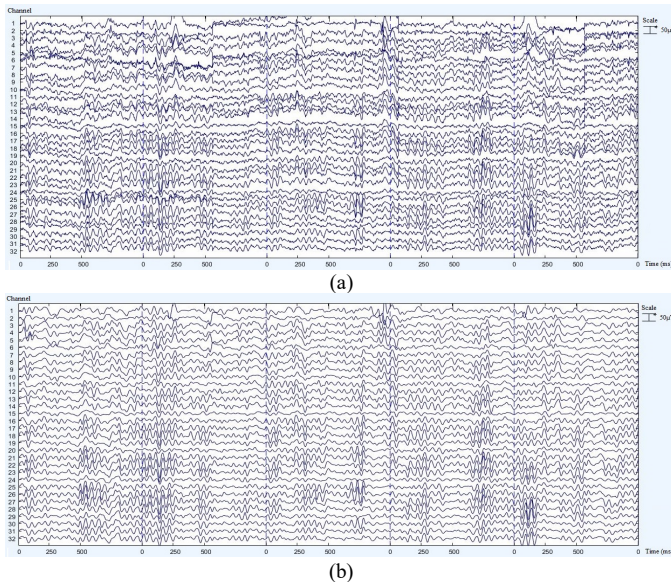


Fig. 7. Original 32 channels EEG signal from dataset of EEGLAB (a) and the filtered signal (b).

We evaluated the performance of SVM in identifying artifactual ICs for its sensitivity as given by

$$\text{Sensitivity} = \frac{TP}{TP + FN} \times 100\%, \quad (5)$$

and for the specificity of the system, as determined by

$$\text{Specificity} = \frac{TN}{TN + FP} \times 100\%. \quad (6)$$

Whereas the overall accuracy of the SVM is thus given by

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \times 100\%. \quad (7)$$

In these formulae, TP represents the number of True Positive, TN the True Negative, FP the False Positive and FN the False Negative events. As shown in Tables I and II, the SVM recorded an average accuracy of 99.1% using the dataset from EEGLAB. A comparison of the performance of SVM with the thresholding method is shown in Table II.

TABLE I
CONFUSION MATRIX FOR IC CLASSIFICATION

	Predicted: Non-Artifactual	Predicted: Artifactual
Actual: Non-Artifactual	(TN) 665	(FP) 5
Actual: Artifactual	(FN) 1	(TP) 33

Confusion matrix for classification of ICs using dataset from EEGLAB.

TABLE II
CLASSIFICATION ACCURACY OF ARTIFACTUAL ICs

	Proposed Method (%)	Thresholding method [1] (%)
Sensitivity	97.1	90.0
Specificity	99.3	98.0
Accuracy	99.1	95.2

Sensitivity, Specificity and Accuracy in identification of artifactual ICs using dataset from EEGLAB.

Using the same dataset from EEGLAB, we also compute the correlation coefficient of the filtered clean EEG signals with the signals before artifacts removal, aiming to confirm that the artifacts removal process did not alter or introduce much distortion to the original EEG signal. The average value of the correlation coefficient achieved by the proposed method is given in Table III, where we also compare results for wavelet-ICA with threshold and also zeroing-ICA (where entire artifactual IC is deleted) with an otherwise similar SVM.

The proposed method performed consistently better and yielded an overall average correlation coefficient of 0.955. On the other hand, the alternate methods of wavelet-ICA with threshold and zeroing-ICA with SVM both had an overall mean correlation coefficient value of 0.946. The proposed method performed better than wavelet-ICA with threshold due to the more accurate identification of artifactual components. False detection rate was lower, resulting in lesser unnecessary removal of wavelet components. Meanwhile, the proposed method also performed better than zeroing-ICA with SVM, as a result of using wavelet artifact removal instead of removing the entire IC with artifactual components, consequently resulting that the cerebral activities of interest are better retained.

V. DISCUSSION

The advantage of the proposed system for multi-channel EEG artifacts removal is that the pre-trained SVM are fitted to estimate a maximum margin hyperplane separating the artifactual ICs from those indicative of cerebral activity. This SVM-based approach to separate artifactual ICs is shown to be more reliable than other existing methods using thresholding, as in [1, 11, 22]. EEG signals characteristically fluctuate in a sporadic and non-stationary pattern, indicative of underlying brain activity. Therefore, an arbitrary threshold defined to separate artifactual and non-artifactual ICs may not hold in all circumstances, especially for signals of amplitude near the boundary of the thresholding value. In contrast, SVM offers a robust and reliable solution by estimating an optimum

TABLE III

COMPARISON OF AVERAGE CORRELATION COEFFICIENT

Electrode Channel	Proposed Method	Wavelet-ICA with threshold [1]	Zeroing-ICA with SVM [2]
1	0.865	0.859	0.827
2	0.826	0.820	0.780
3	0.943	0.939	0.930
4	0.952	0.949	0.941
5	0.948	0.946	0.937
6	0.902	0.888	0.878
7	0.945	0.940	0.932
8	0.958	0.954	0.949
9	0.958	0.954	0.948
10	0.953	0.950	0.941
11	0.966	0.961	0.958
12	0.963	0.957	0.955
13	0.970	0.966	0.964
14	0.964	0.957	0.956
15	0.944	0.941	0.931
16	0.970	0.963	0.964
17	0.966	0.956	0.961
18	0.973	0.963	0.969
19	0.969	0.963	0.963
20	0.975	0.966	0.970
21	0.971	0.957	0.967
22	0.965	0.946	0.961
23	0.973	0.961	0.969
24	0.971	0.963	0.965
25	0.978	0.964	0.975
26	0.971	0.954	0.968
27	0.964	0.944	0.961
28	0.972	0.959	0.969
29	0.976	0.965	0.973
30	0.971	0.952	0.967
31	0.968	0.949	0.965
32	0.970	0.954	0.966

Comparison of correlation coefficients for proposed method (mean: 0.955 ± 0.03), wavelet-ICA with threshold (mean: 0.946 ± 0.03) and zeroing-ICA with SVM (mean: 0.946 ± 0.04) using dataset from EEGLAB.

separating hyperplane using training data from both artifactual and non-artifactual ICs. We used a linear kernel SVM in this paper based on its ability to identify artifactual components that possess features with outlier values extending far across the hyperplane. Additionally, linear kernel SVM also has less computational demand than reiterative thresholding methods [22]. Parameters of the SVM can be further optimized, but this at the risk of overfitting.

Our approach is stepwise, assigning initial selection of training data with features that best describe the artifactual ICs to train the SVM, then, the SVM is used for automatic identification of artifactual ICs. The features of validated artifactual ICs are sent to update the training dataset for future classification on demand. The proposed system has the potential to be extended to accommodate and exclude diverse kinds of artifacts present in future EEG recording. This generalizability can be achieved by selecting statistical features that best represent the target artifactual components, and retraining the SVM using an updated collection of training data.

The selection of features and training data of SVM is thus crucial for the accuracy and effectiveness of the overall system. The training data are first selected by identifying the artifactual components using both visual inspection and assessment of its most salient descriptive features. For the purposes of demonstration, we have so far considered only low frequency eye blink artifacts, as this is the most common and troublesome

artifactual component encountered in EEG signals. The most salient features of eye blink artifacts included the variance, kurtosis, Shannon's entropy and range of amplitude. These features were identified and selected based on their magnitudes being significantly higher in conjunction with an eye blink than in its absence. In general, the features selected for training and testing of SVM must be adequate to describe the artifactual component, which condition is met by the present findings.

This paper also presents a novel integration of SVM into wavelet-ICA for possible removal of multiple artifacts present in any number of multi-channel EEG signal. In other words, integration of SVM suggests a potential possibility to accommodate multiple and various artifacts that exist in the EEG signals. This adaptability can be realized by manipulating the features and training data used in the training of the SVM. For example, training a multi-class SVM using data of ICs containing EMG, cardiac and eye blink artifacts, to simultaneously identify and remove the signal artifacts. Nonetheless, the list of artifactual components other than the eye blink artifacts and their corresponding descriptive features is beyond the scope of this paper. We anticipate that future research should serve to identify the most descriptive features of other artifactual components, and simultaneously remove the artifacts without substantial loss of cerebral signals of interest.

VI. CONCLUSION

We test a new hybrid procedure for automatic identification and removal of EEG artifacts through applying a pre-trained linear kernel SVM to classify artifactual ICs in wavelet-ICA. The SVM substantially improves identification of artifactual components and is found more reliable than standard thresholding method. Moreover, it promises to be generalizable for diverse kinds of artifacts, upon selecting proper features and training data. Our system functions automatically to isolate a distinctly cleaned EEG signal directly from a raw EEG recording, thus potentially lending itself for applications such as clinical diagnosis or BCI. We find that the system delivers satisfactory artifact removal without much degrading the time and frequency resolution of the EEG signal. Future work should serve to identify features best describe artifactual components extending beyond the present focus on those arising from the eye blink.

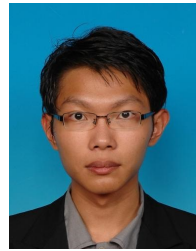
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REFERENCES

- [1] R. Mahajan and B. I. Morshed, "Unsupervised Eye Blink Artifact Denoising of EEG Data with Modified Multiscale Sample Entropy, Kurtosis, and Wavelet-ICA," *IEEE Journal of Biomedical and Health Informatics*, vol. 19, pp. 158-165, 2015.
- [2] L. Shoker, S. Sanei, and J. Chambers, "Artifact removal from electroencephalograms using a hybrid BSS-SVM algorithm," *IEEE Signal Processing Letters*, vol. 12, pp. 721-724, 2005.

- [3] T. P. Jung, S. Makeig, C. Humphries, T. W. Lee, M. J. McKeown, V. Iragui, *et al.*, "Removing electroencephalographic artifacts by blind source separation," *Psychophysiology*, vol. 37, pp. 163-78, 2000.
- [4] J. Gotman, D. R. Skuce, C. J. Thompson, P. Gloor, J. R. Ives, and W. F. Ray, "Clinical applications of spectral analysis and extraction of features from electroencephalograms with slow waves in adult patients," *Electroencephalography and Clinical Neurophysiology*, vol. 35, pp. 225-235, 1973.
- [5] J. C. Woestenburg, M. N. Verbaten, and J. L. Slangen, "The removal of the eye-movement artifact from the EEG by regression analysis in the frequency domain," *Biological Psychology*, vol. 16, pp. 127-147, 1983.
- [6] N. A. de Beer, M. van de Velde, and P. J. Cluitmans, "Clinical evaluation of a method for automatic detection and removal of artifacts in auditory evoked potential monitoring," *J Clin Monit*, vol. 11, pp. 381-91, 1995.
- [7] C. Guerrero-Mosquera and A. Navia-Vazquez, "Automatic removal of ocular artefacts using adaptive filtering and independent component analysis for electroencephalogram data," *IET Signal Processing*, vol. 6, pp. 99-106, 2012.
- [8] J. H. Zhang, K. Janschek, J. F. Bohme, and Y. J. Zeng, "Multi-resolution dyadic wavelet denoising approach for extraction of visual evoked potentials in the brain," *IEE Proceedings - Vision, Image and Signal Processing*, vol. 151, pp. 180-186, 2004.
- [9] M. Mamun, M. Al-Kadi, and M. Marufuzzaman, "Effectiveness of Wavelet Denoising on Electroencephalogram Signals," *Journal of Applied Research and Technology*, vol. 11, pp. 156-160, 2013.
- [10] M. B. Hamaneh, N. Chitravas, K. Kaiboriboon, S. D. Lhatoo, and K. A. Loparo, "Automated Removal of EKG Artifact From EEG Data Using Independent Component Analysis and Continuous Wavelet Transformation," *IEEE Transactions on Biomedical Engineering*, vol. 61, pp. 1634-1641, 2014.
- [11] N. Mammone, F. L. Foresta, and F. C. Morabito, "Automatic Artifact Rejection From Multichannel Scalp EEG by Wavelet ICA," *IEEE Sensors Journal*, vol. 12, pp. 533-542, 2012.
- [12] S. Khatun, R. Mahajan, and B. I. Morshed, "Comparative Study of Wavelet-Based Unsupervised Ocular Artifact Removal Techniques for Single-Channel EEG Data," *IEEE Journal of Translational Engineering in Health and Medicine*, vol. 4, pp. 1-8, 2016.
- [13] A. Delorme and S. Makeig, "EEGLAB: an open source toolbox for analysis of single-trial EEG dynamics including independent component analysis," *Journal of Neuroscience Methods*, vol. 134, pp. 9-21, 2004.
- [14] A. Hyvarinen and E. Oja, "Independent component analysis: algorithms and applications," *Neural Netw*, vol. 13, pp. 411-30, 2000.
- [15] 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, pp. 300-312, 2006.
- [16] A. Hyvarinen, "Fast and robust fixed-point algorithms for independent component analysis," *IEEE Transactions on Neural Networks*, vol. 10, pp. 626-634, 1999.
- [17] T. W. Lee, M. Girolami, and T. J. Sejnowski, "Independent component analysis using an extended infomax algorithm for mixed subgaussian and supergaussian sources," *Neural Comput*, vol. 11, pp. 417-41, 1999.
- [18] C. Chunqi, D. Zhi, Y. Sze Fong, and F. H. Y. Chan, "A matrix-pencil approach to blind separation of colored nonstationary signals," *IEEE Transactions on Signal Processing*, vol. 48, pp. 900-907, 2000.
- [19] C. C. Chang and C. J. Lin, "LIBSVM: A Library for Support Vector Machines," *Acm Transactions on Intelligent Systems and Technology*, vol. 2, p. 27, 2011.
- [20] M. Teplan, "Fundamentals of EEG measurement," *Measurement science review*, vol. 2, pp. 1-11, 2002.
- [21] F. Gabsteiger, H. Leutheuser, P. Reis, M. Lochmann, and B. M. Eskofier, "SVM for Semi-automatic Selection of ICA Components of Electromyogenic Artifacts in EEG Data," in *The 15th International Conference on Biomedical Engineering: ICBME 2013, 4th to 7th December 2013, Singapore*, J. Goh, Ed., ed Cham: Springer International Publishing, 2014.
- [22] H. Nolan, R. Whelan, and R. B. Reilly, "FASTER: Fully Automated Statistical Thresholding for EEG artifact Rejection," *Journal of Neuroscience Methods*, vol. 192, pp. 152-162, 2010.
- [23] D. L. Donoho and J. M. Johnstone, "Ideal spatial adaptation by wavelet shrinkage," *Biometrika*, vol. 81, pp. 425-455, 1994.



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