EFFICIENT AND ENHANCED ARTIFACTS AWARE RELIABLE EEG SYSTEM USING HYBRID METHODOLOGY

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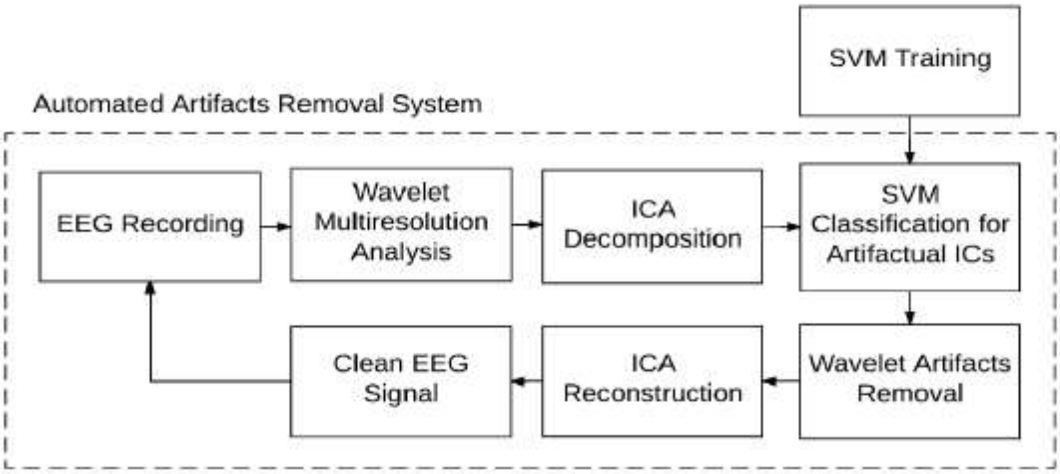
ABSTRACT:
Most importantly, Brain waves obtained by Electroencephalograms (EEG) recording are an vital research area in Bio- medical and health and brain computer interface (BCI). Due to the nature of EEG signal, noises and artifacts can contaminate it, which leads to a serious misinterpretation in EEG signal analysis. These contaminations are referred to as artifacts, which are signals of other than brain activity. Moreover, artifacts can cause significant miscalculation of the EEG measurements that reduces the clinical usefulness of EEG signals. Therefore, artifact handling is one of the cornerstones in EEG signal analysis. This paper provides a review of machine learning algorithms that have been applied in EEG artifacts handling such as artifacts identification and removal. In addition, an analysis of these methods has been reported based on their performance.

Keywords—Independent component analysis, EEG, wavelet, emotion

INTRODUCTION:
One of the current trends in EEG-based emotion recognition is to minimize the human intervention in the processing of the recorded EEG, automatizing emotion recognition systems as much as possible. This automatization should include noise and artefact removal techniques. The common artefacts in EEG include power line noise and physiological artefact mainly originating from heart activity – electrocardiography (ECG), eye movements or blinking – electrooculography (EOG), head and neck muscle activity – electromyography (EMG), and potentials from the brain (cephalic noise) not associated with the task [1]. Emotion related brain activity involves several processes, including processing the emotional stimulus, production of an affective state in response to the stimulus, and the regulation of the affective state [2]. With all these processes in the brain, additional artefacts can be detrimental to the discriminability of emotions from EEG. Digital filters are widely used to reduce artefacts by extracting the relevant brain rhythms of interest, namely delta (0.1-4Hz), theta (4-8Hz), alpha (8-13Hz), beta (13-30Hz), and gamma (>30Hz), from the recorded data. Using appropriate bandpass filters artefacts can be reduced assuming the artefacts' frequencies do not overlap with the targeted band. EMG artefacts cover a wide frequency range (from 0 to >200Hz) and are predominantly present in EEG frequencies higher than 20Hz [2, 3], especially in the temporal electrodes. In some studies EOG artefacts are removed through adaptive filtering [5], however this method requires recording the EOG reference signal and may alter the non-artefactual EEG due to some EEG leaked in the artifact reference sensor. Other studies [6, 8] use independent component analysis (ICA), a blind source separation approach, to remove the EOG, EMG and ECG artefacts from EEG. ICA decomposes the signal into statistically independent components, and the artefactual components can be identified by visual inspection and removed. The cleaned signal is then obtained by recombining the remaining non-artefactual components. Visually inspecting the independent components for artefacts requires some level of expertise, in identifying artefacts in the EEG signal, and can be time consuming when dealing with large datasets or data recorded from multiple subjects. To automate this inspection, various method including correlating the independent components with recorded reference artefacts [8] and thresholding based on high order statistics of the independent components [7] have been proposed. Castellanos et al [9] have proposed a wavelet transform based approach to filter out artefacts from ICA generated independent components, an approach that can be automated. Other automation of ICA artefacts removal include artefact detection approach based on joint spatial and temporal characteristics to identify artefactual components, a method also known as ADJUST [10]. Electroencephalograms (EEGs) are recordings of the electricalpotentials developed by the brain. Analysis of EEG activity hasbeen achieved principally in clinical settings to identify pathologiesand epilepsies. An interpretationof the EEG is used to visual inspection by a neurophysiologist. EEG technology used many electrodes on thehuman skull, such signals givesinformation indirectly about physiological functions, which are related tothe brain, these signals are verynumerous. The EEG integrated technical devices with embedded intelligence andit allows for Brain-ComputerInterfaces (BCI) to analysis EEG design. BCI is composed of signalcollection and processing, pattern identification and control systems.EEG classification has many number of features, it comes from the fact that are,
1.EEG signals are non-stationary, thus, features must be computedin a timevarying manner, and
2. Number of EEG channelsis large.
EEG Signals Measurement The EEG signals measurement is crucial for clinical diagnoses and medical research. The capacitive electrodes are using for non-contact measurement to solving the EEG signal problem that does not require conductive gel and skin allergies, which cannot develop during long-term measurement, because capacitive electrodes are frequently used in clinical medicine. It has various methods for performing non-contact biopotential measurements by using capacitive electrodes. It

developed a capacitive sensor for ECG and EEG monitoring and a tiny capacitive sensor for conducting various biopotential measurements. Additional voltage buffer is required to effectively convey physiological signals to the monitoring devices and increases the cost and complexity of sensing systems. The capacitive sensors require further
packaging, which may limit their applicability. The available conductive fabric are conducting biopotential measurements to popularize the capacitive technique, because EEG signals are low amplitude (approximately 10 to 100 μV), designing EEG monitoring systems and using conventional electrodes. It uses EEG measurements to verify the feasibility of using conductive fabric for capacitive measurements. The EEG signals are collected and preprocessed using special filters and features are extracted using many methods

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 shows the block diagram of the complete system, which is implemented in the MATLAB platform for its robustness in real time applications.

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 kΩ. 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

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 afactor 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 KK = 2 log N$\sigma\sigma$, (3)

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

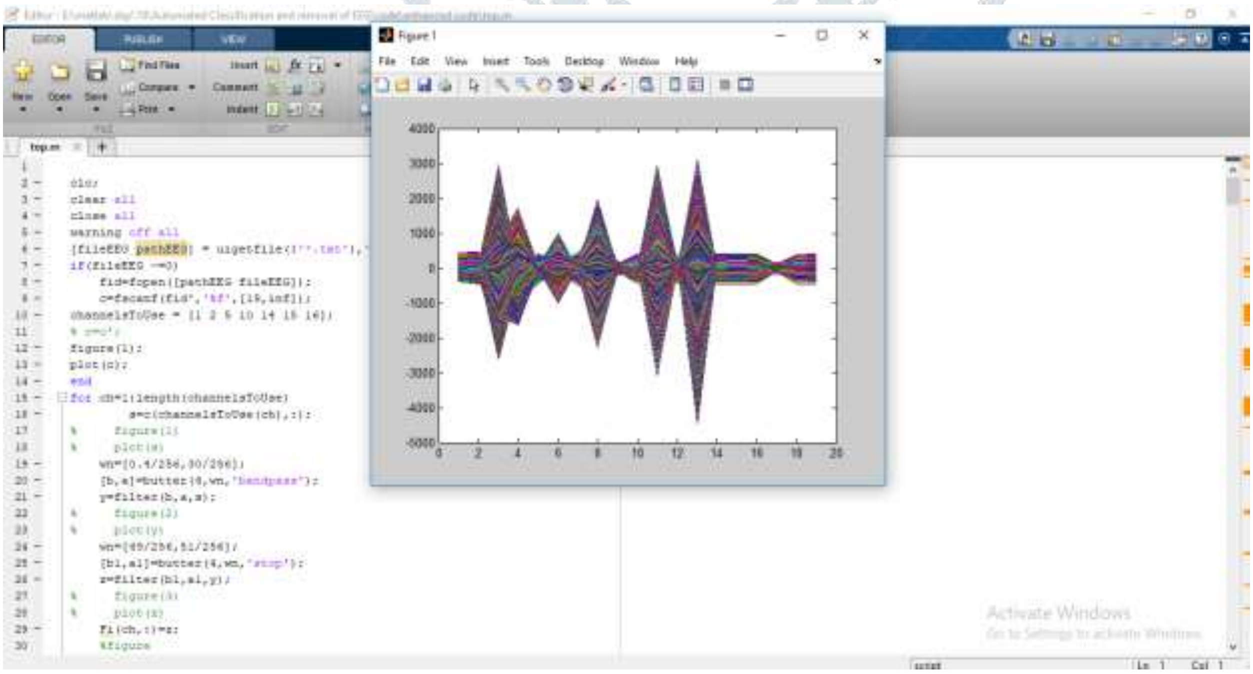
$\sigma\sigma$2 = median(|$WW(jj, kk)$|/0.6745) (4)

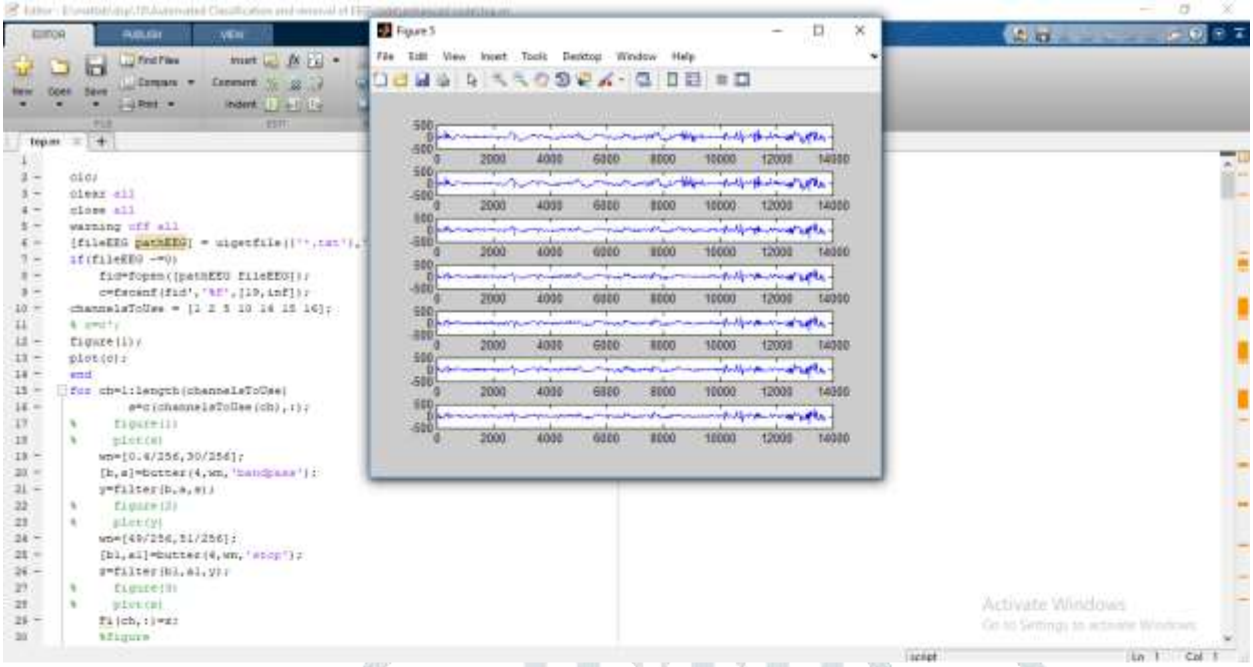
represents the magnitude of neuronal wide band signal. In equation (4), |(jj, kk)| represents the absolute value of the wavelet coefficient, with constant 0.6745 accounting for the Gaussian noise. The selection and calculation for the universal value is discussed in detail in [9, 3].

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.

RESULTS:





CONCLUSION:

The paper has presented a comparison of ICA and the automated version of ICA (ICA-W) as an artefact removal methods using emotion-related EEG datasets. Performance improvement and process automation of emotion recognition were investigated in this study. In additional to the automation advantage provided by ICA-W, the results suggest that EEGbased emotion recognition is improved when ICA-W is used to preprocess the EEG data compared to the regular ICA. Significant increase were found when using statistical features for both methods with ICA-W significantly outperforming all other methods. An analysis of the feature distributions shows some improvement into features separability. Future work will focus on features selection and comparing the performance of ICA-W to other spatial filters and applying the approach in real-time emotion recognition based brain-computer interface (BCIs)

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