Electroencephalogram Signal Processing with Independent Component Analysis and Cognitive Stress Classification using Convolutional Neural Networks

Venkatakrishnan Sutharsan[1 ⋆[0000−0002−8074−3298]],
Alagappan Swaminathan[1 ⋆[0000−0002−1589−687X]],
Saisrinivasan Ramachandran[1[0000−0002−2905−768X]],
Madan Kumar Lakshmanan[2], and
Balaji Mahadevan[1]

[1] Dept. of Electrical and Electronics Engineering, SSN College of Engineering, India
{venkatakrishnansutharsan16119@eee.,alagappan16011@eee.,saisrinivasan16083@eee.,balajim@}ssn.edu.in
[2]CSIR - Central Electronics Engineering Research Institute, Pilani, Rajasthan, India
mklakshmanan@ceeri.res.in

Abstract. Electroencephalogram (EEG) is the recording which is the result due to the activity of bio-electrical signals that is acquired from electrodes placed on the scalp. In Electroencephalogram signal(EEG) recordings, the signals obtained are contaminated predominantly by the Electrooculogram(EOG) signal. Since this artifact has higher magnitude compared to EEG signals, these noise signals have to be removed in order to have a better understanding regarding the functioning of a human brain for applications such as medical diagnosis. This paper proposes an idea of using Independent Component Analysis(ICA) along with cross-correlation to de-noise EEG signal. This is done by selecting the component based on the cross-correlation coefficient with a threshold value and reducing its effect instead of zeroing it out completely, thus reducing the information loss. The results of the recorded data show that this algorithm can eliminate the EOG signal artifact with little loss in EEG data. The denoising is verified by an increase in SNR value and the decrease in cross-correlation coefficient value. The denoised signals are used to train an Artificial Neural Network(ANN) which would examine the features of the input EEG signal and predict the stress levels of the individual.

Keywords: EEG · EOG · Independent Component Analysis · FastICA · Artifacts · CNN;

1 Introduction

Electroencephalography (EEG) signal is that the recording of spontaneous electrical activity of the brain over a period of time. The neurons of the human

⋆ Equal Contribution

brain operate data by ever-changing the flow of electrical currents across their membranes. These ever-changing currents generate electrical and magnetic fields which will recorded from the surface of the scalp by positioning electrodes on the scalp. The potentials between the individual electrodes are then amplified and recorded as the electroencephalogram signal.

The recorded electroencephalogram signal is usually contaminated by spurious signals from different unwanted sources. This sort of contamination in medical nomenclature is termed as artifact. It is a vital task to get rid of these artifacts from the electroencephalogram (EEG) data for additional analysis of EEG properly and the artifacts are tough to get rid of due to: i) higher amplitude than the electroencephalogram signal, ii) the big frequency ranges of the elements and iii) due to their variable geographical distribution.

Among these artifacts, most of them are Electrooculogram(EOG) signals, that are due to the eye blink or eye movement. Eye movement produces electrical activity(EOG signal) that is robust enough to be clearly visible in the electroencephalogram. The EOG is a signal that reflects the potential between the cornea and the retina which changes throughout eye movement. Because of the overlapping of those artifacts over the specified signals, there's a substantial loss of valuable background electroencephalogram activity. An optimized course of action to correct this for an electroencephalogram contaminated with EOG signal is to first discover the EOG signal and then to clean the corresponding electroencephalogram signal component instead of cleaning the whole EEG signal. Generally, the reference electrodes are placed over the mastoid bone (which is that the bone behind the ear) of both the ears. Merits of this method is that it is cheap and economical however suffers from the intense downside of noise from external agents. Hence, this methodology is most popular for low risk functions such as BMI etc.

The 10-20 system or International 10-20 electrode system is an internationally recognized method to explain and apply the location of scalp electrodes for obtaining electroencephalogram signals in non-invasive electroencephalogram . The system is predicated on the link between the position of an electrode and the underlying space of the brain, specifically the cortex. The "10" and "20" refer to the fact that the actual distances between adjacent are either 10% or 20% of the total front-back or right-left distance of the skull. The 10-20 international system of Units has the structure as shown in Fig. 1.

In recent years, a variety of ways have been applied for the removal of artifacts in electroencephalogram. Among these artifacts, ocular artifacts are shown to cause a massive deterioration of electroencephalogram signal. Many ways to get rid of the ocular artifacts have been put forth in the past decades, Arjon Turnip et al.(2014) have suggested the Removal of artifacts from electroencephalogram signal using independent component analysis and principal component analysis. The authors have compared the 2 ways for removing artifacts, i.e. ICA and PCA methodology. From processing with ICA and PCA methods, It was found that the ICA method measures better than PCA in terms of the separation of the electroencephalogram signals from mixed signals. Anusha Zachariah et al.(2013)

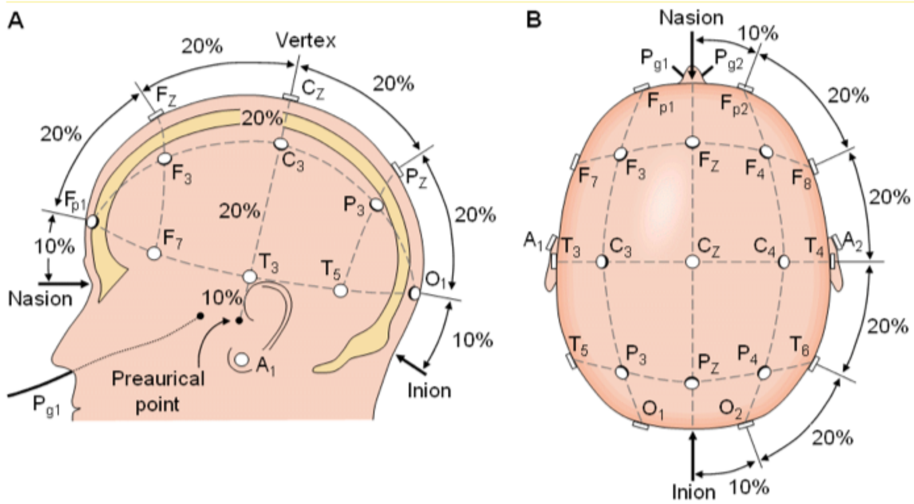

Fig. 1. 10-20 international system electrode placement structure A) lateral view, B) Frontal view.

have suggested the removal of artifacts from electroencephalogram signal using independent component analysis using critical electroencephalogram rhythms. Wavelet decomposition is used in the pre-processing step has shown to increase redundancy and rejection in suitable wavelets. This process has two step identification of artifact content before and after ICA using kurtosis. Yuan Zou et al.(2012) have planned the removal of artifacts from electroencephalogram signal using Hierarchical Clustering to separate artifacts activities. The proposed process has better efficiency in artifacts removal. S. Jirayucharoensak et al.(2013) have planned the removal of artifacts from electroencephalogram signal using independent component analysis. He brought forward a method to extract helpful neural signals using Lifting Wavelet Transform(LWT). Dwi Esti Kusumandari et al.(2015) have suggested the Removal of artifacts from electroencephalogram signal using independent component analysis. The authors have compared two methods for removing artifacts i.e, JADE and SOBI algorithms. From processing with JADE and SOBI methods, It is found that SOBI methodology is better than the other method in terms of the separation of the electroencephalogram signals from the mixed signal.

There are particular features for each cognitive stress which can be used to classify the EEG Signals. These features include Power Spectral Density and many more. Since these traditional methods are prone to errors, we have used Convolutional Neural Network for classifying EEG Signals. Our Convolutional Neural Network will learn the underlying distribution for each signal type like thinking words LAB, COLLEGE, FRIENDS, DOG, CAT. The neural network will do the feature extraction and classification on its own compared to any other algorithm which require both processes to be done separately, thus increasing computational speed and decreasing the complexity.

2 Data Acquisition

2.1 Brief Layout of The Hardware used for EEG Recording

Emotiv Epoc Plus EEG Brainwave Headset, which is used to acquire the EEG signals from the scalp. A PC is used to coordinate data flow and also collect data from the sensors attached to it(hence acting like a data acquisition system). A Monitor to view the waveform of the EEG and EOG signal to ensure proper recording of signals. A Holter is a device commonly used to record ECG signals. In this project, it has been used to acquire EOG signals. A pulse generation system which produces impulses of high magnitude and then injects them into the body of the subject. (this is used to synchronize the EEG and EOG signals). The Emotiv Epoc Plus EEG Headset is placed on the head of the person. This headset is connected to the computer by Bluetooth. The EOG electrodes are connected to the Holter through a HDMI cable. Pulse from a programmable pulse generator is given into the electrode. The purpose of giving the pulse is to create markings in the EEG signal waveform corresponding to each window of data.

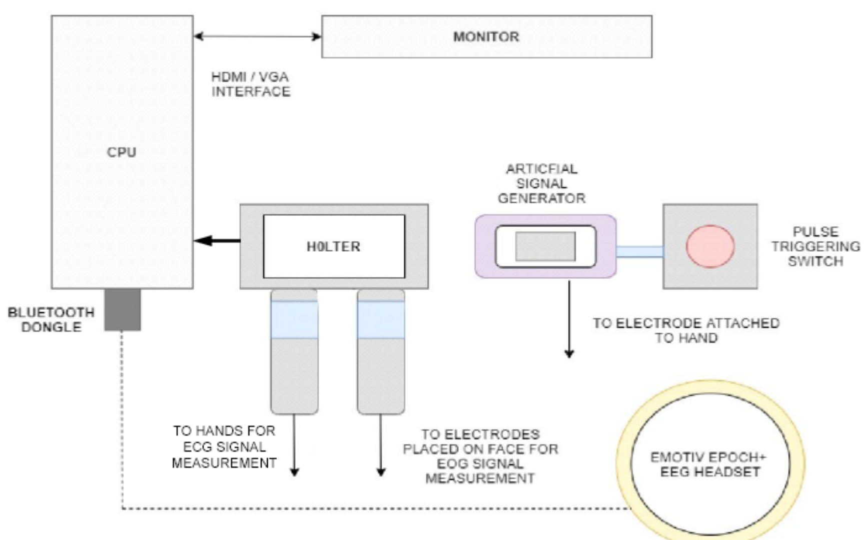

Fig. 2. Data Acquisition setup

The pulse generated from the external square waveform generator is injected into the ECG signal using two clamps placed on the hands of the subject. The main purpose of injecting a number of pulses into the ECG waveform is to mark the start time of recording and the end time of recording. This is also used for the time synchronizing of the EEG and EOG signals. Since EOG and ECG signals are from the same device, synchronizing ECG signal with the EEG signal inherently synchronizes EEG and EOG signal.

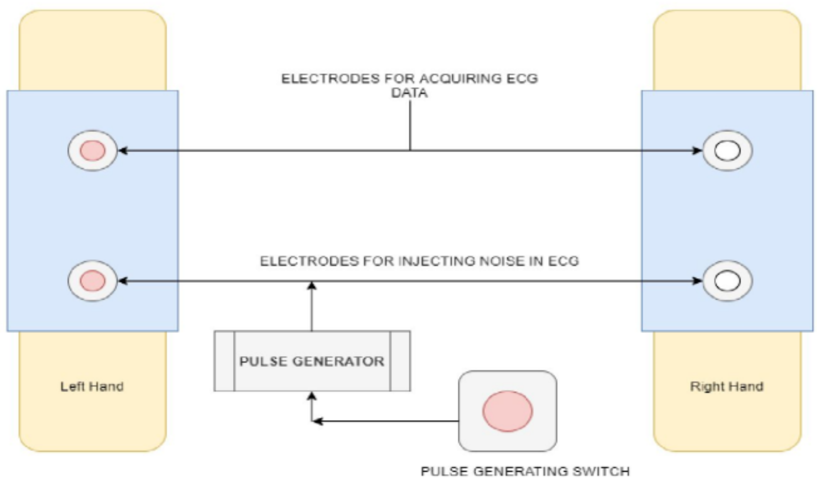

Fig. 3. Pulse injection setup

2.2 Procedure for recording EEG signals

The Emotiv Epoc Plus EEG Headset is placed on the head of the subject. The reference electrodes are placed over the mastoid bone (the bone behind the ear). In the Emotiv Pro software, the connectivity between the headset and the PC is checked. The headset is adjusted to get maximum connectivity. Now, the EOG electrodes are connected to the Holter. The recording is started for both the devices. After 2-3 minutes of recording both EEG, ECG and EOG data, a train of pulses is injected for a duration of 30 seconds – 1 minute. This indicates the starting of EEG signal for processing. The patient is asked to perform certain activity based on the objective of the experiment (like word thinking). Data is recorded for a minimum of 10 minutes and a maximum of 1 hour. Once sufficient data is recorded, a train of pulses with approximately the same duration is given. This serves as a indication for the end time of taking readings from both holter and headset. After the recording is terminated, data from the holter is downloaded into local repository. Headset is removed from the subject's head and the silica gel pads are removed.

2.3 Pulse waveform generation

The pulse waveform is generated in an endless loop. To indicate the start of a recording frame, a single pulse of width 2 seconds is given. Then the output is LOW for a period of 6 seconds. Then two pulses are generated with a 50% duty cycle and time period of 2 seconds.The pulse shown above is generated using an ATMEGA Microcontroller.

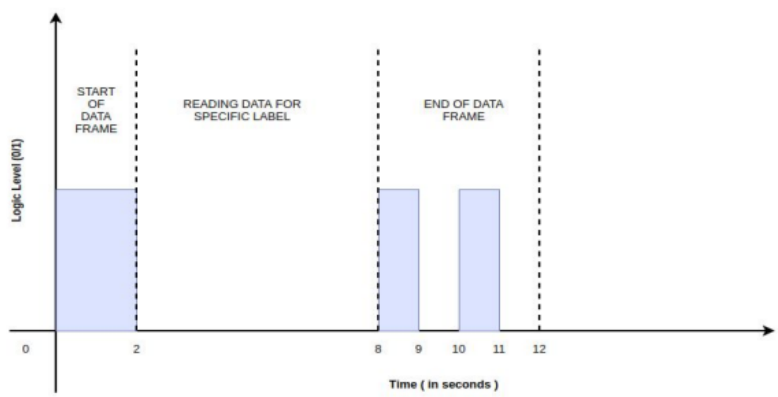

Fig. 4. Pulse waveform generation setup

2.4 Collection of data for feature classification

The subject under observation is asked to look on a monitor. Once a word is displayed on the screen, the subject should think about that in his mind for a certain period of time for 6 seconds. Then the patient is given time to relax his mind and then process repeats till end time of experiment.

2.5 Procedure for classification of cognitive stress

The main aim of the experiment is to predict what the person is thinking of. For that, we have to collect EEG data pertaining to some specific objects. Once all the equipment have been arranged, the PULSE_START_SWITCH of the interfacing circuit is pressed which starts the pulse generation from the microcontroller. At the same time, a program which would display the commands/instructions is executed. The program is as follows:

The word START appears on the screen, indicating the subject that the experiment is about to begin. This screen is displayed for 2 seconds. Then a label is displayed for a period of 6 seconds. Then the screen displays RELAX for 4 seconds and the loop starts over again.

3 Analysis Paradigms

As shown in the block diagram (Fig. 5) there are six steps in this de-noising algorithm. Firstly, the EEG data and the EOG data recorded are pre-processed as per the pre-processing algorithm. After pre-processing the original signals, the second step is to decompose the EEG Signal into multiple Intermediate Components (ICs) using a Blind Source Separation technique called Independent Component Analysis (ICA). Thirdly, the correlation coefficient between all the EEG channels and the time synchronized EOG signal are calculated. Then in the forth step, a threshold is set and all the components having correlation value above the threshold are selected. In the fifth step the selected components are scaled down rather than setting it to zero so that the information is not lost completely. Finally, after the scaling down of the components selected as artifact sources the components are projected back into the a set of artifact free components. Subsequently, EOG-free signals can be reconstructed by Inverse ICA for the artifact free components. This noise-free signal is then sliced (640 samples each) into data and its corresponding labels (word associated with the data). This data-label pair is then used to train the Artificial Neural Network to predict the word that the subject is thinking. According to the block diagram this denoising algorithm can be described in detail as follows:

3.1 Preprocessing

The preprocessing step consists of two main process which include Time Synchronization and Band-pass filtering. Devices which are used to capture the signals of EEG and EOG have different starting time, in order to synchronise the time frame between both the device's signal, we use artificially generated pulses. A plot of the recorded signal is shown in Fig. 6.

Pulses used here are artificial impulse signals inoculated into both the EEG and EOG signals during the start and stop of the process. Since the two devices cannot be started together and therefore a lag between 2 devices can cause inaccurate noise detection. Butterworth Filter is used for preprocessing to remove artifacts present above and below region of interest. It is a signal processing filter designed to have a frequency response as flat as possible in the pass band region. This filter is also referred to as a maximally flat magnitude filter. It was first defined by British physicist Stephen Butterworth. The process is done for a sliding window of 20 sec. The point of synchronization after the peaks are

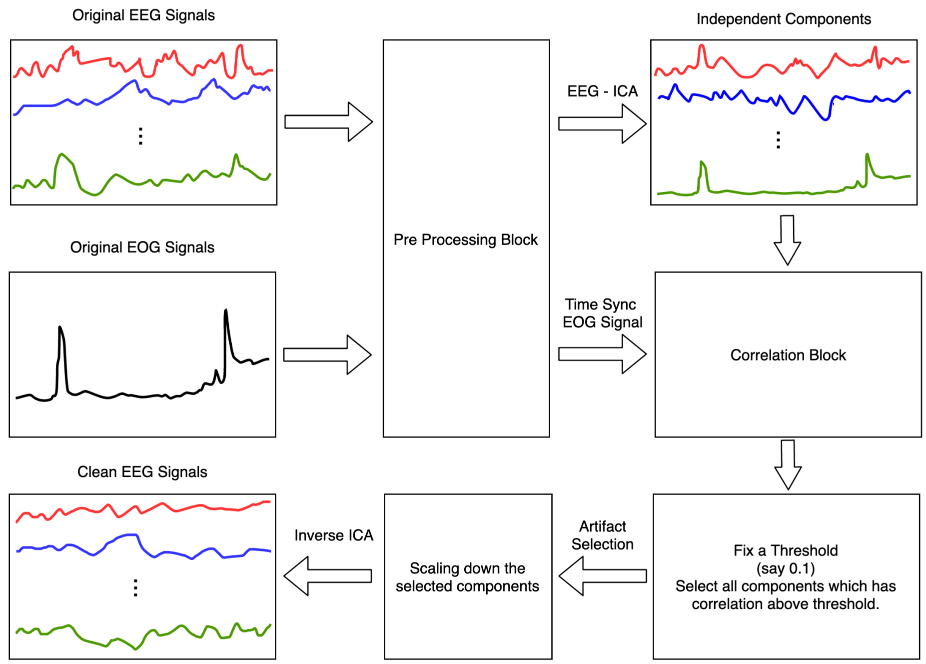

Fig. 5. Algorithm Process Diagram

synchronized are shown in Fig. 7. A plot of the Fourier Transform before and after pre-processing is illustrated in Fig. 8.

Program Algorithm: Data from the devices are imported into the program. Plot the whole recording for both the devices. Input the indexes of the synchronizing point of both the signals. Slice/crop the signals according to the indexes provided by the user. Filter the new data(Time Synchronized) using butterworth filter (5th order - bandpass(0.1Hz to 40Hz) .Write the time synchronized and filtered data into a CSV file.

3.2 Independent Component Analysis

ICA is a well established technique on decomposing a signal into independent sources using kurtosis as the cost function. Independent Component Analysis is an efficient technique to decompose linear mixtures of signals into their underlying independent components. ICA utilises higher order statistics like kurtosis to seek out the independent components. ICA is an extension of a statistical model called Principal Component Analysis (PCA). The main supremacy of ICA is that it extracts the sources by exploring the independence underlying the measured data .Thus, it involves higher order statistics to recover statistically independent signals from the observations of an unknown linear mixture. There are 3

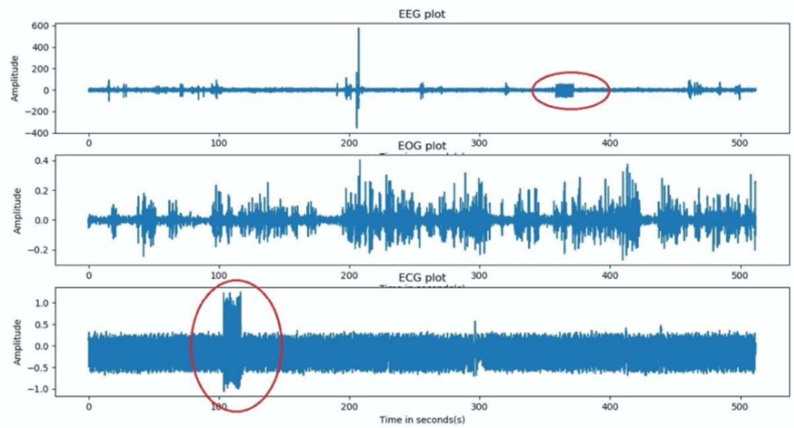

Fig. 6. Plot of the total recorded signals.

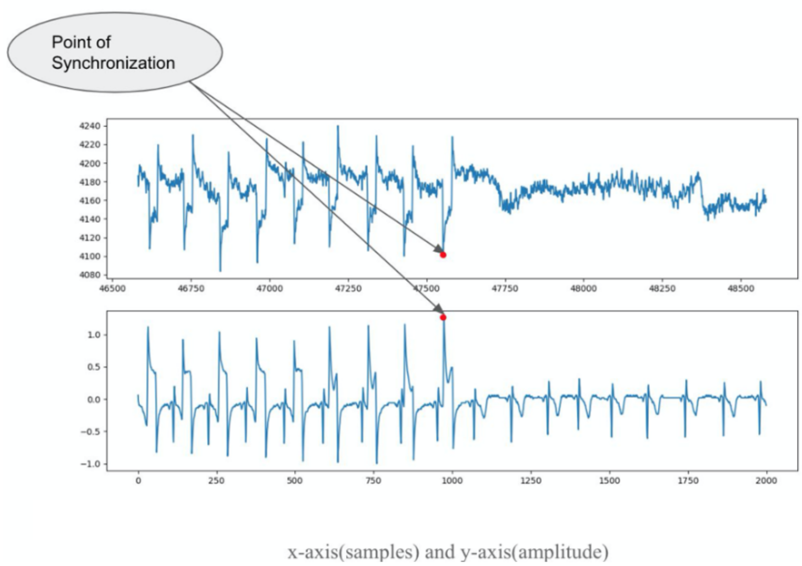

Fig. 7. Point of synchronization.

conditions for the Independent Component Analysis algorithm. First, it should be a linear combination of the source signals. Second, source signals out to be independent and at last, the independent components should be Non-Gaussian. For instance, Let A be the mixing matrix, which is a square matrix of order two.

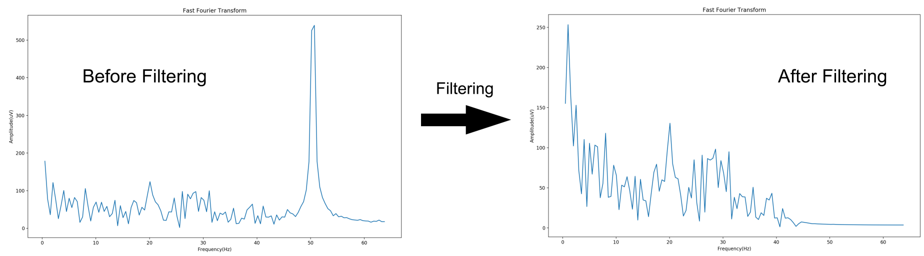

Fig. 8. Butterworth filter Plot

Now, the mixed signal vector X is a result of the product between the source signal vector S and the mixing matrix A, given by the equation below:

$$X = A * S \tag{1}$$

The main aim of Independent Component Analysis is to find the source signals from the mixed signals. This is done by finding the de-mixing matrix (given by W). The de-mixing equation is given as:

$$Y = A^{-1} * X \tag{2}$$

3.3 Computation of Correlation value

The correlation value between two functions define the trend between two variables on how strong the pair of variables are related. The correlation used here is Spearman Correlation named after Charles Spearman. While Pearson correlation assesses linear relationships, Spearman correlation assesses monotonic relationships (whether linear or not). The value usually lies between +1 and -1 where the +1 shows positive trend that is both variables move in same direction and -1 shows negative trend where the 2 variables move in opposite direction while 0 show no relation. The correlation coefficient was found between each channel of EEG signal and EOG data. The absolute value of the correlation is used in this study as to avoid the limitation of ICA and the change in polarity of the electrodes. The value is calculated using the formula presented below:

$$\rho = 1 - \frac{6 \sum d_i^2}{n * (n^2 - 1)} \tag{3}$$

where d is the difference between the rank of the value in the corresponding dataset.

3.4 Selection of Artifactual Components

The eye artifact is found by estimating the component which closely resembles the EOG data.The correlation values calculated using a statistical Spearman correlation is used to select the artifactual component by thresholding a value. Due to practical problems such as voltage bias, the correlation value can change from device to device. The thresholding value was found by experimentation to be 0.1 . The Independent Components having correlation above the threshold is selected as EOG-related components. Additionally visual inspection is used to supervise the selection of the components.

3.5 Reducing of Artifact effect on signal

The selected Independent Components are through a process of scaling down to reduce the effect on EEG signal. This scaling is done in such a way that the component having the most correlation with the EOG data is scaled down more than the component having less correlation. This can be explained by the 2 formulas defined below

$$component = component * (1 - 2 * correlation) \tag{4}$$

$$component = component * (1 - correlation) \tag{5}$$

The equation 4 is used when the correlation is between 0.1 and 0.5 while equation 5 is used when correlation is above 0.5, but the latter formula is applied as an exceptional case. This process of scaling the Indpendent Components helps in reducing the noise in the signal while retaining the feature of the EEG signal. Thus, the process of scaling down allows the de-noising algorithm to remove the noise part and not affect the characteristics of the signal.

3.6 Signal Reconstruction

The artifact signals are selected as EOG-linked ICs and their effect are reduced using the scaling algorithm. After the EOG-linked ICs are scaled down the set of components are projected back on to the same space (Inverse ICA) as the original components, therefore having EOG-free EEG signal.

3.7 Signal learning using Convolutional Neural Network

Apart from the denoising algorithm, in this section we will be training a Convolutional Neural Network to classify the input brain waves. The convolutional layer is the core of a Convolutional Neural Network. The layer's parameters consist of a set of trainable filters (or kernels), which have a small receptive field, but extend through the full depth of the input volume. During the forward pass, every filter is convolved across the batchsize, channel and samples of the input volume, computing the scalar product between the entries of the filter and the input and producing a 1-dimensional activation map of that across channels. As a result, the network learns filters that activate once it detects some specific variety of feature at some spatial position within the input. The signals recorded are then split in keeping with the label and their corresponding signal for coaching. We have used 80% of the recorded data for training the neural network and

20% to check the networks accuracy. Convolutional Neural Networks are usually used for images (2 Dimension) while this can be used in 1-D space (time-series data) to recognize patterns in brain waves. In the Classifier, all the dense layers use the ReLU (rectified linear unit) as the activation function except the final output layer(Sigmoid). The reduction of the samples is by 3 stages of convolution (kernel-3, stride-1, padding-0 along with batch normalization and max pooling) with the ultimate layer giving three hundred channels. Dense layers have 23400 1024 (in the first hidden layer), 1024 512 (in the second hidden layer), 512 256 (in the third hidden layer) and 256 5 (in the fourth hidden layer) mapping to each of the 5 words.

4 Result

4.1 Quantitative Validation Measures

After processing the EEG signals there are standard validation measures such as Signal-to-Noise Ratio (SNR) and Spearman Correlation. The Signal-to-Noise ratio is one of the standard methodology to demonstrate the signals data over noisy data. The SNR of the signal can be found by

$$SNR = 10 * log(Pow(S)/Pow(N)) \tag{6}$$

where S is the Signal and N is the Noise. The power can be calculated as the variance of the time signal by Hjorth Activity. The increase in SNR value show a strong increase in signal which is useful in applications such as Sleep Study for Medical Experimentation.

The Correlation is also another useful parameter to measure the degree to which two variables move in relation to each other. This can be calculate by using the Spearman Correlation using the equation 3.

For neural network the accuracy of the prediction is found out by dividing the count of images predicted correctly by the total number of images subjected to the network.

$$Accuracy = (Total\ correctly\ predicted\ images)/(Total\ images\ to\ the\ network) \tag{7}$$

4.2 Experimental Data

In this study, the planned technique is used to get rid of EOG-related Artifacts from EEG signals. A typical multichannel of real electroencephalogram signals contaminated with eye blinks and the clean electroencephalogram signals once EOG-related signal removal are illustrated in Fig. 9. Especially, the channels close to the eye has shown massivge amplitude of ocular artifacts. The first channel denotes EOG reference.

We can use correlation values between EEG channels and EOG signal to estimate whether the EOG-related signals were removed or not. The Average

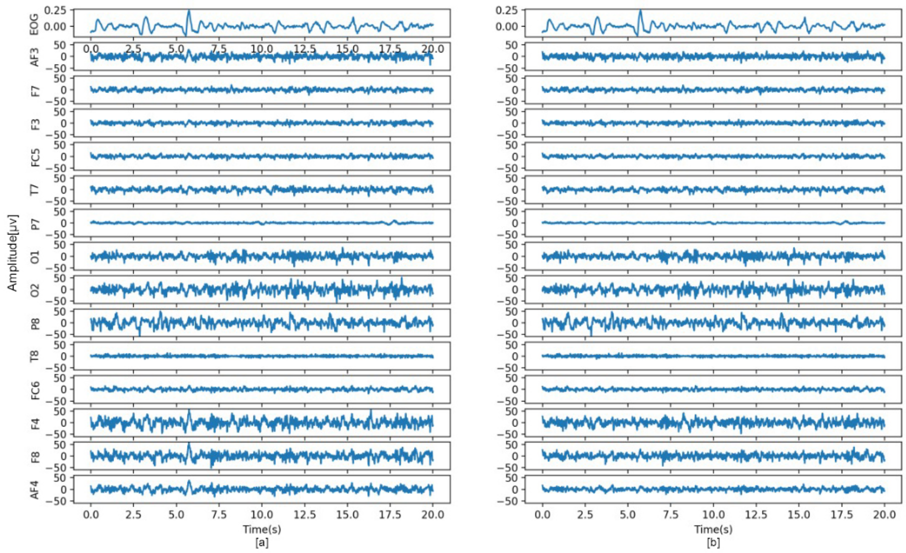

Fig. 9. (a) A typical example of a 14-channel electroencephalogram signal with effect of eye-blinks and the first channel is EOG reference signal. (b) The 14-channel Artifact free EEG signal with first channel EOG reference signal.

correlation value of each electrode before and after denoising was calculated for the data and is illustrated in Table 1. It can be easily understood that the correlation value after denoising is less than the correlation value before denoising. The difference in correlation before and after denoising is dominant in the channels where the EOG related signals have high influence. The channel have lower influence of eye artifact has less denoising effect, thus preserving the details of the signal.

Table 1. Value of Correlation before and after Denoising.

Ch. Name	AF3	F7	F3	FC5	T7	P7	O1	O2	P8	T8	FC6	F4	F8	AF4
Before	0.336	0.041	0.233	0.242	0.015	0.107	0.063	0.043	0.092	0.040	0.170	0.294	0.288	0.450
After	0.139	0.019	0.103	0.142	0.005	0.064	0.001	0.023	0.040	0.008	0.014	0.039	0.020	0.186

Additionally, comparing the waveforms and the correlation value before and after denoising, it can be found that the denoising algorithm has effectively denoised the EEG signal without loss of too much information thus preserving the data for further analysis.

As we don't know the noise and feature signals before denoising we cannot calculate the SNR value before denoising. But after denoising since we know the denoised signal, the noise can be calculated using the Formula 8.

$$Noise = Input\ EEG\ Signal - Clean\ EEG\ Signal \tag{8}$$

With the noise and the clean EEG signal, we can calculate the SNR value by using the Formula 6. The average SNR value for all the subjects for the corresponding electrodes are shown in Table 2.

Table 2. SNR Value for all the 14-electrodes after Denoising.

Ch. Name	AF3	F7	F3	FC5	T7	P7	O1	O2	P8	T8	FC6	F4	F8	AF4
SNR value	11.56	45.58	24.26	25.05	22.82	17.86	42.10	29.47	37.74	46.50	14.97	2.67	3.80	4.12

The SNR value show that there is a significant increase in signal strength. The SNR is found to be high for electrodes which have a higher decrease in correlation between the corresponding electrode and the EOG signal.

Finally, we have successfully developed a convolutional neural network which can predict the state of mind (thinking of DOG, CAT, COLLEGE, LAB and FRIENDS). After the neural network was trained, we subjected the test dataset to the network for label prediction and was found to have an accuracy of 89.91%. This means that the network is able to accurately predict the label for 90 of every 100 images in the dataset. The learning loss of the neural network is shown in Fig. 10.

5 Acknowledgement

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6 Conclusion

In this study, a method proposed for cognitive stress classification was evaluated by real EEG signals acquired from Emotiv Epoc Plus headset. The results indicate that the proposed method can eliminate EOG-related signals from acquired data with minimal loss of information and predict the cognitive stress. This can be seen by the increase in SNR value and also by the decrease in cross-correlation coefficient value. The method proves to remove dominant eye related activity as the effect of EOG signal is higher compared to ECG and EMG signals. Also, The results from the convolutional neural network indicate a very high level of accuracy in classifying the cognitive stress.

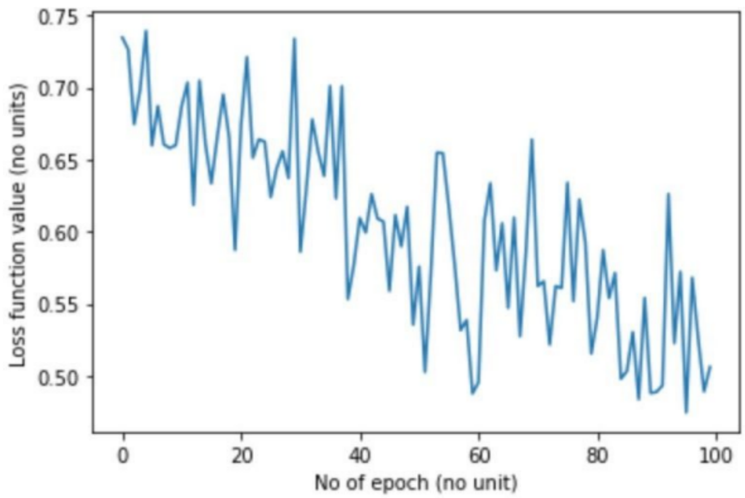

Fig. 10. Loss curve of the neural network

Declaration

Authors' contributions

VKS carried out the experimental studies, participated in the analysis of the signals and drafted the manuscript. AS carried out the experimental studies, participated in the analysis of the signals and drafted the manuscript. BM coordinated the ethics application, provided guidance in the analysis of the results, and confirmed the validity of the results. All authors read and approved the final manuscript. All authors read and approved the final manuscript.

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