Minor Project

ARTIFACT REMOVAL AND NOISE DETECTION IN EEG SIGNALS

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Content

Abstract

Physiological signals such as Electro Encephalogram (EEG) are often corrupted by artifacts during the acquisition and processing. Some of these artifacts may corrupt the important properties of the signal that gives a meaningful information of it. Most of these artifacts are occurred due to the involuntary movements or actions that are done by the human during acquisition process. So, it is recommended to eliminate these artifacts with signal processing approaches. This paper presents two mechanisms of classification and elimination of artifacts, in first step a customized deep network is employed for the classification of clean and artifact included signals. The classification is performed at the feature level with convolutional layers . In the second stage of the work, the artifacts signals are decomposed with Empirical mode decomposition (EMD) which are eliminated with proposed adaptive thresholding mechanism where the threshold value changes for every IMF in iterative mechanism.

Introduction

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Neuro muscle disability persons have adopted the Brain Computer Interface (BCI) technology to communicate with the outside world. EEG signals have the capability to acquiring the brain information in a fast and dynamic way which also has a high temporal resolution but has low spatial resolution. EEG signals are acquired over the scalp through electrodes in extended system [1]. However, these EEG signals are often corrupted by involuntary muscle actions of the human during acquisition process termed as artifacts. The most prevalent artifacts presented in EEG signals are Electro-Oculo-Graphic (EOG) artifacts . . EOG signals which are often present in slow frequency bands and below 5Hz while the other muscle activity artifacts are usually present in medium to high frequency bands between 20-300Hz . Convolutional neural networks have many advantages when compared to other machine learning algorithms.

Literature Survey

S. No.	Title of the Paper	year	approach	Artifacts removal	Noise detection
1	Patel and wang	2021	Machine learning with features	Removal of artifacts are done (yes)	Noise detection is performed successfully
2	Liu et al	2022	neural networks with pre training	Based on many implementations artifacts removal is performed	noise detection is obtained

Project Objectives

The present work has been planned to fulfil the following objectives:

1.To enhance the quality of EEG signals by identifying and eliminating various sources and artifacts .

2.This aim is to provide the accuracy and interpretation in various applications such as BCI interfaces .

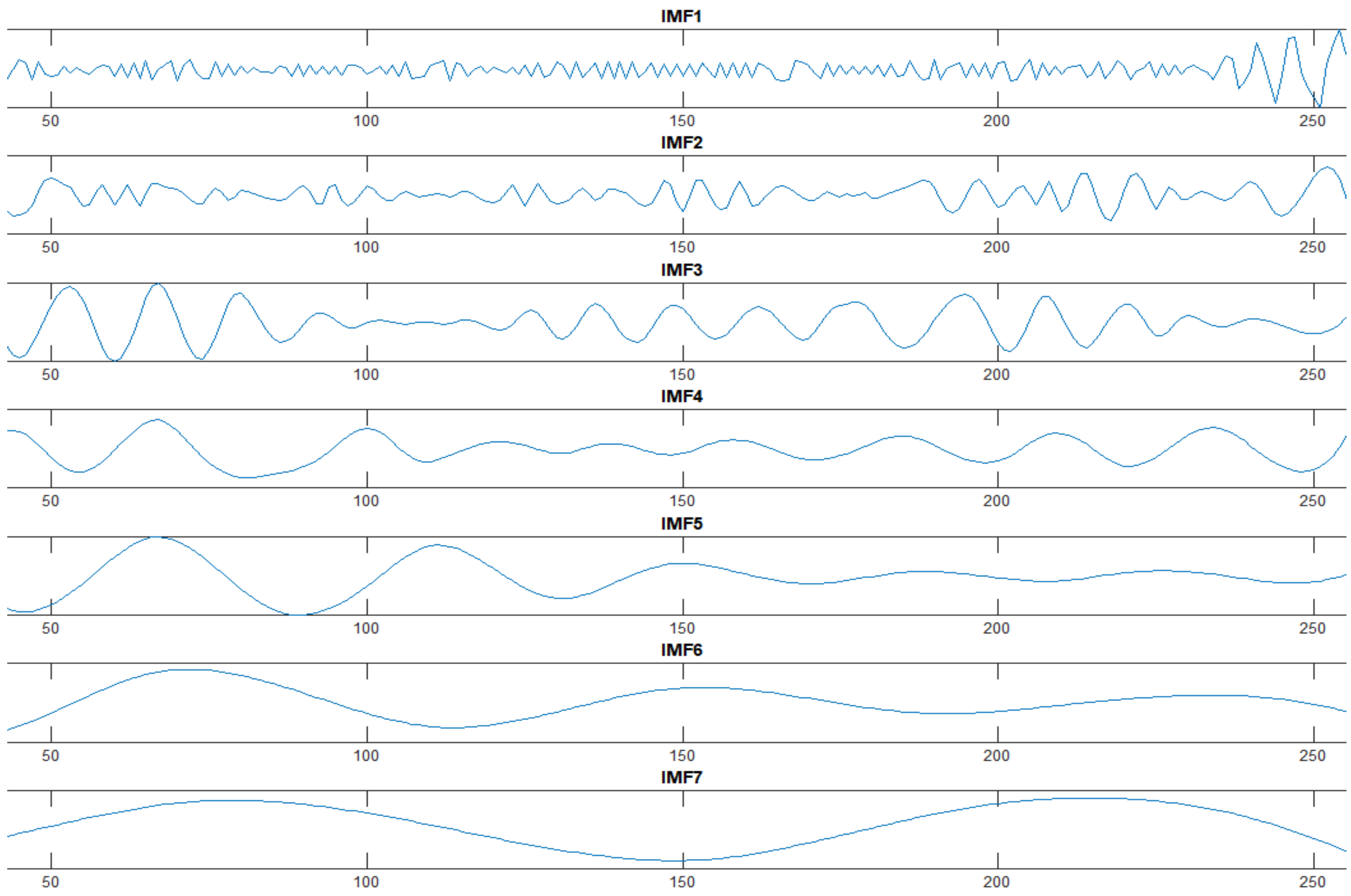
Deep Neural Networks of EEG
and
Empirical mode Decomposition (EMD)

In Machine learning the word "CNN" means Convolutional Neural Network which leads to Forward DNN (Deep Neural Network) which includes one or more convolutional layers combine With pooling and thresholding layers . Merits of CNN includes, they are well suits for end-to-end learning means without any prior feature selection, it learns from the raw data which scales the large data sets . The main drawback of CNN is it gives false outputs or predictions with high confidence . EMD approach is an algorithm analyze the multi component signals that breaks them into many

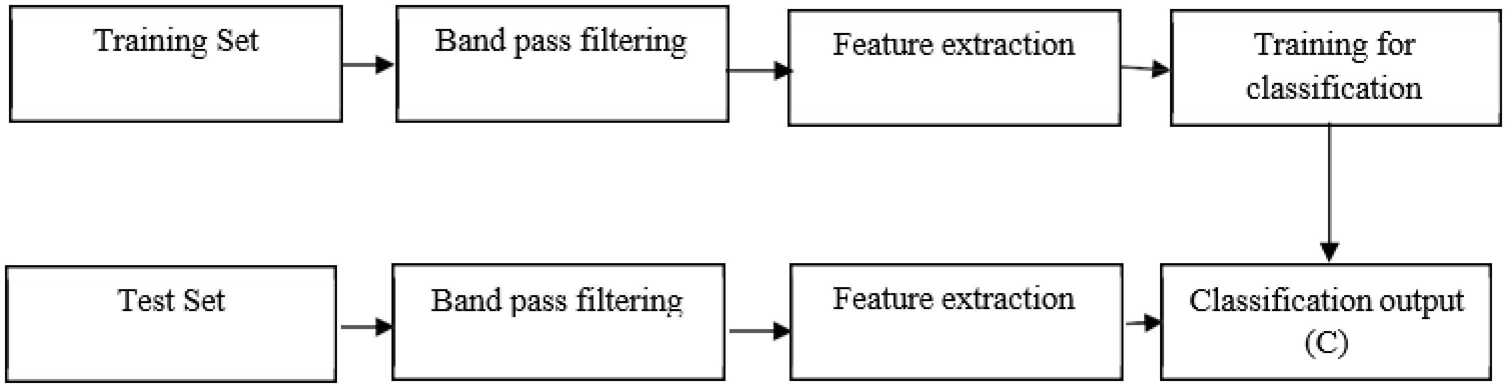
$$x(t) = \sum_{i=1}^{L} h^{i}(t) + dt$$

Proposed approach

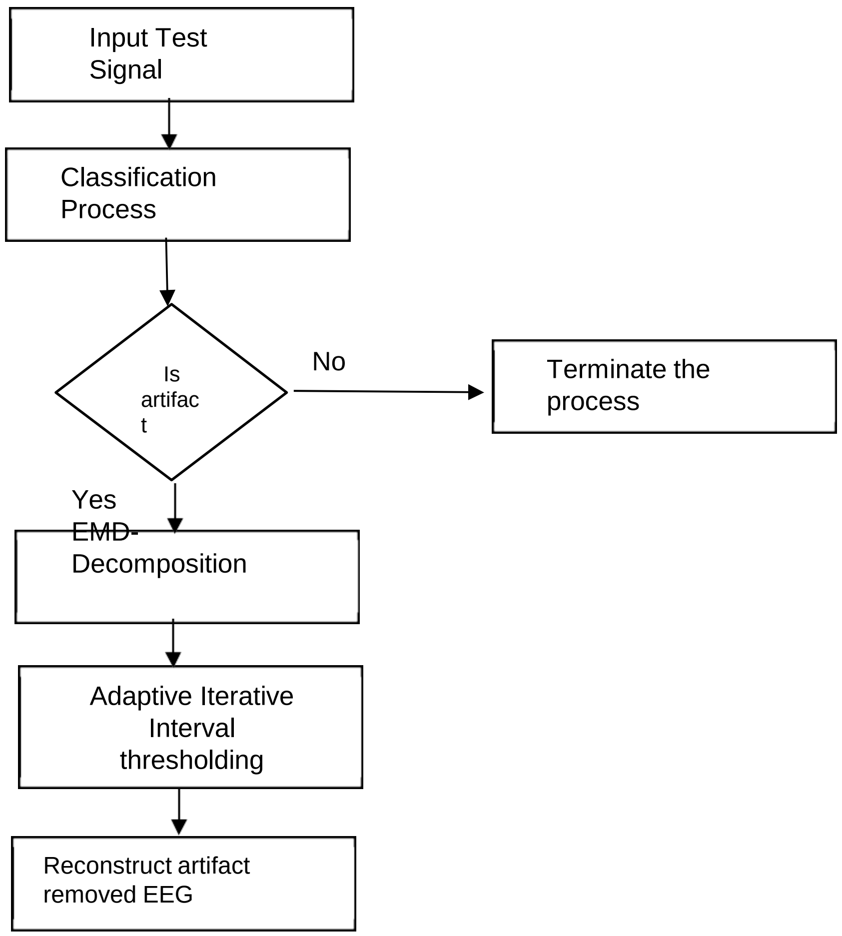
The proposed approach consists of two of stages, firstly the signal classification is performed with deep network and later the artifact removal. Figure 2 depicts the classification process performed in this work and figure 3 represents the artifact removal process



Intrinsic mode functions of EEG signal with Empirical Mode Decomposition



Classification process with CSP and DNN of EEG signal



Adaptive thresholding

- *Algorithm for Iterative Adaptive Thresholding*
- *Input: IMFs* $h^{i}(t)$ *, Output: Reconstructed EEG signal* $\hat{x}(t)$
- Step 1: Decompose the original signal with EMD into IMFs
- Step 2: Randomly change the position of the first IMF and add this to the original IMF
- *Algorithm for Iterative Adaptive Thresholding*

$xalt\ (t) = xorig(t) + h^{1}\ (t)$

Step 3: perform thresholding for the resultant signal

$T = K\sqrt{Ek}(2 * \log(N))$ which is a universal threshold

otherwise

- Step 4: Repeat the steps 2 and 3 for k-1 number of iterations and take the average for the resultant reconstructed signal

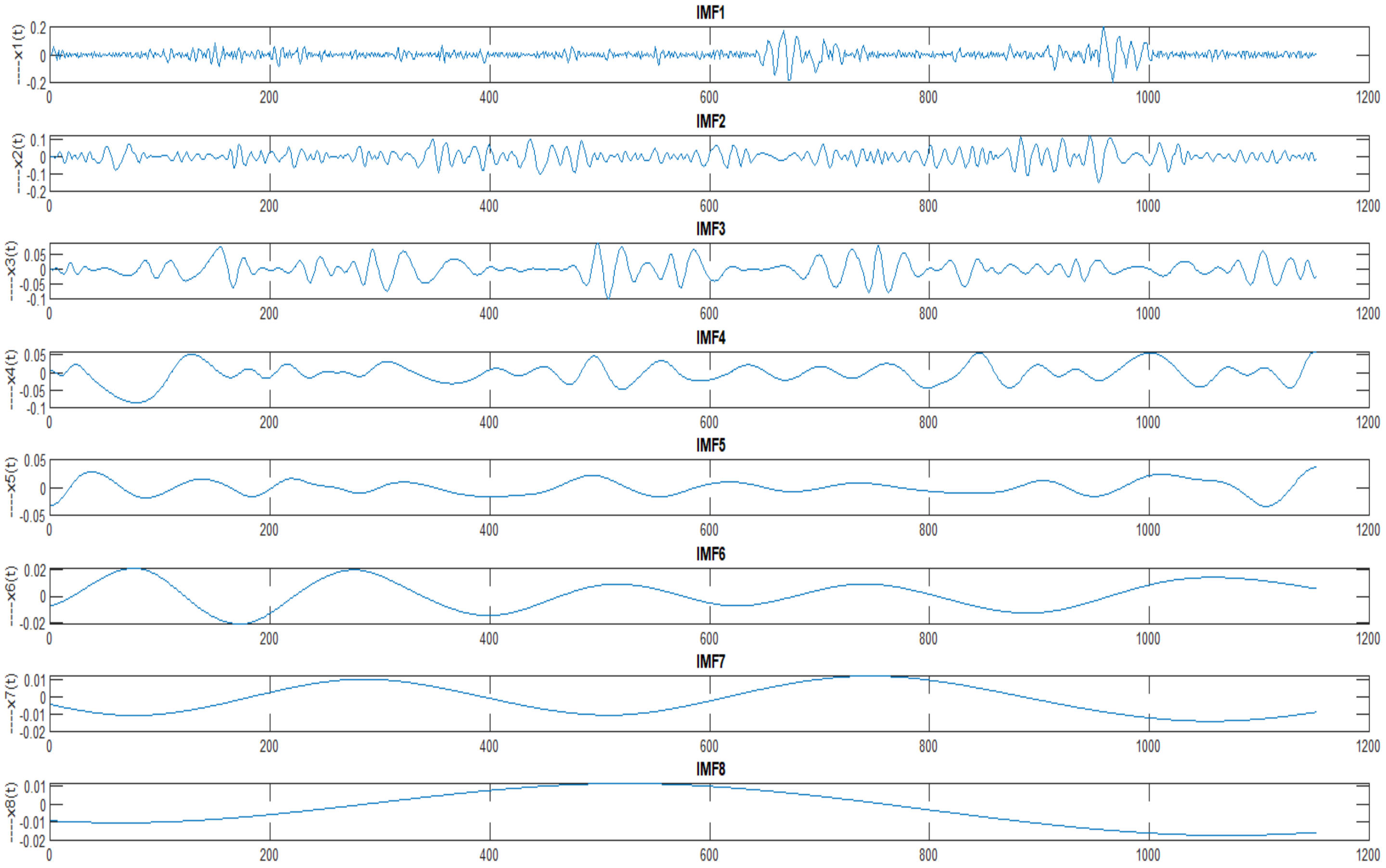
Experimental results and discussions

- The proposed approach is evaluated with BCI competition , dataset signals. The dataset consists of 140 testing trails and 140 training trails recorded with 3 channels. The signals are recorded with 128Hz sampling frequency, and each trail is 0.9 sec long. Initially the signals were passed through band pass filter with cut off frequencies [16-30] Hz, which is beta band, and those signals are processed further to feature extraction .
- . The entire model processing is performed with Matlab 2018a version with DeepNeural toolbox on Intel i7 8th generation PC. After the classification, the signal which are affected with artifacts are moved to be decomposed with EMD and the outcomes of IMFs are processed with adaptive iterative thresholding. The number of decompositions is to be limited to decrease the processing time .

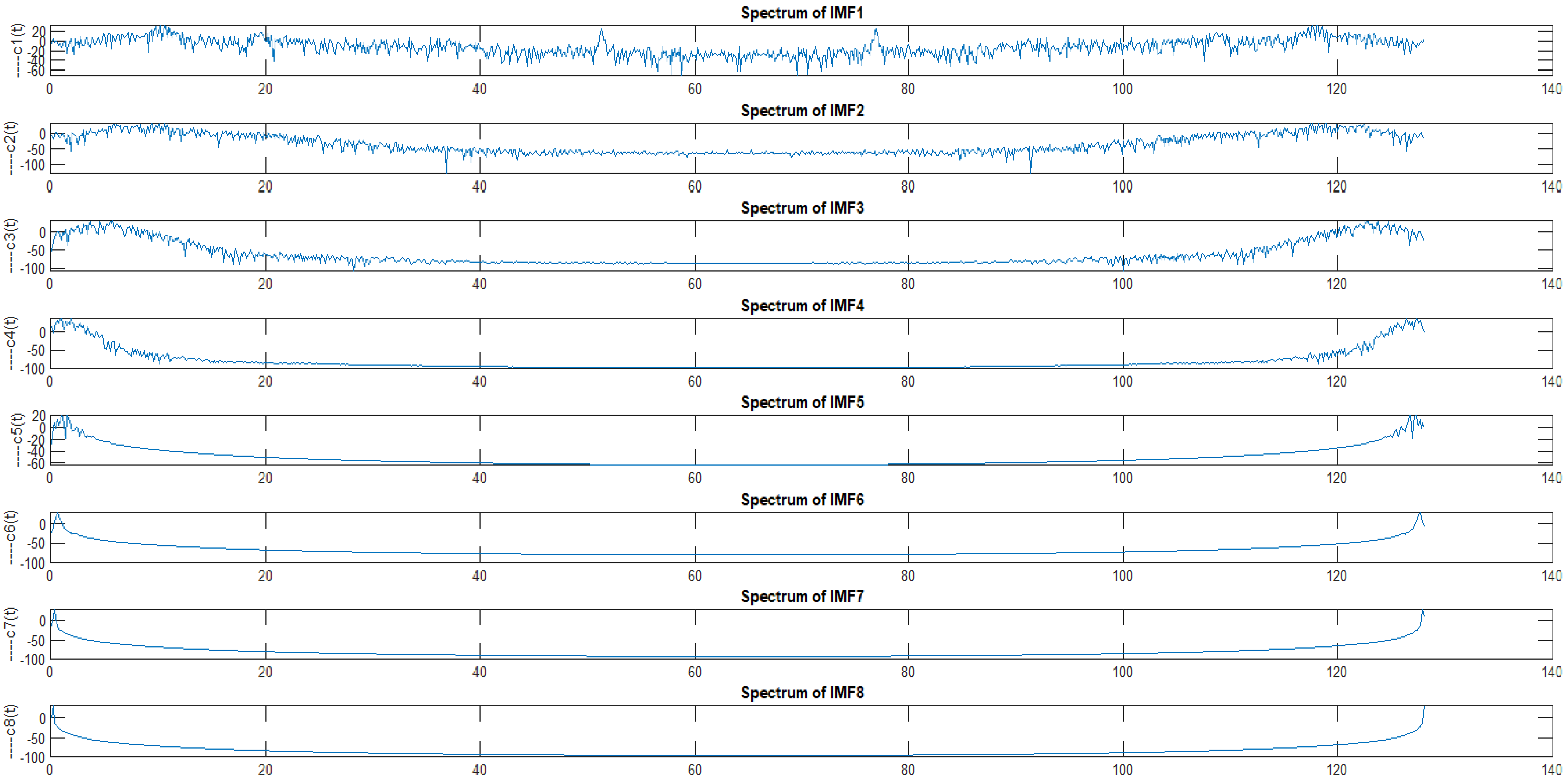
IMF decomposed with EMD

Decomposition of IMF

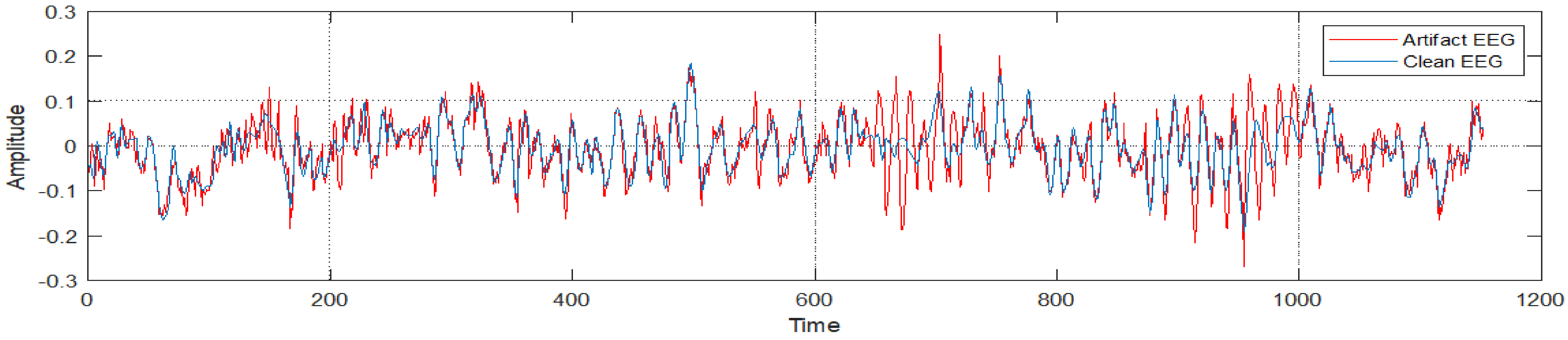
After the classification, the signal which are affected with artifacts are moved to be decomposed with EMD and the outcomes of IMFs are processed with adaptive iterative thresholding. Hence in our experiments the decomposition level 4 is treated as benchmark for which the entire analysis is performed

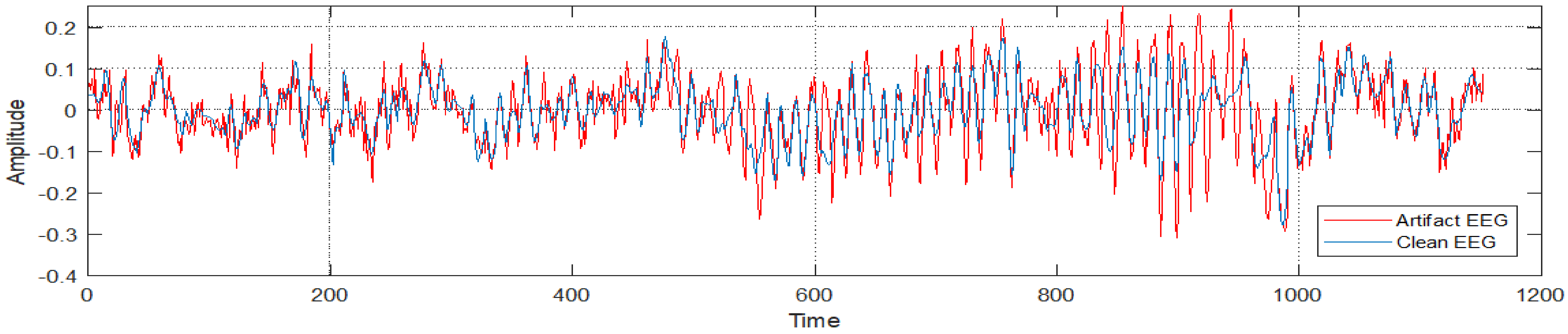


Spectrogram of decomposed IMF



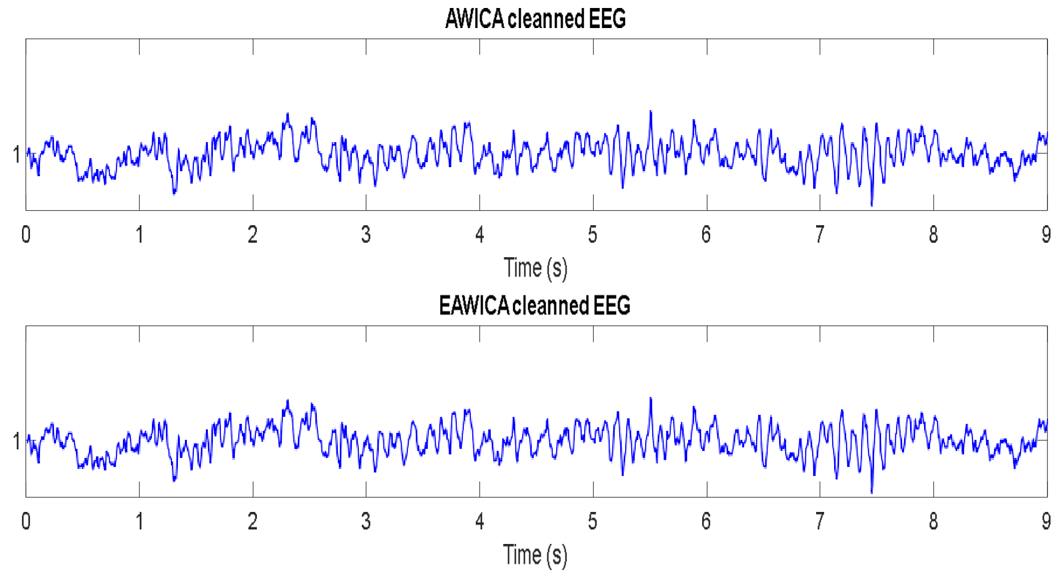
Artifact EEG and its estimated signal





Artifact in EEG

With AWICA and EAWICA METHODS



Conclusion

- This paper presents a customized auto encoder based deep network for the classification of EEG signals. This also presents an iterative adaptive threshold mechanism to minimize the EEG artifacts. The EEG signal is decomposed with EMD, and each decomposed level is iteratively thresholded to attain EEG artifact mitigated signal. The experimental results reveal that this approach could be able to attain superior results than existing AWICA and EAWICA method and show an improvement of correlation coefficients with an average of 0.265 which is almost increased to 1.97 times than the value that was obtained with earlier methods.

References

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THANK YOU