Dynamic Mode Decomposition based Artifact Removal from EEG signals and classification uisng of MI Tasks with hybrid CNN-LSTM network

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Abstract

Data interpretation is crucial for Electroencephalogram (EEG) based Brain-Computer Interfacing (BCI) systems. Artifact interfere with EEG signals leading to misinterpretation of EEG during classification. Hence a proper artifacts removal is always crucial for recognising human tasks using EEG signals. In this work, a method for artifact removal from EEG utilizing Dynamic Mode Decomposition (DMD) is introduced. In order to validate the process the four-class Motor Imagery EEG dataset from BCI Competition IIIa is classified using a hybrid LSTM+CNN classifier. Classification accuracy of 88.28% is obtained with raw EEG signals, while 90.4% accuracy is obtained for pre-processed EEG signals. The results indicate that the artifacts removal method is effective in improving the performance of the system.

Keywords: Artifact removal, DMD, BCI, EEG, Motor Imagery

1. Introduction

Special assistance and rehabilitation are necessary for people with motor impairments. A less complex and cheaper noninvasive EEG-based BCI system provides direct communication between the human brain, and an external device to carry out various tasks. EEG is the recording of electrical signals produced by neurons in the human brain.

The limitation of EEG-based BCI systems is the presence of artifacts signals, that originate from body parts other than the brain or from external sources, that interfere with the recording of brain signals [1]. Various approaches are developed to deal with the artifacts in EEG recording among which the most popular being Independent Component Analysis (ICA), Wavelet Transform and Empirical mode decomposition (EMD). A comprehensive review of various artifact removal techniques in [2] shows that modal decomposition methods were extensively used over the traditional methods which require reference signals to remove artifacts. But these methods encounter certain limitations when it comes to filtering out the artifacts while preserving as much of the original data. In the case of ICA, the artifactual Independent Components(ICs) removed may also contain some residual neural signals, that cause distortion to the EEG signal after reconstruction. EMD algorithm, being very sensitive to noise,often leads to mode mixing problems. One important limitation of PCA (or SVD) is that it fails to extract artifacts from EEG,when amplitudes are comparable, since PCA depends on the higher-order statistical property [2].

DMD can be viewed as the Eigen decomposition of an approximating linear operator that describes the system [3]. Compared to other modal decomposition methods, DMD modes gives the closest approximation of actual modes by capturing their growth.[4] Studies were conducted to analyse the effectiveness of DMD in EEG signal processing, which includes epileptic seizure detection[5], reconstructing and predicting error related potential[6]. The work by Bingni W. Brunton et al[4] demonstrates the advantages of utilizing DMD for detecting and analyzing sleep spindle networks. The computational implementation of DMD, and the interpretation of the extracted modes in the context of neural recordings is depicted in [4]. A Multivariate Dynamic Mode Decomposition is applied for recognising the imagined speech from EEG Signals [7]. Further sleep stage classifcation is using Random Forest is employed with power features of DMD modes of EEG sig-

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nals [8].

Deep neural network models are widely used for EEG classification [9]. Convolutional Neural Network (CNN) have the ability to learn the underlying distinct and important features of data by itself. Long Short Term Memory(LSTM) are very effective in achieving good classification accuracy with time-series data (such as EEG).[9] A hybrid LSTM+CNN network architecture is developed to effectively utilize these advantages and classify the EEG signals.

In this work, an artifact removal method utilizing DMD is introduced. DMD algorithm effectively tracks the dynamics of the signal and spatially decomposes it, which is further observed to eliminate the artifactual components. EEG signals are reconstructed from the processed DMD modes. The artifact removed signal is provided to the hybrid CNN-LSTM deep neural network classifier to classify it into the four motor imagery classes. The effectiveness of the proposed technique is verified by comparing the classifier accuracies for raw and preprocessed EEG signals.

2. Methodology

2.1. Dataset Description

The dataset BCI Competition IIIa obtained from BCI Competition III, consists of EEG signal of 4 motor imagery classes (left hand, right hand, foot, tongue). 60 trials per each class were recorded using 60 channels.[10]

2.2. DMD

DMD has emerged as a powerful tool for analyzing the dynamics of uniformly sampled signals from nonlinear systems [3]. The resulting modes represent the relevant spatial flow structures. The corresponding eigenvalues define growth/decay rates as well as the oscillation frequencies for each mode [3] [11].

Consider a series of snapshots $X_k \in R^n$; sampled at discrete instances in time , t_k , k=0;...;m. Splitting it into two data matrices X and X', the DMD algorithm constructs the leading eigen decomposition of the best-fit operator A, chosen to minimize $\Sigma||x(k+1)–Ax(k)||$, so that

$$X' \approx AX. \tag{1}$$

$$X = \begin{bmatrix} | & | & & | \\ x_0 & x_1 & \ldots & x_{m-1} \\ | & | & & | \end{bmatrix}$$

$$X' = \begin{bmatrix} | & | & & | \\ x_1 & x_2 & \ldots & x_m \\ | & | & & | \end{bmatrix}$$

Computationally, matrix A is obtained as $A = X'X^+$; where X^+ is the pseudoinverse of X and $A \epsilon R^{nxn}$. The dominant eigenvectors corresponding to the least damped eigenvalues of A are the dynamic modes ϕ, and the associated eigenvalues determine how these modes behave in time.[3]To reduce the computational complexity of matrix A, an approximation $\tilde{A}$ is computed such that $\tilde{A} = U * AU$. Singular Value Decomposition(SVD) of the matrix X is computed to obtain $\tilde{A}$. DMD modes are evaluated from $\tilde{A}$.

The algorithm to compute DMD modes from X and X' and to reconstruct the original matrix as in [4] is utilized.EEG signal trials taken in as data matrices follows the algorithm as in [4] and the approximated matrix $\tilde{A}$ is obtained, from which the eigenvalues and DMD modes are computed as,

$$\phi = X'V\Sigma^{-1}W \tag{2}$$

Each column of ϕ is a DMD mode ϕ_i corresponding to eigenvalue λ_i.

2.2.1. Algorithm to find DMD modes

1. To fully capture the dynamics of the EEG signal, the considered trial is taken as a matrix and augmented. The augmented matrix is X and its time-shifted version is X'. A is the system modeling matrix such that
$$X' \approx AX. \tag{3}$$
2. Compute the SVD of data matrix $X = U\Sigma V^*$.
3. The high dimensional matrix A is approximated as $\tilde{A}$,
$$\tilde{A} = U^*AU \tag{4}$$
where U is the orthonormal matrix obtained by SVD of data matrix X.
4. $X = U\Sigma V^*$ is substituted in equation 3 to get,
$$X' = AU\Sigma V^* \tag{5}$$
so that
$$AU = X'V\Sigma^{-1} \tag{6}$$
5. Substitute equation 6 in equation 4 to obtain
$$\tilde{A} = U^*AU = U^*X'V\Sigma^{-1} \tag{7}$$
6. Compute the eigen decomposition of $\tilde{A}$,
$$\tilde{A}W = W\Lambda, \tag{8}$$
where W is the matrix of eigenvectors, and Λ is the diagonal matrix of eigenvalues λ_i. Each eigenvalue λ_i is a DMD eigenvalue.

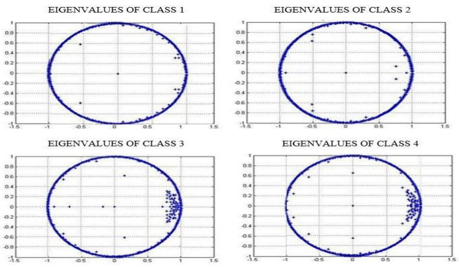

Figure 1. Example of eigenvalues of each class of motor imagery plotted.

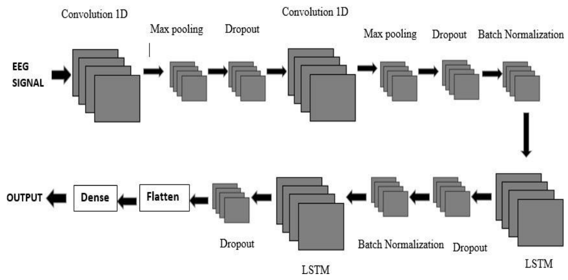

Figure 2. LSTM+CNN Neural network architecture

7. Compute the DMD modes,

$$\phi = X' V \Sigma^{-1} W \tag{9}$$

Each column of ϕ is a DMD mode ϕ_i corresponding to eigenvalue λ_i.

2.2.2. Reconstruction of EEG signal from DMD modes

To reconstruct the signal from the DMD modes, the observed data is considered as simple dynamic model X(t),

$$X(t) = \phi exp(\Omega t)z, \tag{10}$$

where $\Omega = \log(\Lambda)/\Delta t$, t is time, and z is a set of weights to match the first time point measured such that the first time instant in data matrix X given by $x_1 = \phi z$.

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The eigenvalues corresponding to the DMD modes for each class are plotted on a unit circle as shown in figure 1. From figure 1 the stability of the system modeling matrix $\tilde{A}$ can be validated.

2.3. Deep Neural Network Architecture

A hybrid model involving a combination of LSTM and CNN is developed to classify the EEG signal. LSTM+CNN deep neural network model consists of 1-D Convolution layers, 1-D maxpooling layers, and dropout layers followed by LSTM layers. The dropout layer avoids overfitting and the batch normalization layer normalizes the output of previous layer. Batch normalization layers help to improve the training speed and stability of the system. The flatten layer converts the output from the previous layer into a 1D array by creating a single long feature vector. The output layer is the dense layer that classifies the feature vector received from the flattening layer into the four motor imagery classes. The hyper-parameter optimization is carried out using the ”Hyperas” optimizer. Empirically found Leaky ReLU as the activation function and Softmax function in the dense layer for probabilistic classification gives the best performance results of the classifier.

3. Results and Discussions

3.1. Artifact Removal

From Fig.1. it is clear that some eigenvalues show greater variation from the rest. Eigenvalues with variation are identified by calculating the distance of each point from the neighboring points. The eigenvalues which are at a distance of 1.2 or greater, on an average from the neighboring points are empirically found to be artifact components. The average value of *1.2* is fixed as a threshold for the variation of eigenvalue. For each trial, DMD modes corresponding to eigenvalues above the threshold are normalized to remove the artifact components.EEG signal is reconstructed from the processed DMD modes using equation 11.

A comparison between the original and processed EEG signal shown in Fig.3., verifies that the artifact components are eliminated while preserving useful information.The single channel raw EEG

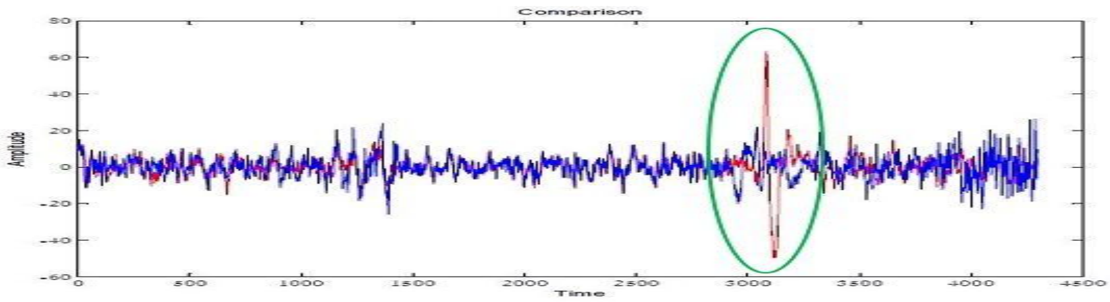

Figure 3. Artifact removed signal(in blue) compared with the original signal(in red). The portion circled shows the removal of unwanted signal from the original EEG.

data is plotted in 'red' and the artifact removed EEG is plotted in'blue. Thus the actual data is reconstructed while the unwanted eye blink artifact is removed by processing the DMD modes extracted.

3.2. *Classification*

The reconstructed EEG signal after pre-processing is split into 60% training, 20% validation, and 20% testing data sets. The model trained for 100 epochs is validated using the validation data set. The classifier is evaluated using both raw and processed EEG test data sets and accuracies of 88.28% with raw data and 90.4% with processed data are obtained.

3.3. *Discussion*

The main difficulty faced in building a powerful BCI using EEG signal is the effective separation of the signal from noise and its meaningful interpretation. In this work, a new method for handling the artifacts in EEG is implemented which improves the performance of the classifier in BCI systems, so that reliable aid can be provided to motion-disabled people.

The raw EEG data underwent Dynamic Mode Decomposition. The DMD modes belonging to artifactual components were identified from corresponding eigenvalues and processed. Artifact removed EEG reconstructed from the processed DMD modes was classified into four motor imagery classes.

A comparison of the performance of different systems those with and without an artifact removal technique employed in the pre-processing stage of four class motor imagery classification is shown in Table 1.It is observed that the artifact removal method employed does improve the accuracy of the classifier. The comparison shows that the proposed artifact removal method using EEG gives promising results by preserving useful EEG data.

Table 1
Comparing the mean accuracies obtained for four class motor imagery classification in various works and the proposed method.

	Artifact Removal Technique	Classifier	Accuracy
Perijun Lu et al.[12]	Band Pass Filter	CNN+LSTM	76.62%
Zeyu Bai et al.[13]	nil	CNN, stacked LSTM and GRU model	72%
Ruilong Zhang et al.[14]	nil	CNN and LSTM	83%
Nijisha Shajil et al.[15]	Butterworth Band-Pass flter (BPF) of order 5.	CNN	87.37±1.68%
Proposed method (using raw EEG)	no technique employed	CNN+LSTM	88.28%
Proposed method (using preprocessed EEG)	Dynamic mode Decomposition	CNN+LSTM	90.4%

In BCI applications where artifact removal becomes a necessity, DMD can offer effective means to achieve better interpretation of the EEG data. DMD is not as vulnerable to mode mixing problem as compared to other modal decompositions like EMD and hence provides better reproduction of non artifactual EEG signal. For ocular artifact removal the proposed method gives good results without any reference EOG signal. DMD is a data driven modelling and hence no specific parameter values are required beforehand. For research ahead, the method proposed here can further be modified, improved or combined with other techniques to build a hybrid system with all the advantages DMD offers.

4. Conclusions

An effective artifact handling method to improve the performance of the BCI system is introduced to aid the motion disabled or elderly people. Preprocessing of EEG signal utilizing DMD improved the accuracy of the hybrid LSTM+CNN classifier by almost 2% when compared to raw EEG. The proposed system has potential in various applications that includes, but is not limited to rehabilitation BCI systems, Medical diagnosis, and Smart Home control.

Conflict of interest

The authors declare that there is no conflict of interest in this paper.

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