Classification of Motor Imagery EEG Signal for Navigation of Brain Controlled Drones

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Abstract. Navigation of drones can be conceivably performed by operators by analyzing the brain signals of the person. EEG signal corresponding to the motor imaginations can be used for generation of control signals for drone. Different machine learning and deep learning approaches have been developed in the state of the art literature for the classification of motor imagery EEG signal. There is still a need for developing a suitable model that can classify the motor imagery signal fast and can generate a navigation command for drone in real-time. In this paper, we have reported the performance of convolutional stacked autoencoder and Convolutional Long short term memory models for classification of Motor imagery EEG signal. The developed models have been optimized using TensorRT that speeds up inference performance and the inference engine has been deployed on Jetson TX2 embedded platform. The performance of these models have been compared with different machine learning models.

Keywords: Motor Imagery · Long Short Term Memory · Convolutional Stacked Autoencoder · Drone · Jetson TX2.

1 Introduction

With the emergence of drone technologies, drones have become an integral and significant component of almost every security and surveillance tasks in civil and military domain. In present scenario, the drones are controlled using handheld remote controller or joystick. This limits the usability of the drones for vast applications as the hands get occupied in the navigation operation. This in effect causes an increase in the effective workload of an operator that lead to under-performance or fatigue of the operator. Thus in order to design a suitable interface for controlling the navigation of a drone, a hands-free control is most desirable solution. In the past decade, researchers across the world have worked towards the development of different hands-free interfaces using human interfaces such as body gesture, eye tracking and EEG signal. Brain controlled interfaces have gained significant attention due to the naturalistic way of human operation.

The need for development of a brain computer interface (BCI) for the navigation of drones has motivated the researchers to develop interface by analysing EEG signal corresponding to different facial expressions, such as, blinking, smiling, raising eyebrows etc., and mapping them to different motions of the drone. The EEG signal corresponding to these actions generate signal patterns that are significant enough to generate a command for the drone. However, the commands generated using facial expressions makes the interface very unreliable and unrealistic.

The most congruous solution to this problem can be achieved by analysing EEG signal corresponding to motor imaginations of the operator and generation of control signals for drone. Motor Imagery(MI) represents the mental process of simulating a motor action. These MI signals are primarily mediated by Mirror Neuron System which is primarily observed over the pre-motor cortex and sensory motor cortex. These signals share similar cognitive processes with actual motor movement execution. The MI signal is generally observed through the computation of suppression and enhancement of mu rhythms(8-12Hz) while performing a motor imagery task[8].

Classification of motor imagery EEG signal has been performed using different machine learning and deep learning approaches since the last two decades. Owing to the fact that the EEG data is non-stationary in nature, most of the classification models are built with the consideration of adaptive parameter learning.

Most of the motor imagery classifications models developed uses a relevant set of features that can learn the necessary fluctuations in the EEG signal corresponding to the motor actions. To understand the underlying structure of the EEG signal, mostly Temporal features, such as, higher order statistical features (variance, skewness, kurtosis etc.), Morphological features, such as, Curve length, Average nonlinear energy, Number of peaks, Hjorth features (activity, mobility and complexity); Frequency and Time-Frequency Features, such as Fourier coefficients, Band Power, Wavelet Coefficients, Wavelet Entropy; Spatial Features, such as Common Spatial Patterns (CSP); and Connectivity Features, such as, Correlation or synchronization between signals from different sensors and/or frequency bands, Spectral Coherence etc. are computed.

Linear discriminant analysis (LDA), Support vector machines (SVM) and Bayesian classifiers have been most commonly used for classification of motor imagery signal for real-time operation. But to deal with EEG non-stationarity, adaptive classifiers has gained significant importance whose parameters are incrementally updated online. Adaptive LDA and Adaptive Bayesian classifier based on sequential Monte Carlo sampling have been developed for MI classification that explicitly model uncertainty in the observed data.

A significant number of researches have been performed using Riemannian geometry classifier (RGC) that maps the EEG data directly onto a geometric space or tangent space and learns a manifold [3]. The RGC computes intrinsic distance between data points in the manifold and classifies the data [9]. Although RGC can provide better generalization capabilities due to manifold learning, these class of classifiers are computationally extensive and thus is not suitable for a real-time online application.

2 Related Work

Dedicated feature extraction and selection requires a long calibration time and it changes for different sessions of data collection. Thus these models are unfit for developing a real-time BCI application. Deep learning methods are thus more suitable to learn the most relevant features for the task at hand. These models are also better suited to model high-dimensional data.

Convolutional Neural Network (CNN) based classifiers provide a better solution to this problem as it generates features of the signal by considering both temporal and spatial variation in the EEG data. Due to the intrinsic structure of using local receptive fields in convolution layers, the temporal variation in EEG automatically gets included. CNN based classifiers have been developed for the classification of motor imagery signal[7]. But due to the static structure of the convolution layers, it does not learn the non-stationarity in EEG data. Autoencoder (AE) based classifiers provide much better solution as it learns the features from the raw signal in unsupervised fashion and provide a good classification performance. Multi-modal stacked AE with separate AEs for EEG signals and other physiological signals has been reported to outperform the traditional classifiers. Sequential LSTM models and Bidirectional LSTM have been developed to learn the temporal variation in the EEG data.

Deep Belief Network (DBN) have been used extensively to classify motor imagery signals is another majorly used EEG classification method [5][2][6][4]. DBN takes the non stationarity into consideration and learns features directly from data in hierarchical manner in unsupervised manner. Thus DBN classifiers outperform most of the other classification techniques. Sparse representation of the high dimensional EEG data can be obtained using sparse-DBN model. An adaptive DBN structure has been developed that can perform Belief Regeneration by using samples generated from a DBN to transfer the learned beliefs to a second DBN. In order to incorporate new knowledge in the model, the generated samples and new data from the stream can be used to train the DBN.

To develop a real-time BCI, we have proposed two deep learning models that learns the features of the EEG data through convolution and classifies the data in unsupervised fashion. The classifier models have been described in the following section.

3 Proposed Method

3.1 Data Description

We have used BCI competition IV data set 2b dataset for our experiments. The dataset consists of EEG data from 9 subjects performing two classes of motor imagery activities, viz., left hand and right hand movement. Five sessions of motor imagery experiments were performed on each of the subjects, among which the first two sessions were recorded without feedback and the other three sessions were recorded with online feedback. Each of the first two sessions contains 120 trials, and each of the rest three sessions (with feedback) includes 160 trials. The EEG data were recorded using three channels, C3, Cz, and C4 with a sampling frequency of 250 Hz.

3.2 Data Pre-processing

The EEG data have been first bandpass filtered between 0.5 Hz and 60 Hz, and a notch filter at 50 Hz was used to remove the power line noise. As the motor imagery occurs due to a change in mu-rhythm (8-13Hz) and beta- rhythm (15-30 Hz) over the central motor cortex, the data is band pass filtered between 8-30 Hz. The data from the first 2 sessions are used for training the model.

Each experimental trial started with a fixation cross and a beep followed by a visual cue of 3 seconds provoking a left or right hand movement. The timing scheme of the motor imagery experimental paradigm has been shown in Fig. 1. The data between the period 4-7 seconds contain the motor imagery data for each trial, i.e., $(3 \times 250 =)750$ samples of data. To incorporate the transition in data from EEG baseline to MI data, we have incorporated 100 milliseconds of data at the start and end of the MI period. Thus the new motor imagery instances are (0.1+3+0.1)= 3.2 seconds long between the time period of 3.9 to 7.1 seconds for each instance, i.e., (3.2*250) =800 samples of data.

Similarly, the non-MI data has been generated by considering data between duration 0-3.2 seconds from each experiment trial.

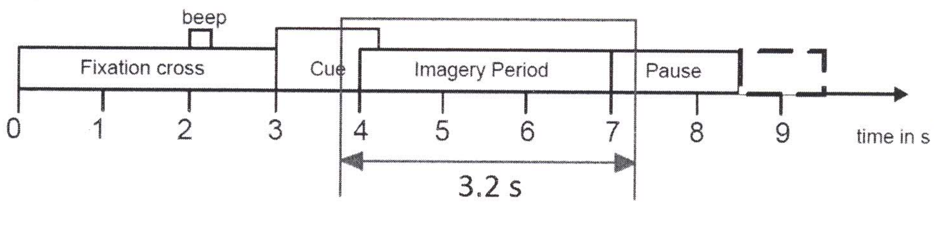

Fig. 1. Timing scheme of motor imagery

Thus we have considered three major classes for the classification problem, viz., Left MI, Right MI and Non MI. The EEG signals corresponding to left and right hand movement has distinct signature as shown in Figure 2 which has been further classified.

All the studies on the dataset reports classification over Left and Right MI, but here we have considered Non Motor Imagery too as our purpose is to generate navigation commands for the drone corresponding to the thoughts of the operator.

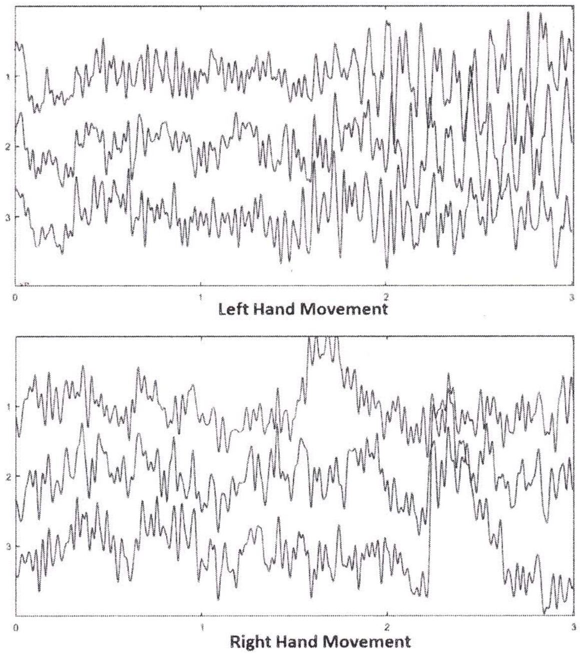

Fig. 2. Motor Imagery EEG for Left and Right hand movement

3.3 Data Augmentation

The number of left and right motor imagery and non-motor imagery data trials obtained from the database is very limited. The number of trials for each of the classes for the first two sessions are enlisted in the table 1. Proper training of a deep learning architecture requires a voluminous dataset. With limited data availability, the learned model overfits and thus lacks the ability of generalization. Thus it is crucial to increase the volume of the dataset by augmentation of new data.

To increase the number of data instances, augmentation of EEG data has been performed. For generation of new realistic EEG data, we have a developed a generative adversarial network [1] architecture. The generator generates new EEG data from random noise using a convolutional network. The discriminator/critic, on the other hand, uses a convolutional architecture to discriminate the generated EEG data from the original EEG data. The similarity between generated and real data is computed using Wasserstein distance.

Wasserstein distance measures the distance between two probability distributions considering optimal transport cost. In Wasserstein GAN, the difference between the true distribution and the model distribution of the data is measured using Wasserstein distance instead of Kullback-Leibler divergence and Jensen-Shannon distance. This helps in alleviating vanishing gradient and the mode

Table 1. Number of trials per class for all subjects

	Left MI	Right MI	Non MI
Subject1	99	101	200
Subject2	99	99	198
Subject3	90	88	178
Subject4	123	123	246
Subject5	119	120	239
Subject6	77	84	161
Subject7	110	108	218
Subject8	121	101	222
Subject9	88	94	182

collapse issues in generator. WGAN continuously estimates the Wasserstein distance by training the discriminator to an optimal model. This helps in keeping the output in specific range even if the input is varied.

The structure of the generator and the discriminator has been shown in Fig. 3 and Fig. 4.

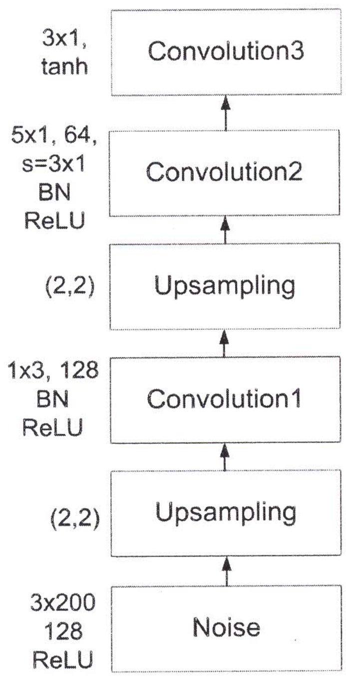

Fig. 3. Generator

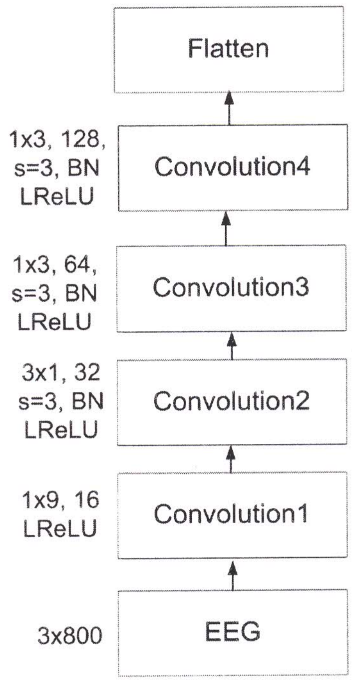

Fig. 4. Discriminator

3.4 Classification

Different dedicated feature extraction is generally performed to obtain signature from clean pre-processed EEG data which includes temporal, spectral, morphological features, viz., Hjorth parameters, Power Spectral Density (PSD), Curve length, number of peaks, Non Linear Energy, and Short Time Fourier Transform (STFT). To deal with the non-stationarity in the EEG data, STFT feature have been used. The STFT takes into consideration the temporal correlation in the data.

Instead of using a dedicated feature extraction module, we have used deep learning architecture to learn features from the EEG data in an automated manner.

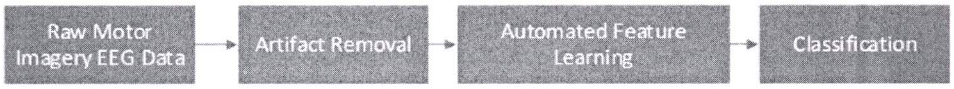

Fig. 5. Motor Imagery Classification with automated feature extraction

We have developed two models for classification of the motor imagery signal. To avoid the inter-person variability of EEG data, one classifier model was learnt for each of the subjects.

LSTM model learns the structure of EEG data by capturing temporal correlation in the data. As LSTM modules can choose to remember and discard the temporal information, it provides a better representation of the EEG data. Whereas the CNN SAE models learn a latent space representation of the data and does not specifically deal with the temporal variation of the data, which is the most prominent feature of EEG data.

Stacked autoencoder models map the data into a latent space and thus learns an unsupervised representation of the data. The convolution layers learn the local variation in the data. The features from the latent compressed representation are used for classification of the data.

3.4.1 Convolutional Stacked Autoencoder Model :

A Convolutional Stacked Autoencoder (CNN-SAE) model, as shown in Figure 6, has been developed to learn features from raw signal in unsupervised fashion and provide good classification performance. CNN-SAE combinatorial architectures provide the advantage of learning features using CNN and then learning the unsupervised SAE classifier on the detailed features.

Autoencoder learns a lower dimensional representation of the data and subsequent reconstruction of the data from the lower dimension space. The architecture of our network consist of two convolution layers followed by three autoencoder layers.

The EEG input is 3.2 seconds long, with the sampling frequency of 250Hz that results in 800 samples for 3 channels. Therefore the input tensor is of dimension 800×3. The first convolution layer performs a temporal convolution over the batch normalized input tensor. 32 filters with kernel size of (1,30) are used. Resultant output is a tensor of shape (771,3,32). The second layer performs a spatial convolution with 64 filters having a kernel size of (3,1) in an overlapping manner giving an output of (78,1,64). Both convolution layers contain Parametric ReLU activation funcion (PReLU). The outcome after temporal and spatial convolution is flattened and fed to the first encoder layer containing 1200 hidden neurons. Two more successive encoders are employed with 600 and 150 hidden neurons. All the autoencoders have ReLU activation function and 25% of neurons are dropped after each encoder. Here the last encoder have the softmax activation function with three outputs indicating whether the input contains a Left MI, a Right MI or a non MI data.

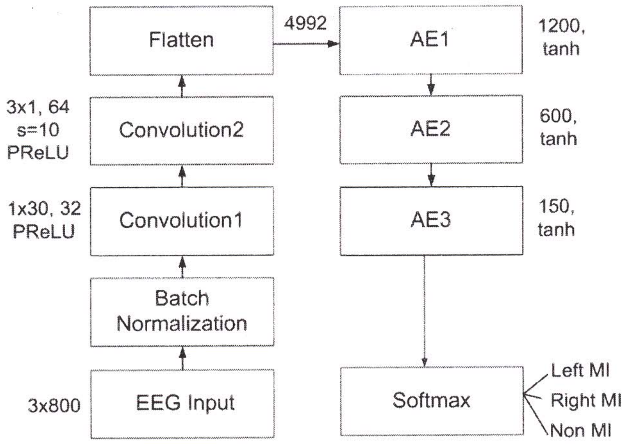

Fig. 6. Proposed CNN-SAE architecture

3.4.2 LSTM based Model : To capture the sequential information in EEG data, LSTM based models have been developed for the classification. Three different models were developed for this purpose.

The first model is a shallow LSTM that uses two LSTM layers with 256 and 128 number of hidden layers respectively. The batch normalized input data is fed to the LSTM model where the output of each layer is passed through the tanh activation function. The output is passed through a dropout layer with dropout=0.2 and recurrent dropout=0.1 to reduce overfitting and improve the classification performance. The second model is a deep LSTM model with 256, 128 and 32 number of hidden layers. The same hyperparameter values are used for this model. The model was trained using RMSProp optimization while considering the categorical cross entropy loss.

The third model is a convolutional LSTM (ConvLSTM) model that learns the structure of the EEG data by capturing the spatio-temporal correlation in the data. The input to state and state to state transitions are computed using convolution. This model captures the variation in the data among different channels placed over the motor cortex as well as the temporal variation in the data.

4 Results and Discussion

The performance of different algorithms for Subject 4 have been reported in Table 2. The SVM and LDA are standard techniques used extensively for motor imagery classification. Extreme Learning Machine (ELM), regularized extreme learning machine (RELM) and Kernel-ELM(KELM) has been used to classify the motor imagery data due the fast computation of the algorithm which is very suitable for real-time EEG data classification. But the performance of unsupervised classification method DBN is the best as it learns the features from the data on its own. Adaptive generative models can be used for better online classification of the non-stationary EEG data.

Table 2. Motor Imagery Classification Accuracy for Subject 4

Method	Accuracy (%)
SVM	93.008
ELM	92.461
RELM	87.961
KELM	91.980
LDA	91.880
DBN	93.751
CNN-SAE	**92.140**
LSTM	**95.330**
ConvLSTM	**92.530**

Although SVM provides a good classification performance, it does not provide a good solution for EEG data from another session. DBN model can classify the efficiently, similar to the CNN-SAE model. The deep learning models developed provide good accuracy at a higher processing speed. As the LSTM model considers the sequential variability in the data, it performs well for the motor imagery classification in real-time.

5 Inferencing on Jetson TX2 platform

The developed algorithm has been deployed onto the embedded platform Jetson Tx2 which improves the performance and power efficiency using graph optimizations, kernel fusion, and half-precision FP16. The developed tensorflow model was optimized using TensorRT that speeds up inference performance. The inference time for each 800×3 block data is ≈ 9-10ms. Thus the model has been further used to serially send navigation commands to the drone.

6 Conclusion

We have proposed a Conv-SAE model, a LSTM model and a Conv-LSTM model for the classification of the motor imagery EEG signal. Stacked autoencoder models map the data into a latent space and thus learns an unsupervised representation of the data. The convolution layers learn the local variation in the data. The features from the latent compressed representation are used for classification of the data. The LSTM models takes the temporal variation into consideration and thus both the spatial as well as temporal characteristics of the data are well considered. The developed LSTM model outperforms the CNN-SAE as well as the Conv-LSTM model. The developed models are well suited and generates navigation commands for drone after every 10 ms duration efficiently. We can further improve classification performance using ensemble models keeping the model complexity in consideration.

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