EEG Dataset Classification for Different Gestures for People Suffering from Spinal Cord Injuries

Abstract

Electroencephalography(EEG) signals are generated by people suffering from spinal cord injuries and can be used to classify various gestures made by a subject. Although data generated by a subject is a low-frequency signal; however, with advances of technologies to detect low signal frequencies, it is now possible to record those signals which can be further analyzed. For further analysis of EEG signals which is spatial-temporal data, we have used one of the methods of Deep Learning which is named Spiking Neural Network (SNN). We have also used NeuCube software for cues classification and the visualization of a network learning.

1. Introduction

We have seen that there are several Deep Learning algorithms which are the state-of-the-art in their respective domains like natural language processing, speech recognition, computer vision, detection and classification. Deep learning uses algorithms which are aware of time dimension which are in speech and video analysis and without time dimension such as image classification and object detection [1]. However, these deep learning algorithms do not work very well with EEG data, maximum accuracy is 55.55% [2]. EEG is a spatio-temporal brain data (STBD) but none of these deep learning algorithms consider this aspect with regards to EEG data. A third generation neural network is SNN [3], it works in a similar way as the brain; it takes into account both spatial and temporal signals received from other connected neurons for a specific stimulus. Each single neuron triggers a signal or spike once its eclectic potential reaches a certain predefined threshold, otherwise it keeps accumulating electric potentials receiving from other neurons over a period of time. Therefore, it is important from where and at what speed a neuron receives signals that triggers new signals or spikes and in which direction. To interpret EEG signals, we have used NeuCube [4] software which is based upon the SNN model; we have used NeuCube for the classification of cues associated with data received by a team from Graz University that have carried out a systematic approach to collect and analyze data [5]. EEG signals are generated by the brain wherever there is an emotional or cognitive activity; sensors present across the scalp record electrical activities and during the course of the brains activity, it is recorded with a rate of thousands of data points in a single second. In this paper we have analyzed the collected EEG signals and processed it using NeuCube SNN architecture for the classification of cues and model. We have also generated a 3D representation of the active area of the brain while performing one of the cues, we have also visualized neurons connectivity among them.

2. Methods

SNN is a model which can be used to analyse EEG data as it processes data similar to brain. SNN uses signal encoder. It takes an input in the form of spikes with two binary values -1 and 1. Since EEG data is a continues signal, so a conversation is needed from continuous data to discrete binary data. Therefore, NeuCube has Threshold-based encoding, Ben's spike encoding, Step-Forward encoding and Moving Window as options for encoding algorithm. We have used **Threshold-based encoding [6]** for the encoding EEG signal, in this a spike is generated when a signal crosses a predefined threshold value otherwise no signal is produced. It results into a long uneven spaced spikes train, after passing the EEG signal through it. SNN has several neural models; SNN neural model is similar to activation function of deep neural network (DNN). NeuCube uses **Leaky Integrate-and-Fire** (LIFM) model [4], this model works similar to a capacitor. Its electric potential does not go beyond a defined level and if it reaches to that defined level then it discharges. Its electric potential leaks with time if it does not receive any electric signal. Next comes the learning where spiking neurons learn the relationships among themselves similar to DNN where each neuron gets weighted input from the previous layer. **Spike-Time Dependent Plasticity (STDP)** [7] is a unsupervised learning algorithm that is used in NeuCube, in this learning, weights are calibrated based on the temporal order of incoming spikes and outgoing spikes. A connection (weight/neural connectivity) is said to be long term potential (LTP) if difference of arrival time of post-synaptic and pre-synaptic is greater than zero otherwise it is said to be long term depression (LTD). **Dynamics Evolving SNN (deSNN)** [4] network is used at the final layer of the SNN and it is used as for supervised learning for the classification of EEG signals. This final layer is connected to each neuron of the SNN. Weights are assigned according to rank order rule i.e. first spike is most valuable then rest of the spikes and then system learns through temporal data using SDTP learning and assigned values to weights to each of the neuron. For each given sample input there is a neuron that is at final layer and connected to each of the neuron of SNN.

Data Source and Acquisition: Data for this paper is collected from the experiment on people suffering from spinal cord injuries at Graz University of Technology, Institute of Neural Engineering, BCI-Lab, Graz Austria [5]. 9 participants were selected for this experiment, each of them sat facing towards the monitor with an arm placed on the pillow and followed instructions displayed on a monitor facing them. All 9 participants (p01- p09) were in the range of 20 - 69 years old, all were male except p04. Each participant was asked to initiate a movement immediately when they see a class cue on the monitor.

There were 9 runs and each run is comprised of 40 trials. The length of each trial was 5 seconds and there was a random break of 1s to 3s between each trail. There were 5 cues classes: pronation, supination, palmar grasp, lateral grasp and hand open which results in 72 trails for each class. The participants were asked not to initiate any other movements such as eye blinking and swallowing while they were carrying out a particular cue. Participants were asked to see cross wire at the start of a trail and 2 seconds latter they were shown cue, based on that, participants were asked to perform attempt action by using their left-over motor abilities. The dataset includes 15 runs for each participant of which 9 for attempted movement, 3 for eye moment runs and 3 rest runs. Each run is stored in a file named according to the participant's identifier and run's identifier. EEG signals were recorded in GDF Format which can be read with BioSig or EEGLAB [8] plugin of MATLAB [9].

Events: trail start, beep, fixation cross, supination class cue, pronation class cue, hand open class cue, palmar grasp class cue, lateral grasp class cue.

Run Type: rest, attempted movement(gesture).

Spatial Data: EEG Electrode placed according to 10-5 system with values shown below. AFz, F3, F1, Fz, F2, F4, FFC5h, FFC3h, FFC1h, FFC2h, FFC4h, FFC6h, FC5, FC3, FC1, FCz, FC2, FC4, FC6, FCC5h, FCC3h, FCC1h, FCC2h, FCC4h, FCC6h, C5, C3, C1, Cz, C2, C4, C6, CCP5h, CCP3h, CCP1h, CCP2h, CCP4h, CCP6h, CP5, CP3, CP1, CPz, CP2, CP4, CP6, CPP5h, CPP3h, CPP, CPP2h, CPP4h, CPP6h, P5, P3, P1, Pz, P2, P4, P6, PPO1h, PPO2h, POz, EOG left, EOG middle, EOG right

Temporal Data: Data sampled at the rate of 256Hz for each run. For every run, each trial lasts for approximately 5 seconds for an event(cues) with rest of 2 or 3 seconds. There are 40 trials in each run, therefore there are approximately 76,544 points for each run.

Previous Researches on Dataset:

1) [5] Hand movement classification for people injured with spinal cord injury, they have achieved classification with accuracy of 45% among five classes.
2) [10] They have discussed the calibration of BCI with small data set using semi-supervised learning. They proposed to use their study with complex data set that we have used to enhance their study.
3) [11] They have used Hero device for replicate experiment that was performed while gathering the data and analyzed it.

4) [12] They have used the data set analysis accuracy results [5] to compare with their data set analysis results.
5) [13] They used the dataset for comparative analysis to select minimum features selection but to mentation high level of accuracy.

3. Experiment

Preprocessing: First, we imported data into EEGLAB by importing a file for the subject p1 for the run 03, it has data related to five classes supination, pronation, hand open, palmar grasp, lateral grasp. Since it has data for 40 trials and each trail is of length 5 seconds and data sampled with rate 256Hz which results into 76,544 records. We used MATLAB to make sample compatible to NeuCube i.e. each trial is saved into a file named sam{X}.csv where X is attempted trail for five seconds and it belongs to one of the cues. Similarly, we performed the same process for the run 04, now, we had total 80 samples for five cues and 64 features/electrodes for each record.

After getting raw EEG signals for each sample we encoded them to binary spikes by using NeuCube software as shown in fig 1.

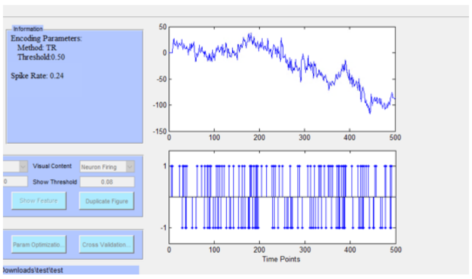


Fig 1. Spike Encoding of EEG signals (Encoding Method = Thresholding Representation, Spike Threshold = 0.5, Training Set ratio = 0.5 feature = F4, sample = 1)

Next we performed SNN cube initialization for that we used Talairach brain template [14]. After that we mapped our coordinates and labels of our feature electrodes and result to a 3D shaped brain model as shown in fig 2. Initial connection among neurons can be shown in fig 3, it is initialized using small-world connectivity rule with radius is 2.5 and 80% of all neurons assigned with a positive weight value.

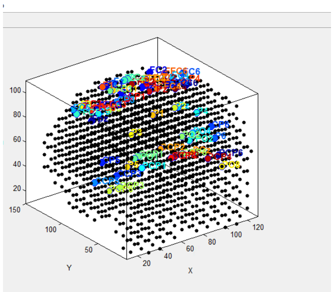
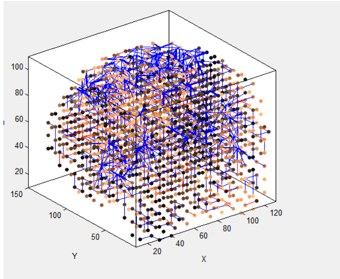
 

Fig 2. 3D mapping of neurons in SNN after initialization. Fig 3. Initial connections before training by using small world connectivity with radius 2.5 and 80% positive weight value.

Next, we trained the SNN model, which is an unsupervised learning, we have chosen LIFM for neuron model and STDP for learning. This learning will create connections among neurons according to trains of spikes coming from encoding input. We have used default values for other hyperparameters:

Potential Leak Rate: it is leak in neuron's electric potential when it does not trigger.

Threshold of firing: it is an electric potential after which it triggers neuron.

Refractory time: it is a time when neuron does not fire once it has triggerd a spike.

STDP rate: it's a learning rate of STDP algorithm.

Training round: it's a number of iterations for unsupervised learning.

LDC probability: it's a probability for making a long-distance connection among neurons.

After learning, a trained SNN cube has been shown in fig 4. Fig 5 has shown another representation of the trained SNN, it shows the membrane potential of each neuron. Fig 6 has shown histogram positive and negative triggered spikes.

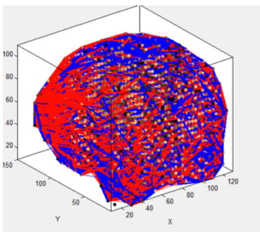
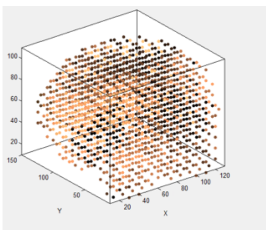
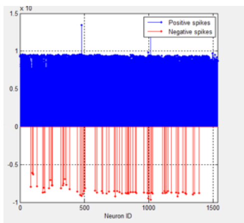
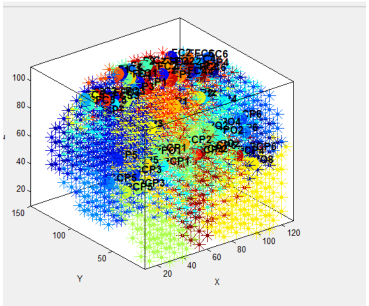
  

Fig 4. Unsupervised trained model, given figure shows connections among spike neurons with threshold value of weight 0.08. Fig 5. Activation level diagram of trained spike neurons. Fig 6. Histogram of trigged spikes during unsupervised learning.

Next we performed network analysis, first we did analysis based on connection weights among neurons, second, we performed a spikes clustering that is spikes communication among neurons during learning as shown in fig 7 and fig 8 respectively.



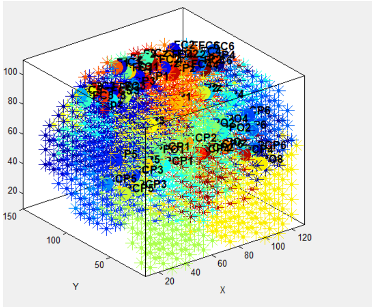
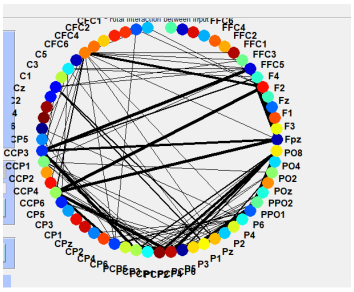


Fig 5. Cluster analysis using connection weights. Fig 6. Cluster analysis using spike communication.

After that we did input interaction total analysis using connection weights among input neurons and we also did tracing using max spike gradient as shown in fig 7 and fig 8 respectively.



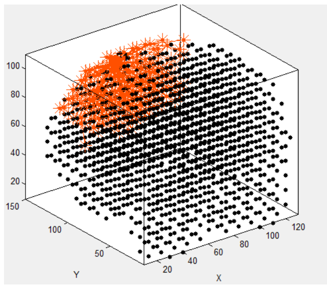


Fig 7. Total input analysis among input neurons using connection weights. Fig 8. Trace analysis using spike gradient.

Next we trained deSNN which takes input from trained SNN and performed supervised learning and could be used as classifier for given sample data. After that we performed verification by using 50% of the data that we kept aside other than training data by choosing Training Sample Rate = 0.5 at the time of SNN cube training. Next we performed cross-validation by using default hyper parameters with fold 2 and obtained result.

Results and Discussion

In previous assignment, we had analyzed and classified for a subject p01 for 5 runs which include events of hand gestures, using k-nearest, SVM and linear discriminant analysis with the accuracy of 68.75%, 75% and 50% respectively. Data was divided into two classes, palmar grasp and lateral grasp. 20% of data was used as testing for cross-validation by using k-fold (1*1).

In current assignment, we have performed verification and get following accuracies: Overall accuracy: 19.05%, Class 1 accuracy: 18.18%, Class 2 accuracy: 0.00%, Class 3 accuracy: 25.00%, Class 4 accuracy: 37.50% and Class 5 accuracy: 11.11%, and result of cross-validation is: Overall accuracy: 13.75%, Class 1 accuracy: 9.52%, Class 2 accuracy: 45.45%, Class 3 accuracy: 12.50%, Class 4 accuracy: 6.67% and Class 5 accuracy: 5.88%.

The accuracy from the first assignment was achieved due to cleaning and removing noise and outlier channels but in the current experiment we did not perform data cleaning and linear decrement analysis to reduce dimension; this resulted into a poor verification result.

Practical application: Results that we obtained can further be improved by cleaning data and removing outlier and noise. Once we will reach a satisfying point, this solution could be used to design neuro-prostheses Brain Computer Interface that could help a person with spinal cord injuries to perform everyday work like grasping and door opening.

Conclusion

In this paper we have analyzed EEG data of people injured from spinal cord injuries. Because the injury data was not clear and very weak. We converted the data to make it compatible to NeuCube so that further analysis could be performed. We performed SNN analysis on the same data using NeuCube and performed unsupervised learning to train neurons and supervised learning to classify classes using spatial and temporal brain data (STBD). We encoded EEG signals into trains of spikes using Threshold algorithm and fed them into SNN for STDP unsupervised learning among neurons. We have used LIFM as neuron model. Furthermore, we have used deSNN for supervised learning to classify classes of cues. We visualized spikes and connections learning among input neurons and also visualized tracing of spikes based on its number of spikes it emits. Finally, we verified data using split and cross-validation methods and compared it with previous results.

In the future, data can be collected by using different subjects who belong to different classes such as gender, age group, right hand and left hand. An additional analysis could move in a direction where we use more gestures and do comparative studies of delays in stimuli for a subject and reaction time among subjects. Further work would be to find a way to increase the accuracy of cues classification so that trained SNN cube could be used for robotics arm or neuro-prostheses designing.

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