Telekinesis: Multi-User Multi-Class Classification of EEG Data

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For people with severe motor disabilities, independent mobility is one of their biggest challenges. For people not capable of operating manual or remote controlled wheelchairs are heavily dependent on their attendants for all their basic needs. Therefore, there is a need for developing smart brain controlled wheelchairs which can help such people with basic movements without assistance. The project will generalise the use of EEG (electroencephalography) data for various multi user multi class classification tasks. Currently most EEG applications involve training and testing the classifier on the subject′s own data, which makes it hard for Brain Controlled devices to be ubiquitous.

In order to do that, we used a Convolutional Neural Network on a 64 channel EEG Motor Imagery dataset from PhysioNet[5] to train a Convolutional Neural Network (CNN) that takes in learned representations of the data which are built using an Auto-Encoder and obtained a classification accuracy of 75% when trained and tested on different dataset. We also run a user study using the Emotiv EPOC+ Headset to collect data under similar conditions as the training dataset, and test our network and obtain a classification accuracy of 65%

Additional Key Words and Phrases: EEG, motor imagery classification, BCI

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1 INTRODUCTION

People who have had paralytic attacks in most cases have slurred speech so a developing a voice controlled wheelchair would be difficult as it will difficult to train any machine learning model to identify commands. Using gesture or eye-movement to control movement will not be feasible because gesture recognition would require a grid of sensors/cameras being placed around the subject which is not possible in an outdoor environment. Therefore, there is a need for developing efficient Brain Controlled Systems to help these people lead better lives. There has been considerable amount of work being done on developing brain controlled wheelchairs and emergency response systems, but one of the biggest problems with the state of the art is that the need for extensive training of the system on a subject by subject basis. This can be mentally tiring for the subject and the subject might be incapable of undergoing such training. For such reasons, there is a need for performing multi-class multi-user classification of brain activity, so that this technology can be deployed in wider and complex practical scenarios. The proposed solution aims to collect EEG data from a group of people asked to perform certain basic mental tasks, analyse their brain activity, identify correlation between the EEG signals received from different people and build a multi-class classifier to classify what task the test user is thinking of performing. So, when the end user uses the system, he is able to control his wheelchair or the system with no or minimal training. This

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will make EEG truly ubiquitous.
Our key contributions would be:

(1) Attempt to generalize EEG Data over multiple people performing Motor Imagery Task and obtain results comparable to the state of the art
(2) Implement a novel architecture to perform multi-user, multi-task classification. As per our knowledge this architecture has never been implemented for EEG data classification.

This system if made real-time can have various applications. One of them can be developing smart brain controlled wheelchairs can help people with motor disabilities lead independent lives to a certain extent. Building a brain controlled wheelchair that requires minimal training for operation will put minimal mental strain on such patients and increase the user base of this technology and enable the usage of brain controlled robots in community care centres since wheelchairs can now be shared among different people thus reducing their cost of operation. Other examples of applications can be brain controlled emergency response systems.

1.1 CHALLENGES

The biggest challenge to tackle for this project is to identify correlations between brain activities of different people and to identify if it is possible to classify brain activity with good amount of confidence in order to control a system.
EEG data is prone to be noisy and dealing with that and removing noises is also a challenge.
The other challenges are investigate the size of the dataset required to perform accurate predictions of what the user is thinking of and to build a classifier that is lightweight enough, so that can be deployed on a small processor/cloud or real time.
The dataset that we are using to train was recorded from 64 electrodes whereas the Emotiv headset has 14 electrodes. To overcome this mismatch we are planning to use principal component analysis (PCA) to reduce the number of dimensions for the training data.

2 RELATED WORK

The work [2] [3] that has been done on brain controlled robots primarily use the subjects own data to train and test the classifier, making the training process time consuming and stressful for the user. There are a lot of existing datasets that give pre-processed EEG data for subjects asked to perform different activities. There has been some recent work [15],[8] where classifiers were trained on existing EEG datasets and tested on EEG data collected by them, which has yielded significantly good results. Therefore, there is scope for extending this idea to control a mobile manipulator, with a pre-trained neural network.
Figure 1 shows some of the methods currently being used for task classification from EEG data.
Existing literature show extensive usage of Deep Learning techniques like Convolutional Neural Networks [6] [7] [8] [10] [11] and Recurrent Neural Networks [14] for multi-class classification of EEG data. There has also been some work on extracting hand-crafted features and using various classifiers to predict activities, but they have been shown not to perform very well because of the nature of the data, which is a multi-channel time series data.

3 EEG DATA

The EEG is a multivariate time signal recorded from electrodes placed on the scalp. These electrodes capture the electrical activity of the brain which has propagated from the cortex to the scalp. The parameters that govern the nature of EEG data are: the spatial and temporal resolution of the data. Spatial resolution refers to the spatial proximity of data recording points while temporal resolution refers to sampling frequency.

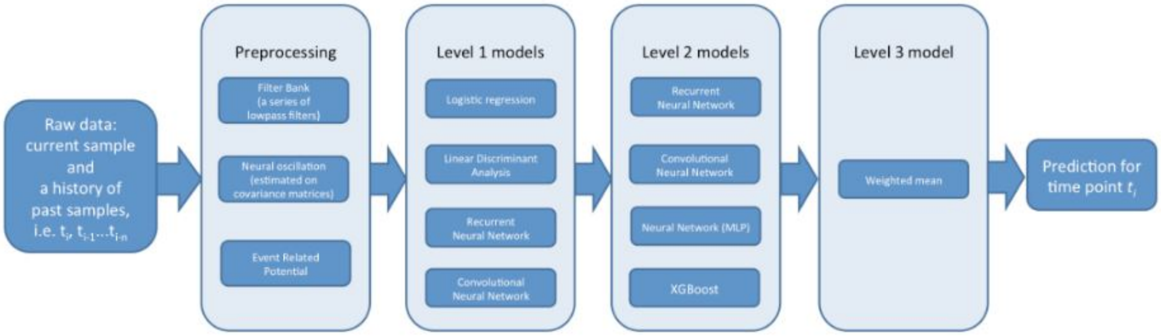

Fig. 1. State of the Art Methods for EEG Data Classification

EEG can be very high in temporal resolution based on the sampling rate used for data collection but has a limitation of spatial resolution. Low spatial resolution of EEG is mainly due to the summation of all activity from all sources inside the brain.

Motor Imagery (MI) is defined as "the mental rehearsal of movements without the movements being executed". An example of MI would be the imagination of hand movement versus the actual execution. When movement is imagined, the activity in the brain is similar to the real movement (i.e. activation of the motor cortex). BCI systems have utilized MI to control the action of devices such as wheelchairs. In MI-BCI systems, there are two main aspects: what the subject is doing, and how the computer is interpreting the input signals. In a typical MI task, a subject focuses on a screen where a cue for MI is shown to him. The subject is then required to perform motor imagery based on the shown direction.

4 METHOD

4.1 HARDWARE DESCRIPTION

We use the Emotiv EPOC+ 14 channel EEG headset which collects electrical impulses from the AF3, AF4, F3, F4, FC5, FC6, F7, F8, T7, T8, P7, P8, O1, O2 electrodes from the Frontal (F), Temporal (T), Parietal (P), Occipital (O), and Central (C) regions of the brain. The sampling rate of the headset is 128 samples per second. The positions of these electrodes on the head are shown in the figure below.

Fig. 2. EmotivEPOC+ 14 Channel EEG Headset

4.2 DATASET DESCRIPTION

We use the Motor Imagery dataset [9] from PhysioNet [5] to train our model, where the data was recorded with the help of a 64-channel EEG headset, for 109 subjects and the candidate was asked to perform a series of 4 tasks, 3 times in the following sequence.

(1) Opening one Fist
(2) Imagine opening one fist
(3) Opening Both Fists
(4) Imagine Opening Both Fists

We use the data collected by us to test the learned network to produce predictions.

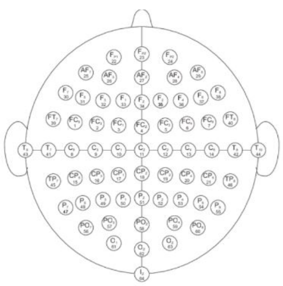

Fig. 3. Electrode Positions for 64 channel data

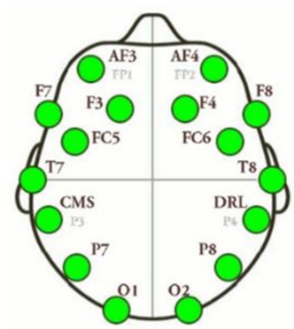

Fig. 4. Electrode Positions for the EmoticEPOC+ 14 channel headset

4.3 PRE-PROCESSING

The training dataset used is of high granularity and is of a fairly good quality, so it was just normalized with respect to the mean of the baseline for each individual.

The data from the EEG headset is extremely noisy because of facial movement and eye blinks. Therefore, artifacts in the data was removed by compensating for DC Offset, Normalizing with respect to the median value, Limiting the slew rate to eliminate impulses and high pass filtering. This is shown in Figure 5:

4.4 MOTOR IMAGERY CLASSIFICATION

We have used a CNN (Convolutional Neural Network) in conjunction with an Auto-Encoder to perform the task of motor imagery classification. An Auto-Encoder is an artificial neural network used for unsupervised learning of efficient latent codings. The aim of an Auto-Encoder is to learn a representation (encoding) for a set of data. First, the encoder transforms the input data x to the corresponding representation h by the encoder weights and biases. The decoder then transforms the hidden layer data h to the output layer data x by the decoder weights and biases. At the end of training we get a feature representation of the EEG dataset, with learned encodings.

After this we perform PCA (Principal Component Analysis) of the learned representation which consists of 64 channels and reduce the feature vector to 14 channels as our collected dataset consists of data which has 14 channels. The PCA after the Auto-Encoder helps us get the features from the 14 most relevant channels.

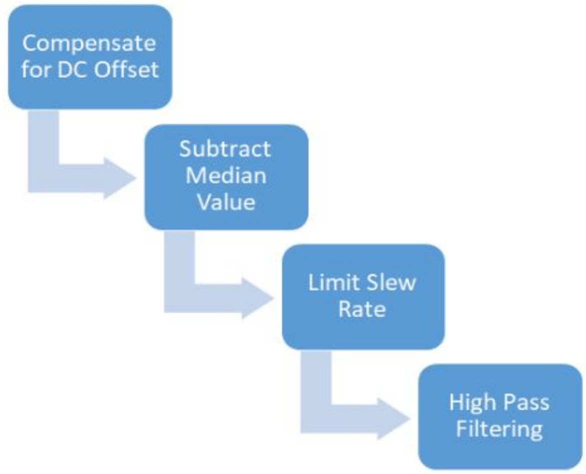

Fig. 5. Pre-processing steps for artifact removal

The final part of the classification model is the Convolutional Neural Network which finally performs the task of classification. Since our data is time sensitive, we have used a CNN with a window convolving over time. The window size used here is 4 seconds which corresponds to how long the subject has performed the task. This pipeline has been shown in Figure 6.

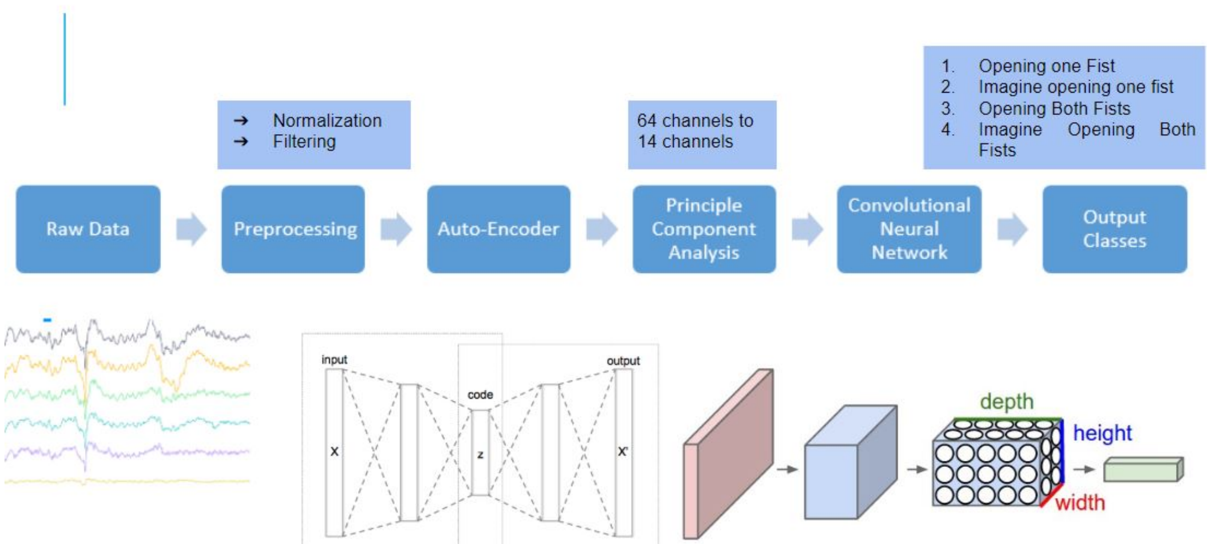

Fig. 6. Motor Imagery Classification Pipeline

4.5 IMPLEMENTATION DETAILS

We use the PyTorch toolbox of Python to implement the auto-encoder and the convolutional neural network, the EEGLab toolbox of MATLAB to analyze and visualize the data and the EmotivPRO tool to extract raw data from the headset. We write a Python script to preprocess the data.

5 USER STUDY

The user study was performed on 6 subjects who are students of University of Massachusetts, Amherst. They were asked to perform the same tasks as in the dataset used for training, in the same order in response to visual cues as shown in Figure 7 and Figure 8. Each task was performed for one minute by each subject.

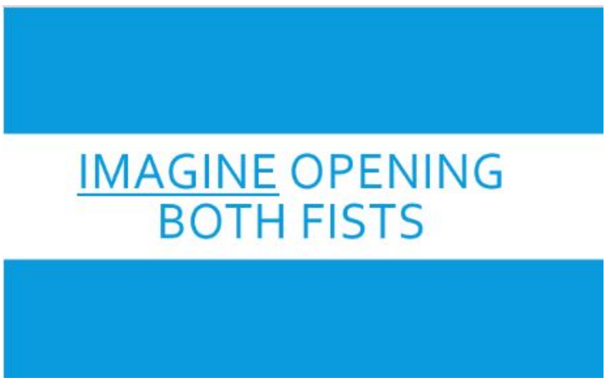

Fig. 7. User Study Visual Cue

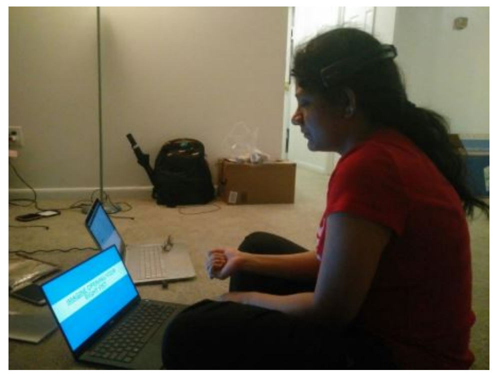

Fig. 8. User Study Setup

6 RESULTS

We trained the entire model from the Motor Imagery [9] dataset over 28 subjects. We left one subject from the PhysioNet dataset and one subject from our own collected dataset for testing purposes. We used accuracy as a measure for testing for our model. The accuracy score on the physionet subject was around 75 % whereas the accuracy on the data collected from our subject was 65

The following table shows test accuracies of our model on a part of the Motor Imagery dataset and on the collected dataset.

Table 1. Accuracy scores on Motor Imagery dataset and Collected dataset

Accuracy	Motor Imagery data	Collected Data
Score	75 %	65 %

We have not been able to test the model on the complete dataset of 109 subjects due to resource constraints, so using more data to train our models will make the model more robust.

7 DISCUSSION

As we can see from the results, the proof of concept model was able to generalise well on different subjects on the Motor Imagery dataset. It was not able to generalise as well as it did for the Motor Imagery dataset, on our

collected dataset but there can be multiple reasons for this. The data collected was on a hardware whose number of channels were different from the number of channels in the hardware used to collect the Motor Imagery dataset. The sampling frequencies of the two EEG headsets are also different.
Also data collection can be made more robust by providing a distraction free environment for the subjects. This will ensure intra subject variability between the tasks and will also help in reducing noise.

8 CONCLUSION AND FUTURE WORK

This work shows that it is possible to build a generalizable model for multi-user multi-task classification of the EEG data to predict the task the user intends to perform.
Since EEG data is time dependent, we can use classification methodologies like RNN(recurrent neural networks) and LSTM (Long short term memory) networks to perform classification on the time domain, as these kind of networks are known to preserve time information. A new architecture called WaveNet [13] can also be explored, which uses Convolutional Neural Networks with dilated convolutions.
We can also experiment with finding correlation indices between the same tasks performed by the same subjects vs. the same tasks performed by different subjects to analyze the patterns in the data.
We can also attempt the system real-time, so that it can be used for applications like brain controlled wheel-chairs and emergency response systems.

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