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**MTEch KE5105**

**Knowledge engineering project**

# SYSTEM DESIGN REPORT

# Understanding of EEG Signal (Motor Imagery) variation over days and subjects for general classification purpose

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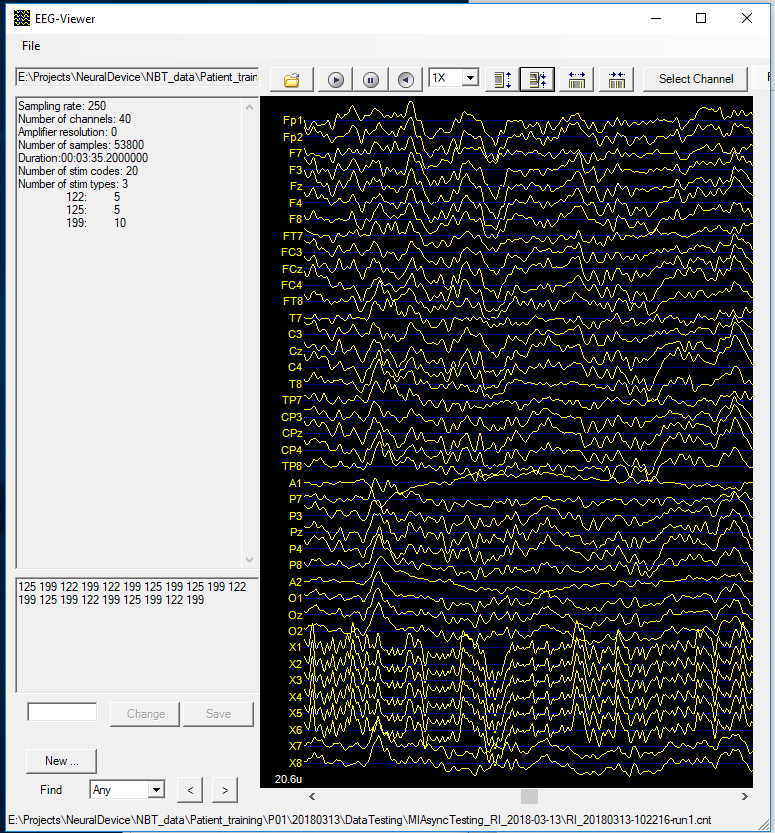
# 1.0 Introduction

# 1.1 Problem description

Imagine having to turn off the alarm, get dressed, brush your teeth, make coffee, drinking coffee as you prepare for work. Now imagine doing the above tasks again without the use of your hands.

Patients who have lost hand function because of neurological disabilities or amputation face this reality every day. To restore a patient’s basic daily life with a brain-computer interface (BCI) prosthetic device would increase their quality of life. Right now, there are low-risk and affordable options for neurologically disabled patients to control external prosthetics with brain activity.

A brain-computer interface (BCI) system is a means to convey instructions or neural signals separate from the brain’s normal output. We can record brain activity using standard scalp-recording electroencephalogram (EEG), electrocorticogram (ECoG), and near infrared spectroscopy (NIRS). EEG signals are considered as the input in most BCI systems due to its affordability and effectiveness. In this case, Electroencephalography (EEG) is a technique of recording brain signals from the human scalp.



*Figure 1: EEG signals for 7 channels*

The relationship between brain activity and EEG signals is complicated and seldom comprehended beyond specific laboratory tests. The development of affordable, low-risk, non-invasive BCI devices is dependent on further study of EEG signals.

# 1.2 Project Scope and objectives

Motor impairment is a prevalent problem that can arise from diseases such as spinal cord injury, cerebral palsy and amyotrophic lateral sclerosis (ALS) disease. The reasons for such impairment include the central nervous system being unable to transmit signals to the muscles and muscle degeneration. The understanding of nervous or brain signals can help scientists and clinicians to develop a brain computer interface (BCI) system to aid patient’s mobility (i.e. a mind-controlled wheelchair). The key to understanding these brain signals, electroencephalogram (EEG) signals, are often found in motor imagery data obtained from healthy and motor impaired patients.

The objective is to build a model that can predict / classify subject’s action as below:

1. Label data when hand is grasping, lifting, and replacing an object using EEG data that was taken from healthy subjects as they did these activities. Understand the relationship between EEG signals and hand movements is critical to developing a BCI device that would give patients with neurological disabilities more autonomy.
2. Developing an **inter subject EEG classification system** for Agency for Science, Technology and research (A\*STAR), the organisation can use our system to develop a decoder for brain signals that will aid in developing BCI devices for patients with ALS or heavy motor impairment using the open source dataset.
3. Developing an **inter-day** **EEG classification system** for Agency for Science, Technology and research (A\*STAR)

# 1.3 Benefits and Costs

Clinicians often use the electroencephalogram (EEG) as a tool for neuroimaging and the features extracted from such imagery are unique to the individual and varies across time. The ability to classify motor signals based on motor imagery can drive the development of brain computer interface devices that recognise motor signals and further aid patient movement, that are cheap and affordable as compared to other available alternatives described in introduction.

**1.3.1 Schedule:**

|  |  |  |  |
| --- | --- | --- | --- |
| Astar – EEG variation over days and subjects | | | DURATION (days) |
| START DATE | END DATE | DESCRIPTION |
| 1/8/19 | 1/31/19 | Conduct knowledge/Data acquisition | 23 |
| 1/15/19 | 2/15/19 | Complete domain familiarization | 30 |
| 2/1/19 | 3/15/19 | Literature Review | 44 |
| 3/16/19 | 4/30/19 | Initial System Design | 44 |
| 5/1/19 | 6/15/19 | Baseline Model | 44 |
| 6/15/19 | 6/30/19 | Feature Engineering & First Model | 15 |
| 7/1/19 | 7/10/19 | Hyper parameter tuning for model | 9 |
| 7/11/19 | 7/20/19 | Transfer Learning to adopt to Astar Dataset | 9 |
| 7/21/19 | 8/21/19 | Literature review for second approach | 30 |
| 8/1/19 | 8/30/19 | Modelling and data pipelines | 29 |
| 9/1/19 | 9/30/19 | Hyper parameter tuning for model | 29 |
| 10/1/19 | 11/15/19 | Transfer Learning to adopt to Astar Dataset | 44 |
| 11/16/19 | 12/10/19 | Prepare Deployable and extract trained models | 24 |
| 12/11/19 | 12/22/19 | Complete Report & Closure | 11 |

*Figure 2: Project Timeline and Gantt Chart*

**1.3.23 Cost (only Effort):**

|  |  |  |
| --- | --- | --- |
| **Component** | **Description** | **Cost (in $ / Labour)** |
| Labor Cost of Literature Study | To go through International papers that have tried to solve this problem and extract any usable information for our solution | 80 Manhours |
| Labor cost of Development | To analyze, Clean and try various solutions | 100 Manhours |
| Development & Testing Feedback | Build a workable model | 40 Manhours |
| **Total Cost** | | **220 manhours** | |

*Table 1: Manpower costs of project*

# 1.4 Solution Outline

EEG readings have been the one of the least expensive methods used to understand the brain waves and can be used to interpret the actions or intended actions of the person in question. However, EEG poses a grave challenge on its usage to classify actions of healthy or impaired patients due to various reasons. They are

1. Uncertainties in EEG signals: many neurophysiologic factors that are used to determine the characteristics of transitions between complex cognitive brain states but consequently, electrophysiological signals generate inconsistent patterns due to a varying level of subject’s awareness, mental status, motivation and fatigue among others.
2. Position of Electrodes: Position of electrodes placed on the position of the subject s scalp may vary from day to day and person to person and cannot be exactly placed at the same positions for everyone. Electrodes might short circuit each other and the EEG readings might not be accurate.
3. Motor impairment and disability: for example, an ALS patient has recorded eeg signals which is perceived to be of some action (i.e. imaging right limb movement), but there is no way of verifying if the patient really imagined that action as there are no physical signs.

A screenshot of a cell phone

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Figure 3: Quik-cap with 40 electrodes and Neuroscan amplifier with Scan 4.5

The above-mentioned problems are real and some of the solutions have been provided by veterans and researchers in this industry.

To find the variation of EEG across days for a given subject, we intend to take two approaches:

1. We intend to find a transfer function, such that, when it is applied on a given day shall yield the EEG readings of the subject of the following day / another day
2. Ignore any variation in readings of the subject and just build a model that can classify various actions of the subject

Based on the outputs and trials, a concrete and workable approach will be developed. There will be no user interface or support modules. Trained Neural Net model will be validated based on Test data to cross check whether desired results are achieved. The same will be documented based on standard practices.

# 2.0 System Description

This project is research / exploration topic. A full-fledged system shall not be built to demonstrate this proof of concept. The objective is to develop a solution to classify EEG signals on different days and on different subjects with a better accuracy based on the above-mentioned approaches and does not target to integrate the model with any BCI device. Signals from EEG will be stored and pre-processed to be able be predicted by the already trained model.

We have two sources of data for two similar problems

1. **Open Source Dataset for multisubject classification:**

This data set contains EEG recordings of subjects doing grasp-and-lift (GAL) actions/trials. There are 12 subjects in total, 10 series of trials for each subject, and approximately 30 trials within each series. The number of trials varies for each series. The training set contains the first 8 series for each subject. The test set contains the 9th and 10th series.

For each GAL experiment, the events are

1. HandStart

2. FirstDigitTouch

3. BothStartLoadPhase

4. LiftOff

5. Replace

6. BothReleased

The events are ordered as above. The **data is collected across multiple subjects on the same day**. This is used for solving classification of EEG readings across the subjects and will predict one of the above events as the output of the model.

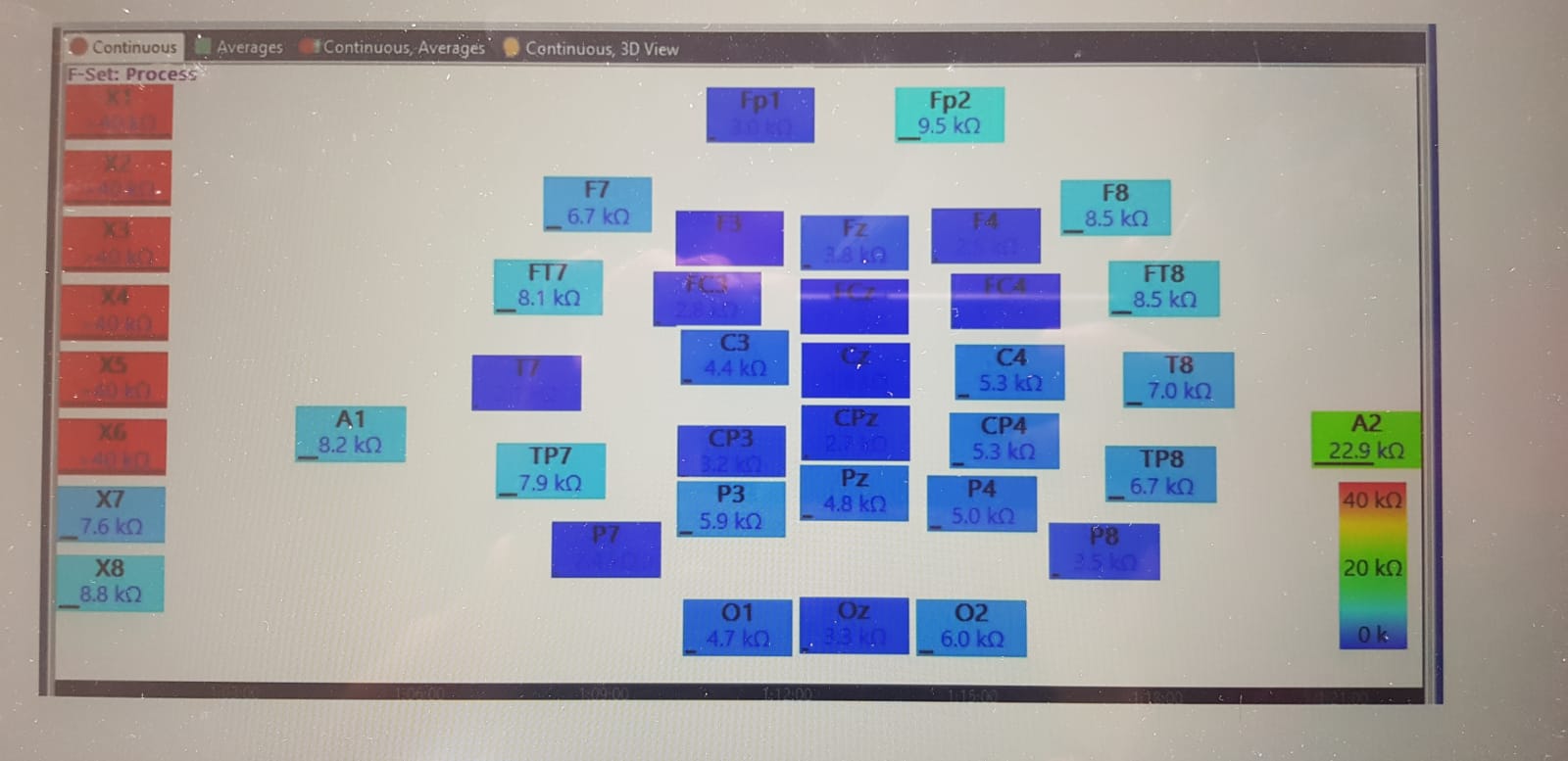
1. **A \*STAR I2R ALS Patient Data set:**

A\*STAR data set is slightly different. It has the **EEG readings collected from one ALS patient for over a period of more than 6 months**. The data can be used to solve the problem of variation of EEG readings for the same subject over a period (i.e. EEG variation over days) who are also suffering from ailments. The outcome of this model will be the number of days since it is comparing the event of the same patient across the days based on some mapping / transfer function.

Both the datasets will be converted to a common format (csv format) using matlab scripts so that same set of codes can be executed on the both the sets and processed.

# 2.1 Operational Context

A few health subjects are identified and Quik-cap with 40 electrodes are used on them. In addition, Neuroscan amplifier with Scan 4.5 are used in scalp EEG data acquisition. To set a reference, A1 and A2 are placed at left and right ear lobe respectively. Impedance of each channel are kept below 10 kΩ.



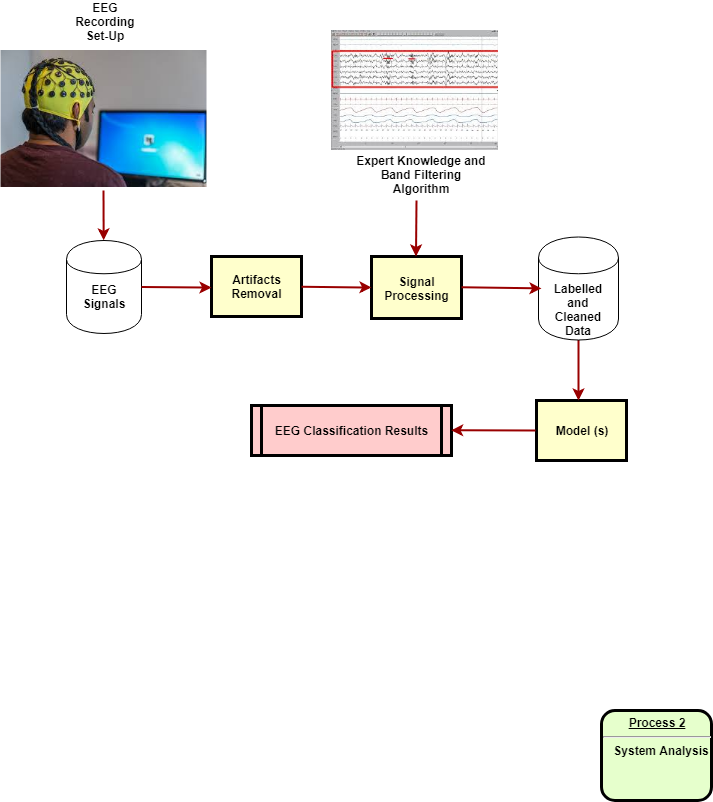
*Figure 4: Impedances associated with each channel on scalp*

The health subjects were first given 2 seconds of preparation time, then they were told to imagine, right hand movement; when the subject is idle, he or she does not imagine movement. Each motor imagery lasted 4 seconds. Right hand avatar and a gray disc were displayed on a wide screen monitor to indicate the starting of the right and idle motor imagery respectively.

EEG signals are collected and stored as .cnt files which can be **loaded**, **extracted** and **filtered** (4 to 40 Hz) before passing the data into the model. To **load** the data from .cnt files, the data in byte format is being unpacked with Python struct module, and the following meta information fields are extracted: number of channels, sampling rates, channel lists and EEG raw data. The data fields are saved in a Python class object (ContEeg) and these are known as raw train and test data. The full channel list that is loaded from file is 'F7', 'F3', 'Fz', 'F4', 'F8', 'FT7', 'FC3', 'FCz', 'FC4', 'FT8', 'T7', 'C3', 'Cz', 'C4', 'T8', 'TP7', 'CP3', 'CPz', 'CP4', 'TP8', 'P7', 'P3', 'Pz', 'P4', 'P8', 'O1', 'Oz', 'O2', 'PO1', 'PO2'.

For us to **extract and clean** the data, we distinguish right limb movement trials in the raw data and remove artifacts such as tongue relaxation. After which, Chebyshev Type II filter and noise filter are applied to the data. The data is passed into the model and classification results (binary or multiclass) are obtained. For open-source data set, .csv are passed directly into the model.

The other Open source model also works similarly



*Figure 5: EEG Signal Processing and Model Data Workflow*

# 2.2 Functional description

As the signal from the channels are one-dimensional, a classification model in the form of a shallow convolutional neural network has a 1D convolution as the input layer. For the inter subject variation of EEG signals, the output of our models will be 6 classes for the Open Source data set and the output of the model on internal A\*STAR dataset is right limb movement and idle. For the study of EEG signal variation over days, the output of the model is the number of days. This project is an exploration on categorising EEG signals across subjects and days, and this will aid other researchers to develop devices. Intended design of the device if the prediction is successful (Double click the image to see the demo).



*Figure 6: Device based on classification of EEG Signals*

# 2.3 Knowledge / Data structure & Representation

As described above, there are two sets of data being used and will be described separately.

**2.3.1 Open-Source Data Set**

The dataset is obtained from the Grasp and lift trail as mentioned [here](https://www.kaggle.com/c/grasp-and-lift-eeg-detection#evaluation) and the details if the complete experiment is provided [here](https://www.nature.com/articles/sdata201447) along with a demonstration video**.** The columns in the data files are labeled according to their associated electrode channels. You may make use of the spatial relationship between the electrode locations, as shown in this diagram:

![A close up of a logo

Description automatically generated](data:image/jpeg;base64,/9j/4AAQSkZJRgABAQEASABIAAD/4RCyRXhpZgAATU0AKgAAAAgAAodpAAQAAAABAAAIMuocAAcAAAgMAAAAJgAAAAAc6gAAAAgAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAFkAMAAgAAABQAABCAkAQAAgAAABQAABCUkpEAAgAAAAMwMAAAkpIAAgAAAAMwMAAA6hwABwAACAwAAAh0AAAAABzqAAAACAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAA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*Figure 7: Electrodes on Cap and the respective Channel Positions*

In the training set, there are two files for each subject and series combination:

* the \*\_data.csv files contain the **raw 32 channels EEG data** (sampling rate 500Hz)
* the \*\_events.csv files contain **the ground truth frame-wise labels** for all events

The events files for the test set are not provided and must be predicted. Each timeframe is given a unique id column according to the subject, series, and frame to which it belongs. The six label columns are either zero or one, depending on whether the corresponding event has occurred within ±150ms (±75frames). A perfect submission will predict a probability of one for this entire window.

**Ground Truth Data:**

The outcome of the event is stored in a separate dataset with the labels as event names and will have them marked as 1 if that event occurred against each event id.

**Columns/ Fields:**

Id, HandStart, FirstDigitTouch, BothStartLoadPhase, LiftOff, Replace, BothReleased

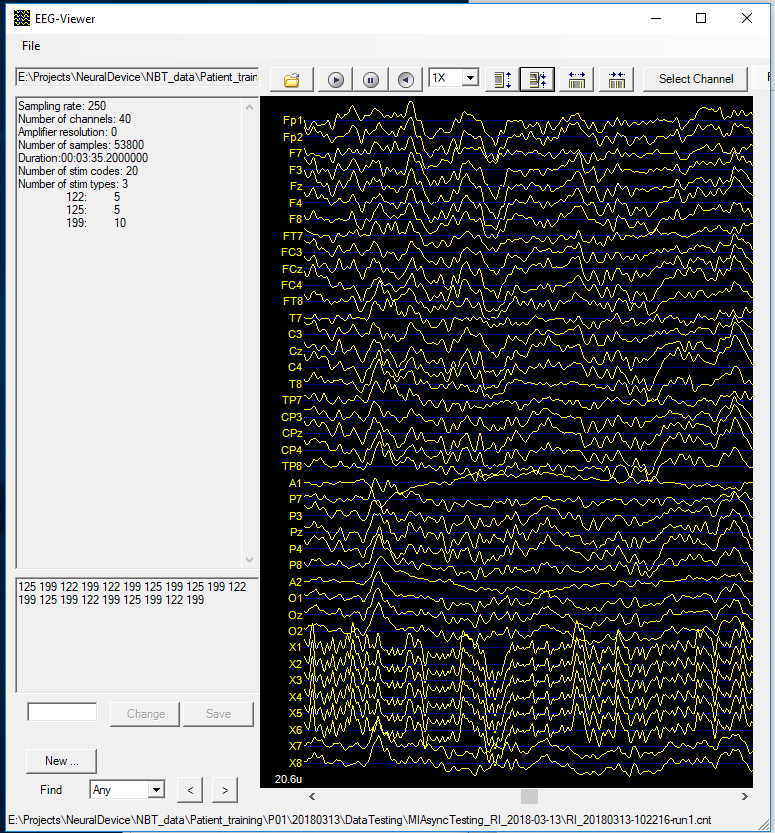
**Future data rule:**

For example, when we are predicting labels for id subj1\_series9\_11, we cannot read any frame values after 11 of series 9 from subject 1. However, Frame values pertaining to other subjects may be used.

**2.3.2 A\*STAR Institute of Infocomm Research (I2R) Dataset**

The ALS patient is tasked to imagine moving right limb. The EEG signals are recorded daily over a duration of 10 months. Electrode channels used in the ALS patient dataset consists of the following 32 channels and the electrode locations and resistances are as follows. The data is sampled at a rate of 250 Hz.

A total of 9 frequency bands were observed ranging from 4 Hz to 40 Hz and data from 32 channels are displayed as follows (with the associated electrodes). The eeg signals are labeled for a given range to identify the action or perceived action taken by the subject. The same future data rule as described above applies to A\*STAR ALS dataset as well.



*Figure 9: Full Channel Data Set Sample from A\*STAR I2R*

# 2.4 Problem solving ParadIGM

Many methods have been proposed for classification of motor imagery. For instance, Filter Bank Common Spatial Pattern (FBCSP) has been the gold standard for motor imagery classification (Krishna et al., 2016). Aside from FBCSP, deep learning techniques have been rarely used in motor imagery classification (Kumar et al., 2016).

To solve inter subjects and variation of EEG across the days, we will employ deep Convolutional Neural Nets to classify EEG signals across patients and days. First, the model will be trained to classify the trained events across different subjects using the filter bank approach as described below. Then the trained model is taken and used against the dataset of ALS patient across different days using transfer function (dataset is compatible) using convolutional neural nets / LSTM. This way, the base model has been trained based on different subjects who are healthy, and the data is collected on the same day. This eliminates any uncertainty factors due to readings collected on different days and that the subject performs the perceived action, not any other action. We will also experiment other neural network architectures and tune the parameters in order to maximise the yield from the model.

For Opensource dataset, the approach is as described below. Similar approach will be used for AStar as well, but the architecture may be modified in order to achieve better results based on the need. From an EEG point of view, brain patterns related to hand movement are characterized by spatio-frequential change in EEG signal. Depending on the event you try to classify, it was a prediction problem, or a detection problem.

The 6 events were representing different stages of a sequence of hand movements (hand starts moving, starts lifting the object, etc.). One of the challenges is to consider the temporal structure of the sequence i.e. the sequential relationship between events. In addition, some events are overlapping, and some others are mutually exclusive. As a result, it is difficult to decide whether to approach this as Finite State Machine or Multi class problem.

Finally, true labels are extracted from EMG signal, and provided as a +/-150ms frame centered around the occurrence of the event. This 300ms frame has no physiological meaning i.e. there is no fundamental difference between a time sample at +150ms and another one at +151ms, while they have different labels. Therefore, another difficulty was to increase the sharpness of the prediction to minimize occurrence of false positives around edges of the frames.

In the above context, we built a 3-level classification pipeline:

Level1 models are subject-specific, i.e. will be trained independently on each subject. Most of them are also event-specific. Their main goal is to provide support and diversity for level2 models by embedding subject and events specificities using different types of features.

Level2 models are global models (i.e. not subject-specific) that are trained on level1 predictions (metafeatures). Their main goal is to consider the temporal structure and relationship between events.

Level3 models are ensembles of level 2 models with reducing overfitting and better performance.

# 2.5 Technical Architecture & Design

The deep learning algorithm that we plan to develop to classify motor imagery across different subjects should be close to or even surpass the classification performance of FBCSP. The classification problem that this project aims to solve is to classify movement motor imagery (i.e. subject moves hand or thinks of moving a hand) from idle motor imagery (i.e. subject does not move or think of moving a hand). Current FBCSP Algorithm has a classification accuracy of approximately 82% to 83% (T. Yang *et al*., 2016) and this project aims to match or surpass this classification accuracy.   EEG signals are bandpass-filtered to obtain signals in a 9 frequency bands and CSP filters are applied to the signals and time series are observed. This will be achieved as illustrated in the diagram below.



*Figure 9: Data Processing Pipeline*

**Data Preprocessing**

Although the raw data is well structured and cleaned, Signals contain noise of varying frequency and should be pre-processed. For instance, a very high sampling frequency of the EEG in contrast with the relatively low rate of change of the performed action can create different issues: data changes very rapidly, but the action stays the same, thus the any change in signal data is meaningless and can be deemed as noise. Also, a time series model would receive a lot of quickly changing data while the classification output never changes.

The first possible step is to filter the data with a low-pass filter. After that, we can balance the data by subsampling, i.e. we can keep only one data point every 100,500, etc. This also helps reducing the time dimensionality and reduces the correlation. Others include removing the singularity of the data, excluding bad trials by inspection and profiling and eliminating noise based on certain rules such as using low pass filter to eliminate all high frequency and medium frequency information that does not contain any information pertaining to the user action or user perceived action. Other methods also can be used based on the quality of the data.

# 2.5.1 Architecture - Model Pipeline

In this section we provide an overview of the 3-level model pipeline that was used in the solution.

**Level 1**

The validation mode models are trained on series 1-6 and predictions are produced on series 7-8 - these predictions are the training data (metafeatures) for level2 models. The testing mode trains models on series 1-8 and predicts on test series 9-10.

**Cov** - Covariance matrices are features used for detection of hand movement from EEG. They contain spatial information (i.e. correlation between channels) and frequential information (i.e. variance of the signal). Covariance matrices are estimated using a sliding window (about 500 samples) after bandpass filtering of signal. We have two types of covariance features:

1. **AlexCov** - events' labels are mapped to a sequence of 7 (consecutive) brain states. For each brain state, the geometric mean of associated covariance matrices is estimated (log-Euclidean metric) and the Riemannian distance to each centroid is calculated, producing a feature vector of size 7. This is known as supervised manifold embedding with Riemannian metric.
2. **RafalCov** - like AlexCov but applied on events individually, producing a 12-element feature vector (class 1 and class 0 for each event).

**FBL** – as signal contains predictive information at low frequencies, we introduced a "Filter Bank" approach. It consisted of concatenating together results from applying several 5th order Butterworth lowpass filters (cutoff frequencies at 0.5, 1, 2, 3, 4, 5, 7, 9, 15, 30 Hz) on the signal.

**FBL\_delay** - as FBL, but a single row/observation is also augmented with 5 past samples that together spanned an interval of 2 seconds (1000 samples in the past, only taking each 200th sample). These additional features allow models to capture temporal structure of events.

**FBLC** - Filter Bank and Covariance matrices features concatenated together into a single feature set.

**LDA** (with different normalizations applied to train and test data prior to learning) built on above features provided an event-specific view on the data. There will be also two level 1 Neural Network approaches that are not event-specific (i.e. trained on all events simultaneously).

**CNN** - this is a small 1D/2D convolutional neural network (input -> dropout -> 1D/2D conv -> dense -> dropout -> dense -> dropout -> output) that is trained on a current sample and a subsampled portion of past samples.

**Level 2**

These models are trained on predictions of *level 1* models. They are trained in *validation* and *test* modes. *Validation* will be done in a cross-validation fashion, with splits done per series (2 folds). Predictions from folds are then meta-features for *level 3* models.

**AdaBoost** - gradient boosting machines can achieve good performance and provide diversity for next level models. They are trained for each event separately and will have each subjects' IDs included as a feature to calibrate predictions between subjects. By heavily subsampling input data, we can introduce regularization and reduce overfitting.

**RNN** – RNNs are computationally inexpensive and achieve a very high AUC when trained with the ADAM optimizer (1 epoch for convergence). The RNN architecture can be modified as follows (input -> dropout -> GRU -> dense -> dropout -> output).

**CNN** - shallow (single convolution layer without pooling, followed by single dense layer) will be trained on a subsampled history time course of 3s. We span filters across all predictions for a single time sample and introduce strides between time samples. Such models provide diversity required in *Level 3* models.

**Level 3**

*Level 2* predictions are ensembled using Random Forest or such algorithms to maximize AUC and reduce overfitting.

# 2.6 Future Work

As such to improve the accuracy of the predictions and continuously evolve with respect to every single subject using the BCI, we are considering using Reinforcement learning to improve the accuracy.

GAN’s may be used to simulate or generate the signals pertaining to that specific user. If the method is successful, BCI can be further extended to a variety of similar patients affected by seizures and epilepsy.

# 3.0 HARDWARE & SOFTWARE

The workstation that we used for this project is equipped with 16.0 GB RAM, Intel® Core™ i7-6700HQ CPU with 8 cores, each at 2.60 GHz. The GPU of the workstation used is NVIDIA GeForce GTx 960M (4G). For ease of test running models on smaller datasets that were uploaded, we also used Google’s Collaboratory with 2 Intel® Xeon® CPUs running at 2.20 GHz each or Tesla K80 GPU.

We develop our models in Python 3.6 with the following libraries.

1. Scikit-learn 0.20.1
2. Matplotlib 3.0.2
3. Numpy 1.15.14
4. Scipy 1.1.0
5. Tensorflow 1.12
6. PyTorch 1.0
7. Keras 2.1.6
8. Python 2.7
9. [pyriemann](https://github.com/alexandrebarachant/pyRiemann) 0.2.2 (from sources)
10. [mne](https://github.com/mne-tools/mne-python) 0.10.dev0 (from sources)
11. [XGBoost](https://github.com/dmlc/xgboost) 0.40 (from sources)
12. Theano 0.7.0
13. CUDA 7.0.27
14. [Lasagne](https://github.com/Lasagne/Lasagne) 0.2.dev1 (from sources)
15. [nolearn](https://github.com/dnouri/nolearn) 0.6adev (from sources)
16. [hyperopt](https://github.com/hyperopt/hyperopt) 0.0.2 (from sources)

Entirety of the code will be run on Ubuntu 16.04.

For the A-Star dataset, using transfer learning-

Chassis: Silent Mid-Tower Chassis, 650W 80PLUS Gold PSU, 3 x 3.5" internal drive bays, USB 3.0 and Audio in front

Motherboard:

* + Intel® Xeon® W series processor, (8) DDR4 RDIMM slots (up to 512GB memory), 3x PCI-E 3.0 x16 and 1x PCI-E 3.0 x4 (16/16/16/NA or 8/16/16/4), Intel® C422 Chipset, Dual 1GbE RJ45 ports, 7.1 HD Audio, USB 3.0
  + CPU: (1) Intel Xeon W-2155 (10-core) \*\* 3.30GHz / 13.75MB L3 / 140W / 2666Mhz
  + Memory: (192) GB DDR4-2666 ECC RDIMM - 32GB x 6pcs
  + Graphics/GPU: (1) NVIDIA GTX 1080 Ti, 3584 CUDA cores, 11GB GDDR5X

# 3.1 Appendix

1. EEG – Electroencephalogram
2. ALS – Amyotrophic Lateral Sclerosis
3. BCI – Brain Control Interface
4. CPU – Central Processing Unit
5. GPU – Graphical Processing Unit
6. CUDA – Compute Unified Device Architecture
7. FBLC – Filter bank low pass and covariances
8. FBL – Filter bank Lowpass
9. FBCSP – Filter Bank common spatial pattern
10. LDA - Linear Discriminant Analysis
11. CNN – Convolutional Neural Network
12. RNN – Recurrent Neural Network
13. ADABoost – Adaptive Boost
14. LSTM - Long Short-Term Memory networks

# 4.0 References

1. T. Yang *et al*., "EEG Channel Selection Based on Correlation Coefficient for Motor Imagery Classification: A Study on Healthy Subjects and ALS Patient," *2018 40th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, Honolulu, HI, 2018, pp. 1996-1999.

doi: 10.1109/EMBC.2018.8512701

2. S. Kumar, A. Sharma, K. Mamun and T. Tsunoda, "A Deep Learning Approach for Motor Imagery EEG Signal Classification," *2016 3rd Asia-Pacific World Congress on Computer Science and Engineering (APWC on CSE)*, Nadi, 2016, pp. 34-39.

doi: 10.1109/APWC-on-CSE.2016.017

3. B. Blankertz, R. Tomioka, S. Lemm, M. Kawanabe and K. Muller, "Optimizing Spatial filters for Robust EEG Single-Trial Analysis," in IEEE Signal Processing Magazine, vol. 25, no. 1, pp. 41-56, 2008.  
doi: 10.1109/MSP.2008.4408441

4. B. Blankertz, R. Tomioka, S. Lemm, M. Kawanabe and K. Muller, "Optimizing Spatial filters for Robust EEG Single-Trial Analysis," in IEEE Signal Processing Magazine, vol. 25, no. 1, pp. 41-56, 2008.  
doi: 10.1109/MSP.2008.4408441

5. Alexandre Barachant, Stéphane Bonnet, Marco Congedo, Christian Jutten. *Classification of covariance matrices using a Riemannian-based kernel for BCI applications*. Neurocomputing, Elsevier, 2013, 112, pp.172-178.

6. Alexandre Barachant, Stéphane Bonnet, Marco Congedo, Christian Jutten. *Multiclass BrainComputer Interface Classification by Riemannian Geometry*. IEEE Transactions on Biomedical Engineering, Institute of Electrical and Electronics Engineers, 2012, 59 (4), pp.920-928.

7. Steven C. Schachter, Joseph I. Sirven. *How to Read an EEG*. Retrieved from: https://www.epilepsy.com/learn/diagnosis/eeg/how-read-eeg

8. **Sucholeiki, R. *Normal EEG Waveforms*. Retrieved from:** <https://emedicine.medscape.com/article/1139332-overview>.

9. Honchar, A. *Deep learning: the final frontier for signal processing and time series analysis.* Retrieved from: https://medium.com/@alexrachnog/deep-learning-the-final-frontier-for-signal-processing-and-time-series-analysis-734307167ad6.

10. Jones, G. *Using Machine Learning to Predict Epiletic Seizures from EEG Data*. Retrieved from: <https://www.mathworks.com/company/newsletters/articles/using-machine-learning-to-predict-epileptic-seizures-from-eeg-data.html>.

11. Fahimi, F., Zhang, Z., Goh, W. B., Lee, T, Ang, K. K. Guan, C. *Inter-subject Transfer Learning with End-to-end Deep Convolutional Neural Network for EEG-based BCI.*

12. Schirrmeister, R. T., Springenberg, J. T., Fiederer, L. D. J., Glasstetter, M., Eggensperger, K., Tangermann, M., Hutter, F., Burgard W., and Ball, T. (2017). Deep learning with convolutional neural networks for EEG decoding and visualization. Human Brain Mapping.

13. Di Palo, N. *From brain waves to robot movements with deep learning: an introduction*. Retrieved from: <https://towardsdatascience.com/from-brain-waves-to-arm-movements-with-deep-learning-an-introduction-3c2a8b535ece>.

14. I. Iturrate, L. Montesano and J. Minguez, "Robot reinforcement learning using EEG-based reward signals," 2010 IEEE International Conference on Robotics and Automation, Anchorage, AK, 2010, pp. 4822-4829. doi: 10.1109/ROBOT.2010.5509734

*15. Adapting Brain Signals With Reinforcement Learning Strategies for Brain Computer Interfaces, Dr. Elmar Rueckert; Prof. Dr. Jan Peters; Dr. Ing. Moritz Grosse-Wentrup*

*16. Within- and across-trial dynamics of human EEG reveal cooperative interplay between reinforcement learning and working memory; Anne G. E. Collins ; Michael J. Frank*

*17. Kay Gregor Hartmann, Robin Tibor Schirrmeister and Tonio Ball, “EEG-GAN: Generative adversarial networks for electroencephalograhic (EEG) brain signals”, 5 Jun 2018*

*18. M. Arvaneh, C. Guan, K. K. Ang and C. Quek, "Optimizing Spatial Filters by Minimizing Within-Class Dissimilarities in Electroencephalogram-Based Brain–Computer Interface," in*IEEE Transactions on Neural Networks and Learning Systems*, vol. 24, no. 4, pp. 610-619, April 2013.  
doi: 10.1109/TNNLS.2013.2239310*

*19. EEG data space adaptation to reduce intersession nonstationarity in brain-computer interface.;Arvaneh M, Guan C, Ang KK, Quek C.*

*20. Using Machine Learning to Predict Epileptic Seizures from EEG Data* [*https://www.mathworks.com/company/newsletters/articles/using-machine-learning-to-predict-epileptic-seizures-from-eeg-data.html*](https://www.mathworks.com/company/newsletters/articles/using-machine-learning-to-predict-epileptic-seizures-from-eeg-data.html)