BCI Cursor Control

EEG-Based Cursor Control with Deep Recurrent Convolutional Neural Networks

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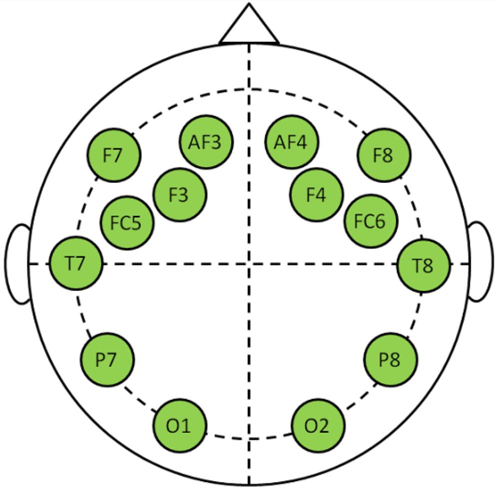
Introduction



BCI

Brain–computer interface (BCI) systems are allowing humans and non-human primates to drive prosthetic devices such as computer cursors and artificial arms with just their thoughts.
Invasive BCI systems acquire neural signals with intracranial or subdural electrodes, while **noninvasive** BCI systems typically acquire neural signals with scalp electroencephalography (EEG)

EEG

EEG refers to the recording of the brain's spontaneous electrical activity over a period of time, as recorded from multiple electrodes placed on the scalp.

Related Study

In previous study, a decoder model of Multiple Linear Regression was used to predict the velocity of the computer cursor from EEG.

Cursor Movement

Measured by a vector

Magnitude: RNN regression

Direction: CNN classification

REGRESSION

PIPELINE

EEG RAW DATA

FILTING

PARAMETER SETTINGS

LSTM RNN

EVALUATION

01

STEP

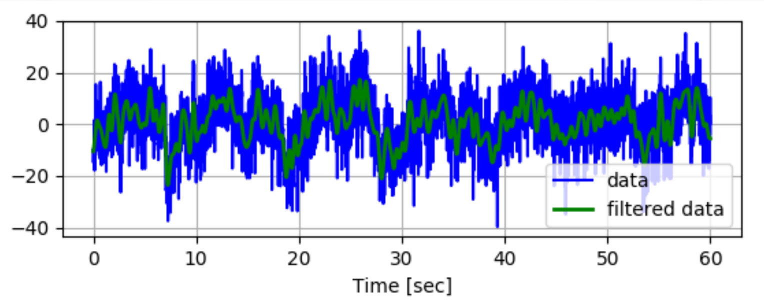
EEG RAW DATA

- 34 subjects
  - 10 trials/subject
    - 14 channels/trial
      - 60 seconds/channel
        - 128 samples/second

34 models
1 million samples/model

02
STEP

FILTING



Why Low Pass?

Alpha wave:	8-13 Hz
Beta wave:	13-30 Hz
Theta wave:	4-7Hz
Effective brain wave in Cursor Control (eye movement):	<5Hz
Optimal band pass:	TBD

03 PARAMETER SETTINGS

Passband selection → Channel significance → NN algorithm → Lag time selection

Butterworth Filter

Cut off frequency

Significant Channel

Horizontal: F7 & F8
Vertical: TBD

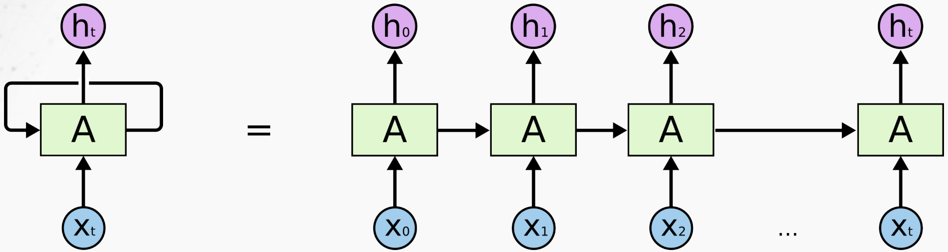
RNN

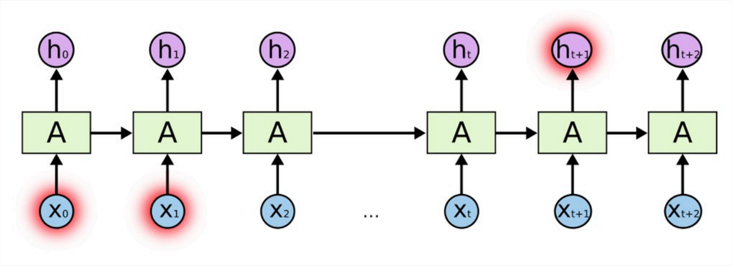
LSTM
GRU

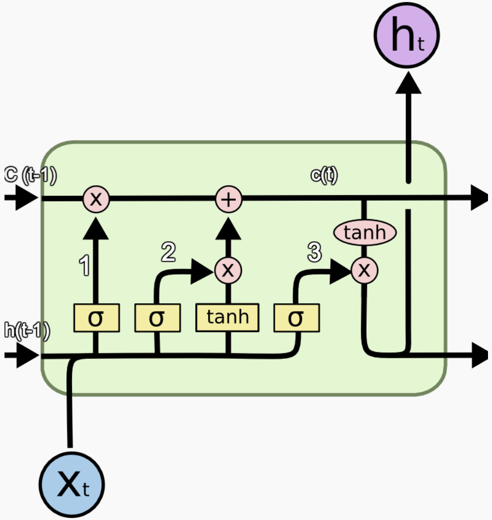
Perception Lag

Memory effect
Input size

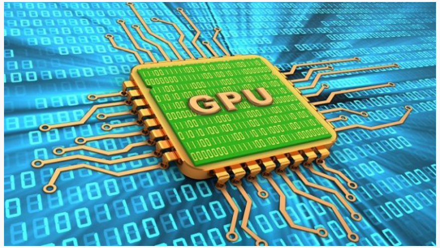
04 LSTM RNN







Speed Up!



05 EVALUATION

Quests

Some questions we may answer through this research

1. Higher prediction precision
2. Useful facts such as perception lag, channel relations
3. Other NN algorithms and filters
4. Online implementation

Cursor Movement Classification

PIPLINE ❯

01 Input data

02 Preprocessing

03 Basic Models

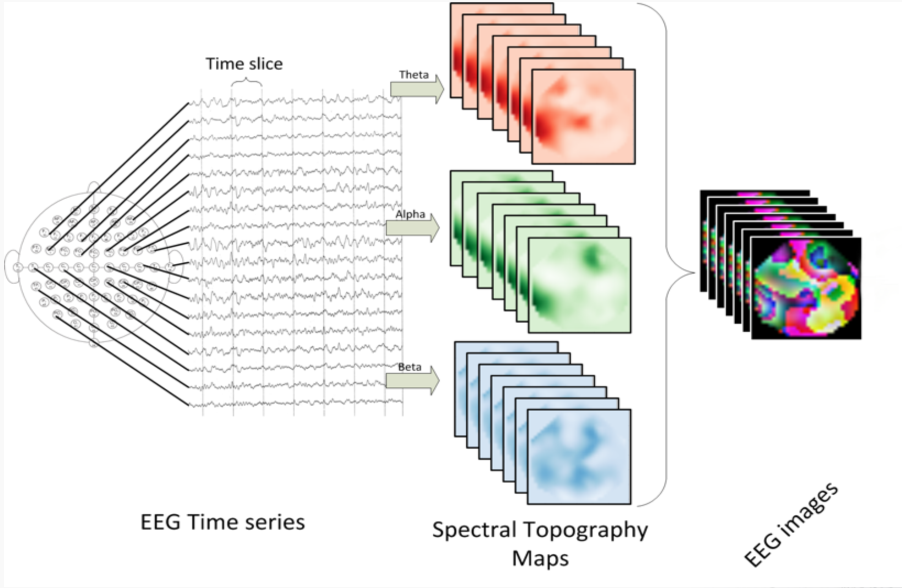
04 Training & Ensembling

01 INPUT

-Raw EEG data from 14 electrodes of the EEG headset, sampling rate at 128Hz
-Collected from 34 subjects, each practiced 10 trials, 5 trials in horizontal direction and 5 trials in vertical direction.

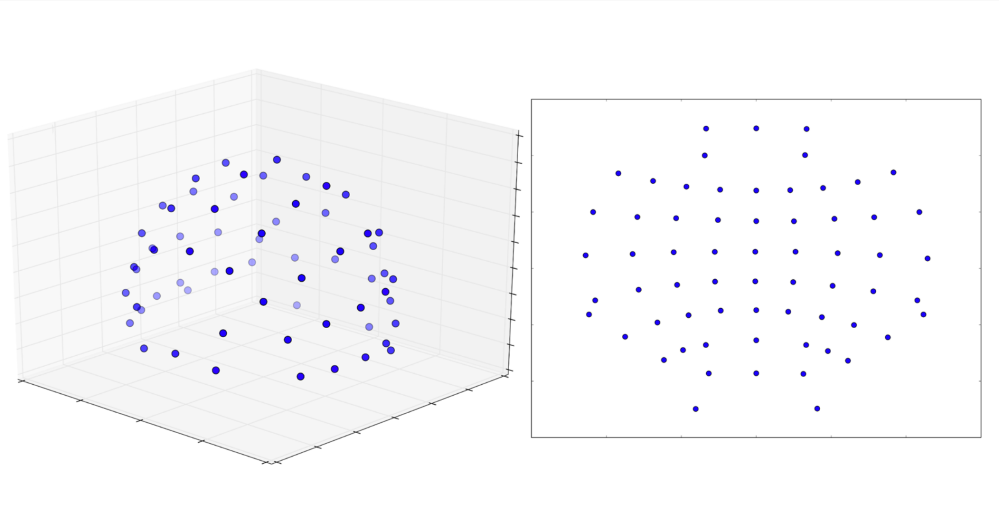
02 PREPROCESSING

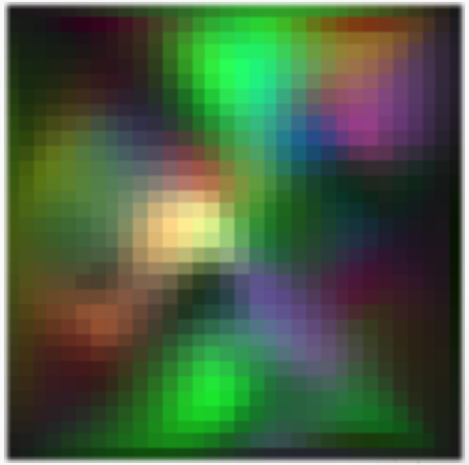
-Transform EEG activities into a sequence of topology-preserving multi-spectral images such that the **spatial**, **spectral** and **temporal** structure of the EEG data are preserved



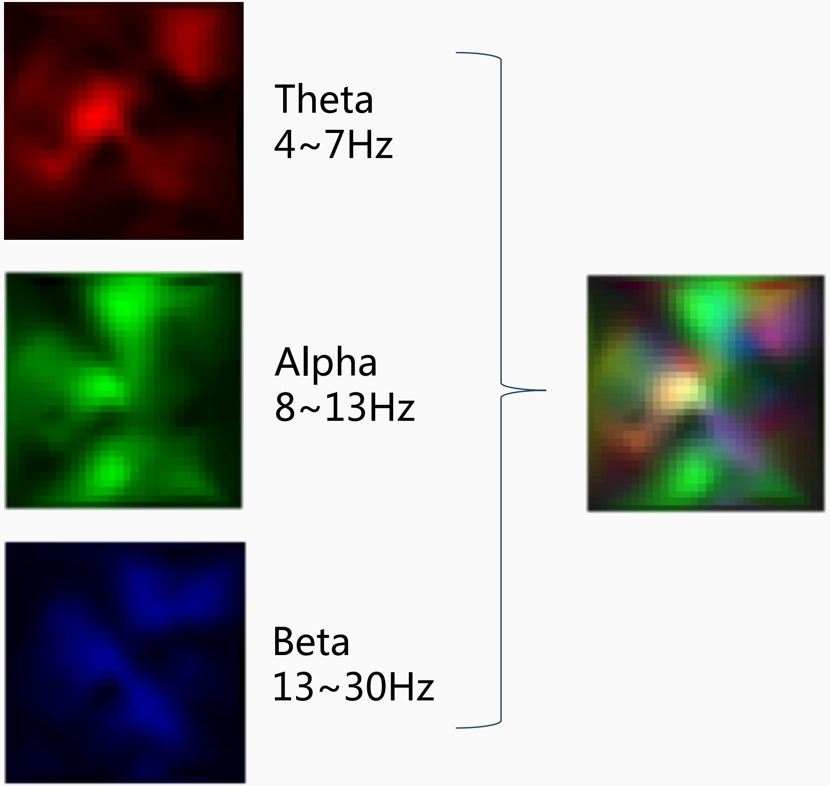
SPATIAL

Given the 3-D coordinates of the 14 electrodes, project them into 2-D surface using **Azimuthal Equidistant Projection** such that the relative distance between the neighboring electrodes are preserved. To make the image, Apply **Clough-Tocher scheme** to interpolate the scatted power measurement over the scalp and to estimate the values between the electrodes over a certain size of mesh.





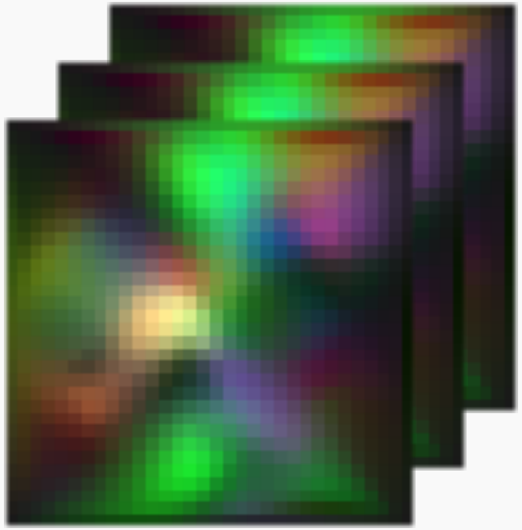
SPECTRAL



-The three colors corresponds to **three different frequency** of interest. Then the three spatial maps are merged to form a image with three color channels.

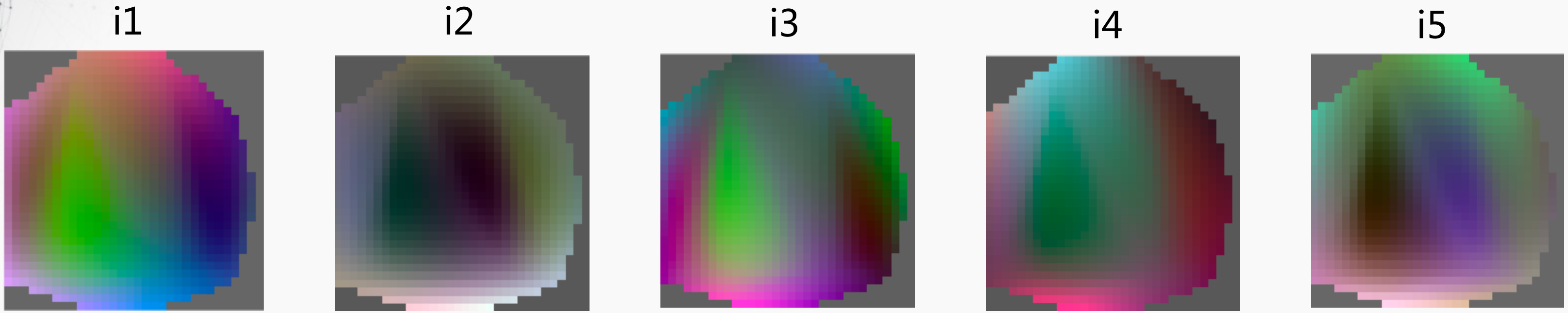
-Each image describes the **bandpower** of each frequency for the 14 electrodes within a certain **time interval**. In our case, each trial last for 60s with 128Hz sampling rate. Hence we decide the time interval to be **1s or 1.5s or 2s**.

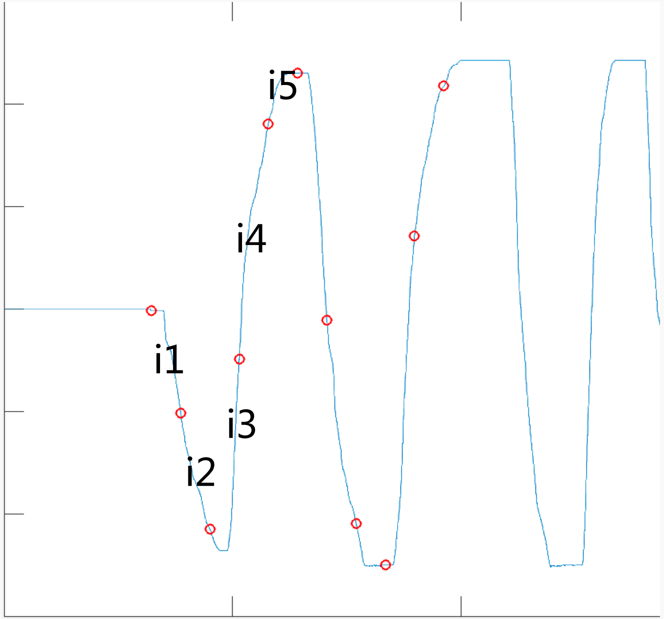
TEMPORAL



60 images per trial if the time interval set to be 1s

Those sequence of images put together produce “EEG movies”, given as an input to the models for classification. In this case, the temporal structure of EEG data is preserved



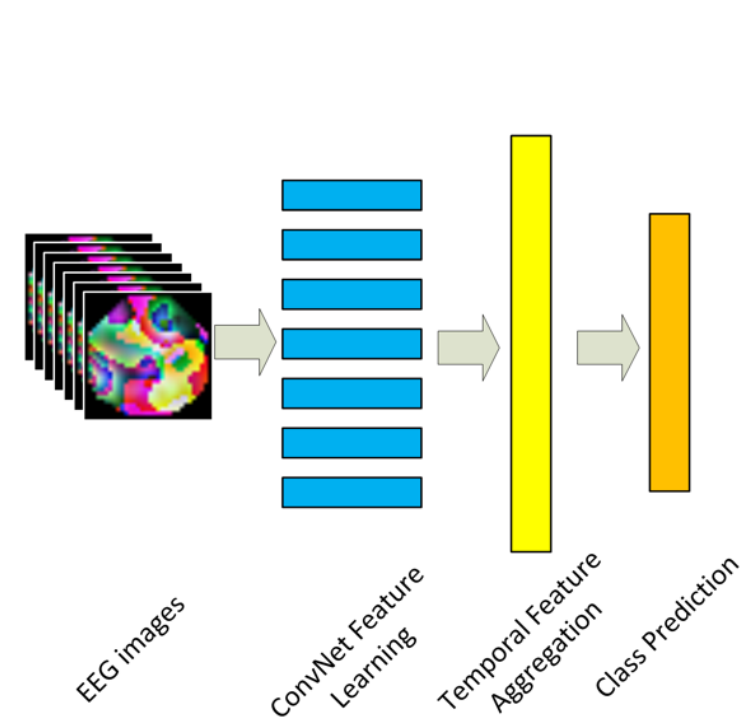


👆images made from the first 5 second EEG signal of subject 1’ s first horizontal trial

R: Theta 4~7 G: Alpha 8~13 B: Beta 13~30

👈The ground truth cursor movement of the horizontal trial

03 BASIC MODELS



-Since **CNNs** are robust to **partial translation** and **deformation** of input patterns, and **RNNs** delivers state-of-art performance to applications involving dynamics in **temporal sequences**, we plan to implement a **combination** of these two networks.

-First apply **ConvNet** to single frame to find the best CNN structure configuration, then apply the best configuration to every single frame. After that, we apply the outputs of each images to some **RNN** structure like **LSTM** to do the temporal feature aggregation

04 Training & Ensembling

Training different multi-frame architectures and apply several regularization method to avoid overfitting. After that, apply Gradient Boosting to find the optimal model with the highest accuracy.

Reference:

Bashivan, et al. "Learning Representations from EEG with Deep Recurrent-Convolutional Neural Networks." International conference on learning representations (2016).

THANKS