EEG-Based Cursor Control with Recurrent and Convolutional Neural Networks

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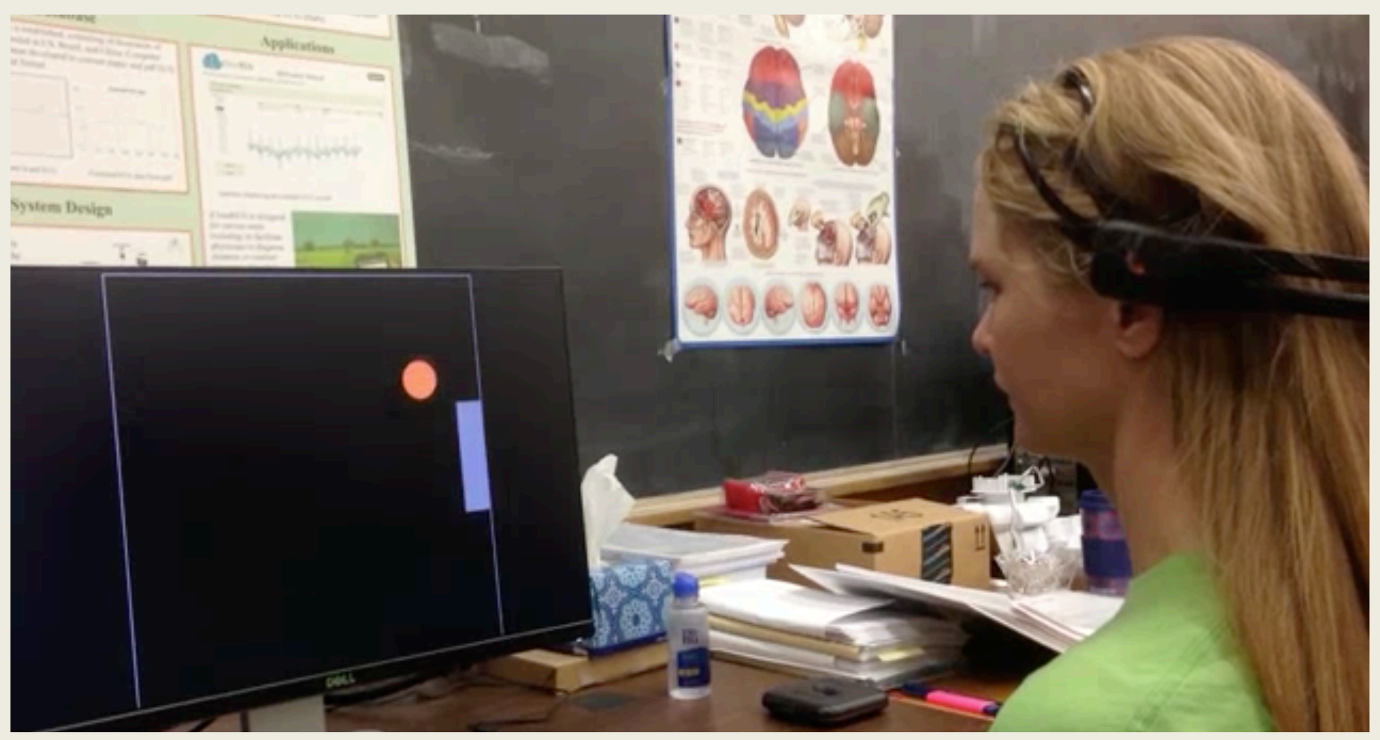
Introduction

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** 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.



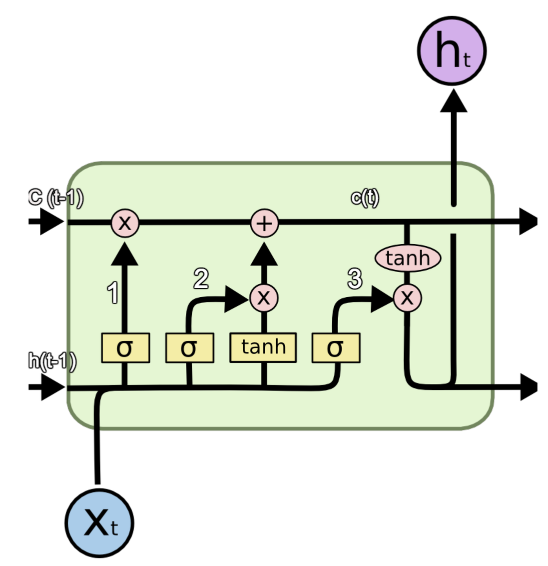
A picture captured during EEG-based Cursor Control experiments[2]

Objectives

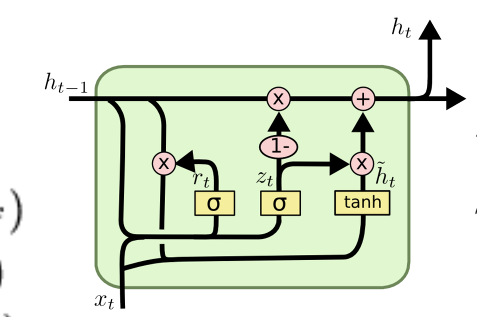
Task A: Build RNN regression models to predict the velocity of the cursor.

Task B : Build a binary classifier between horizontal and vertical cursor movement by transforming EEG activities into topology-preserving multi-spectral images and training a VGG like CNN to classify the images.

LSTM vs GRU



The Data are fed into the BasicLSTMCell and GRUCell respectively. Through input layer, hidden cell layer, and output layer, the prediction result will be compared to the velocity of the real cursor movement. These two neural network models will be evaluated by the final MSE result.



$$f_t = \sigma_g(W_f x_t + U_f h_{t-1} + b_f)$$
$$i_t = \sigma_g(W_i x_t + U_i h_{t-1} + b_i)$$
$$o_t = \sigma_g(W_o x_t + U_o h_{t-1} + b_o)$$
$$c_t = f_t \circ c_{t-1} + i_t \circ \sigma_c(W_c x_t + U_c h_{t-1} + b_c)$$
$$h_t = o_t \circ \sigma_h(c_t)$$

$$z_t = \sigma\left(W_z \cdot [h_{t-1}, x_t]\right)$$
$$r_t = \sigma\left(W_r \cdot [h_{t-1}, x_t]\right)$$
$$\tilde{h}_t = \tanh\left(W \cdot [r_t * h_{t-1}, x_t]\right)$$
$$h_t = (1 - z_t) * h_{t-1} + z_t * \tilde{h}_t$$

Cross Validation

Leave one out cross validation method is used for testing. Since every subject has 5 trials in one direction, we use 4 of them for training and the rest for testing. This is to prevent the possible overfitting problem, especially when we are having a relatively small data set.

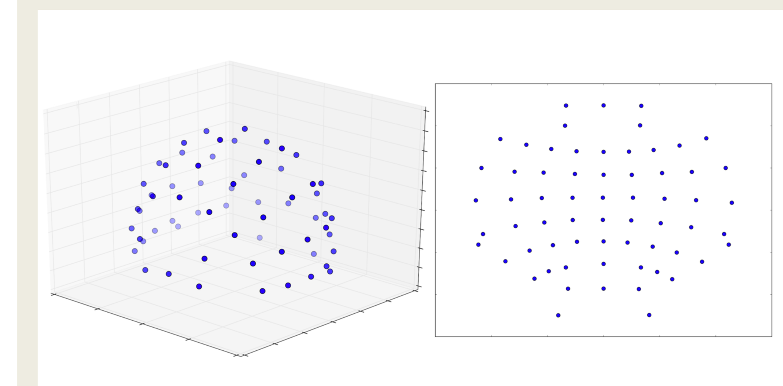
Parallel Programming

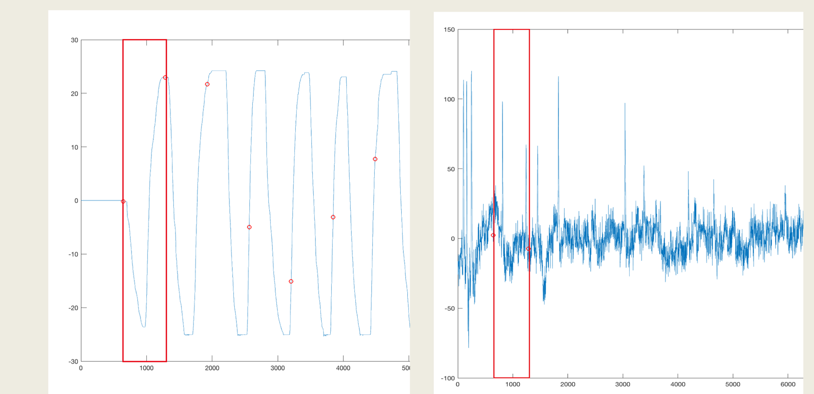
Since the horizontal and vertical data will be trained separately, and we are generating the individual model for each subject, 68 models will be generated. And for each model, multiple parameters in the learning program need to be determined. By using parallel programming, we can boost the calculation speed, therefore, the more appropriate parameter settings can be found faster.

Preprocessing

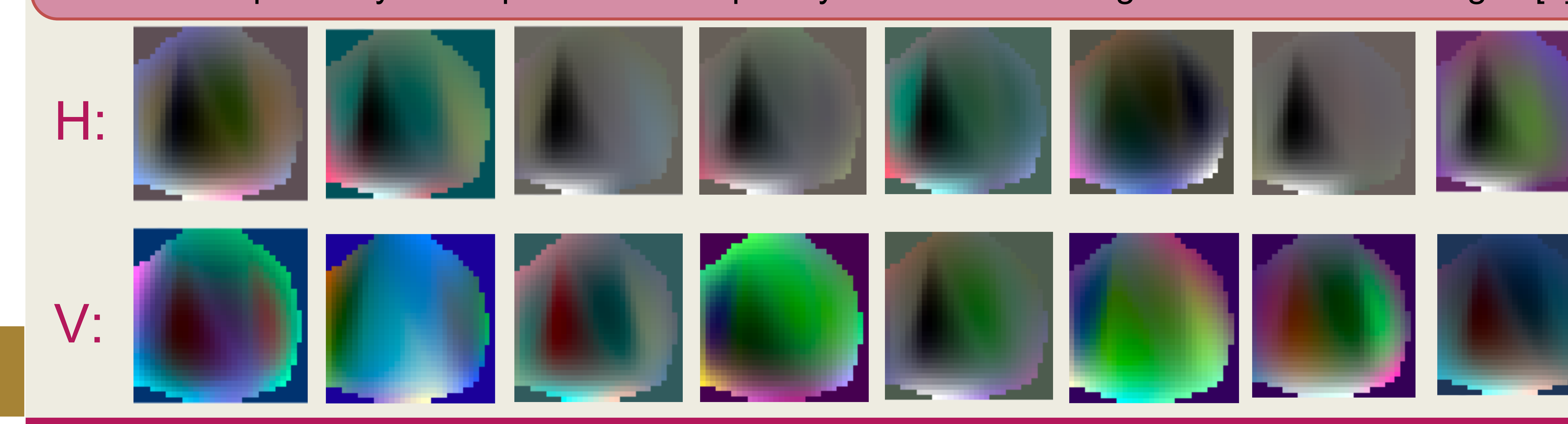
Project 3-D electrode location to 2-D surface using **Azimuthal Equidistant Projection**

Chop the input data into 12 time window, each last for 5 sec.



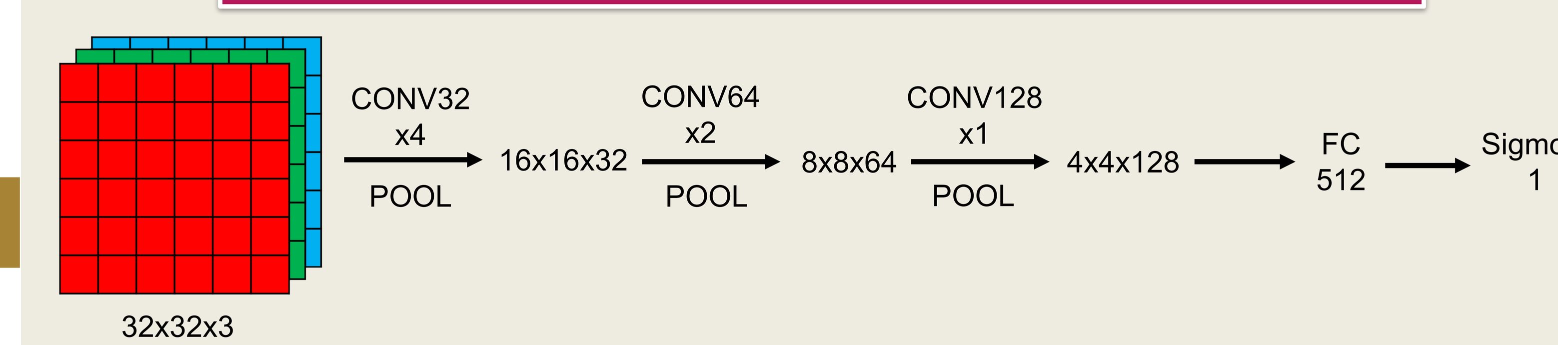


Calculate the band power of each time interval with 3 frequency band(**Delta**, **Theta**, **Alpha**). Then apply **Clough-Tocher Scheme** to interpolate the scattered power into 3 spatial maps in R,G,B channels respectively corresponds to 3 frequency bands. Then merge them into RGB images [1]



Modelling & Cross Validation

CONV=3x3 filter, s=1 MAX-POOL=2x2, s=2 Sample size=120



Batch Normalization is applied after each CONV layer to accelerate the training by reducing internal covariance shift.

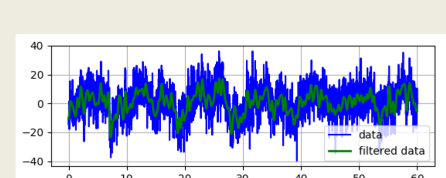
Dropout at a rate of 0.5 is applied after each POOL layer to reduce overfitting by preventing complex co-adaptations on training data

Model / Accuracy (avg.)	CONV32*4,CONV64*2,CONV128*1	CONV32*2,CONV64*2,CONV128*1	CONV32*4,CONV64*2,CONV128*1,no BatchNorm	CONV32*4,CONV64*2,CONV128*1,no DropOut
TEST SET (Train#=100,Test#=20)	69.0%	71.43%	51.25%	73.0%
Leave one trial out C.V. (Trial#=10)	64.17%	62.67%	35.0%	55.0%

Task A: Regression

Pipeline

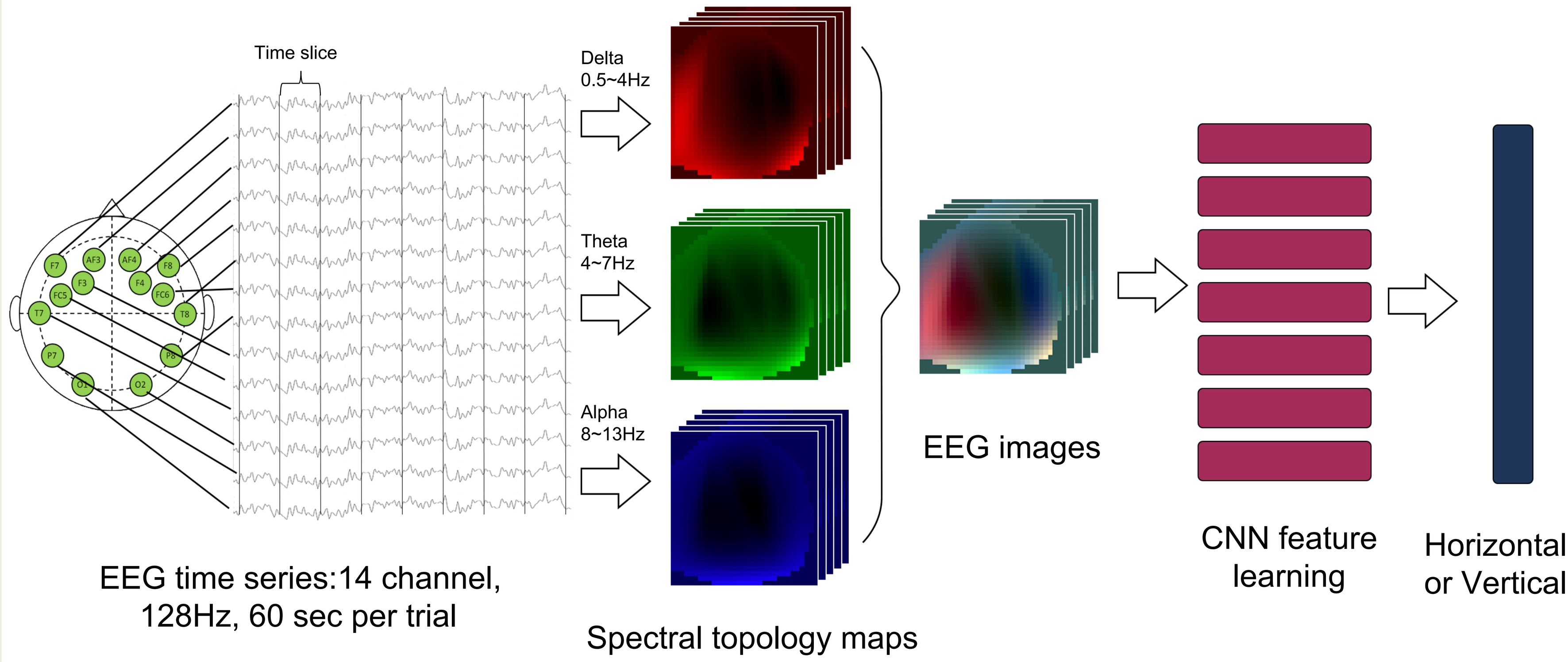
EEG RAW DATA	10 trials/subject, 14 channels/trial, 60 seconds/channel, 128 samples/second
FILTING	Low Pass Butterworth Filter Cut off freq: 2 Hz
PARAMETER SETTINGS	Passband Selection, Channel Significance, NN Algorithm, Lag Time Selection
RNN	Long Short Term Memory (LSTM) Gated Recurrent Unit (GRU)
EVALUATION	Leave One Out Cross Validation Measurement: Squared Error



Task B: Classification

Pipeline

Input → Preprocessing → Modelling&CV → Prediction



Future Work

- Integrate the regression model and classification model for real time cursor control
- Try other NN algorithms and filters, improve prediction precision

Acknowledgements

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- BP High Performance Computing Team

References

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

[2] Video 2. Brain Controlled Computer Cursor: A novel approach for fast training in cursor control task. Available: http://volweb.utk.edu/~rabiri/