Gaze-independent Brain Computer Interface based on Covert Shifts in Attention

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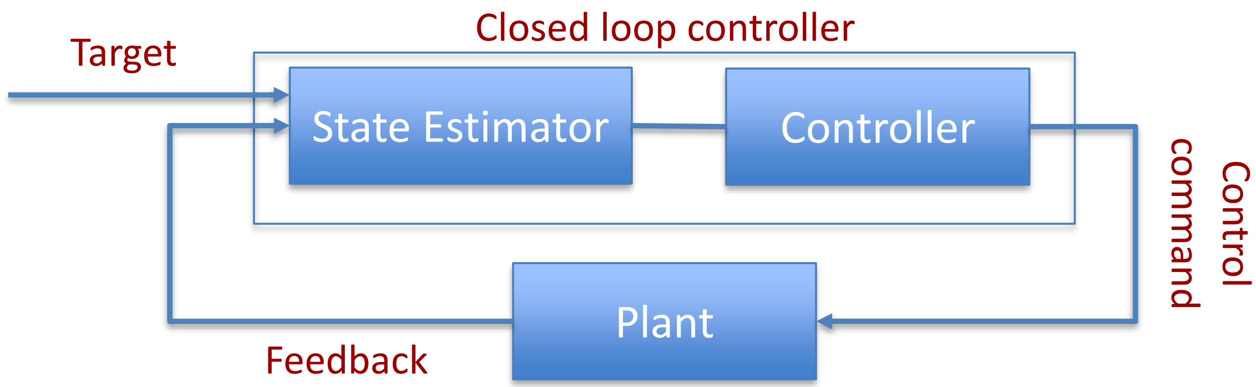
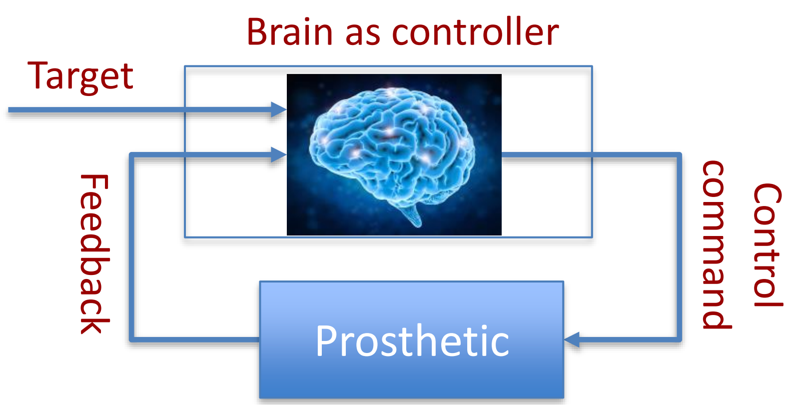
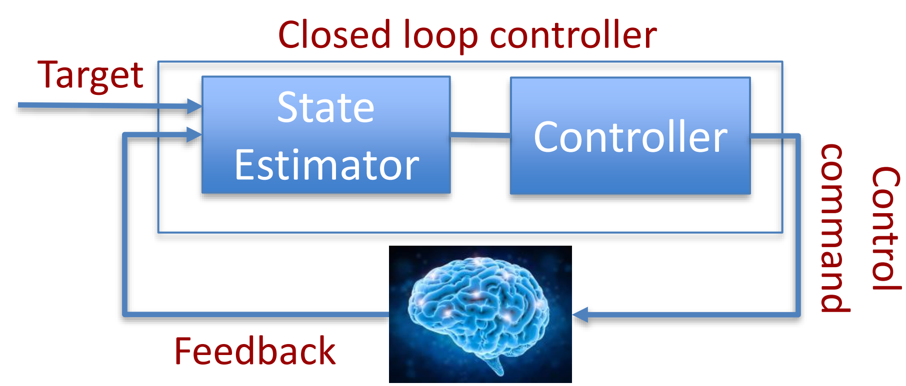
What is a Brain Computer Interface?



Type I BCI



Type II BCI



Motivation

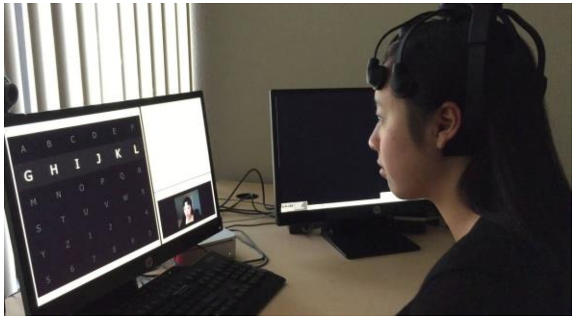


Fig. 1: P300 Speller

Renders very good performance upon fixating user's eyes on the screen => strenuous for use over long duration of time

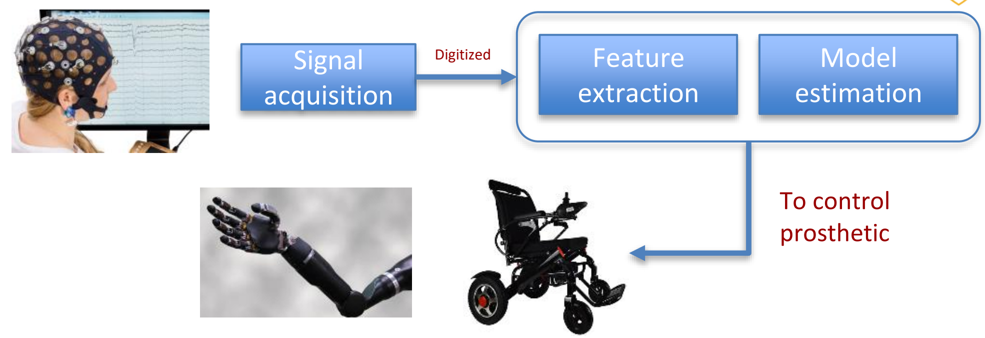


Fig. 2: BCI based on Motor Imagery

- *Affected by the noise in eye movement*
- *Twitches in limbs can cause noise and affect the BCI performance*

Can we develop a BCI paradigm which is gaze-independent?

[1] P. Sauseng W. Klimesch W. Stadler M. Schabus M. Doppelmayr S. Hanslmayr W. R. Gruber N. Birbaumer, **A shift of visual spatial attention is selectively associated with human EEG alpha activity,** *European Journal of Neuroscience* **22,** 11(Dec 2005)

[2] Matthias S Treder, Ali Bahramisharif, Nico M Schmidt, Marcel AJ van Gerven & Benjamin Blankertz , **Brain-computer interfacing using modulations of alpha activity induced by covert shifts of attention,** *Journal of Neuroengineering and Rehabilitation* **8**, 24(2011)

Previous Work

[1]

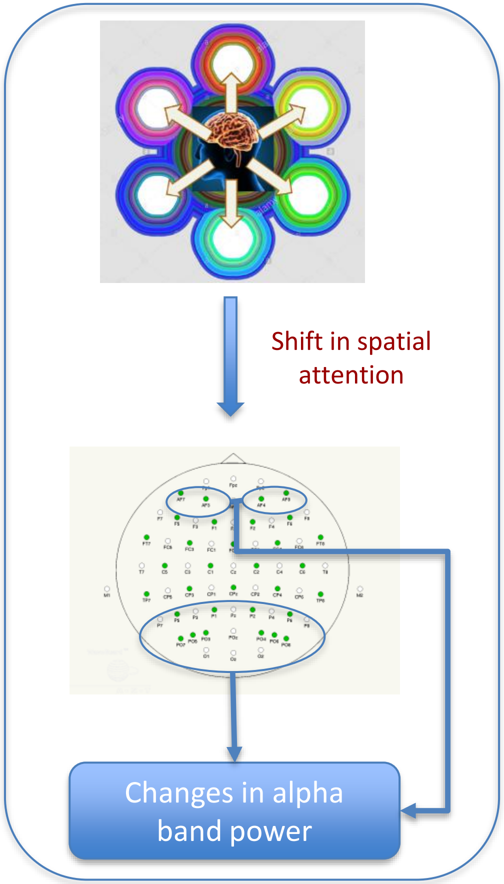
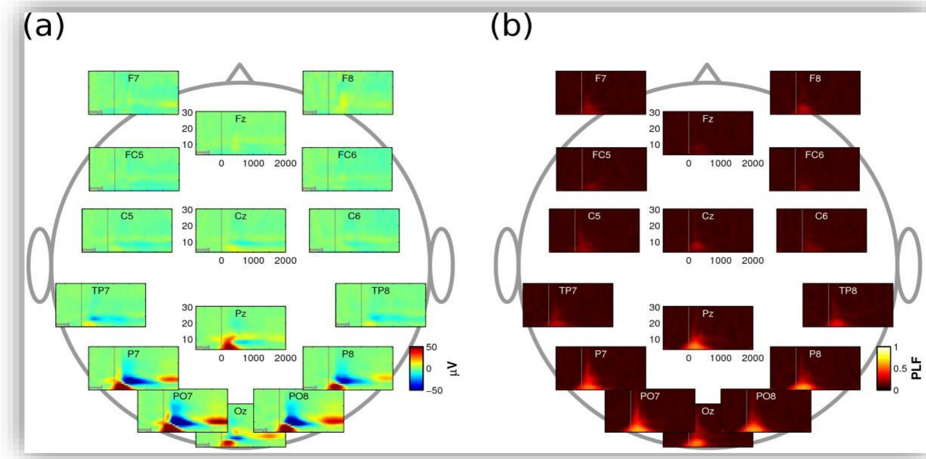


Fig. 3: Illustration of neurophysiology of changes in attention



[2]

Fig. 4: Typical plots of (a)wavelet spectra and (b) phase-locking that indicate the neurophysiological aspect of covert shifts in attention of a participant

Study [2] shows that at the onset of cue, there is a synchronization in the delta and theta power bands, an initial desynchronization and a subsequent synchronization in the alpha power band in the parieto occipital regions of the cortex

Modelling covert shifts in attention

User shifts attention covertly

Data from Neurotechnology Group, TU Berlin

EEG data acquisition

Pre-processing and feature extraction

Model Estimation

To control an external device

Fig. 5: Open loop neural decoding of EEG signals associated with coverts shifts in direction of attention

What data was this study based on?

[2]

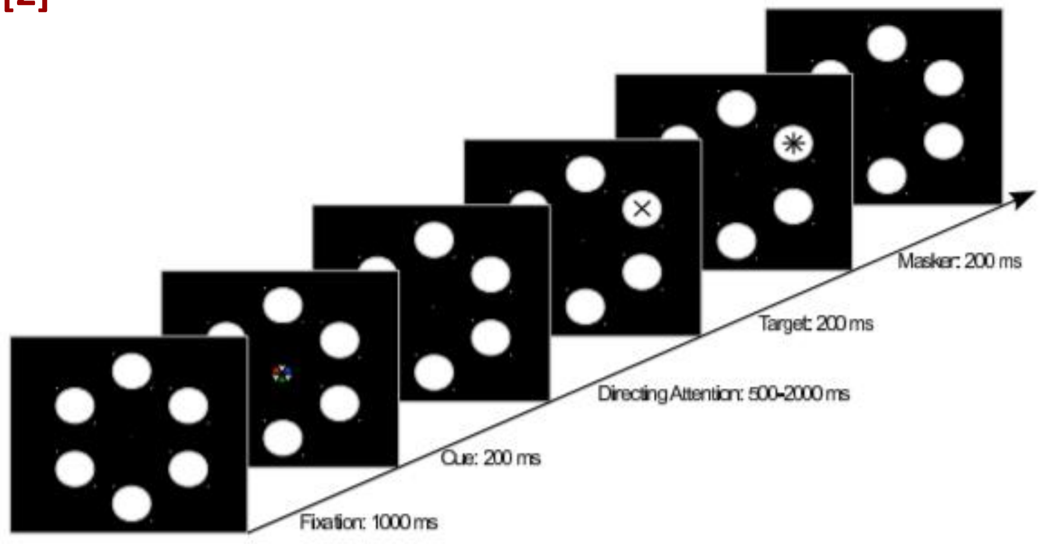


Fig. 6: Sequence of cues in the EEG data acquisition task per trial

- Electroencephalography (EEG) data was obtained from BCIHorizon2020 data repository released by Neurotechnology Group, TU Berlin
- Data corresponds to 8 healthy participants
- 600 trials per participant

Theory

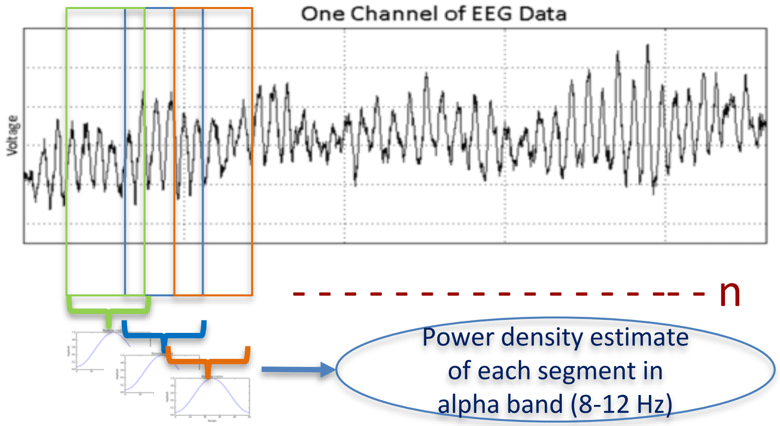


Fig. 7: Illustration of Band power estimation using Welch method

Model estimation was done by training a binary classifier for each pair of directions for each participant.
Used the Generalized linear model family of models for model estimation.

Logistic regression: GLM with binomial random component and logit link function
Poisson regression: GLM with Poisson random component and log link function

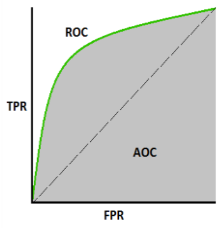
1) Accuracy of classification

$$acc = 1 - \frac{\sum_{i=1}^{N} \mathbb{1}_{(y^{(i)}_{predicted} \neq y^{(i)}_{true})}}{N}$$

2) F-Score

$$Fscore_{(c)} = \frac{2TP_{(c)}}{2TP_{(c)} + FP_{(c)} + FN_{(c)}}$$

3) Area under the receiver-operating curve (AOC)



Details of Implementation

Feature Extraction

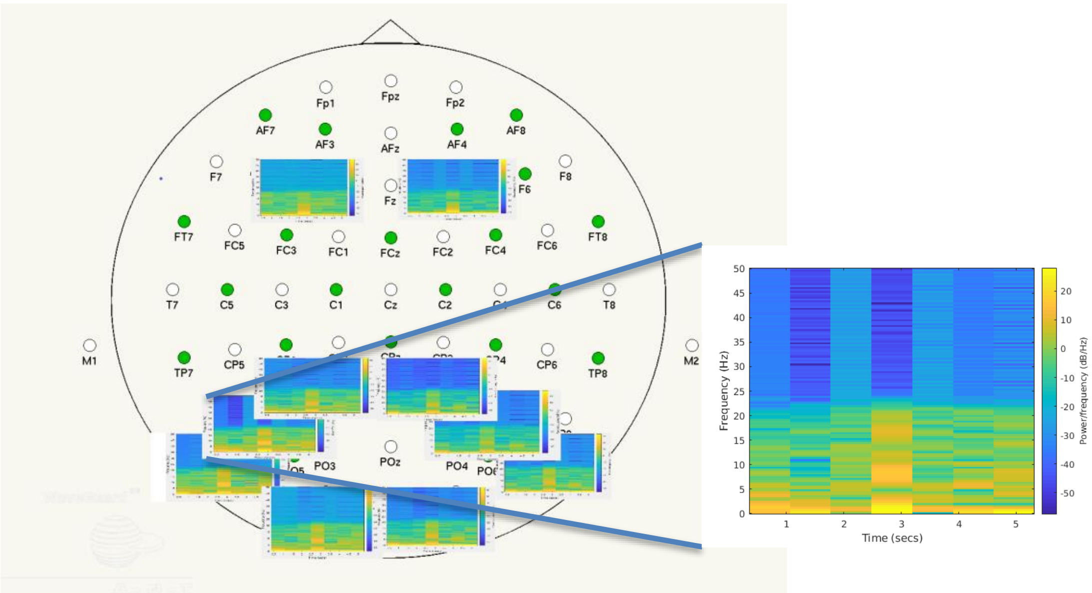


Fig. 8: Typical power spectrogram plot over pre-frontal and parieto occipital regions across one trial

Alpha band powers [8-12 Hz] over the electrodes corresponding to the parieto-occipital region (['PO9', 'PO10', 'PO7', 'PO3', 'PO4', 'PO8', 'O1', 'O2']) when the user shifted attention covertly were used as features.

Model Estimation

80% of data used for training

Generalized linear model fit

L2-regularizer to handle overfitting

10-fold cross validation

Results for Poisson Model

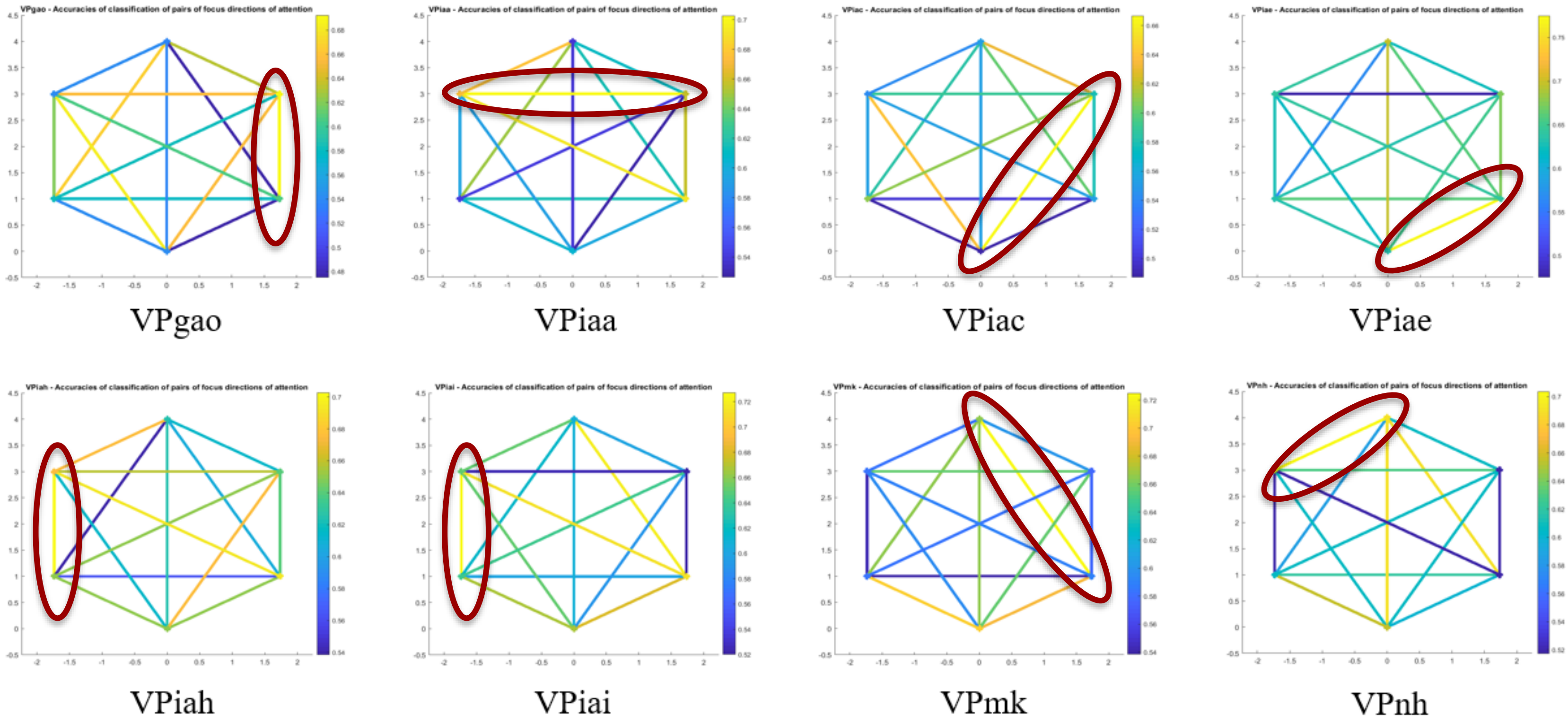
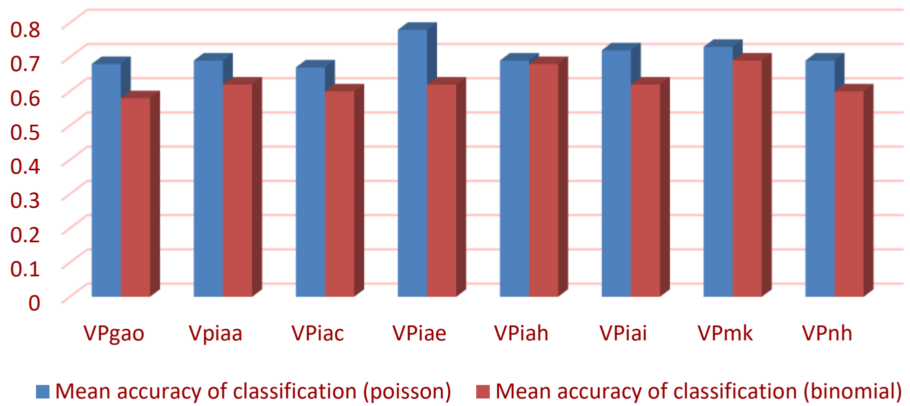


Fig. 9: Accuracies in classification for different pairs of directions across participants – classification using Poisson model

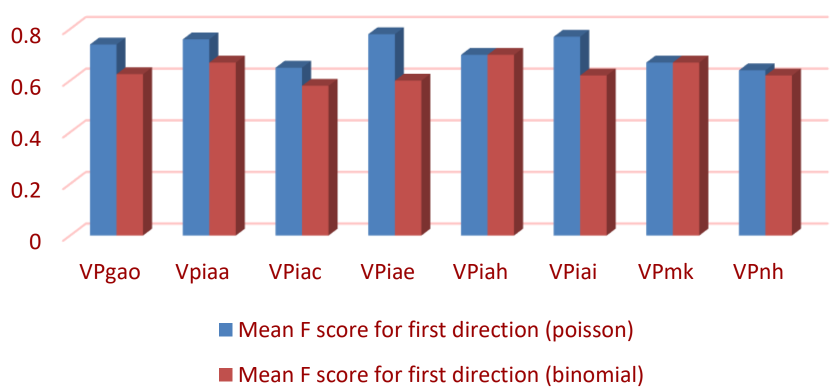
(Highlighted are the most distinguishable pair of directions)

Results

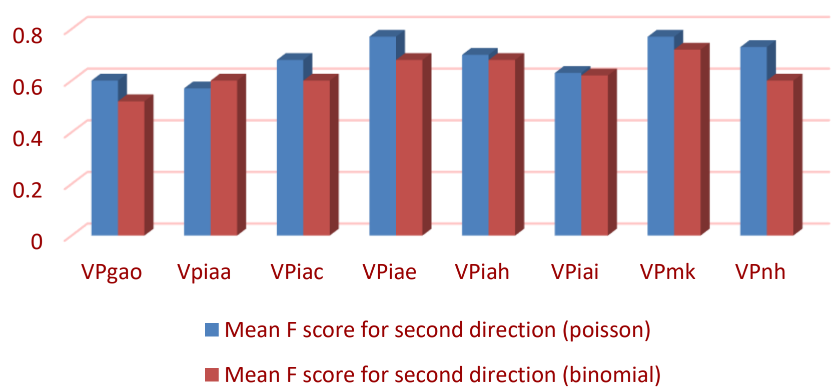
Comparison of mean classification accuracy



Comparison of mean F score for the first direction



Comparison of mean F score for the second direction



Observations

1) Increase in alpha band power in the parieto-occipital regions are good indicators of direction of covert attention shifts. This region being the visual processing center of the brain might contribute to the visualization of spatial attention

2) Although the alpha band power increases in the pre-frontal cortex too, it is not distinguishable between different directions of attention shifts.

3) Fig. 9 indicates that the most distinguishable directions of attention are subject-dependent. It also indicates that for certain participants such as VPiac, VPmk and VPiae, only one or two pairs of directions were distinguishable.

4) The Poisson regression model renders better average performance per participant than logistic regression. This indicates that the target variable might not be dichotomous.

Conclusion

- This study confirms the conjecture in [1] and [2] that changes in alpha band power in the parieto occipital region of the brain can be used to design a brain computer interface based on covert shifts in attention.
- As it is gaze-independent, it can potentially be used over long durations of time.
- The results from model estimation suggest that the underlying distribution of the target variable could be better fit to a Poisson than a binomial.

Future Work

- This study can be extended to understand the effects of inability to pay attention due to mental fatigue.
- With availability of larger amount of data, more complex models can be explored.
- This study was based on a dataset which was collected in a controlled environment and was very clean. It might be interesting to understand the effects of potential corruption in data while performing navigational tasks which require directed spatial attention.

References

[1] P. Sauseng W. Klimesch W. Stadler M. Schabus M. Doppelmayr S. Hanslmayr W. R. Gruber N. Birbaumer, **A shift of visual spatial attention is selectively associated with human EEG alpha activity,** *European Journal of Neuroscience* **22,** 11(Dec 2005)

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[3] Cuntai Guan, M. Thulasidas and Jiankang Wu, **High performance P300 speller for brain-computer interface,** *IEEE International Workshop on Biomedical Circuits and Systems*, 2004., Singapore, 2004, pp. S3/5/INV-S3/13, doi: 10.1109/BIOCAS.2004.1454155.

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[5] Brendan Z. Allison et al., **Towards Practical Brain Computer Interfaces,** *Biological and Medical Physics, Biomedical Engineering,* DOI 10.1007/978-3-642-29746-5 1, Springer-Verlag Berlin Heidelberg 2012.

[6] P.C. Consul, Felix Famoye, **Generalized poisson regression model,** *Communications in Statistics – Theory and Methods*, **21,** 1(1992)

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