Using Feedback Related Error Signals to Train Brain-Computer Interfaces

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Background

The parameters of a non-invasive brain-computer interface (BCI) determine the ability of the interface to decode electroencephalographic (EEG) brain signals to decipher a subject's intentions. Usually, the computer must learn these parameters during a separate training session that takes place before regular usage of the BCI.

However, this training session is often long and may need to be repeated several times for long-term usage. Thus, I propose a method of tuning the parameters continuously during normal usage of the BCI, using the Feedback Related Negativity (FRN), a signal generated in the anterior cingulate cortex that scales with prediction error [1].

Fig. 1 - EEG Cap for BCI

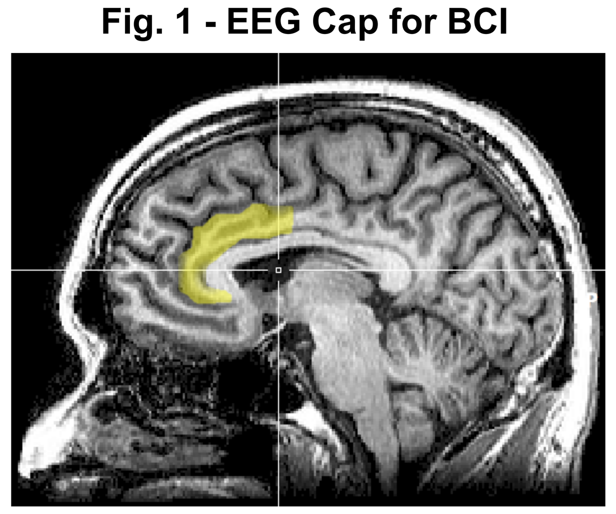

Fig. 2 - Anterior Cingulate Cortex

Motivation

Intellectual Merits – This project explores the mechanics of the FRN signal, which has been linked to learning; by creating a model of how prediction error is encoded in the brain, we can observe how the brain itself learns. Additionally, this project explores machine learning concepts based on noisy feedback, which is a topic of research in the machine learning community.

Broader Impacts - This project will hopefully drastically shorten the training time required to use BCIs. It will also enable longer-term usage of BCIs between training sessions, as the FRN training will continuously retrain the BCI. This functionality is important in neural prostheses for the disabled, as a person may wear the prosthesis for extended periods of time. Additionally, shorter training time will allow end-users to easily attach and remove the prosthesis, making this technology much more useful to the public.

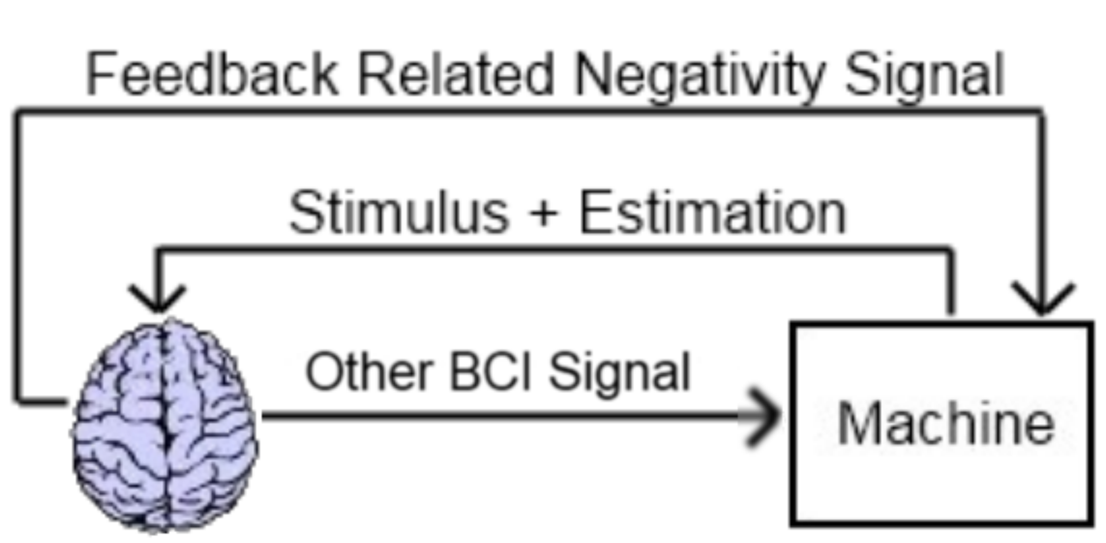

Fig. 3 - Generic Block Diagram for Proposed Feedback System

Goals

1) Develop a method to extract prediction error from FRN signal on a trial-by-trial basis.
2) Develop a generic method to use prediction error to train parameters of existing BCI.
3) Explore the effect of providing continuous versus discrete feedback on the FRN signal.

1) FRN Extraction

The FRN signal is present in the theta band of EEG (around 4-8 Hz). The prediction error can be extracted by examining signal patterns between medial and lateral electrode sites over the anterior cingulate cortex [1]. A statistical model for the patterns of activations can be created, and a Bayesian inference filter can produce the prediction error. Additionally, this statistical model will likely be tuned using a system identification algorithm like Expectation-Maximization, which iteratively converges on model parameters given a general model.

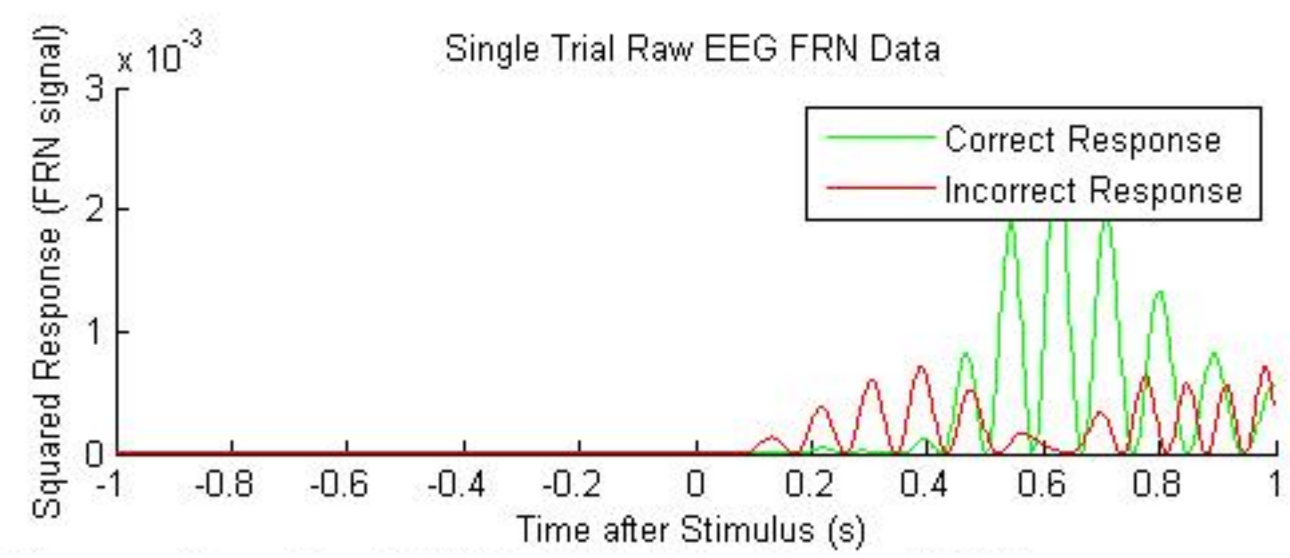

Fig. 4 - One FRN Trial; FRN Signal should appear ~250 ms after stimulus

2) Training BCI

For this part, I will choose the motor signal BCI, since it has applications in neuroprosthetic limbs. Using Common Spatial Analytical Patterns to train the motor signal BCI produces a characteristic matrix, which can then be used to determine if the subject is attempting to move “left” or “right”[3]. For FRN training, the relationship between this matrix, the estimated classification, and the prediction error must be determined; the matrix can then update based on the prediction error, actively training the BCI. This method will be generalized, using a theoretical approach, to apply this same system to other BCIs.

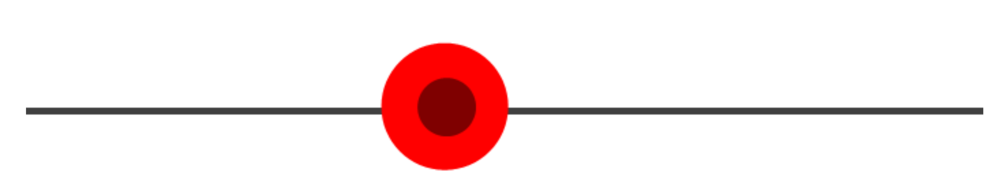

Fig. 5 - Ball used for Feedback; when small ball grows to size of large ball, the large ball will move to either the left or right, providing feedback to the user

3) Continuous Feedback

The vast majority of FRN studies deal with purely discrete feedback; I propose to study how the FRN responds to more continuous feedback, as well as its' use in BCI training. Since most feedback in the real world is continuous, this goal is important for any kind of neural prosthesis implementation. Using the same methodology as utilized in Goal 1, data from using continuous feedback will be acquired. A model of how the FRN behaves temporally with continuous feedback will be created both theoretically from extending the discrete case and empirically from the data. This will eventually be applied to a BCI in the same fashion as in Goal 2.

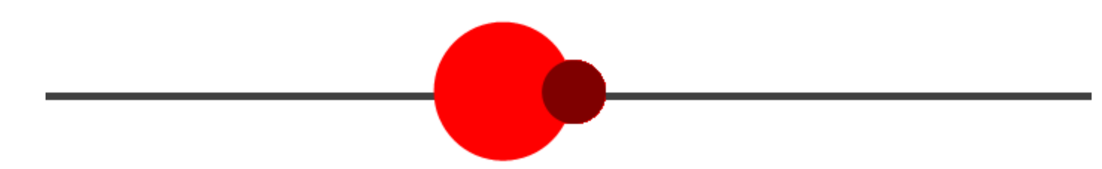

Fig. 6 - Continuous Feedback; when the small ball escapes the large ball, the large ball moves in the direction of the small ball

Potential Pitfalls

1) Extracting the FRN from EEG data is non-trivial, due to movement artifacts and eye-blinks, especially since the FRN is not generated on the outside cortex. This can be addressed with an artifact rejection scheme using an algorithm like Independent Component Analysis [4].
2) Since the brain learns at the same time as the machine, this project treads on coadaptive systems. To complete this project, I may have to adopt a model for the brain's learning as well as the machine's learning.
3) Continuous feedback will probably smear the FRN temporally, since the FRN signal is generally delayed from the stimulus by ~250 ms, which will likely require some temporal blind source separation.

References

[1] D. A. Steines, “A Stochastic Control Framework For The Design Of Observational Brain-Computer Interfaces Based On Human Error Potentials,” M.S. Thesis, ECE, UIUC, Champaign, IL, 2011.

[2] R. Chavarriaga and J. R. Millan, “Learning From EEG Error-Related Potentials in Noninvasive Brain-Computer Interfaces,” vol. 18, no. 4, pp. 381-8, Aug . 2010.

[3] M. McCormick, R. Ma and T. Coleman, “An Analytic Spatial Filter and A Hidden Markov Model for Enhanced Information Transfer Rate in EEG-based Brain Computer Interfaces,” ICASSP, Dallas, TX, Mar. 2010, accepted Sep. 2009.

[4] T-P Jung, et al., "Removing electroencephalographic artifacts by blind source separation," Psychophysiology, vol. 37, pp. 163-78, 2000.