Online SSVEP based Controller using Adaptive Riemannian Geometry

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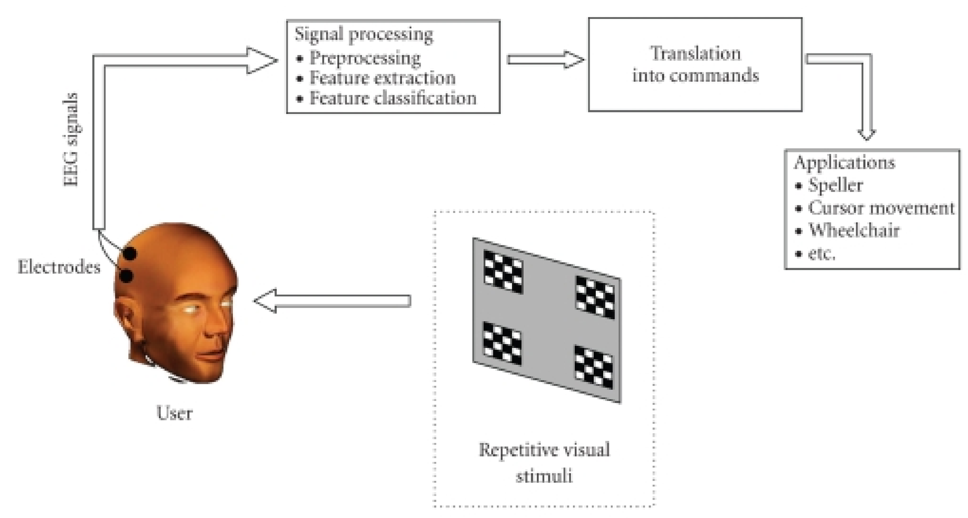
Abstract

Brain-Computer Interface (BCI) are devices that translate measured brain activity into tangible actions, allowing humans and other animals to interact with the physical environment without using their muscular system. To record brain signals in BCI systems, the most common choice is to rely on electroencephalography (EEG). Steady-State Visually Evoked Potentials (SSVEP), which are potential emerging when a subject concentrates his attention on a stimulus blinking at a given frequency. Shortly after the user concentrates on this stimulus, brain waves in the visual cortex could be observed with matching frequencies.

Introduction

Steady state visually evoked potentials (SSVEP) are signals that are natural responses to visual stimulation at specific frequencies. When the retina is excited by a visual stimulus ranging from 3.5 Hz to 75 Hz, the brain generates electrical activity at the same (or multiples of) frequency of the visual stimulus. Due to very high information transfer rate and excellent signal to noise ration, SSVEPs are used commonly for controlling BCIs. Moreover, compared to other modalities of BCI such as Motor Imagery, SSVEP based an intensive training for subjects is not needed to operate the BCI.

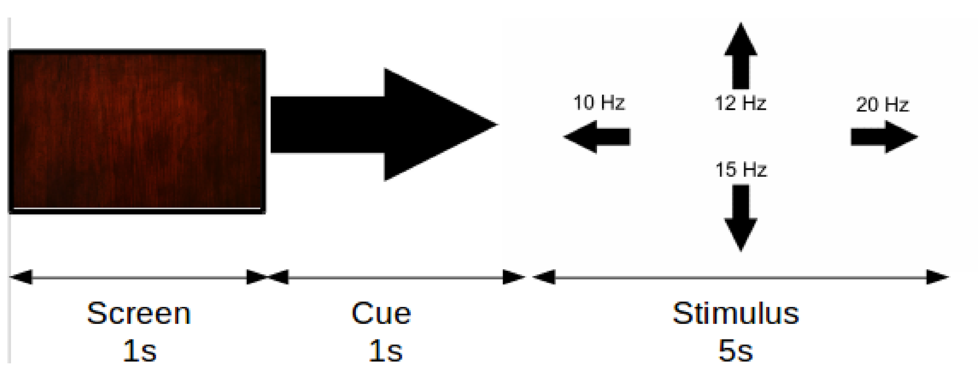
BCI pipeline



SSVEP based BCI

1. **Signal acquisition:** Brain activity is recorded
2. **Signal processing:** The recorded signal is prepared and analysed
3. **Feature translation:** The signal is translated into computer commands to operate applications
4. **Sensory feedback:** The changes in the environment caused by the BCI are fed back to the brain via stimulation

SSVEP experimental protocol



The experiment timeline

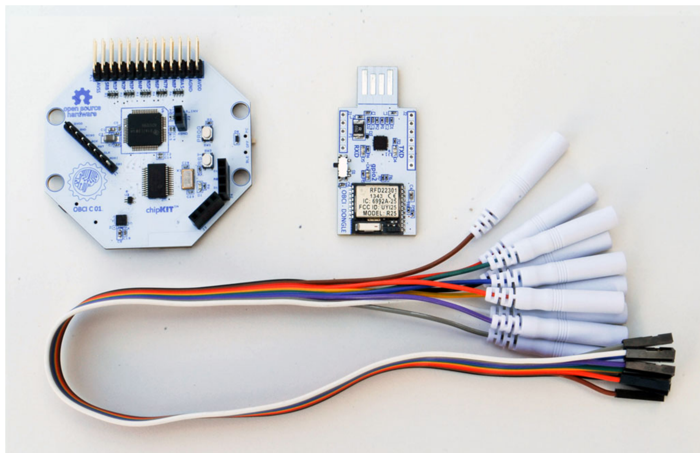
- The experiment that we plan to use is based on single graphics stimuli(displayed on LCD screen).
- Every trial consists of a rest screen followed by a cue and then followed by the stimulus screen on a lcd monitor (as shown with frequencies)

Signal Acquisition

Neural Signal

- ElectroEncephaloGram (EEG) is used to monitor electrical activities of the brain non invasively
- EEG measures voltage fluctuations resulting from ionic current within the neurons of the brain
- volume conduction affects the potential field as different biological layers do not have the same electrical properties
- 6 active electrodes according to the 10/20 electrode system (Oz, O1, O2, POz, PO3, and PO4) are used to monitor electrical activities.

Recording



OpenBCI

- OpenBCI is an open-source brain-computer interface platform, that can measure and record electrical activity produced by the brain (EEG)
- For syncing between the stimulus shown and signal recorded, we use LabRecorder, part of Lab Streaming Layer(LSL) library.

Signal Filtering

- Electric Line noise (50 Hz)
- Low frequency noise - applied high pass filter
- Movement artifacts - Subject is instructed to not show any movement when stimulus is displayed (plan to use ICA in future)

Feature Extraction

- Works on covariance features of the signal.Covariances are reliable features as they contain the power and spatial information of a signal.
- A covariance matrix in EEG contains the covariances and variances of the channels with each other and self, respectively. This is the spatial information that it gives.
- Given an EEG recording epoch, $E \in R^{n\times t}$ where n is the number of channels and t is the number of samples. The spatial covariance matrix $P \in R^{n\times n}$ is given by:

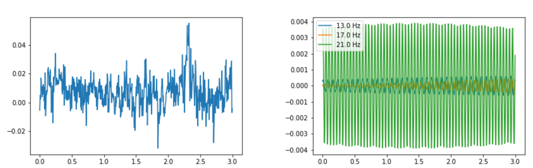
$$P = \frac{1}{t-1}EE^T$$

$$P = \begin{bmatrix} Var_1 & Cov_{1,2} & Cov_{1,3} \\ Cov_{1,2} & Var_2 & Cov_{2,3} \\ Cov_{1,3} & Cov_{2,3} & Var_3 \end{bmatrix}$$

- SSVEP is based on frequency response of a signal. So, direct covariance of channels is of little use here.

  Solution: Generating extended signal

  We have to filter the signal in the narrow bands around the stimulation frequencies In our case, be- tween (9.9-10.1), (11.9-12.1), (14.9-15.1), (19.9-20.1). This gives us new signal components. Now we concatenate these new signals to generate the extended signal ready for covariance extraction



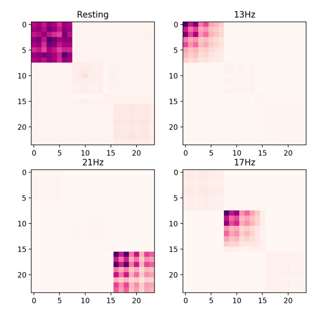
Raw and narrow bandpass filtered signals(as can be seen, the 21 Hz signal is dominant)

The SSVEP signal $X \in R^{C\times N}$ is extended to include the filtered signal for each stimulation frequency as follows:

$$X_{ext} = \begin{bmatrix} X_{freq_1} \\ X_{freq_2} \\ . \\ . \\ X_{freq_F} \end{bmatrix} \in R^{FC\times N}$$

Here F,C, and N denote the number of stimulation frequencies, number of channels and number of samples respectively

The following is an example of a spatial covariance matrix extracted from an SSVEP data:



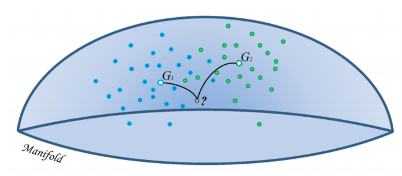
Covariance matrices of 4 trials corresponding to 4 different classes

Feature Classification

The computation of means of training covariance matrices is crucial to the classier performance. There are various classifiers for classification of EEG signals. A few of them namely:

- Linear Discriminant Analysis(LDA)
- Minimum Distance to Mean(MDM)
- Support Vector Machines(SVM)

We plan on using MDM for our project.



MDM calculates mean center for each class. For prediction on a new sample, MDM calculates the Riemannian distance to every center and returns the class with the minimum distance. G1 corresponds to the center of class 1 and similarly, G2 corresponds to the center of class 2 The new sample is denoted by ?. The lines denote the geodesic and the length of it is the Riemannian distance between the centers and the sample. We return the class label of one with the minimum distance in Riemannian space.

Result

- Testing accuracy: 98.7%
- Cross-trials accuracy: 96%
  - train_size=158
  - test_size=78
- Ten-fold cross validation average accuracy: 99%

Conclusion

Riemannian approaches have been successfully applied on EEG signals for brain-computer interfaces. Straightforward algorithms, such as Minimum Distance to Mean, provide competitive results with state-of-the-art methods, without requiring meticulous parametrization or optimization. Working on covariance matrices in Riemannian spaces over a wide choice of distances, embedding desirable invariances: it is thus possible to avoid the computation of user-specific spatial filters which are sensitive to artifacts and outliers. Nonetheless, the estimation of the Riemannian geometric mean has a strong impact on the classifier accuracy.

References

1. Emmanuel Kalunga et al.. From Euclidean to Riemannian Means: Information Geometry for SSVEP Classification. Geometric Science of Information, Oct 2015
2. Emmanuel Kalunga et al.. Online SSVEP-based BCI using Riemannian geometry. Neurocomputing, Elsevier, 2016