BCI Classification based on Signal Plots and SIFT Descriptors

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4th International Winter Conference on BCI

February 22nd, 2016, Yongpyong Resort, Korea

Outline

Introduction

- BCI challenging technology.
- Outstanding advances but yet its push into mainstream technology has not fully materialized.
- More clinical and physician Involvement: devise mechanisms to help them stay in the loop.

Motivation

- Is it possible to discriminate EEG signals and their corresponding cognitive processes based on their plots?
- Are those visual wiggles simple noise or can we extract something meaningful from them ?

What we aim to do

- Establish a Fruitful connection between Image Processing and EEG Analysis
- Provide a Framework to analyze visually relevant features from EEG.
- Assess the method by performing Binary Classification on known datasets.

Method

Signal Transformation

Single Channel transformation of the EEG multichannel time series matrix into an image

$$\mathscr{T}\{x(t, c, V) = 0\} \mapsto I(z_1, z_2, \mathcal{C}, \mathcal{I}) = 0 \qquad (1)$$

where t is time, c is the specified channel, V is the voltage value for the signal, $\mathcal{C}$ is the color channel for an image and $\mathcal{I}$ is the pixel value intensity.

Plot Generation: The EEG matrix is transformed to a binary bidimensional image $(t, c, V) \mapsto (t, V, Grey, \mathcal{I})$ with $\mathcal{I} = 0$ or $\mathcal{I} = 255$ for each c.

Signal Transformation: Visually centering the signal over the image.

First the non-zero media is removed from the signal.

$$\tilde{x}(t,c) = \lfloor \delta.(x(t,c) - \bar{x}(c)) \rfloor \quad (2)$$

And the signal is centered on the image

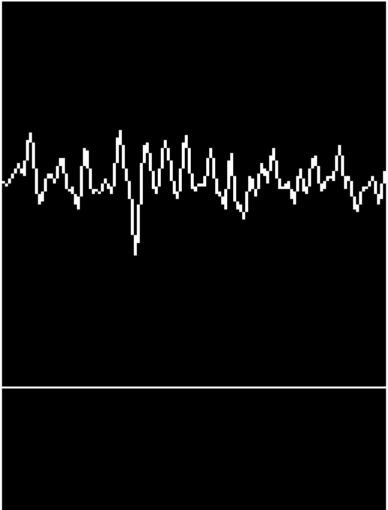
$$h(c) = (\max \tilde{x}(t,c) - \min \tilde{x}(t,c)) + \sigma \quad (3)$$

$$Z(c) = \lfloor \frac{h(c)}{2} \rfloor - \lfloor \frac{\max \tilde{x}(t,c) + \min \tilde{x}(t,c)}{2} \rfloor \quad (4)$$

where t is time, δ is scale factor, c is the channel parameter, $x(t,c)$ is the EEG matrix whereas $\bar{x}(c)$ is the mean value for each channel, $h(c)$ is the height of the image in pixels, σ is the descriptor size and $Z(c)$ is the horizontal pixel at which the zero value of the signal will be located.

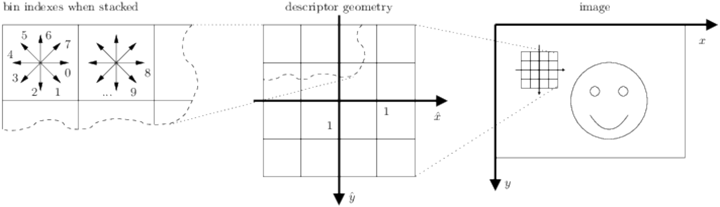
Signal Transformation: Binary Image generation.

$$I(z_1, z_2) = \begin{cases} 255 & z_1 = \delta \cdot t; z_2 = \tilde{x}(t, c) + Z(c) \\ 0 & \text{otherwise} \end{cases} \quad (5)$$



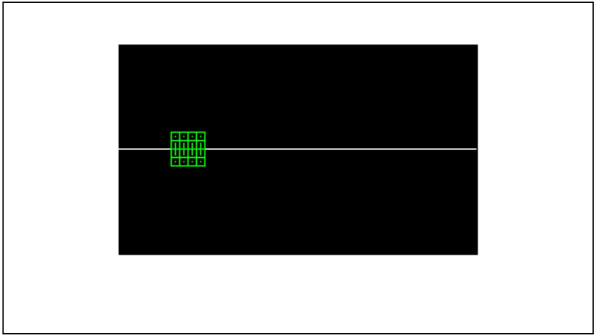
Features: SIFT[1] Descriptors

Scale Invariant Feature Transform Descriptors are local features of an image that represents gradient changes in intensities. They are 128-dimensional vectors that contains the histograms of relative gradient directions on each of the blocks that each patch is divided (4x4=16 blocks, 8 rotational directions on each). A single scale ($\sigma = 1$) is composed of 4 blocks of 3 pixels on each side (12x12).



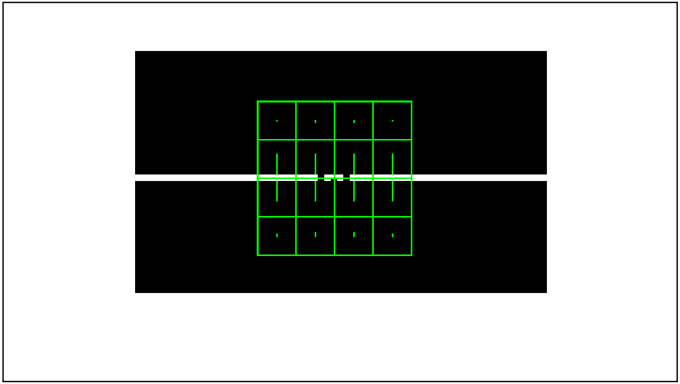
[1] Lowe 2004.

SIFT Descriptors



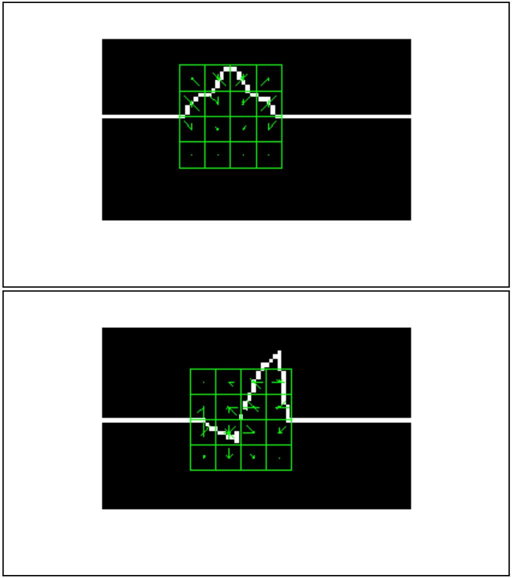
SIFT Descriptor $[z_1, z_2, \theta, \sigma]$ where (z_1, z_2) are the 2D coordinates where the *Keypoint* is located, θ is the descriptor general orientation and σ is the descriptor size.

SIFT Descriptors



SIFT Descriptor with its corresponding gradient tendencies.

SIFT Descriptors



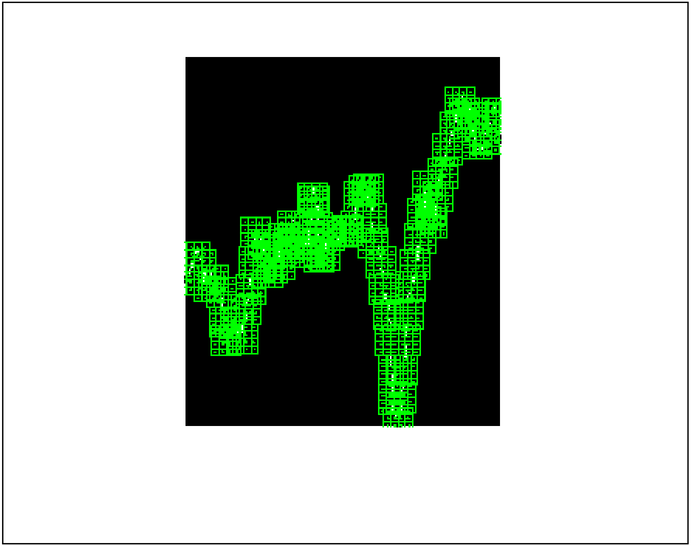
Sample Descriptors from artificial signals.

SIFT Descriptors

0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
17	22	22	17	173	173	173	173	40	51	51	40	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	40	51	51	40	173	173	173	173	17	22	22	17
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Sample descriptor values of the given patch.

Keypoint Localization



Keypoints are (z_1, z_2) points on the image where descriptors are extracted.

Classification

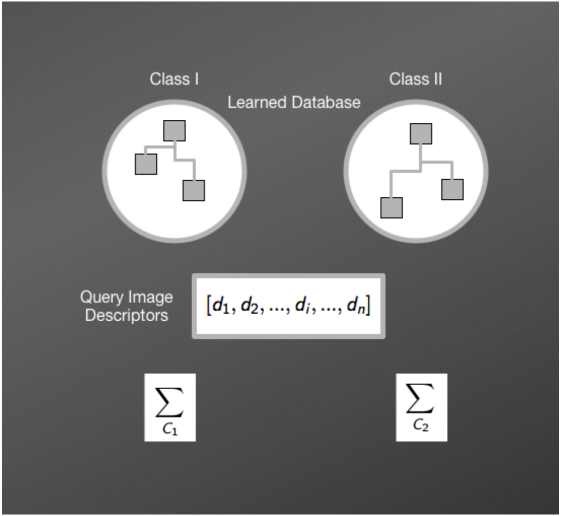
- Discriminative Semi-supervised classification method was used: Naive Bayes Nearest Neighbor, NBNN[2] algorithm:

$$\hat{C} = \arg\min_{C} \sum \|d_i - NN_C(d_i)\|^2 \qquad (3)$$

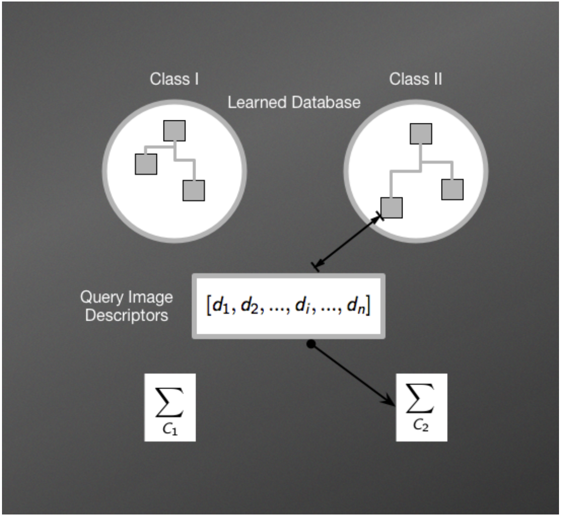
where $\hat{C}$ is estimated Class to which this image (and underlying EEG signal windows) should belong whereas d_i is the i-th descriptor obtained from the query image and $NN_C(d_i)$ is the near neighbor descriptor for each class.

[2] **Boiman, Shechtman, Irani 2008.**

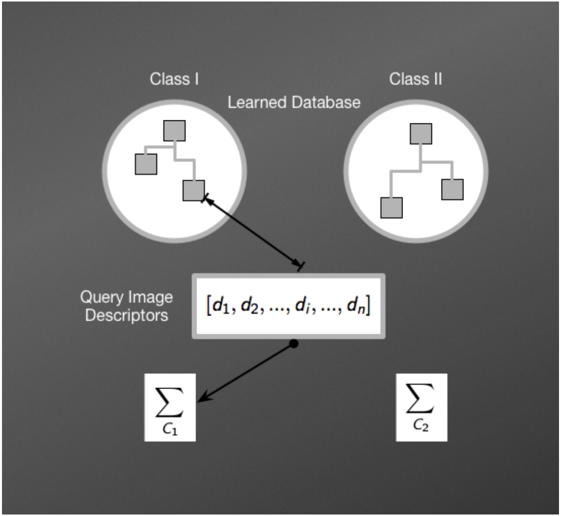
Classification



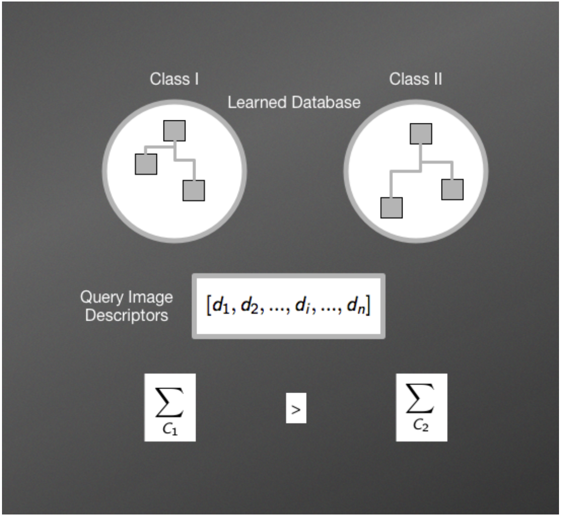
Classification



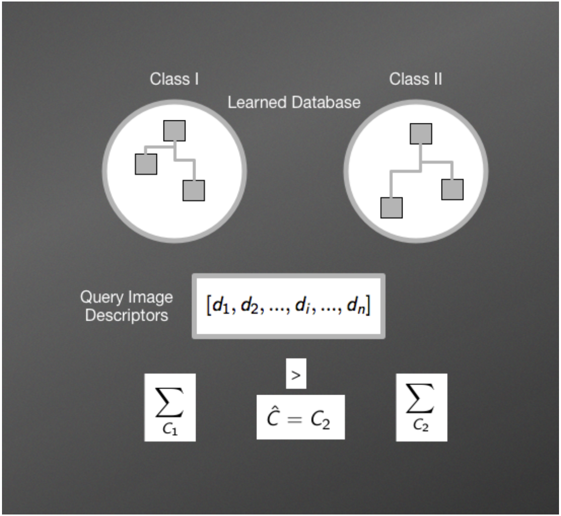
Classification



Classification

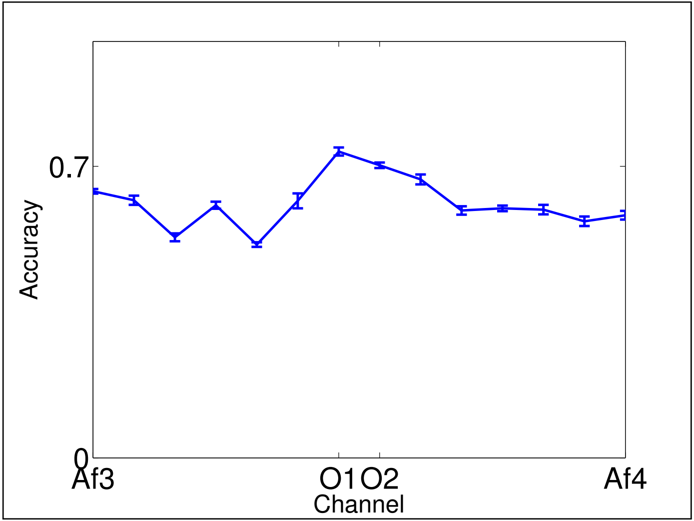


Classification



Offline Results

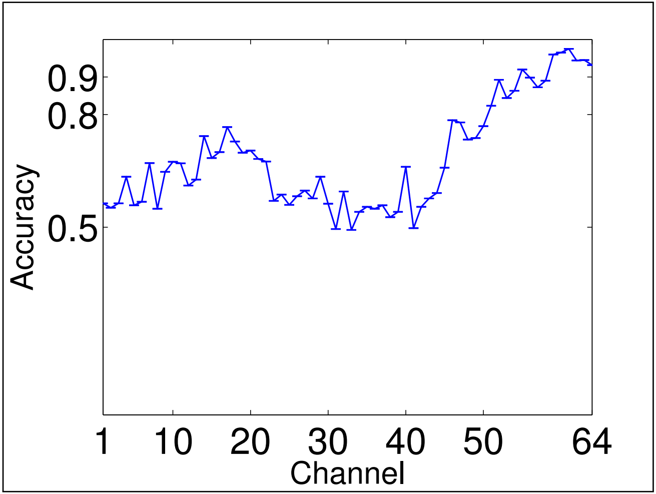
Dataset I: Subject Independent α Waves[3]



10-Fold Cross validated accuracy values for 10 subjects.

[3] Ramele, Villar, Santos 2014.

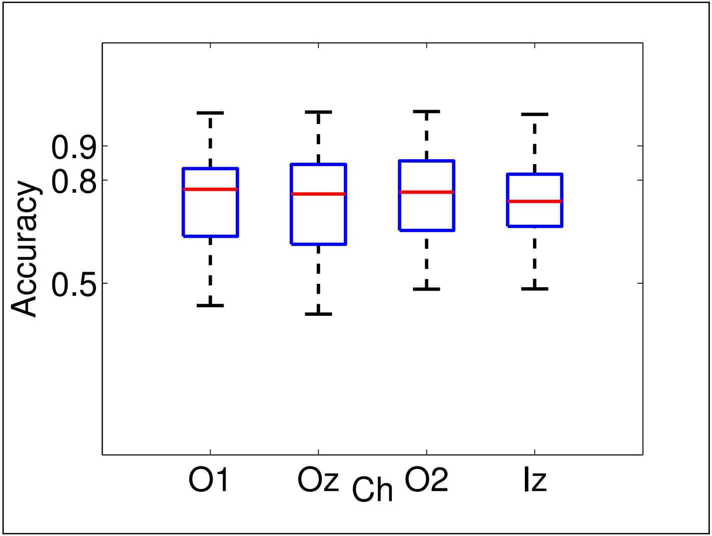
Dataset II: EEG Dataset, Runs 1 and 2[4]



10-Fold Cross validated accuracies values for one random subject.

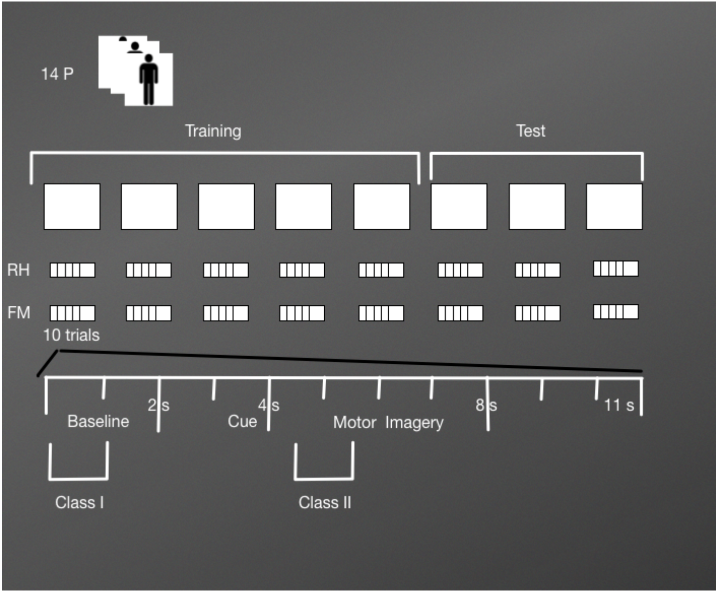
[4] Goldberg et al 2000, Schalk 2004.

Dataset II: EEG Dataset, Runs 1 and 2[5]

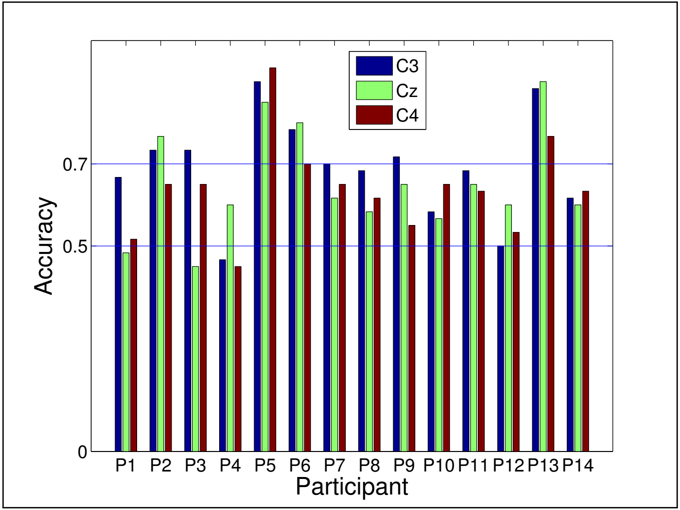


10-Fold Cross validated accuracies for O1, Oz, O2 and Iz channels for 25 subjects.

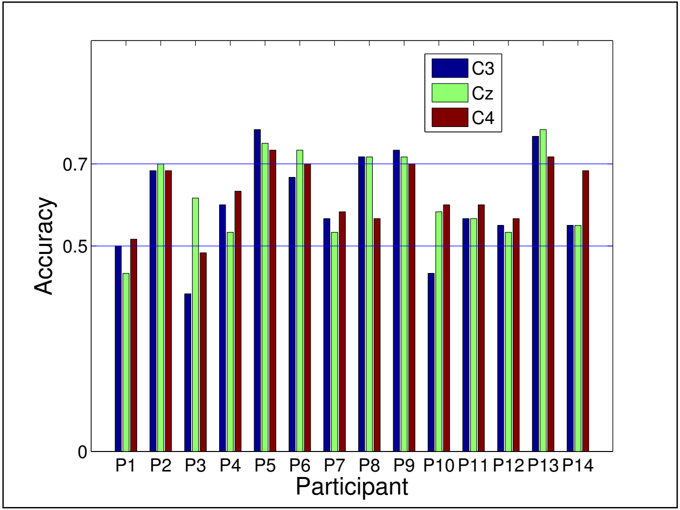
Dataset III: Motor Imagery[6]



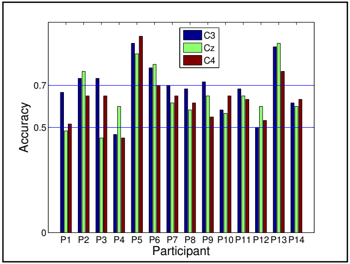
[6]Steyrl, Scherer et al 2015.

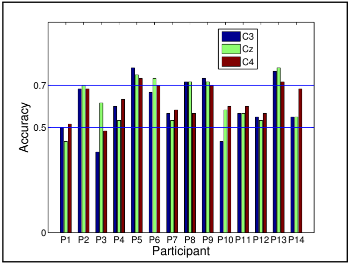


Accuracy for the BCI Simulation classifying Baseline vs. RH (Right Hand) motor imagery.



Accuracy for the BCI Simulation classifying Baseline vs. FM (Feet Movement) motor imagery.





Comparative results obtained for the Offline BCI Simulation using MI RH (left) and MI FM (right)

Conclusion

- A method to analyze EEG signals was presented.
- A signal transformation algorithm was introduced.
- A classification scheme was implemented.
- Offline Alpha Waves presence was detected from signal plot with an accuracy level 10-fold cross validated of 70%.
- Offline BCI Simulation of single trial asynchronous triggering for right hand MI based on signal plots was implemented with a level of success of 70% for 7 out of 14 Participants.

References

- Lowe 2004
- Boiman, Shechtman, Irani 2008
- Ramele, Villar, Santos 2014
- Goldberg et al 2000, Schalk 2004
- Steyrl, Scherer et al 2015