

Histogram of Gradient Orientations of EEG Signal Plots for Brain Computer Interfaces

Dissertation Defense

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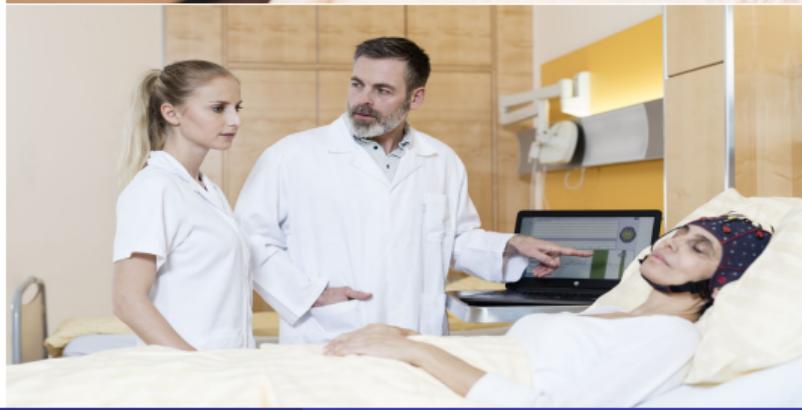
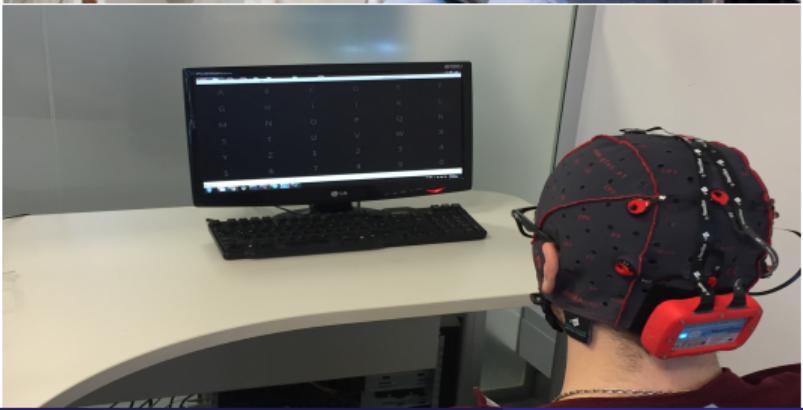
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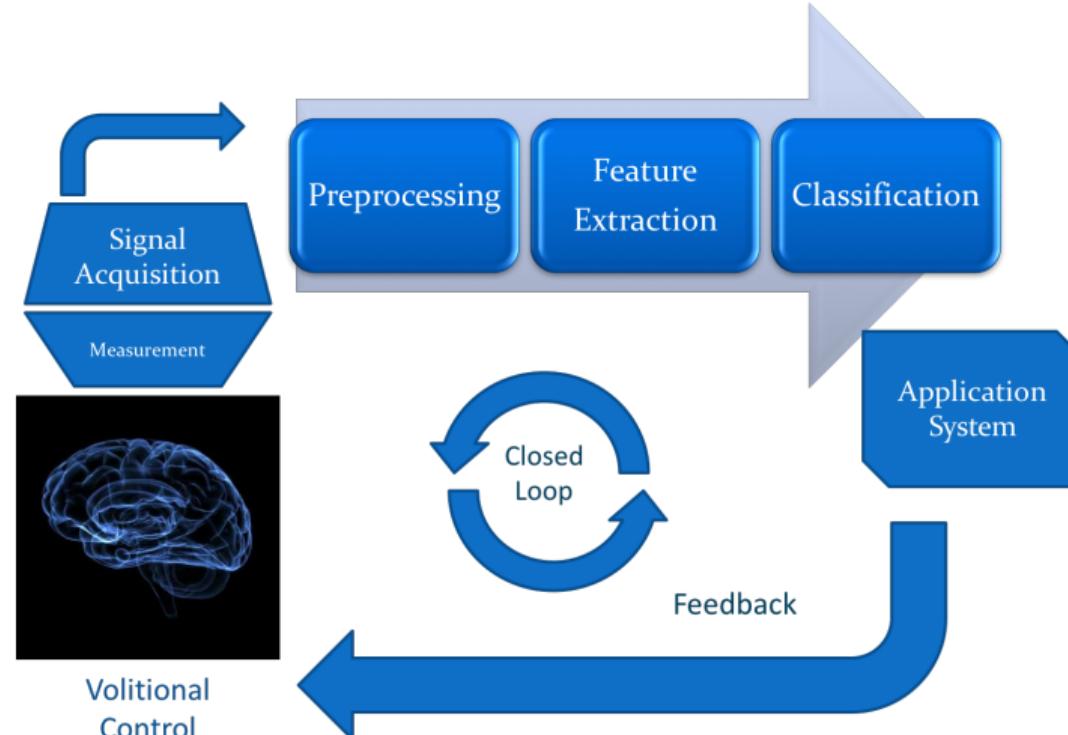
Outline

- 1 Introduction
- 2 Motivation
- 3 The Histogram of Gradient Orientations
- 4 The Histogram of Gradient Orientations
- 5 Experimental Validation
- 6 Conclusion
- 7 References
- 8 Questions

Brain Computer Interfaces

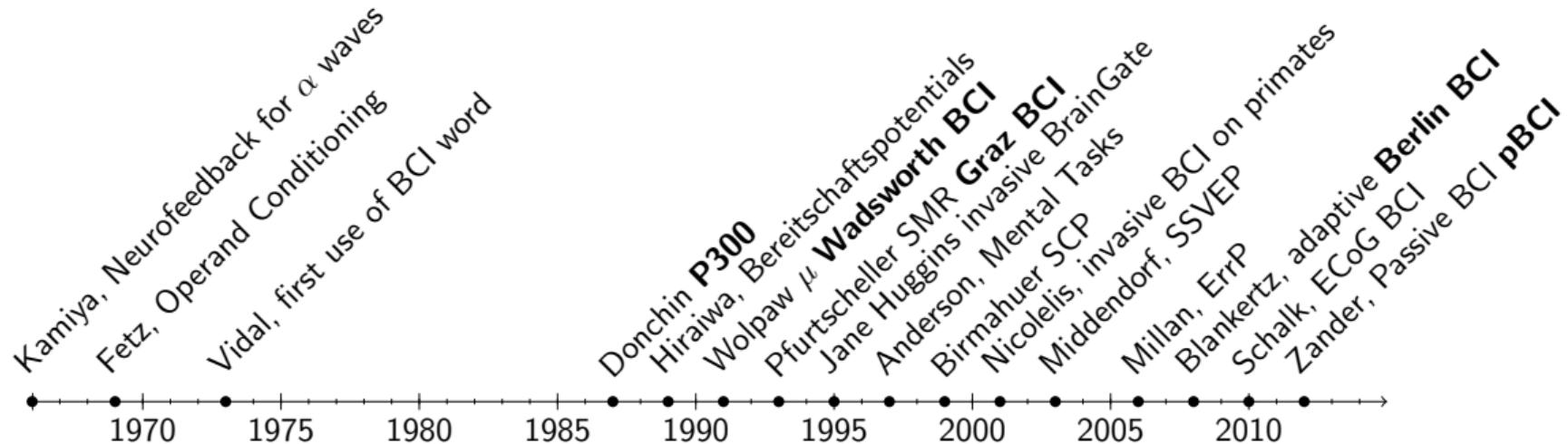


Brain Computer Interfaces



General components of a BCI system.

Brain Computer Interfaces - Chronology



Brain Computer Interfaces

Evoked Potential

Steady State Visual Evoked Potential

SSVEP
SSAEP
SSSEP

Bereitschaftspotentials

Motor Imagery:

ERD/ERS: Event Related Desynchronization-Synchronization

Wadsworth BCI
Graz BCI

Selective Attention

P300,N400
Visual Spatial Evoked Attention

Mental Tasks

Tübingen BCI

Operant Conditioning:

Slow Cortical Potentials
ErrP

Berlin BCI

BCI Paradigms

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.
- (+) ITR, SNR, reliability, portability, usability.
- (-) biocompatibilities, setup, training time, calibration time, subject inter/intra variability.
- The search for practical, relevant, and invariant features that convey good-enough information¹.
- Ethical aspects should be revised².

¹Perdikis2014.

²Yuste2017.

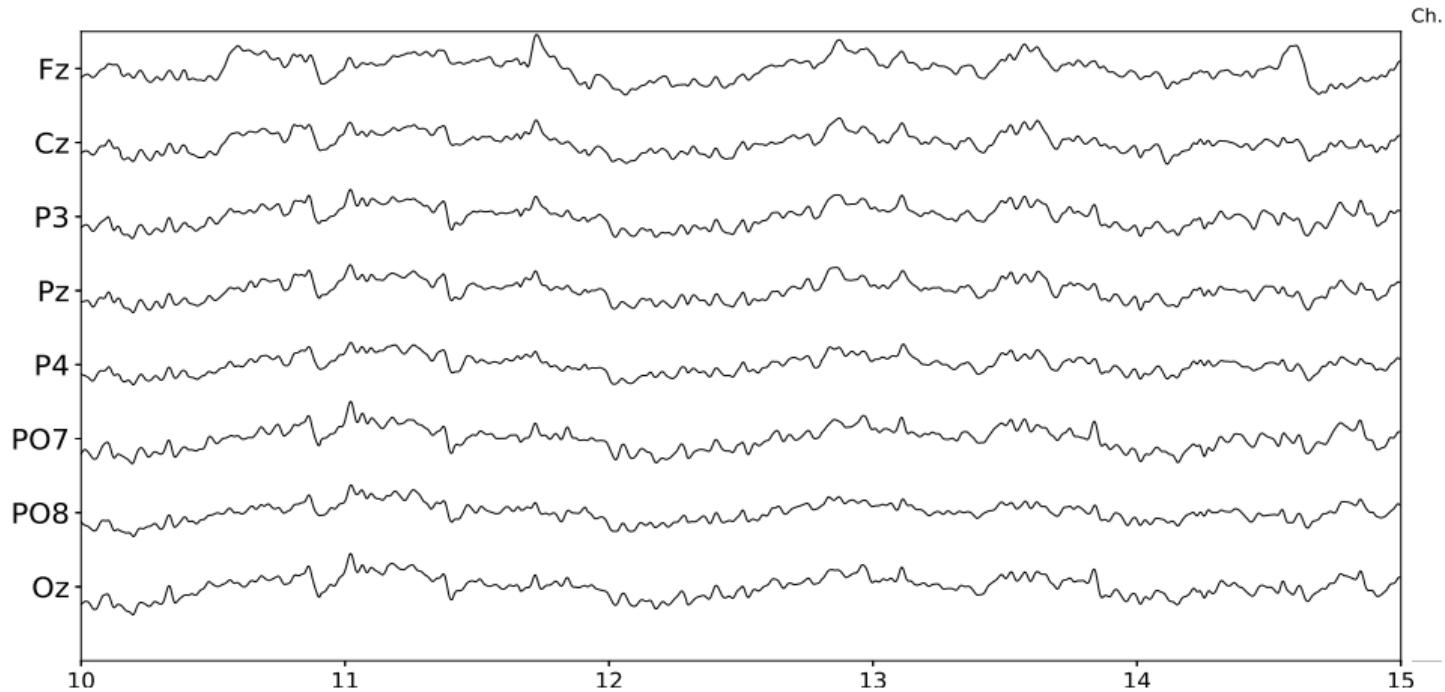
Motivation

- This thesis tries to unravel the following question: is it possible to analyze and discriminate electroencephalographic signals by automatic processing the shape of the waveforms using the Histogram of Gradient Orientations ?

What we aim to do

- A procedure to construct analyzable 2D-images based on one-dimensional signals.
- An enhancement over the Histogram of Gradient Orientation technique to allow non-squared patches and to adapt it to signal plots.
- A mapping procedure to link EEG time-series characteristics to features of 2D-images.
- A feature extraction method for EEG signals that can be used objectively to encode a representation of the waveform.
- A classification algorithm that use the encoded representation with the purpose of comparing and identifying waveforms for BCI applications.

Electroencephalography



Sample EEG signal obtained from (g.Nautilus, g.Tec, Austria). Time axis is in seconds and five seconds are displayed. The eight channels provided by this device are shown.

Electroencephalography

- Permutation Entropy

Electroencephalography

- Permutation Entropy
- SHCC

Electroencephalography

- Permutation Entropy
- SHCC
- Matching Pursuit

Electroencephalography

- Permutation Entropy
- SHCC
- Matching Pursuit
- MIDS

Electroencephalography

- Permutation Entropy
- SHCC
- Matching Pursuit
- MIDS
- Local Binary Patterns

Electroencephalography

- Permutation Entropy
- SHCC
- Matching Pursuit
- MIDS
- Local Binary Patterns
- Peak Picking/aEEG/PAA

The Histogram of Gradient Orientation

The Histogram of Gradient Orientations

① Signal Preprocessing

The Histogram of Gradient Orientations

- ① Signal Preprocessing
- ② Signal Segmentation

The Histogram of Gradient Orientations

- ① Signal Preprocessing
- ② Signal Segmentation
- ③ Signal Plotting

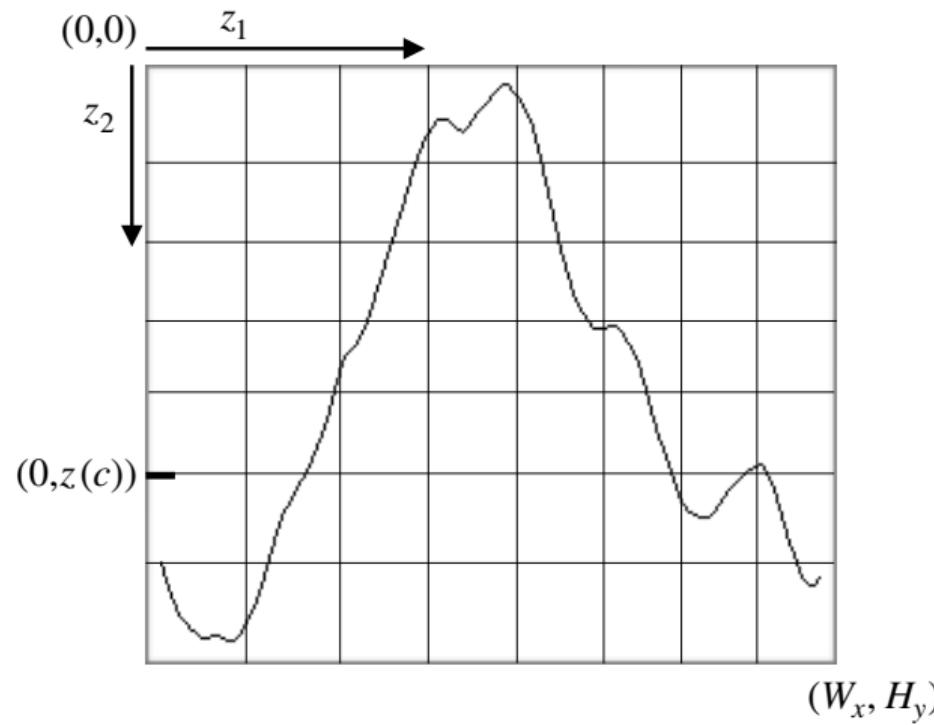
The Histogram of Gradient Orientations

- ① Signal Preprocessing
- ② Signal Segmentation
- ③ Signal Plotting
- ④ Keypoint Localization

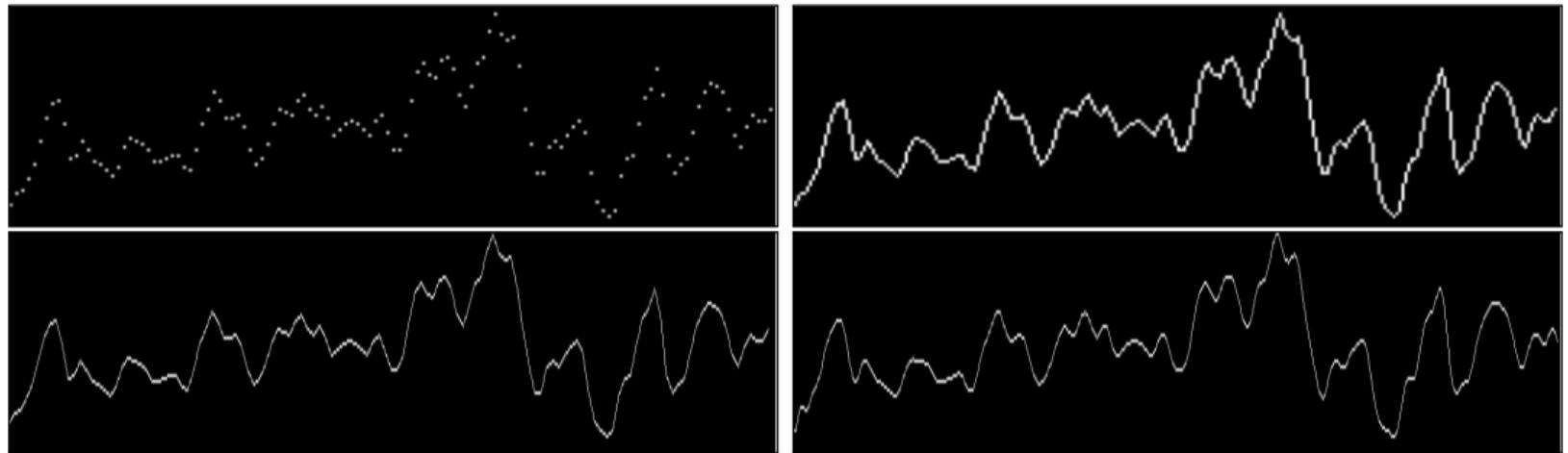
The Histogram of Gradient Orientations

- ① Signal Preprocessing
- ② Signal Segmentation
- ③ Signal Plotting
- ④ Keypoint Localization
- ⑤ Calculation of the Histogram of Gradient Orientation

The Histogram of Gradient Orientations

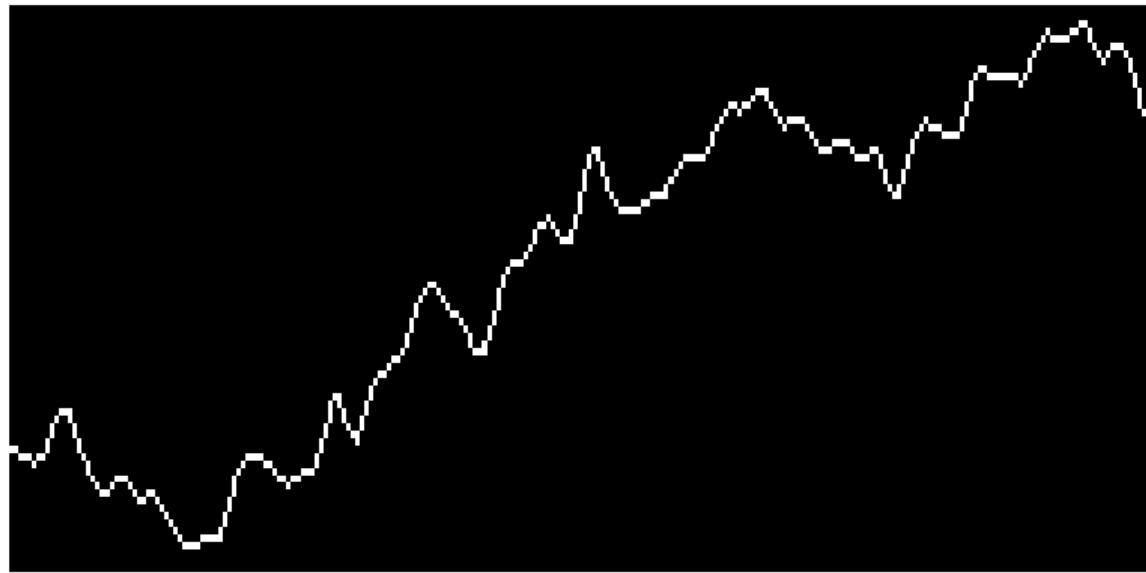
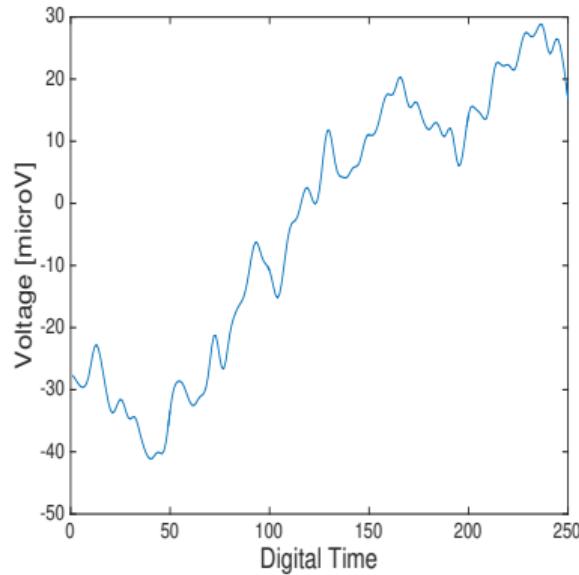


The Histogram of Gradient Orientations

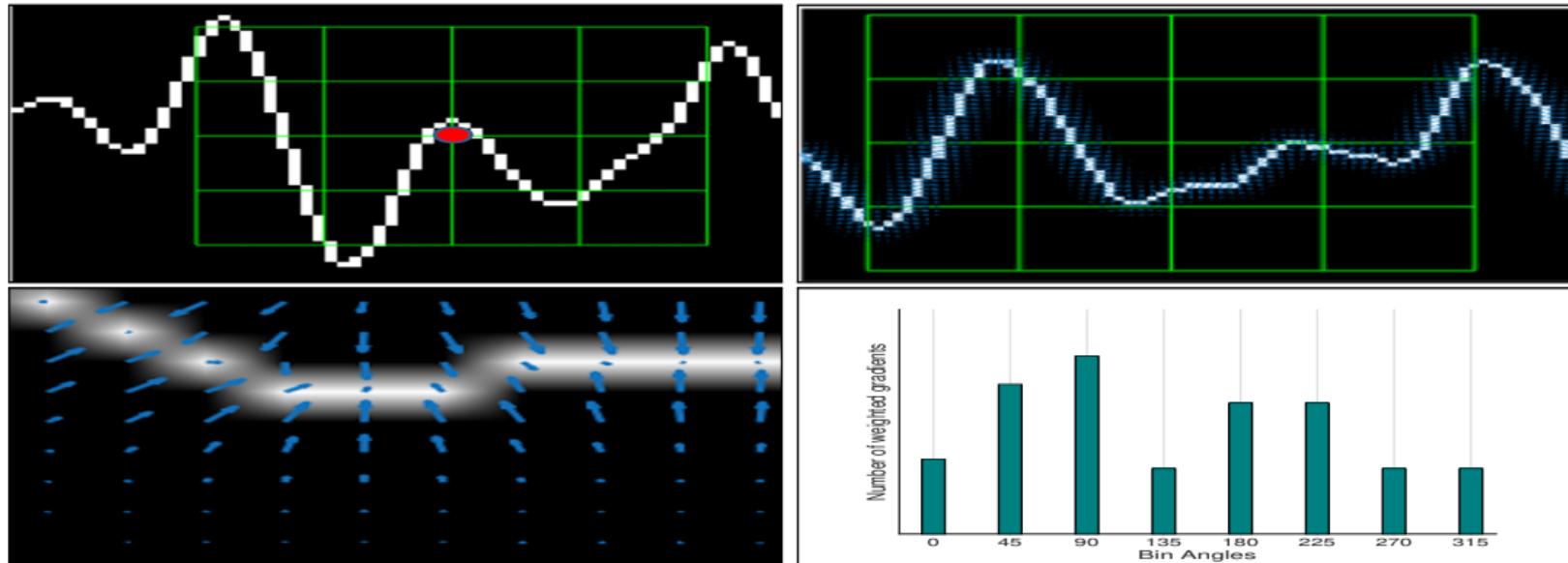


Generated images based on different interpolation schemes.

The Histogram of Gradient Orientations



The Histogram of Gradient Orientations



Patch and vector field of oriented gradients.

The Histogram of Gradient Orientations

Hence, for each spatial bin $i, j = \{0, 1, 2, 3\}$, corresponding to the indexes of each block $B_{i,j}$, the orientations are accumulated in a 3-dimensional histogram h through the following equation:

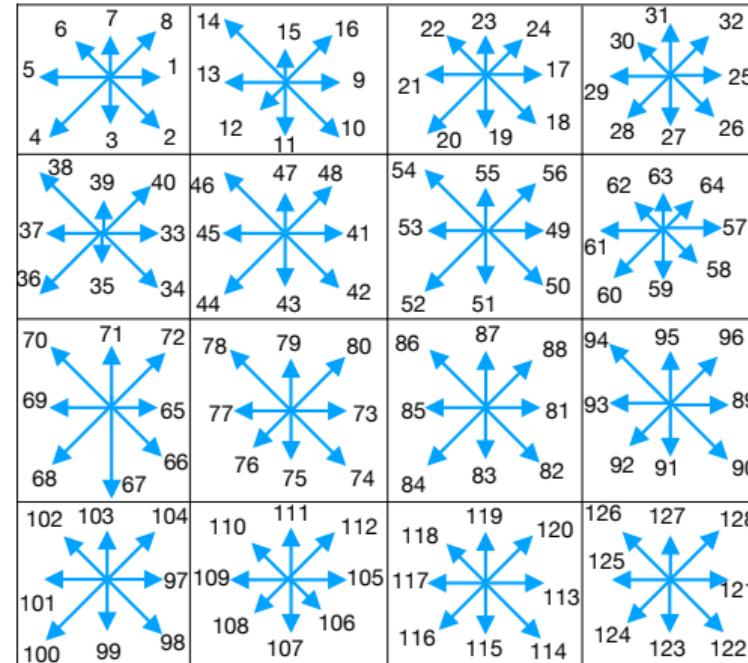
$$h(\theta, i, j) = \sum_{\mathbf{p}} \omega_{\text{ang}}(\angle J(\mathbf{p}) - \theta) \omega_{ij} (\mathbf{p} - \mathbf{k}\mathbf{p}) \|J(\mathbf{p})\| \quad (1)$$

where \mathbf{p} is a pixel from within the patch, θ is the angle bin with $\theta \in \{0, 45, 90, 135, 180, 225, 270, 315\}$, $\|J(\mathbf{p})\|$ is the norm of the gradient vector in the pixel \mathbf{p} , computed using finite differences, and $\angle J(\mathbf{p})$ is the angle of the gradient vector. The scalar $\omega_{\text{ang}}(\cdot)$ and vector $\omega_{ij}(\cdot)$ functions are linear interpolations used by³ and⁴ to provide a weighting contribution to eight adjacent bins.

³Lowe2004.

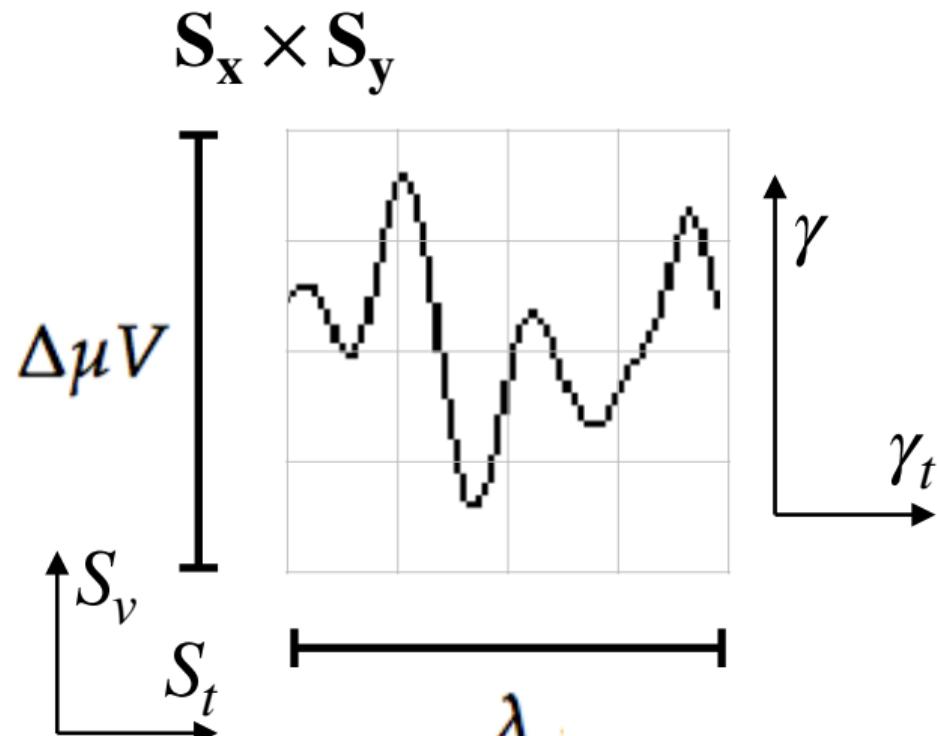
⁴Vedaldi2010.

The Histogram of Gradient Orientations



A scheme of the orientation's histogram computation. The first eight orientations of the first block B_{1,1} are labeled from 1 to 8 clockwise. The orientation of the second block B_{1,2} is labeled from 9 to 16 clockwise. The orientation of the third block B_{1,3} is labeled from 17 to 24 clockwise. The orientation of the fourth block B_{1,4} is labeled from 25 to 32 clockwise.

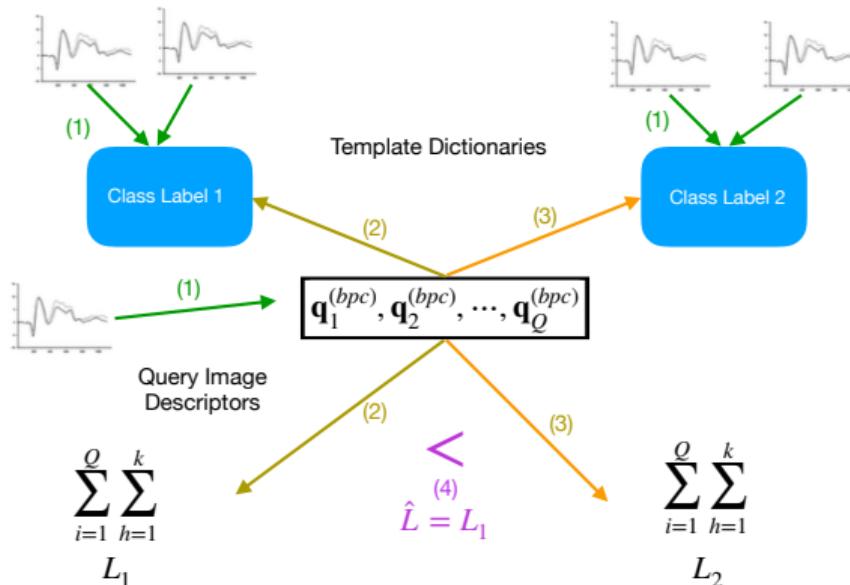
The Histogram of Gradient Orientations



The Histogram of Gradient Orientations

$$\hat{L} = \arg \min_L \sum_{i=1}^Q \sum_{h=1}^k \left\| \mathbf{q}_i^{(bpc)} - \mathbf{d}_h^{(bpc)} \right\|^2 \quad (2)$$

The Histogram of Gradient Orientations



Classification Algorithm: **Step 1** Two Dictionaries are created from templates descriptors obtained in a calibration session for two different classes, labeled 1 and 2. On the other hand, a set of query descriptors are extracted from a new image that needs to be categorized. **Step 2** Distances from every descriptor q_i are calculated against the closest one from the dictionary of class 1. Distances

Experimental Validation

- Alpha Waves Wiggles

Experimental Validation

- Alpha Waves Wiggles
- Mu Greek Letter

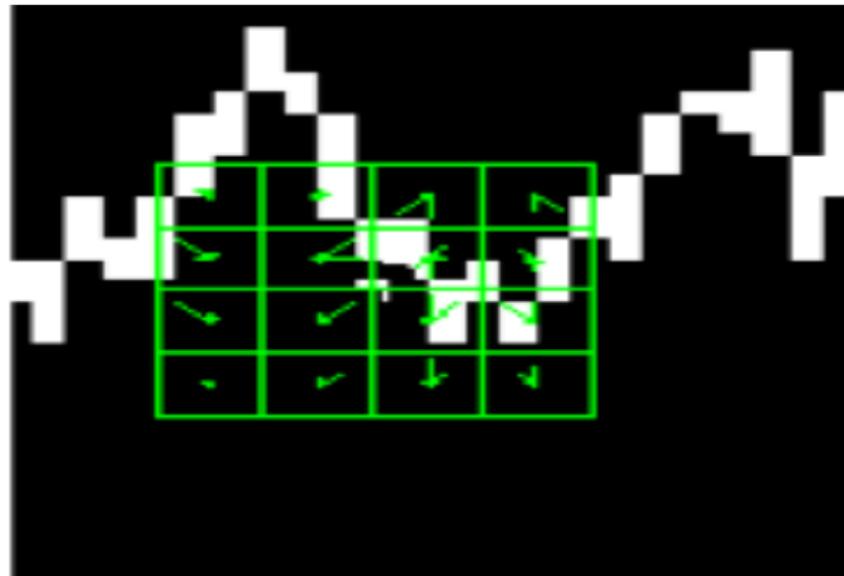
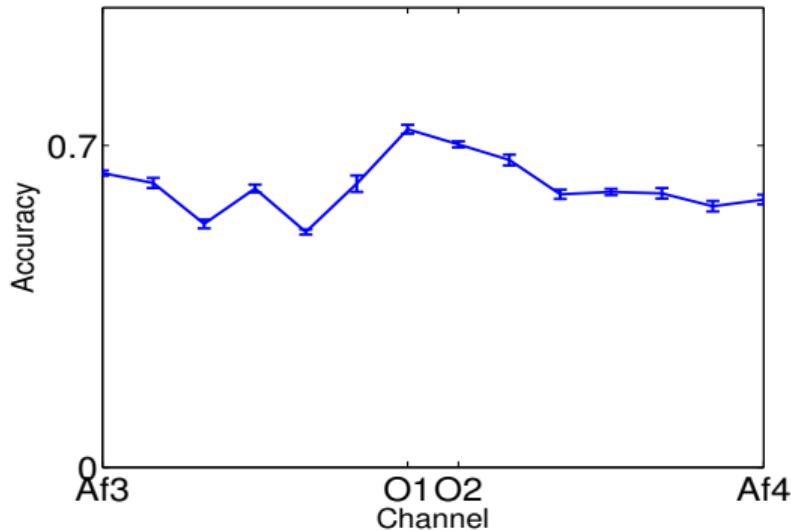
Experimental Validation

- Alpha Waves Wiggles
- Mu Greek Letter
- The P300 Wave

Alpha Waves wiggles

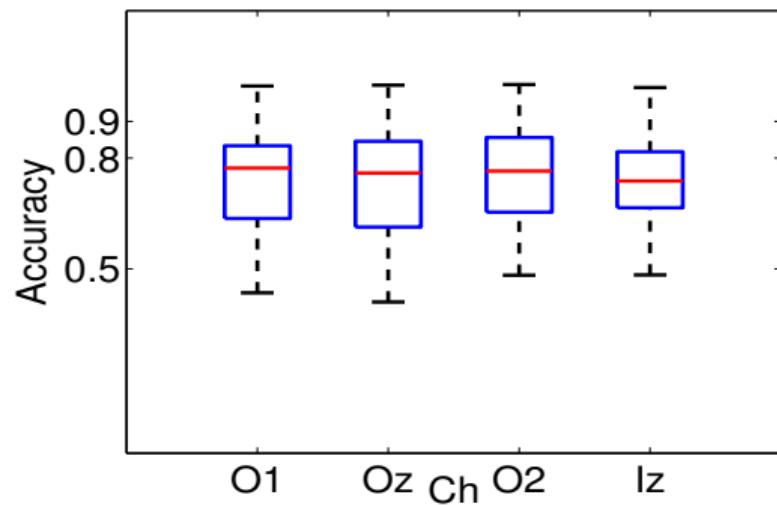
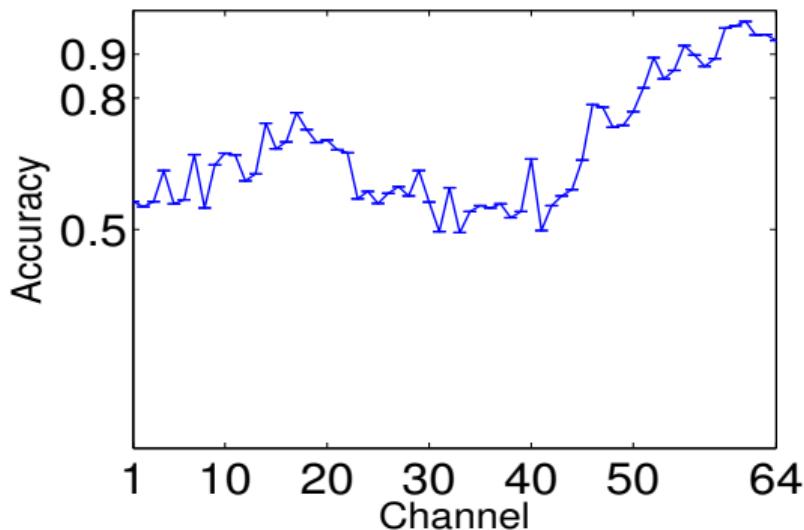
Alpha Waves wiggles

Alpha Waves wiggles



Dataset I: The classification accuracy is maximum on occipital channels O1 and O2. The horizontal patch scale S_t and the vertical patch scale S_v are set to 1, whereas γ and γ_t are set to 2, which corresponds to a variation of $\Delta\mu V = 10$ microvolts in the signal amplitude during $\lambda = 0.08$ seconds.

Alpha Waves wiggles

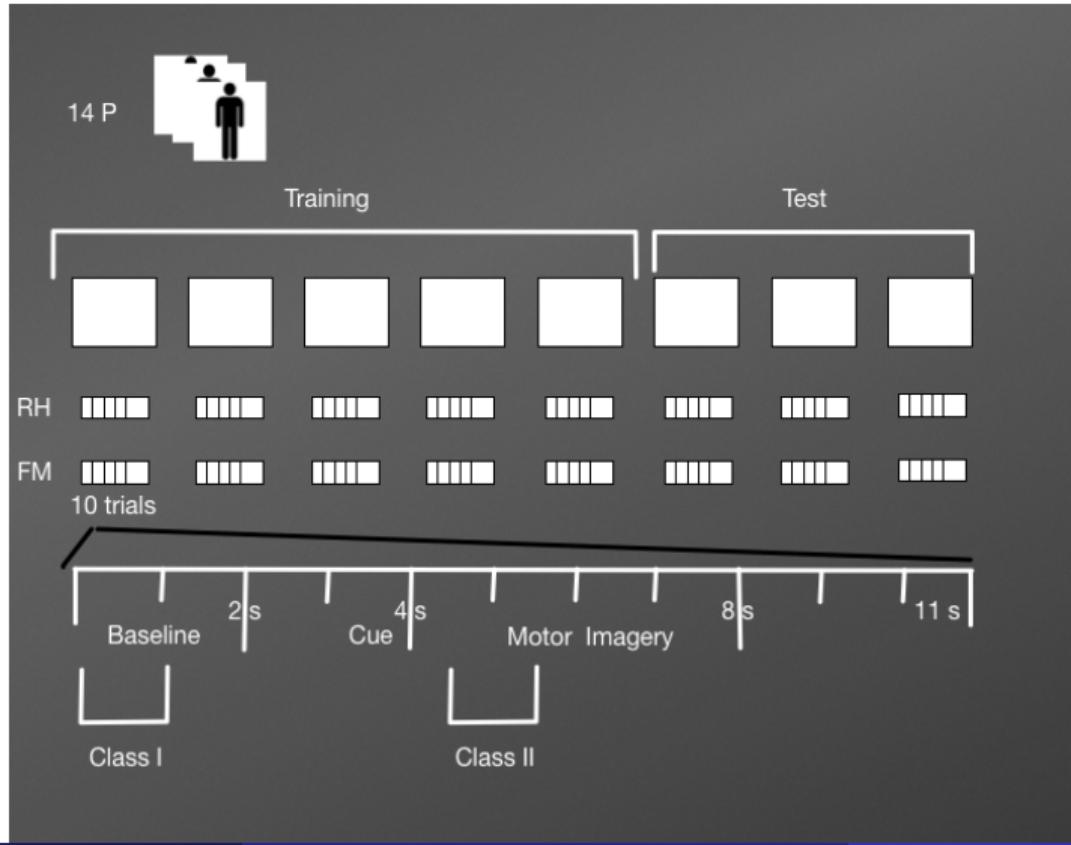


Dataset II: Classification Accuracy for segments of 1s ($N = 160$) of EEG, between class 1 and class 2.
In this case as the sampling frequency F_s is lower, the signal span is $\lambda = 0.06$ s

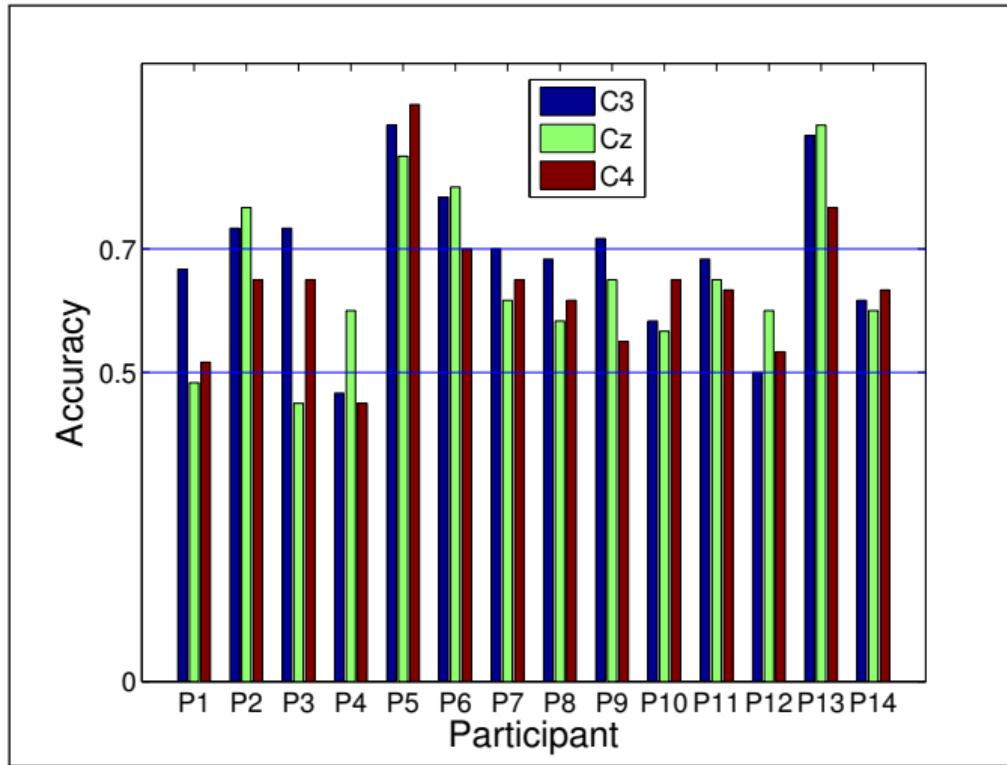
Mu a Greek letter

Mu a Greek letter

Mu a Greek letter

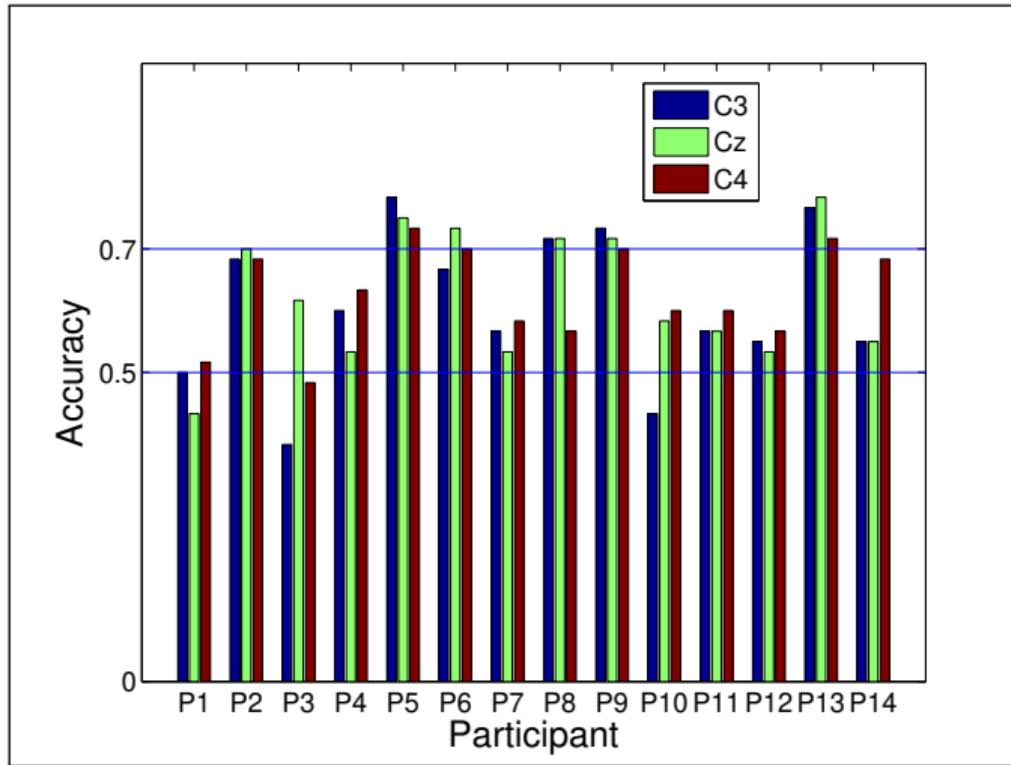


Mu a Greek letter



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

Mu a Greek letter



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



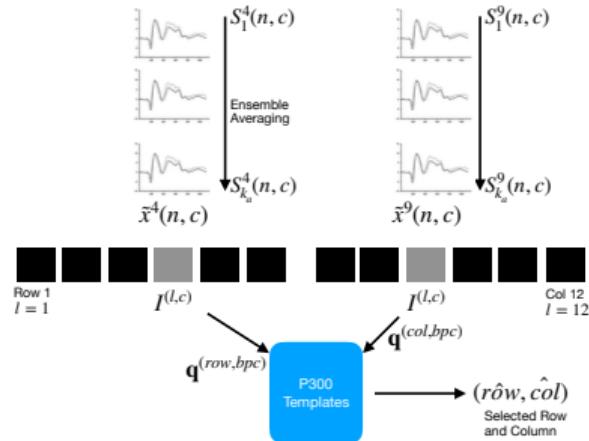
The P300 Wave

The P300 Wave



Example of the 6×6 Speller Matrix from the OpenVibe software. Rows and columns flash in random permutations.

The P300 Wave



For each column and row, an averaged, standardized and scaled signal $\tilde{x}^l(n, c)$ is obtained from the segments S_i^l corresponding to the k_a intensification sequences with $1 \leq i \leq k_a$ and location l varying between 1 and 12. From the averaged signal, the image $I^{(l,c)}$ of the signal plot is generated and each descriptor is computed. By comparing each descriptor \mathbf{q} against the set of templates, the P300 ERP can be detected, and finally the desired letter from the matrix can be inferred.

The P300 Wave

Step D: Match to the calibration template T^{bpc} by computing

$$\hat{row} = \arg \min_{I \in \{1, \dots, 6\}} \sum_{h=1}^k \left\| \mathbf{q}^{(I, bpc)} - \mathbf{d}_h^{(bpc)} \right\|^2 \quad (3)$$

and

$$\hat{col} = \arg \min_{I \in \{7, \dots, 12\}} \sum_{h=1}^k \left\| \mathbf{q}^{(I, bpc)} - \mathbf{d}_h^{(bpc)} \right\|^2 \quad (4)$$

with $\mathbf{d}_h^{(bpc)}$ belonging to the set $N_T(\mathbf{q}^{(I, bpc)})$, which is defined, for the best performing channel, as $N_T(\mathbf{q}^{(I, bpc)}) = \{\mathbf{d}_h^{(bpc)} \in T^{bpc} / \mathbf{d}^{(bpc)} \text{ is the } k\text{-nearest neighbor of } \mathbf{q}^{(I, bpc)}\}$. This procedure is a unary classification scheme, an adapted version of the algorithm described in Section ?? to the letter identification required in the BCI-Based P300 Speller implementation.

The P300 Wave

- Dataset I - P300 ALS Public Dataset

The P300 Wave

- Dataset I - P300 ALS Public Dataset
- Dataset II - P300 for healthy subjects

The P300 Wave

- Dataset I - P300 ALS Public Dataset
- Dataset II - P300 for healthy subjects
- Dataset III - P300 Pseudo-Real Dataset Generation

The P300 Wave

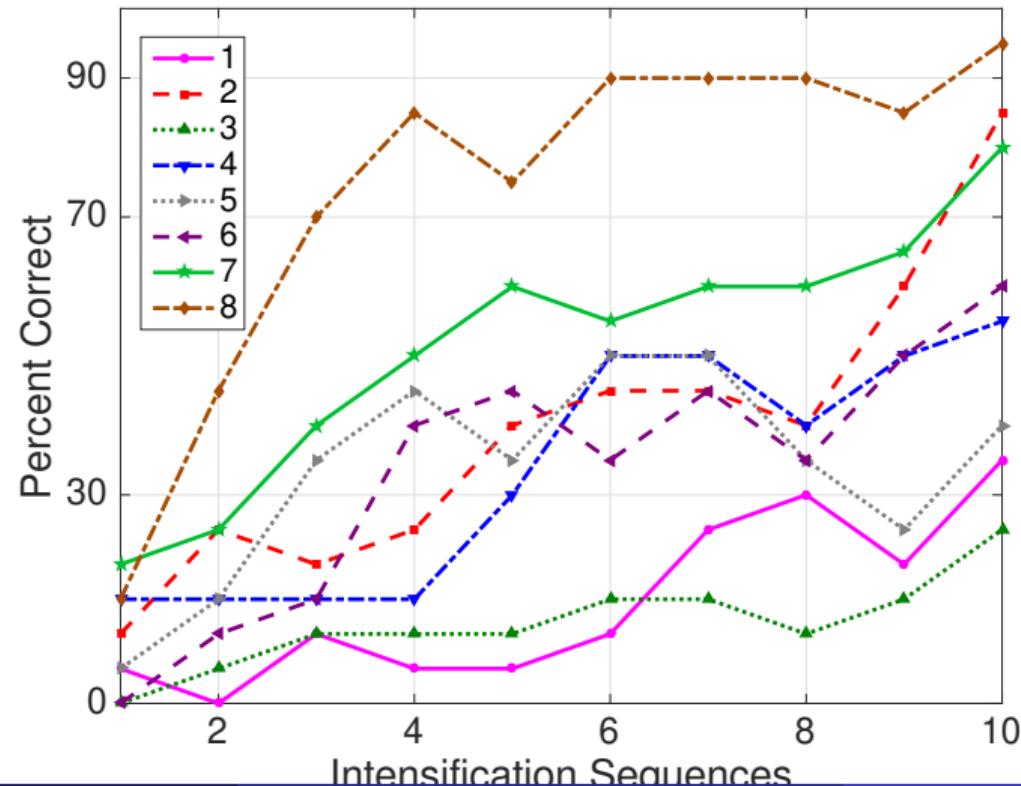
- Dataset I - P300 ALS Public Dataset
- Dataset II - P300 for healthy subjects
- Dataset III - P300 Pseudo-Real Dataset Generation
- Dataset IV - P300 Dataset IIb BCI Competition II (2003)

The P300 Wave

Table: Dataset I: Character recognition rates for the public dataset of ALS patients using HIST calculated from single-channel plots. Performance rates using single-channel signals with the SVM classifier are shown for comparison. The best performing channel *bpc* for each method is visualized

Participant	<i>bpc</i>	HIST	<i>bpc</i>	Single Channel SVM
1	Cz	35%	Cz	15%
2	Fz	85%	PO8	25%
3	Cz	25%	Fz	5%
4	PO8	55%	Oz	5%
5	PO7	40%	P3	25%
6	PO7	60%	PO8	20%
7	PO8	80%	Fz	30%
8	PO7	95%	PO7	85%

The P300 Wave



The P300 Wave

Table: Dataset II: Character recognition rates and *bpc* using HIST calculated from single-channel signals. Performance rates using single-channel signals with the SVM classifier are shown for comparison.

Participant	<i>bpc</i>	HIST	<i>bpc</i>	Single Channel SVM
1	Oz	40%	Cz	10%
2	PO7	30%	Cz	5%
3	P4	40%	P3	10%
4	P4	45%	P4	35%
5	P4	60%	P3	10%
6	Pz	50%	P4	25%
7	PO7	70%	P3	30%
8	P4	50%	PO7	10%

HIST method has an improved performance at letter identification than SVM that process the signals on a channel by channel strategy (Wilcoxon signed-rank test, $p = 0.004$ for both



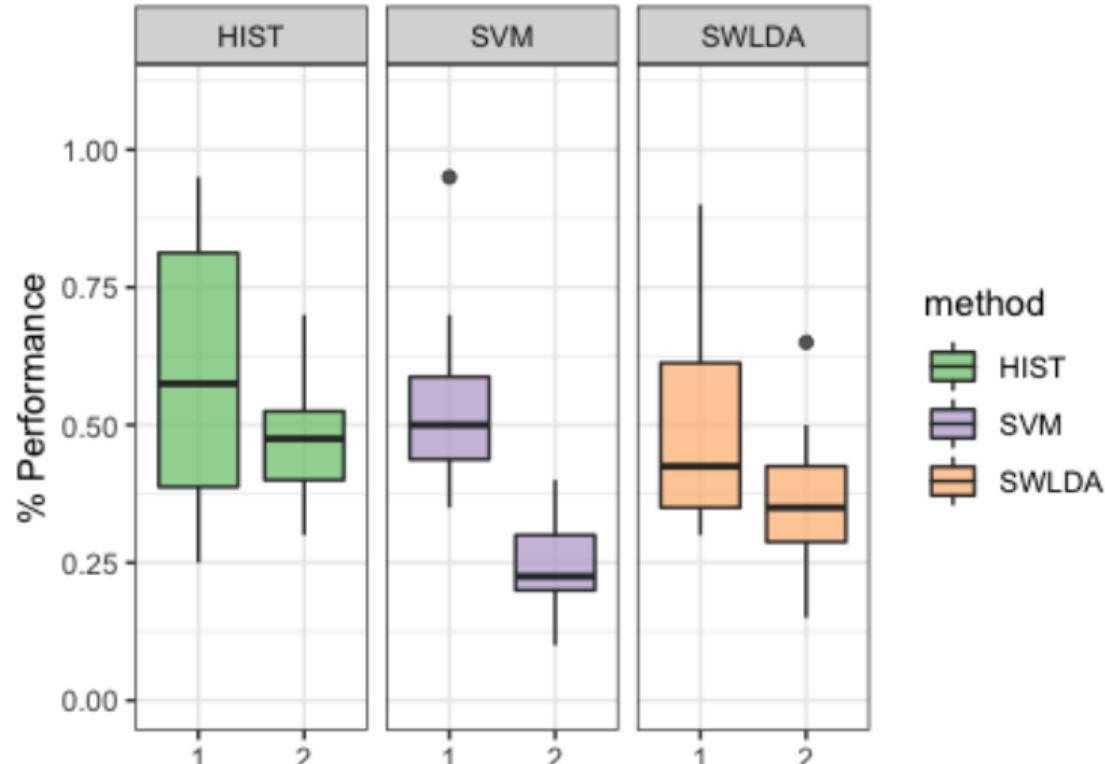
The P300 Wave

Table: Character recognition rates and the best performing channel bpc for the public dataset I using the HIST versus performance rates obtained by SWLDA and SVM classification algorithms with a multichannel concatenated feature.

Participant	bpc for HIST	HIST	Multichannel SWLDA	Multichannel SVM
1	Cz	35%	45%	40%
2	Fz	85%	30%	50%
3	Cz	25%	65%	55%
4	PO8	55%	40%	50%
5	PO7	40%	35%	45%
6	PO7	60%	35%	70%
7	PO8	80%	60%	35%
8	PO7	95%	90%	95%

The P300 Wave

Performance by Dataset and Method

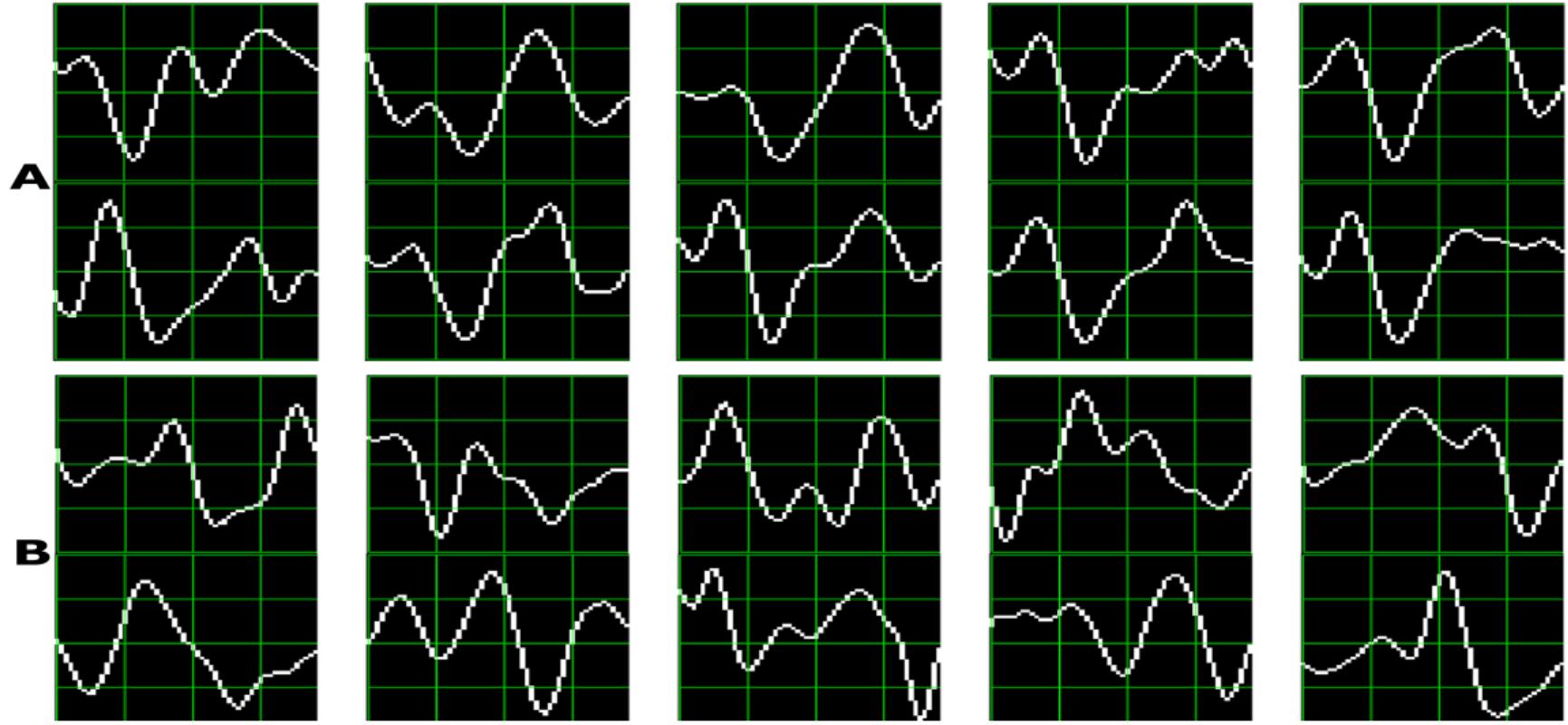


The P300 Wave

Table: Character recognition rates and the best performing channel bpc for the dataset II using HIST versus performance rates obtained by SWLDA and SVM classification algorithms with a multichannel concatenated feature.

Participant	bpc for HIST	HIST	Multichannel SWLDA	Multichannel SVM
1	Oz	40%	65%	40%
2	PO7	30%	15%	10%
3	P4	40%	50%	25%
4	P4	45%	40%	20%
5	P4	60%	30%	20%
6	Pz	50%	35%	30%
7	PO7	70%	25%	30%
8	P4	50%	35%	20%

The P300 Wave



The P300 Wave

Additionally, the stability of the P300 component waveform has been extensively studied in patients with ALS [**SellersandEmanuelDonchin2006**, **TomohiroMadarame2008**, **Nijboer2009**, **Mak2012**, **McCane2015**] where it was found that these patients have a stable P300 component, which were also sustained across different sessions. In line with these results we do not find evidence of a difference in terms of the performance obtained by analyzing the waveforms, by using the HIST method, for the group of patients with ALS and the healthy group of volunteers (Mann-Whitney U Test, $p = 0.46$). Particularly, the best performance is obtained for a subject from the ALS dataset for which, based on visual observation, the shape of they P300 component is consistently identified.

Dissertation Contributions

- A procedure to construct analyzable 2D-images based on one-dimensional signals.
- The introduction of the HIST method as an enhancement on the SIFT technique to allow non-squared patches and to adapt it to signal plots.
- A mapping procedure to link EEG time-series characteristics to features of 2D-images.
- A feature extraction method for EEG signals that can be used objectively to encode a representation of the waveform.
- A classification algorithm that use the encoded representation with the purpose of comparing and identifying waveforms for BCI applications.

Conclusion

Conclusion

- EEG Waveforms can be analyzed by this method.
- Oscillatory processes can be studied by this methodology.
- The stability of ERP transient components can be studied objectively with the proposed methodology.

References

Questions

Questions?

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Sample frame title

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Sample frame title

- Notch filter:
- Band-pass filter
- Decimation or Downsizing:
- Segmentation
- Baseline Removal
- Artifact Rejection
- Spatial Filter

An excellent review can be found here [**Simons2016**].

Sample frame title

$$\omega_{\text{ang}}(\alpha) = \sum_{r=-1}^1 \omega\left(\frac{8\alpha}{2\pi} + 8r\right) \quad (5)$$

Sample frame title

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Remark

Sample text

Important theorem

Sample text in red box

Examples

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Method

Signal Transformation

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

$$\mathcal{T}\{x(t, c, V) = 0\} \mapsto I(z_1, z_2, \mathcal{C}, \mathcal{I}) = 0 \quad (6)$$

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.

$$\tilde{x}(t, c) = \lfloor \delta \cdot (x(t, c) - \bar{x}(c)) \rfloor \quad (7)$$

And the signal is centered on the image

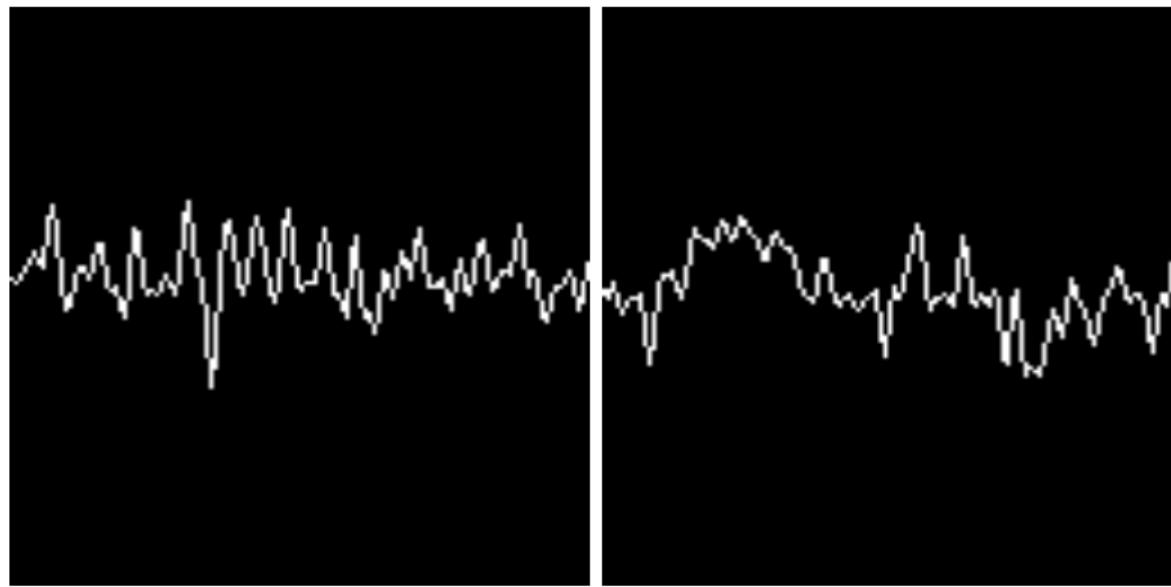
$$h(c) = (\max \tilde{x}(t, c) - \min \tilde{x}(t, c)) + \sigma \quad (8)$$

$$Z(c) = \lfloor \frac{h(c)}{2} \rfloor - \lfloor \frac{\max \tilde{x}(t, c) + \min \tilde{x}(t, c)}{2} \rfloor \quad (9)$$

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.

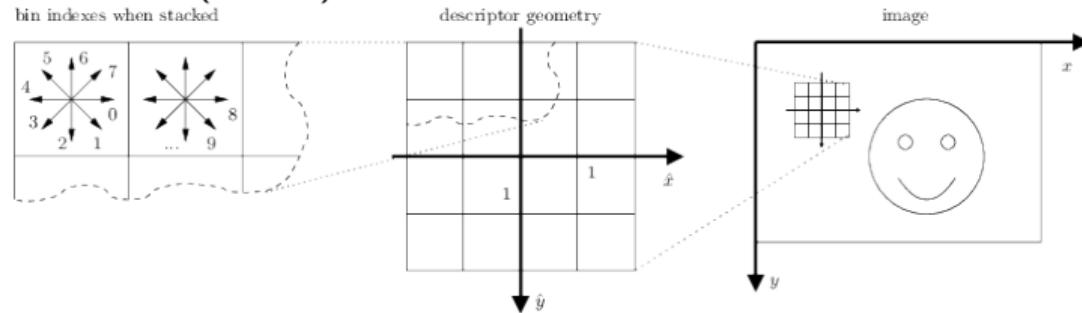
Signal Transformation: Binary Image generation.

$$I(z_1, z_2) = \begin{cases} 255 & z_1 = \delta \cdot t; z_2 = \tilde{x}(t, c) + Z(c) \\ 0 & \text{otherwise} \end{cases} \quad (10)$$



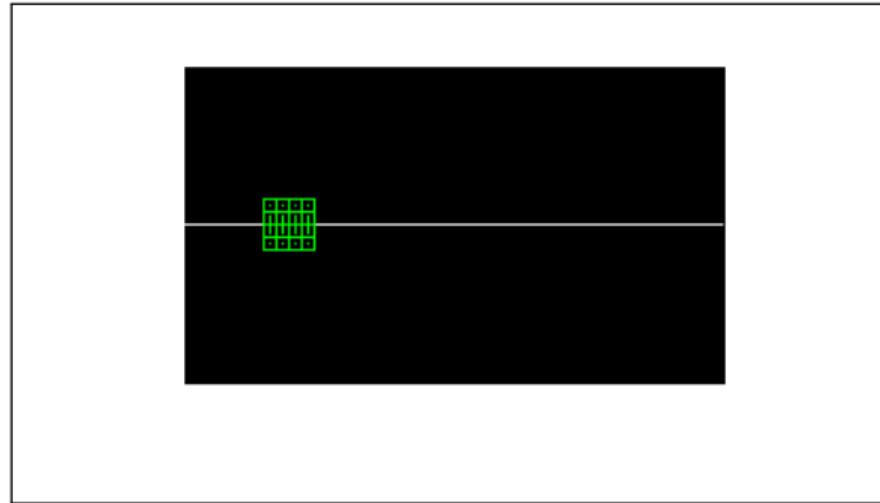
Features: SIFT⁶ Descriptors

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 ($4 \times 4 = 16$ blocks, 8 rotational directions on each). A single scale ($\sigma = 1$) is composed of 4 blocks of 3 pixels on each side (12x12).



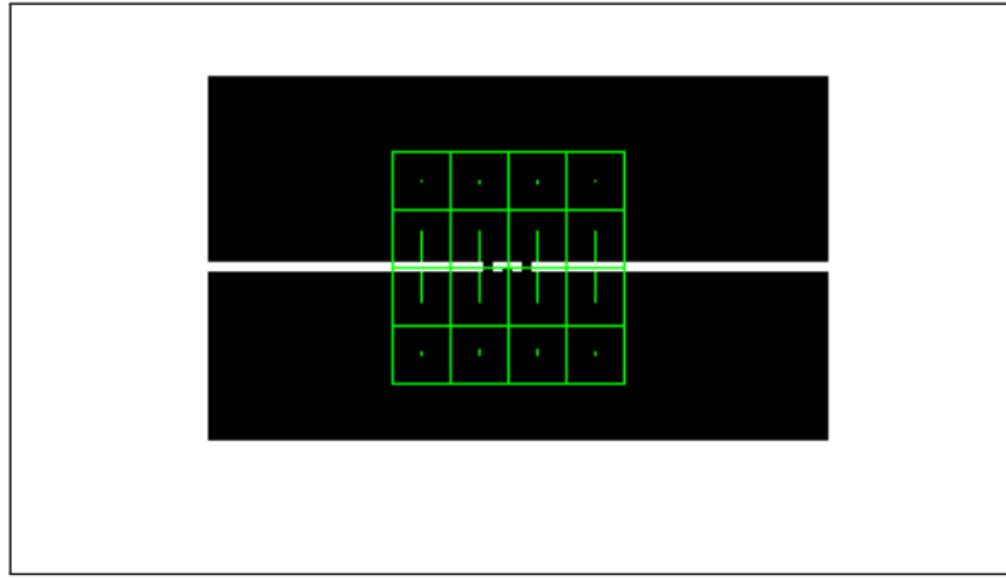
⁶Lowe 2004.

SIFT Descriptors



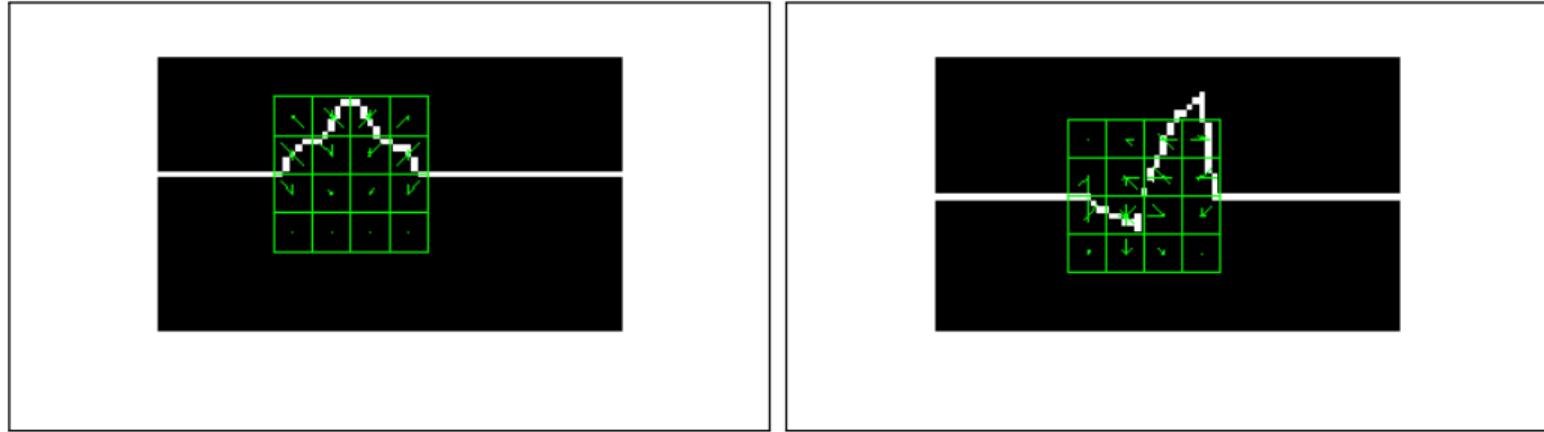
SIFT Descriptor $[z_1, z_2, \theta, \sigma]$ where (z_1, z_2) are the 2D coordinates where the *Keypoint* is located, θ is the descriptor general orientation and σ is the descriptor size.

SIFT Descriptors



SIFT Descriptor with its corresponding gradient tendencies.

SIFT Descriptors



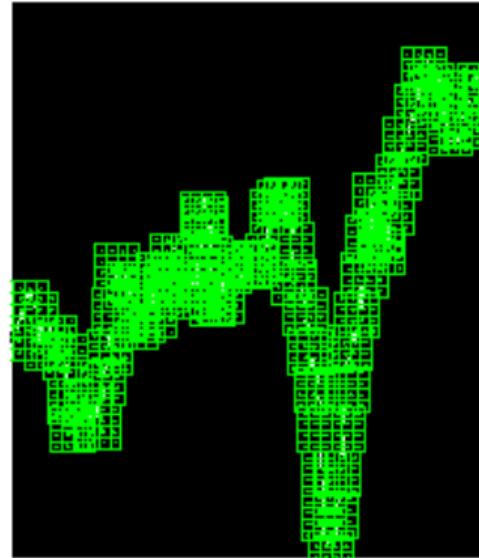
Sample Descriptors from artificial signals.

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	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	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	22	17	0	0	0
0	0	0	0	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



Classification

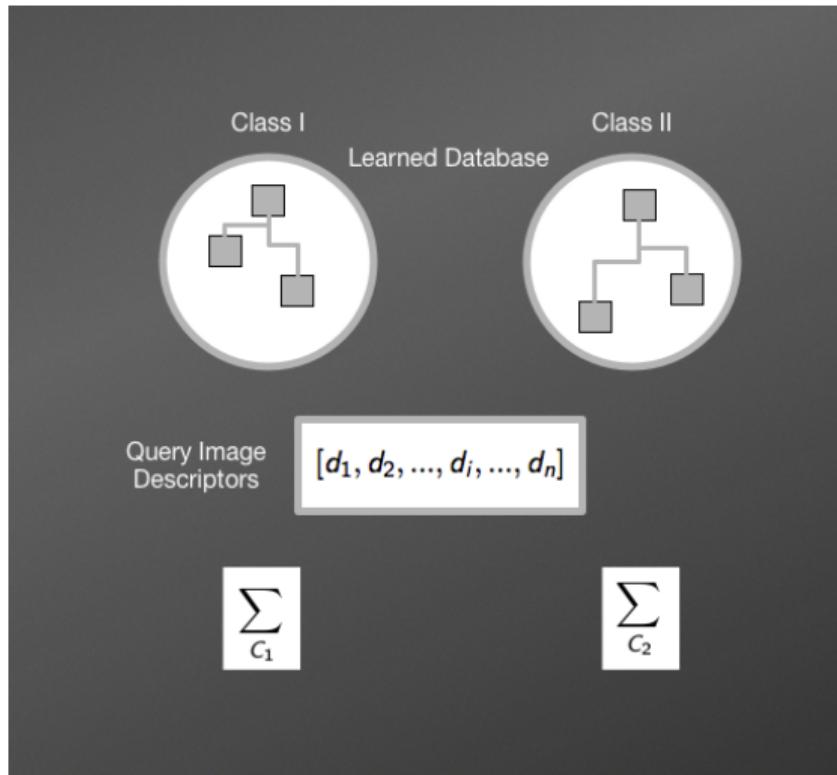
- Discriminative Semi-supervised classification method was used: Naive Bayes Nearest Neighbor, NBNN⁷ algorithm:

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

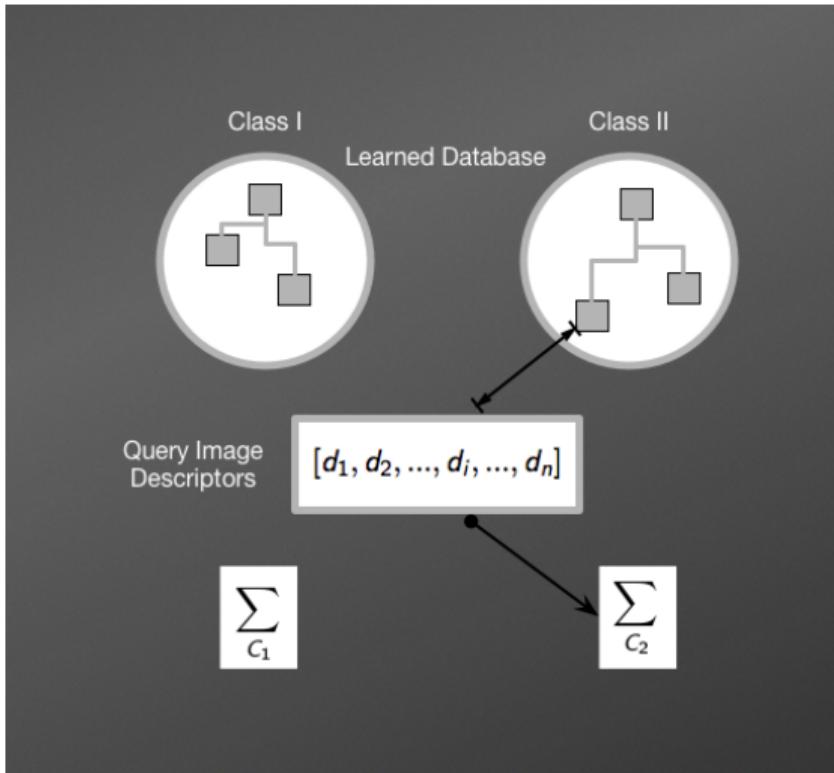
where \hat{C} is estimated Class to which this image (and underlying EEG signal windows) should belong whereas d_i is the i-th descriptor obtained from the query image and $NN_C(d_i)$ is the near neighbor descriptor for each class.

⁷Boiman, Shechtman, Irani 2008.

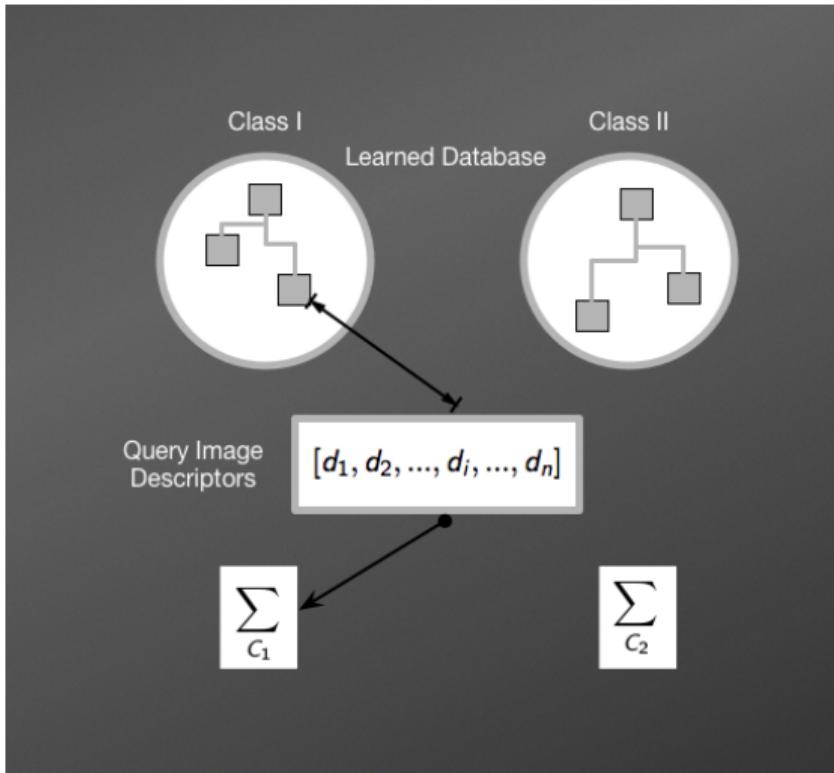
Classification



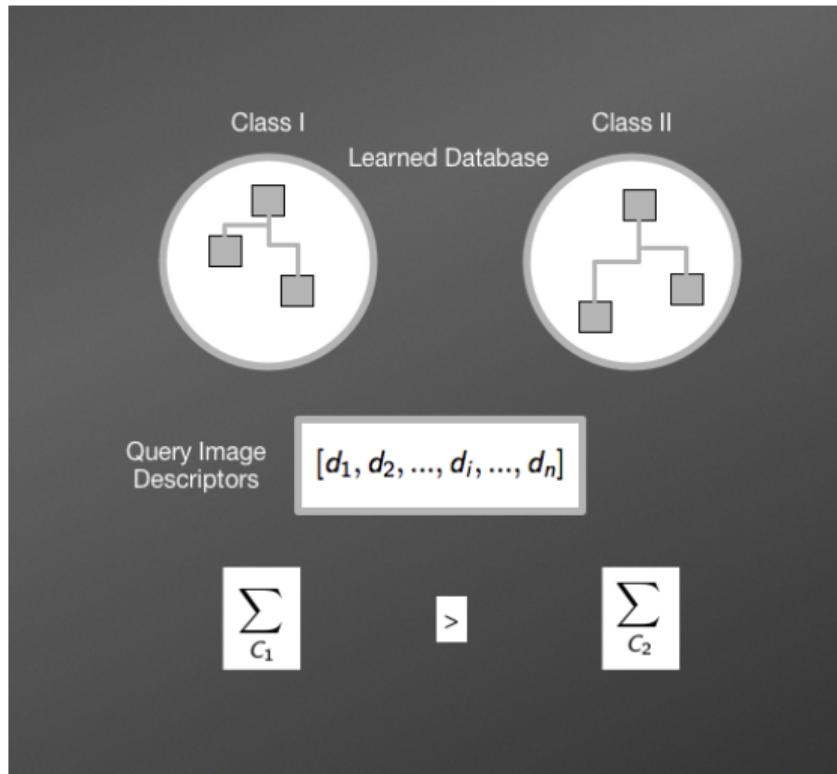
Classification



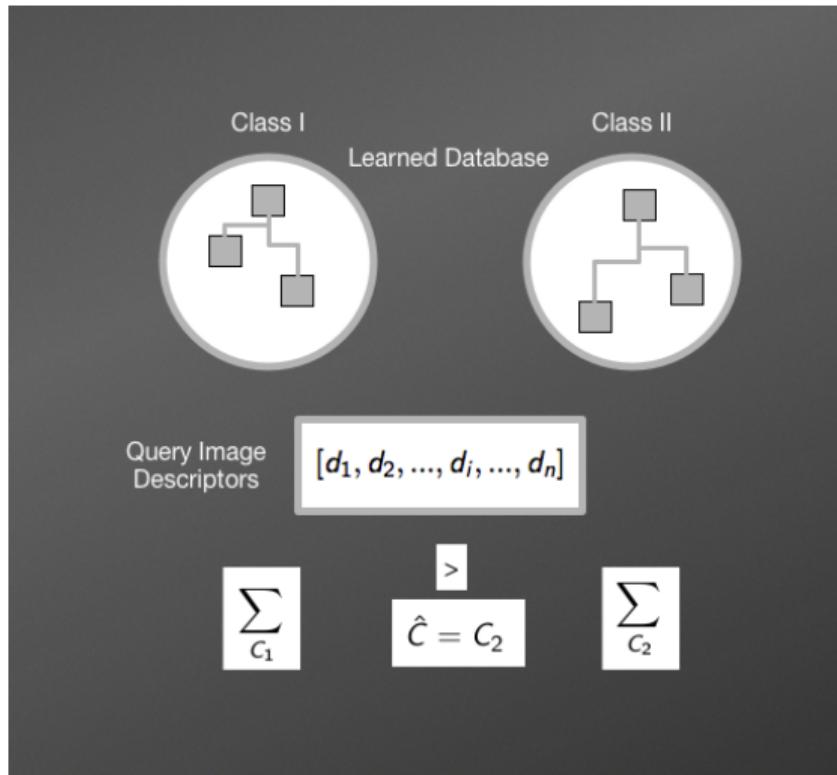
Classification



Classification

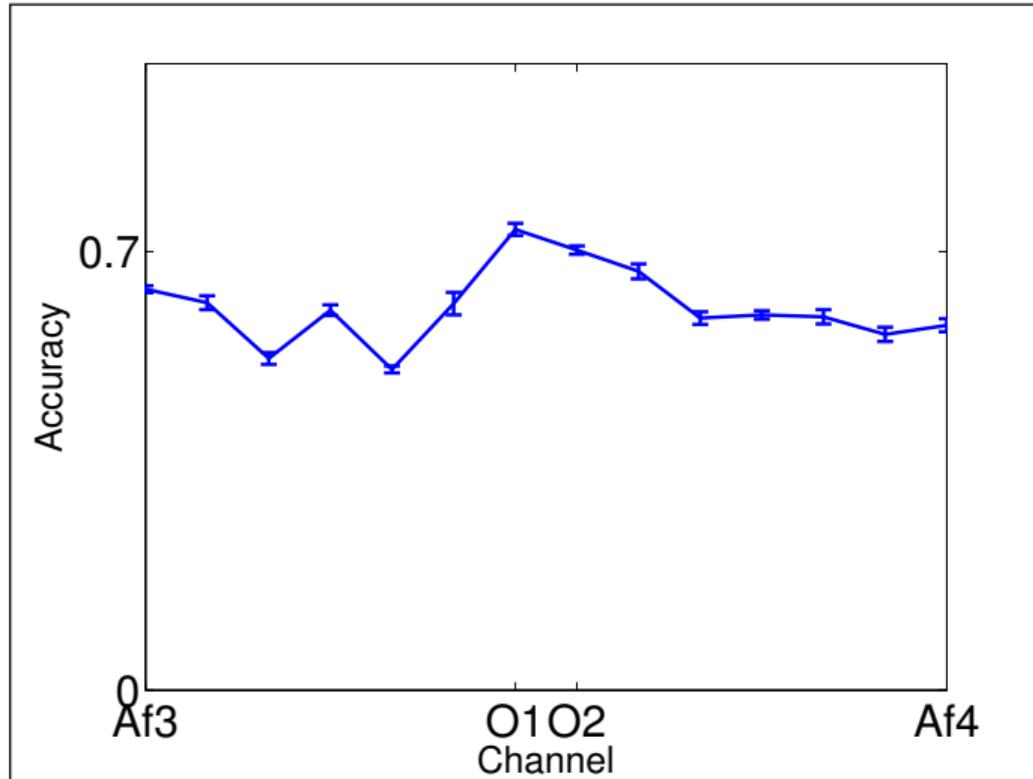


Classification

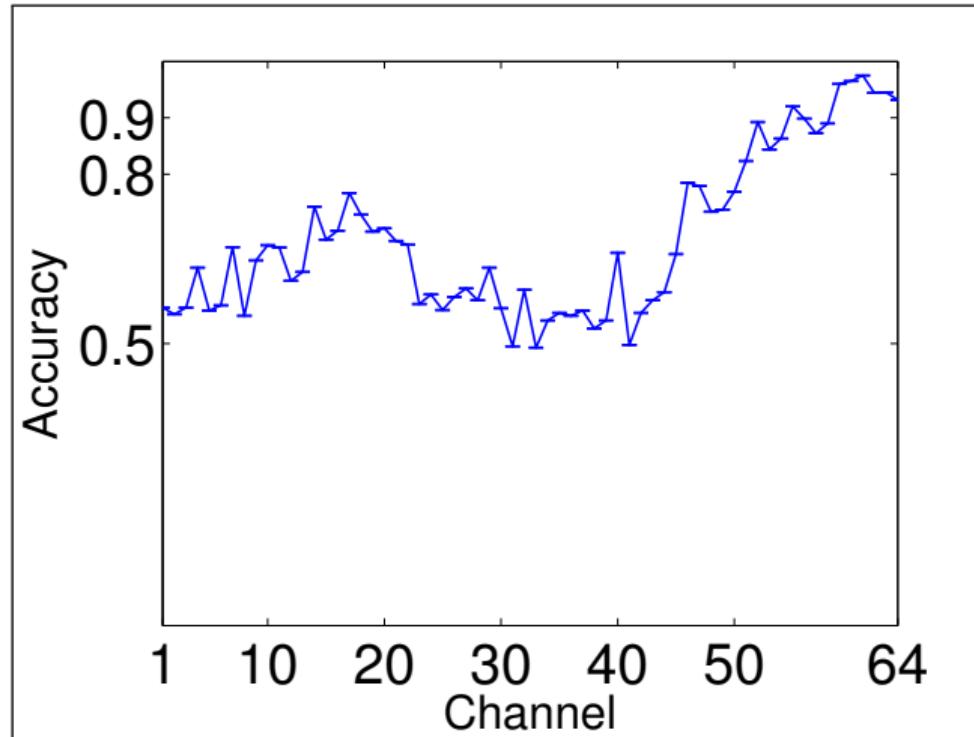


Offline Results

Dataset I: Subject Independent α Waves⁸

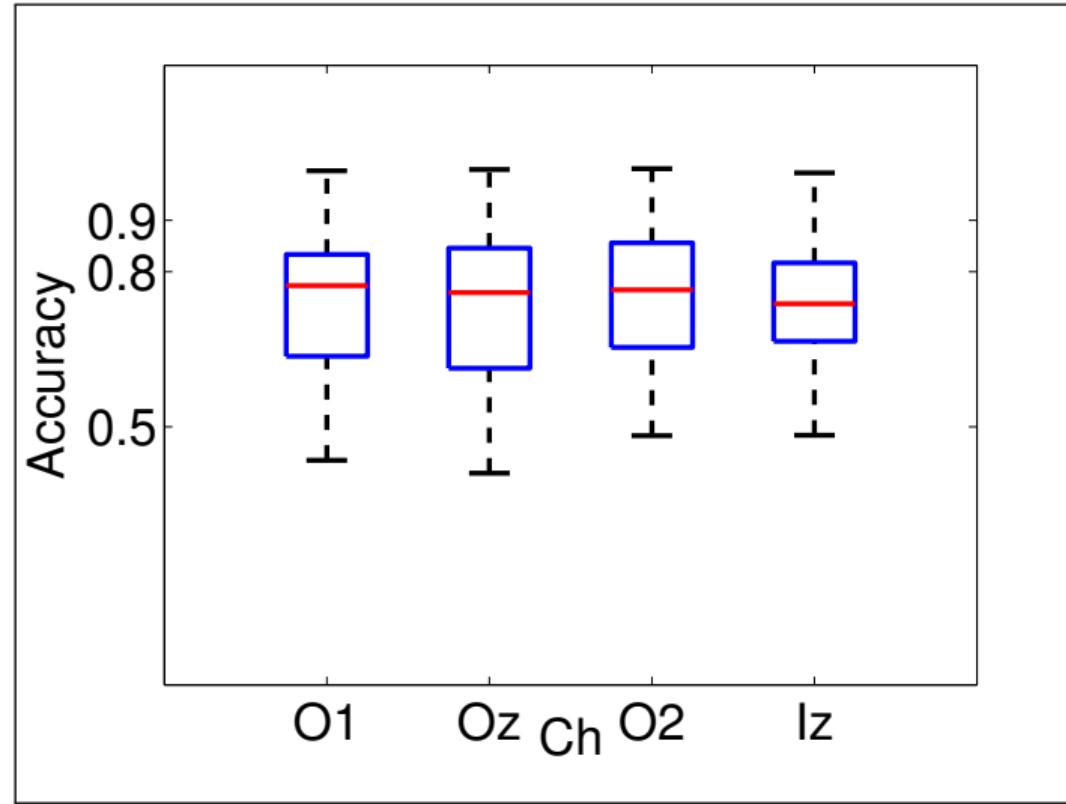


Dataset II: EEG Dataset, Runs 1 and 2⁹

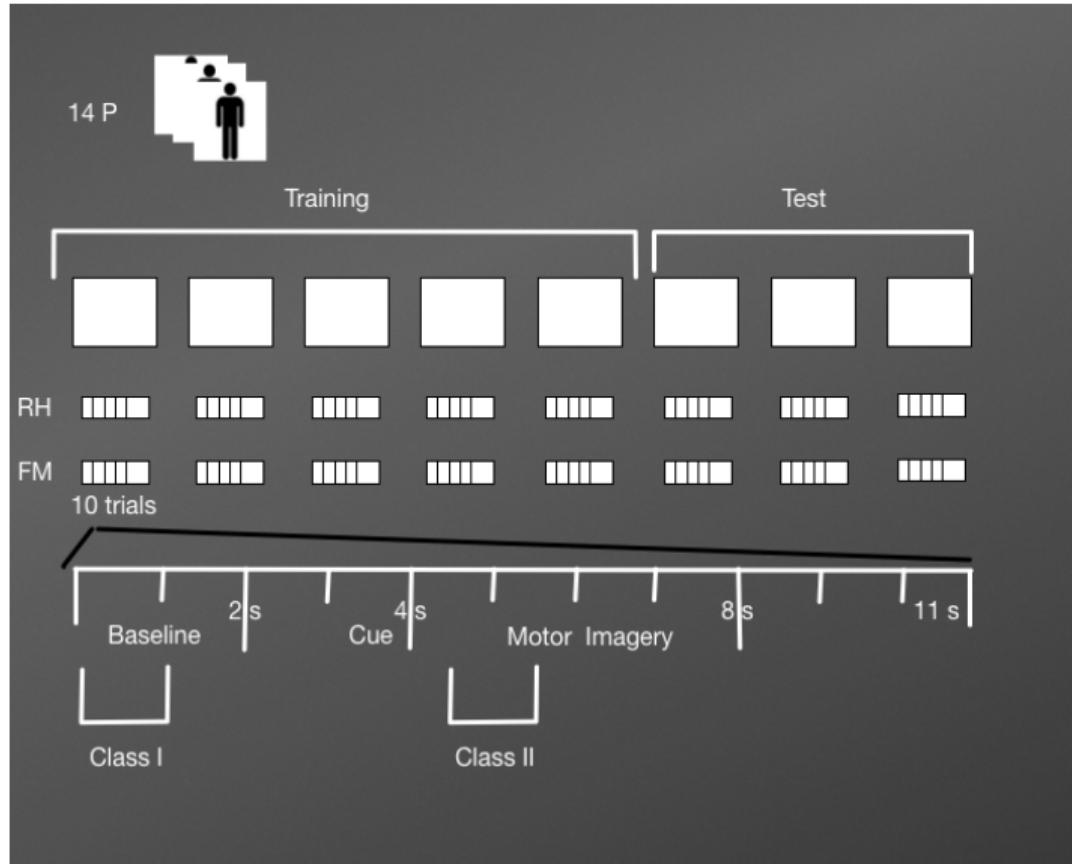


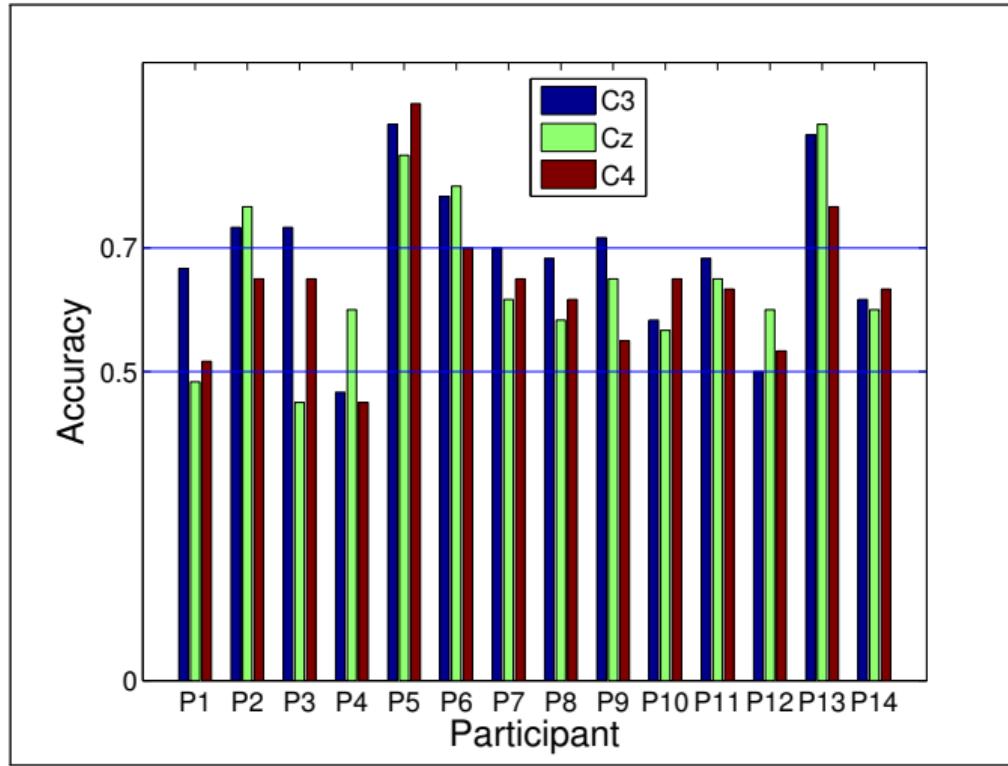
10-Fold Cross validated accuracies values for one random subject.

Dataset II: EEG Dataset, Runs 1 and 2¹⁰

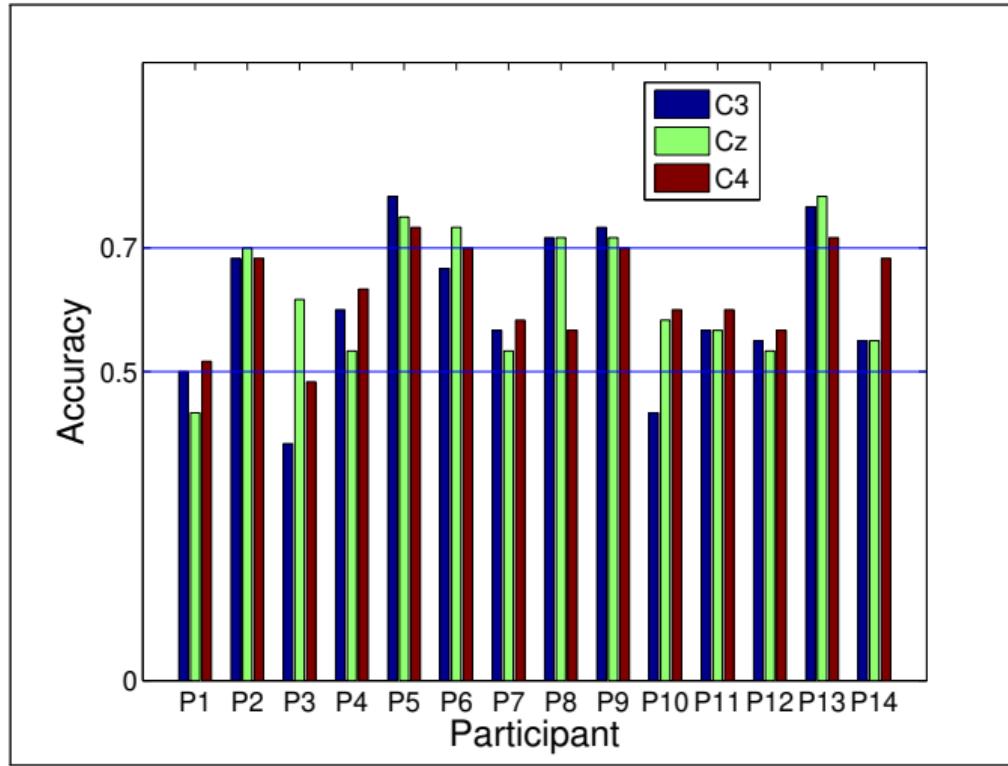


Dataset III: Motor Imagery¹¹

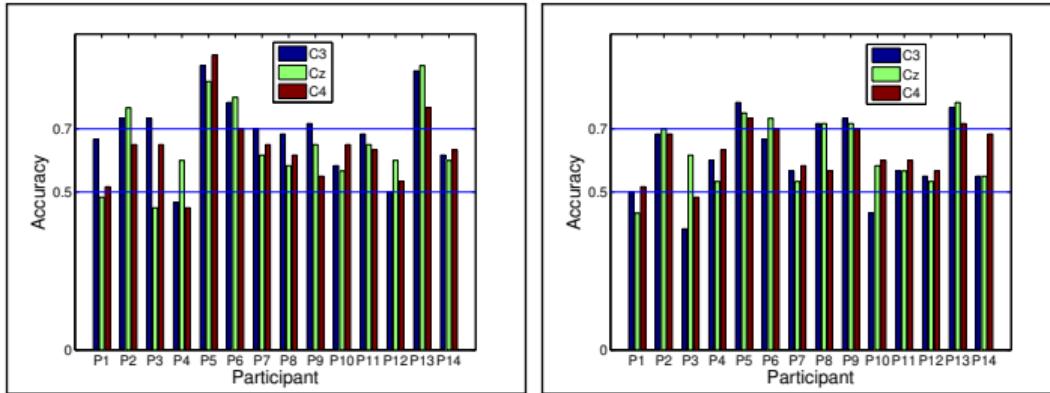




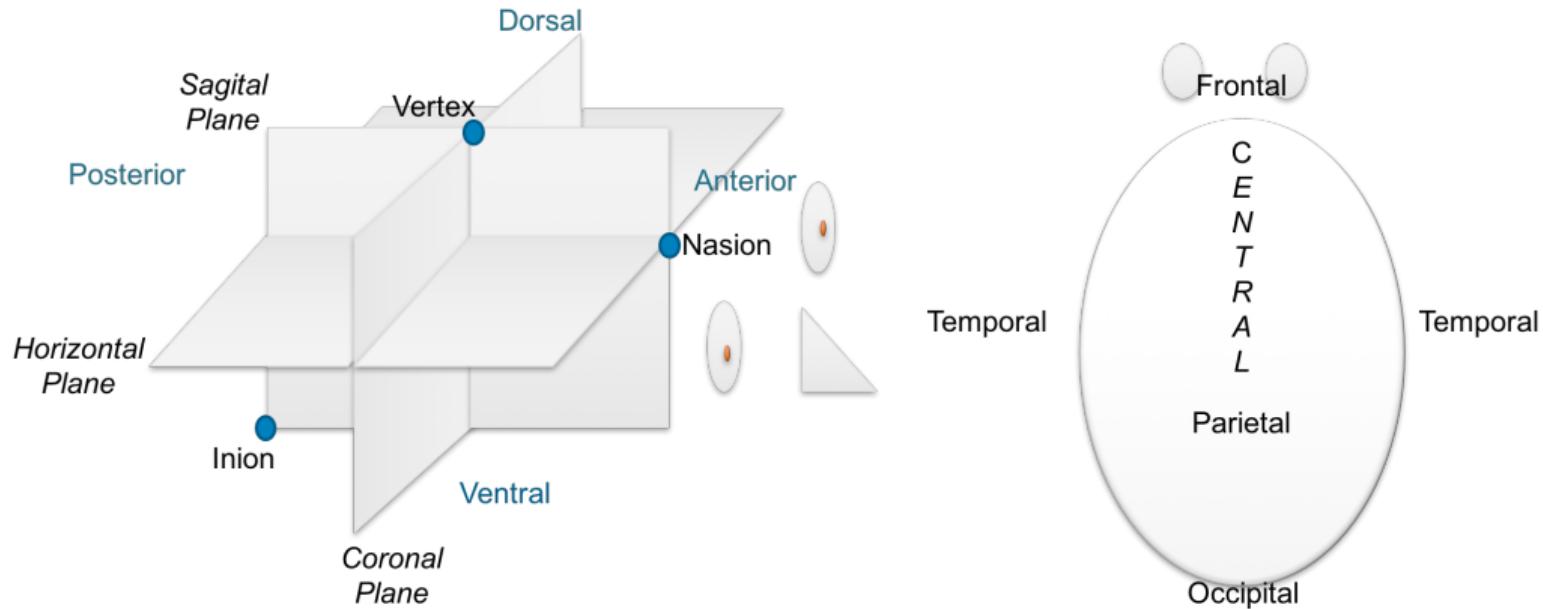
Accuracy for the BCI Simulation classifying Baseline vs. RH (Right Hand) motor imagery.



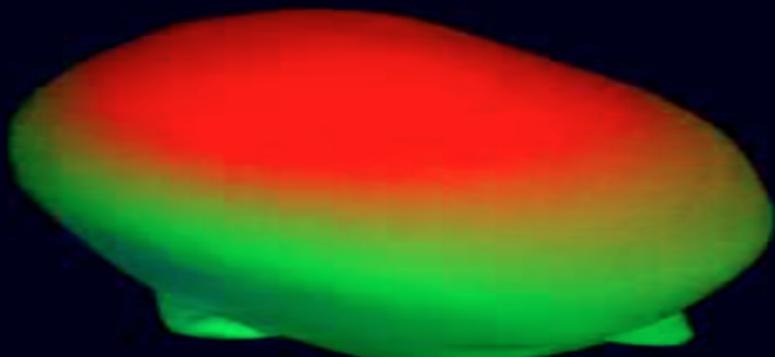
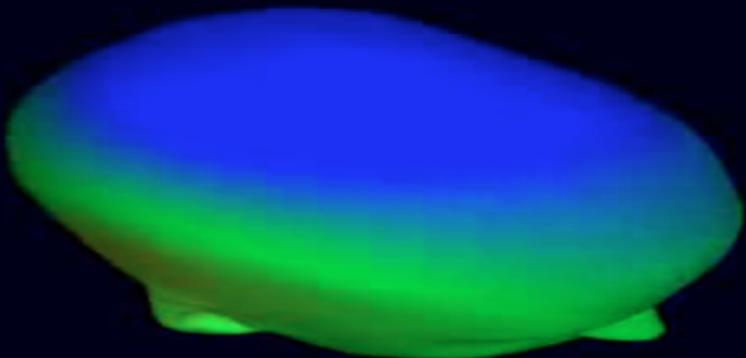
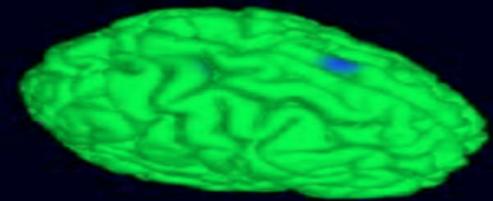
Accuracy for the BCI Simulation classifying Baseline vs. FM (Feet Movement) motor imagery.



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



Neuronal Planes regularly used in neuroscience research. In BCI they are used to understand electrode location and spatial filters.





Digital and wearable electroencephalographs.



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HIST of EEG for BCI



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Table: EEG waveforms descriptions found in the surveyed literature.

Method	Phenomena
Positive Rounded Component	α -Waves, Epilepsy
Rising and Falling Phase	Epilepsy
Terminal plateau	Epilepsy
Ripples and Wiggles	Epilepsy, ERP
Sinusoidal Shape	Epilepsy
Sawtooth	Motor Imagery, Sleep
Sharpness or Spike-like	Epilepsy
Rectangular	Epilepsy
Line length	Anomaly Detection
Root Mean Square	Anomaly Detection
Wicket Shape	Epilepsy
Peak and Trough Sharpness Ratio	Epilepsy
Symmetry between rise and decay phase	Epilepsy
Slope Ratio	Sleep

Table: EEG waveforms descriptions found in the surveyed literature.

Method	Phenomena
Positive/Negative Peak Amplitude	ERP
Positive vs Negative Ratio	Sleep K-Complex
Base-to-Peak Amplitude	ERP
Peak-to-Peak Amplitude	ERP
Positive/Negative Peak Latency	ERP
Integrated Activity	ERP, Epilepsy, ICU
Cross-Correlation Coupling	ERP, Epilepsy, Sleep
Cross Frequency, Phase-Amplitude, Phase-Phase	Sleep
Period Amplitude Analysis	ERP, Epilepsy