

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

Dissertation Defense

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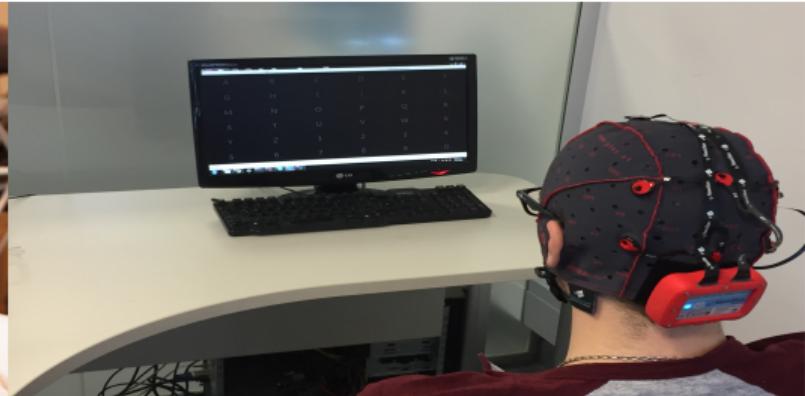
Doctorado en Ingeniería en Informática
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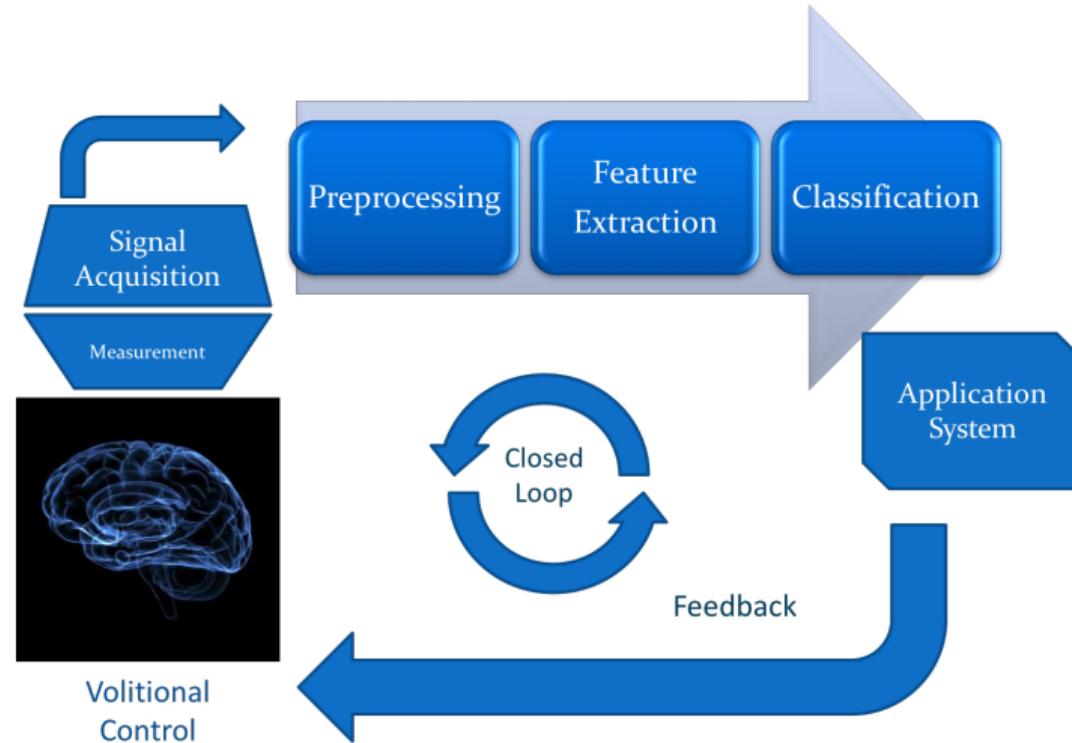
Outline

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

Brain Computer Interfaces - Current trends



Brain Computer Interfaces - System Components



Brain Computer Interfaces - BCI Paradigms

Evoked Potential

Steady State Visual Evoked Potential

SSVEP
SSAEP
SSSEP

Visual Spatial Covert Attention

Motor Imagery: ERD/ERS: Event Related De/Synchronization

Wadsworth BCI
Graz BCI

Bereitschaftspotentials

Selective Attention

P300,N400

Tübingen BCI

Mental Tasks

Operant Conditioning:

Slow Cortical Potentials
ErrP

Berlin BCI

Brain Computer Interfaces - Problem Statement

- Clinical and Physician involvement¹

¹**Yuste2017.**

²**Perdikis2014.**

Brain Computer Interfaces - Problem Statement

- Clinical and Physician involvement¹
- Practical, relevant, and invariant features that convey good-enough information².

¹**Yuste2017.**

²**Perdikis2014.**

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

- ➊ Construct analyzable 2D-images.

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- ① Construct analyzable 2D-images.
- ② Adaptation to the SIFT method to EEG time-series

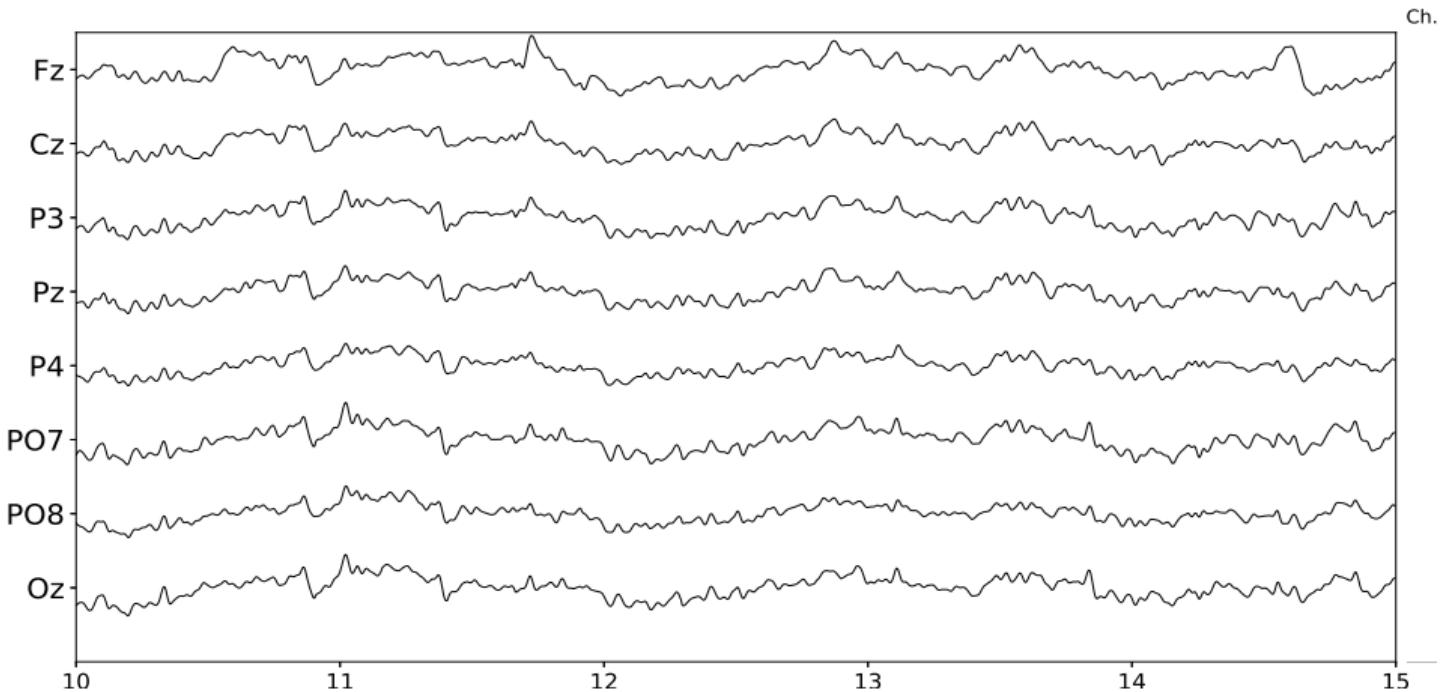
What we aim to do

- ① Construct analyzable 2D-images.
- ② Adaptation to the SIFT method to EEG time-series
- ③ Feature extraction procedure

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- ① Construct analyzable 2D-images.
- ② Adaptation to the SIFT method to EEG time-series
- ③ Feature extraction procedure
- ④ Classification algorithm

Electroencephalography



Sample 8-channel EEG signal obtained from (g.Nautilus, g.Tec, Austria). Voltage in μ V vs time in seconds. Five seconds are displayed.

Waveform-Based Algorithms

- Peak Picking/aEEG/PAA

Waveform-Based Algorithms

- Peak Picking/aEEG/PAA
- Merge of Increasing and Decreasing Sequences

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- Peak Picking/aEEG/PAA
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- Permutation Entropy

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- Matching Pursuit

Waveform-Based Algorithms

- Peak Picking/aEEG/PAA
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- Permutation Entropy
- Matching Pursuit
- Slope Horizontal Chain Code

Proposal

The Histogram of Gradient Orientation

The Histogram of Gradient Orientations - Feature Extraction Algorithm

① Signal Preprocessing

The Histogram of Gradient Orientations - Feature Extraction Algorithm

- ① Signal Preprocessing
- ② Signal Segmentation

The Histogram of Gradient Orientations - Feature Extraction Algorithm

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

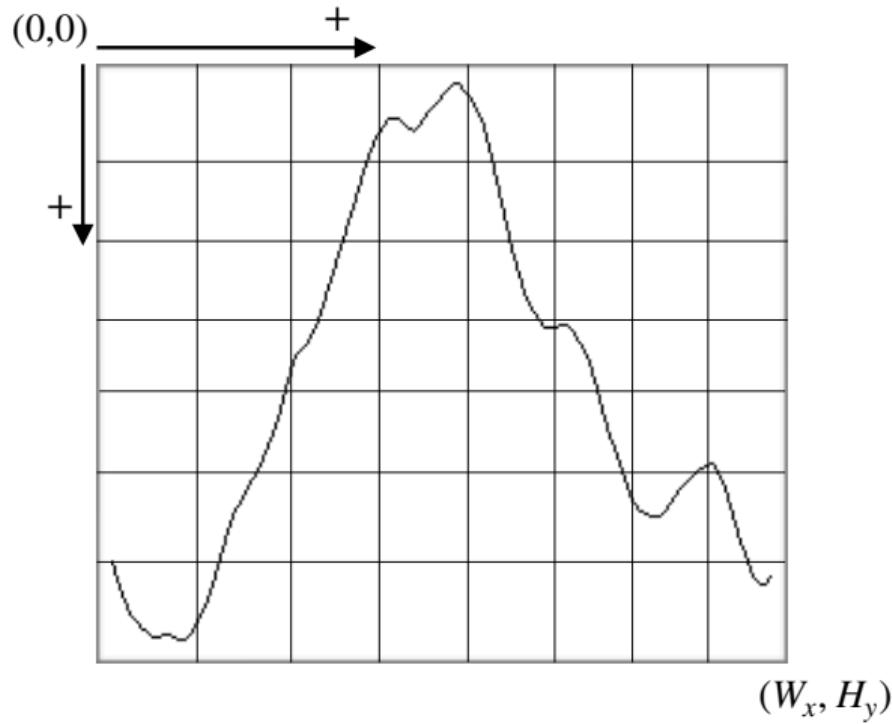
The Histogram of Gradient Orientations - Feature Extraction Algorithm

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

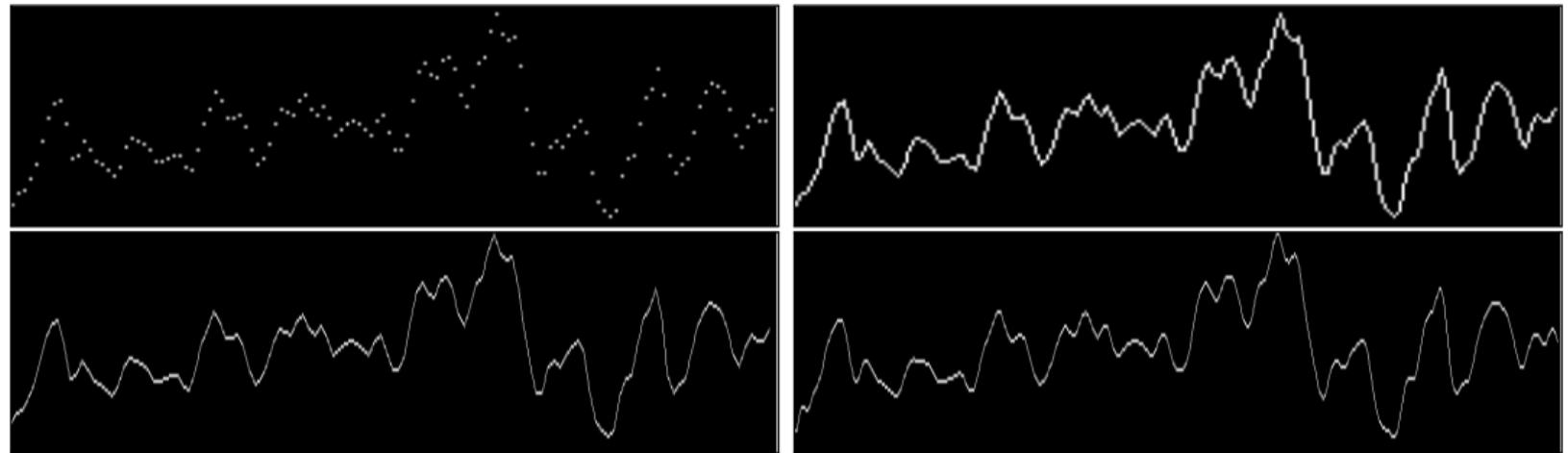
The Histogram of Gradient Orientations - Feature Extraction Algorithm

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

Image Coordinate System

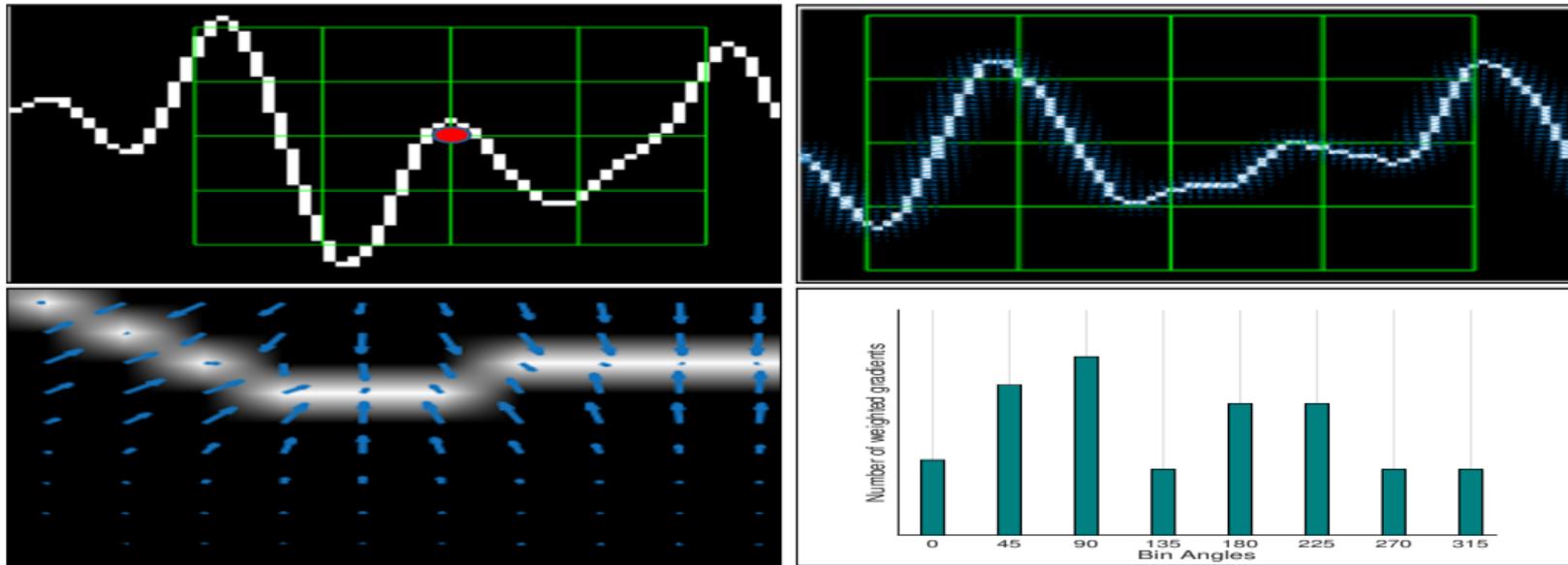


Signal Plotting



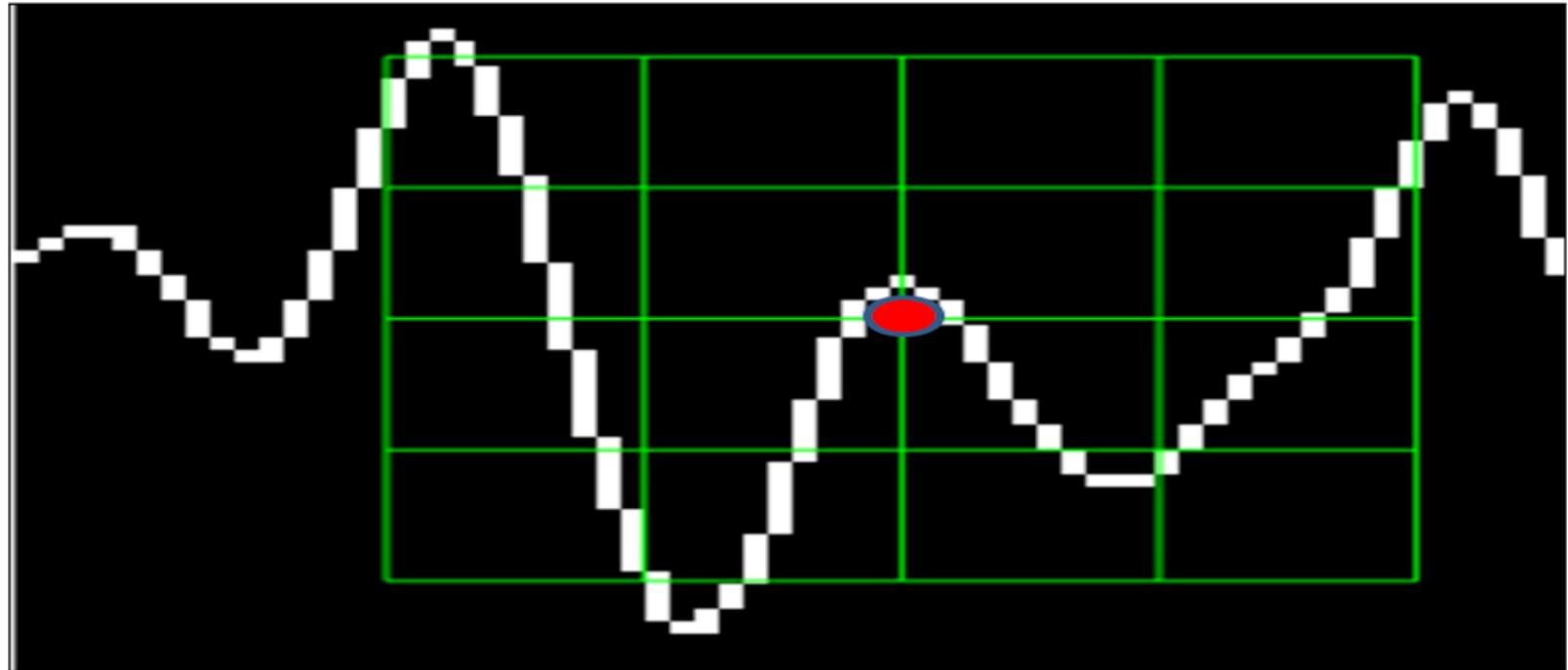
Generated images based on different interpolation schemes.

The Histogram of Gradient Orientations



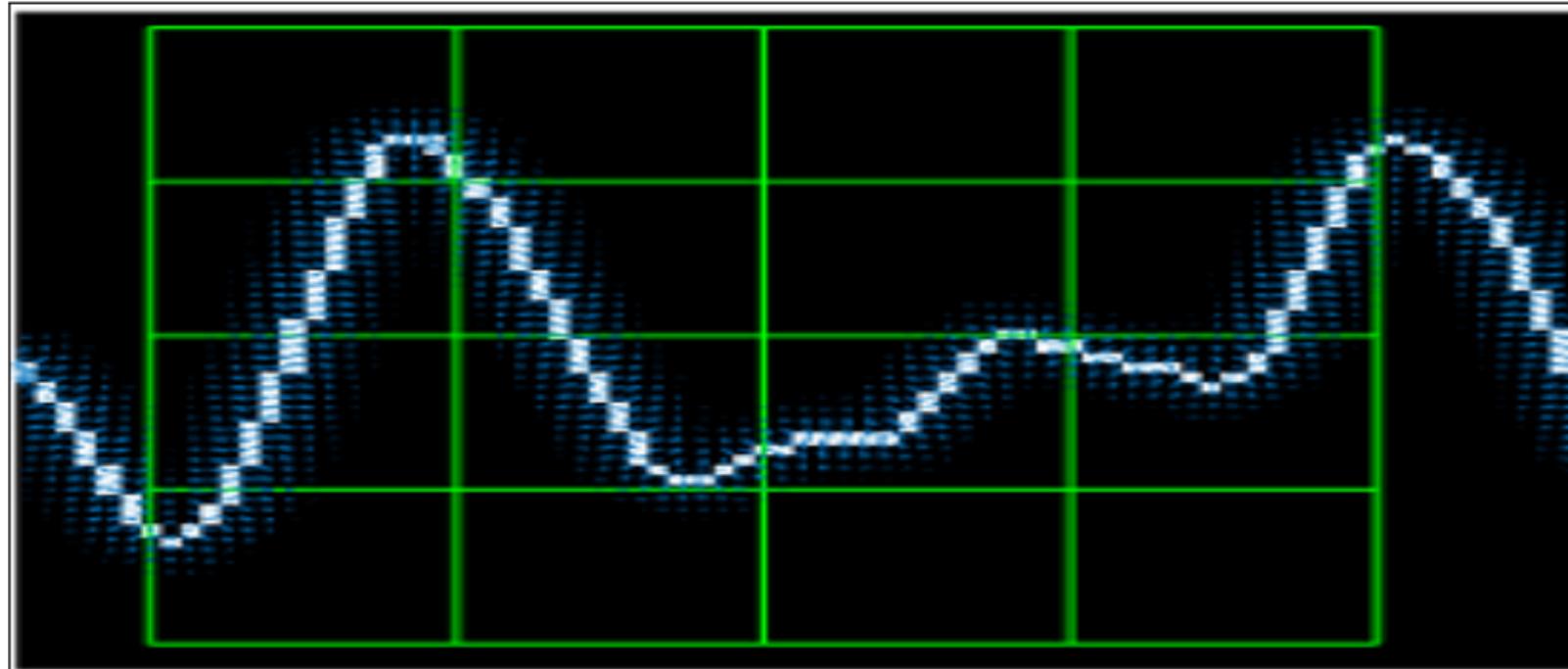
Patch and vector field of oriented gradients.

Keypoint Localization



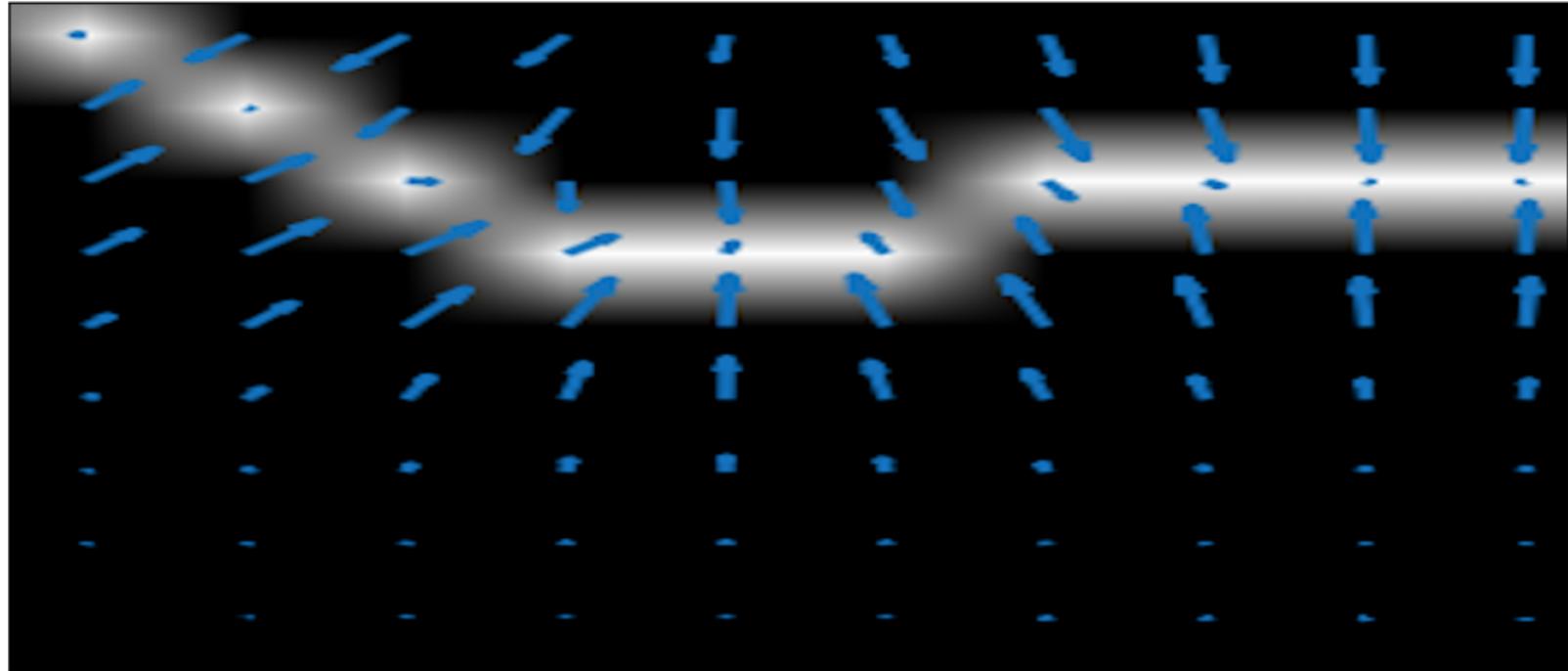
Patch and vector field of oriented gradients.

Pixel Gradient Vector Field



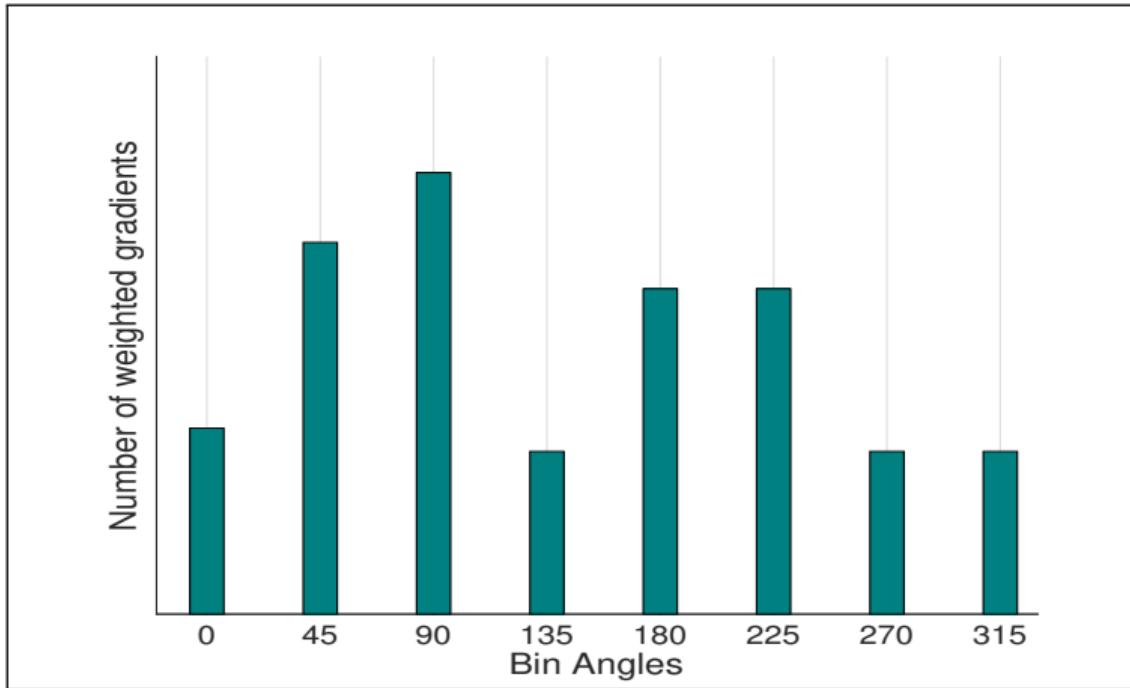
Patch and vector field of oriented gradients.

Pixel Gradient Vector Field



Patch and vector field of oriented gradients.

Orientation histogram



Patch and vector field of oriented gradients.

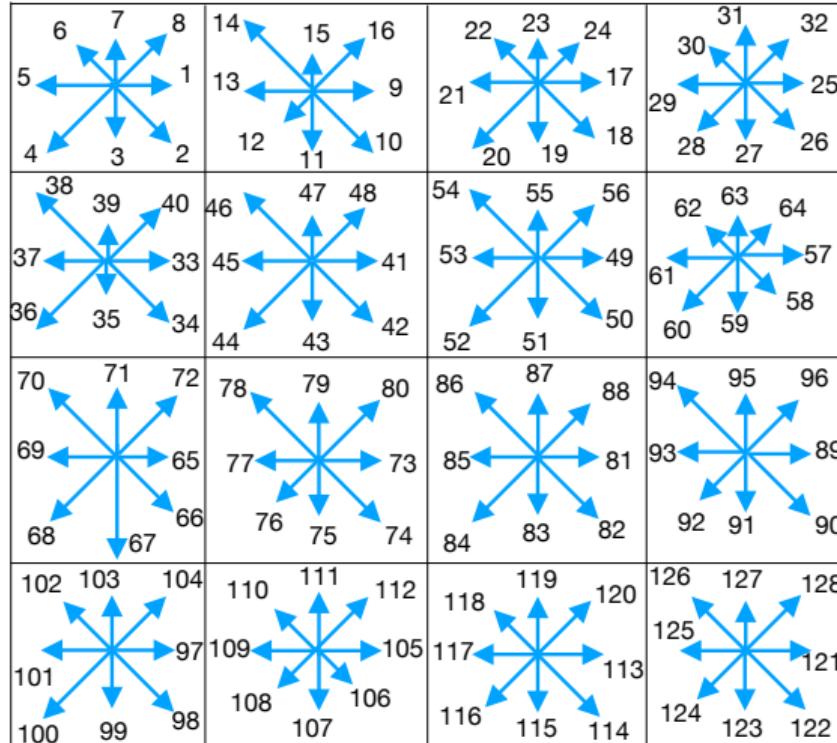
Histogram Calculation

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

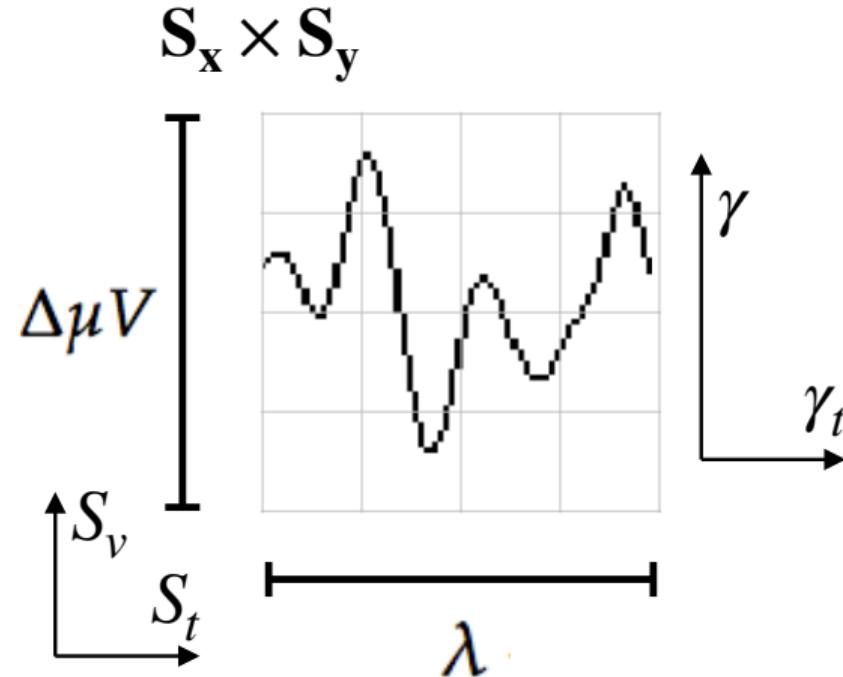
- θ is the angle bin with $\theta \in \{0, 45, 90, 135, 180, 225, 270, 315\}$.
- $i, j = \{0, 1, 2, 3\}$ indexes of the 16 grid blocks.
- \mathbf{kp} is the keypoint center location.
- \mathbf{p} is a pixel from within the patch, centered around \mathbf{kp} .
- $\angle J(\mathbf{p})$ is the angle of the gradient vector.
- $\|J(\mathbf{p})\|$ is the norm of the gradient vector in the pixel \mathbf{p} .
- $\omega_{\text{ang}}(\cdot)$ scalar and $\omega_{ij}(\cdot)$ vector linear interpolation functions³.

³Lowe2004, Vedaldi2010.

Descriptor



Patch Geometry



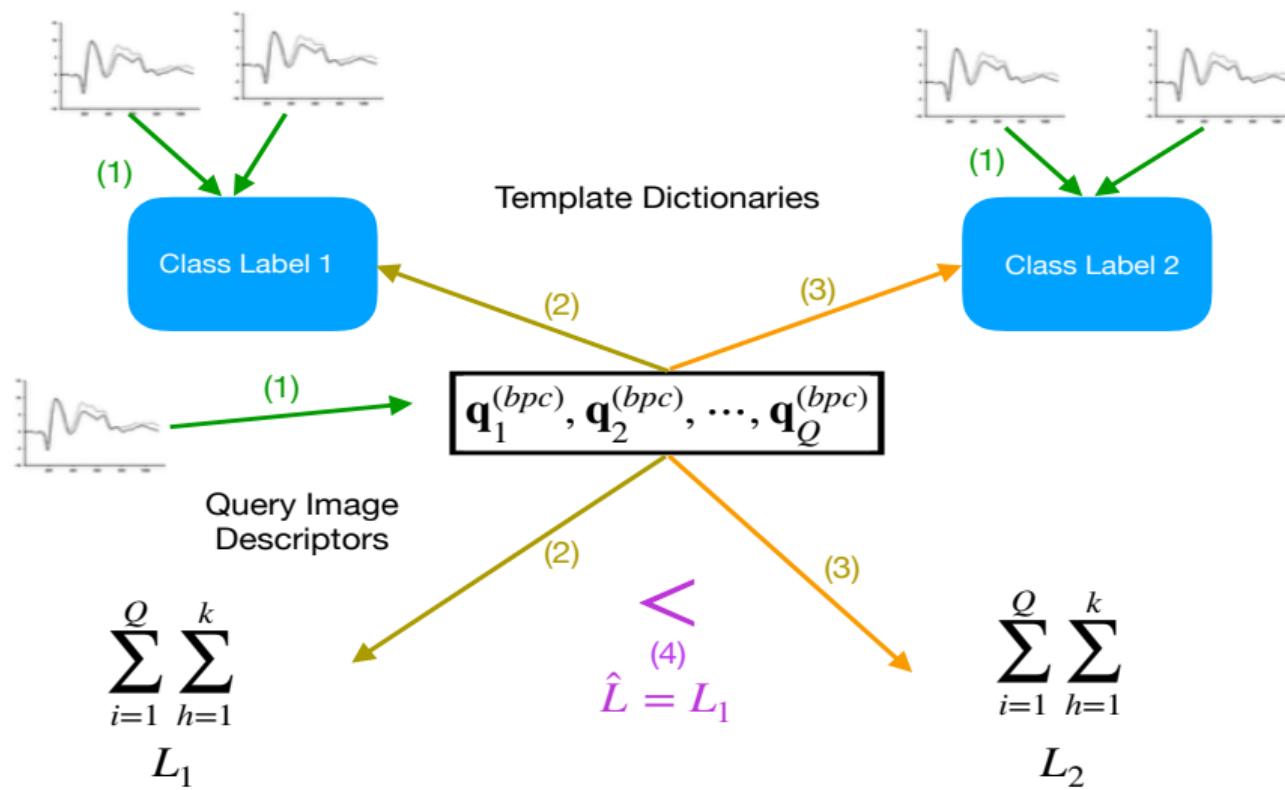
Proposed Classification Method

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

- L class label.
- Q number of descriptors extracted from the query image.
- $\mathbf{q}_i^{(bpc)}$ query descriptors.
- $\mathbf{d}_h^{(L,bpc)}$ neighbors descriptors from template dictionary of class L .
- $\mathbf{d}_h^{(L,bpc)} \in N_T(\mathbf{q}_i^{(bpc)})$.
- $N_T(\mathbf{q}_i^{(bpc)}) = \{\mathbf{d}_h^{(bpc)} \in T_L^{bpc} / \mathbf{d} \text{ is the } k\text{-nearest neighbor of } \mathbf{q}_i^{(bpc)}\}$.
- \hat{L} predicted class label.
- k the number of neighbors to pick from the template⁴.

⁴Boiman2008.

Classification Algorithm



Experimental Validation

Experimental Validation

- Alpha Waves Wiggles

Experimental Validation

- Alpha Waves Wiggles
- μ Rhythm

Experimental Validation

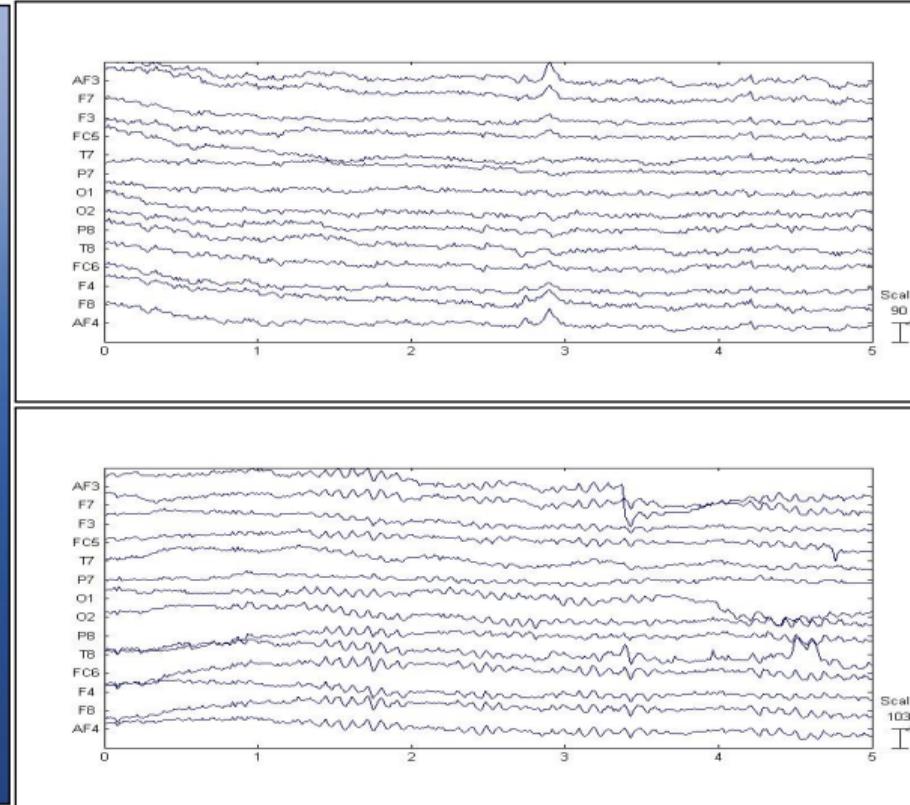
- Alpha Waves Wiggles
- μ Rhythm
- The P300 Waveform

Alpha Waves wiggles

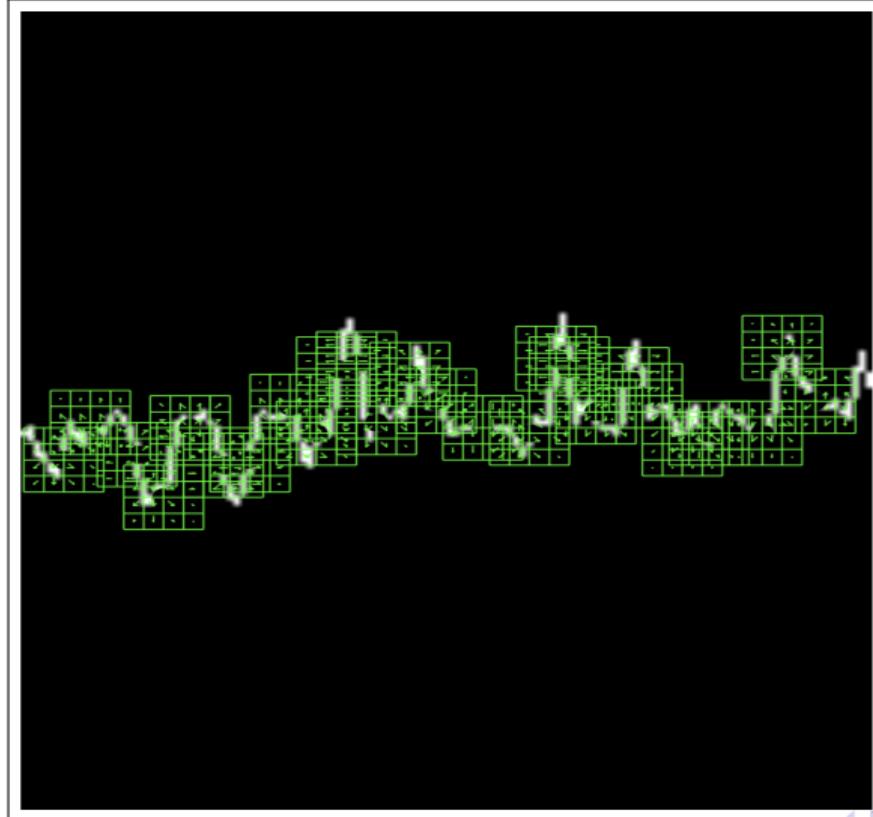
Alpha Waves Datasets

- Dataset I: 128 Hz, 14 channels, 10 subjects, 10 class 1 vs 10 class 2.
- Dataset II: 160 Hz, 64 channels, 25 subjects, Run 1 vs Run 2, 60 vs 60.

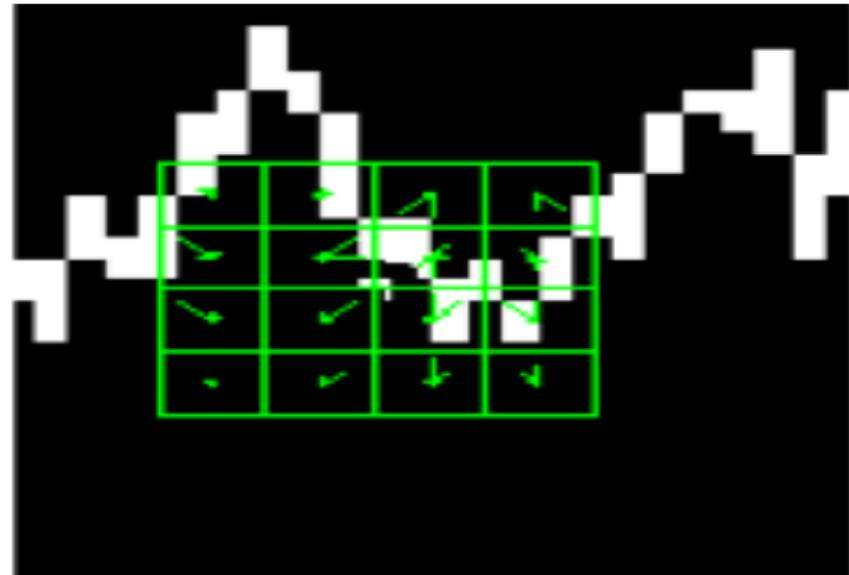
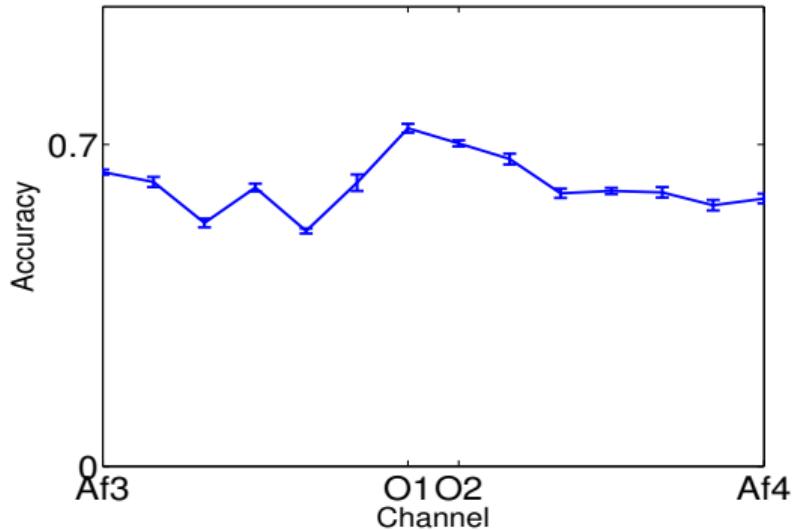
EEG Consumer Grade Digital Device and EEG Signals



Keypoint populations

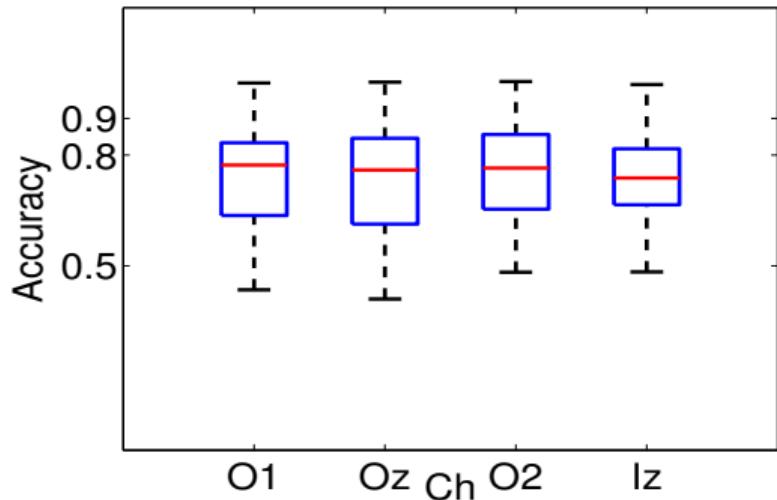
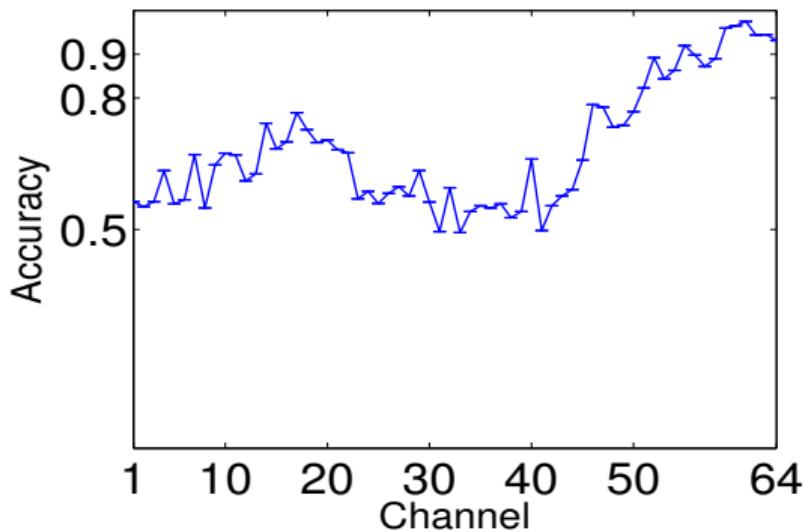


Alpha Waves wiggles



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

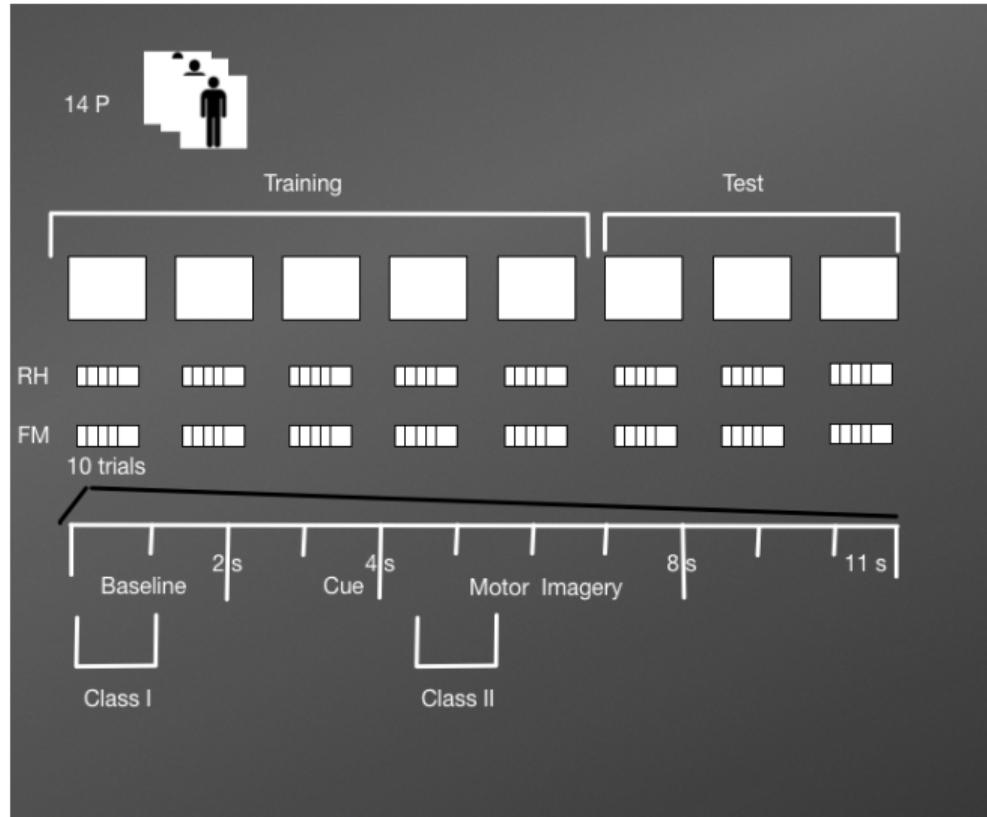


Dataset II: Classification Accuracy for segments of 1s ($N = 160$) of EEG, between class 1 and class 2.
In this case as the sampling frequency F_s is lower, the signal span is $\lambda = 0.06$ s

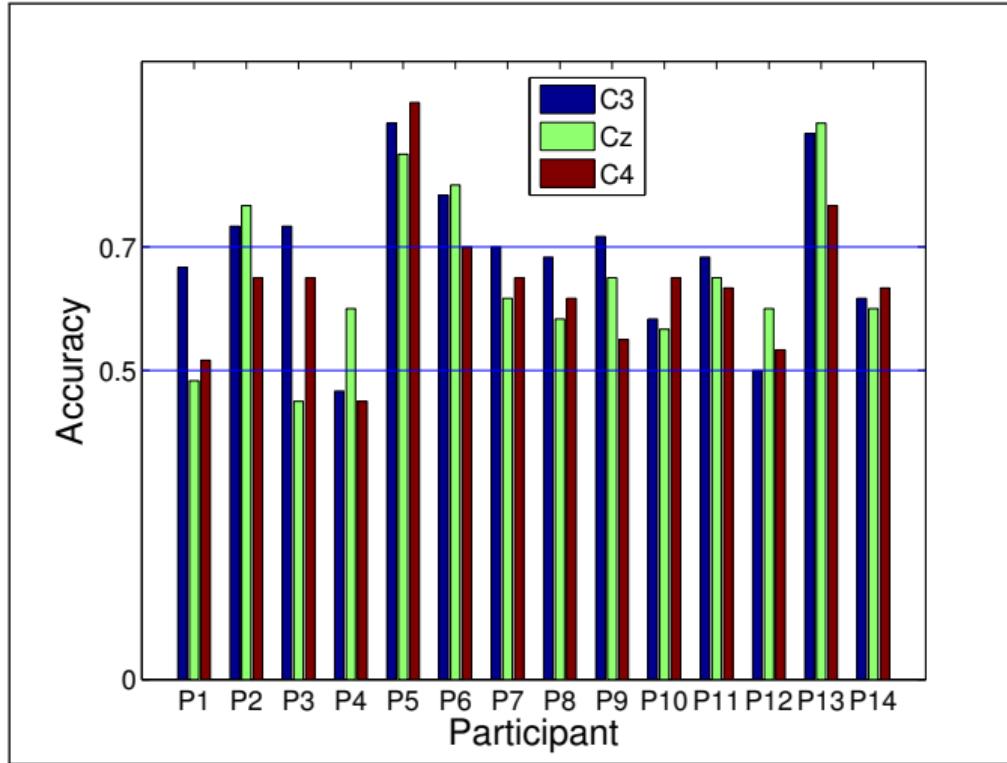
Experimental Validation

μ Rhythm

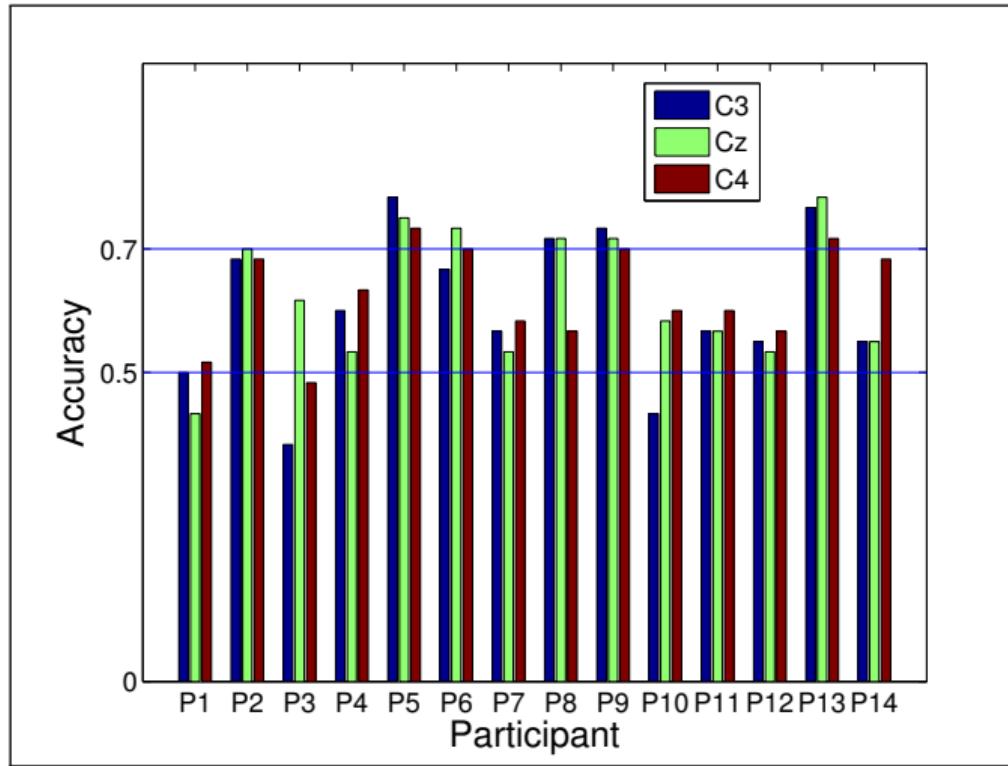
Dataset 002-2014 BNCI-Horizon 2020 (Steyrl, Scherer et al 2015)



μ Rhythm



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.



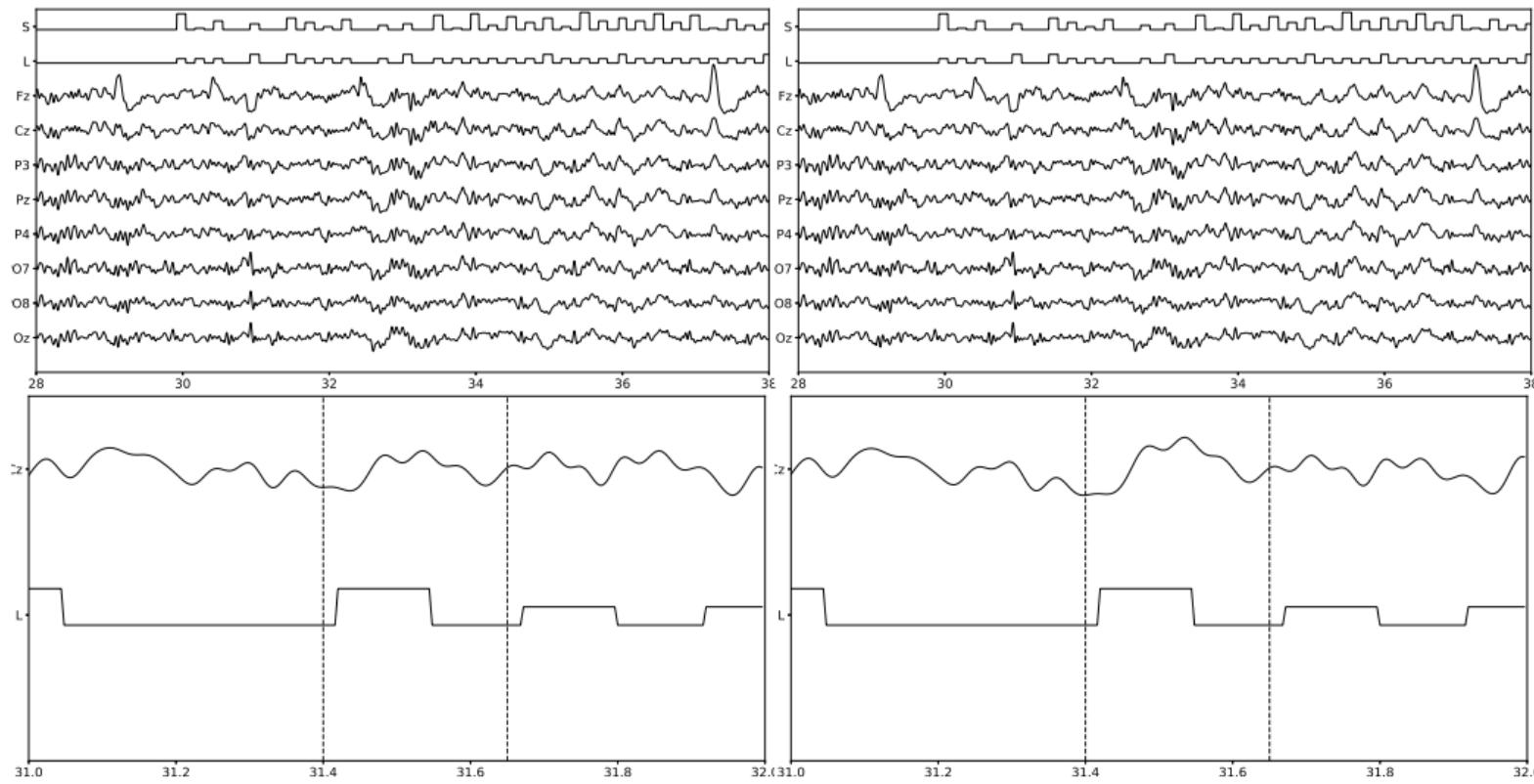
The P300 Waveform

P300-Based Speller Matrix

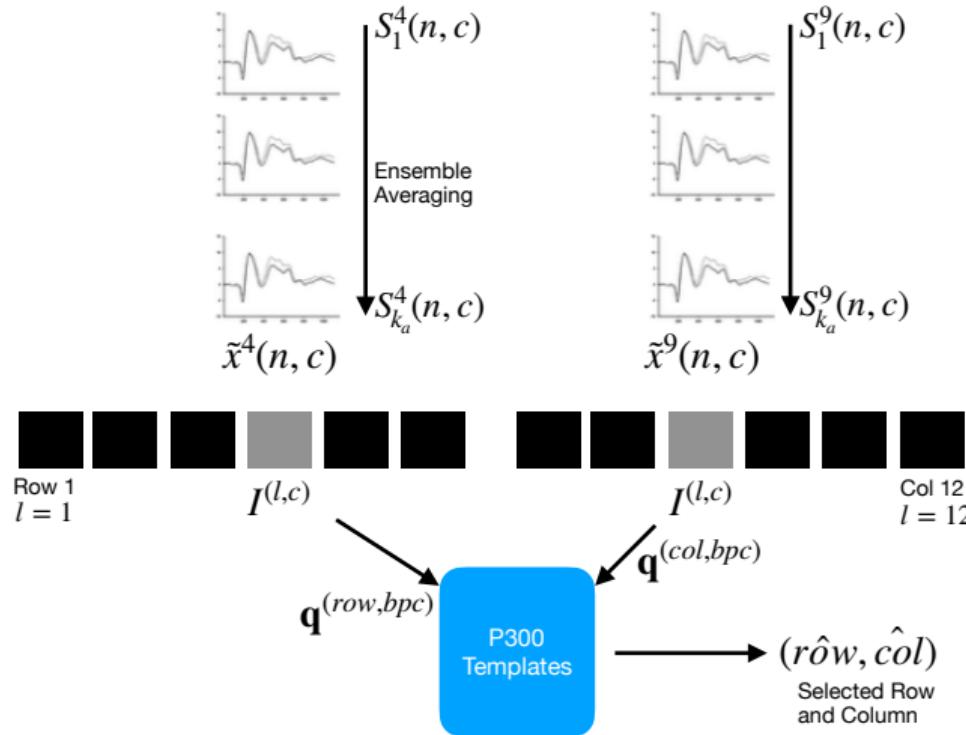


Example of the 6×6 Speller Matrix from the OpenVibe software. Rows and columns flash in random permutations.

The P300 Waveform - Signal Preprocessing



Signal Averaging



P300-Based BCI Speller - Letter Identification

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

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

- $l \in \{1, \dots, 12\}$ speller matrix row/col index.
- \hat{row} and \hat{col} predicted row and col of the speller matrix.
- $\mathbf{q}^{(l, bpc)}$ query descriptor of matrix index l .
- $\mathbf{d}_h^{(bpc)}$ neighbors descriptors from the template.
- $\mathbf{d}_h^{(bpc)} \in N_T(\mathbf{q}^{(l, bpc)})$.
- \hat{L} predicted class label.
- k the number of neighbors to pick from the template⁵.

⁵Boiman2008.

P300 Datasets

- Dataset I - P300 ALS Public Dataset

P300 Datasets

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

P300 Datasets

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

P300 Datasets

- 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)

Alternative Methods used for comparison

- SVM.

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- SWLDA.

Alternative Methods used for comparison

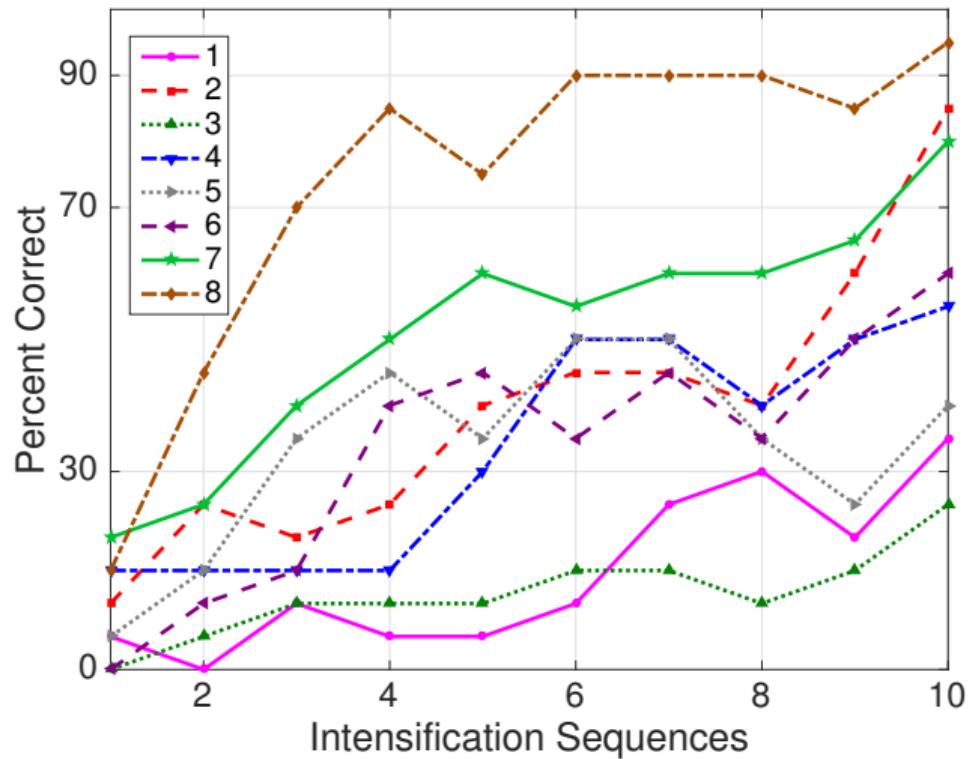
- SVM.
- SWLDA.
- PE, MP-1, MP-2, SHCC.

P300 Waveform - Dataset I

Table: Character recognition rates public dataset of ALS patients.

Participant	bpc	HIST	bpc	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%

Character Identification Rates - Dataset I



The P300 Waveform - Dataset II

Table: Character recognition rates for the Dataset of Healthy volunteers.

Participant	bpC	HIST	bpC	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%

(Wilcoxon signed-rank test, $p = 0.004$ for both datasets).

Dataset I Multichannel comparison

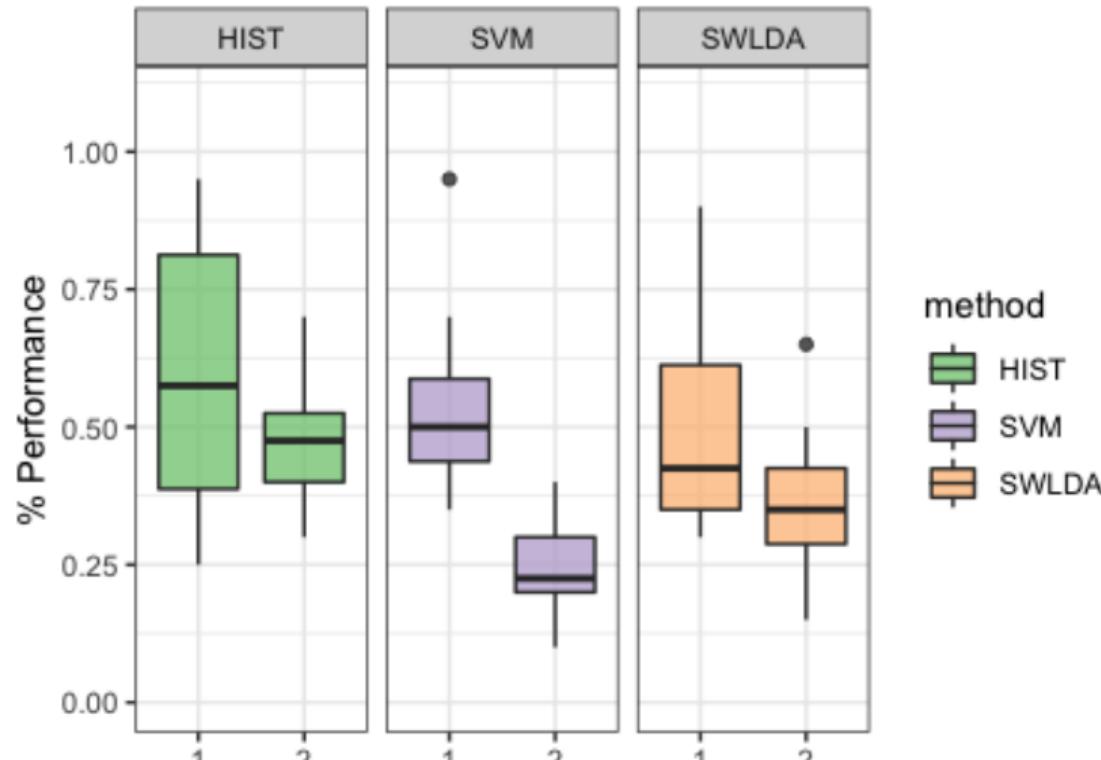
Participant	<i>bpc</i> for HIST	HIST	Multichannel SWLDA	Multichannel SVM
1	Cz	35%	45%	40%
2	Fz	85%	30%	50%
3	Cz	25%	65%	55%
4	PO8	55%	40%	50%
5	PO7	40%	35%	45%
6	PO7	60%	35%	70%
7	PO8	80%	60%	35%
8	PO7	95%	90%	95%

Dataset II Multichannel Comparison

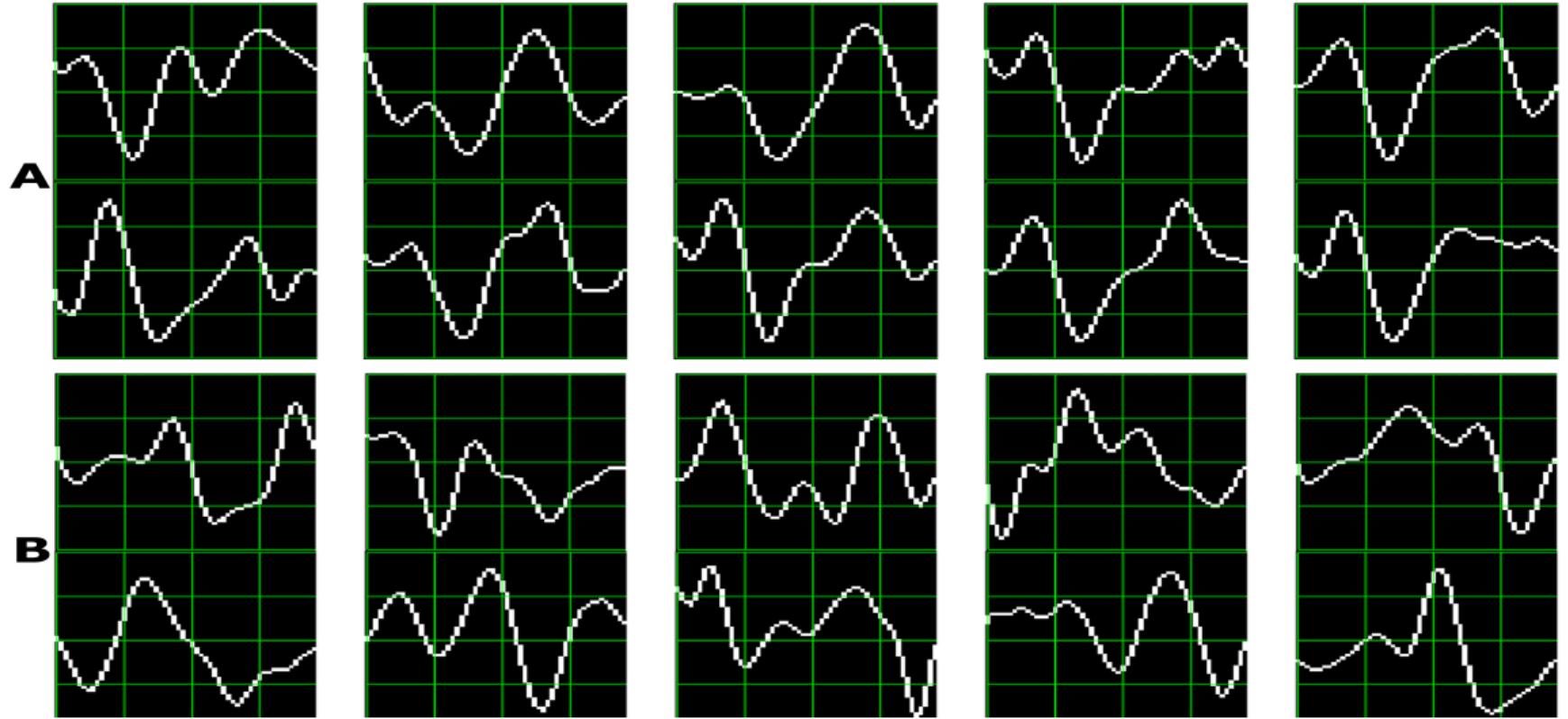
Participant	<i>bpc</i> for HIST	HIST	Multichannel SWLDA	Multichannel SVM
1	Oz	40%	65%	40%
2	PO7	30%	15%	10%
3	P4	40%	50%	25%
4	P4	45%	40%	20%
5	P4	60%	30%	20%
6	Pz	50%	35%	30%
7	PO7	70%	25%	30%
8	P4	50%	35%	20%

Character Identification Rates for Dataset I and II

Performance by Dataset and Method



P300 Waveforms for Subject 8 (A) and 3 (B)



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.

P300 Pseudo-Real Dataset III Performance Results

Method	<i>bpc</i>	Performance		
		Experiment 1	Experiment 2	Experiment 3
MP 1	PO8	67%	15%	50%
MP 2	PO7	24%	6%	10%
HIST	PO8	91%	18%	66%
PE	Cz	61%	9%	32%
SHCC	P4	98%	31%	80%
SVM	PO8	78%	7%	53%

The P300 Wave - Dataset IV BCI Competition 2003

Method	<i>bpc</i>	Performance
MP 1	FC2	50%
MP 2	CPz	22%
HIST	Cz	67%
PE	PO8	22%
SHCC	Cz	61%
SVM	C1	32%

Conclusion

- EEG Waveforms features can be objectively analyzed.
- The stability of ERP transient components.
- Intelligible System foster clinical collaboration.

Future Work

- Multichannel extension.
- Keypoint localization.
- Neuroimaging.

Questions

Questions?

Thank you very much

Sample frame title

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

An excellent review can be found here⁶.

⁶Simons2016.

Sample frame title

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

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

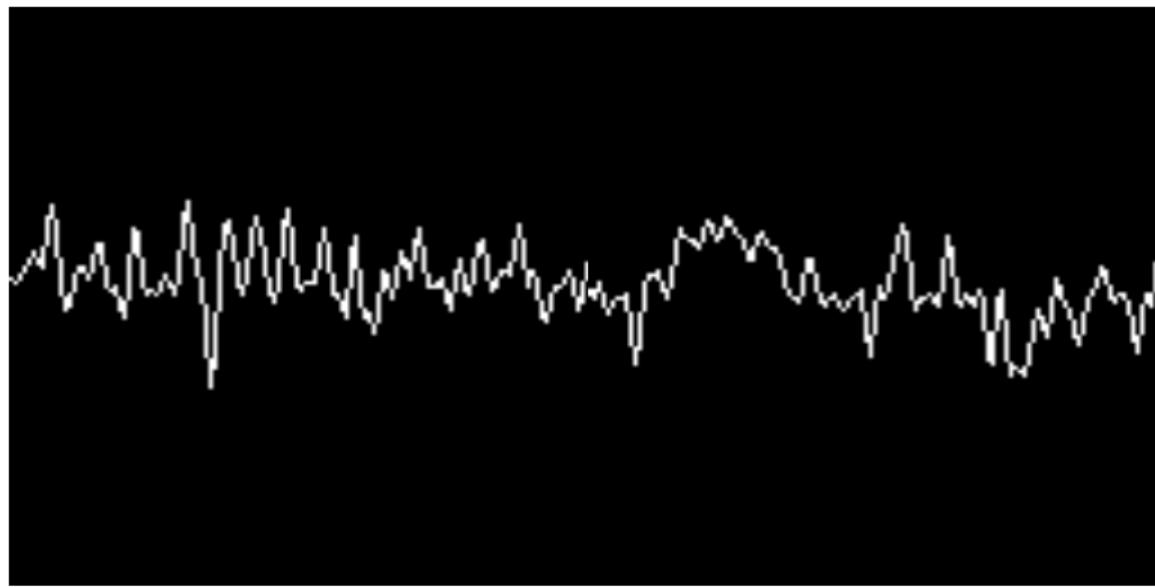
$$h(c) = (\max \tilde{x}(t, c) - \min \tilde{x}(t, c)) + \sigma \quad (8)$$

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

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.

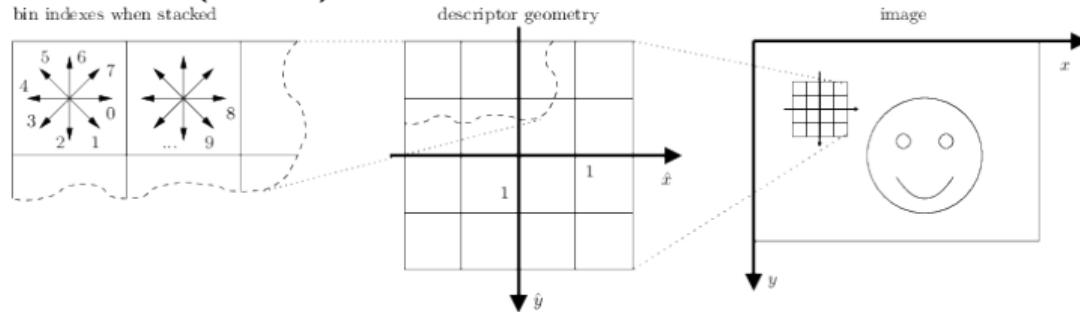
Signal Transformation: Binary Image generation.

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



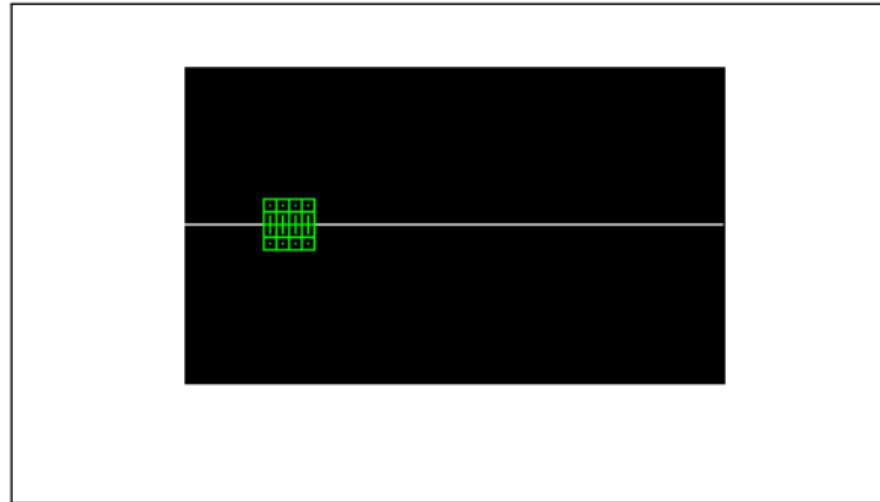
Features: SIFT⁷ Descriptors

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).



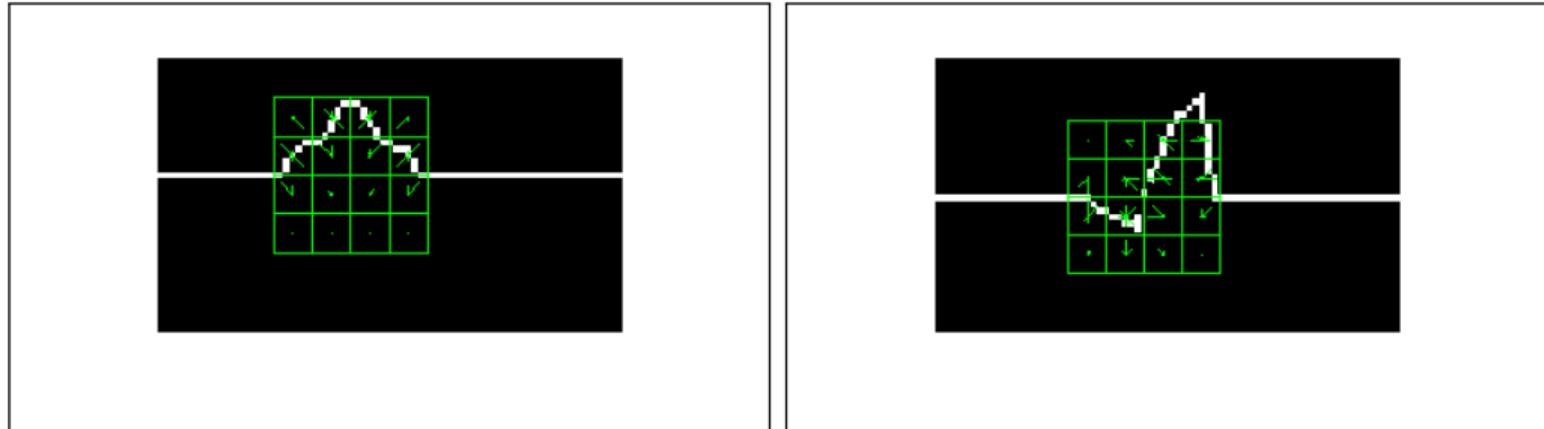
⁷Lowe 2004.

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



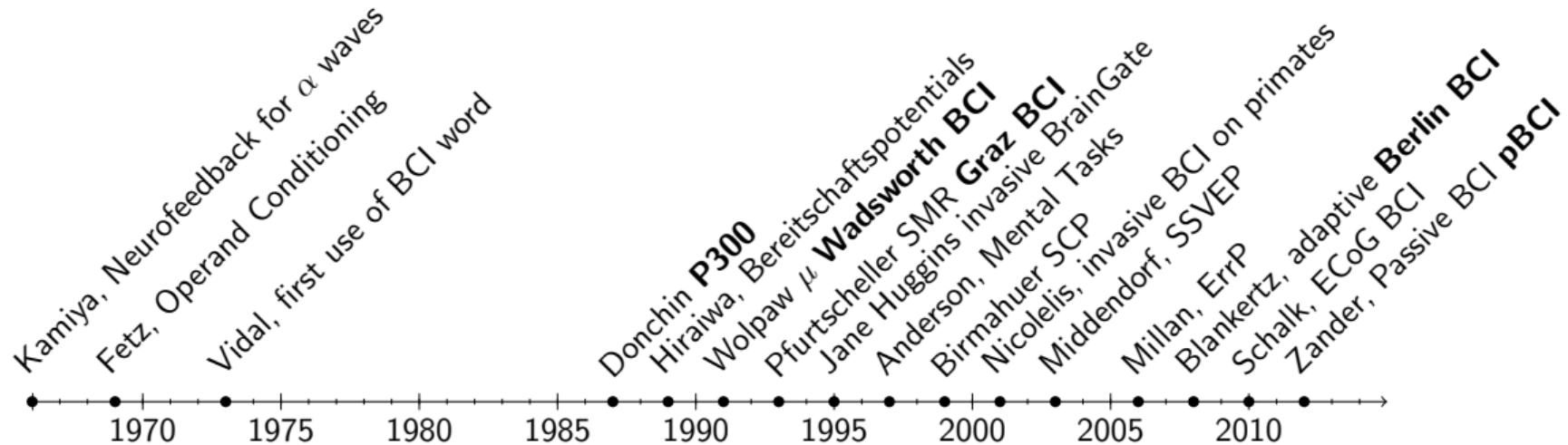
Sample Descriptors from artificial signals.

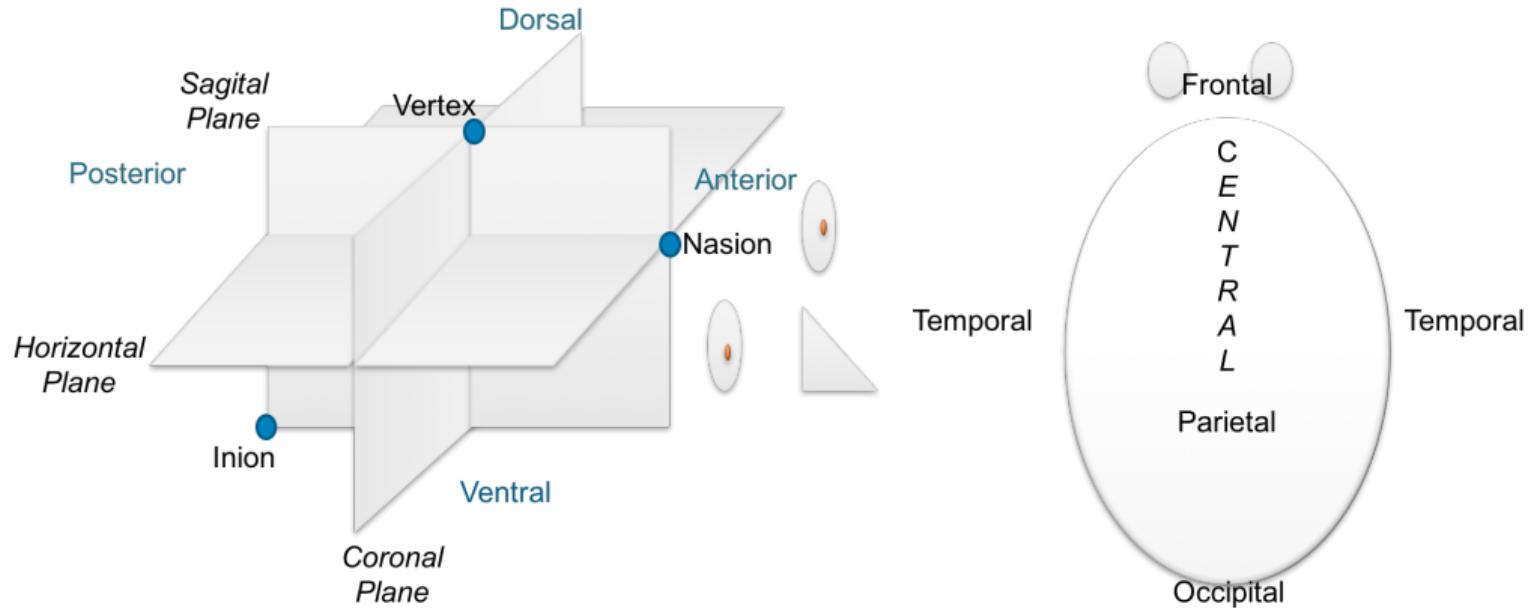
SIFT Descriptors

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

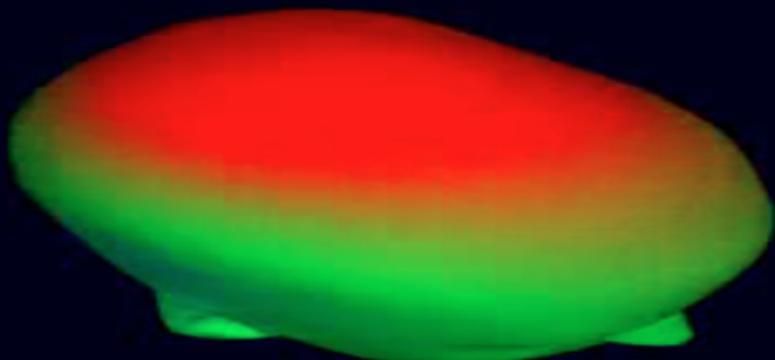
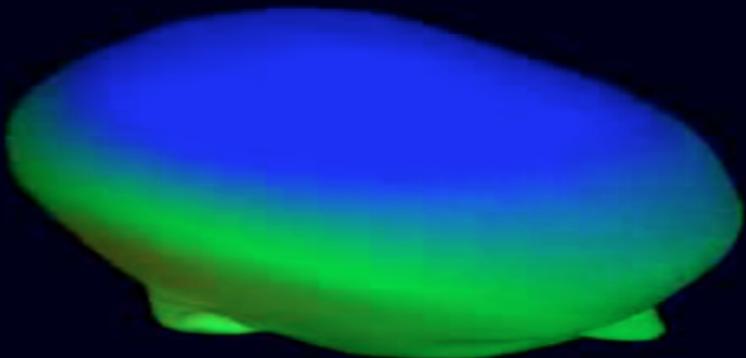
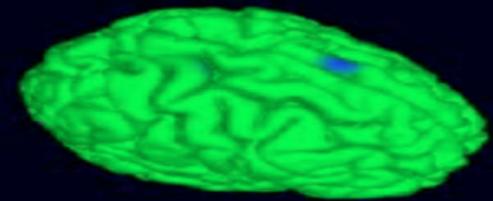
Sample descriptor values of the given patch.

Brain Computer Interfaces - Chronology



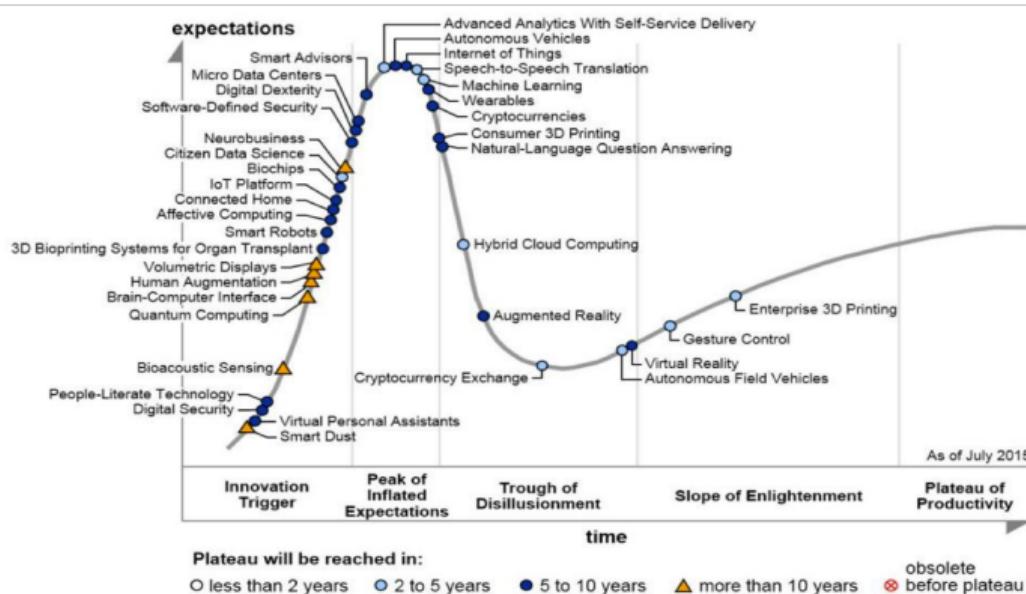


Neuronal Planes regularly used in neuroscience research. In BCI they are used to understand electrode location and spatial filters.





Digital and wearable electroencephalographs.



<http://www.gartner.com/newsroom/id/3412017>

► Brain Computer Interfaces

► Human Augmentation: Cyborgs

Prothesis
Exoskeletons
Assistive Devices

► BioChips

Cochlear Implant

► NeuroBusiness

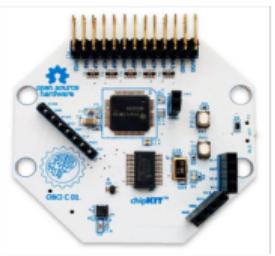
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Neuroergonomics
Neurorehabilitation

► Wearables

mHealth
Personal Analytics



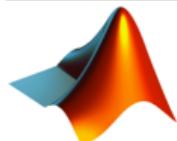
NeuroSky



OpenBCI



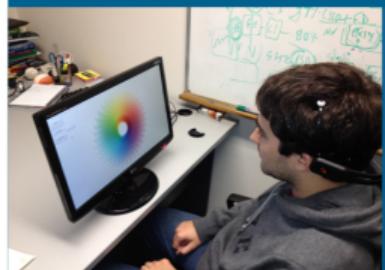
g.Tec g.Nautilus



NumPy



EPOC Emotiv



<https://www.itba.edu.ar/id/centro-de-inteligencia-computacional/>



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Se buscan alumnos para realizar experimentos en Interfaces Cerebro Computadoras

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Ramele, Rodrigo (ITBA)

HIST of EEG for BCI

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29, 30 & 31 October

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