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

Dissertation Defense

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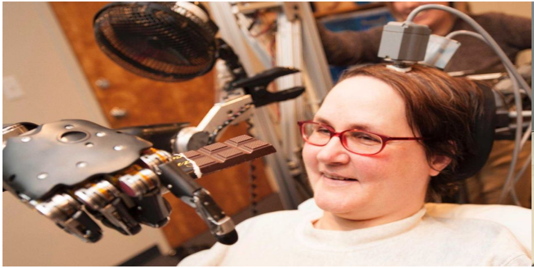
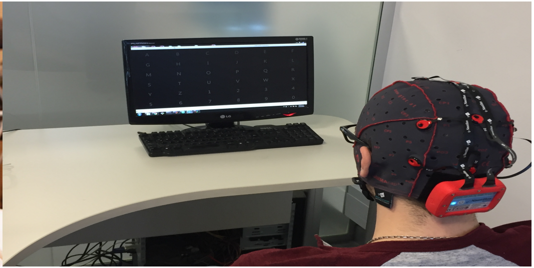
Noviembre 29 2018

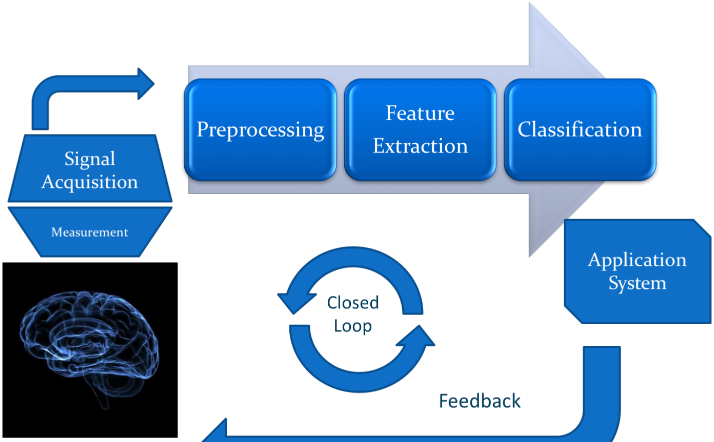
Outline

Brain Computer Interfaces - Current trends





Brain Computer Interfaces - System Components



Brain Computer Interfaces - BCI Paradigms

Evoked Potential	Motor Imagery:	Selective Attention	Operant Conditioning:
Steady State Visual Evoked Potential	**ERD/ERS: Event Related De/S-ynchronization**	**P300,N400**	Slow Cortical Potentials ErrP
SSVEP SSAEP SSSEP	**Wadsworth BCI** **Graz BCI**	**Tübingen BCI**	**Berlin BCI**
Visual Spatial Covert Attention	**Bereitschaftspotentials**	**Mental Tasks**	

Brain Computer Interfaces - Problem Statement

- Clinical and Physician involvement[1]

[1] **Yuste2017**.
[2] **Perdikis2014**.

Brain Computer Interfaces - Problem Statement

- Clinical and Physician involvement[1]
- Practical, relevant, and invariant features that convey good-enough information[2].

[1] **Yuste2017**.
[2] **Perdikis2014**.

Motivation

Is it possible to analyze and discriminate electroencephalographic signals by automatic processing the shape of the waveforms using the Histogram of Gradient Orientations ?

1. Construct analyzable 2D-images.

What we aim to do

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2. Adaptation to the SIFT method to EEG time-series

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3. Feature extraction procedure

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1. Construct analyzable 2D-images.
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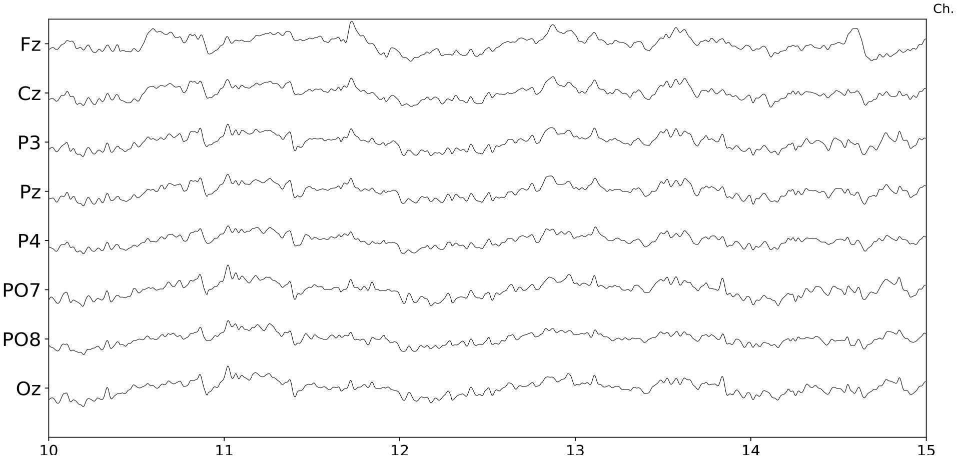
3. Feature extraction procedure
4. Classification algorithm

Electroencephalography



Sample 8-channel EEG signal obtained from (g.Nautilus, g.Tec, Austria). Voltage in μV 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
- Merge of Increasing and Decreasing Sequences
- 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

1. Signal Preprocessing
2. Signal Segmentation
3. Signal Plotting

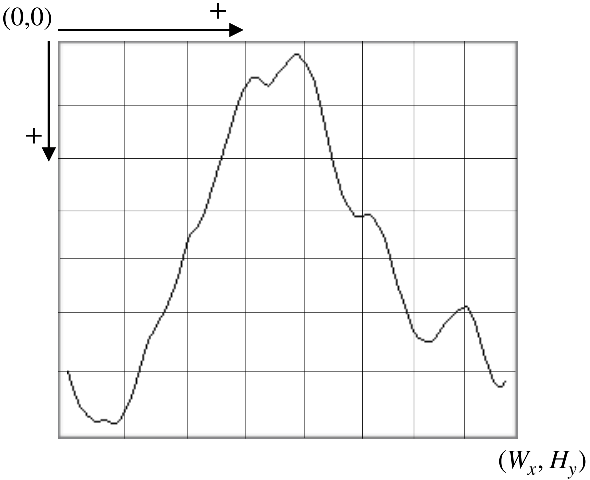
The Histogram of Gradient Orientations - Feature Extraction Algorithm

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

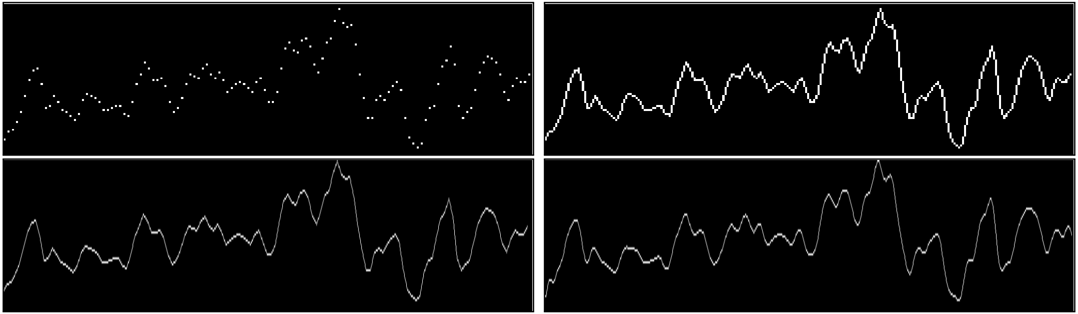
The Histogram of Gradient Orientations - Feature Extraction Algorithm

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

Image Coordinate System

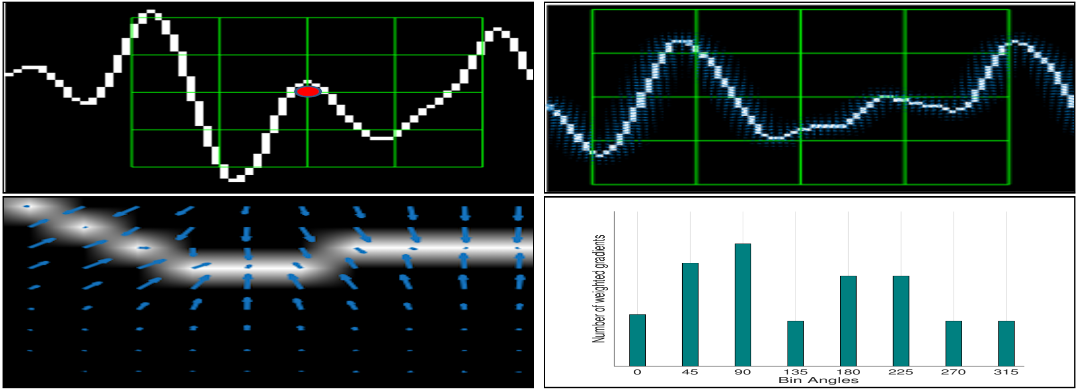


Signal Plotting



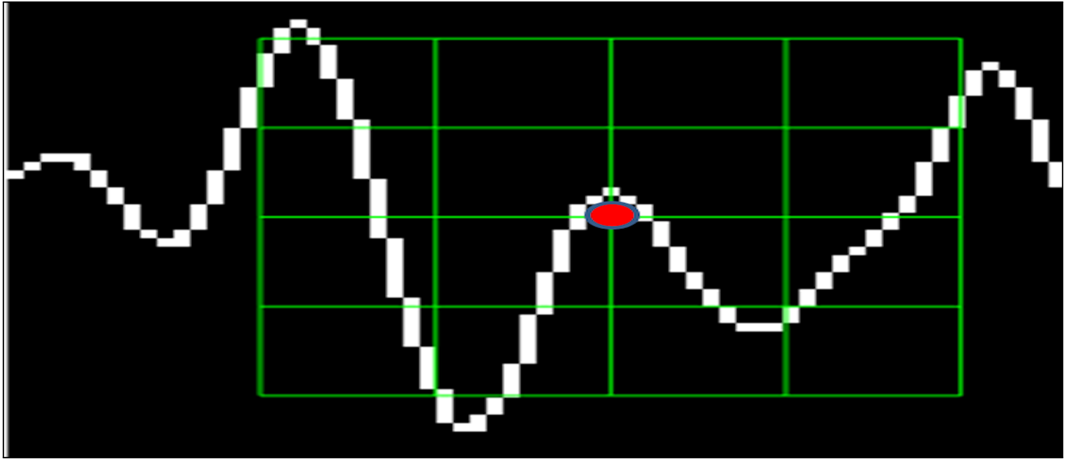
Generated images based on different interpolation schemes.

The Histogram of Gradient Orientations



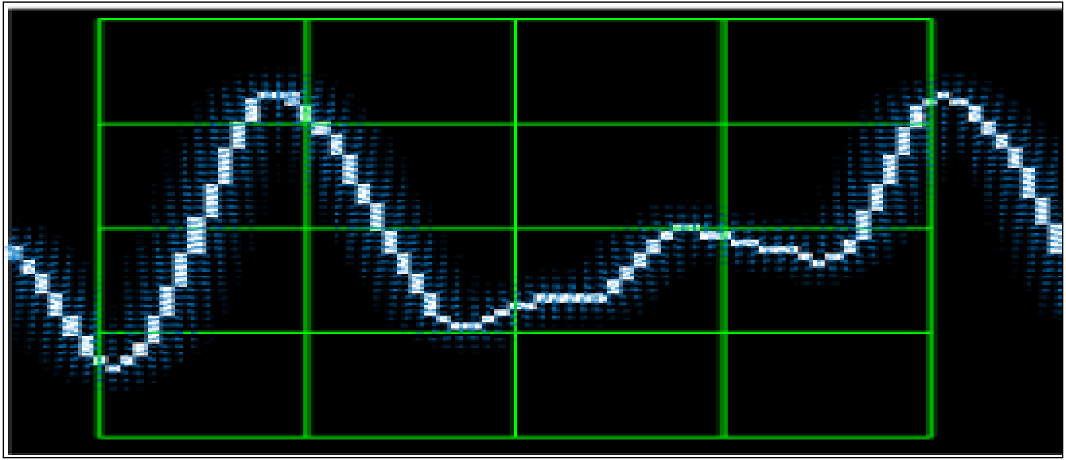
Patch and vector field of oriented gradients.

Keypoint Localization



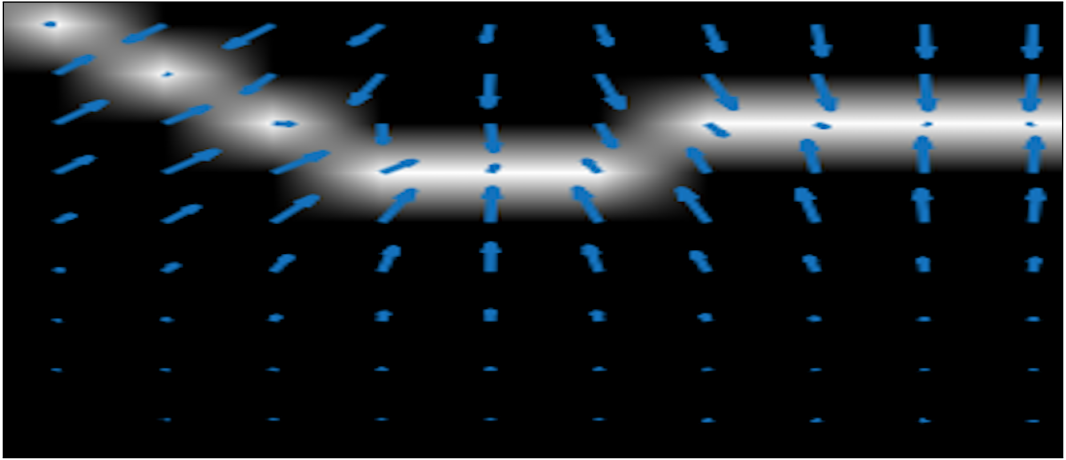
Patch and vector field of oriented gradients.

Pixel Gradient Vector Field



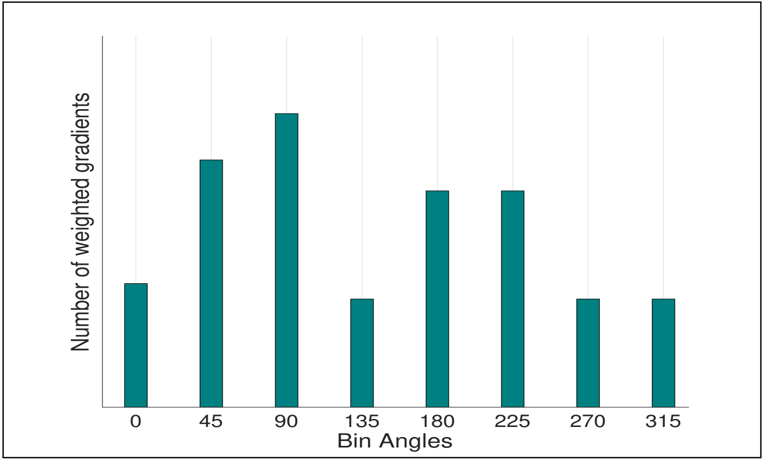
Patch and vector field of oriented gradients.

Pixel Gradient Vector Field



Patch and vector field of oriented gradients.

Orientation histogram



Patch and vector field of oriented gradients.

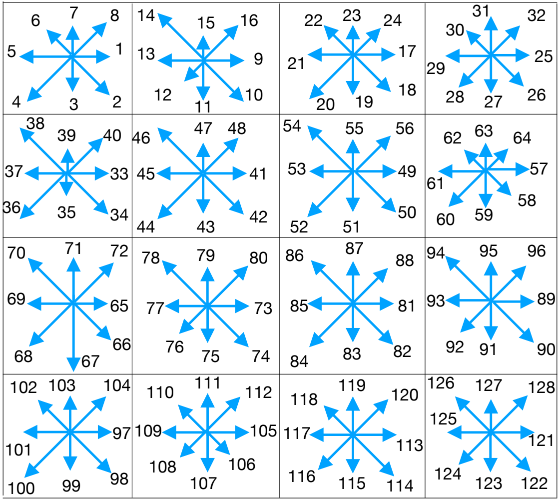
Histogram Calculation

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

- 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.
- **kp** is the keypoint center location.
- **p** is a pixel from within the patch, centered around **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 **p**.
- $\omega_{\mathrm{ang}}(\cdot)$ scalar and $\omega_{ij}(\cdot)$ vector linear interpolation functions[3].

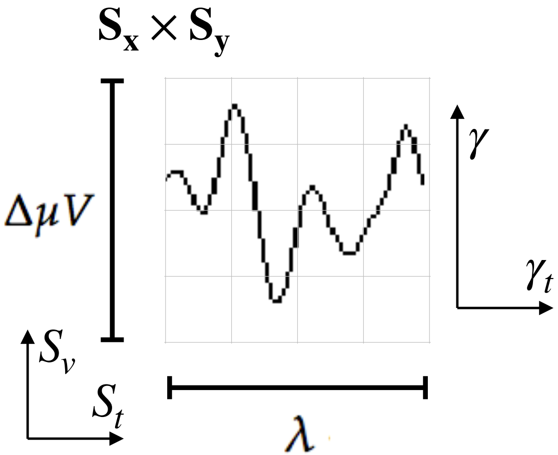
[3] **Lowe2004**, **Vedaldi2010**.

Descriptor



6 7 8 5 1 4 3 2
14 15 16 13 9 12 11 10
22 23 24 21 17 20 19 18
31 32 30 25 29 28 27 26
38 39 40 37 33 36 35 34
46 47 48 45 41 44 43 42
54 55 56 53 49 52 51 50
62 63 64 57 61 58 60 59
70 71 72 69 65 66 68 67
78 79 80 77 73 76 75 74
86 87 88 85 81 84 83 82
94 95 96 93 89 92 91 90
102 103 104 97 101 100 99 98
110 111 112 109 105 108 106 107
118 119 120 117 113 116 115 114
126 127 128 125 121 124 123 122

Patch Geometry



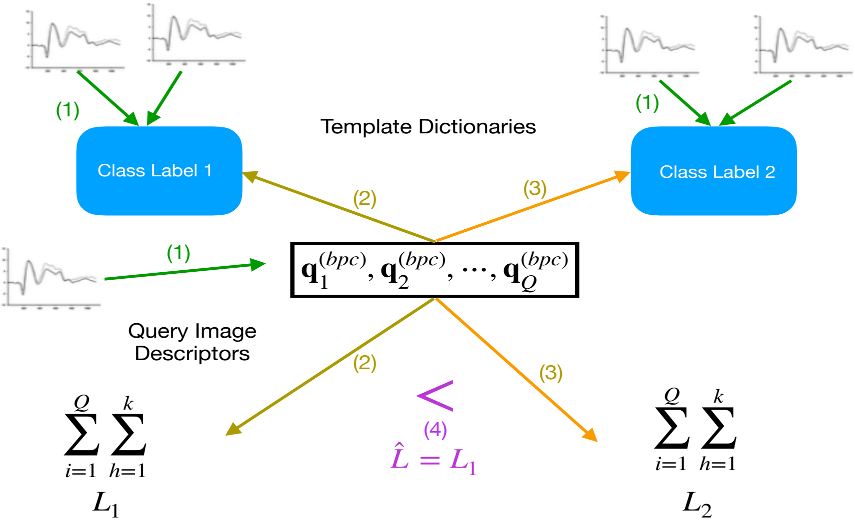
Proposed Classification Method

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

- 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.
- $\mathbf{d}_h^{(L,bpc)} \in N_T(\mathbf{q}_i^{(bpc)})$.
- $N_T(\mathbf{q}_i^{(bpc)}) = \{\mathbf{d}_h^{(bpc)} \in T_L^{bpc} / \mathbf{d}$ is the k-nearest neighbor of $\mathbf{q}_i^{(bpc)}\}$.
- $\hat{L}$ predicted class label.
- k the number of neighbors to pick from the template[4].

[4] **Boiman2008**.

Classification Algorithm



Experimental Validation

Experimental Validation

- Alpha Waves Wiggles

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- Alpha Waves Wiggles
- μ Rhythm

Experimental Validation

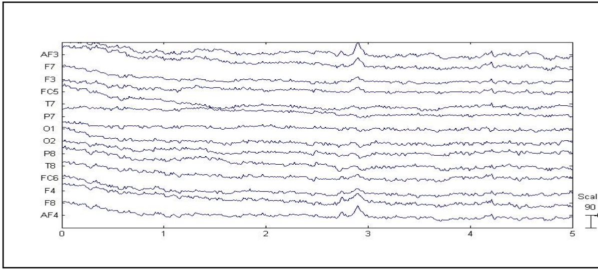
- Alpha Waves Wiggles
- μ Rhythm
- The P300 Waveform

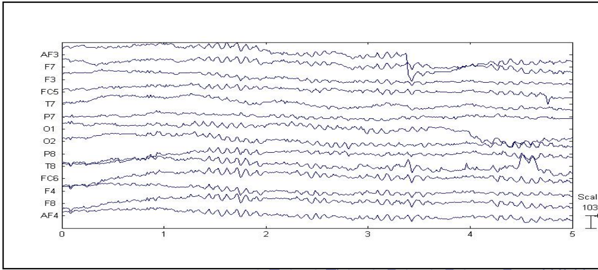
Alpha Waves wiggles

Alpha Waves Datasets

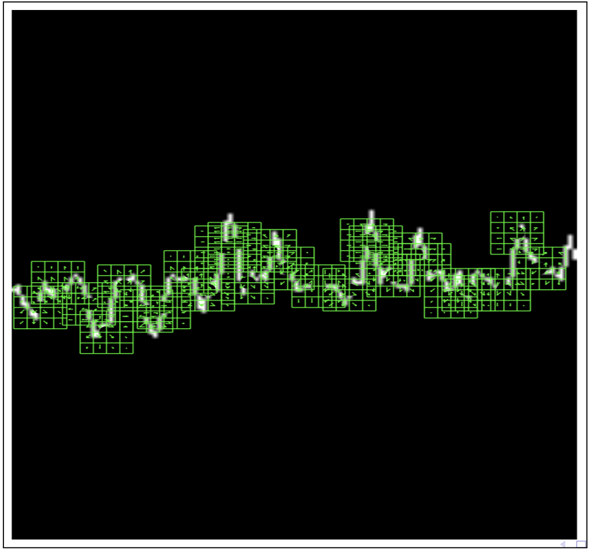
- Dataset I: 128 Hz, 14 channels, 10 subjects, 10 class 1 vs 10 class 2.
- Dataset II: 160 Hz, 64 channes, 25 subjects, Run 1 vs Run 2, 60 vs 60.

EEG Consumer Grade Digital Device and EEG Signals

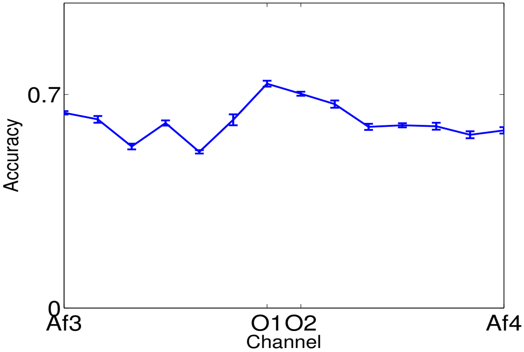


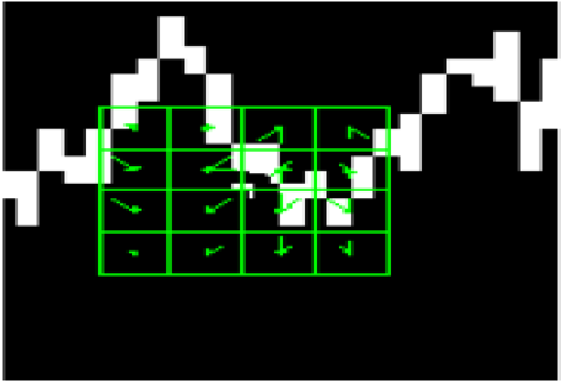


Keypoint populations



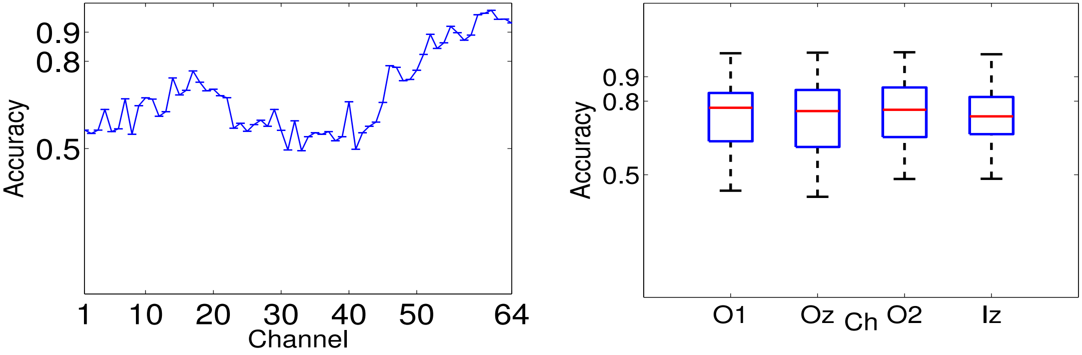
Alpha Waves wiggles





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

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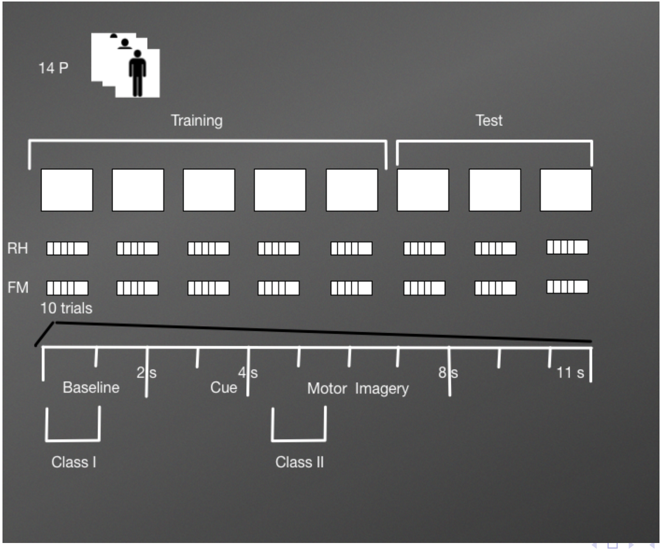
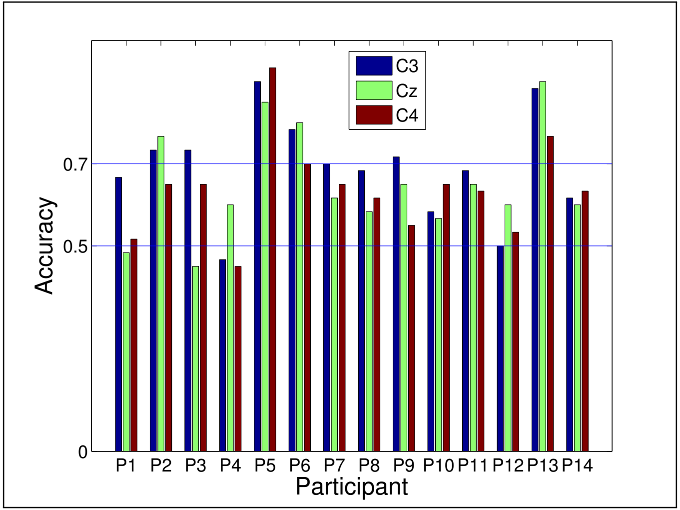
Experimental Validation

μ Rhythm

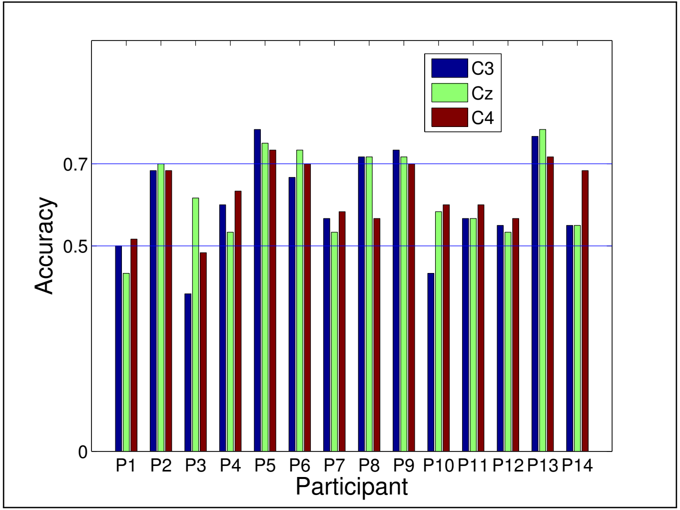
Dataset 002-2014 BNCI-Horizon 2020 (Steyrl, Scherer et al 2015)



μ Rhythm



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



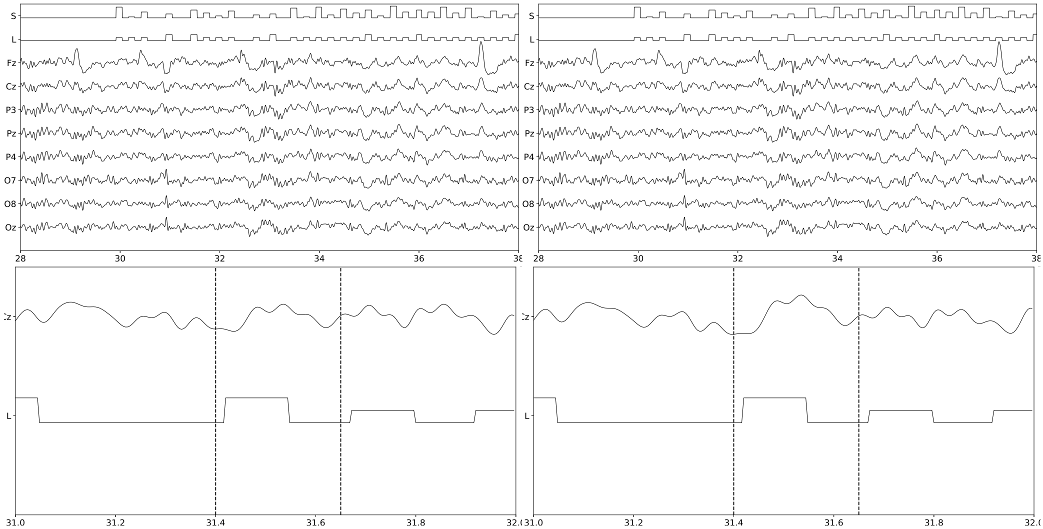
Accuracy for the BCI Simulation classifying Baseline vs. FM (Feet Movement) motor imagery.

The P300 Waveform

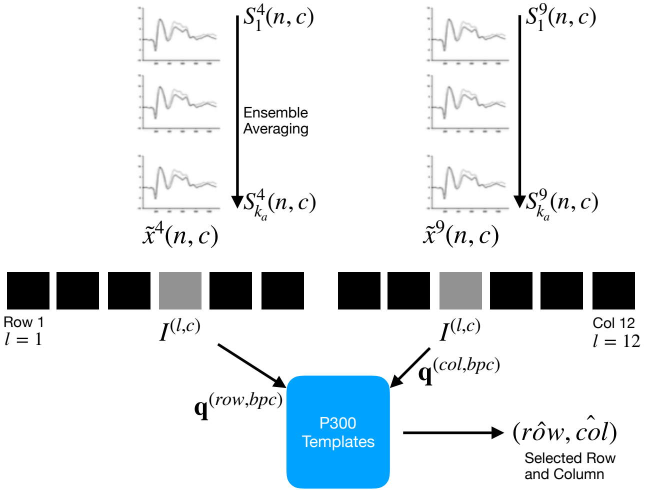
P300-Based Speller Matrix

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

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

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

- $l \in \{1, \ldots, 12\}$ 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 template[5].

[5] **Boiman2008**.

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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- SVM.
- SWLDA.

Alternative Methods used for comparison

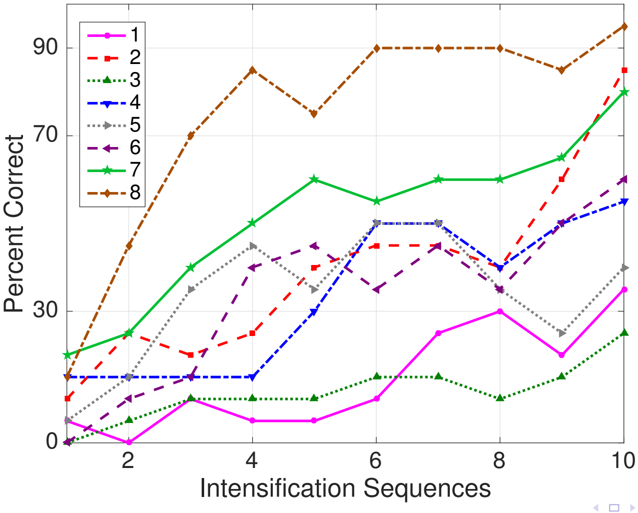
- SVM.
- SWLDA.
- PE, MP-1, MP-2, SHCC.

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).

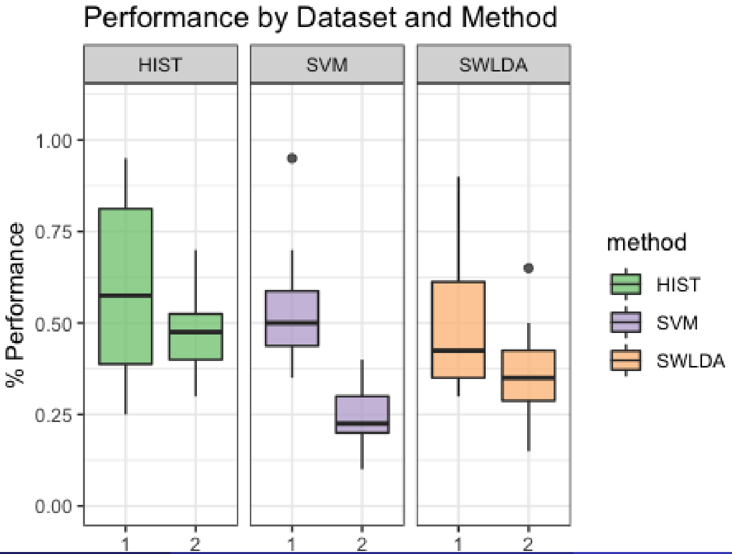
Dataset I Multichannel comparison

Participant	*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%

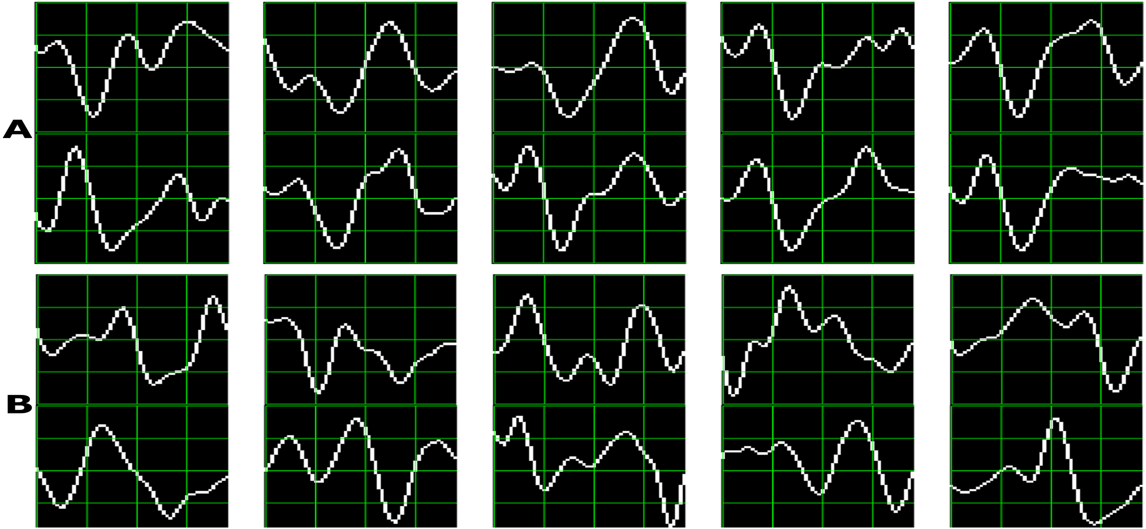
Dataset II Multichannel Comparison

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%

Character Identification Rates for Dataset I and II



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



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	*bpc*	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	*bpc*	**Performance**
MP 1	FC2	50%
MP 2	CPz	22%
HIST	Cz	67%
PE	PO8	22%
SHCC	Cz	61%
SVM	C1	32%

Conclusion

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?

Thank you very much

Sample frame title

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Sample frame title

This is a text in second frame. For the sake of showing an example.

- Text visible on slide 1

Sample frame title

This is a text in second frame. For the sake of showing an example.

- Text visible on slide 1
- Text visible on slide 2

Sample frame title

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- Text visible on slide 3

Sample frame title

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- Text visible on slide 4

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

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

Sample frame title

In this slide, some important text will be highlighted beause it's important. Please, don't abuse it.

Remark

Sample text

Important theorem

Sample text in red box

Examples

Sample text in green box. "Examples" is fixed as block title.

Method

Signal Transformation

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

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

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.

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

And the signal is centered on the image

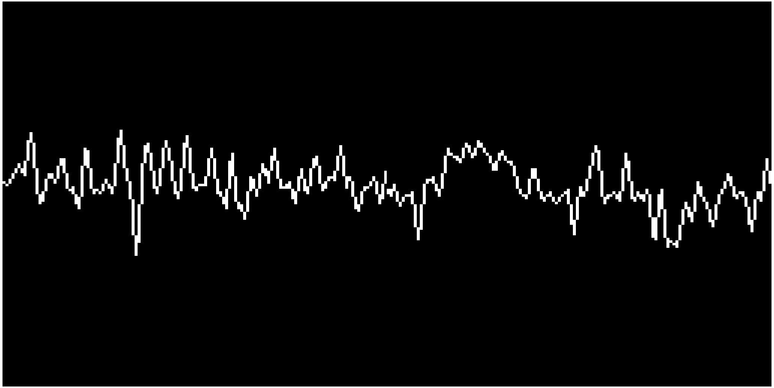
$$h(c) = (\max \tilde{x}(t,c) - \min \tilde{x}(t,c)) + \sigma \tag{8}$$

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

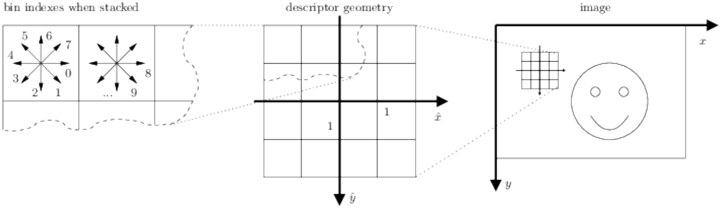
where t is time, δ is scale factor, c is the channel parameter, $x(t,c)$ is the EEG matrix whereas $\bar{x}(c)$ is the mean value for each channel, $h(c)$ is the height of the image in pixels, σ is the descriptor size and $Z(c)$ is the horizontal pixel at which the zero value of the signal will be located.

Signal Transformation: Binary Image generation.

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

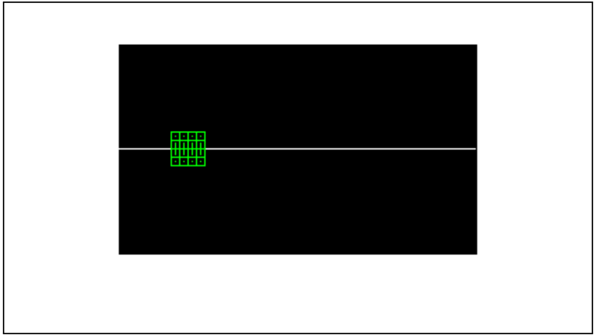


Scale Invariant Feature Transform Descriptors are local features of an image that represents gradient changes in intensities. They are 128-dimensional vectors that contains the histograms of relative gradient directions on each of the blocks that each patch is divided (4x4=16 blocks, 8 rotational directions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



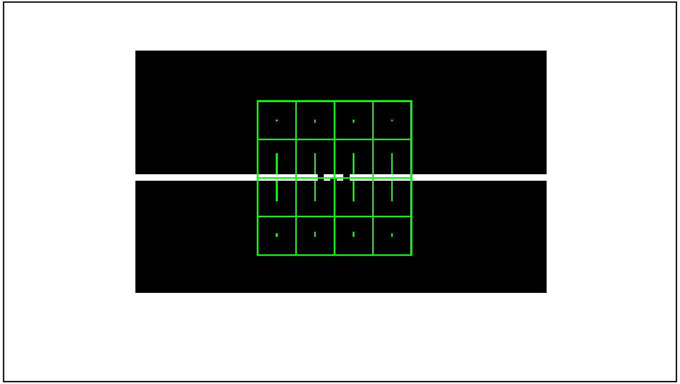
[6] **Lowe 2004**.

SIFT Descriptors



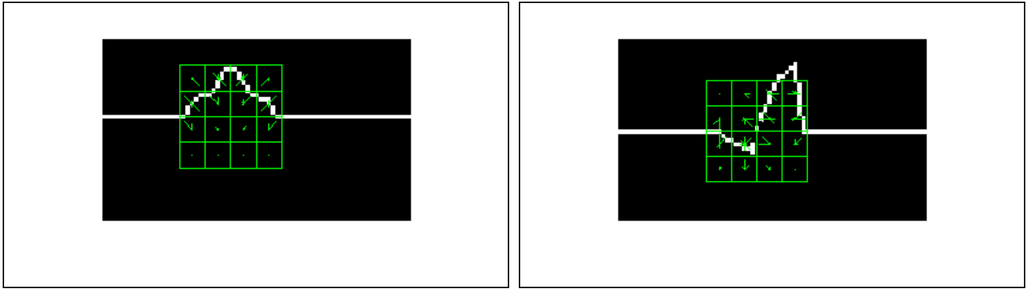
SIFT Descriptor $[z_1, z_2, \theta, \sigma]$ where (z_1, z_2) are the 2D coordinates where the *Keypoint* is located, θ is the descriptor general orientation and σ is the descriptor size.

SIFT Descriptors



SIFT Descriptor with its corresponding gradient tendencies.

SIFT Descriptors



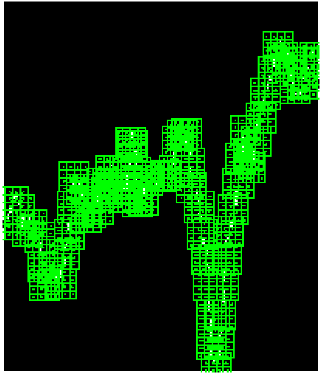
Sample Descriptors from artificial signals.

SIFT Descriptors

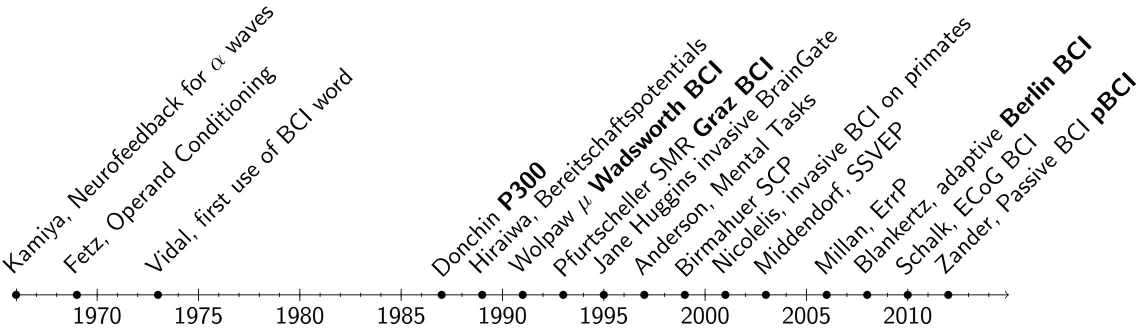
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
17	22	22	17	173	173	173	173	40	51	51	40	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	40	51	51	40	173	173	173	173	17	22	22	17
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Sample descriptor values of the given patch.

Keypoint Localization



Brain Computer Interfaces - Chronology



Classification

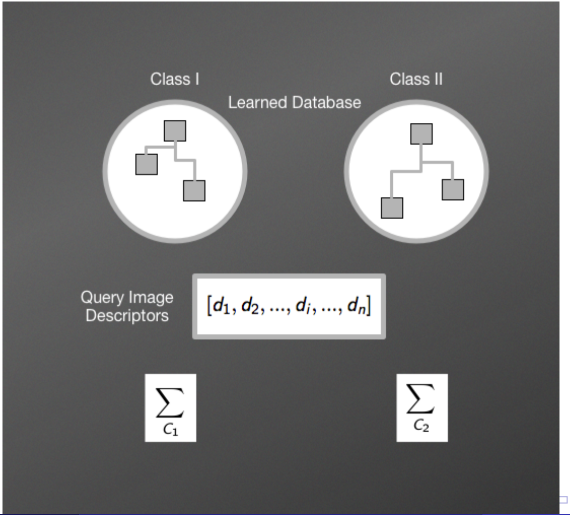
- Discriminative Semi-supervised classification method was used: Naive Bayes Nearest Neighbor, NBNN[7] algorithm:

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

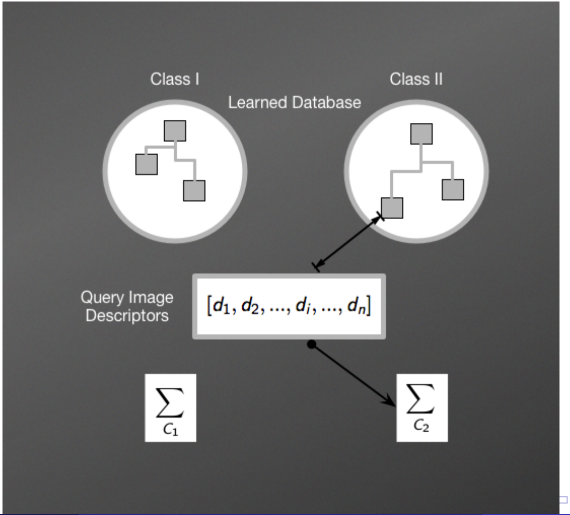
where $\hat{C}$ is estimated Class to which this image (and underlying EEG signal windows) should belong whereas d_i is the i-th descriptor obtained from the query image and $NN_C(d_i)$ is the near neighbor descriptor for each class.

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

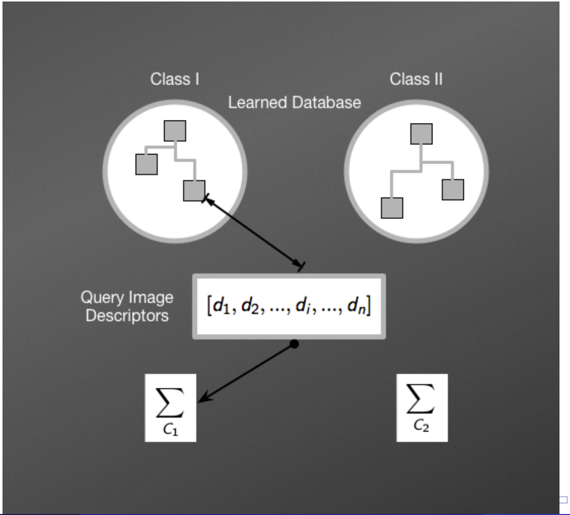
Classification



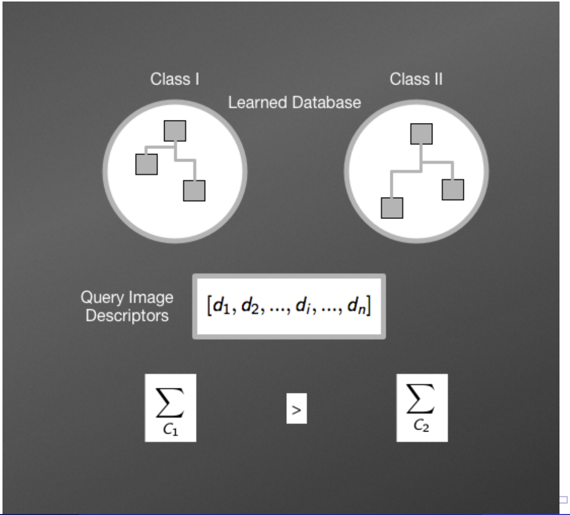
Classification



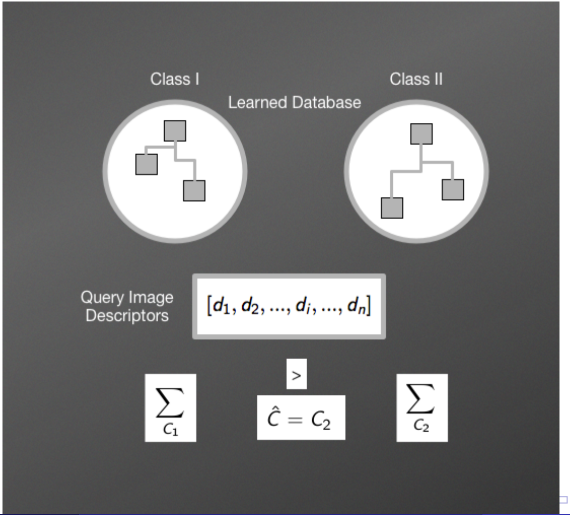
Classification



Classification

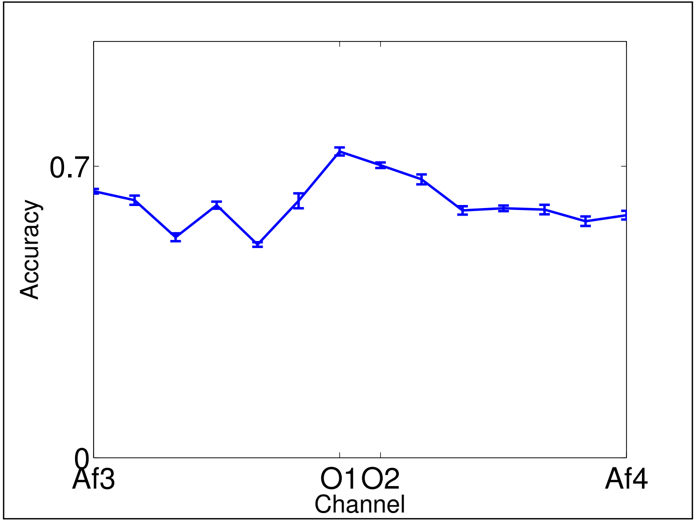


Classification



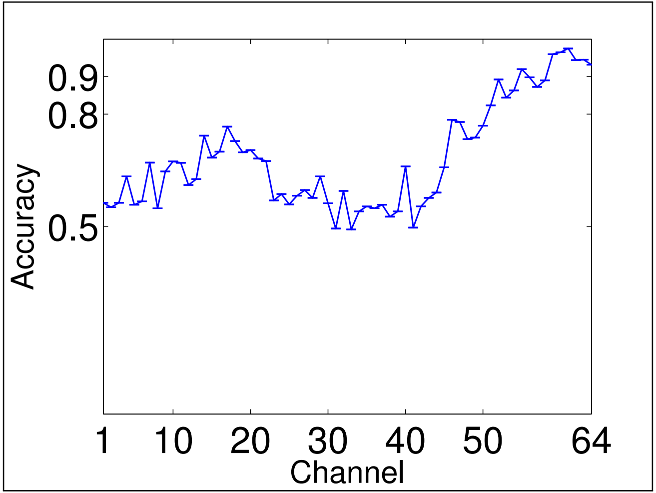
Offline Results

Dataset I: Subject Independent α Waves[8]



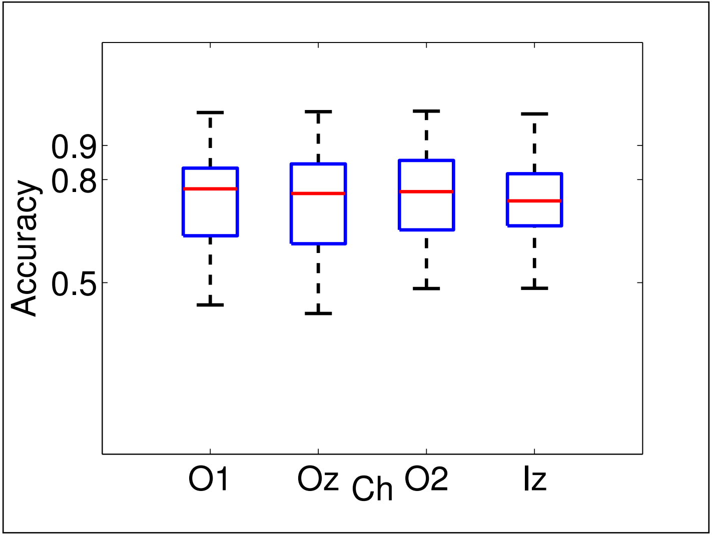
10-Fold Cross validated accuracy values for 10 subjects.

Dataset II: EEG Dataset, Runs 1 and 2[9]

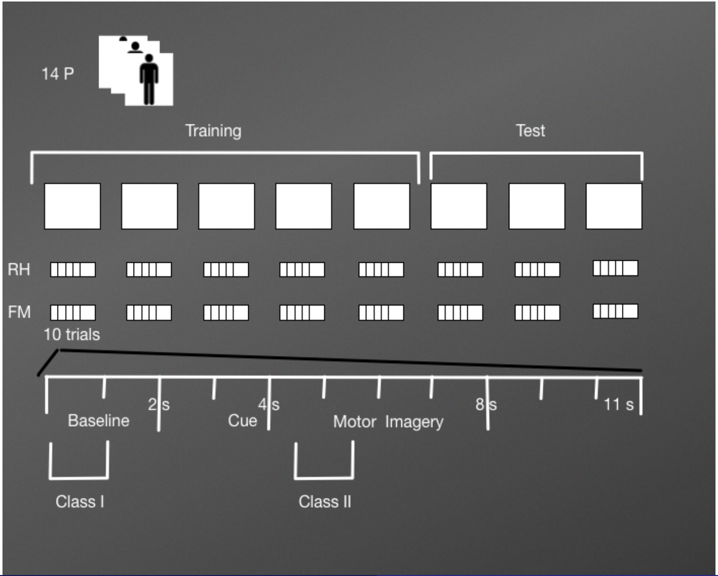


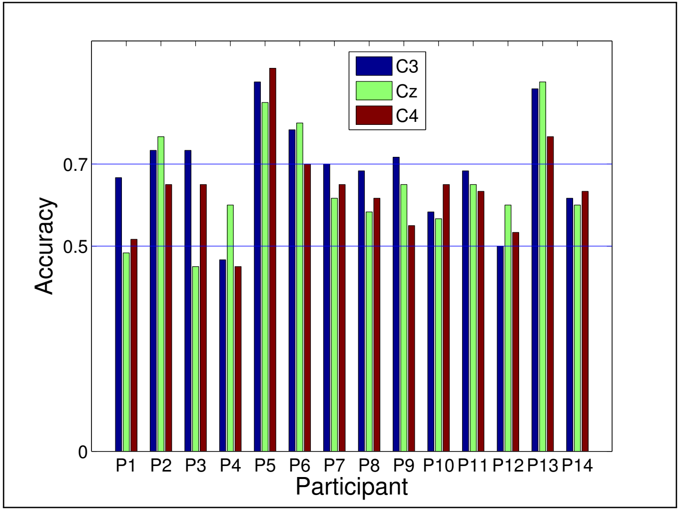
10-Fold Cross validated accuracies values for one random subject.

Dataset II: EEG Dataset, Runs 1 and 2[10]

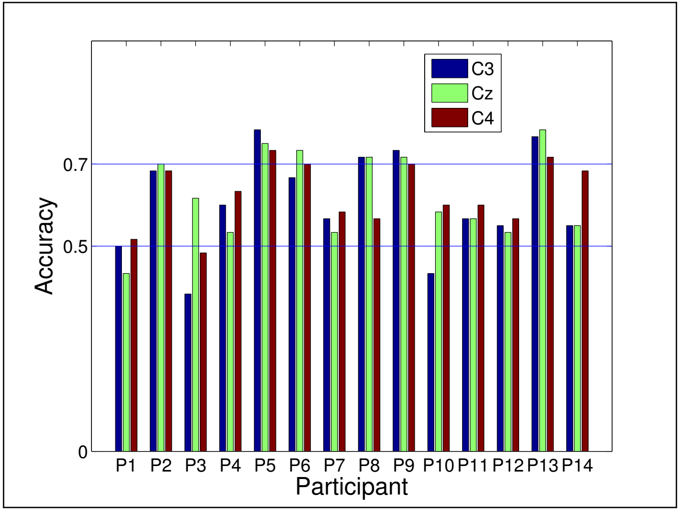


Dataset III: Motor Imagery[11]

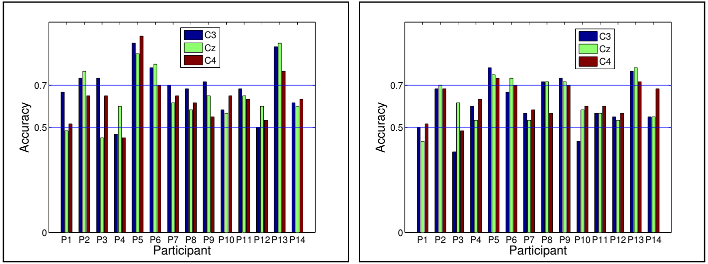




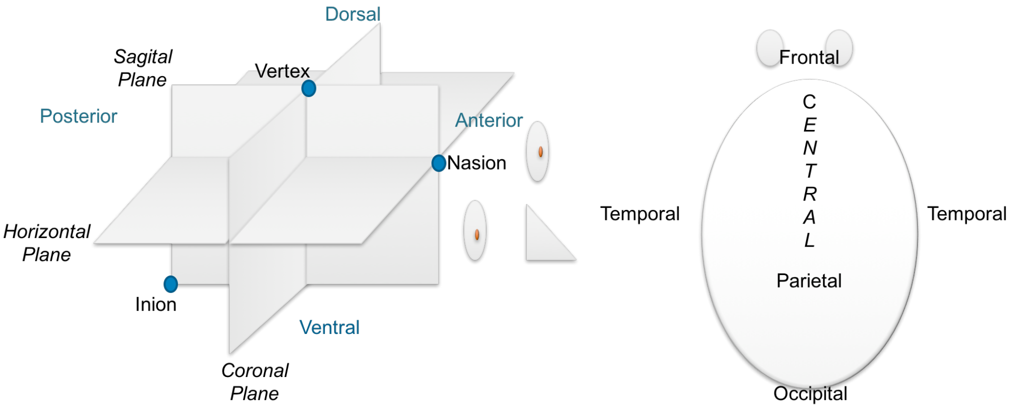
Accuracy for the BCI Simulation classifying Baseline vs. RH (Right Hand) motor imagery.



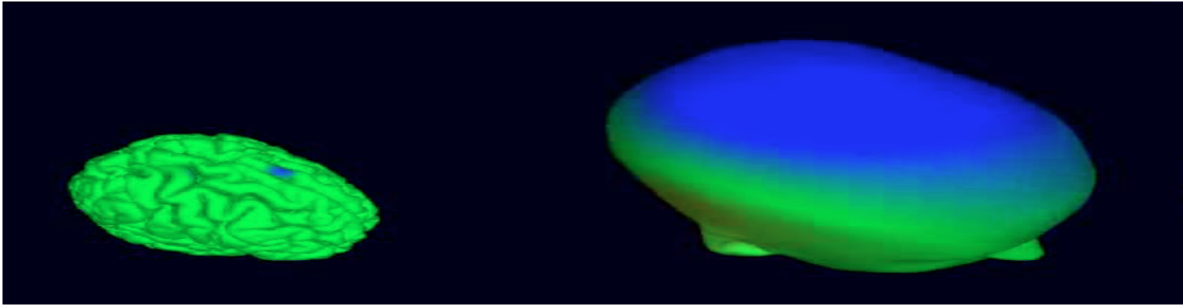
Accuracy for the BCI Simulation classifying Baseline vs. FM (Feet Movement) motor imagery.



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

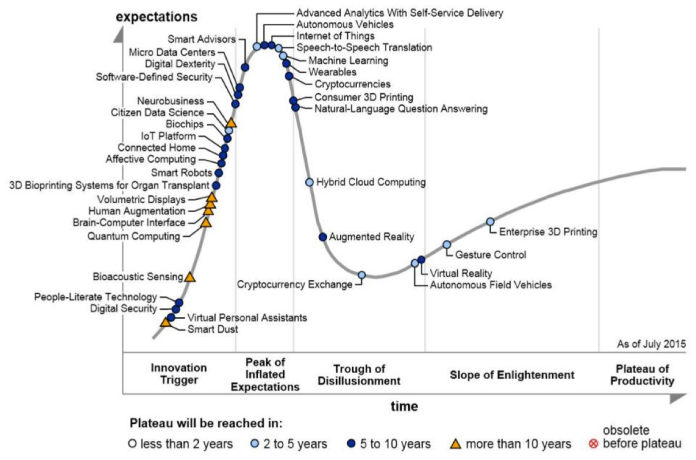


Neuronal Planes regularly used in neuroscience research. In BCI they are used to understand electrode location and spatial filters.



A source signal with positive/negative polarity is generated in a very specific region of the brain but due to volume conduction their influence affects a widespread area of the scalp where sensors are located (Image of the brain from Swartz Center for Computational Neuroscience).

Digital and wearable electroencephalographs.



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

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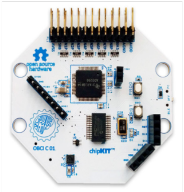
NeuroSky



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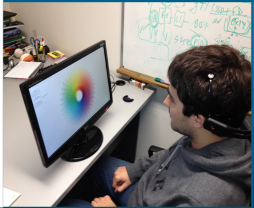
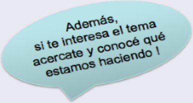


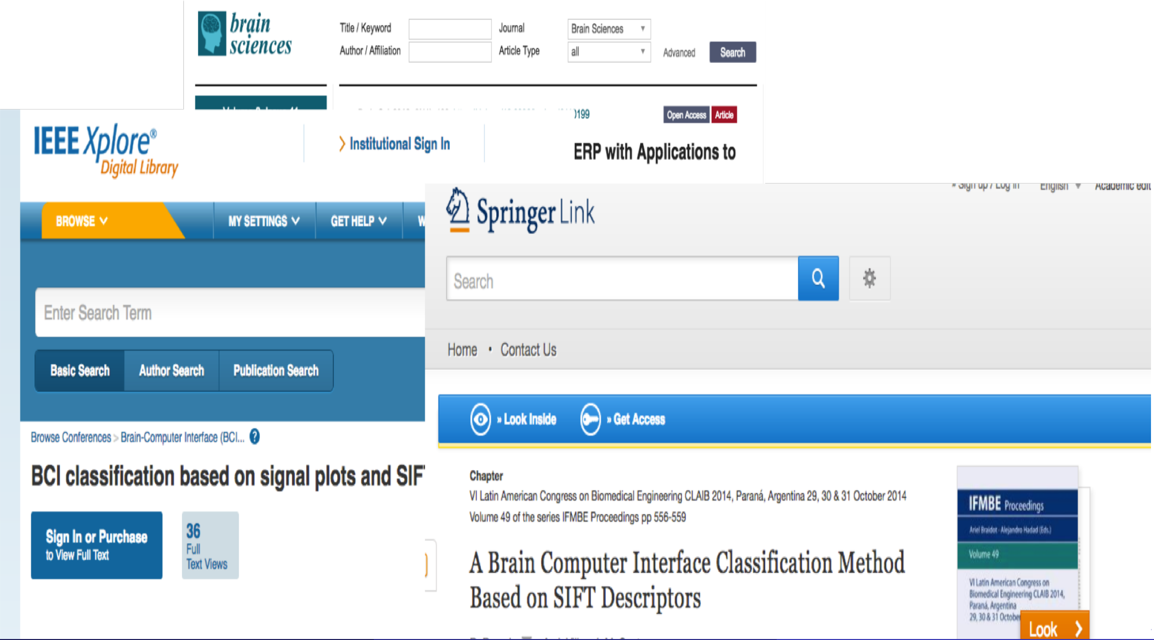
Convocatoria de Alumnos Voluntarios

Se buscan alumnos para realizar experimentos en Interfaces Cerebro Computadoras

No son más de 20 minutos y te damos un alfajor ! (Free Alfajor !)



Si te interesa, envía un email a: rramele@itba.edu.ar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A Brain Computer Interface Classification Method Based on SIFT Descriptors
IFMBE Proceedings
Volume 49
Look

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	ERP, Epilepsy, Sleep
Coupling	
Cross Frequency, Phase-Amplitude, Phase-Phase	Sleep
Period Amplitude Analysis	ERP, Epilepsy