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

Dissertation Defense

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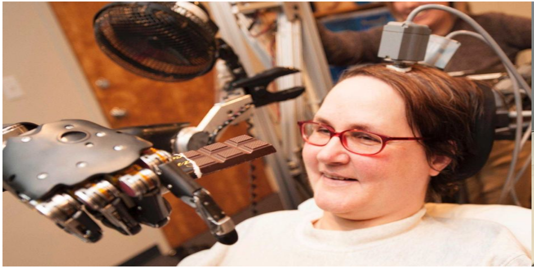
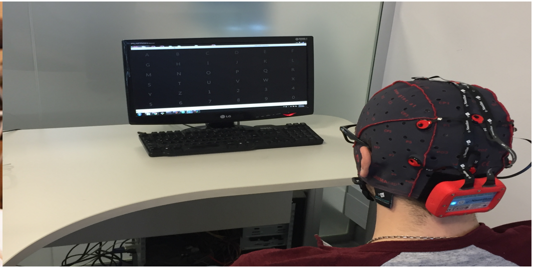
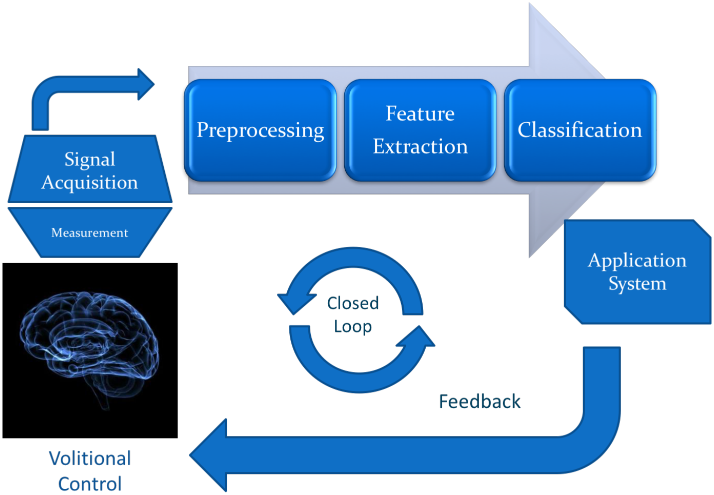
Outline

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**	

- Clinical and Physician involvement[1]

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

- 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-image plots.

What we aim to do

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

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3. Feature extraction procedure

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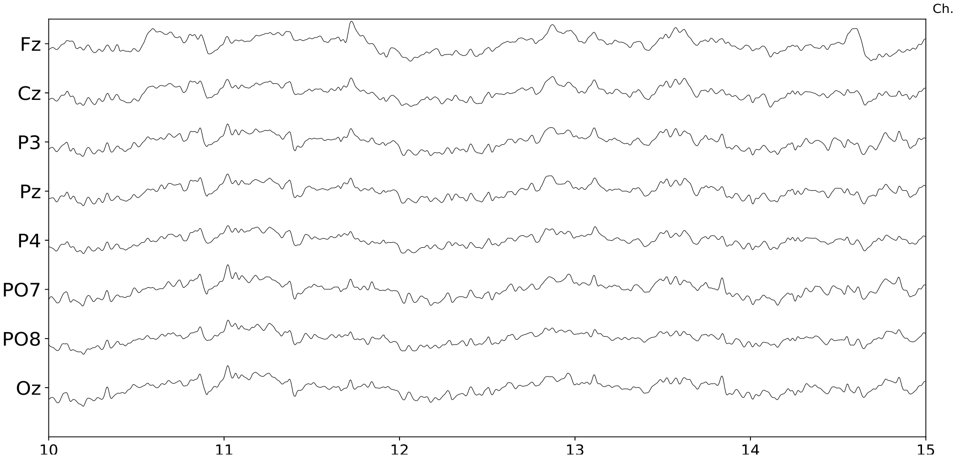
3. Feature extraction procedure
4. Classification algorithm

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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- Permutation Entropy - PE

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Waveform-Based Algorithms

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

Proposal
The Histogram of Gradient Orientation

The Histogram of Gradient Orientations - Feature Extraction Algorithm

1. Signal Preprocessing

1. Signal Preprocessing
2. Signal Segmentation

The Histogram of Gradient Orientations - Feature Extraction Algorithm

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

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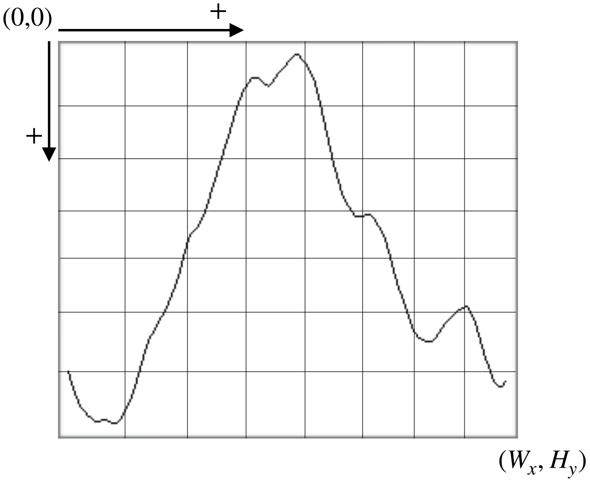
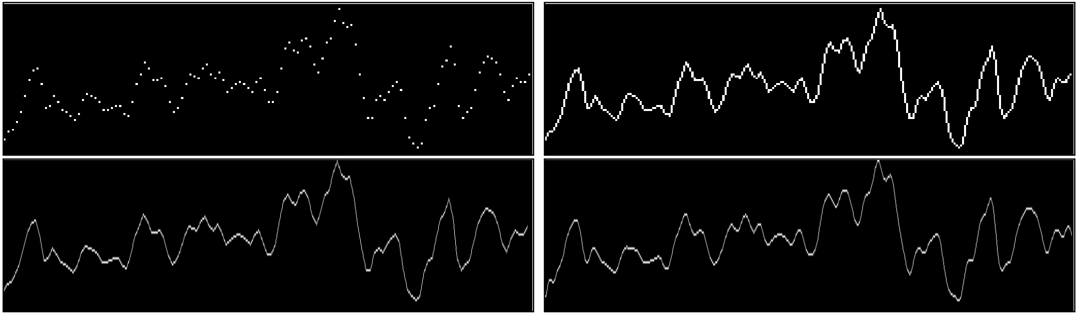
2. Signal Segmentation
3. Signal Plotting
4. Keypoint Localization

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

Image Coordinate System

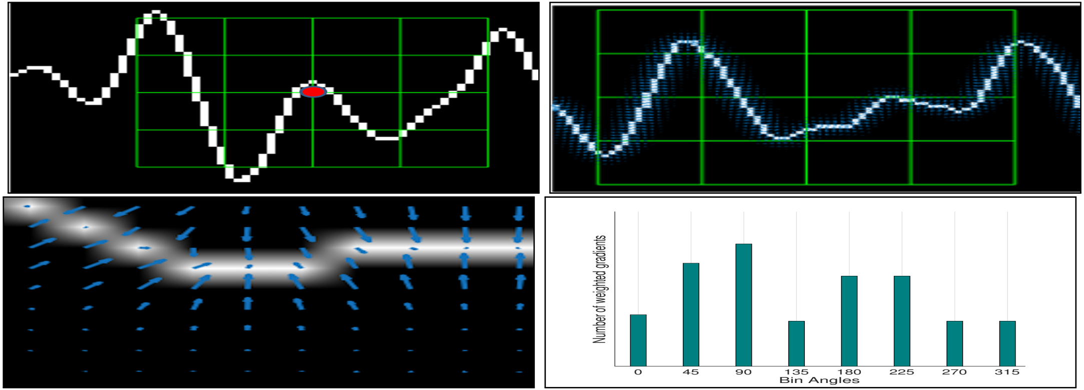


Signal Plotting

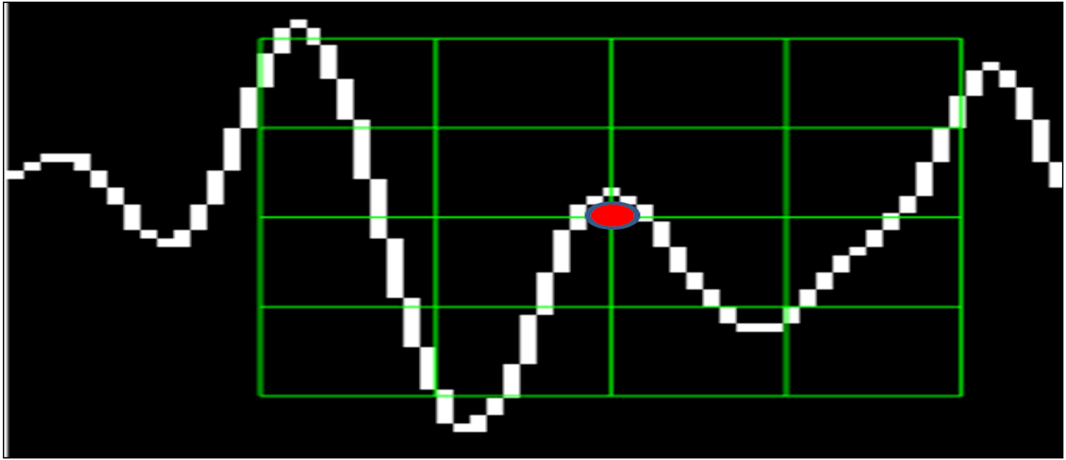


Generated images based on different interpolation schemes.

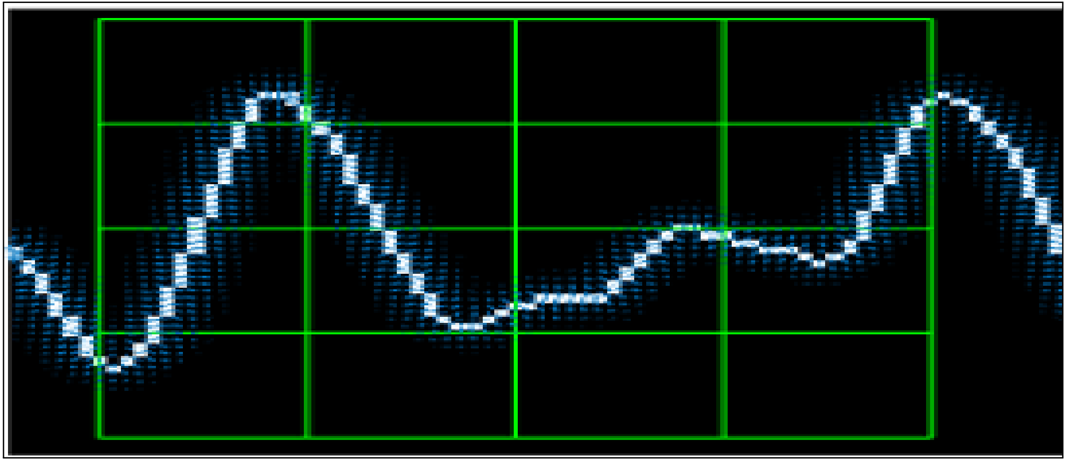
The Histogram of Gradient Orientations



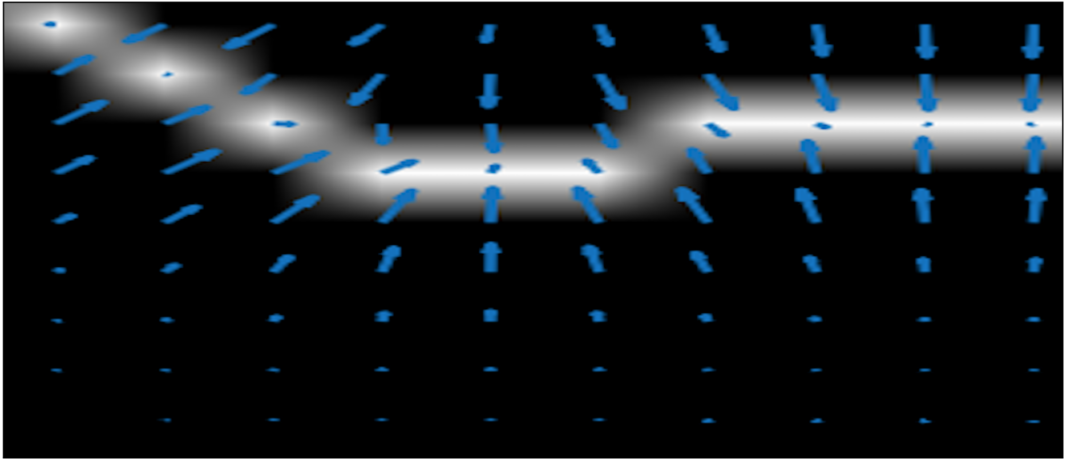
Keypoint Localization



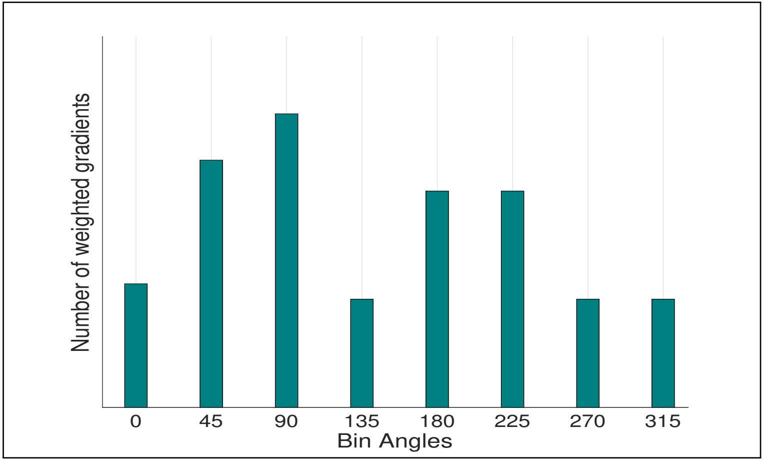
Pixel Gradient Vector Field



Pixel Gradient Vector Field



Orientation histogram

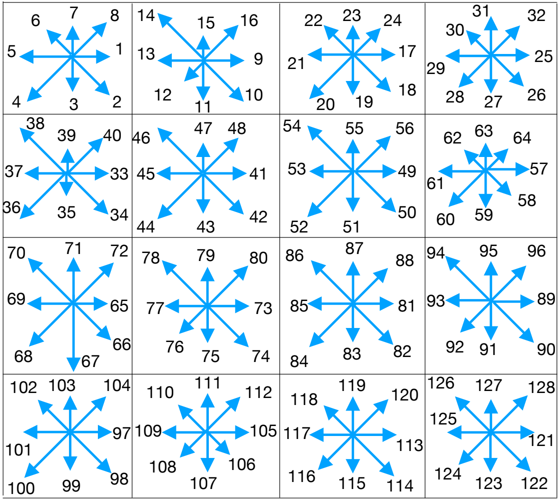


Histogram Calculation

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

- 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**.
- $\omega_{\text{ang}}(\cdot)$ scalar and $\omega_{ij}(\cdot)$ vector linear interpolation functions[3].

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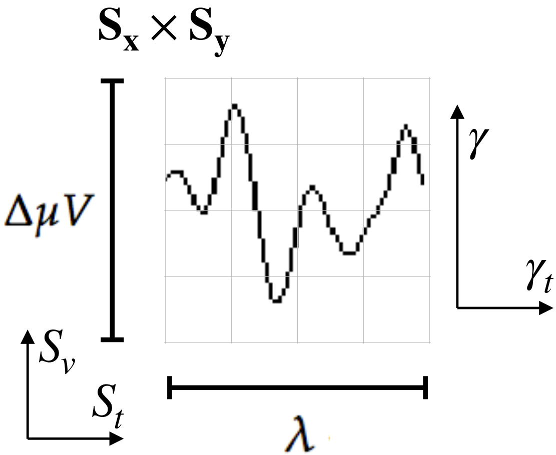
Patch Geometry



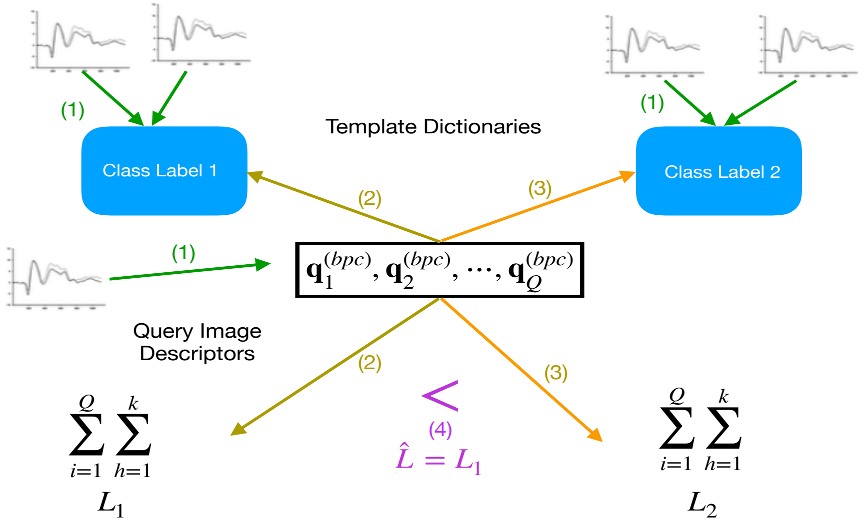
Proposed Classification Method

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

- 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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- μ Rhythm

Experimental Validation

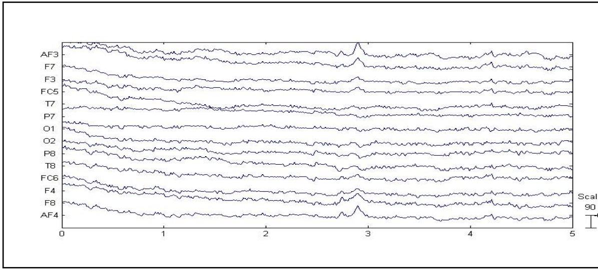
- Alpha Waves Wiggles
- μ Rhythm
- The P300 Waveform

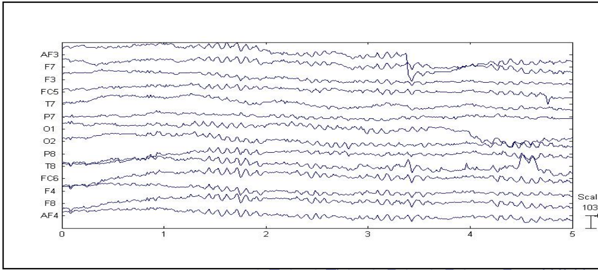
Alpha Waves wiggles

Alpha Waves Datasets

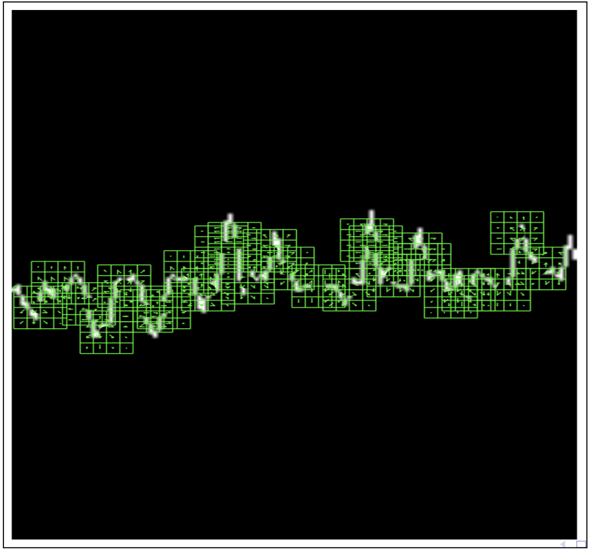
- Dataset I: EPOC Emotiv Consumer Grade EEG Device
  - 128 Hz, 14 channels, 10 subjects, 10 class 1 vs 10 class 2.
- Dataset II: EEG MI NHS PhysioNet
  - 160 Hz, 64 channels, 25 subjects, Run 1 vs Run 2, 60 vs 60.

EEG Consumer Grade Digital Device and EEG Signals

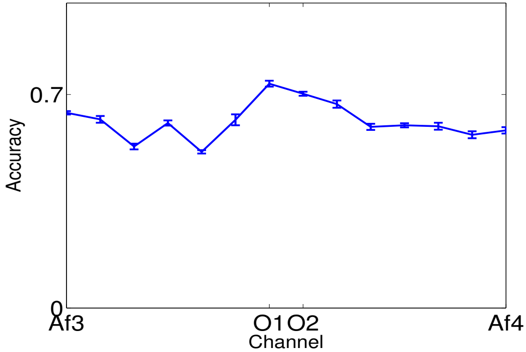


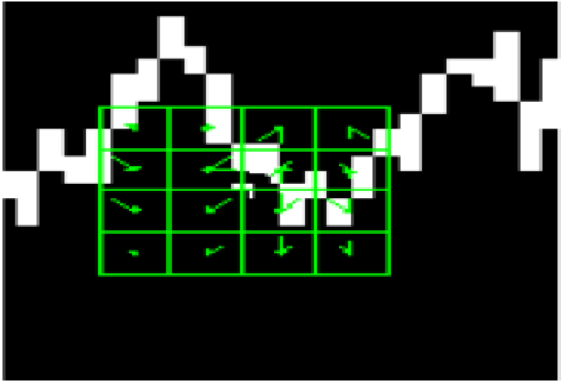


Keypoint populations



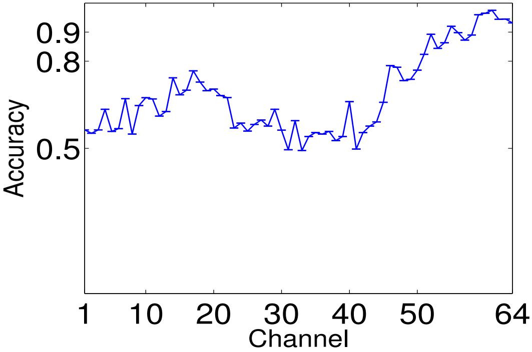
10-Fold Cross Validated Binary Classification Accuracy - Dataset I

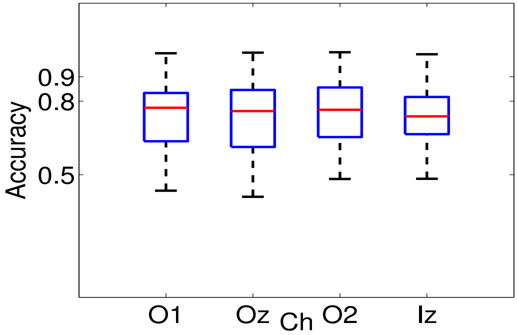




The horizontal patch scale S_t and the vertical patch scale S_v are set to 1, whereas γ and γ_t are set to 2, which corresponds to a variation of $\Delta \mu V = 10$ microvolts in the signal amplitude during $\lambda = 0.08$ seconds.

10-Fold Cross Validated Binary Classification Accuracy - Dataset II

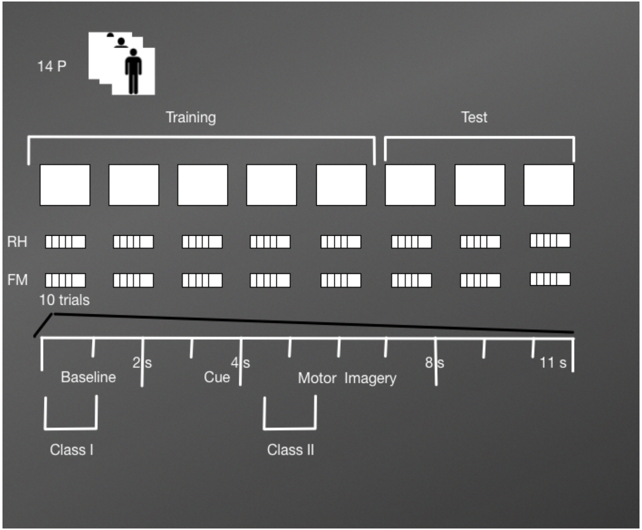




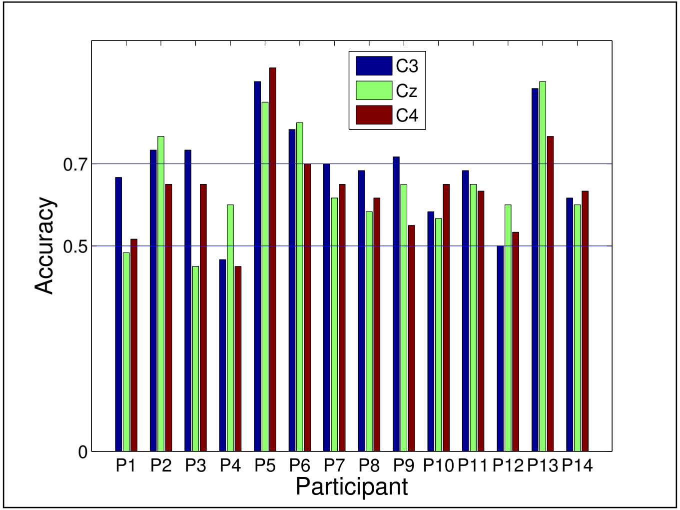
Binary classification accuracy for subject 25 and boxplots obtained for the 25 subjects on 4 occipital channels

μ Rhythm

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

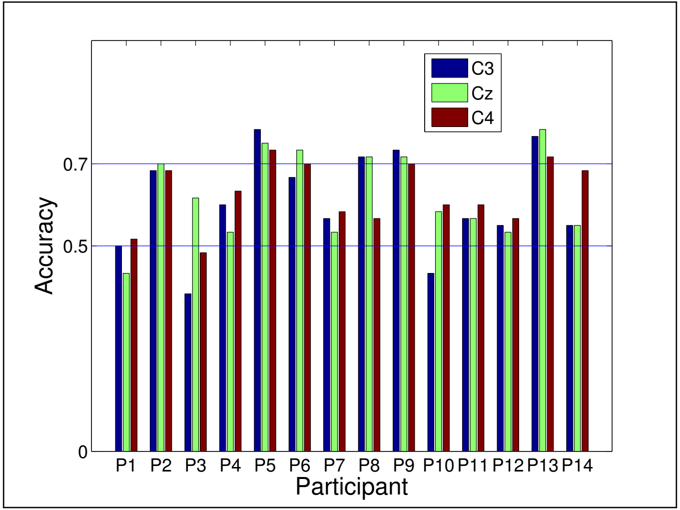


μ Rhythm



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

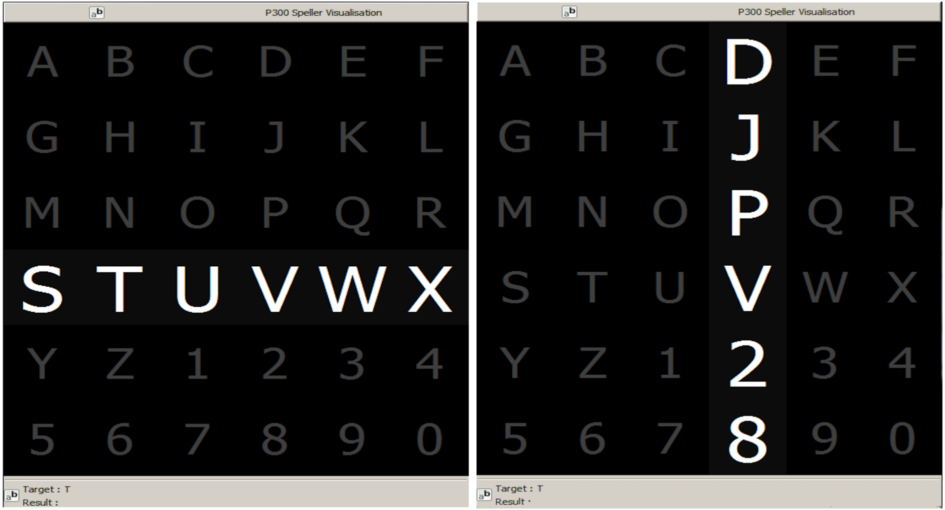
μ Rhythm



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

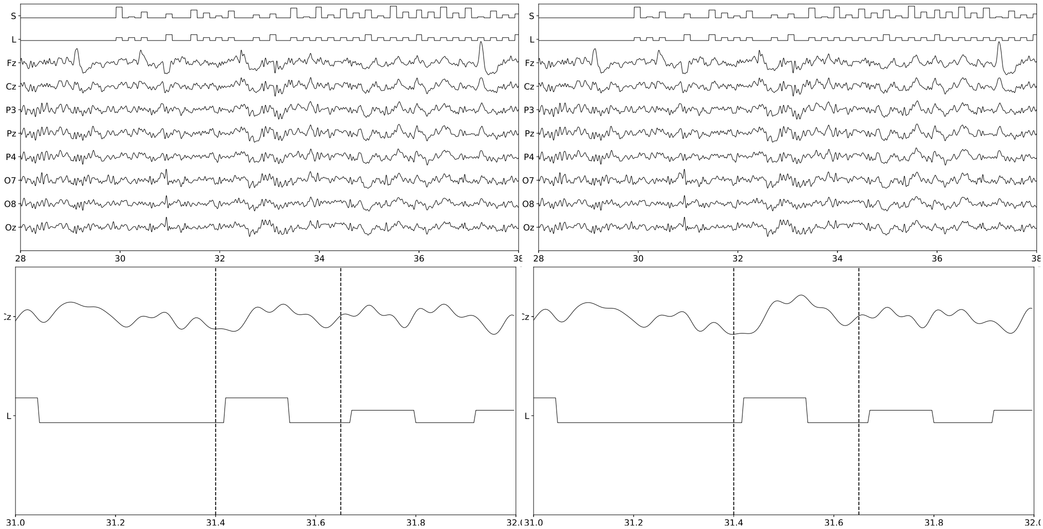
The P300 Waveform

P300-Based Speller Matrix

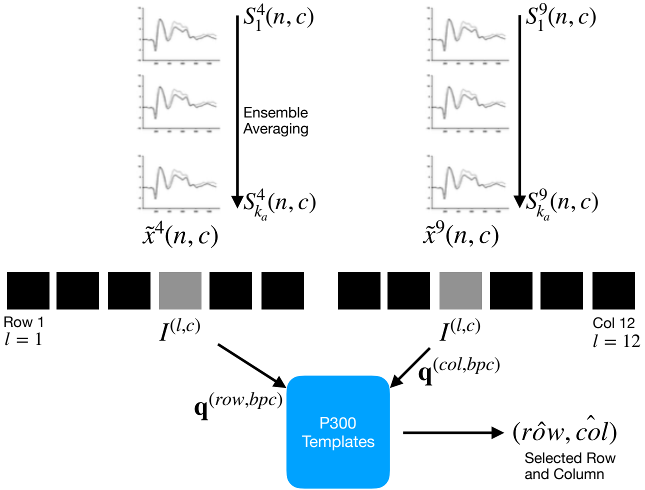


OpenVibe software 6 × 6 Speller Matrix. Rows and columns flash in random permutations.

The P300 Waveform - Signal Preprocessing



Signal Averaging



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

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

- $l \in \{1, \ldots, 12\}$ 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
  - 8 subjects, 8 channels, Fs=256 Hz, 7 words, 5 letters, ISI=0.125 s, 10 epochs

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- Dataset III - P300 Pseudo-Real Dataset
  - 1 subject, null-signals

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- Dataset II - P300 for Healthy subjects
- Dataset III - P300 Pseudo-Real Dataset
    - 1 subject, null-signals
- Dataset IV - P300 Dataset IIb BCI Competition II (2003)
    - 1 subject, 64 channels, Fs=240 Hz, 73 trials, 42 train and 31 test, ISI=0.25 s, 15 epochs

Alternative Methods used for comparison

- Support Vector Machine SVM

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- Stepwise Linear Discriminant Analysis SWLDA.

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Alternative Methods used for comparison

- Support Vector Machine SVM
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- Matching Pursuit 2 MP-2

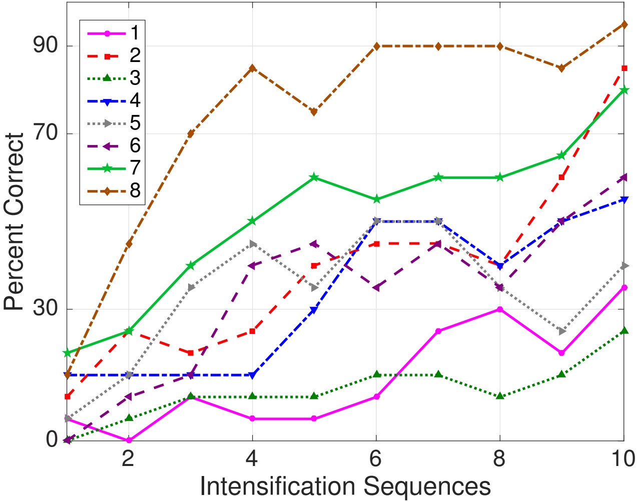
Alternative Methods used for comparison

- Support Vector Machine SVM
- Stepwise Linear Discriminant Analysis SWLDA.
- Permutation Entropy
- Matching Pursuit 1 MP-1
- Matching Pursuit 2 MP-2
- Slope Horizontal Chain Code SHCC.

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%

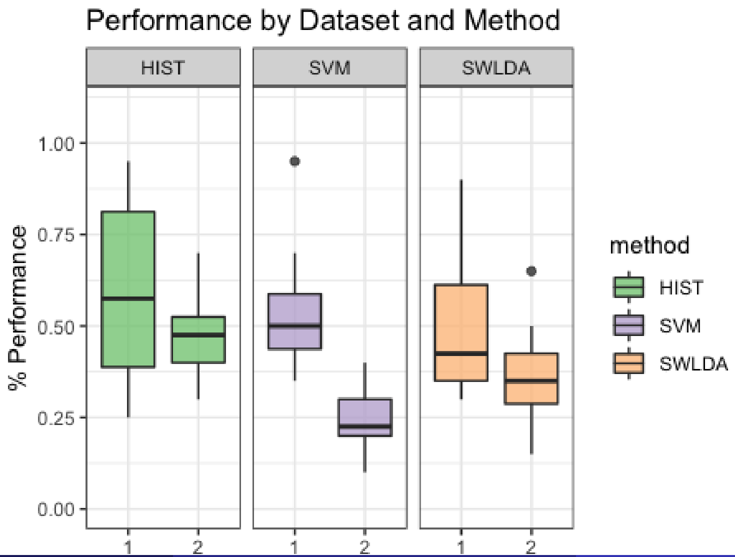
Dataset I Multichannel comparison

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%

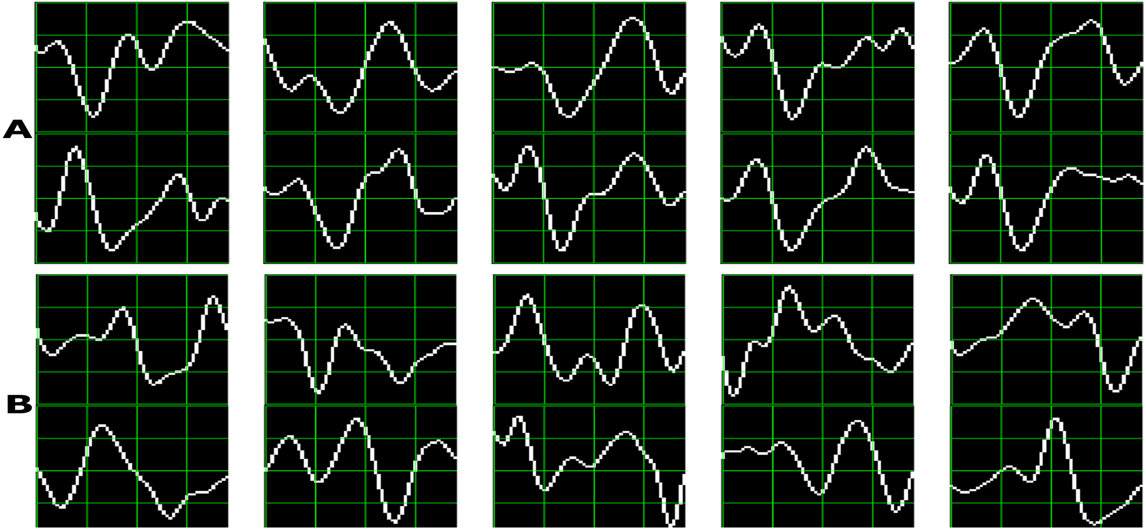
Dataset II Multichannel Comparison

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)



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

Findings

- α and μ waves can be identified by their waveforms.
- Occipital regions more prominent P300 waveforms.
- The stability of ERP transient components in ALS patients
  - Mann-Whitney U Test, $p = 0.46$
- Latency jitter
  - Wilcoxon rank sum test, one tail, $p = 0.0022$
- Amplitude resistance
  - Wilcoxon rank sum test, two tails, $p = 0.17$

Thesis Contributions

- Method to construct analyzable image plots.
- EEG Waveform Feature Extraction Procedure
- SIFT extension and modification: HIST
- Classification algorithm

Practical Contributions

- P300-Dataset on Kaggle
- Registered as EEGWave Code Ocean Reproducible Research Online Platform
- Online Application based on OpenVibe and LSL.
- BCI Online Blog
- Matlab toolbox for Computer Vision EEG Analysis.

Conclusion

- EEG Waveforms can be objectively analyzed.
- Inherent Intelligible System may foster clinical collaboration.

Future Work

- BCI Paradigms Potential Universal Applicability
- Multichannel extension.
- Keypoint localization.
- Neuroimaging.

Questions?

Thank you very much

Preprocessing steps

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

An excellent review can be found here[6].

[6] **Simons2016**.

Histogram of Gradient Orientation - Trilinear Interpolation

$$\omega_{ij}(\mathbf{v}) = \omega\left(\frac{5\ v_x}{\Delta_s\ S_t} - x_i\right)\omega\left(\frac{5\ v_y}{\Delta_s\ S_v} - y_i\right) \tag{5}$$

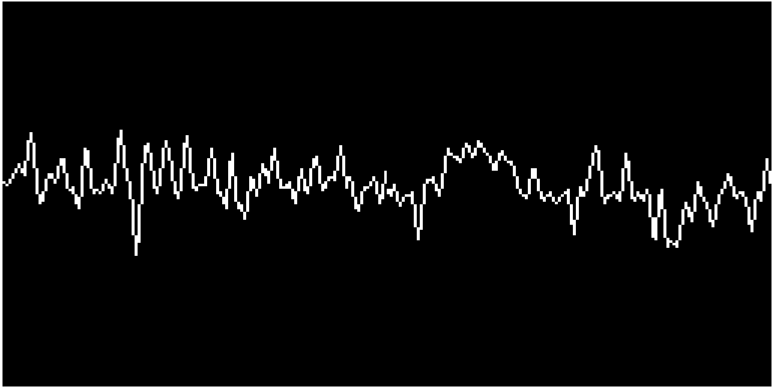
$$\omega_{\mathrm{ang}}(\alpha) = \sum_{r=-1}^{1} \omega\left(\frac{8\alpha}{2\pi} + 8r\right) \tag{6}$$

EEG Signal Plot - Zero Level and Standardization

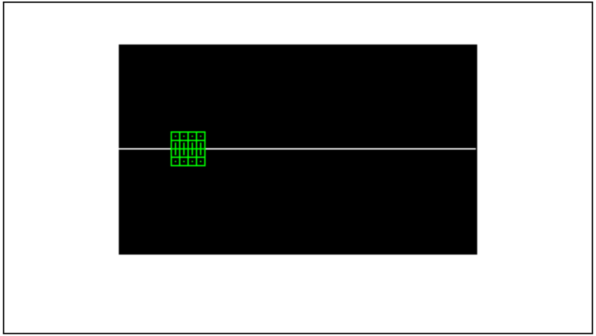
$$\tilde{x}(n,c) = \frac{x(n,c) - \bar{x}(c)}{\hat{\sigma}(c)} \tag{7}$$

$$z(c) = \left\lfloor \frac{\max_n \tilde{x}(n,c) - \min_n \tilde{x}(n,c)}{2} \right\rfloor - \left\lfloor \frac{\max_n \tilde{x}(n,c) + \min_n \tilde{x}(n,c)}{2} \right\rfloor \tag{8}$$

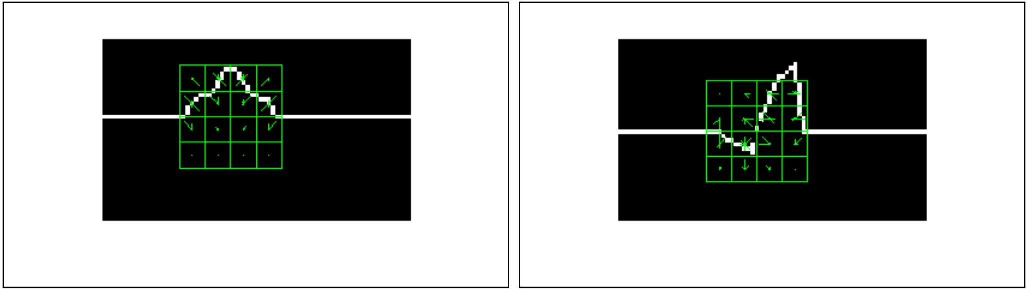
$$\mathcal{I}^{(c)}(z_1, z_2) = \begin{cases} 255 & \text{if } z_1 = \gamma_t \; n \quad \text{and} \quad z_2 = \lfloor \gamma \; \tilde{x}(n,c) \rceil + z(c) \\ 0 & \text{otherwise} \end{cases} \tag{9}$$



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.



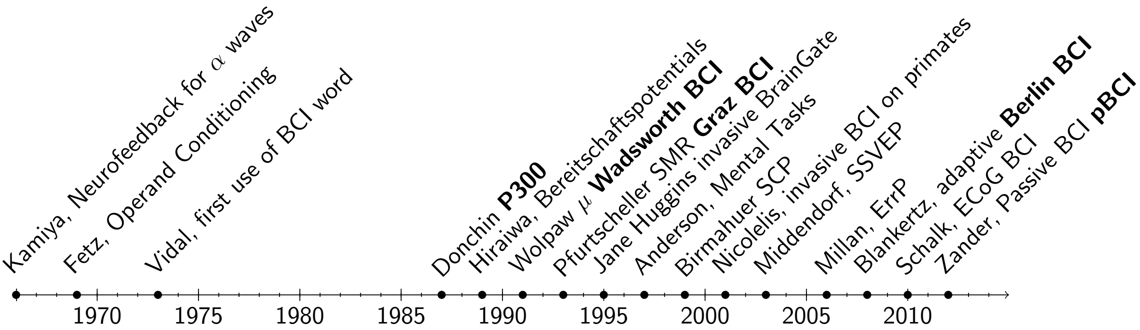
Sample Descriptors from artificial signals.

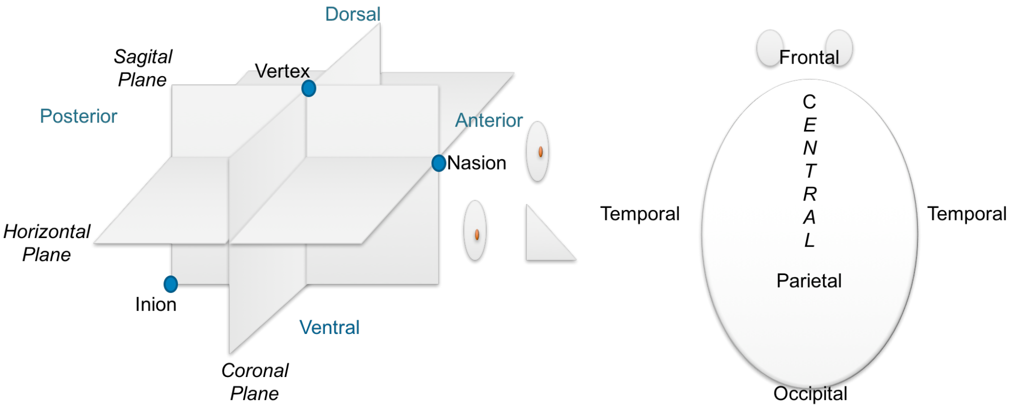
SIFT Descriptors

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

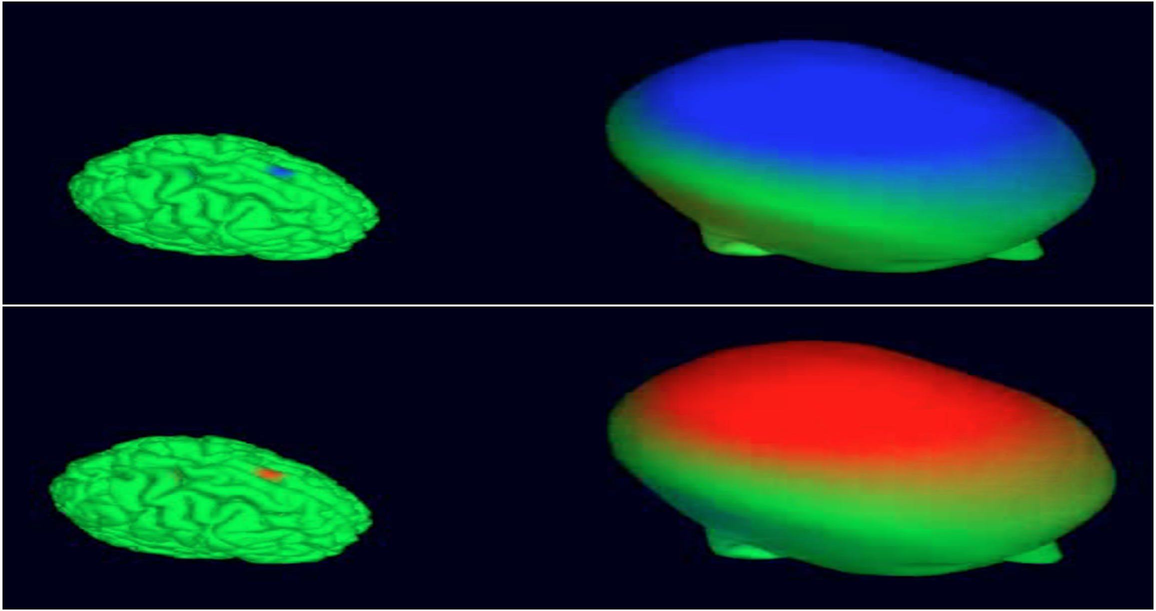
Sample descriptor values of the given patch.

Brain Computer Interfaces - Chronology



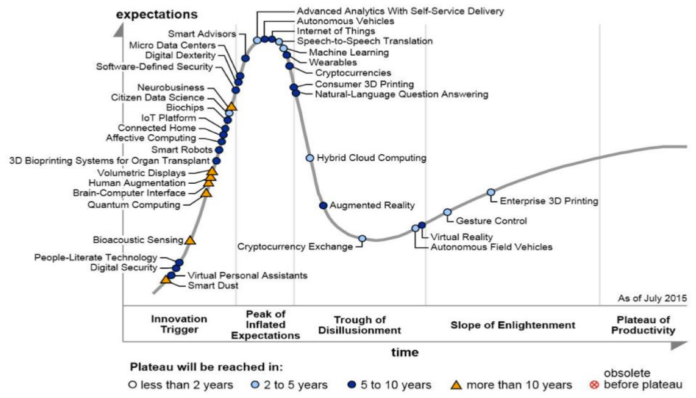


Neuronal Planes regularly used in neuroscience research. In BCI they are used to understand electrode location and spatial filters.



A source signal with positive/negative polarity is generated in a very specific region of the brain but due

Digital and wearable electroencephalographs.



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- **Brain Computer Interfaces**
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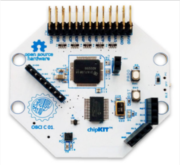
  - Prothesis
  - Exoskeletons
  - Assistive Devices
- **BioChips**
  - Cochlear Implant
- **NeuroBusiness**
  - Neuromarketing
  - Neuroergonomy
  - Neurorehabilitation
- **Wearables**
  - mHealth
  - Personal Analytics

Digital and wearable electroencephalographs.

NeuroSky



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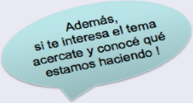

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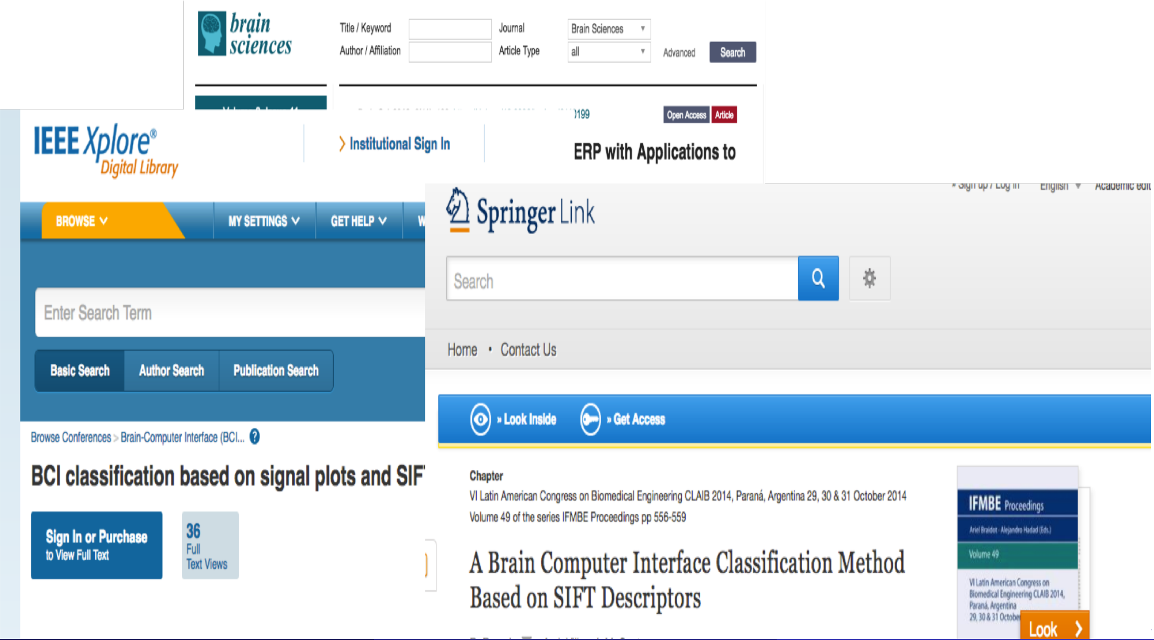
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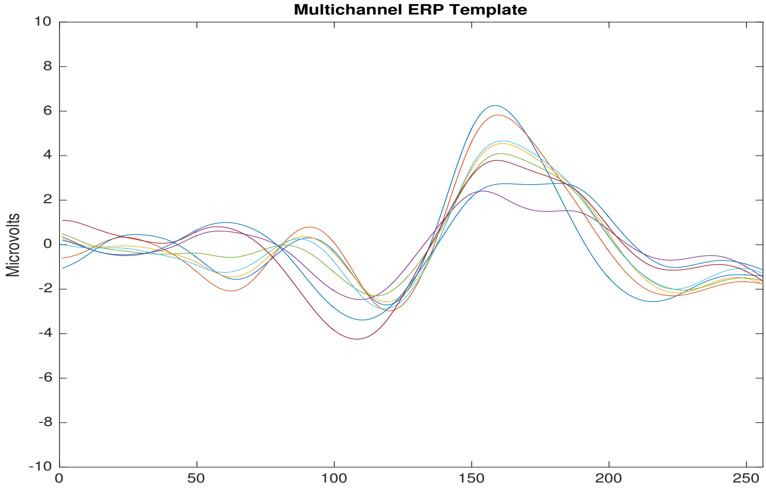
Additionally, the stability of the P300 component waveform has been extensively studied in patients with ALS[7] where it was found that these patients have a stable P300 component, which were also sustained across different sessions. In line with these results we do not find evidence of a difference 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.

[7] **SellersandEmanuelDonchin2006**, **TomohiroMadarame2008**, **Nijboer2009**, **Mak2012**, **McCane2015**.

P300 ERP Template for Dataset III



Performance Curves for Dataset IV (Dataset IIb BCI Competition II 2003)

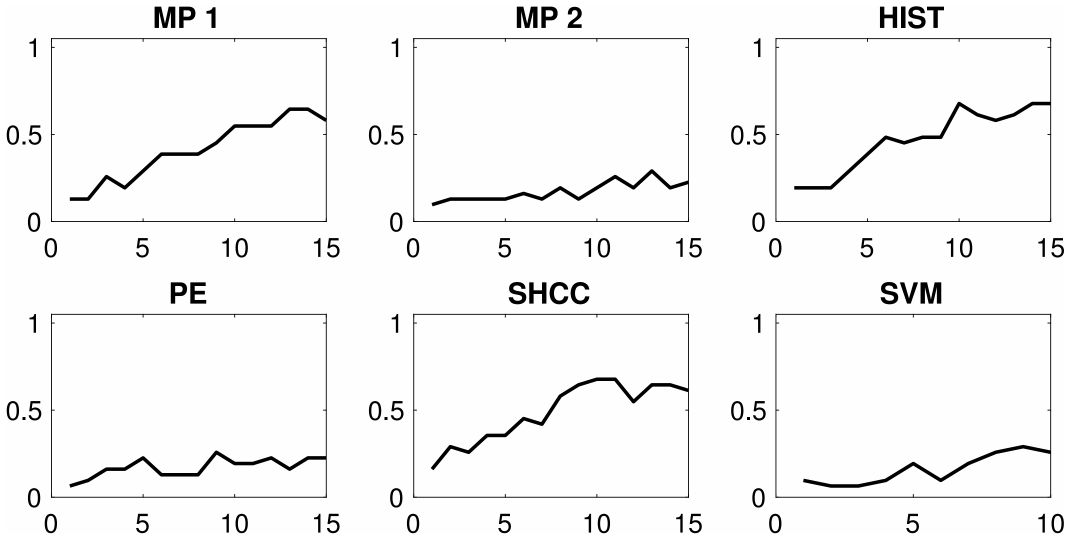


Table: EEG waveforms descriptions found in the surveyed literature.

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