Méthodes d'analyse et de débruitage multicanaux à partir d'ondelettes pour améliorer la détection de potentiels évoqués sans moyennage

application aux interfaces cerveau-ordinateur

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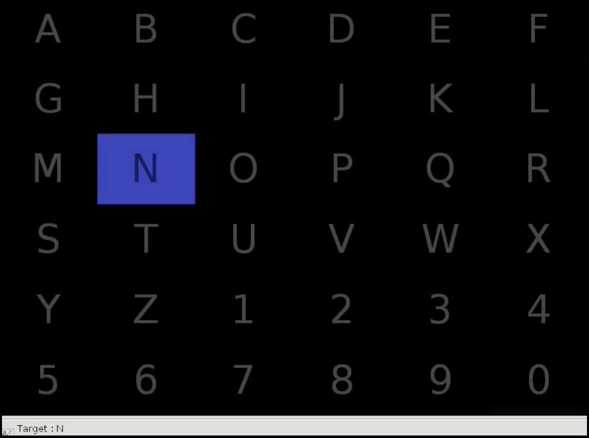
François Cabestaing	Professeur, Université Lille 1
Anne Boyer	Professeur, Université de Lorraine
Bernard Girau	Professeur, Université de Lorraine
Laurent Bougrain	Maître de Conférences, Université de Lorraine

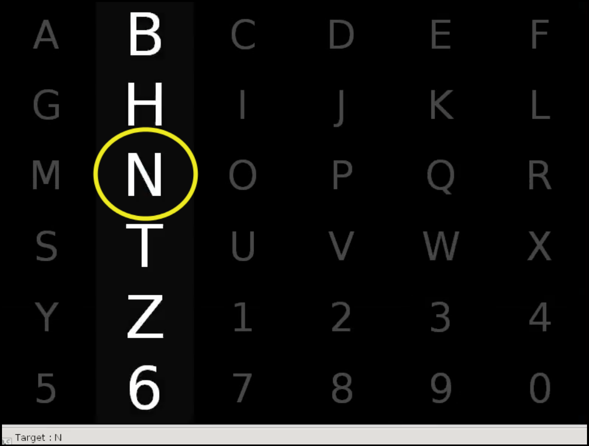
Overview: A speller for communication purposes

"Look at the blue letters!"



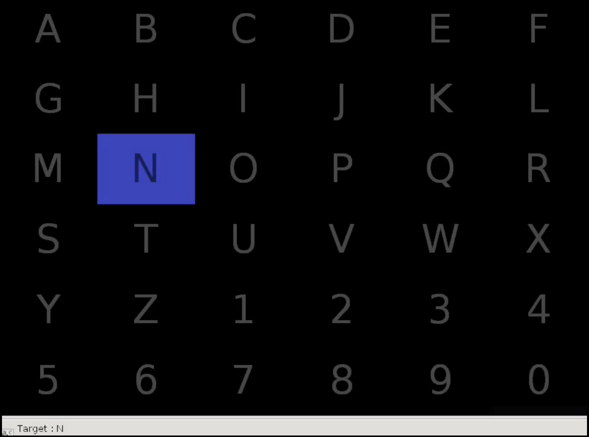
Overview: A speller for communication purposes

"Count when the letter is flashed!"

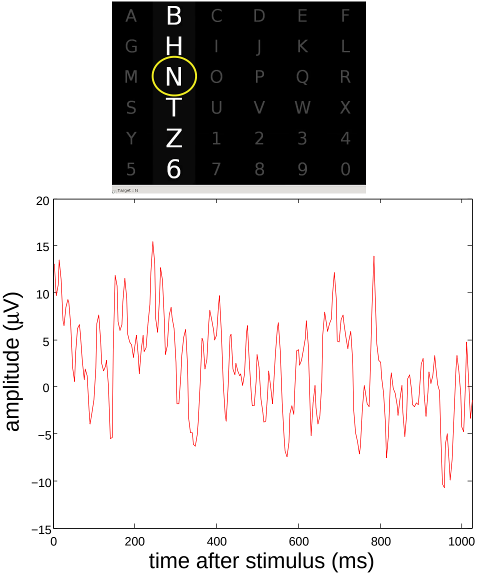


Overview: A speller for communication purposes

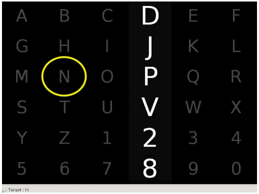
”Look at the blue letters and count the flashes!”

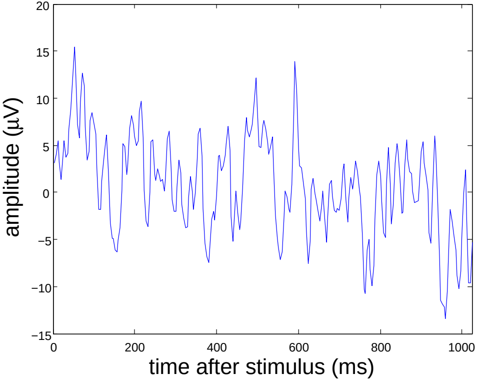


Target Response

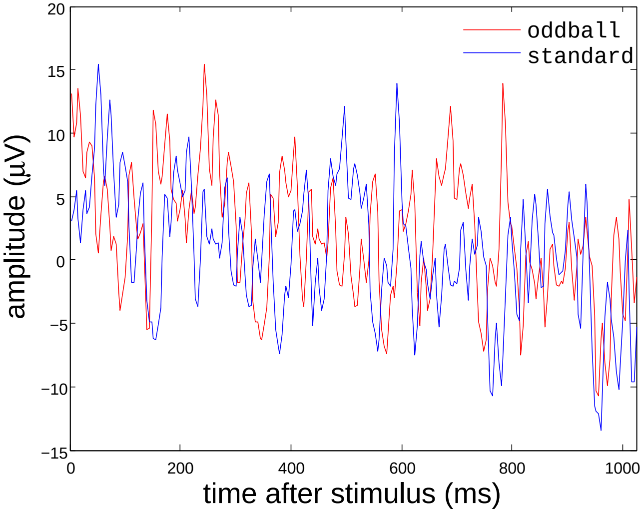


Non-target Response





Overview: Detection of Event-Related Potentials in EEG in Single Trial



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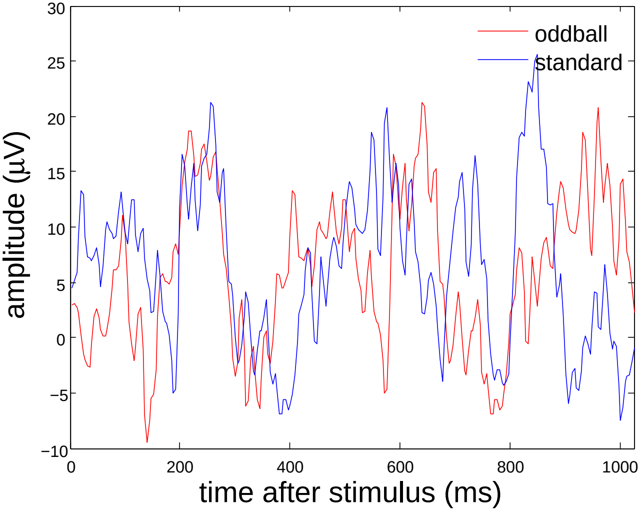

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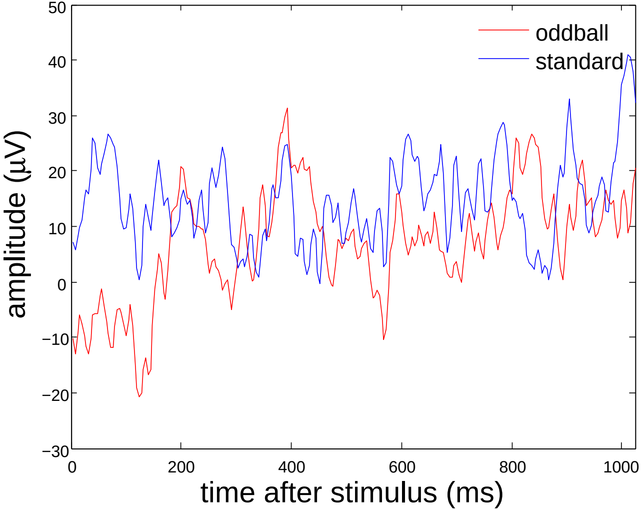

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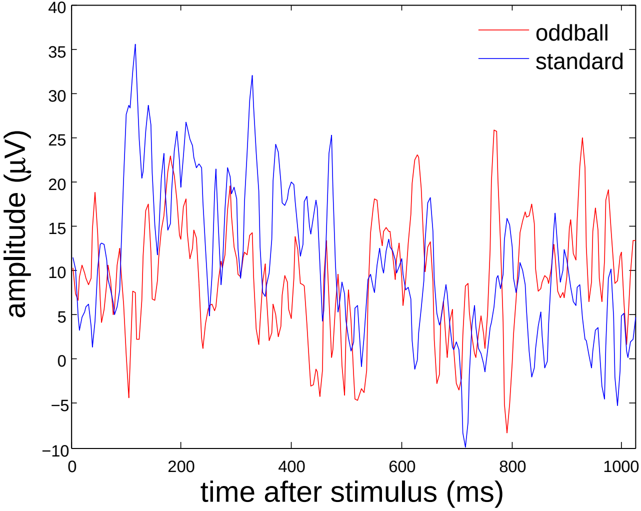

Overview

Problem

- Detection of Event-Related Potentials
  - in Noisy signal
  - in Single trial

Approaches

- 1. Denoising method
- 2. Analysis method
- Based on Wavelet theory
- Using multichannel information

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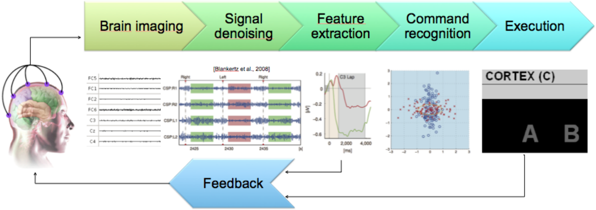
Outline

Plan

Brain-Computer Interfaces (BCI)

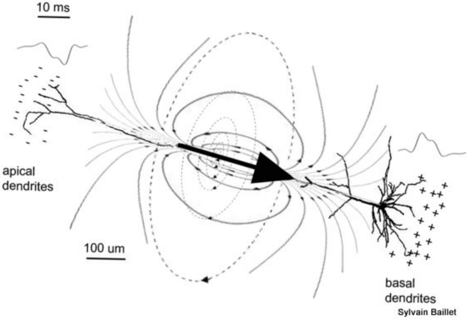
Definition [Wolpaw et al., 2000]

"A brain–computer interface is a communication system that does not depend on the brain's normal output pathways of peripheral nerves and muscles."

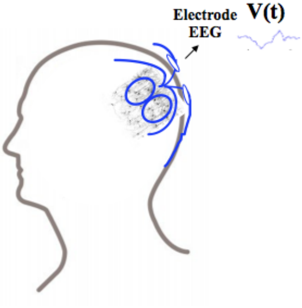


Electroencephalography (EEG)

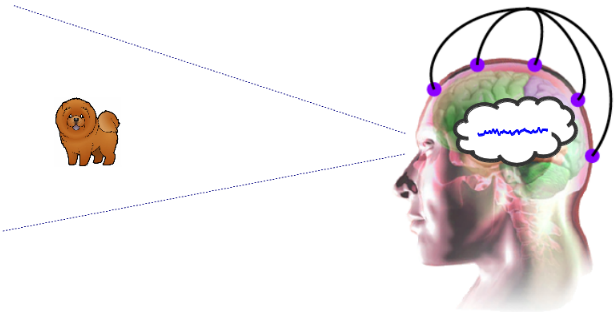
Origin



Observation



Oddball Paradigm: Searching for Lassie



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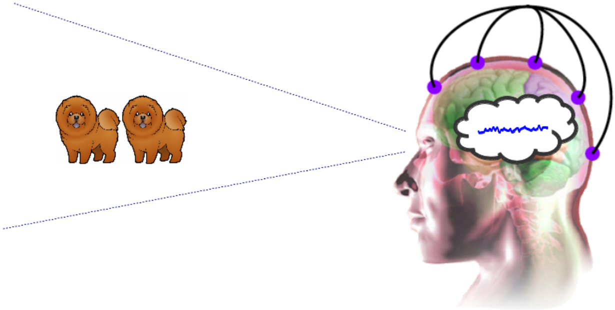

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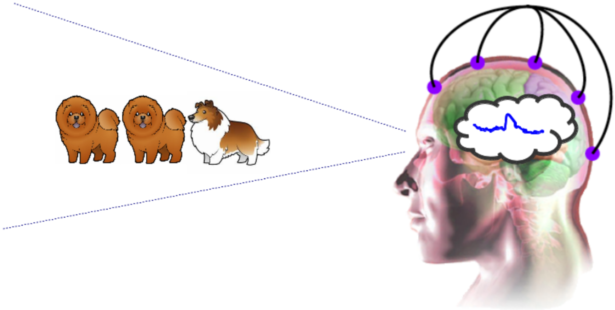

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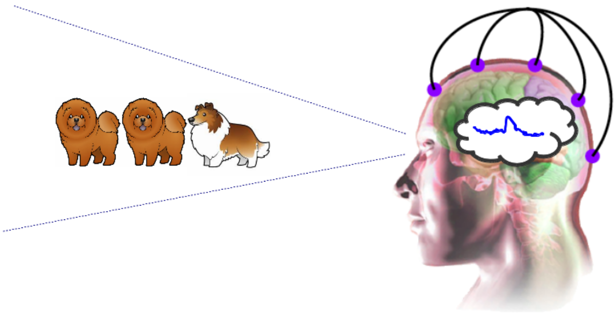
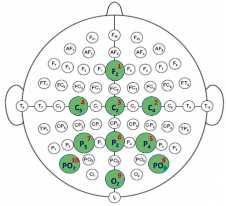


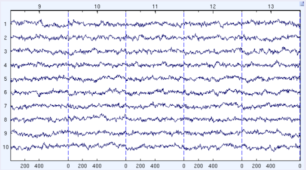


P300

- Positive amplitude
- Around 300 ms after the stimulus

Noise and Artifacts

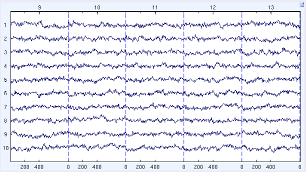
Noise



- Background neurological activity including other brain activities

Noise and Artifacts

Noise



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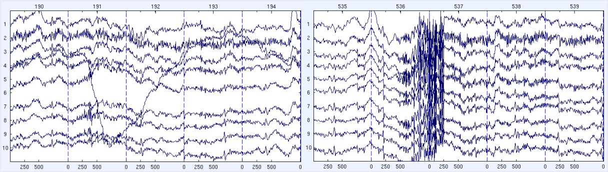

- Hardware
- Body
- Environmental

P300 Averaging

Problem

EEG background signal magnitude is usually one-order larger than ERP components.

P300 Averaging

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EEG background signal magnitude is usually one-order larger than ERP components.

Solution

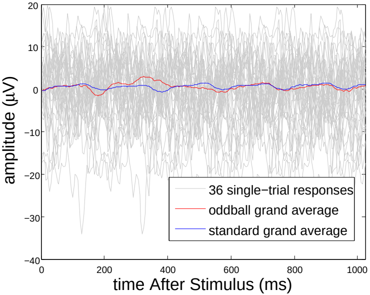
Averaging several responses to the same stimulus increases the P300 responses and reduces the EEG background

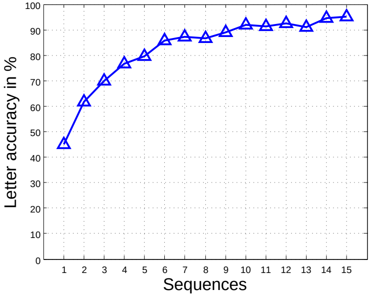
- 1 sequence = each stimulus is flashed
- 1 averaging = 2 to 15 sequences

P300 Averaging

Advantages

- Increase the signal-to-noise ratio
- The ERP shape and latency is more visible
- The ERP detection performance increases with the number of sequences





P300 Averaging

Drawbacks

- The communication transfer bit-rates of the system decreases

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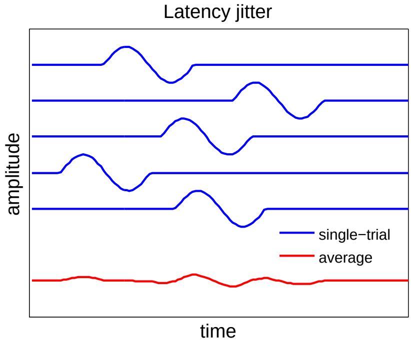
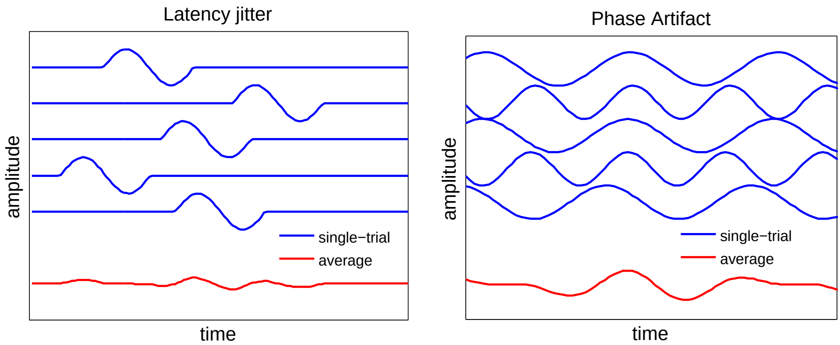


P300 Averaging

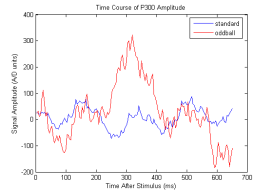
Drawbacks

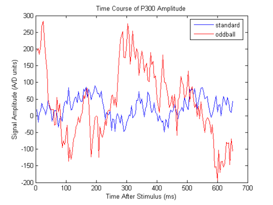
- The communication transfer bit-rates of the system decreases
- The latency jitter in trials can smooth out the ERP
- Fake ERPs can appear due to “phase artifacts”

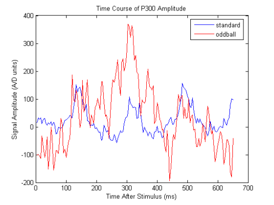


P300 Variability

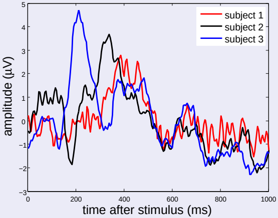
Intra-subject variability



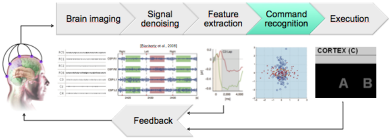




Inter-subject variability



P300 Classification



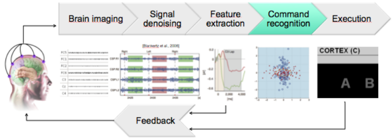
Key points for classification

- a high variability
- a high-dimensional space

Linear classifiers

- LDA
- StepWise LDA
- **LSVM**
- Bayes' classifier

P300 Classification



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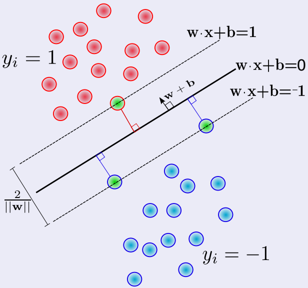
LSVM



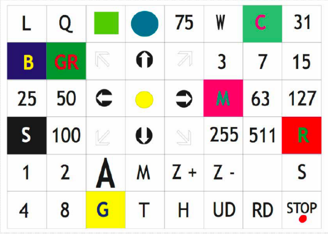
- Separating hyperplane
- Maximize the margin

BCI Based on P300 Examples

Mugler et al., 2008

BCI Based on P300 Examples

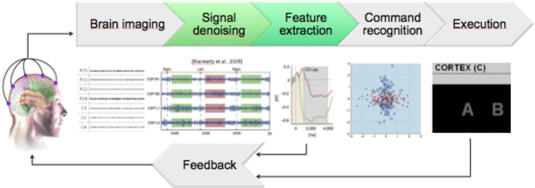
Mugler et al., 2008



Kübler et al., 2008

@Adi Hoesle,2008

Plan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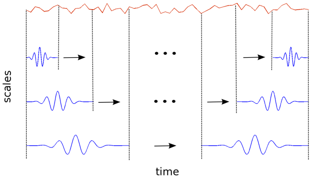
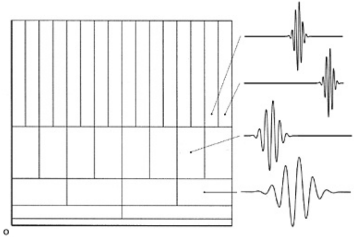
Wavelet Transform

Represents a signal $x(t)$ using scaled and shifted versions of a mother wavelet $\psi(t)$

$$W_\psi^x(a,b) = \langle x(t), \psi_{a,b}(t) \rangle \qquad \psi_{a,b}(t) = \frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right)$$





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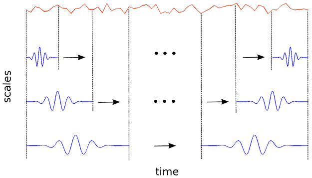
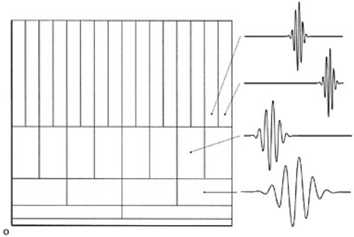




Mother wavelets must

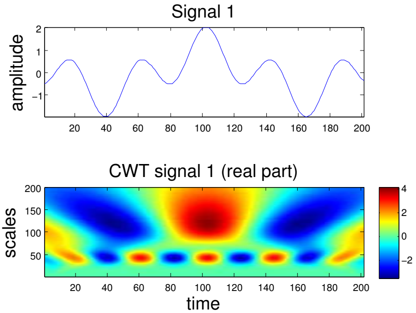
Have a finite bandwidth both in time and in frequency

Admissibility condition

$$C_\psi = \int_0^\infty \frac{|\mathcal{F}_\psi(\omega)|^2}{\omega} d\omega < \infty$$

Continuous Wavelet Transform

$$W_\psi^x(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} x(t)\psi^*\left(\frac{t-b}{a}\right) dt$$

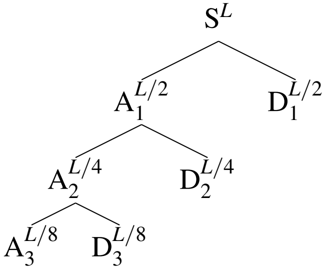


- a and b change continuously
- Reconstruction theoretically possible under *admissibility condition*
- Often performed using a sumation
- Reconstruction depends on the resolution

Discrete Wavelet Transform

$$W_\psi^x(m,n) = \int_{-\infty}^{\infty} x(t)\psi_{m,n}(t)dt$$

$$\psi_{m,n}(t) = \frac{1}{\sqrt{2^m}}\psi\left(\frac{t-2^m n}{2^m}\right)$$



Properties

- Sufficient information for reconstruction
- Sampled version of CWT
- Easier to implement (Mallat)

Classic Wavelet Thresholding

Based on the Discrete Wavelet Transform (DWT)

$$z(t) = x(t) + n(t)$$

The objective is to reduce the noise $n(t)$ and to recover $x(t)$

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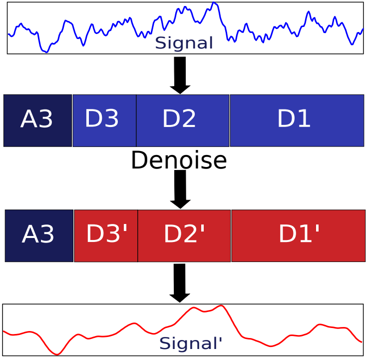
Thresholding Strategy

1. Decompose
2. Threshold detail coefficients
3. Reconstruct

Classic thresholds

- Universal threshold
- SURE threshold
- Minimax threshold



Wavelet Semblance [Cooper and Cowan, 2008]

Cross-Wavelet Spectrum [Torrence, 1998]

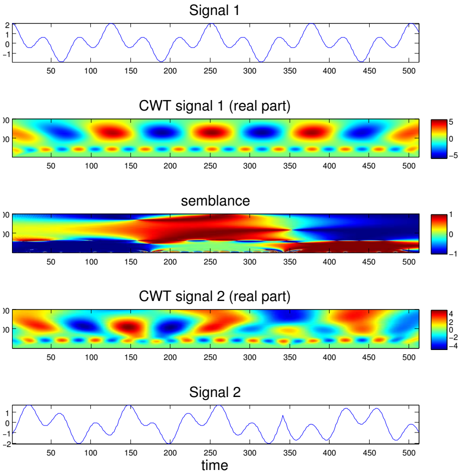
$$W_\psi^{x,y} = W_\psi^{x} W_\psi^{y*}$$

- Amplitude:

$$A = |W_\psi^{x,y}|$$

- Phase:

$$\theta = tan^{-1}(\Im(W_\psi^{x,y})/\Re(W_\psi^{x,y}))$$



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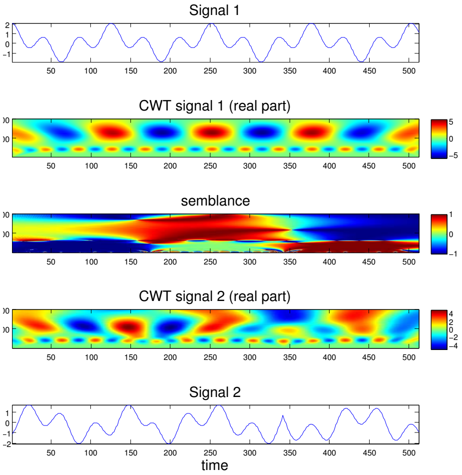

Semblance measure

$$S = cos^n(\theta)$$

n integer greater than zero and odd

- $S = 1$ correlated
- $S = 0$ uncorrelated
- $S = -1$ inversely correlated

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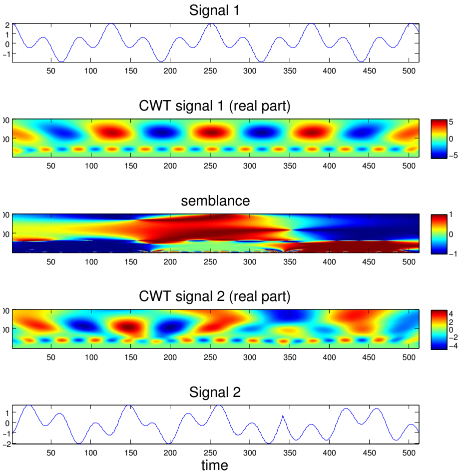

Adding amplitude information

$$D = cos^n(\theta)|W_\psi^x W_\psi^{y*}|$$

Wavelet Mean Resultant Length (MRL) [Cooper, 2009]

$$MRL(a,t) = \frac{\sqrt{(\sum_{i=1}^{N} \Re(W_{\Psi}^{i}(a,t)))^2 + (\sum_{i=1}^{N} \Im(W_{\Psi}^{i}(a,t)))^2}}{\sum_{i=1}^{N} |W_{\Psi}^{i}(a,t)|}$$

- $MRL = 1$ correlated,
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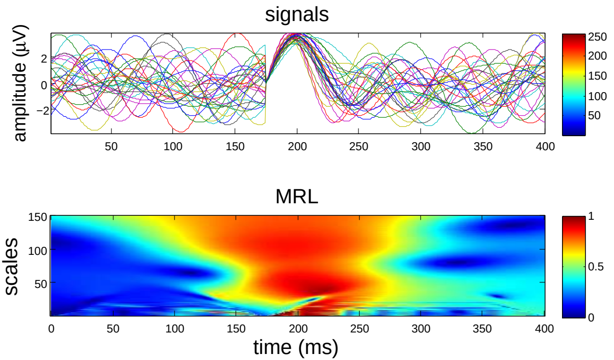

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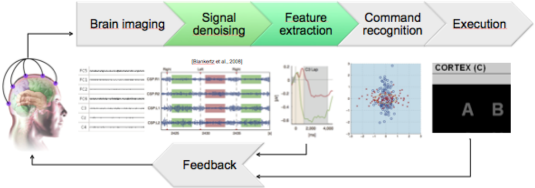

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Single-trial BCI

Why do we want to work with single trials?

- Improve the transfer bit-rates
- Avoid latency jitter
- Avoid phase artifacts
- Apply BCI in other domains

Disadvantage:
Low signal to noise ratio (SNR)
Problem:
Low recognition rate (classification)

The use of single trials force the development of pre-processing techniques to deal with the low SNR

Our Strategy

- (1) Improve the denoising technique
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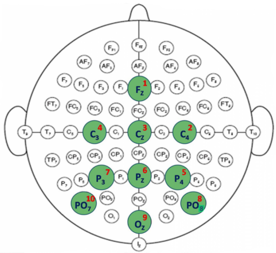
(1) Wavelet Thresholding for EEG

- Current wavelet thresholding techniques denoise one channel at the time
- The target information in EEGs is redundant through the channels



Our Approach

To denoise by analyzing the channels information jointly in the wavelet domain

Analysis Tool

The MRL measure considers the phase angle relationships between channels

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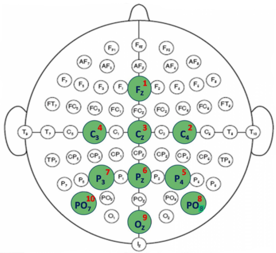

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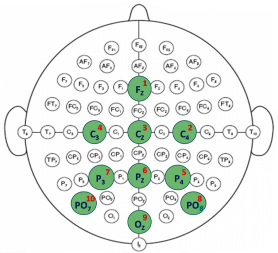

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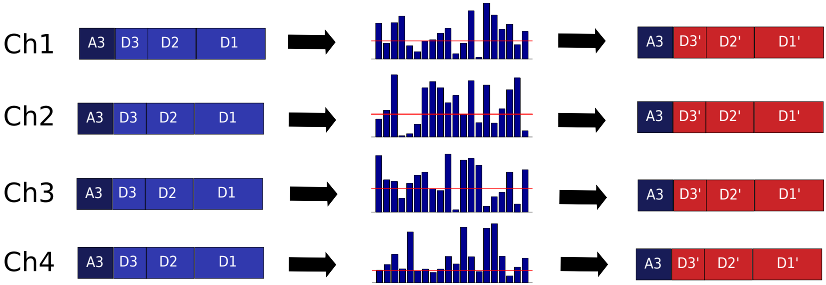
Multichannel EEG Thresholding by Similarity (METS)



1. Compute the Discrete Wavelet Transform (DWT) coefficients for each channel
2. Compute the Mean Resultant Length (MRL) to obtain common coefficients
3. Set to zero all coefficients below a given threshold
4. Reconstruct the signal for each channel using the inverse DWT based on the denoised MRL coefficients

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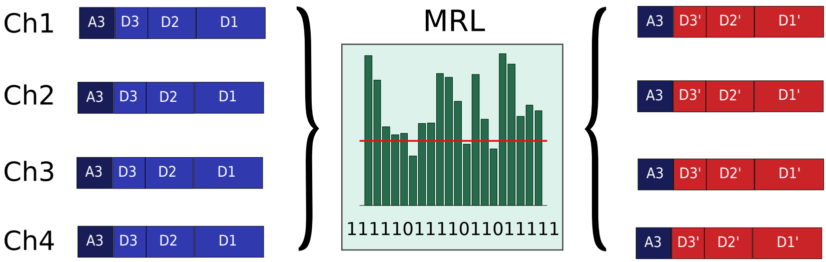

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- The fixed size window include non-informative features
- These features have a strong impact in classification

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Select a thinner temporal window adapted to each subject

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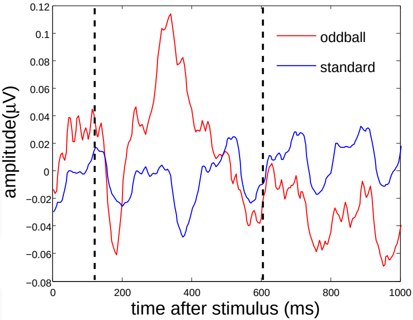
Semblance measure including the amplitude (D measure)



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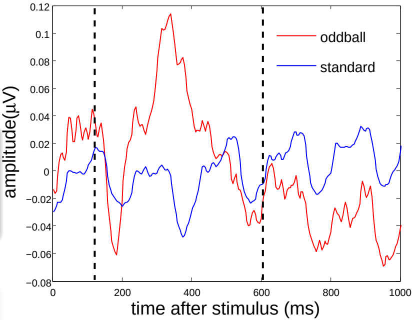

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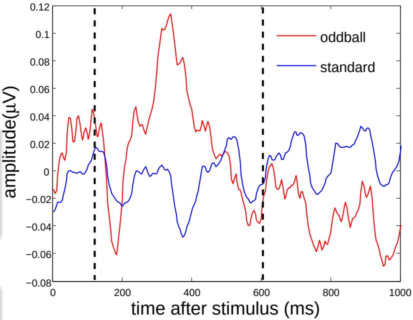
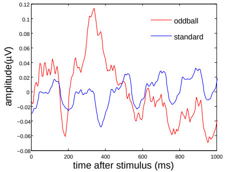
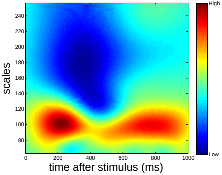


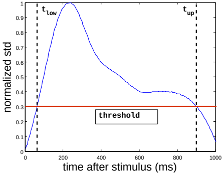
1. Compute the averages for the target and non-target responses.
2. Compute the Continuous Wavelet Transform (CWT) of the averages
3. Compute *D* through the semblance
4. Compute the standard deviation of *D* over the scales (and standarize)
5. Compute the lower and upper boundary using a threshold

Two versions

- SEWS-1: compute a different window for each channel
- SEWS-2: compute the same window for all channels







Semblance-based ERP Window Selection (SEWS)

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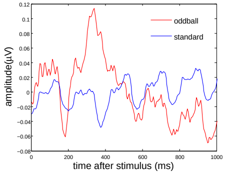

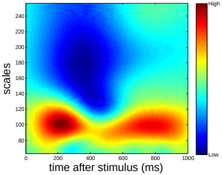

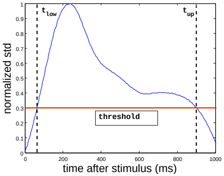

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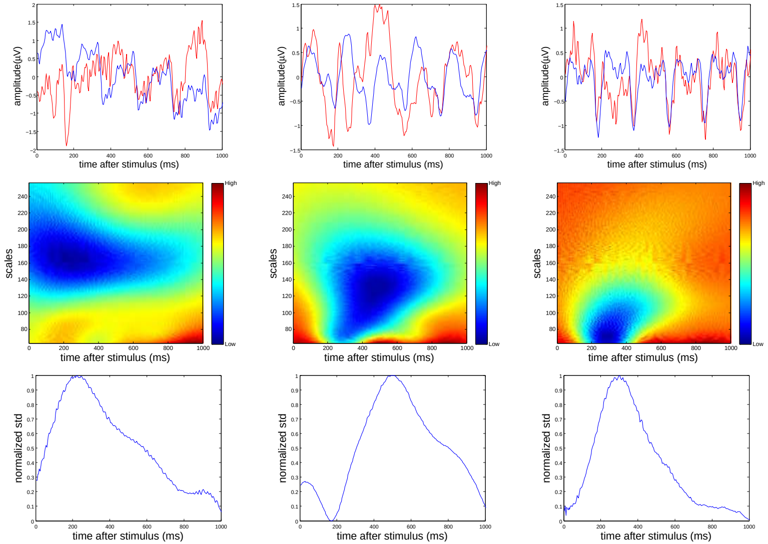
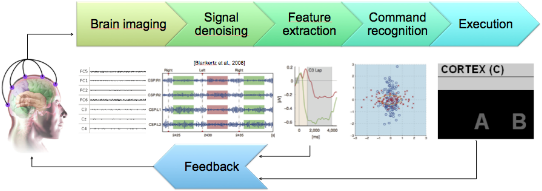
SEWS: Subjects Examples

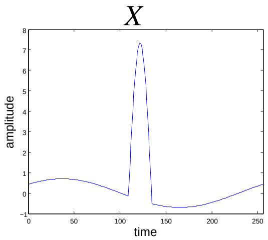


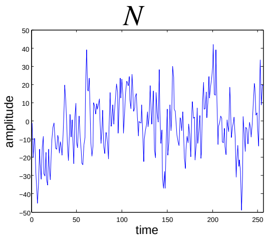
Plan



Brain imaging
Signal denoising
Feature extraction
Command recognition
Execution
[Blankertz et al., 2008]
CORTEX (C)
A B
Feedback

Artificial Data [Yeung et al., 2004]





$$Z = X + N$$

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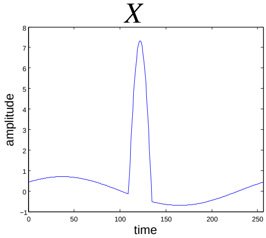

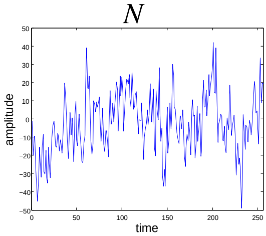

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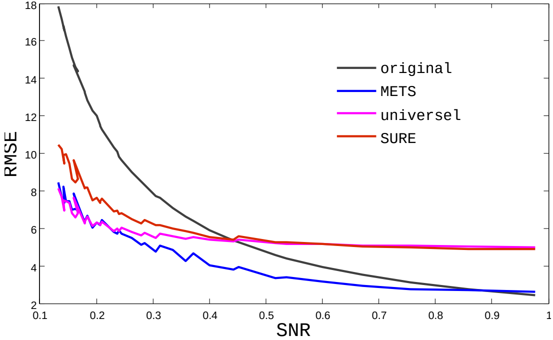
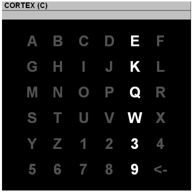


$$SNR = \sigma(X)/\sigma(N)$$

$$RMSE = \sqrt{E[\hat{X} - X]^2}$$

Data base UAM: P300 Speller [Farwell and Donchin, 1988]

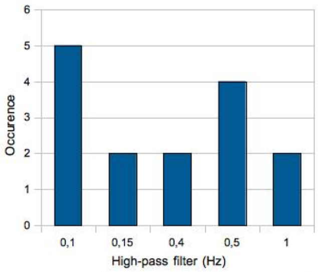
- Speller matrix: 36 characters
- Rows and columns flashed randomly
- Two P300s are identified to recognize a letter

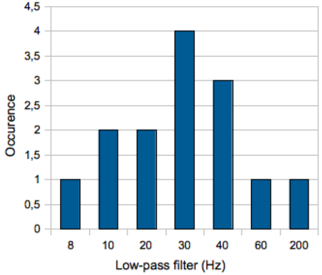


- 22 first-time healthy subjects
- 10 EEG channels recorded
- 5520 single trials for training (1 second)
- 5895 single trials for testing (1 second)

http://akimpech.izt.uam.mx/p300db

Pre-processing filtering





27 articles on P300 detection (BCI conference 2011)

Low Cutoff Frequencies

High Cutoff Freq.	8	10	20	30	40	60
0.1	52.71	53.23	**53.60**	52.15	50.51	**48.23**
0.15	52.43	53.07	**53.56**	**52.16**	**50.56**	48.16
0.4	52.76	53.38	**53.72**	51.66	50.04	47.44
0.5	53.01	**53.74**	53.17	51.42	50.00	47.51
1	**53.13**	**53.83**	52.50	50.62	48.95	46.22

Results: Letter Accuracy

- Probability to detect the correct row or column is 1/6
- Probability to detect a letter 1/36
- Using only single trials

Pre-processing	μ	σ	**min**	**max**	t-test p-value (1%)
[0.1-20] Hz Filter	53.60	14.14	28.25	79.52	
SURE	54.80	13.90	33.02	78.57	-
Minimax	55.00	13.93	32.70	79.05	0.0028
Universal	55.07	13.92	33.02	79.05	0.0055
METS	55.20	**13.19**	33.65	79.05	0.0017
METS & SEWS-1	**56.00**	13.64	**35.56**	**80**	0.0004
METS & SEWS-2	55.91	14.13	34.44	78.97	0.0005

Summary

The average, minimum and maximum results are improved

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xDAWN Spatial Filter [Rivet et al., 2009]

Their EEG model is:

$$\mathbf{X} = \mathbf{D}\mathbf{A} + \mathbf{N}$$

- **A**: Time course of a single P300 response
- **D**: Positions of target stimuli that should evoke a P300
- **N**: Noise

Enhance the P300 response

Maximize the signal to signal plus noise ratio using the spatial filter $\hat{\mathbf{U}}$

$$\hat{\mathbf{U}} = \arg\max_{\{\mathbf{U}\}} \frac{Tr(\mathbf{U}^T\hat{\mathbf{A}}^T\mathbf{D}^T\mathbf{D}\hat{\mathbf{A}}\mathbf{U})}{Tr(\mathbf{U}^T\mathbf{X}^T\mathbf{X}\mathbf{U})}$$

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Results: Comparison with xDAWN using Single Trials

Pre-processing	μ	σ	**min**	**max**
Filter [1-20] Hz	52.50	13.49	30.48	76.41
xDAWN	51.03	15.80	24.44	80.00
METS & SEWS-1	**56.00**	**13.64**	**35.56**	**80**
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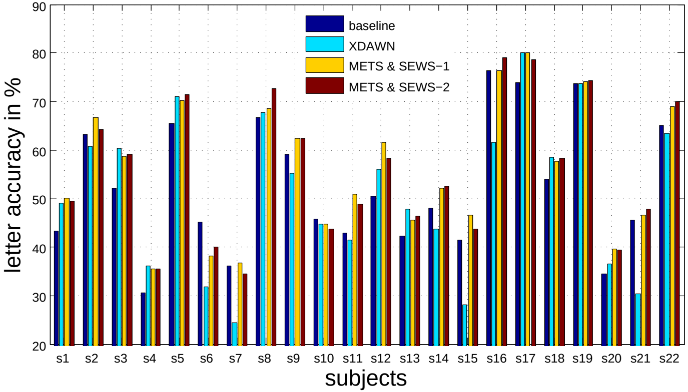
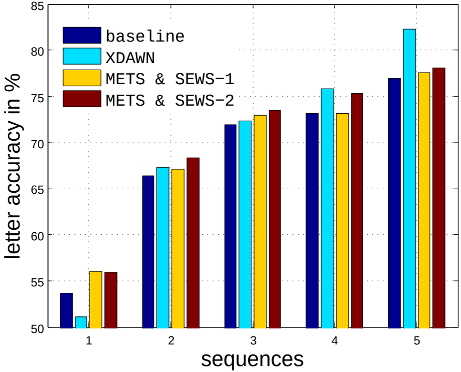


- Better performances in 16 out of 22 subjects
- Similar results when the subjects have a high accuracy rate
- For subjects with low performances our methods are consistenly better
- Our algorithms always improve the baseline

Results: Comparison with xDAWN using Sequences



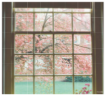
- Easier to enhance the ERP if the SNR is increased
- Average naturally removes uncorrelated components
- Useless features have less impact if the classification is easier

Data Base EPFL

- 8 subjects (4 able-bodied subjects and 4 disabled subjects)
- 32 channels recorded at 2048 Hz using a Biosemi Active Two system.
- Right ear reference and a right mastoid ground.
- Inter-stimulus interval of 400 ms








http://mmspg.epfl.ch/BCI_datasets

Results: Image Accuracy in Single Trials

We used the database blindly

- Same mother wavelet
- Same scales analyzed with CWT
- Same DWT level of decomposition
- Same thresholds for METS and SEWS

- **s1** to **s4** are disabled subjects
- **s5** to **s8** are able-bodied subjects

Subject	Baseline	METS	METS & SEWS-1	METS & SEWS-2
s1	44.53	40.88	42.34	**45.26**
s2	41.41	49.22	49.22	**50.00**
s3	58.33	62.88	**64.39**	**64.39**
s4	49.21	48.41	**52.38**	50.00
s5	44.62	46.15	**46.92**	43.08
s6	48.18	54.01	**60.58**	55.47
s7	**72.93**	65.41	70.68	**72.93**
s8	45.31	53.12	55.47	**62.50**

Plan

Concluding Remarks

Main contributions

- Improved the time-frequency analysis measuring channel's similarity
  - METS: a novel denoising technique for EEG
- Evoked potential localization in time through time-frequency analysis
  - SEWS-1: independently for each channel
  - SEWS-2: jointly for all channels

- Studied the impact of some of the most known techniques used for ERP
  - SWLDA vs LSVM
  - Wavelet mother selection
  - Band-pass filter selection
- Comparison with techniques based on wavelet and spatial filters
- Validated using synthetic data
- Validated using two different real databases
- Our techniques can be applied to other domains with similar conditions

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- Analyze quantitatively deeper METS
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Méthodes d'analyse et de débruitage multicanaux à partir d'ondelettes pour améliorer la détection de potentiels évoqués sans moyennage

application aux interfaces cerveau-ordinateur

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Anne Boyer	Professeur, Université de Lorraine
Bernard Girau	Professeur, Université de Lorraine
Laurent Bougrain	Maître de Conférences, Université de Lorraine

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Soft vs Hard Thresholding