Pattern recognition in peripheral and central signaling

Guillaume Chanel[1], Julien Kronegg[1], Didier Grandjean[2], Iulian Alecu[1], Thierry Pun[1]

[1]Multimodal Interaction Group, Computer Vision and Multimedia Laboratory
Univ. of Geneva (http://vision.unige.ch/MMI)

[2]Swiss Center for Affective Sciences, Univ. of Geneva (http://affect.unige.ch)

([1]Support from EU project Similar)

([2]Support from EU project Humaine)

4. Conclusions (1)

Pattern recognition in peripheral and central signaling:

- signal preprocessing and features extraction to simplify analysis;
- usually boils down to a classification problem;
- large variety of techniques, depending on the problem, few being clearly superior and few having reached wide consensual acceptance ...

Outline

1.1 Pattern recognition - Overview

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The goal is to analyze and classify physiological signals to, e.g.:

- recognize affective states;
- recognize mental tasks.

Central signals: EEG – electroencephalograms.

Peripheral signals:

- ECG – electrocardiogram;
- cardiac rythm (plethysmograph to measure blood pressure);
- EMG – electromyogram;
- GSR – galvanic skin resistance, or skin conductance;
- skin temperature;
- breathing rythm, or chest cavity expansion.

1.1 Pattern recognition - Overview

General characteristics of these physiological signals:

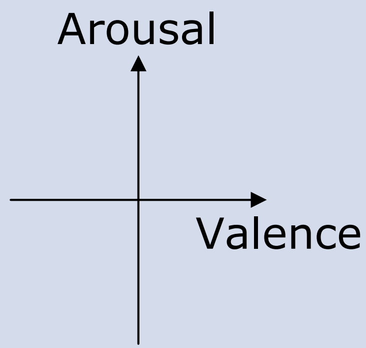
- 1D, stochastic;
- non-stationary (assumed stationary during short time intervals);
- prior information available;
- noisy;
- vary btw. trials, btw. subjects, often only one instance available.

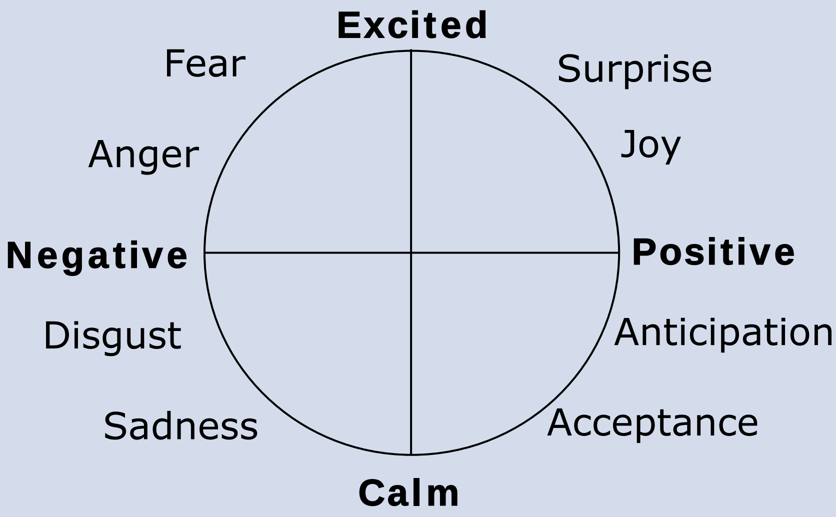
Steps to perform **pattern recognition and classification**:

- determination of the target representative space;
- preprocessing of the signals;
- features selection and extraction;
- classification, learning;
- evaluation.

Determination of the target representative space, e.g.:

- continuous space: [valence, arousal], for emotion recognition:





- discrete space (classification problem): 1 of N mental tasks, for BCI.

1.1 Pattern recognition - Overview

3 fundamental dimensions to analyze signals:

- time: variation of signal amplitude along time;
- space: >1 signals, at various locations, e.g. EEG;
- frequency.

Preprocessing of the signals, such as:

- time: baseline subtraction, per signal or over all signals;
- space: local surface Laplacian to estimate surface cortical activity;
- frequency: power line removal, denoising;
- frequency: frequency bands selection.

1.1 Pattern recognition - Overview

Features selection and extraction (trial and error, using prior info):

- time, e.g.: template matching, AR (auto-regressive) models, spike/peaks detection;
- frequency: FT (Fourier transform);
- space, e.g.: PCA/ICA (principal/independent components analysis).

Combination of {time, frequency, space}:

- time-space, e.g.:
  - > amplitudes, ratios and differences, coherence and synchronization;
  - > inverse models, from EEG to source dipoles;
- time-frequency, e.g.: STFT (short-time FT), WT (wavelet transform);
- time-frequency-space, e.g.: STFT over multiple electrodes.

Issue: how to reduce number of features and select best ones.

1.1 Pattern recognition - Overview

Classification, learning:

- non-parametric, e.g.: k-Nearest neighbor;
- linear discriminant functions, e.g.: Fischer LD, SVM (support vector machines);
- multilayer neural networks;
- stochastic methods, e.g. genetic algorithms;
- non-metric methods, e.g. CART (classification and regression trees).

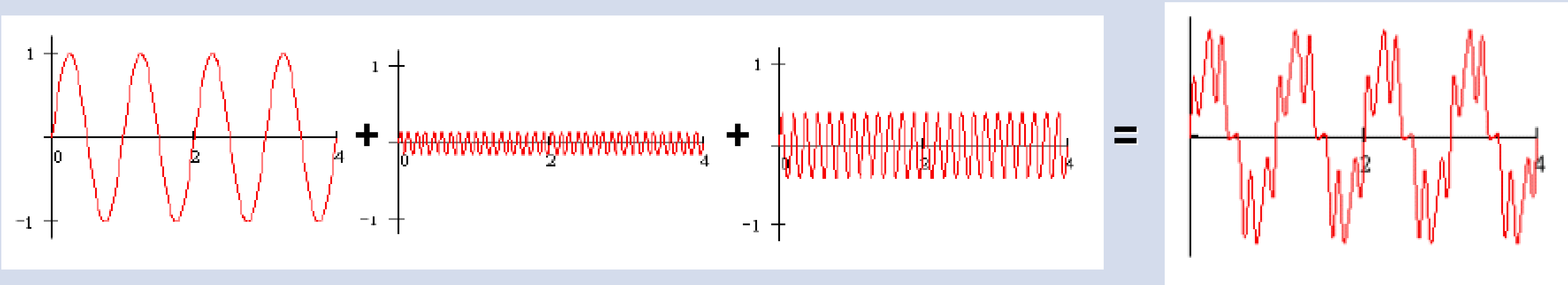
Generic approaches, e.g. resampling, boosting.

Evaluation:

- ground truth ("Gold standard");
- learning set vs. test set, cross-validation;
- bias and variance determination.

Time, frequency, and time-frequency.

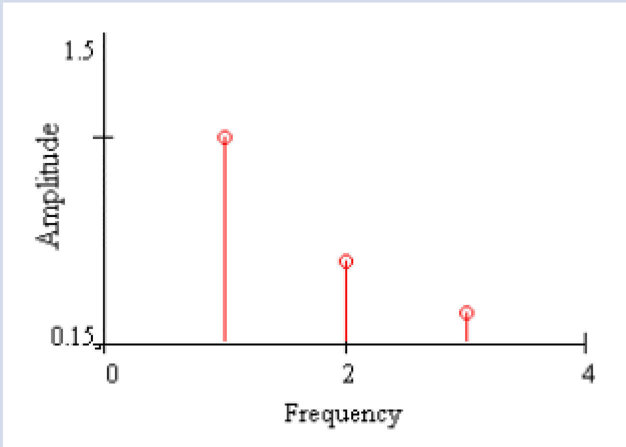
1D signal obtained by summing 3 sine waves[1]:



Fourier transform (FT), frequency spectrum:

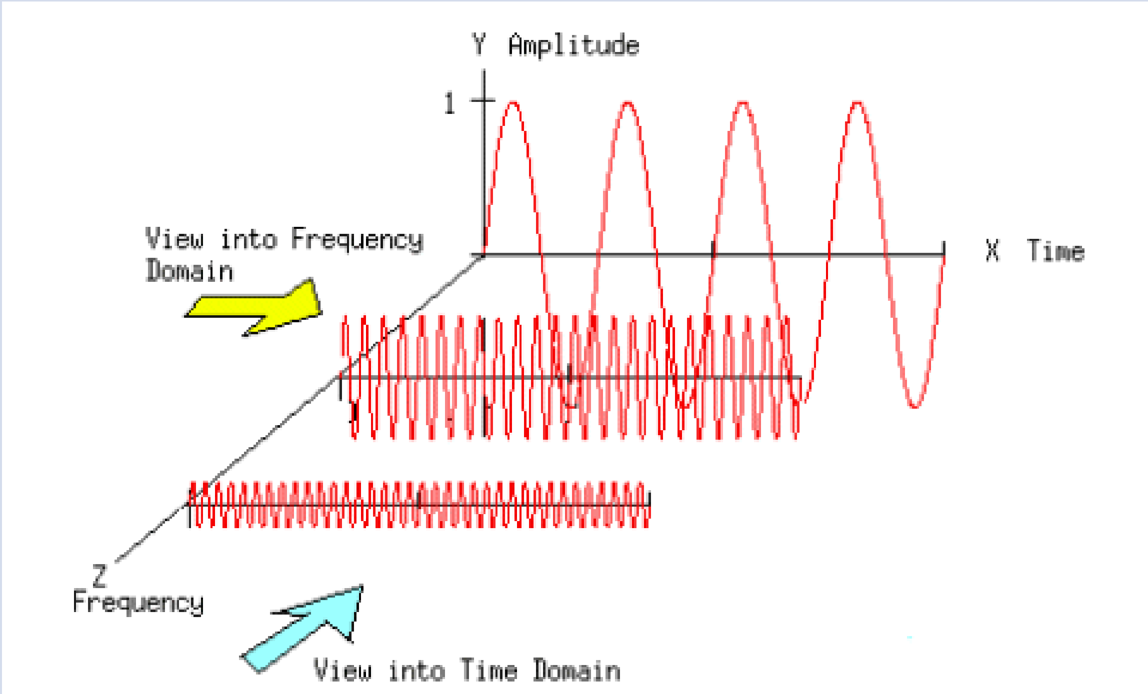
f=0: continuous component = average value (here 0)

f=0$\rightarrow$4: low to high frequency



[1]Figures from www.complextoreal.com

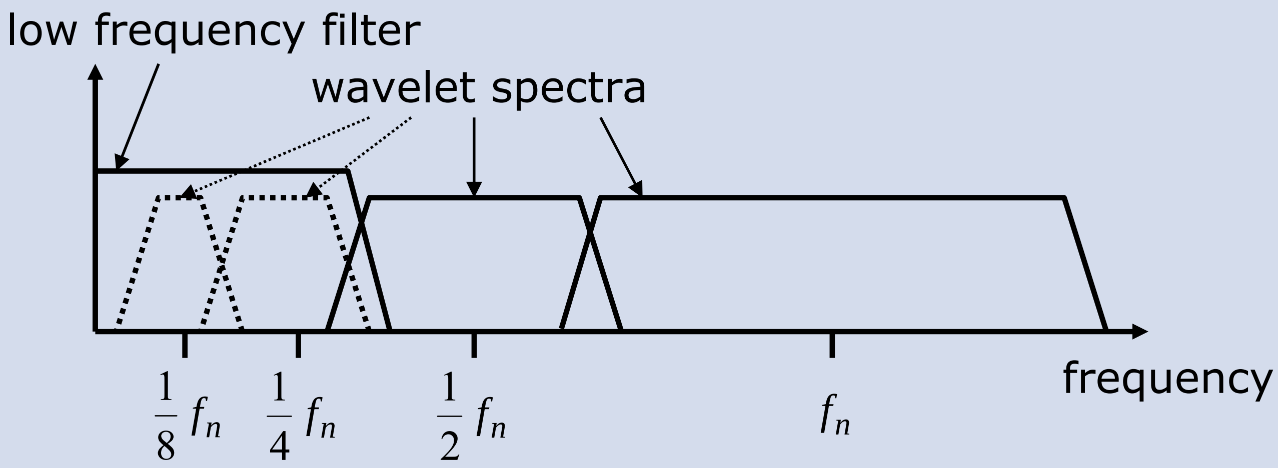
Time-frequency representation:



The Short-time FT (STFT) does FT by time slices, which might overlap.

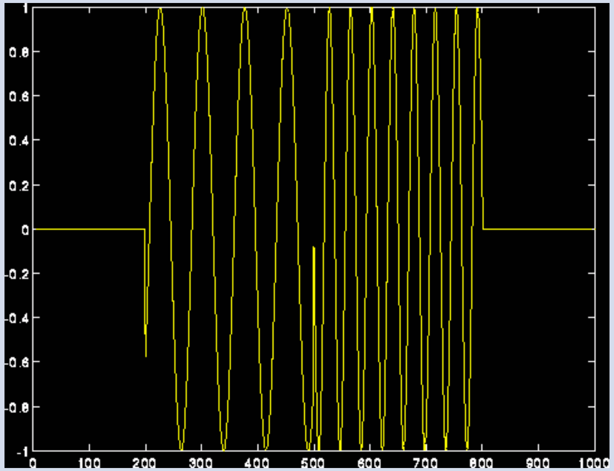
Continuous wavelet transform (CWT):

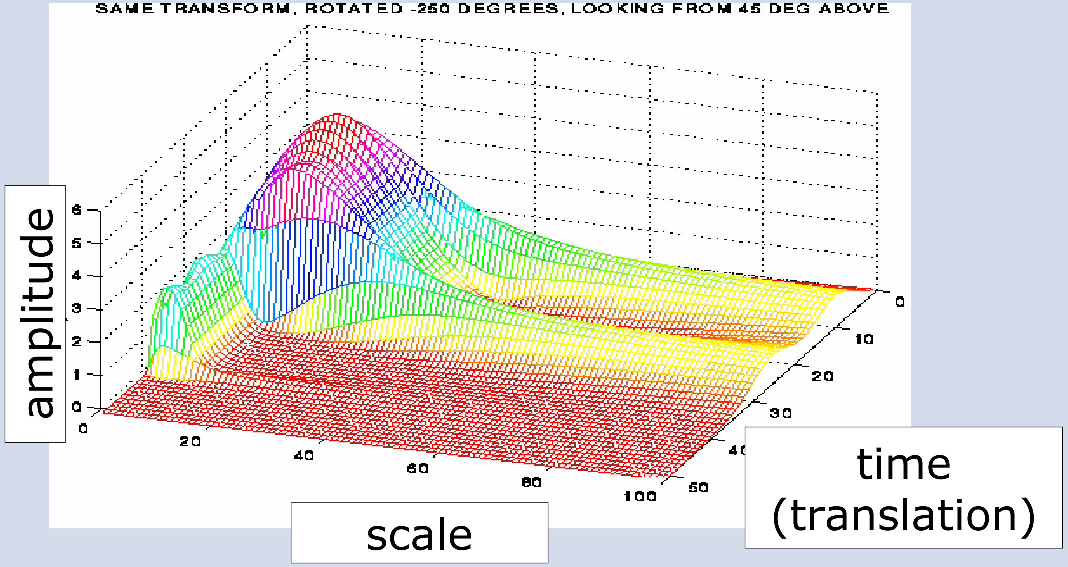
- at various times...
- ... filter signal with a series of bandpass filters, i.e. of varying scales.



Continuous wavelet transform (CWT) (cont.).

1D signal → **2D** time-frequency representation:





Difference w.r. STFT: varying time and frequency scales.

Discrete wavelet transform (DWT).

1D signal $\rightarrow$ **1D** time-frequency representation:

- rather than varying the wavelet scale, 2 filters are used:
  - > high-pass h(k),
  - > low-pass l(k);
- after each filtering stage (recursively):
  - > 2 filtered signals with frequency bands = low and high halves of the original frequency band;
  - > décimation: 1 sample over 2 is kept;
  - > repeat with the new signals;
- the filtered signals are appended: the DWT has the same size as the original.

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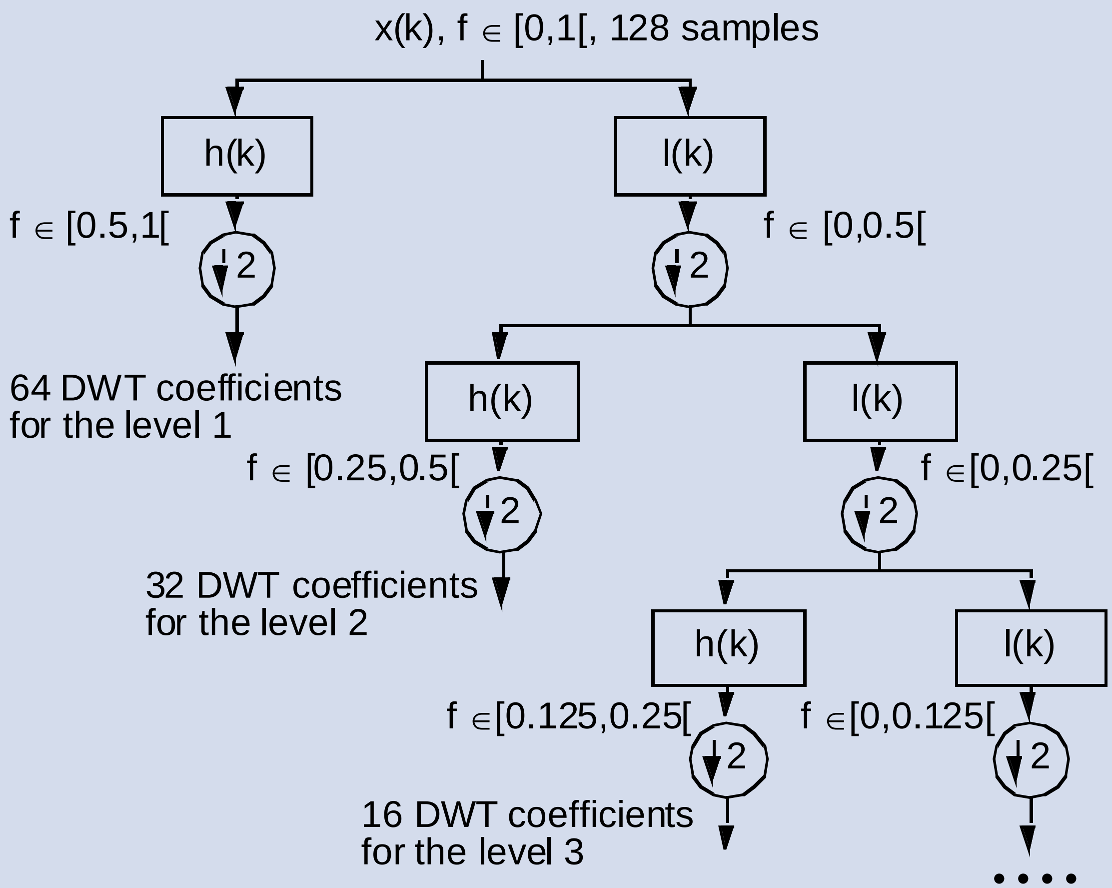
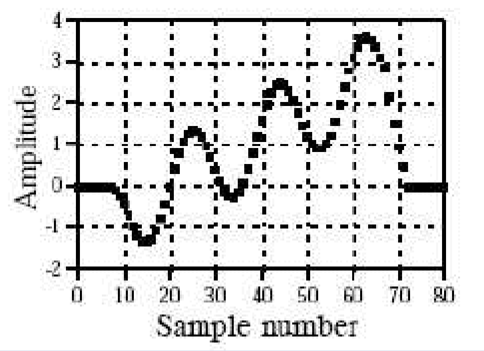
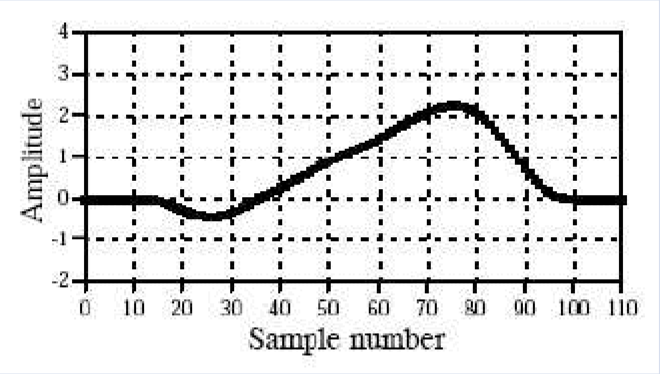
Discrete wavelet transform (DWT) (cont.).



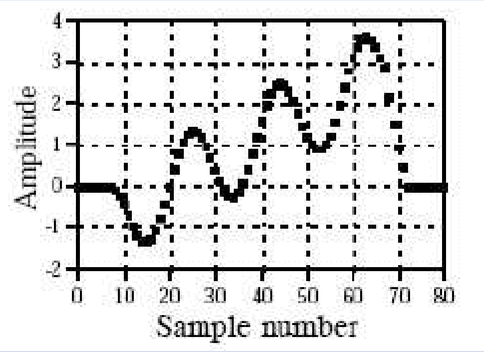
Preprocessing by **filtering**:

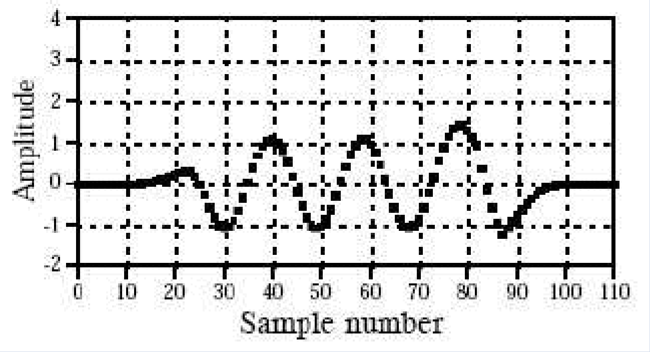
- low-pass filter, such as moving average:

input 

output 

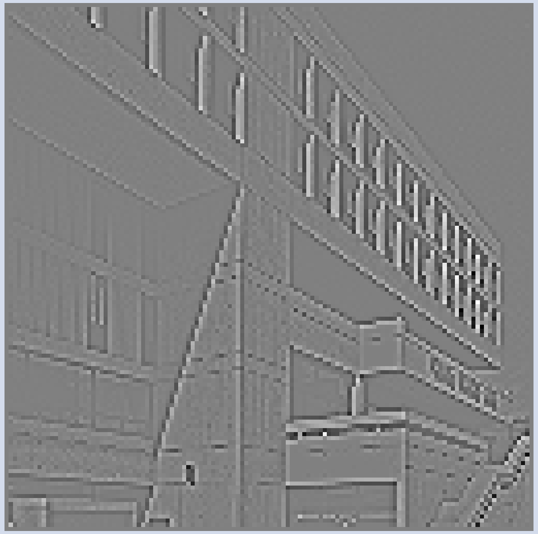
- high-pass filter, such as 1st derivative or 2nd derivative (Laplacian):

input 

output 

Preprocessing by **filtering**:

original | low-pass | 2nd derivative-Laplacian



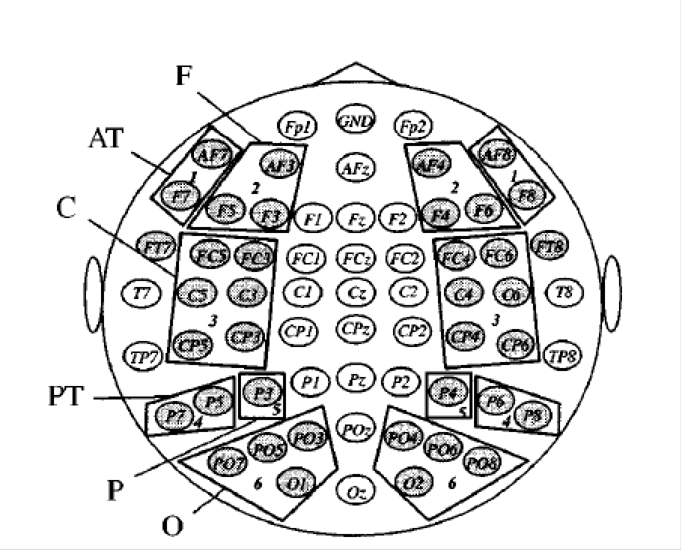
1.2 PR - Preprocessing, features extraction

Preprocessing and features extraction examples:

- EEG;
- plethysmograph (blood pressure);
- GSR;
- respiration.

EEG: selection of electrodes and frequency bands.

space

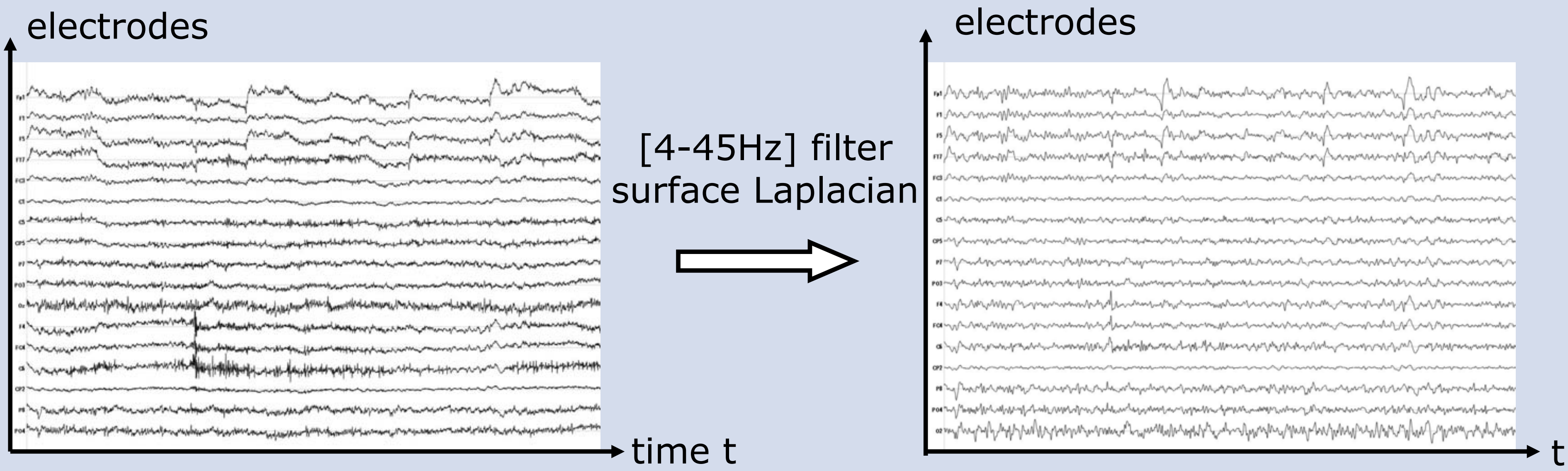


frequency

Location	Frequency band
[PT;P;O]	θ_1 (4-6Hz)
	θ_2 (6-8Hz)
	γ (30-45Hz)
[AT;F]	α_2 (10-12Hz)
[AT;F;C]	β_1 (12-18Hz)
[C;PT;P;O]	β_3 (22-30Hz)

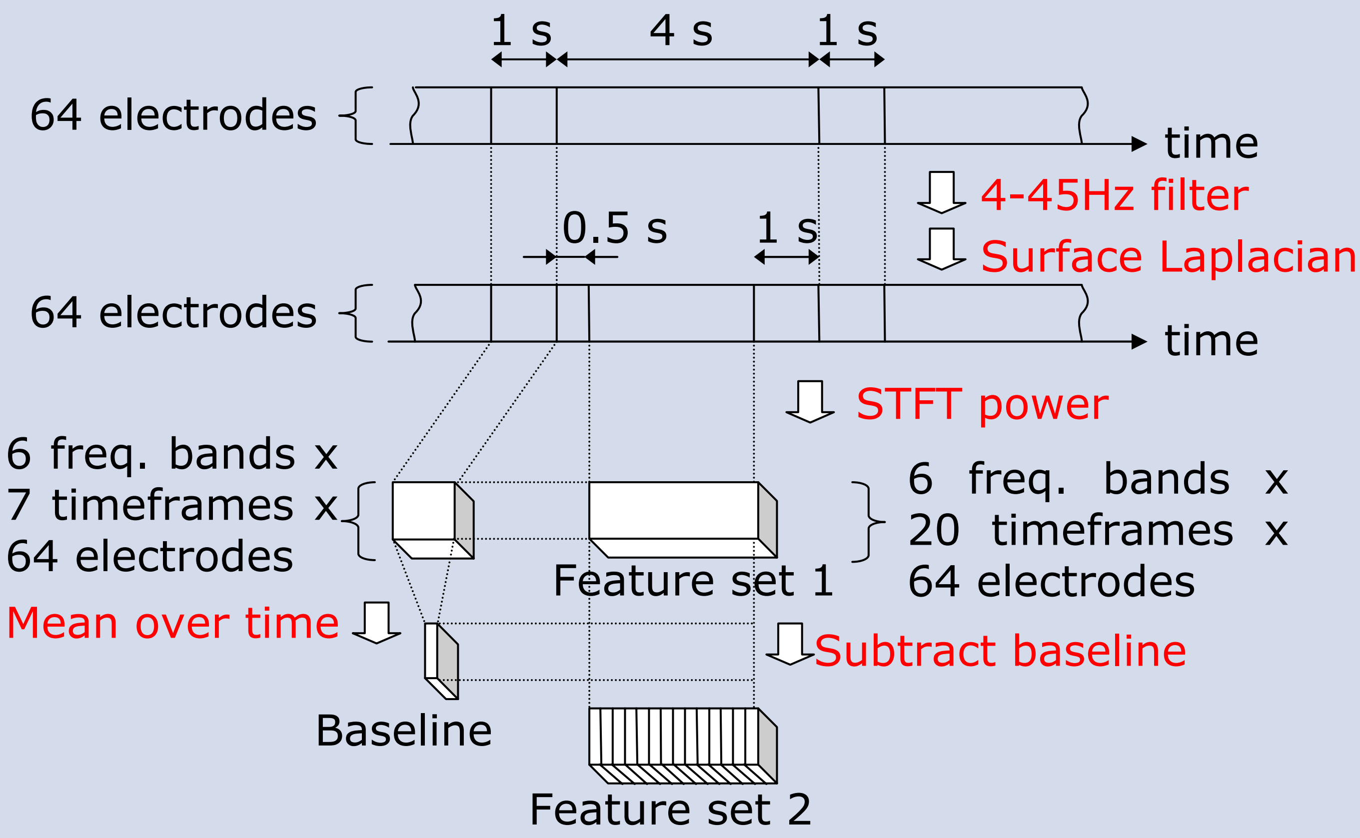
1.2 PR - Preprocessing, features extraction

EEG: frequency bands selection by bandpass filtering, and surface Laplacian computation (between neighboring electrodes).



sampling frequency Fs = 1024 Hz
64 electrodes, 8 seconds

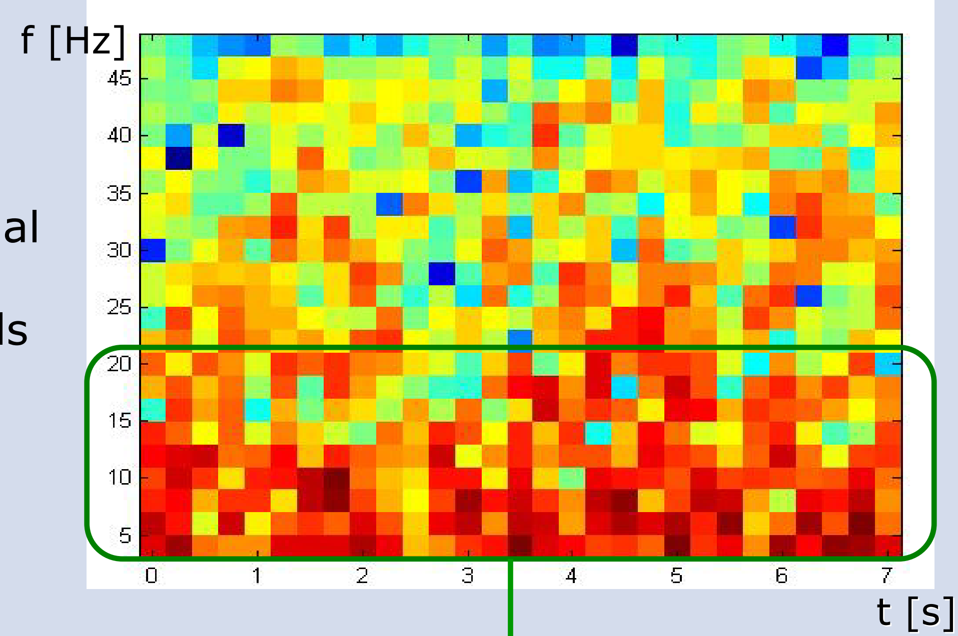
EEG: baseline substraction over all signals (here BCI protocol).



EEG: features extraction.

STFT preferred over DWT/CWT (for its redundancy); stationarity assumed over 500ms periods.

STFT for each signal
(64 electrodes)
Window = 512 spls
Half overlap



29 time frames
257 frequency bands
(0Hz - 512Hz)
$\Delta f = 2Hz$

Selection of
9 frequency band:
4Hz – 20Hz

total of
29 * 9 * 64 = 16’704 features

Plethysmograph: to compute heart rythm in BPM (beats per mn).

Correlates with stress and pleasure.

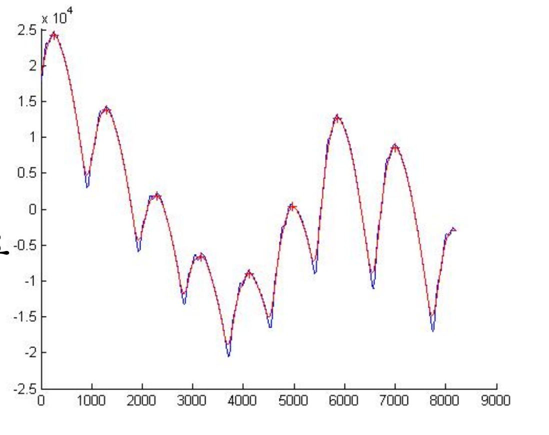
Steps:

- moving average (128 spls);
- identification of maxima by derivation.

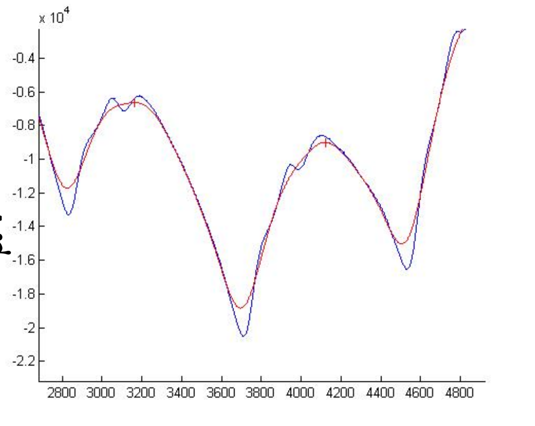
original signal and moving average

heart rythm

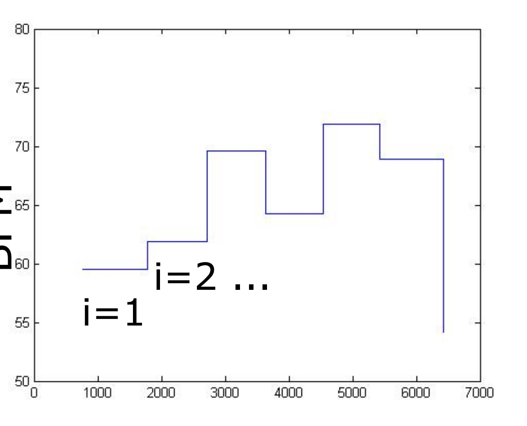
μV



μV



BPM



samples

samples

samples and periods i

1.2 PR - Preprocessing, features extraction

Plethysmograph (cont.).

Features:

- average signal value over time samples k, for the entire pleth. signal:

$$x_{Plet}^{1} = \overline{Plet[k]}$$

- average heart rate over periods i:

$$x_{Plet}^{2} = \overline{BPM[i]}$$

- heart rate variability, and trend from derivative:

$$x_{Plet}^{3} = std(BPM[i]) \qquad x_{Plet}^{4} = \overline{BPM'[i]}$$

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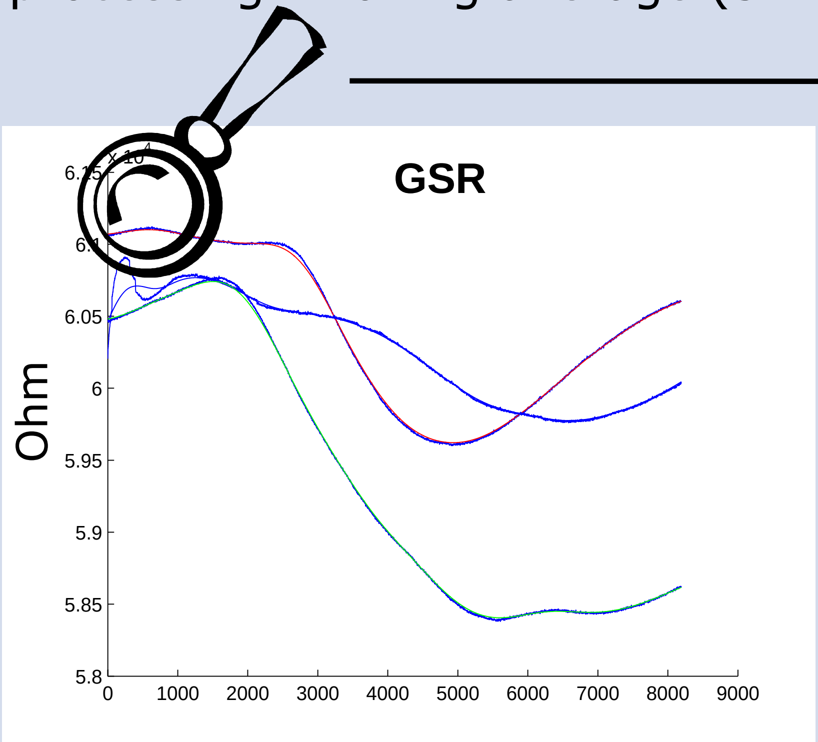
GSR (galvanic skin resistance).

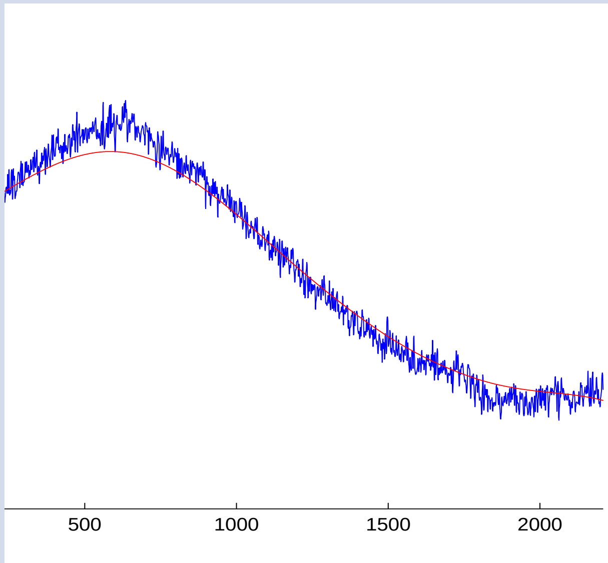
Mean value linearly correlates with arousal ratings.

Characterized by: latency, amplitude, decay time, half recovery time.

Preprocessing: moving average (512 samples).



Samples



samples

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GSR (cont.).

Features:

- average signal value over samples k:

$$x_{GSR}^{1} = \overline{GSR[k]}$$

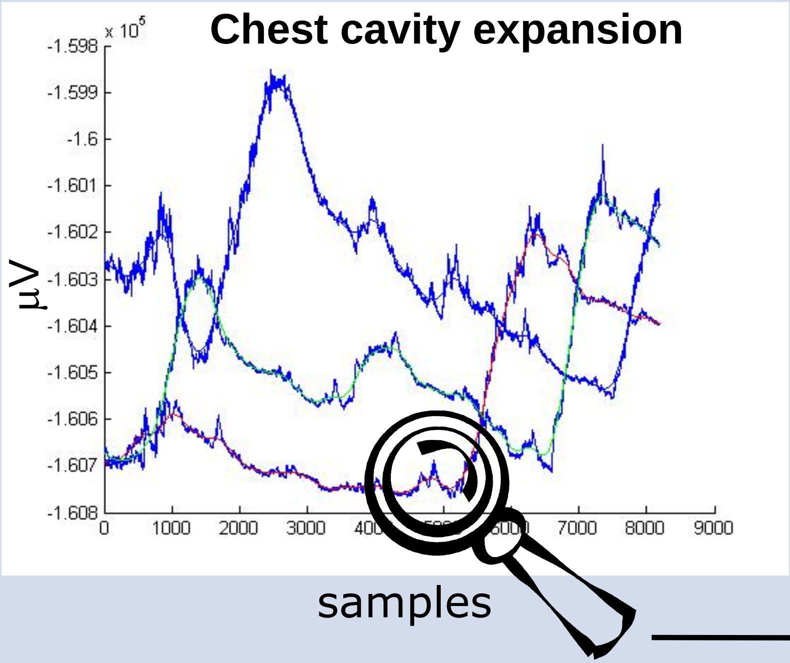
- from derivative, computation of values linked to decay time and amplitude:
  - > average GSR variation: $x_{GSR}^{2} = \overline{GSR'[k]}$
  - > average decrease rate during decay time: $x_{GSR}^{3} = \overline{GSR'[k]} \quad \forall k \mid GSR'[k] < 0$
  - > ... or during trial duration:

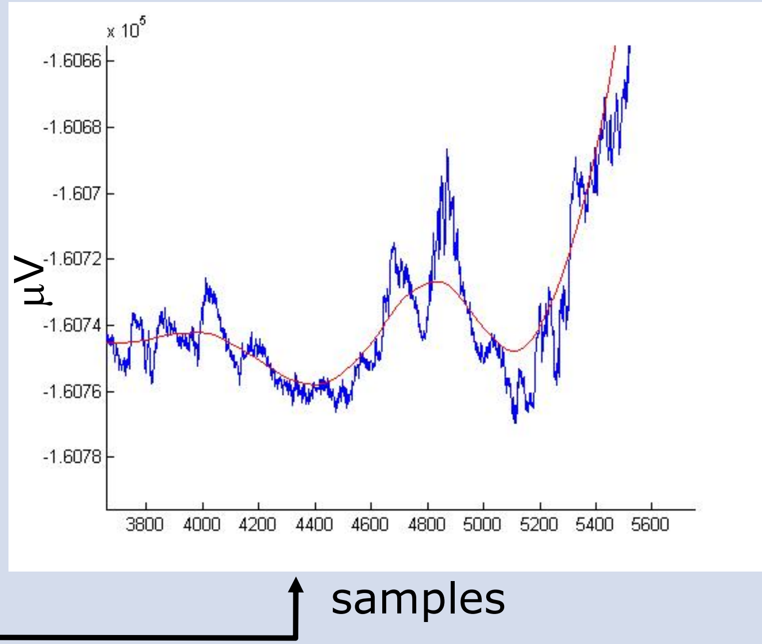
$$x_{GSR}^{4} = \frac{\sum_{k \mid GSR'(k) < 0} GSR'[k]}{N}$$

Breathing rythm or chest cavity expansion.

Correlates with emotions such as fear, anger, sadness, happiness.

Preprocessing: $Resp$ = moving average (256 samples)





Breathing rythm or chest cavity expansion (cont.).

Computation of the FT on the *Resp* signal:

- 10 frequency bands [0.25Hz – 2.5Hz]
- Δf = 0.25Hz

Features:

- first 10 features are the power of the *ith* frequency band:

$$x_{Resp}^{i} = P_{Resp}^{i.\Delta f} \quad \forall i \in [1;10]$$

- average signal value over samples k:

$$x_{Resp}^{11} = \overline{Resp[k]}$$

- variation of respiration signal:

$$x_{Resp}^{13} = std(Resp[k]) \qquad x_{Resp}^{14} = \overline{Resp'[k]}$$

- dynamic range:

$$x_{Resp}^{12} = Max(Resp[k]) - Min(Resp[k])$$

Classification, general principle.

Each observation is characterized by a number of features, e.g.:

- 1 observation: 4s recording of EEG + GSR + *Resp* + ...
- features: 16’704 STFT features + 4 GSR features + 4 *Resp* features + ...

The features define the feature space, usually of high dimension.

In the feature space, the goal is to determine classes, e.g.:

- 2 classes: "negative valence" or "positive valence", for emotion;
- N classes: 1 of N mental tasks, for BCI.

Example with 3 classifiers:

- Bayes classifier;
- Fischer linear discriminant;
- Support Vector Machines - SVM.

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Naïve Bayes classifier:

- ω_i : class *i*, $i \in [1;N]$;
- *x* : *vector of features;*
- $P(\omega_i)$: *a-priori* probability of class ω_i ;
- $P(x/\omega_i)$: probability of observing *x* assuming class ω_i ;
- $P(\omega_i/x)$: probability of having class ω_i having observed *x*.

Bayes rule (here *N* = 2 classes):

$$P(\omega_i \mid \mathbf{x}) = \frac{P(\mathbf{x} \mid \omega_i) P(\omega_i)}{\sum_{j=1}^{2} P(\mathbf{x} \mid \omega_j) P(\omega_j)}$$

Decide ω_i where $P(\omega_i \mid \mathbf{x})$ is maximum

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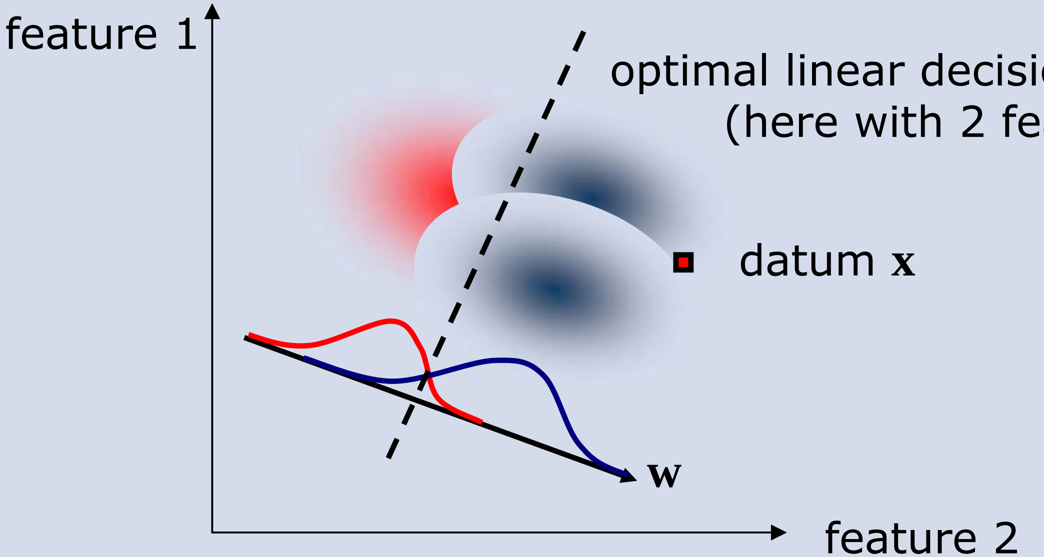
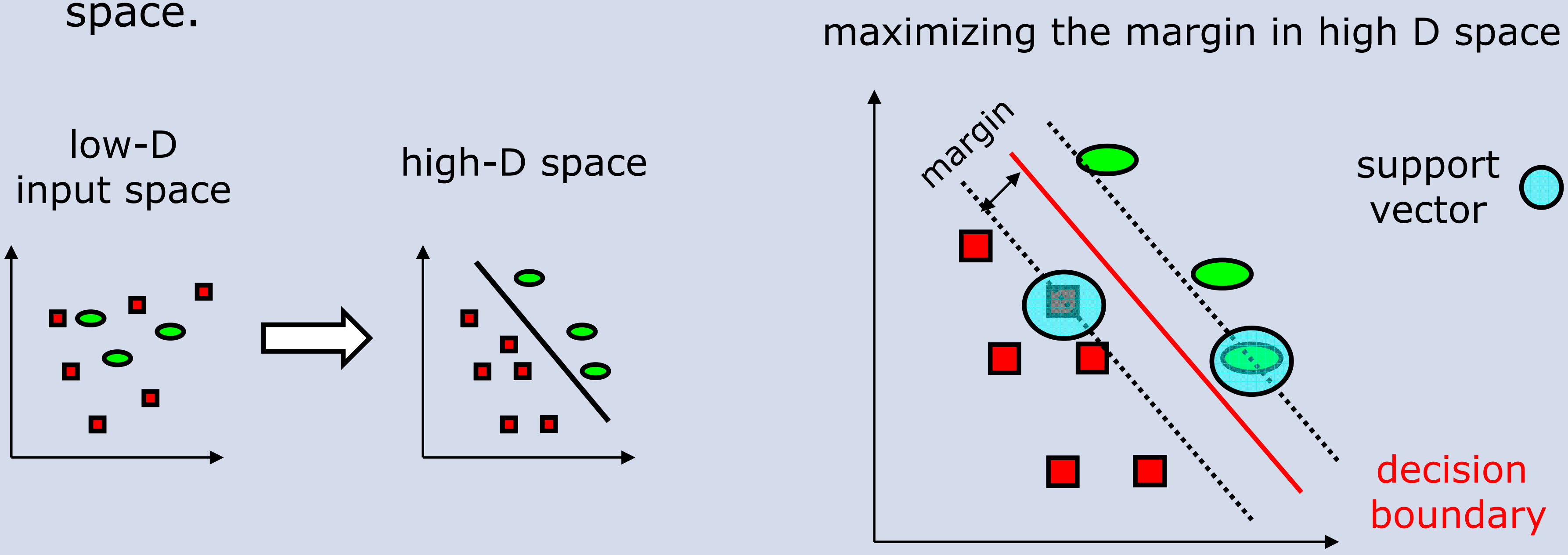
Fisher linear discriminant analysis:

- project data $\mathbf{x}$ on a vector $\mathbf{w}$ in the feature space to obtain more separable classes, to maximize: $J(\mathbf{w}) = \frac{|m_1 - m_2|^2}{s_1 + s_2}$
- after projection, find linear decision boundary:



Support vector machines (SVM), binary classifier:

- map training data non-linearly into a higher-dimensional feature space;
- in high-D space, construct a separating hyperplane with maximum margin;
- this linear hyperplane corresponds to a non-linear decision surface in input space.



(Recently: **Relevance Vector Machines.**)

Outline

2. Emotions assessment

Goal: assess user emotional status from multiple physiological signals.

Why ?

Human Computer Interface applications: adapt to user mood.

Emotions are incitation to action:

⇨ anticipation of actions;

⇨ add emotional content to actions.

Application examples: *lifeblog*, games, monitoring, etc.

Physiological signals cannot be easily faked.

Equipment: 64 EEG electrodes, peripheral sensors, all from Biosemi.

2.1 Emotions - Protocols & signal acquisition

Protocol 1, “IAPS”

Stimuli: images from the IAPS (International Affective Picture System).

Images selection:

- 100 images of low and high arousal (50% each);
- 100 images of positive and negative valence (50% each).

Protocol:

- presentation of images:

- Self-assessment of own emotional state: simplified version of SAM (Self-Assessment Manikin), 2 x 5 values.

2.1 Emotions - Protocols & signal acquisition

From protocol 1, two experiment were conducted:

- **Experiment "IAPS/IAPS"**

Images are labeled according to IAPS judgments:

> calm vs. excited states;

> positive vs. negative states.

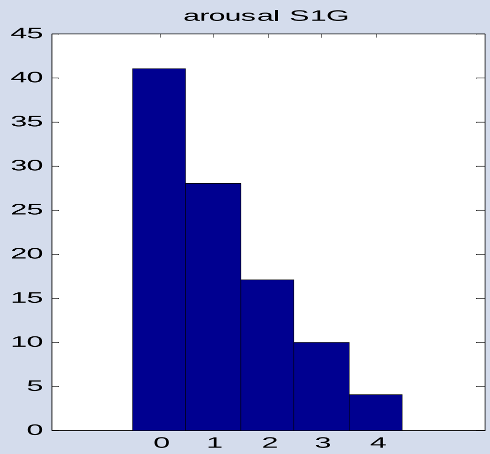
- **Experiment "IAPS/self"**

Images are labeled according to self-assessments.

Division in 2 or 3 arousal classes:

> 2 classes: division in 2 sets at the median of self-evaluations;

> 3 classes: division in 3 sets (calm, neutral, excited).



2.1 Emotions - Protocols & signal acquisition

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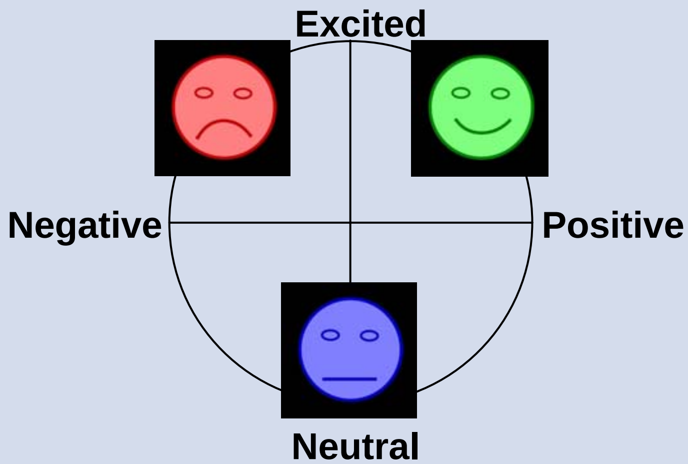
Protocol 2, "Recall"

Stimuli: imagination or recall of emotional events.

Participant imagines or recalls emotional events among 3 possibilities:

- exciting positive: joy, hope, pride etc.;
- exciting negative: disgust, anger, pain, hate, fear, etc.;
- calm neutral: participant asked to stay calm and relax.

Protocol:



Trials are directly labeled into the 3 classes above.

2.2 Emotions - Classification

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Contents of databases

Preprocessing as previously described.

Experiment “IAPS/IAPS”

- 6 features for EEG, 18 for peripheral activity
- 50 trials per class (calm vs. excited, positive vs. negative)

Experiment “IAPS/self”

- 6 features for EEG, 18 for peripheral activity
- 100 trials divided in 2 or 3 class according to self-assessment
  - ⇨ problem of unbalanced classes (less exciting instances than calm)

Experiment “Recall”

- 16’704 features for EEG, 22 for peripheral activity
- 100 trials per class (calm neutral, exciting negative, exciting positive)
  - ⇨ problem of large number of features, curse of high dimensionality

2.2 Emotions - Classification

Problem of **unbalanced classes**

Classifiers tends to answer majority class.

Bayes : force a-priori probability to 1/*N* (*N*: number of classes).

$$P(\omega_i \mid \mathbf{x}) = \frac{P(\mathbf{x} \mid \omega_i)P(\omega_i)}{\sum_{j=1}^{N} P(\mathbf{x} \mid \omega_j)P(\omega_j)}$$

$$P(\omega_i) = \frac{1}{N}$$

Decide ω_i where $P(\omega_i \mid \mathbf{x})$ is maximum

Problem of **high dimensional feature space**

Concept of distance is not meaningful.

Increase in computation time, problems of singularity…

⇨ Feature selection from prior knowledge.

⇨ Automatic feature selection:

- filter methods (statistical, discrimination based…);
- wrapper methods (forward, backward, stepwise, heuristical…).

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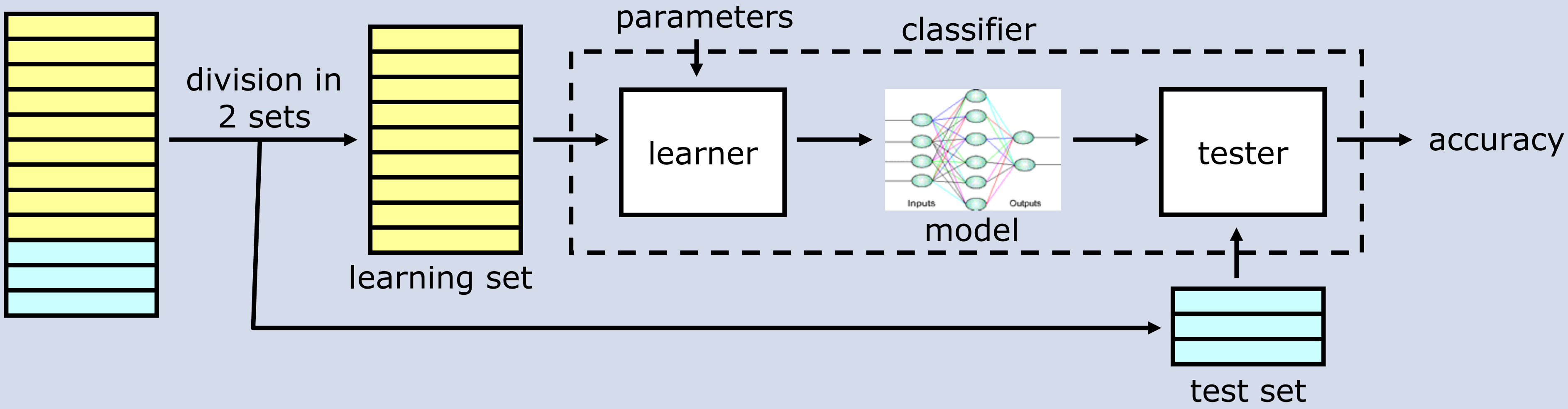
Cross-validation : how to evaluate the generalization of a classifier?



Several strategies:

- k-fold or leave-v-out:
  - > Computation of mean accuracy and standard deviation;
- leave-one-out:
  - > computation of mean accuracy;
  - > maximal size of the learning set.

2.2 Emotions - Classification

Three **classifiers** were used:

- naïve Bayes;
- linear discriminant;
- linear SVM.

Fusion of modalities

2 modalities: peripheral signals and EEG signals.

Fusion can be done:

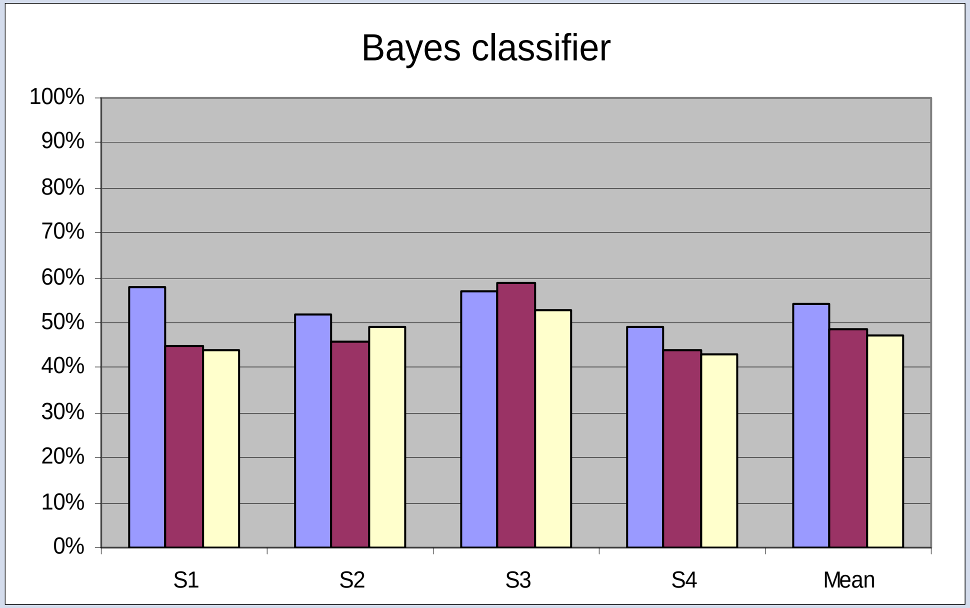
- at the features level, concatenation of the features vectors;

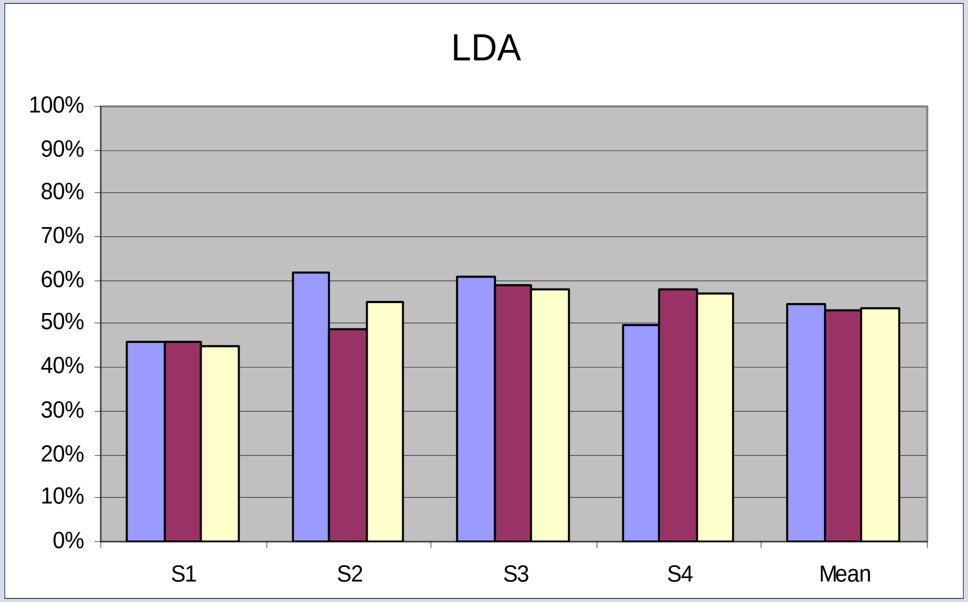
$$X_{Fusion} = [X_{EEG} \; X_{peripheral}]$$

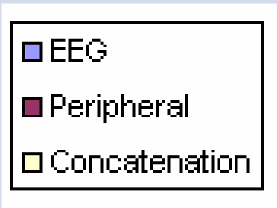
- at the decision level

  majority voting, level of confidence (ie: Bayes probability, SVM or LDA distance to the hyperplane)…

Protocol 1, experiment "IAPS/IAPS": 2 classes (calm vs. excited).







EEG signals better than peripheral

Fusion does not improve results

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Protocol 1, experiment "IAPS/Self": 2 classes (calm vs. excited).

Self assessment is important

Fusion poorly improves results

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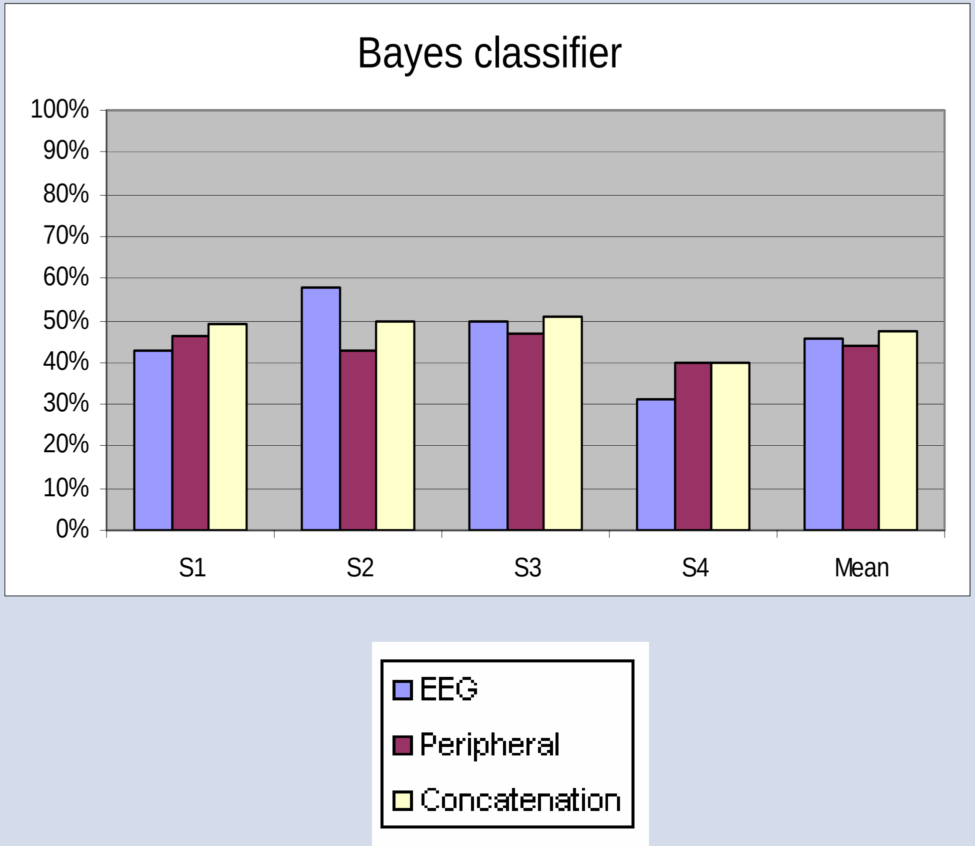
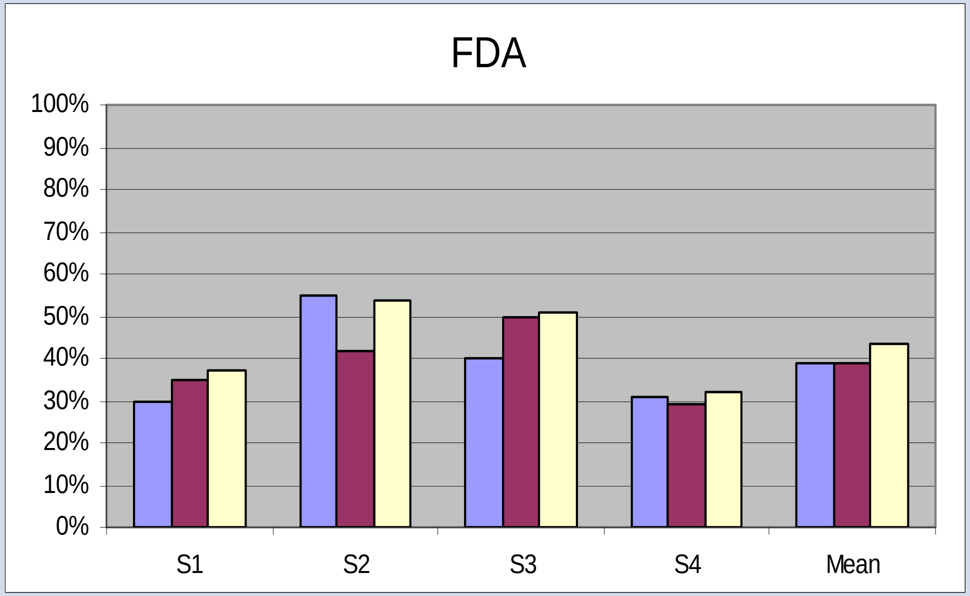
Protocol 1, experiment "IAPS/Self": 3 classes (calm, neutral, excited).

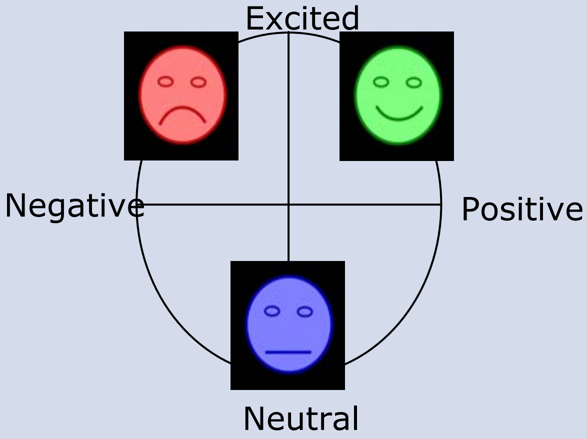


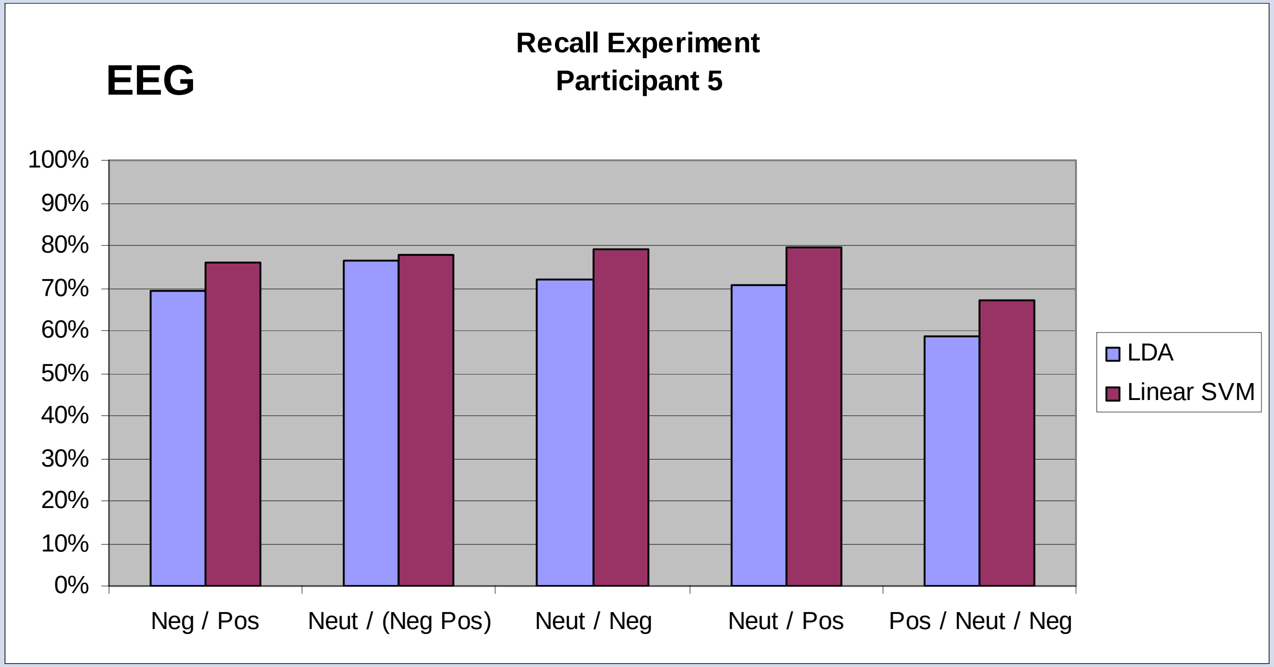


Fusion does improve results

3. Recall experiment – Results

Protocol 2 “Recall”, EEG signals:





	Neg / Pos	Neut / (Neg Pos)	Neut / Neg	Neut / Pos	Pos / Neut / Neg
LDA	70%	77%	72%	71%	59%
Linear SVM	76%	78%	79%	80%	67%

3. Recall experiment – Results

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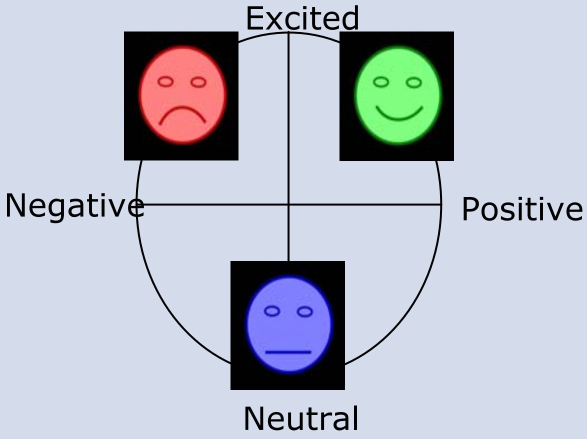
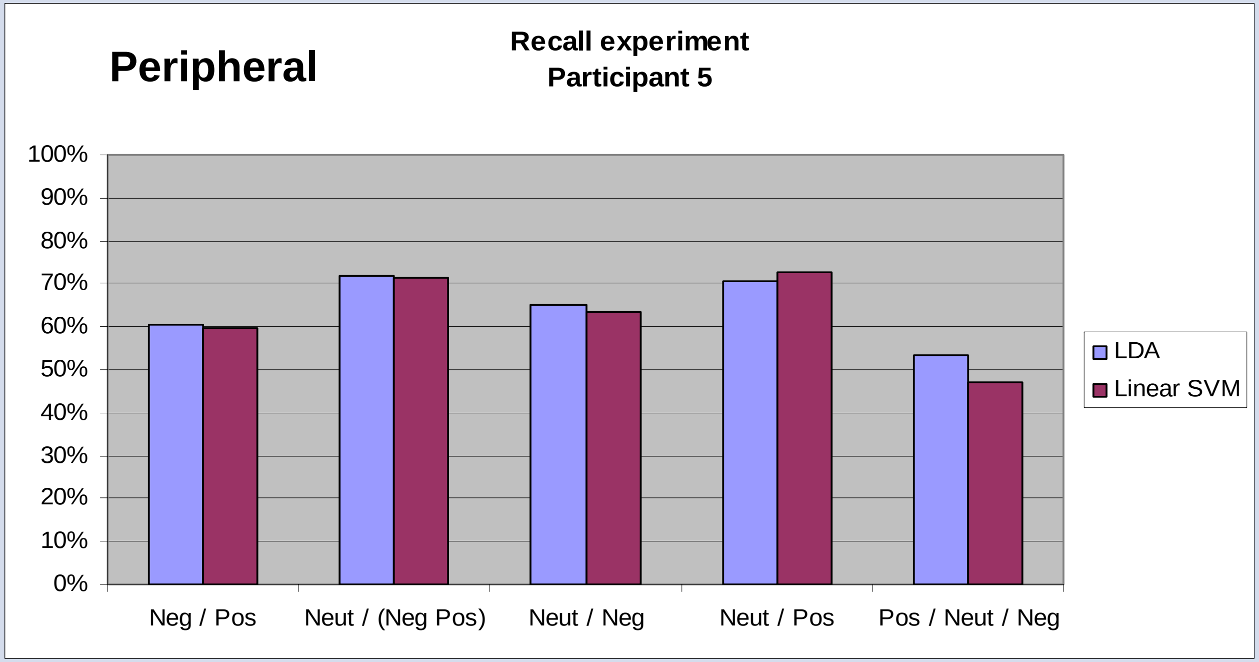
Protocol 2 "Recall", peripheral signals:





	Neg / Pos	Neut / (Neg Pos)	Neut / Neg	Neut / Pos	Pos / Neut / Neg
LDA	61%	72%	65%	71%	53%
Linear SVM	60%	71%	64%	73%	47%

2.4 Emotions – Conclusions & ongoing work

IAPS Experiment:

- self-assessment of emotion better than IAPS' provided evaluations;
- EEG modality can be used for arousal detection;
- modality fusion can improve results (esp. for the 3 classes problem).

Recall experiment: EEG modality can assess valence and arousal.

Ongoing and future work:

- improve feature selection;
- recall experiment: more participants, classification across users;
- other classifiers;
- fusion of modalities (decision level).

Outline

3. Other examples

Brain-computer interaction (BCI) (J. Kronegg):

- communication between human and machine using EEG's;
- application examples: disabled, tele-robotics, gaming;
- our work:
  - > optimization of information transfer rate;
  - > state-of-the-art, full system implementation.

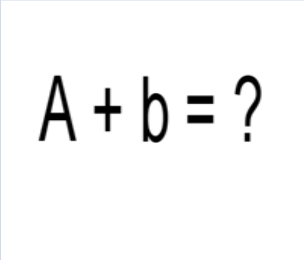
Brain sources reconstruction (I. Alecu):

- localization of active brain areas from surface EEG's;
- possible application for emotion assessment: locate active areas.

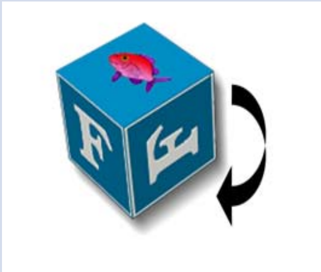
Cognitive impairment detection (J. Kronegg, with P. Missonier and P. Giannakopoulos from the Neuroimaging Unit, Dept. of Psychiatry, Univ. Hospitals of Geneva).

3.1 Other examples - BCI

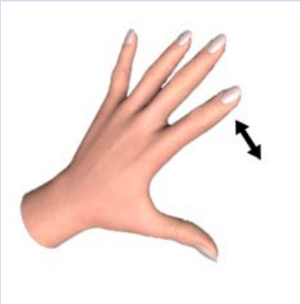
Alphabet of thoughts (one mental state = one command):



mental computation



imagination of a rotating object

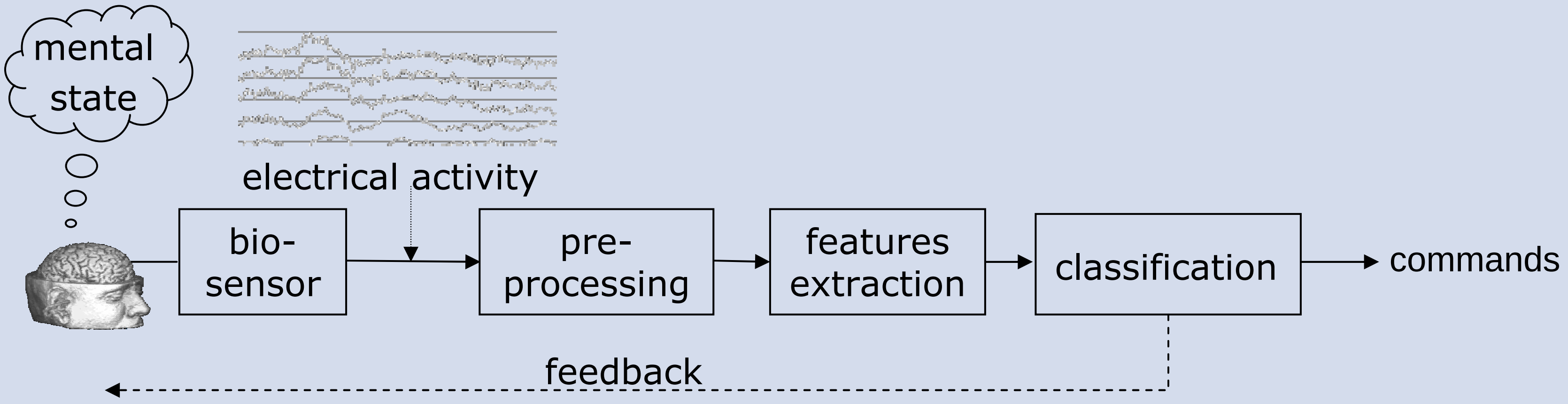


imaginary finger movement

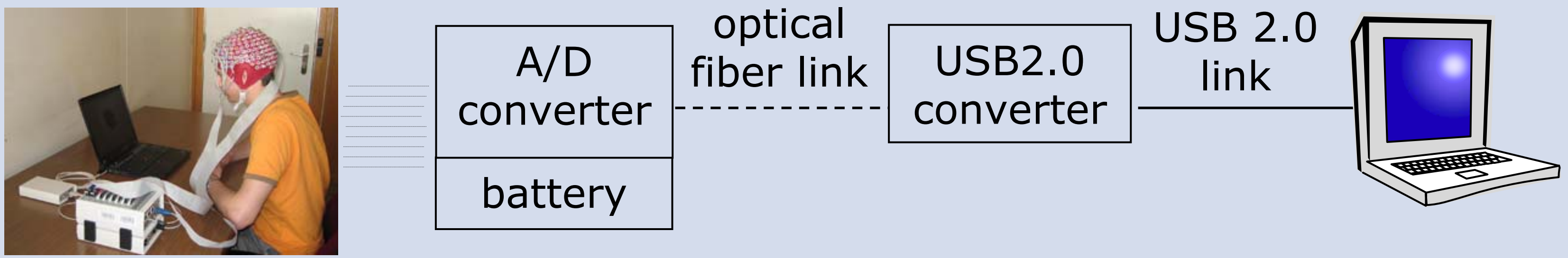
imagination of a music tune

3.1 Other examples - BCI

Brain-computer interaction is a classification problem:



Biosemi Active 2 acquisition system, 64 electrodes:

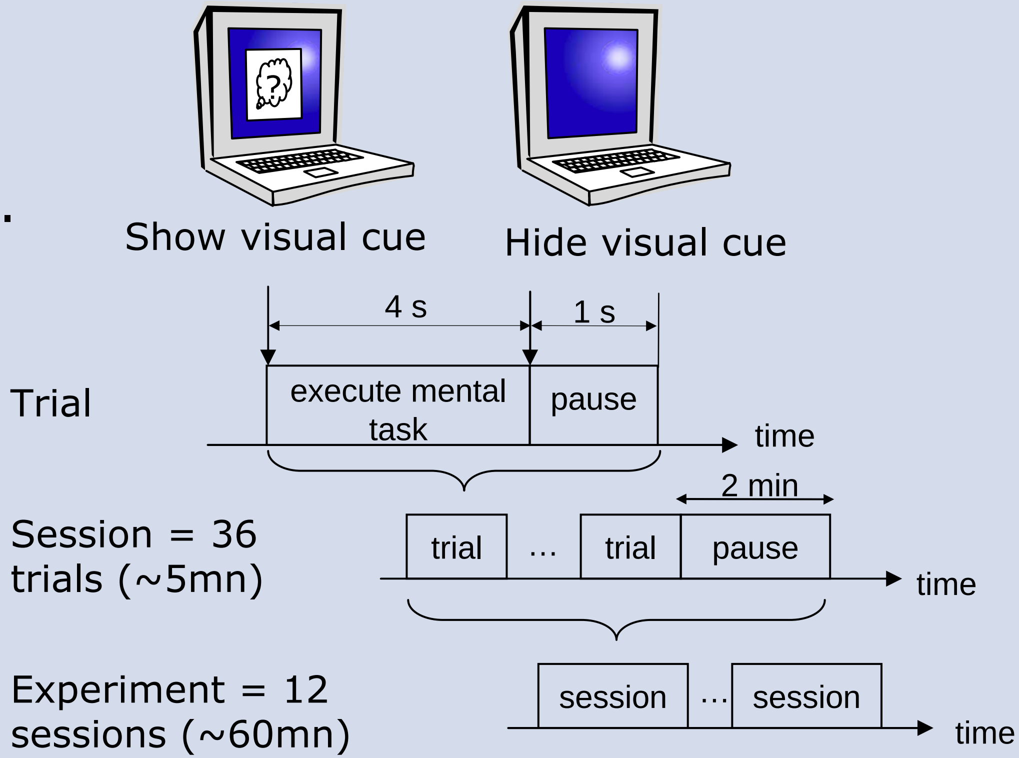


3.1 Other examples - BCI

Protocol:

- trial → session → experiment;
- visual stimulus;
- no feedback;
- 1 experiment

  = 108 trials per mental task.



3.1 Other examples - BCI

Signal processing and classification:

- 64 electrodes;
- band-pass filtering [4-45 Hz];
- Laplacian filtering;
- STFT Power feature extraction (8-30 Hz, 4 s), with baseline subtraction
  → 7’680 features.

Classification: SVM, LDA, decision trees (CART).

Cross-validation: stratified leave-v-out.

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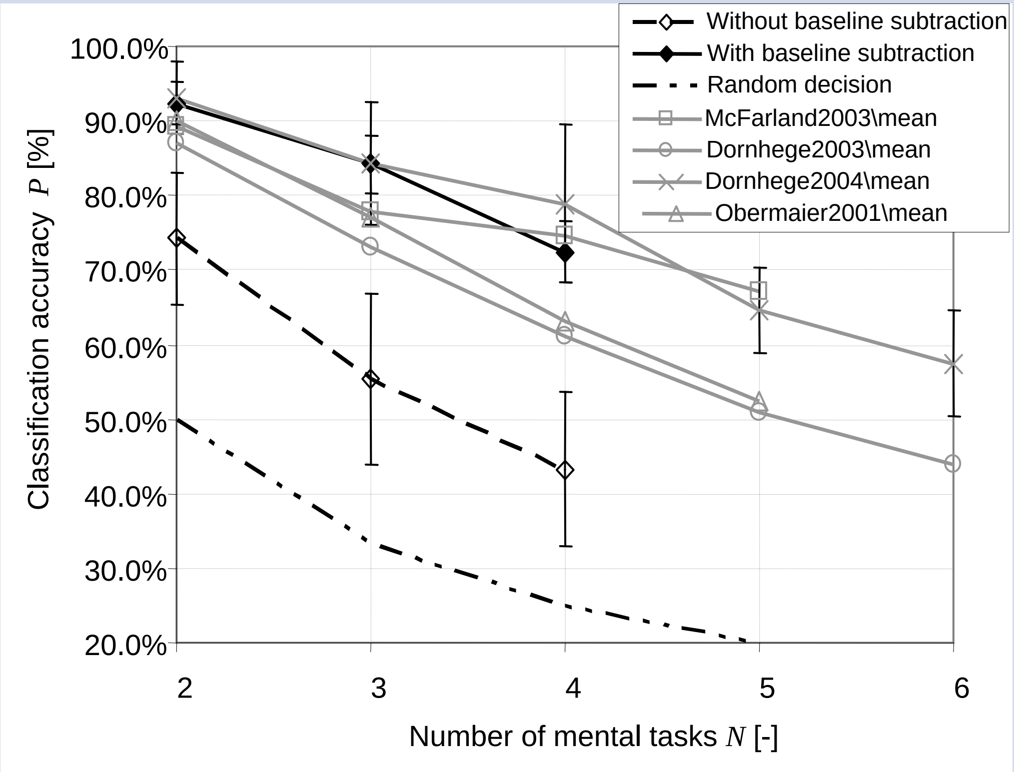
Results.

Classification accuracy:



Task combinations:

Combination	Average classification accuracy [%]
Mental calculation Auditory evocation	92.4
Mental calculation Cube rotation	91.1
Cube rotation Imagined movement	88.5
Imagined movement Auditory evocation	86.6
Mental calculation Cube rotation	81.0
Cube rotation Auditory evocation	80.3

3.1 Other examples - BCI

BCI performance optimization.

Information transfert rate B:

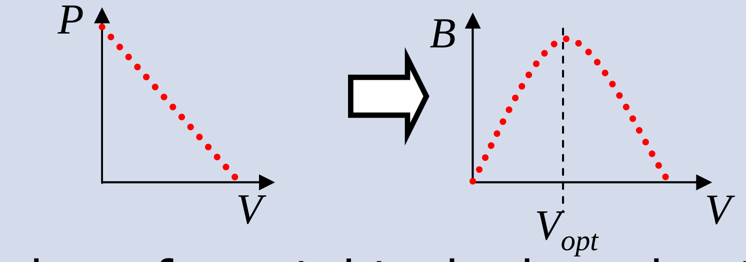
$$B = V \cdot \left(\log_2 N + P \cdot \log_2 P + (1-P) \cdot \log_2 \frac{1-P}{N-1} \right)$$

P : classifier accuracy [0..1]

V : protocol speed [trials/s]

N : number of tasks

Protocol speed-based optimization

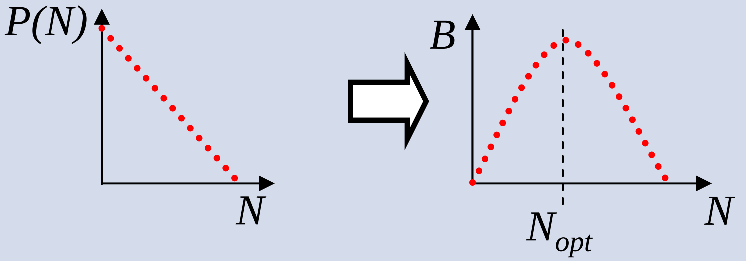


For P300-based BCIs:

$$V_{opt} \cong \frac{\log Q}{t \cdot \log \left(\frac{8}{30} \cdot \log N \right)}$$

Q, t: trials error and duration

Number of mental tasks-based optimization



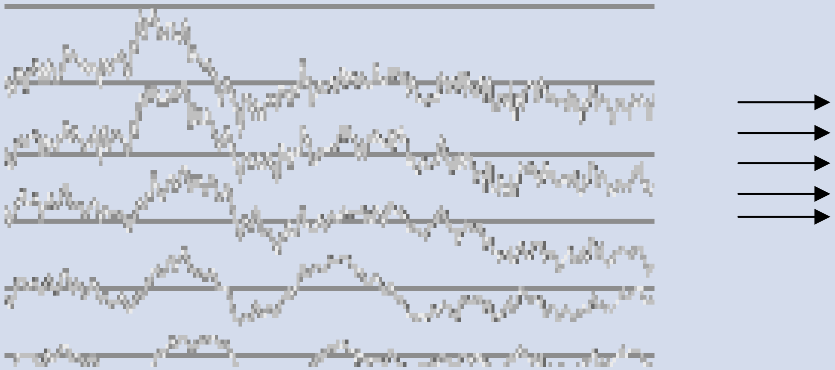
For BCIs based on thought alphabets:

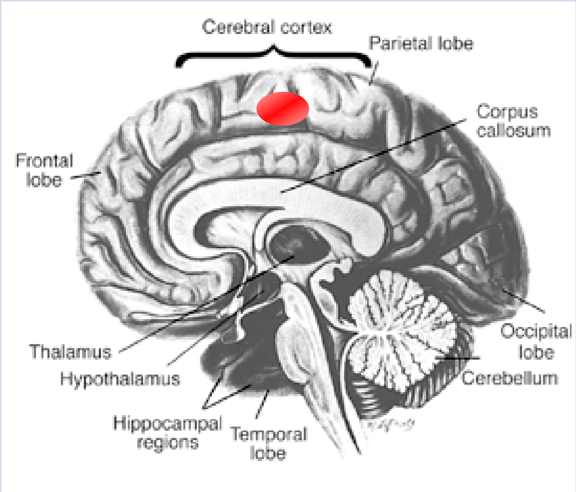
$$P(N) = a \cdot N + b$$

$$N_{opt}(a) = \frac{c_1}{c_2 - a}$$

3.2 Other examples - Sources reconstruction

Goal: map back the measured potentials to active brain areas.





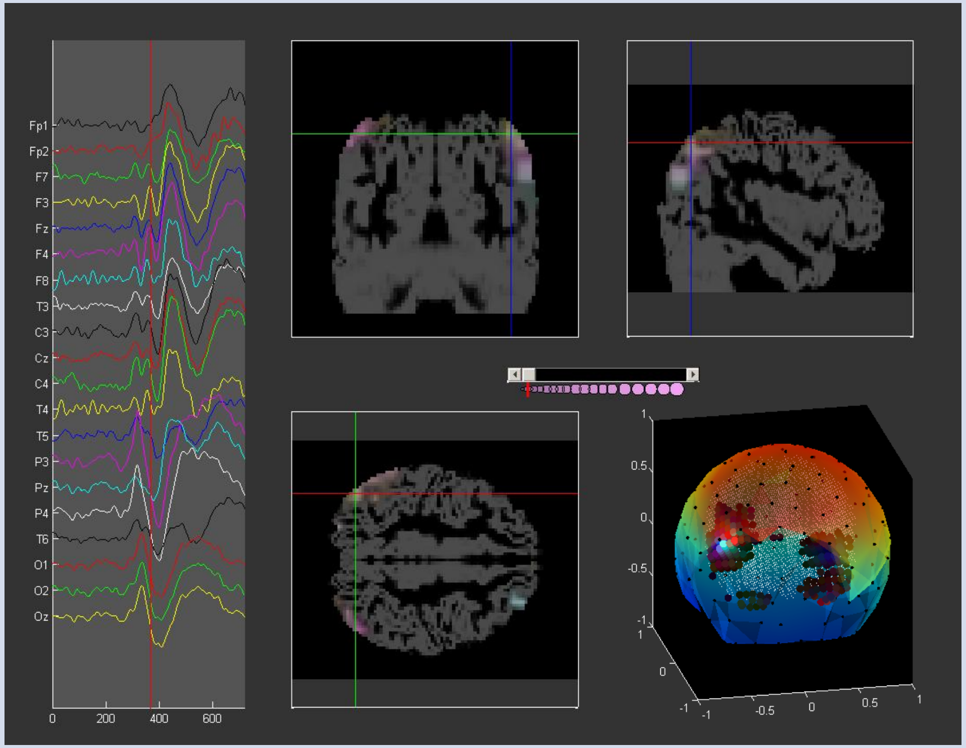
Why:

- provides spatial information reg. sources position in brain;
- understanding how the brain works, e.g. for emotions;
- diagnosis: epileptic source localization;
- command for Brain Computer Interfaces.

Focalized brain-sources reconstruction for active brain areas identification.

From EEGs to sources:

- distributed sources model;
- linear problem in amplitudes but huge under-determination;
- MAP stochastic approach;
- Gaussian Transform to represent non-Gaussian distributions as Infinite Mixtures of Gaussians (IMG).



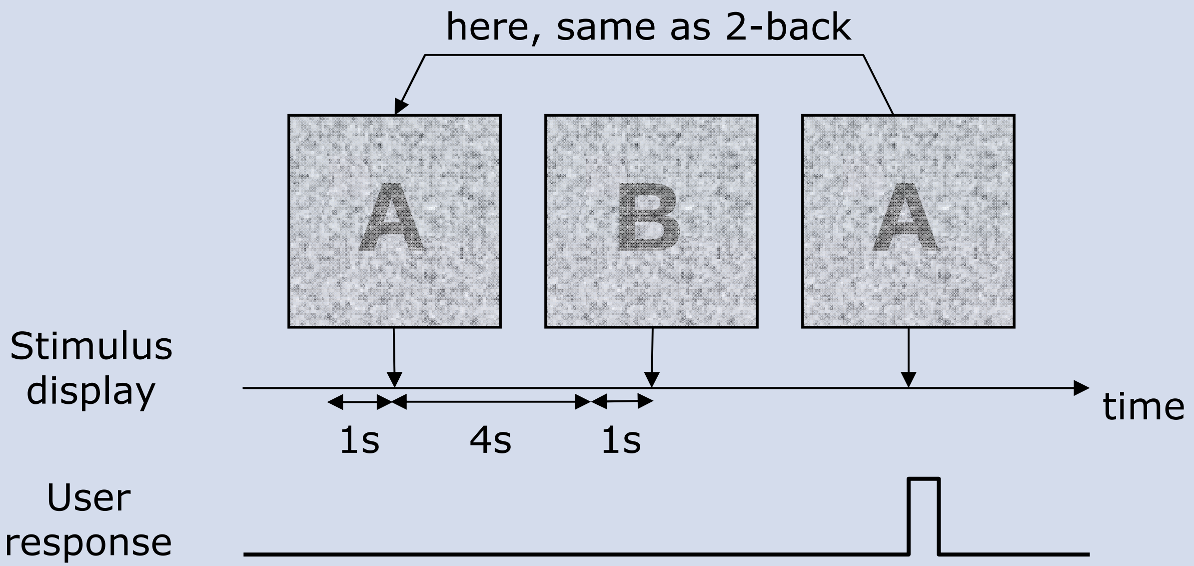
3.3 Other examples - Cognitive impairment

Problem:

- predict cognitive impairment before it appears (Alzheimer disease);
- 3-classes classification problem: control, Stable MCI (Mild Cognitive impairment), Progress MCI.

Protocol: working memory tasks (0-back, 1-back, 2-back).

Example:



3.3 Other examples - Cognitive impairment

Signal processing and classification

- 21 electrodes;
- band-pass filtering [4-45 Hz];
- Laplacian filtering;
- STFT Power feature extraction (4-46 Hz, 4s total, 230ms - 50% overlapping windows), with baseline subtraction
  → 6’930 features.

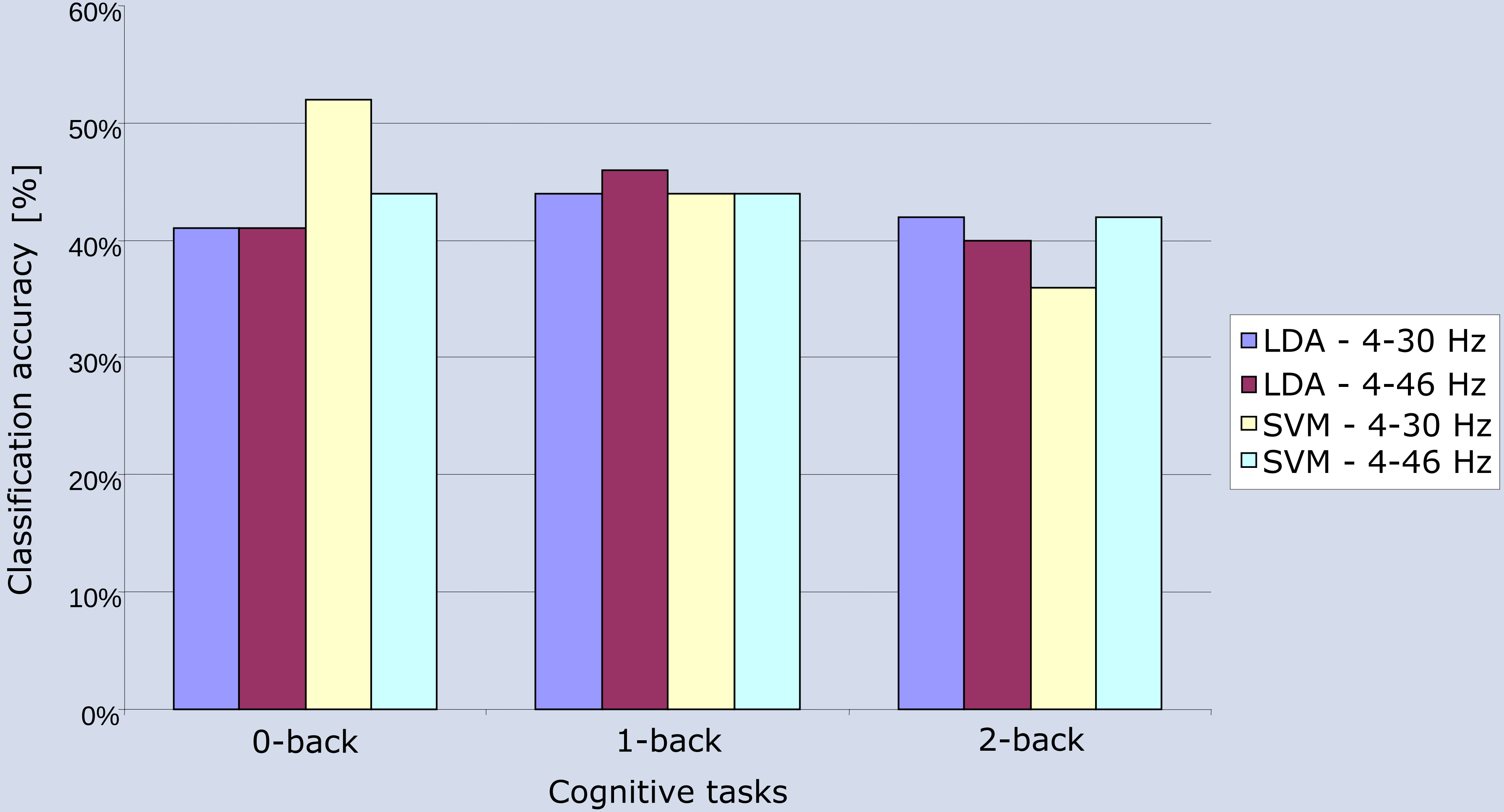
Classification:

- SVM: [4-30Hz], [4-46Hz];
- LDA: [4-30Hz], [4-46Hz].

Cross-validation: variant of leave-one-out.

3.3 Other examples - Cognitive impairment

Results:



Outline

4. Conclusions (2)

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Pattern recognition in peripheral and central signaling:

- signal preprocessing and features extraction to simplify analysis;
- usually boils down to a classification problem;
- large variety of techniques, depending on the problem, few being clearly superior and few having reached wide consensual acceptance ...

... needs a-priori information, expertise, to methodically explore possible avenues ...

Hot issues:

- task selection: *a-priori* knowledge to select best tasks;
- features selection: how to find a limited number of discriminative ones;
- fusion of modalities, and at which level;
- feedback, on-line adaptation.