Enhancing Brain-Computer Interfaces by Machine Learning Techniques

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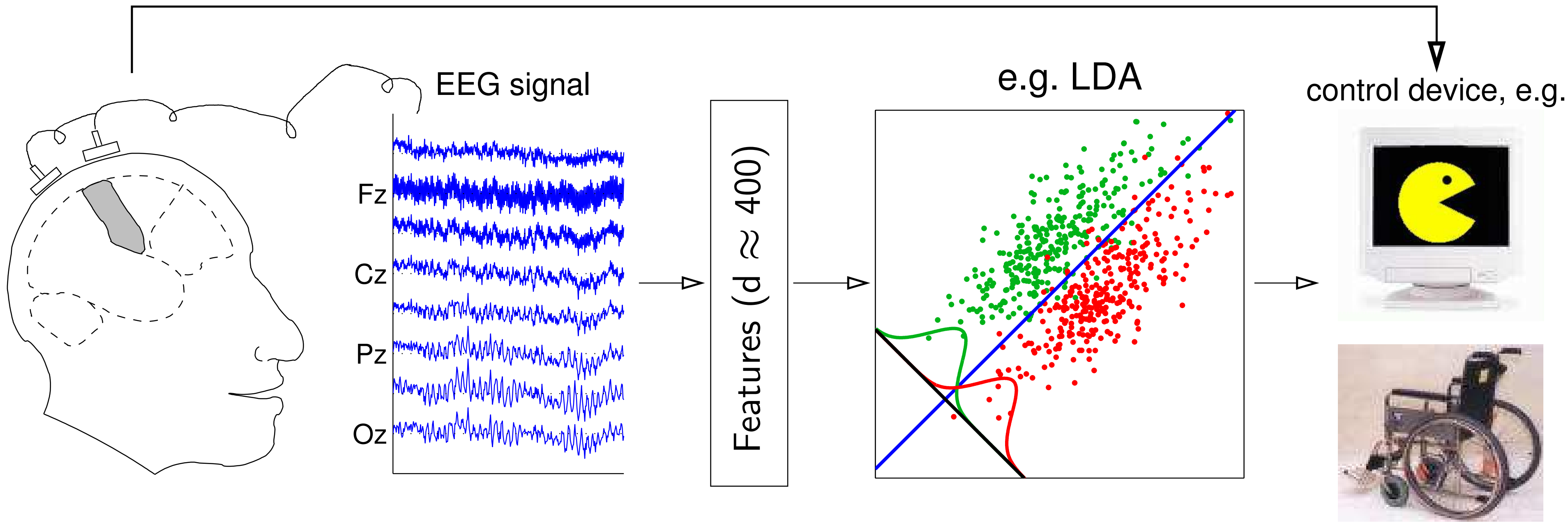
Overview of the Talk

- BCI research
  - introduction
  - invasive, dependent, evoked potential BCIs
  - operant conditioning vs. detection of cognitive states
- Can ML help BCI research?
- The Berlin BCI project
  - BBCI system design
  - recent developments

Brain-Computer Interfacing



BCI: Translation of human intentions into a technical control signal
without using activity of muscles or peripheral nerves

Different Ways to Do It

invasive
implanted sensors (electrode array, needle electrodes, subdural ECoG)

non-invasive
without penetrating the scalp, mostly EEG

dependent
on non CNS activity, e.g., controlled eye movement

independent
from peripheral muscles and nerves, using only CNS activity

evoked potentials
require stimuli, users modulate (automatic or voluntarily) brain responses

unstimulated brain signals
users can voluntarily produce the required signals

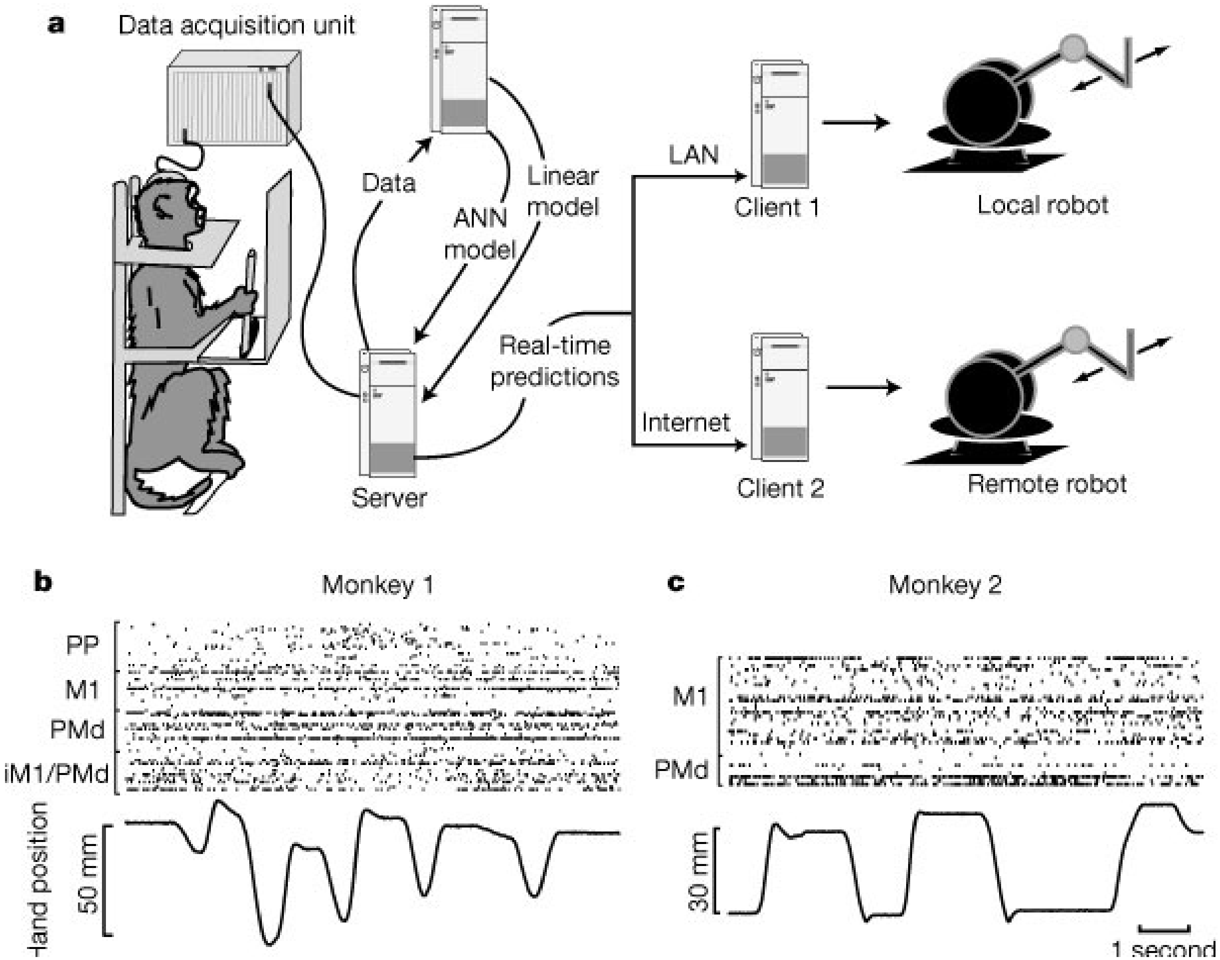
synchronous
commands can only be emitted synchronously with an external pace

asynchronous
the system detectes when the user wants to emit a command

operant conditioning

detection of mental states

Invasive BCIs, e.g., Nicolelis et al.



Brain activity of monkeys is measures from implanted electrodes.

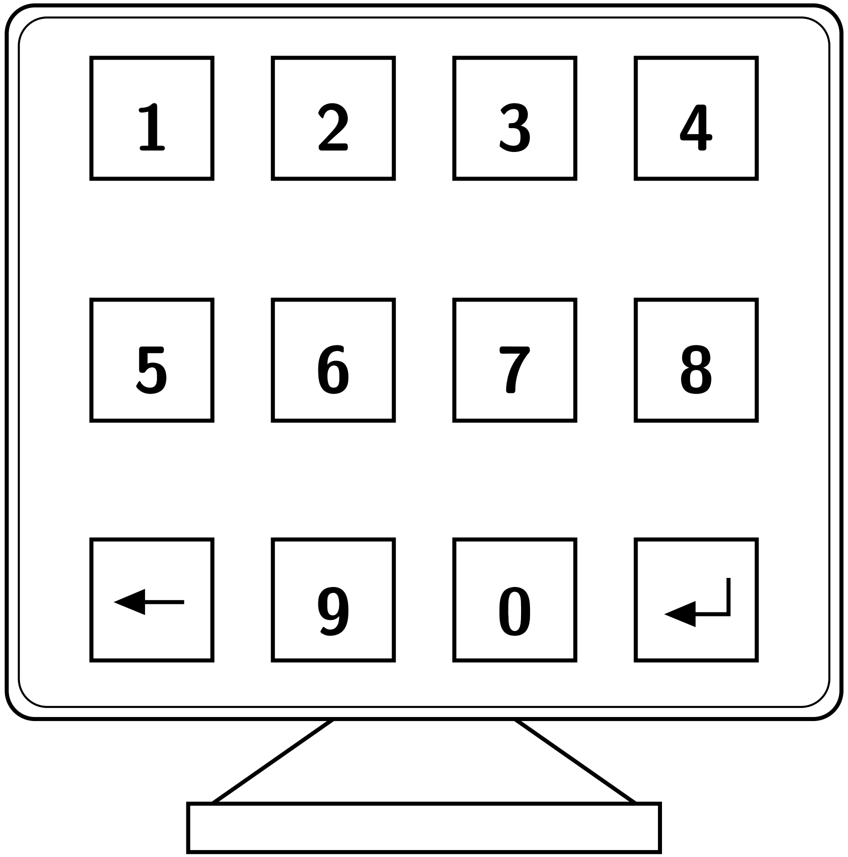
After training an algorithm on the firing rates while performing real movements, the monkey can control a robotic arm by brain activity alone.

Figure taken from [Nicolelis et al, 2000]

[Laubach *et al.*, 2000, Kennedy *et al.*, 2000, Reina *et al.*, 2001, Levine *et al.*, 2000]

BCI using SSVEP

Regarding a stimulus blinking at a frequency between 7 and 30 Hz evokes a rhythm of the same frequency in the visual cortex.



In the Beijing setup each button flashes at an individual frequency. By spectral analysis of the EEG the regarded button can be detected from 1 s windows.

[dependent, asynchronous, evoked potentials]

[Middendorf *et al.*, 2000, Cheng *et al.*, 2002]

BCI using the P300 Component

An awaited infrequent stimulus (deviant) in a series of standard stimuli elicits a P300 component at central scalp position.

In the Donchin setup the subject concentrates on a letter of a 6×6 symbol matrix. Rows and columns are highlighted several times in random order.

P300 components are most strongly elicited when the row resp. column is flashed which contains the selected letter.

[independent?, synchronous, evoked potentials]

[Farwell and Donchin, 1988, Meinicke *et al.*, 2003]

Opposing BCI Approaches

In the following only non-invasive, independent, unstimulated BCIs will be considered.

Operant Conditioning.

- **subjects learn** to voluntary control changes of particular components/features of the EEG.

procedure:

- provide feedback of a specific EEG feature, e.g. as cursor movement;
- subjects concentrate on moving the cursor to a given target.
- typically some parameters are dynamically adapted, but the bulk of the learning load is on the user.

Detection of Mental States.

- **machines learn** to recognize the specific mental states of the particular user.

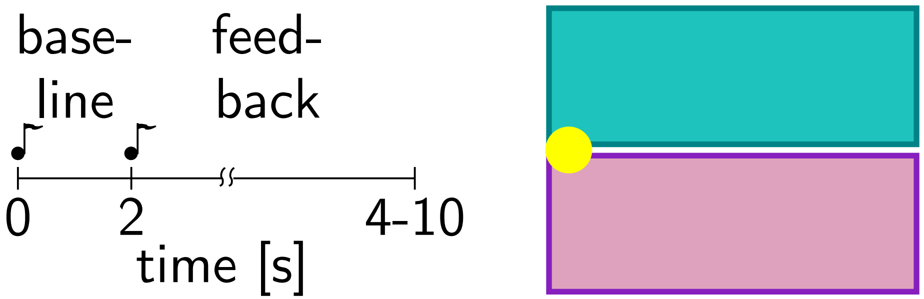
procedure:

- a set of mental states is chosen (discriminability, appropriateness for application).
- in a controlled measurement subjects produce brain signals according to requested mental states.
- after training a classifier the natural mental states of the subject can be recognized without subject training.

Operant Conditioning: the Tübingen Group

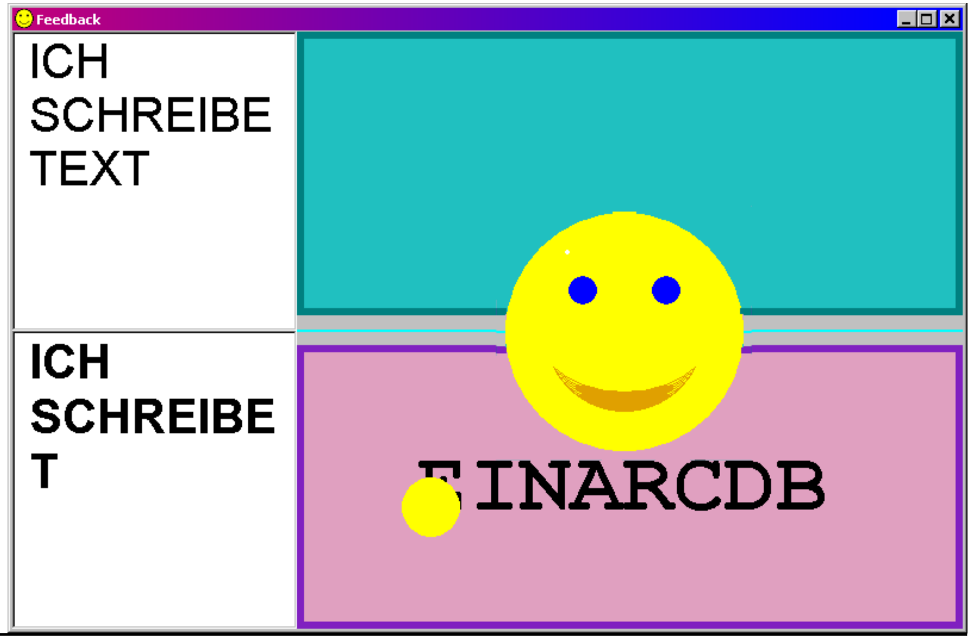
The **slow cortical potentals (SCPs)** at central scalp position can be voluntary controlled. But this learning process might require many training sessions.

The yellow ball travels at a constant speed from left to right, vertically controlled by SCPs. When the ball reaches the right border one of the targets gets selected.



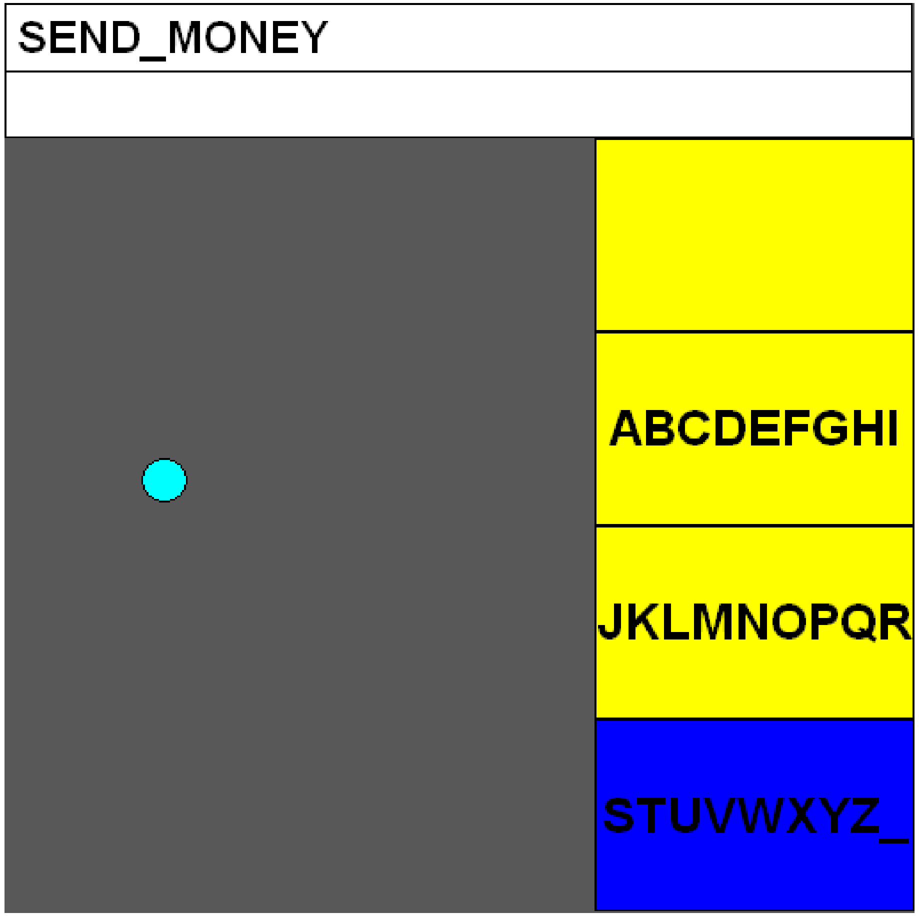
[Birbaumer *et al.*, 2000, Hinterberger *et al.*, 2004]

When an acceptable accuracy is reached after some training sessions, subjects are switched to a language support program.



Operant Conditioning: the Albany Group

The μ rhythm in sensorimotor cortex is known to be susceptible to conditioning. However, learning the voluntary control takes several training sesions.

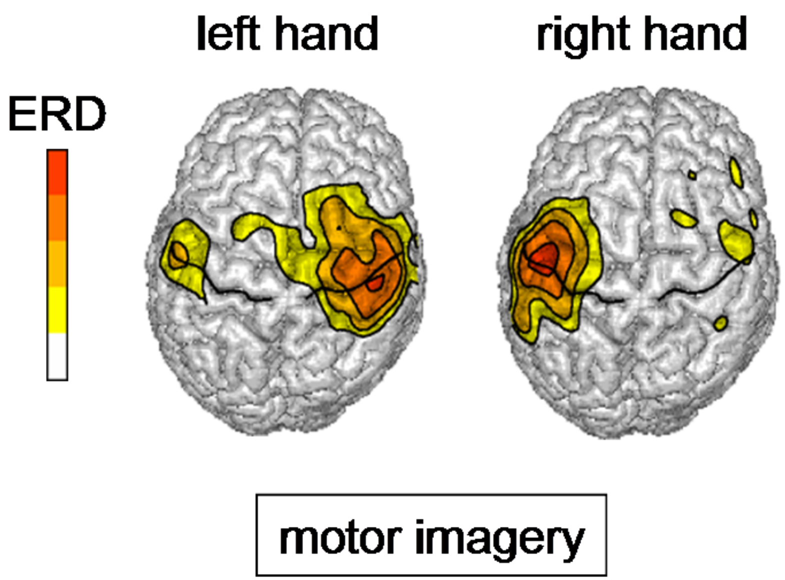


The blue ball travels at a constant speed from left to right. Vertical movement is determined by a linear equation from spontaneous μ and/or β power at 1 to 3 Laplace filtered electrodes.

[Wolpaw *et al.*, 2003, McFarland *et al.*, 2000]

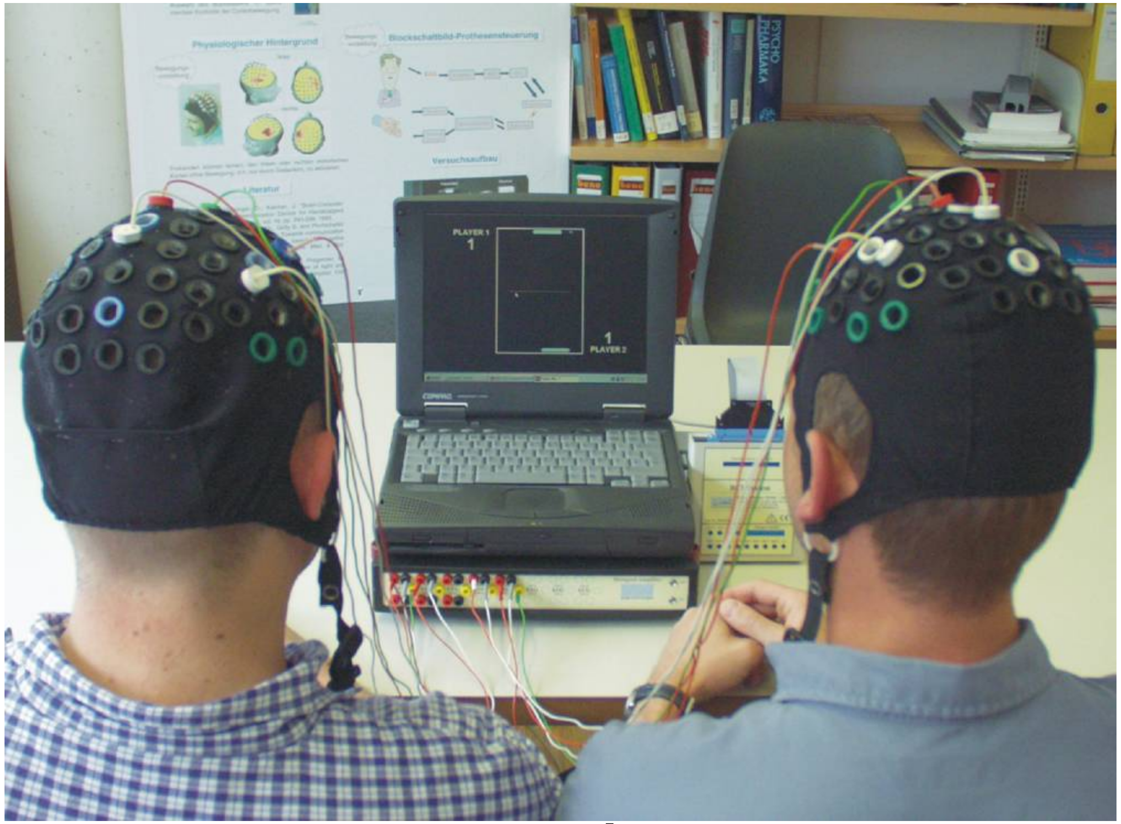
Detection of Mental States: the Graz Group

Motor related mental states are characterized by a modulation (ERD) of the μ-rhythm.



[Pfurtscheller *et al.*, 2003, Peters *et al.*, 2001]

This can be used for BCI systems that do not require extensive training time. In the teletennis game below the racket can be controlled by left vs. right hand imagery.



other groups, e.g., [Sykacek *et al.*, 2003, Millán *et al.*, 2002, Parra *et al.*, 2002]

Challenges in BCI Research

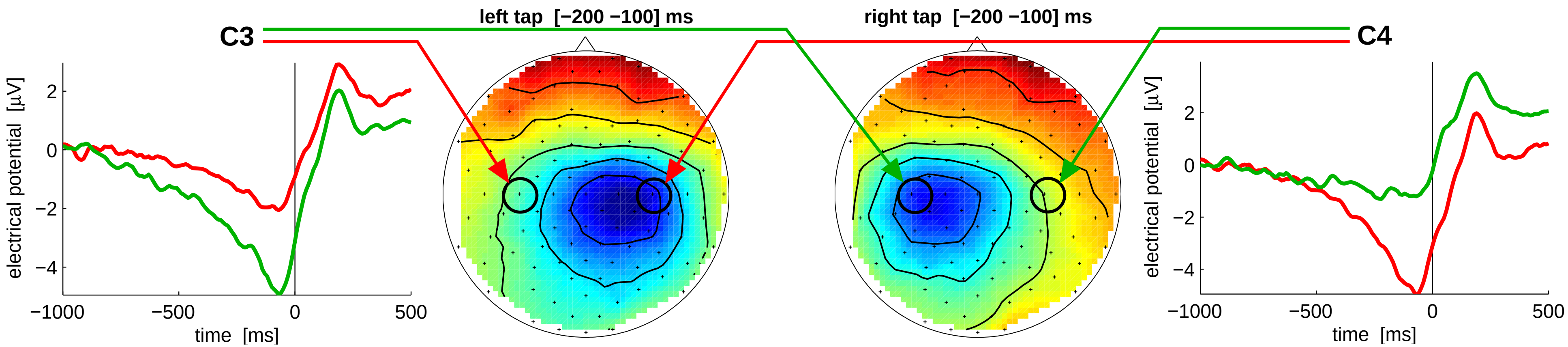
At present, the applicability of such a system is severely limited by

- high subject variability in performance
- low detection rates of mental states
- slow command speed
- low number of possible decisions per command
- slow response times
- cumbersome preparation

When those limitations are overcome to a sufficient degree, a whole range of new user interface applications might emerge.

Why a Machine Learning Approach?

- The neurophysiology of the mental states that are used in BCIs are well-known.
- For example, the intention for a hand movement is reflected by the so called **lateralized readiness potential** (LRP): a negative shift of the brain potentials contralateral to the hand.

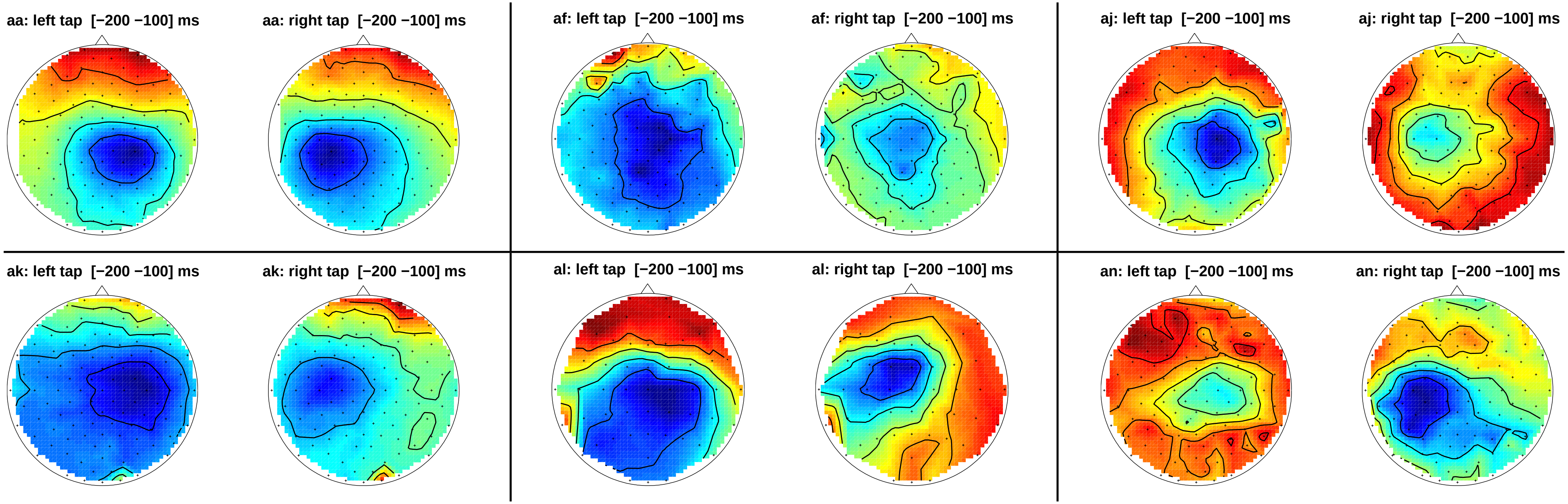


➤ It seems possible to extract simple features that very well distinguish between the mental states.

- What the hack do we need ML for?

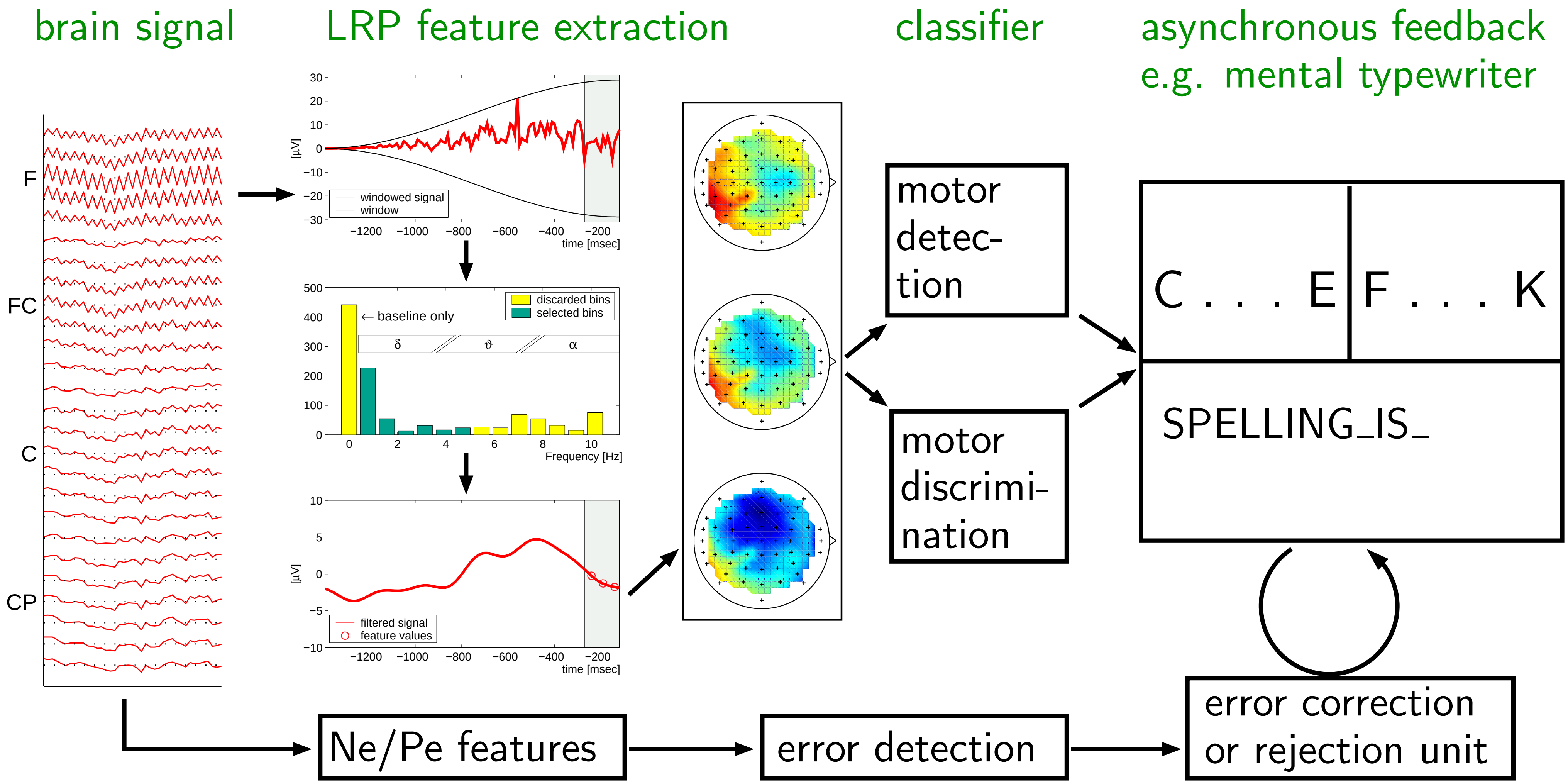
Subject-Specificity

- Traditional neurophysiology shows you only the ›**average brain**‹.
- In BCIs we need to classify **single-brain** single-trials.
- Even averages of single brains' signals show a great diversity:

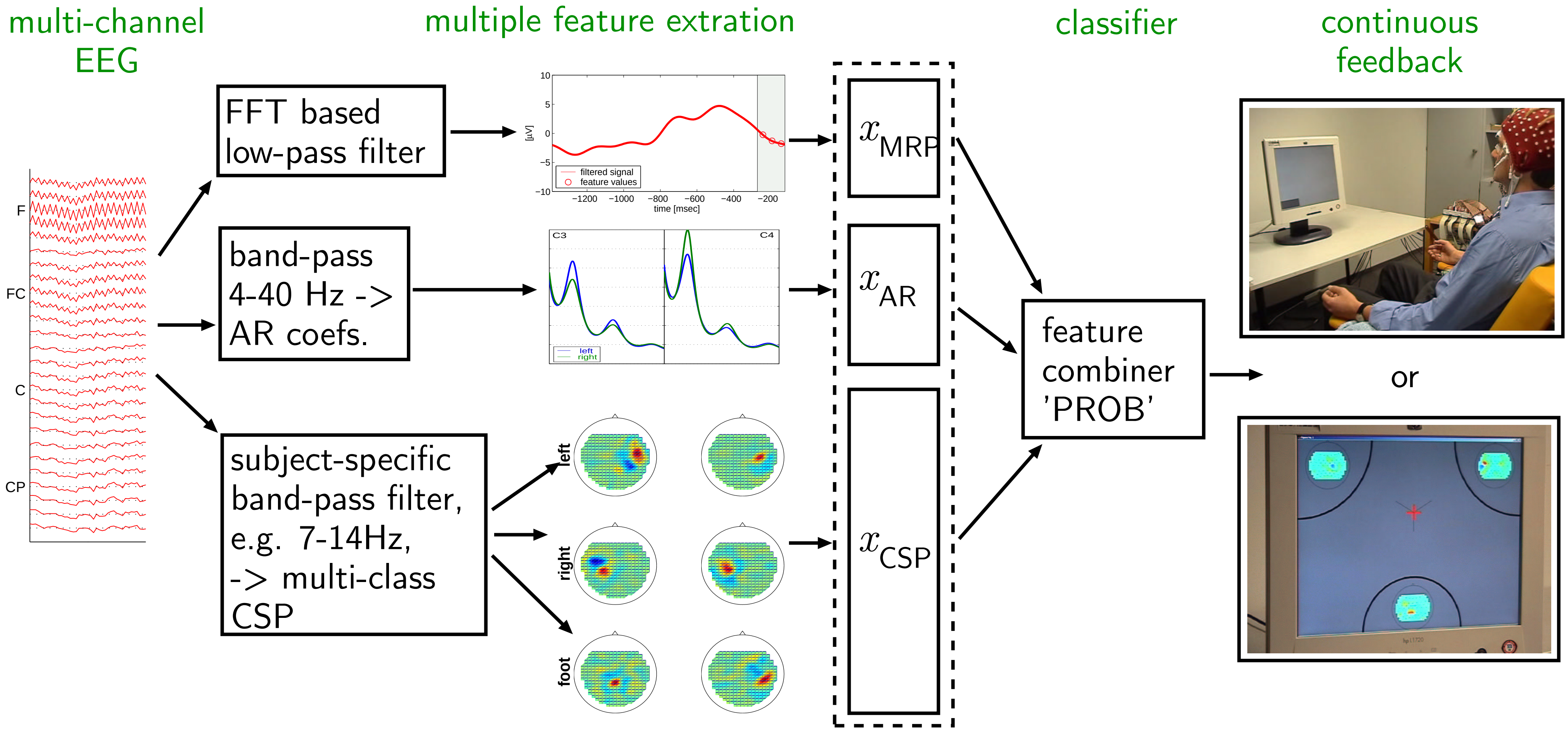


- Above are intra-subject averages of the pre-movement period -200 to -100 ms prior to a left resp. right hand finger tap.

BBCI towards Patient Applications

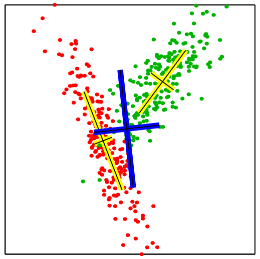


BBCI towards Gaming Applications

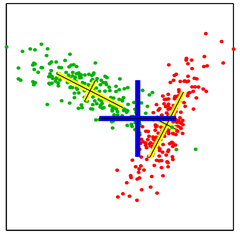


- So far, for online feedback we used only the CSP features.

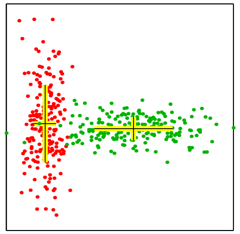
Common Spatial Patterns (CSP) for Two Classes



Original data: Each class has a specific spatial extension.
Let Σ_1 and Σ_2 be the covariance matrices of the two classes.
The blue cross visualizes the covarianz matrix of $\Sigma_1 + \Sigma_2$.



Make a whitening of $\Sigma_1 + \Sigma_2$, i.e., determine matrix P such that $P(\Sigma_1 + \Sigma_2)P^\top = I$ (possible due to positive definiteness of $\Sigma_1 + \Sigma_2$).
➤ Principal axis of the classes are perpendicular. Define: $\hat{\Sigma}_i = P\Sigma_i P^\top$.



Calculate orthogonal matrix R and diagonal maxtrix D by spectral theory such that $\hat{\Sigma}_1^\top = RDR^\top$. Therefore $\hat{\Sigma}_2^\top = R(1-D)R^\top$ since $\hat{\Sigma}_1 + \hat{\Sigma}_2 = I$.
➤ Variance along the axis of input space is complementatory with respect to the two classes.

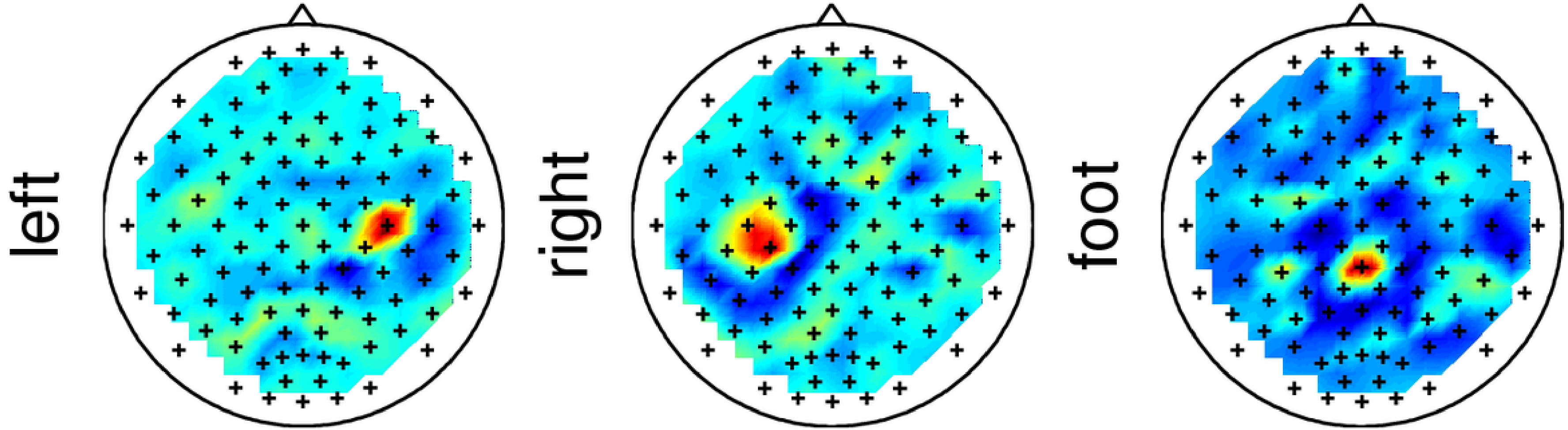
Essential idea for multi-class extension:
CSP is based on the **simultaneous diagonalization** of two covariance matrices with corresponding eigenvalues summing up to 1.

Extension of CSP to Multi-Class Problems

Find matrix R and diagonal $(D_i)_{i=1,\dots N}$ with elements in $[0,1]$, such that

$$R\Sigma_i R^\top = D_i \text{ for all } i = 1, \dots, N \text{ and } \sum_{i=1}^{N} D_i = I.$$

For $N > 2$ only approximate solutions exist. Choose patterns corresponding to the highest eigenvalue score defined by score$(\lambda) := \max(\lambda, \frac{1-\lambda}{1-\lambda+\lambda(N-1)^2})$.



CSPs of band-pass filtered EEG signals reflect ERD/ERS effects.

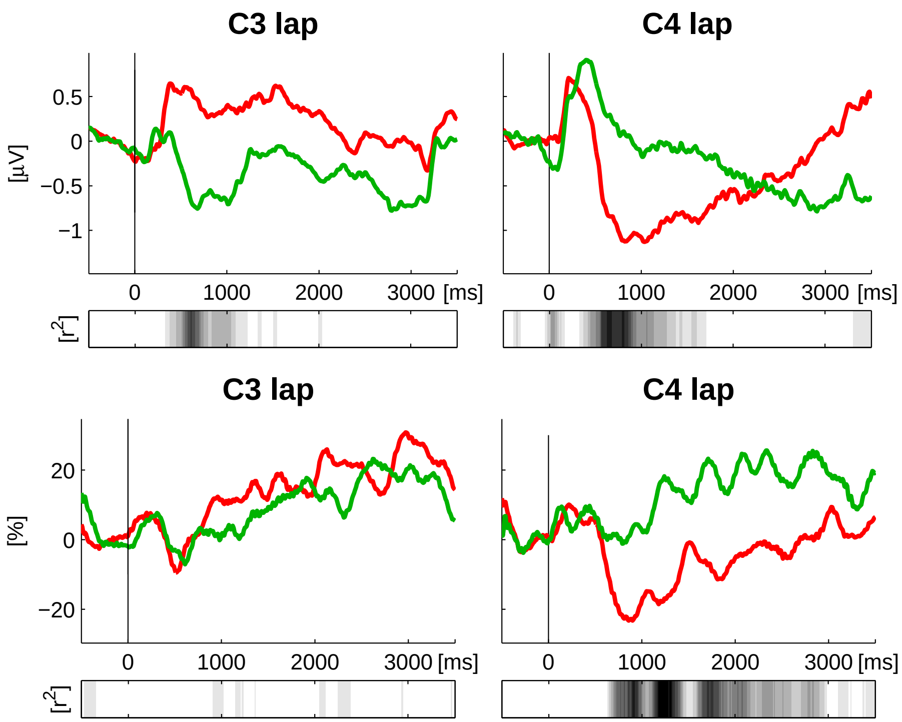
As features vectors variances of the projected signals are calculated. Then use your favorite multi-class classifier. [Dornhege *et al.*, 2004a, Dornhege *et al.*, 2004b]

Combination of EEG features

Some mental activities or states are reflected by different neurophysiological features. Motor related brain activity (actual movement, imagery, intentions) is reflected by

Lateralized Readiness Potential (LRP)

Event-Related Desynchronization (ERD)

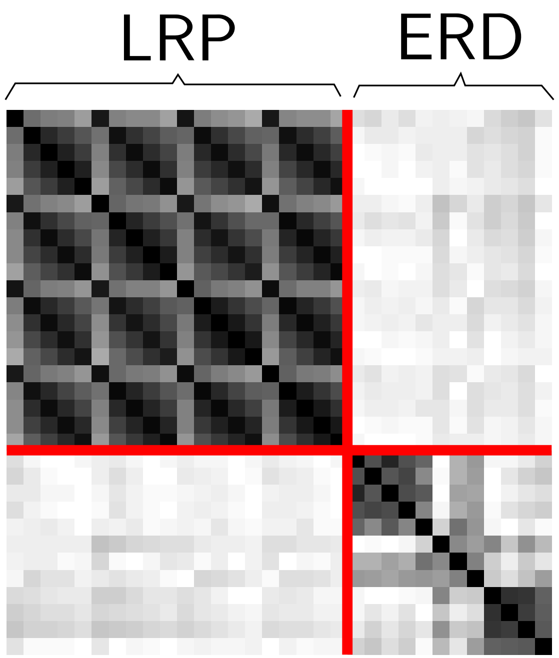


➤ **early** distinction between the signals of **left** and **right** trials.

➤ **long persisting** distinction between the signals of **left** and **right** trials.

➤ As seen from the time courses, the LRP and the ERD seem to reflect *independent* cortical processes. [Dornhege *et al.*, 2003, Dornhege *et al.*, 2004a]

Combination of EEG features



When different EEG features provide **complementary information**, a suitable feature combination is likely to boost classification rates.

The covariance matrix of a concatenated feature vector (LRP and ERD features) reveals only **little inter-feature correlation**. ➤ independence might be a valid model assumption.

Furthermore combined features have the potential of being more robust against artifacts, since

- oscillatory features, as ERD, are susceptible to EMG artifacts, while
- slow potential features, as LRPs, are susceptible to EOG and drift artifacts.

Feature Combination Based on Independence

Goal: find the Bayes optimal classifier under the assumption that the features are normally distributed with equal covariance matrices and independent.

Let X_i for $i \in F$, e.g., $F = \{\text{LRP, ERD}\}$, be random variables for the features and $Y \in L$, e.g., $L = \{\text{L, R, F}\}$ for the labels. Assume

- $(X_i|Y = y) \sim \mathcal{N}(\mu_{i,y}, \Sigma_i)$ for all $i \in F, y \in L$ and
- $(X_i|Y)_{i \in F}$ are independent.

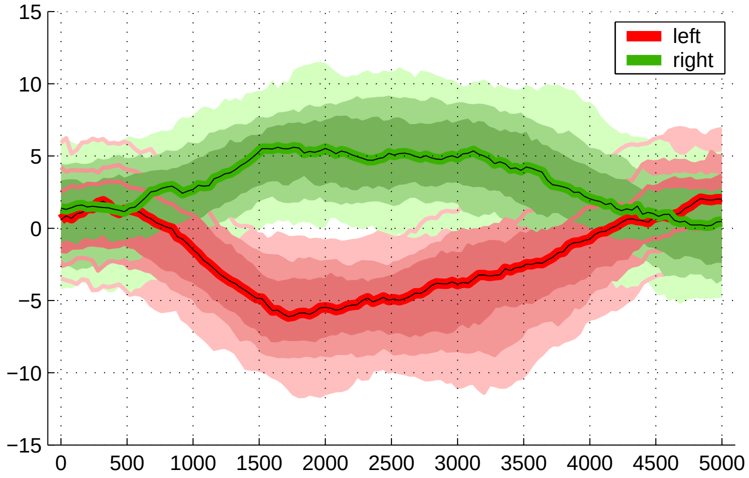
This leads to the following decision rule for observed x_i:

$$\text{Decide for class } \operatorname{argmax}_{y \in L} \sum_{i \in F} w_{i,y}^\top x_i + b_{i,y}$$

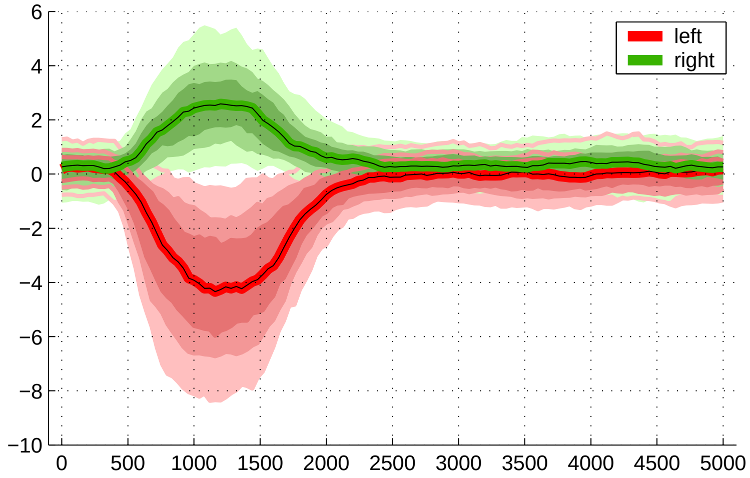
$$\text{with } \; w_{i,y} := \Sigma_i^{-1} \mu_{i,y} \text{ and } b_{i,y} = -0.5 \mu_{i,y}^\top w_{i,y} \text{ for } i \in F, y \in L$$

Different Quality of LRP and ERD Features

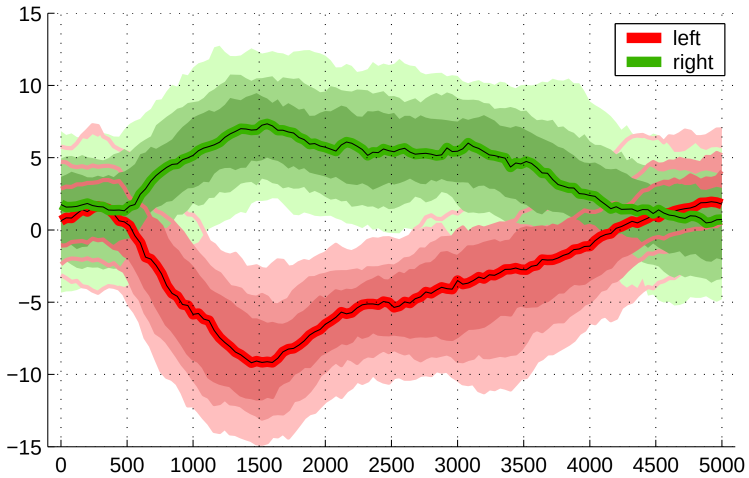
based on ERD features



based on LRP

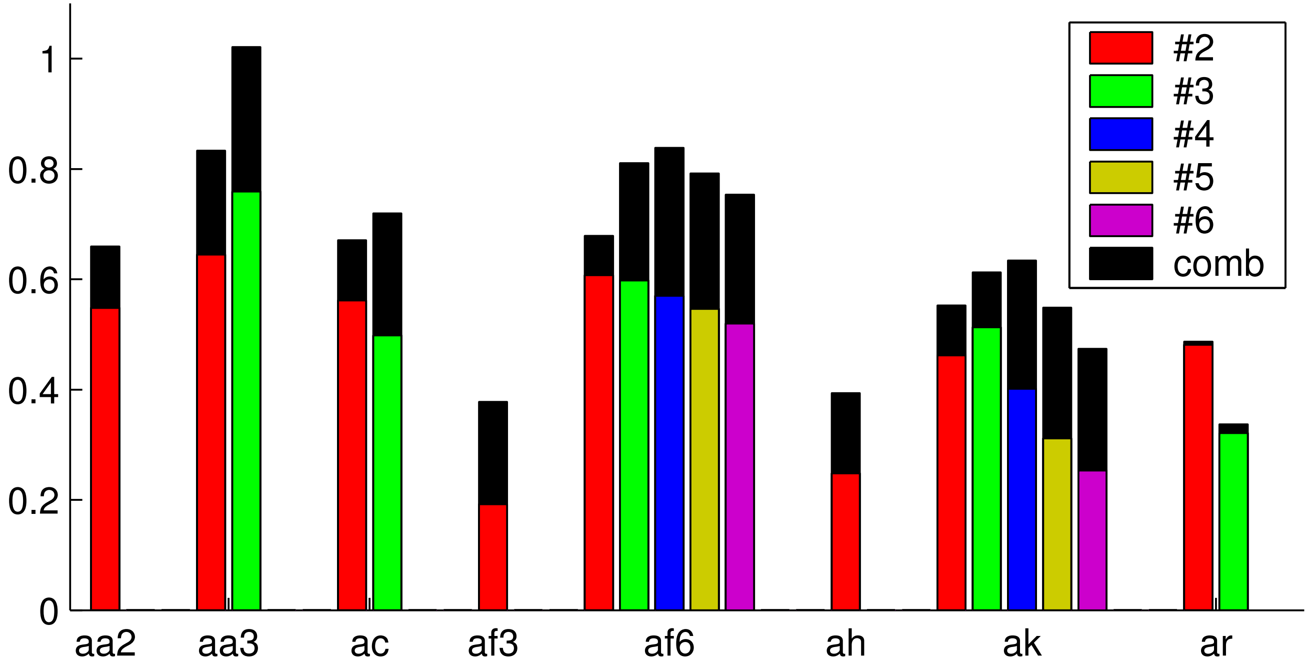


based on combination of the two



The combination of ERD and LRP features exploits the merits of the two: **rapid response** of LRP features and the **persistence** of ERD features.

Multi-Class Feature Combination Results



Information Transfer Rate [bits per decision] for 6 subjects in an imagery experiment with up to 6 mental states. Black toppings shows the gain obtained by feature combination.

- ➤ To use more than 2 classes in all but one case useful. In both experiments with more than 3 classes the best result is achieved with 4 classes.
- ➤ Our feature combination method essentially improve classification performance. Note that without this methods best results are at 3 not at 4 classes.

Conclusion

- ML adapts BCIs to the brain of the particular user.
- ML can decrease the learning load imposed on the user.
- feature combination can boost classification accuracies and combine the merits of the single features.

Ongoing Research in the Berlin BCI project

- improve on 2-D cursor control
- feedback experiments with feature combination
- further feedback applications including mental typewriter
- online adaptve CSP version to account for EEG non-stationarity
- detection of movement intentions regarding phantom limbs in amputees

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[Publications of the Berlin BCI group]

see **http://ida.first.fhg.de/projects/bci/bbci_official/**

[BCI Competition: watch out for the next one]

see **http://ida.first.fhg.de/projects/bci/competition/**

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