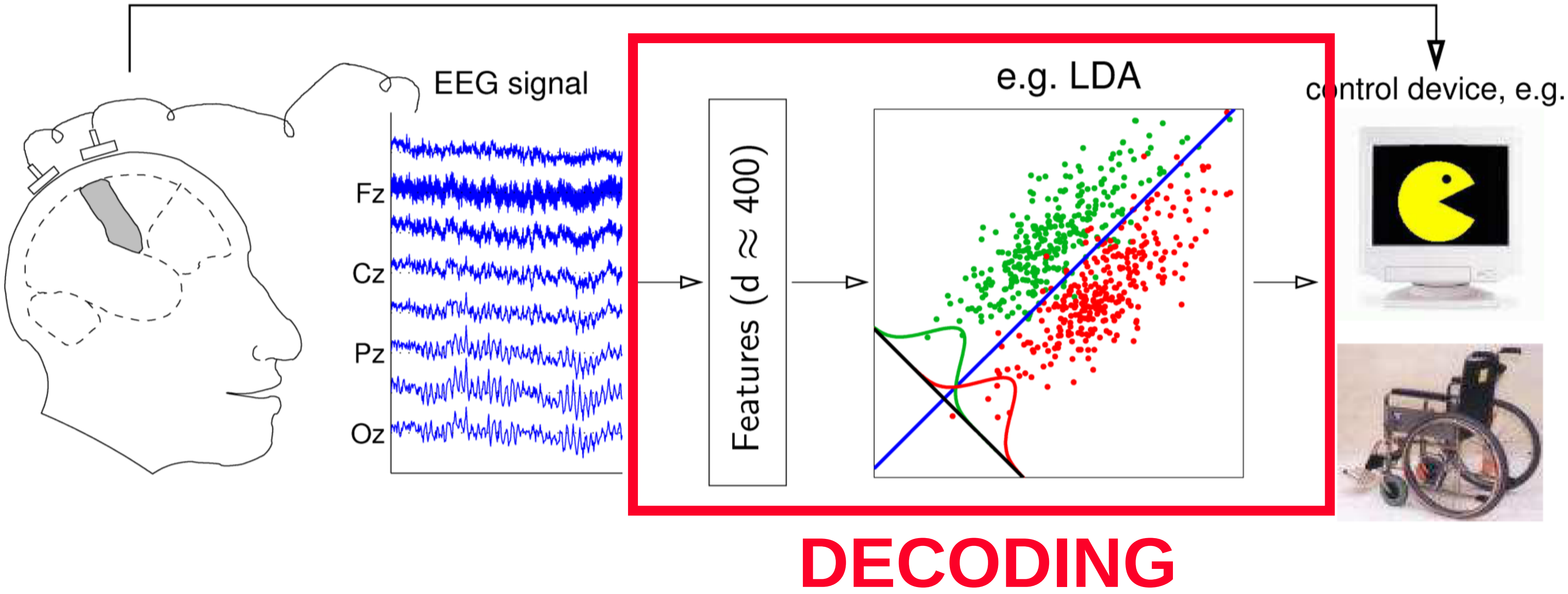
Toward Brain Computer Interfacing

Klaus-Robert Müller, Benjamin Blankertz, Carmen Vidaurre, Michael Tangermann, Gabriel Curio et al.

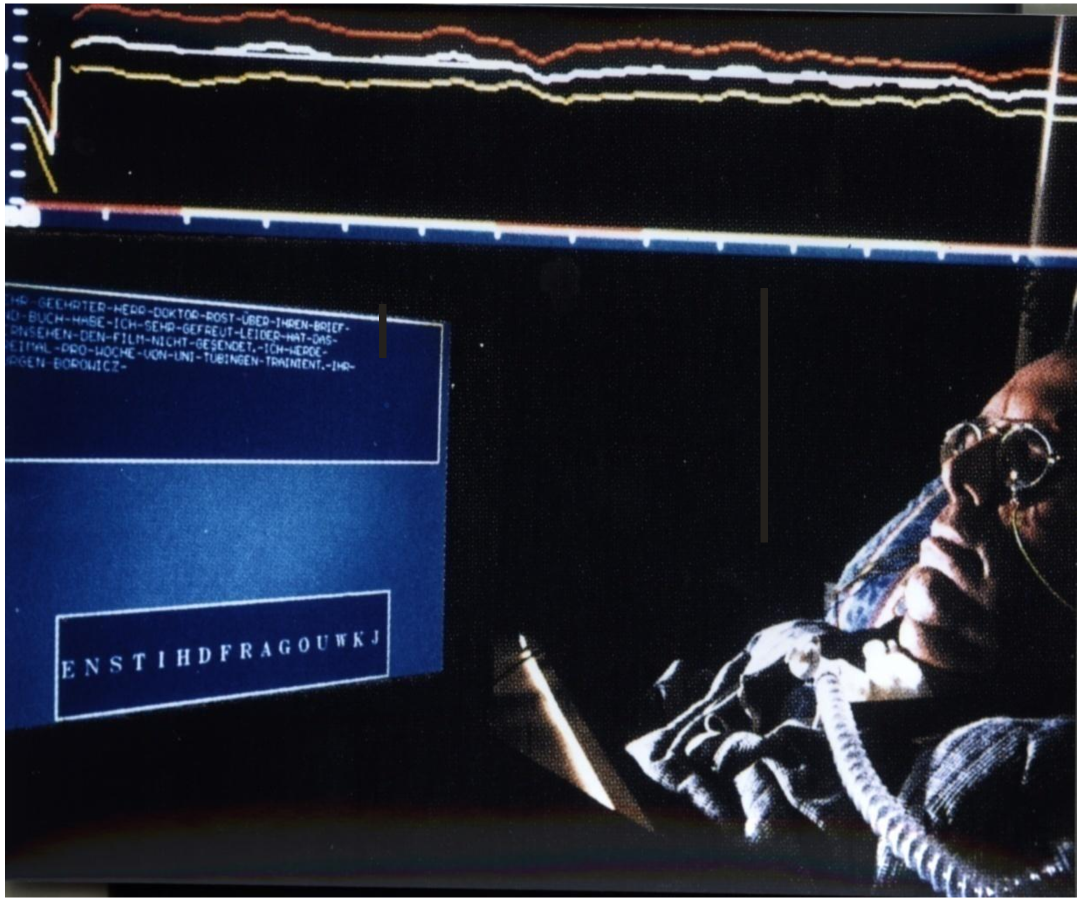
Noninvasive Brain-Computer Interface



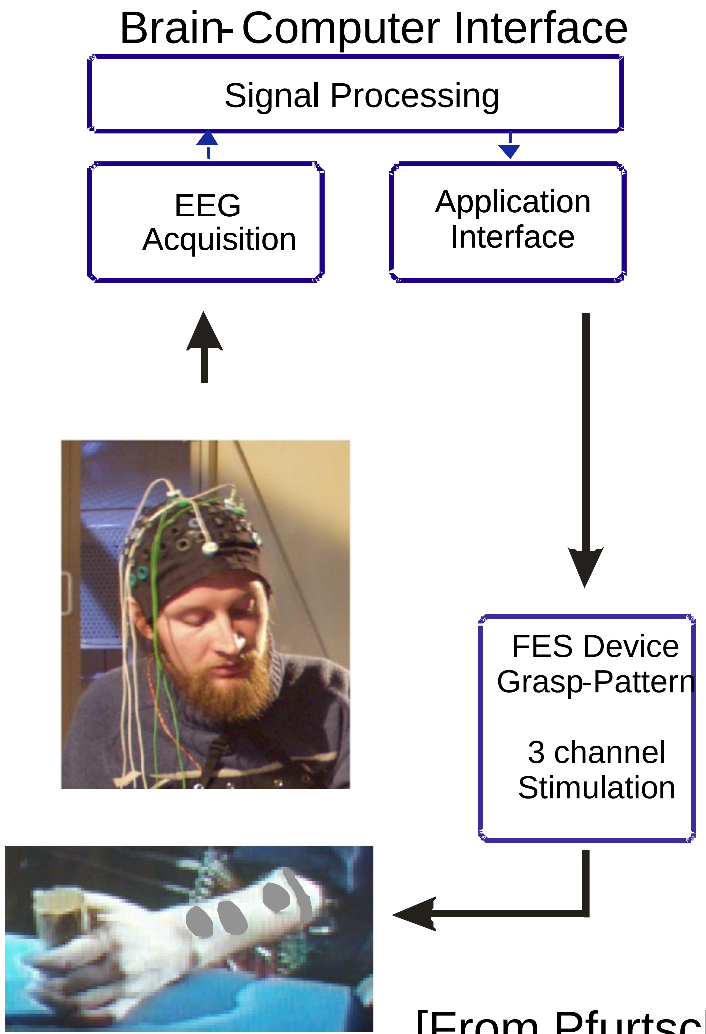
BCI: Translation of human intentions into a technical control signal **without using activity of muscles or peripheral nerves**

‚Brain Pong‘ with BBCI

Noninvasive BCI: clinical applications



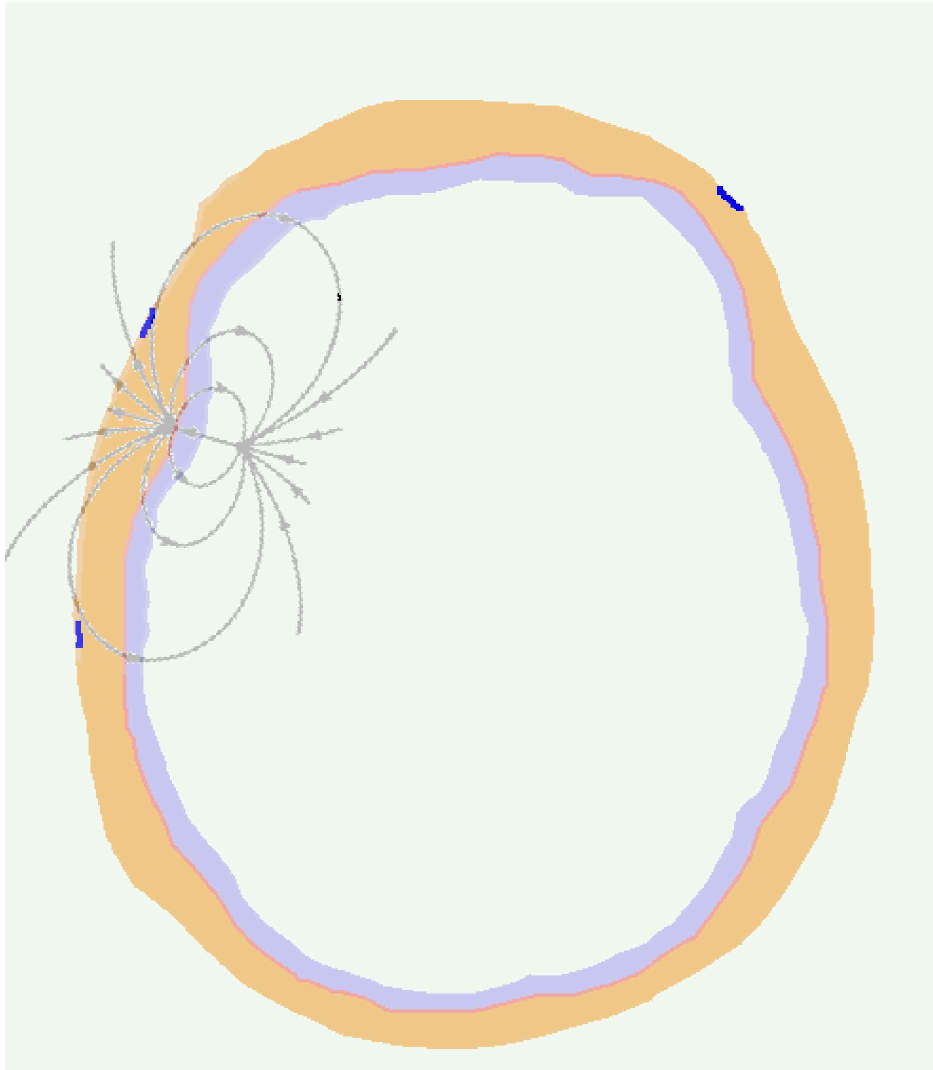
[From Birbaumer et al.]



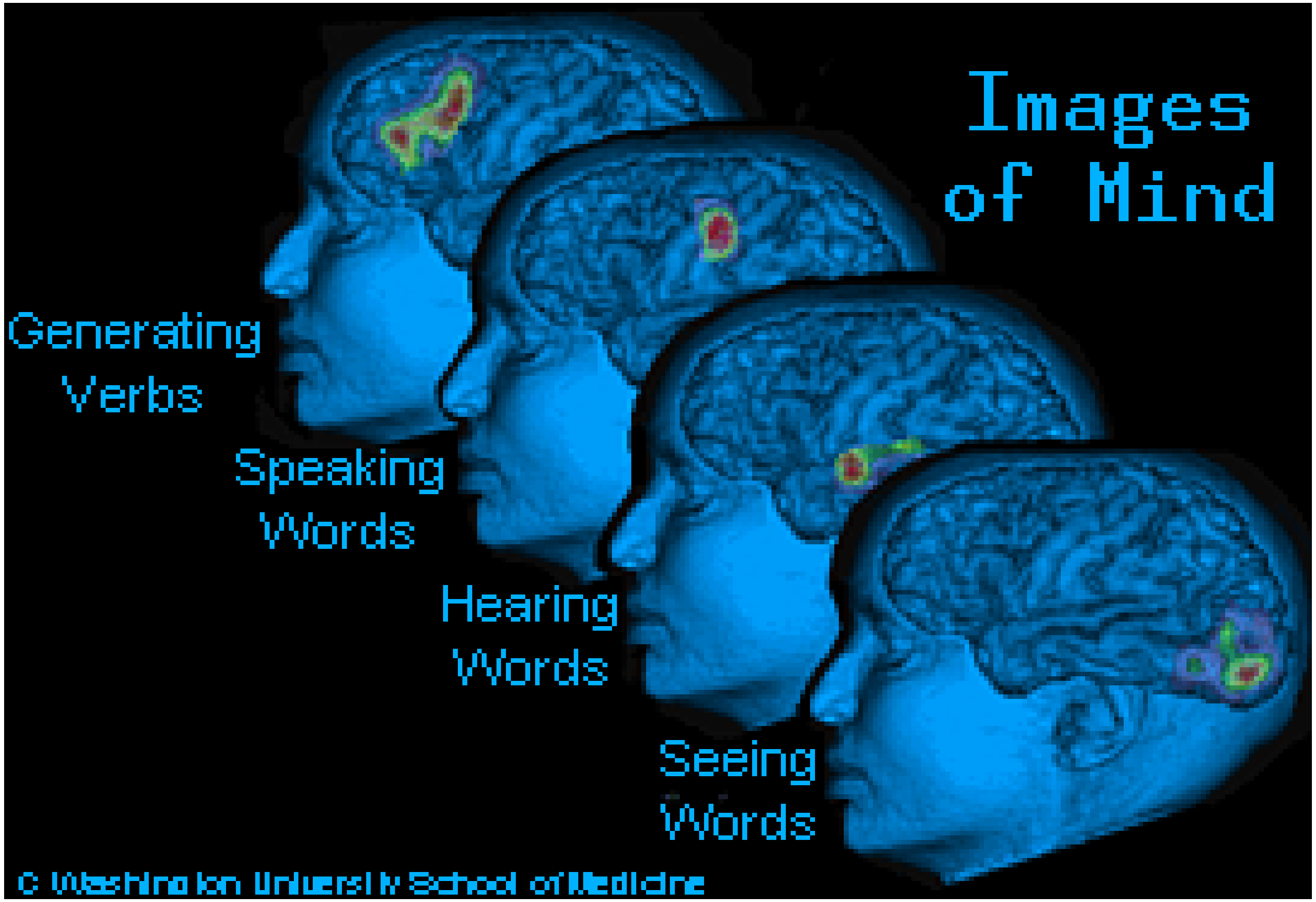
[From Pfurtscheller et al.]

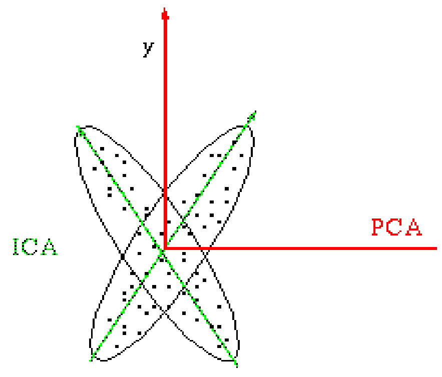
BBCI: Leitmotiv: *›let the machines learn‹*

EEG based noninvasive BCI



The cerebral cocktail party problem





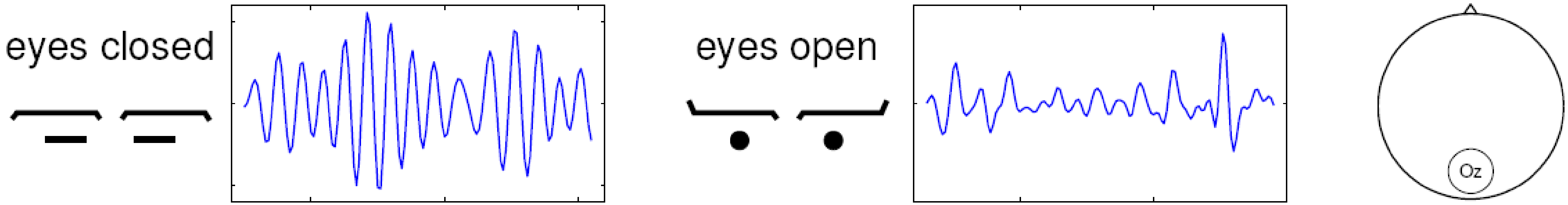
- use ICA/NGCA projections for artifact and noise removal
- feature extraction and selection

[cf. Ziehe et al. 2000, Blanchard et al. 2006]

Towards imaginations: Modulation of Brain Rhythms

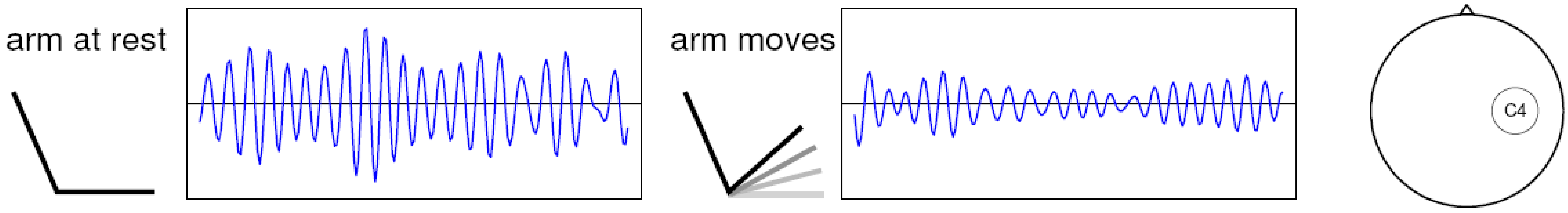
Most rhythms are idle rhythms, i.e., they are **attenuated** during activation.

- α-rhythm (around 10 Hz) in visual cortex:



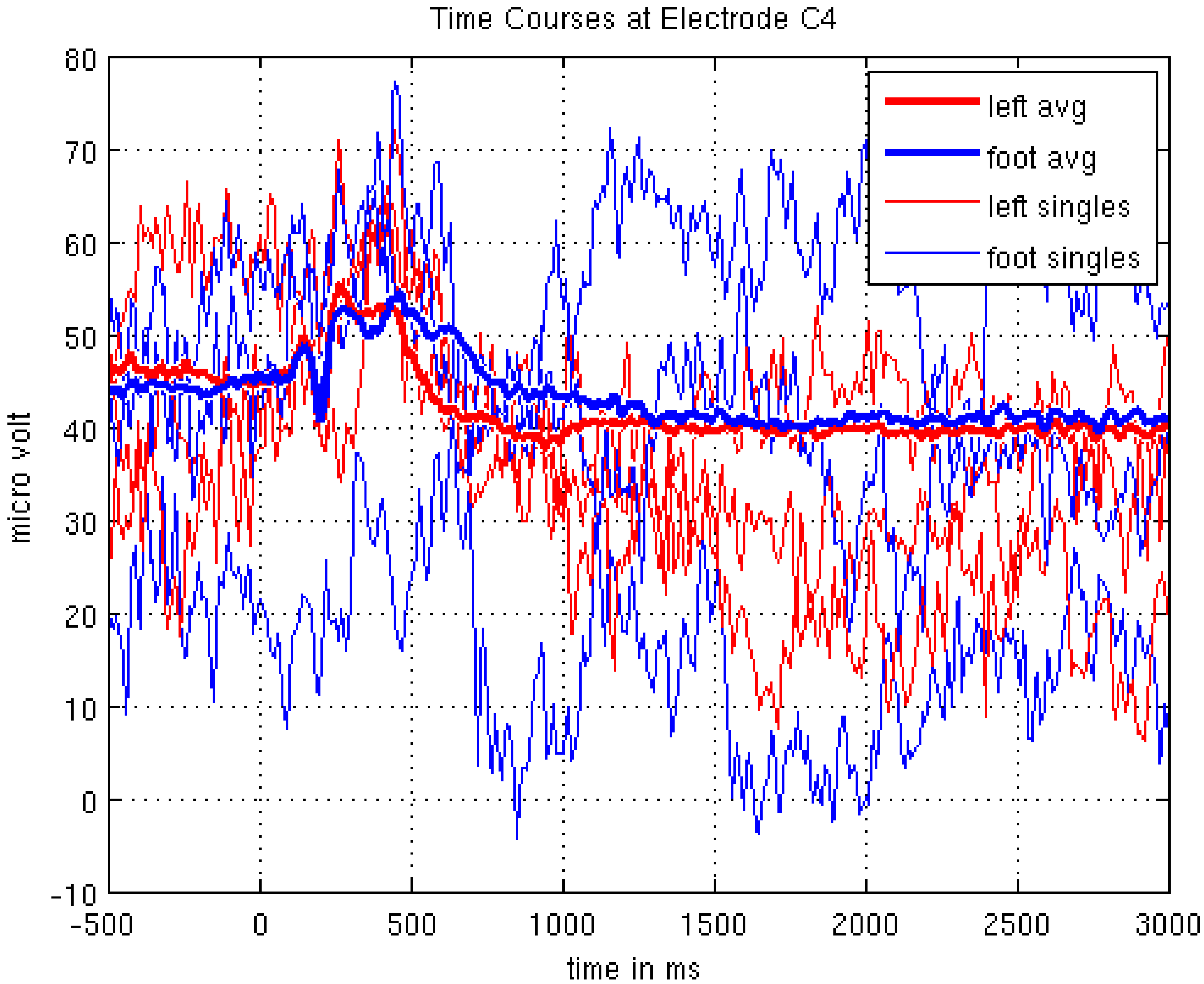
Single channel

- μ-rhythm (around 10 Hz) in motor and sensory cortex:



IMAGINATION of left arm

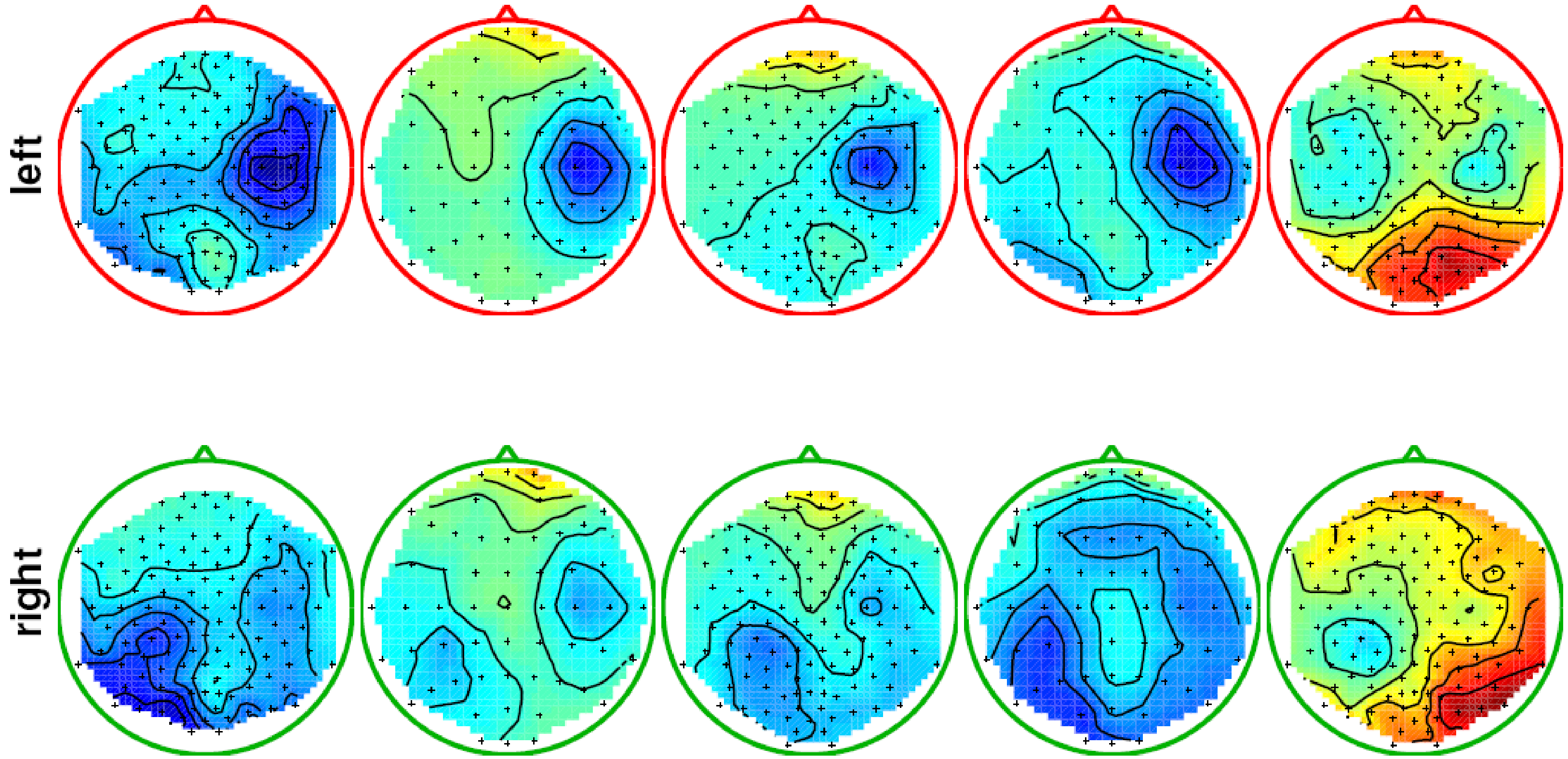
Variance I: Single-trial vs. Averaging



Single channel

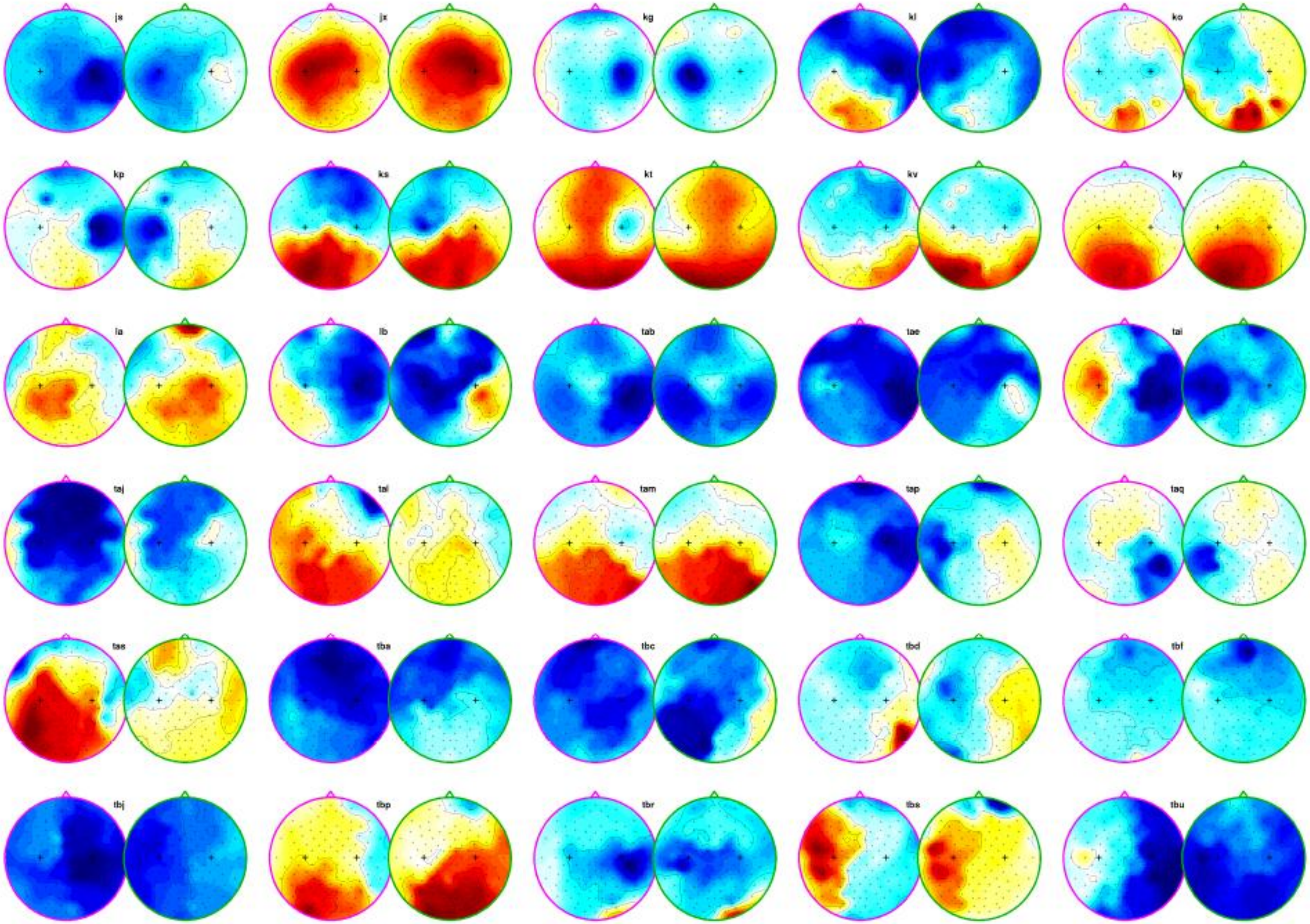
Variance II: Session to Session Variability

- Experiment: **One subject** imagined **left** vs. **right** hand movements on different days.
- Even though each ERD map represents an **average** across 140 trials, they exhibit an apparent diversity.

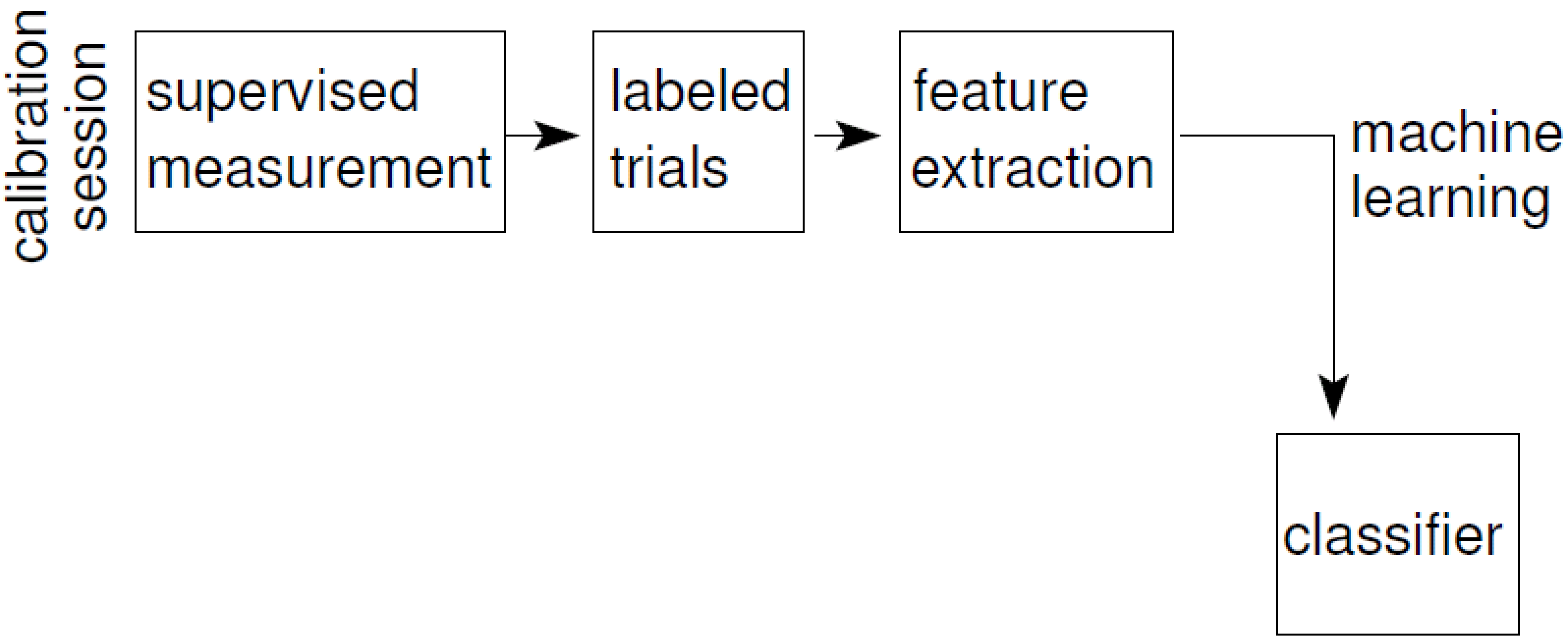


maps

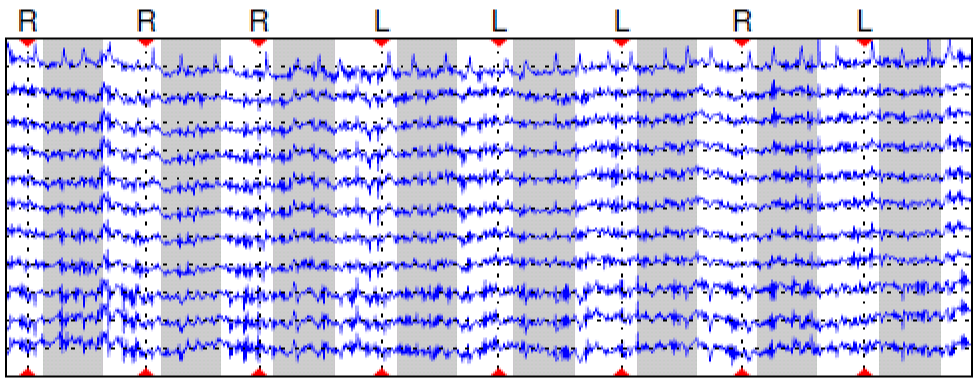
Variance III: inter subject variability [l vs r]



BCI with machine learning: training



offline: calibration (10–20 minutes)



collect training samples

BBCI paradigms

Leitmotiv: *›let the machines learn‹*

- healthy subjects *untrained* for BCI

A: training 20min: right/left hand **imagined** movements

$\longrightarrow$ infer the respective brain acivities (ML & SP)

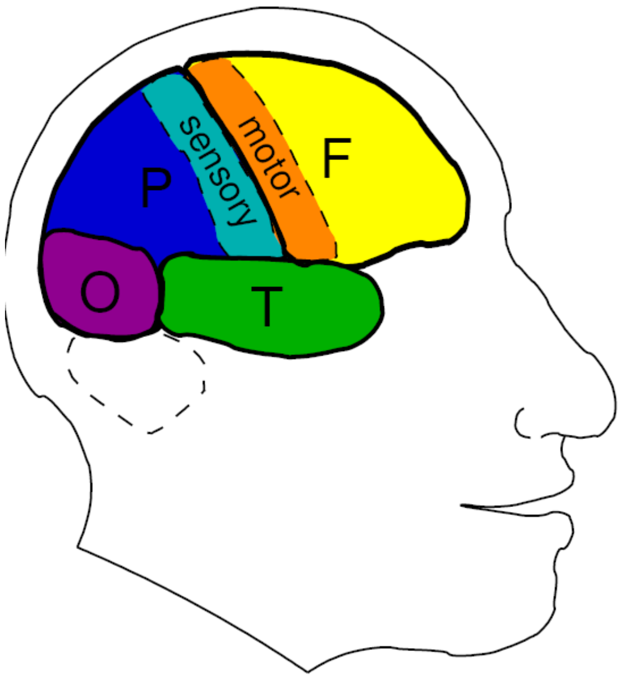
B: online feedback session

BBCI paradigms

Leitmotiv: *›let the machines learn‹*

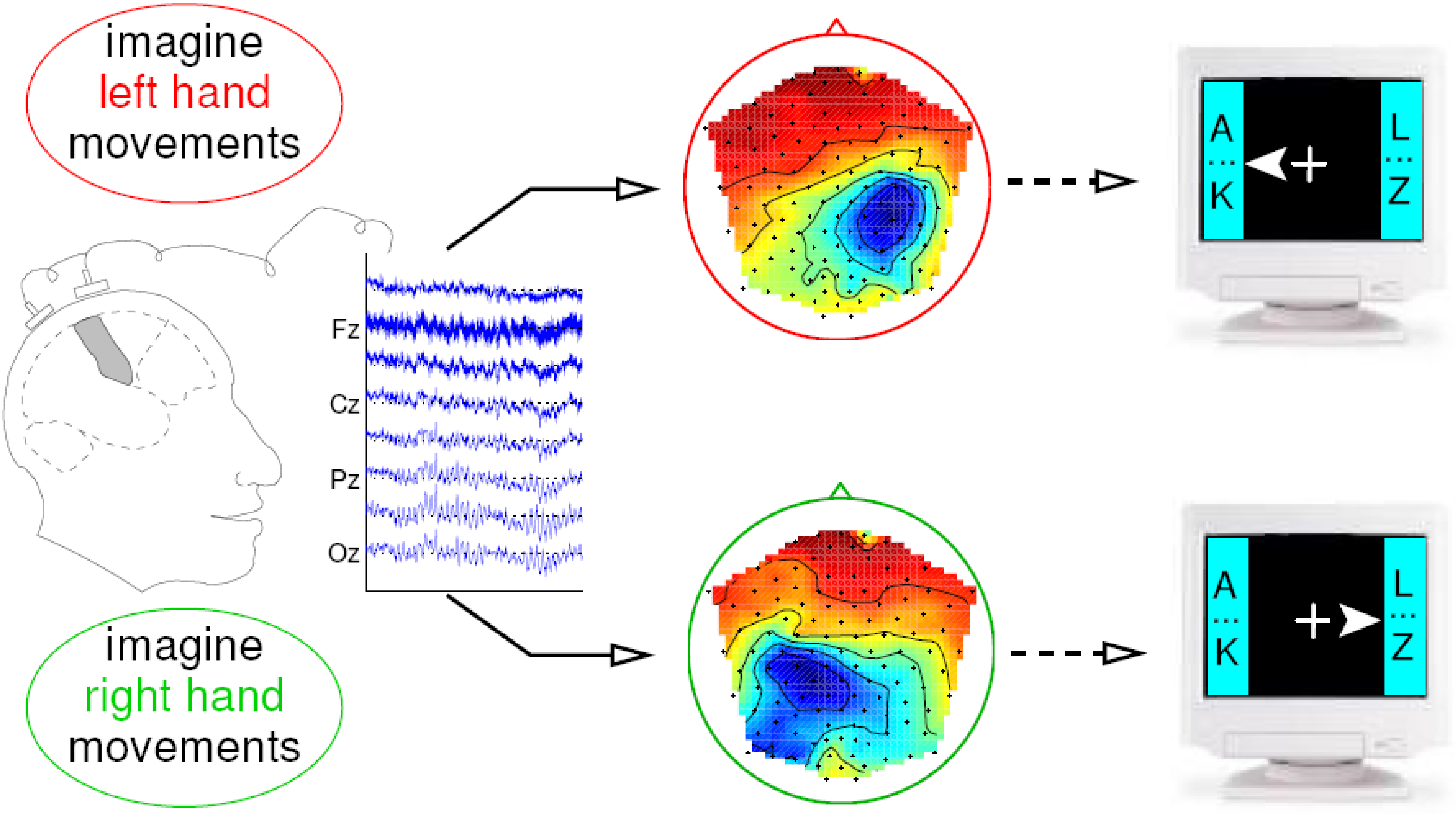
- healthy subjects (BCI *untrained*) perform "imaginary" movements (ERD/ERS)

- instruction: imagine
    - squezzing a ball,
    - kicking a ball,
    - feel touch



Playing with BCI: training session (20 min)

Machine learning approach to BCI: infer prototypical pattern

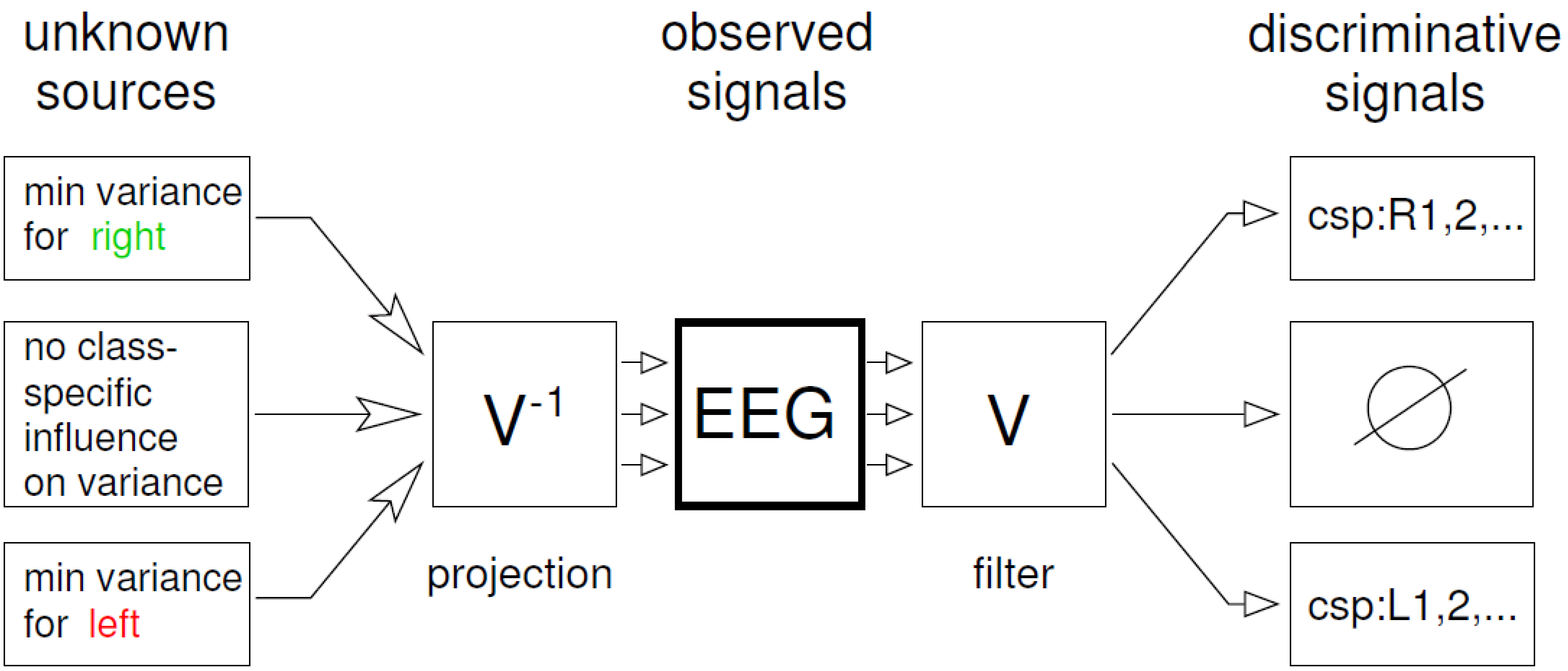


Inference by CSP Algorithm

Common Spatial Pattern Analysis

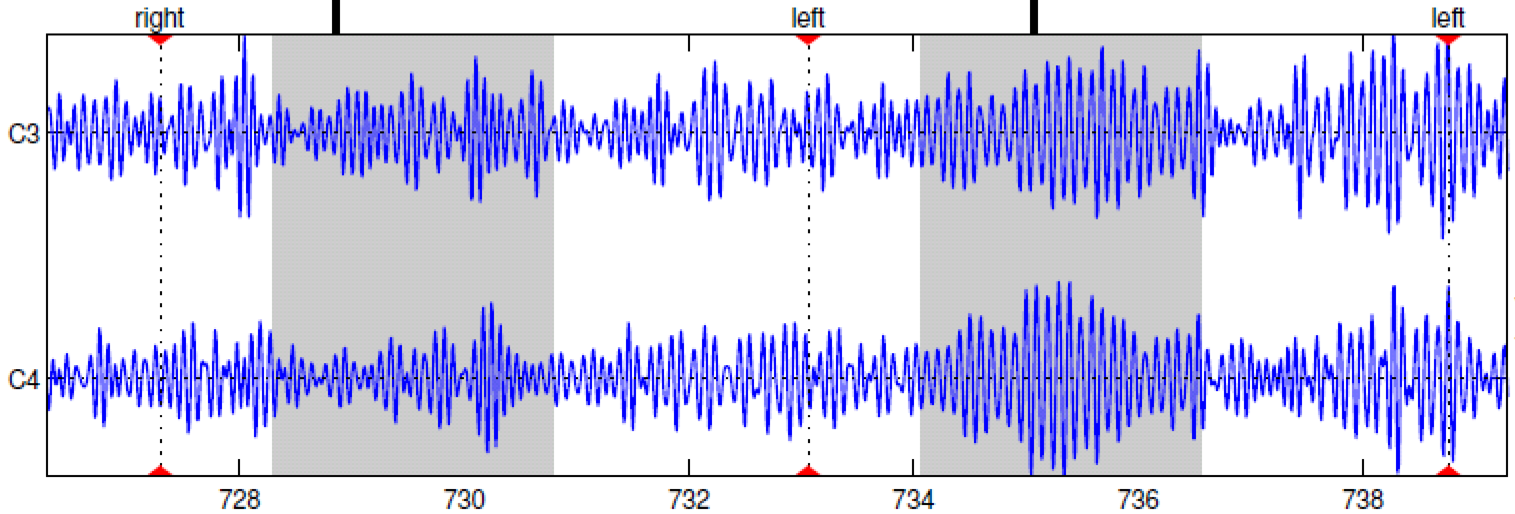
Goal: Find spatial filters that optimally capture modulations of brain rhythms

Observation: power of a brain rhythm $\sim$ variance of band-pass filtered signal.



CSP I

EEG-signals during **motor imagery**, band-pass filtered (here 9–13 Hz):



left data X_{L} (time×chans)

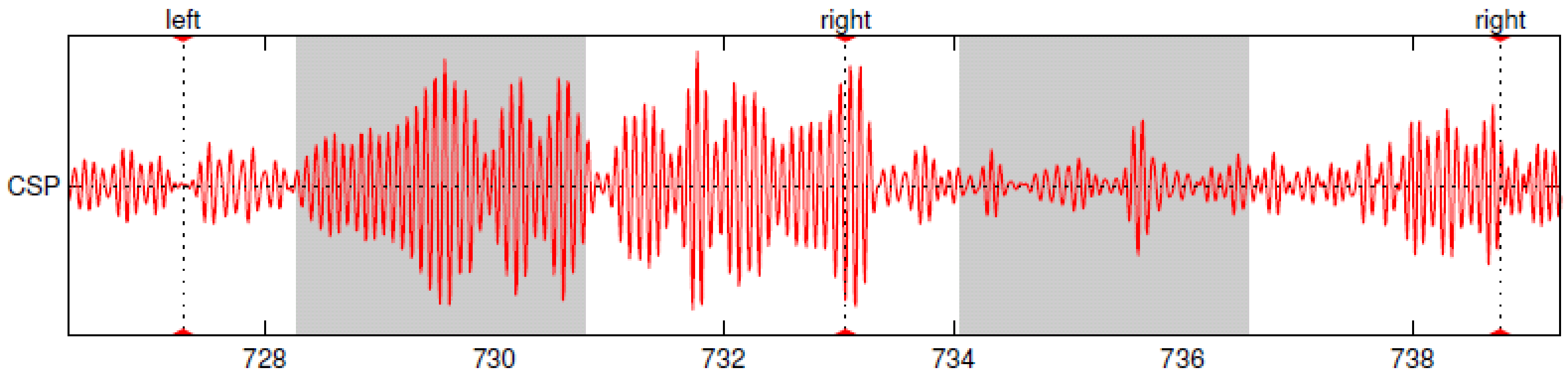
right data X_{R} (time×chans)

$\Sigma_{\mathsf{L}} := X_{\mathsf{L}}^{\top} X_{\mathsf{L}}$

$\Sigma_{\mathsf{R}} := X_{\mathsf{R}}^{\top} X_{\mathsf{R}}$

$$V^{\top} \Sigma_{\mathsf{L}} V = D \quad \& \quad V^{\top}(\Sigma_{\mathsf{L}} + \Sigma_{\mathsf{R}})V = I$$

$\rightarrow$ choose eigenvector v_i from V that has a **large** eigenvalue d_i w.r.t. Σ_{L}.

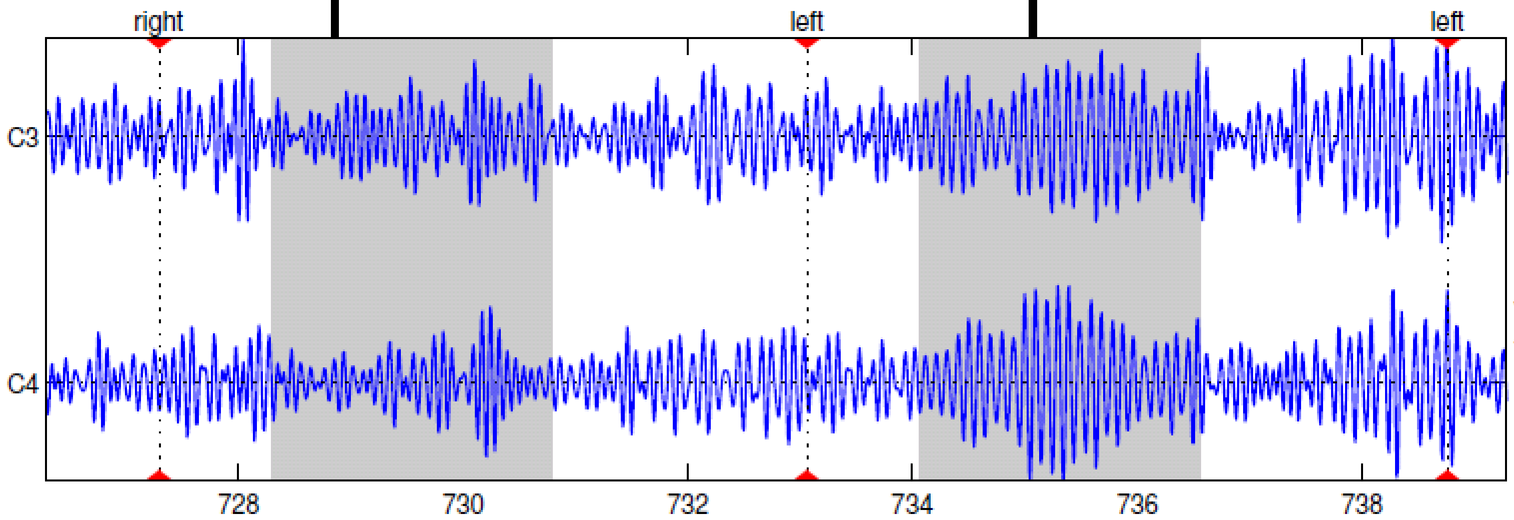


$\mathrm{var}(X_{\mathsf{L}} v_i) = d_i$ large

$\mathrm{var}(X_{\mathsf{R}} v_i) = 1 - d_i$ small

CSP II

EEG-signals during **motor imagery**, band-pass filtered (here 9–13 Hz):



left data X_L (time×chans)

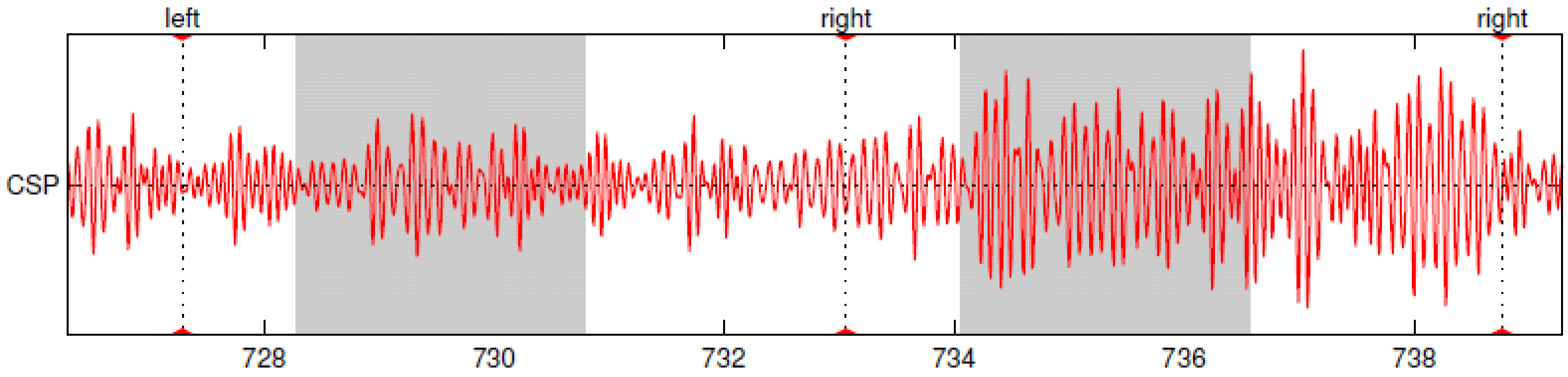
right data X_R (time×chans)

$$\Sigma_\mathsf{L} := X_\mathsf{L}^\top X_\mathsf{L}$$

$$\Sigma_\mathsf{R} := X_\mathsf{R}^\top X_\mathsf{R}$$

$$V^\top \Sigma_\mathsf{L} V = D \quad \& \quad V^\top(\Sigma_\mathsf{L} + \Sigma_\mathsf{R})V = I$$

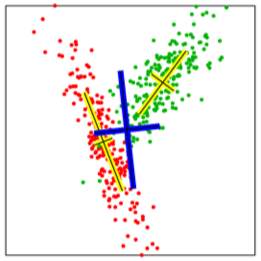
$\rightarrow$ choose eigenvector v_i from V that has a **small** eigenvalue d_i w.r.t. Σ_L.



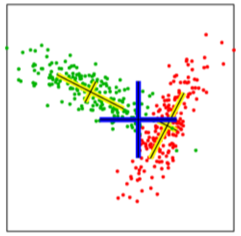
$\mathrm{var}(X_\mathsf{L} v_i) = d_i$ small

$\mathrm{var}(X_\mathsf{R} v_i) = 1 - d_i$ large

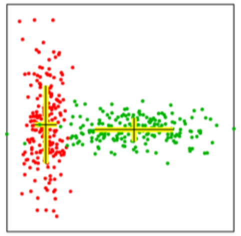
Common Spatial Patterns for 2 classes



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 $\Sigma_1 + \Sigma_2$.



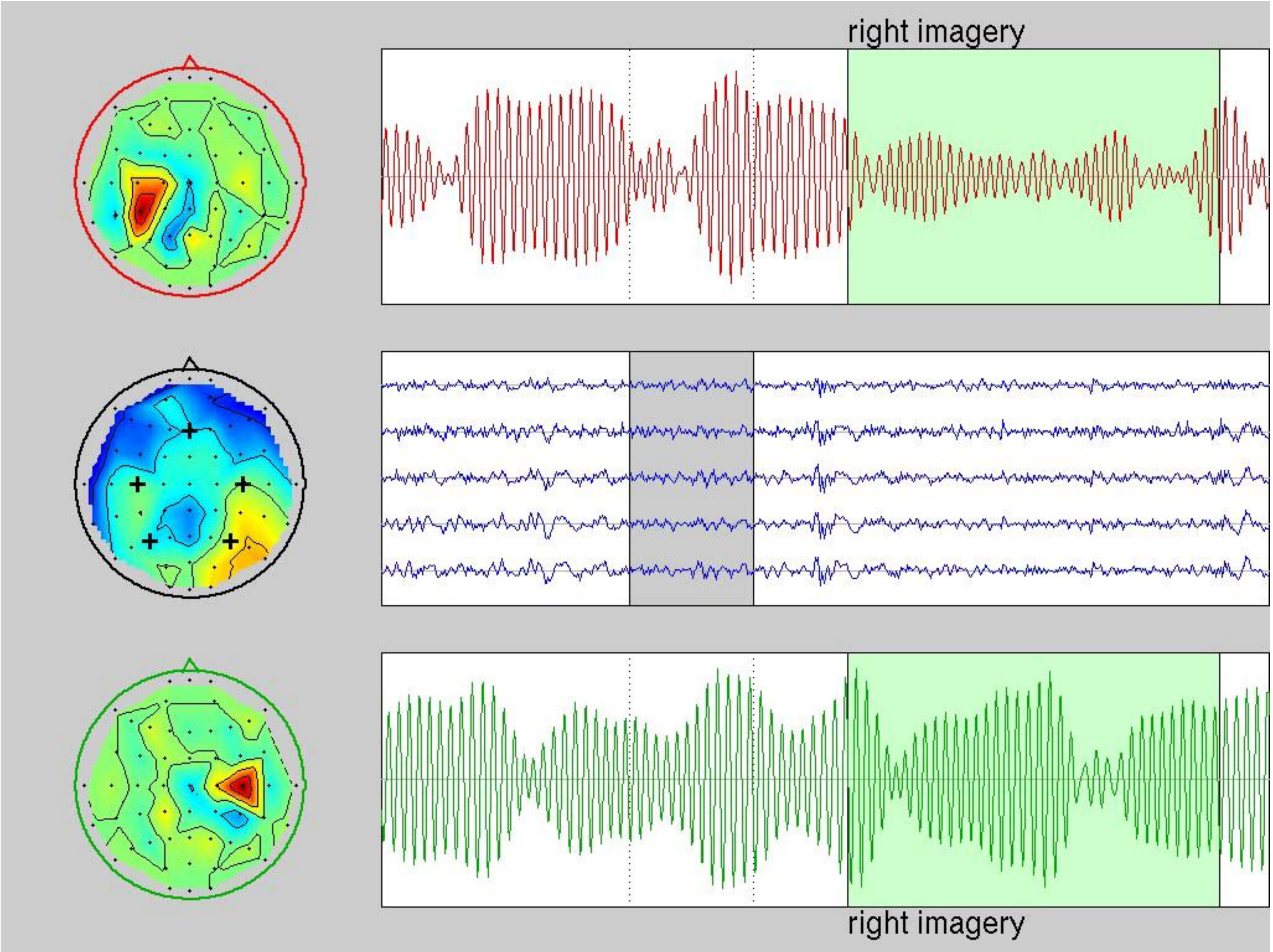
Make a whitening of $\Sigma_1 + \Sigma_2$, i.e., determine matrix P such that $P(\Sigma_1 + \Sigma_2)P^\top = I$ (possible due to positive definiteness of $\Sigma_1 + \Sigma_2$).
➤ Principal axis of the classes are perpendicular. Define: $\hat{\Sigma}_i = P\Sigma_i P^\top$.



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.

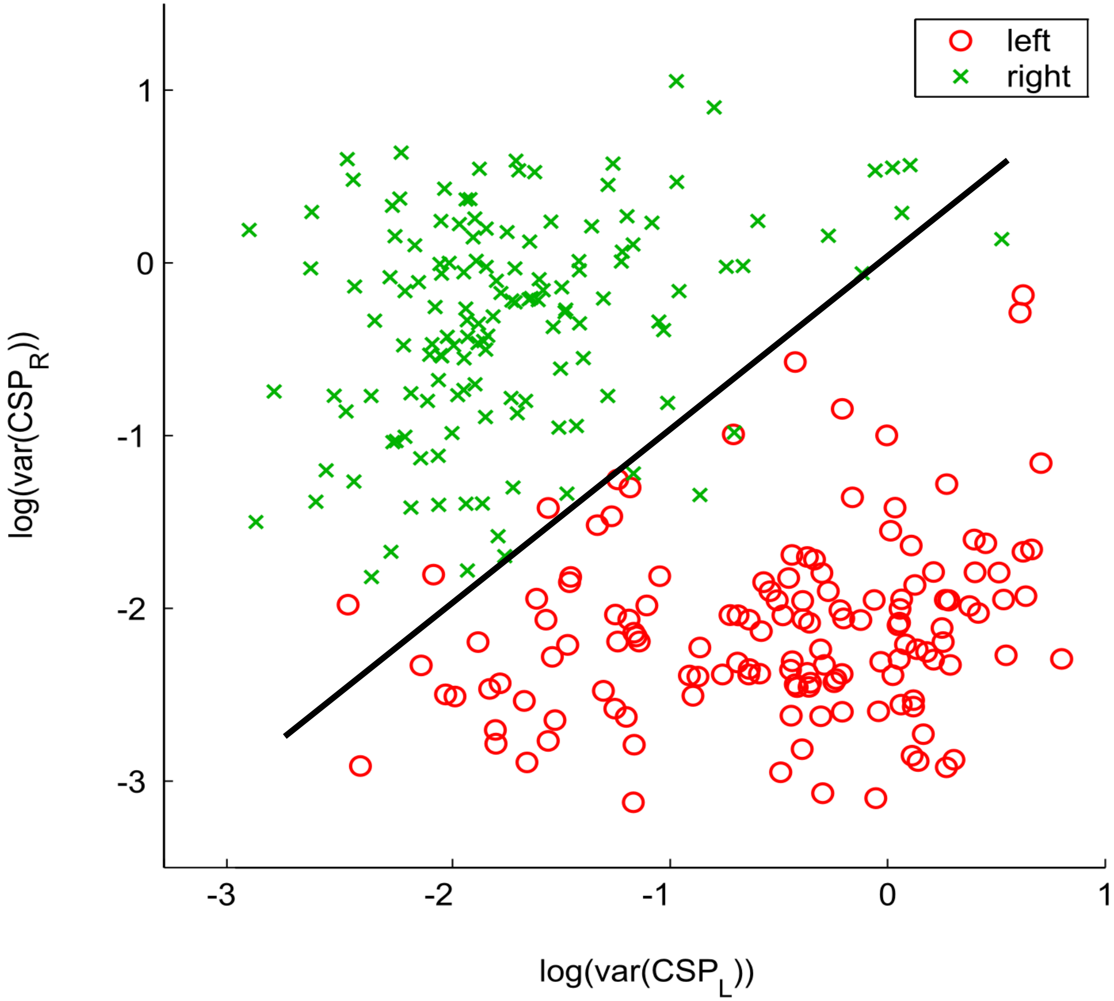
Essential idea for multi-class extension:
CSP is based on the **simultaneous diagonalization** of two covariance matrices with corresponding eigenvalues summing up to 1.

[cf. Blankertz et al. 2008, Lemm et al. 2005, Dornhege et al. 2006, Tomioka & Müller in Press]

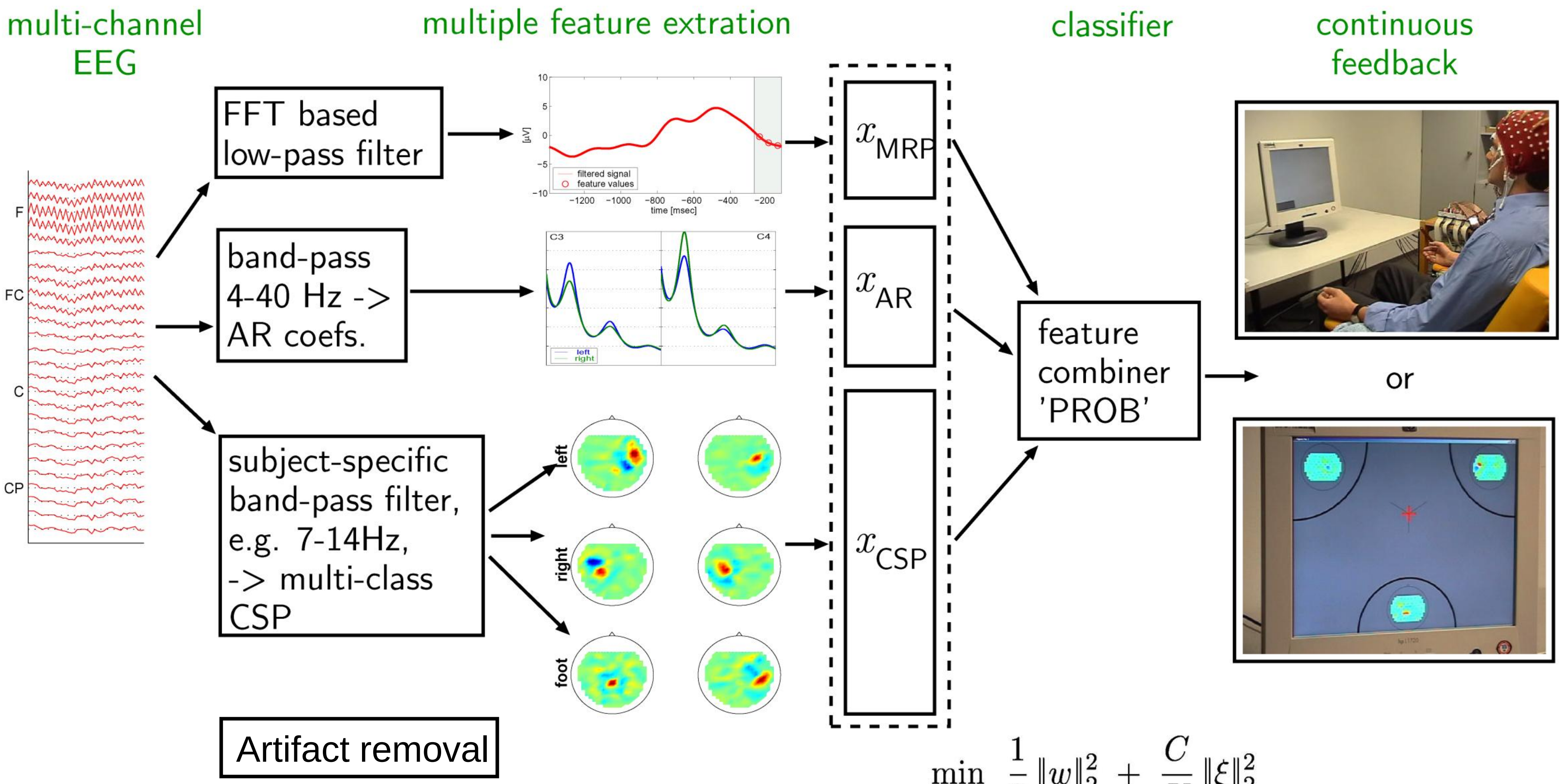


right imagery
right imagery

Distribution of EEG features



BBCI Set-up

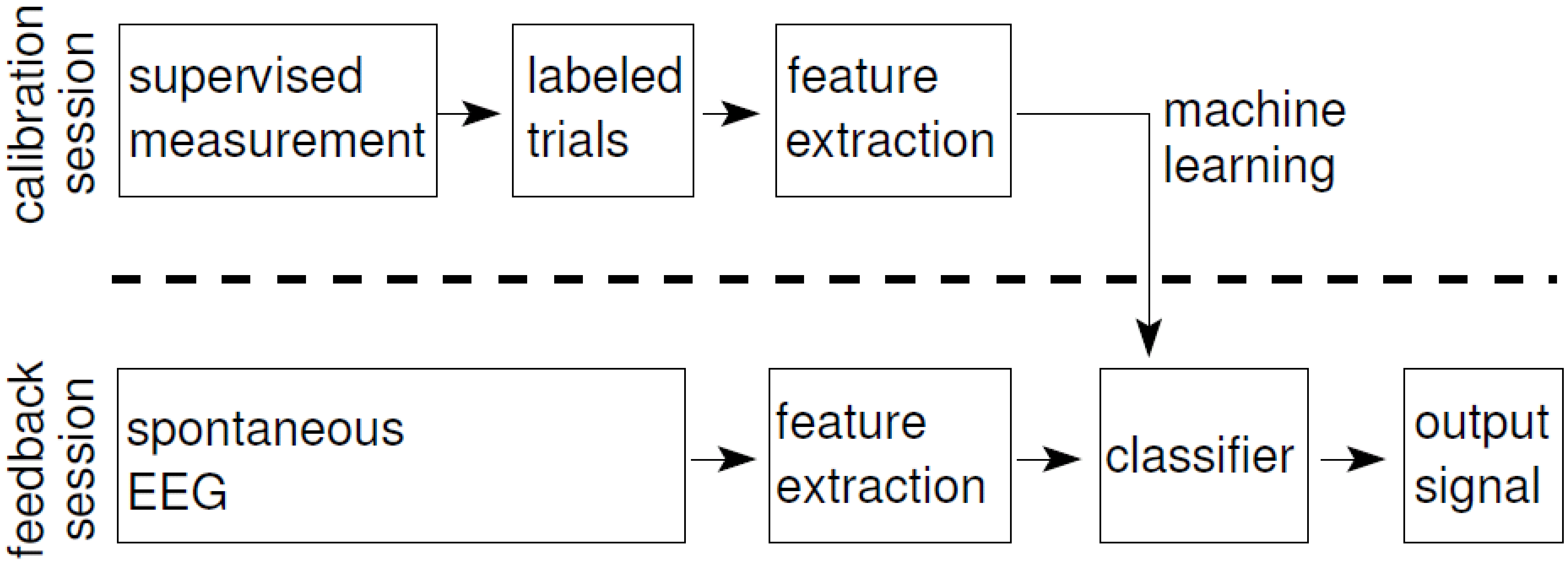


$$\min_{w,b,\xi} \ \frac{1}{2}\|w\|_2^2 + \frac{C}{K}\|\xi\|_2^2$$

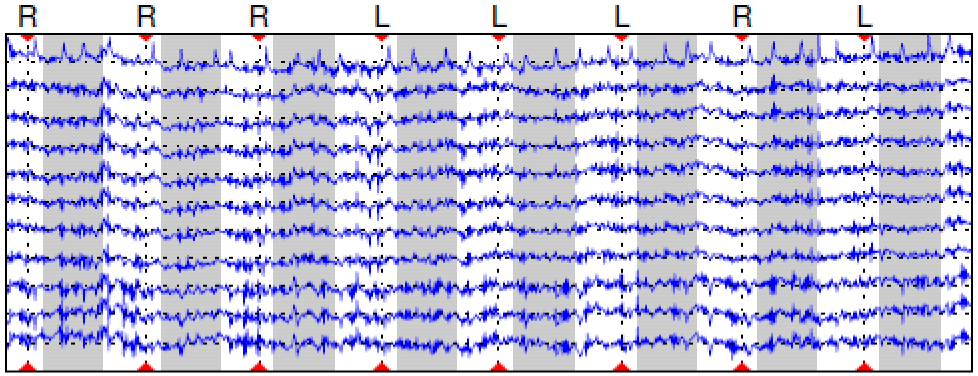
$$\text{subject to} \qquad y_k(w^\top x_k + b) = 1 - \xi_k \quad \text{for } k = 1, \ldots, K$$

[cf. Müller et al. 2001, 2007, 2008, Dornhege et al. 2003, 2007, Blankertz et al. 2004, 2005, 2006, 2007, 2008]

BCI with machine learning: feedback

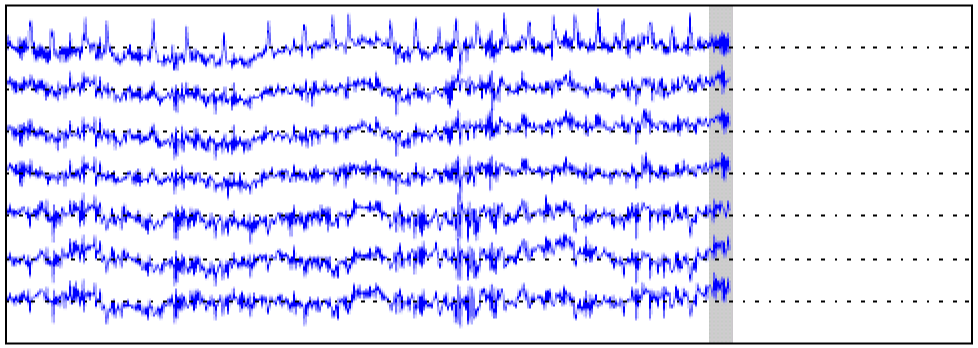


offline: calibration (10–20 minutes)



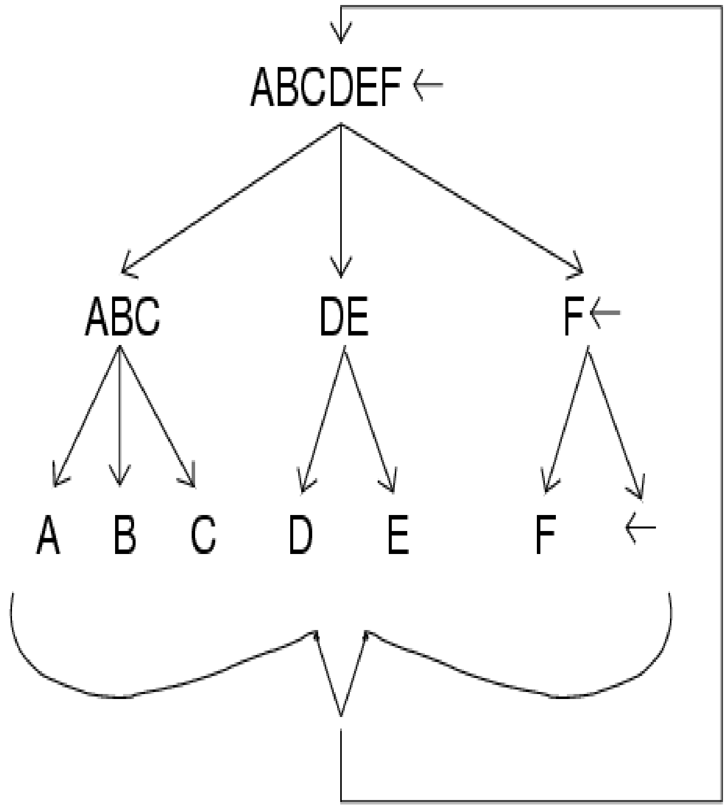
collect training samples

online: feedback (up to 6 hours)

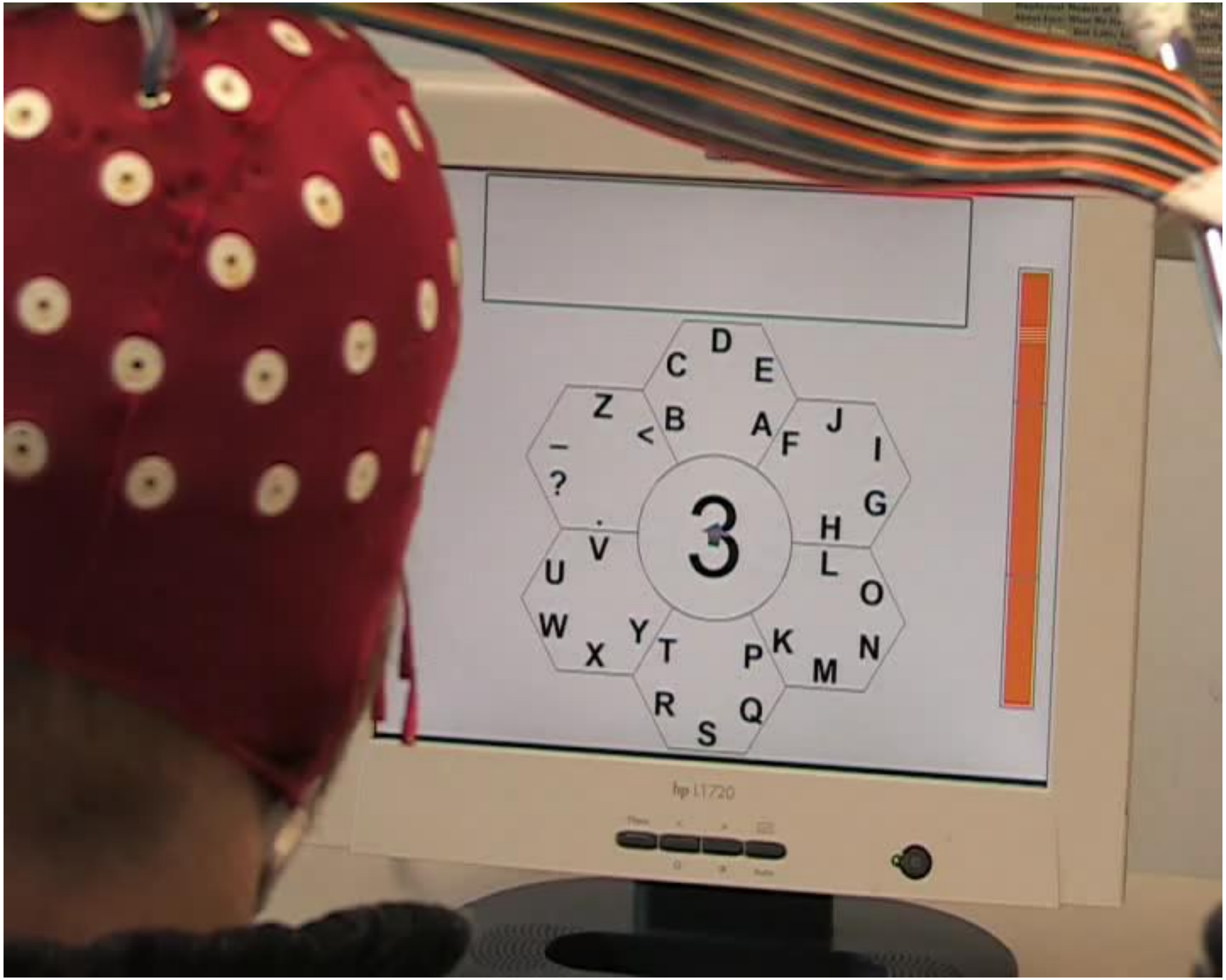


classification of sliding windows ($\leq$ 1s)

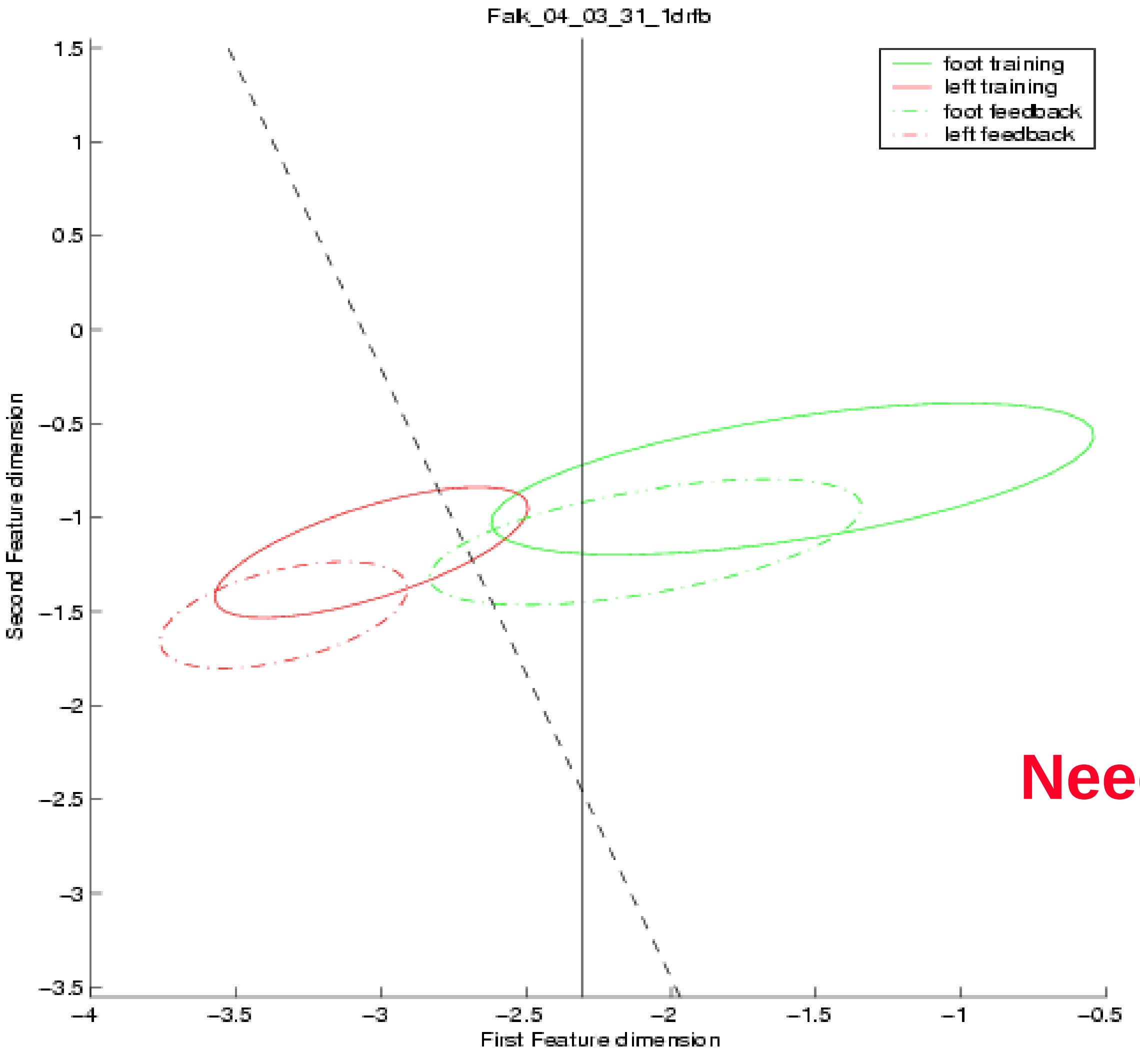
Spelling with BBCI: a communication for the disabled I



Spelling with BBCI: a communication for the disabled II



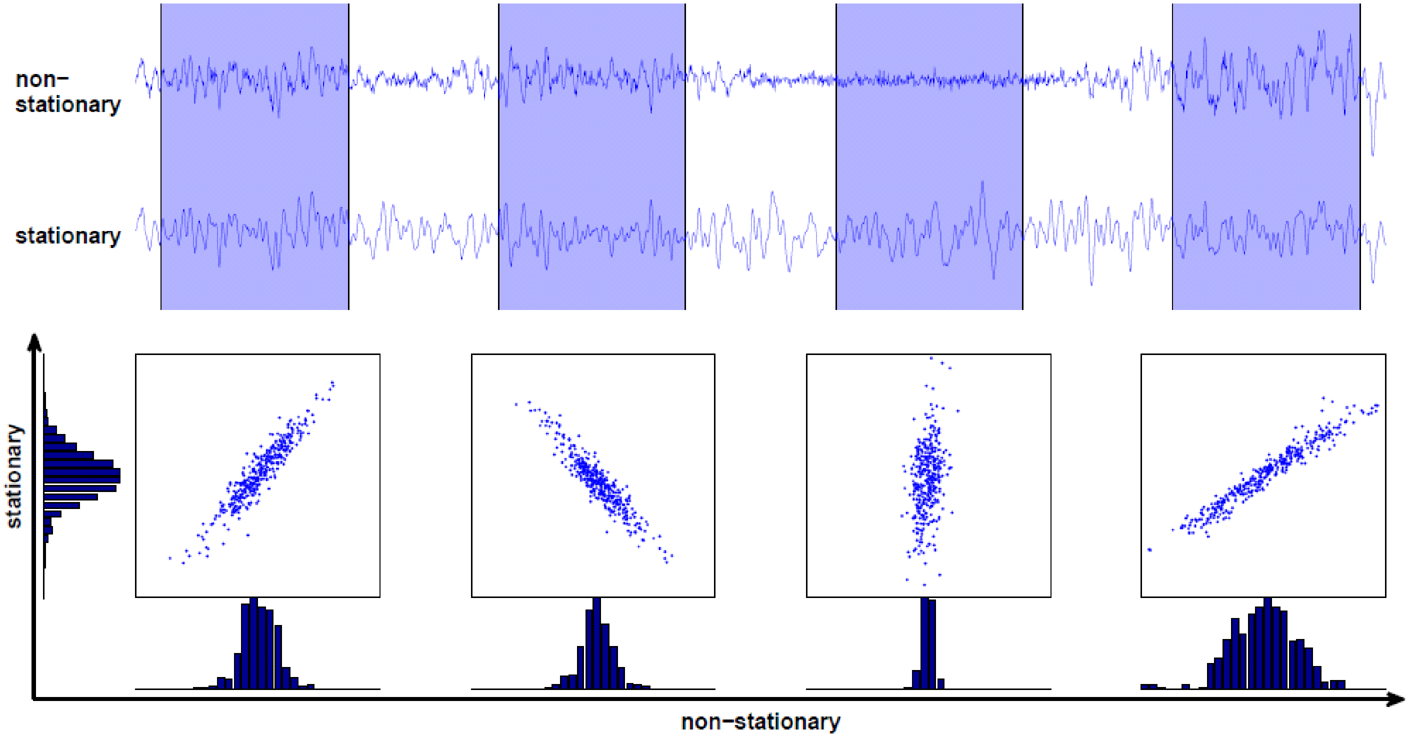
Variance IV: covariate shift: from training to feedback



Need for adaptation !

[cf. Sugiyama & Müller 2005, Shenoy et al. 2005,
Sugiyama et al. 2007]

Splitting into stationary and nonstationary subspace: SSA



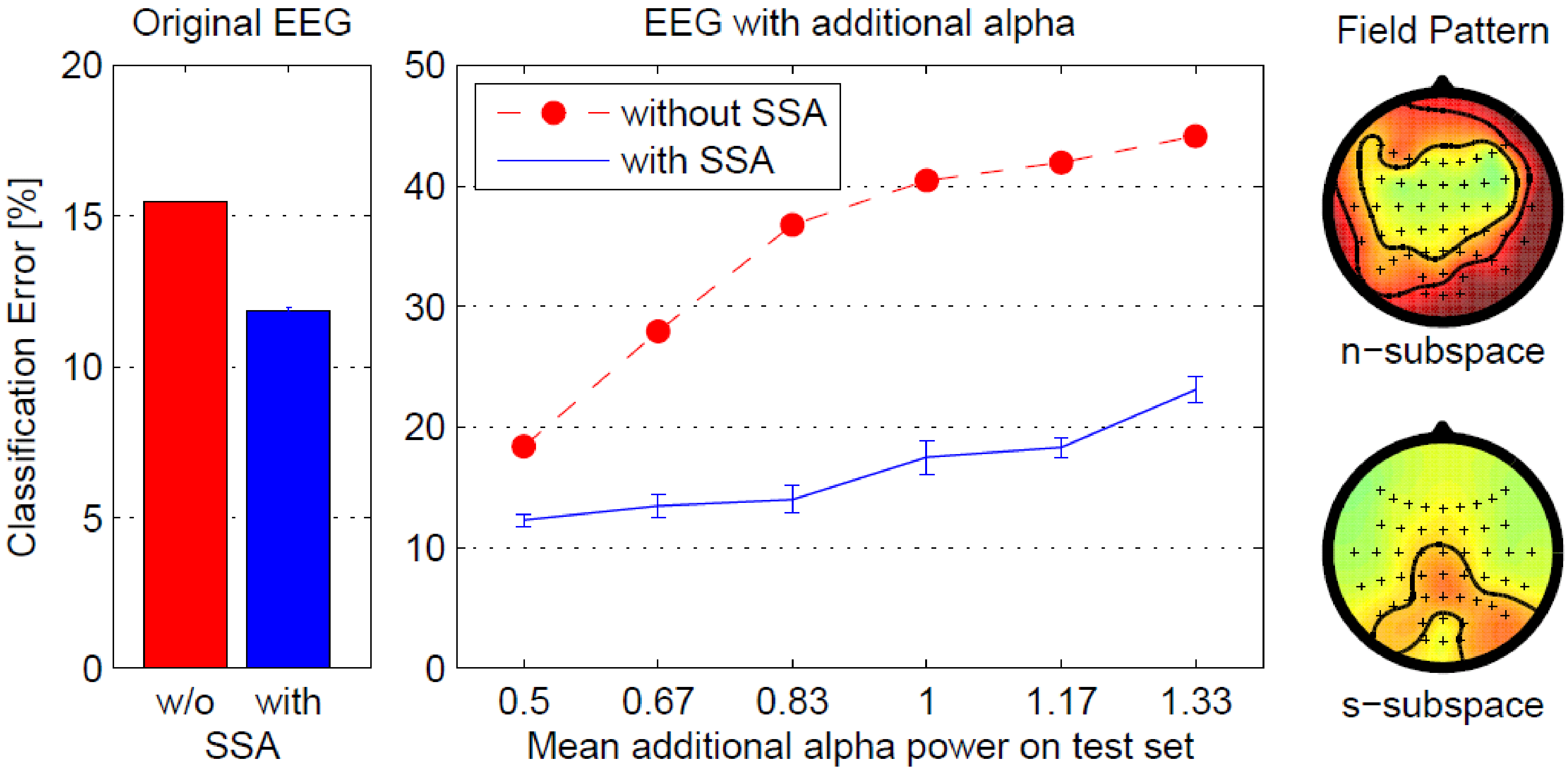
- d stationary source signals $s^{\mathfrak{s}}(t) \in \mathbb{R}^{d}$
- $D - d$ non-stationary source signals $s^{\mathfrak{n}}(t) \in \mathbb{R}^{(D-d)}$
- Observed signals: instantaneous linear superpositions of sources

$$x(t) = As(t) = \begin{bmatrix} A^{\mathfrak{s}} & A^{\mathfrak{n}} \end{bmatrix} \begin{bmatrix} s^{\mathfrak{s}}(t) \\ s^{\mathfrak{n}}(t) \end{bmatrix}$$

invert

[cf. Bünau, Meinecke, Kiraly, Müller PRL 09]

Splitting into stationary and nonstationary subspace: SSA II



Towards Application: Predicting drowsiness

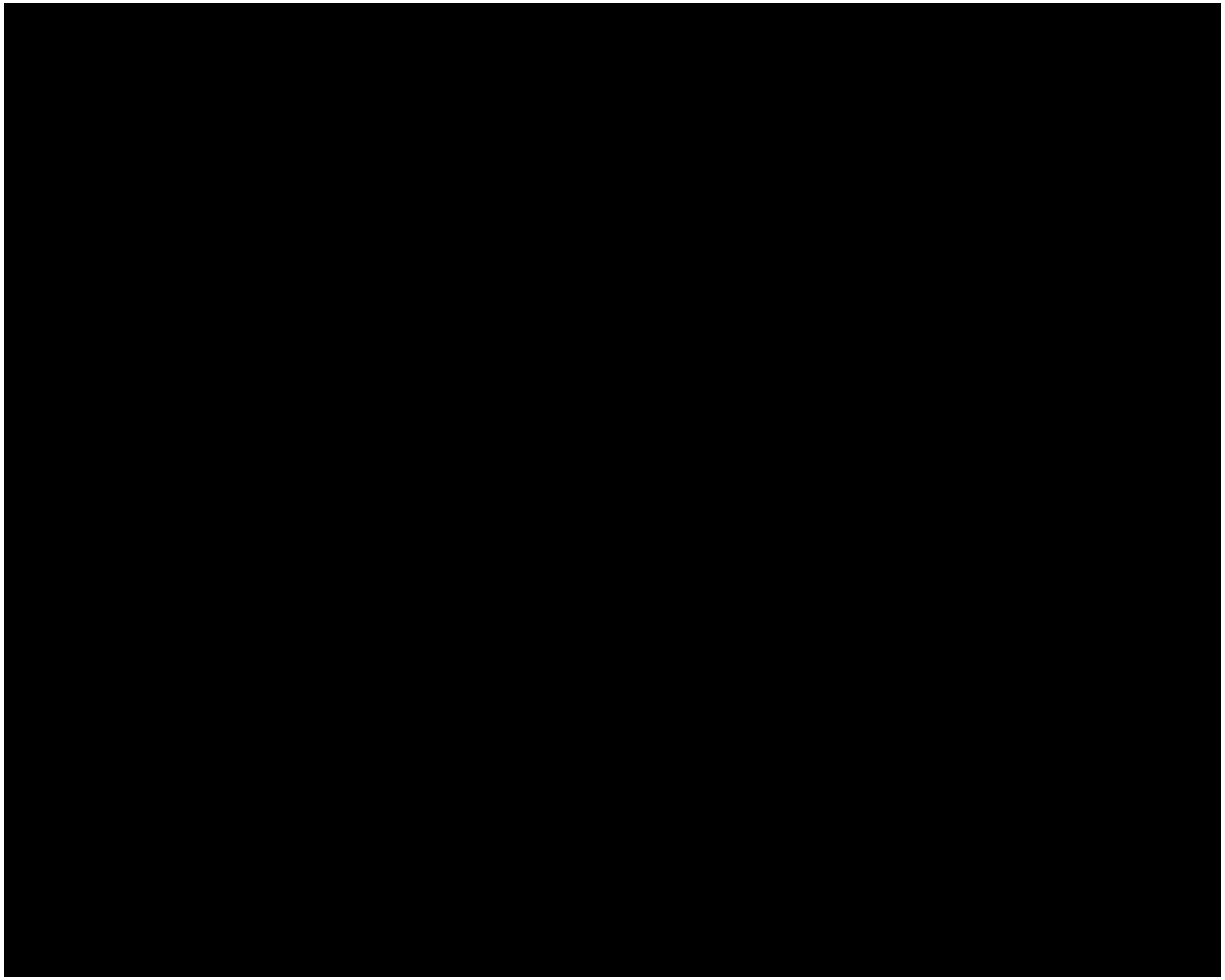
Application: Cognitive workload and drowsyness assessment

Assess workload with BCI and balance it by smart driver assistent system

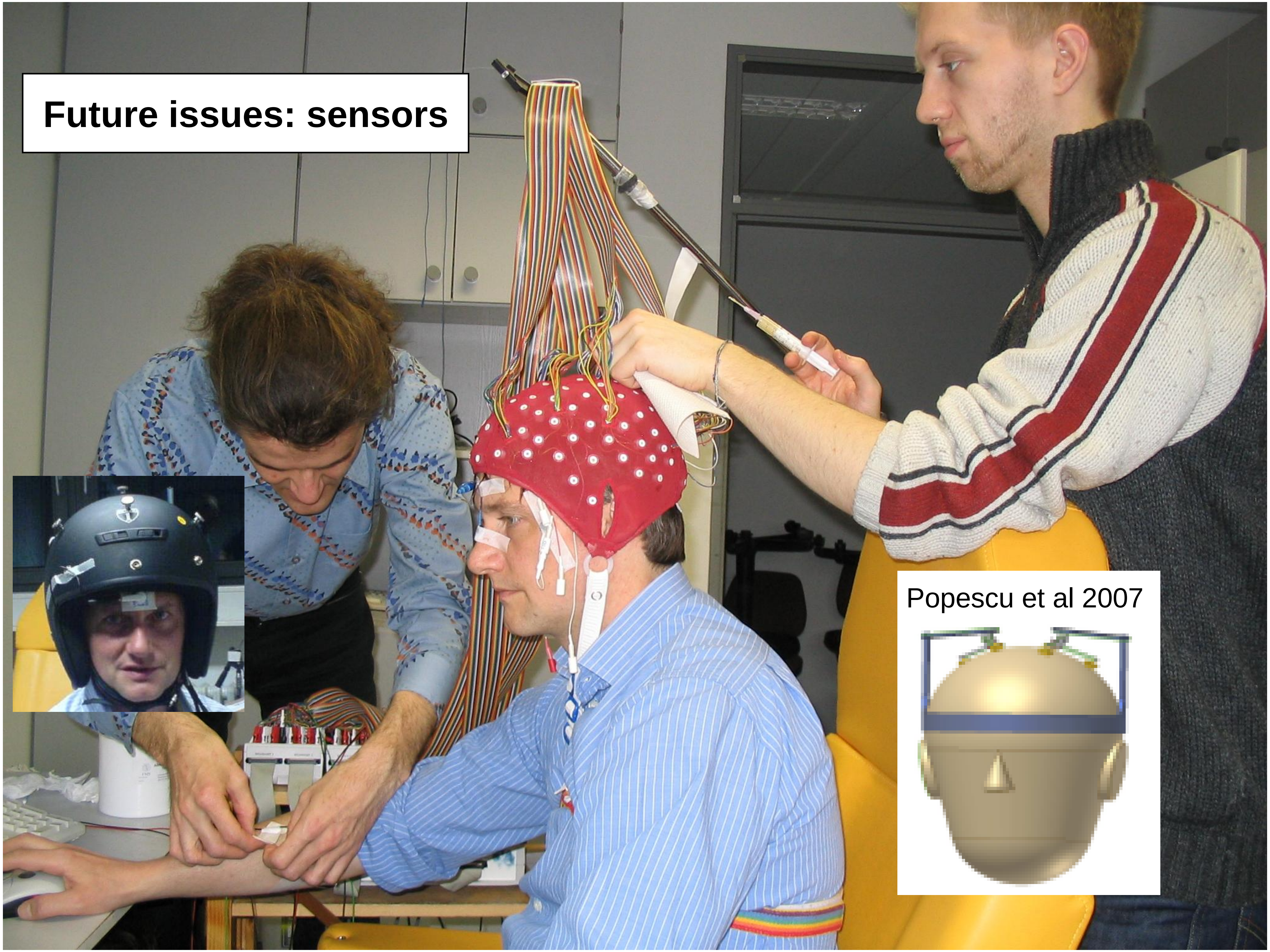
Assess cognitive alertness

[Kohlmorgen, Müller et al 2007]

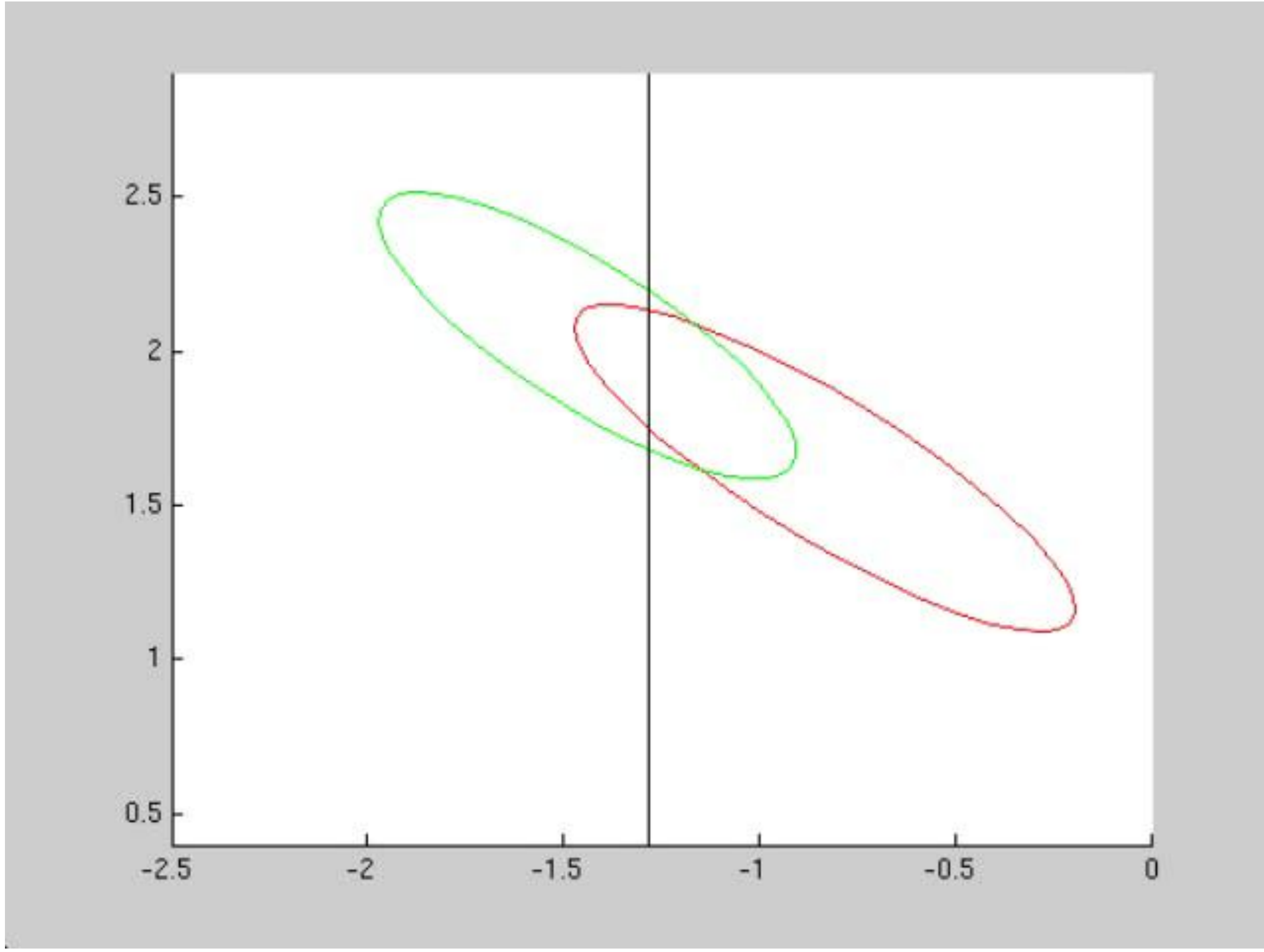
Real Man Machine Interaction



Future issues: sensors



Future Issues: Shifting distributions within experiment



Conclusion

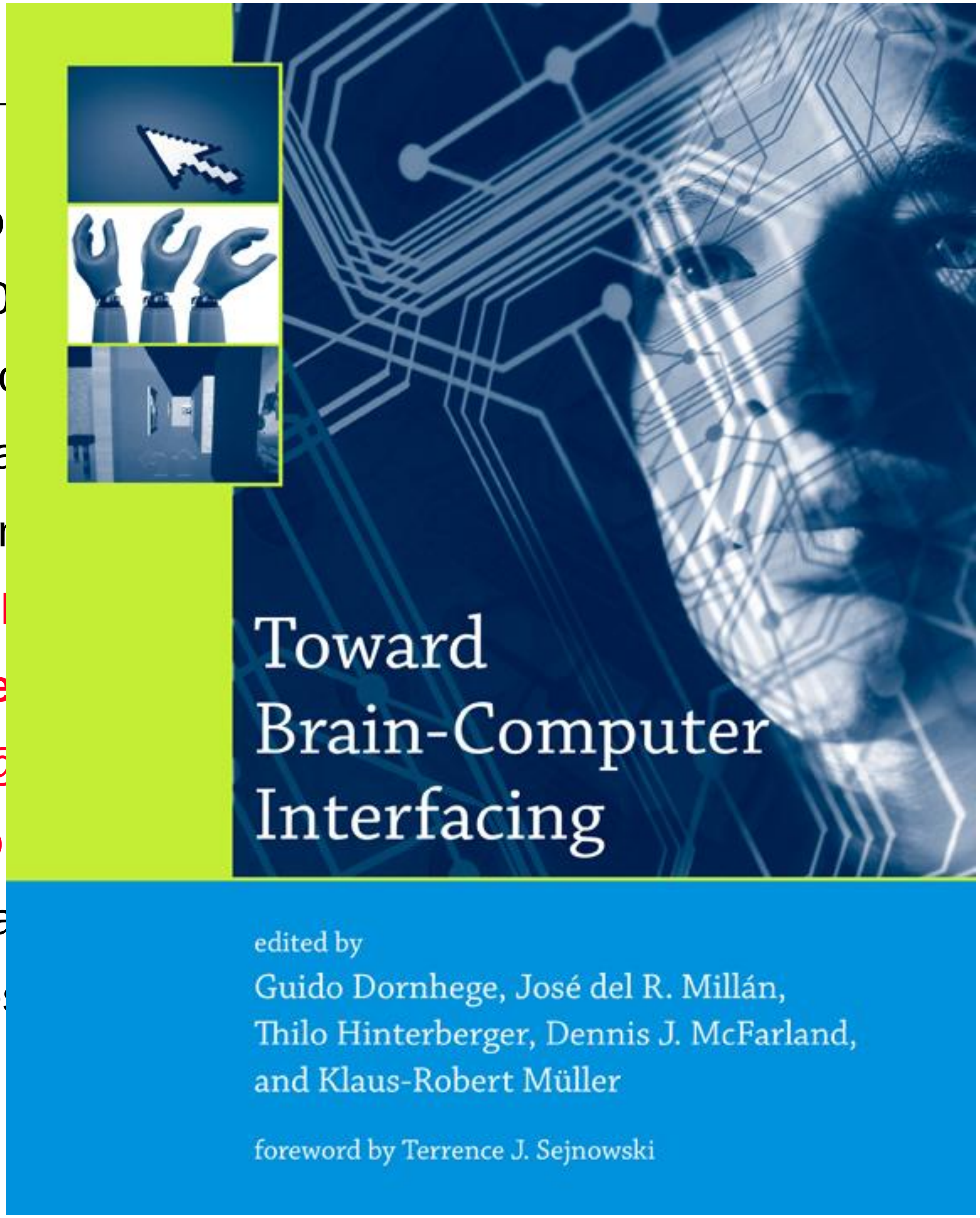
- BBCI: non-invasive with high Info
- BBCI: Untrained, Calibration < 20
- 5-8 letters/min mental typewriter c
- Machine Learning and modern da
- Applications: communication vs. r

  Rehabilitation: **TOBI EU IP, EU I**

  Computational Neuroscience: **Be**

  Man Machine Interaction: **brain@**
- BBCI Sensors, software: **IDA sp**
- towards no training, non-coopera
- ‚illiterates', nonstationarity, wireles

FOR INFORMATION SEE:
www.bbci.de



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Overview of BCI Competitions

BCI competition I	BCI competition II
December 2001 – June 2002	December 2003 – June 2004
3 datasets	6 datasets
10 submissions	59 submissions
[Sajda et al., 2003]	[Blankertz et al., 2004]

BCI Competition III

- Dec 12th 2004 – May 31st 2005
- announcement of the results: between June 14th and 19th 2005
- 8 datasets from 5 different BCI groups with different tasks

For BCI IV Competition see www.bbci.de

BBCI

berlin
brain computer
interface

FOR INFORMATION SEE: www.bbci.de

Machine Learning open source software initiative: MLOSS see

www.jmlr.org