Toward Brain Computer Interfacing

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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.]
EEG based noninvasive BCI
The cerebral cocktail party problem

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

Towards imaginations: Modulation of Brain Rhythms

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

- \( \alpha \)-rhythm (around 10 Hz) in visual cortex:

  ![Waveform](image)

  **Single channel**

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

  ![Waveform](image)
Variance I: Single-trial vs. Averaging

Time Courses at Electrode C4

- left avg
- foot avg
- left singles
- foot singles

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.
Variance III: inter subject variability [l vs r]
**BCI with machine learning: training**

- **calibration session**
  - supervised measurement
  - labeled trials
  - feature extraction

- **machine learning**
  - classifier

**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
   → infer the respective brain activities (ML & SP)

B: online feedback session
BBCI paradigms

Leitmotiv: «let the machines learn»

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

- instruction: imagine
  - squeezing a ball,
  - kicking a ball,
  - feel touch
Playing with BCI: training session (20 min)
Machine learning approach to BCI: infer prototypical pattern

Imagine left hand movements

Imagine right hand movements

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.

- **unknown sources**
  - min variance for right
  - no class-specific influence on variance
  - min variance for left

- **observed signals**
  - $V^{-1}$ projection
  - $V$ filter

- **discriminative signals**
  - csp:$R1,2,...$
  - csp:$L1,2,...$

$V^{-1}$ represents the projection step, and $V$ represents the filter step.
EEG-signals during **motor imagery**, band-pass filtered (here 9–13 Hz):

\[
\begin{align*}
\Sigma_L & := X_L^T X_L \\
\Sigma_R & := X_R^T X_R
\end{align*}
\]

\[
V^T \Sigma_L V = D \quad \& \quad V^T (\Sigma_L + \Sigma_R) V = I
\]

→ choose eigenvector \( v_i \) from \( V \) that has a **large** eigenvalue \( d_i \) w.r.t. \( \Sigma_L \).

\[
\text{var}(X_L v_i) = d_i \quad \text{large} \\
\text{var}(X_R v_i) = 1 - d_i \quad \text{small}
\]
EEG-signals during **motor imagery**, band-pass filtered (here 9–13 Hz):

\[ \Sigma_L := X_L^T X_L \]
\[ \Sigma_R := X_R^T X_R \]

\[ V^T \Sigma_L V = D \quad \& \quad V^T (\Sigma_L + \Sigma_R) V = I \]

→ choose eigenvector \( v_i \) from \( V \) that has a **small** eigenvalue \( d_i \) w.r.t. \( \Sigma_L \).

\[ \var(X_L v_i) = d_i \text{ small} \]
\[ \var(X_R v_i) = 1 - d_i \text{ large} \]
Common Spatial Patterns for 2 classes

Original data: Each class has a specific spatial extension. Let $\Sigma_1$ and $\Sigma_2$ be the covariance matrices of the two classes. The blue cross visualizes the covariance 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: $\hat{\Sigma}_i = P\Sigma_iP^\top$.

Calculate orthogonal matrix $R$ and diagonal matrix $D$ 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 complementary 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.

Distribution of EEG features
BBCI Set-up

multi-channel EEG → FFT based low-pass filter → band-pass 4-40 Hz -> AR coeffs. → subject-specific band-pass filter, e.g. 7-14Hz, -> multi-class CSP

Artifact removal

multiple feature extraction

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

subject to $y_k(w^T x_k + b) = 1 - \xi_k$ for $k = 1, \ldots, K$

BCI with machine learning: feedback

**offline:** calibration (10–20 minutes)
- Collect training samples

**online:** feedback (up to 6 hours)
- Classification of sliding windows ($\leq 1$ s)
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!
Splitting into stationary and nonstationary subspace: SSA

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

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

[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

Popescu et al 2007
Future Issues: Shifting distributions within experiment
Conclusion

- BBCI: non-invasive with high Information transfer rates
- BBCI: Untrained, Calibration < 20min
- 5-8 letters/min mental typewriter on CeBit 06, Brain2Robot@Medica 07
- Machine Learning and modern data analysis are of central importance for BCI
- Applications: communication vs. measuring

Rehabilitation: TOBI EU IP, EU MUNDUS
Computational Neuroscience: Bernstein Centers Berlin
Man Machine Interaction: brain@work

- BBCI Sensors, software: IDA spinoffs
- towards no training, non-cooperative
- 'illiterates', nonstationarity, wireless

FOR INFORMATION SEE:
www.bbci.de
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**Overview of BCI Competitions**

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<th>BCI competition I</th>
<th>BCI competition II</th>
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<td>3 datasets</td>
<td>6 datasets</td>
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<tr>
<td>10 submissions</td>
<td>59 submissions</td>
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<td>[Sajda et al., 2003]</td>
<td>[Blankertz et al., 2004]</td>
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**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.bbcisi.de
Machine Learning open source software initiative: MLOSS see www.jmlr.org