Application to Brain-Computer Interfacing

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BRAINPONG
Brain-Computer Interface

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

[From Vigario]
Averaged Bereitschaftspotential

![Graph showing averaged Bereitschaftspotential with time in ms and voltage in µV, comparing right and left hands.](image)
Variance I: Single-trial vs. Averaging

**LEFT hand (ch. C4)**

**RIGHT hand (ch. C3)**
Variance II: Inter-Subject Differences

- 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 Set-up

multi-channel EEG

FFT based low-pass filter

band-pass 4-40 Hz -> AR coefs.

subject-specific band-pass filter, e.g. 7-14Hz, -> multi class CSP

Artifact removal

multiple feature extraction

classifier

continuous feedback

feature combiner 'PROB'

or
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
Playing with BCI: training session (20 min)
Weighted Linear Regression

Given training samples

\[ \{(x_i, y_i) \mid y_i = f(x_i) + \epsilon_i\}_{i=1}^n \]

for some function \( f \) and linearly independent basis functions \( \Phi = \{\varphi_i(x)\}_{i=1}^p \), find

\[ \alpha^* = (\alpha_1^*, \alpha_2^*, \ldots, \alpha_p^*)^\top \] which minimizes

\[ \min_{\{\alpha_i\}_{i=1}^p} \left[ \sum_{i=1}^n w(x_i) \left( \hat{f}(x_i) - y_i \right)^2 + \langle R\alpha, \alpha \rangle \right]. \]
LDA and Regression

For an application to Brain-Computer Interface data, we formulated the Linear Discriminant Analysis (LDA) problem

$$\min_{\{\alpha_i\}} \sum_{i=1}^{n} w(x_i) \left( \hat{f}(x_i) + b - y_i \right)^2 + \langle R\alpha, \alpha \rangle$$

by setting $\varphi_{p+1}(x) := 1$ for all $x$. The weights were calculated as $w(x_i) = \frac{p_{fb}(x_i)}{p_{tr}(x_i)}$, with the class-specific multivariate normal probability density estimates.
Weighted Linear Regression Solution

The solution:
Define $X$ and $D$ by

$$X_{i,j} = \varphi_j(x_i)$$

and

$$D_{i,i} = \frac{p_t(x_i)}{p_x(x_i)}.$$  

Then $\alpha^* := \widehat{L}_u y$ with

$$\widehat{L}_u = (X^\top DX)^{-1} X^\top D$$
solves the above regression problem.
Variance III: covariate shift: from training to feedback
Gaming with BBCI: Tetris – a cognitive-motor mix
Overview of BCI Competitions

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<td>[Sajda et al., 2003]</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
- Prize: winning algorithms will be described in an article in *IEEE TNSRE*.
- Information and Download:  