EEG techniques for BCI
and
The Berlin BCI System

CSE 599e: Brain-computer Interfaces

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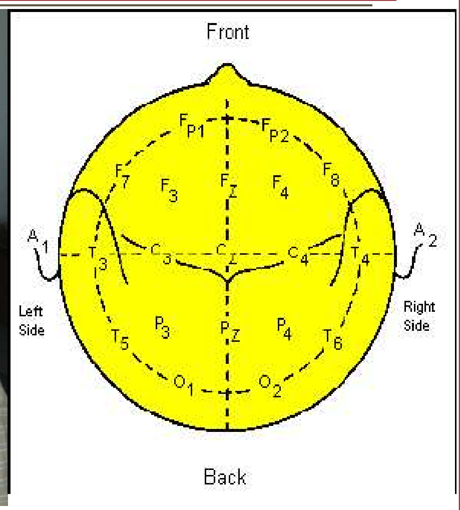
Outline

- A "theory of EEG" for BCI
  - EEG phenomena usable for BCI.
- The Berlin BCI
  - design, algorithms, performance, adaptivity.

EEG Acquisition



EEG Acquisition – the sob story

- Very low signal-noise ratio
  - Best BCIs only manage 20-30 bits/min, only discrete (binary) signals.
- Artifacts and noise
  - muscle movement, eye blink, head shake, ambient 60Hz noise >> signal.
  - recordings from any 2 sessions *qualitatively* similar but *quantitatively* very different.
- Lack of thorough understanding
  - only 2-3 reliably reproducible phenomena used by the BCI community.

A “theory of EEG” for BCI

- Phase-locked response (ERPs).
  - repeatedly present discrete stimulus, average raw EEG responses across presentations.
  - Characteristic features (e.g., P300).
- Frequency-band changes (ERD/ERS).
  - Perform (or imagine) motor action.
  - Average *spectral features* across presentation.
  - Characteristic suppression/increase in power.

The P300 Event-related Potential

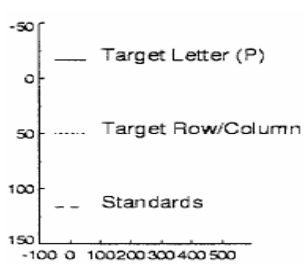
- Characteristic signal seen in EEG in response to discrete event
  - Can be visual, or auditory event.
  - Spontaneous response (a mental “a-ha”).
  - Positive, with latency of ~300ms.
- Clearly seen in averages over many trials, stronger for rarer/attended-to events, stronger in the midline electrodes.

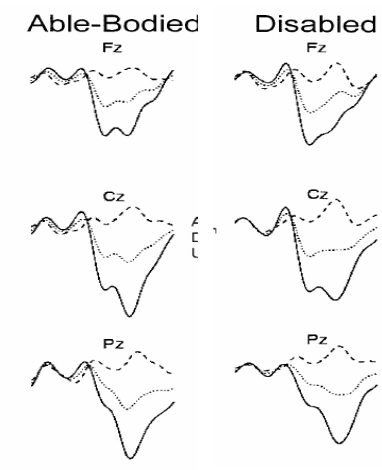
The P300 Speller

- Rows and columns flashed in random order.
- Subject focuses on particular letter.
- EEG responses for each row/column averaged and compared.
- Data from Donchin et al., TNSRE 2000.

The P300 Event-related Potential

- Attended-to rows and columns produce P300.
- Response also seen in disabled (paraplegic) users.

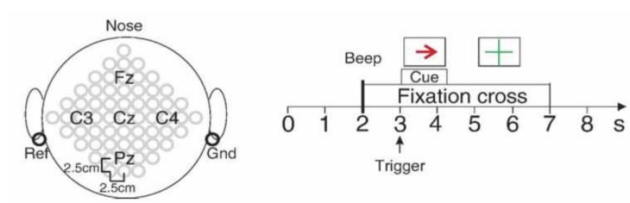




Event-related (De)Synchronization

- Characteristic change in oscillatory nature of EEG signal
  - suppression or increase in power in the so-called "mu" and "beta" bands.
- Induced by voluntary motor activity or imagery.
- Clearly visible in bandpower averages over multiple trials, in electrodes over motor cortex.
  - shows scalp distributions that differ based on body part involved.

Quantifying ERD/ERS

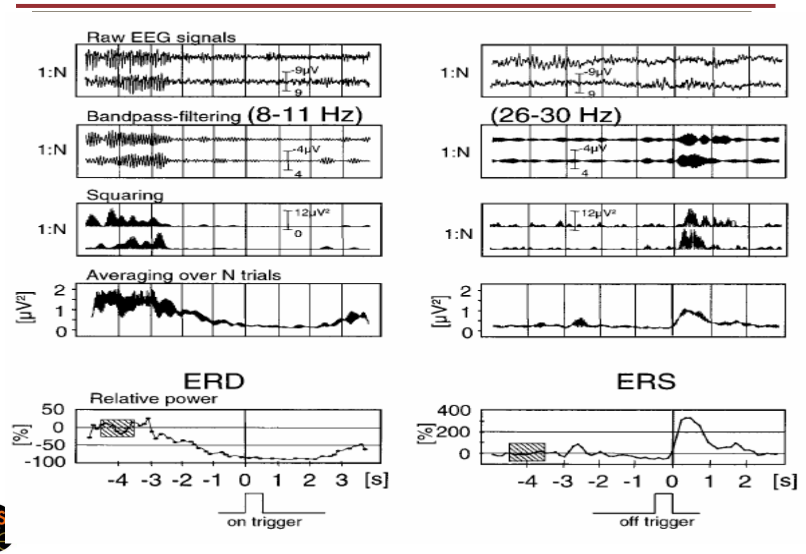


- 4 classes of sustained motor imagery (left & right hands, foot, tongue).
- Imagery performed for multiple 4s length trials in response to visual cues.
- Details in Pfurtscheller et al., NeuroImage 2006.

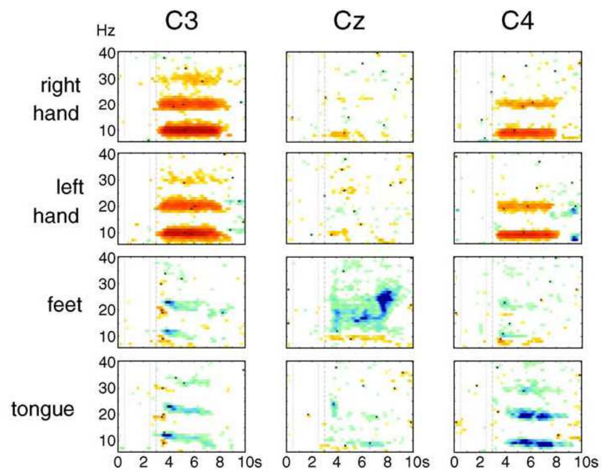
Quantifying ERD: methods

1. Bandpass filter the EEG Signal
2. Square samples, average over all trials
3. Normalize to average power in a 1s reference interval (before trial).
4. Repeat for every 2hz bin, use statistical test to label band with most significant increase as the *mu band*.

MethodsWithPictures™



Example ERD Maps: over time



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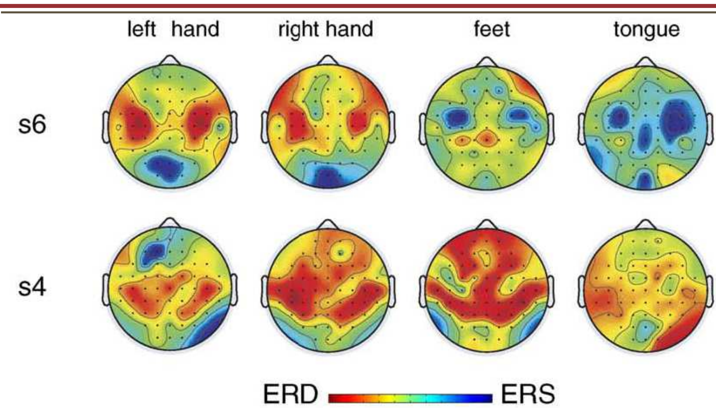
Example ERD Maps: over space



Fraction of increase/decrease in [10-12]Hz band power between 5.5 and 6.5s of trial, for subjects s6 & s4

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The Berlin BCI System

- Use mu-rhythm changes for control:
  - collect data during motor imagery.
  - Select spectral features (by hand), spatial features (CSP).
  - Train classifier in feature space (LDA).
- Use classifier online:
  - continuously classify windows of data, use classifier output to control cursor.

BBCIWithVideos™

BBCI: Eine schnitstelle zwischen gehirn und computer!

http://www.youtube.com/watch?v=qCSSBEXBCbY

http://www.youtube.com/watch?v=yhR076duc8M

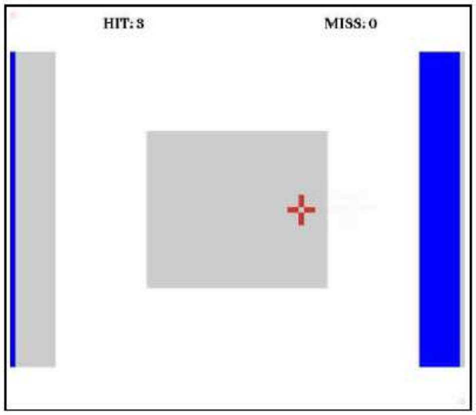
BBCI: Design goals

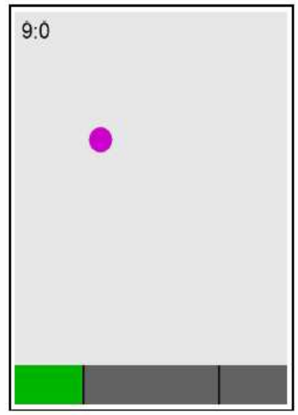
- *Computer learns,* instead of user
  - 30min training time, immediate use.
  - cf. Wadsworth BCI: weeks/months of training.
- *Asynchronous control* of cursor
  - allows for ~ 30 bits/min information transfer.
  - cf. Graz BCI: external "clock" based control, 1 bit every ~8s.
- Effectively use *high-dimensional* data
  - 128 channels of EEG.

Training data

- Visual stimulus presented for 4s-intervals
  - one of 4 classes: left/right/tongue/foot, subject imagines appropriate movement.
  - 60-100 repeats per class.
- Subject tracks a moving object with eyes:
  - makes classifier robust to eye-movement artifacts.
- Muscles monitored with EMG electrodes
  - reduces chance of accidental movement.

Feedback schemes





Feedback schemes

- Classify 1s-wide overlapping windows:
  - band-pass filter, project down to 2-6 dimensions, compute variance of feature over window.
  - Update cursor position 20 times/s.
- Real-valued output mapped to:
  - position on screen: “absolute control”.
  - change in position: “rate-control”.

Spectral features

- Examine spectra using *feature scores* (r^2 values)
  - Visually pick most discriminative band.
- Notion of a "performance predictor":
  - area under discriminative (mu) band indicative of user performance.
- Recent work (coming up in class) combines spectral/spatial filtering.

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SpectralFeaturesWithPictures™

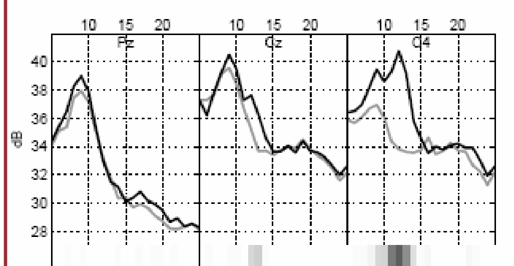

Figure 1: The plot shows the spectra for one subject during left hand (light line) and foot (dark line) motor imagery between 5 and 25 Hz at scalp positions Pz, Cz and C4. In both central channels two peaks, one at 8 Hz and one at 12 Hz are visible. Below each channel the r^2-value which measures discriminability is added. It indicates that the second peak contains more discriminative information.

- r^2 values guide selection of frequency band.
- Important because of inter-subject variability, e.g., here the "second peak" in data is more discriminative.

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Spatial Features

- Common Spatial Patterns (CSP) algorithm.
  - Linear projection that *maximizes* variance of projection for one class while simultaneously *minimizing* variance for the other class.
  - cf. PCA, which maximizes overall projected variance.
  - Can visualize as weights for each electrode, and it makes sense (usually).
- Creates 2-6 dimensional representation of 128-channel data.

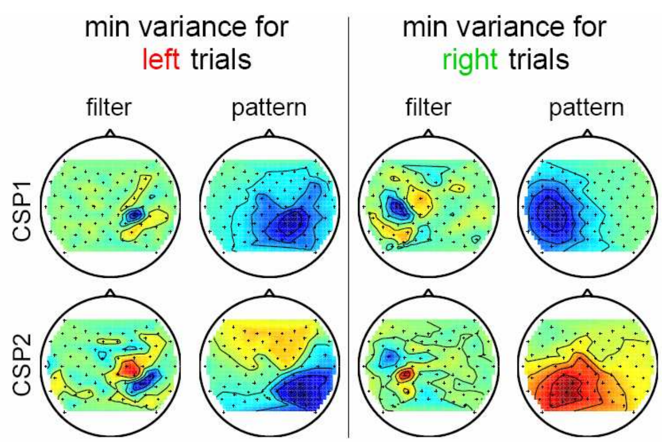
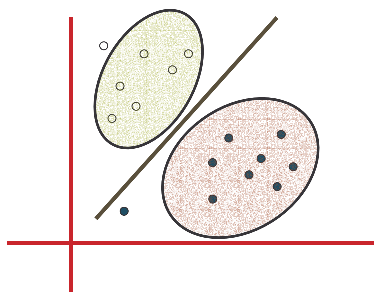


Figure 2: The common spatial pattern (CSP) algorithm determines spatial structures which represent the optimal discrimination between two classes with respect to variance. The patterns illustrate how the presumed sources project to the scalp. They can be used to verify neurophysiological plausibility. The filters are used to project the original signals. They resemble the patterns but their intricate weighting is essential to obtain signals that are optimally discriminative with respect to variance. Here two filters (resp. patterns) per class are shown (CSP1 and CSP2).

Linear classifiers: LDA



Assume each class is a *gaussian cloud*

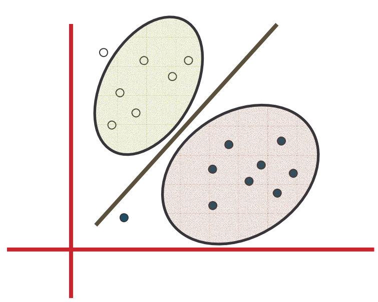
$N(\mu_k, \Sigma_k)$, $k = 1,2$

Use $\Sigma=0.5*(\Sigma_1+\Sigma_2)$

Define w as follows:

$w = \Sigma^{-1}(\mu_2 - \mu_1)$

Linear classifiers: LDA



- Output: *continuous value* signifying distance from boundary.
- Works well in low dimensions.
- Can "move boundary" parallel to itself by adding a small bias.

BBCI performance

Table 1: Information transfer rates (ITR) obtained in the feedback sessions measured in bits per minute as obtained by Shannon's formula. For each feedback session the first column reports the average ITR of all runs, while the second column reports the peak ITR of all runs. Subject 2 did not achieve BCI control.

	training acc [%]	cursor abs overall	cursor abs peak	cursor rel overall	cursor rel peak	basket overall	basket peak
1	95.4	7.1	15.1	5.9	11.0	2.6	5.5
2	64.6	–	–	–	–	–	–
3	98.0	12.7	20.3	24.4	35.4	9.6	16.1
4	78.2	8.9	15.5	17.4	37.1	6.6	9.7
5	78.1	7.9	13.1	9.0	24.5	6.0	8.8
6	97.6	13.4	21.1	22.6	31.5	16.4	35.0
mean	85.3	10.0	17.0	15.9	27.9	8.2	15.0

Predicting performance

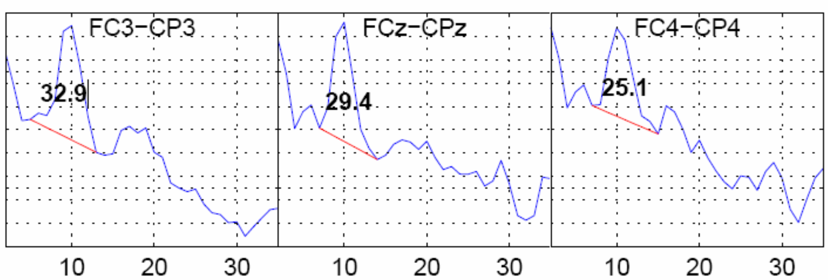


Figure 3: Illustration of the calculation of the performance predictor. The plots show the spectra of a relax measurement (eyes open) of one subject for three bipolar channels over sensorimotor cortex.

Area under mu-band of spectrum during resting is an indicator of performance.

Predicting Performance II

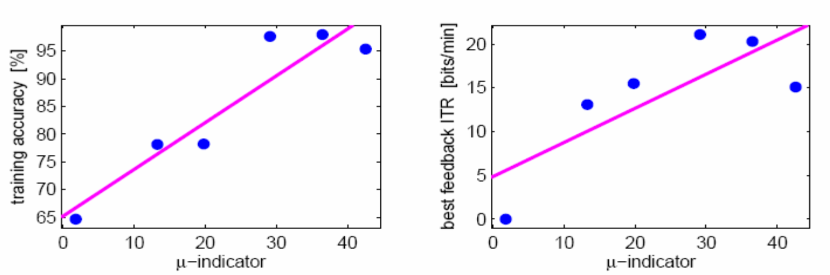
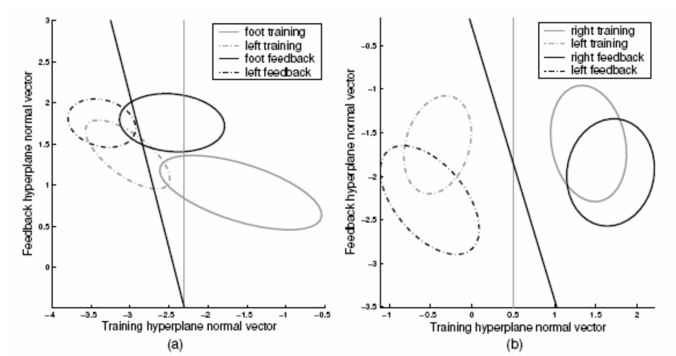


Figure 4: Left panel: Performance indicator vs. classifier accuracy (100 - generalization error) on the training data. Right Panel: Performance indicator vs. information transfer rate (ITR) in the feedback session with absolute cursor control.

What if the data changes?

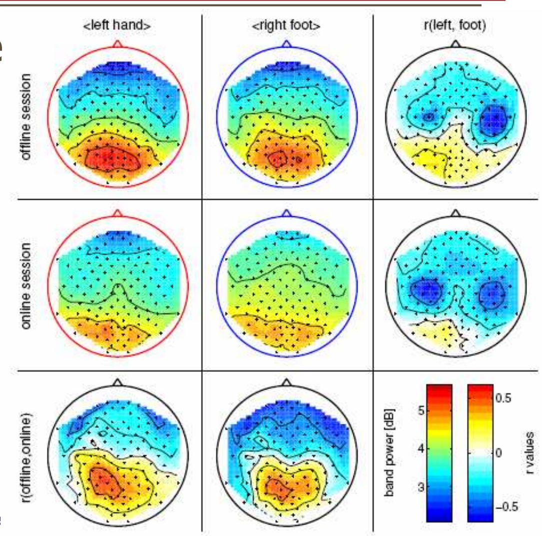


- Training and online data often look different.
- May or may not lead to decreased performance--e.g., subjects (a) and (b) above.

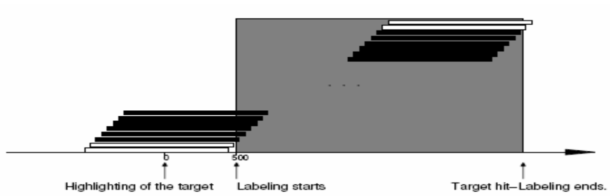
Possible cause: visual feedback

Class difference is the same.

However, α– rhythm in parietal region is suppressed.



Adaptive possibilities: offline study



- Take data from online sessions, relabel, examine.
- "Cheat": use data from immediate past to tweak classifier for upcoming points.
- Consider extreme-ness of adaptivity along 2 dimensions:
  - how much new data to use.
  - how radically to change classifier.

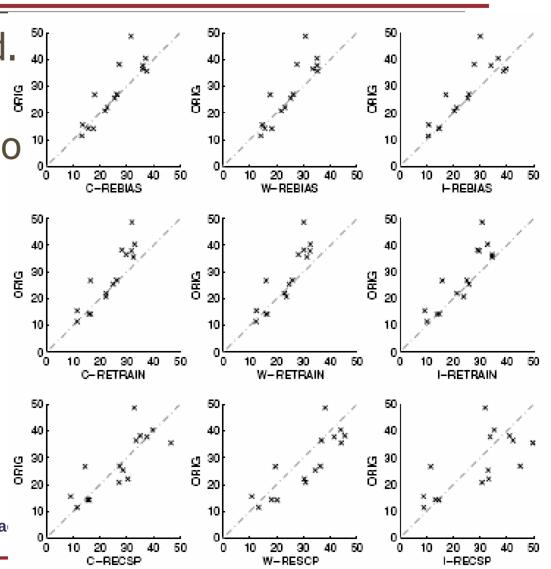
Adaptive algorithm bake-off

- Data "complexity" axis:
  - use (a) all data upto now, (b) a small window from the immediate past, or (c) a small window from beginning of session
- Adaptive "complexity" axis:
  - (a) change classifier output with a *bias,* (b) retrain classifer, (c) retrain feature projection and classifier.
- Compare *each pairing* against original classifier.

Adaptive algorithm bake-off

X: Data, Y: Method.

- Many methods do improve performance.
- Simplest is best.
- Most complex method suffers from data shortage.



EEG-based BCIs: Philosophy

- Research in BCI must address:
  - *interpretability* of data and methods, especially due to artifacts.
  - proof of *generalizability*, see above.
  - better/wider *theory* and understanding of brain processes.

References

- Donchin, E, KM Spencer, and R Wijesinghe. "The Mental Prosthesis: Assessing the Speed of a P300-Based Brain-Computer Interface. " *IEEE Trans. Rehab. Engineering* 8 (2000): 174-179
- Mu rhythm (de)synchronization and EEG single-trial classification of different motor imagery tasks. G. Pfurtscheller, C. Brunner, A. Schloegl, and F.H. Lopes da Silva, NeuroImage 2006
- The Berlin Brain-Computer Interface: report from the feedback session. Blankertz, B.; Dornhege G.; Krauledat, M; Mueller, K-R.; Curio, G. Technical Report 1, Fraunhofer FIRST.
- Towards Adaptive Classification for BCI. P. Shenoy, M. Krauledat, B. Blankertz, R. Rao, K.-R. Mueller. J Neural Eng. 3 (2006)

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