

Brain-Computer Interfacing

WS 2018/2019 – Vorlesung #08

(half a lecture)



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Overview of the Course

Time-locked activity

- ✓ ERP analysis
- ✓ spatio-temporal features
- ✓ LDA with shrinkage

Linear model of EEG

- ✓ propagation from sources to sensors (and back)
- ✓ interpretation of discriminative models

Spontaneous oscillations

- ▶ spectra; ERD/ERS analysis
- ▶ log variance (band-power) features
- ▶ CSP analysis

Special topics

- ▶ issues in validation
- ▶ signal decomposition methods
- ▶ adaptation of classifiers

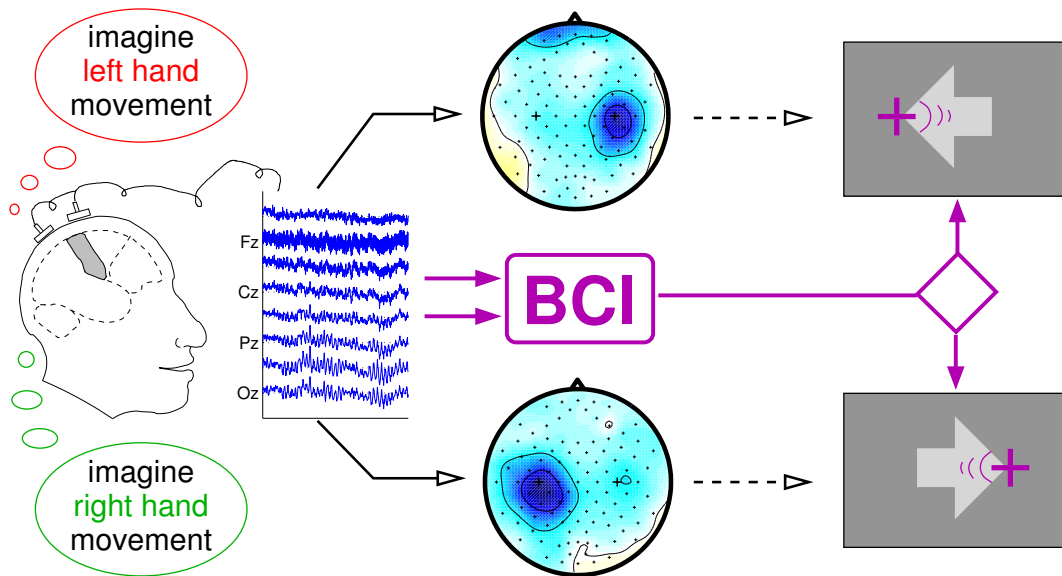
Today's Topics

- ▶ Modulations of brain rhythms
- ▶ Power spectral density and some prominent spatial filter
- ▶ Event-Related Desynchronization (ERD) curves
- ▶ **Spectral** features (log band power), which reflect modulations of the amplitude in specific frequency bands

Note:

The new content of today's lecture is not relevant for exam #1, but for exam #2.

Recap (from first lecture): SMR-based BCI Systems

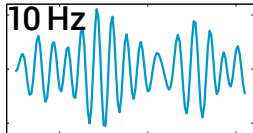


Recap: Modulation of Brain Rhythms

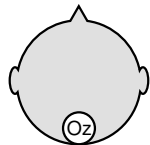
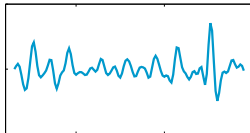
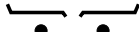
Most rhythms are idle rhythms. They reflect **synchronous** neural activity, and they are **attenuated** during active processing.

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

eyes closed

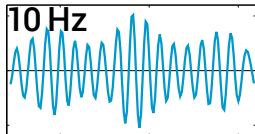
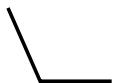


eyes open

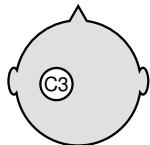
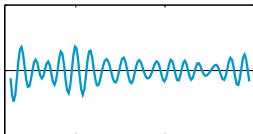


- ▶ μ -rhythm (also SMR, around 10 Hz) in motor and sensory cortex:

arm at rest



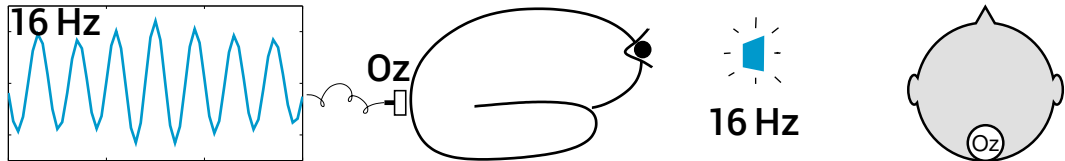
arm moves



Note the Difference: Induced Oscillations

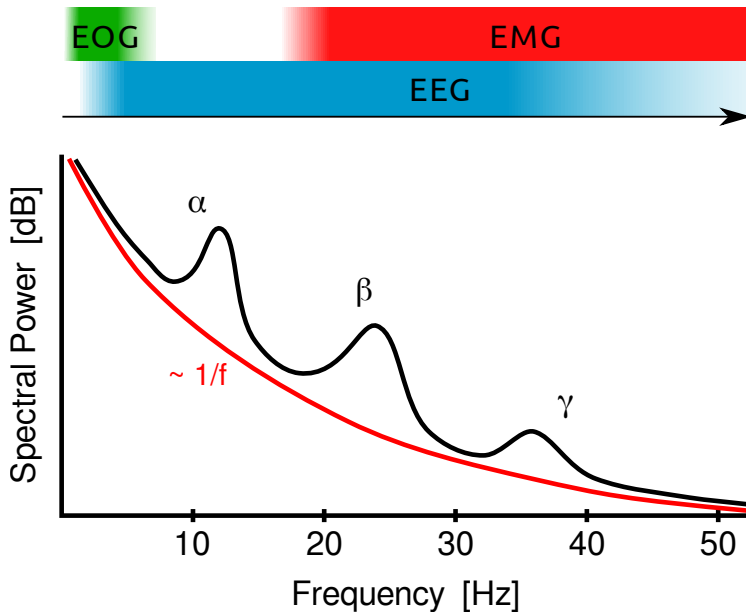
A different kind of oscillations are the

- **induced oscillations**, e.g., steady-state visual evoked potentials (SSVEP), auditory steady-state response (ASSR), which are evoked by and synchronous to a periodic external stimulus.

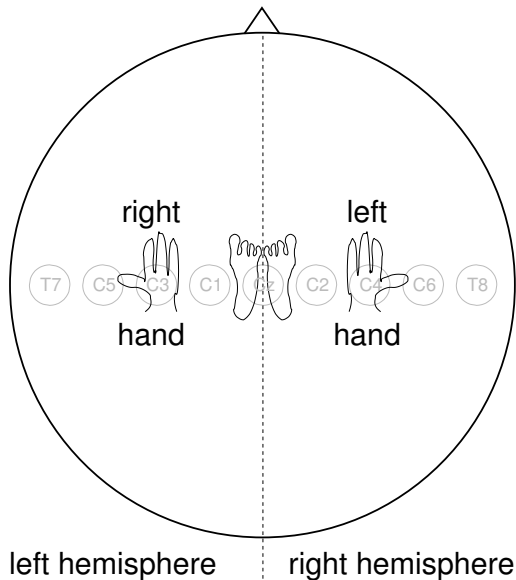
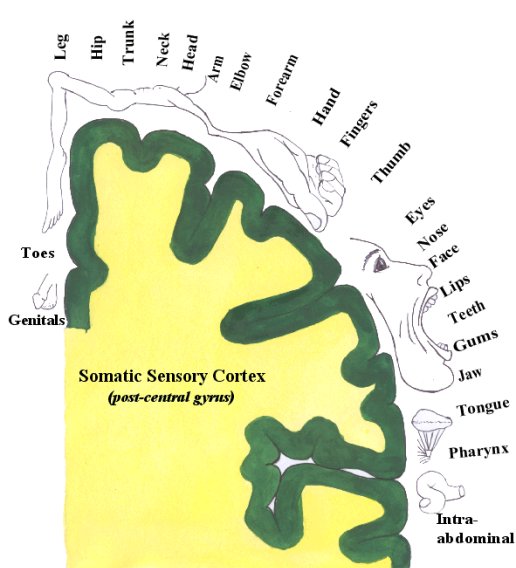


This is an example of **exogeneous** brain activity (as ERPs), while the examples from the previous slide represent **endogeneous** activity.

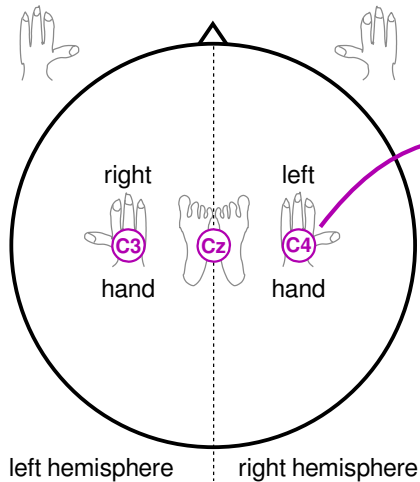
Spectrum of Macroscopic Brain Activity



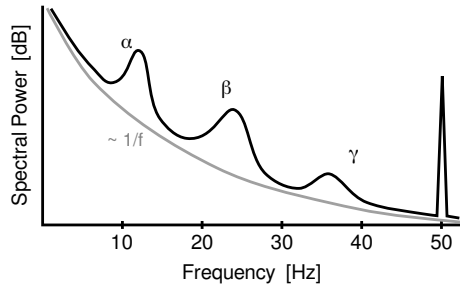
Topographic Mapping in Somatic Sensory Area



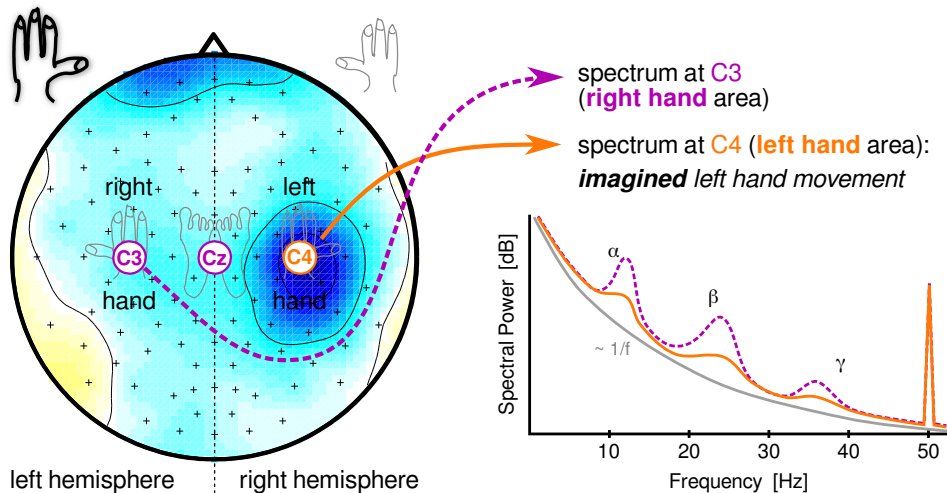
Neurophysiology: Sensorimotor Rhythms



spectrum at **C4** (left hand area):
hand at rest

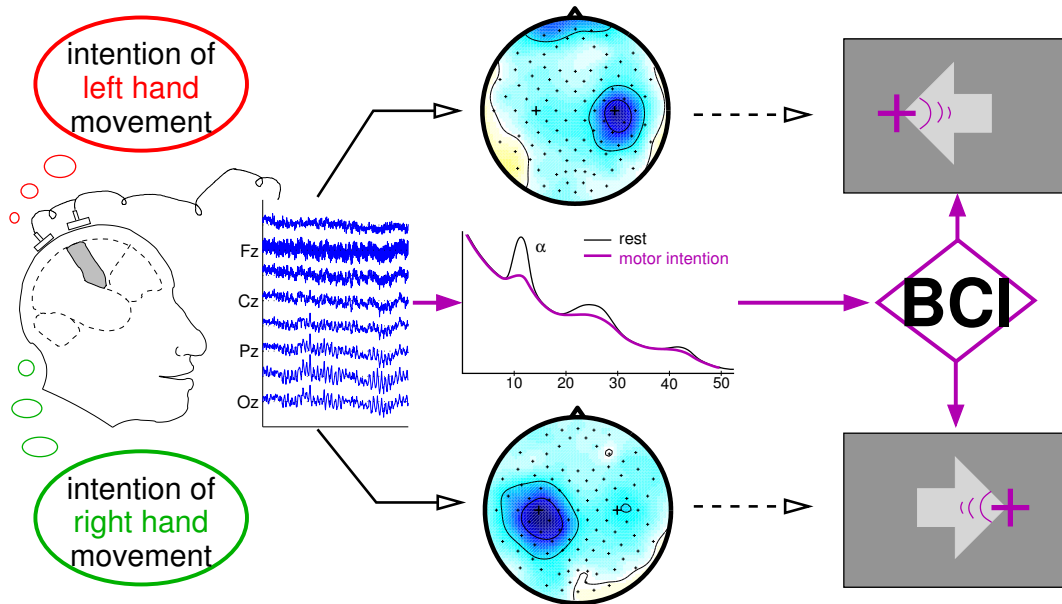


Neurophysiology: Sensorimotor Rhythms



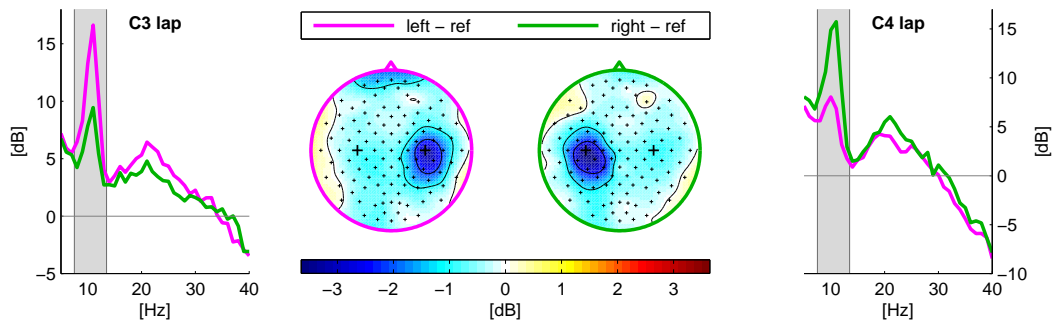
Imagining a movement of a limb causes a local blocking of the corresponding sensorimotor rhythm (SMR), see [Neuper & Klimesch 2006; Pfurtscheller et al., 2006; Pfurtscheller & da Siva 1999].

SMR-based BCI Systems: Basis for Classification



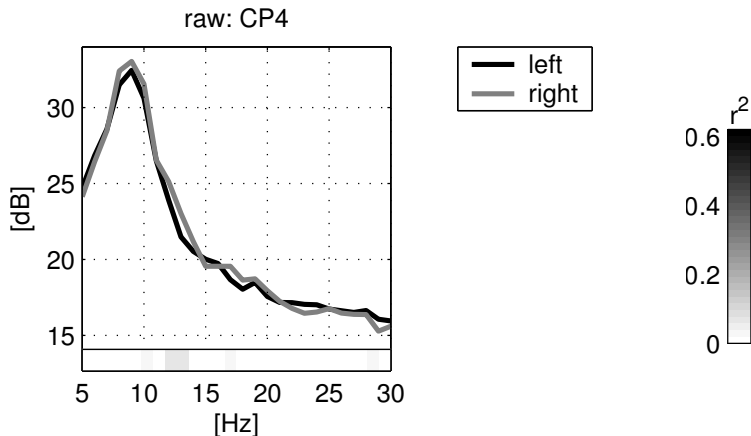
Modulation of SMRs in Motor Imagery

Data from an individual with very clear and prototypical patterns:



Spatial Smearing Affects Spectra

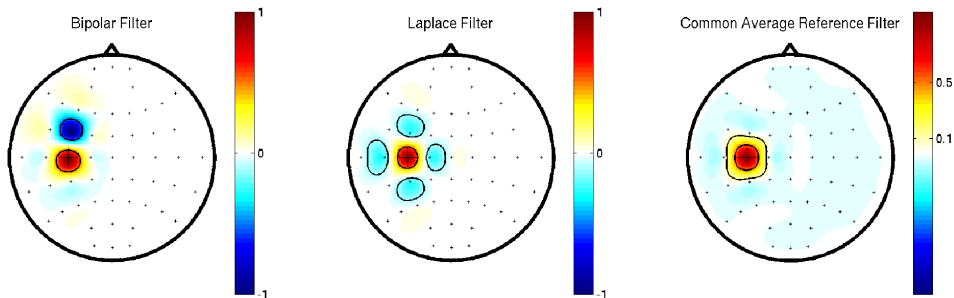
In practice, the difference might show up less pronounced:



One reason for that is spatial smearing (see lecture #01).

Some Spatial Filters

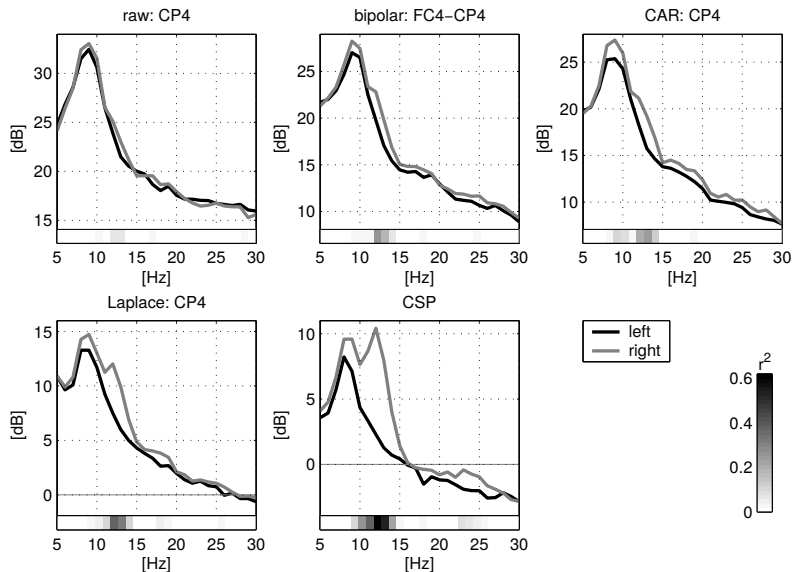
- ▶ **Bipolar:** Subtract values from two electrode positions, e.g.: $\text{Bip}_{C3,FC3} = C3 - FC3$
- ▶ **Common Average Reference (CAR):** Subtract the average of all EEG electrodes ($C = \{F3, Fz, F4, C3, Cz, C4, \dots\}$) from the given electrode: $C3_{\text{CAR}} = C3 - \frac{1}{|C|} \sum_{C \in C} C$
- ▶ **Laplace (Lap):** Subtract from each channel the average of its immediate neighbours: $C3_{\text{Lap}} = C3 - \frac{1}{4}(FC3 + C1 + CP3 + C5)$



Data Driven Spatial Filters

- ▶ **Principal Component Analysis (PCA):** A data-driven method that can be used, e.g., to extract components of most variance in the data (to be introduced in a future lecture).
- ▶ **Independent Component Analysis (ICA):** Data-driven methods that extract components of independent activity. If succesful, these components correspond to sources in the brain (to be introduced in a future lecture).
- ▶ **Common Spatial Patterns (CSP):** A data-driven method that can be used to find optimized filters that reflect amplitude modulations of brain rythms (to be introduced in the next lecture).

The Effect of Spatial Filtering



Just one example. In another dataset it might look quite different.

Relevant Channels to Capture SMR Modulations

In order to determine the frequency band that best displays the modulation of the SMRs, it is helpful to know approximately at which channel these are to be expected.

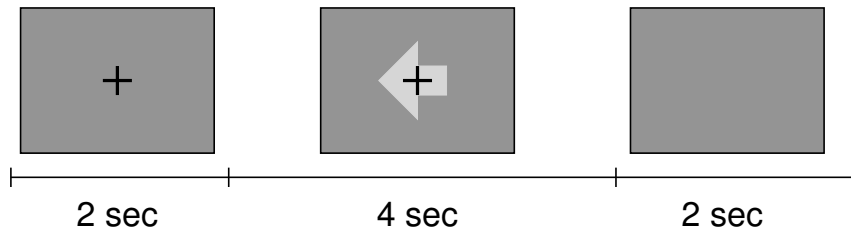
Generally, positions C3 and C4 are described to be over the sensorimotor areas of the hands. On the next two slides, we will investigate the location of the SMR related to motor imagery of the hand, based on the data of a large scale study with 80 participants [\[Blankertz et al, 2010\]](#).

Experimental Design – Calibration

Large scale study with 80 participants.

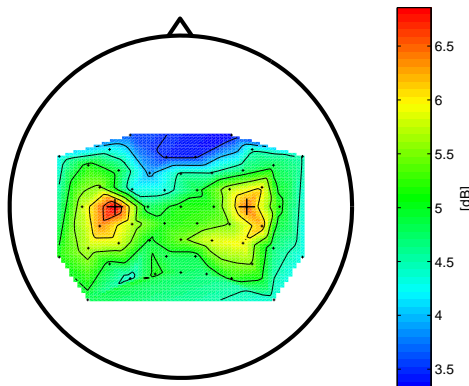
Visual cues (arrows) indicate which type of motor *imagery* is to be performed: left hand, right hand, right foot.

Every 15 trials, a break of 15 s is given. In total 75 trials of each motor imagery condition are recorded.



Average Topography of Idle SMR

For each Laplace filtered channel in a relax recording, the strength of the local rhythm was estimated. The grand average over 80 participants is displayed as topographic mapping:

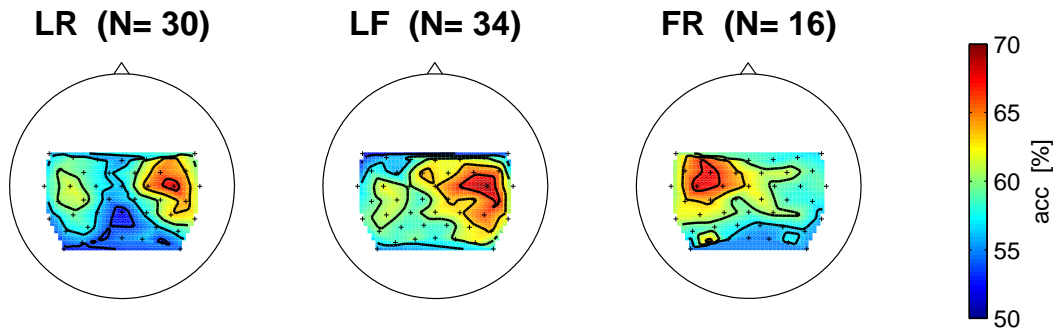


Conclusion

Locations C3 and C4 are good candidates to observe SMR modulations. These cover the sensorimotor areas of the right and the left hand.

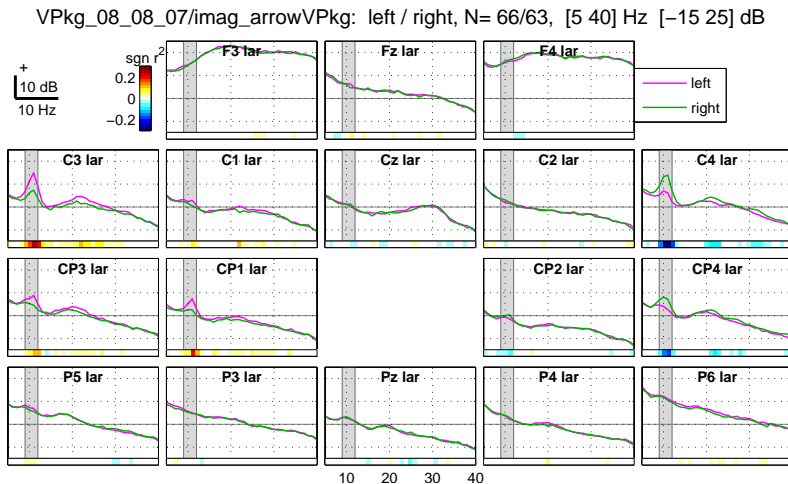
Average Topography of Single-Channel Classification

For each Laplace filtered channel in a motor imagery recording, the classification accuracy was determined for single-channel classification. The grand average over 80 participants is displayed as topographic mapping.



Classification was performed to binary combinations of motor imagery conditions (**L**: left, **R**: right, **F**: foot).

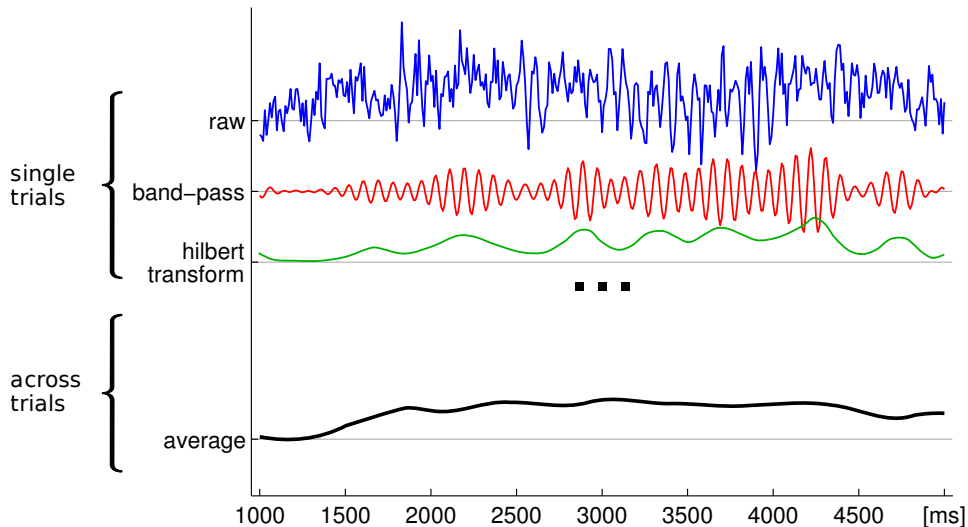
Analysis of Motor Imagery Conditions: Spectra



First step: determine a suitable frequency band that shows good discrimination between the conditions.

Next, we investigate the time course of band power.

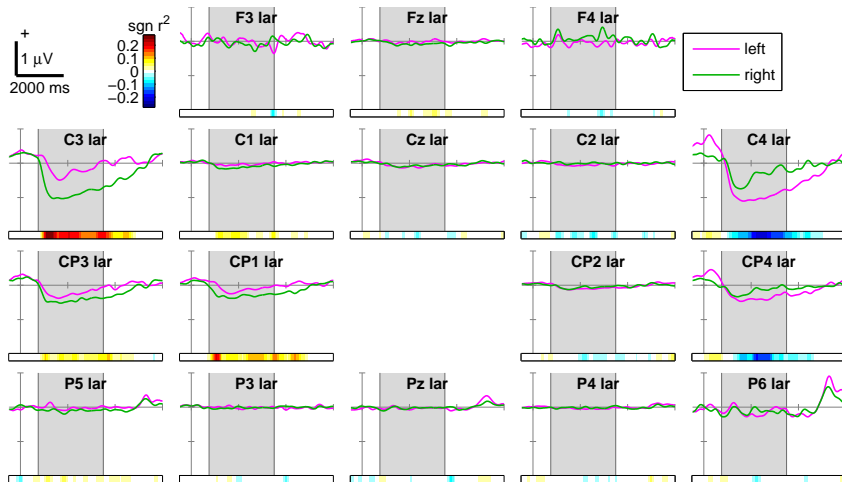
Calculation of ERD/ERS Curves



Using Hilbert transform, a hull curve of narrow band signals can be determined. This can be used to calculate ERD/ERS curves of single-trials.

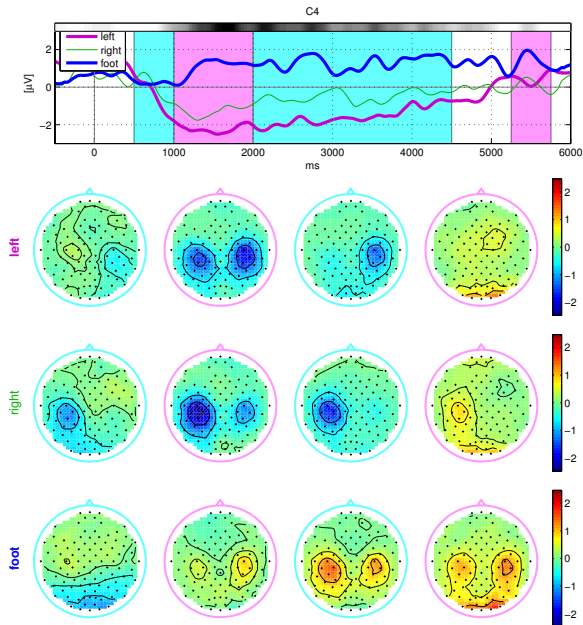
ERD/ERS Curves of Motor Imagery

VPkg_08_08_07/imag_arrowVPkg: left / right, N= 66/63, [-500 6000] ms [-2 1] μ V

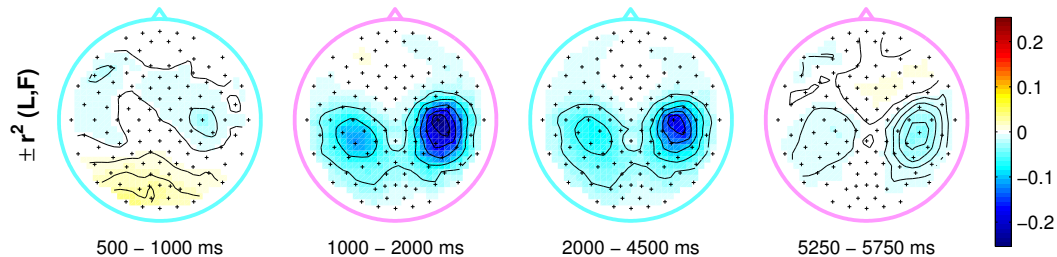


Second step: **determine a suitable time interval** that shows good discrimination between the conditions.

Topography of ERD Curves of Motor Imagery



Topography of ERD Curves of Motor Imagery: r^2 -Values



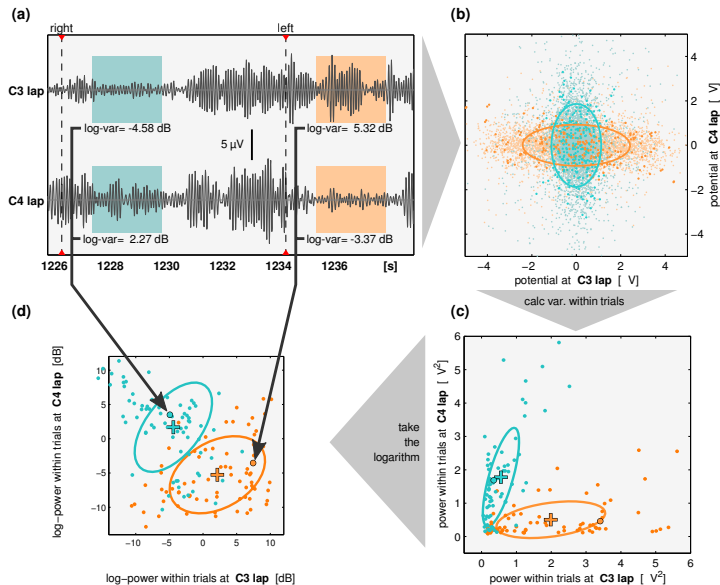
Different Ways to Classify Modulations of Brain Rhythms

- ▶ **[PDS Features:]** Calculate the **power spectral density** for 1 Hz bins in the relevant frequency band (use dB scale), concatenate for all channels, classify with Shrinkage-LDA
- ▶ **[ERD/ERS Features:]** Band-pass filter continuous data, calculate **hull curves** of trials and classify as ERPs (spatio-temporal features and Shrinkage-LDA)
- ▶ **[Log Band-Power Features:]** Band-pass filter continuous data, calculate **logarithmized variance** of trials (to be explained on the next slide) and classify with Shrinkage-LDA

However, in many cases, these approaches **do not work well**. An explanation will be given below.

The next lecture will devoted to present a better method.

Log Band-Power Features (of uncorrelated(!) signals)



Note that this illustration assumes the ideal case of unmixed signals.

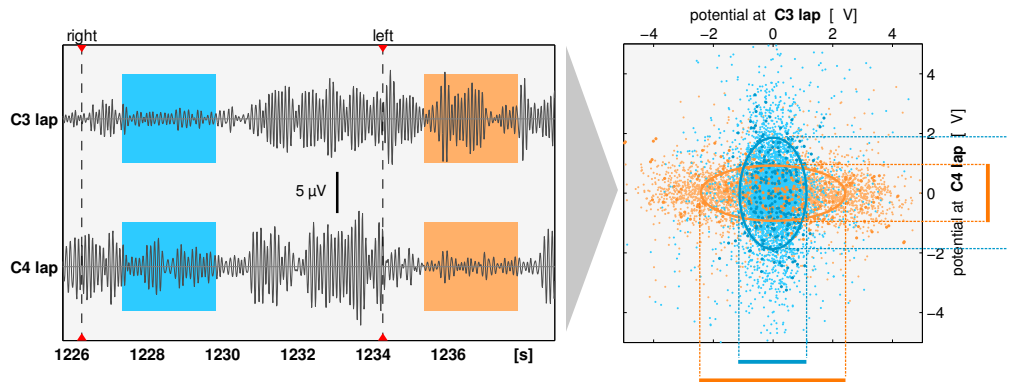
Comment to the Previous Slide

The band-power features (c) are neither close to Gaussian distributed nor are the covariance matrices of both classes similar. Therefore, classification with LDA cannot be expected to be appropriate.

Taking the logarithm transforms the distributions close to Gaussians and assimilates the covariance matrices. Therefore LDA is appropriate For those **log band-power features** (d).

A Closer Look

Assuming signals to be filtered within the frequency band of interest.

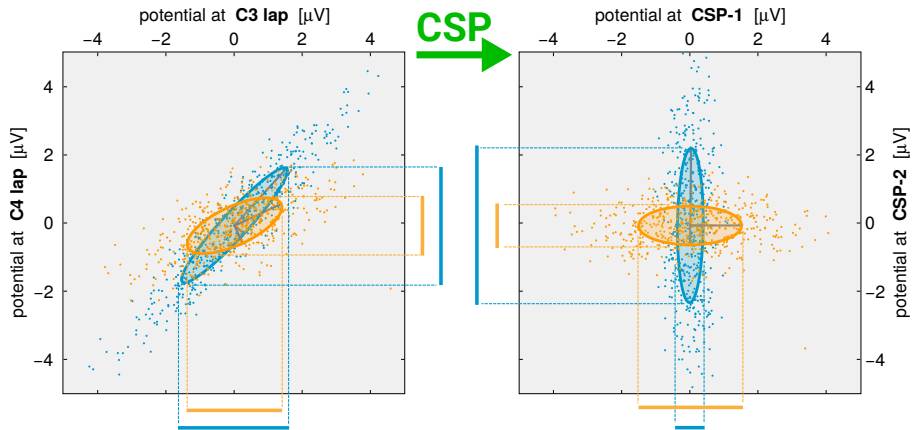


band-power features:
(here for two channels)



Demixing has to be Performed Before Feature Extraction

But signals are more mixed across channels than in the previous figure:



- ▶ Calculating band-power features in raw channels (left) would make the mixing of information irreversible for subsequent classification.
- ▶ Spatial filtering (e.g. CSP) has to be performed beforehand!

Conclusion wrt Preprocessing for Band-Power Features

In order to obtain good band-power features, we need to apply some spatial filtering **before** calculating **log band-power**.

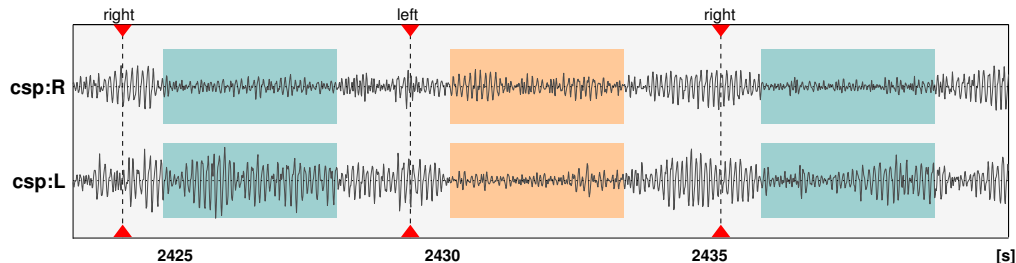
Note, that for ERP features, spatial filtering was done implicitly by the classifier. The extraction of band-power features involves non-linear processing. In that case, spatial filters have to be applied in advance.

This can be accomplished, e.g., by the Current Source Density (CSD) [Perrin et al, 1989/1990] technique, which is based on sensor locations only (i.e., not requiring EEG data for calibration).

For classification, **Common Spatial Patterns (CSP) Analysis** [Fukunaga 1990] is a useful technique. The goal of CSP is to determine spatial filters that optimally contrast modulations of brain rhythms in two conditions.

The Goal of Common Spatial Pattern (CSP) Analysis

The goal of CSP: Determine spatial filters such that (log-) variance in an epoch of each filtered signal is indicative of the class.



In other words: The spatially filtered signal should have high variance for trials of one class and low variance for trials of the other class.

After this lecture you should

- ▶ have knowledge about the modulations of brain rhythms due to motor imagery including a bit of neurophysiology
- ▶ be aware of the importance of spatial filtering for spectral analysis
- ▶ be capable of determining ERD/ERS curves (w/ hilbert transform)
- ▶ be familiar with distributions of band-pass filtered signals during motor imagery
- ▶ know log band-power features,
 - the reason for taking the log,
 - and the need to apply spatial filters before

References I

- ▶ Blankertz, B., Sannelli, C., Halder, S., Hammer, E. M., Kübler, A., Müller, K.-R., Curio, G., and Dickhaus, T. (2010). [Neurophysiological predictor of SMR-based BCI performance.](#) *NeuroImage*, 51(4):1303–1309.
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- ▶ Perrin, F., Pernier, J., Bertrand, O., and Echallier, J. (1990). [Corrigenda eeg 02274.](#) *Electroencephalogr Clin Neurophysiol*, 76(6):565 – 566.
- ▶ Pfurtscheller, G., Brunner, C., Schlögl, A., and da Silva, F. L. (2006). [Mu rhythm \(de\)synchronization and EEG single-trial classification of different motor imagery tasks.](#) *NeuroImage*, 31(1):153–159.
- ▶ Pfurtscheller, G. and da Silva, F. H. L. (1999). [Event-related EEG/MEG synchronization and desynchronization: basic principles.](#) *Clin Neurophysiol*, 110(11):1842–1857.