



Central European Institute of Technology
BRNO | CZECH REPUBLIC

Simultaneous EEG-fMRI Applications

Radek Mareček

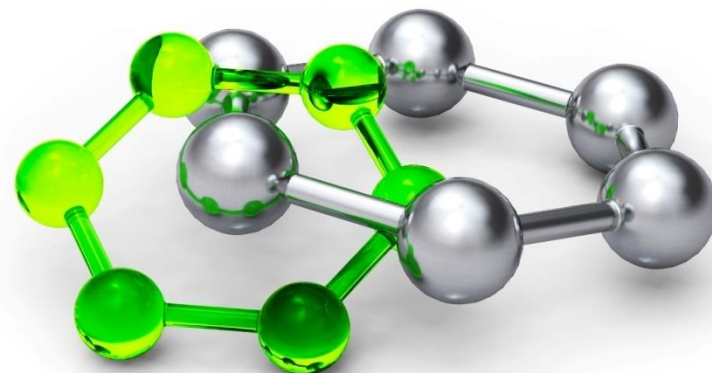
Brno, November 15th 2016



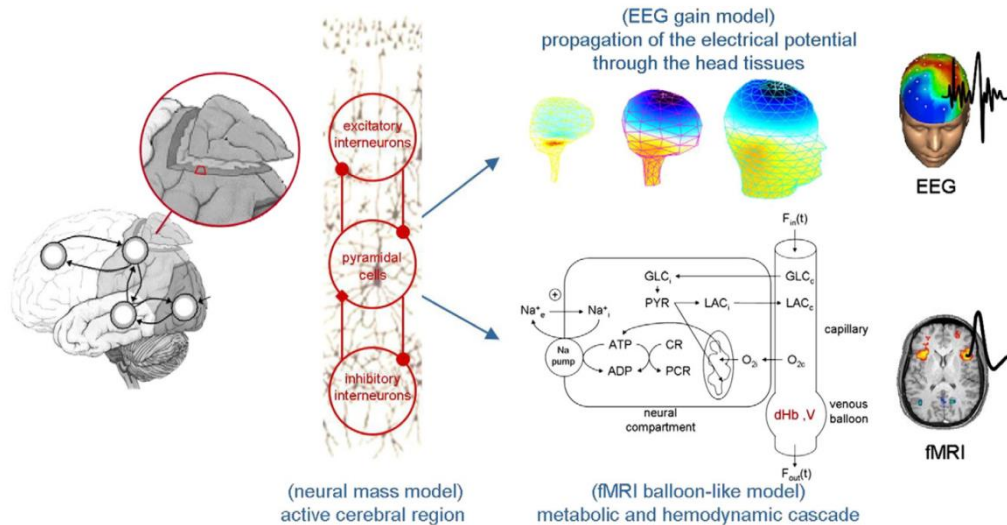
EUROPEAN UNION
EUROPEAN REGIONAL DEVELOPMENT FUND
INVESTING IN YOUR FUTURE



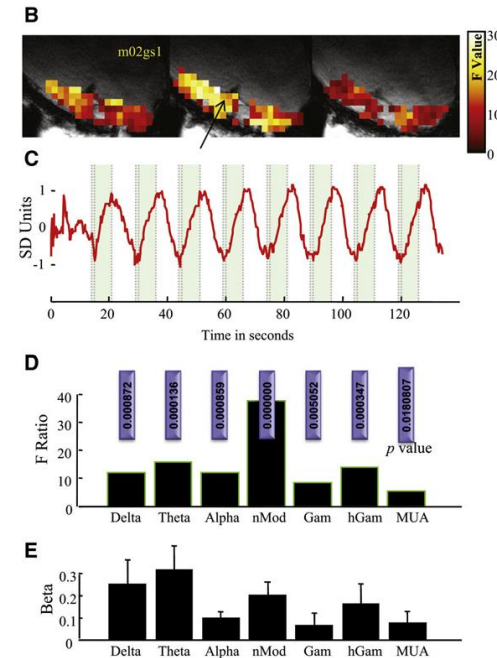
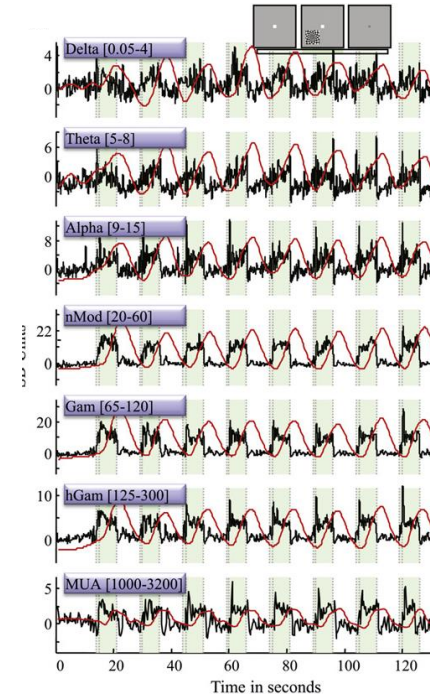
**OP Research and
Development for Innovation**



INTRODUCTION



- both modalities capture neuronal activity in an indirect way
- BOLD correlates with fluctuations of local field potentials
- common driver – postsynaptic potentials

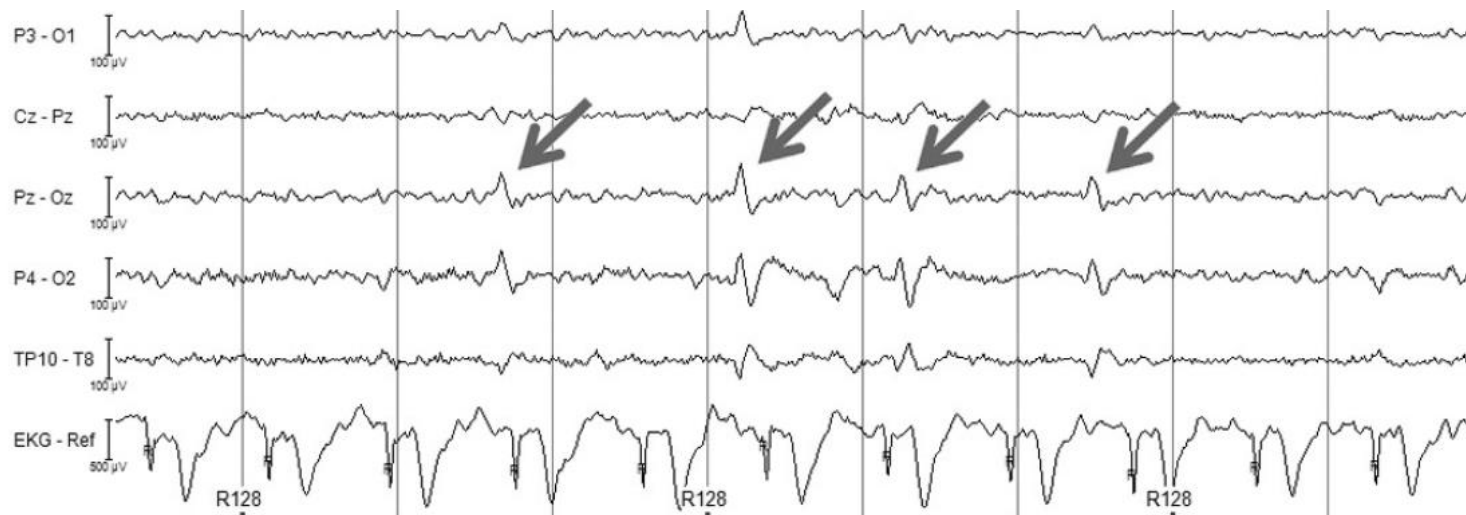


OUTLINE

- EEG – fMRI as a clinical tool in **epilepsy**
- EEG – fMRI as a tool for studying **large scale brain networks**
- other applications

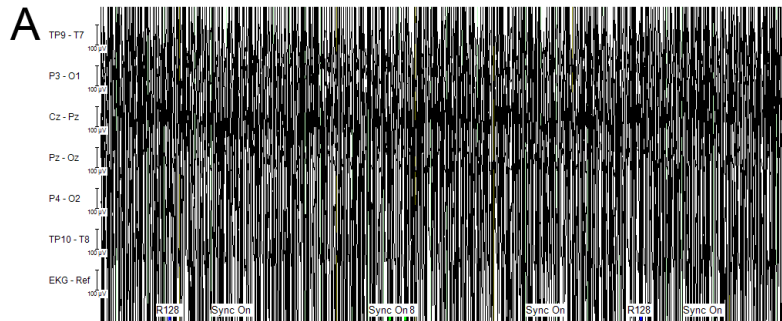
EEG-fMRI in epilepsy principles

- a presence of interictal epileptiform discharges (IEDs) in scalp EEG shows that the neural activity and consequently perfusion and hemodynamic fluctuations are affected during interictal periods
- the data may help to localize epileptogenic focus – the potential target for resection treatment of pharmacorezistant epilepsy



EEG-fMRI in epilepsy principles

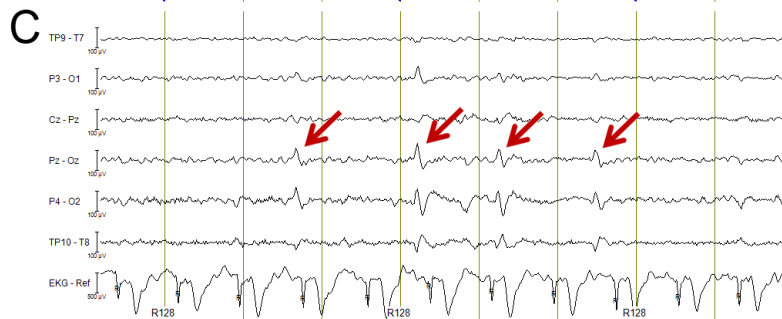
raw data



gradient
artifact
removal



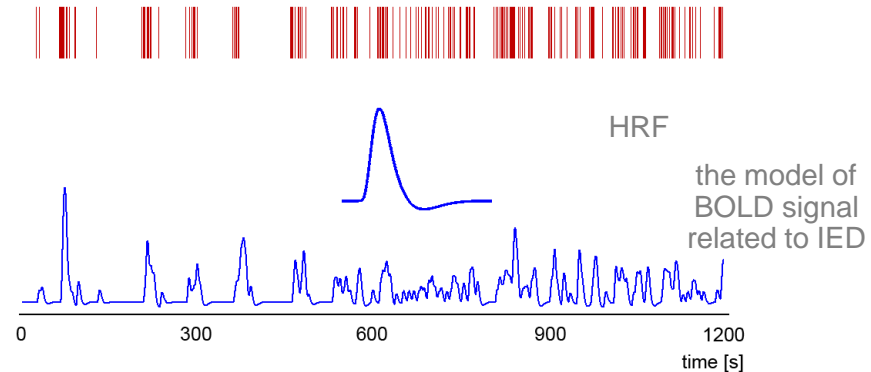
“clean”
EEG



„spike informed“ GLM

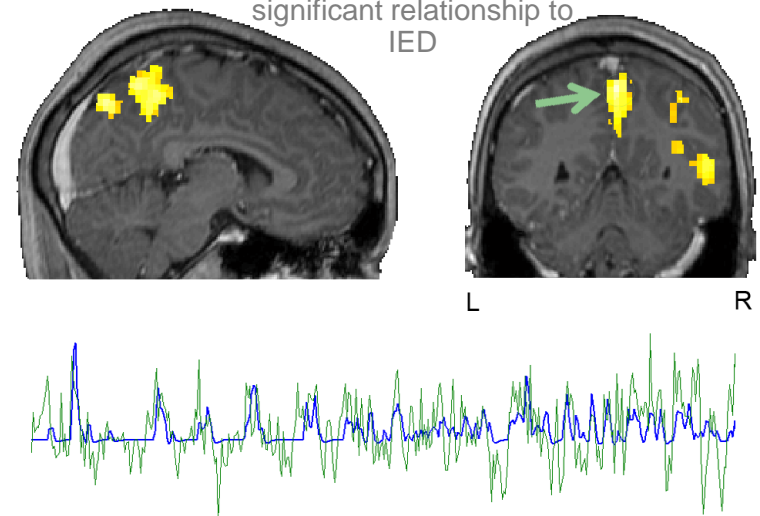
time-series of
IED occurrence

D



the statistical parametric
map showing regions with
significant relationship to
IED

E



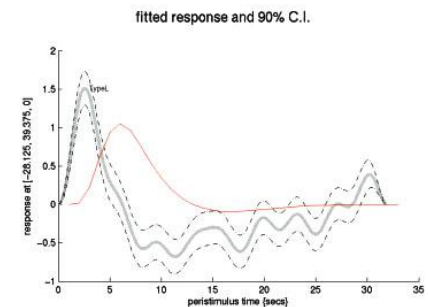
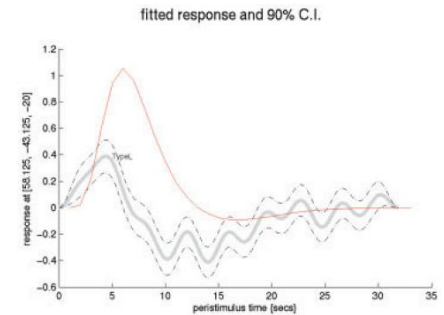
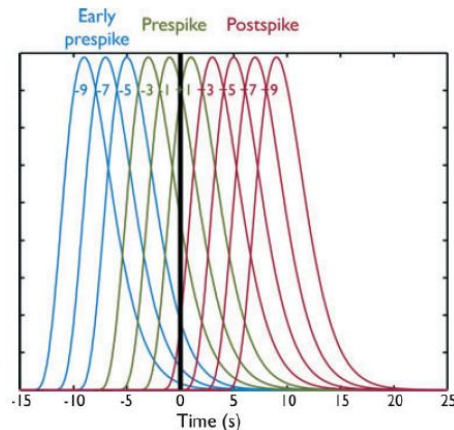
EEG-fMRI in epilepsy

methodological aspects – IED identification

- **accurate** identification of IED is **crucial**
 - ideally, all IED should be identified
 - the statistical power depends on the number of IEDs (to many / to few....)
 - it is highly subjective
 - can be all IEDs seen on scalp EEG recordings?
- sorting of IEDs
- no identifiable IEDs in EEG for ~30% of cases, despite the fact, that clinical EEG does contain IEDs

EEG-fMRI in epilepsy methodological aspects – HRF

- sensitivity depends on prior assumptions made about shape and timing of HRF
- canonical HRF??
- allow for slight variability in shape and timing of HRF
 - various basis sets for HRF
 - e.g. several time-shifted HRFs
 - e.g. including HRF derivatives (“SPM” approach)
 - reasonable in cases with the hemodynamic system strongly affected by structural or ischemic lesions



Lemieux et al.
2008

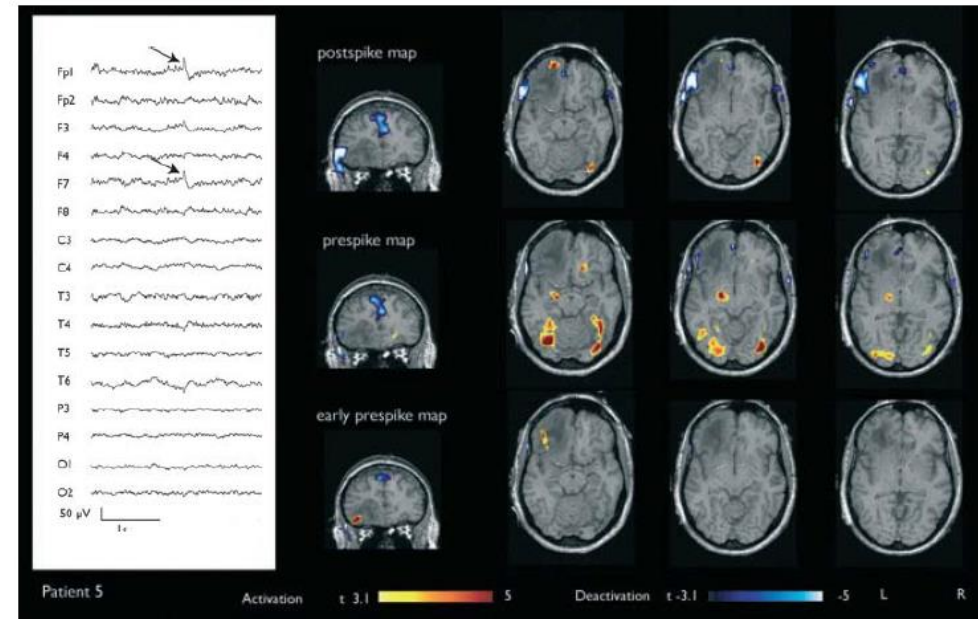
Bagshaw et al., 2004; Rathakrishnan et al. 2010

EEG-fMRI in epilepsy methodological aspects – negative BOLD

- **positive** BOLD response
 - **sources and propagations** of IED

- **negative** BOLD response

- ??

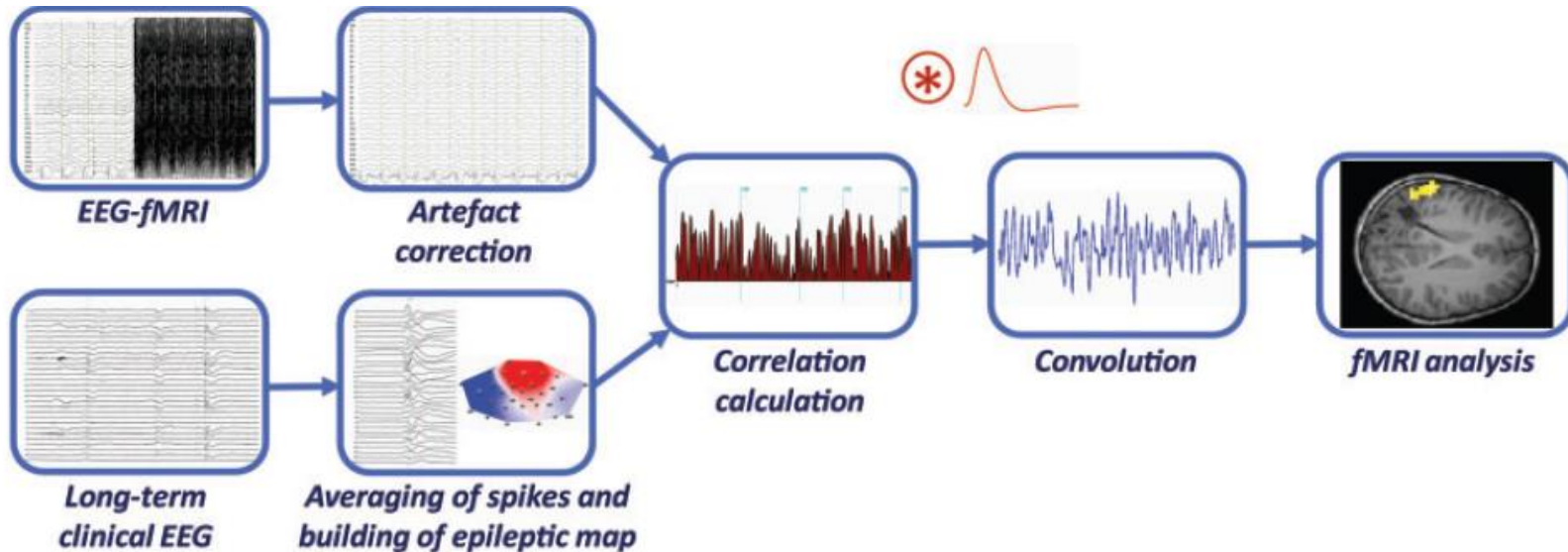


Rathakrishan et al. 2010

- **resting state networks**, which decrease their activity during pathological; “internal” stimuli (Laufs 2007)
- **anti-ictogenic role** – inhibition in local and distant regions (Chaudhary 2011; Gotman BACI2013)
- specific to slow wave discharges ?? (Gotman BACI2013)

EEG-fMRI in epilepsy clinical implications

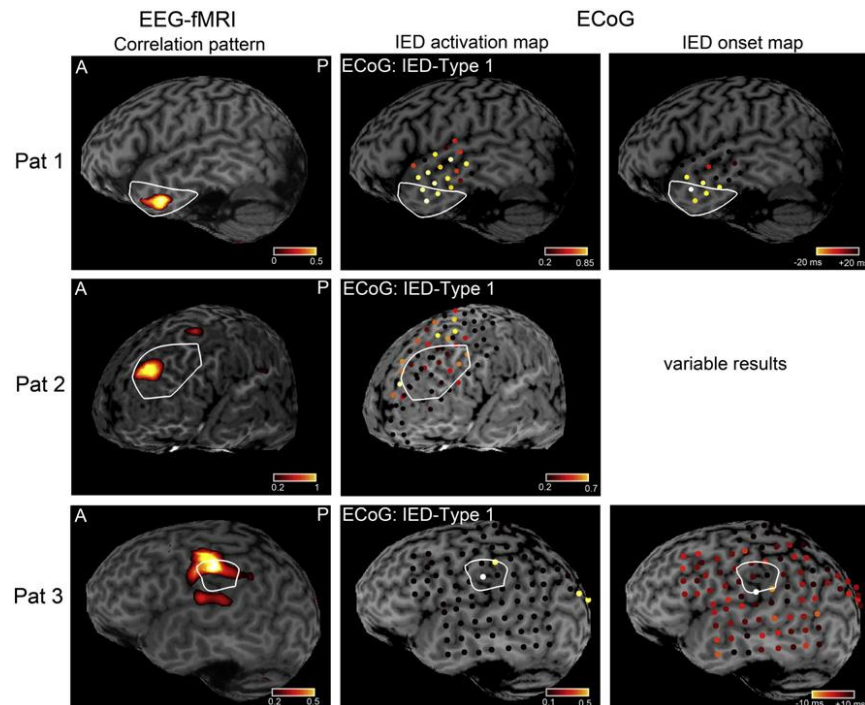
- IEDs generated in irritative zone
 - may be or may not be concordant with seizure onset zone
- considerable portion of subjects with “nonactive” EEG



- Grouiller et al. 2011
 - interesting way how to analyze nonactive EEG

EEG-fMRI in epilepsy clinical implications - sensitivity

- Pittau et al. 2012
 - 14 patients
 - in 12 concordance of BOLD response localization with intracerebral electrodes / MR lesion
- Van Houdt et al. 2013
 - in all 16 patients at least one IED-related BOLD response concordant to the interictally active ECoG



EEG-fMRI in epilepsy

clinical implications - reproducibility

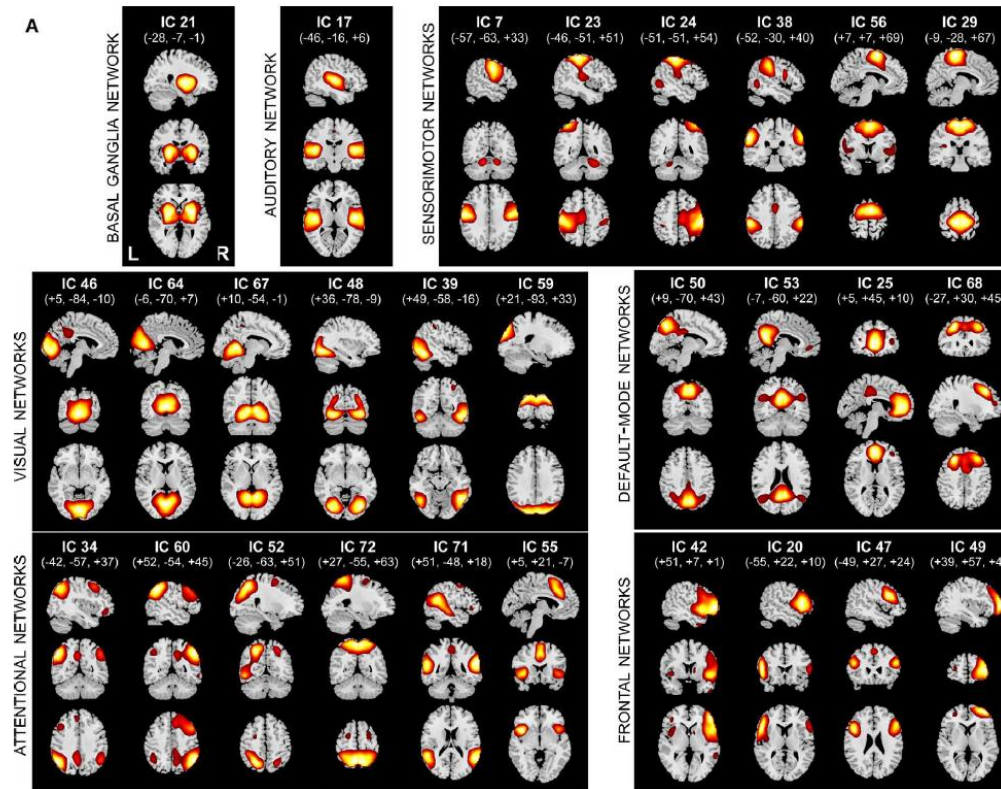
- Gholipour et al. 2011
 - 15 patients recorded twice (1.5T/3T in 8 cases; 3T/3T in 7 cases)
 - in 12 reasonable reproducibility of results
 - in 4 patients results from 3T more significant than in from 1.5T

EEG-fMRI in epilepsy conclusion

- nowadays widely used in presurgical patient evaluation being complementary to the traditional methods for focus localization, e.g., scalp EEG description or more recently proposed IED Source Imaging
- precise identifying of IEDs is **crucial**
- can not be viewed as a stand-alone modality for EPI focus localization
- brings valuable information to the process of EPI surgery planning

Brain rhythms

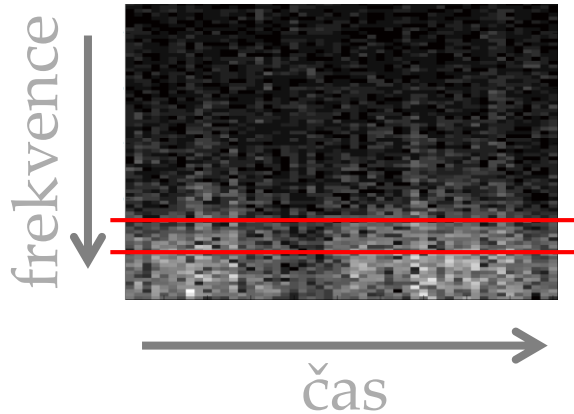
- the functional connectivity studies show, that human brain is organized into the large scale brain networks
- are there any markers of these networks in EEG data??



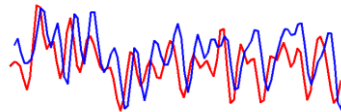
Allen et al., 2011

Brain rhythms

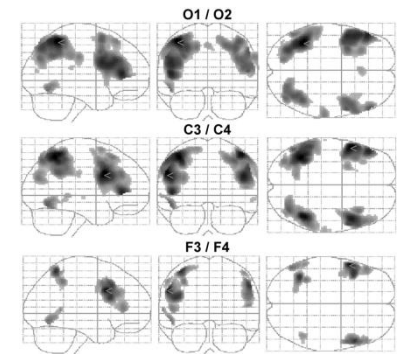
- examination of relationships between EEG activity and large scale brain networks



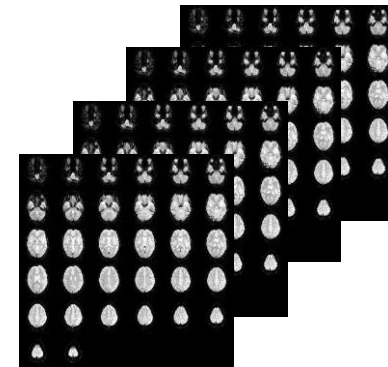
fluctuations in power within alpha band



hemodynamic fluctuations



H. Laufs et al., 2003

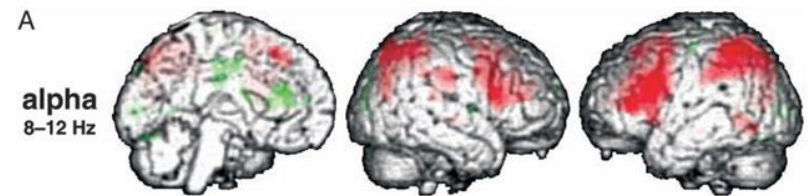


Brain rhythms

Laufs et al., 2003

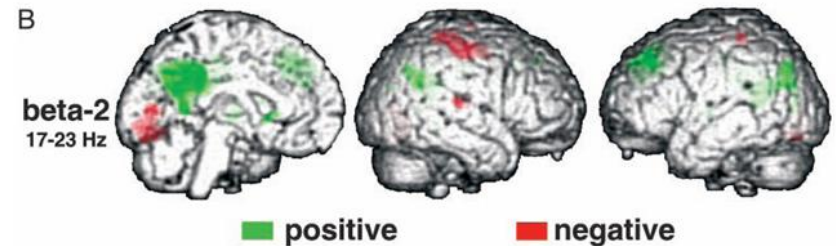
ALFA

- ❑ desynchronization when attentional network goes on
- ❑ positive correlation with hemodynamic fluctuation in thalamus, negative in fronto-parietal regions (attentional network)



BETA

- ❑ positive correlation with hemodynamic fluctuations in default mode network



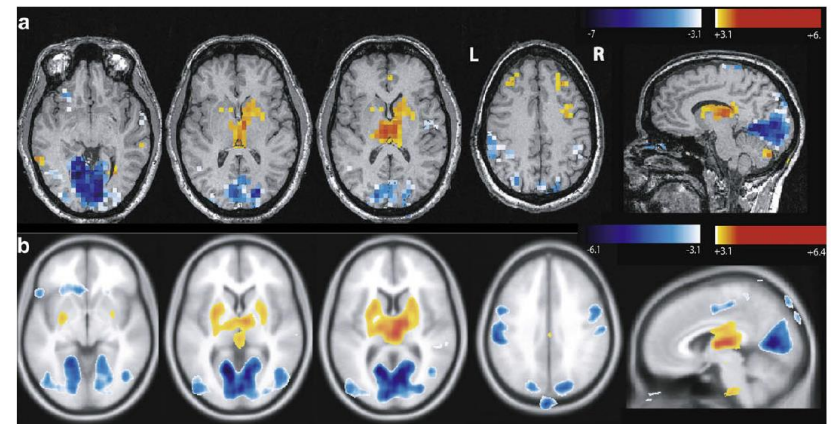
Brain rhythms

Tyvaert et al., 2008

L. Tyvaert et al. / Clinical Neurophysiology 119 (2008) 2762–2774

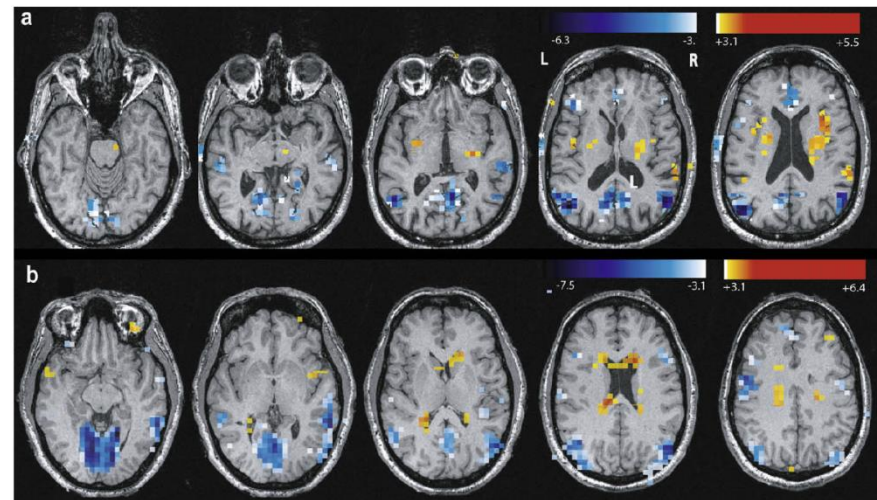
ALFA

- positive correlation with hemodynamic fluctuation in thalamus
- the rhythmic thalamic activity related to cortico-cortical component that contributes to the generation of a cortical domain of alpha and its propagation over the cortex



THETA

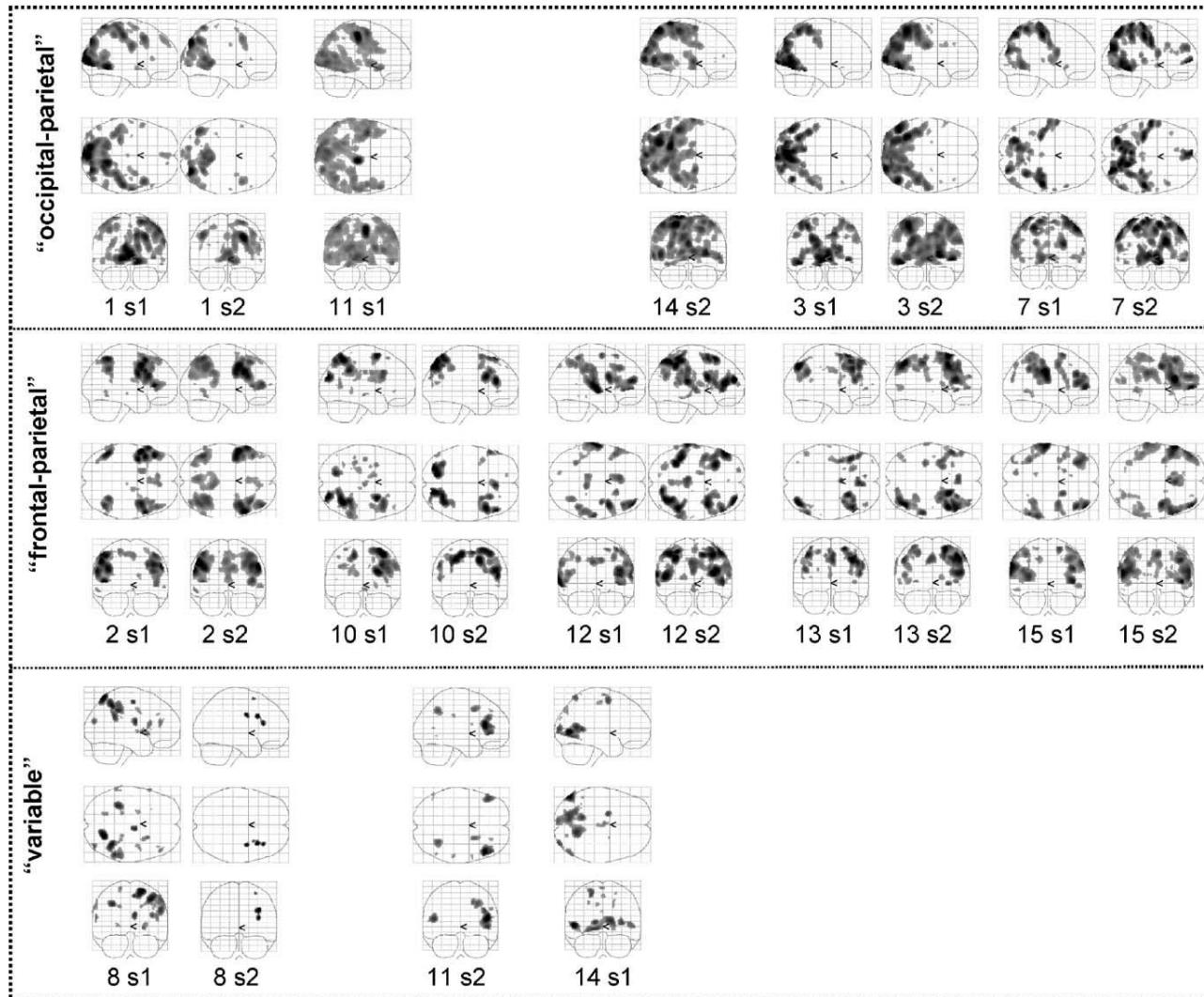
- theta seems related to default mode network



Brain rhythms

Laufs et al., 2006

ALFA



Brain rhythms

In general, there is a consensus that a distinct fMRI network may correlate with multiple brain rhythms and, conversely, distinct brain rhythm may correlate with multiple fMRI networks.

de Munck et al. 2009; Laufs 2008

WHY??

probably due to strict constraints in the stage of EEG preprocessing

- ❑ preselected subgroups of electrodes
- ❑ averaging the signal across electrodes
- ❑ preselected frequency band of interest
- ❑ unknown shape and timing of hemodynamic response

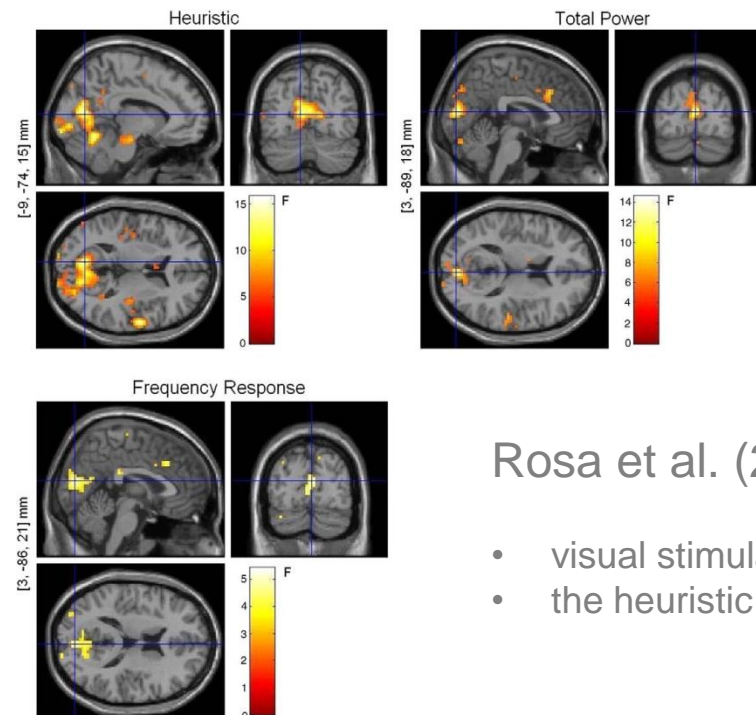
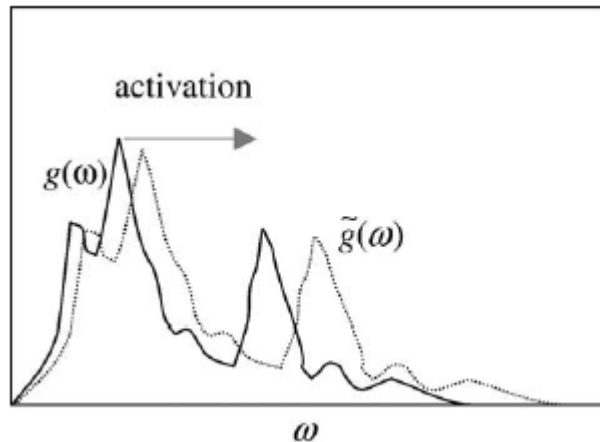
employ data-driven methods without any prior constraints applied to the spatial and temporal dimensions or to the shape of a frequency band of interest when seeking information hidden in the structure of EEG activity

Brain rhythms

Kilner et al. (2005)

- theoretical neurophysiology model (“Heuristic”)
- activation causes:
 - increased energy dissipation
 - decreased effective membrane time constants
 - increased effective coupling among neuronal ensembles
 - a shift in the EEG spectral profile to higher frequencies

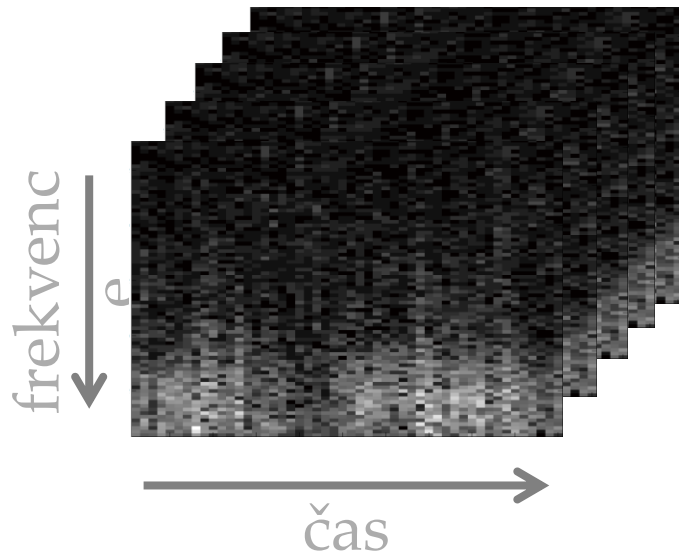
$$\left[\frac{\tilde{b}}{b}\right]^2 \propto (1 + \alpha)^2 \propto \frac{\int \omega^2 \tilde{p}(\omega) d\omega}{\int \omega^2 p(\omega) d\omega}$$



Rosa et al. (2005)

- visual stimulation
- the heuristic is the best

Brain rhythms



=> 3D spectrogram

PARAFAC

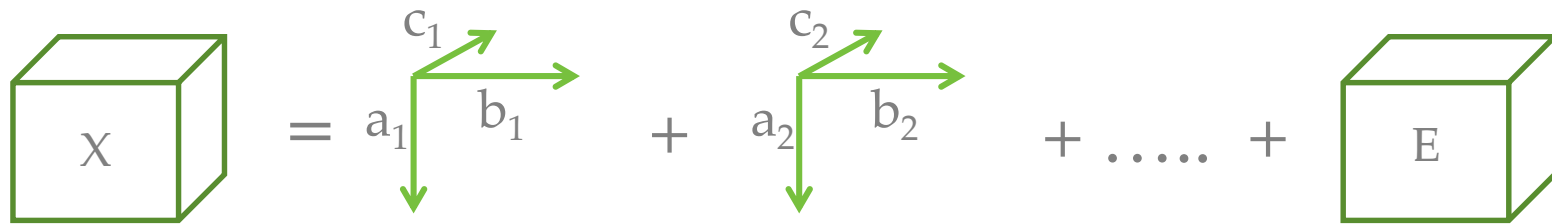
- blind decomposition of 3D data (in general N-dimensional)
- a kind of analogy of PCA to higher dimensions

Brain rhythms

Parafac model

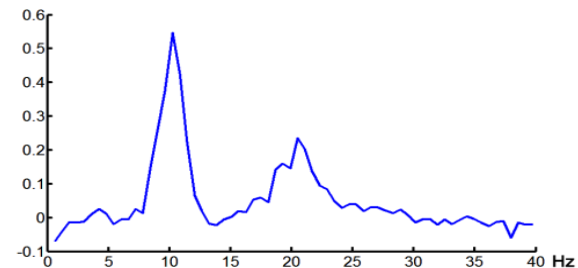
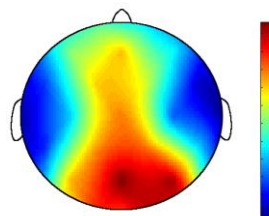
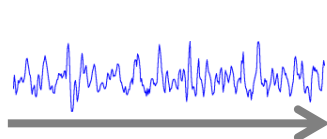
$$x_{ijk} = \sum_{f=1}^F a_{if} b_{jf} c_{kf} + e_{ijk}$$

- decomposition of 3D matrix into components



- each component has 3 signatures

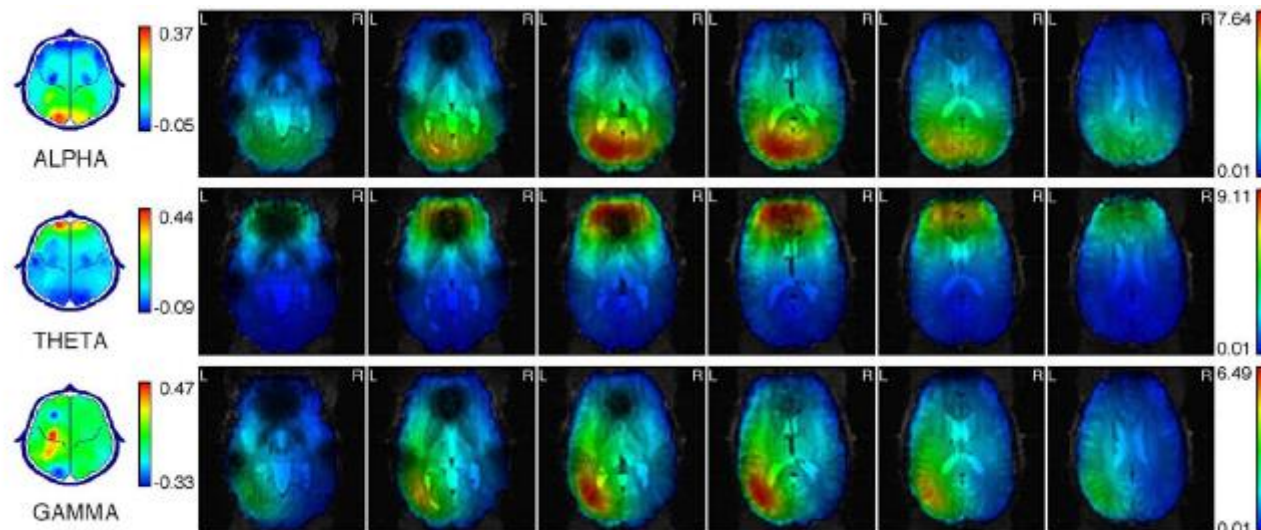
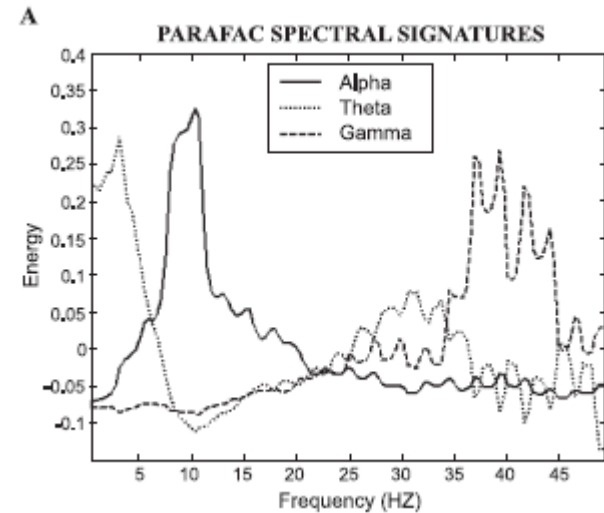
- spectral pattern
- scalp topography
- time-series of power fluctuations



Brain rhythms

Martinez-Montes et al., 2004

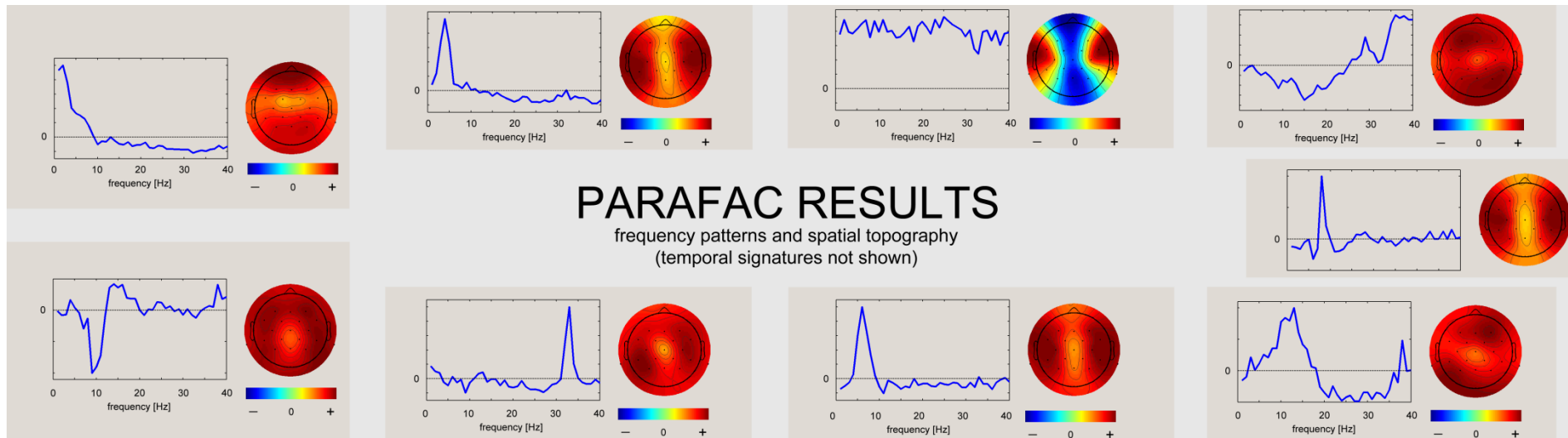
- EEG-fMRI data
- resting state
- identified 3 components in EEG (atoms)
- time-series signaters used as a regressors for fMRI analysis



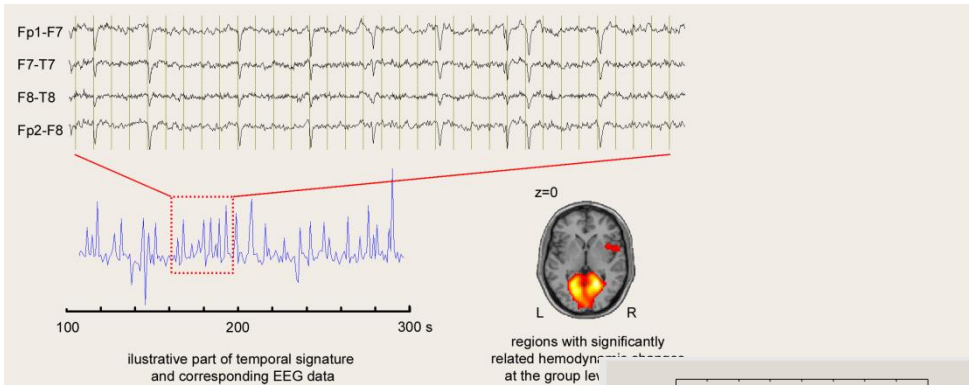
Brain rhythms

Marecek et al., 2016

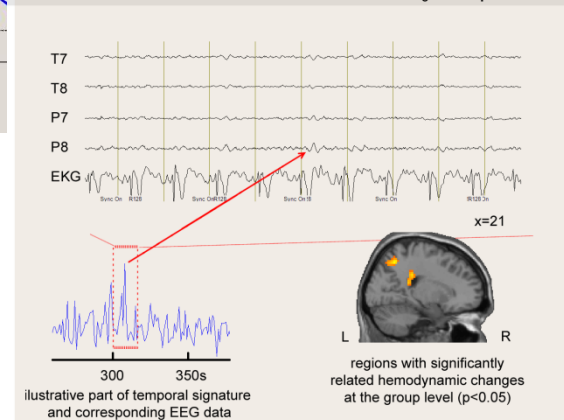
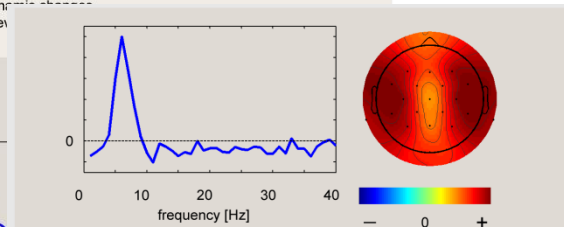
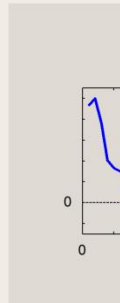
- EEG-fMRI data
- semantic decision task
- identified 9 components
- time-series signatures used as a regressors for fMRI analysis



Brain rhythms

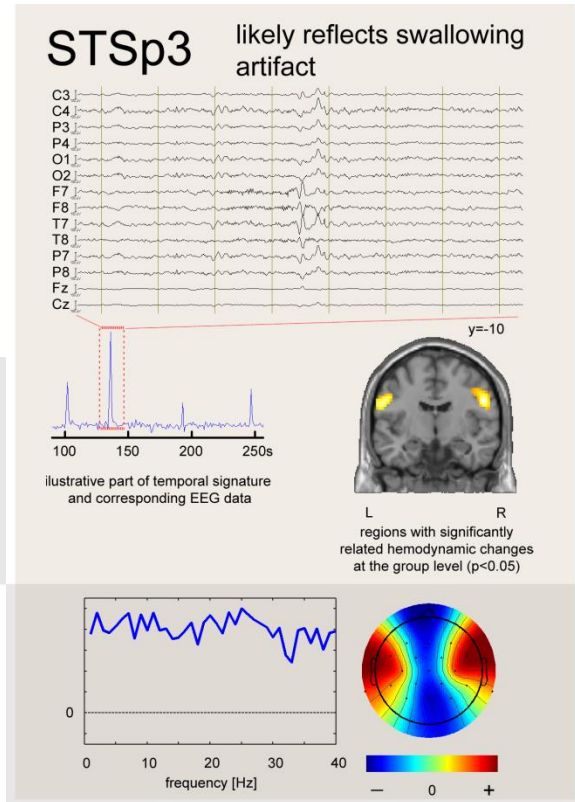


STSp1
eye blinks artifact

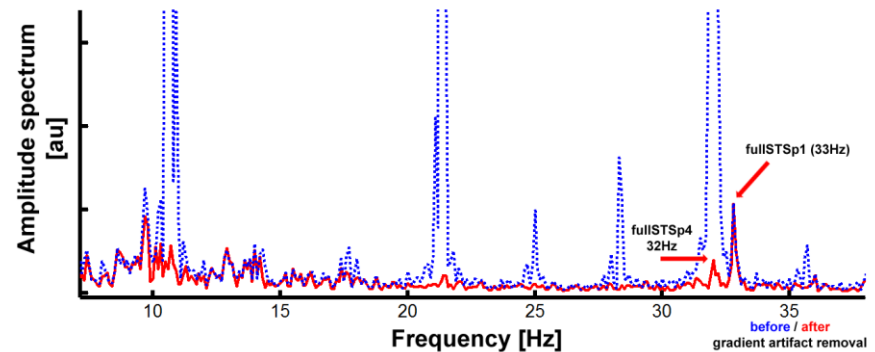
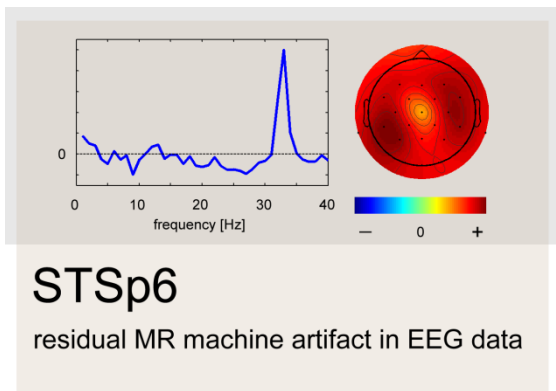


STSp7

likely residual heart beat artifacts in EEG

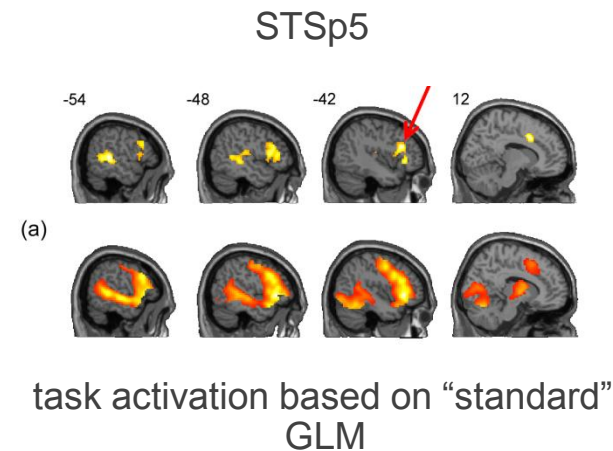
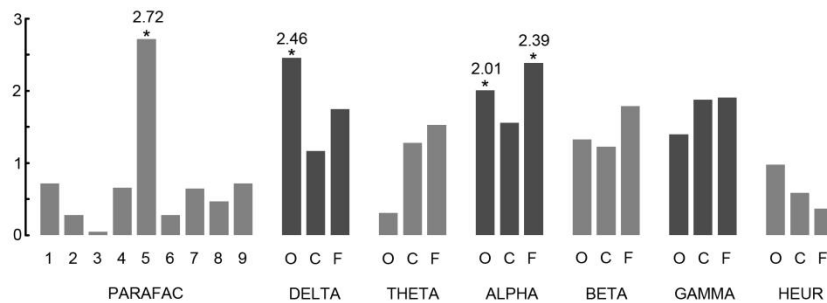
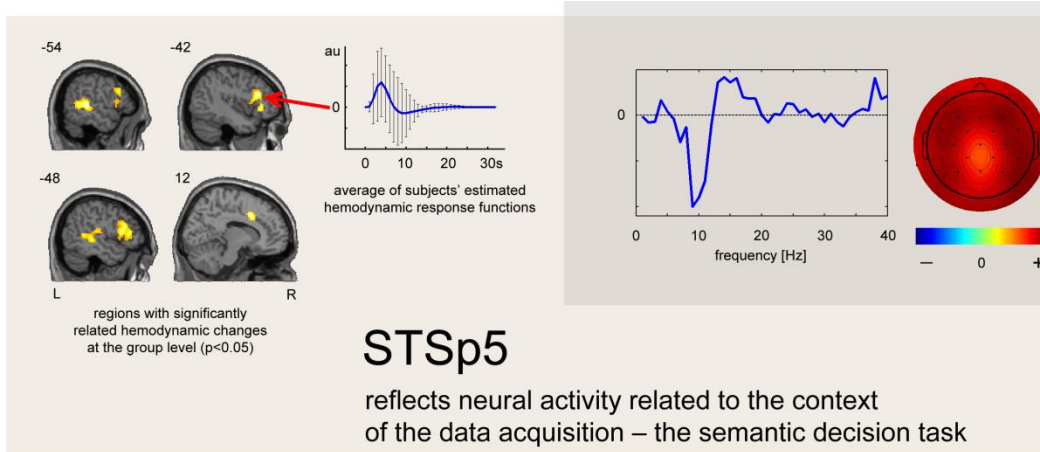


Brain rhythms



Supplementary figure 1: Amplitude spectrum of EEG before and after gradient artifact removal. The figure shows data from representative subject 28. The spectra are computed from a 10s period of EEG and averaged across channels. The blue line depicts the spectra before artifact removal – predominantly the peaks at 10.7, 21.3 and 32 Hz, i.e. harmonics of gradient artifact and other peaks at 25, 28.3, 33 and 35.7Hz. The red line shows the spectra after artifact removal. Please note, that there is left small amount of power of 3th harmonic of gradient artifact at 32Hz and full power of peak at 33Hz (depicted by red arrow). The similar situation can be seen for every subject.

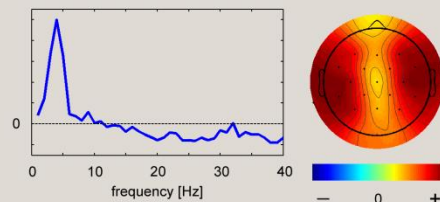
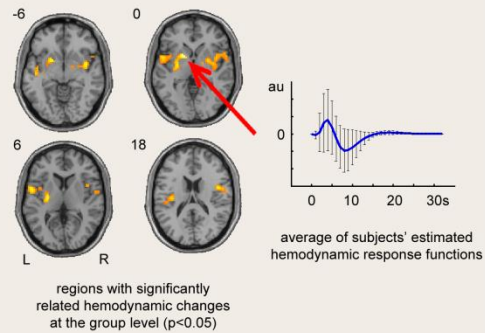
Brain rhythms



Brain rhythms

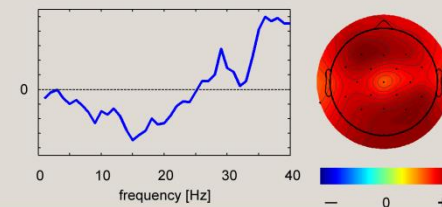
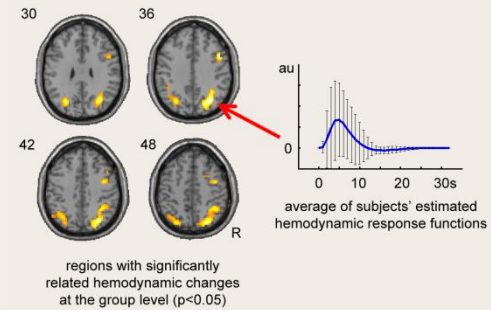
STSp2

likely reflects outwards
manifestation of striatal activity

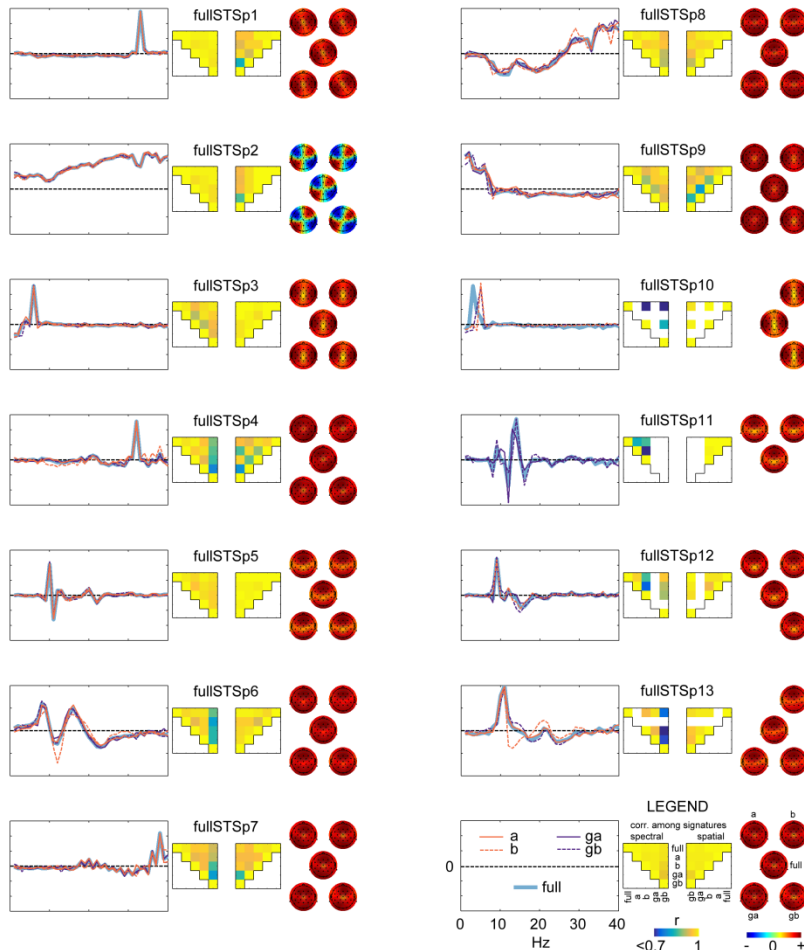


STSp4

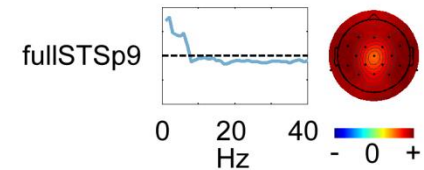
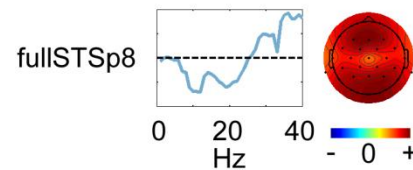
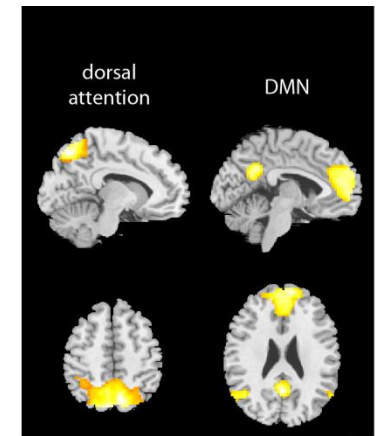
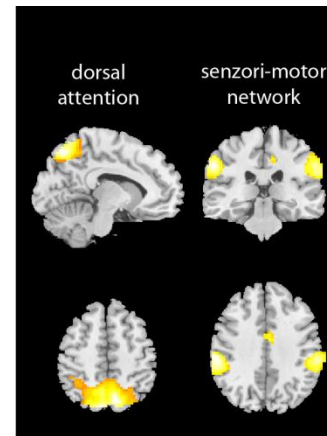
the EEG spectral pattern of attentional
resting state network



Brain rhythms



Marecek et al., 2016



- EEG-fMRI data divided to subsets
- PARAFAC estimation of each subset of data
- high stability of decomposition
- stable correspondence of some patterns to large scale brain networks

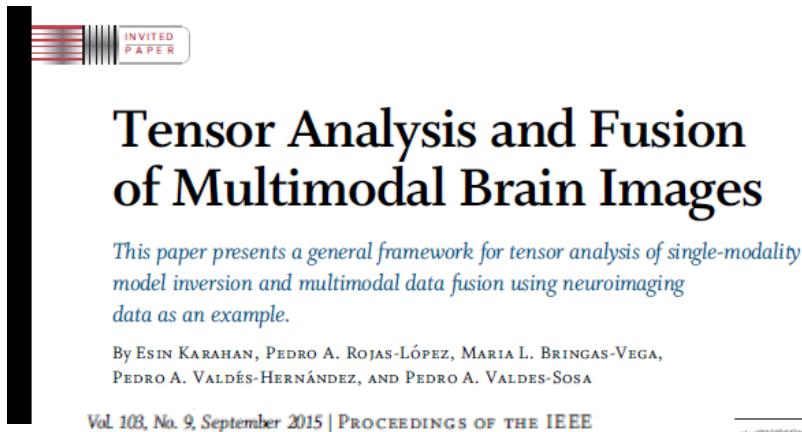
Brain rhythms

- there is a relationship between brain rhythms in EEG and hemodynamic fluctuations in large scale brain networks
- it seems that it is reasonable to use data driven methods
- some spatial-temporal-spectral patterns of EEG activity have stable correspondence to the large scale brain networks

Tensors in EEG

Perhaps new trends in EEG-fMRI data processing

- tensor representation – multiway-array data representation
- blind decomposition



Tensor Decompositions for Signal Processing Applications

From Two-way to Multiway Component Analysis

A. Cichocki, D. Mandic, A.-H. Phan, C. Caiafa, G. Zhou, Q. Zhao, and L. De Lathauwer

2015

Journal of Neuroscience Methods 248 (2015) 59–69



Contents lists available at ScienceDirect

Journal of Neuroscience Methods

journal homepage: www.elsevier.com/locate/jneumeth



Computational neuroscience

Tensor decomposition of EEG signals: A brief review

Fengyu Cong^{a,b,*}, Qiu-Hua Lin^c, Li-Dan Kuang^c, Xiao-Feng Gong^c, Piia Astikainen^d, Tapani Ristaniemi^b

^a Department of Biomedical Engineering, Faculty of Electronic Information and Electrical Engineering, Dalian University of Technology, Dalian, China

^b Department of Mathematical Information Technology, University of Jyväskylä, Jyväskylä, Finland

^c School of Information and Communication Engineering, Faculty of Electronic Information and Electrical Engineering, Dalian University of Technology, Dalian, China

^d Department of Psychology, University of Jyväskylä, Jyväskylä, Finland



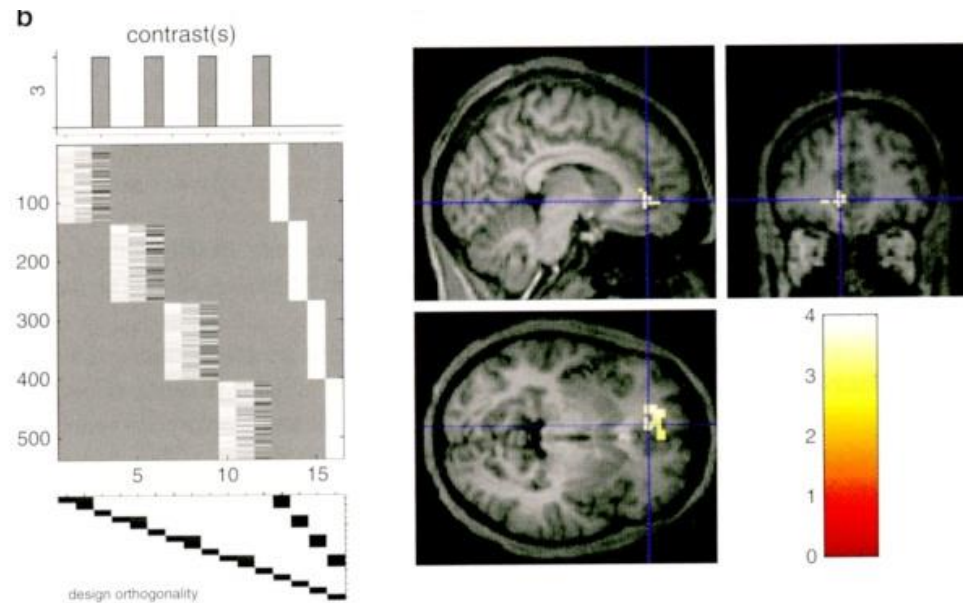
HIGHLIGHTS

- EEG signals are naturally born with multi modes.
- EEG signals can be represented by the high-order multi-way array, tensor.
- Tensor of EEG can be exploited by tensor decomposition for multi-way analysis.

ERP and hemodynamics

Relationships between ERP features and BOLD

- Benar et al. 2007
- activity of anterior cingulum is significantly related to the amplitude of P300 wave in oddball task



Benar et al. 2007

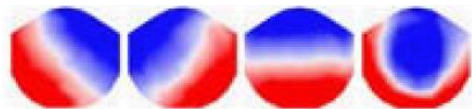
Microstates and BOLD

Relationships between topography of scalp EEG and BOLD

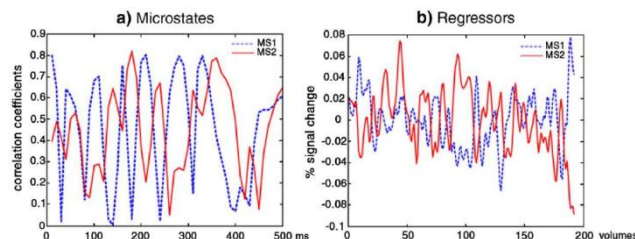
- Britz et al. 2010
- relationship between occurrence of microstates and resting state networks

Microstates

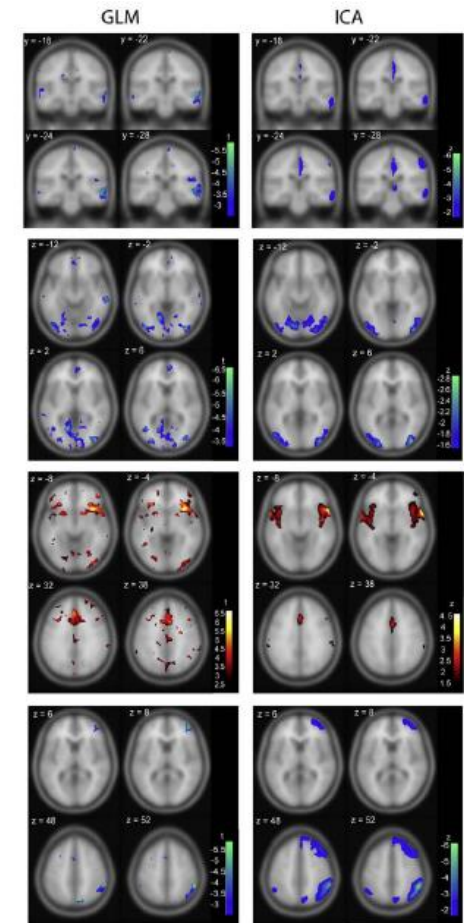
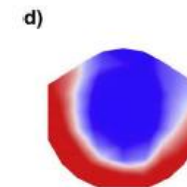
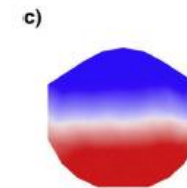
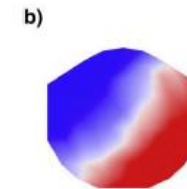
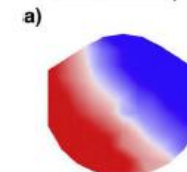
- the concept of short-term stable topographies



- the time-series of microstate occurrences used to process fMRI data



Microstate Maps

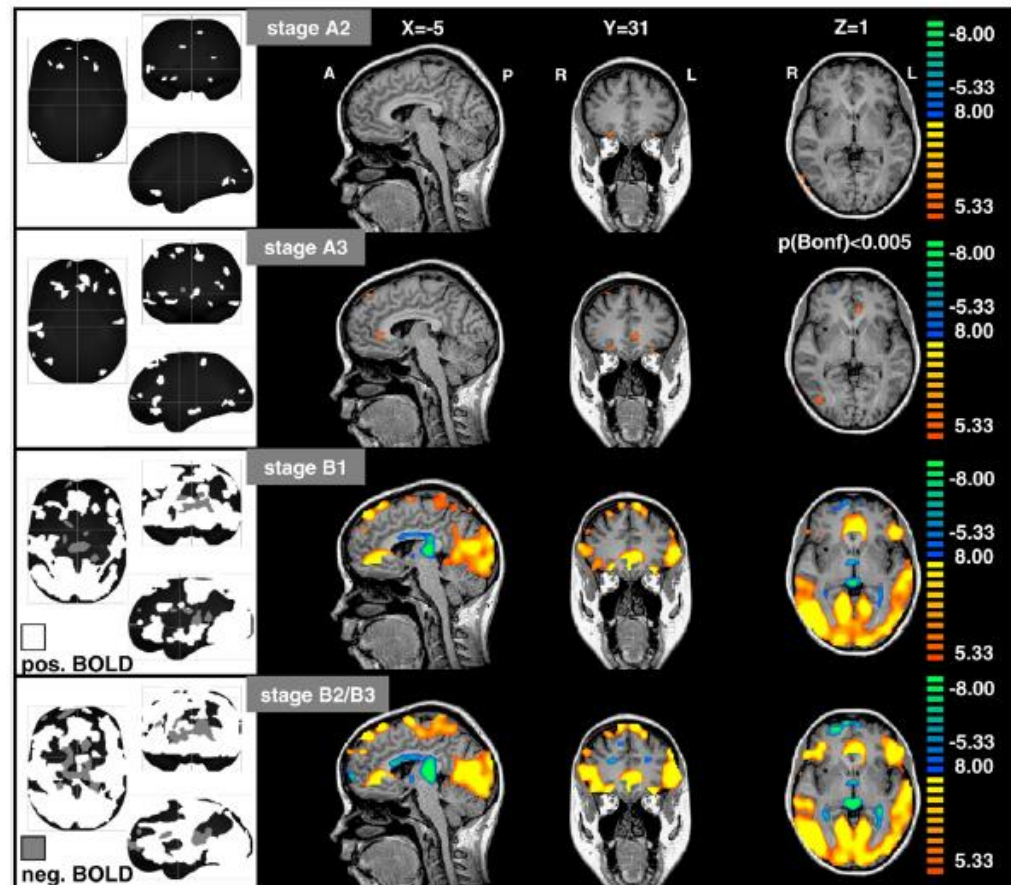
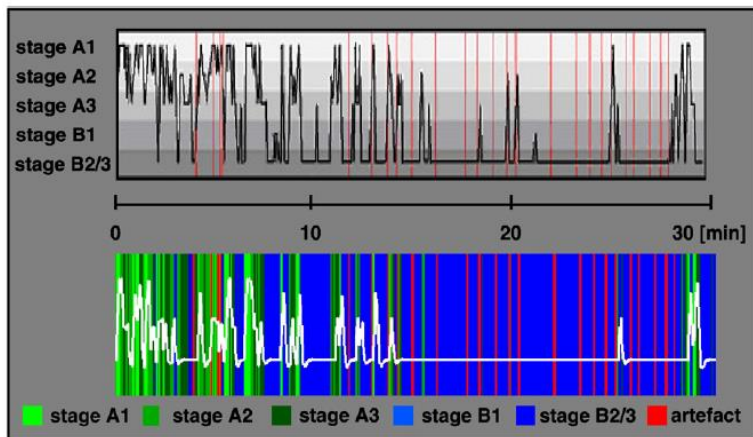


Britz et al. 2010

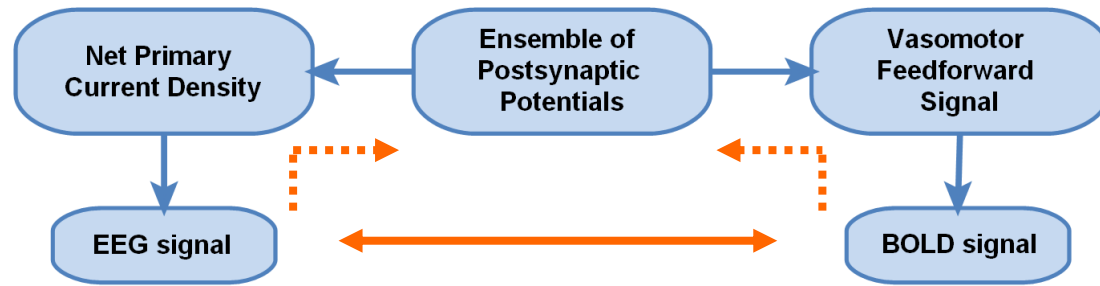
Sleep research

- the sleep research (Olbrich et al. 2009)

<div style="display: flex; align-items: center;"> <div style="writing-mode: vertical-rl; transform: rotate(180deg);">Alertness</div> <div style="flex-grow: 1; border-left: 1px solid black; border-right: 1px solid black; position: relative;"> <div style="position: absolute; top: 0; bottom: 0; left: 0; right: 0; border-left: 1px solid black; border-right: 1px solid black; background: linear-gradient(to bottom, transparent 49%, black 49% 51%, transparent 51%);"></div> <div style="position: absolute; top: 50%; left: 50%; transform: translate(-50%, -50%);">EEG-Vigilance</div> </div> <div style="writing-mode: vertical-rl; transform: rotate(180deg);">Drowsiness</div> </div>	EEG-stage A	A1	F3	
		alpha power (O1+O2) > 55% of alpha power (F3+F4+O1+O2)	O1	
		alpha power (8-12 Hz) in F3, F4, O1 or O2 >50% of total power (2-12 Hz)	F3	
		rest of A stage segments	O1	
		A3	F3	
		alpha power (F3+F4) > 55% of alpha power (F3+F4+O1+O2)	O1	
	EEG-stage B	B1	F3	
		total power (F3+F4+O1+O2)-alpha power (F3+F4+O1+O2) <200 μ V ²	O1	
		B2/B3	F3	
		total power (F3+F4+O1+O2)-alpha power (F3+F4+O1+O2) >=200 μ V ²	O1	



Data fusion – current research



Valdes-Sosa et al., 2009

- the most of methods use direct comparison between acquired EEG and fMRI signals (or parameters derived from the signals)
- the current directions of research is aimed on forward models and their incorporation to the data processing pipelines

Thank you for your attention



Central European Institute of Technology
c/o Masaryk University
Žerotínovo nám. 9
601 77 Brno, Czech Republic

www.ceitec.eu | info@ceitec.cz



EUROPEAN UNION
EUROPEAN REGIONAL DEVELOPMENT FUND
INVESTING IN YOUR FUTURE



**OP Research and
Development for Innovation**

