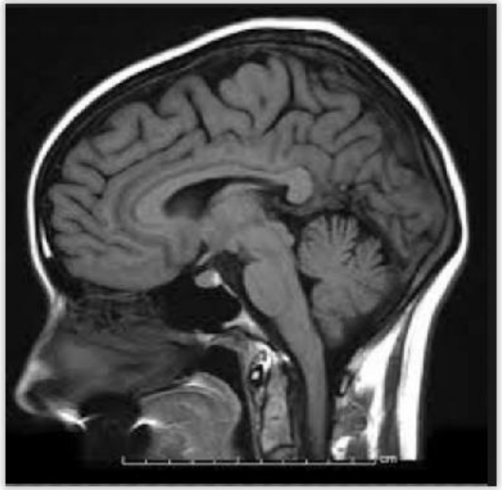
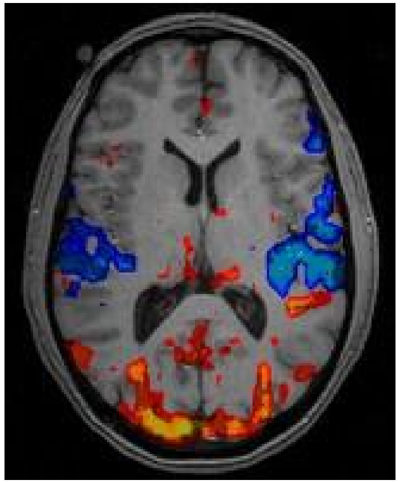
Data analysis in time-resolved non-invasive neuroimaging

Signal processing issues in electro- and magnetoencephalography

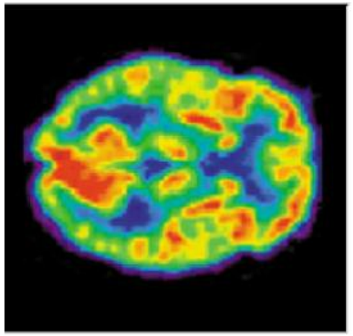
Alex Ossadtchi, Ph.D.,
professor of the DDAAI @ HSE,
senior researcher of the Center for Cognition and Decision making @ HSE

Technology behind the non-invasive neuroimaging

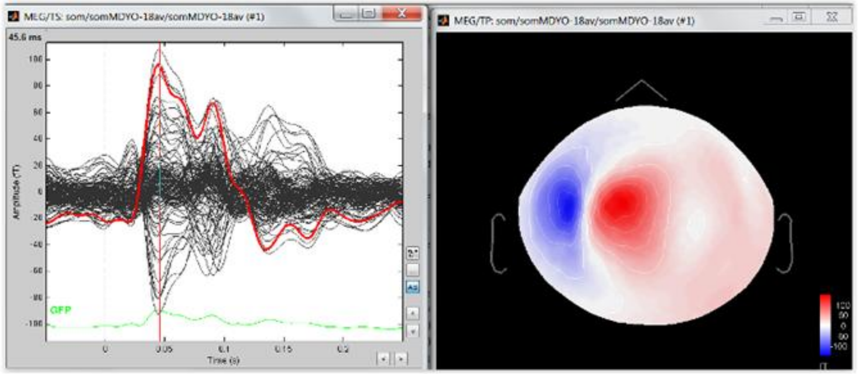


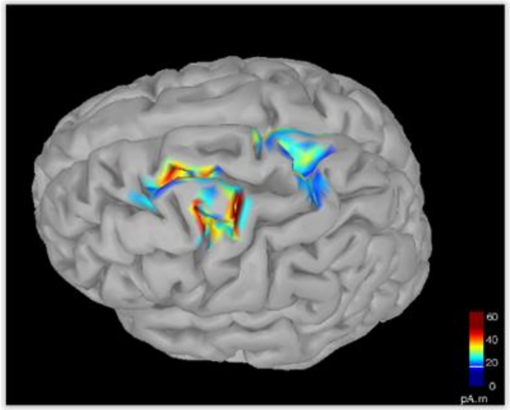


Structural & Functional
Magnetic resonance tomography (MRI, fMRI)



Positron emission tomography (PET)

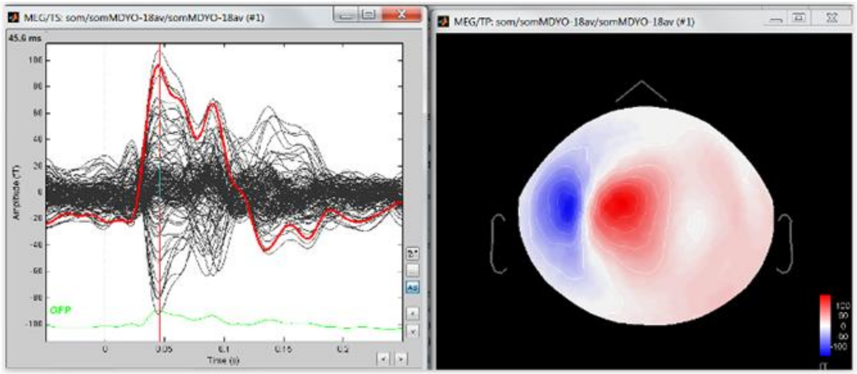


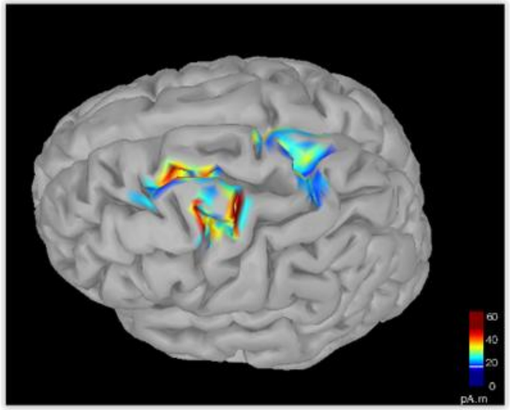


Electro and magnetoencephalography

Go EEG , MEG!

- Magnetic resonance tomography (functional & structural) (MRI, fMRI)
- Positron emission tomography (PET)
  - Hemodynamic and metabolic correlates -> low time resolution, not so high spatial resolution(functional)





- MagnetoEncephaloGraphy and ElectroEncephaloGraphy
  - Measures electrical acitivity -> high temporal resolution
  - Fantastic opportunity in mapping brain function and its fine temporal scale dynamics
  - Spatial accuracy **heavily depends on the mathematical algorithms used for solving the inverse problem**

Many uses

- Brain research labs around the world
  - Basic functions (e.g. perception, action, learning)
  - Complex functions (e.g. decision making, conformity, consciousness)

- Diagnostic
  - Epilepsy, ADHD, Depression, Parkinsonism, Schizophrenia, Stroke
  - Sports mild brain injury
  - Brain state monitoring (e.g. anesthesia)

- Rehabilitation and peak performance training
  - Brain-computer interface
  - Neurofeedback (patients, operators, classical music performers, sportsmen)

- Computer game industry

Class outline (topics to be covered)

- Neurophysiological basics of the origin of the MEG and EEG data
- Methods for solving the inverse problem
  - parametric and non-parametric Bayesian approaches
- EEG/MEG data mining for dynamic networks
  - Synchrony measures, estimators, standard and brand new techniques
- Brain-computer interfaces
  - Types and typical signal processing algorithms

Level 1

Calculus
- Complex numbers
- Fourier transform
- Functional spaces
- Norms, scalar products
- Vector differential calculus
- Differential equation
- Partial differential equations

Linear Algebra & analytical geometry
- Abstract vector spaces
- Notion of norm, cross-product
- 2-nd order curves and surfaces

Probability Theory
- Vector random variables
- Scatter diagram
- Moments
- Gaussian r.v.
- Conditional r.v., Bayes rule, Chain rule
- Covariance matrix

Statistics I(parametric)
- Descriptive stats
- Robust stats
- Param estimation, estimator properties
- Hypothesis testing,
- Parametric tests
- Non-parametric tests

Level 2

Operational calculus
- Laplace transform
- Solving differential eqs
- Root analysis, stability

Advanced topics in LA
- SVD
- PCA
- Simultaneous diagonalization
- Subspace correlation
- Overdetermined/underdetermined systems of eqs
- Min-norm principle

Random processes
- Stationarity
- Autocorrelation function
- Power spectral density
- Narrow-band processes
- Hilbert envelope, phase
- Cross-spectum., coherence
-

Statistics II
- Regression analysis
- GLM
- ANOVA
- Post-hoc analysis
- Multiple hypothesis testing
- Multiple comparisons problem
- Randomization tests
- Family-wise error rate control
- False discovery rate control

Level 3

Linear Systems Theory
- Time invariance
- Impulse response
- Convolution
- Causality
- Stability
- Discrete systems
- Z-transform
- Eigenfunctions of LTI
- Transfer function

Digital signal processing
Sampling theorem

DFT, FFT

Digital filters design

Wavelet transform

Coherence

Estimation & Detection Theory
ML estimation

MAP estimation

Sufficient statistics

Kramer-Rao bound

Matched filters

Kalman filter

Extended KF

Monte-Carlo methods

ROC analysis

Optimization theory
Linear programming

Derivative free techniques

Quadratic optimization

Non-quadratic o., preconditioners

Formal Class Description

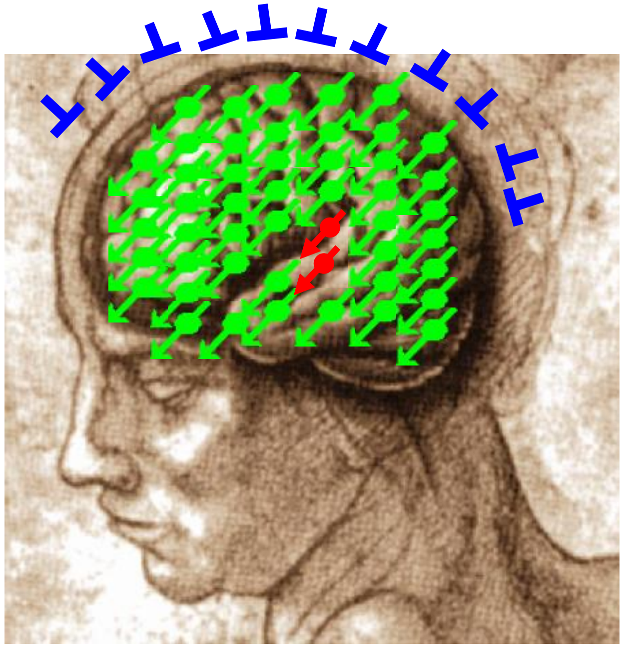
- Prerequisite courses
  - Linear algebra
  - Mathematical analysis
  - Probability theory and Statistics
  - Physics(101)

- Programming skills
  - Matlab

- Format
  - 8-10 1.5 hour sessions
  - 4-5 HW assignments (all involve Matlab programming)

- Equipment use
  - Opportunity to use EEG setup and explore your own brain activity with methods learnt

EEG/MEG measurement equation



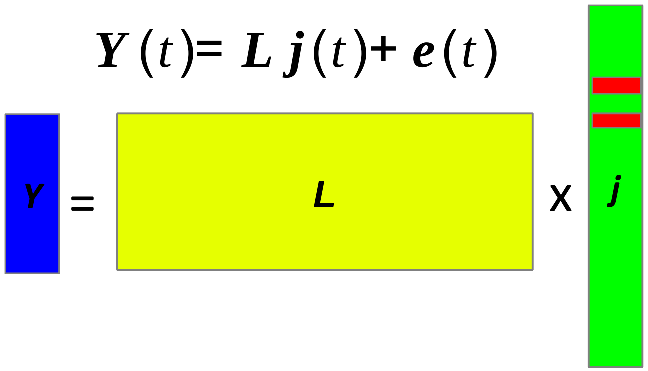
m(*t*) - measurement vector at time instance *t*. Dimension of ***m****(t) is equal to the number of sensors*

L *- forward matrix, whose i-th column is obtained by solving the forward problem for the given sensor configuration and for a single dipolar source located in the i-th voxel.*

j(t) – UNKNOWN vector of activations of dipolar sources at time t

e(t) *– vector of unaccounted random error (or noise)*

$$\boldsymbol{Y}(t) = \boldsymbol{L}\,\boldsymbol{j}(t) + \boldsymbol{e}(t)$$



- Regularization techniques are used. Most can be described within Bayesian maximum aposteriory probablity (MAP) framework.

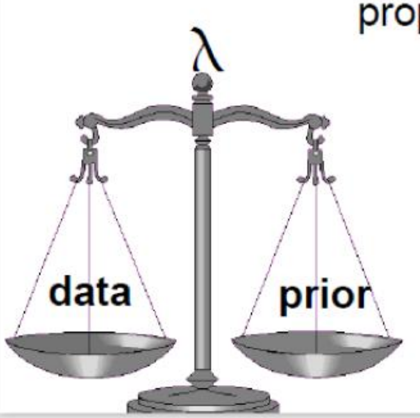
- Allows to achieve a trade off between data and a priori knowledge about the properties of the solution

- Simplest min-norm regularization boils down to the following optimization problem

$$min\left[norm_{Q^{-1}}(\boldsymbol{j})+\lambda\, norm_{\Sigma_{\epsilon}^{-1}}(\boldsymbol{G}\,\boldsymbol{j}-\boldsymbol{m})\right]$$

Prior term, e.g. Desired solution properties expressed mathematically

Data term. How much do we trust the data?



$$\lambda=0-ignore\ the\ data\ completely\ ,\ \boldsymbol{j}=\boldsymbol{0}$$

$$\lambda=\infty-fully\ trust\ the\ data\ ,\ N_{solutions}=\infty$$

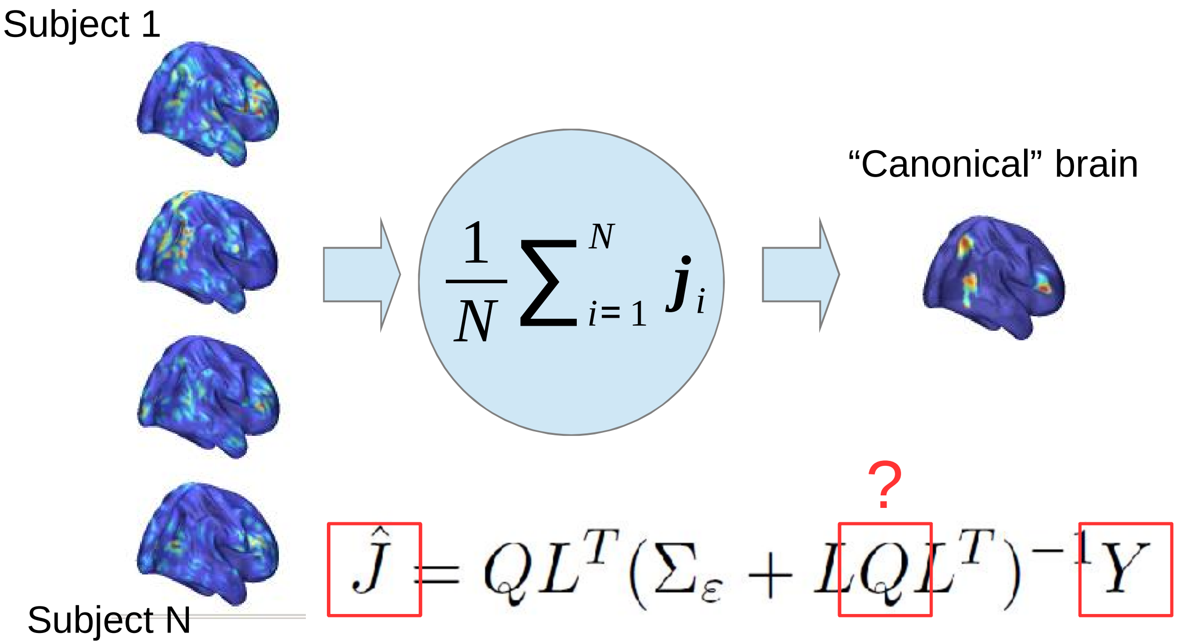
GALA: Group analysis leads to accuracy (with V. Kozunov)

- In a traditional setting individual inverse solutions are found and then warped onto the average or some canonical brain

$$Y_1 = L_1 j_1 + \epsilon_1$$

$$Y_2 = L_2 j_2 + \epsilon_2$$

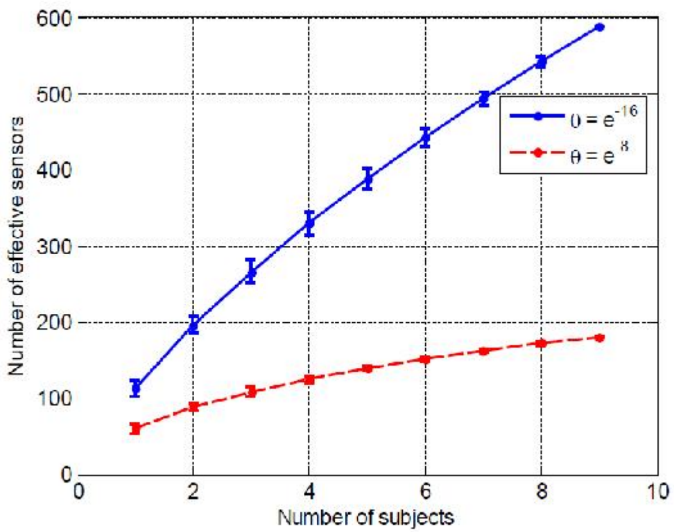
$$Y_2 = L_2 j_2 + \epsilon_2$$



$$\hat{J} = QL^T(\Sigma_\varepsilon + LQL^T)^{-1}Y$$

Simultaneous algebraic inverse

$$\begin{bmatrix} Y_1 \\ \vdots \\ Y_N \end{bmatrix} = \begin{bmatrix} L_1 \\ \vdots \\ L_N \end{bmatrix} \hat{J} + \begin{bmatrix} \varepsilon_1 \\ \vdots \\ \varepsilon_N \end{bmatrix}$$



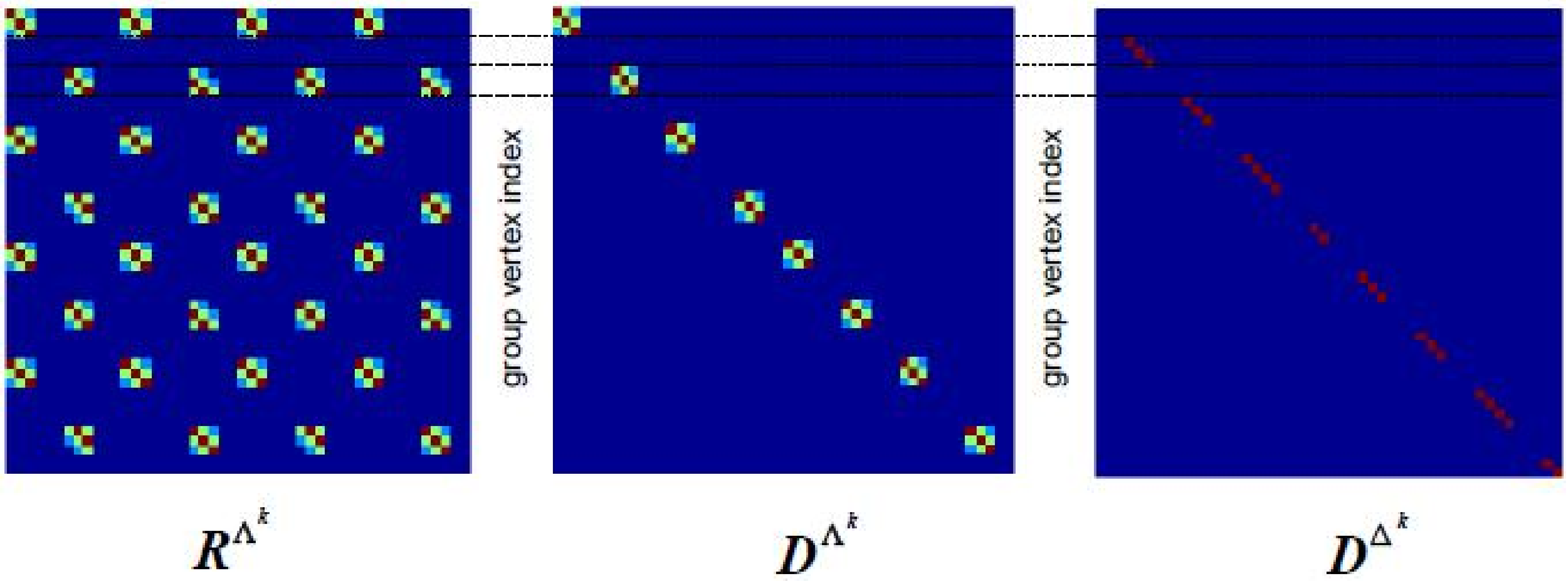
Want to be more flexible

$$\begin{bmatrix} Y_1 \\ \vdots \\ Y_N \end{bmatrix} = \begin{bmatrix} L_i & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & L_N \end{bmatrix} \begin{bmatrix} J_1 \\ \vdots \\ J_N \end{bmatrix} + \begin{bmatrix} \varepsilon_1 \\ \vdots \\ \varepsilon_N \end{bmatrix}$$

$$\boldsymbol{J}_1 \approx \boldsymbol{J}_2 \approx \ldots \approx \boldsymbol{J}_N$$

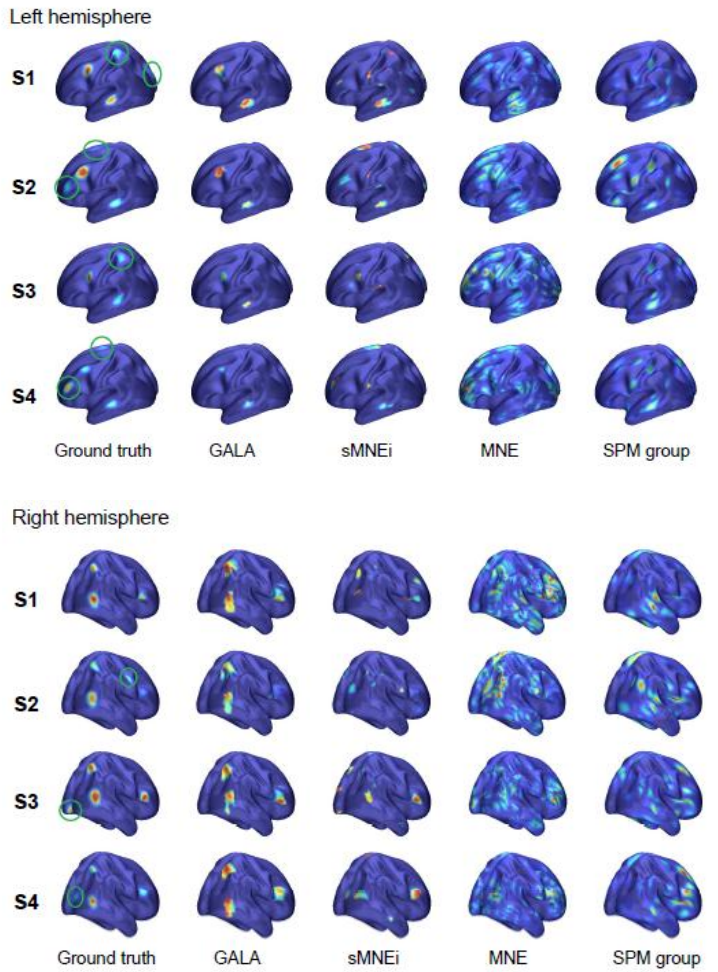
In a probabilistic sense

How to model dissimilar across subjects activity that IS present?

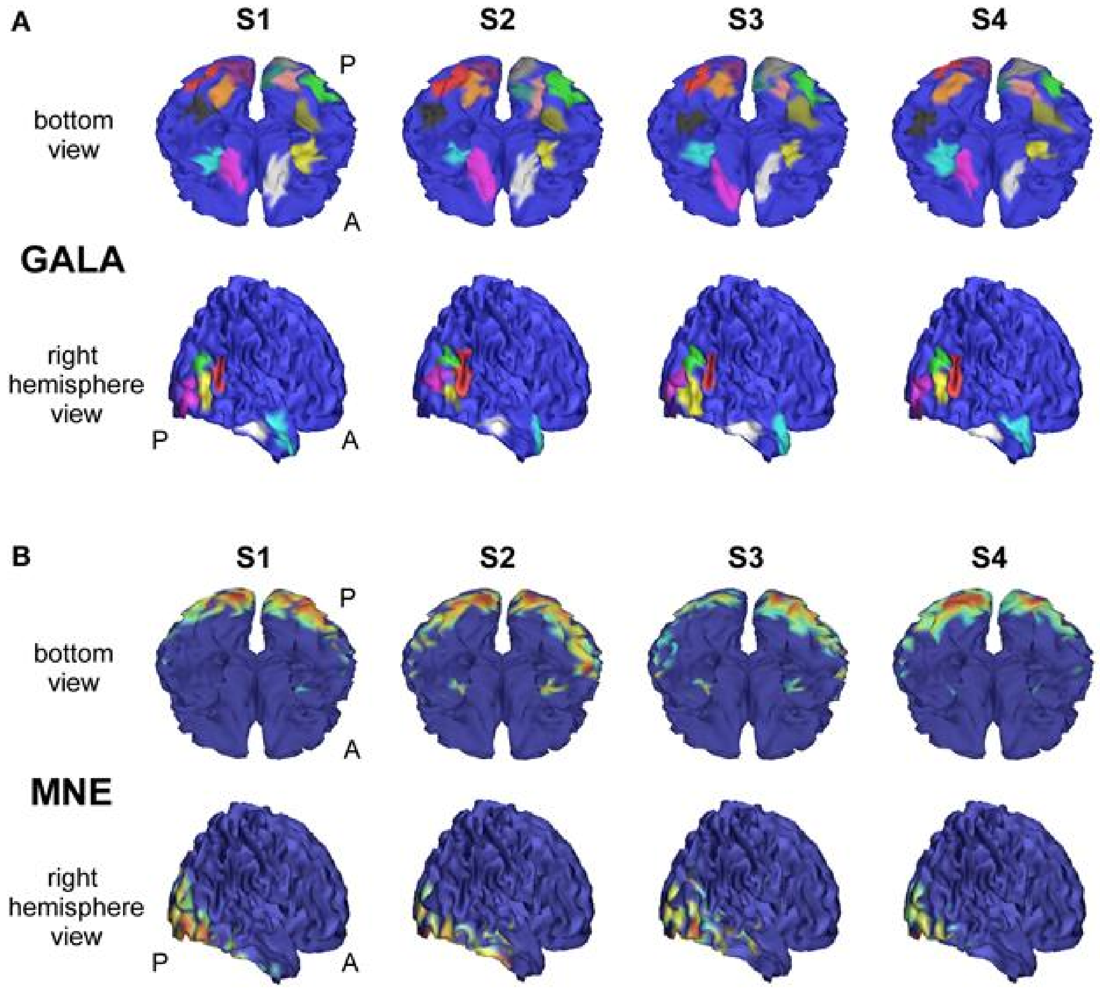


$$Q^k = h_2^k R^{\Lambda^k} + h_3^k D^{\Lambda^k} + \sum_{j=2}^{k} h_{2+j}^k D^{\Delta^j}$$

Simulation results

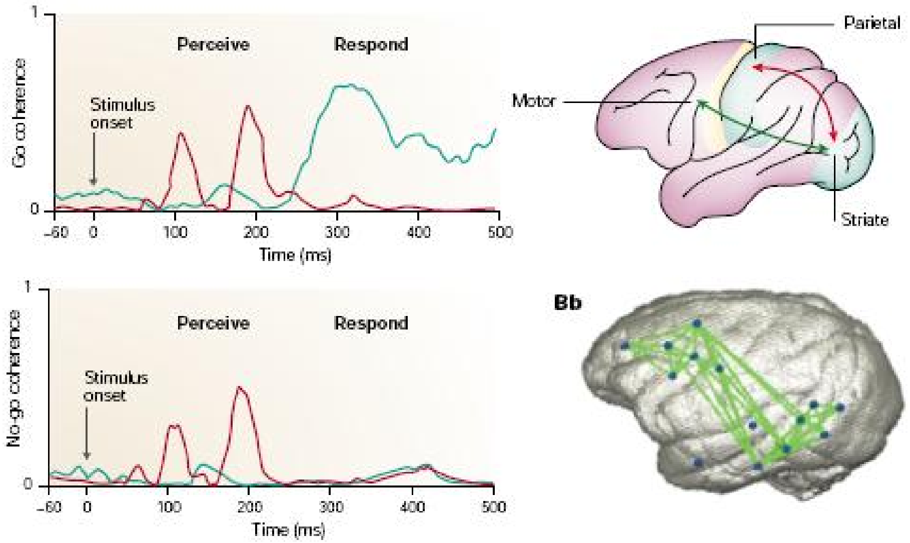


Face vs scrambled face visual stimuli



Power and shift independent imaging of coherent sources(PSIICOS) - a novel technique for detection of within frequency interactions

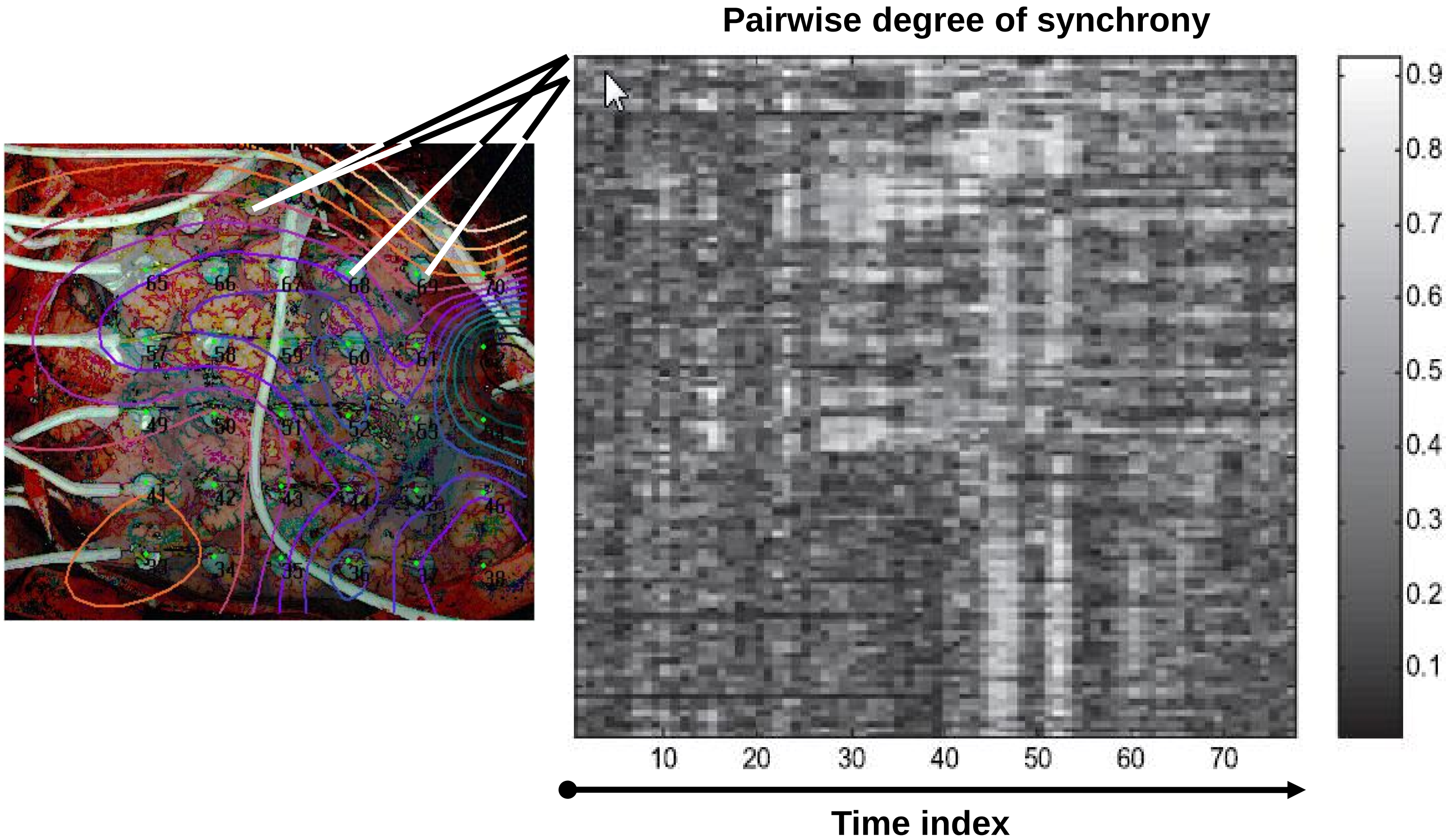
Transient networks



Go-no-Go task in a behaving cat waiting for a visual pattern to change

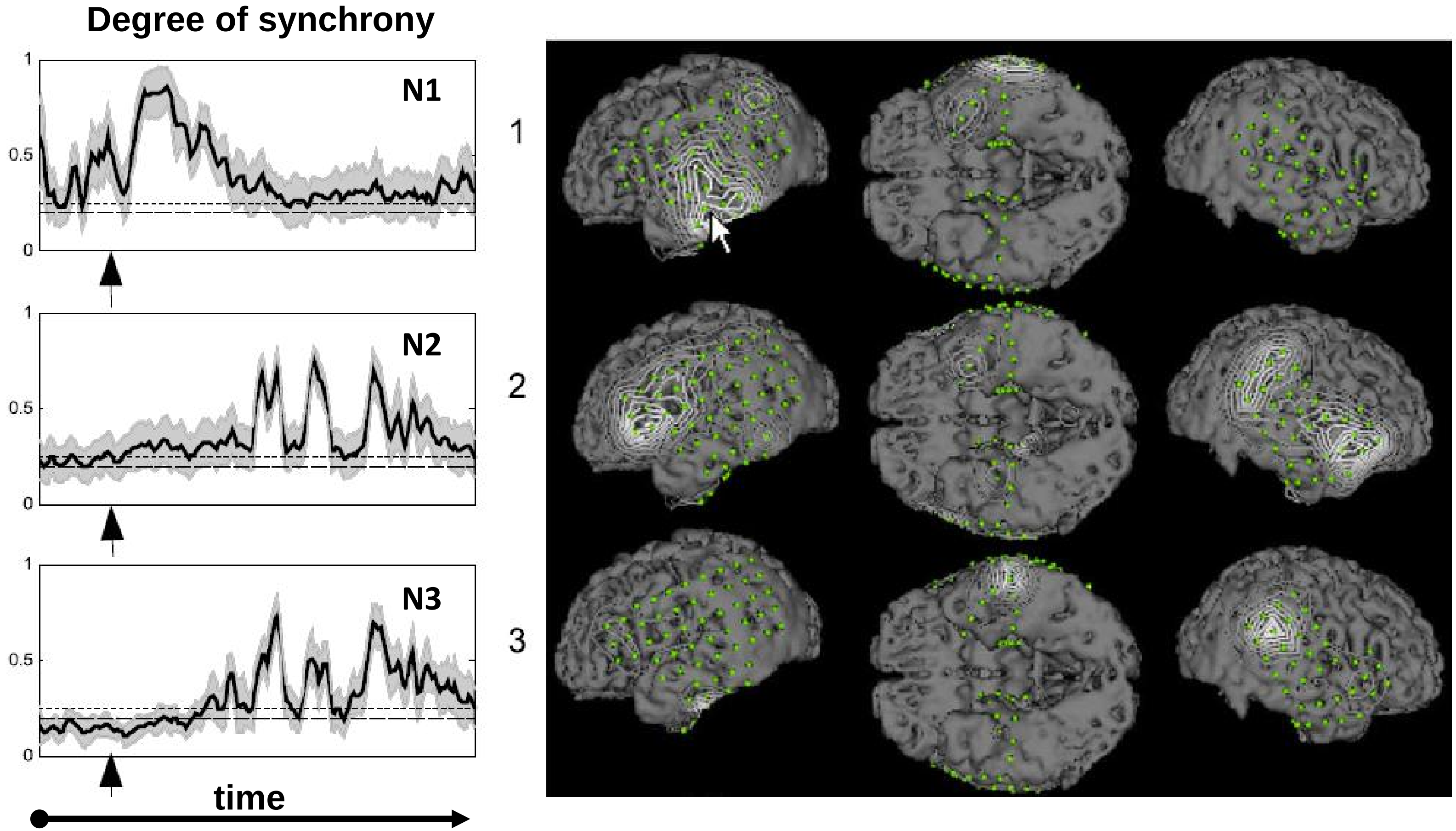
Varela et al., Brainweb, Nature Review Neuroscience, 2001,2,229-239

Network clusters seen in dynamics



A. Ossadtchi, R.E. Greenblatt, V.L. Towle, M.H. Kohrman, K. Kamada, Inferring Spatiotemporal Network Patterns from Intracranial EEG Data, *Clin, Neurophysiology*, 2010

Concurently active networks at seizure onset in gamma band



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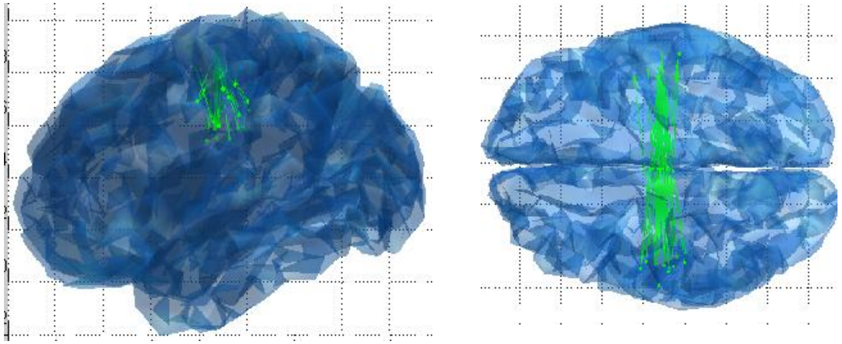
Experimental Setting

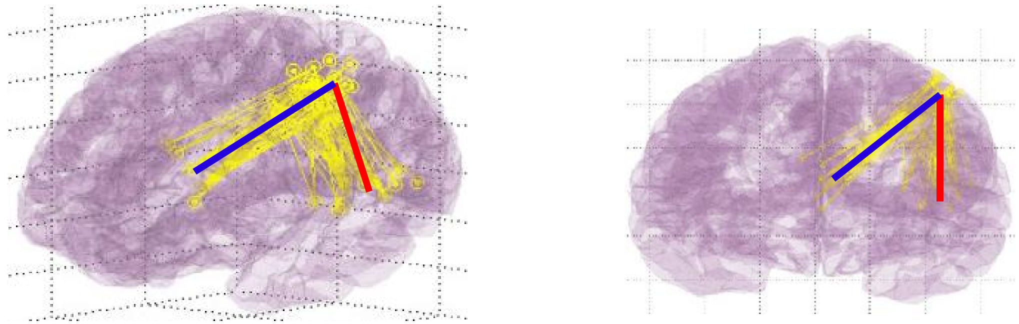
The Center of
Neurocognitive
Research
Moscow MEG Center

- Odd-ball, movement related words (randomized design)
  - Brosym, Brosym, …, Brosai, Brosym, …, Brosok
- 120 of odd balls of each type
- Neuromag Vectorview 306 sensor MEG machine

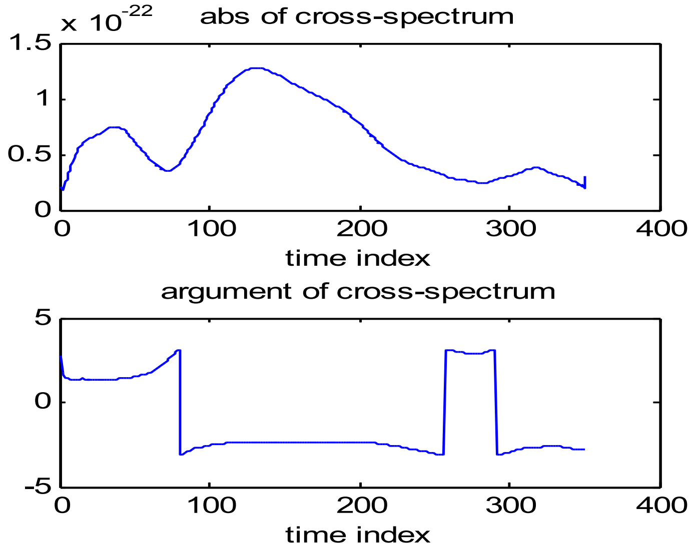
Transient networks from real MEG data

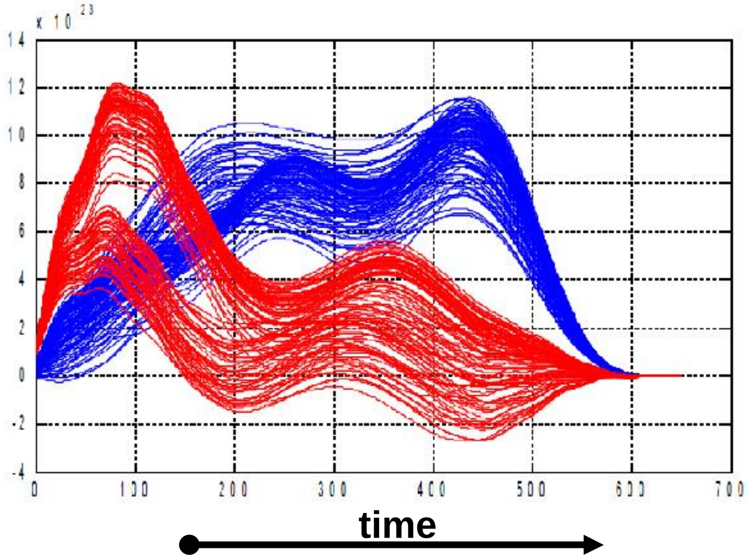
Spatial structure



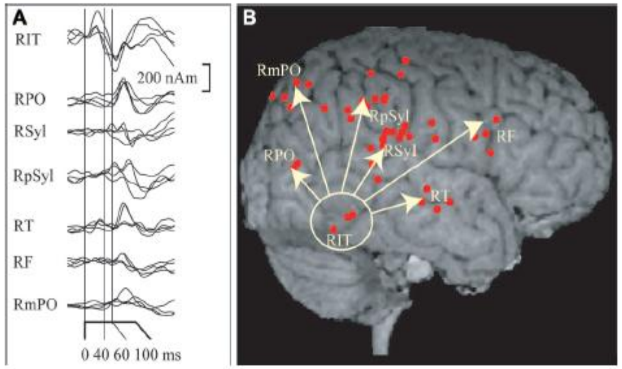


Network coupling strength over time

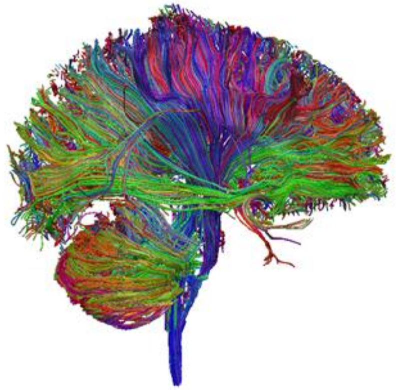




Propagation of spikes along epileptogenic network

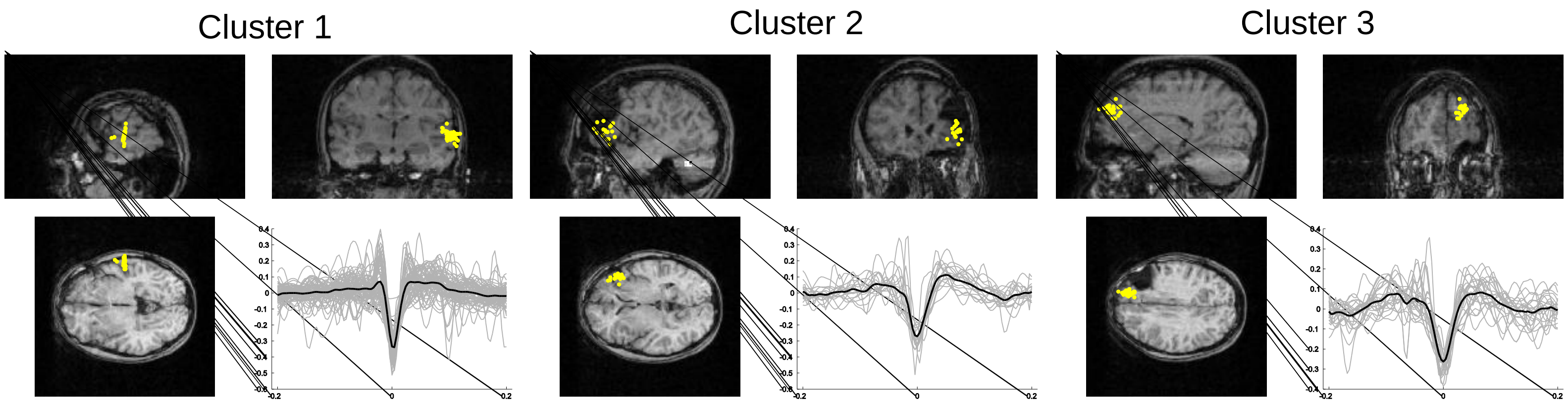


Makela et al, Neurosurgery, 2006



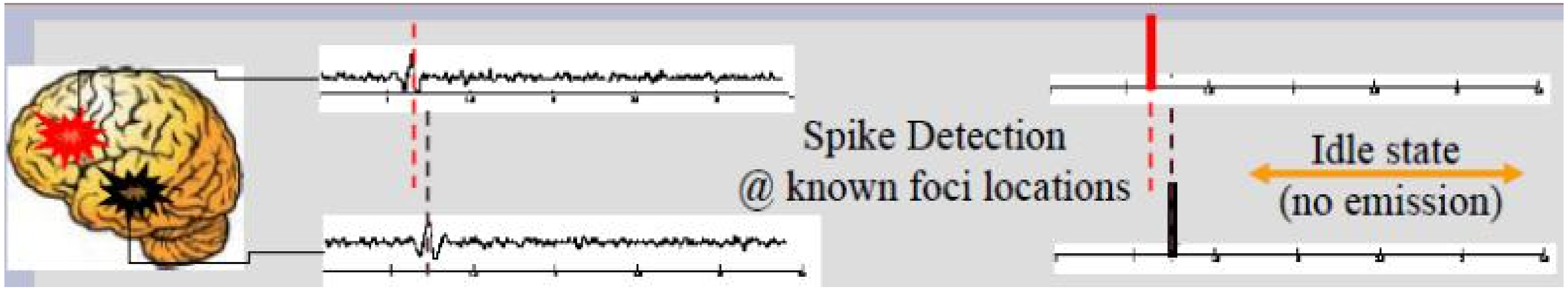
- Interictal spikes serve as a diagnostic marker for epilepsy (presence, location, type)
- When modeled with current dipoles tend show propagation effects and form spatial distal clusters
- Spike propagation analysis allows to discover the primary epileptogenic region

Automatic spike detection
finds several regions that emit spikes



Which one is the primary region?

Markov model for epileptogenic network modeling



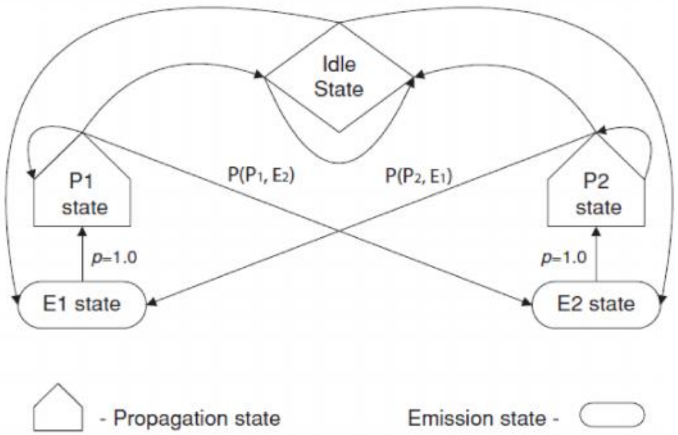
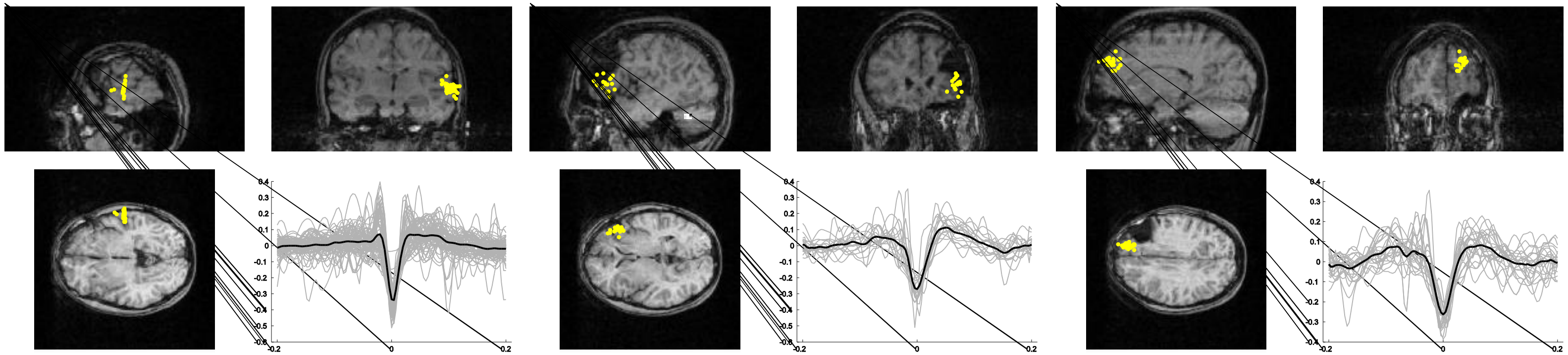


Figure 1. Simple two-cluster interaction Markov model. The number of foci is $N_f = 2$, the number of states is $N_s = 2N_f + 1 = 5$ and the number of allowed transitions is $N_t = 11$.

	$\mathcal{S}(t+1)$				
$\mathcal{S}(t)$	I	P_1	E_1	P_2	E_2
I	$p(I\|I)$	0	$p(E_1\|I)$	0	$p(E_2\|I)$
P_1	$p(I\|P_1)$	$p(P_1\|P_1)^*$	0	0	$p(E_2\|P_1)^*$
E_1	0	1	0	0	0
P_2	$p(I\|P_2)$	0	$p(E_1\|P_2)^*$	$p(P_2\|P_2)^*$	0
E_2	0	0	0	1	0

Case study

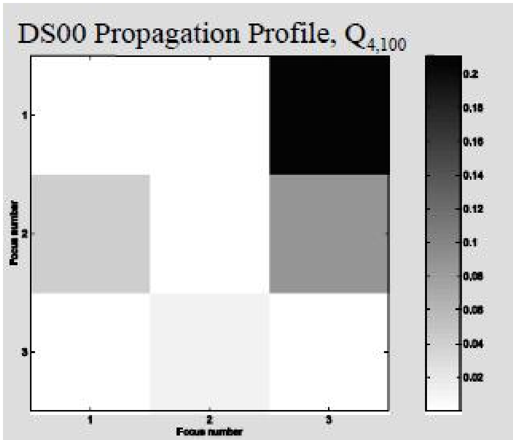
Cluster 1 Cluster 2 Cluster 3



Cluster 1

Cluster 2

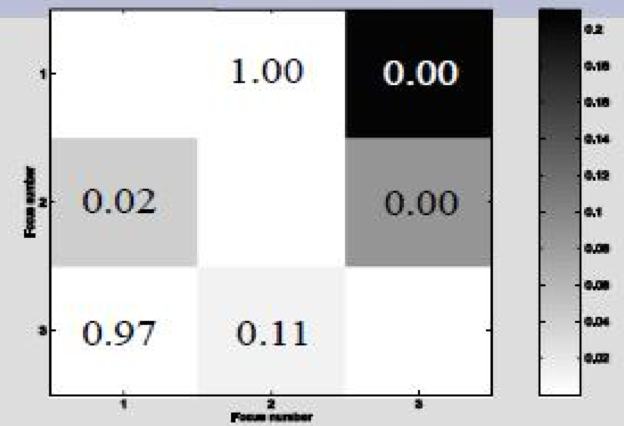
Cluster 3



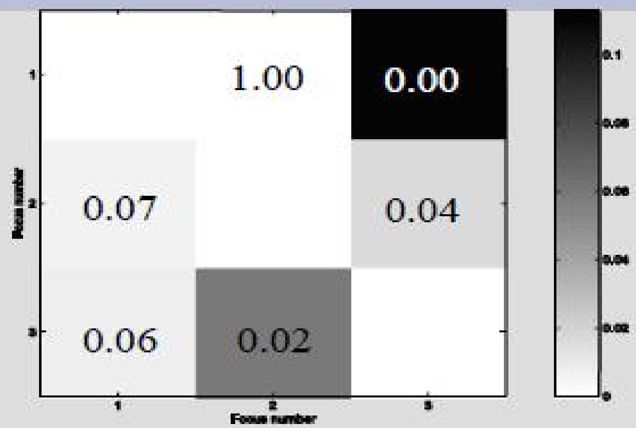
Ossadtchi et al, Physics in Medicine and Biology, 2005

Consistency and statistical significance of the results

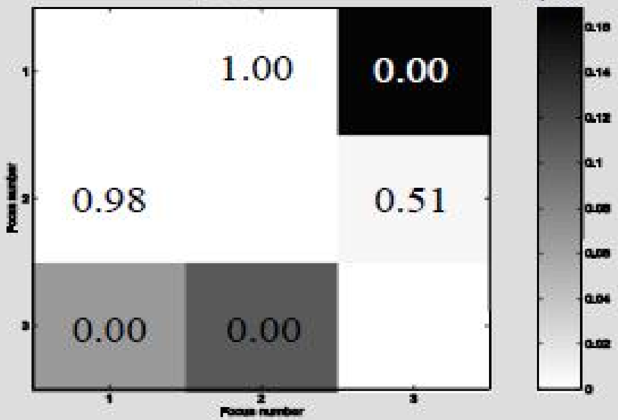
DS00 Propagation Profile, $Q_{4,100}$



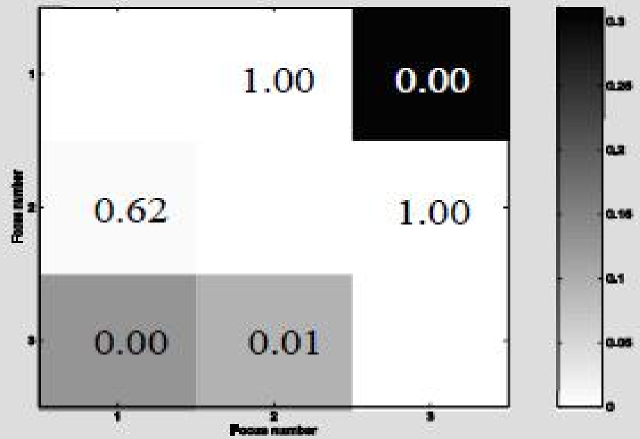
DS01 Propagation Profile, $Q_{4,100}$



DS03 Propagation Profile, $Q_{4,100}$

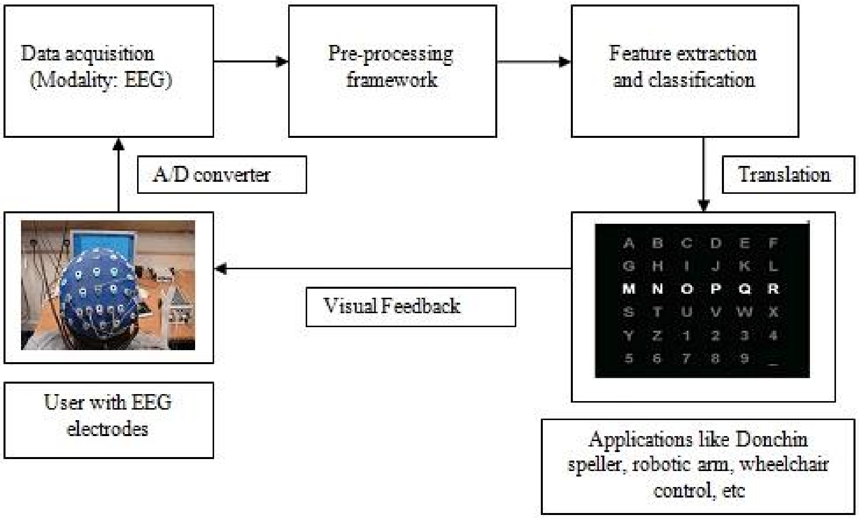


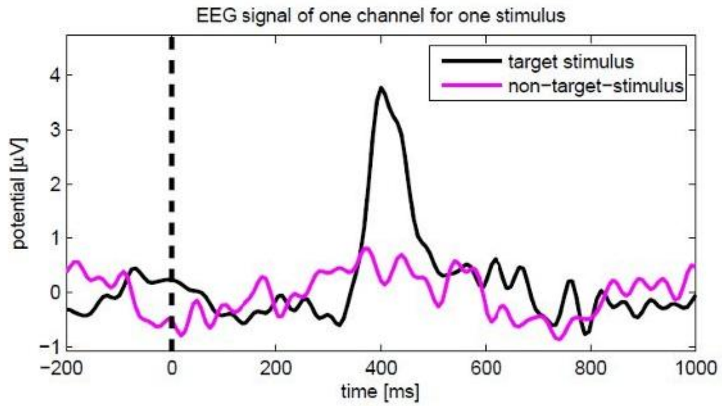
DS05 Propagation Profile, $Q_{4,100}$



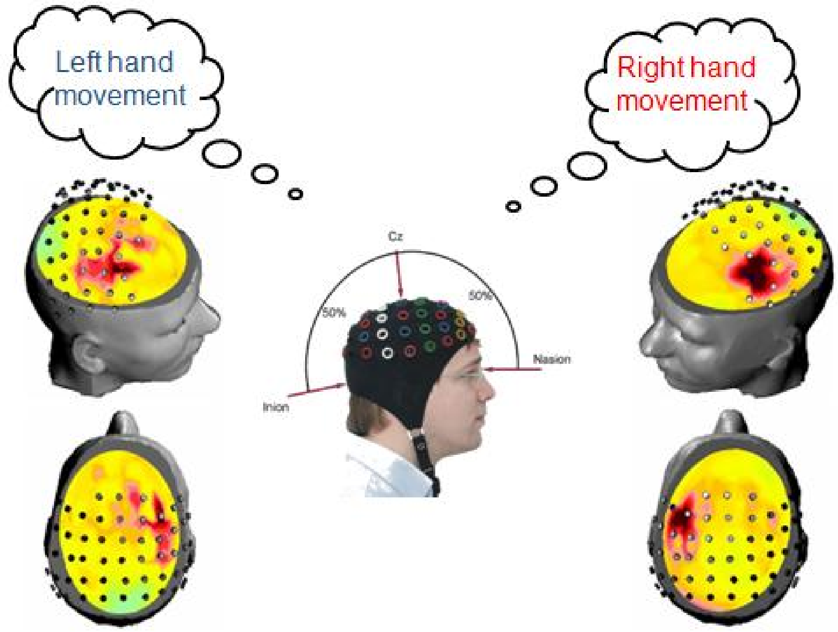
Brain-computer interfacing

P300-based speller

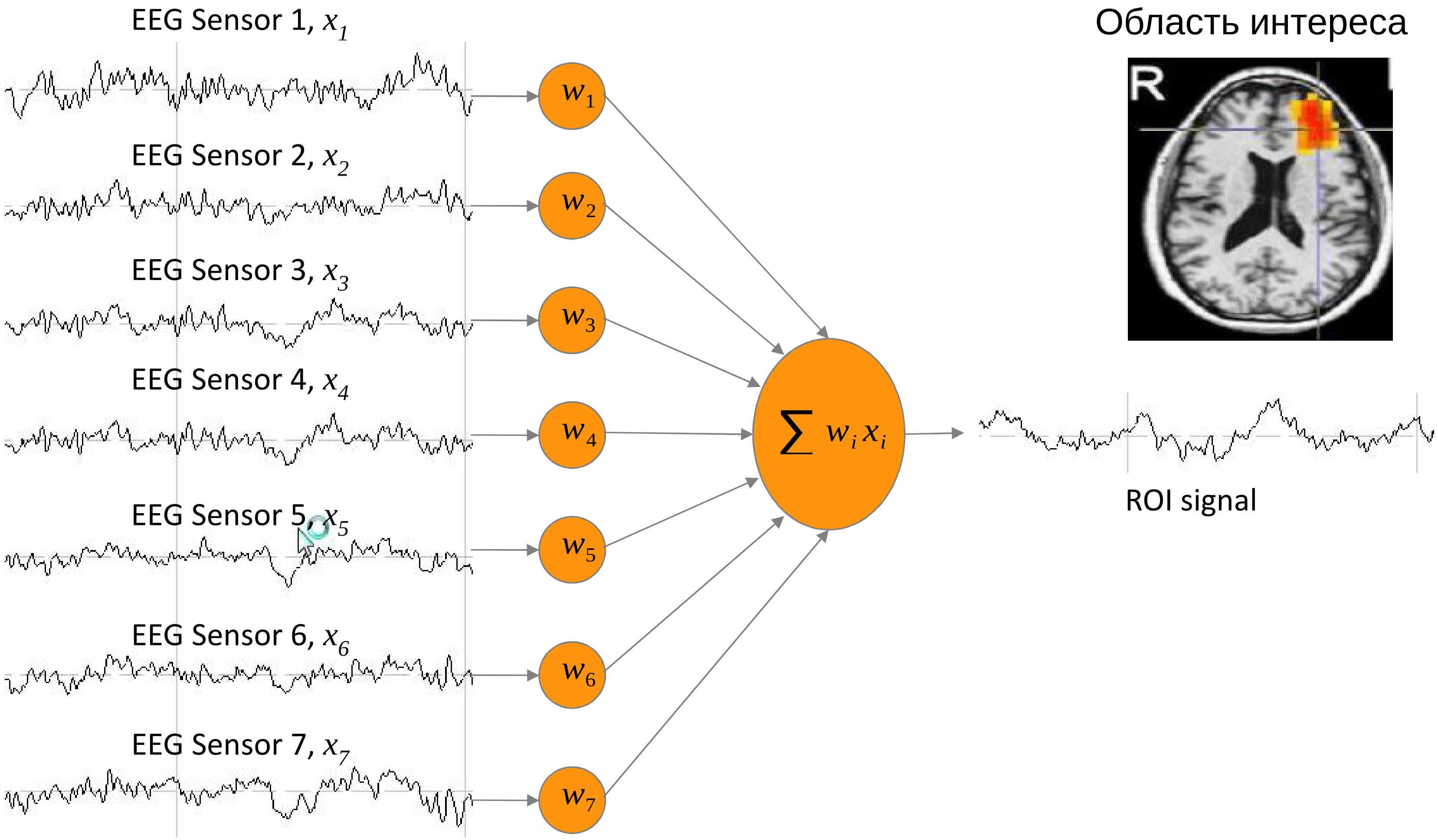




Motor imagery BCI

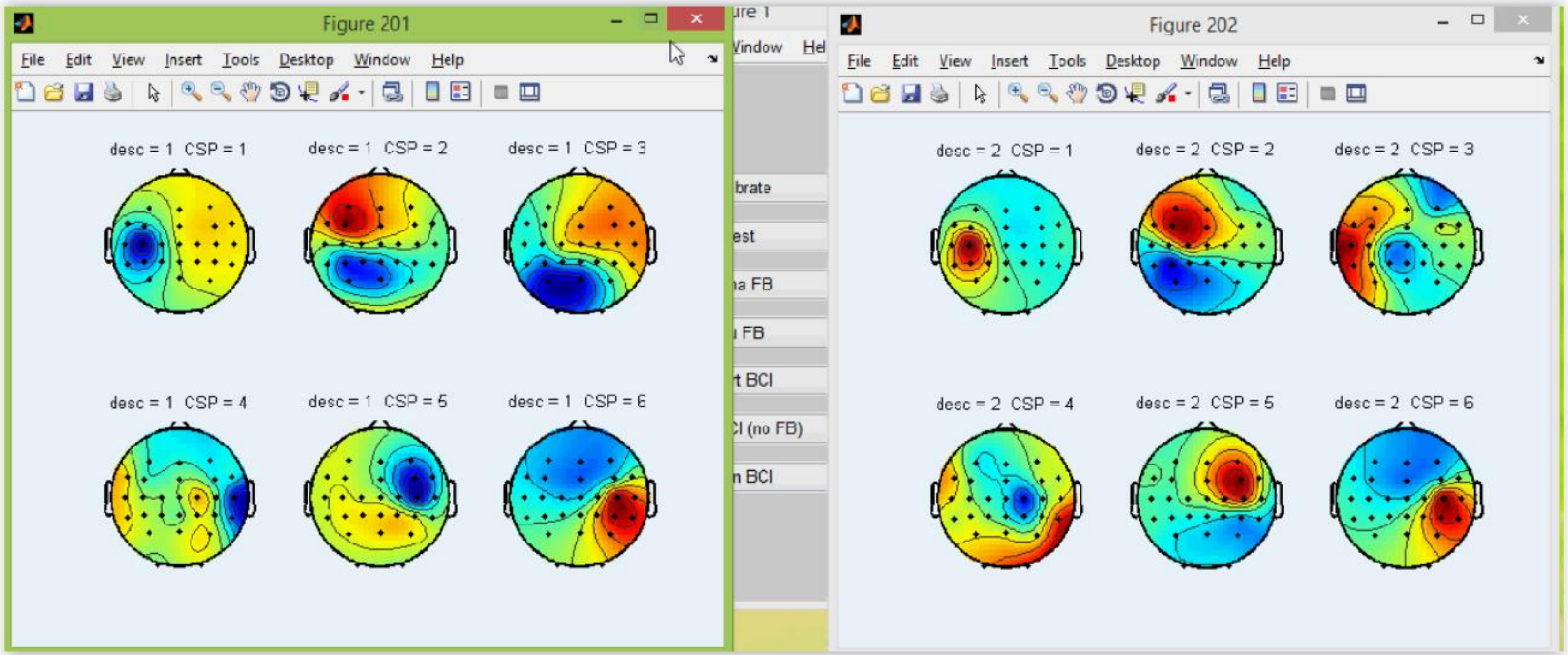


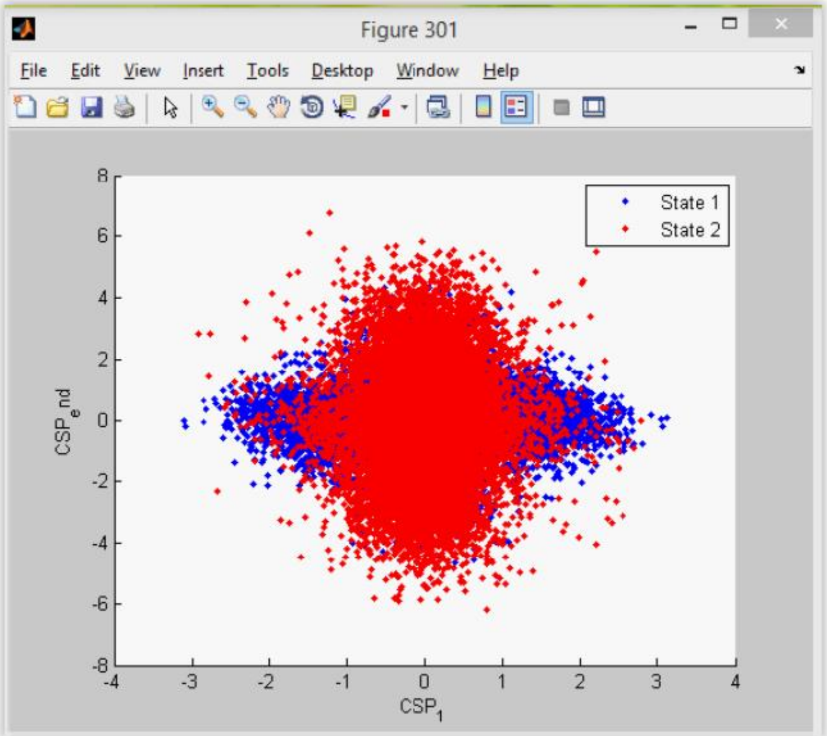
Сигнал активности ОИ как линейная комбинация сигналов сенсоров



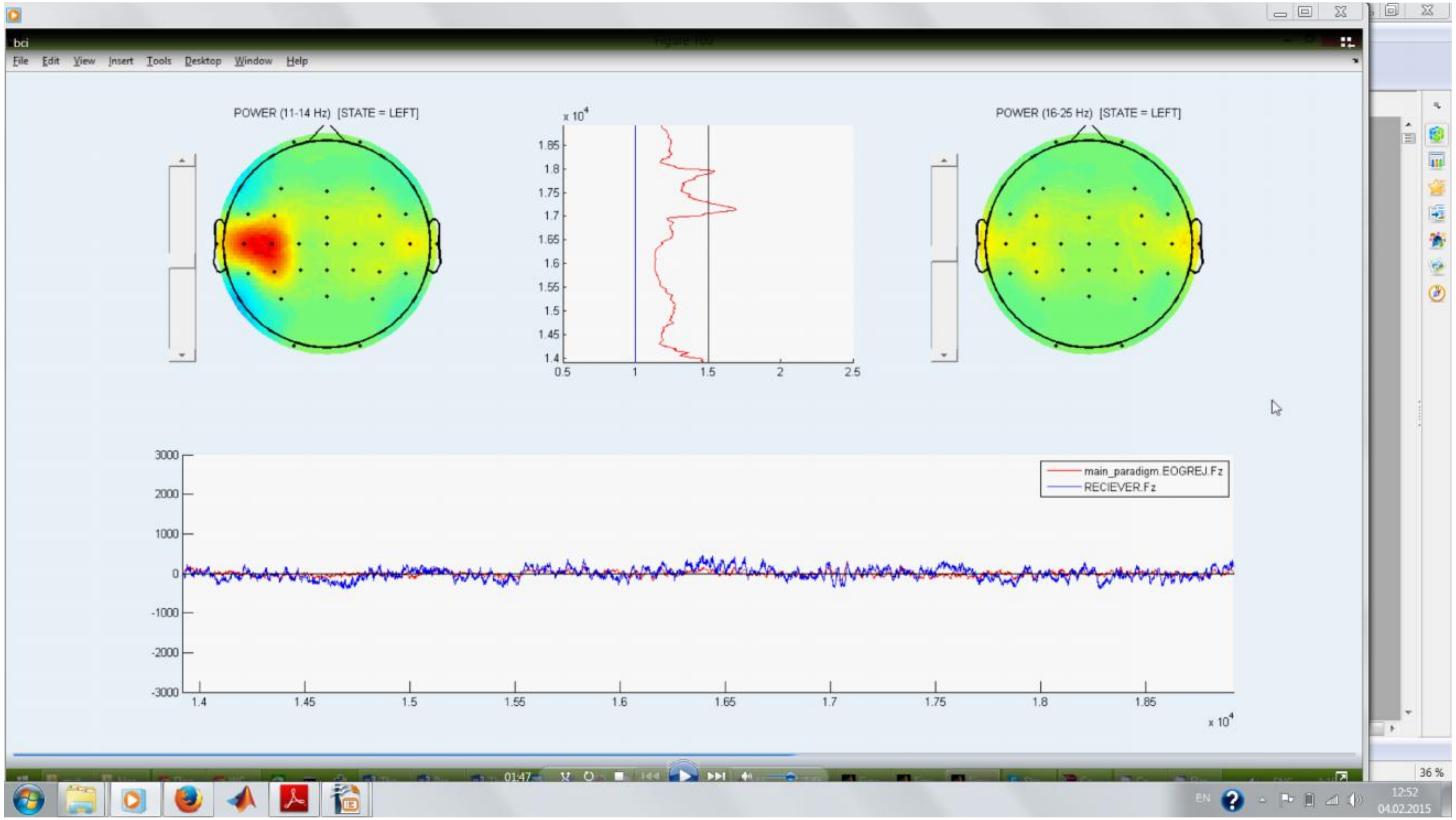
Настройка пространственных фильтров

$$\frac{\boldsymbol{w}^T \boldsymbol{R}_1 \boldsymbol{w}}{\boldsymbol{w}^T \boldsymbol{R}_2 \boldsymbol{w}} \rightarrow max$$





$$\frac{\boldsymbol{w}^T \boldsymbol{R}_1 \boldsymbol{w}}{\boldsymbol{w}^T \boldsymbol{R}_2 \boldsymbol{w}} \rightarrow max$$


bci
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POWER (16-25 Hz) [STATE = LEFT]
main_paradigm.EOGREJ.Fz
RECIEVER.Fz
x 10^4
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04.02.2015
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Welcome to

Data analysis in non-invasive Neuroimaging class!