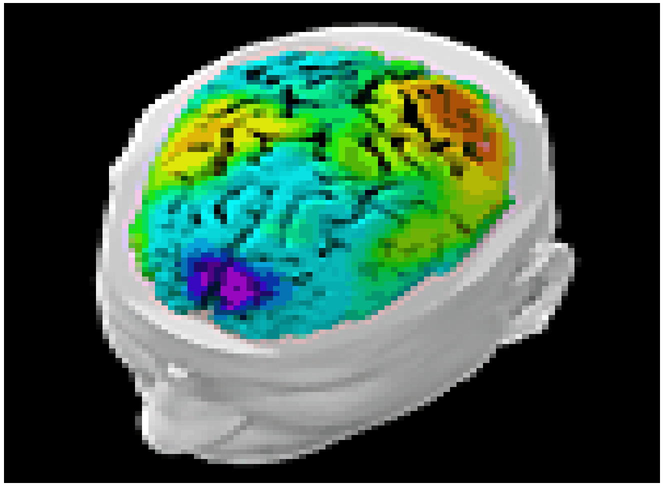
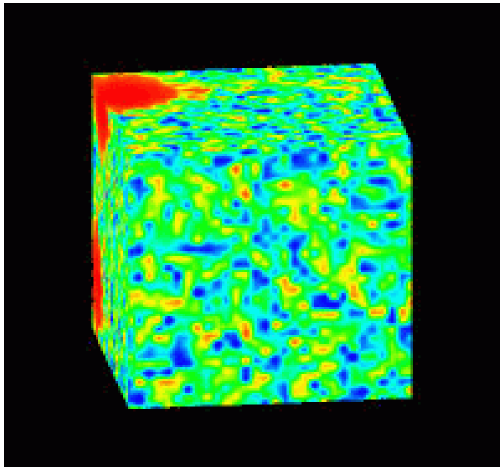
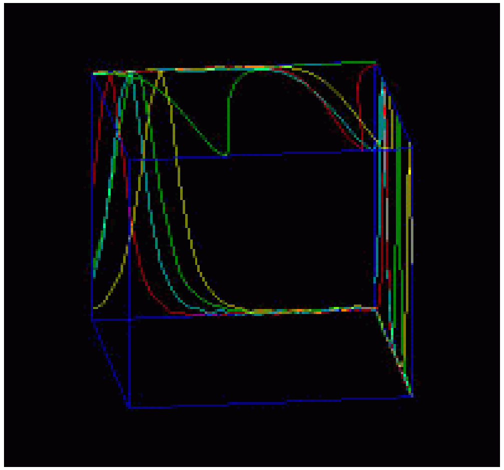
Brain Computer Interface Using Tensor Decompositions and Multi-way Analysis

Andrzej CICHOCKI







Laboratory for Advanced Brain Signal Processing

http://www.bsp.brain.riken.jp/~cia/.

RIKEN, Brain Science Institute, JAPAN

Outline

LABSP BSI RIKEN

- Motivation and objectives, Problem formulations
- Promising paradigms for noninvasive EEG BMI:

Motor Imaginary (mu /beta rhythms, ERD/ERS), P300 N170, N200 ERPs and SSVEP

- Signal Processing and Machine Learning Methods and Tools Tensor/Matrix factorizations and Multiway Blind Source Separation
- Experimental results: Demos and computer simulations
- **Future perspectives: Hyper-scanning, Brain to Brain Interface**
- Potential applications for rehabilitation, therapies, training

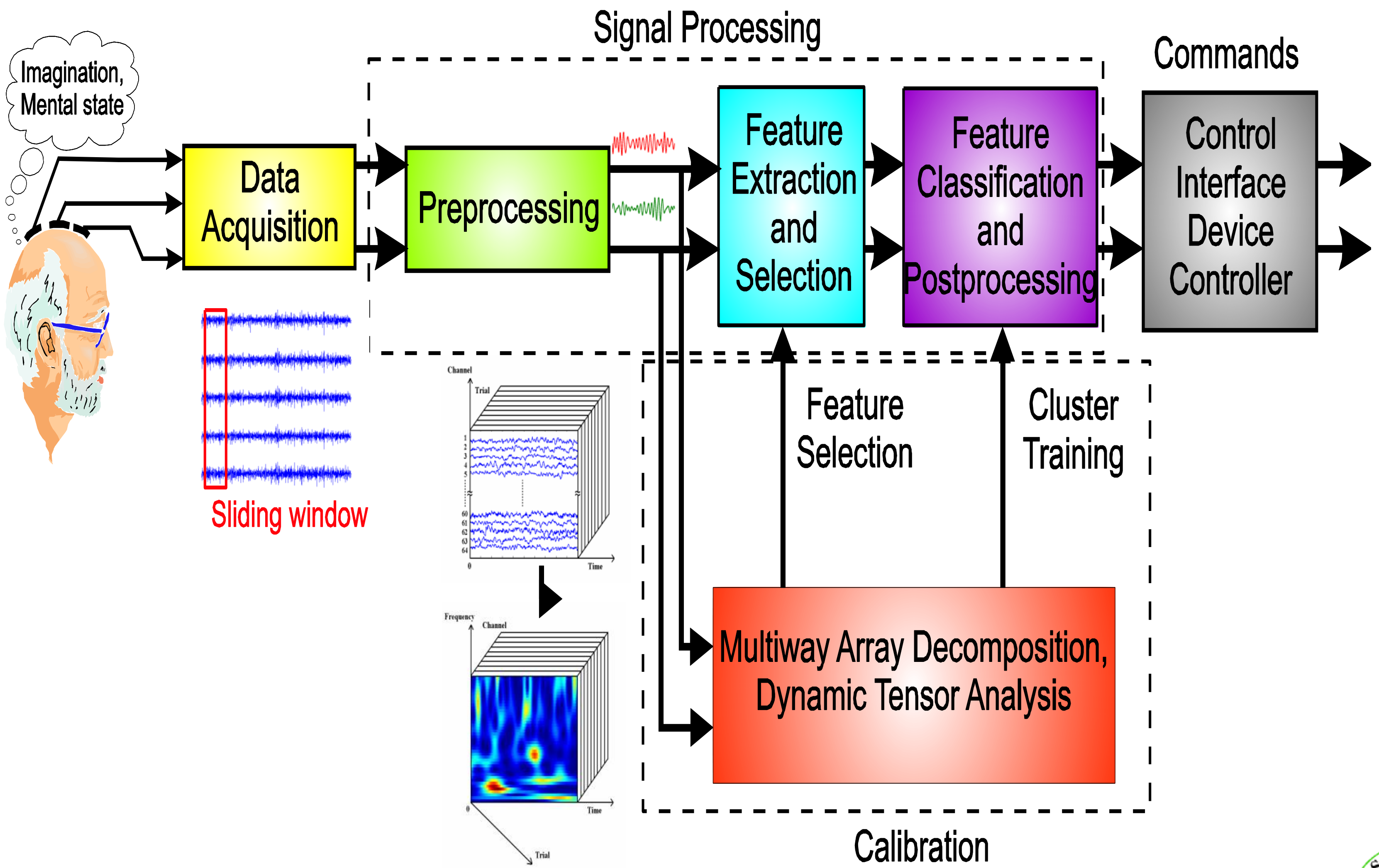
Goals in BCI :

Develop a safe, noninvasive and user friendly brain interface capable of controlling multiple independent channels

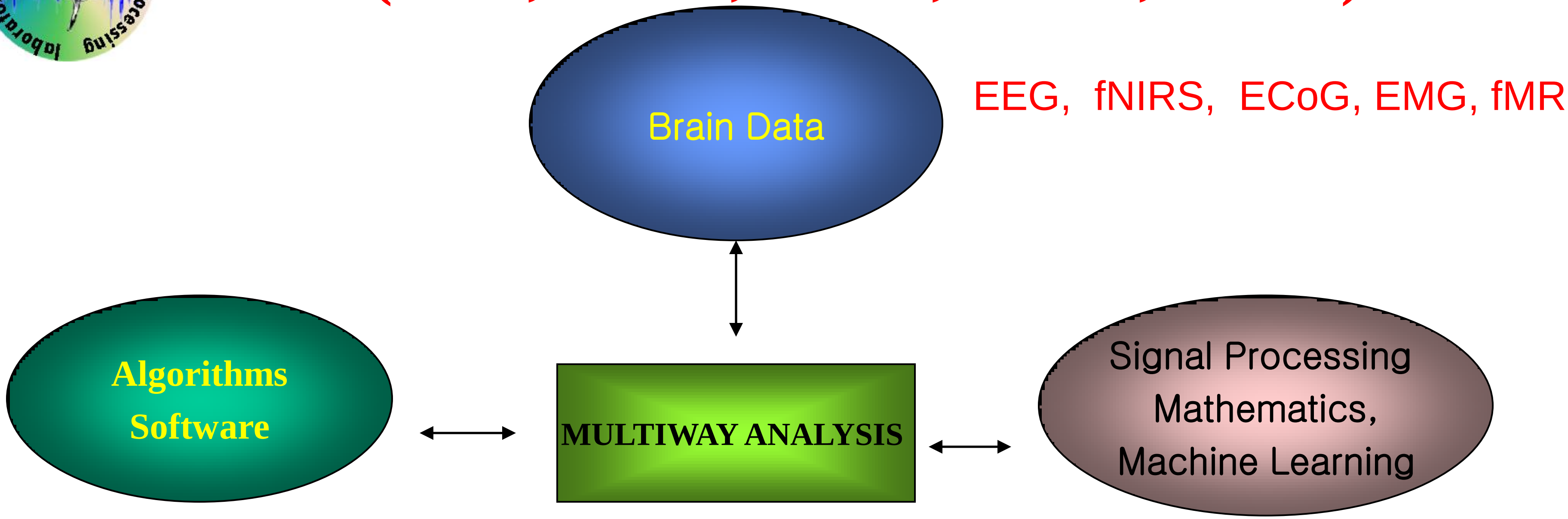
On-line (real time) multi-command BMI system with

Wireless connection with computer or robot

Application of multi-way array (tensor) decompositions in BCI



Our Research Noninvasive Human Brain Data (EEG, ECoG, EMG, fNIRS, fMRI)



Raw (noninvasive) brain data usually does not provide useful knowledge or information.

Signal Processing and Mathematics are necessary to analyze massive complex HUMAN brain datasets to extract information and knowledge and also visualize and interpret results.

A BRAIN MACHINE INTERFACE IS A SYSTEM THAT INCLUDES: A MEANS FOR MEASURING NEURAL SIGNALS FROM THE BRAIN, A METHOD ALGORITHM FOR DECODING THESE SIGNALS AND A METHODOLOGY FOR MAPPING THIS DECODING TO A BEHAVIOR OR ACTION.

A BCI is a mechanism that allows a user to interact with the outside world through the measurement of correlates of neural activity associated with mental processes or perception.

KEY ISSUES IN BCI RESEARCH

An interdisciplinary endeavor

- neuroscience
- physiology/psychology
- engineering
- mathematics
- computer science
- rehabilitation

Translation algorithms should be as simple as possible

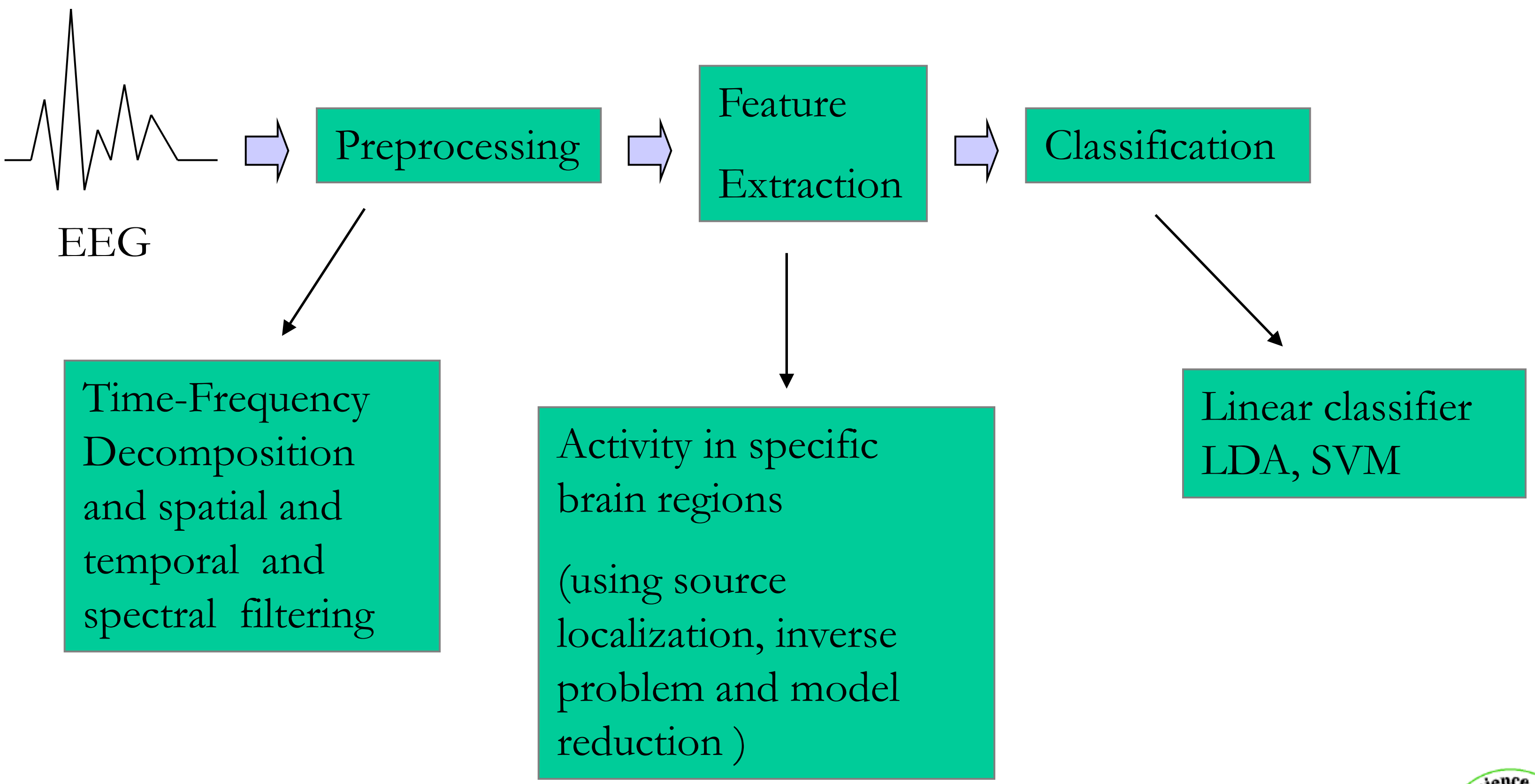
- Adjust for spontaneous variations
- Avoid instabilities
- Robustness to env. noise

Our BCI experiments are based on EEG and fNIRS
Our Experimental Facilities

Our unique High Density Array EEG Systems +NIRS + EMG

General principal

- How to identify or extract the "brain patterns" ?

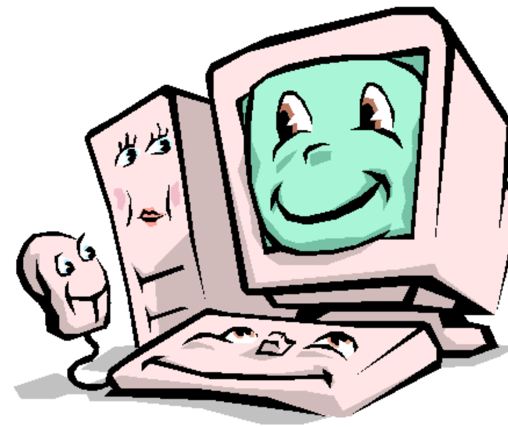


Brain-Machine Interface (BMI) with Neuro-feedback

Neuro-feedback

Measurement of ElectroEncephaloGrams (EEG)

Brain activity processing

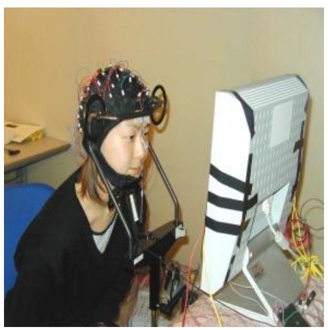


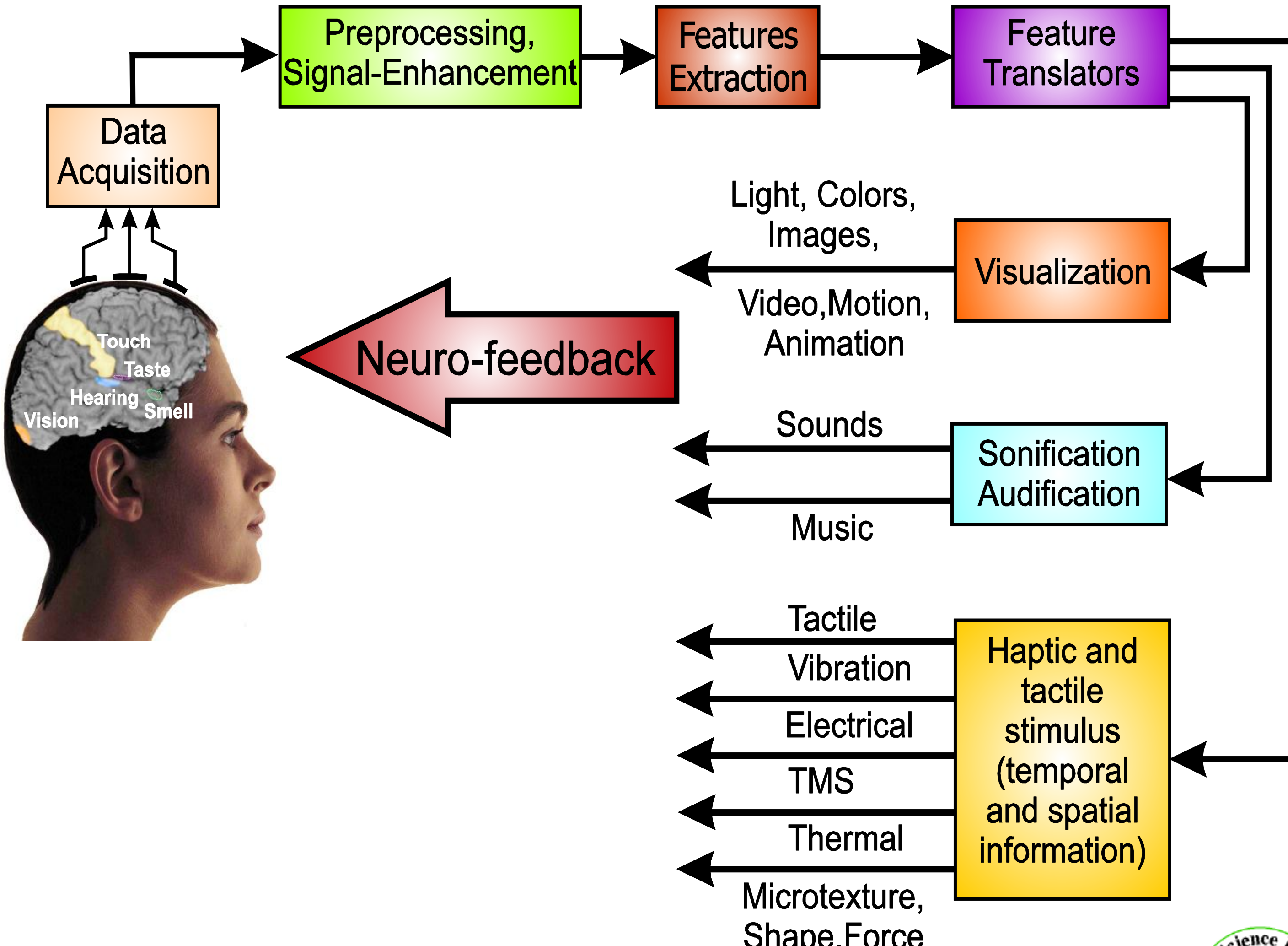
Translation into a command

The brain machine Interface work usually with neuro-feedback. From one side subject must adopt to machine or computer and machine should also adopt to the user. The process is performed on-line.

Brain/Human Computer Interface (B/HCI)

Enhanced Neurofeedback for BCI



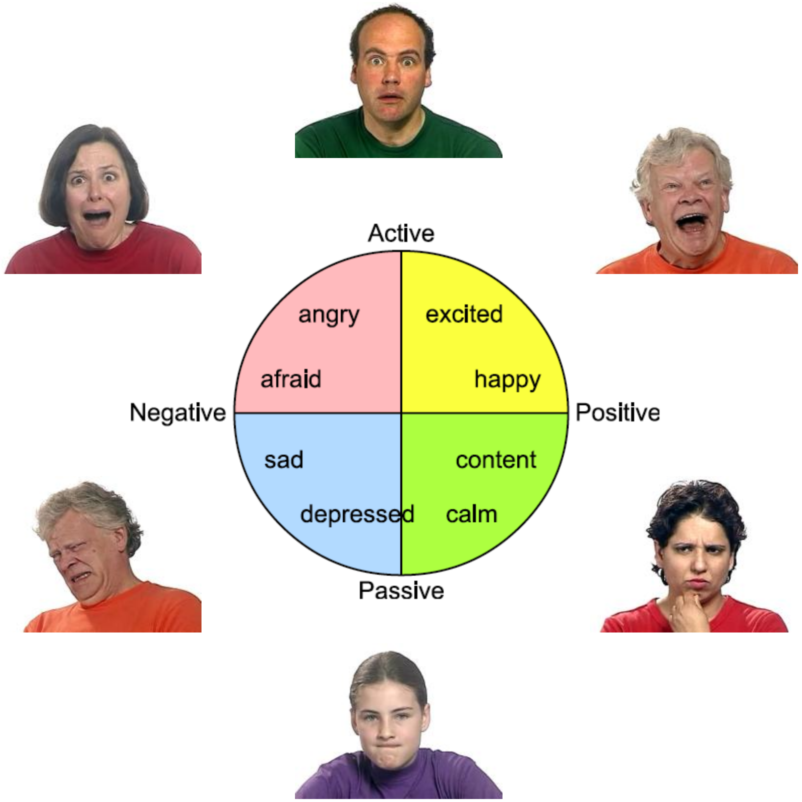


Beyond P300 Affective BMI

The brain activations can carry information about the affective and cognitive state of a subject, and that the interaction between humans and machines can be aided by the recognition of those user states.

Research contents:

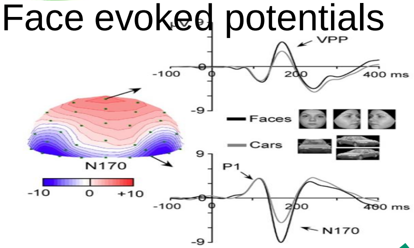
- Emotion elicitation and data collection for affective BMI
- Detection of affect and mental state via BMI and other modalities
- Data analysis for cognitive-related ERP using tensor technology



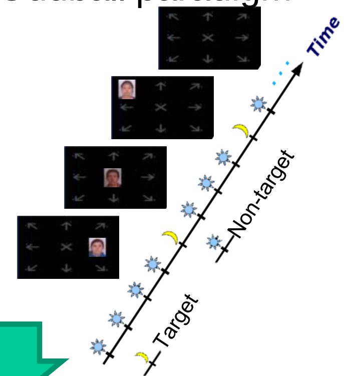
Novel Affective BCI using multiple ERPs

Please see our nomination the Annual BCI Research Award Q. ZHAO, A. ONISHI, Y ZHANG and A. CICHOCKI

Face evoked potentials



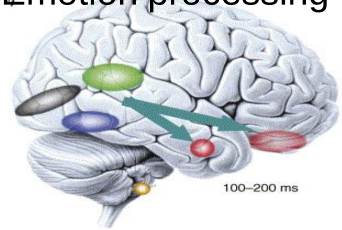
Oddball paradigm



Single trial classification (ITR)
Multi-way discriminative analysis

(D) Classification

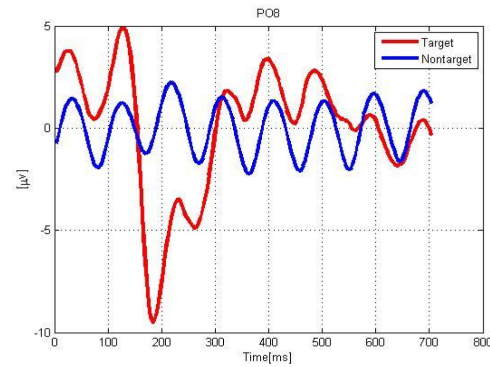
Emotion processing

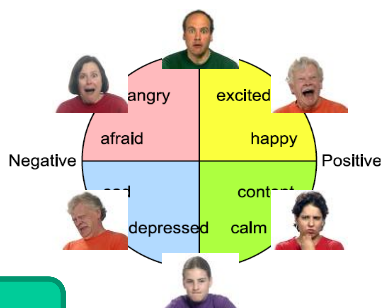


N. Tsuchiya, et al, 2007

Affective BCI

(C) ERPs



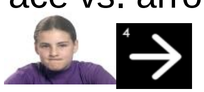


Multiple ERP components (N170, N250, VPP, LPP)

(A) Stimuli

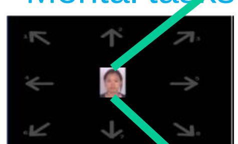
(B)Mental tasks

Face vs. arrow



Flash order:
Random vs. sequential

Mental tasks

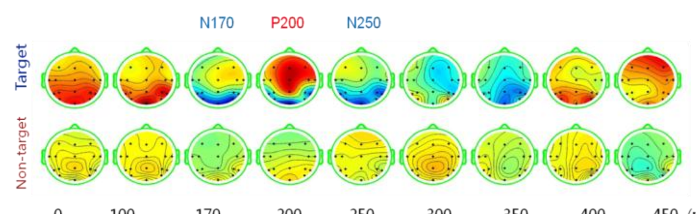


Emotion comparison

Emotion recognition

Face identity

Attention

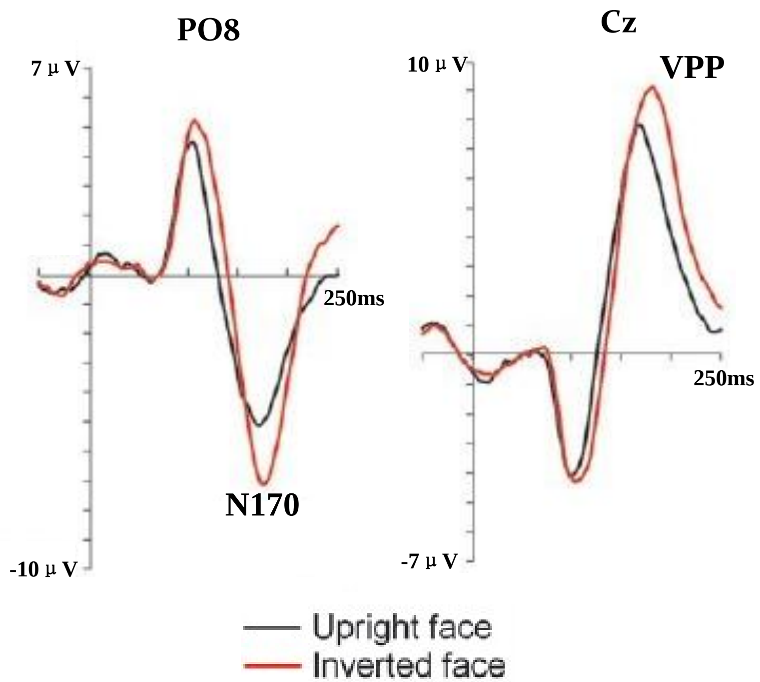


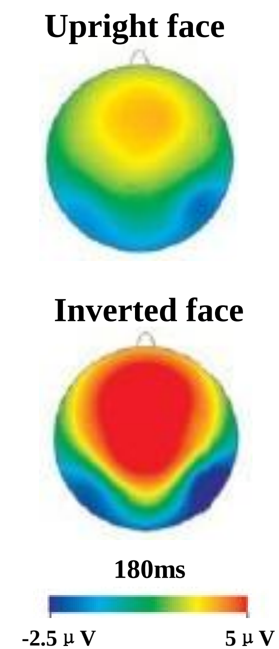
Configural processing of faces

Results will be published in Journal of Neural Engineering

Basis

Face perception has been suggested to rely more on configural information (i.e., prototypical spatial relationships between parts of face) than other visual object perception.

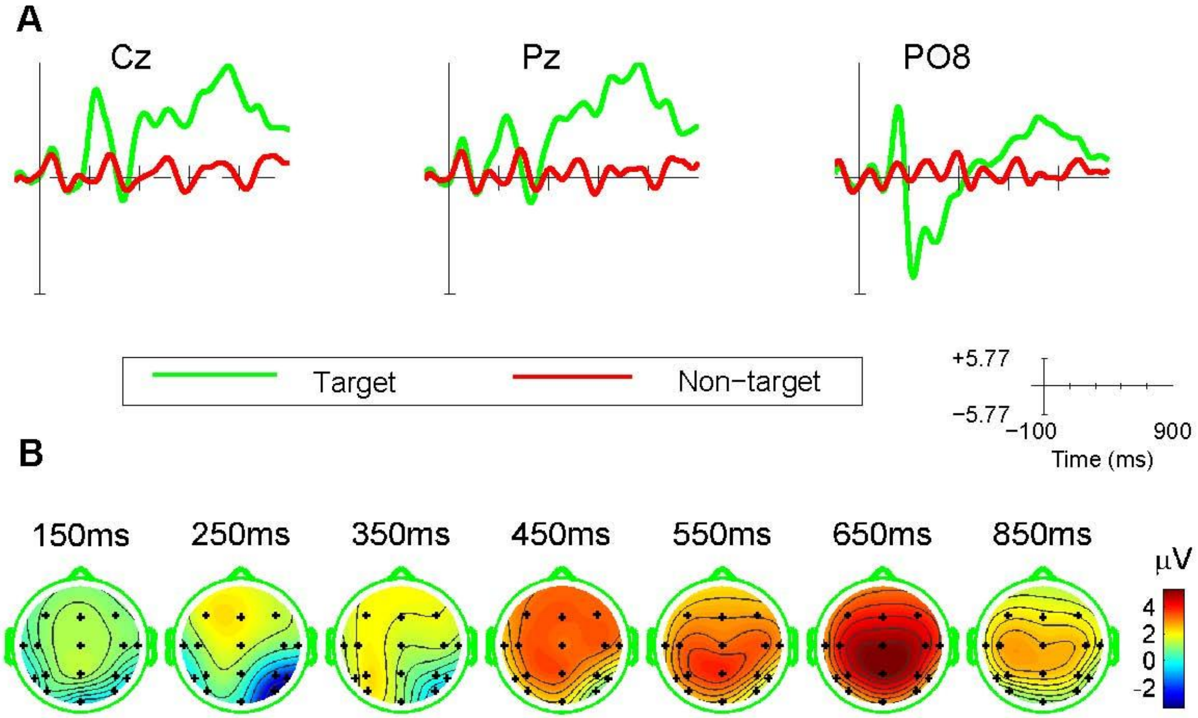




- Inversion of face can disrupt the configural face information, thereby making the face processing slower and more difficult.
- The increased difficulty for inverted face perception recruit additional selectivity mechanisms besides those for upright face perception.
- The two components N170 and VPP are believed to reflect the configural processing of the face and their amplitudes and latencies can be modulated by the inversion of face.

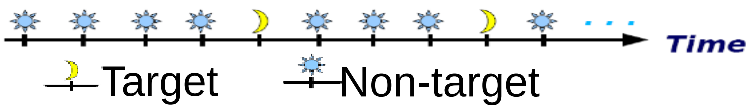
(Tanaka et al. 1993; Moscovitch et al. 1997; Rossion et al. 1999; Eimer 2000, 2010; Itier et al. 2002, 2004; Marzi et al. 2007; Sadeh et al. 2010; Rosburg et al. 2010)

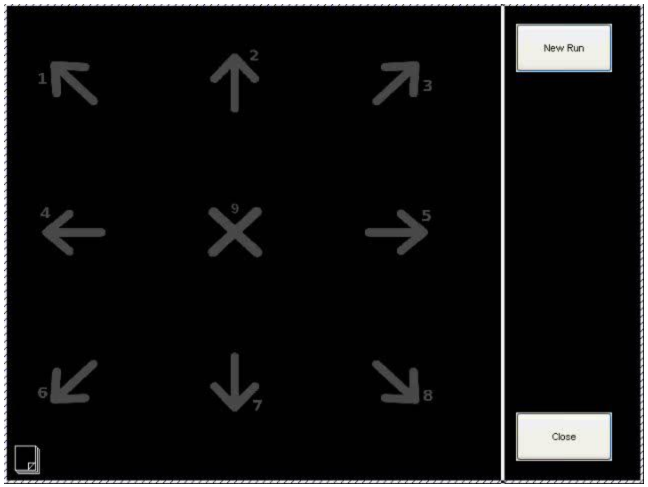
Main idea is to analyze complex ERPs and their components for face image stimuli

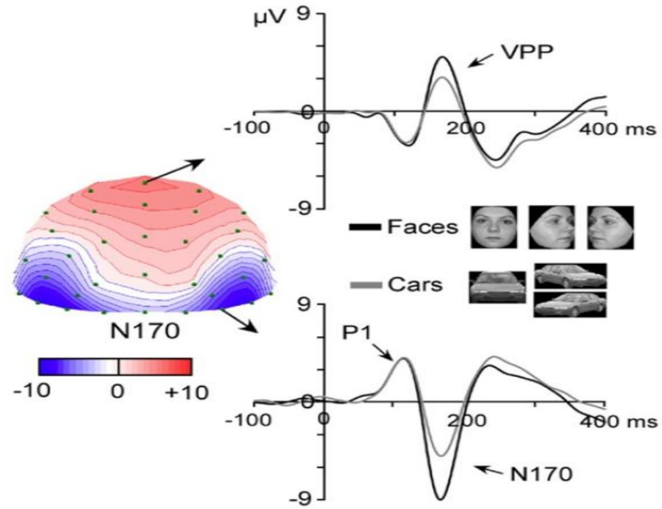


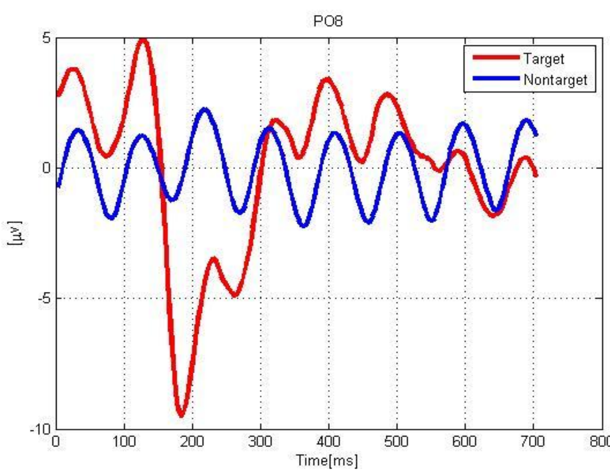
We observed the significant VPP at Cz ($F(1,18) = 14.15$, $p < 0.02$), P300 at Cz ($F(1,18) = 24.29$, $p < 0.0001$) and LPP at Cz ($F(1,18) = 7.98$, $p < 0.012$), indicating the effects of face identification task for oddball paradigm. The similar difference are also clear at Pz such as VPP ($F(1,18) = 13.71$, $p < 0.02$), P300 ($F(1,18) = 12.84$, $p < 0.0022$) and LPP ($F(1,18) = 17.2$, $p < 0.0006$). Due to the faces stimulus, the N170 at PO8 is clearly observed ($F(1,18) = 6.37$, $p < 0.02$).

N170/P300 BMI Paradigm



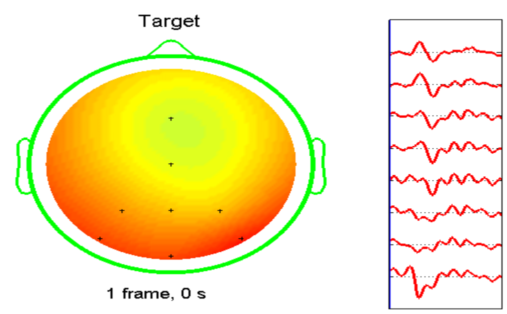




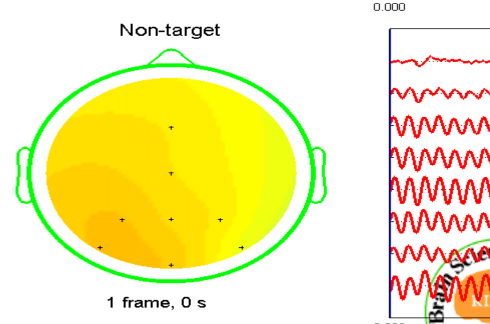


100% accuracy 2 averaged trials

Target



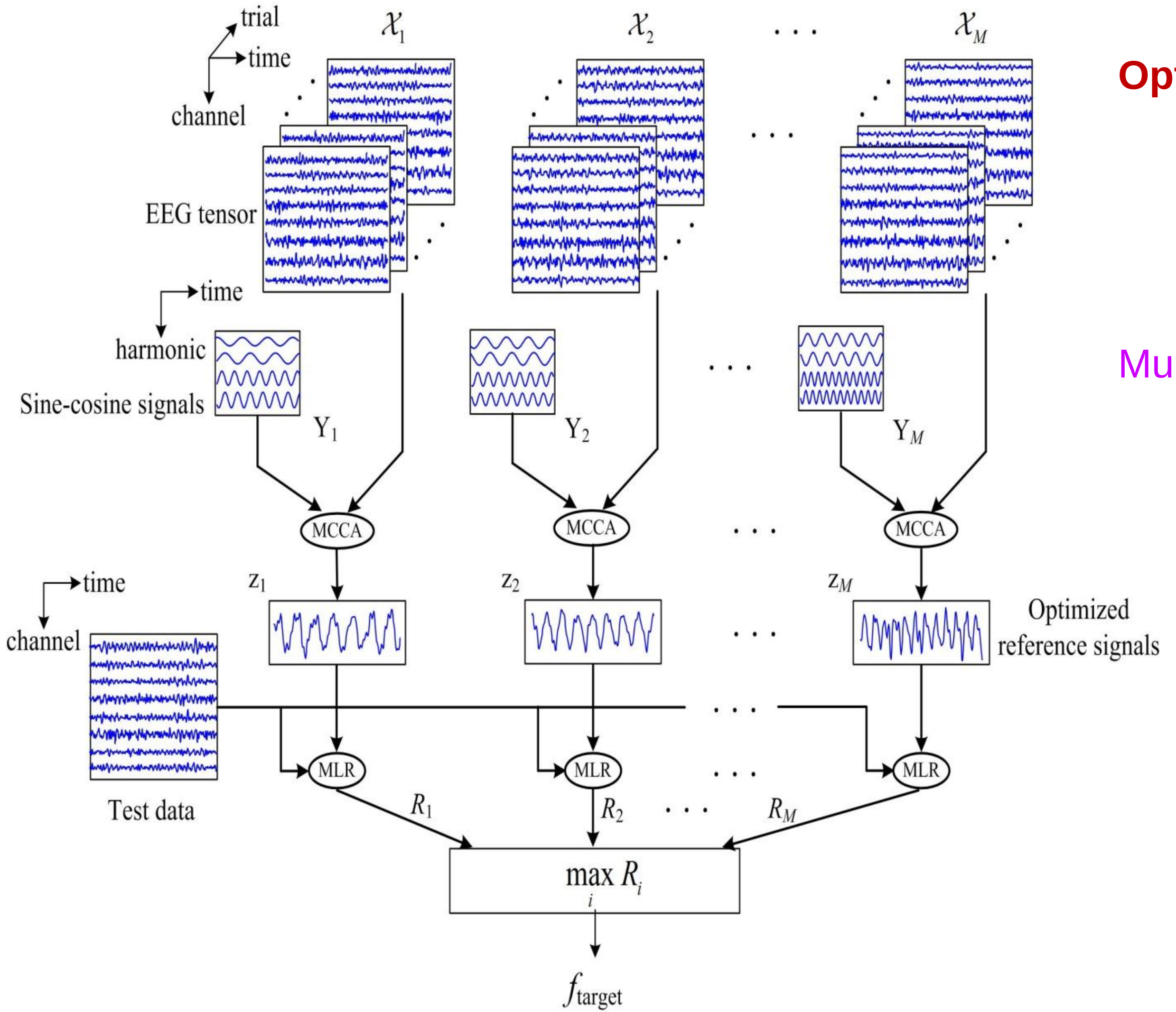
Non-target



Tensor (MULTIWAY) CCA for SSVEP Recognition

Y. Zhang et al. ICONIP 2011

Recognition mode



Optimized reference signals

$$\mathbf{z}_m = X_m \times_1 \mathbf{w}_{m,1}^T \times_3 \mathbf{w}_{m,3}^T$$
$$(m = 1, 2, \ldots, M)$$

Multiple Linear Regression (MLR)

$$\mathbf{z}_m = \mathbf{X}\boldsymbol{\beta}_m + \mathbf{e}_m$$
$$\hat{\boldsymbol{\beta}}_m = (\mathbf{X}^T\mathbf{X})^{-1}\mathbf{X}^T\mathbf{z}_m$$
$$\hat{\mathbf{z}}_m = \mathbf{X}\hat{\boldsymbol{\beta}}_m = \mathbf{X}(\mathbf{X}^T\mathbf{X})^{-1}\mathbf{X}^T\mathbf{z}_m$$
$$R_m = \sqrt{1 - \frac{\|\mathbf{z}_m - \hat{\mathbf{z}}_m\|_2^2}{\|\mathbf{z}_m - E[\mathbf{z}_m]\|_2^2}}$$

Our Directions and Trends in BCI/BMI research

- From binary decision to multi-command BCI
- From open-loop to closed-loop control (neurofeedback)
- From laboratory tests to practical trials and implementations in real environment

- **Apply Multiway Analysis (MBSS) and Tensor Decompositions.**

Why Blind Source Separation (ICA, SCA, NMF MCA) ?

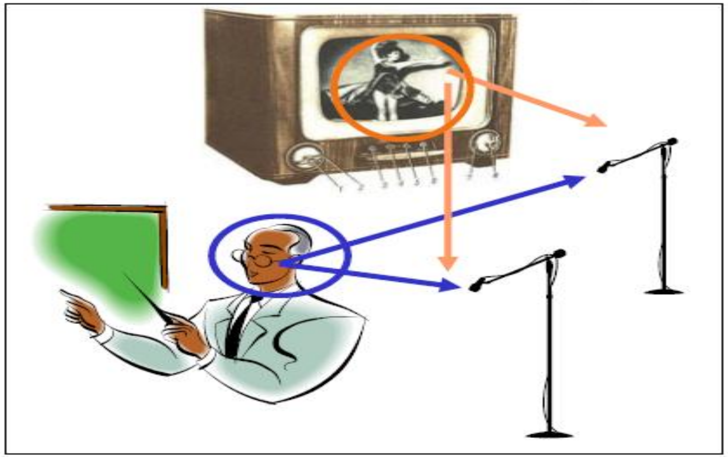
Signal Mixtures are Everywhere

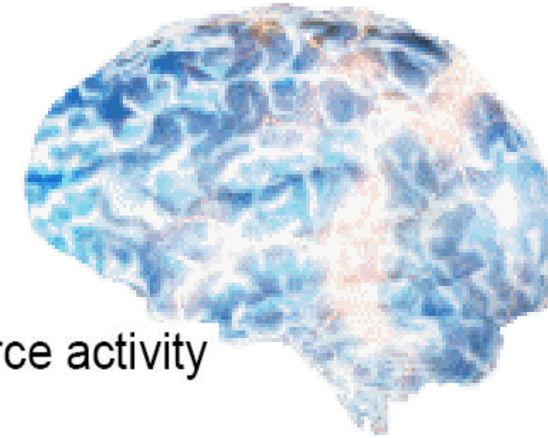
- EEG/MEG , EMG,
- fMRI, PET
- Audio and music processing
- Gene Microarray clustering

How do we make sense of it all?

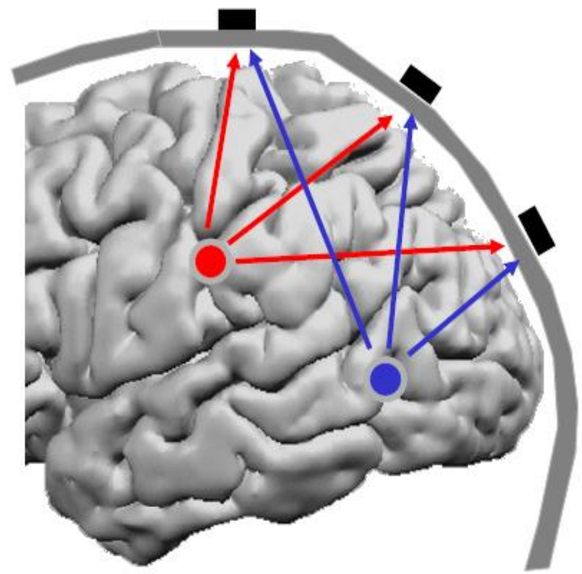
What is Blind Source Separation and Why Blind Source Separation and ICA are important for EEG/MEG?

Cocktail Party





Mixture of Brain source activity



Scalp EEG signals are produced by partial synchronization of cortical field activity. They can be considered as mixture of locally synchronous electrical activities of many cortical areas [Scott Makeig Terry Sejnowski 2004]

Independent Component Analysis (ICA)

$$\mathbf{Y} = \mathbf{A}\,\mathbf{X} + \mathbf{E}$$

Matrix of Observed data

Mixing Matrix of Basis Vectors

Matrix of ***independent*** components X

Challenge -- to estimate both A and X, using Y

Nonnegative Matrix Factorization (NMF)

$$\mathbf{Y} = \mathbf{A}\,\mathbf{X} + \mathbf{E}$$

Matrix of Observed data

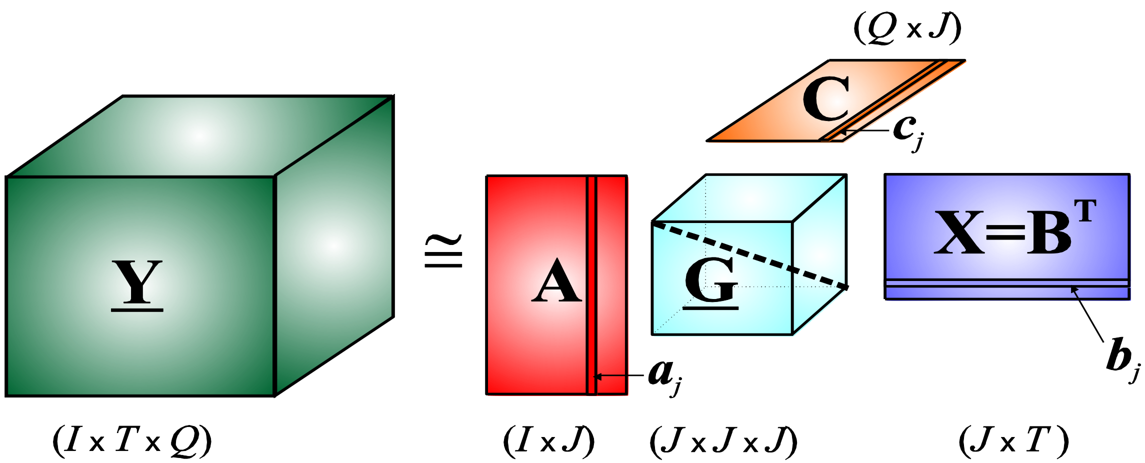
Mixing Matrix of Basis Vectors with Nonnegativity Constraints

Matrix of ***Nonnegative*** Components (All elements of X are nonnegative)

Challenge -- to estimate both A and X, using Y

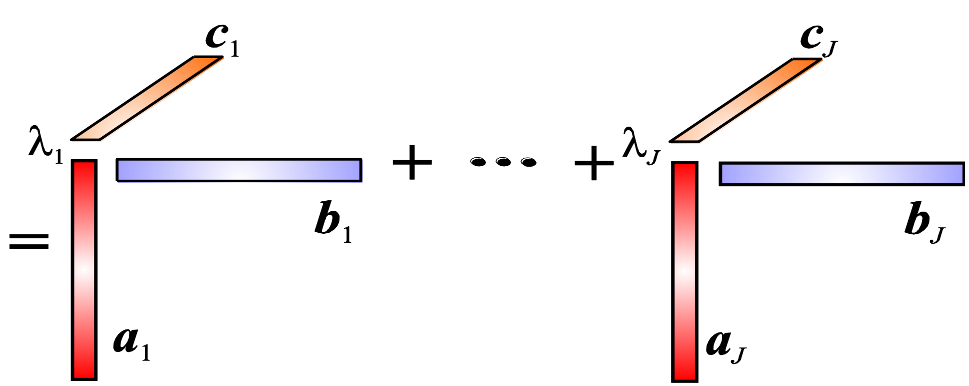
3D Tensor Decomposition Tucker, PARAFAC (CANDECOMP), NTD, NTF,

Searching for common factors, hidden components, sparse representation, dimensionality reduction, canonical decomposition, multi-way clustering



$$\underline{\mathbf{Y}} = \sum_{j=1}^{J} \lambda_j \, \mathbf{a}_j \circ \mathbf{b}_j \circ \mathbf{c}_j + \underline{\mathbf{E}}$$

$$\underline{\mathbf{Y}} = \underline{\mathbf{G}} \times_1 \mathbf{A} \times_2 \mathbf{B} \times_3 \mathbf{C} + \underline{\mathbf{E}}$$



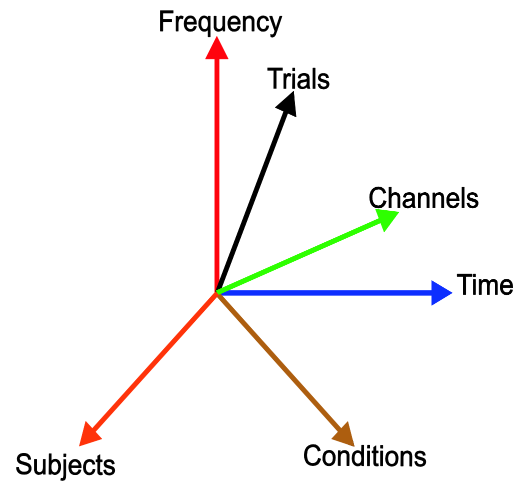
$$\mathbf{Y}_q = \mathbf{A} \; \mathbf{D}_q(\mathbf{c}_q)\, \mathbf{B}^T + \mathbf{E}_q, \quad (q = 1, 2, \dots, Q)$$

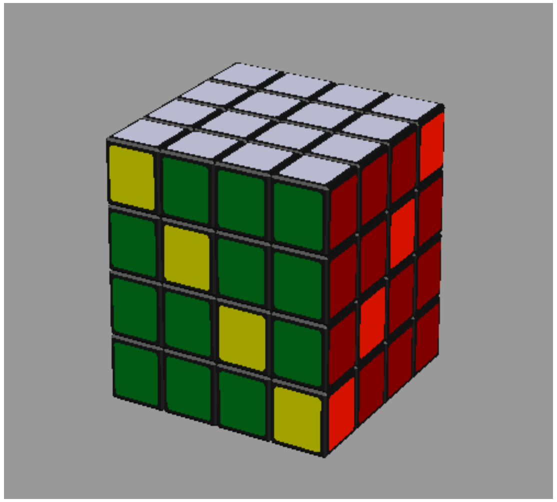
Why tensor factorizations in EEG

- Real-world recorded brain data are affected by multi-mode factors and hidden variables

For example multichannel EEG data are affected by

- ► stimuli
- ► conditions
- ► number of channels and their location
- ► subjects, trials, frequency

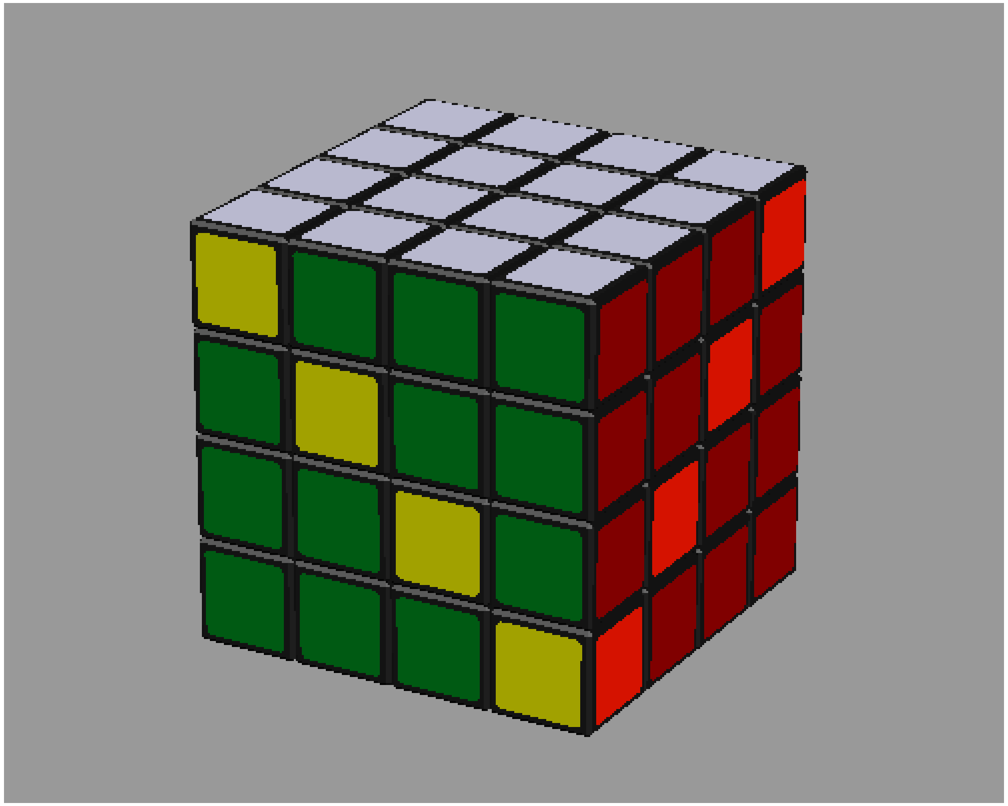




- The observed (recorded) brain data evolves differently along the variation of different factors and conditions.

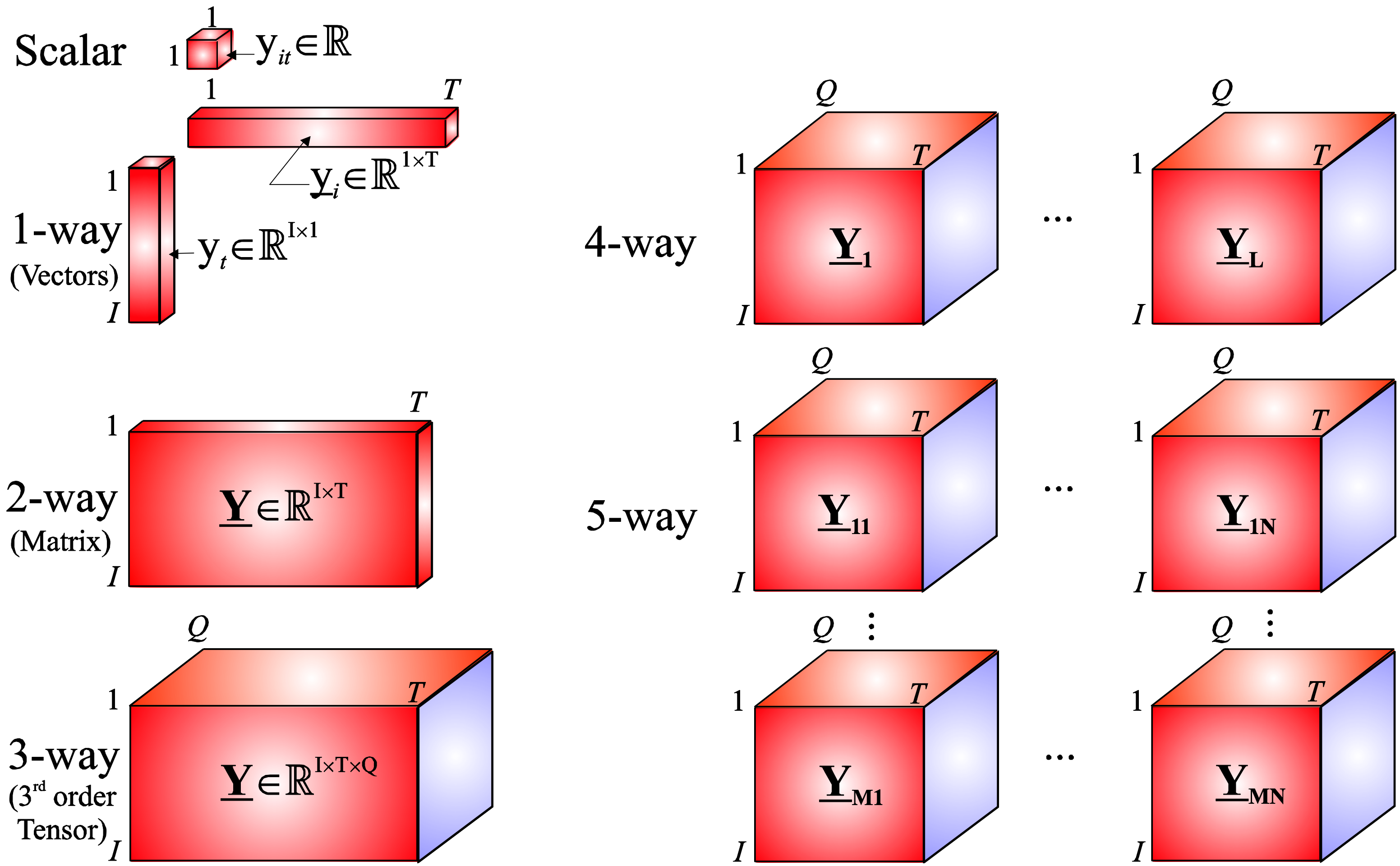
Tensor Basic Concepts and Operations

- Tensor: multi-dimensional (or multi-way) arrays of components



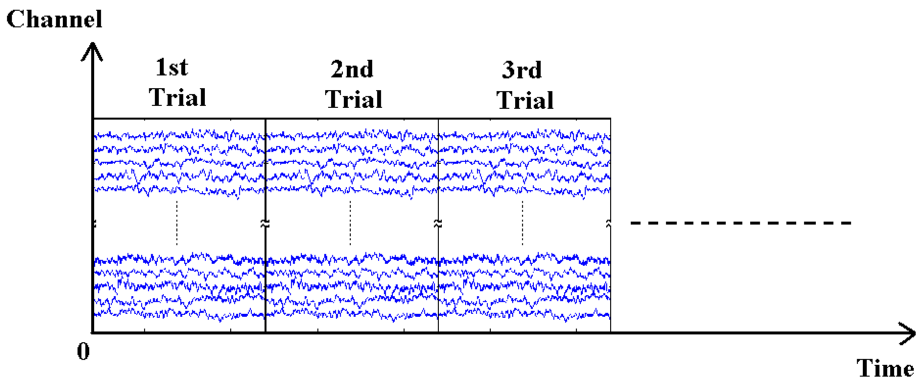
A. Cichocki LABSP

Multi-way arrays Tensors

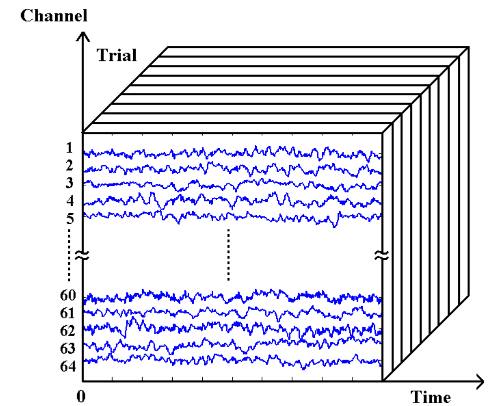


Higher dimensional data and unfolding

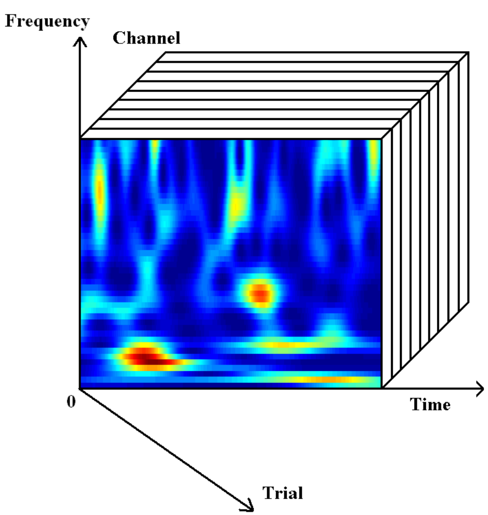
2D



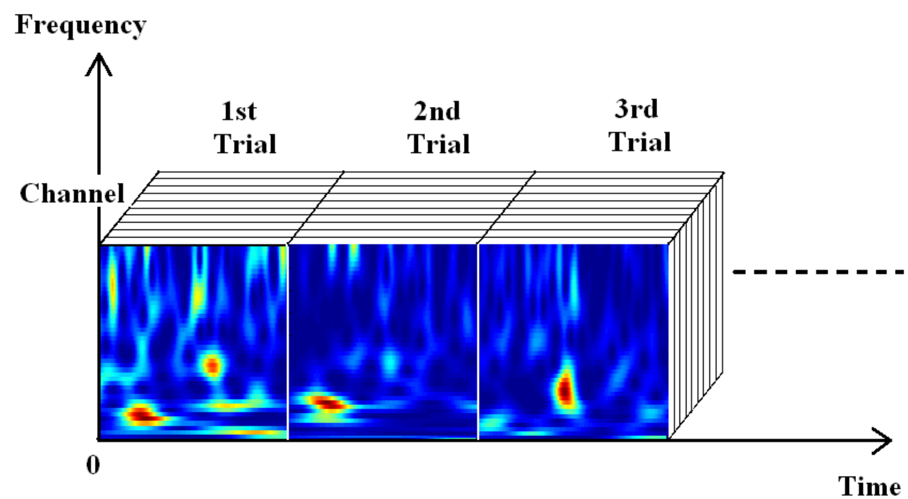
3D



4D



4D Unfolded



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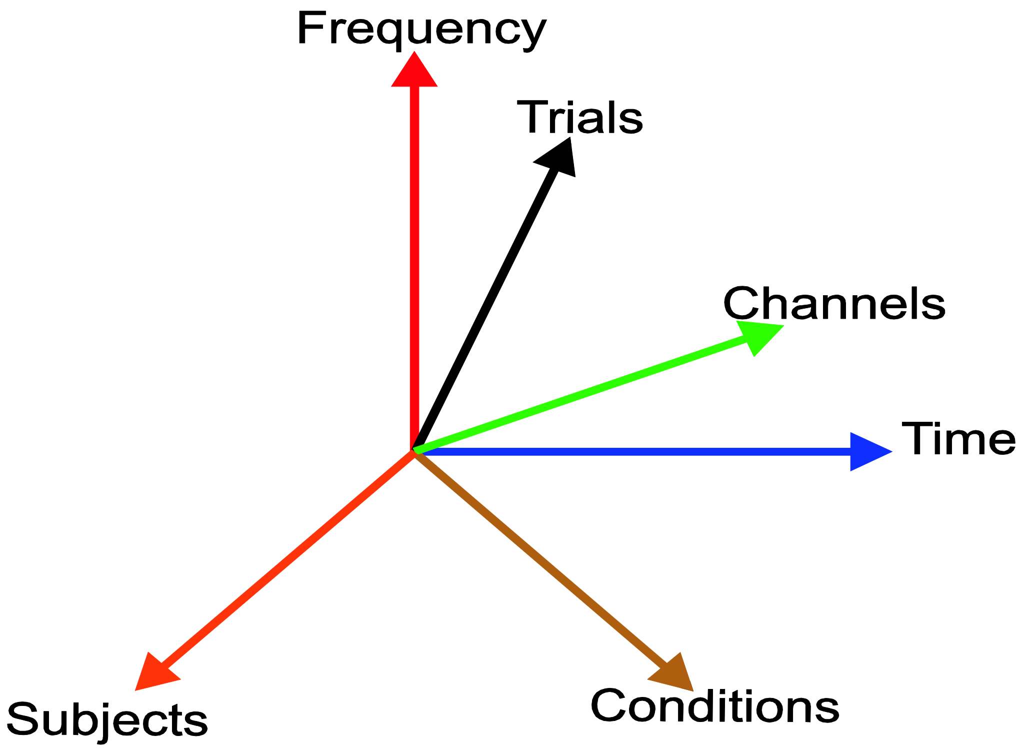
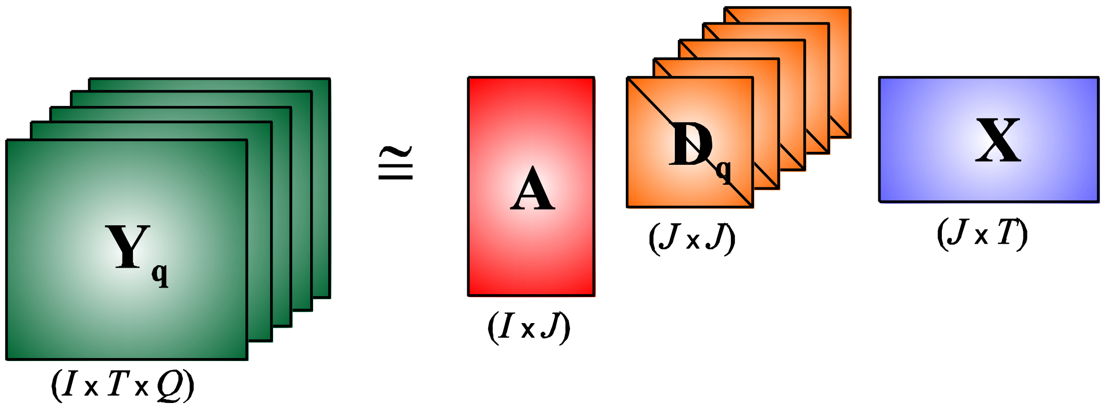
Multi-way representation of data



CP/NTF (Alternative representations)

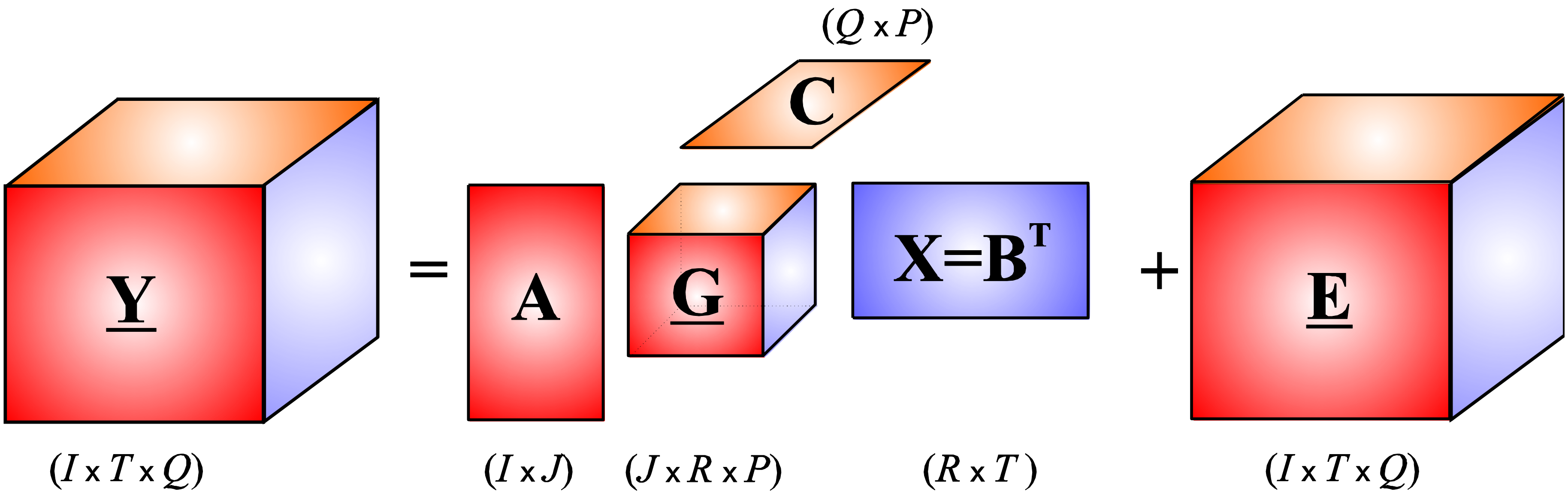
Converting the problem to set minimization of set of the cost functions



$$\mathbf{Y}_q = \mathbf{A}\,\mathbf{D}_q\,\mathbf{X} + \mathbf{E}_q \qquad q = 1, 2, \ldots, q$$

$$J_q(\mathbf{A}, \mathbf{D}_q, \mathbf{X}) = \|\,\mathbf{Y}_q - \mathbf{A}\,\mathbf{D}_q\,\mathbf{X}\,\|_F^2 \qquad q = 1, 2, \ldots, q$$

TUCKER 3 Model (1966)



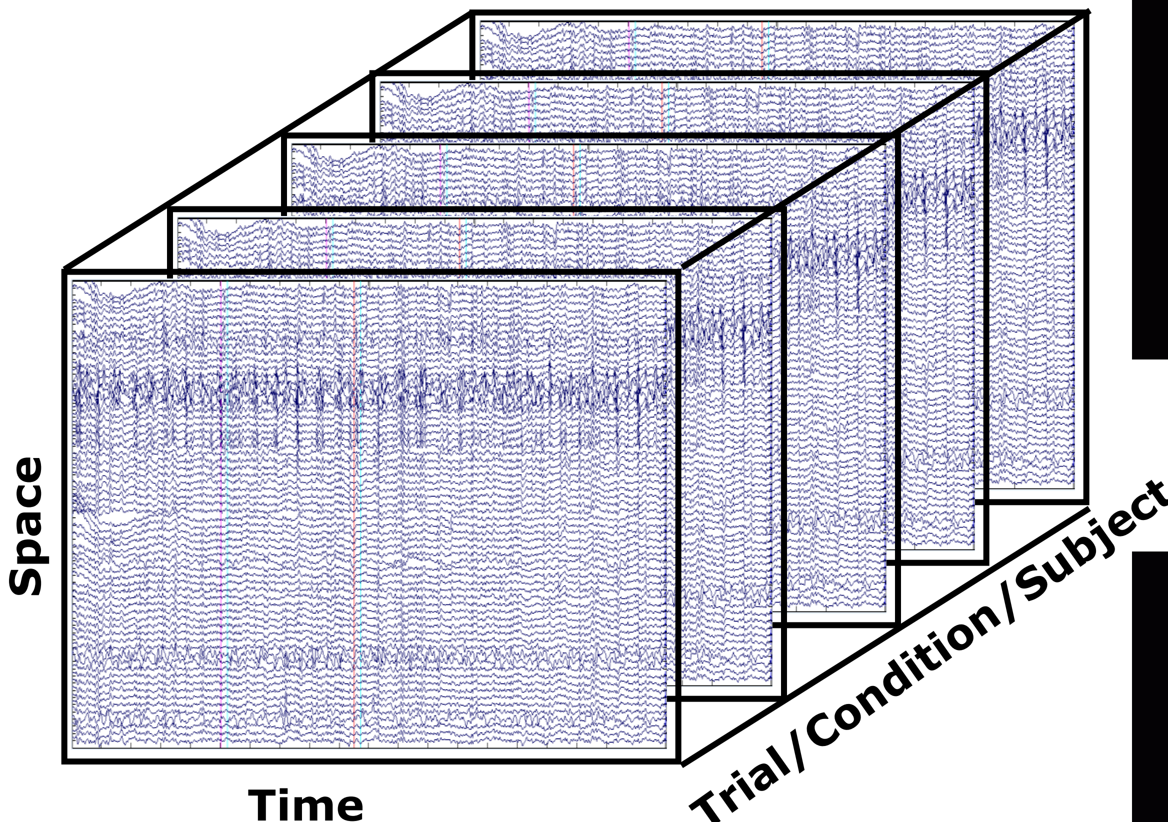
$$\underline{\mathbf{Y}} = \underline{\mathbf{G}} \times_1 \mathbf{A} \times_2 \mathbf{B} \times_3 \mathbf{C} + \underline{\mathbf{E}}$$

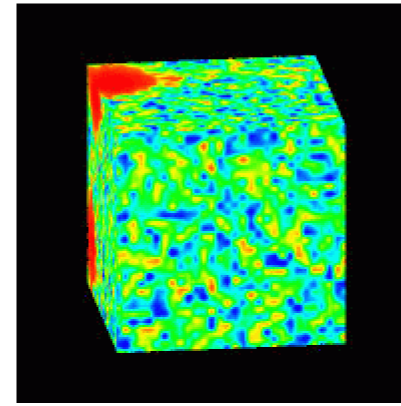
$$\underline{\mathbf{Y}} = \sum_{jrp} g_{jrp} (\mathbf{a}_j \circ \mathbf{b}_r \circ \mathbf{c}_p) + \underline{\mathbf{E}}$$

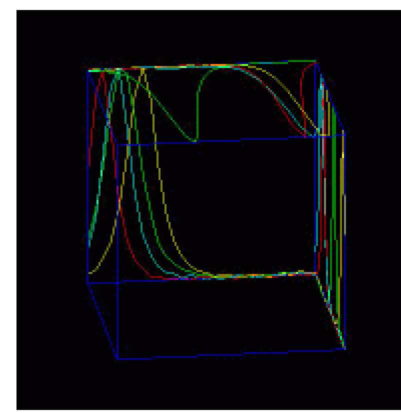
Application of tensor decompositions

From Two-way to Multi-way Analysis

Integration and Fusion of Various Modalites EEG+fNIRS +fMRI







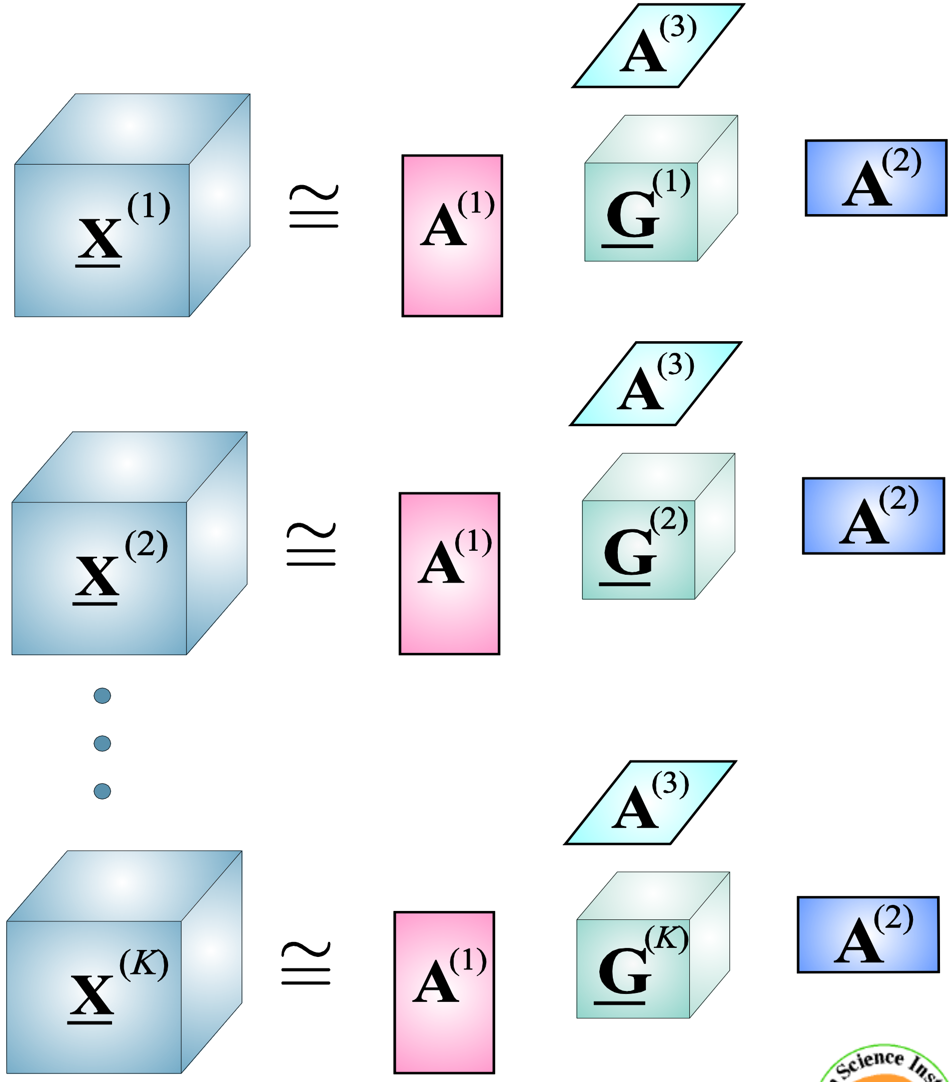
We have developed unsupervised learning methods and software to find the hidden causes and underlying hidden structure in the data. (Exploratory and multi-way blind source separation and tensor factorizations)

Tensor decomposition approach to feature extraction

- Find common factors $\mathbf{A}^{(n)}$ so that for all K tensors $\underline{\mathbf{X}}^{(i)}$ can factorize with the **same bases**

- Lead to K simultaneous TUCKER models.

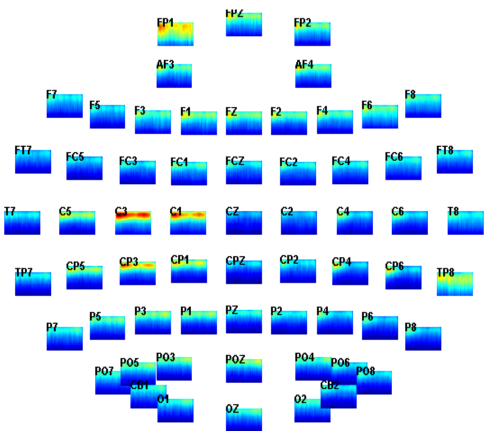
- Coefficient of core tensors represent **features** of corresponding tensors $\underline{\mathbf{X}}^{(i)}$



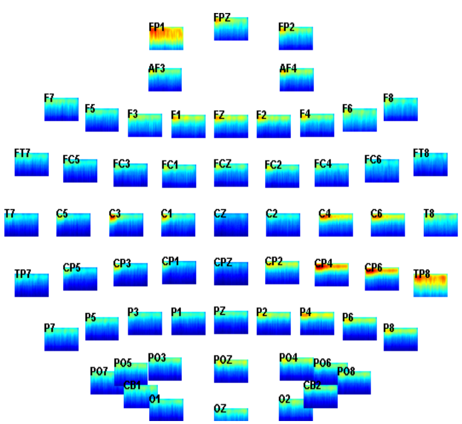
Novel Visualization of Spatio-temporal-spectral Components for Motor Imagery EEG BCI

$$\mathbf{X}^{channel \times time-frequency \times class}$$

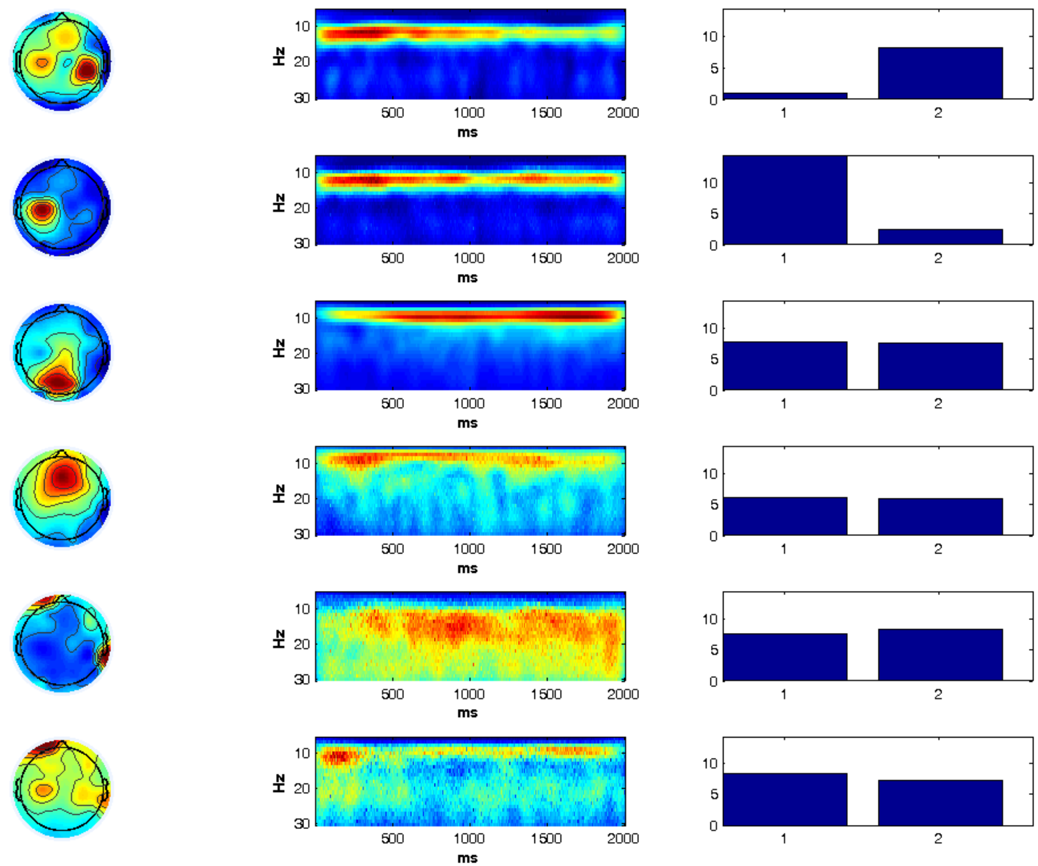
Left hand



Right hand



Channel Time-frequency Class



$$\mathrm{ERSP}(c, f, t) = \frac{1}{N}\sum_{n}^{N} |X(c, f, t, n)|^2,$$

Sparseness on *channel* and *classes* modes

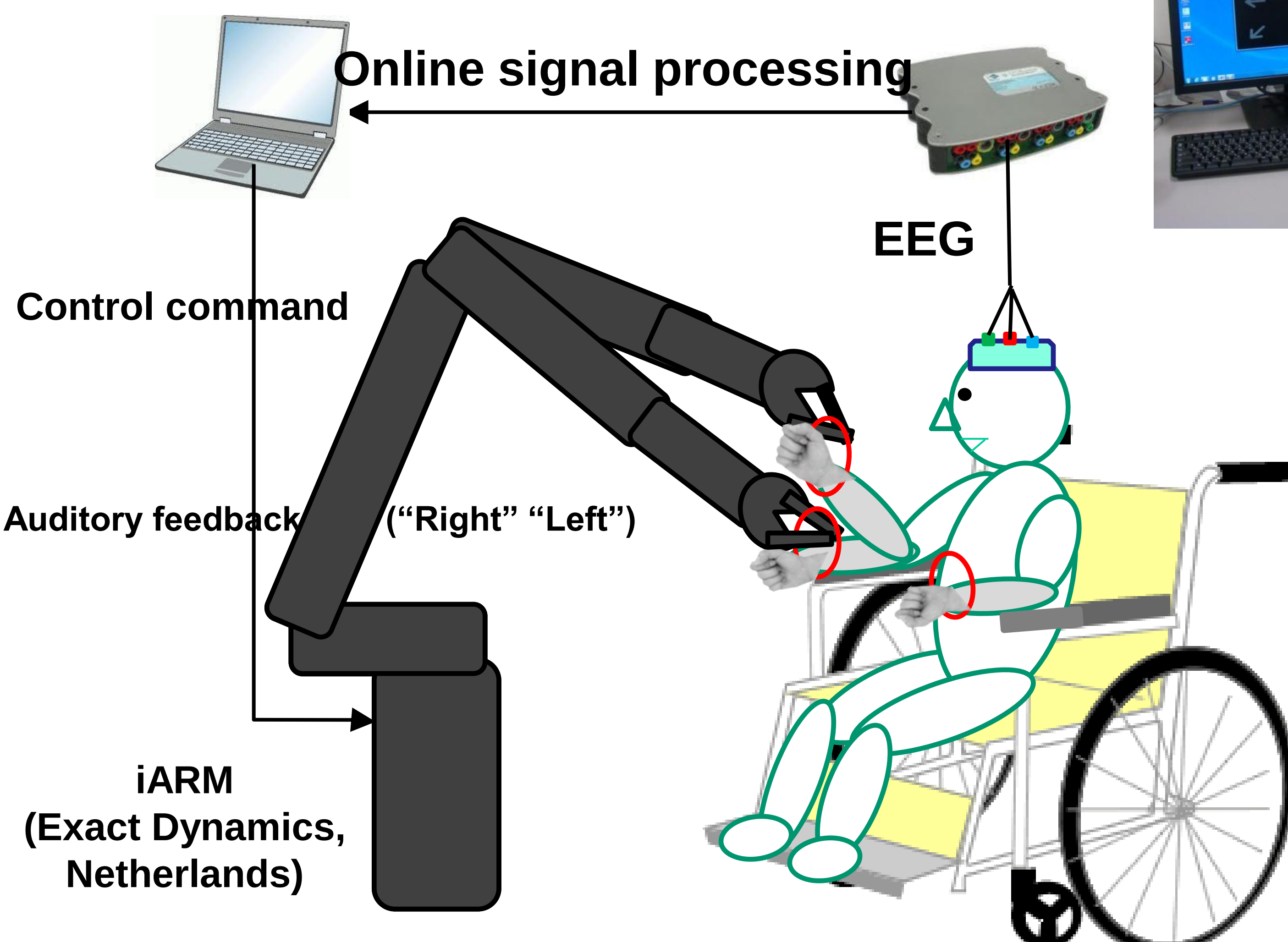
Motor Imagery (MI mu + beta rhythms) BCI

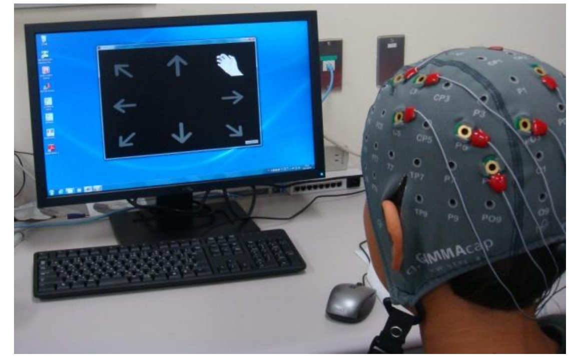
Wheelchair controlled via BCI; On-line BCI Demo

Imagery Hands and Feet Movements

36

BMI with robot arm

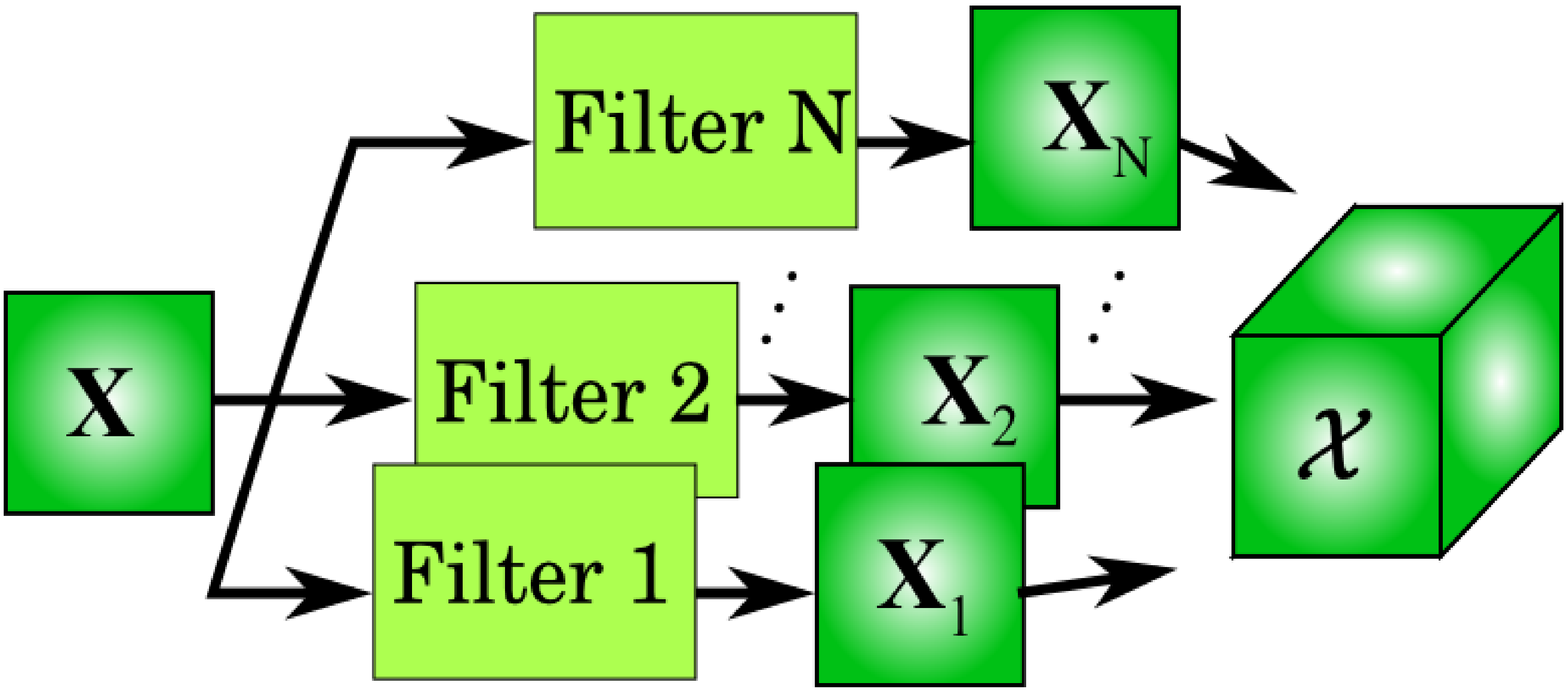




P300-BCI

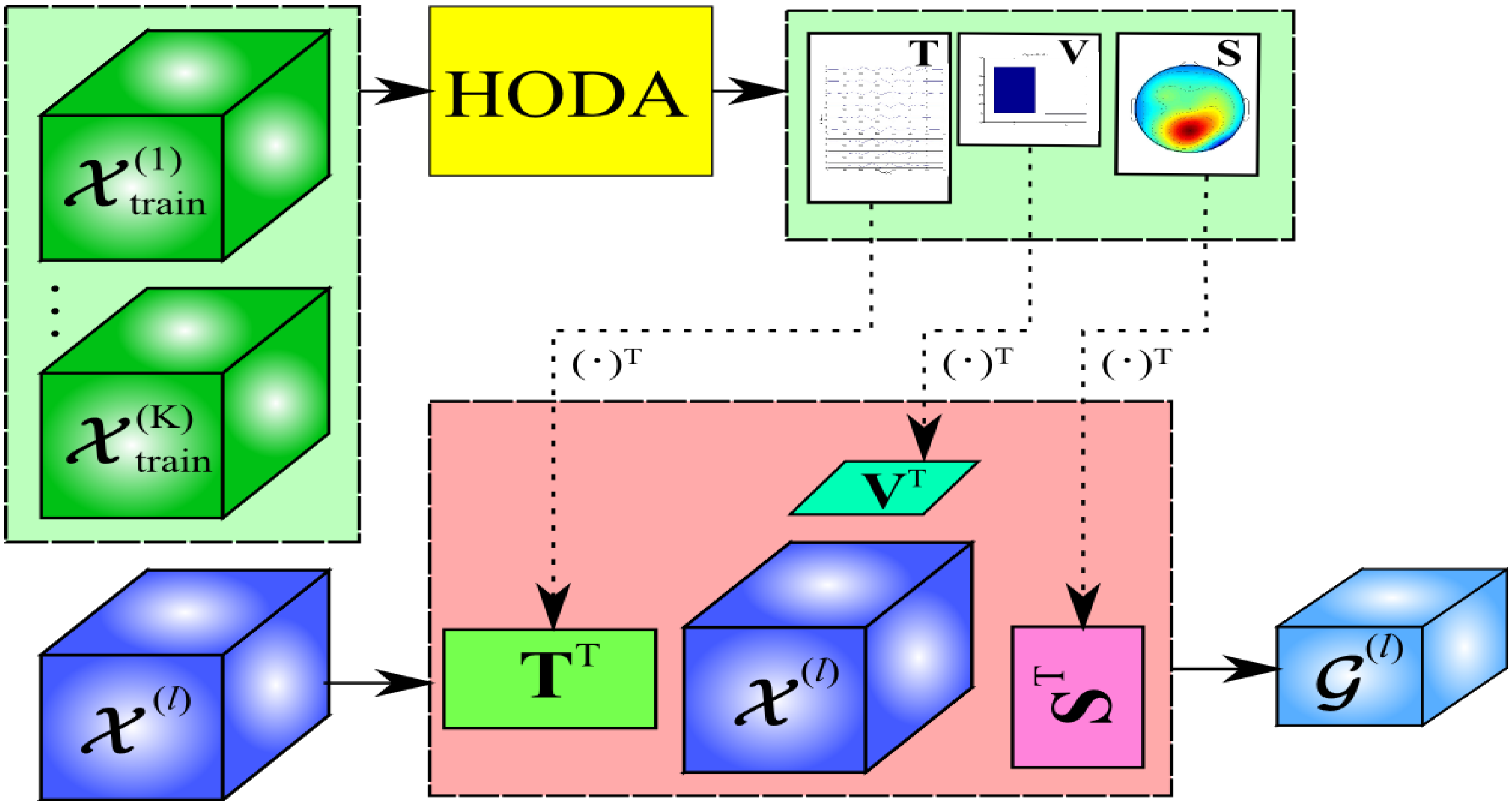
3-dimensional tensorization

- 2-dimensional data can be tensorized by applying different filters.



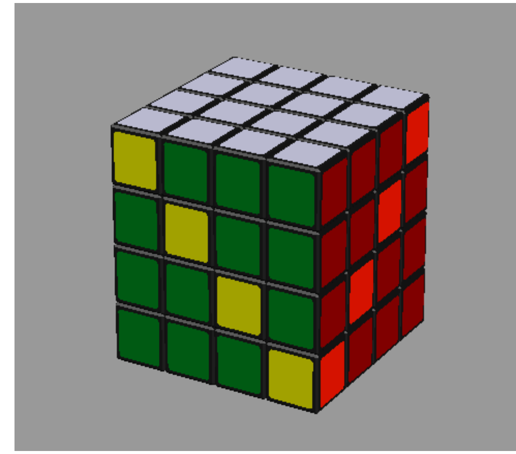
Projection by basis factors

- The newly obtained data can be projected into the core tensor. We employed vectorized core tensors as features.

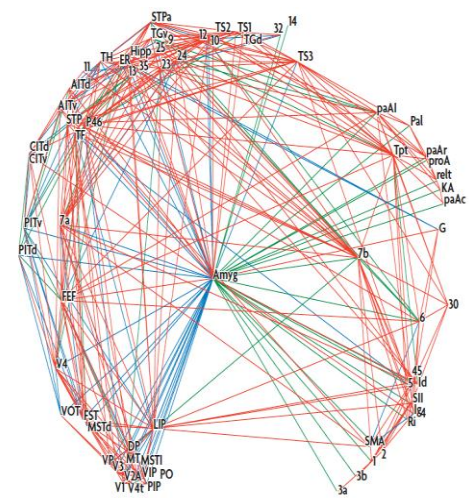


Current and Future Problems in Modeling and Analysis of Human Brain Data

► How to extract hidden brain patterns? How does the brain patterns look like?



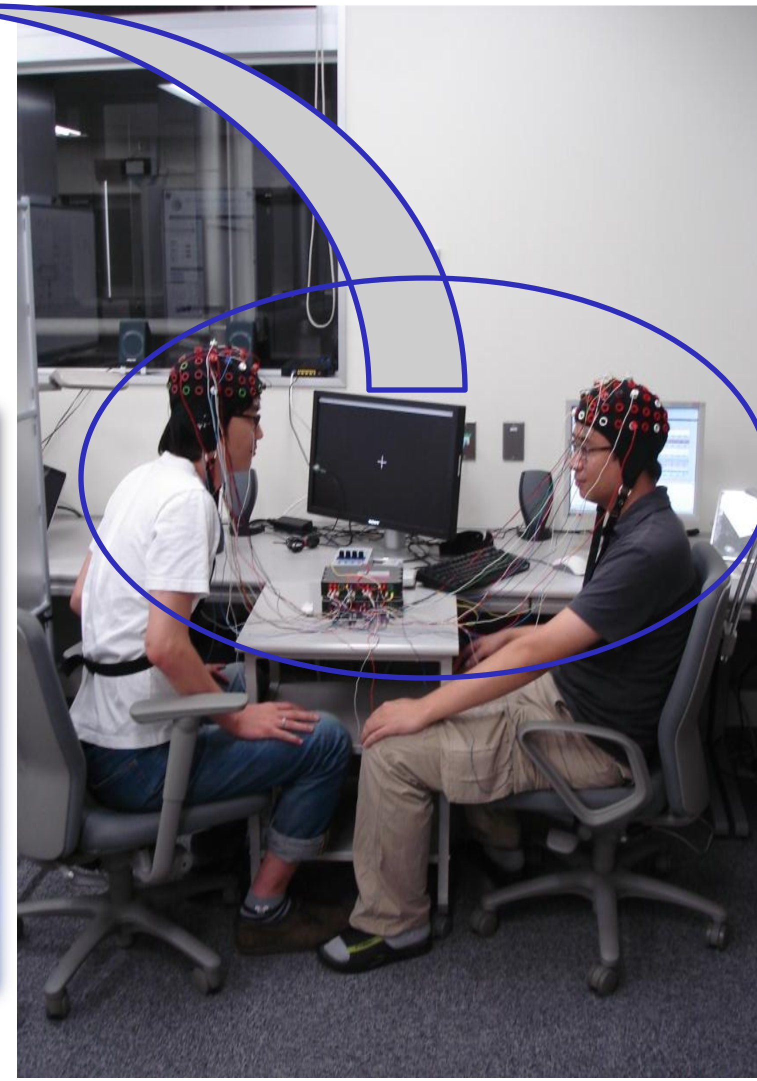
► **What is 'normal'/'abnormal' components? Which patterns/laws hold ?**



► How interact different components Sub-networks How do they evolve? Functional and effective connectivity

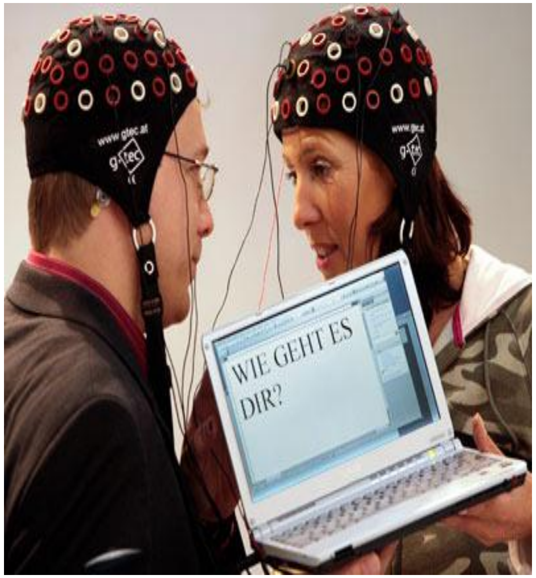
► How to extract and select features and classify them depending on mental tasks

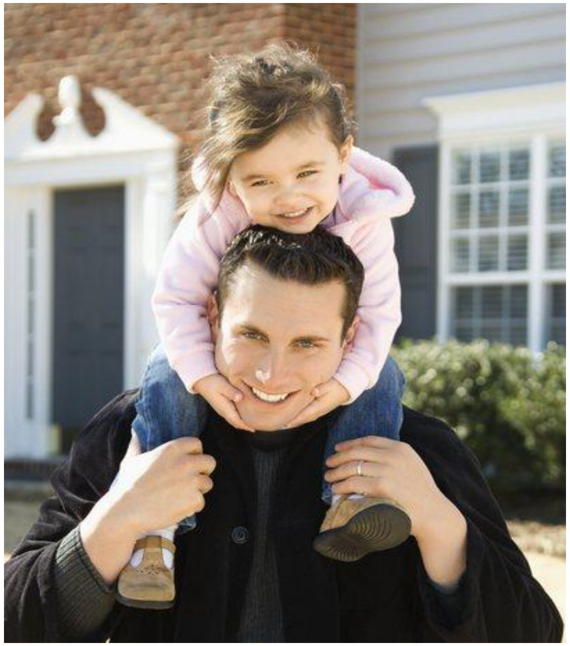
Synchronized Minds for Mutual Understanding , “Click” with Potential Application to Therapy and Rehabilitation

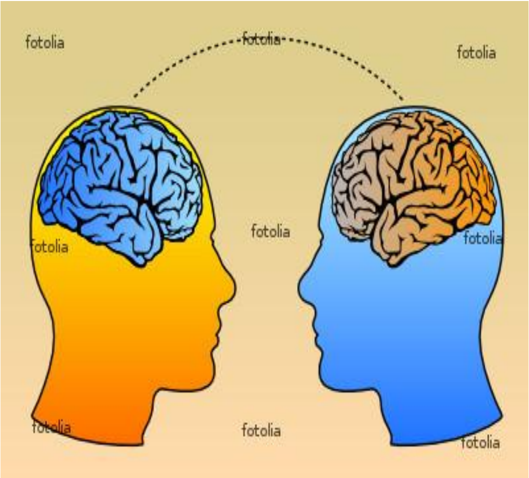


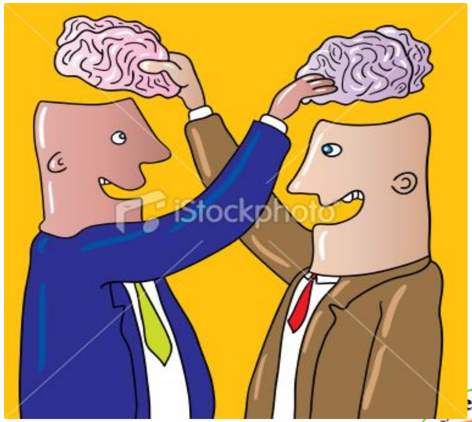
Social interactions and emotions related experiments
Using high density array EEG and NIRS in BTCC

Social Interactions of Two Persons

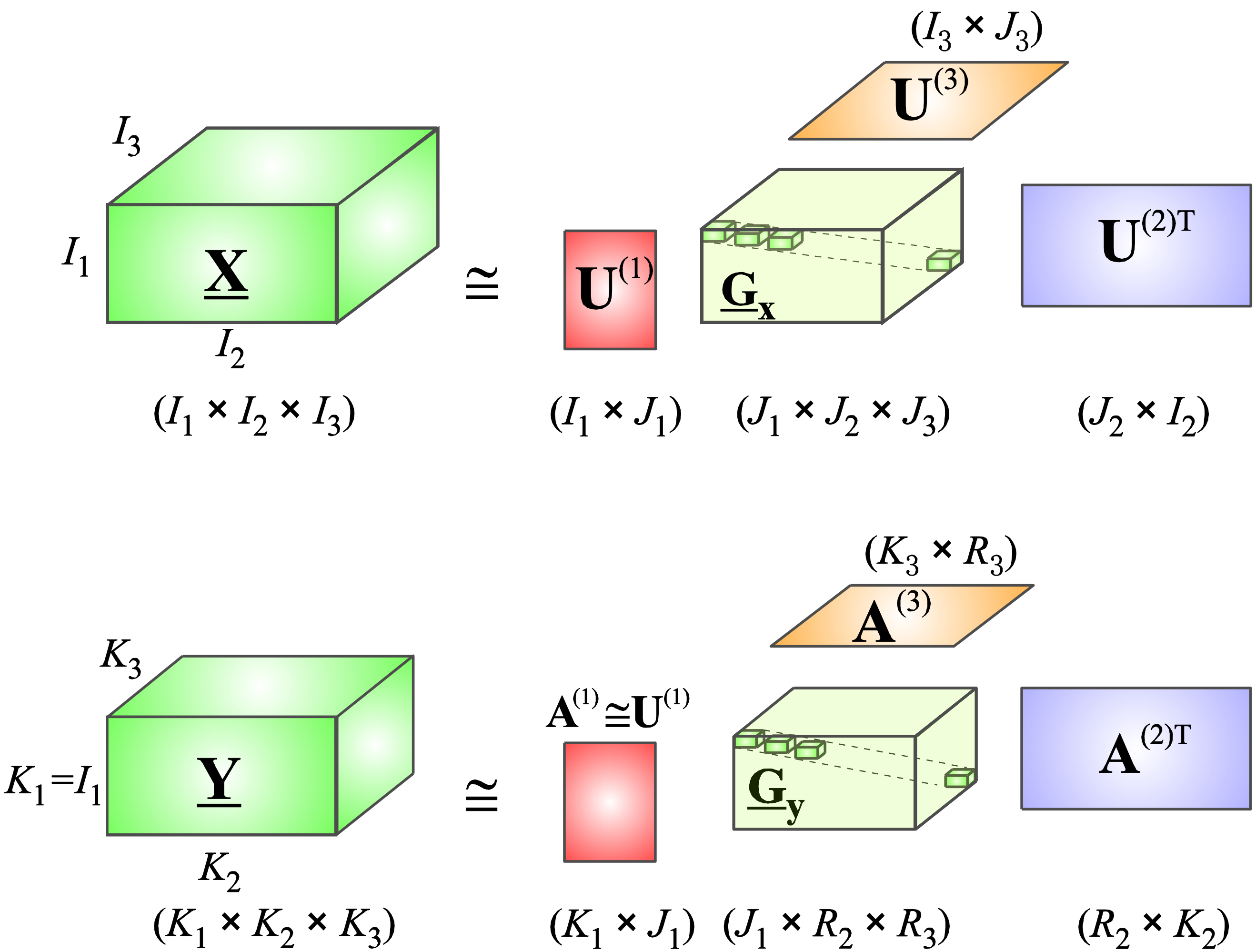




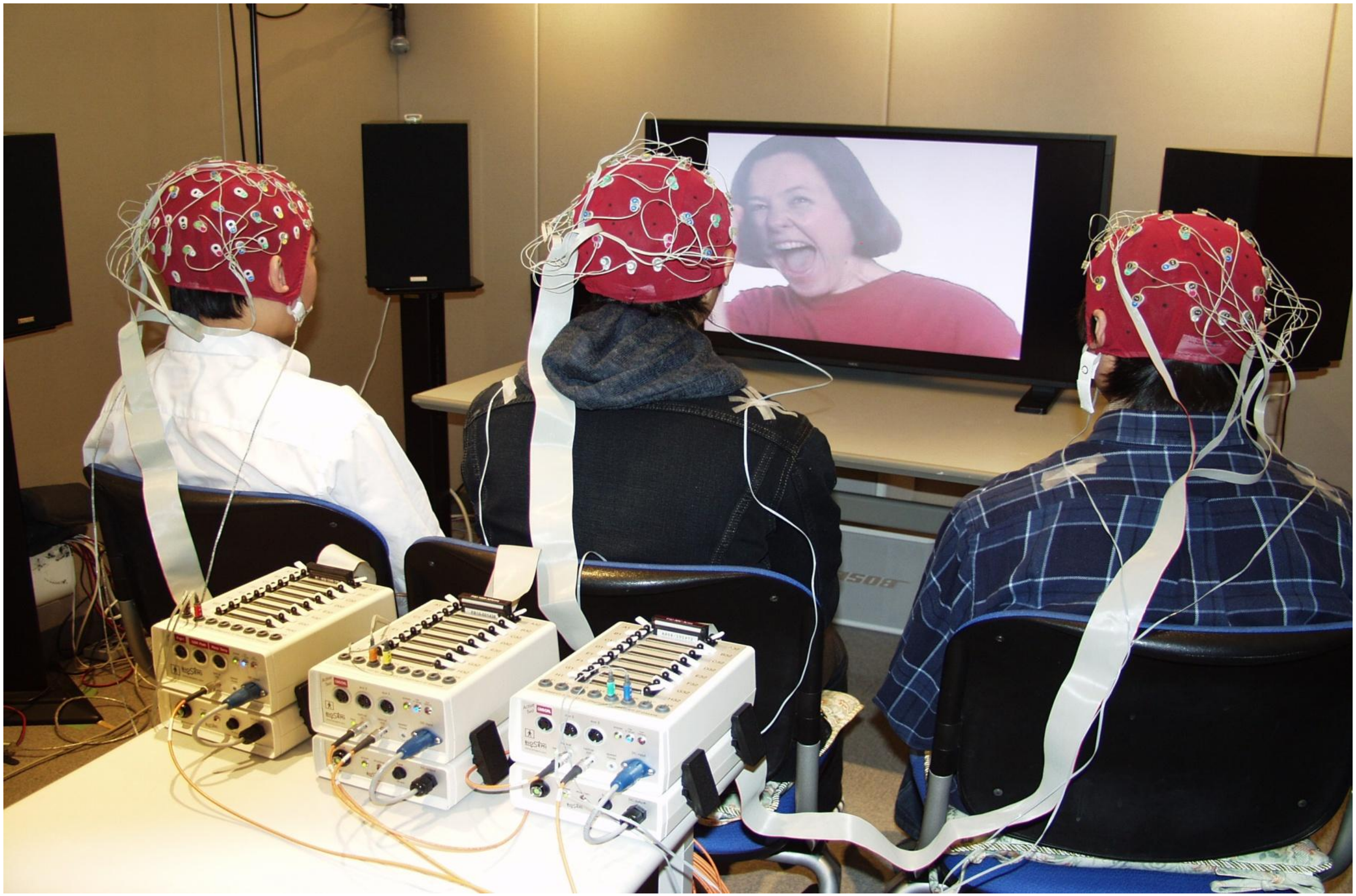




What kind of links and synchronizations occur between two brains CCA? PLS? What kind of common components can we extract?

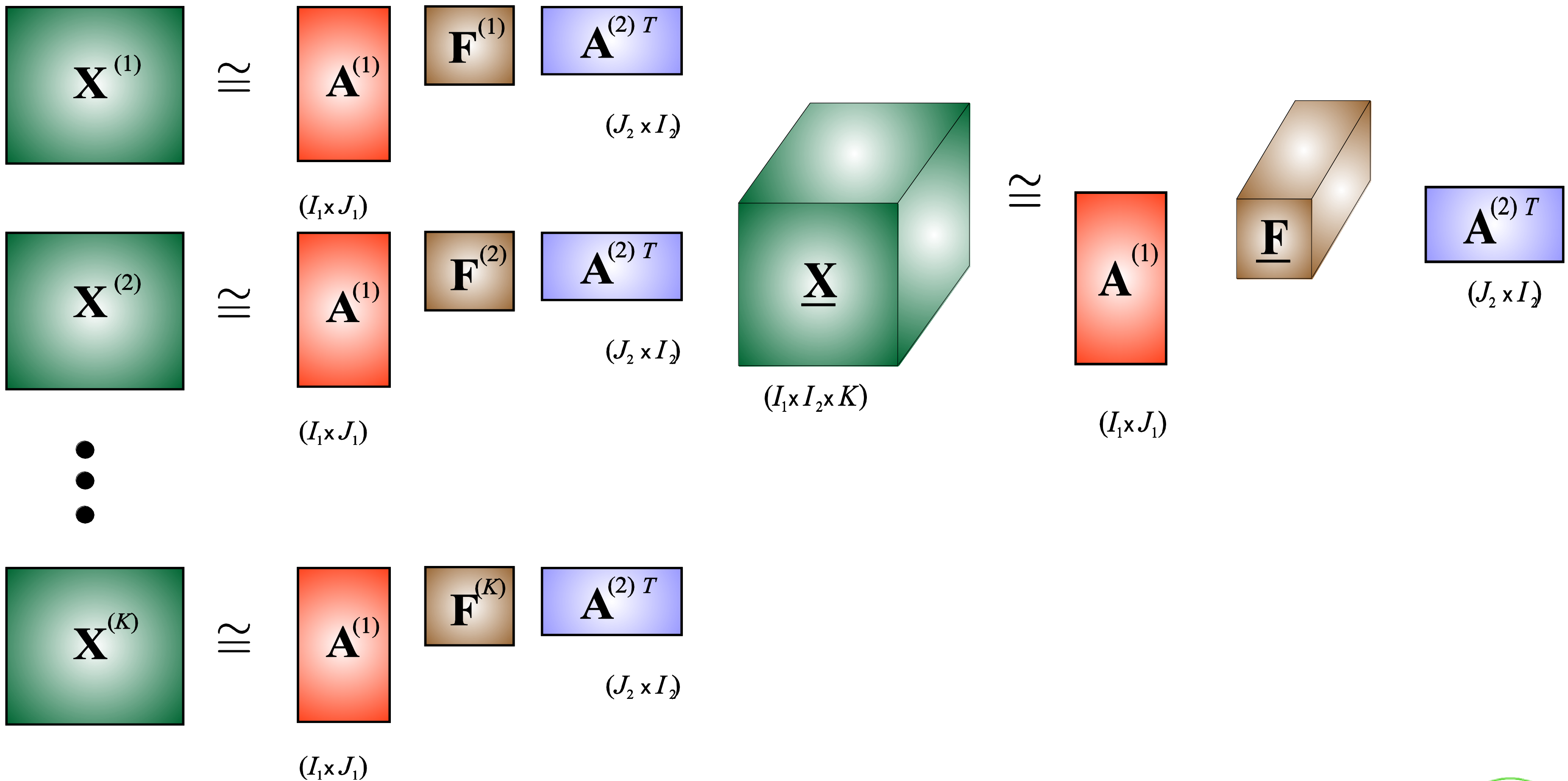


EEG HYPER-SCANNING
of 3 subjects observing affective stimuli
LABSP



Tensor decomposition approach to feature extraction 2D example

(Generalization of Joint Approximate Diagonalization – JAD)



Conclusions

1. We firstly succeeded to control wheelchair smoothly online

- By using imagery movement of hands and feet
- By applying novel feature extraction and classification technique (tensor decompositions)
- By developing simple neuro-feedback

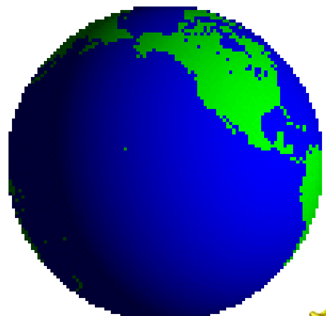
2. We increased MI , SSVEP and P300/N170 /VPP BMI performance with short training and developed a single-trial BCI based on visual affective stimuli

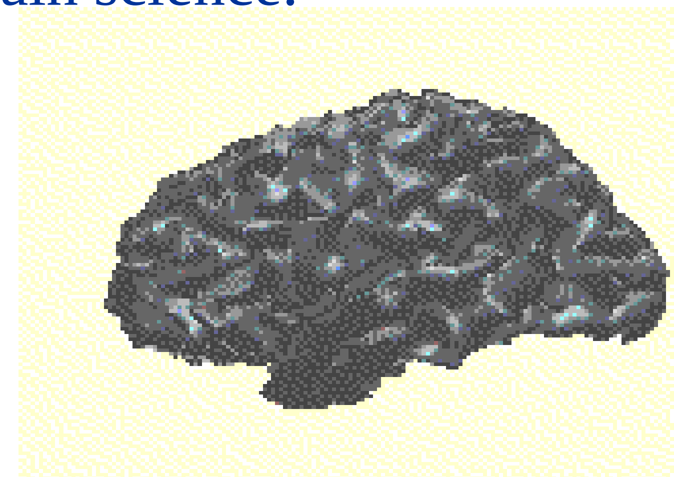
- We used virtual hands animation and emotional faces
- We developed improved SP methods for removing artifacts, features extractions and clustering
- We visualized on line brain activity related with specific mental tasks

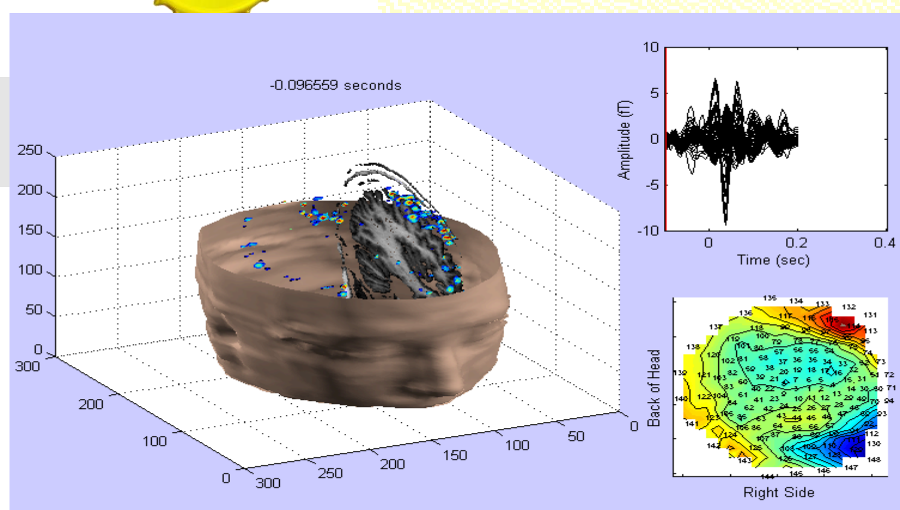
Final word: **Our brain is not static neither flat**

We need powerful and flexible technologies.

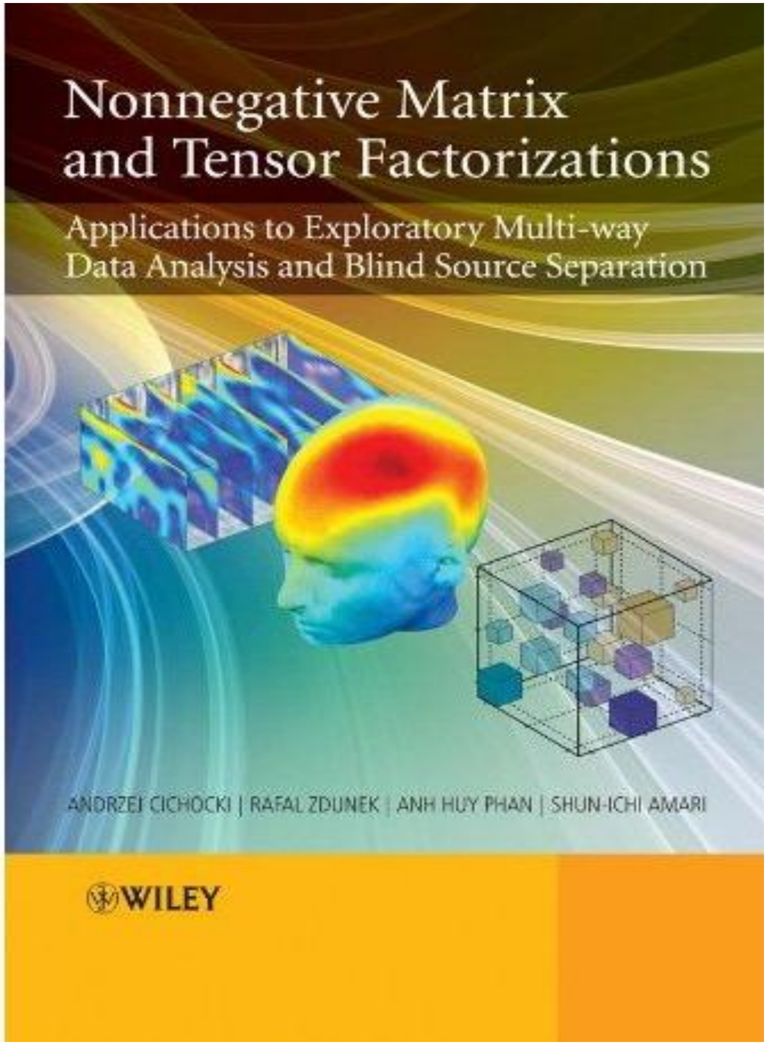
Modern and advanced signal processing and machine learning is not only useful but also necessary in brain science.







Additional Information



- **A. Cichocki, R. Zdunek, A. H. Phan and S. Amari, Nonnegative Matrix and Tensor Factorization.** Wiley NY 2009.

  http://www.bsp.brain.riken.jp/~cia/NMF_NTF_book/NMF-NTF-book-Chapter1_2-contents.pdf

- Publications and reports available on our web pages

  http://www.bsp.brain.riken.jp/page3.html

- MATLAB Tensor Toolboxes (NTFLAB, MULTIWAYLAB, TENSOR-TOOLBOX)

LABSP BSI RIKEN

ONE OF OUR GOAL IN BMI RESEARCH IS TO DEVELOP SYSTEMS CAPABLE OF DECODING NEURAL REPRESENTATIONS OF NATURAL MOVEMENTS PLANNING AND EXECUTION

We hope in the near future our robots can detect our intentions, habits, moods and emotions

Robots can play important roles in rehabilitation and therapies.