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iMinds | Medical Information Technologies Department

The power of TENSOR Decompositions in *Smart Patient Monitoring*

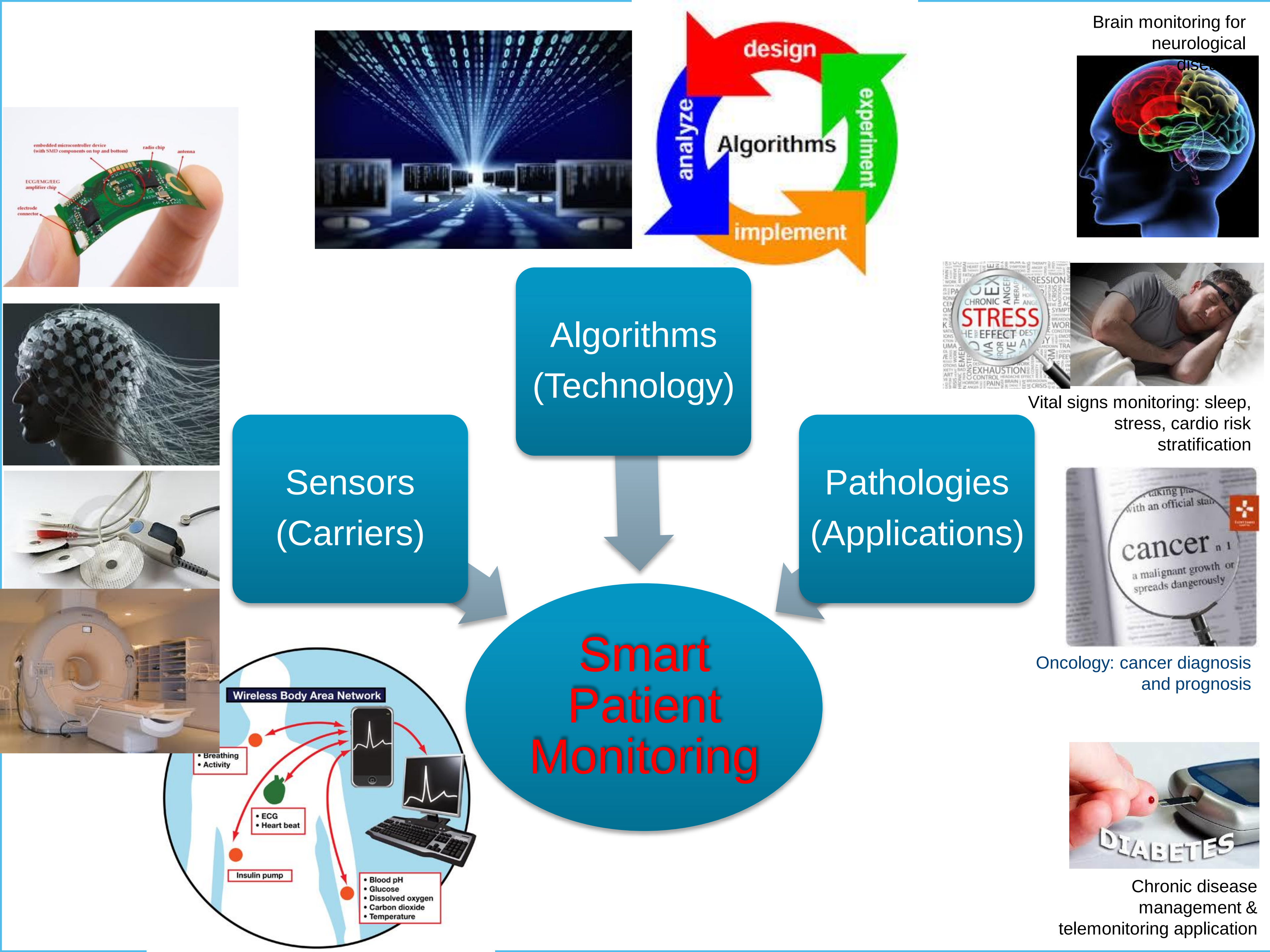
TDA 2016 Symposium
Leuven, Belgium
January 18-22, 2016

Prof. Sabine Van Huffel

European Research Council
Established by the European Commission

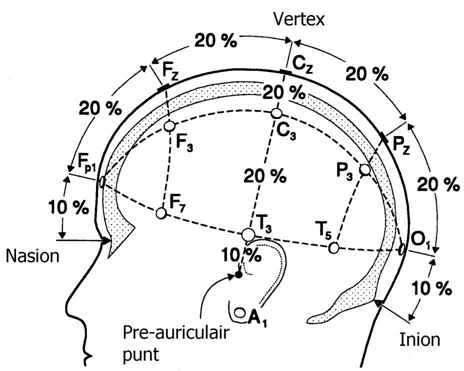
Contents Overview

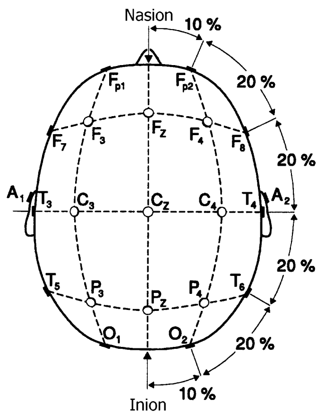
- Introduction
  - Smart Patient Monitoring
  - EEG and epileptic seizure monitoring
  - Blind Source Separation
- Tensor Decompositions
- Examples in EEG monitoring
- Conclusions and new directions



Brain monitoring for neurological disea
design
experiment
implement
analyze
Algorithms
Algorithms (Technology)
Sensors (Carriers)
Pathologies (Applications)
STRESS
Vital signs monitoring: sleep, stress, cardio risk stratification
cancer
Oncology: cancer diagnosis and prognosis
DIABETES
Chronic disease management & telemonitoring application
Smart Patient Monitoring
Wireless Body Area Network
• Breathing
• Activity
• ECG
• Heart beat
Insulin pump
• Blood pH
• Glucose
• Dissolved oxygen
• Carbon dioxide
• Temperature

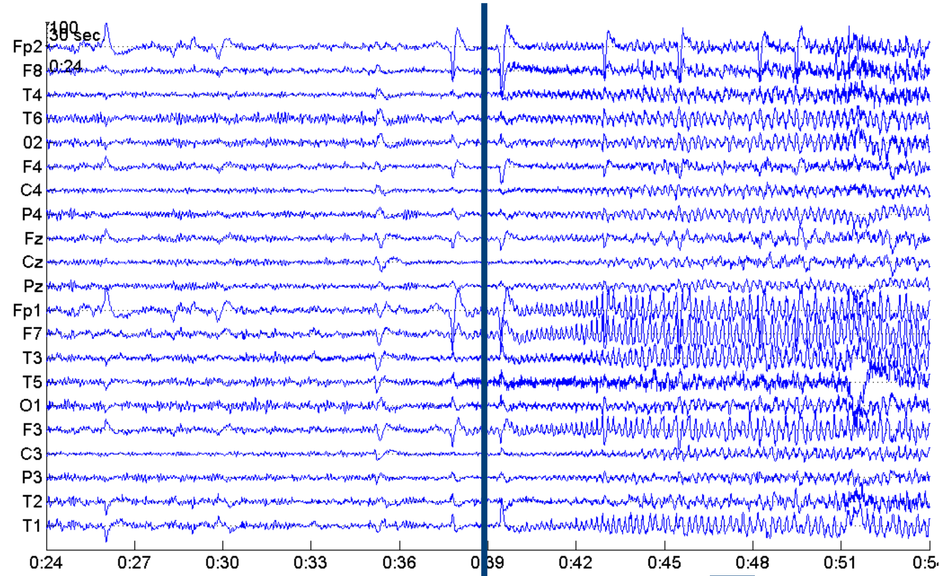
EEG and epileptic seizure monitoring



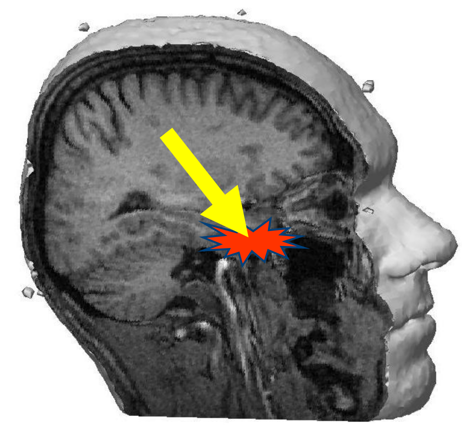


EEG

Seizure

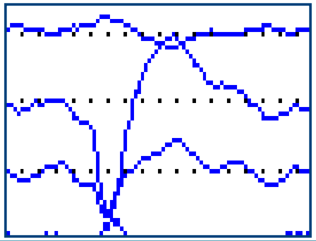


Spikes, slow waves
(epileptiform activity ?)

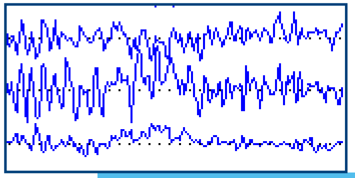


Seizure localization

eye blink

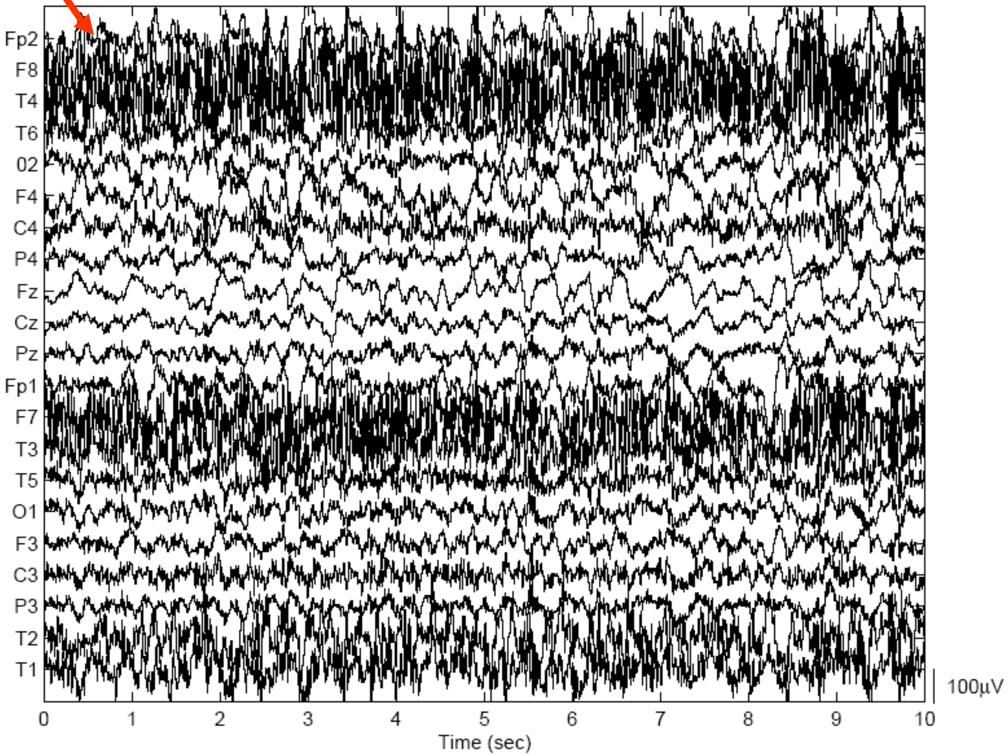


muscle



21 electrode positions
@UZ Gasthuisberg

Muscle artefacts affect EEG during seizures (>90%)



Solution? REMOVE using ***Blind Source Separation***

De Clercq et al, IEEE TBME 2006, Vergult et al, Epilepsia 2007

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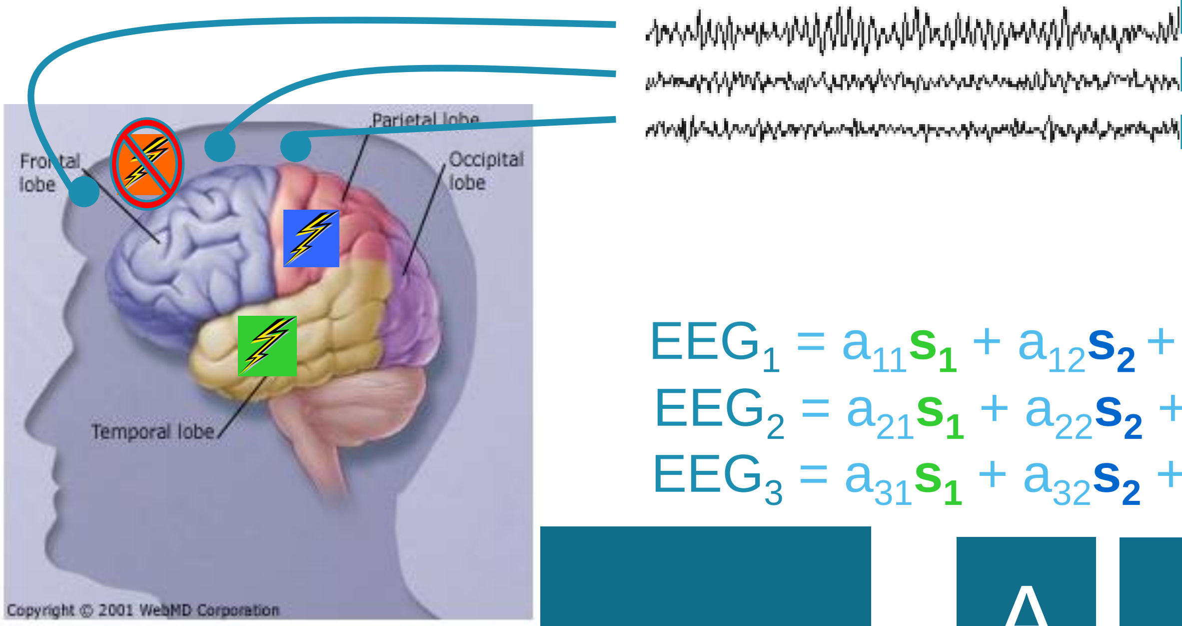
Blind source separation

EEG analysis difficult because of artefacts → REMOVE

Matrix based Blind Source Separation (BSS)

Non-unique → *Constraints are needed!*

- sources orthogonal (PCA),
- sources statistically independent (ICA)
- **sources uncorrelated and of different autocorrelation (CCA)**



$$EEG_1 = a_{11}\mathbf{s_1} + a_{12}\mathbf{s_2} + \cancel{a_{13}\mathbf{s_3}}$$
$$EEG_2 = a_{21}\mathbf{s_1} + a_{22}\mathbf{s_2} + \cancel{a_{23}\mathbf{s_3}}$$
$$EEG_3 = a_{31}\mathbf{s_1} + a_{32}\mathbf{s_2} + \cancel{a_{33}\mathbf{s_3}}$$

$$\text{EEG} = A\,?\;S^T\,?$$

Contents Overview

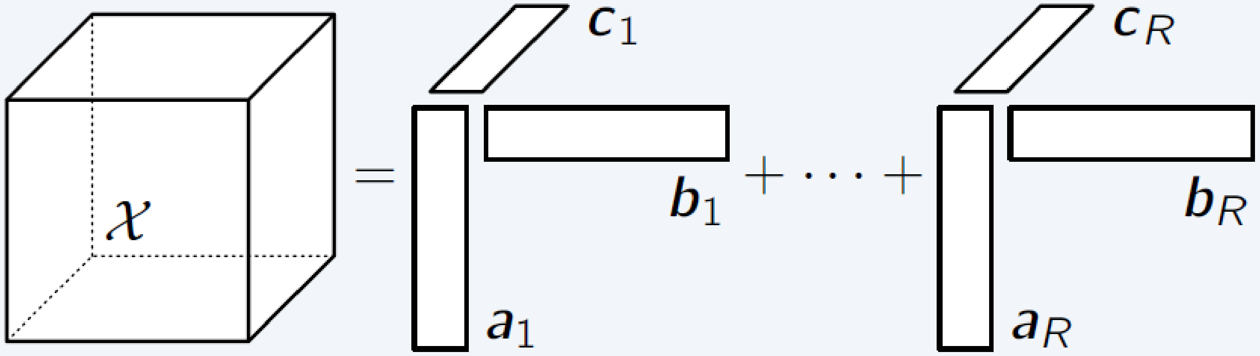
- Introduction
- Tensor Decompositions
    - Canonical Polyadic Decomposition (CPD)
    - Block Term Decompositions
    - Tensor-based data fusion
- Examples in EEG monitoring
- Conclusions and new directions

Canonical Polyadic Decomposition (CPD)

Without constraints, matrix decompositions are not unique

$$X = A \cdot B = (A \cdot M) \cdot (M^{-1} \cdot B) = \hat{A} \cdot \hat{B}$$

Tensor decompositions can be unique under mild conditions!
For example, the vectors $\boldsymbol{a}_r$, $\boldsymbol{b}_r$ and $\boldsymbol{c}_r$ in the CPD

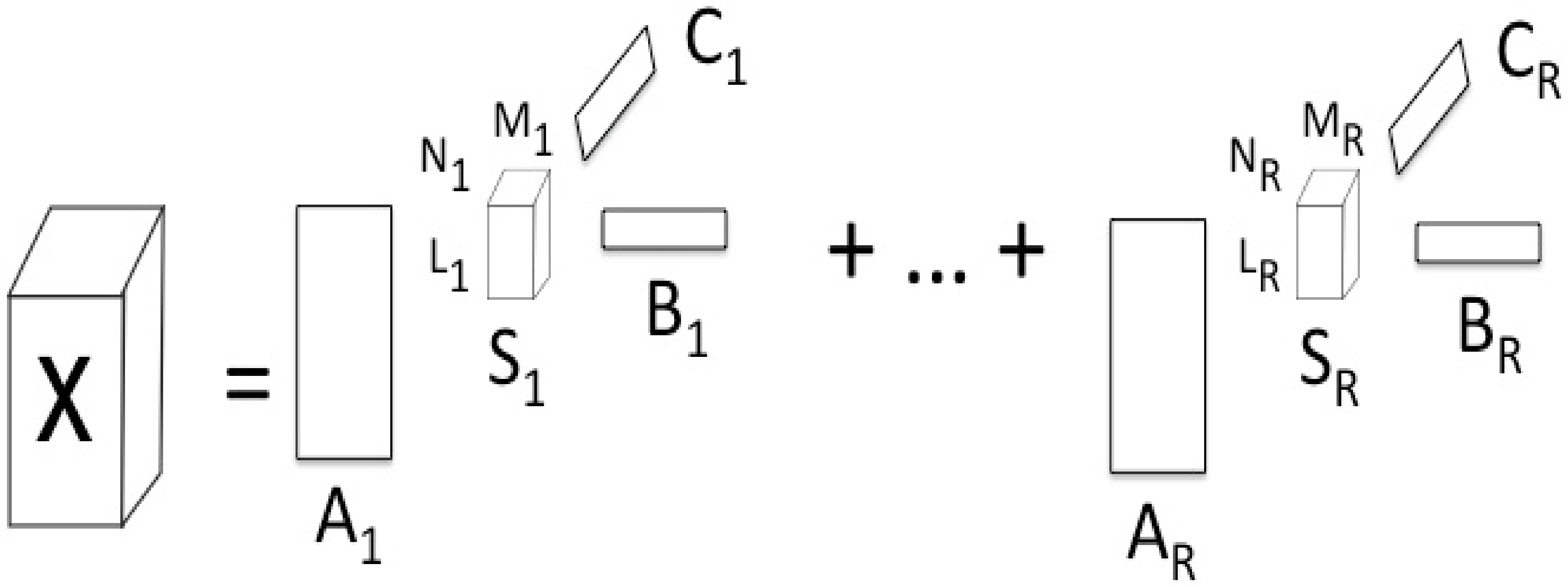


are generically unique when $k_A + k_B + k_C$ >= 2*R+2

$A=[a_1,\ldots,a_R]$
$B=[b_1,\ldots,b_R]$
$C=[c_1,\ldots,c_R]$

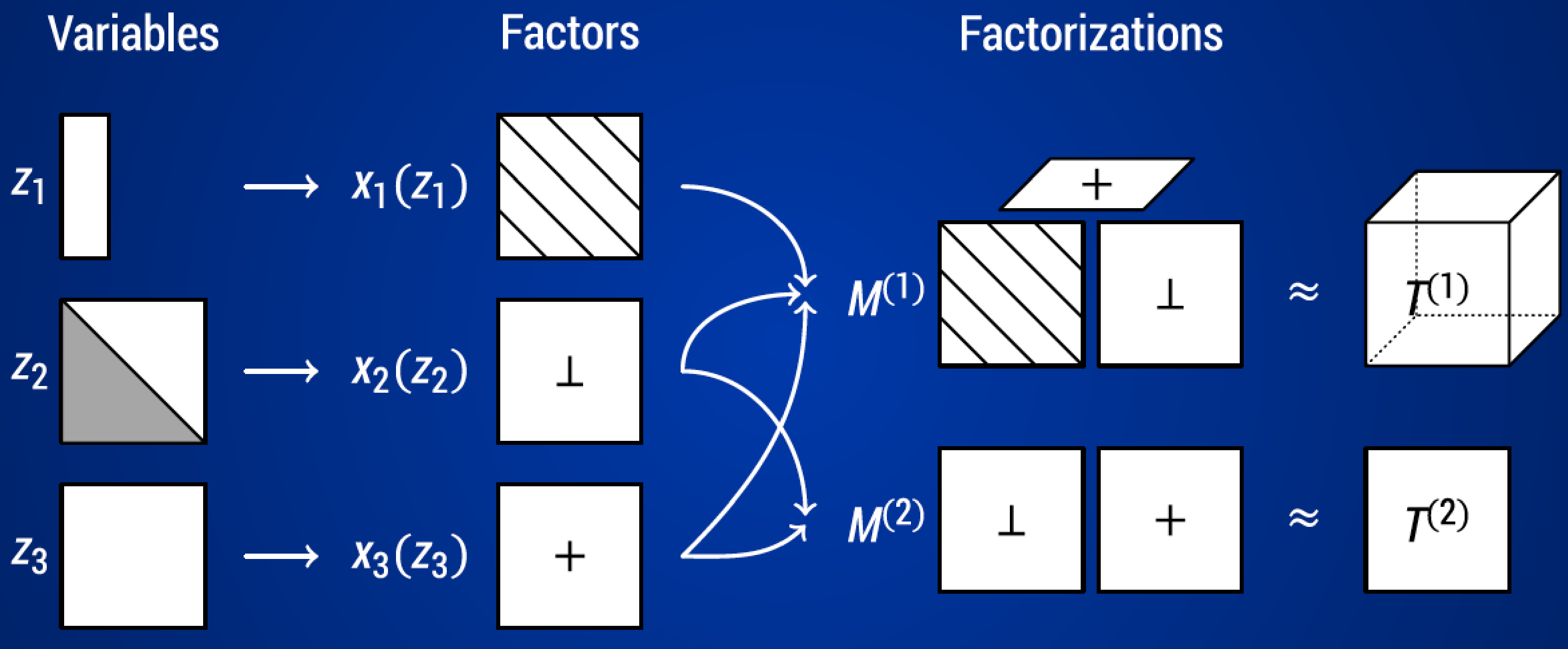
Contributors (nonexhaustive list):
L. De Lathauwer, P. Comon, T. Kolda, B. Bader, L-H Lim, C. Van Loan, E. Acar, A. Cichocki, O. Alter, R. Bro, M. Morup, N. Sidiropoulos, I. Domanov, M. Sorensen, L. Sorber, M. Ishteva, L. Albera, M. Haardt, …. and collaborators

Block Tensor Decomposition (BTD)



De Lathauwer et al., SIMAX, 2008; Sorber et al., SIOPT, 2013

STRUCTURED DATA FUSION



$$\underset{z}{\text{minimize}} \quad \sum_d \omega_d \left\| M^{(d)}(X(z)) - T^{(d)} \right\|^2$$

Sorber L, Van Barel M, De Lathauwer L, *IEEE J. of Selected Topics in Signal Proc., 2015*

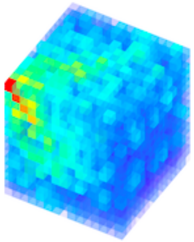
WWW.TENSORLAB.NET

www.tensorlab.net — Tensorlab

Reader

Tensorlab

A MATLAB toolbox for tensor computations



About

Tensorlab is a MATLAB toolbox that offers algorithms for

- **structured data fusion:** define your own (coupled) matrix and tensor factorizations with structured factors and support for dense, sparse and incomplete data sets,
- **tensor decompositions:** canonical polyadic decomposition (CPD), multilinear singular value decomposition (MLSVD), block term decompositions (BTD) and low multilinear rank approximation (LMLRA),
- **complex optimization**: quasi-Newton and nonlinear-least squares optimization with complex variables including numerical complex differentiation,
- **global minimization of bivariate polynomials and rational functions:** both real and complex exact line search (LS) and real exact plane search (PS) for tensor optimization,
- **and much more:** cumulants, tensor visualization, estimating a tensor's rank or multilinear rank, …

Download the Tensorlab user guide (preview on the right) to get started with Tensorlab. Alternatively, see Tensorlab's Contents.m for an overview of the toolbox's functionality. For questions, bug reports or other inquiries, please contact tensorlab@esat.kuleuven.be.

Download 2014-05-07

To download Tensorlab, please fill out the form below. Your email address will not be used for marketing purposes, sold or shared with third parties.

First name

Last name

Institution/company

Applied mathematics   Field of expertise

userguide.pdf

Tensorlab

User Guide 2014-05-07

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Contents

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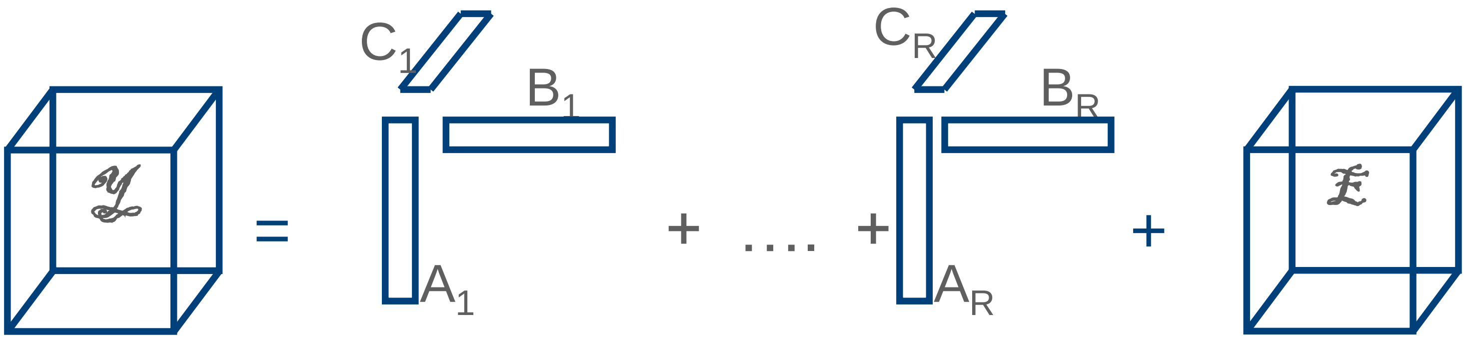
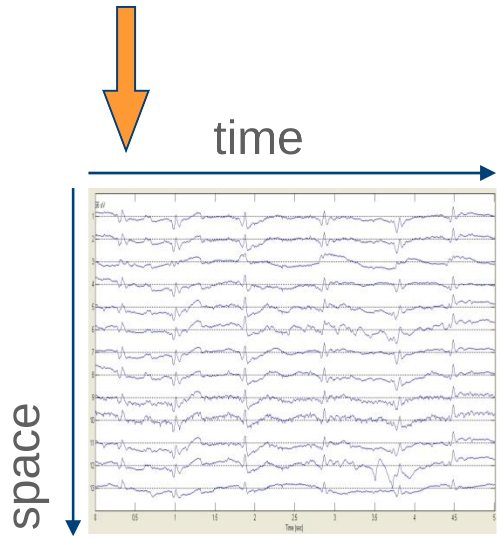
    1. Seizure onset localization
    2. Neonatal brain monitoring
    3. Event-Related Potential Analysis
    4. Combined EEG-fMRI Analysis
- Conclusions and New Directions

1

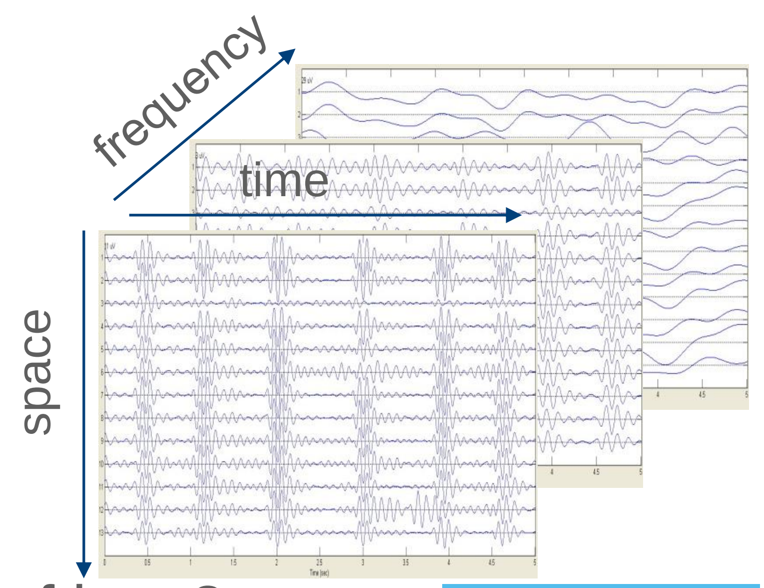
Seizure onset localization:

CPD





Split EEG in different frequencies using wavelets.



=> Analysis in 3 dimensions instead of just 2

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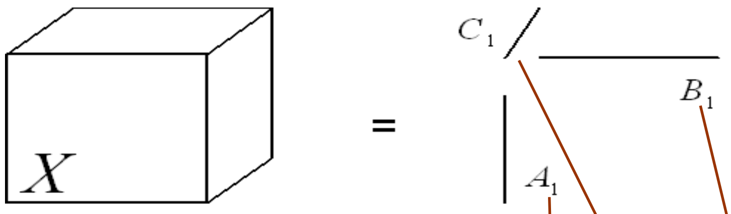
Interpretation of a trilinear component

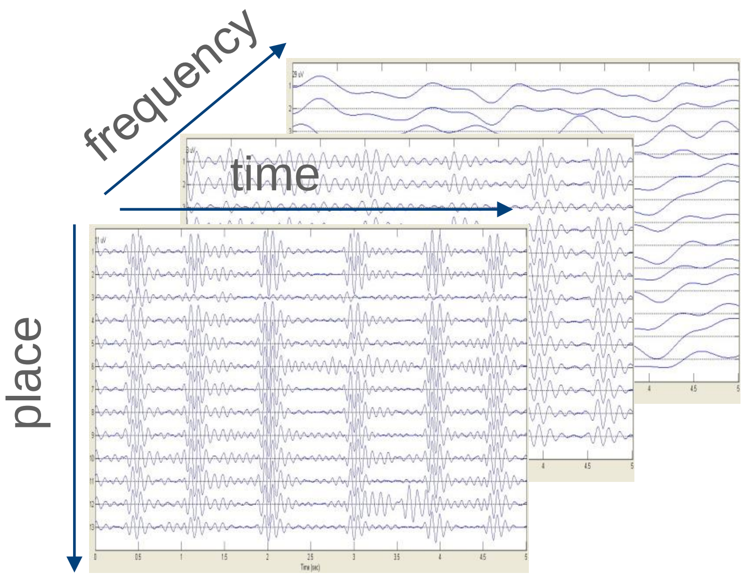
CPD: Example extracting 1 component

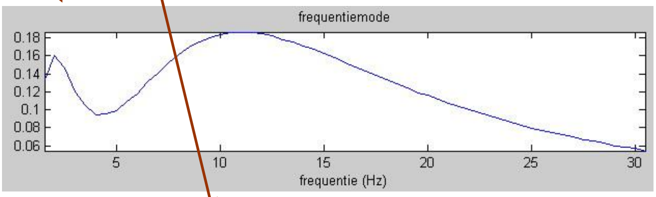


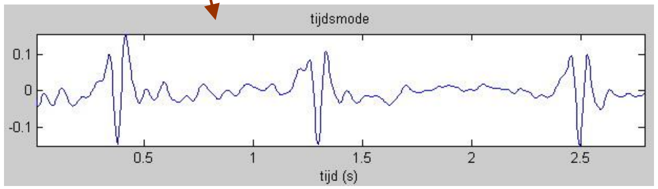
B_1: time course

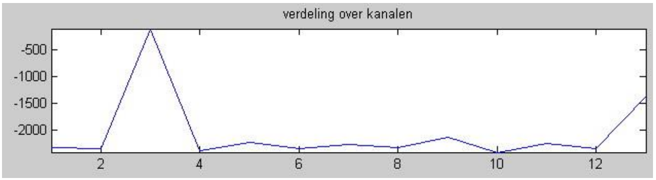
A_1: distribution over channels

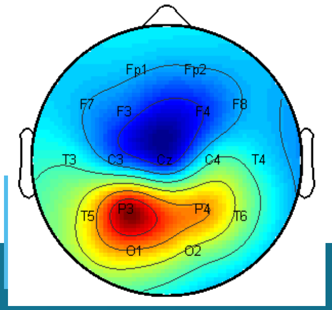
C_1: frequency content (distribution across scales).





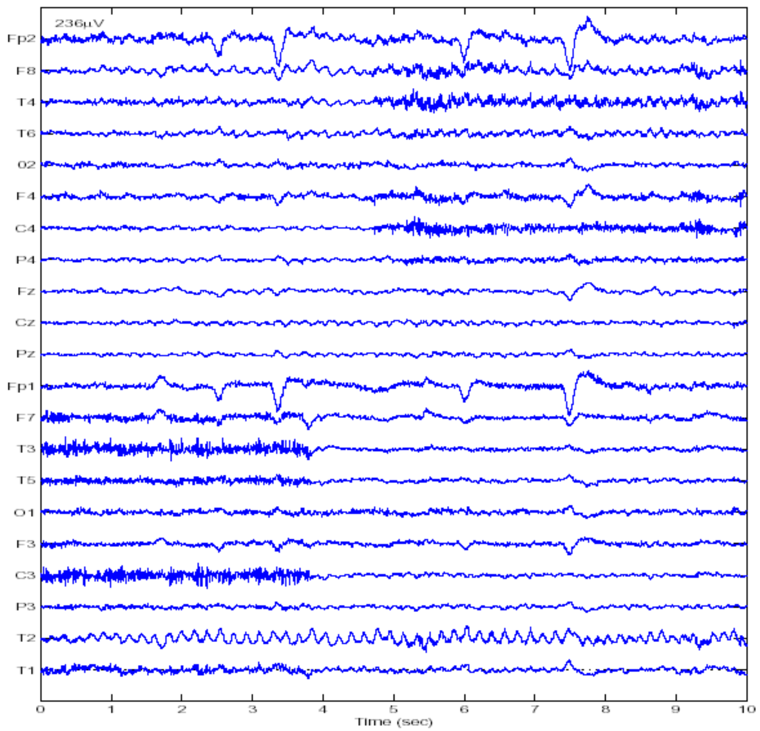


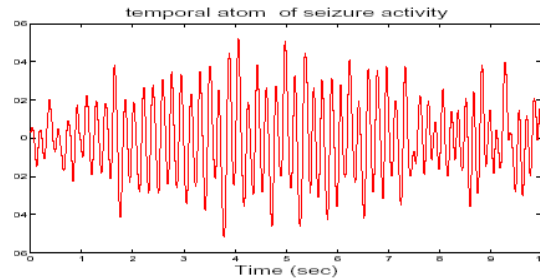




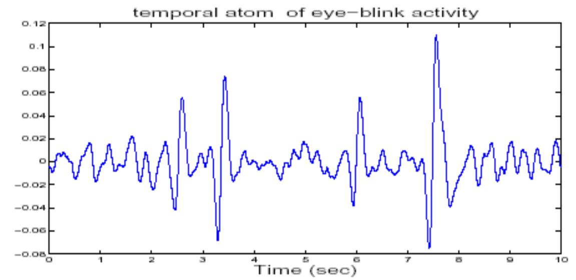
CPD for seizure onset localization

European Research Council
Established by the European Commission

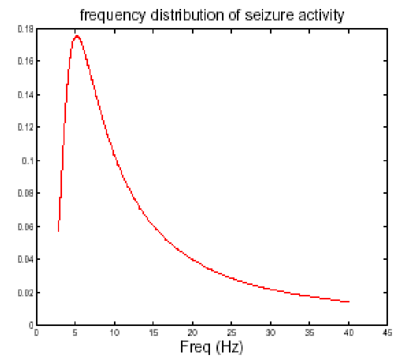




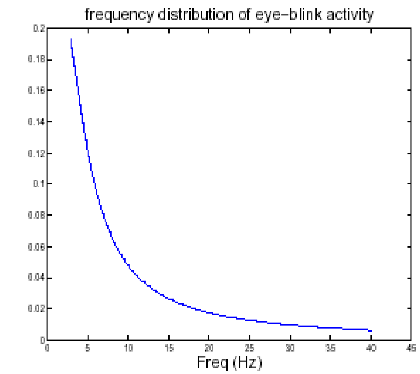
$\mathbf{B}_1$



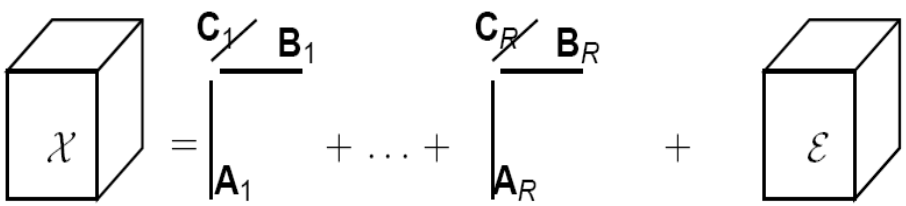
$\mathbf{B}_2$

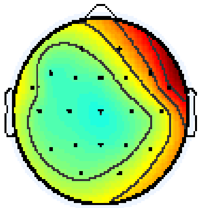


$\mathbf{C}_1$

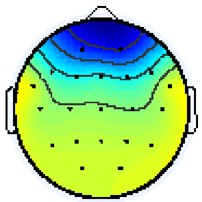


$\mathbf{C}_2$





$\mathbf{A}_1$



$\mathbf{A}_2$

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Why trilinear structure to extract seizures?

- CPD models as much variance as possible in the tensor that fits in a trilinear structure.

$\Rightarrow$ Sensitive for activity that is present during the entire epoch (2-10 sec), stable in localization and frequency

$\Rightarrow$ ***Oscillations in EEG meet requirements, e.g. seizures***

$\Rightarrow$ Muscle artifacts don’t fit into trilinear structure since they are distributed over frequencies by wavelet transformation

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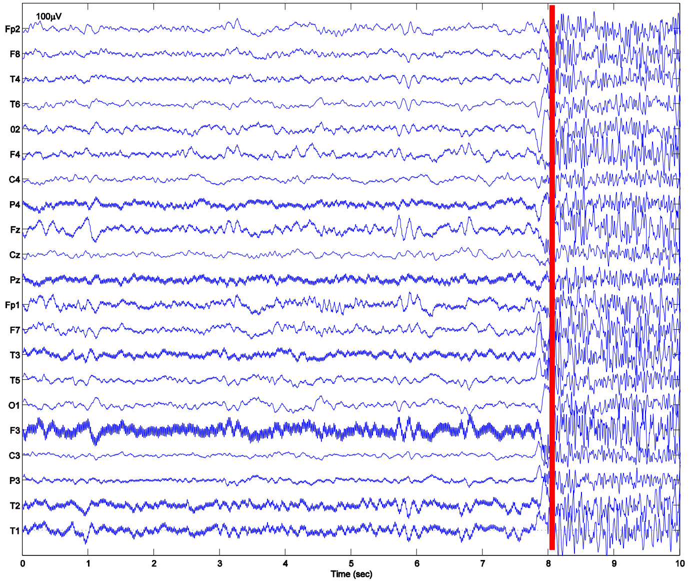
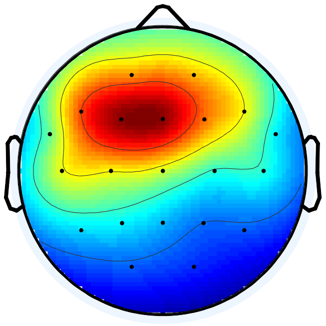
Added value in clinical practice?

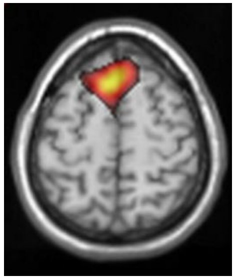
Validation study with UZ Leuven→ seizure EEG of 37 patients

- Visual EEG analysis : 21 well localized
- Using CPD : 34 well localized

→ more reliable!







(De Vos et al., NeuroImage 2007) (E. Acar et al, Bioinformatics 2007)

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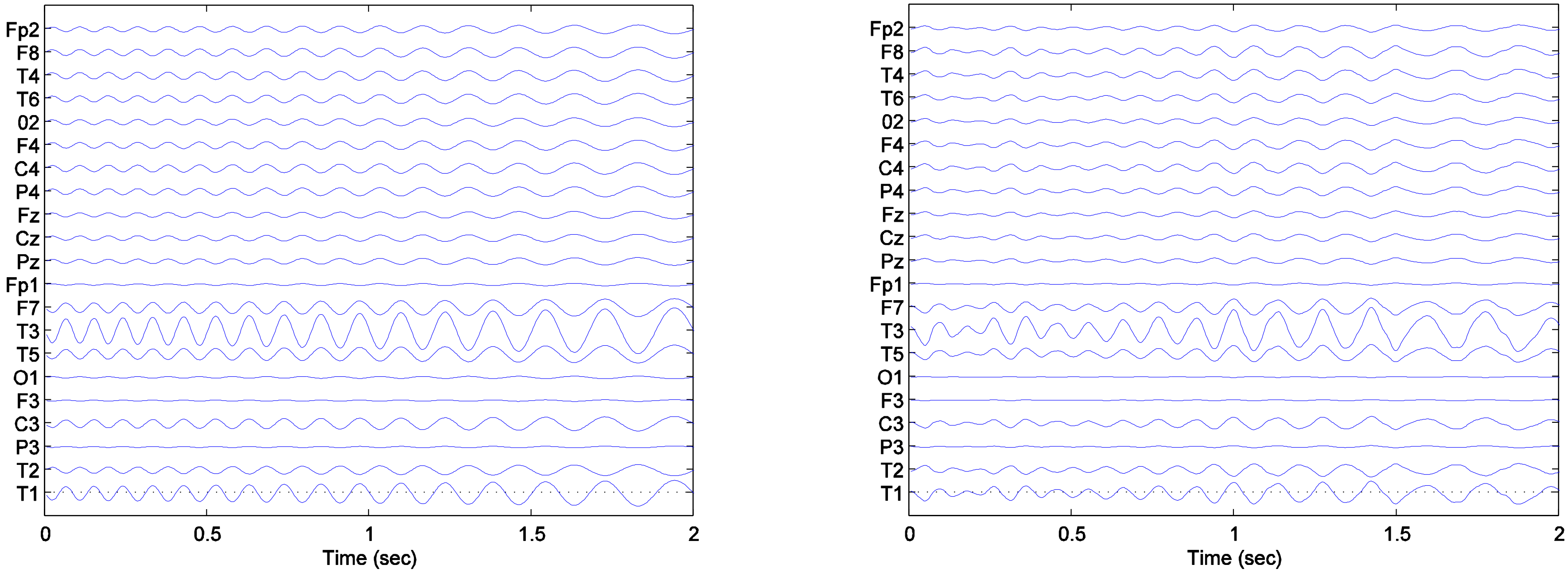
Limits of CPD

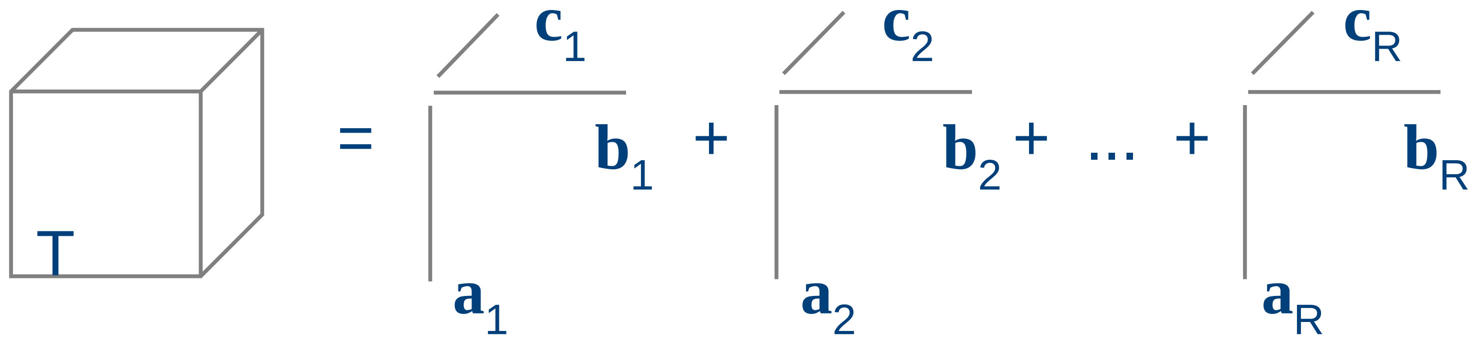


Limits of a trilinear model

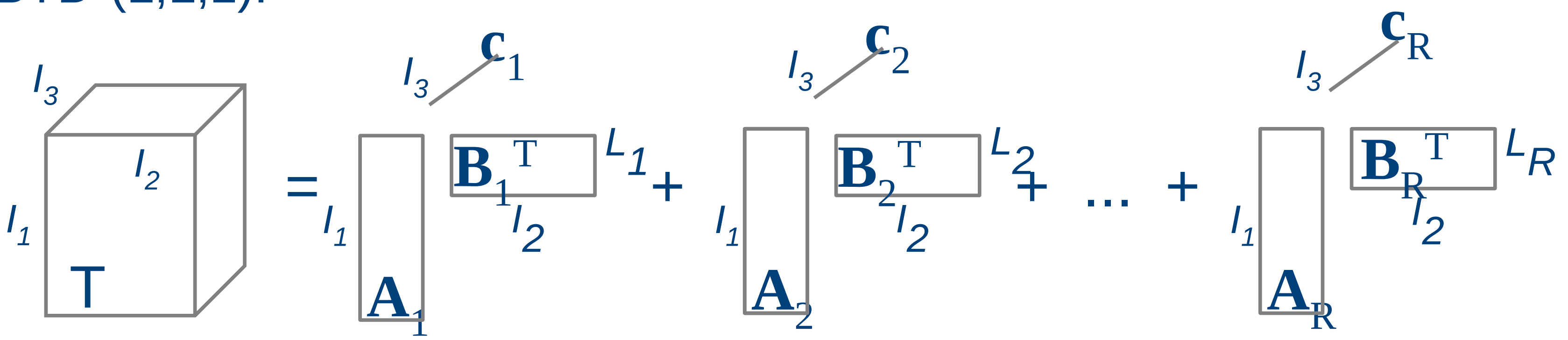
- Signal is not always perfectly recovered (e.g. freq.change)
- But it is still well localized!

Block Term Decomposition

CPD:



BTD-(L,L,1):



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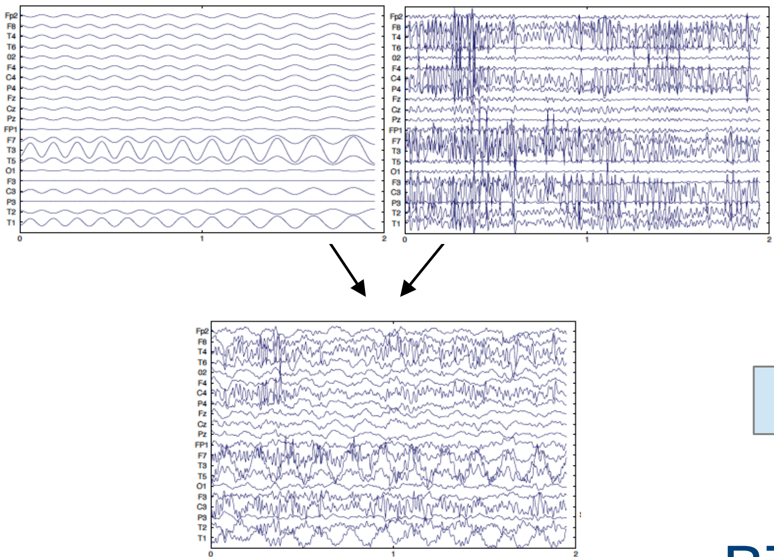
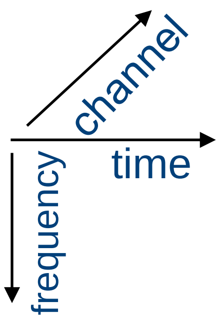
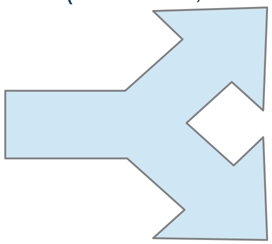
BTD of wavelet expanded EEG tensors

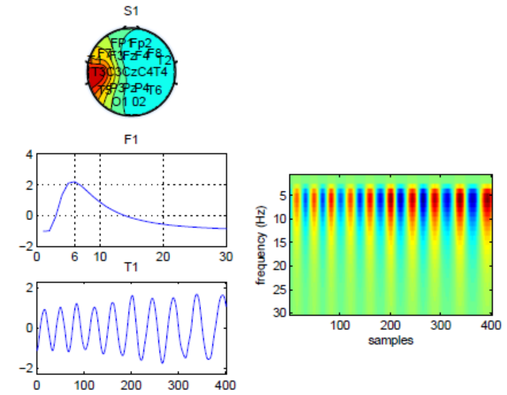






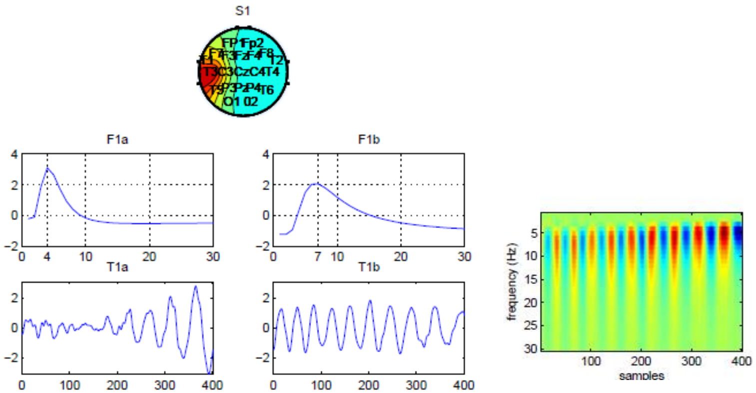
CPD

(Acar 2007, De Vos 2007)

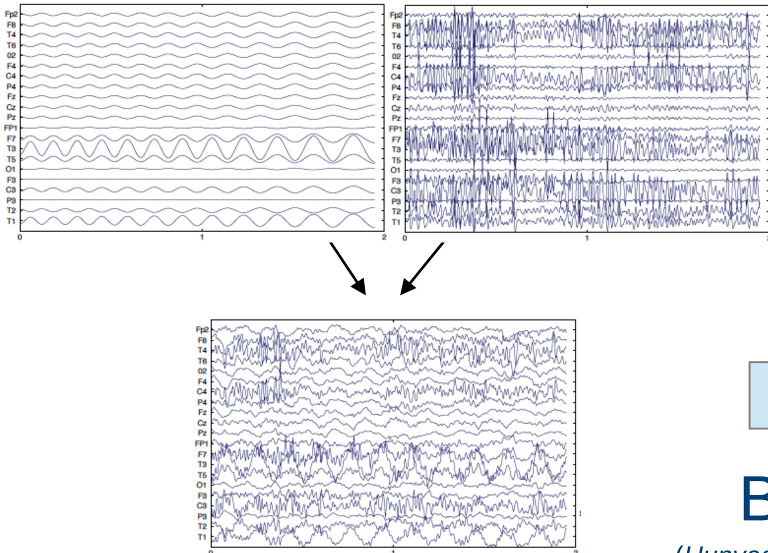


BTD

(*Hunyadi, JASP, 2014*)

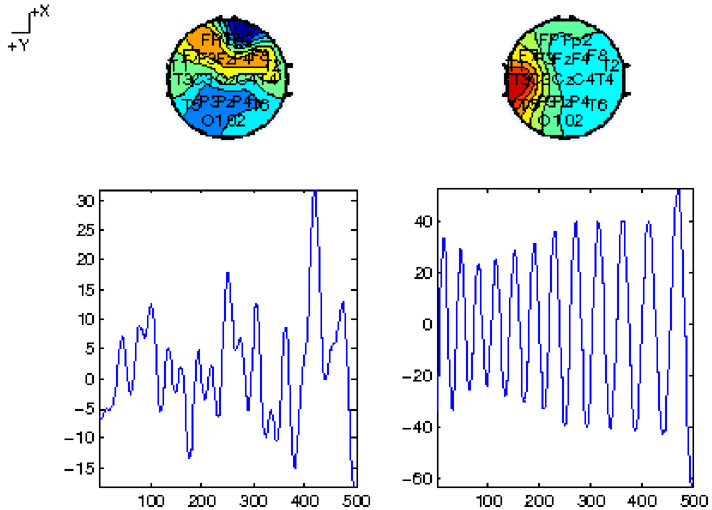


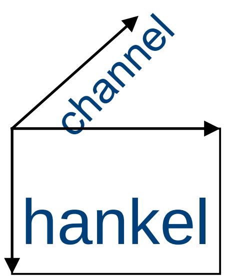
BTD of Hankel expanded EEG tensors



BTD

(*Hunyadi, JASP, 2014*)

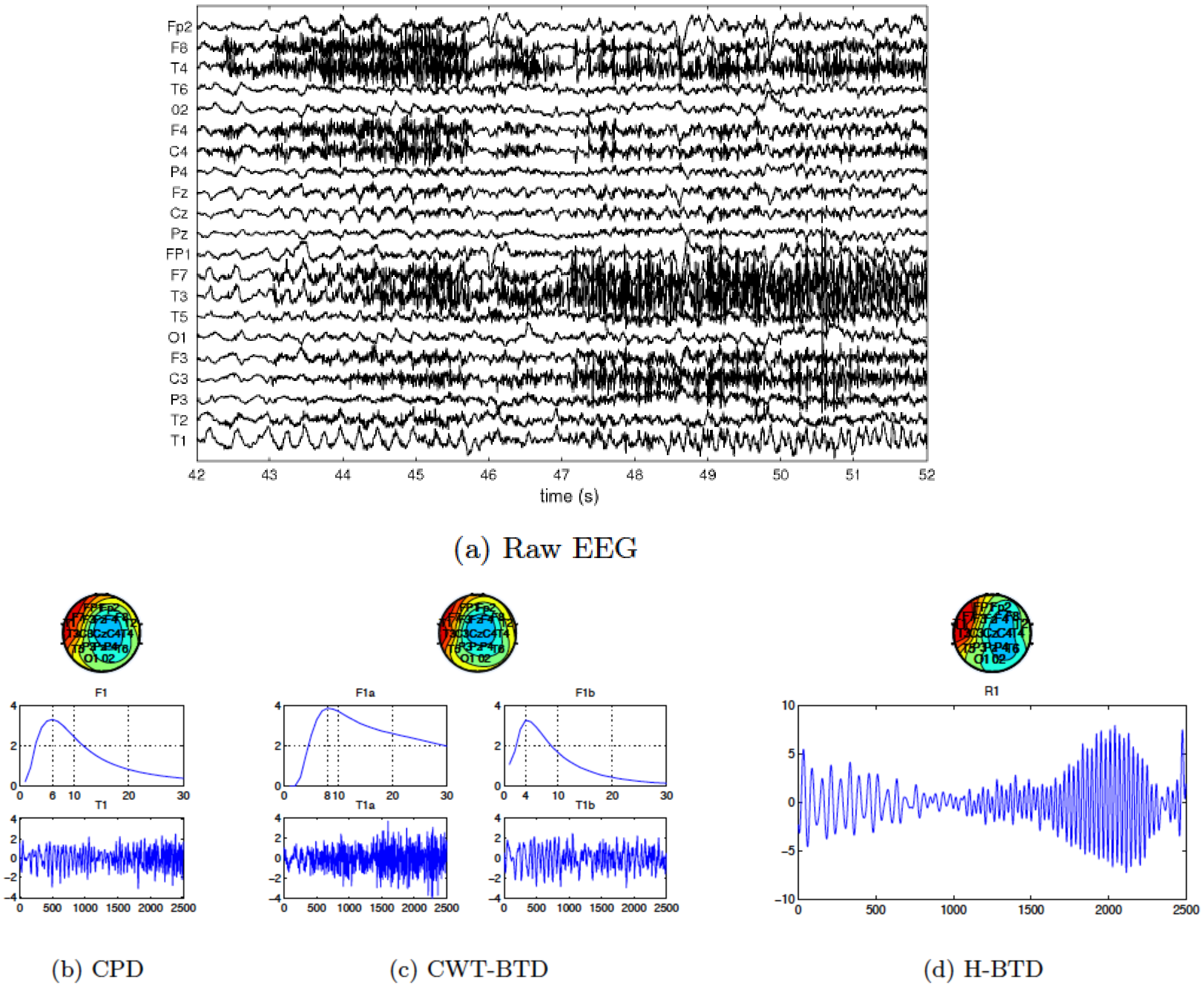




$$\begin{bmatrix} a_1 & a_2 & a_3 & \cdots & a_K \\ a_2 & a_3 & \cdots & a_K & a_{K+1} \\ a_3 & \cdots & a_K & a_{K+1} & a_{K+2} \\ \vdots & ⋰ & ⋰ & ⋰ & ⋰ \\ a_J & a_{J+1} & \cdots & a_{S-1} & a_S \end{bmatrix}$$

Alternatives: space-time-wave vector TDs ***(****Becker et al, NeuroImage, Phd)*

Clinical examples



(a) Raw EEG

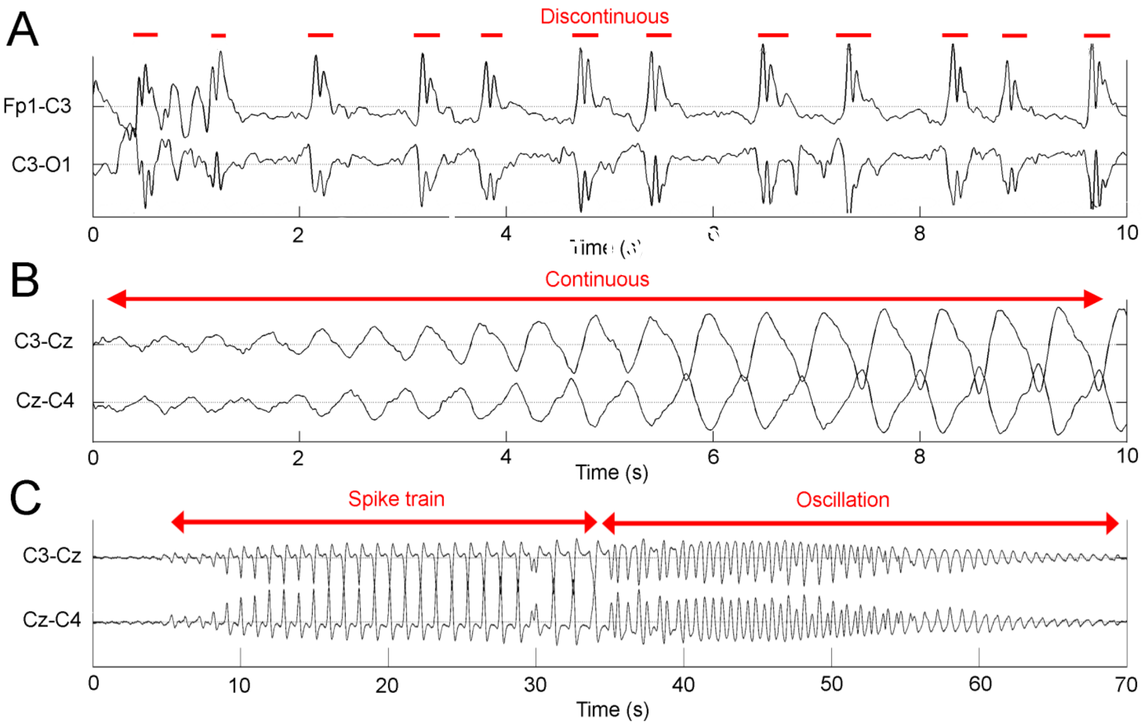
(b) CPD

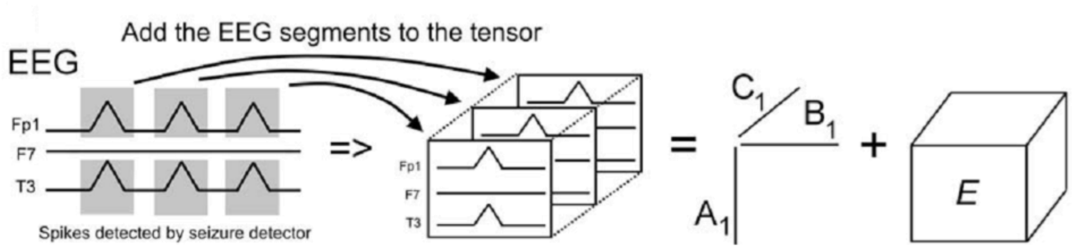
(c) CWT-BTD

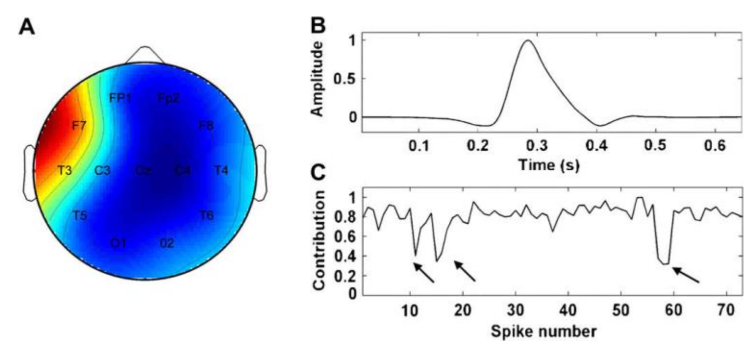
(d) H-BTD

2

Neonatal Brain Monitoring:
Seizure detection







(Deburchgraeve et al., Clinical Neurophysiology, 2008 & 2009)

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NeoGuard : decision support

Brain injury estimate

- Detection of neonatal epileptic seizures
- **Seizure onset localization**
- Inter-burst intervals

Clinician's expertise

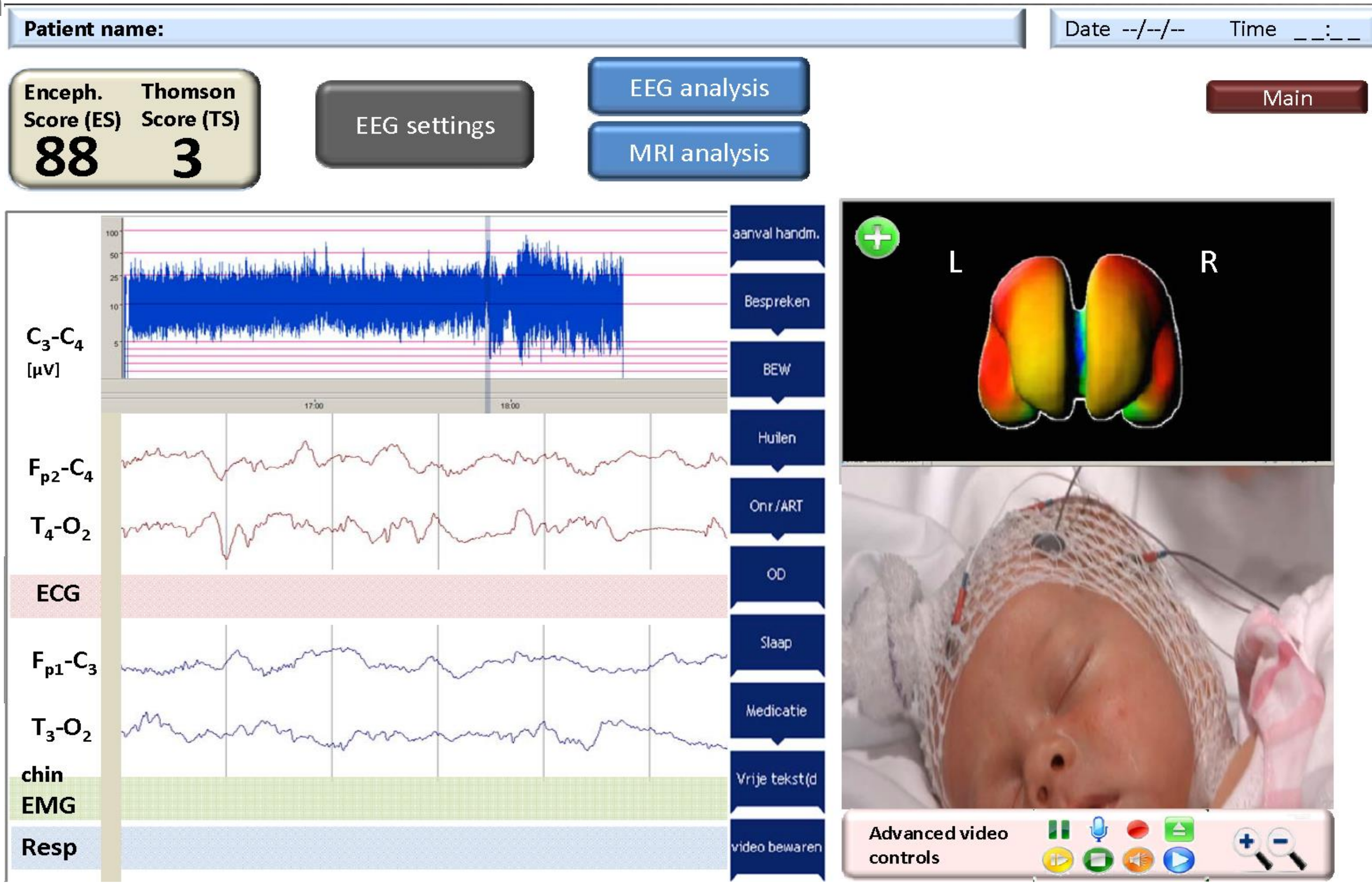
- Neurophysiological knowledge included in algorithms

Brain Monitoring

- **Recovery after damage**
- Maturation in preterms

Outcome prediction

- Good
- Poor



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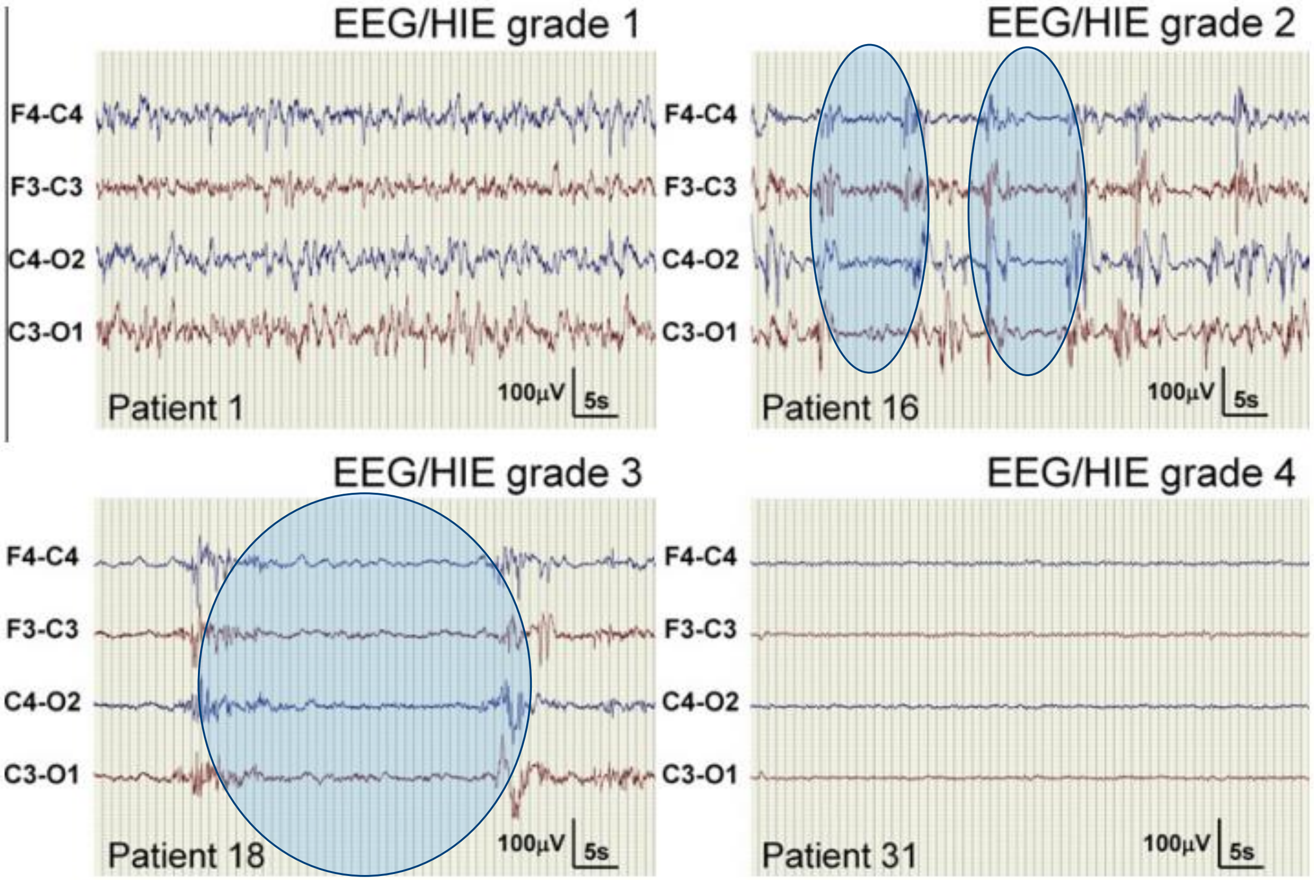
How Assessing Brain Recovery?
→ monitor abnormality of Background EEG

mildly abnormal **moderate**ly abnormal

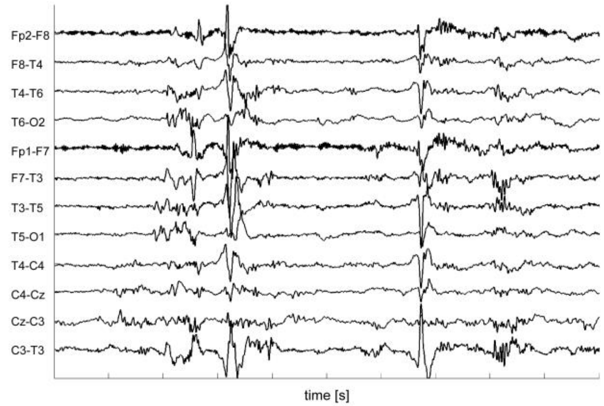


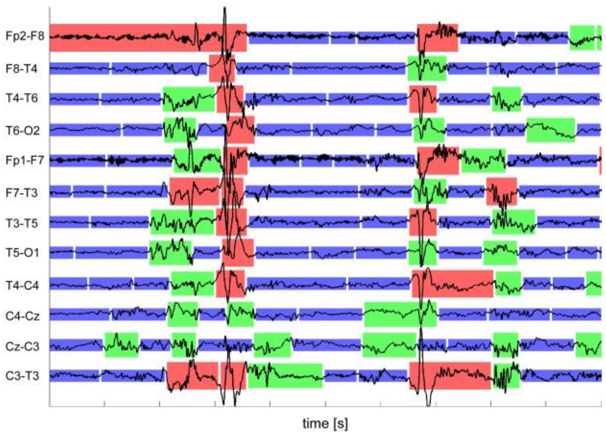
severely abnormal

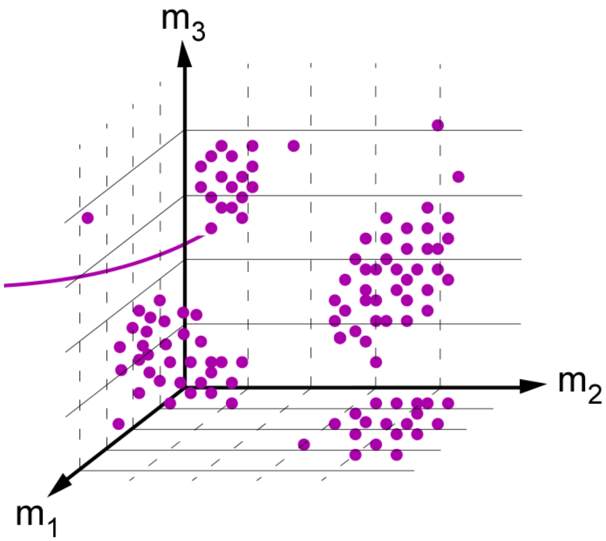
Ideal examples, taken from [Korotchikova et al., 2011]

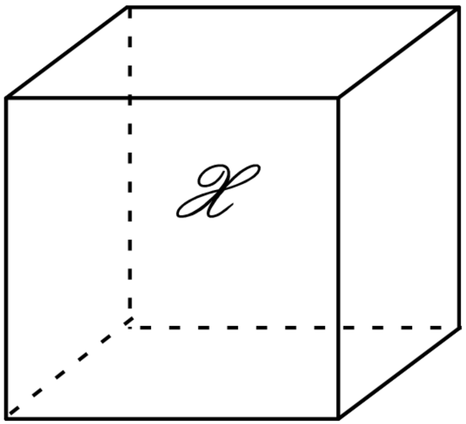
Monitoring neonatal background EEG:

The power of structuring data









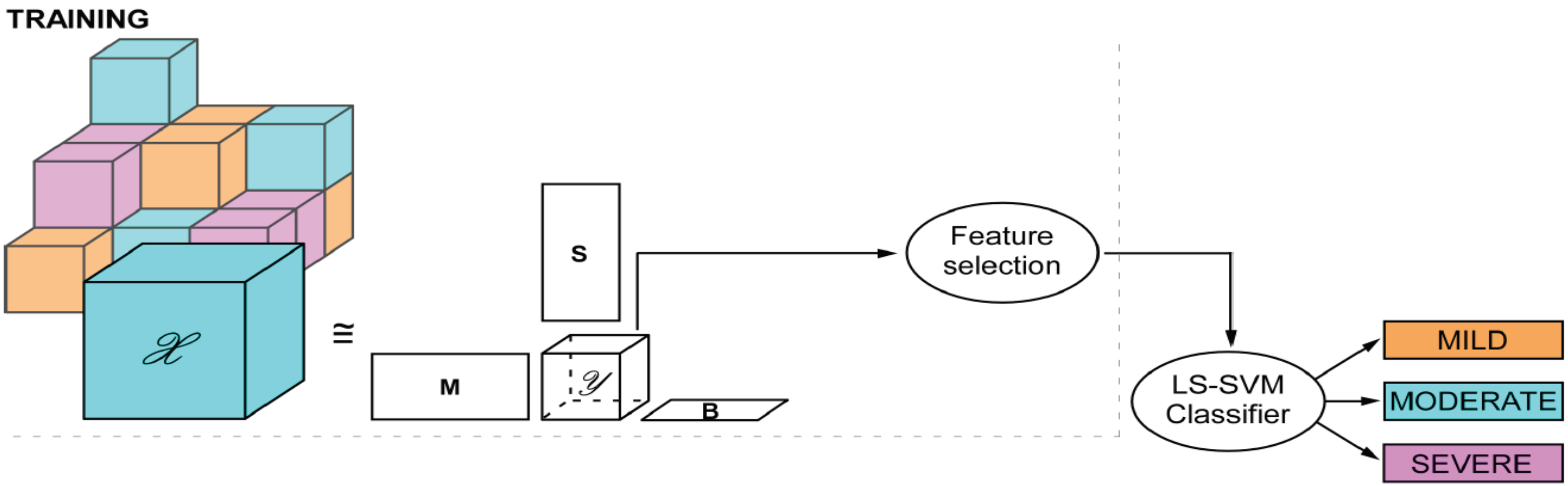
V. Matic et al., J. Neural Engineering, Oct. 2014

Higher Order Discriminant Analysis

-> compute simultaneous LMLRA

-> factors M, S, B common and orthogonal

-> maximizing the Fisher ratio between core tensors



Phan A and Cichocki A, Nonlinear Theory Appl., IEICE, 2010

Phan A, 2011, Matlab Software Toolbox

(www.bsp.brain.riken.jp/˜phan/nfea/nfea.html)

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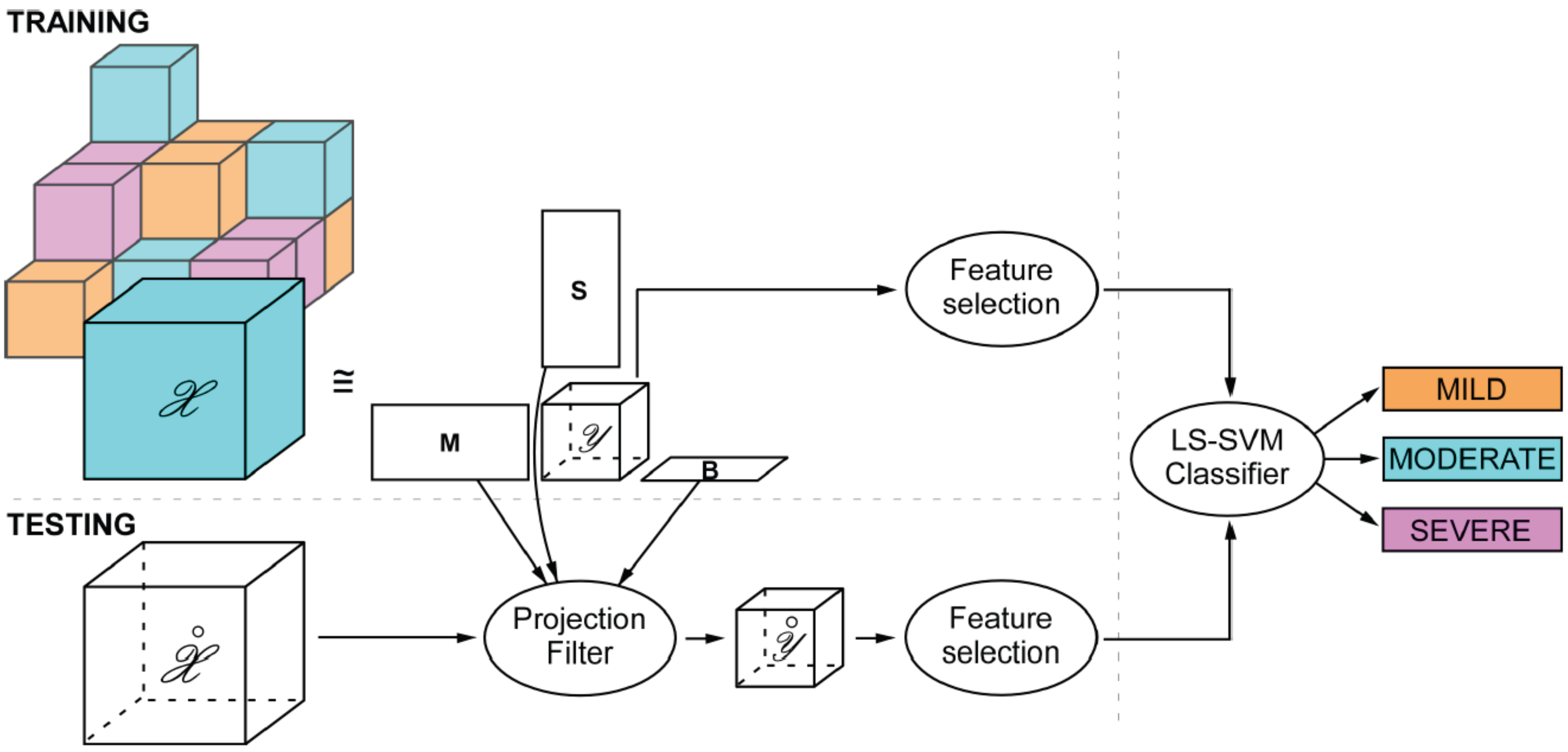
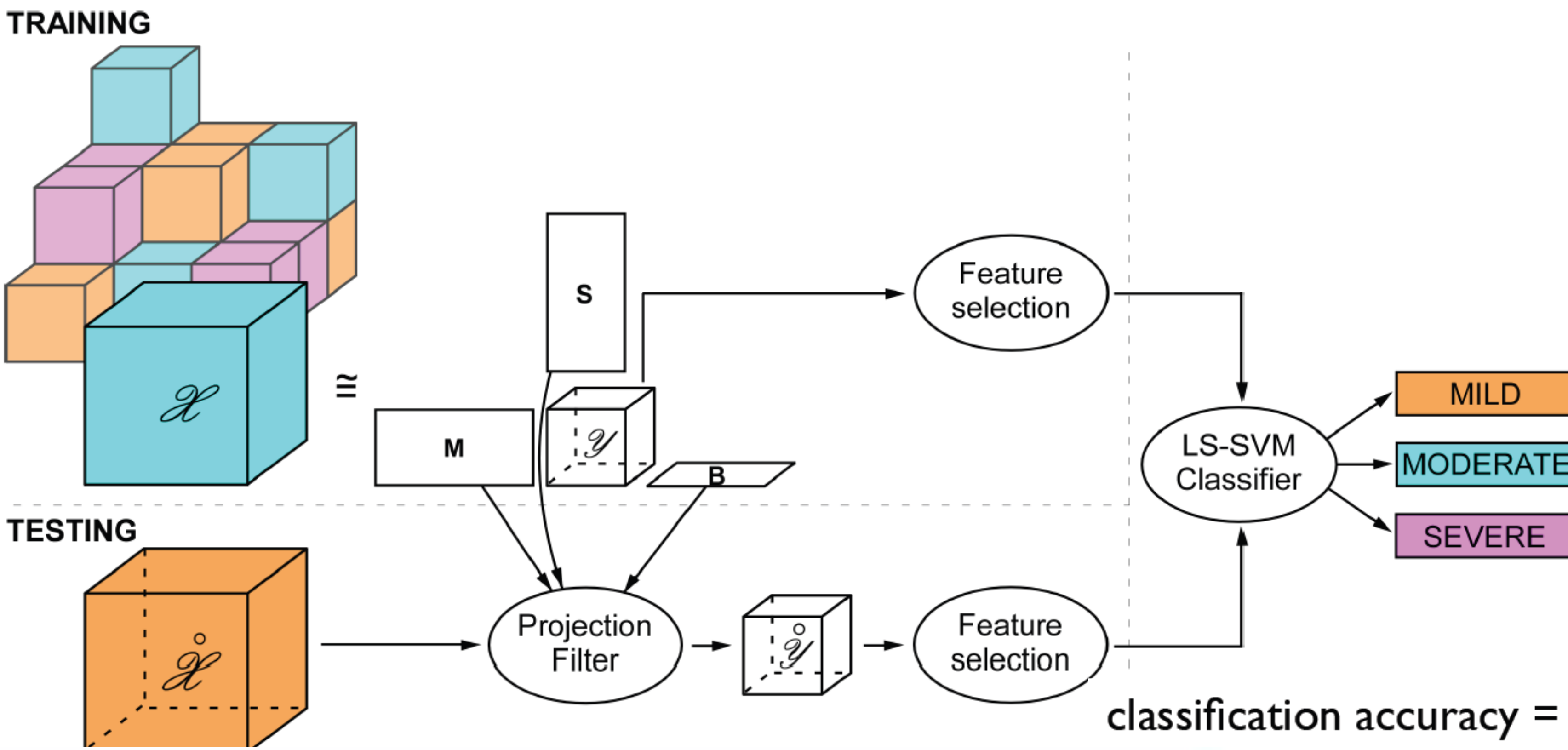
Higher Order Discriminant Analysis



Higher Order Discriminant Analysis



classification accuracy = 89%

Automated \ Expert EEG reader	MILD	MODERATE	SEVERE
MILD	73 (91%)	6	1
MODERATE	7	44 (76%)	7
SEVERE	0	8	126 (94%)
Achieved accuracy	91%	76%	(94%)

(V. Matic et al, J. Neural Eng. 11, 2014)

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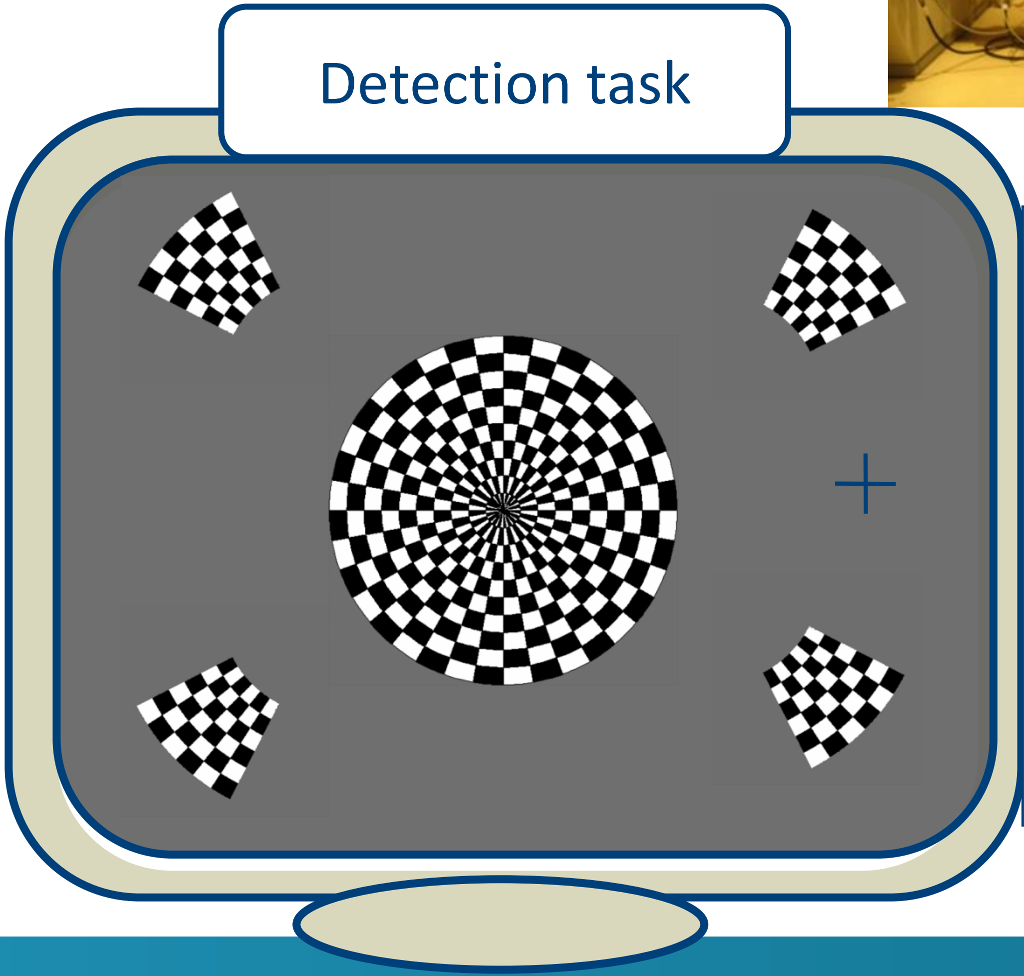
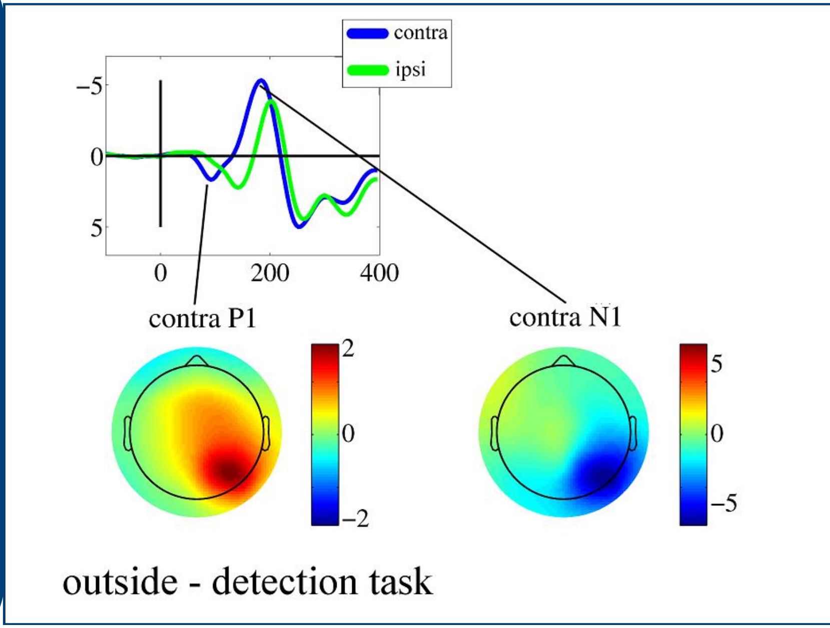
3

ERP analysis:

Brain responses evoked due to mental task





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Event-Related Potential Analysis

ERPs have very low SNR and suffer from artifacts caused by non-brain and brain sources

Variety of CPD (and BTD) Applications, e.g.:

-Brain topography *(Field and Graupe, Brain Topogr. 1991)*

-Brain-computer interfacing *(A. Cichocki et al, IEEE computer society Mag. 2008 and IEEE SP Mag. 2015) (R. Zink et al, JNE 2016)*

- Detection of rhythmic activity, e.g. (α, θ), during cognitive task *(Miwakeichi et al., NeuroImage 2004) (Martinez-Montes, NeuroImage 2004) (Vanderperren et al., MBEC 2008)*

-Inter-trial phase coherence analysis in event-related EEG *(Mørup et al., NeuroImage 2005)(M. Weiss et al., ICASSP 2009)*

- Event-related EEG during simultaneous fMRI acquisition

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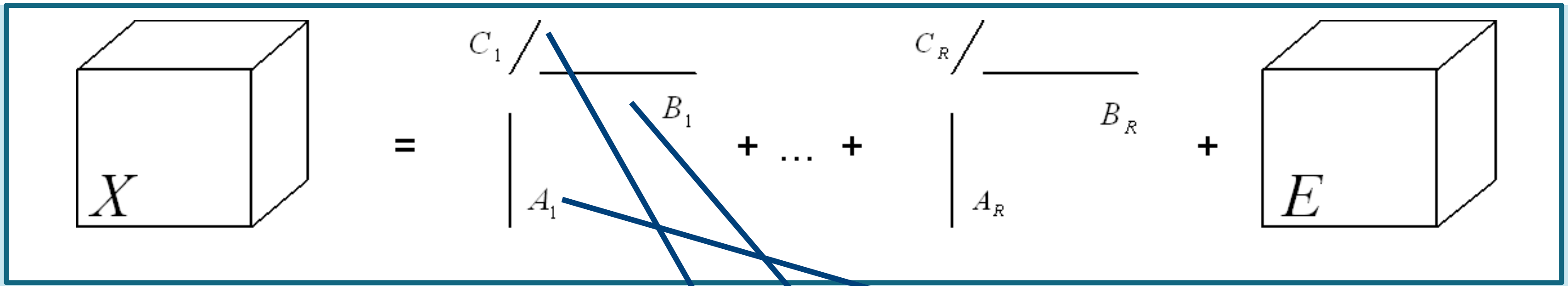
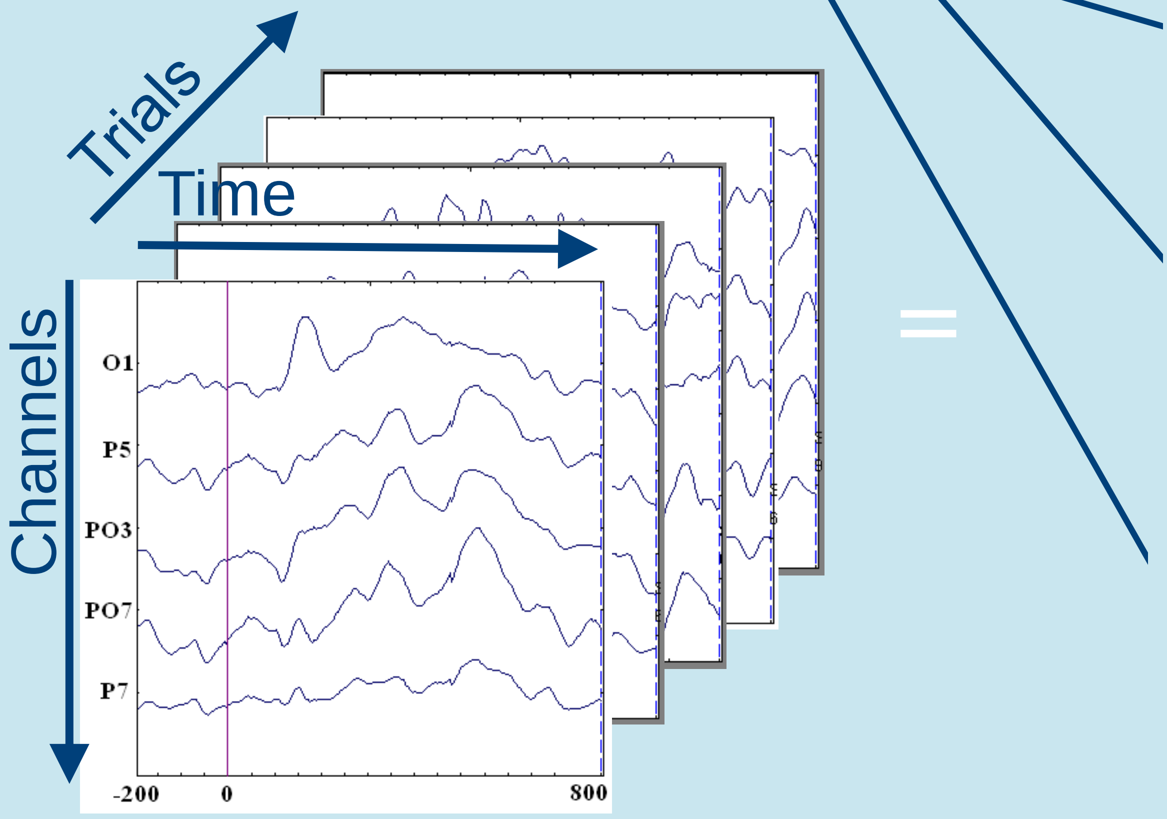
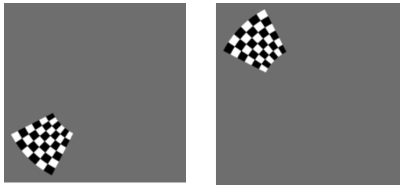
Single-trial ERP analysis: CPD on channels x time x trials



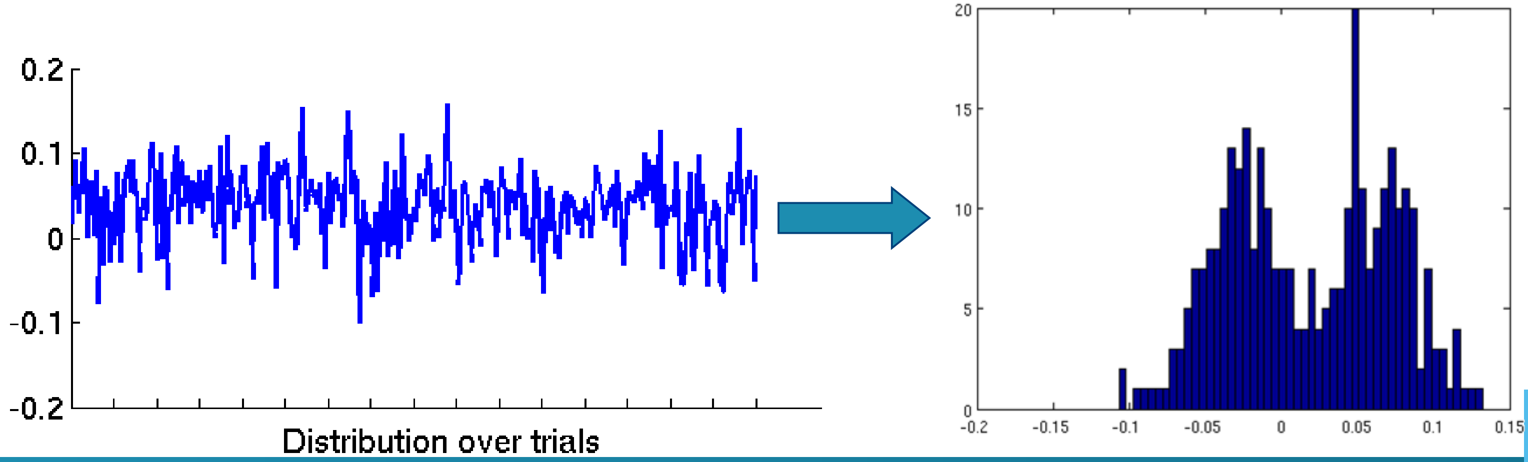


Validation: classification of trial type

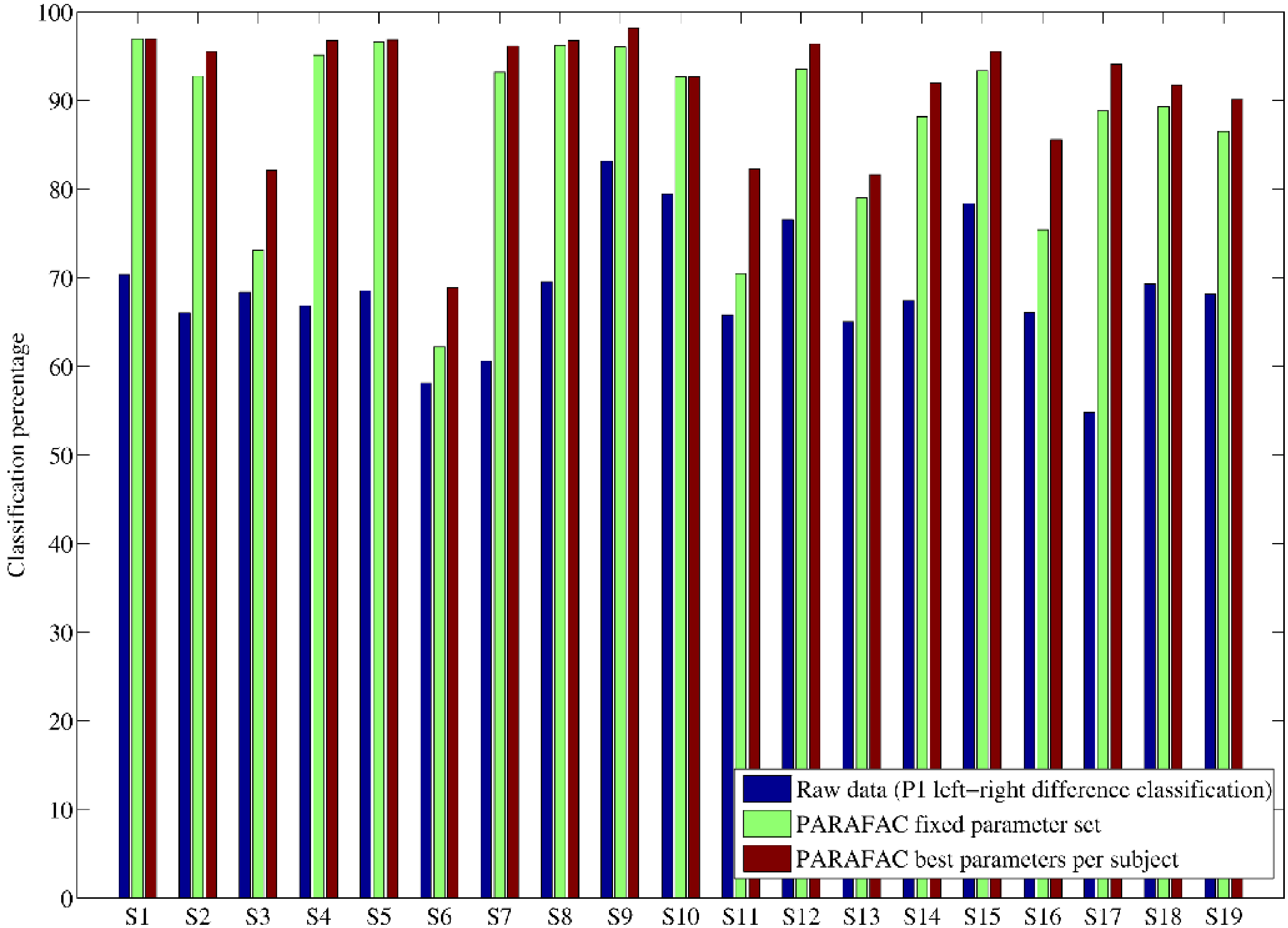


Left vs. right stimuli

- Raw data: based on difference in P1 amplitude (left – right hemispheres)
- CPD: based on 1 trial mode of decomposition
- In both cases: ½ trials for training, ½ for testing



Single trial reading: outside L-R results



Single trial ERP reading with CPD

European Research Council
Established by the European Commission

- CPD allows the extraction of task-related ERP information on a **single trial** basis
- Data Preprocessing important (artefacts, constraints, parameters)
- Performance is better than raw data characteristics
- Both for left-right and 4 quadrant distinction
- Also possible for EEG-fMRI data acquisition: *more difficult but still better than raw data classification*
- Promising for BCI

K. ***Vanderperren***, *B. Mijović, N. Novitskiy, B. Vanrumste, P. Stiers, B.R.H. Van den Bergh, L. Lagae, S. Sunaert, J. Wagemans, S. Van Huffel and M. De Vos. Single trial ERP reading based on Parallel Factor Analysis. Psychophysiology, 2013*

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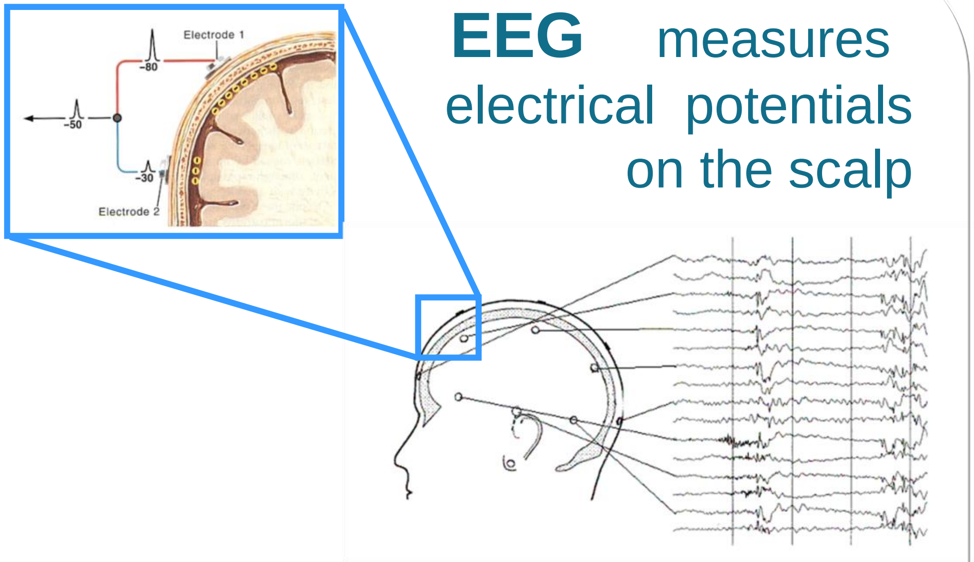
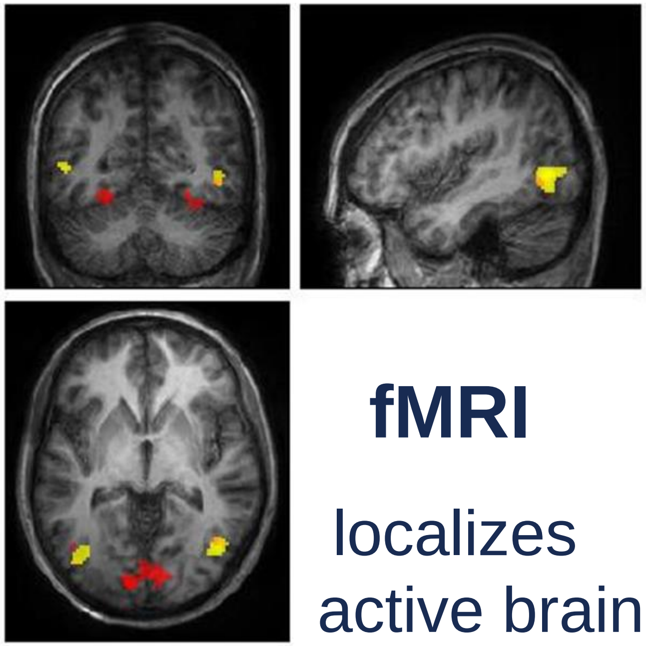
4 Combined EEG-fMRI analysis



EEG measures electrical potentials on the scalp



fMRI

localizes active brain regions

Combining EEG and fMRI:

- ***EEG** good **temporal resolution** (~ ms)*
- ***fMRI** good **spatial resolution** (~ mm)*

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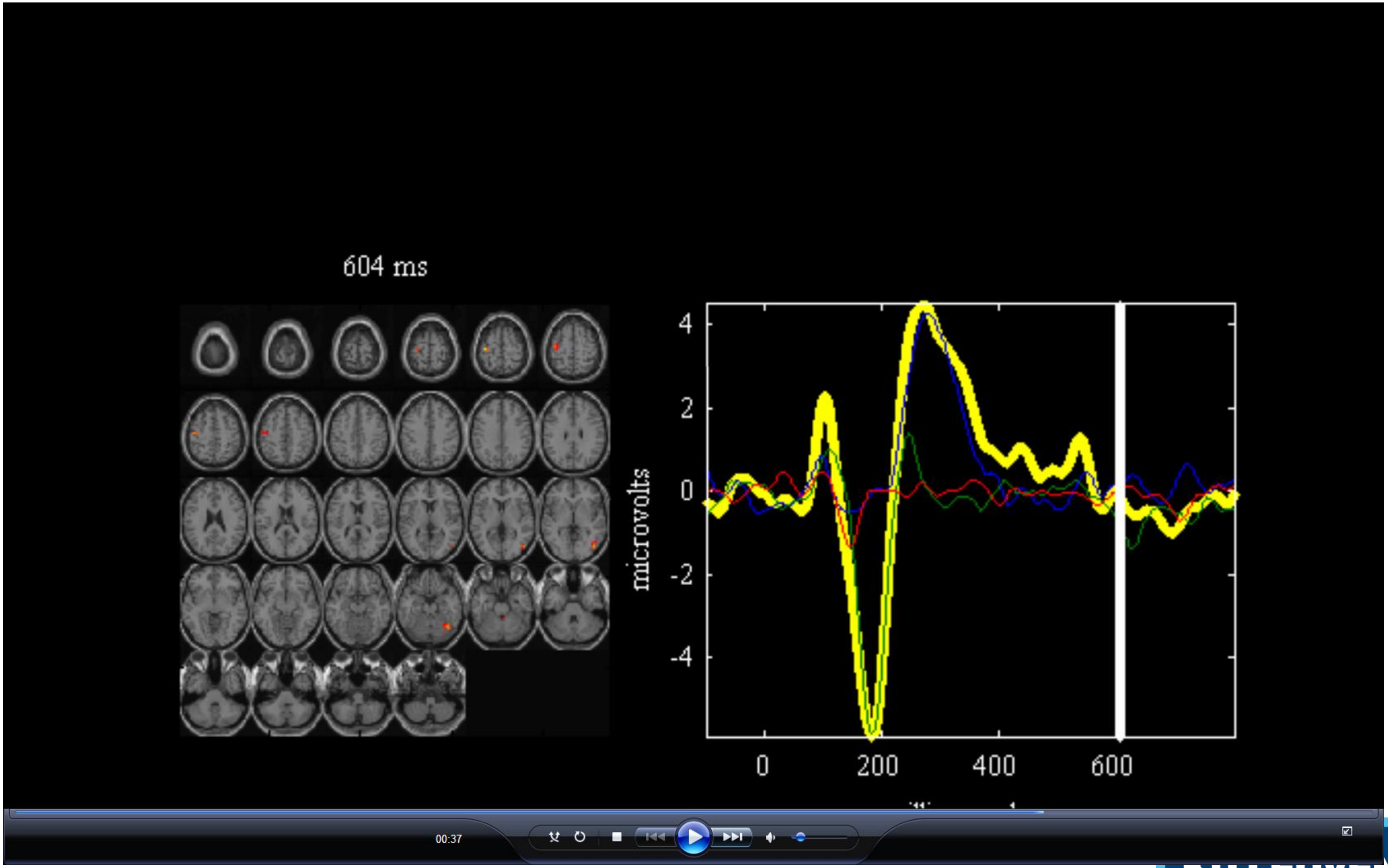
Combined EEG-fMRI analysis



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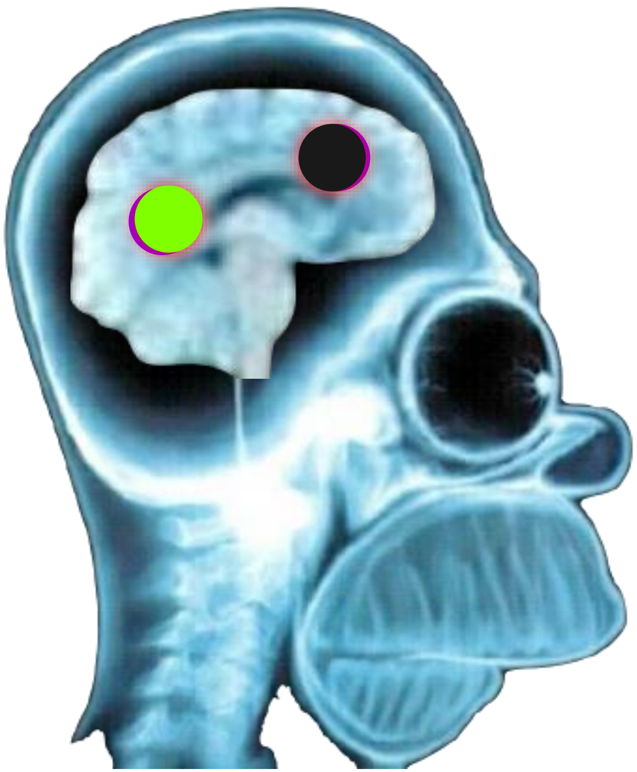
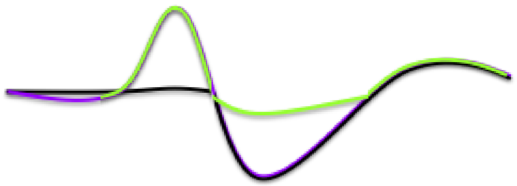
Symmetric EEG-fMRI approaches: Joint ICA

Calhoun et al., (2006), NeuroImage





JointICA Output

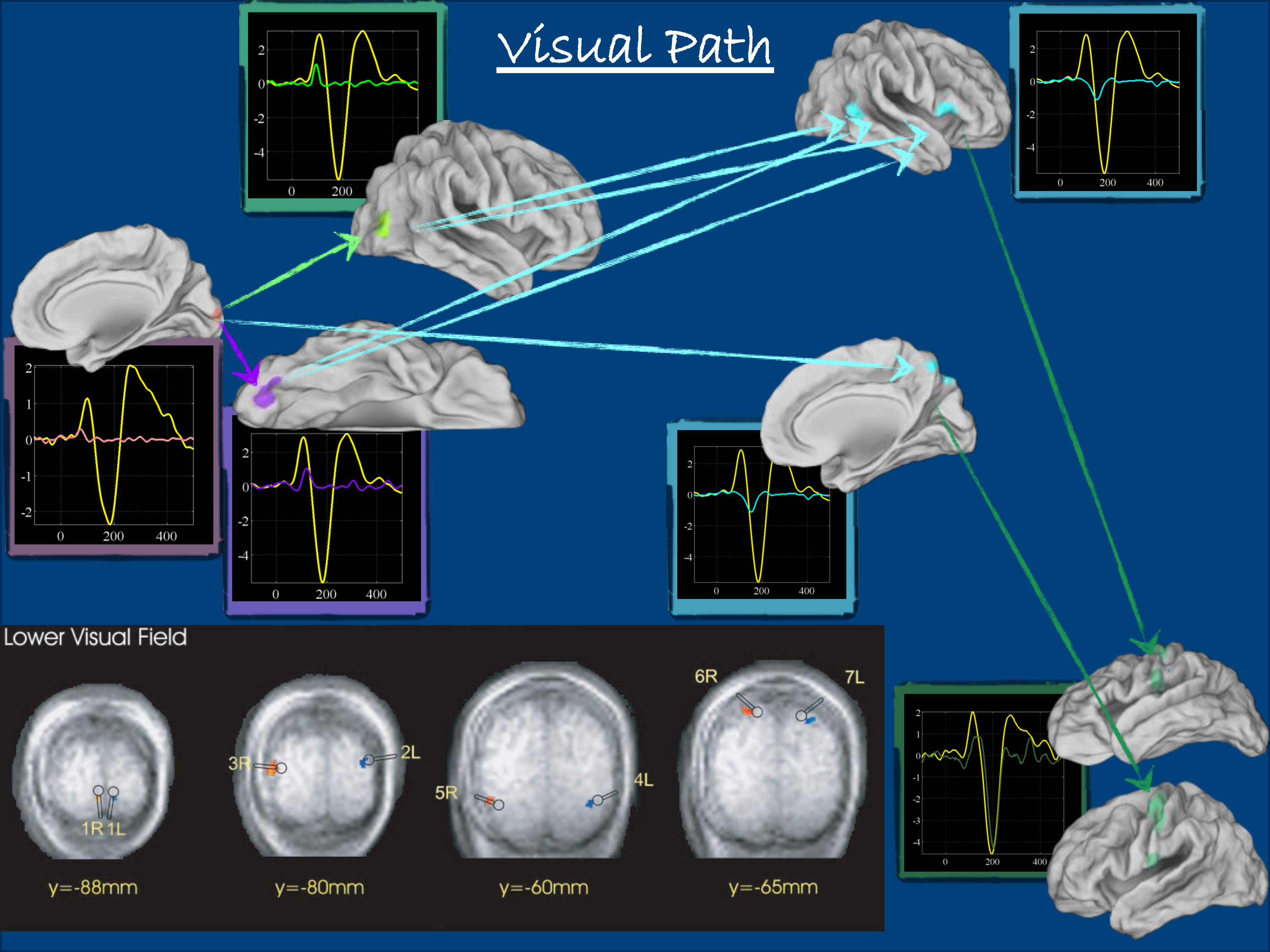
Alternatives: Parallel ICA, EEG informed fMRI, fMRI informed EEG, …

Joint Independent Component Analysis (JointICA)

(Mijovic et al, NeuroImage, Vol. 60, 2012, pp. 1171-1185)

$\mathbf{X}^{\mathrm{fMRI}}$ $\mathbf{X}^{\mathrm{EEG}}$ = Mixing Matrix ∘ Estimated Sources (fMRI) Estimated Sources (EEG)

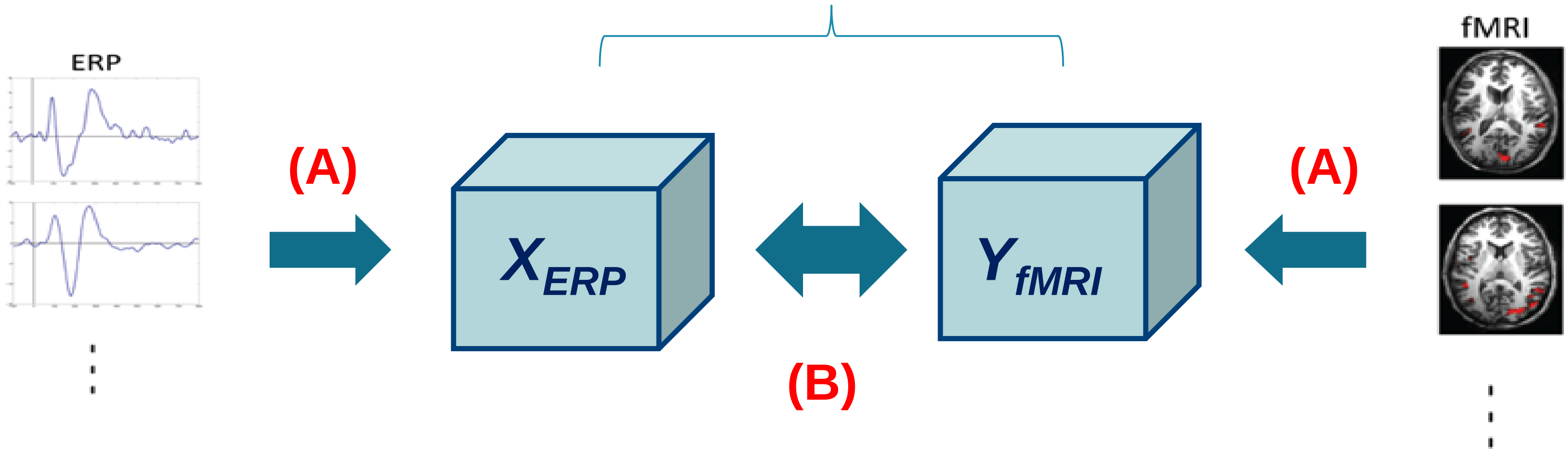
Extensions: add more conditions *(Mijovic et al, NeuroImage, Vol. 88, 2014, pp. 10-21)*
add extra electrodes *(W. Swinnen et al, Proc. EUSIPCO 2014, Lisbon)*



Visual Path
Lower Visual Field
1R 1L
3R
2L
5R
4L
6R
7L
y=-88mm
y=-80mm
y=-60mm
y=-65mm

ERP analysis: EEG-fMRI integration

Integration by **coupled tensor-tensor CPD/BTD**



A. Find appropriate data tensorization **(A)**
B. Investigate relevant constraints in coupled CPD/BTD **(B)**
C. Apply to Cognitive Functioning and presurgical Seizure Localization

Contents Overview

- Introduction
- Tensor Decompositions
- Examples in EEG monitoring
- Conclusions and new directions

Conclusions and new directions

- Successful applications, e.g. epileptic seizure onset localization, neonatal brain monitoring, single-trial ERP, EEG-fMRI
- Mostly restricted to CPD via alternating least squares, more robust NLS algorithms exist, comparable memory/cost
- Other TD applications: *bioinformatics (O. Alter, E. Acar), BCI (Cichocki, Mørup, Martinez-Montes, Zink), chemo/ psycho-metrics (Bro)*
- Use of tensorial kernels in classification promising *(Signoretto)*

New directions? ***See talks/posters at TDA 2016***

- *Adaptive tensor decompositions, rank & structure estimation*
- *Applications increasing in BCI, (single-trial) ERP, ECG, MRSI*

→ *exploit full potential of Tensor toolbox for Data Fusion*

Acknowledgment

University Hospitals Leuven Gasthuisberg
ZNA Middelheim, Queen Paola Children's hospital
EMC Rotterdam
KU Leuven, Dept. Electrical Engineering-ESAT, division STADIUS & MICAS
Ghent University, Dept. Telecommunication and Information Processing, TELIN-IPI
Eindhoven University of Technology

ERC advanced grant 339804 BIOTENSORS
in collaboration with L. De Lathauwer and group

Thank you!