iMinds | Medical Information Technologies Department

KU LEUVEN

The power of MATRIX and TENSOR Decompositions in *Smart Patient Monitoring*

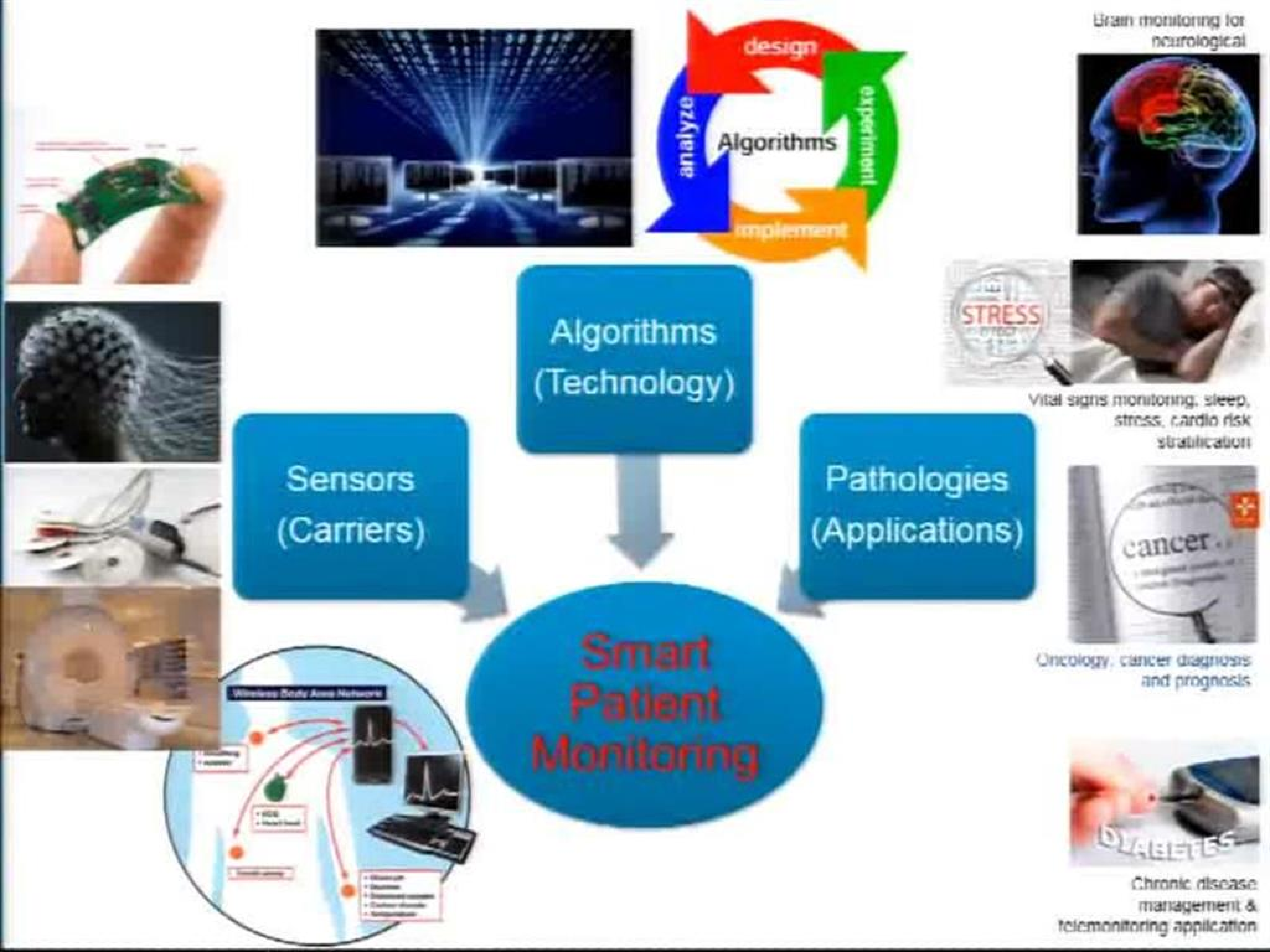
SIAM CSE 2015 Symposium
Salt Lake City, USA
March 14-18, 2015

Prof. Sabine Van Huffel

erc

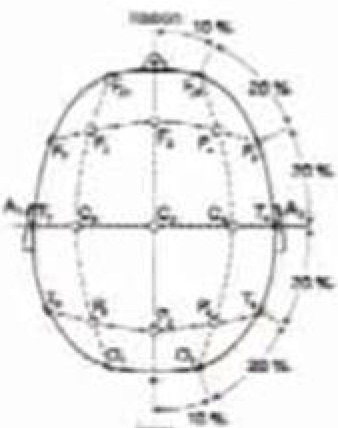
Contents Overview

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


design
experiment
implement
analyze
Algorithms
Brain monitoring for
neurological
Algorithms
(Technology)
Sensors
(Carriers)
Pathologies
(Applications)
Smart
Patient
Monitoring
STRESS
Vital signs monitoring, sleep,
stress, cardio risk
stratification
cancer
Oncology, cancer diagnosis
and prognosis
DIABETES
Chronic disease
management &
telemonitoring application

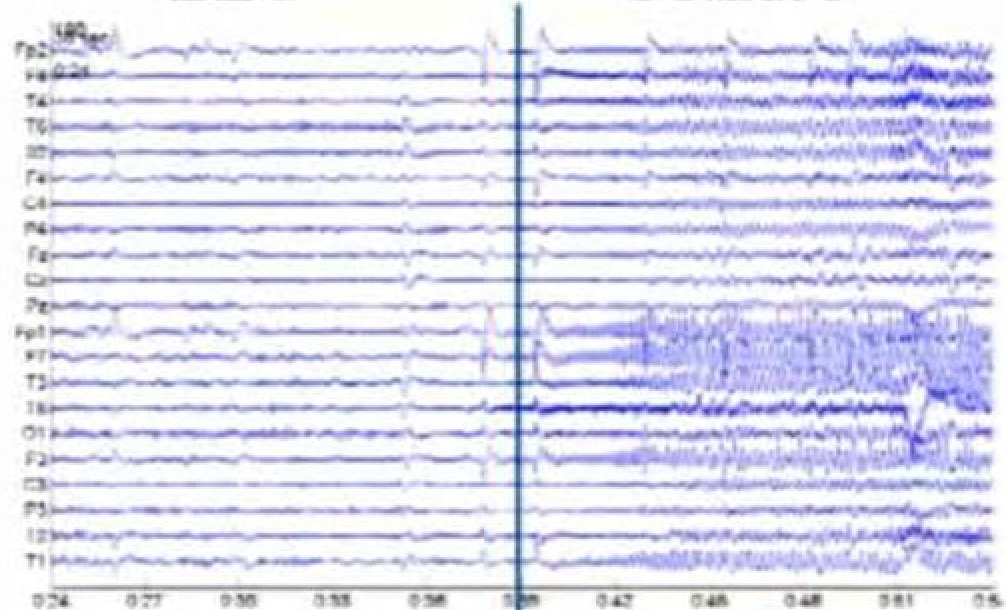
EEG and epileptic seizure monitoring

erc

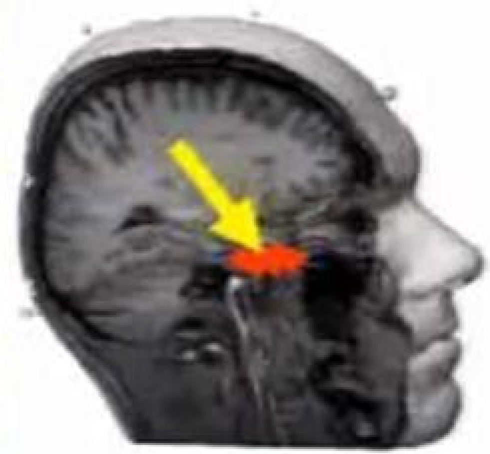


EEG

Seizure

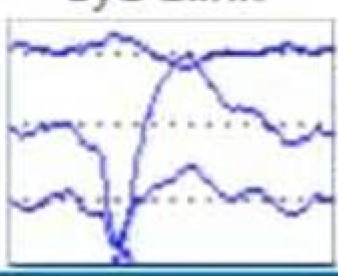


Spikes, slow waves
(epileptiform activity ?)

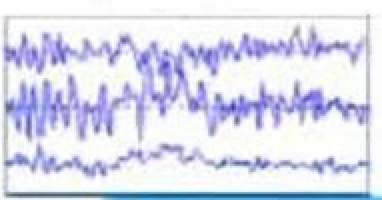


Seizure localization

eye blink



muscle



21 electrode positions
@UZ Gasthuisberg

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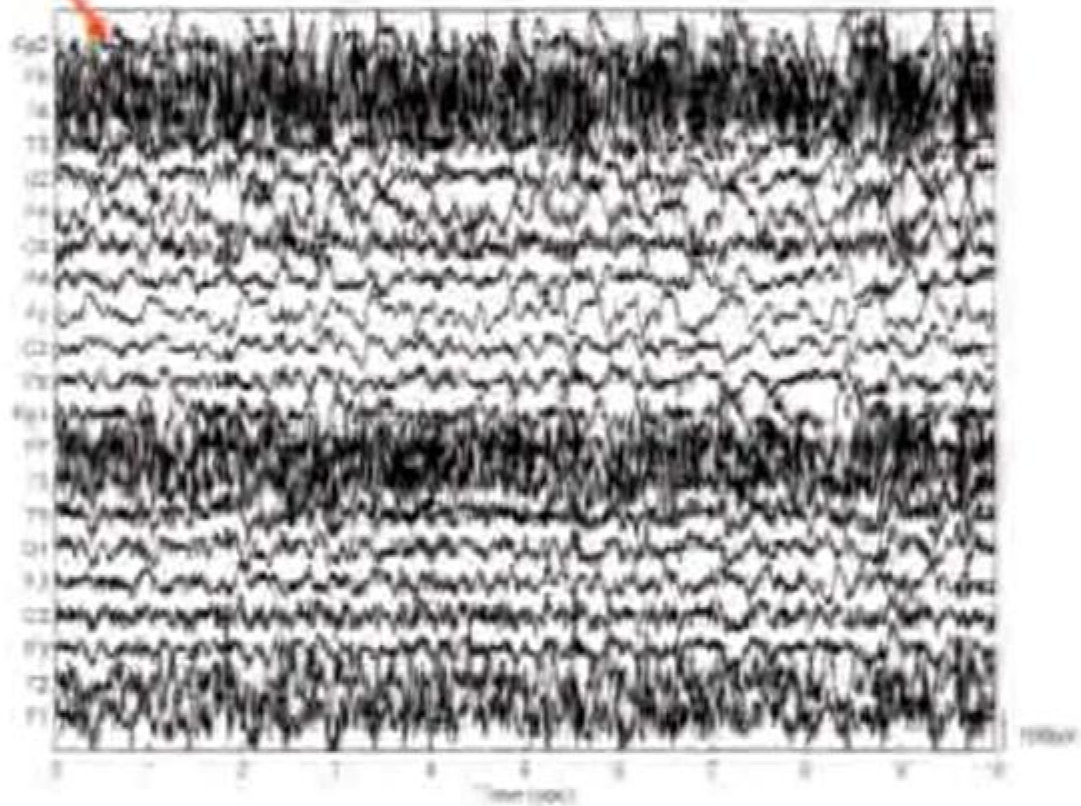
Muscle artefacts affect EEG during seizures (>90%)



⟹ **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

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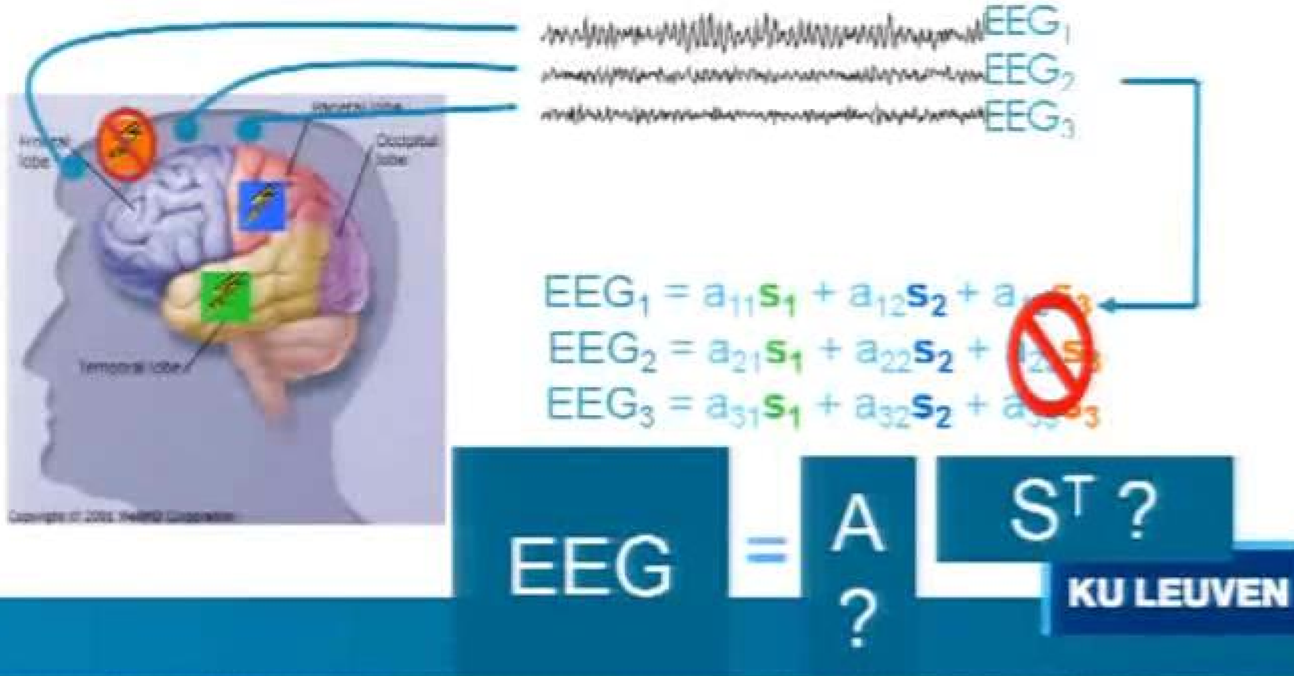
EEG analysis difficult because of artefacts → REMOVE

Matrix based Blind Source Separation (BSS)

Non-unique → *Constraints are needed!*



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Muscle artefact removal – BSS by CCA

$$X = \begin{pmatrix} x_1(1) & \cdots x_m(1) \\ & \\ x_1(N-1) & \cdots x_m(N-1) \end{pmatrix} \qquad Y = \begin{pmatrix} x_1(2) & \cdots & x_m(2) \\ & & \\ x_1(N) & \cdots & x_m(N) \end{pmatrix}$$

G.H. Golub and C.F. Van Loan, Matrix computations, John Hopkins, University Press, Baltimore, third edition, 1996

$X = Q_X R_X$ $\qquad$ $Y = Q_Y R_Y$

$$Q_X^T Q_Y = U \Sigma V^T$$

Sources: $S^T = Q_x U$

Auto-correlation coefficient= $\mathrm{diag}(\Sigma)$

Regression weights : $W_x = R_X^{-1} U$,

Muscle artefact removal – BSS by CCA

$$X = \begin{pmatrix} x_1(1) & \cdots x_m(1) \\ \vdots & \end{pmatrix} \qquad Y = \begin{pmatrix} x_1(2) & \cdots & x_m(2) \\ \vdots & & \end{pmatrix}$$

Compared to ICA algorithms:

- No iterative optimization required
- Same output for identical data
- Auto-correlation is a well-defined measure→1 method

$X=Q_X R_X$ $\qquad$ $Y=Q_Y R_Y$

$$Q_X^T Q_Y = U \Sigma V^T$$

Sources: $S^T = Q_x U$

Auto-correlation coefficient= diag(Σ)

Regression weights : $W_x = R_X^{-1} U$,

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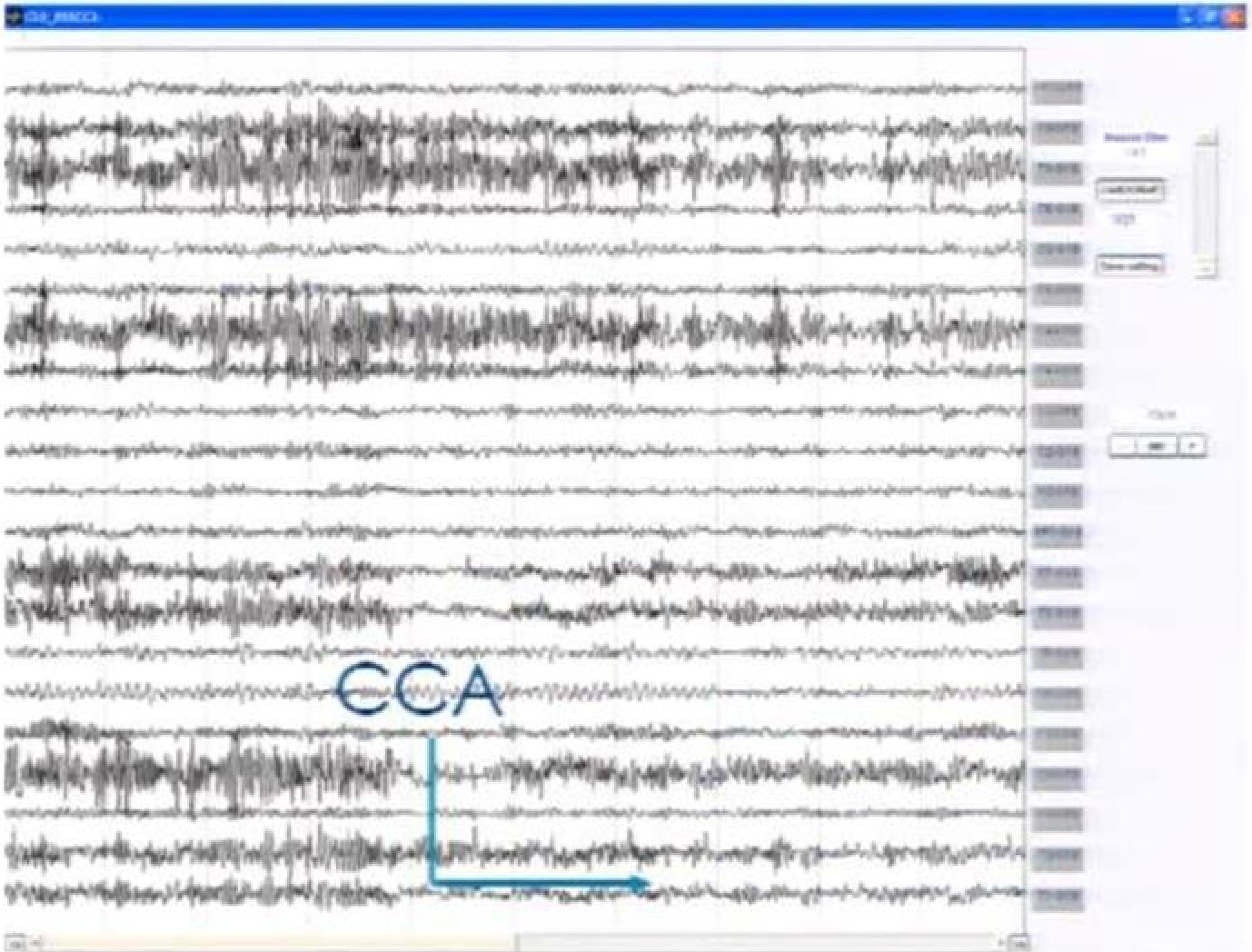
Muscle artefact removal- Simulation



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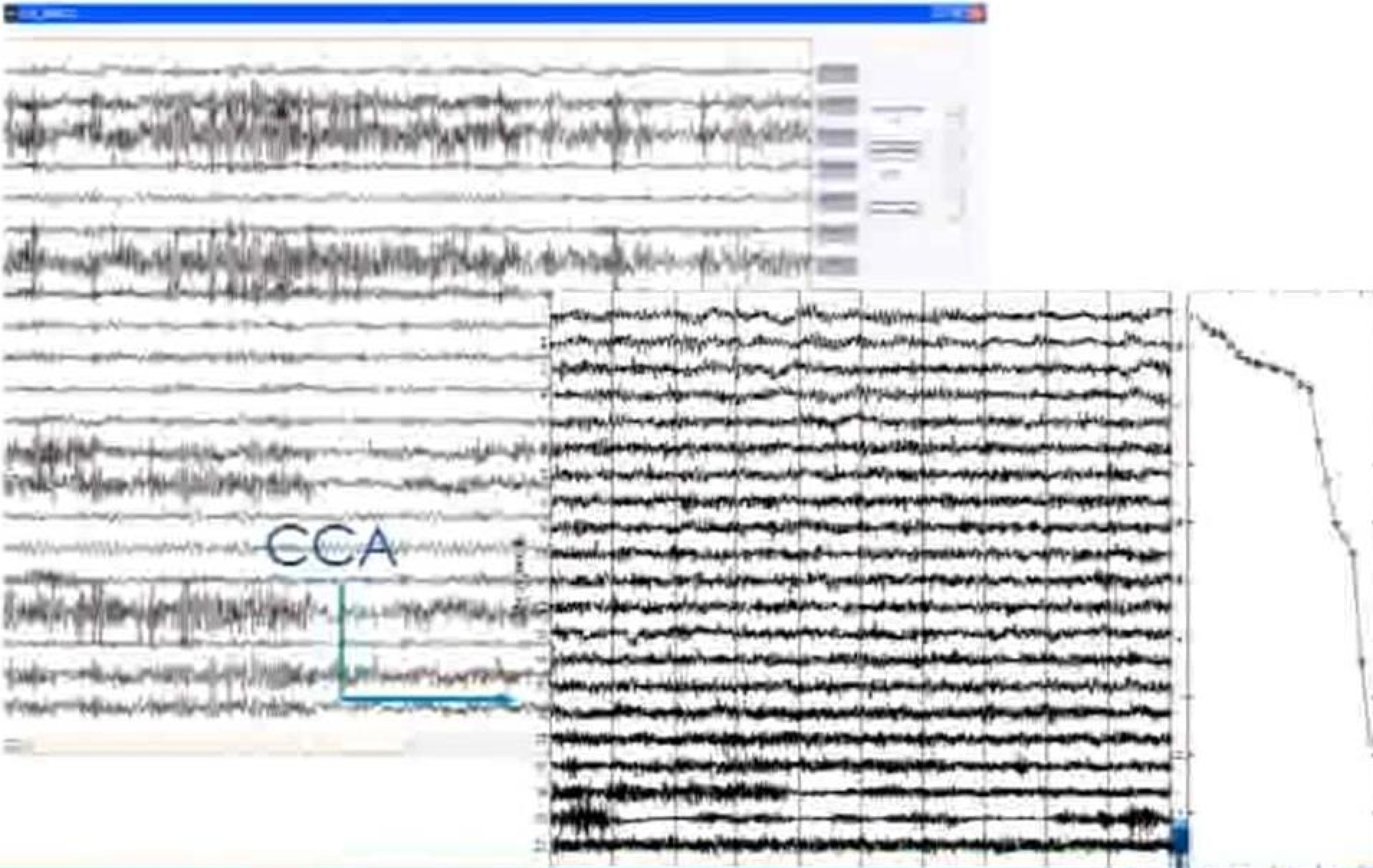
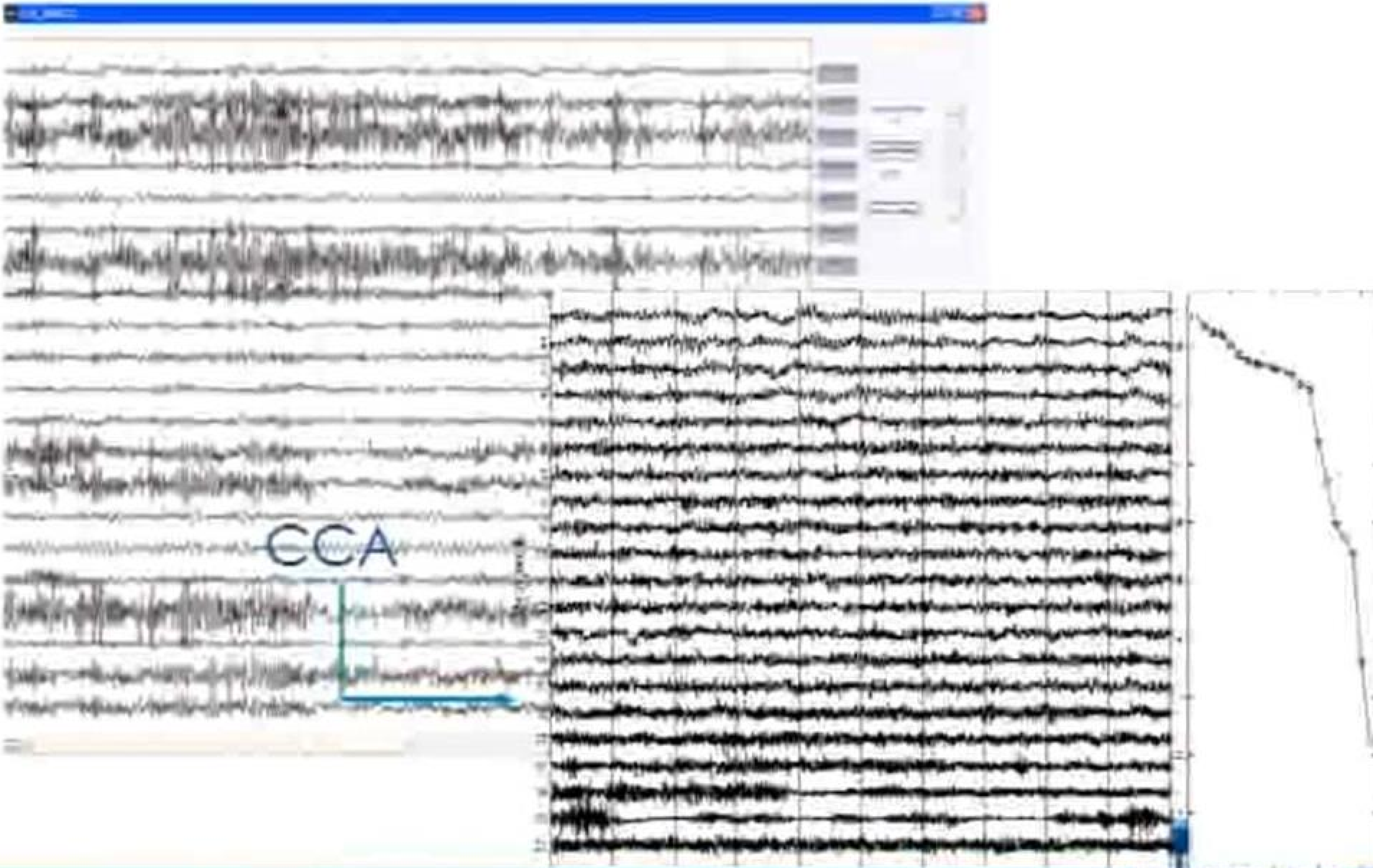
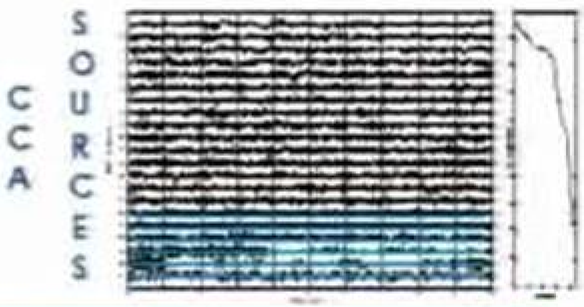
Muscle artefact removal- Simulation



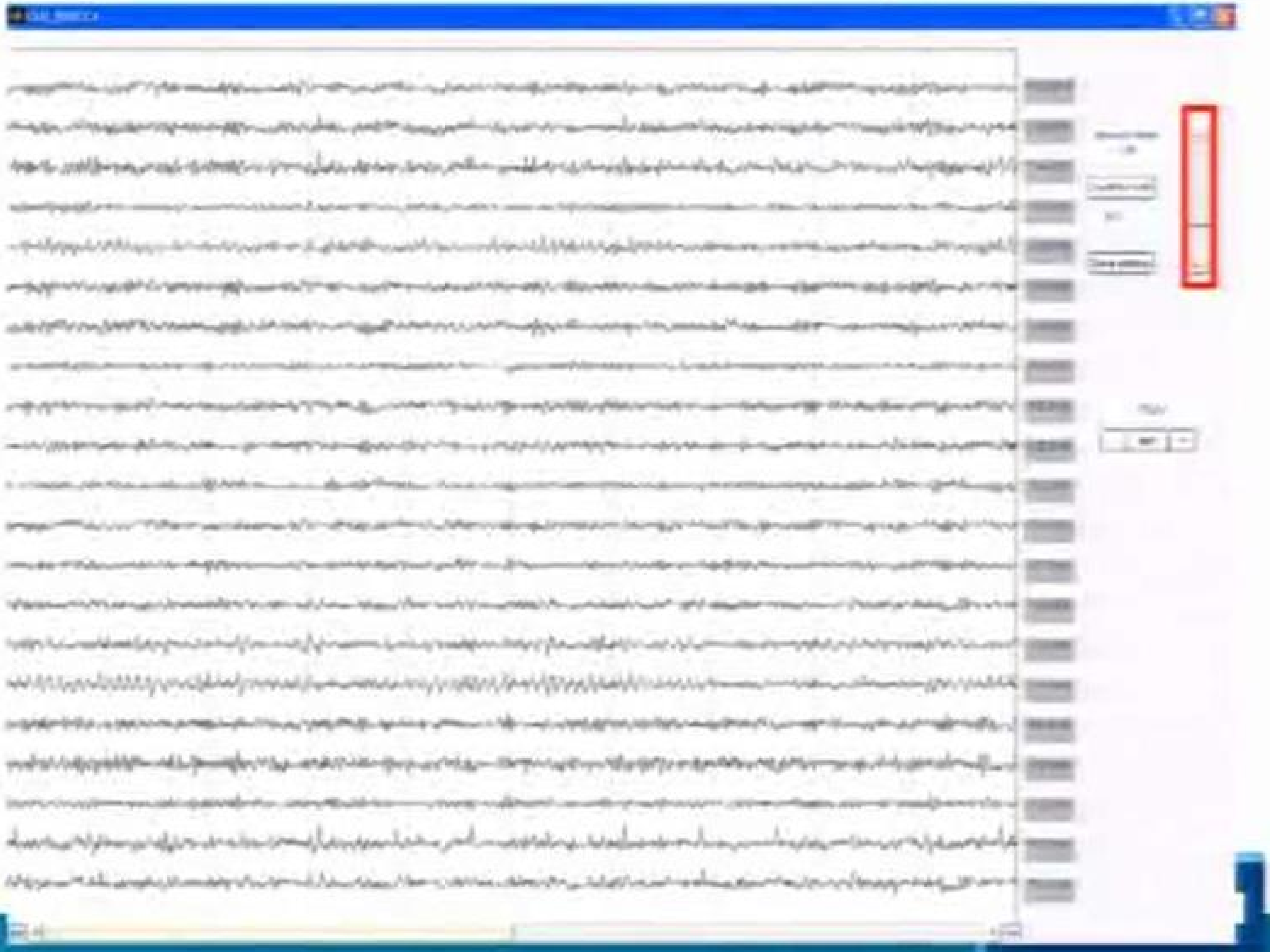
Muscle artefact removal- Simulation



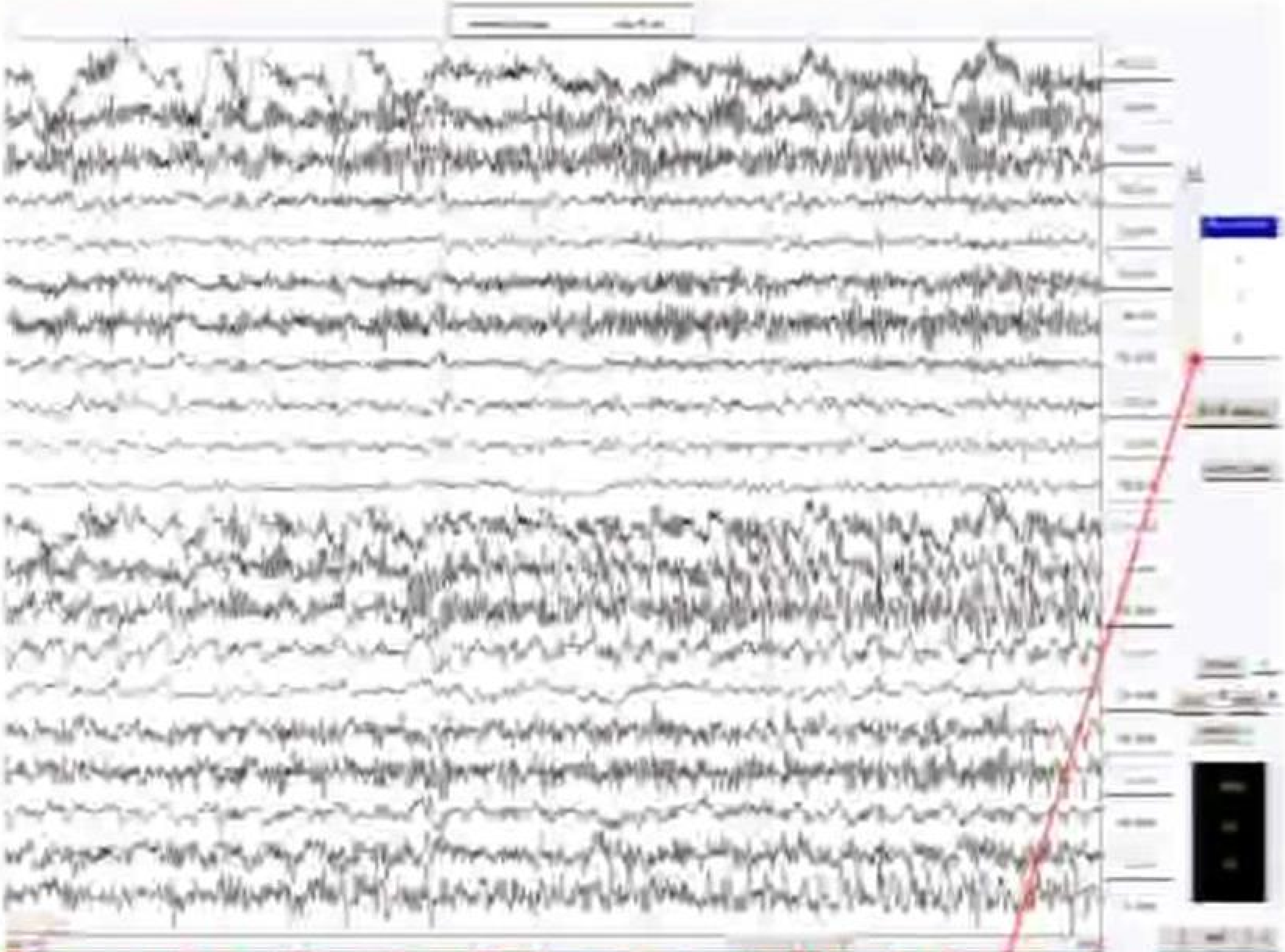
Muscle artefact removal –
Simulation study



BSS-CCA processed EEG



Muscle artefact removal via BSS-CCA – Real Seizure



The cursor is positioned on the lowest source. At each clique one source is removed from the EEG.

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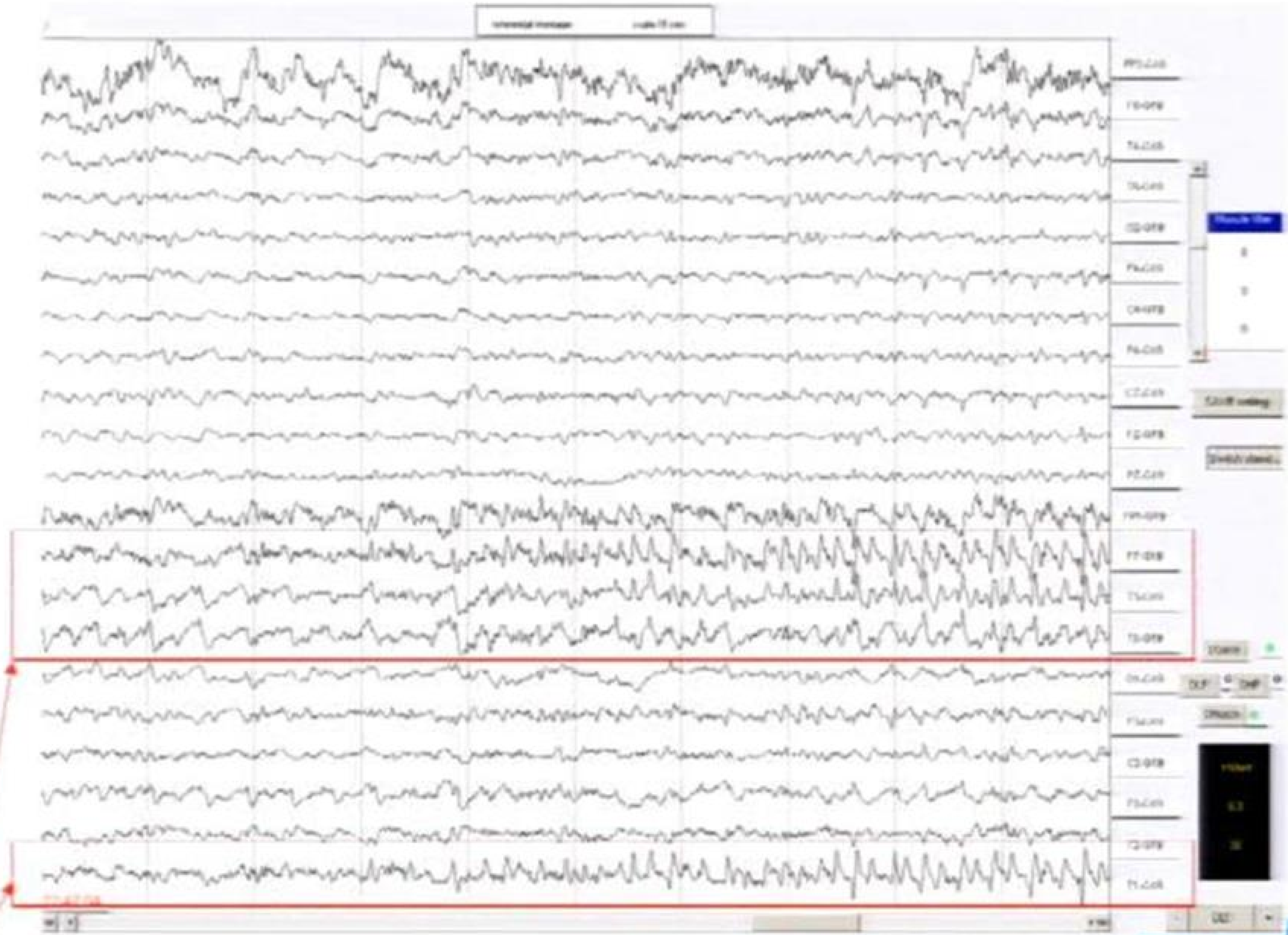
Muscle artefact removal via BSS-CCA – Real Seizure



After removal of all muscle artefact sources epileptic activity is better visible in the left temporal lobe

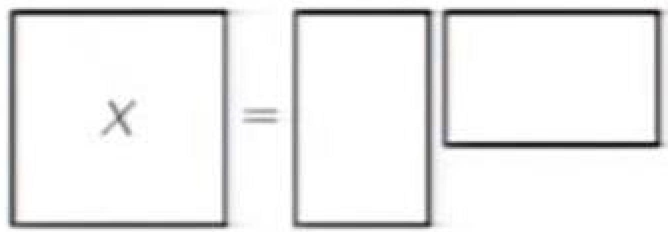
Contents Overview

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

From Matrix to Tensor rank

At its core, a matrix decomposition is

or



with some constraints

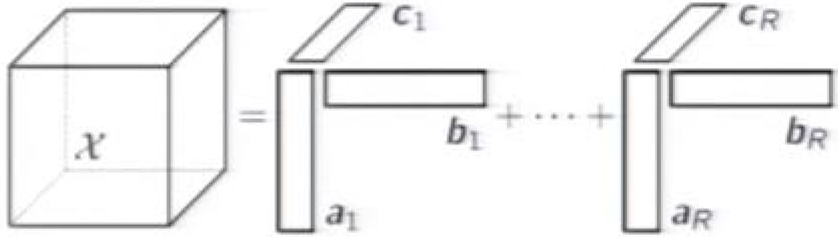
Two equivalent ways to define matrix rank

- Minimal number of rank-one matrices that sum to X
- Dimension of column (or row) space of X

For tensors, these are two different concepts!

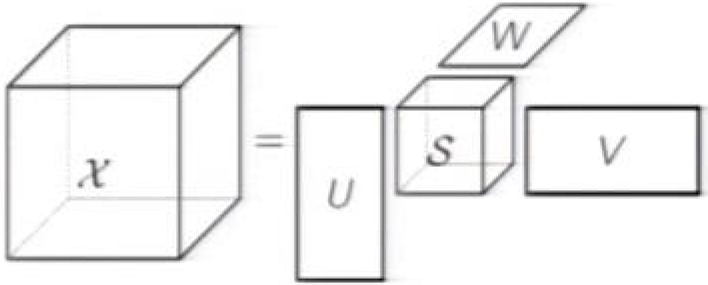
Tensor Decompositions

The canonical polyadic decomposition (CPD) decomposes a tensor into a minimal number of rank-one tensors R



The tensor's rank is defined as R

A low multilinear rank approximation (LMLRA) decomposes a tensor into a core tensor $\mathcal{S}$ and matrices U, V and W



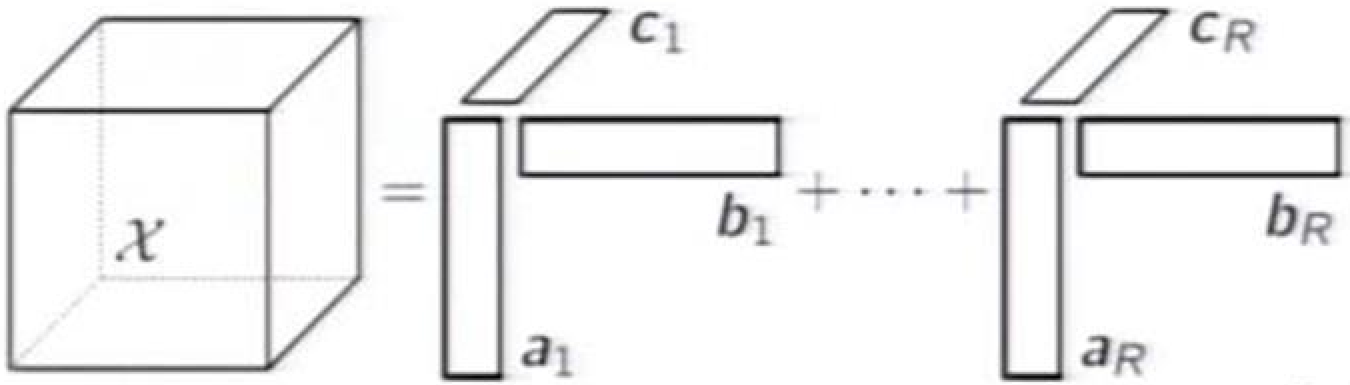
The tensor's multilinear rank is defined as the triplet $(\text{rank}(U), \text{rank}(V), \text{rank}(W))$

Uniqueness means Interpretable

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

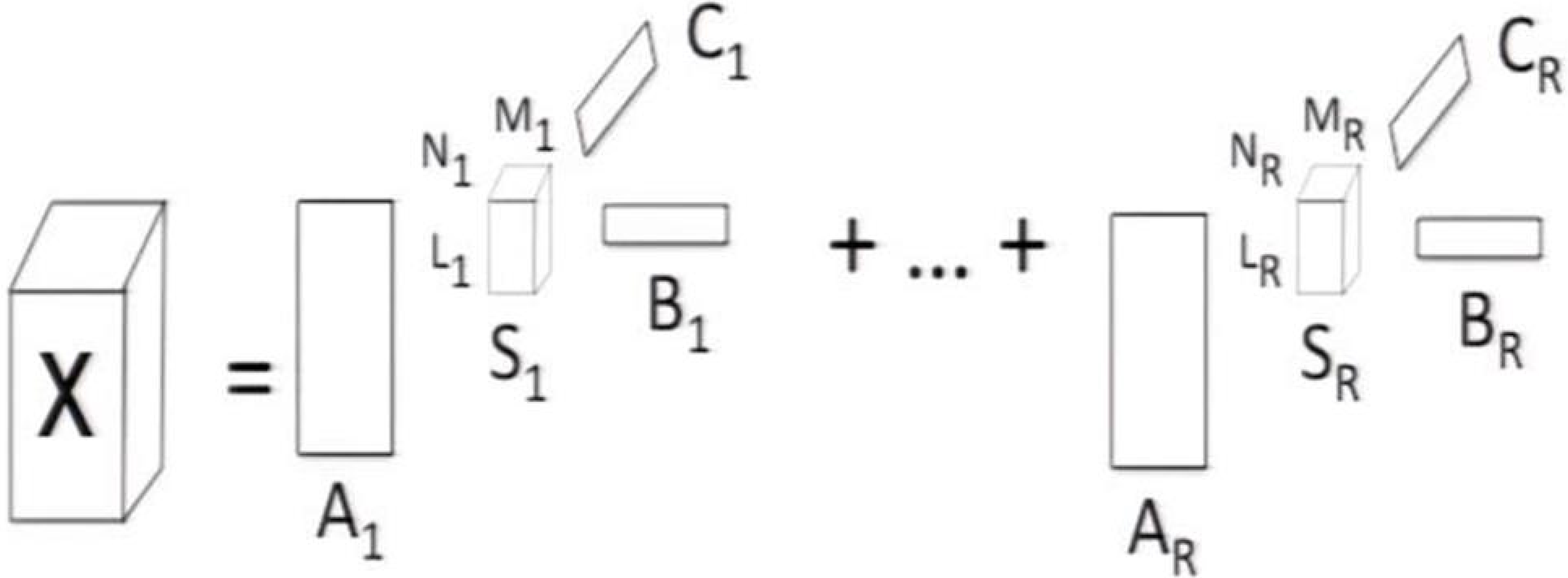


are generically unique when $k_A + k_B + k_C \;>= 2*R+2$

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

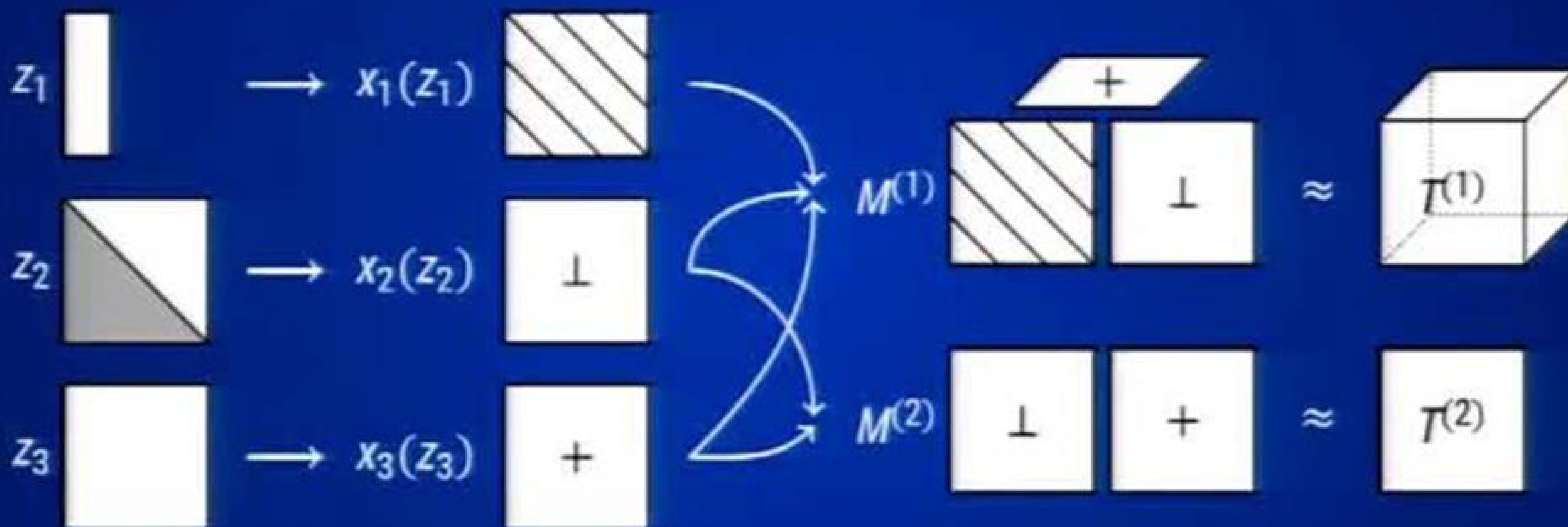
Contributors (nonexhaustive list):
L. De Lathauwer, P. Comon, T. Kolda, B. Bader, L-H Lim, C. Van Loan, E. Acar, A. Cichocki, O. Alter, R. Bro, M. Morup, N. Sidiropoulos, I. Domanov, M. Sorensen, L. Sorber, M. Ishteva, L. Albera, M. Haardt, ... and collaborators

Block Tensor Decomposition



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

STRUCTURED DATA FUSION



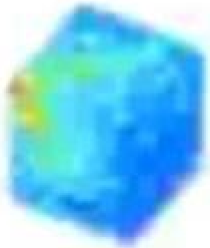
$$\underset{z}{\text{minimize}} \quad \sum_d \omega_d \left\| M^{(d)}(X(z)) - T^{(d)} \right\|^2$$

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

WWW.TENSORLAB.NET

Tensorlab

A MATLAB toolbox for tensor computations



About

Tensorlab is a MATLAB toolbox that offers algorithms for:

- **structured data fusion:**
- **tensor decompositions:** canonical polyadic decomposition (CPD), multilinear singular value decomposition (MLSVD), block term decompositions (BTD) and low multilinear rank approximation (LMLRA)
- complex optimization
- **global minimization of bivariate polynomials and rational functions:**
- **and much more:**

Download

First name

Last name

Institution/company

Tensorlab

Contents

ALGORITHMS

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

- User's choice of underlying solver
  Quasi-Newton, nonlinear least squares, ...
- Solver exploits the structure in the factors
  Nonnegative, orthogonal, inverse, ...
- Solver exploits the structure of the decomposition
  CPD, LMLRA, BTD, TT, ...
- Based on complex optimization
  Solve complex-valued problems with the same code

Properties of Tensor Algorithms

CPD Algorithms:

ALS: Alternating Least Squares (Smilde, Bro, and Geladi, 2004) → **most popular**

- *easy-to-use, usually fast (unless factors collinear), convergence not guaranteed*

Matrix-free Nonlinear Least Squares → currently most efficient and robust

- *More general in use (allows constraints)* (Sorber et al, SIOPT, 2013)
- *Exploits structure in GN approx. of Hessian: memory cost* ⬇ *computational load* ⬇
- *Efficient preconditioning accelerates convergence*
- *Line and plane search*
- *allows parallelisation*

Online? *Online CPD (Nion and Sidiropoulos, 2009)*

BTD and coupled TD (via structured data fusion)

- *Complex quasi-Newton and NLS optimization , generalizes above algorithms*
- *Supports sparse and incomplete tensors,*
- *Supports structured factors, joint factorization, regularization*

Computer power? *If #(X) <10^6, still feasible on laptop (if compressed, #(X)< 10^{18})*

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- Introduction
- Tensor Decompositions
- Examples in EEG monitoring
  - Seizure onset localization
  - Neonatal brain monitoring
  - Combined EEG-fMRI Analysis
- Conclusions and New Directions

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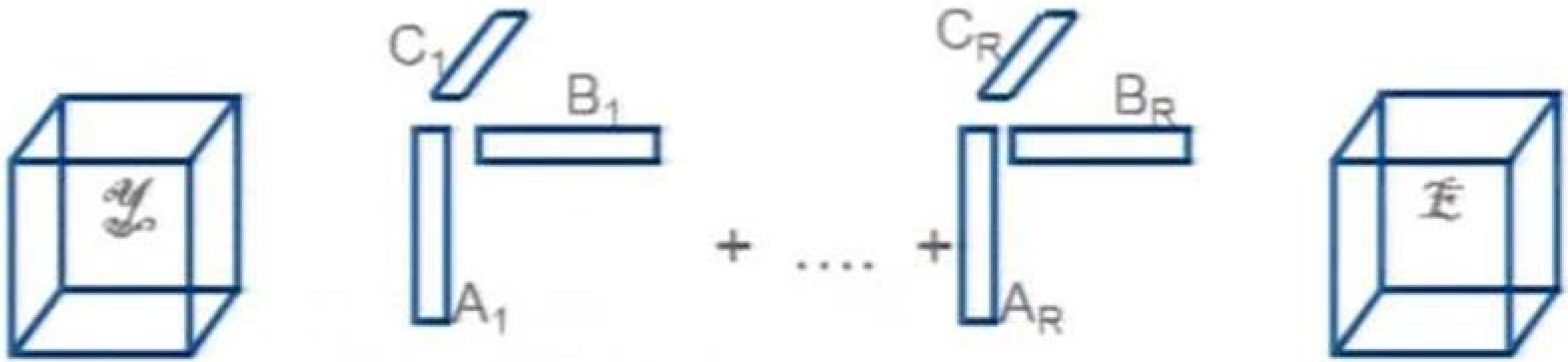
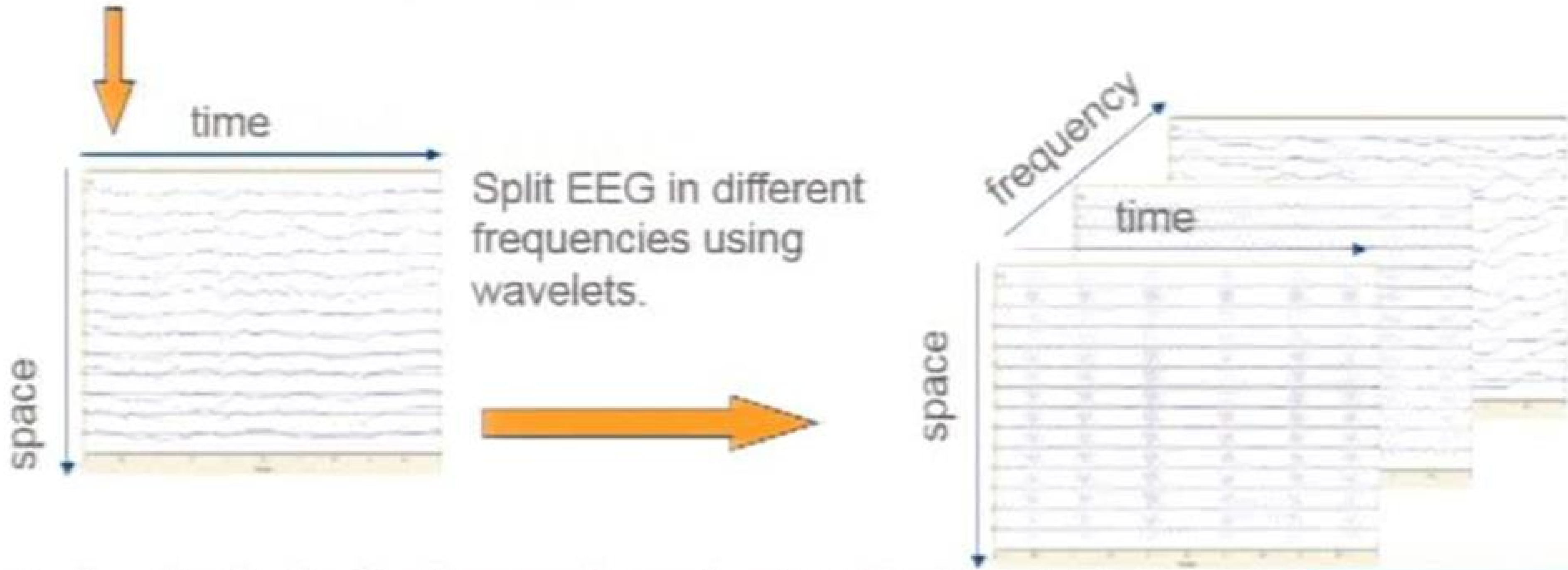
1 Seizure onset localization: CPD





=> Analysis in 3 dimensions instead of just 2

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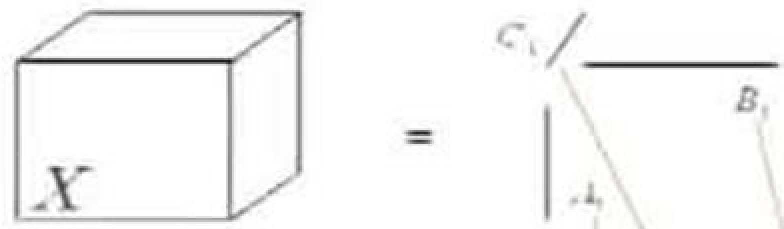
Interpretation of a trilinear component

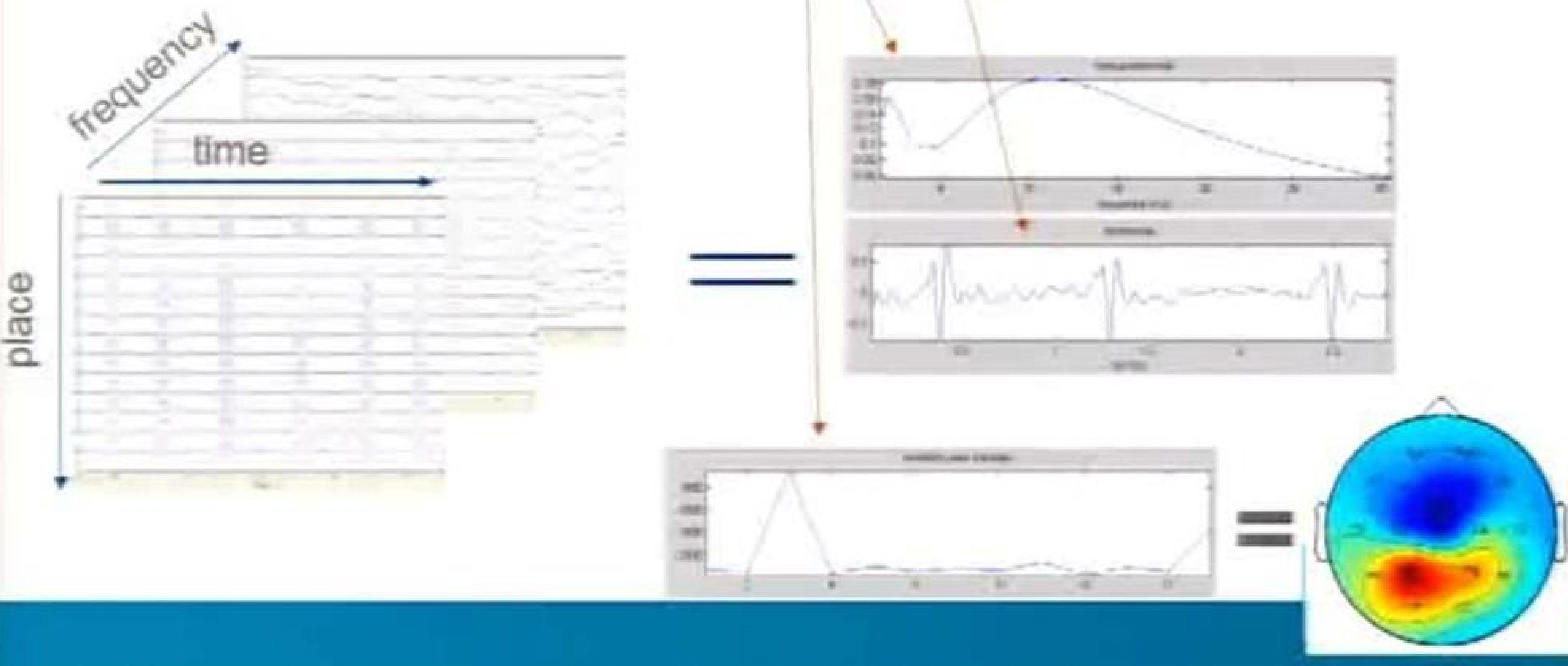
CPD: Example extracting 1 component



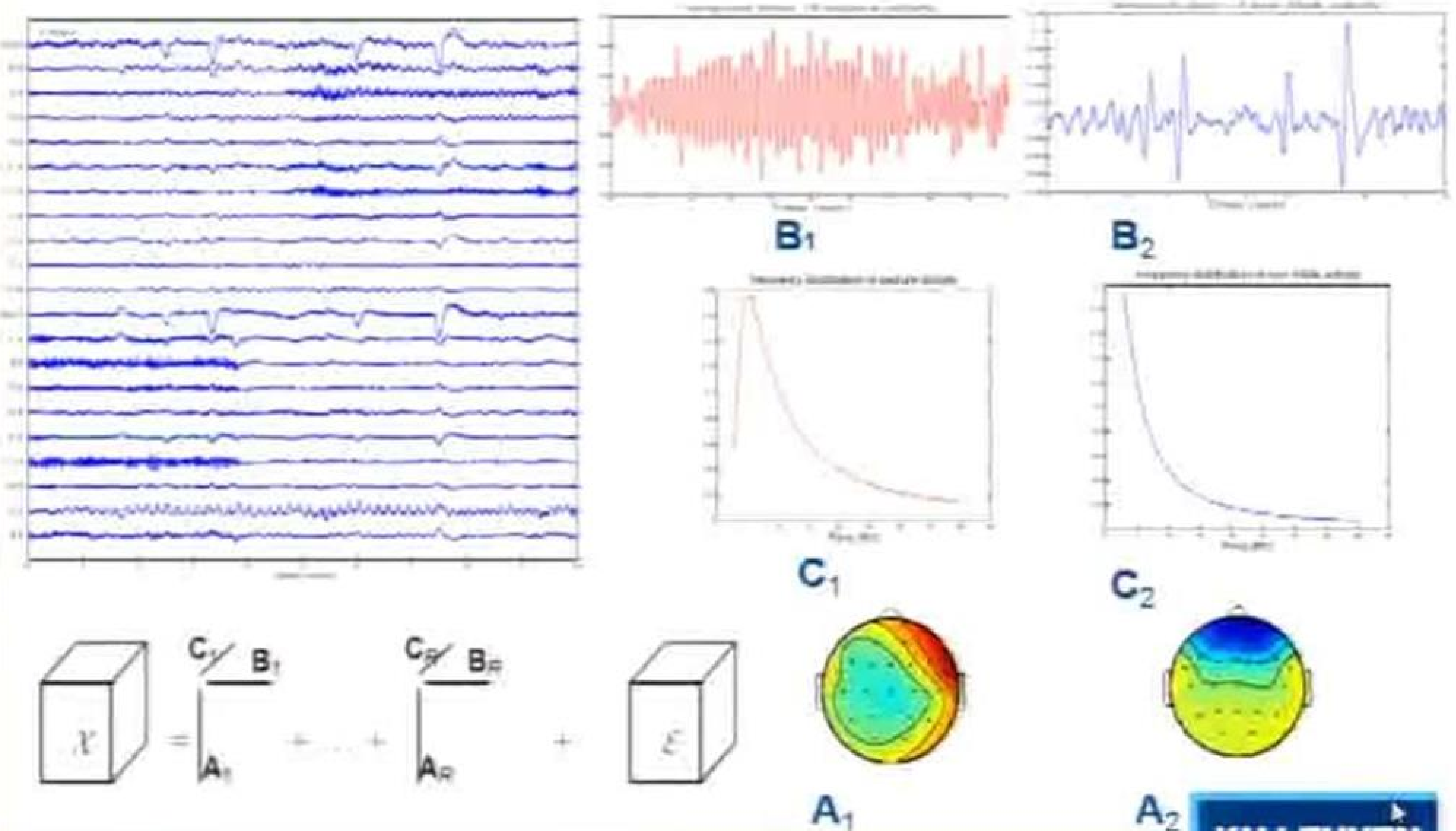
B_1: time course

A_1: distribution over channels

C_1: frequency content (distribution across scales).



CPD for seizure onset localization



Why trilinear structure to extract seizures?

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

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

⇒ ***Oscillations in EEG meet requirements, e.g. seizures***

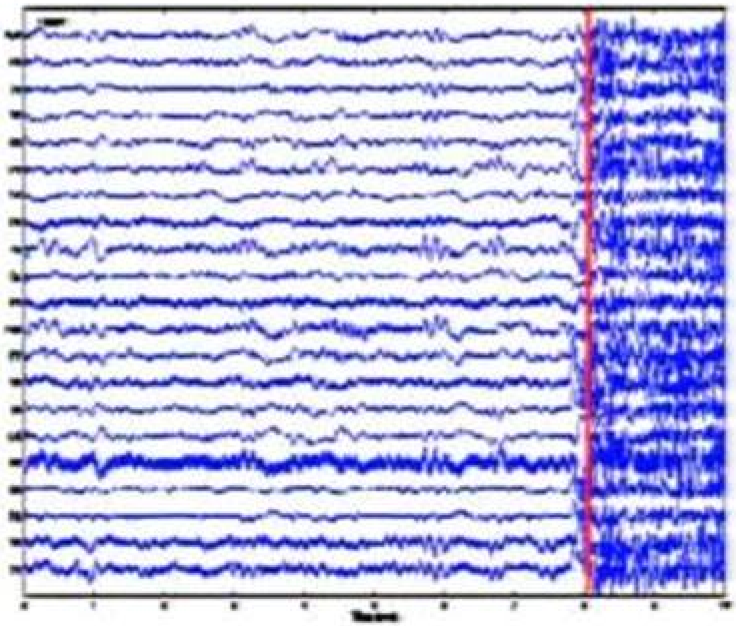
⇒ Muscle artifacts don't fit into trilinear structure since they are distributed over frequencies by wavelet transformation

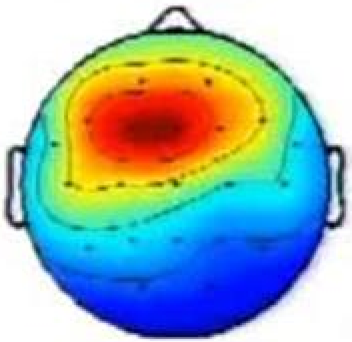
Added value in clinical practice?

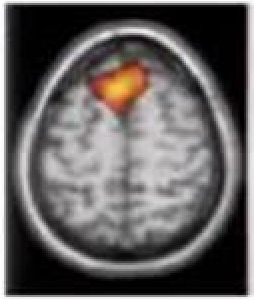
Validation study with UZ Leuven→ seizure EEG of 37 patients

- 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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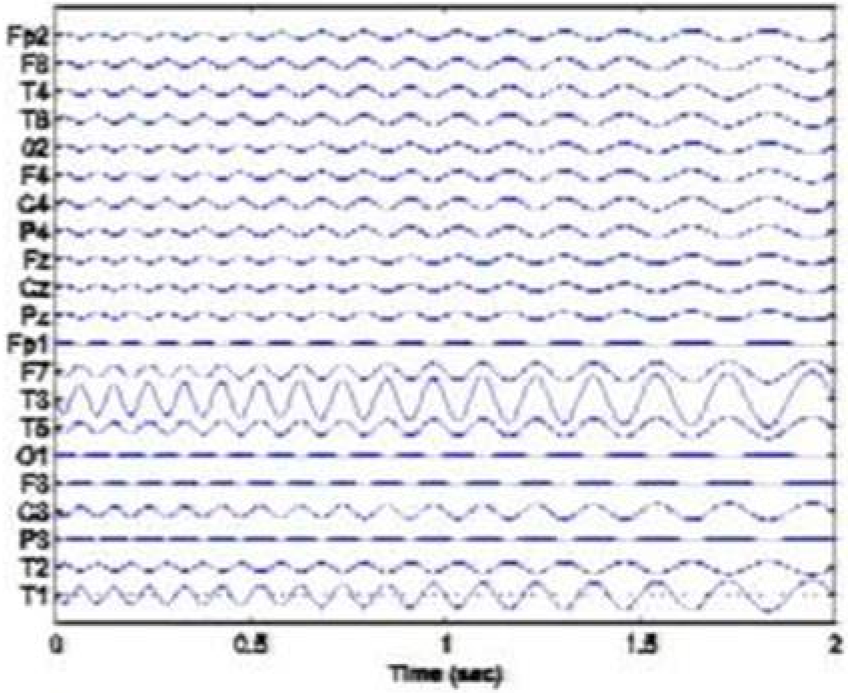
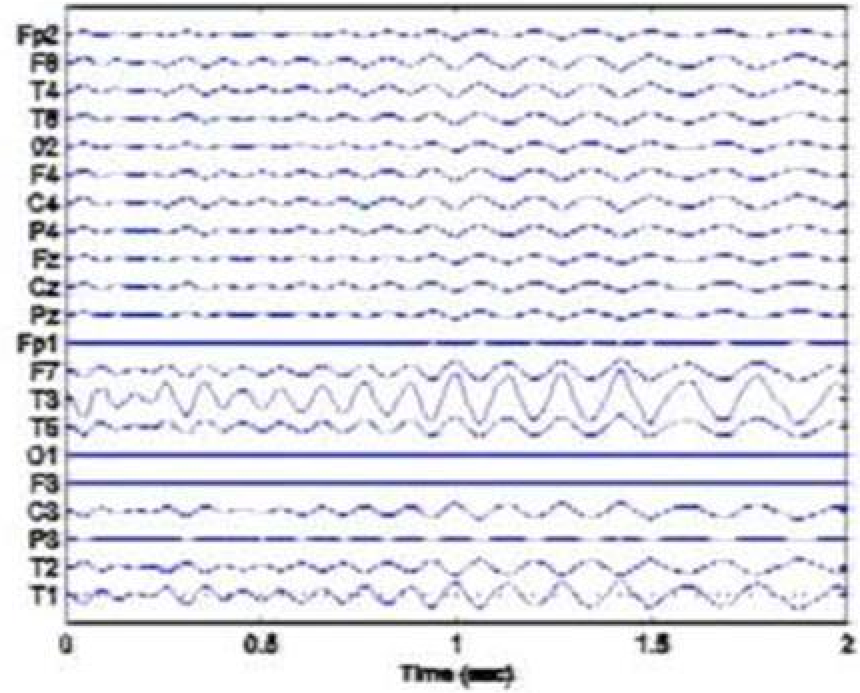
Limits of CPD



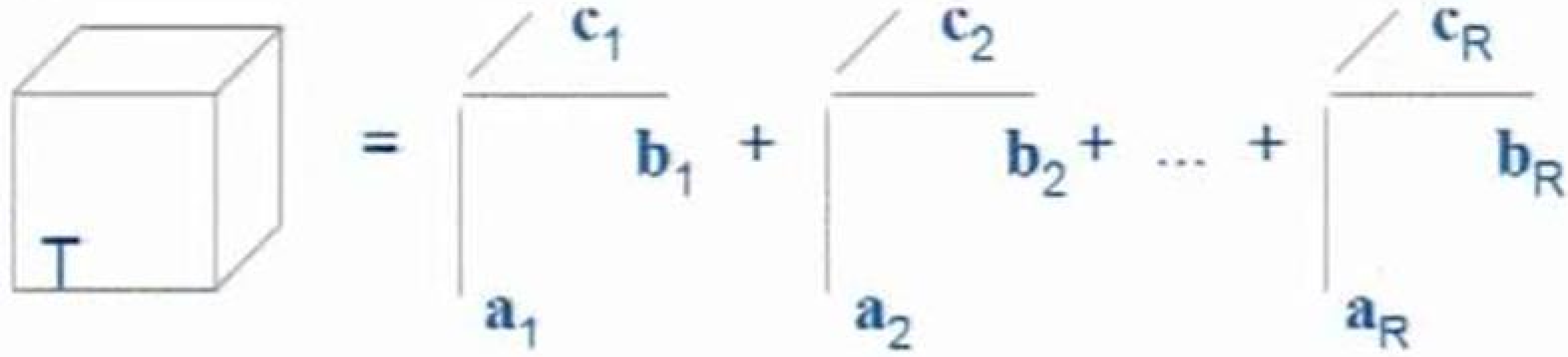


Limits of a trilinear model

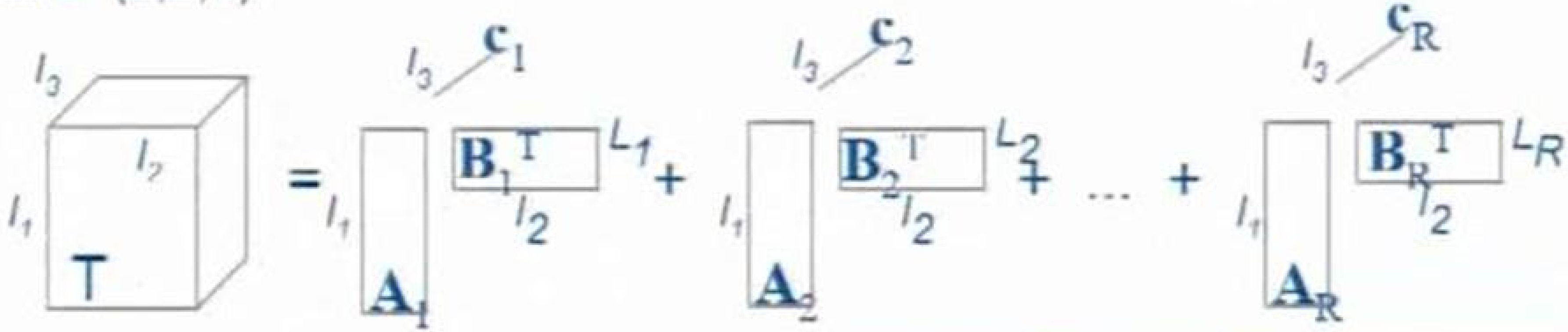
- Signal is not always perfectly recovered (e.g. freq.change)
- But it is still well localized!

Block Term Decomposition

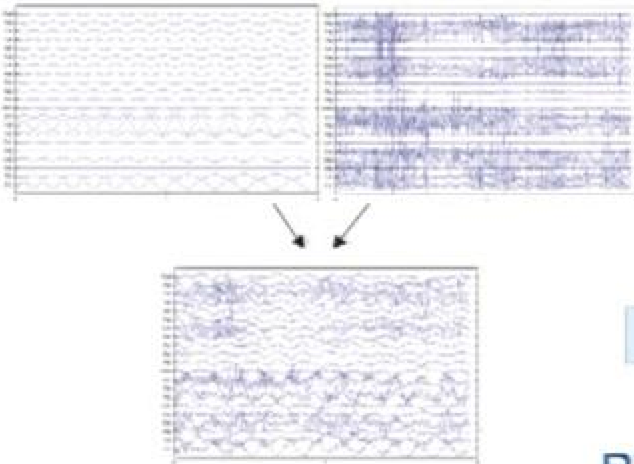
CPD:

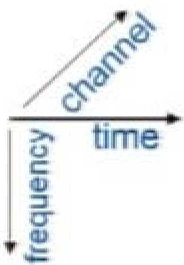


BTD-(L,L,1):



BTD of wavelet expanded EEG tensors



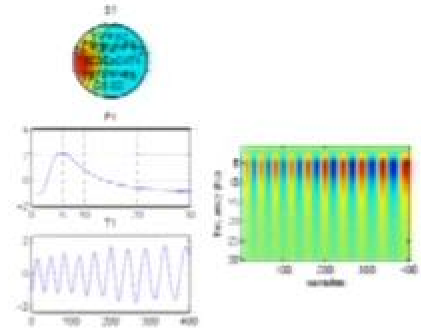


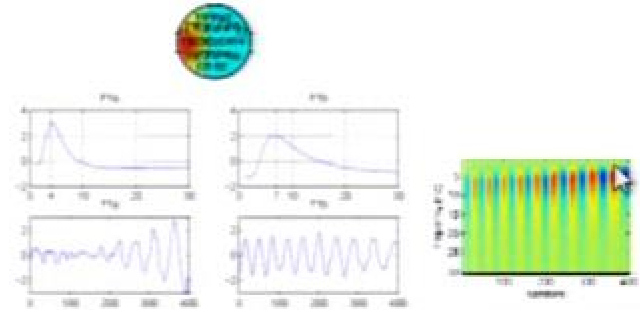
CPD

(Acar 2007, De Vos 2007)

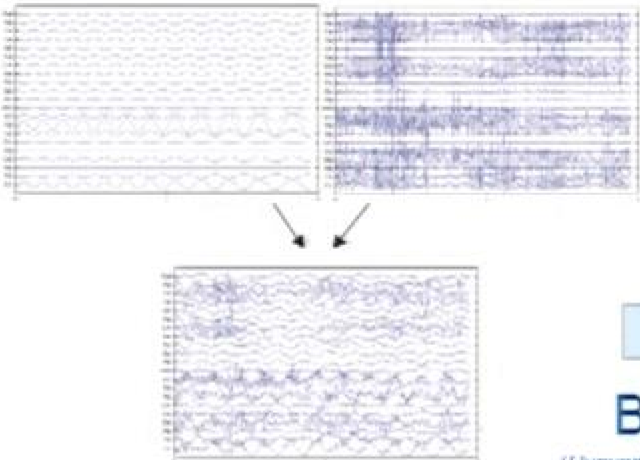
BTD

(Hunyadi, JASP, 2014)



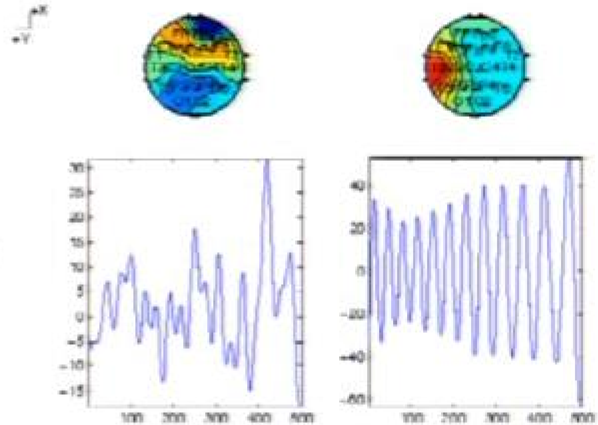


BTD of Hankel expanded EEG tensors



BTD

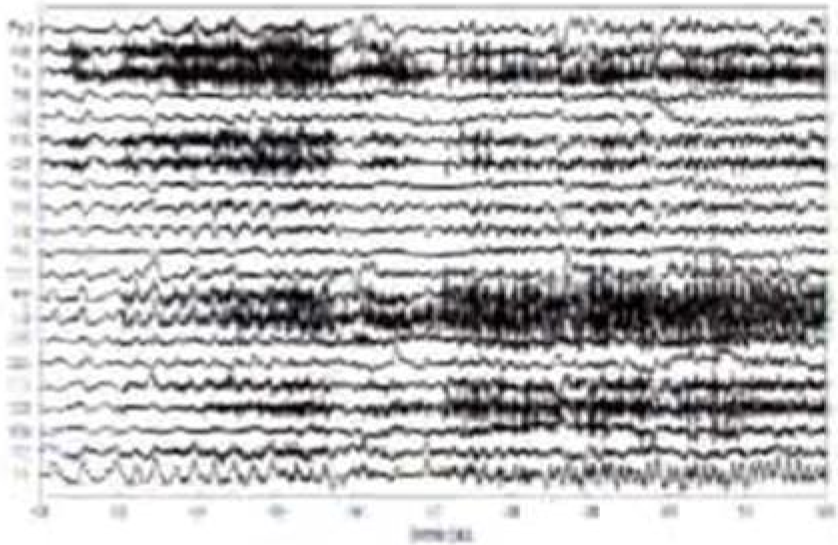
(Hunyadi, JASP, 2014)



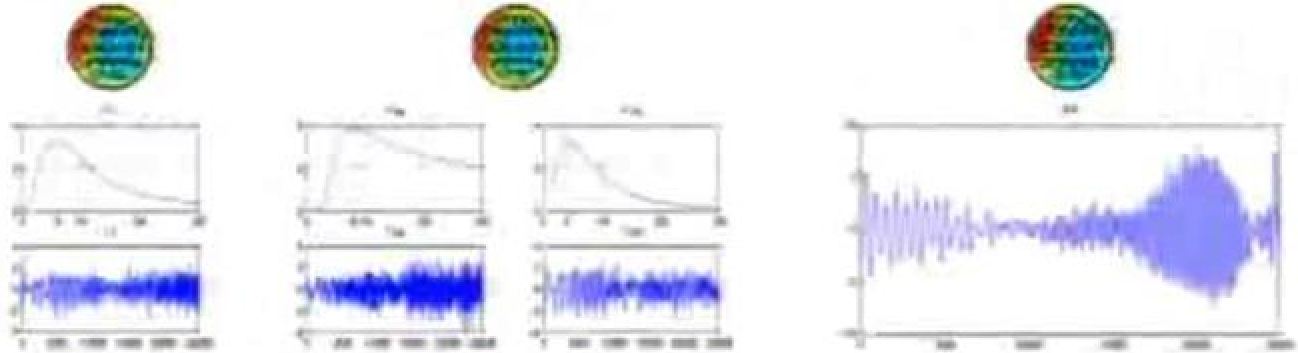
$$\begin{bmatrix} a_1 & a_2 & a_3 & \cdots & a_K \\ a_2 & a_3 & \cdots & a_K & a_{K+1} \\ a_3 & \cdots & a_K & a_{K+1} & a_{K+2} \\ \vdots & \iddots & \iddots & \iddots & \iddots \\ a_J & a_{J+1} & \cdots & a_{S-1} & a_S \end{bmatrix}$$

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

Clinical examples



(a) Raw EEG



(b) CPD

(c) CWT-BTD

(d) H-BTD

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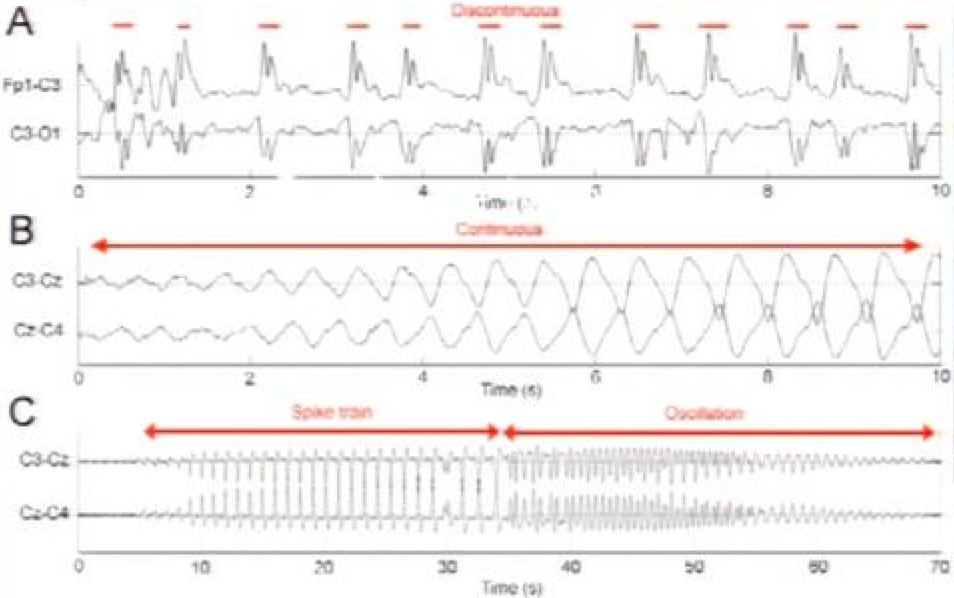
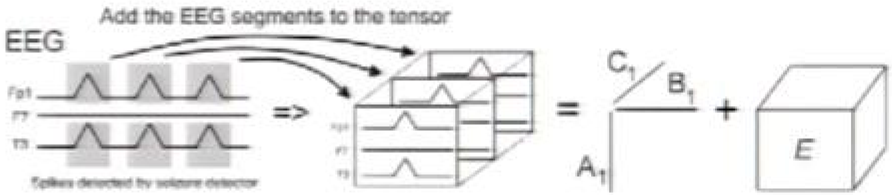
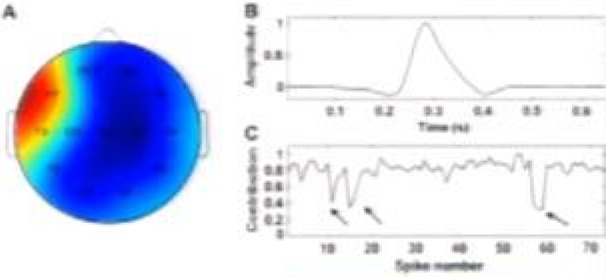
Neonatal Brain Monitoring:

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 background EEG
- Maturation in preterms

Outcome prediction

- Good
- Poor

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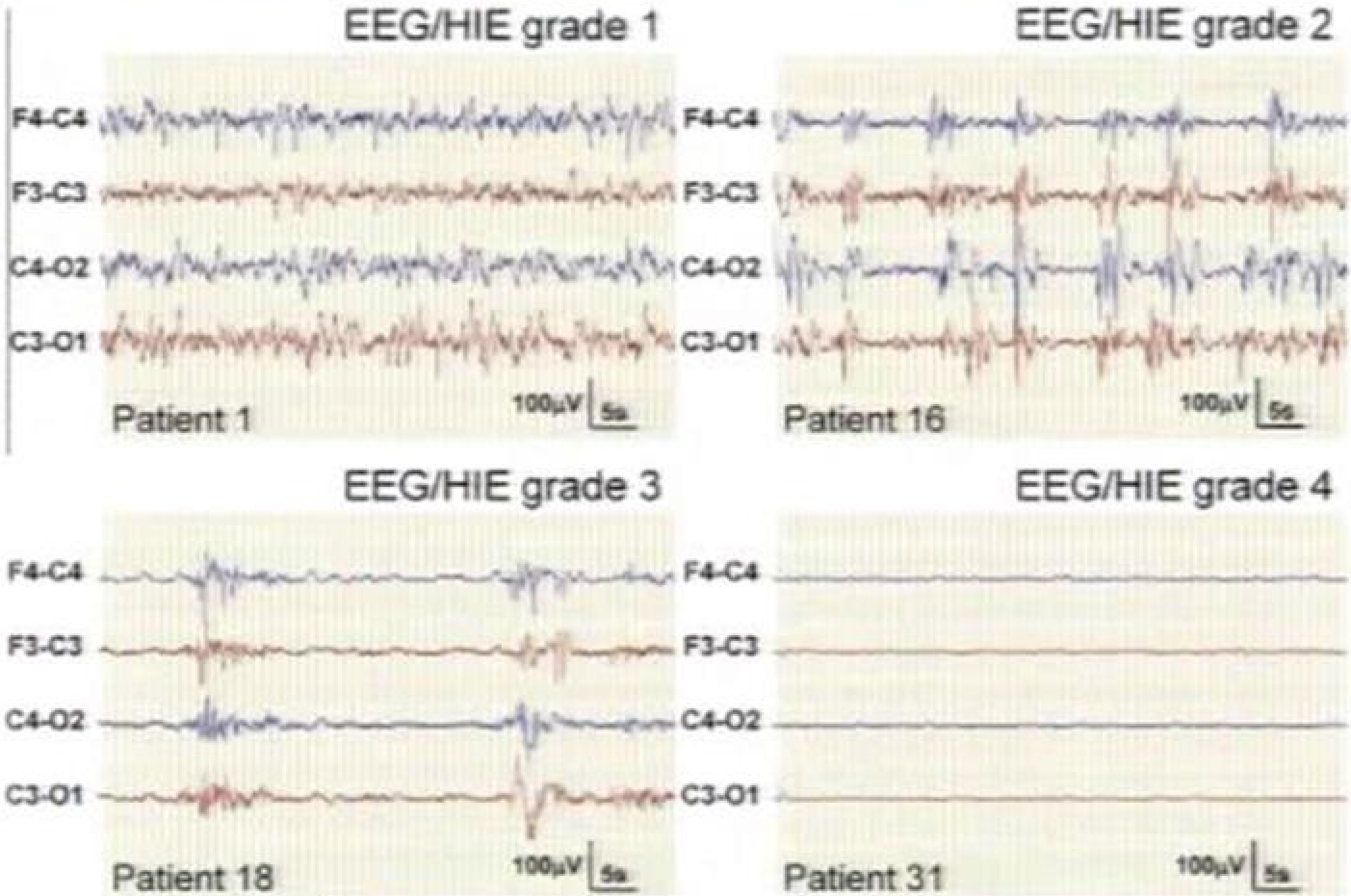
Goal: Background EEG assessment

mildly abnormal　　**moderate**ly abnormal



severely abnormal

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

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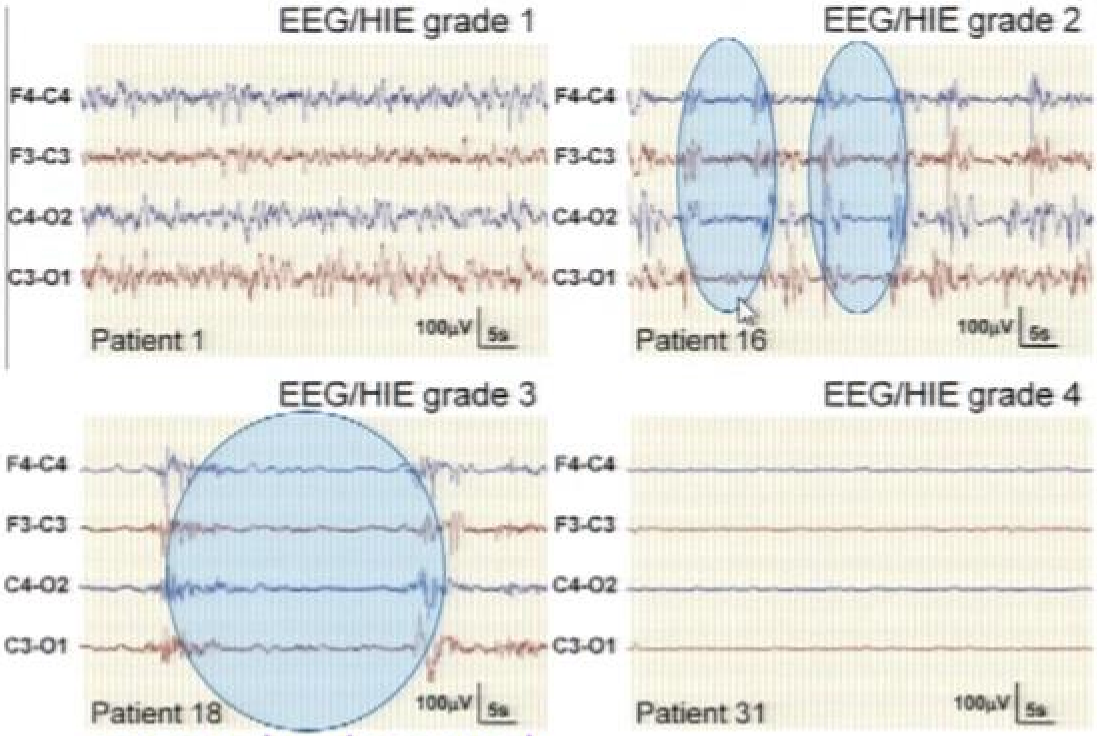
Goal: Background EEG assessment

mildly abnormal   **moderate**ly abnormal



severely abnormal

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

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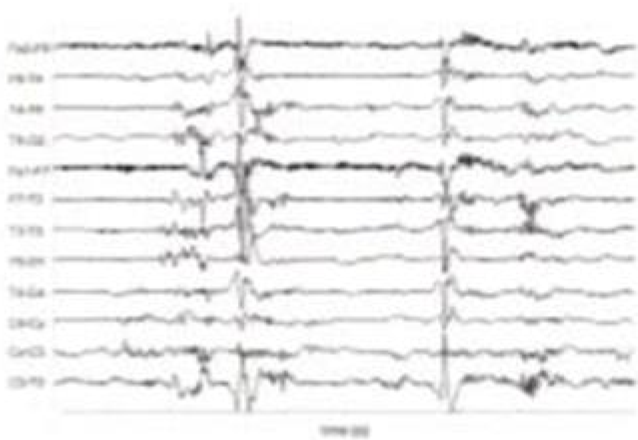
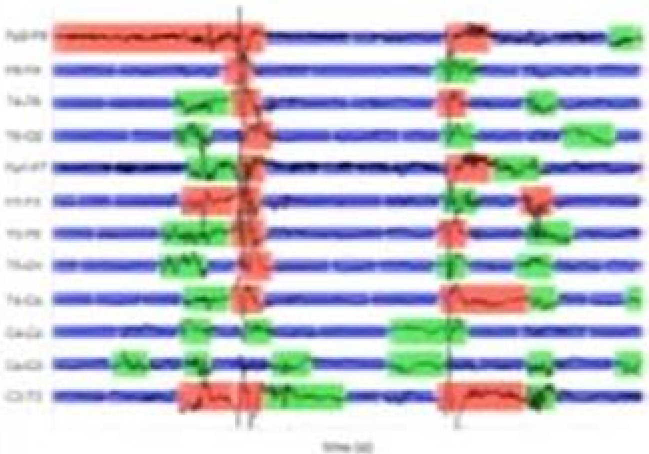
Monitoring neonatal background EEG:

The power of structuring data





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

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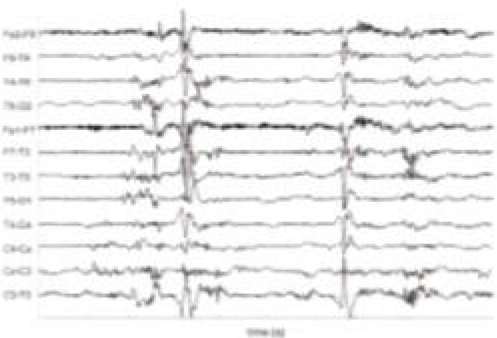
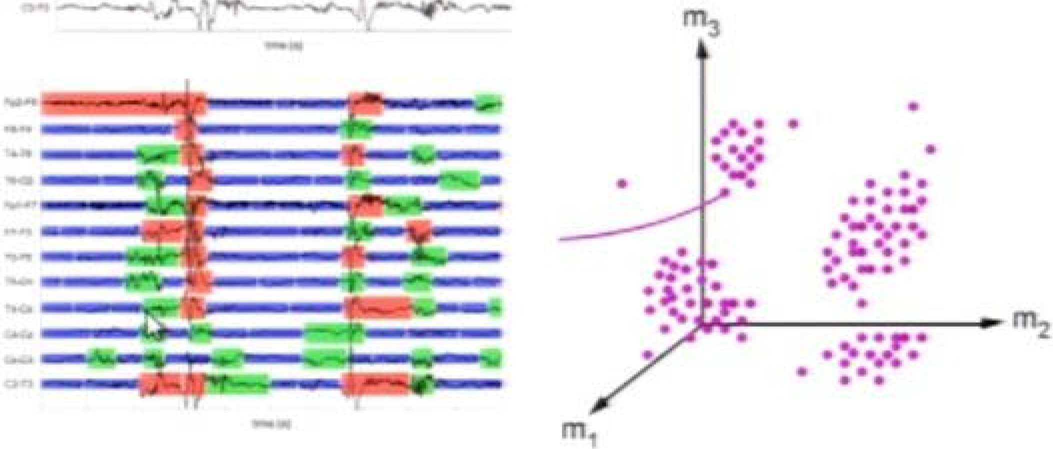
Monitoring neonatal background EEG:

The power of structuring data





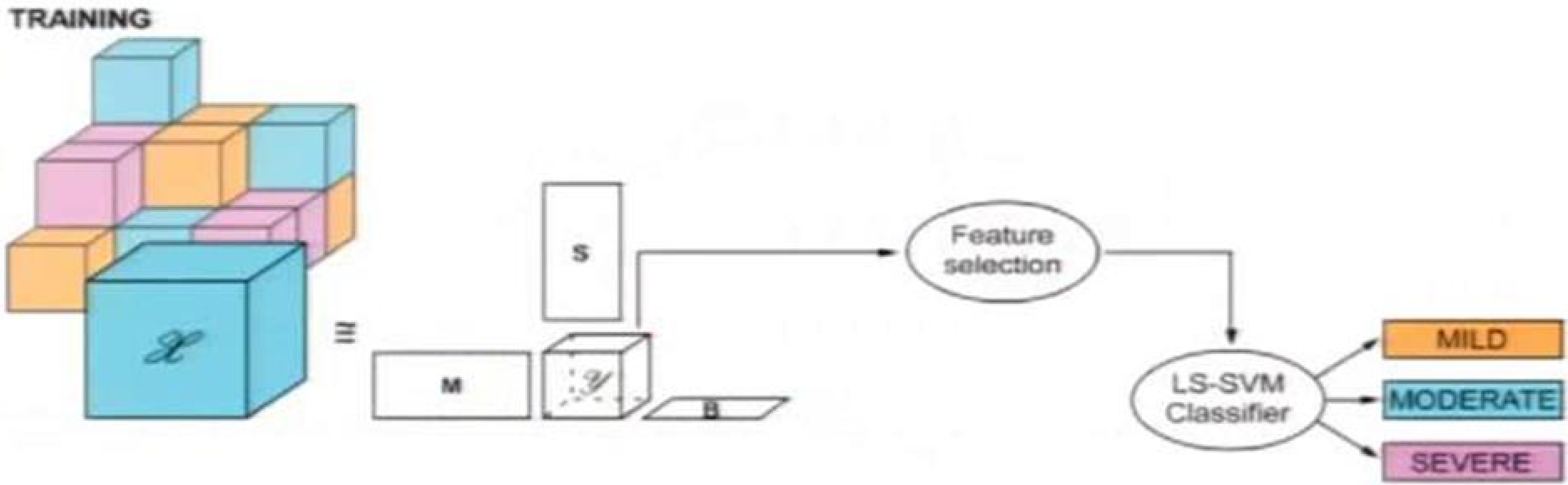
V. Matic et al., J. Neural Engineering, Oct. 2014

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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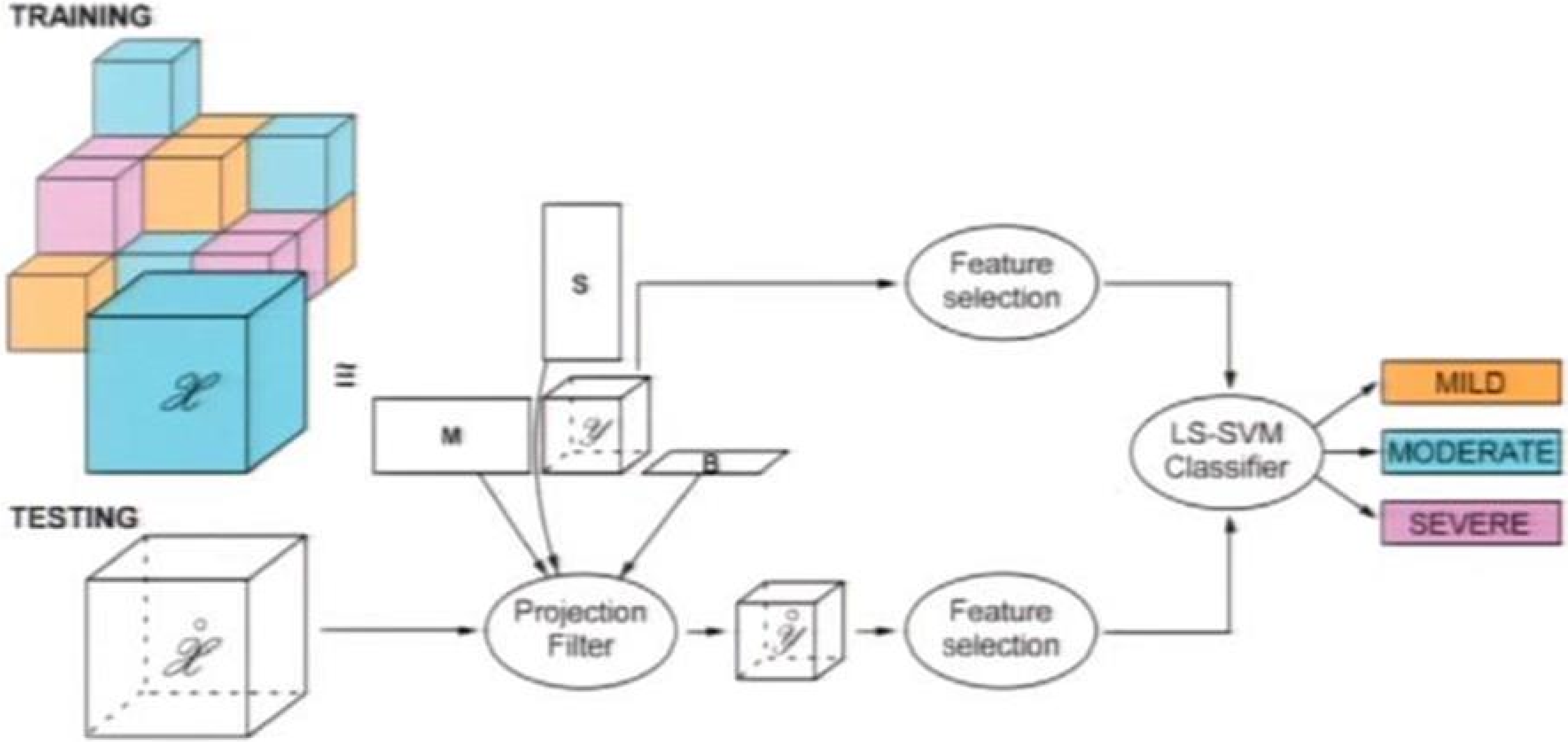
Higher Order Discriminant Analysis



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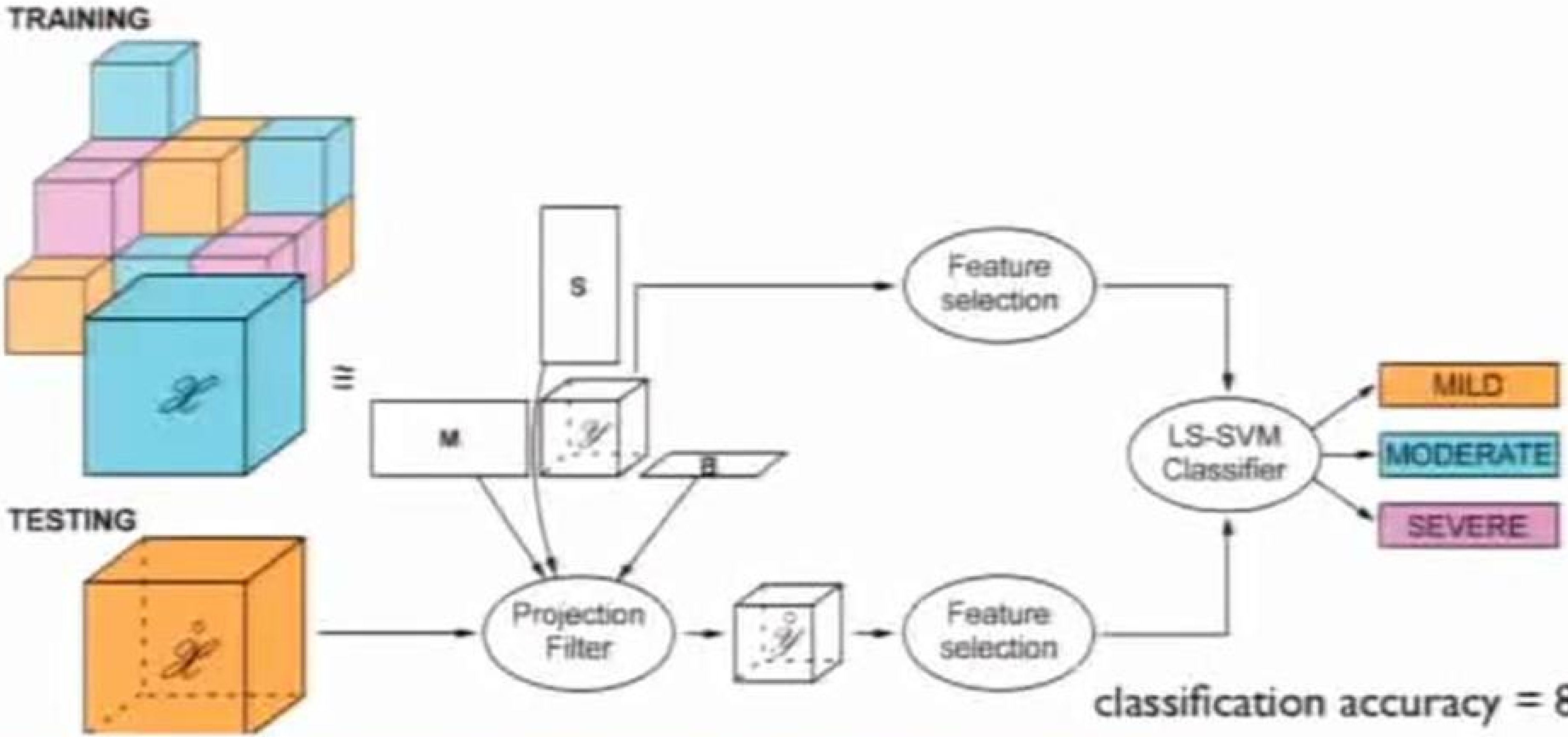
Higher Order Discriminant Analysis



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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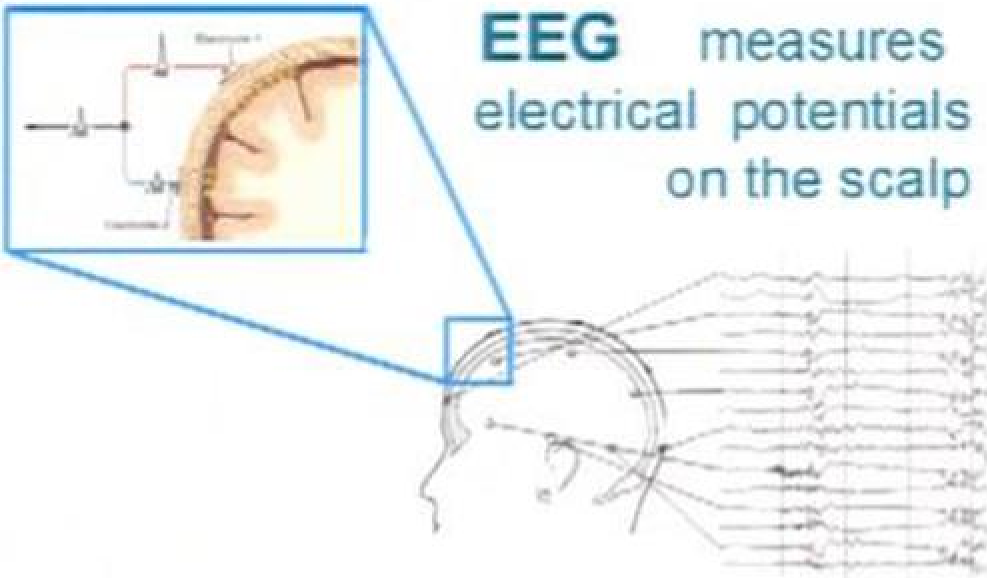
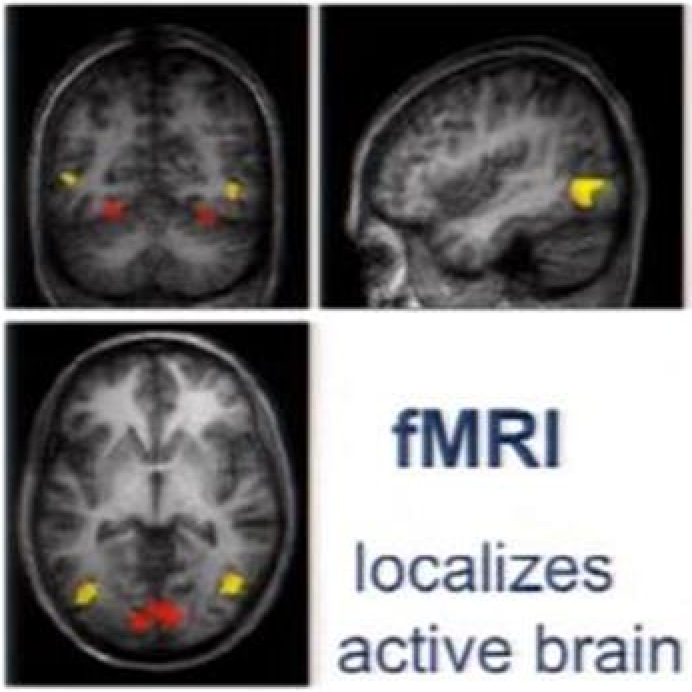
3 Combined EEG-fMRI analysis



EEG measures electrical potentials on the scalp



fMRI

localizes active brain regions

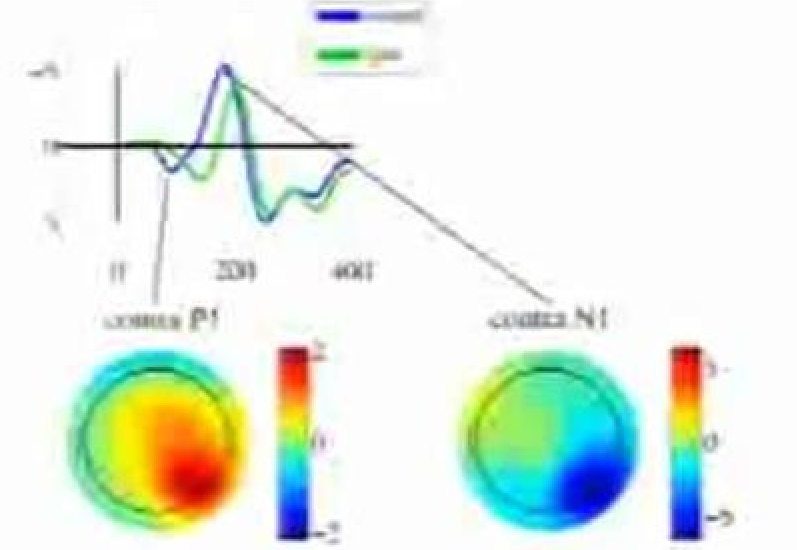
Combining EEG and fMRI:

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

ERP analysis:

Brain responses evoked due to mental task

Detection task



outside - detection task

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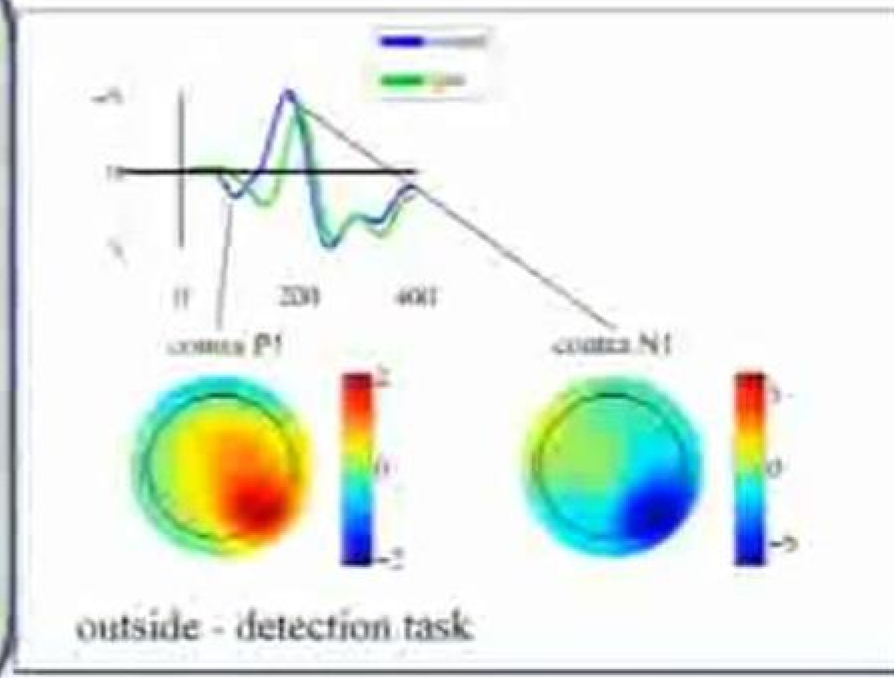
ERP analysis:

Brain responses evoked due to mental task

Detection task



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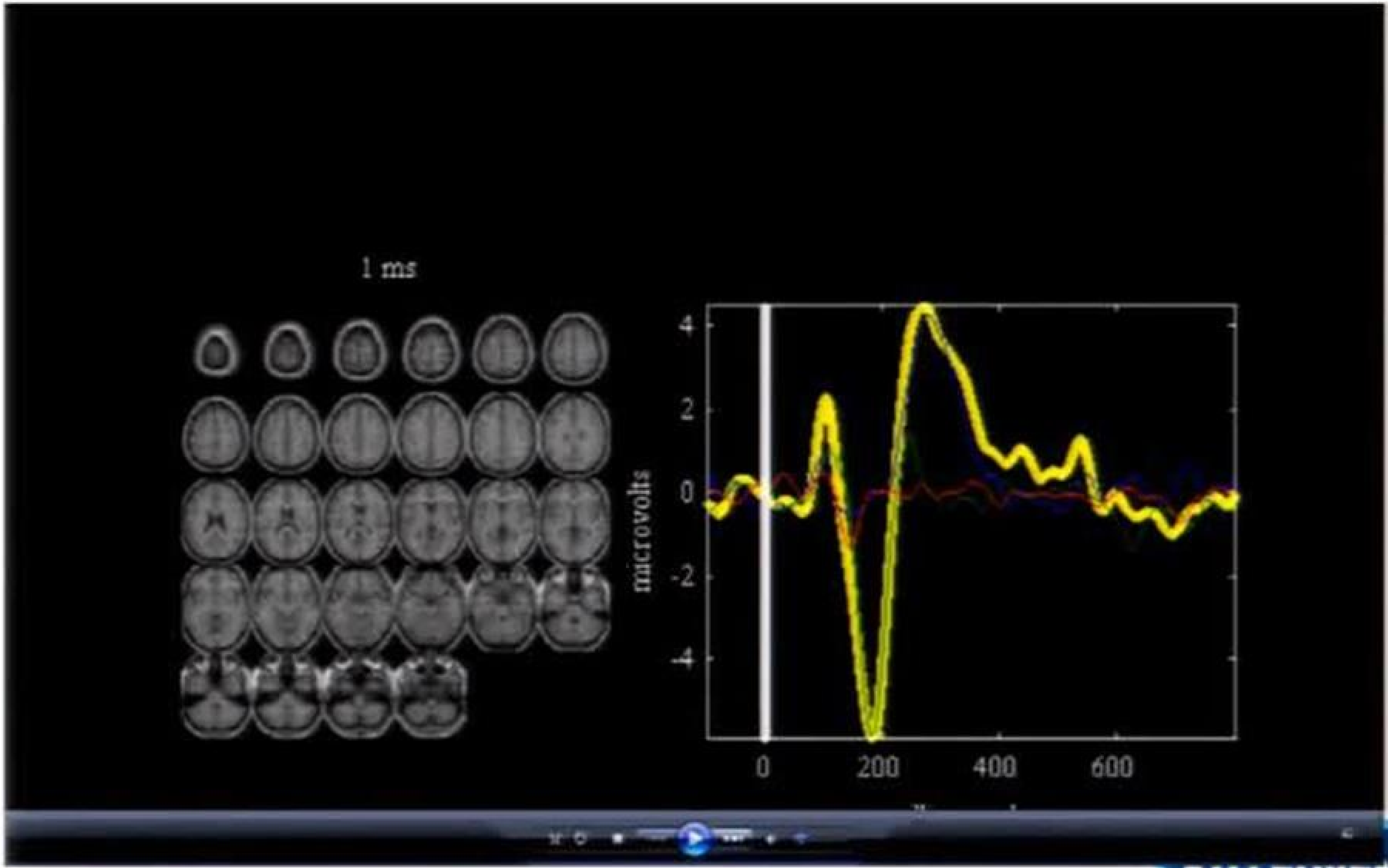
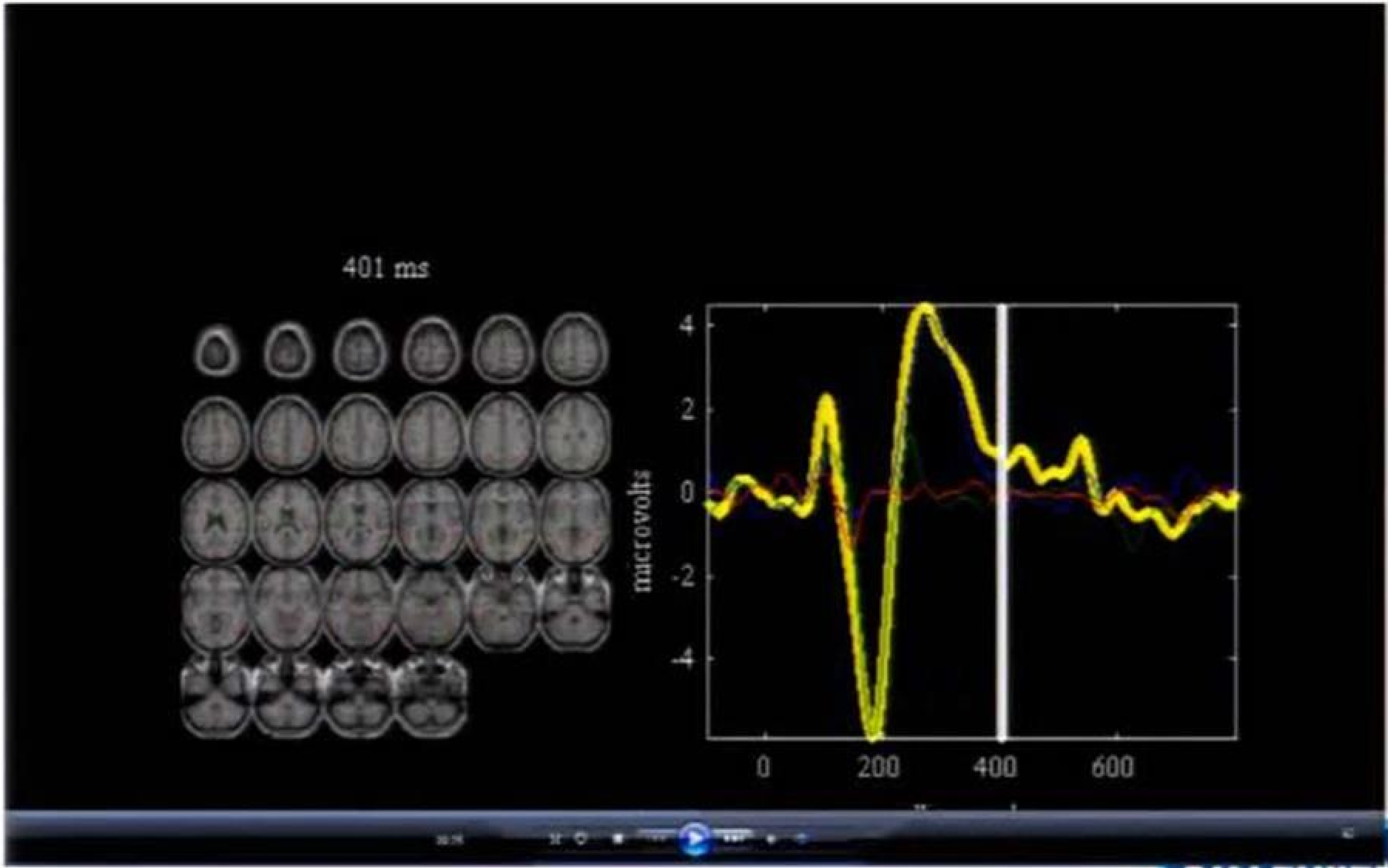
Combined EEG-fMRI analysis

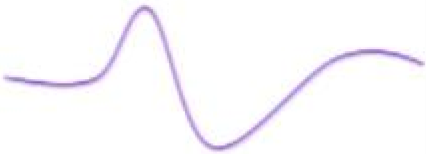


Combined EEG-fMRI analysis



Symmetric EEG-fMRI approaches: Joint ICA

Calhoun et al., (2006), NeuroImage



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

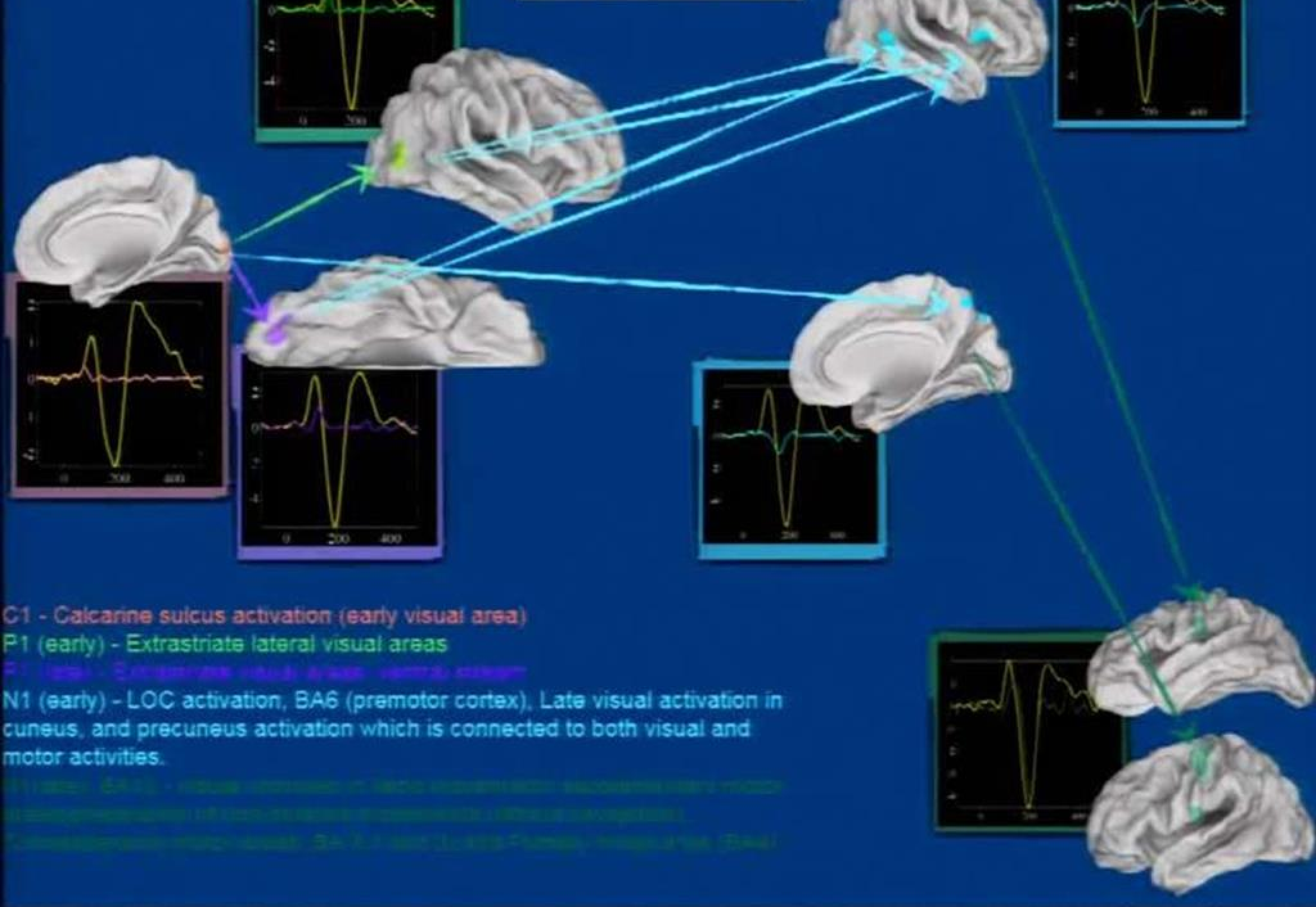
Joint Independent Component Analysis (JointICA)

X^{fMRI} X^{EEG} = Mixing Matrix $\circ$ Estimated Sources (fMRI) Estimated Sources (EEG)

Extensions: add more conditions
add extra electrodes

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

Visual Path



C1 - Calcarine sulcus activation (early visual area)

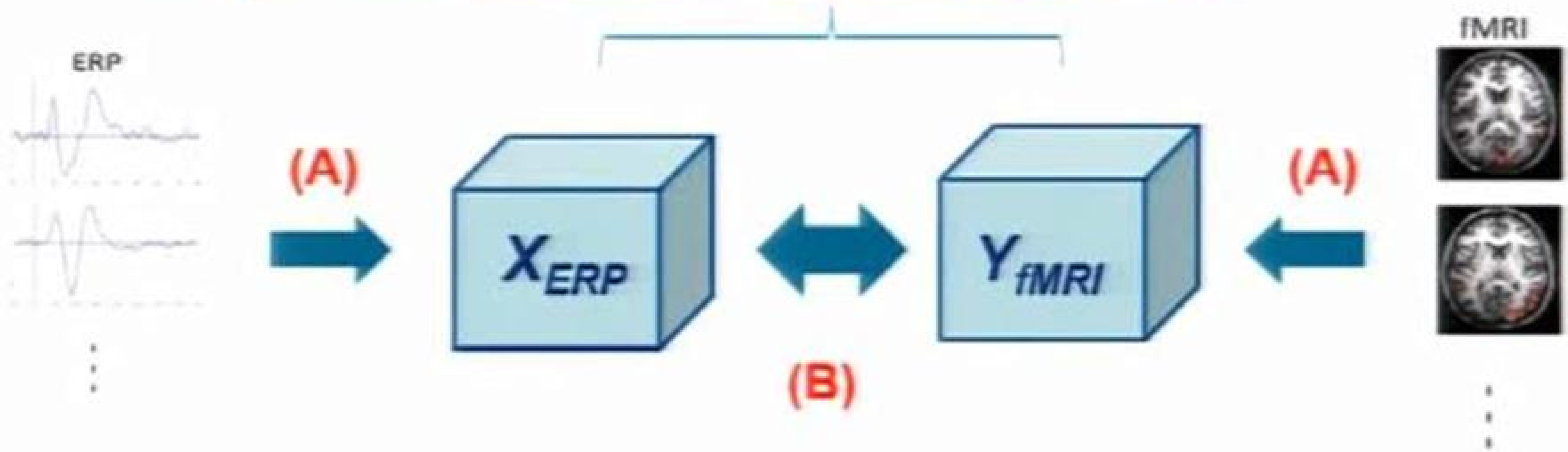
P1 (early) - Extrastriate lateral visual areas

N1 (early) - LOC activation, BA6 (premotor cortex), Late visual activation in cuneus, and precuneus activation which is connected to both visual and motor activities.

ERP analysis: EEG-fMRI integration

erc

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

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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, ERP-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), chemo/psychometrics*
- Use of tensorial kernels in classification promising *(Signoretto)*

New directions?

- *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

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Thank you!

TDA 2016 @ KU Leuven

http://www.esat.kuleuven.be/stadius/TDA2016/

Workshop on Tensor Decompositions and Applications
January 18 - 22, 2016, Leuven, Belgium

Local Organisers: Sabine Van Huffel and Lieven De Lathauwer

Confirmed Speakers

Orly Alter
Pierre Comon
Eva Ceulemans
Harm Derksen

Nicolas Gillis
Daniel Kressner
Lek-Heng Lim
Ivan Markovsky

Morten Mørup
Nikos Sidiropoulos
Bart Vandereycken
Frank Verstraete

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