BIOMEDICAL DATA FUSION

using tensor-based blind source separation

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10-9-2018

Contents Overview

1. Introduction

- Keytool: Blind Source Separation
- Biomedical Data fusion: Applications
- Tensor Decompositions

2. BIOTENSORS Project

3. Examples

4. Conclusions and Future Directions

KEYTOOL : Blind source separation

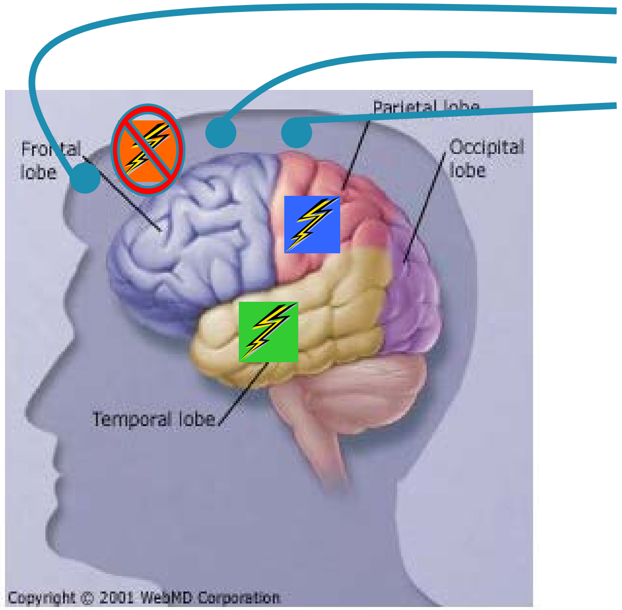
Signal analysis difficult because of artefacts → **REMOVE**

Matrix based Blind Source Separation (BSS)

- ***Non-unique*** →*Constraints are needed (orthogonal, independency)*

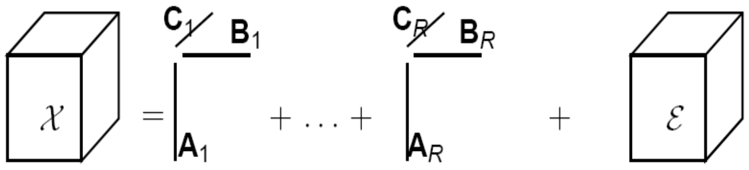
TENSOR based BSS: unique under mild conditions

ADD extra problem-specific constraints (nonnegative, sparse)



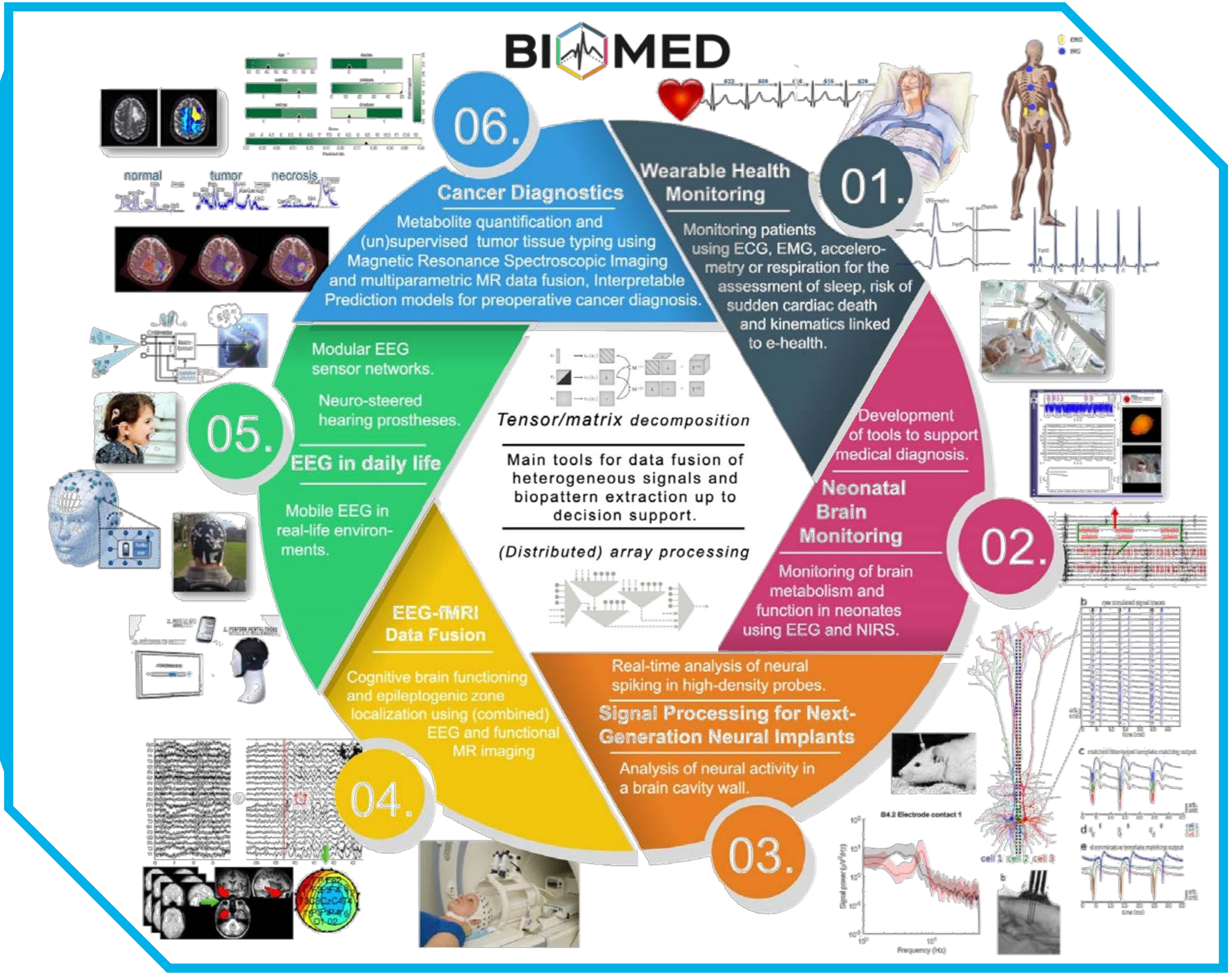
$$EEG_1 = a_{11}\mathbf{s_1} + a_{12}\mathbf{s_2} + \cancel{a_{13}\mathbf{s_3}}$$
$$EEG_2 = a_{21}\mathbf{s_1} + a_{22}\mathbf{s_2} + \cancel{a_{23}\mathbf{s_3}}$$
$$EEG_3 = a_{31}\mathbf{s_1} + a_{32}\mathbf{s_2} + \cancel{a_{33}\mathbf{s_3}}$$

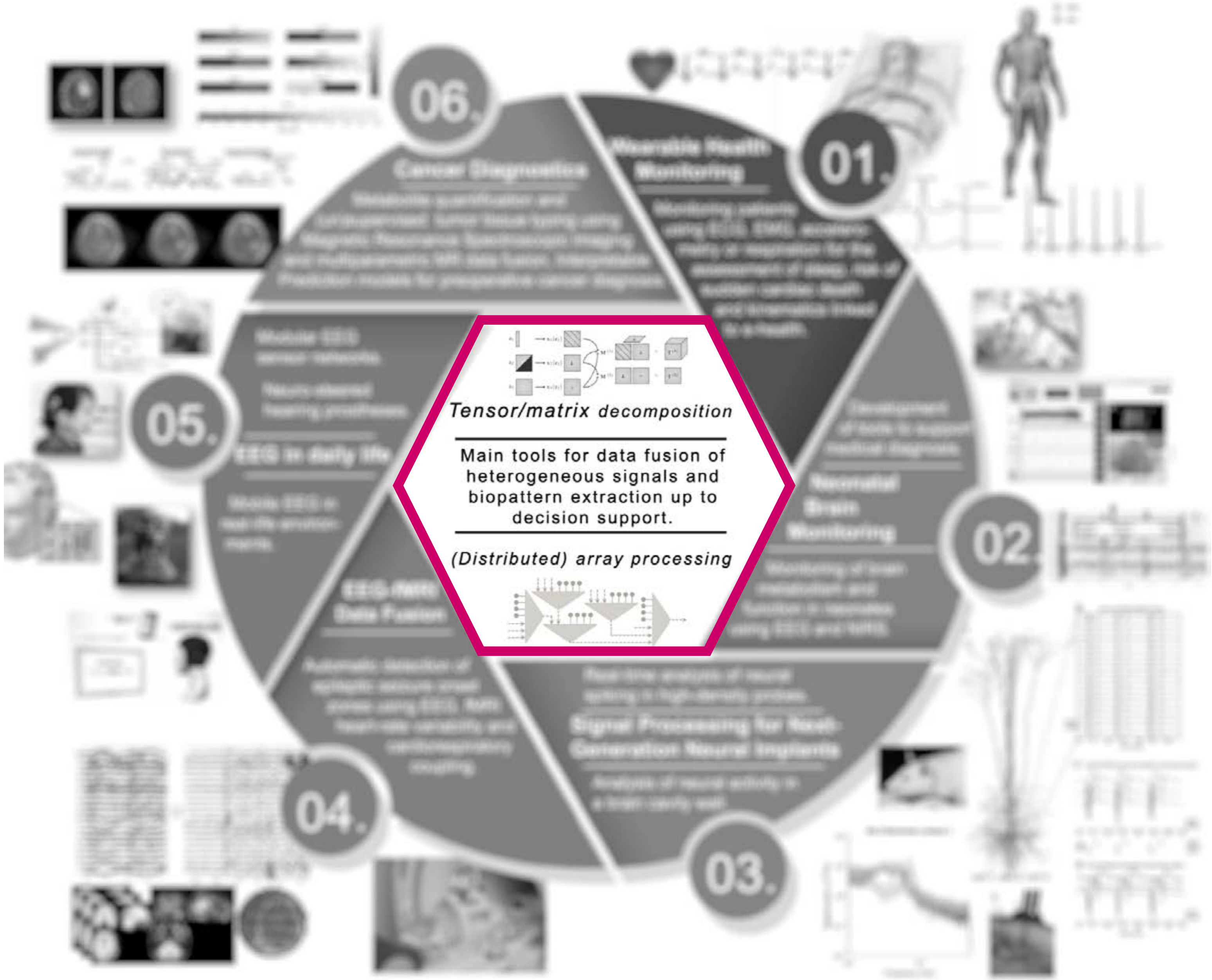
CPD



EEG = A ? S^T ?

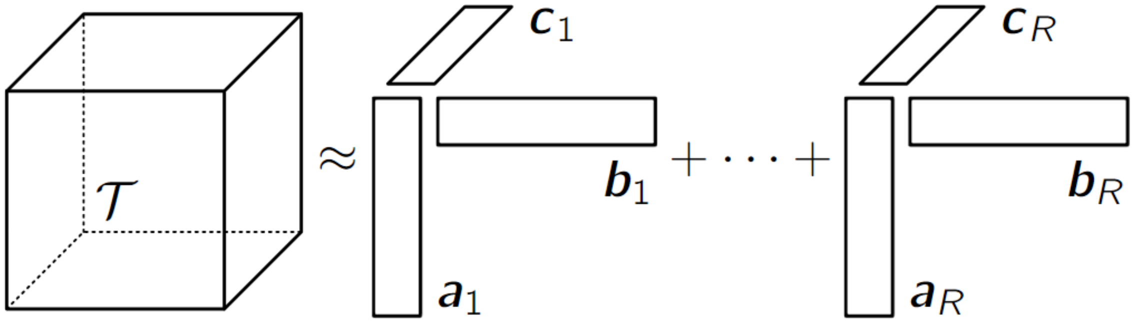
Research in close collaboration with




06.
01.
02.
03.
04.
05.
Tensor/matrix decomposition
Main tools for data fusion of heterogeneous signals and biopattern extraction up to decision support.
(Distributed) array processing

Tensor Decompositions:

Canonical Polyadic Decomposition - CPD

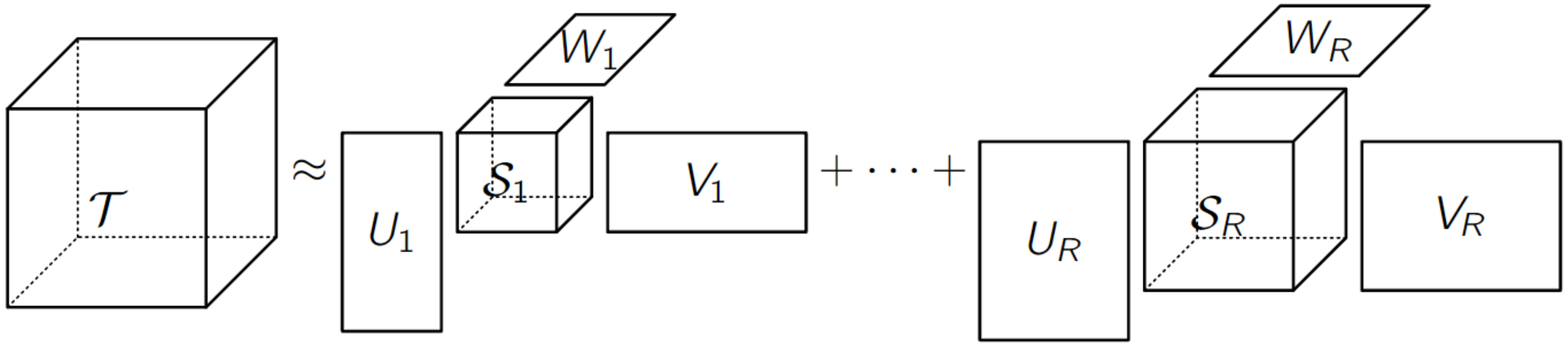


Tensorlab

A MATLAB package for tensor computations.

www.tensorlab.net

From CPD to Block Tensor Decomposition



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

Contents Overview

Birth of BIOTENSORS

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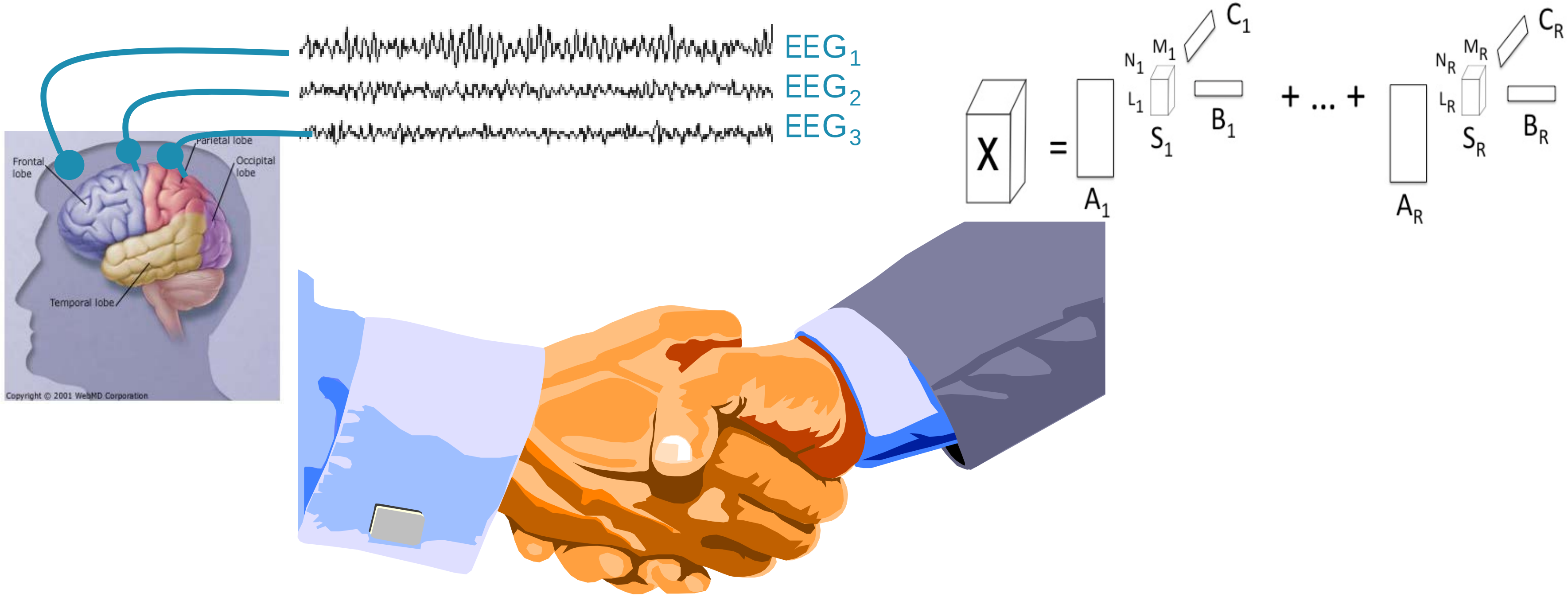
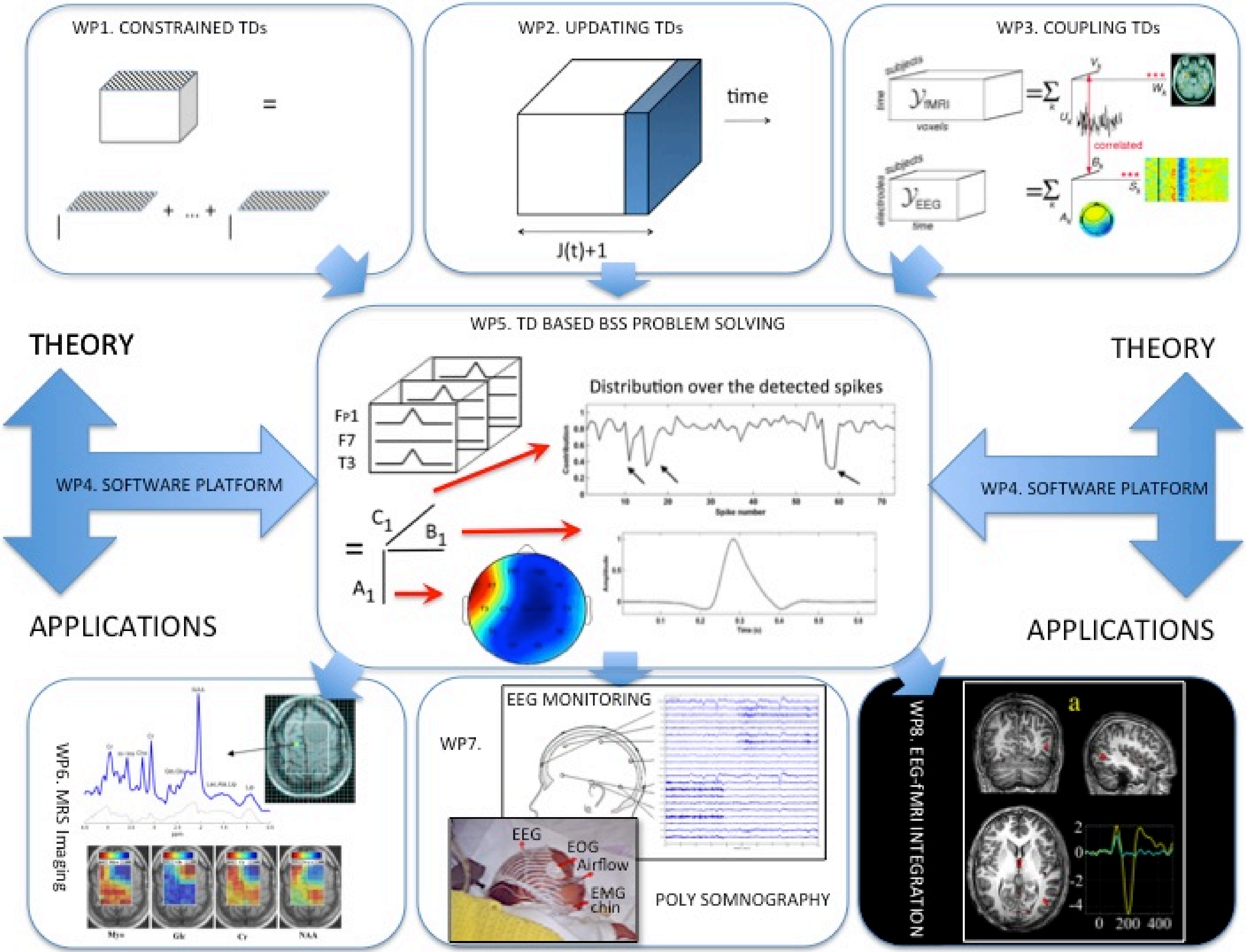
> 1982: Advanced (multi)linear Algebra as CORE in SISTA (later: SCD, now: Stadius)

> 1990: Birth Biomedical Data Processing Research in SISTA (HEADed by Sabine VH)

> 1992: Birth MULTIlinear Algebra Research in SISTA (HEADED by Lieven DL)

- ***BIOTENSORS: Joining expertise of Lieven and Sabine***
  - Idea: Christmas 2011
  - ERC Adv.grant: Submitted (Feb & Nov 2012) → Accepted (July 2013) → Start (April 2014)




WP1. CONSTRAINED TDs
WP2. UPDATING TDs
time
J(t)+1
WP3. COUPLING TDs
correlated
WP5. TD BASED BSS PROBLEM SOLVING
Distribution over the detected spikes
Fp1
F7
T3
THEORY
WP4. SOFTWARE PLATFORM
APPLICATIONS
THEORY
WP4. SOFTWARE PLATFORM
APPLICATIONS
WP6. MRS Imaging
WP7.
EEG MONITORING
EEG
EOG
Airflow
EMG
chin
POLY SOMNOGRAPHY
WP8. EEG-fMRI INTEGRATION

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WP1: Computing (constrained) tensor decompositions (1)

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Task 1.1 Basic algorithms

- *High-performance algorithms to solve Linear Systems with Kronecker Product-constrained solution (e.g. LS-CPD), providing broad framework for analysis of multilinear systems.*
- *Relaxed conditions (compared to Kruskal) for generic uniqueness proven for several tensor decompositions, including block terms, constraints and coupling. Extensions to missing fibers.*
- *New algorithms for the exact computation of the decomposition of a tensor into a sum of multilinear terms. Extended to CPD of large-scale tensors with missing fibers.*
- *Tensor optimization, improving computationally global minimization in line and plane search subproblems*
- *Exploiting sparsity, low-rank properties and incompleteness,allows decomposition of very large-scale tensors and even break the curse of dimensionality:*
  - *Randomized block sampling enabling decomposition of very large-scale tensors (e.g. 10^{18} entries) by sampling very few entries (e.g. 10^{5}).*
  - *Numerical framework exploiting efficient tensor representation enable large computational gains.*
- *Efficient algorithm for weighted CPD using low-rank weights*

Task 1.2 Constraints

- *New constraints embedded in tensor decompositions implemented: including nonnegativity, orthogonality, structure (Vandermonde, Kronecker, Khatri-Rao, exponential, Cauchy,…) and finite differences*

TALK WE AUG 29 11h15-12h: Nico Vervliet “Numerical optimization-based tensor algorithms”
TALKS MO & TU AUG 27 & 28 & 31: Lieven De Lathauwer ``The curse and blessing of dimensionality’’
TALK FR AUG 31 14h15-15h : Martijn Boussé ``Linear Systems with a CPD constrained solution’’
POSTERS WE AUG 29 16h: Ignat Domanov, Martijn Boussé

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WP1: Computing (constrained) tensor decompositions (2)

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Task 1.3 Source modeling

- *Exploiting Exponential polynomial model (Σ and/or Π of exponentials, sinusoids, polynomials), Rational model (Löwner matrices) and sparseness (compressive sampling)*
- *Segmentation is novel tensorization technique: useful for large-scale (instantaneous) blind source separation and (convolutive) blind system identification. It exploits property that sources/ inputs and/or mixing vectors/system coefficients are modelled as low-rank matrices or tensors.*
- *New signal separation techniques presented in tensor framework: including exponential polynomials, rational functions and Kronecker-product structured sources. Corresponding structured tensor algorithms (CPD, Tensor Train, Hankel, Löwner...) optimized in speed and data storage (no need to expand to full tensor).*
- *Löwner-based BSS technique developed to enable deterministic separation of signals into rational functions with applications in fetal ECG extraction and water removal using MRSI.*
- *Computationally efficient algorithms developed for tensor-based convolutive signal separation.*
- *Methods comparing tensor factors without computing the decompositions have been developed*

Contributors: Ignat Domanov, *Otto Debals, Mikael Sorensen, Xiao-Feng Gong,* Martijn Boussé, *Paul Smyth, Frederik Van Eeghem, Marco Signoretto, Chuan Chen, Alwin Stegeman,* Nico Vervliet, Michiel Vandecapelle

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WP2: Updating tensor decompositions

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Task 2.1 Updating in one dimension

- *NLLS algorithm developed for CPD updating of Nth order tensor with(out) low-rank weighting of tensor entries*.

  → *Outperforms state-of-the-art algorithm from Nion and Sidiropoulos (IEEE TSP 2009)*

Task 2.2 Updating in several dimensions

- *NLLS Algorithm generalized to allow updating in any number of dimensions*

Contributors: *Geunseop Lee,* Michel Vandecapelle, Nico Vervliet

WP3: Coupling tensor decompositions

Task 3.1 Algorithms

- *Coupled CPD models extended to coupled multilinear rank-($L_{r,n}$, $L_{r,n}$,1) terms with proven relaxed uniqueness conditions and allowing algebraic computation*
- *Coupled CPD modeling framework developed for solving Multidimensional Harmonic Retrieval problem and the Gaussian mixture parameter estimation.*

  → *Uniqueness conditions are most relaxed ones.*

  → *Very promising in sensor array processing enabling to exploit multiple spatial sampling structures (in contrast to ordinary CPD models)*
- *Algebraic Double Coupled-CPD algorithm presented based on a coupled rank-1 detection mapping for joint BSS, outperforming standard CPD based BSS methods*

Task 3.2 Coupling constraints

- *Tensor lab introduces Domain specific language (DSL) to easily represent various couplings and facilitate creation of models with approx. equal factor matrices*

Contributors: Lieven De Lathauwer, Laurent Sorber, Mikael Sorensen, Ignat Domanov, Frederik Van Eeghem, Nico Vervliet

TALK WE AUG 29 11h15-12h: Nico Vervliet “Numerical optimization-based tensor algorithms

POSTER WE AUG 29 16h: Ignat Domanov

WP4: Software platform for tensor-based BSS

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Powerful software tools allow to face current grand challenges in biomedical data fusion

Task 4.1 General purpose tensor toolbox

- *Algorithms in WP1-3 efficiently implemented in Tensorlab 3.0 and 4.0.*
- *Tensorlab allows to decompose structured tensors directly, avoids full tensor expansion*
  → very useful in tensorizations!
- *Improved user friendliness by simplifying model construction and adding visualization routines, documentation and demos.*
- *Matlab-based GUI facilitates visual inspection of 3rd order tensor CPD*

Task 4.2 Software platform for tensor-based biomedical source separation

- *Platform accessible to experts and non-experts (medical doctors)*
- *Integrate keytool Matlab implementations of WP6-8 as* ***easy-to-use toolboxes with GUI***

Contributors: *Laurent Sorber*, Nico Vervliet, *Otto De Bals,* Martijn Boussé, Griet Goovaerts, Borbála Hunyadi, HN Bharath, Stijn Dupulthys, Rob Zink, *Matthieu Vendeville, Vasile Sima*

TALK WE AUG 29 11h15-12h: Nico Vervliet “Numerical optimization-based tensor algorithms”
DEMOS MO & TU & FR AUG 27 & 28 &31: by Lieven De Lathauwer & Team, by Sabine Van Huffel & HN Bharath and Griet Goovaerts
POSTERS WE AUG 29 16h: Stijn Dupulthys, Martijn Boussé

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WP5: Tensor formulation of biomedical BSS problems (1)

Translate biomedical problem into an ``interpretable”tensor decomposition

Task 5.1 Artefact removal

- *Remove noise, irrelevant signals, …*

Task 5.2 Preprocessing

- *Low-pass filtering and downsampling effective measures to improve source extraction via CPD, e.g. in cognitive EEG*

Task 5.3 Tensorization

- *Various ways of tensorization* (Hankel, Löwner, decimation,…)
- *Segmentation especially useful for both large-scale (instantaneous) blind source separation and large-scale (convolutive) blind system identification.*
- *Strong properties of tensorized data revealed, efficient Tensorlab implementations, promising applications in biomedical BSS problems, e.g.:*
    - *ECG: beat-by-beat, segmentation strategy, Löwner tensorization*
    - *EEG: Hilbert-Huang transformation, Hankel expansion, trial-by-trial, multiscale expansion*
    - *MRSI: symmetric XX^T expansion, Löwner tensorization, Hankel expansion*

WP5: Tensor formulation of biomedical BSS problems (2)

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Task 5.4 Choice of decomposition type

- *CPD, BTD, MLSVD, convolutive mixture, …? Trade-off between simplicity and model accuracy.*
- *Supervised decompositions, e.g. HODA, might outperform unsupervised ones (e.g. MLSVD) for machine learning, e.g. classification in the LS-CPD setting.*

Task 5.5 Choice of decomposition parameters

- *Estimate rank and multilinear rank (Core Consistency Diagnostic, Pareto optimization, …)*
- *Can be automated by thresholding ML singular values in MLSVD using energy constraints*
  → applied to multichannel ECG compression.
- *Robustness improved by adding prior knowledge (e.g. templates).*

Task 5.6 Definition of constraints

- *Introduce relevant mathematical constraints (orthogonality, NN, periodicity, …)*

General framework presented for making informed choices in case of epileptic EEG-fMRI

Contributors: Rob Zink, Borbála Hunyadi, Simon Van Eyndhoven, *Otto De Bals,* Martijn Boussé, Griet Goovaerts

TALK TH AUG 30 16h45-18h15 by Borbála Hunyadi
TALKS FR AUG 31 8h45-9h45 by Sabine Van Huffel & HN Bharath and 11h15-12h45 by Griet Goovaerts
POSTERS WE AUG 29 16h: Sibasankar Padhy, Martijn Boussé, Simon Van Eyndhoven

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WP6: Tensor based BSS in Magnetic Resonance Spectroscopic Imaging

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Task 6.1 Metabolite quantification and artefact removal

- *Exponential and Löwner modeling of MRSI signals/spectra*
- *All-at-once water component removal from 2D/3D MRSI → outperforms voxel-wise approach*

Task 6.2 Brain tumour tissue typing

- *Extensions of NMF to NN CPD factorization*
- *Adjust multilinear rank to handle artefacts and incorporate prior knowledge*
- *Extension to multiparametric MRI (FLAIR, T1/T2, DWI, PWI)*

EXTRA Results:

- *NN CPD algorithm to detect longitudinal pathological changes → multiple sclerosis lesions* ***(this talk!)***
- *Supervised voxel classification using CNN and MLSVD-based regularization*
- *Supervised tissue segmentation using superpixel 2-stage random forest with MLSVD input*

Contributors: Bharath HN, ***Diana Sima, Nicolas Sauwen, Claudio Stamile***

WP7: Tensor based BSS in Functional monitoring (1)

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Task 7.1 Epileptic seizure detection in multichannel EEG

- *Seizure localization & artefact removal (eye, …) using wavelet expansion + CPD*

  → *If nonstationary : use wavelet expansion+ BTD or Hankel expansion+ (L,L,1)-BTD*
- *Supervised Nonconvulsive seizure detector using signatures from CPD/BTD of HHT tensor*
- *Adult EEG, neonatal EEG → preterm EEG*

Task 7.2 Neonatal Brain Monitoring

- *Supervised EEG background abnormality assessment using holistic tensor-based HODA approach*
- *Automated Sleep stage classification of preterm EEG using multiscale entropy + CPD **(this talk!)***

EXTRA: *physical activity recognition from single arm-worn accelerometer using HODA approach **(this talk!)***

Contributors: Borbála Hunyadi, Ofelie De Wel, Stijn Dupulthys, *Vladimir Matic,* Yissel Aldana Rodriguez, Lieven Billiet

TALK TH AUG 30 16h45-18h15: Borbála Hunyadi “Tensor-based blind source separation in simultaneous EEG-fMRI integration”
POSTERS WE AUG 29 16h: Yissel Aldana Rodriguez, Stijn Dupulthys, Ofelie De Wel

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WP7: Tensor based BSS in Functional monitoring (2)

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EXTRA to Task 7.2: Cardiac Monitoring using multichannel ECG

- *T-wave alternans detection using beat-by-beat tensor CPD and PARAFAC2*
- *Irregular heartbeat detection using CPD and Kronecker Product Equations*
- *Atrial fibrillation detection using wavelet & beat-by-beat expansions and MLSVD*
- *Fetal heart extraction using Löwner tensor and segmentation approaches*
- *Prediction of in-hospital cardiac arrest using tensor CPD*

EXTRA: Multiscale Analysis-by-synthesis approaches using MLSVD and multichannel ECG

- *ECG compression*
- *Detection & localization of myocardial infarction*
- *T-wave alternans Detection*

Contributors: Griet Goovaerts, Carolina Varon, Sibasankar Padhy , Simon Geirnaert

TALK FR AUG 31 11h15-12h45: Griet Goovaerts “Tensor-based blind source separation in cardiac monitoring ”
POSTERS WE AUG 29 16h: Simon Geirnaert, Sibasankar Padhy, Martijn Boussé

WP8: Tensor based BSS in simultaneous EEG-fMRI integration

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Focus on 2 studies: Cognitive functioning and Seizure localization

Extra to Task 8.1: Cognitive Functioning using mobile EEG

- *Auditory P300 recognition in single-trial ERP without subject-specific calibration phase using structured CPD*
  → *further extended to structured BTD approach* ***(this talk!)***
- *Alpha and low-beta oscillatory wave extraction using wavelet transformed EEG + CPD*
- *Extraction of N100 and P300 across subjects using CPD*

Task 8.2 New EEG-fMRI integration approaches based on (coupled) CPD/BTD

Epileptic zone localisation

- *Coupled Matrix-Tensor Factorization (CMTF) approach outperforming (multichannel) joint ICA*

Cognitive functioning (spatiotemporal brain path characterisation during visual detection task)

- *Multichannel extension of jointICA*
- *Structured CMTF with Toeplitz factor to model neural-hemodynamic coupling via flexible EEG-fMRI fusion*

Contributors: Borbála Hunyadi, *Wout Swinnen,* Simon Van Eyndhoven, Rob Zink, Stijn Dupulthys

TALK TH AUG 30 16h45-18h15: Borbála Hunyadi “Tensor-based blind source separation in simultaneous EEG-fMRI integration”
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Contents Overview

Cancer & MS Diagnostics

UZ Leuven departments

Imaging & Pathology

Radiology

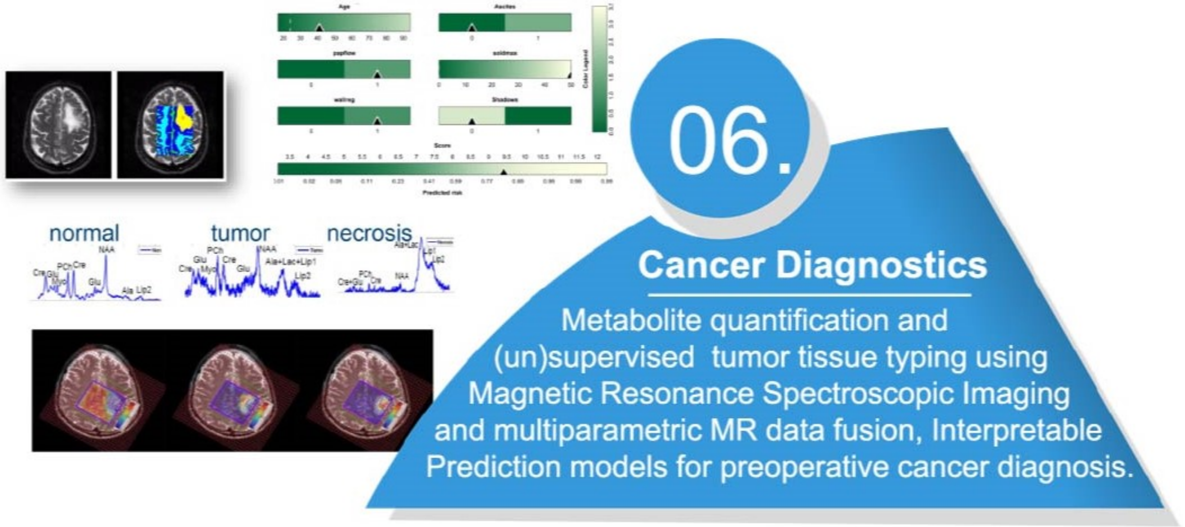
Neurosurgery

Development and Regeneration

Université Claude Bernard Lyon 1

Radiology

Neurology



EXAMPLE

TENSOR-BASED BSS FOR WHITE MATTER FIBER-BUNDLE ANALYSIS IN MULTIPLE SCLEROSIS

Collaborator: joint PhD of Claudio Stamile

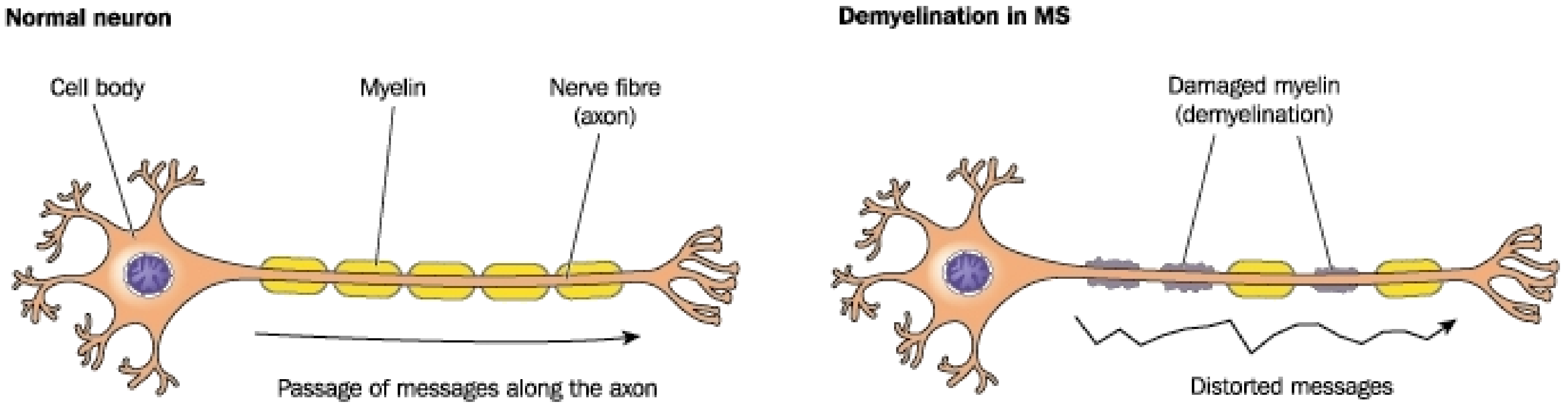
(Université Claude Bernard Lyon 1 + KU Leuven)

http://tinyurl.com/stamile-phd

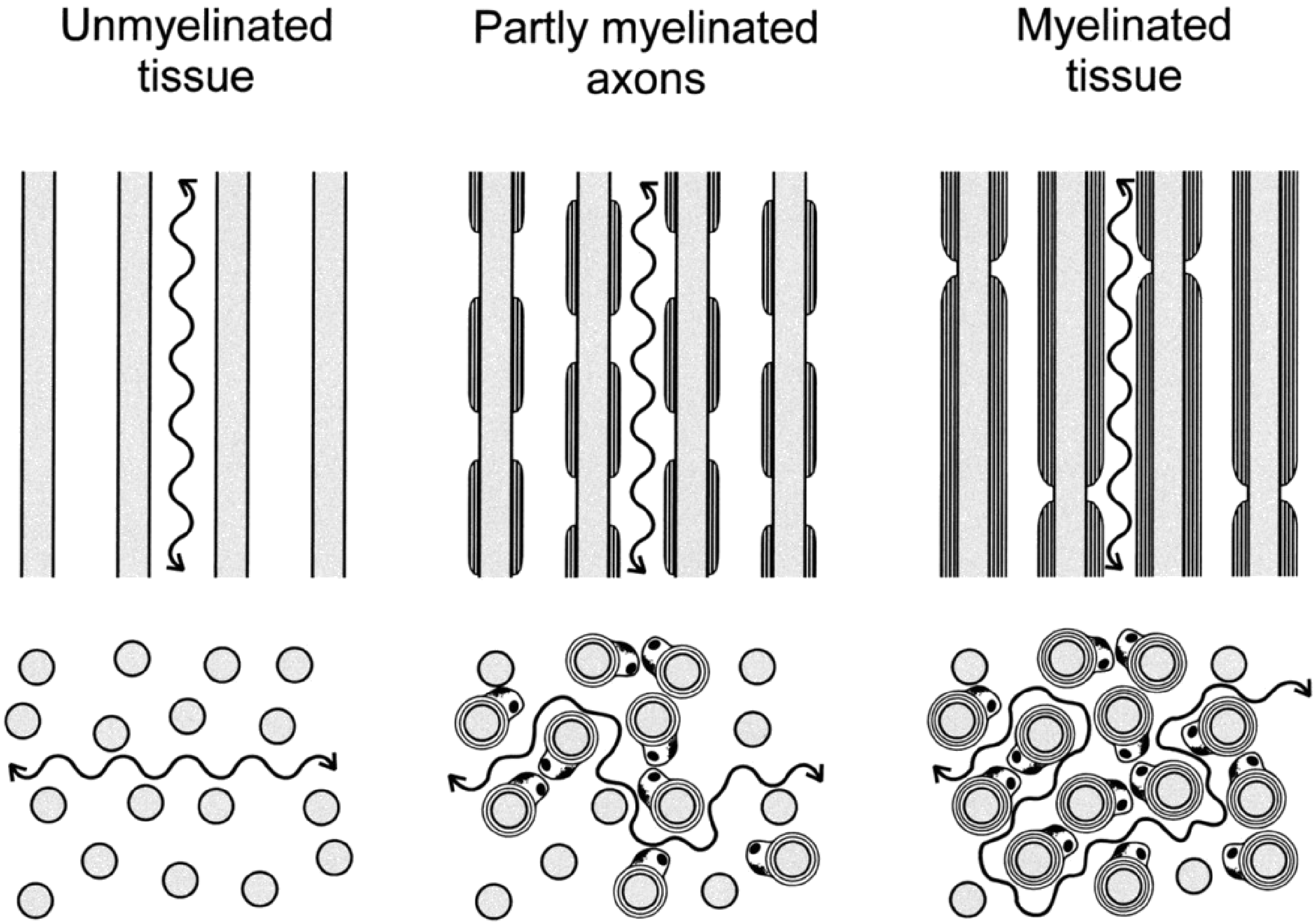
MULTIPLE SCLEROSIS

Multiple Sclerosis (MS) is a chronic disease of the central nervous system

- Demyelinating and Inflammatory Component
  - White Matter Lesions
- Neurodegenerative Component
  - Axonal loss

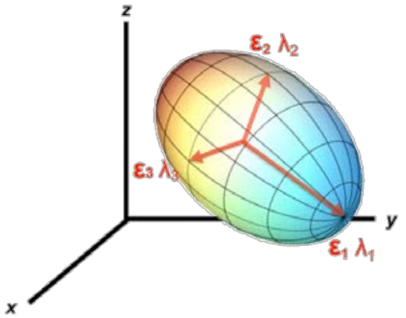


DIFFUSION IMAGING



- Movement of the water inside the tissue
- Provide indirect measure of the tissue architecture

DIFFUSION TENSOR IMAGING

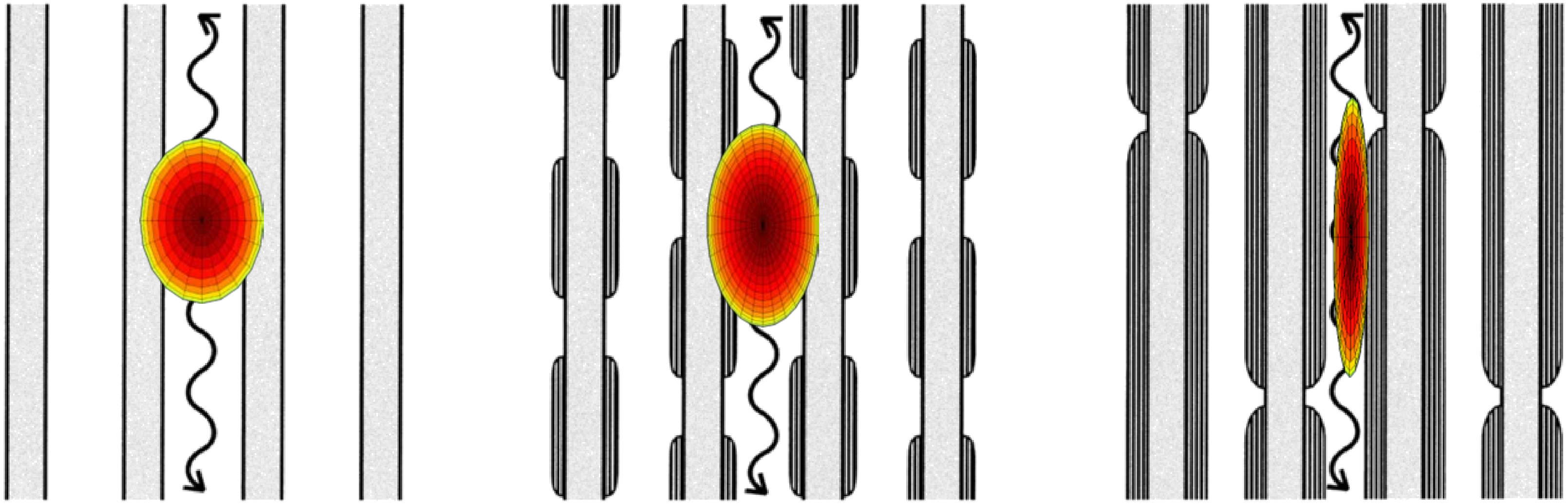


$$D = \begin{pmatrix} D_{xx} & D_{xy} & D_{xz} \\ D_{xy} & D_{yy} & D_{yz} \\ D_{xz} & D_{yz} & D_{zz} \end{pmatrix} = \begin{pmatrix} \lambda_1 & 0 & 0 \\ 0 & \lambda_2 & 0 \\ 0 & 0 & \lambda_3 \end{pmatrix} \begin{pmatrix} \vec{\epsilon_1} \\ \vec{\epsilon_2} \\ \vec{\epsilon_3} \end{pmatrix}$$

Unmyelinated tissue

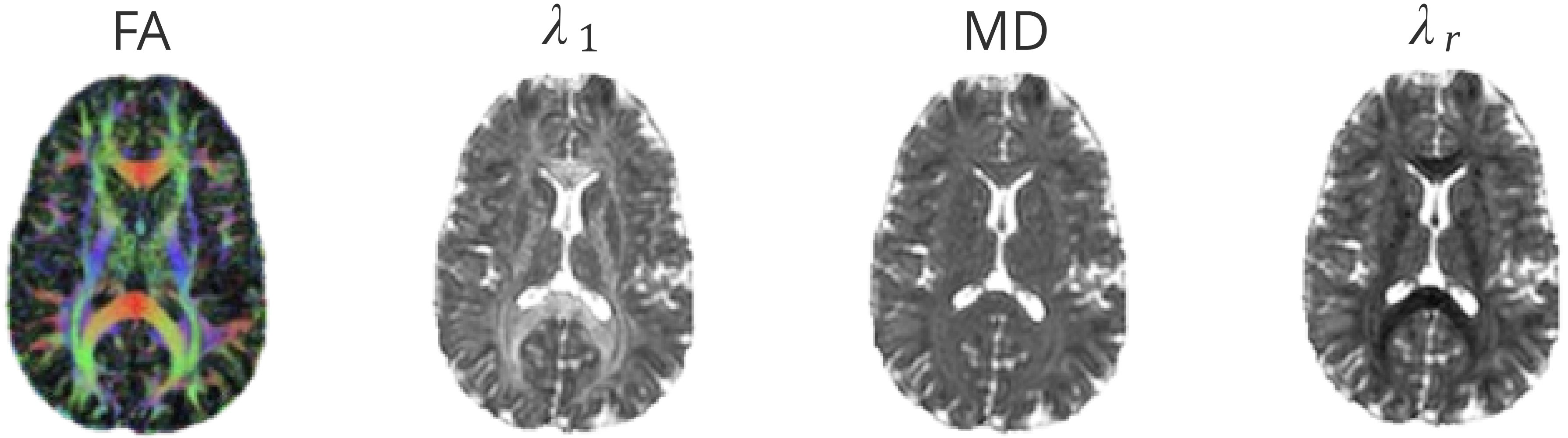
Partly myelinated axons

Myelinated tissue

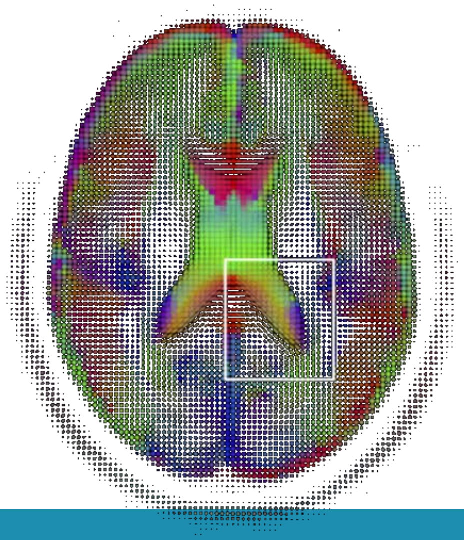


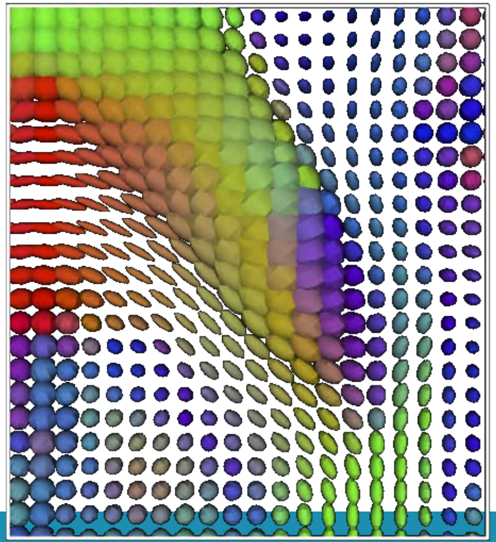
Shape of the ellipsoid changes according to the tissue structure

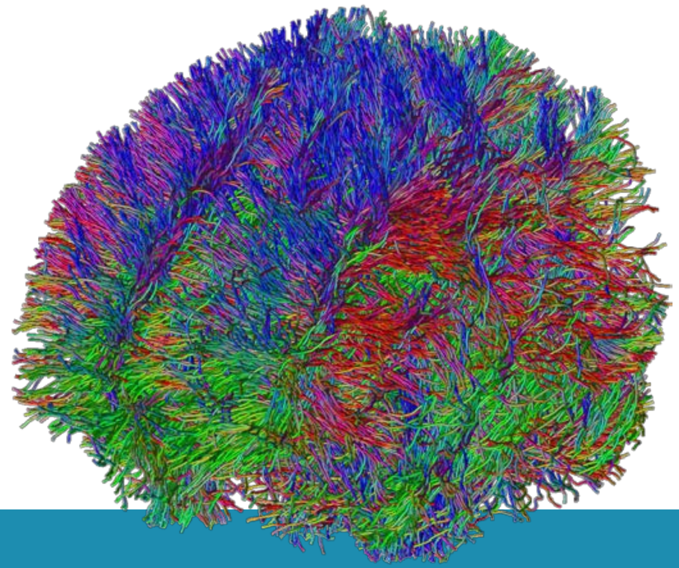
DIFFUSION TENSOR IMAGING



Quantitative information



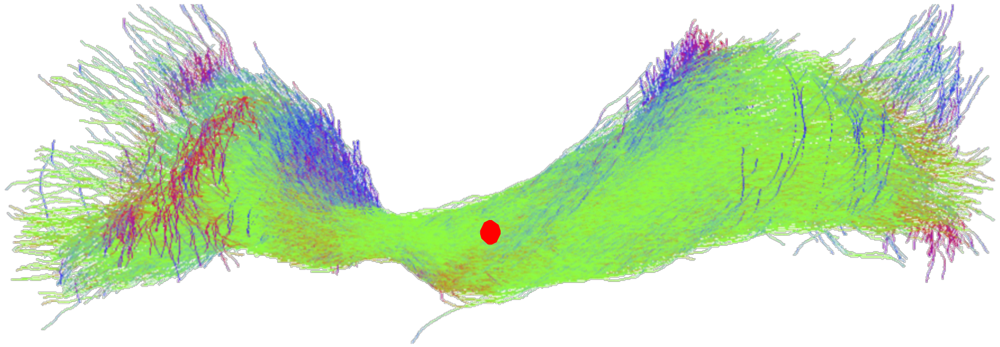




Structural information

MAIN OBJECTIVES

Demyelination and inflammation lead to alterations in fiber-bundles signal conduction



Objectives :

1. Provide a better characterization of fiber-bundles profile:
   - Sensitive detection of WM lesions
   - Analyze afferent and efferent pathways
2. **Longitudinal fiber-bundle analysis → This talk!**

Evidence-based decision making for personalized treatment of beginning MS patients to reduce disease severity at an early time-point.

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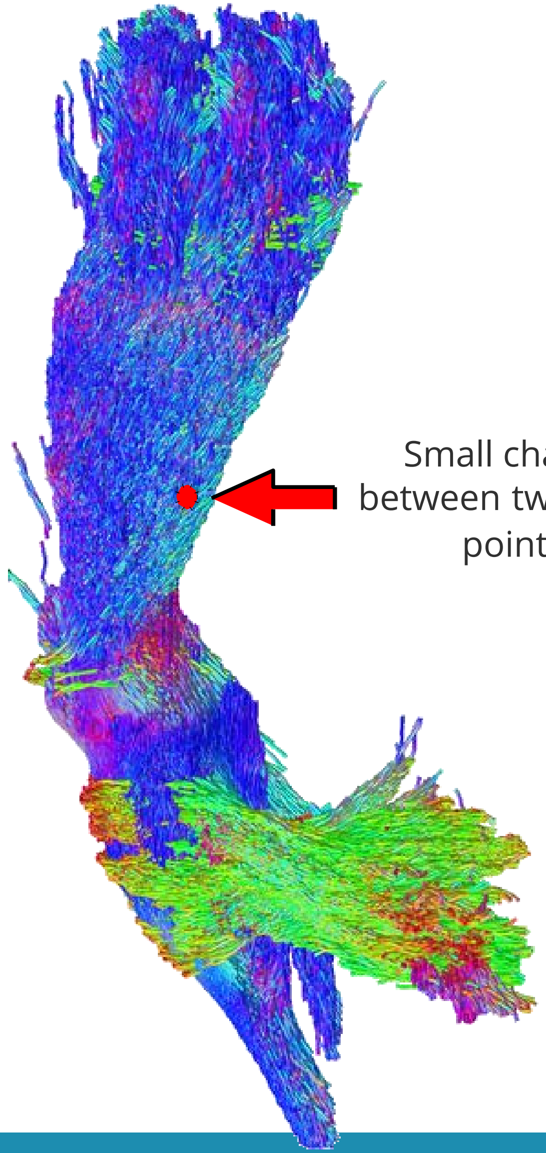
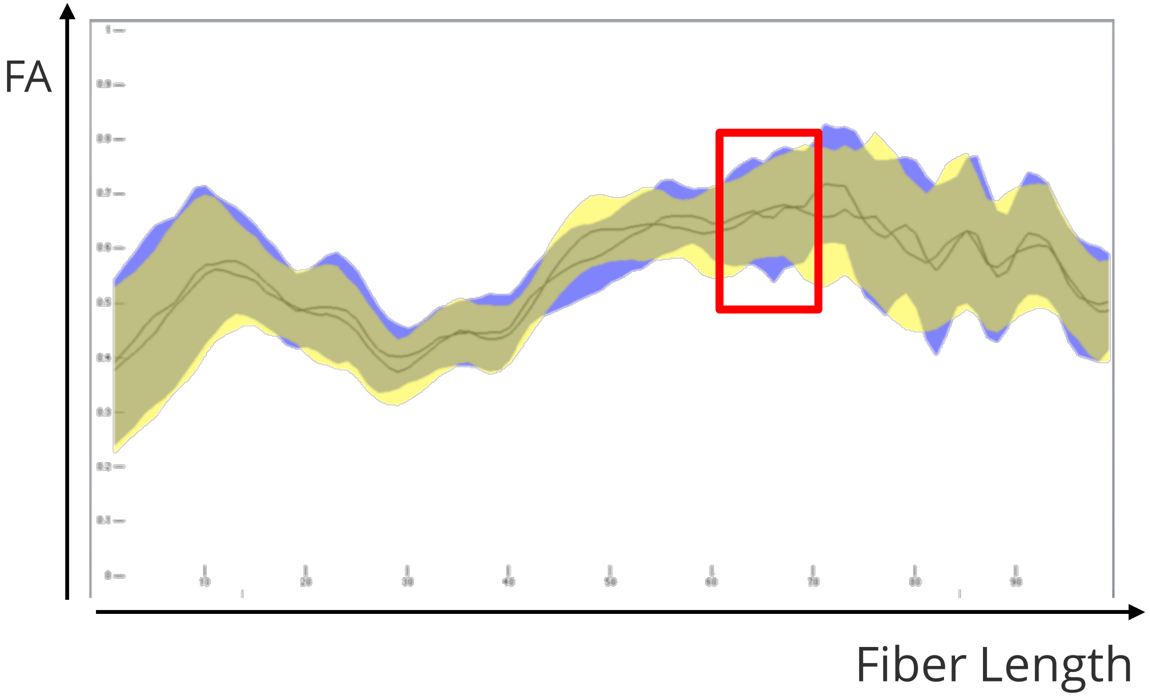
"MEAN" FIBER PROFILE ANALYSIS



Small change between two time-points

Time Point 1

Time Point 2

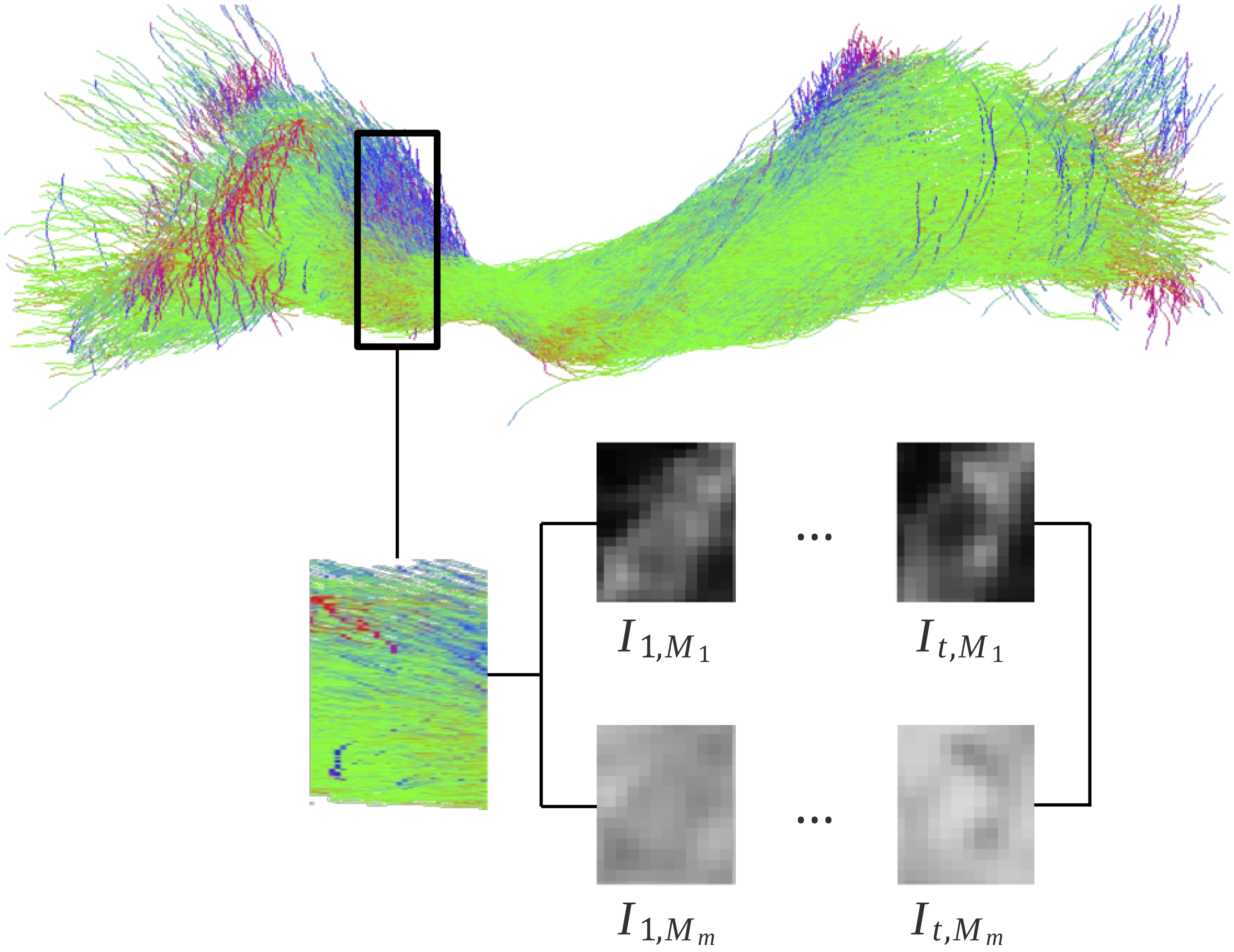


Not sensitive enough to detect small changes

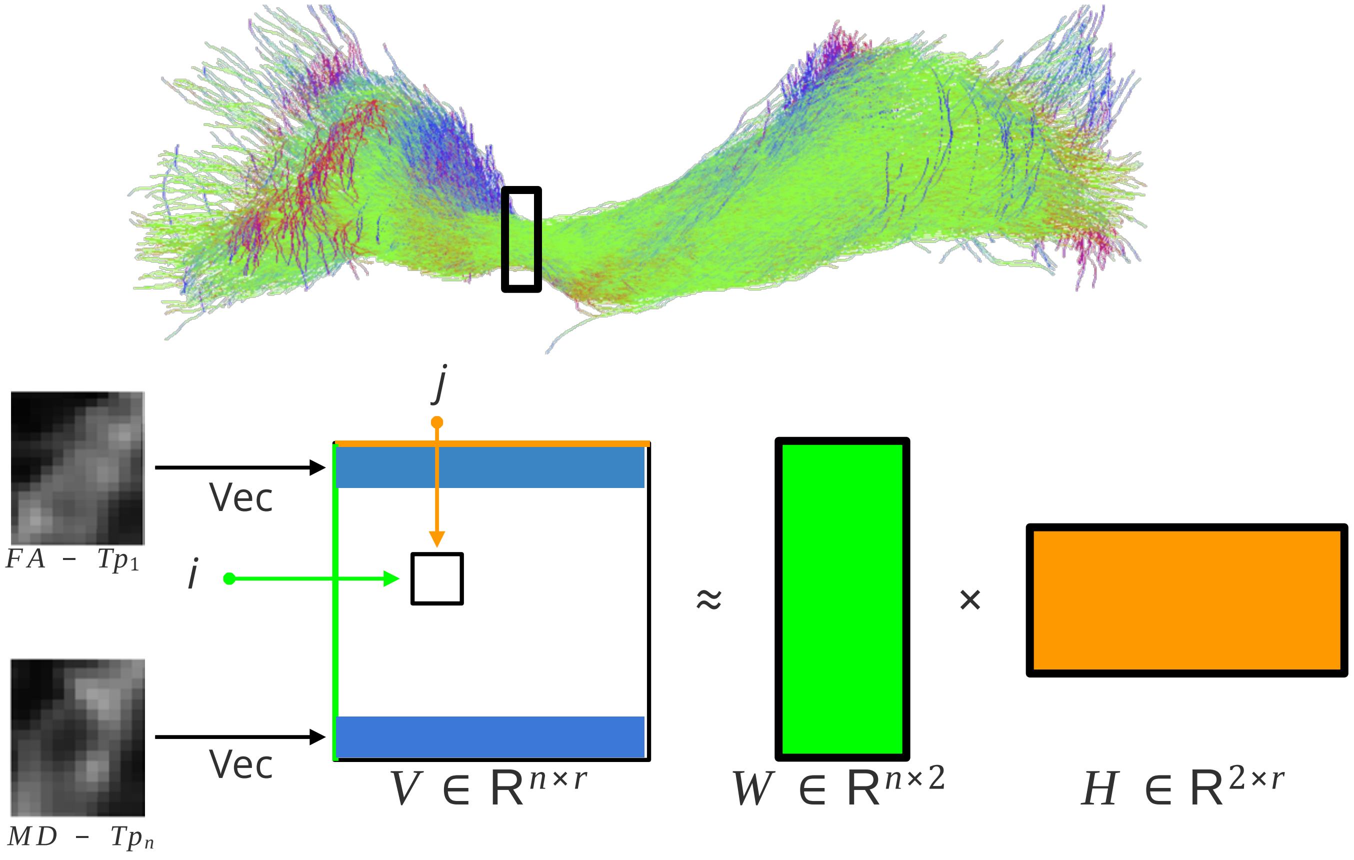
LONGITUDINAL ANALYSIS

NON-NEGATIVE MATRIX FACTORIZATION

NON-NEGATIVE MATRIX FACTORIZATION



NON-NEGATIVE MATRIX FACTORIZATION



$V_{i,j}$ = Value of the *i-th* modality/time-point for the *j-th* voxel of the cross-section

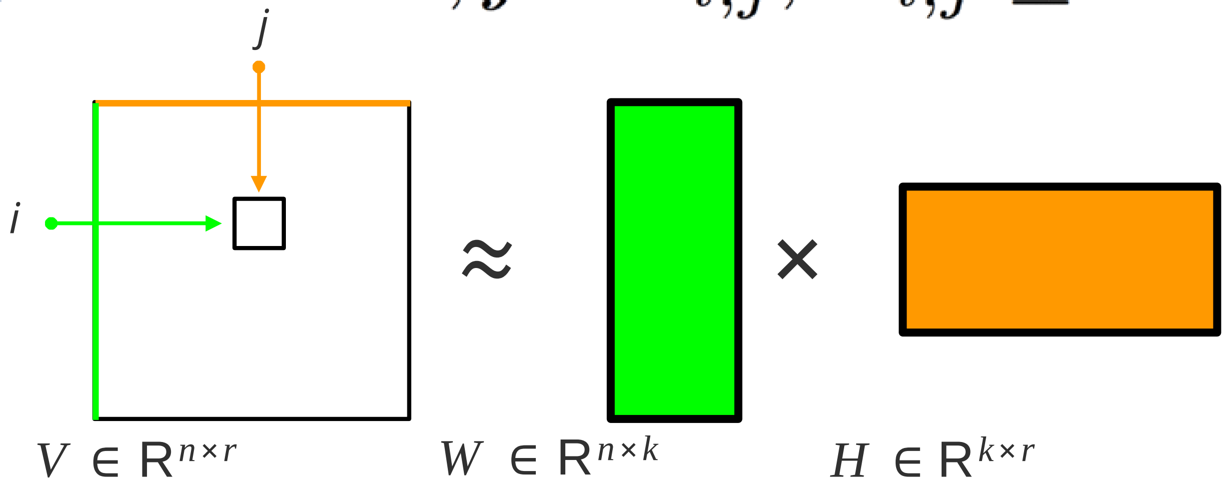
W Longitudinal modality contribution

H Segmentation of "normal" and "pathological" voxels

NON-NEGATIVE MATRIX FACTORIZATION

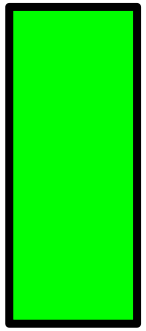
$$\underset{\boldsymbol{W},\boldsymbol{H}}{\text{minimize}} \quad f(\boldsymbol{W},\boldsymbol{H}) = \frac{1}{2}\|V - W \times H\|_F^2$$

$$\text{subject to} \quad \forall\, i,j : W_{i,j}, H_{i,j} \geq 0$$



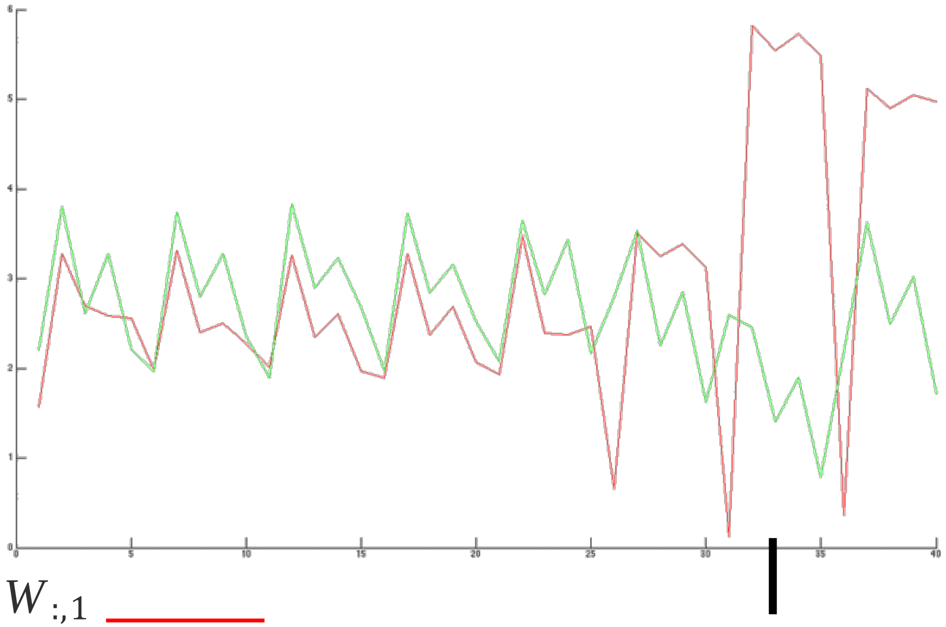
- Non Convex optimization problem → Apply sequentially = Recursive NMF
- Different algorithms proposed in literature:
  - Alternating Least Squares (ALS) ,Multiplicative Update, Hierarchical ALS

NON-NEGATIVE MATRIX FACTORIZATION



$W \in \mathbb{R}^{n\times 2}$

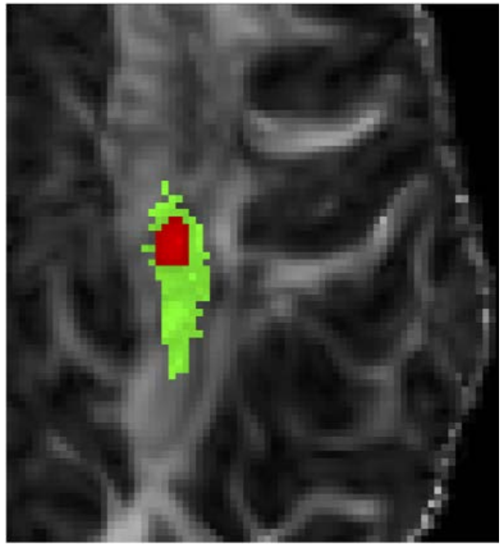
$H \in \mathbb{R}^{2\times r}$



$W_{:,1}$

$W_{:,2}$

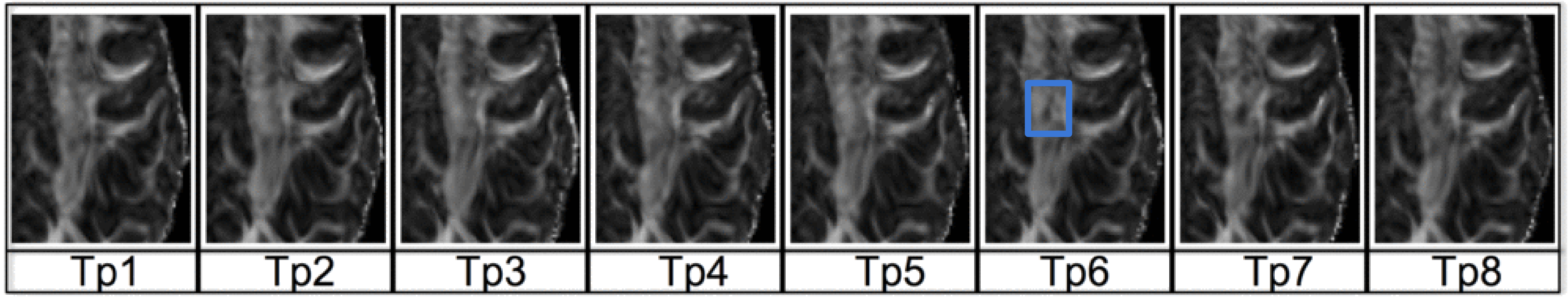
Local Outlier Factor(LOF)

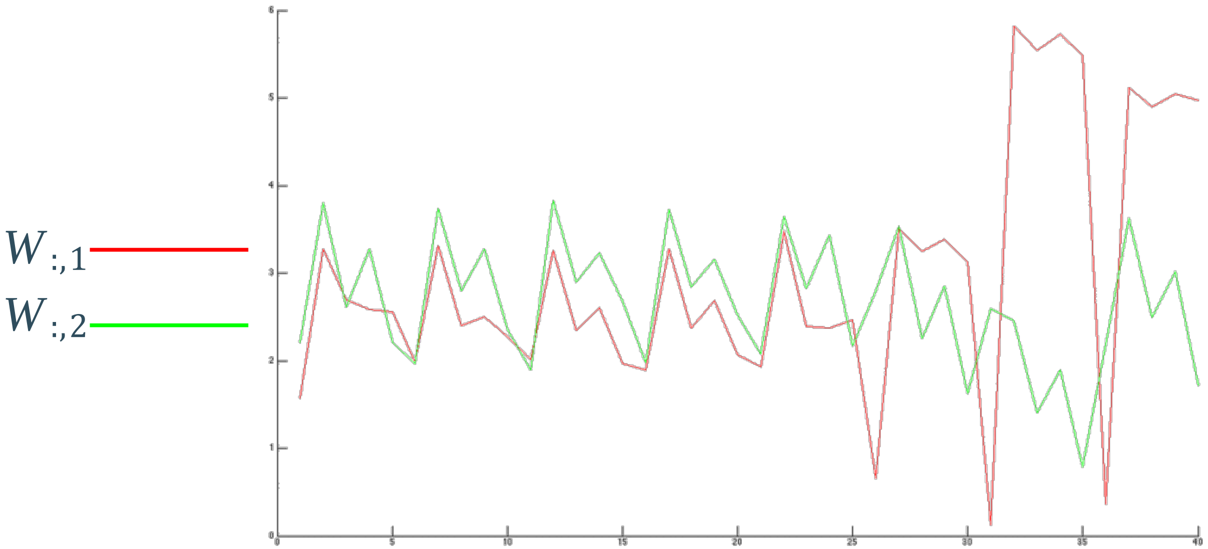


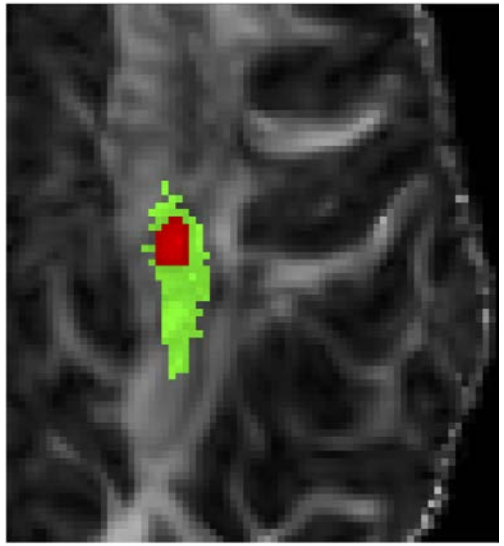
$H_{1,:}$

$H_{2,:}$

APPLICATION ON MS PATIENTS





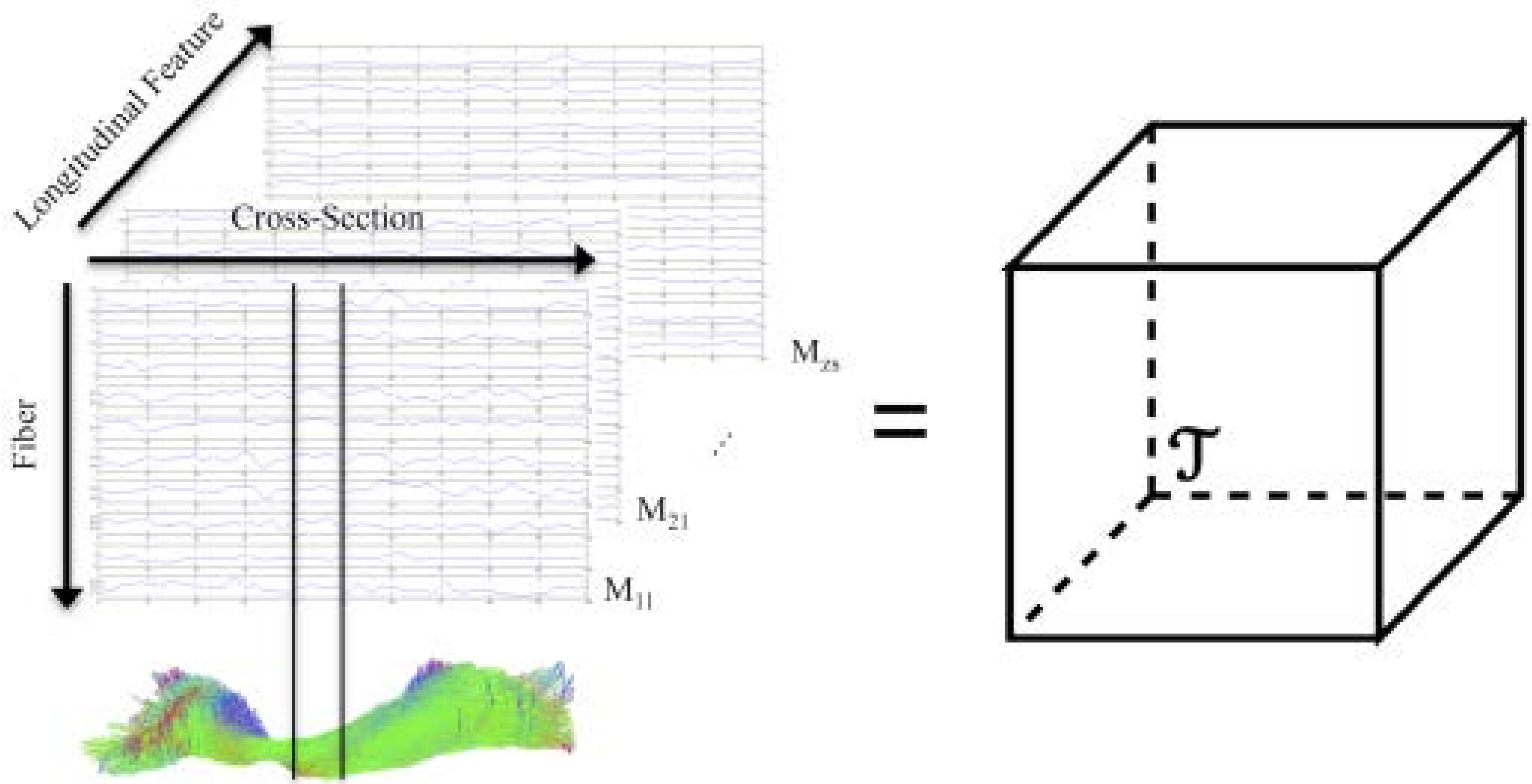


$H_{1,:}$

$H_{2,:}$

LONGITUDINAL ANALYSIS

NON-NEGATIVE TENSOR FACTORIZATION



Stamile et al., ICIAR, *2016*
Stamile et al., IEEE JBHI, *submitted*

NON-NEGATIVE TENSOR FACTORIZATION

- z : Number of features
- s : Number of time-points
- M_{ij}: *i-th* feature at *j-th* time-point

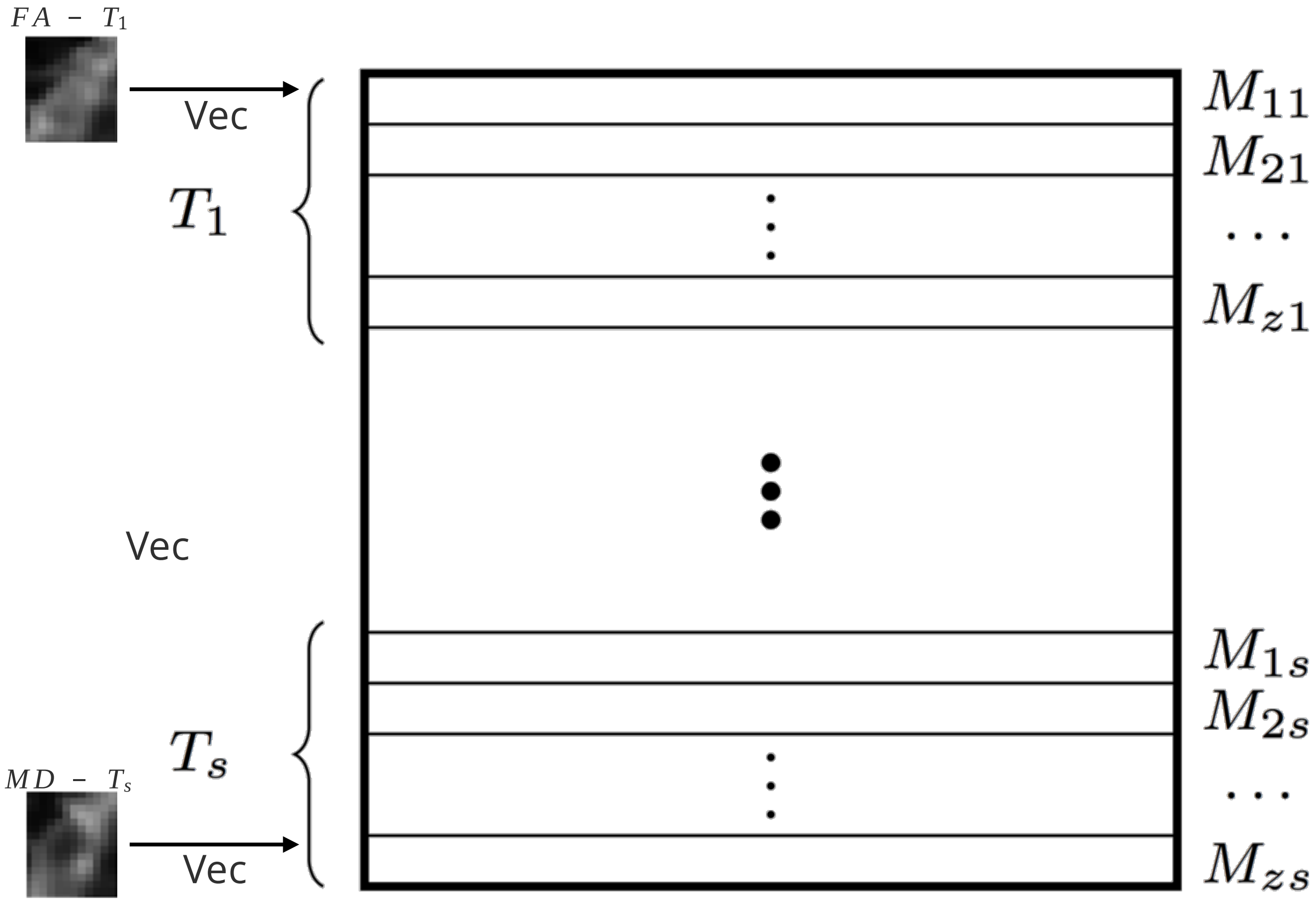
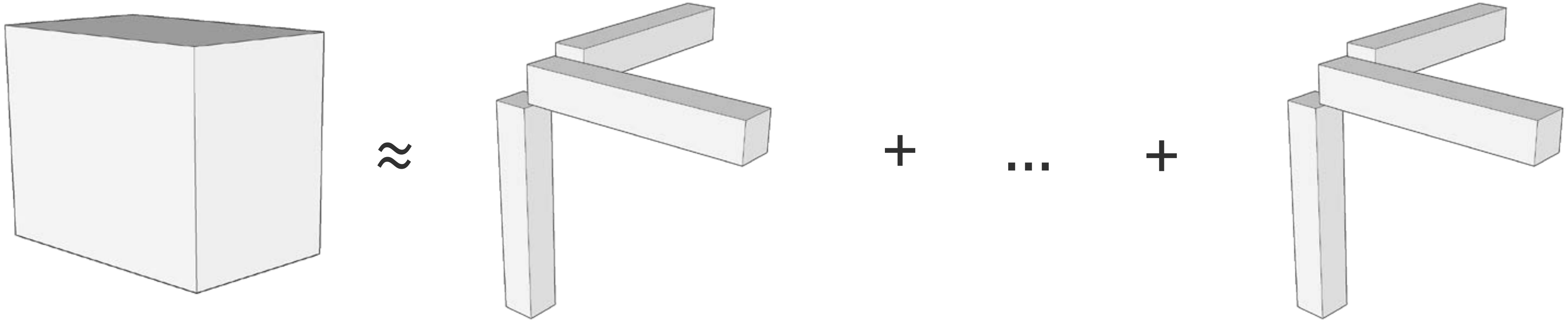


Illustration of the 3^{rd} mode of the tensor T

NON-NEGATIVE TENSOR FACTORIZATION

Canonical Polyadic Decomposition (CPD) is a decomposition of a tensor T into sum of rank-1 tensors



$\mathcal{T} \approx a_1 \circ b_1 \circ c_1 + \dots + a_R \circ b_R \circ c_R$

The rank (*R*) of a CPD is the number of rank-1 tensors used to approximate $a_i, b_i, c_i \geq 0$

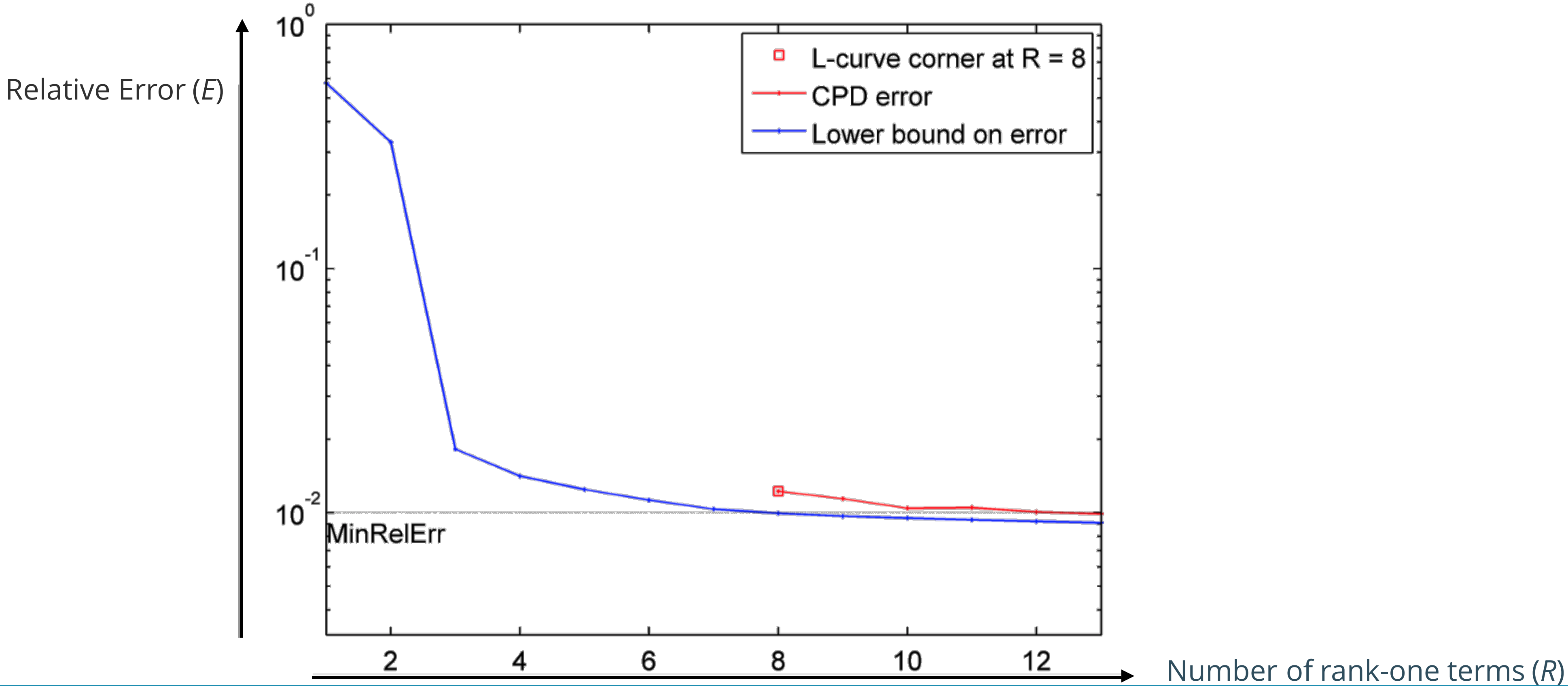
$$\min_{\boldsymbol{a_i} \geq 0, \boldsymbol{b_i} \geq 0, \boldsymbol{c_i} \geq 0 \quad i=1,\dots,R} \left\| \mathcal{T} - \sum_{i=1}^{R} \boldsymbol{a_i} \circ \boldsymbol{b_i} \circ \boldsymbol{c_i} \right\|_F^2$$

- Non Convex optimization problem. A set of algorithms available in [TensorLab]

NON-NEGATIVE TENSOR FACTORIZATION

Rank estimation R (using *rankest* from Tensorlab, based on L-curve)

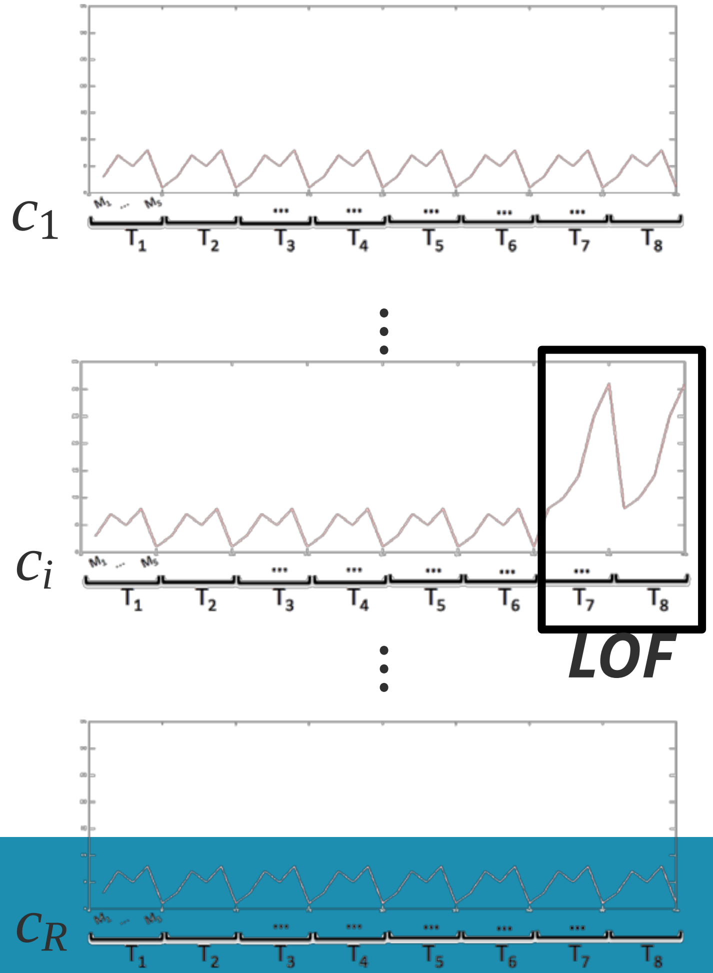
1. The number of rank-one terms (R) is increased
2. The relative error (E) of the approximation is computed
3. If E < *MinRelErr* the rank is defined



NON-NEGATIVE TENSOR FACTORIZATION

Identification of components

1. Identify the rank-one components containing information related to "pathological longitudinal changes"



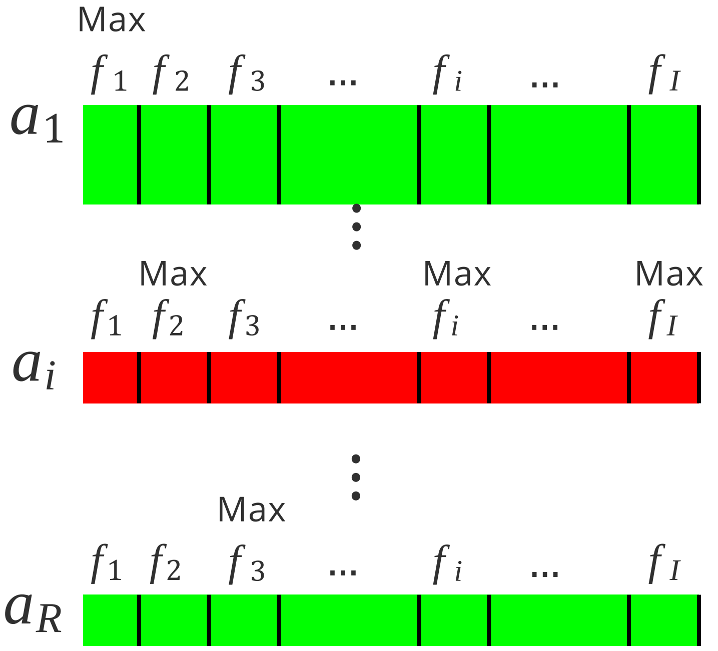
The algorithm collects the indices of all the rank-one terms containing outliers identified by LOF

$$P = \{c_i \; 1 \leq i \leq R \mid c_i \; contains \; Outliers\}$$

NON-NEGATIVE TENSOR FACTORIZATION

Pathological fibers identification:

1. Identifies the set P of fibers represented by rank-one terms identified as "outliers" by the previous step.



For each $f_j \in F$:

if $a_{ij} = max(A_{[i,:]}, i \in P)$

is Pathological

else

is Normal

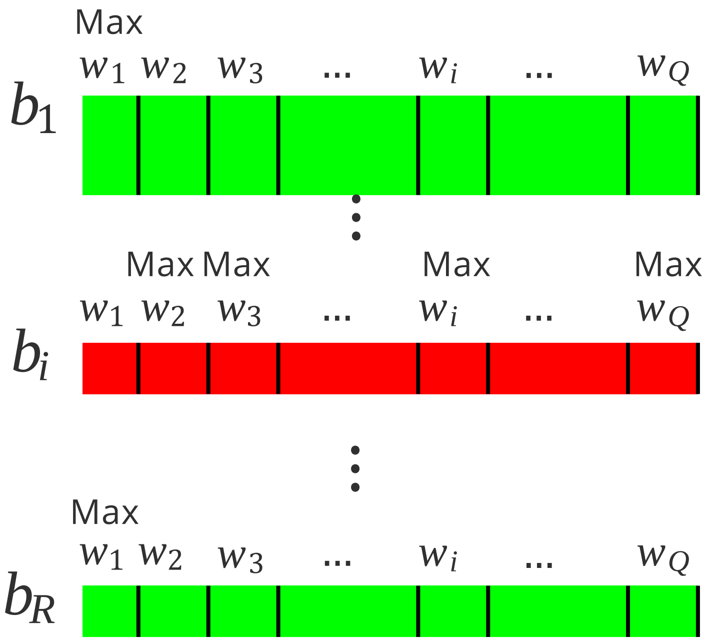
$\{f_2, f_i, f_I\}$ Are detected as pathological fibers

- They have maximal contribution in terms detected as outlier in the previous step

NON-NEGATIVE TENSOR FACTORIZATION

Pathological cross-sections identification:

1. Identifies the set H of cross-sections represented by rank-one terms identified as "outliers" by the previous step.



For each $w_j \in F$:

if $b_{ij} = max(B_{[i,:]}, i \in P)$

$is\ Pathological$

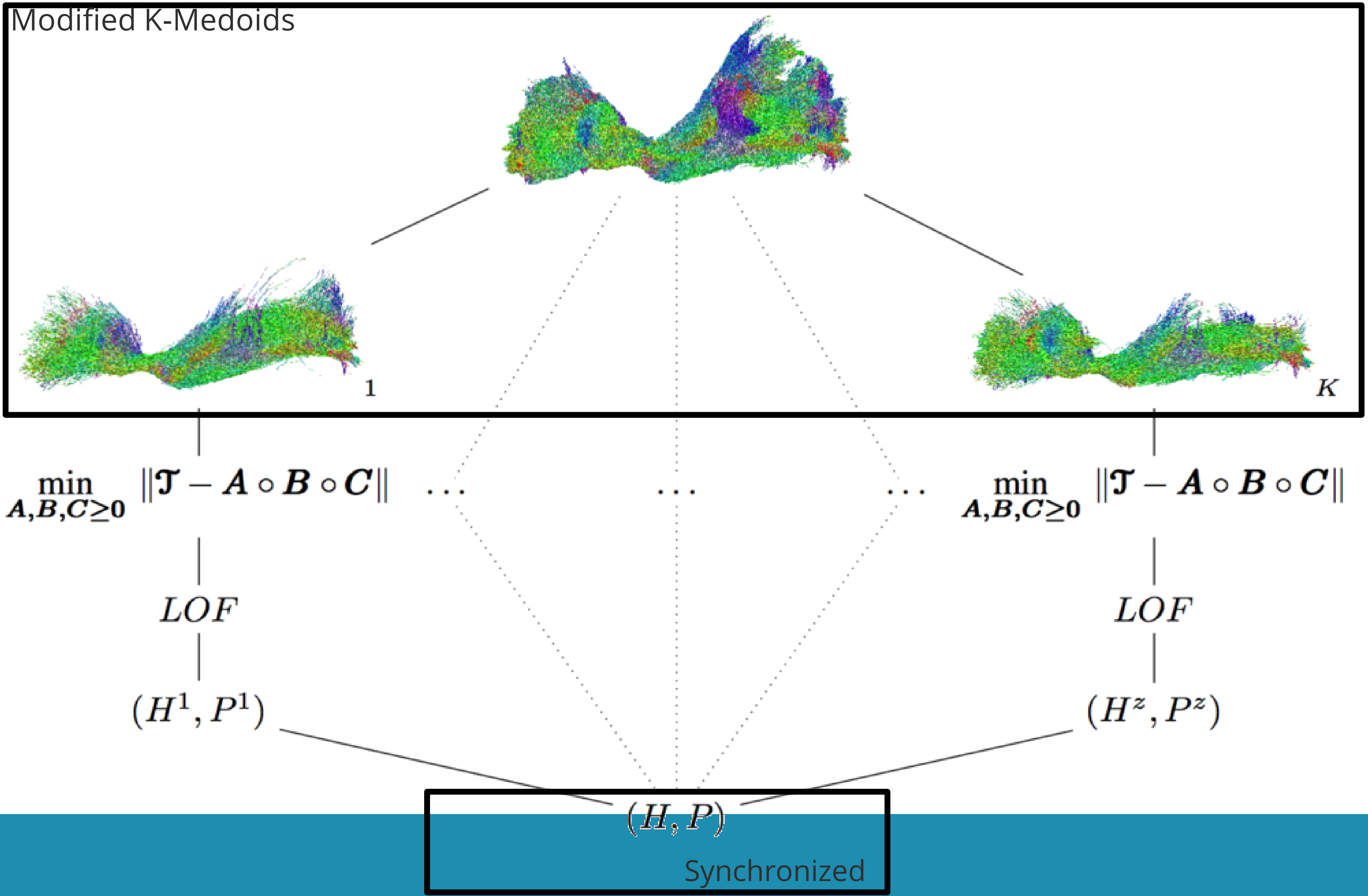
else

$is\ Normal$

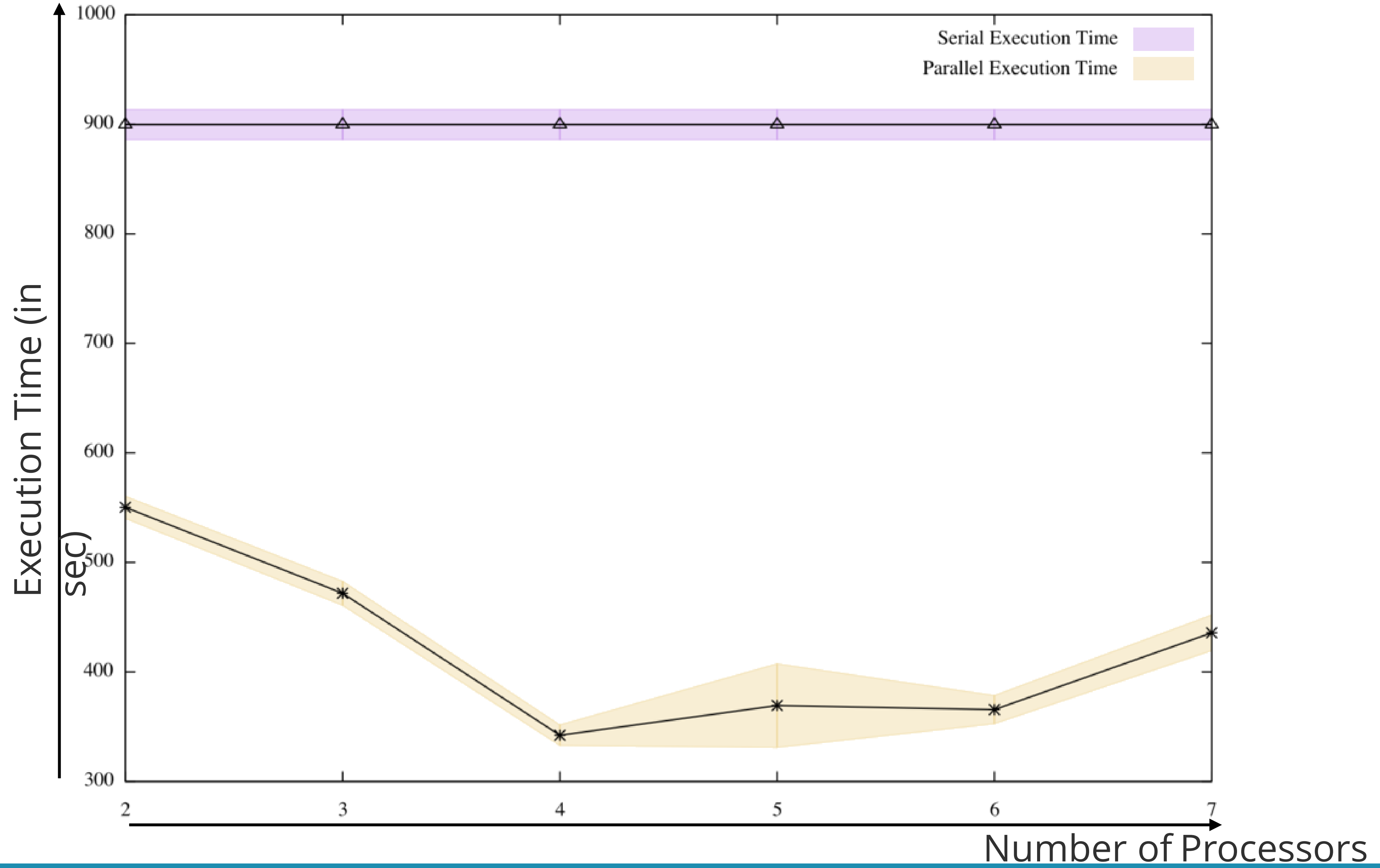
$\{w_2, w_3, w_i, w_Q\}$ are detected as pathological cross-sections

- They have maximal contribution in terms detected as outlier in previous step

PARALLEL IMPLEMENTATION



PARALLEL IMPLEMENTATION-RESULTS



- Min Speed-up factor: 1.63 (*K=2*)
- Max Speed-up factor: 2.60 (*K=4*)

RESULTS ON SIMULATED DATA

- 100 longitudinal variations were simulated on control subject
- LVS simulation model was used
- Variations were generated along 10 different fiber-bundles
- Different features extracted from diffusion maps obtained from the data
- Extensive grid search was performed in order to find the best parameters for the algorithm

RESULTS ON SIMULATED DATA

Detection of pathological fibers

	Accuracy	Precision	Sensitivity
λ_2,λ_3	**0.97 (0.06)**	**0.79 (0.08)**	**0.40 (0.11)**
λ_2,λ_3, FA	0.77 (0.29)	0.73 (0.11)	0.20 (0.02)
λ_2,λ_3, FA, MD	0.79 (0.32)	0.76 (0.15)	0.23 (0.05)
KLA,AA	0.71 (0.23)	0.69 (0.13)	0.16 (0.01)
KLA,FA,AA	0.77 (0.20)	0.66 (0.15)	0.15 (0.04)

Detection of pathological cross-sections

	Tensor Factorization			Non-Negative Matrix Factorization		
	Accuracy	Precision	Sensitivity	Accuracy	Precision	Sensitivity
λ_2,λ_3	0.63 (0.10)	0.98 (0.02)	**0.95 (0.15)**	0.65 (0.12)	0.60 (0.08)	0.92 (0.10)
λ_2,λ_3, FA	0.40 (0.12)	**1.00 (0.01)**	0.56 (0.12)	**0.74 (0.11)**	0.68 (0.04)	0.90 (0.09)
λ_2,λ_3, FA, MD	0.47 (0.13)	0.97 (0.03)	0.74 (0.23)	**0.74 (0.08)**	0.68 (0.12)	0.89 (0.11)
KLA,AA	0.30 (0.10)	0.96 (0.03)	0.64 (0.30)	0.59 (0.07)	0.55 (0.12)	0.91 (0.10)
KLA,FA,AA	0.32 (0.12)	0.96 (0.03)	0.63 (0.28)	0.56 (0.11)	0.53 (0.09)	0.85 (0.05)

Detection of pathological time-points

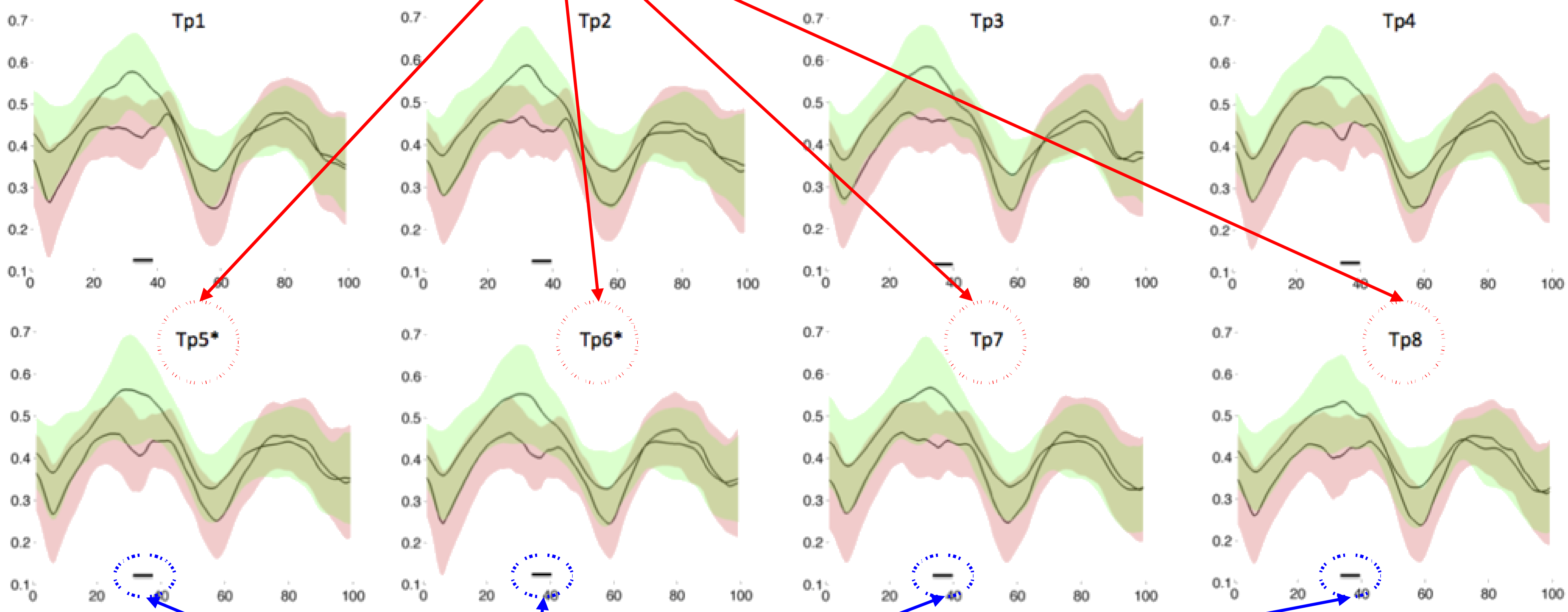
	Tensor Factorization			Non-Negative Matrix Factorization		
	Accuracy	Precision	Sensitivity	Accuracy	Precision	Sensitivity
λ_2,λ_3	**0.84 (0.12)**	**0.93 (0.09)**	**0.96 (0.13)**	0.72 (0.30)	0.86 (0.18)	0.78 (0.31)
λ_2,λ_3, FA	0.60 (0.20)	0.76 (0.10)	0.54 (0.16)	0.57 (0.36)	0.75 (0.17)	0.53 (0.35)
λ_2,λ_3, FA, MD	0.73 (0.30)	0.87 (0.18)	0.81 (0.32)	0.67 (0.36)	0.84 (0.18)	0.78 (0.33)
KLA,AA	0.50 (0.30)	0.71 (0.21)	0.82 (0.30)	0.50 (0.36)	0.67 (0.19)	0.56 (0.37)
KLA,FA,AA	0.50 (0.32)	0.74 (0.19)	0.75 (0.20)	0.50 (0.36)	0.66 (0.19)	0.57 (0.34)

APPLICATION ON MS PATIENTS

- **Subjects**:
  - 5 Relapsing Remitting (RR) Multiple Sclerosis Patients
  - Lesions verified by expert neurologist
    - Along 10 fiber-bundles
- **Protocol**:
  - EPI Acquisition: TE/TR = 60/8210 ms ; FOV = 224x224x120mm
  - 32 gradient directions $b = 1000 s.mm^{-2}$
  - Voxel Size: 0.875x0.875x2.0mm^3

APPLICATION ON MS PATIENTS

Time-points detected as "pathological"



Cross-sections detected as "pathological"

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CONCLUSION

- A new tensor-based framework for the analysis of longitudinal changes occurring along WM fiber-bundles.
- Multi time-points (> 2), multi-features and multi dimensional:
  - Fibers, Cross-sections and Time-Points
- The method was tested on real simulated data with extensive parameters search
- Improved computational speed using parallel programming

→ **Tensor factorization is a potential tool to analyze multi-dimensional data in MRI based studies**

- **Limitation:** Low sensitivity in pathological fibers detection

Wearable Health Monitoring

UZ Leuven departments:

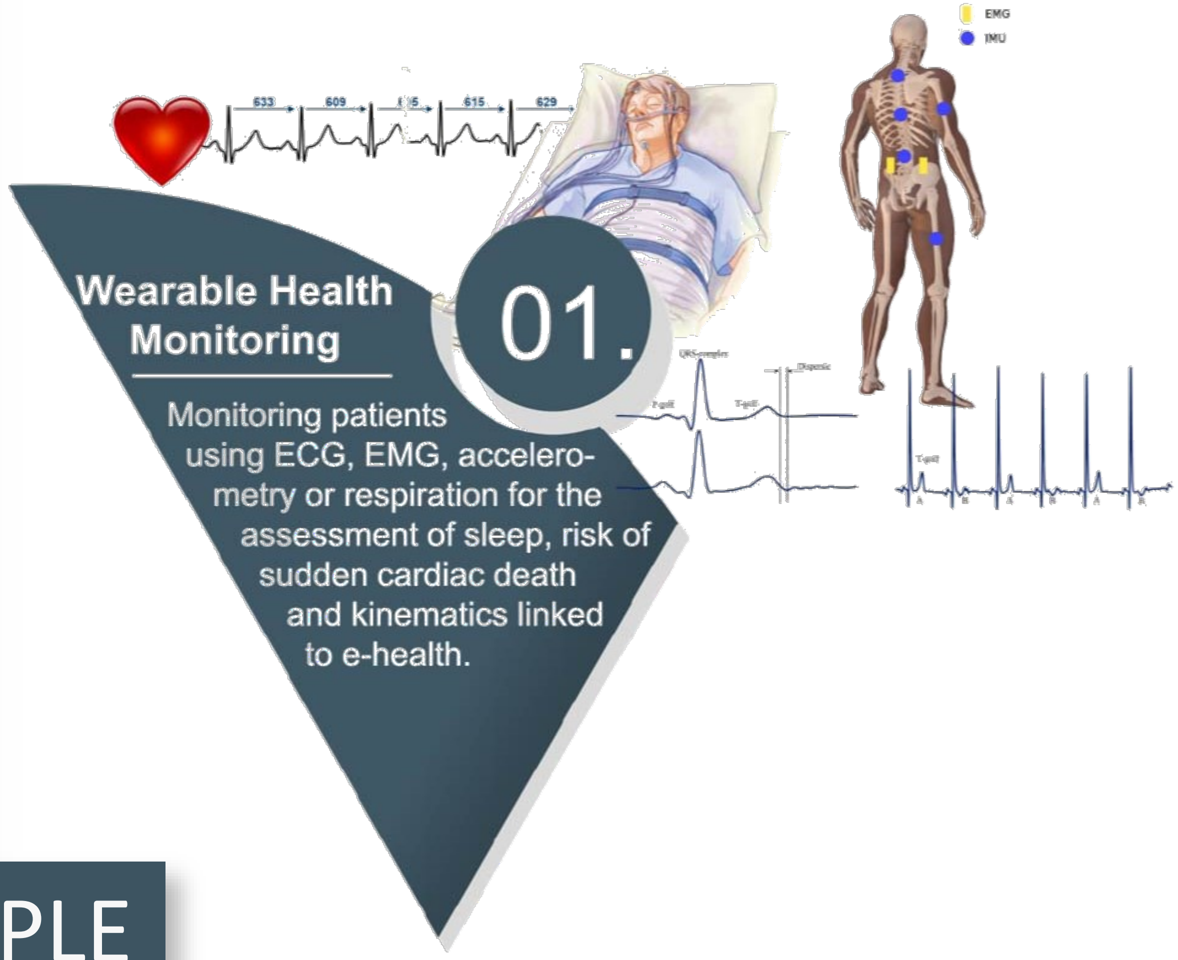
Cardiology

Neurology

Pneumology

Rheumatology

Pulderbos Revalidation Center



EXAMPLE

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BIOMED

erc

Recognition of Physical Activities from Wearable Sensors: a Multiway approach

Collaborator: Lieven Billiet

DISSERTATION (KU LEUVEN, OCT. 2018)

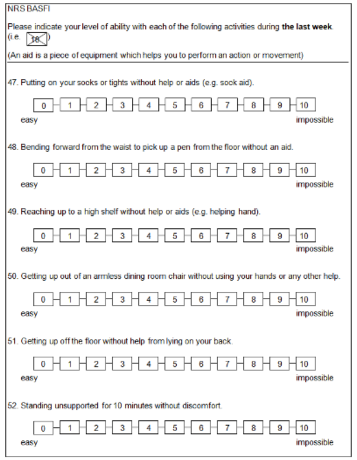
Clinical Decision Support: Interpretability and Applications in Patient Monitoring

Van Huffel, Sabine (Supervisor); Van Belle, Vanya (Cosupervisor)

Background

Patient-reported outcomes

Bath Ankylosing Spondylitis Functional Index BASFI



NRS BASFI

Please indicate your level of ability with each of the following activities during **the last week**.
(i.e. ☒)

(An aid is a piece of equipment which helps you to perform an action or movement)

47. Putting on your socks or tights without help or aids (e.g. sock aid).

0 1 2 3 4 5 6 7 8 9 10
easy impossible

48. Bending forward from the waist to pick up a pen from the floor without an aid.

0 1 2 3 4 5 6 7 8 9 10
easy impossible

49. Reaching up to a high shelf without help or aids (e.g. helping hand).

0 1 2 3 4 5 6 7 8 9 10
easy impossible

50. Getting up out of an armless dining room chair without using your hands or any other help.

0 1 2 3 4 5 6 7 8 9 10
easy impossible

51. Getting up off the floor without help from lying on your back.

0 1 2 3 4 5 6 7 8 9 10
easy impossible

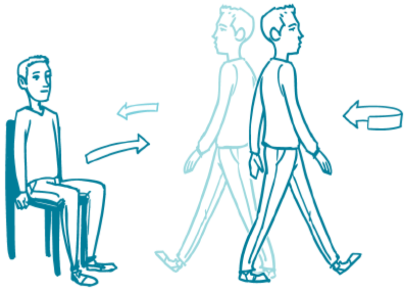
52. Standing unsupported for 10 minutes without discomfort.

0 1 2 3 4 5 6 7 8 9 10
easy impossible

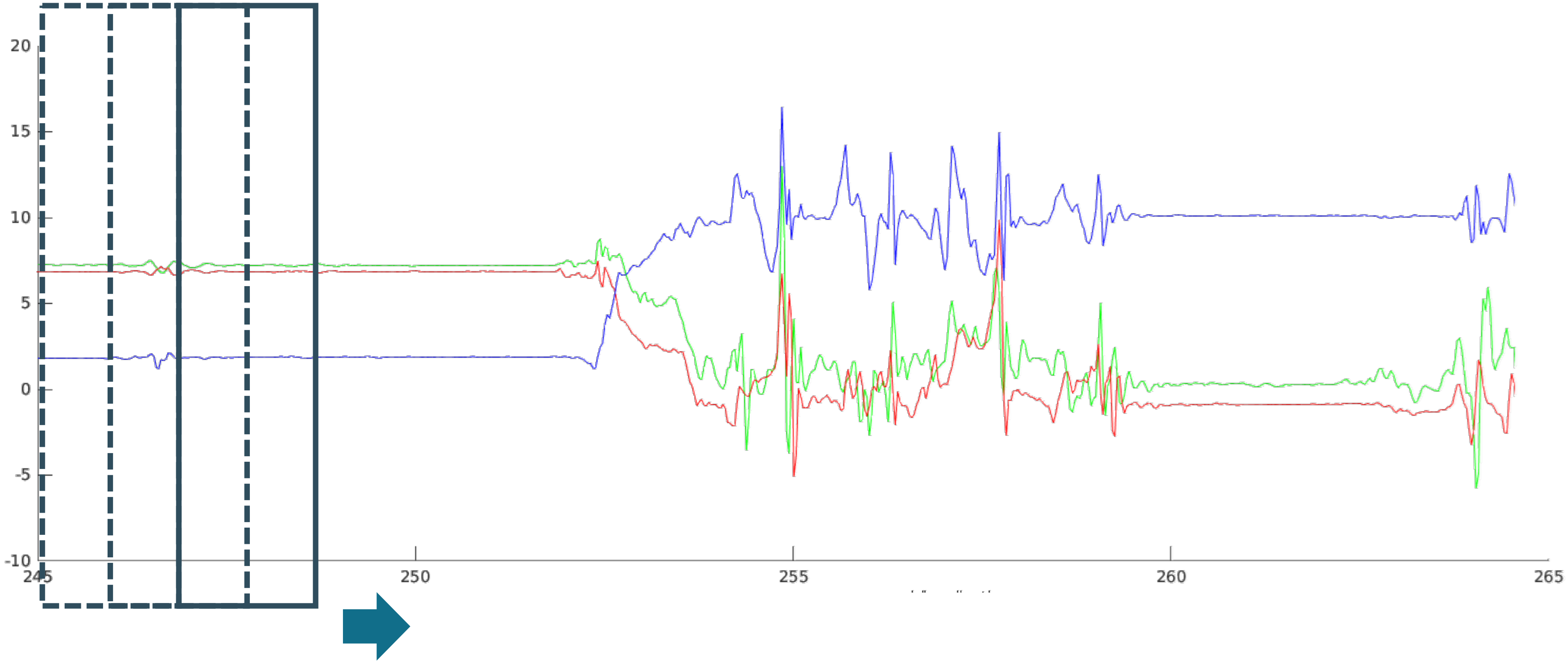
AXIAL SPONDYLOARTHRITIS

ASSESSMENT ACTIVITY LIMITATIONS

Performance-based tests

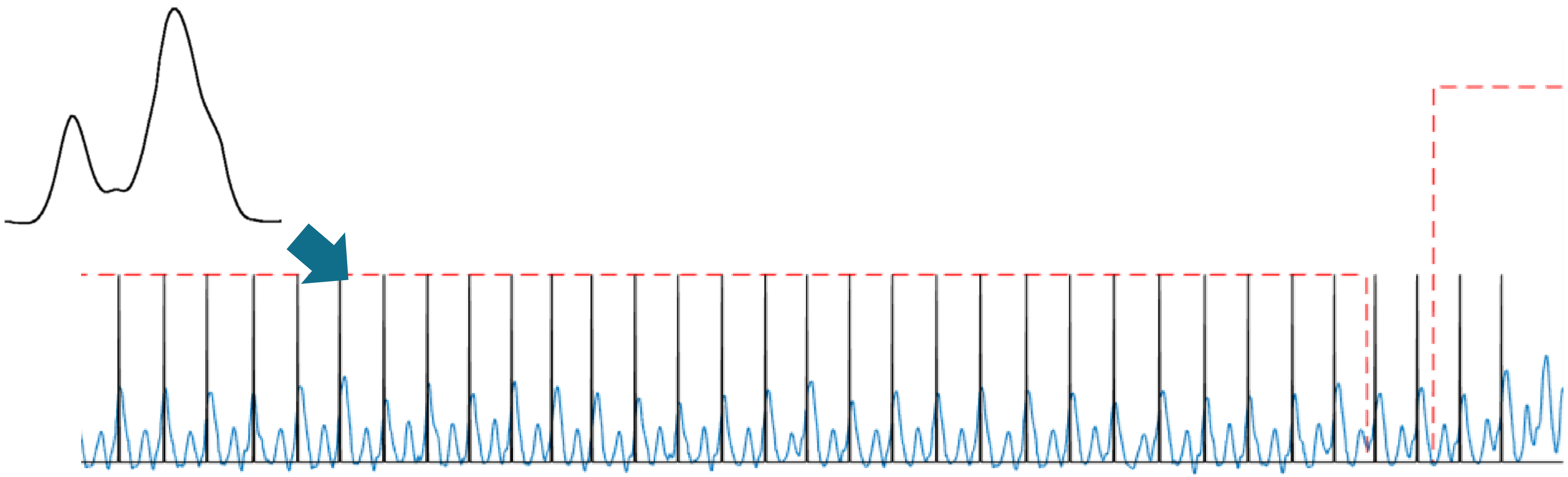


Activity recognition: sliding windows



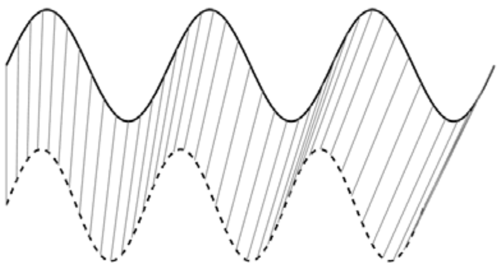
- ✔ Poses, repetitive activities
- ✔ Good accuracies
- ✘ Transitions
- ✘ Details

Activity recognition: pattern matching



- Scale?
- Variability?

DTW



Data

- 39 axSpA patients

- 28 equipped with SenseWear Pro (Bodymedia Inc.)
  10 equipped with Shimmer3 (Shimmer Inc)

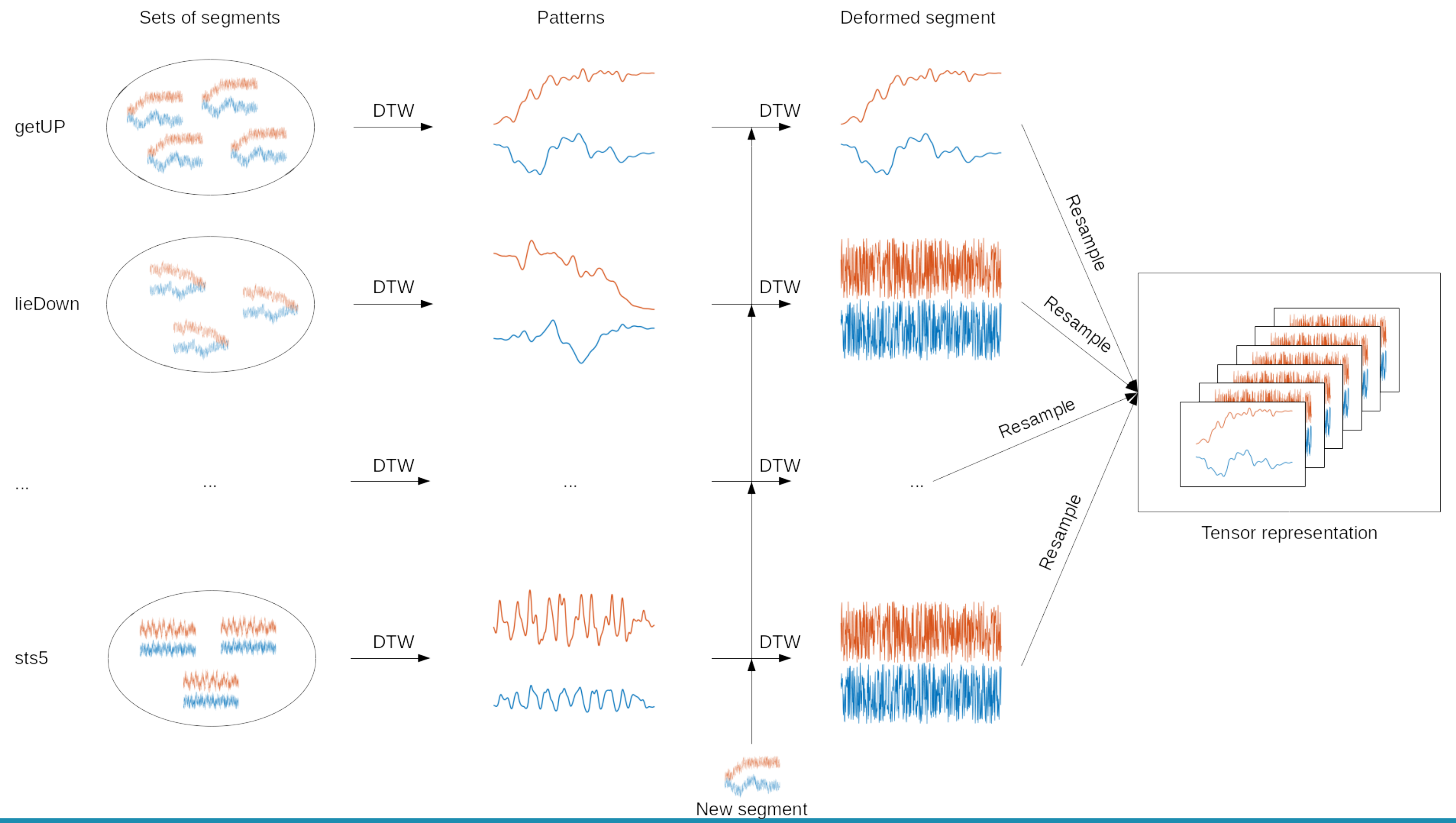
- 6 BASFI activities

Get up	Maximal reach 5x
Lie down	Pick up a pen 5x
Maximal reach	Sit-to-stand 5x

- 7-class problem (NULL class)

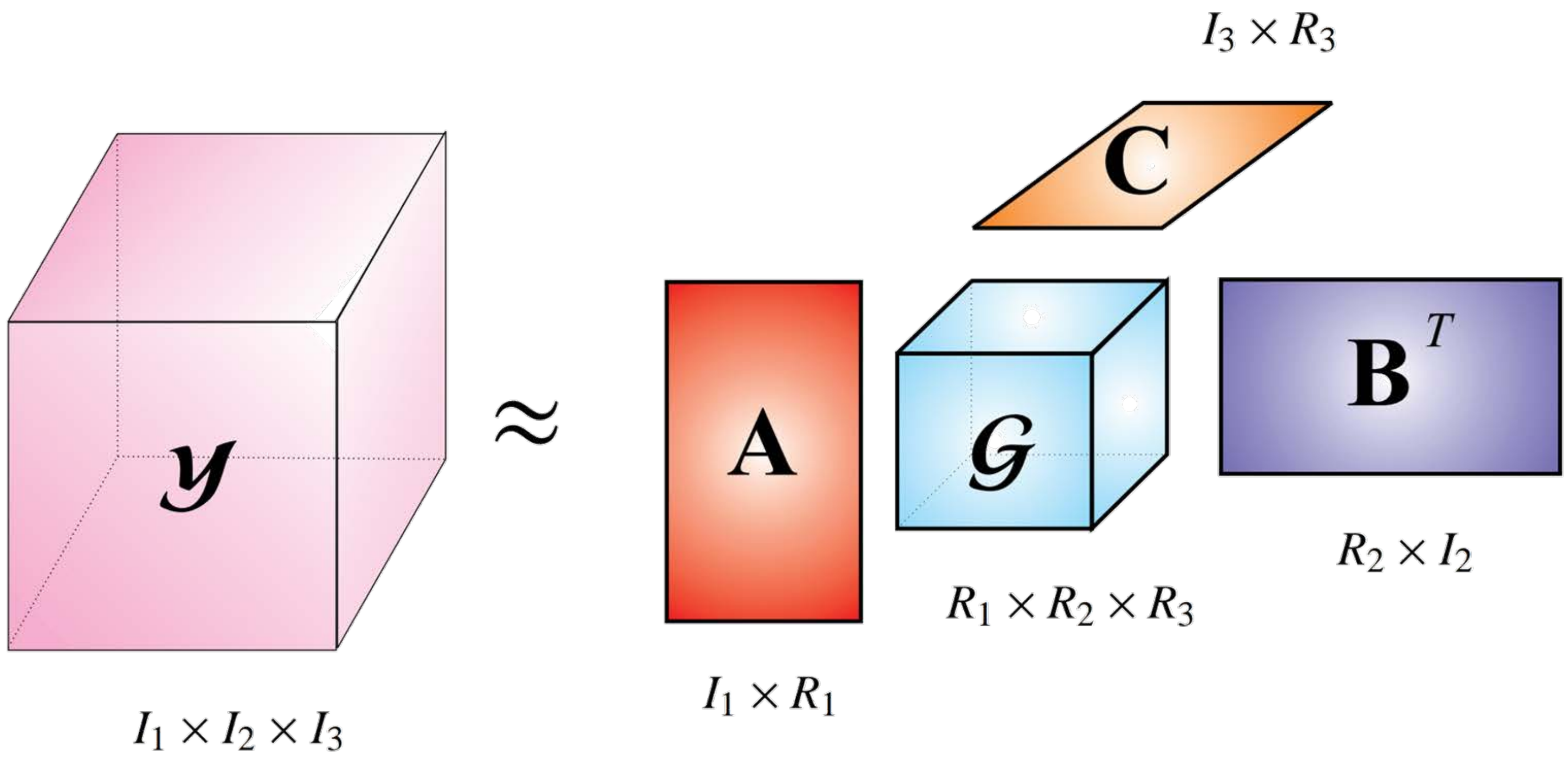
Billiet et al. *Informatics* (2018)

Data representation



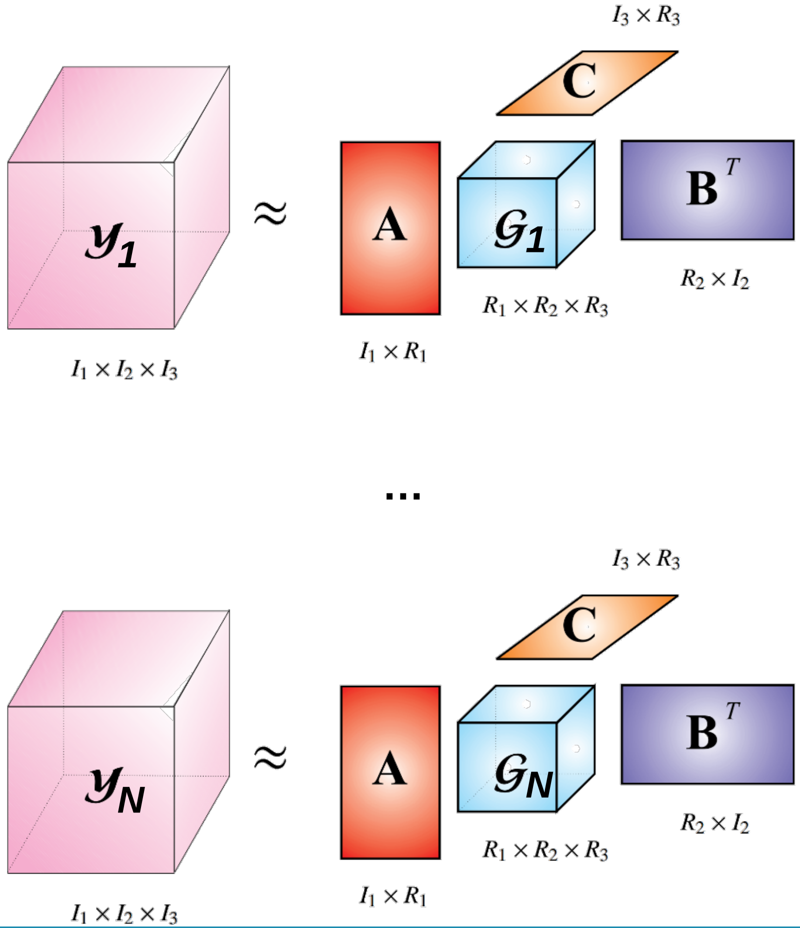
HODA

- Tucker decomposition



HODA

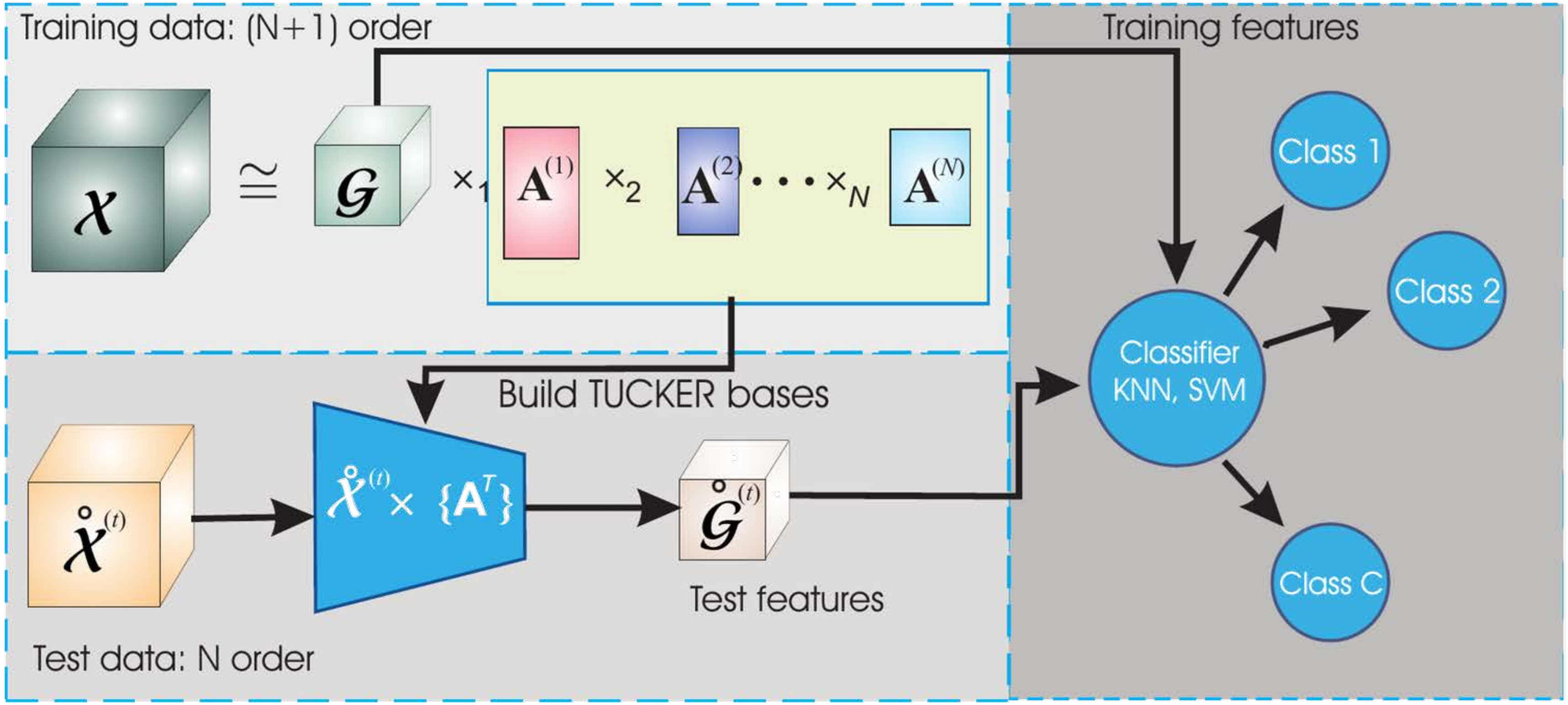
- Joint Tucker decomposition for data compression



Billiet et al. *Informatics* (2018)

HODA

- Joint Tucker decomposition with discriminant analysis



Results

- Detection True Positive Rate: 85.4 ± 15.8%
- Number of false detections: 2.90 ± 3.32
- Dice coefficient: : 89.3 ± 12.0%

- LoSo

	HODA	SIMPLE (DTW distances)
$Accuracy_1$:	**86.7** ± 14.2%	82.9 ± 20.4%
$Accuracy_2$:	**62.3** ± 25.0%	44.1 ± 20.7%

- SenseWear LoSo HODA
  - $Accuracy_1$: **91.2** ± 7.9%
  - $Accuracy_2$: **74.5** ± 17.0%
- Drawback: high computational load due to DTW, not suitable for real-time use

Conclusions

- Patterns are a viable option for recognition of physical activity
  - Combined with statistical features
  - Using structure/HODA
    - quit segmentation/rejection?
- Future work
  - Impact of different sensors
  - Combining structure and statistical features

Neonatal Brain Monitoring

UZ Leuven departments:

Neonatology

Pediatric neurology

Eindhoven University of Technology

Maxima Medical Centre

Oxford University:

Dept. of Engineering Science

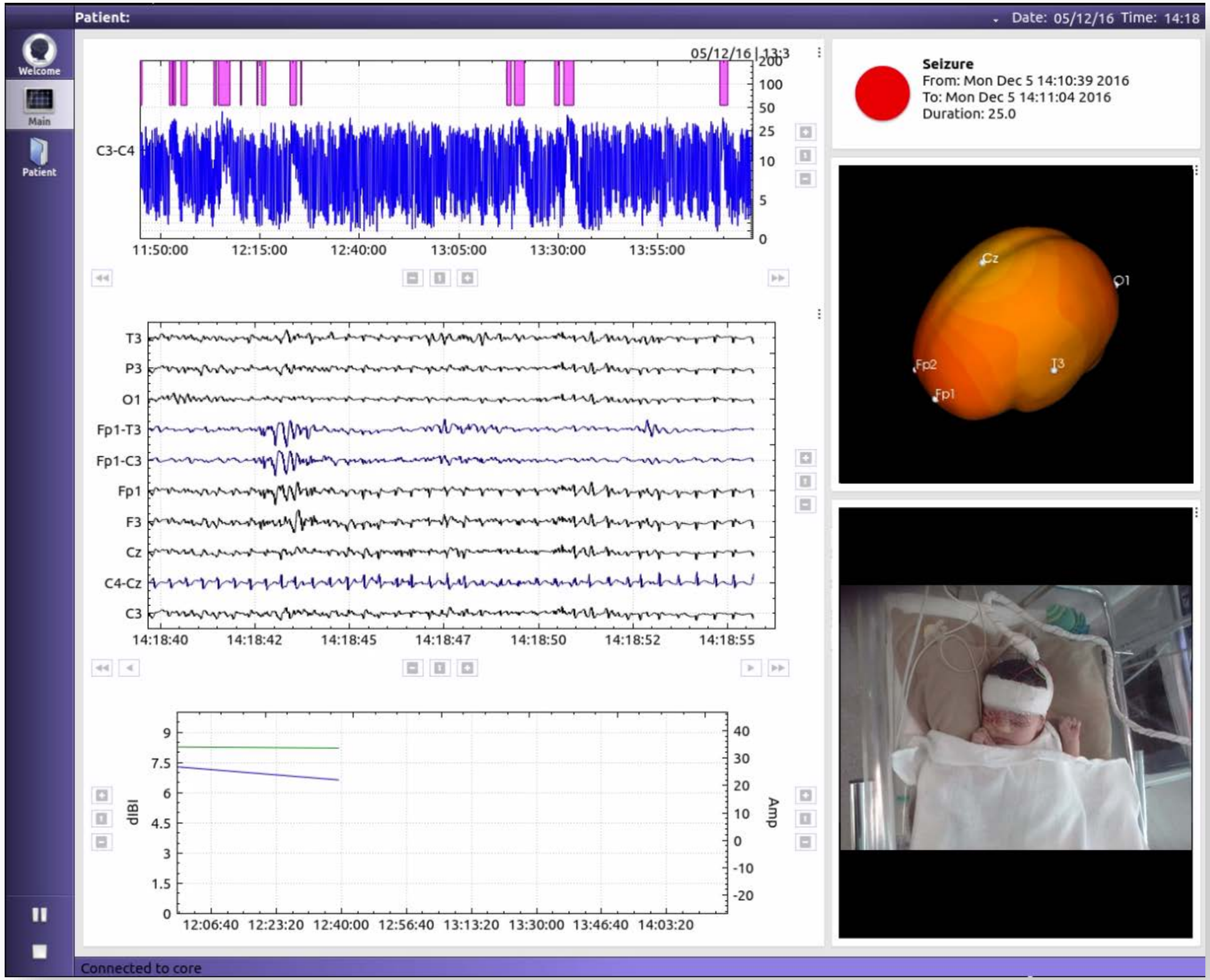
EXAMPLE

NeoGuard : decision support

Partners

KU Leuven-ESAT (Stadius & MICAS), *UZ Leuven neonatology, EMC Rotterdam, ZNA Middelheim*, Ghent University (TELIN)

- Brain injury estimate
  - Detection of neonatal epileptic seizures
  - Seizures localization
  - Inter-burst intervals
- Incorporated expertise
  - Knowledge of neurophysiologists are incorporated into algorithms
- Monitoring
  - Recovery after brain damage
  - **Brain Maturation in prematures**
  - **Sleep staging**
- Outcome prediction

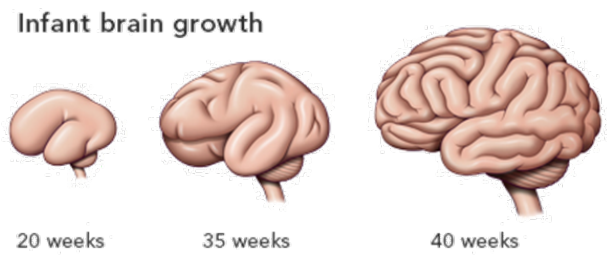


Decomposition of a Multiscale Entropy Tensor for Sleep Stage Identification in Preterm Neonates

Collaborator: Ofelie De Wel

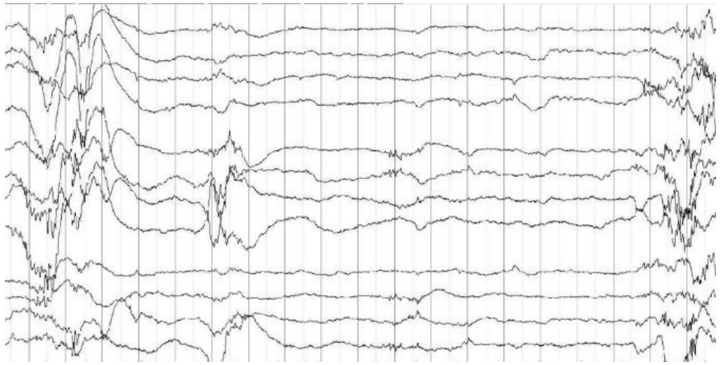
Problem Statement

- Sleep ➔ brain development

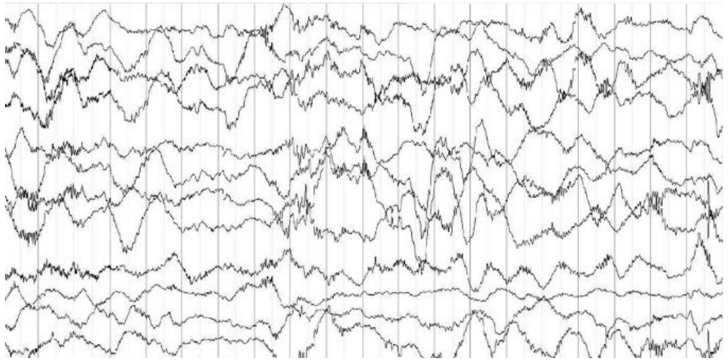


- Neonatal sleep
  - Quiet sleep
  - Nonquiet sleep (awake, active sleep & indeterminate sleep)

Quiet sleep

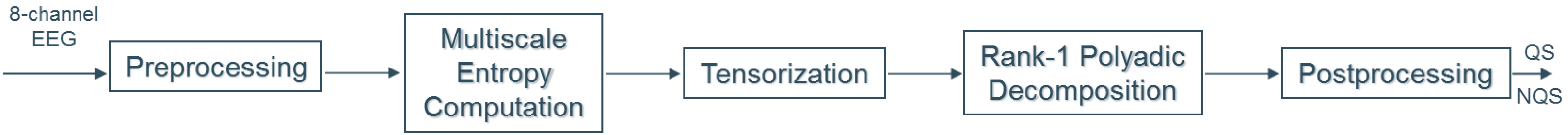


Nonquiet sleep



Problem Statement

- Objective: discriminate quiet sleep from nonquiet sleep



Database

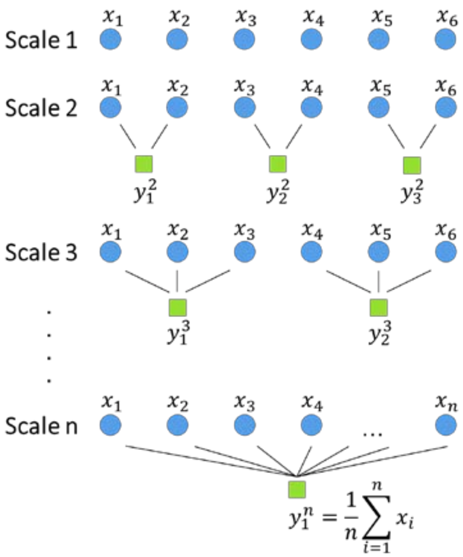
- 88 EEG recordings from 25 preterm neonates
- 8 monopolar EEG channels
- Postmenstrual age: 27 – 42 weeks
- Quiet sleep annotated by expert clinician

Preprocessing

- 1-20 Hz bandpass filtering
- Resampling to 125 Hz
- Segmentation into 100s windows

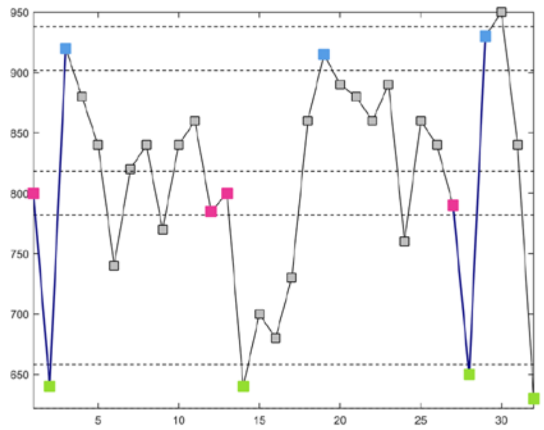
Multiscale Entropy Computation

1) Coarse Graining

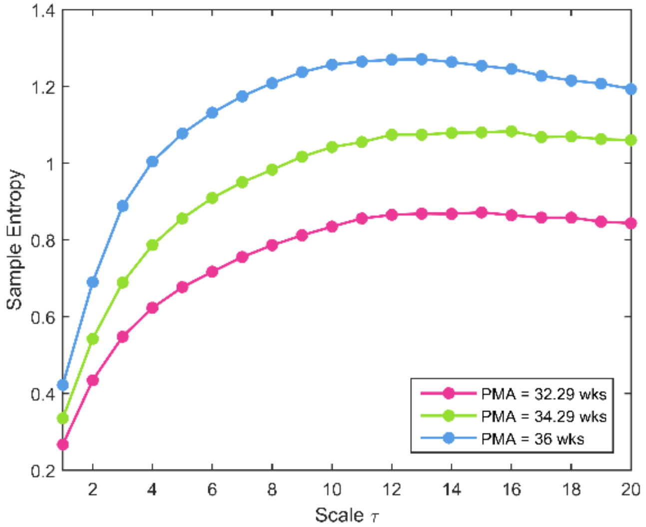


$$y_1^n = \frac{1}{n}\sum_{i=1}^{n} x_i$$

2) Sample Entropy Computation

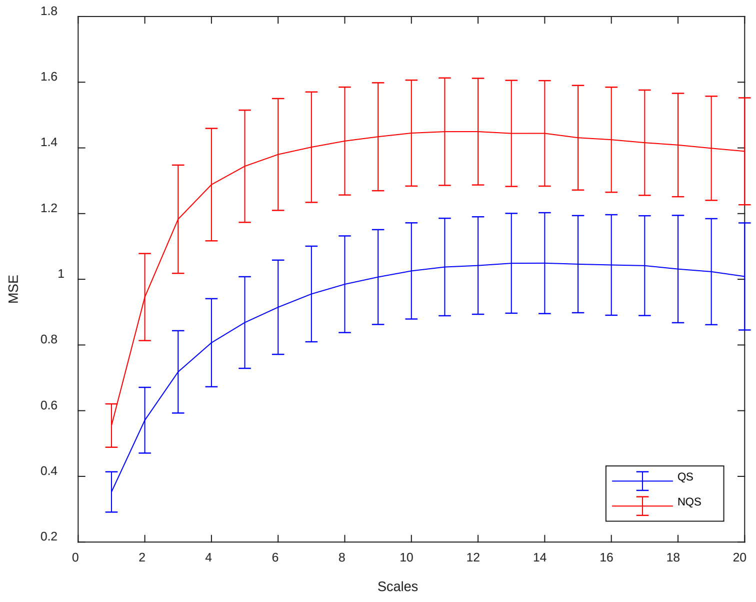


3) Multiscale Entropy Curve

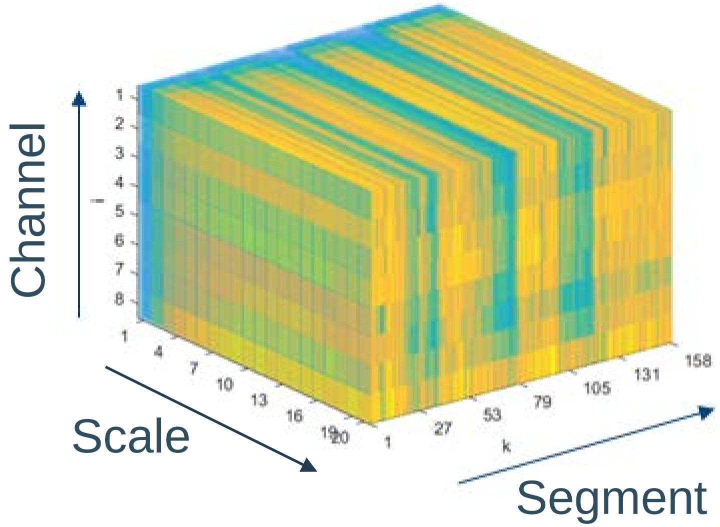


Tensorization

MSE curve is reduced during QS compared to NQS



3rd order tensor:
8 channels x 20 scales x segments



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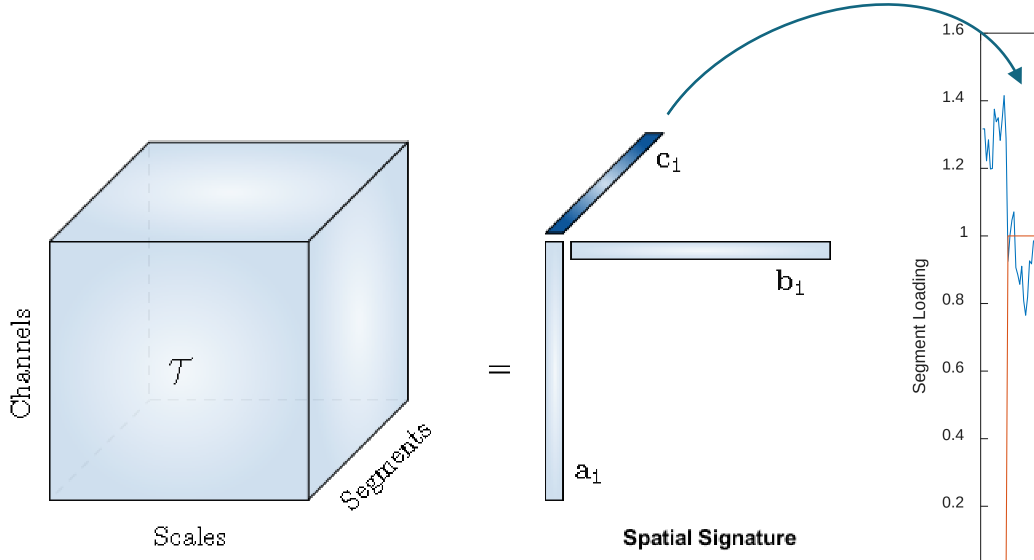
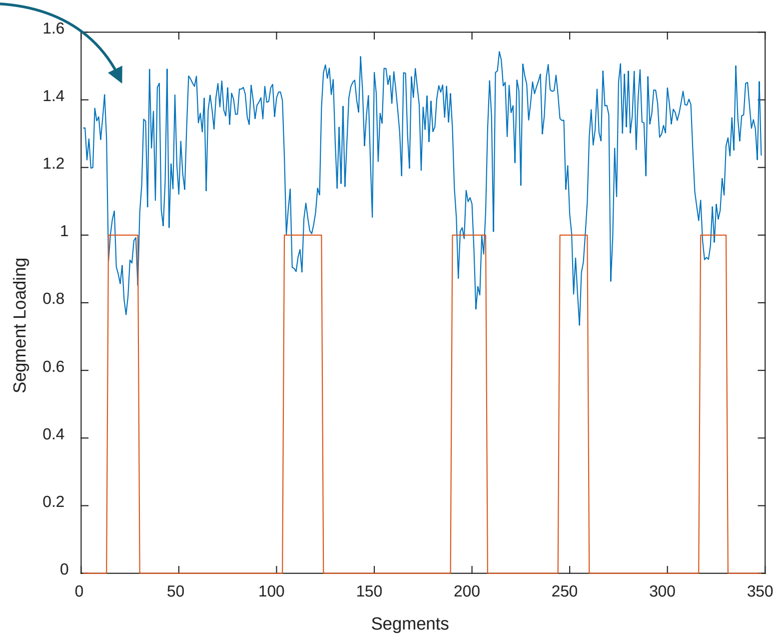
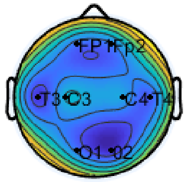
Rank-1 Polyadic Decomposition

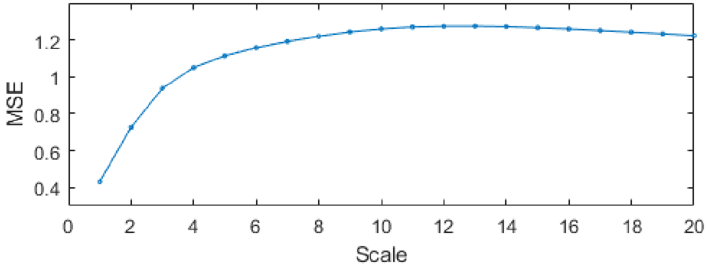




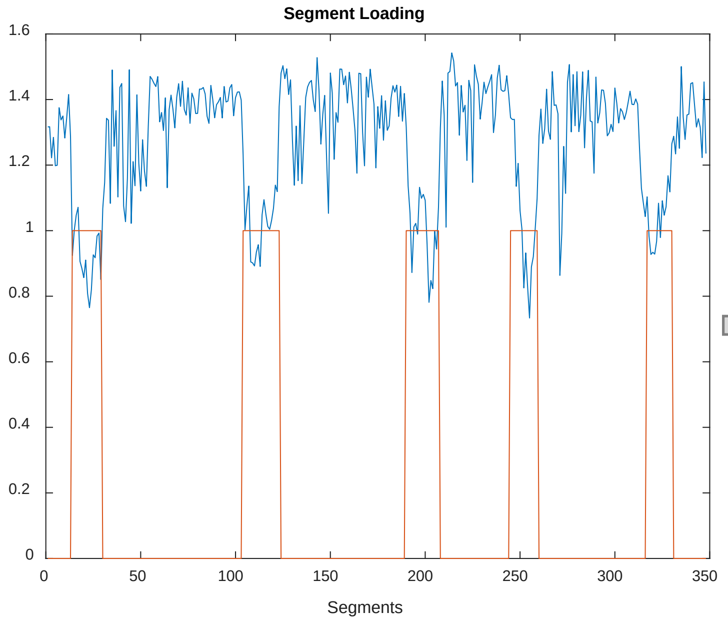
Spatial Signature



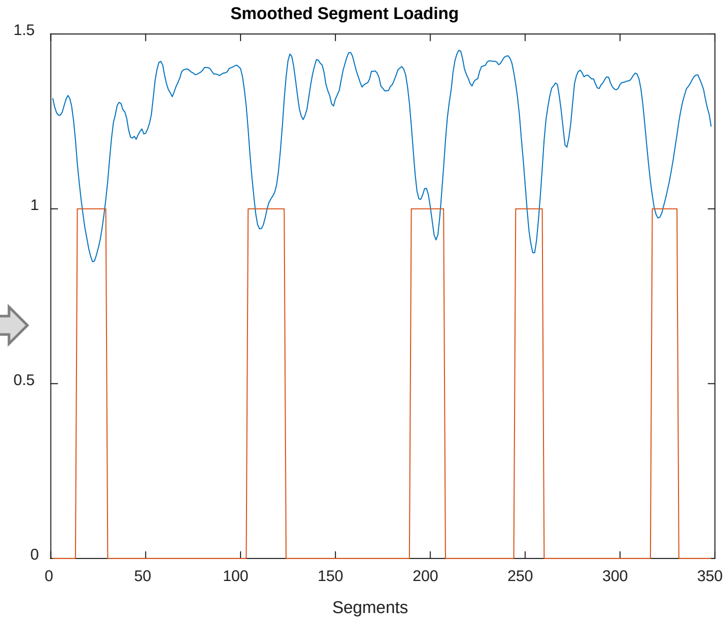
Scale Signature



Postprocessing



Moving
Average
Filter

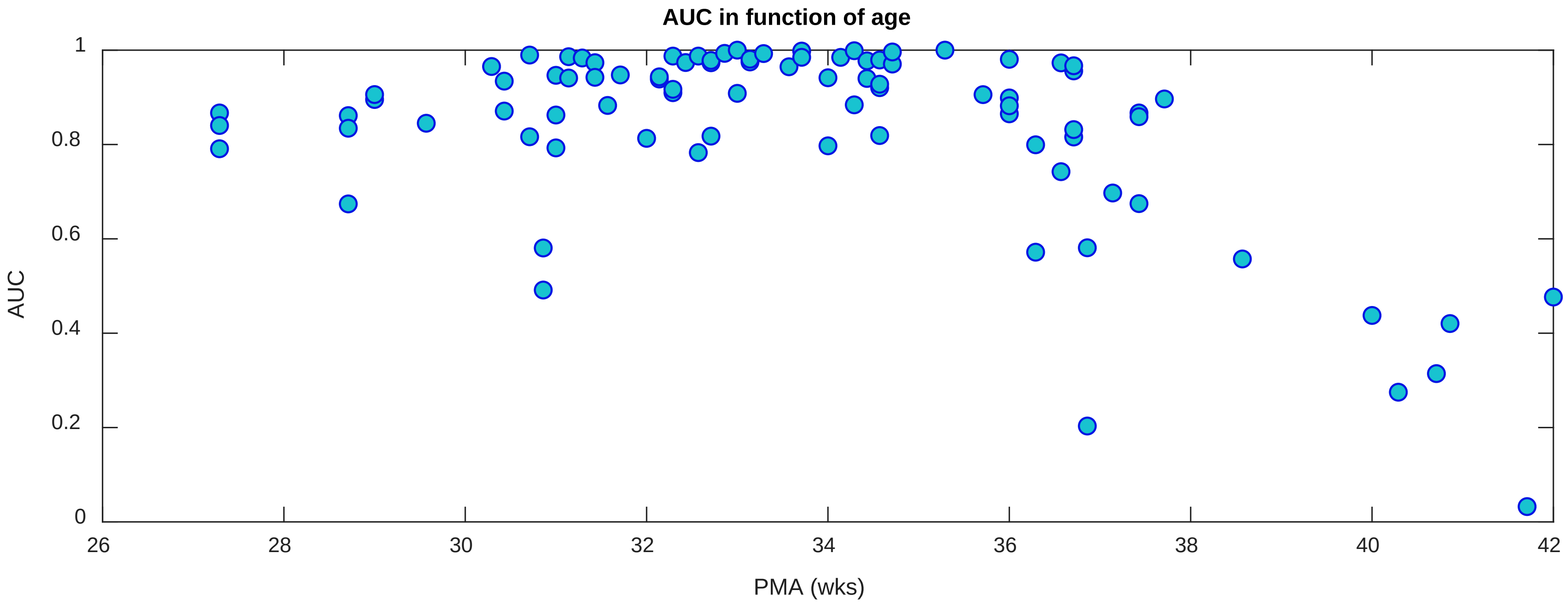


Performance

- K-means clustering

Performance Measure	Average over all recordings
Silhouette Coefficient	0,81
Sensitivity	0,71
Specificity	0,82
Accuracy	0,79

Performance



- Average AUC = 84%

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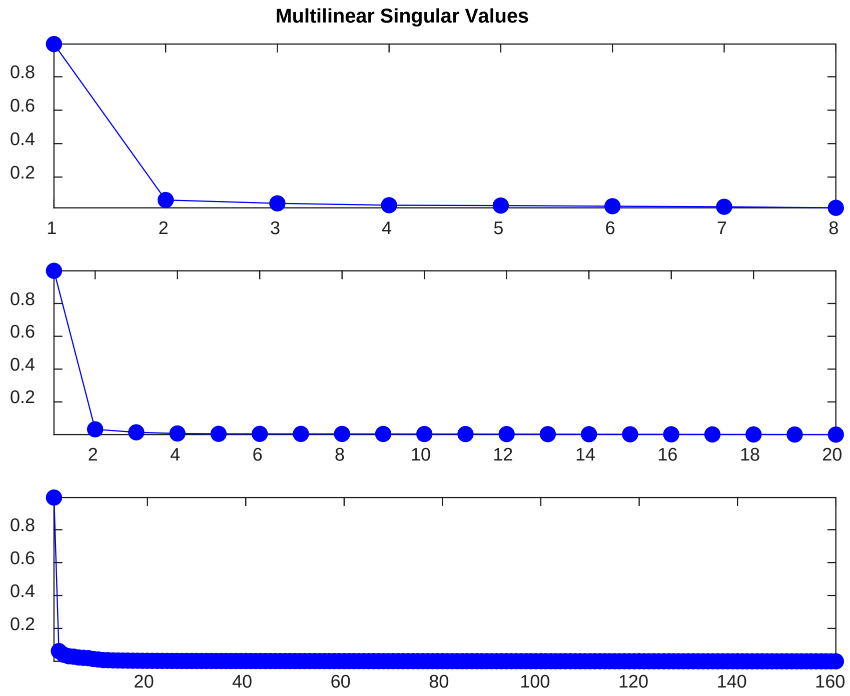
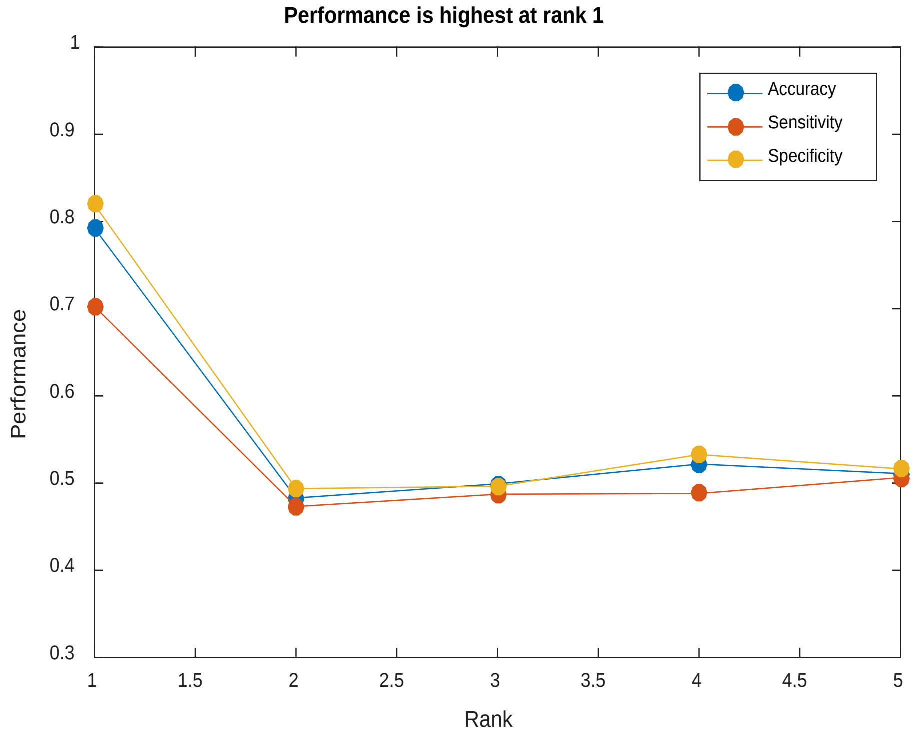
Choice rank

- Mean Relerr = 0,11





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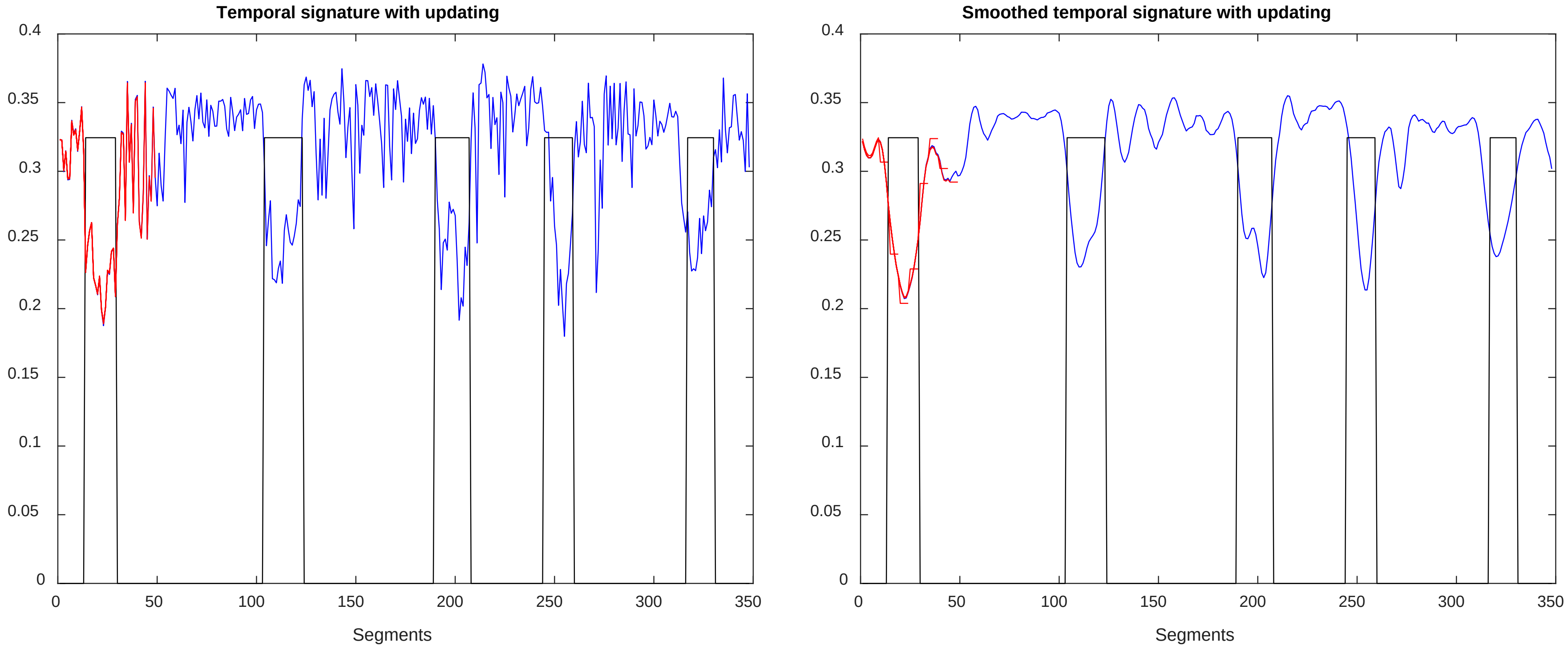
Updating

- Real time sleep monitor ➔ update CPD



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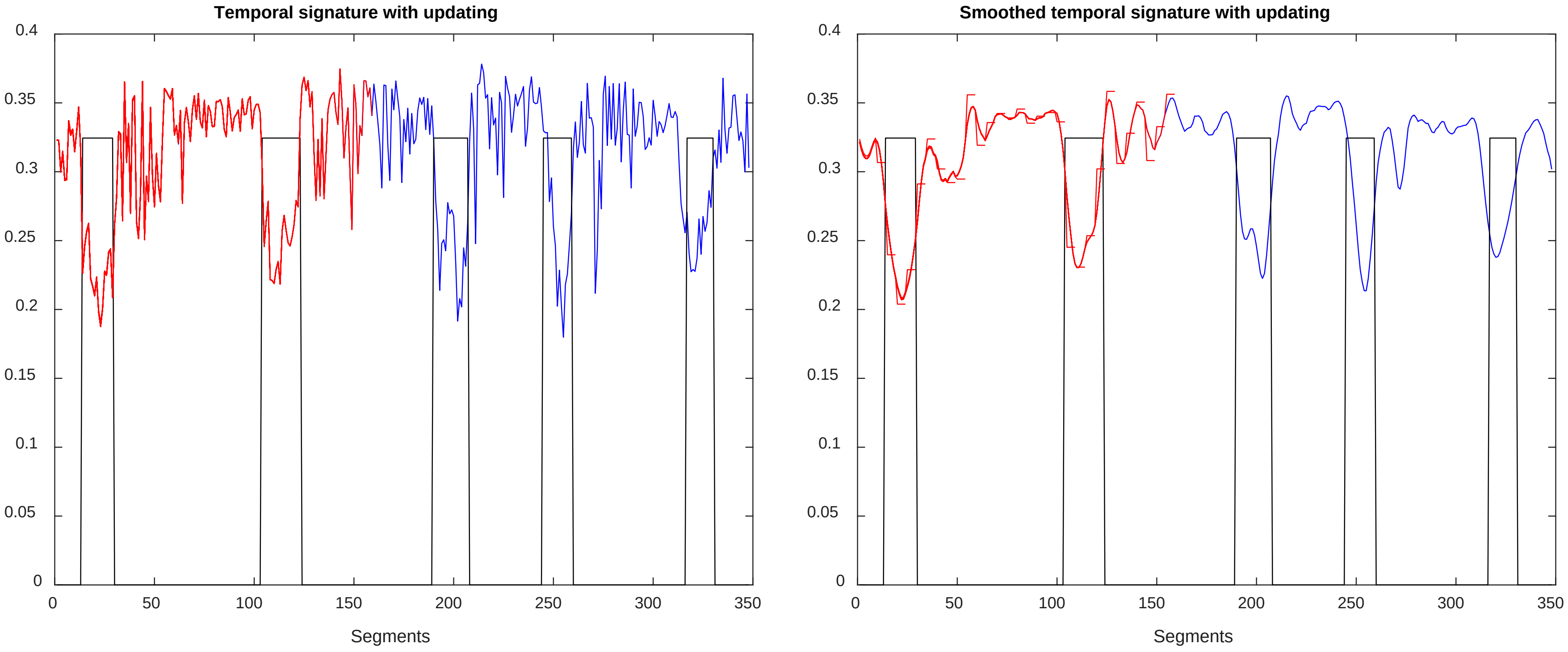
Updating

- Real time sleep monitor ➔ update CPD



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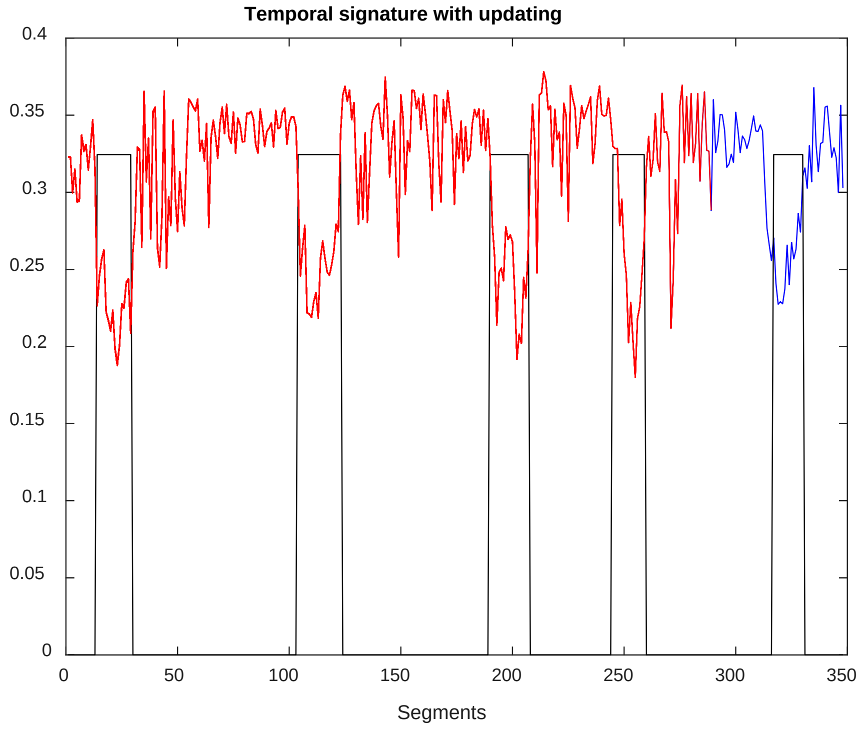
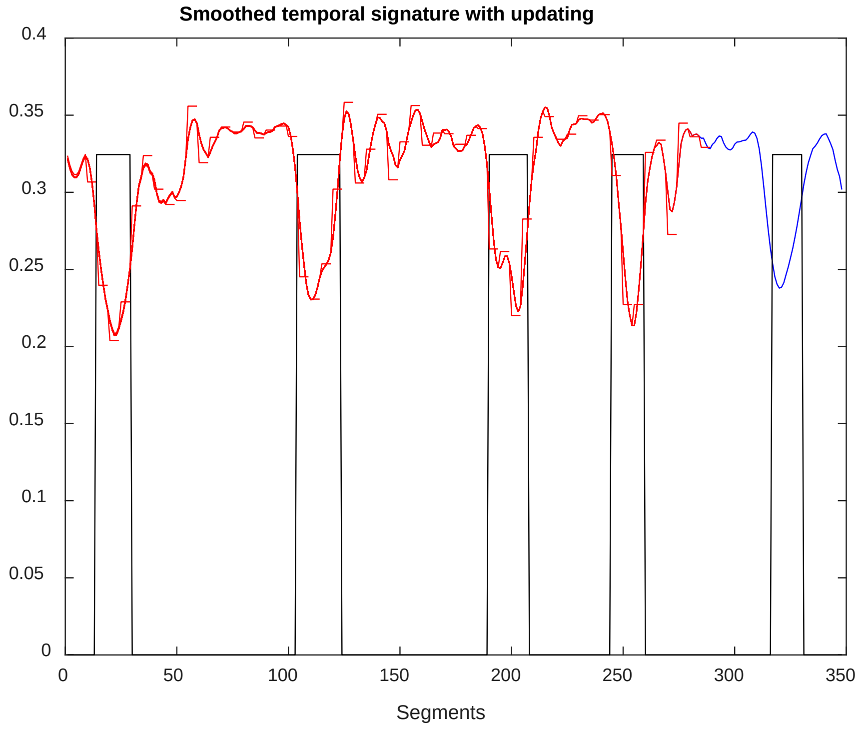
Updating

- Real time sleep monitor ➔ update CPD





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Conclusions

- EEG complexity is different depending on sleep state

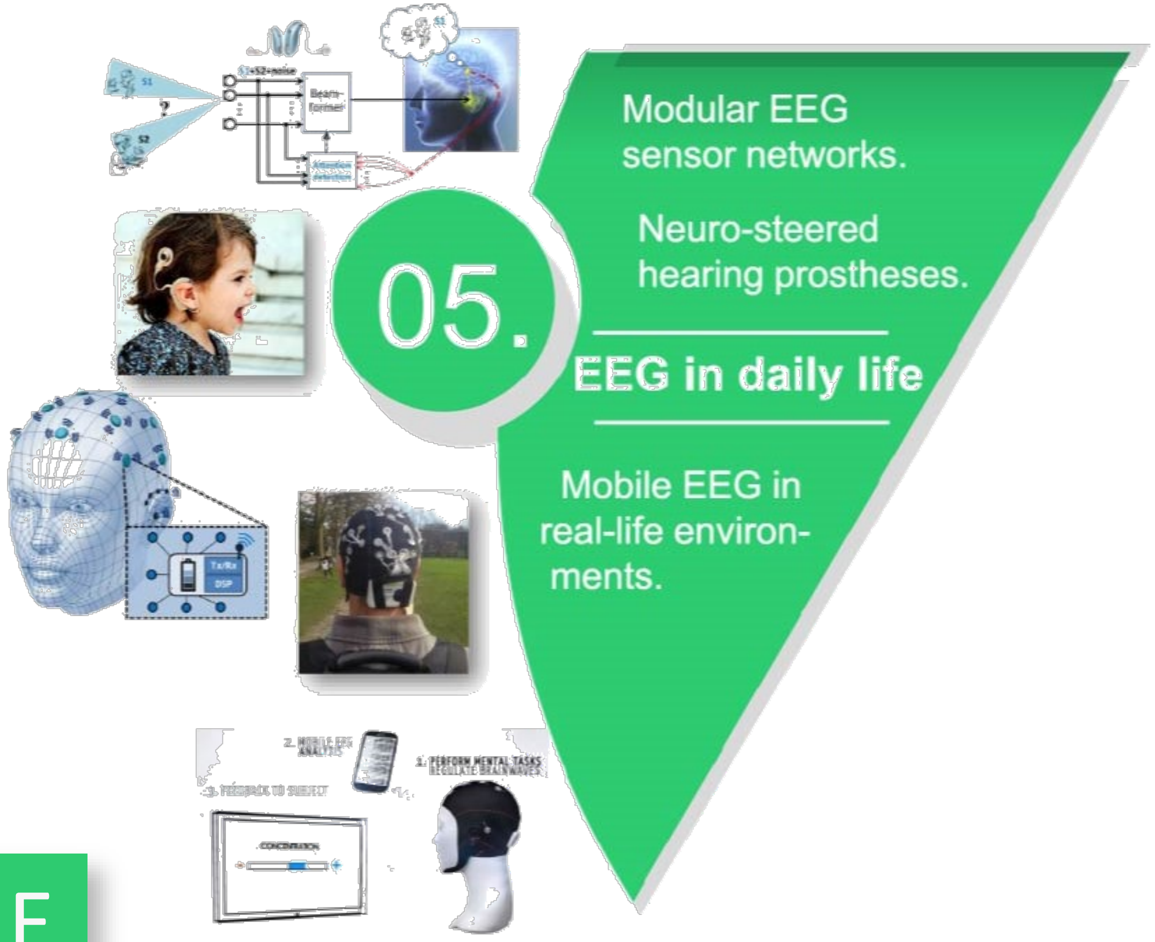
- Rank 1 CPD of multiscale entropy tensor can be used to discriminate QS from NQS in an unsupervised way.

EEG in daily life

UZ Leuven partners:
Tom Francart (experimental otorhinolaryngology)

Oxford University Dept. of Engineering Science:
Maarten De Vos

EXAMPLE



Use of Tensor Decompositions in auditory BCI (mobile EEG)

Rob Zink | KU Leuven

European Research Council
Established by the European Commission

DISSERTATION

Mobile EEG and Tensor Approaches for Auditory Attention Analysis in Real-life
Zink, Rob; Van Huffel, Sabine (Supervisor); De Vos, Maarten (Co-Supervisor)
December 2017

Brain computer interfaces & Human performance

Brain computer interfaces (**BCI**) **utilize brain activity patterns** to **control** a technical device by **thought alone**. Most BCI applications rely on electroencephalogram (**EEG**) signals in response to motor imagery or visual sensory input, but recently non-invasive auditory BCIs using **auditory attention** and imagery EEG responses have been developed.

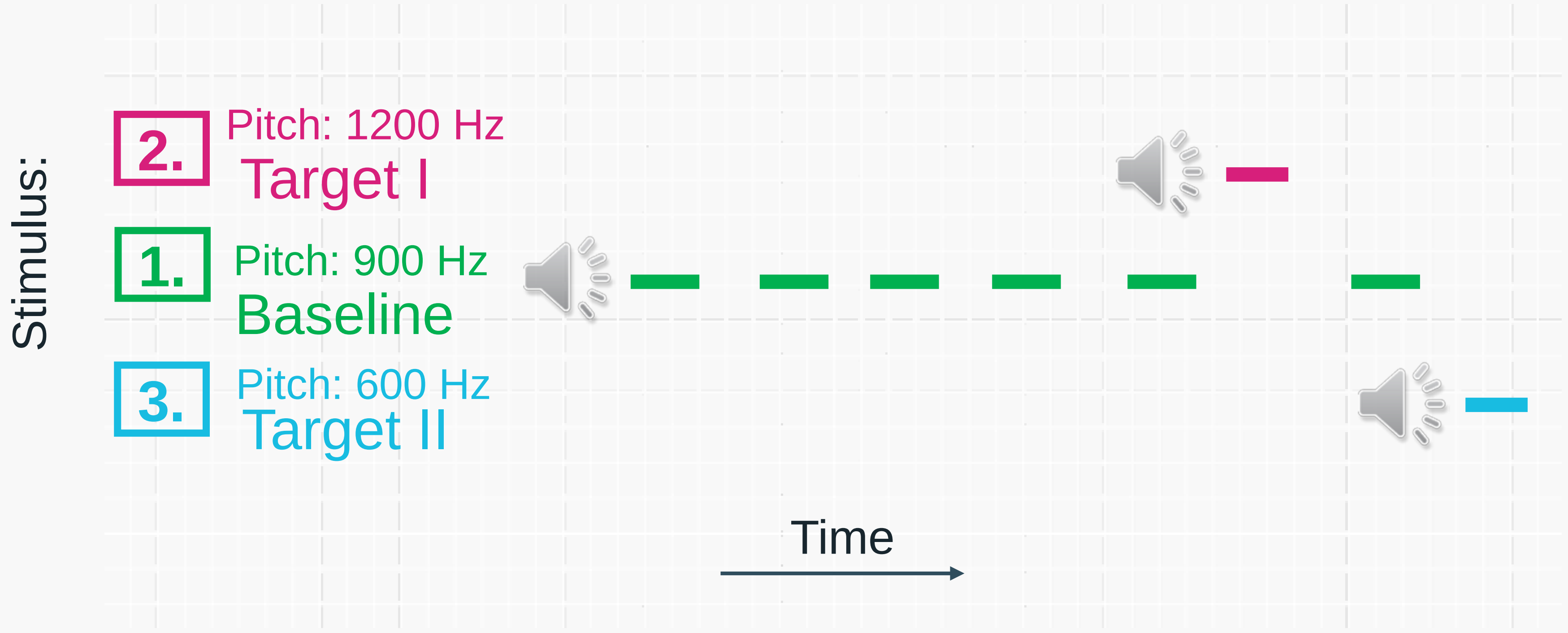
Truly **mobile BCI systems** are emerging to allow BCIs that can be operated in **real-life environments** by means of **mobile EEG**.

Understand the more complex EEG (i.e. *both signal and noise*) patterns in **real unconstrained environments**.

The **challenge** to **disentangle** observed **changes in EEG activity** due to increase in **cognitive demands** by the complex natural environment or due to **physical involvement**.

3-class Auditory Oddball

Binary BCI paradigm



Attended Targets generate a P300 ERP

Non-Attended Targets do not (fully)

Attended Targets generate a P300 ERP
Non-Attended Targets do not (fully)

Data Driven Classification

Structured decompositions of mobile EEG

Divide Dataset into Train-Test set

Train classifier on Training Data → Obtain discriminative features/model

→ Apply classifier model on Test data

Cons for (mobile) BCI applications:

1. **Always need Training Data** (costs time/effort subject)

2a. Classifier is **dependent on the Training data**.

2b. **High variability** between subjects and even within sessions (non-stationarity)

Our aim:

Can we model the P300 differences in a data-driven (structured) way, removing the training phase?

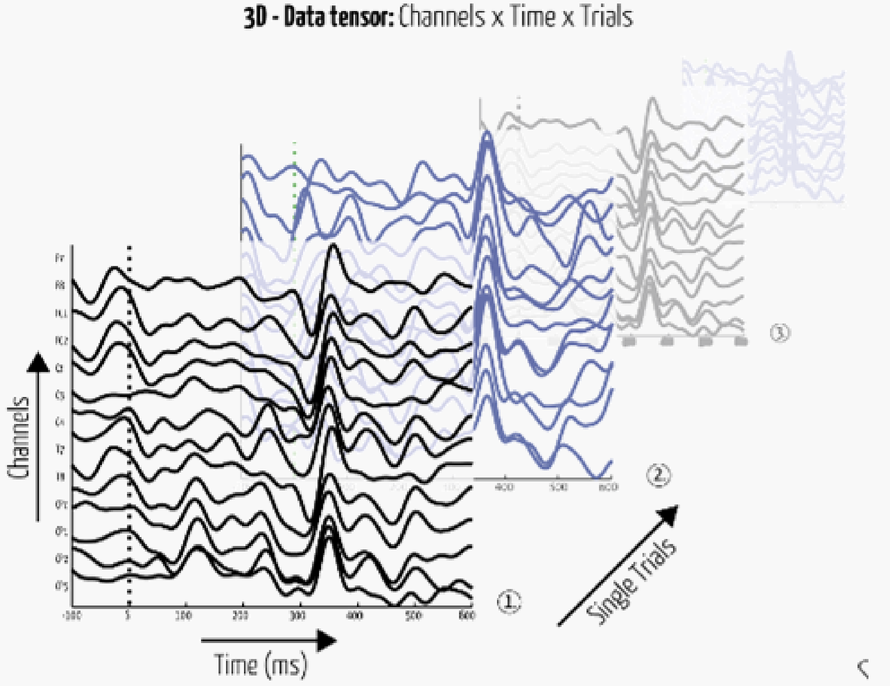
Data Driven Classification

Structured decompositions of mobile EEG

Data (external):

- 20 subjects (mean age 24.6 years)
- 14 channels (wet electrodes) – F3, Fz, C3, FPz, Tp10, Cz, O1, O2, F4, C4, TP9, Pz, P4, P3 (Afz, FCz).
- Sampling rate 128Hz
- Eye blinks removed using ICA
- Data epochs (trials) -200 to 800ms with respect to stimulus
- Baseline correction, Rereferencing, 1-20Hz BPfilter.
- **Sit and Walking outside**

Structure data as **channels x time x trials tensor**

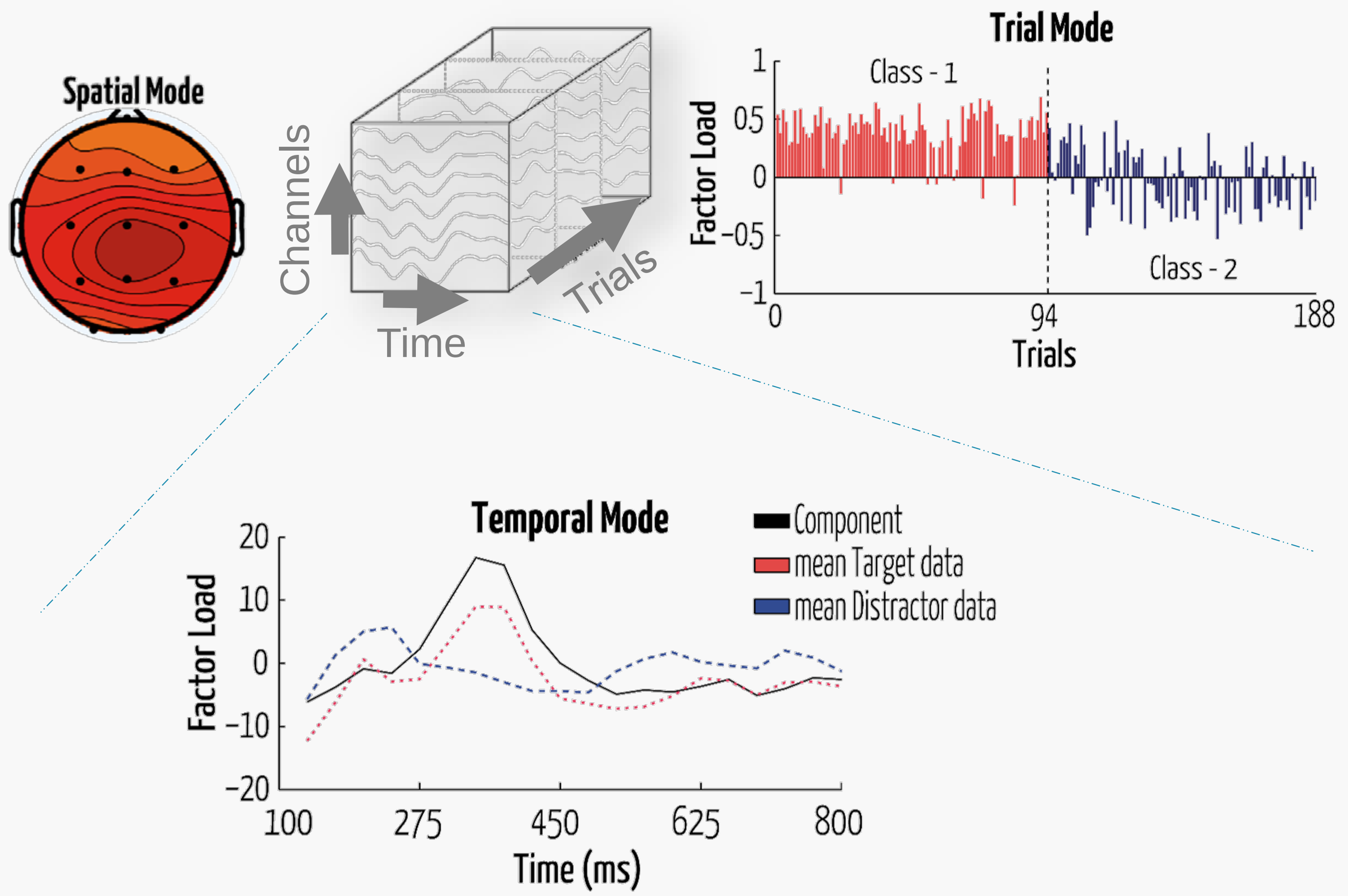


Data from:

De Vos, Maarten, Katharina Gandras, and Stefan Debener. "Towards a truly mobile auditory brain–computer interface: Exploring the P300 to take away."*International Journal of Psychophysiology* 91.1 (2014): 46-53.

Proof of concept of CPD on (auditory) ERP data

12 channels x 15 time points x 188 trials/epochs



81% Accuracy

Data Driven Classification

Parameters

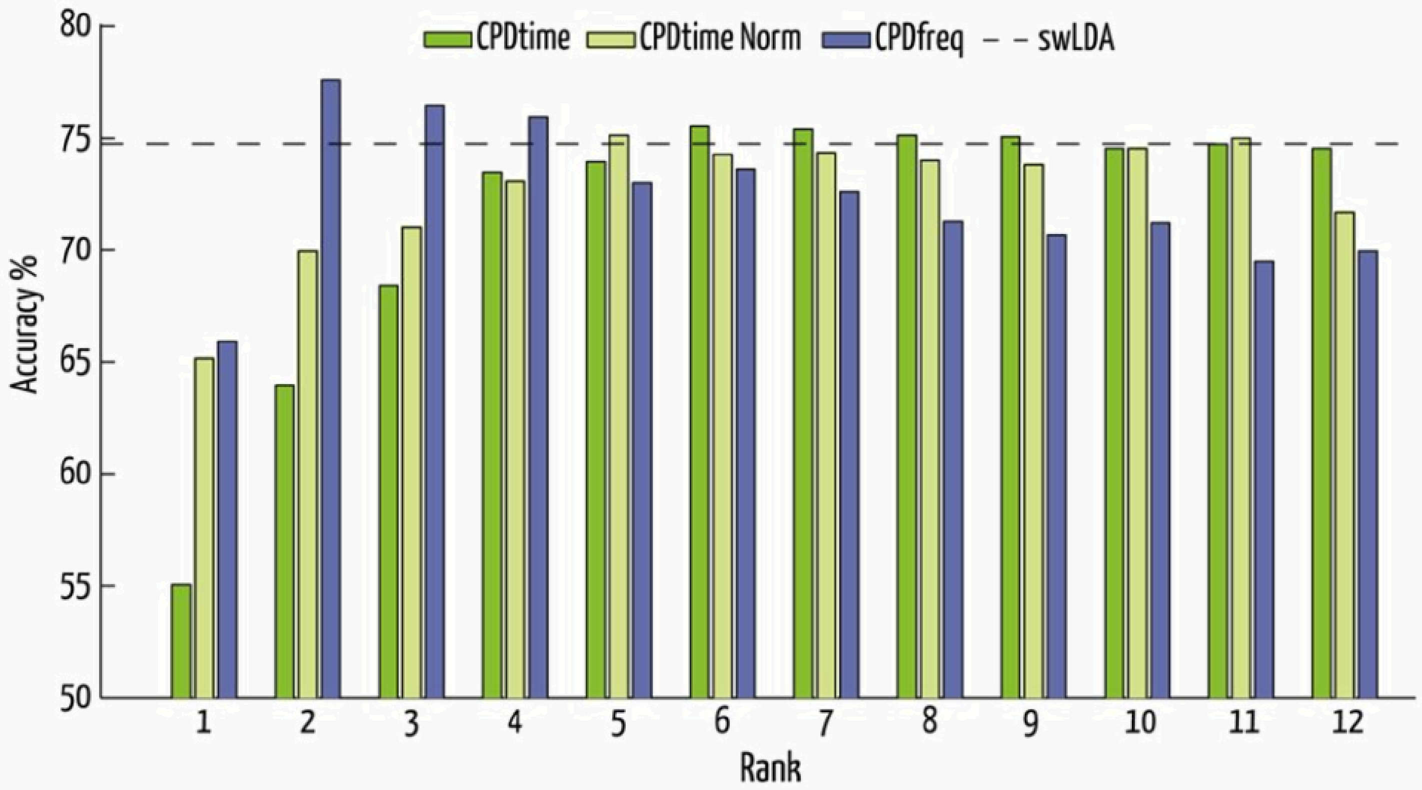
- Results based on 100 random **initializations**.
- The rank (*R*) is expected to differ with the complexity of the dataset.

  (Semi)-automatic rank determination algorithms → tend to greatly overestimate the rank.
- First work we evaluated the results for **different ranks ranging from 1 to 12**

- **Channels x (norm)Time x trials**
- **Channels x Frequency x trials**

Data Driven Classification

Proof-of-concept



Published in:

Zink, R., Hunyadi, B., Van Huffel, S., & De Vos, M. (**2015**, April). **Exploring cpd based unsupervised classification for auditory BCI with mobile EEG**. In *7th International IEEE/EMBS Conference on Neural Engineering (NER)* (pp. 53-56). IEEE.

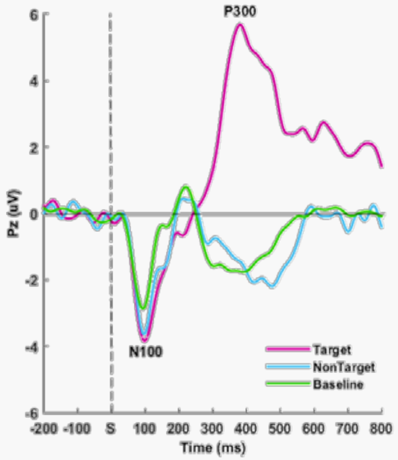
Summary

- ✓ Proof-of-concept of CPD based models for ERPs → novel way to **analyze mobile auditory BCI data unsupervised**.
- ✓ Time and frequency decompositions provide signal components that represent approximately similar underlying source activation.
- ✓ Concept holds for small tensor with only few trials (ten trials). (not shown)

- × **Only possible offline scenarios**
- × inability to identify extracted clusters.

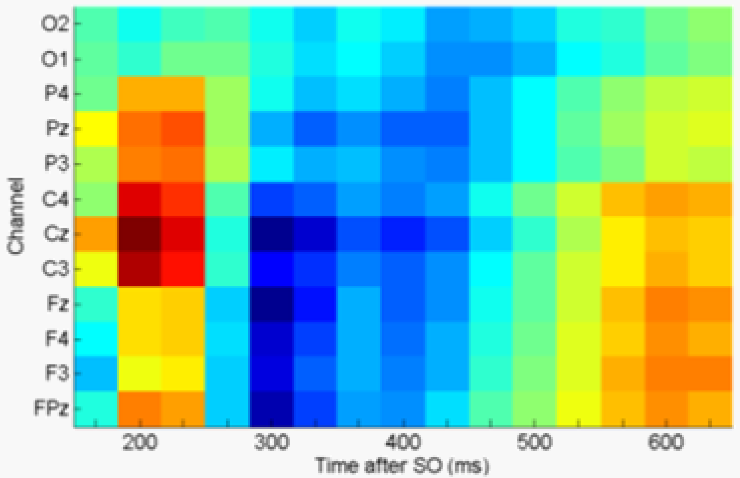
Data Driven Classification

Adding general knowledge about stimuli classes

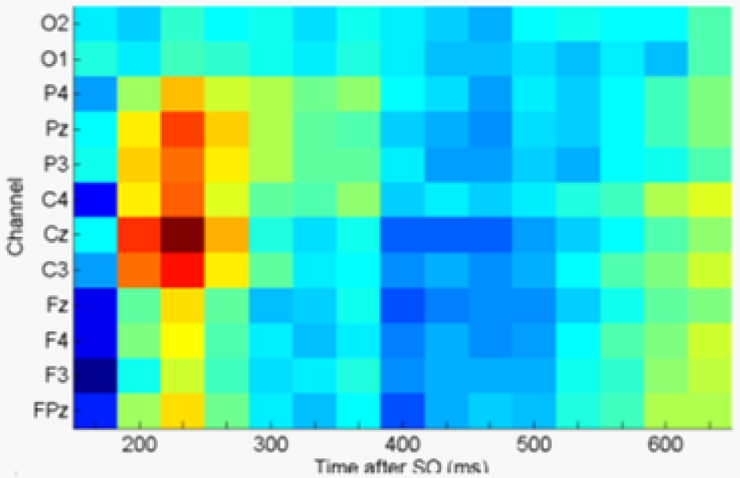


Grand-Average ERP matrices

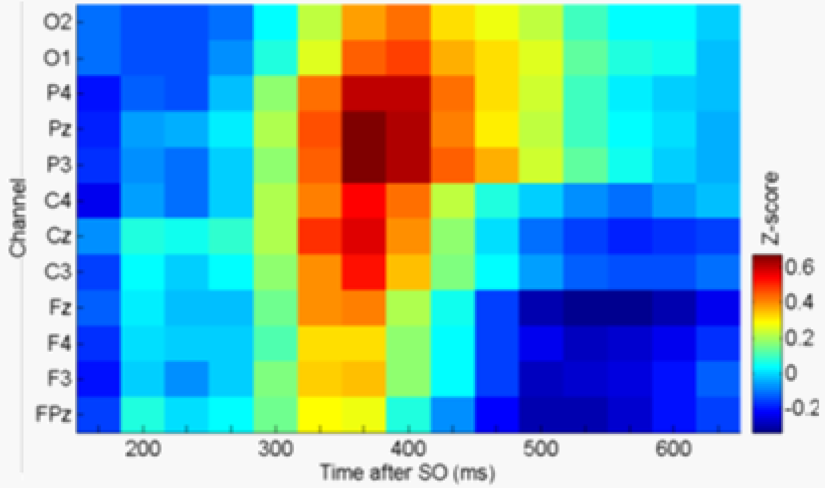
Baseline



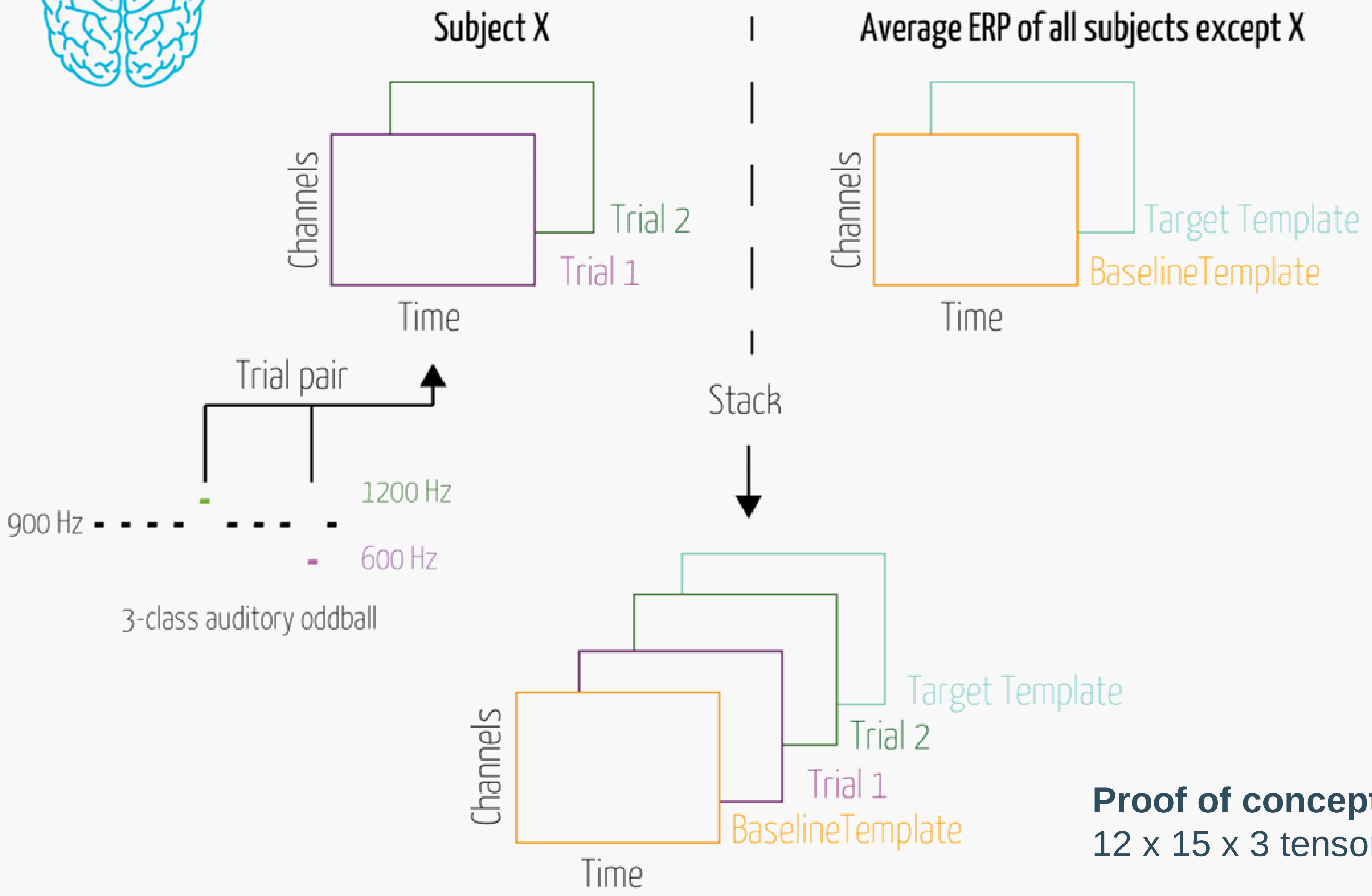
Non-target



Target



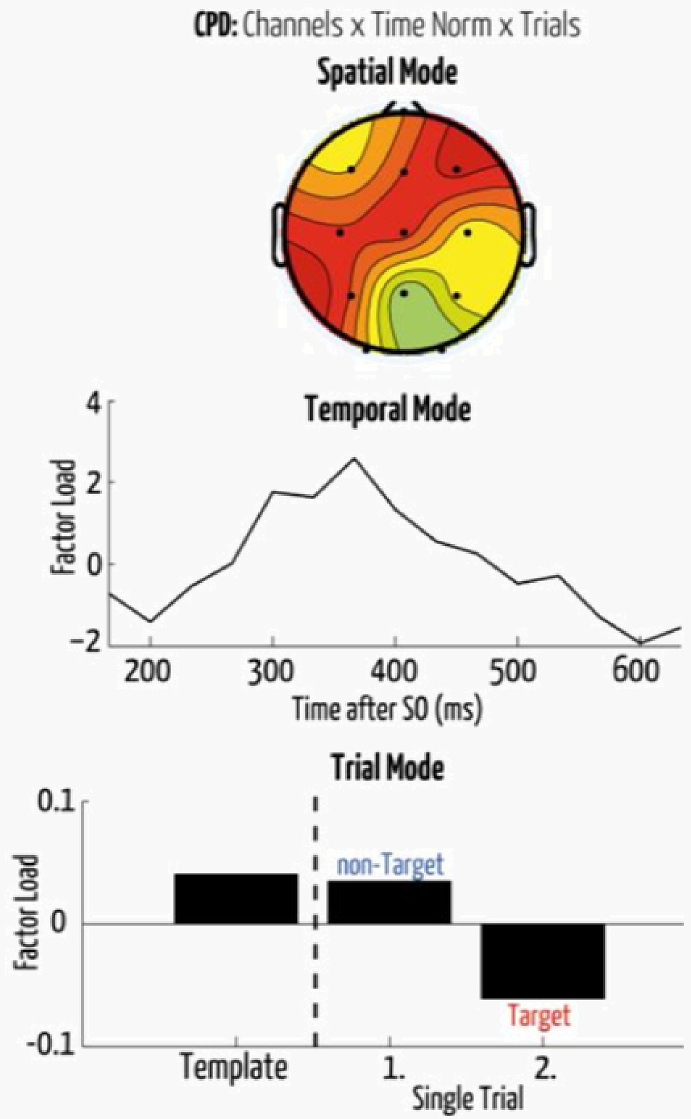
Online scenario: Identify classes with non-specific templates



Proof of concept
12 x 15 x 3 tensor

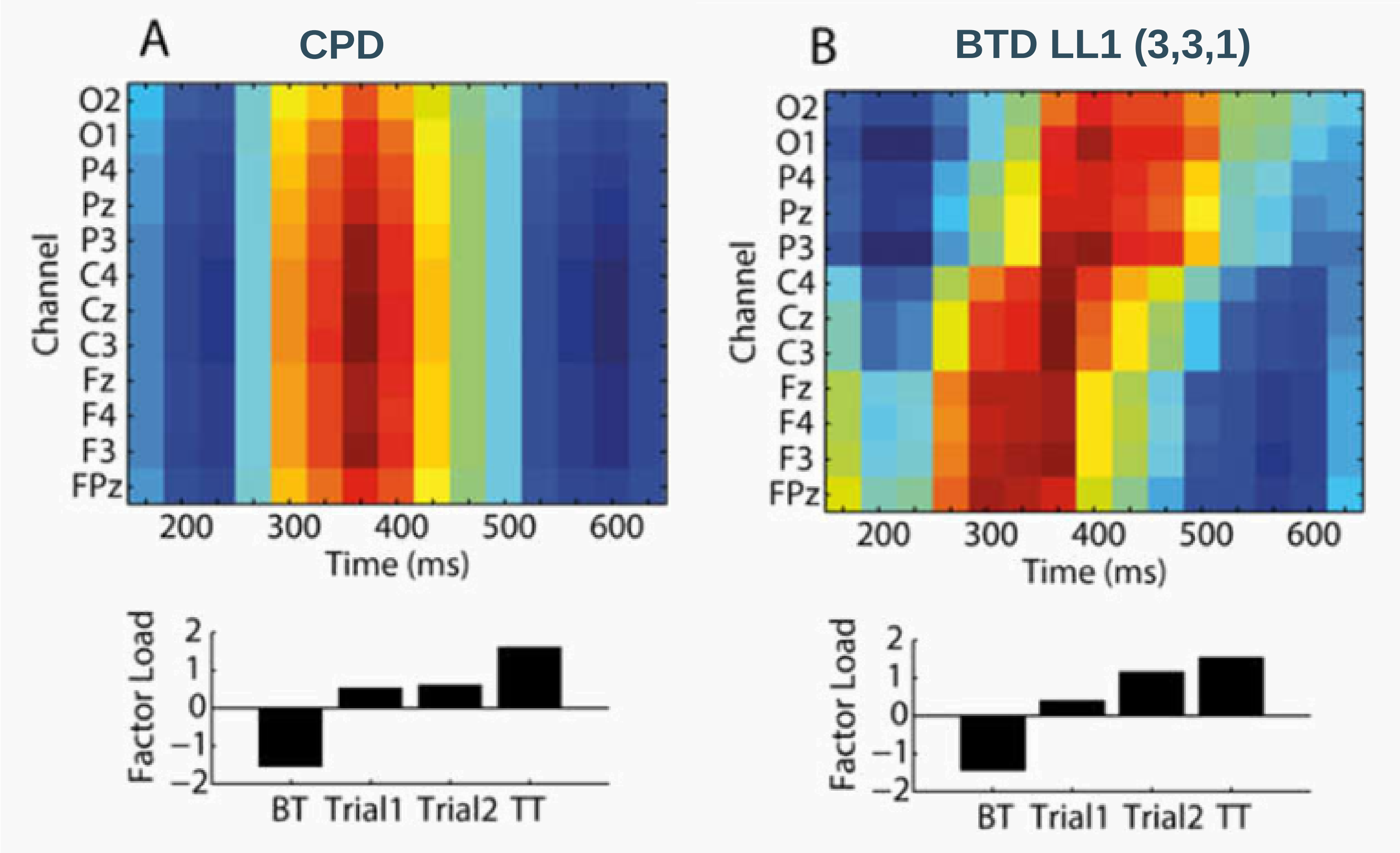
Rank 1

Example Component



Compare CPD and LL1-Block Tensor Decomposition on ERP data

Example components

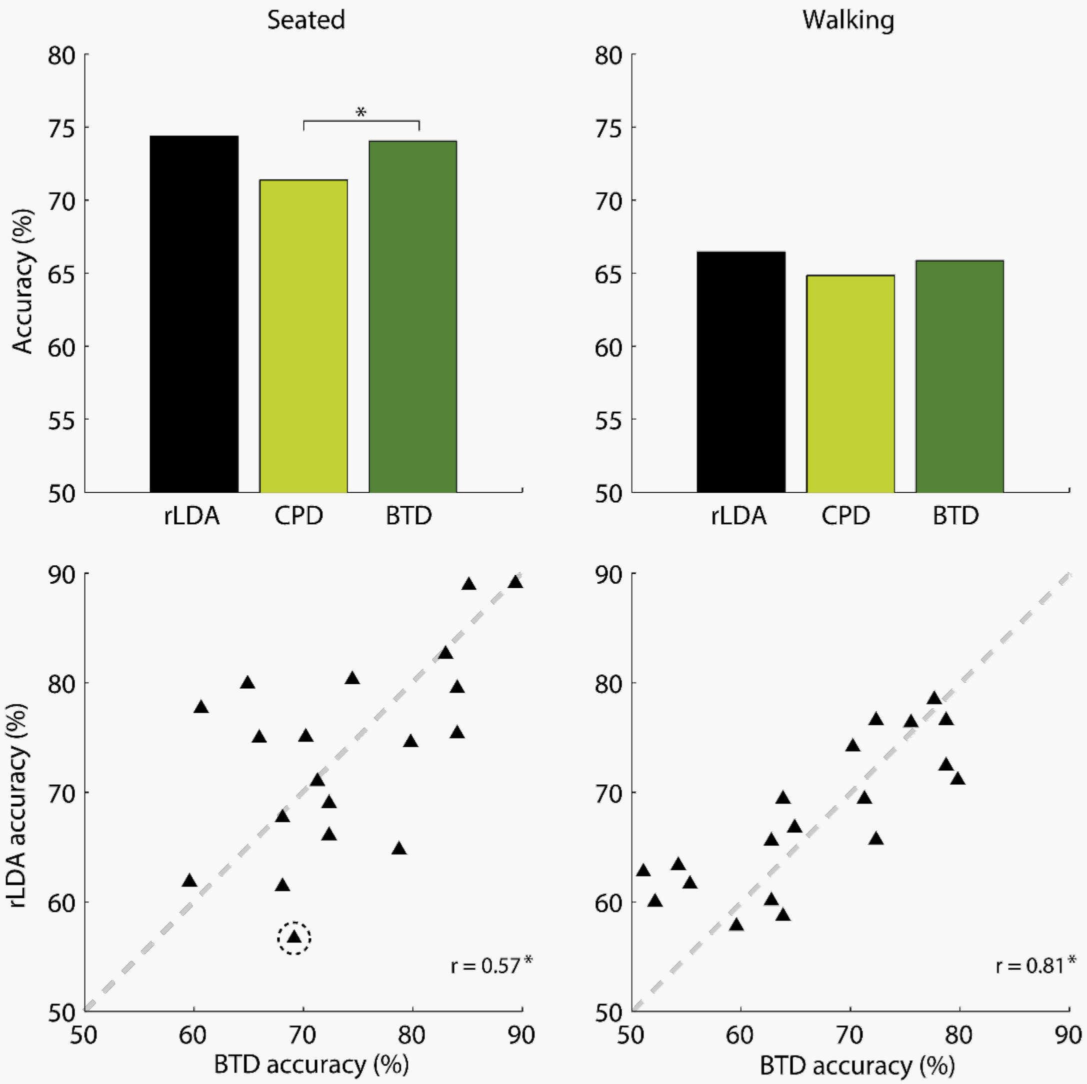


Per binary command: 12 x 15 x 4 tensor:
2 known-templates and 2 unknown-trials

Values of 2 to 5 for L*r* were explored.

Parietal Occipital shift of activity.

BTD to BCI

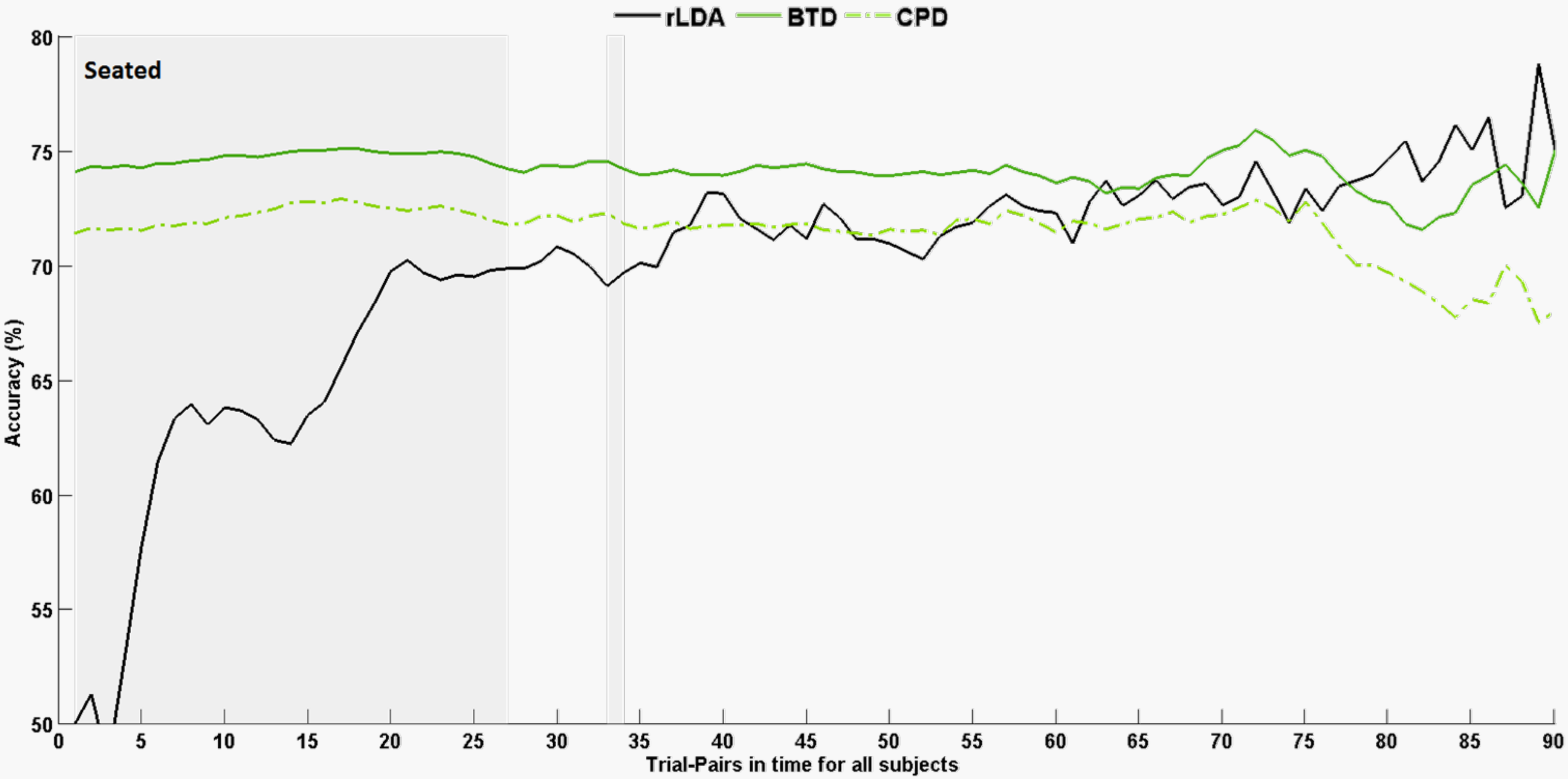


- **Higher accuracy of BTD as compared to CPD**
- **Individual differences between rLDA and CPD/BTD**

Published in:

Zink, R., Hunyadi, B., Van Huffel, S., & De Vos, M. (**2016). Tensor-based classification of an auditory mobile BCI without a subject-specific calibration phase.** Journal of Neural Engineering, 13(2), 026005.

Time-wise online analysis scenario
Sit condition



Shaded area: significant differences to rLDA ($p<0.05$)

Summary

✓ The **BTD** method presented here has a **forthright link to the original P300 ERP** signal and achieves good classification results.

✓ Important step towards constructing intuitive classification methods by **exploiting data signatures from other subjects and structural paradigm information.**

× **Dependence on the response patterns of the subject**. Between-subject differences remain. Walking condition lower accuracies.

Future

♦ Understanding of the fluctuations in brain responses (and noise levels) on single trials.

♦ Assess the ‘maximum achievable’ classifications (Human Performance) – **100% accuracy is not possible on this type of data.**

Published in:

Zink, R., Hunyadi, B., Van Huffel, S., & De Vos, M. (**2016). Tensor-based classification of an auditory mobile BCI without a subject-specific calibration phase.** Journal of Neural Engineering, 13(2), 026005.

Contents Overview

Conclusions

MANY BLIND SOURCE SEPARATION PROBLEMS IN SMART PATIENT MONITORING OF LOW RANK

- *Solve via (constrained) matrix or tensor factorizations*
- *BIOTENSORS Project with TENSORlab: huge step forward*

BIOTENSORS Achievement 1:

- *Development of **advanced algorithms for computation of tensor decompositions**, firmly based on numerical mathematics with proven uniqueness properties. This also includes more general studies, involving block terms, coupled data sets and various types of constraints, relevant for biomedical applications.*

BIOTENSORS Achievement 2:

- *Introduction of **advanced approaches to BSS**, based on BTD instead of CPD, involving multimodal data, exploiting source structure as an alternative to statistical independence, and allowing exploitation of broad set of constraints.*

TENSORlab Achievement:

- *Above algorithms efficiently implemented in Tensorlab 3.0 and 4.0. User friendliness improved significantly by simplifying model construction and adding visualization routines, documentation and demos.*

ABOVE IMPROVEMENTS ALLOW TO FACE CHALLENGES IN BIOMEDICAL DATA FUSION

- *Successful examples: MS diagnostics, Neonatal Sleep Staging, Wearable Health monitoring, Mobile EEG*
- *Other examples: **See talks/posters at EURASIP Summer school Tensor-based Signal Processing***

Future directions

- *Adaptive tensor decompositions, rank & structure estimation*
- *Multiscale multimodal approaches*
- *New emerging applications, e.g. in C(hr)onnectome analysis*
  modelling dynamic brain connectivity networks

→ ***exploit full potential of existing Tensor(lab) toolboxes***

Thank you!

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| Eindhoven University of Technology

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