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Tensor Based Approaches in Magnetic Resonance Spectroscopic Signal Analysis

Sabine Van Huffel, H. N. Bharath and Diana Sima

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Outline

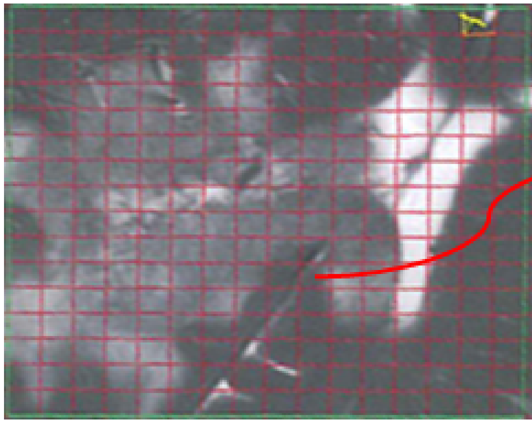
APPLICATION 1: water suppression in Magnetic Resonance spectroscopic imaging (MRSI)

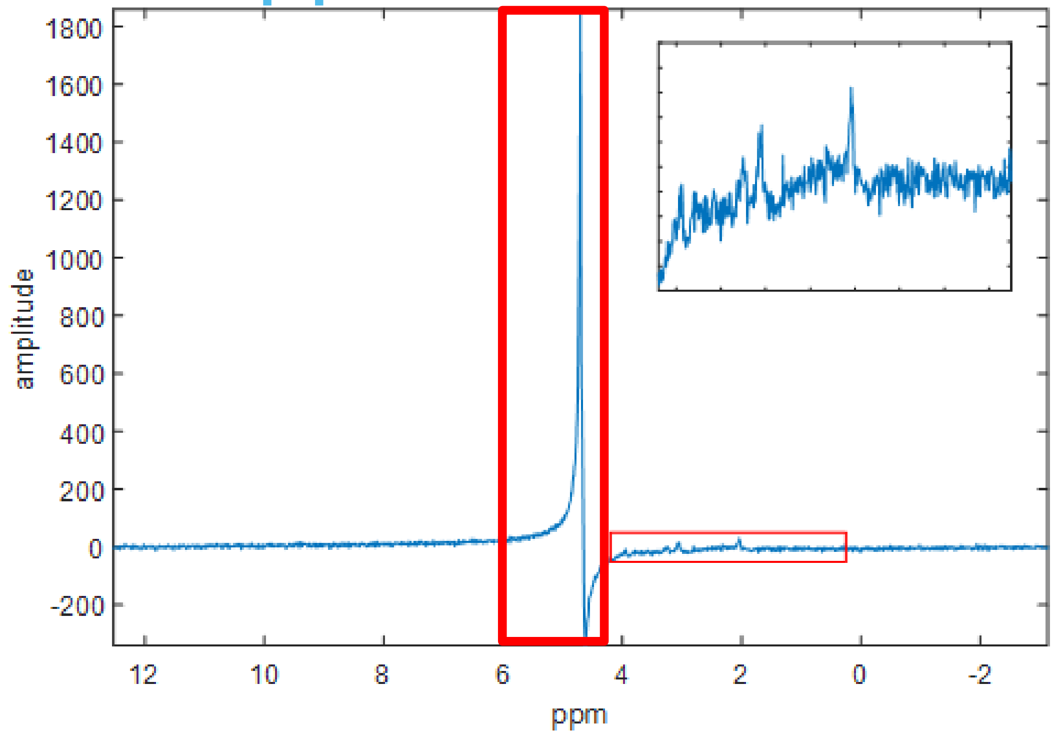
- Method → Löwner based tensor approach applied to MRSI

APPLICATION 2: Tissue type differentiation of gliomas

- Method 1→ Non-negative (N) CPD applied to MRSI
- Method 2→ NCPD applied to multi-parametric MRI

APPLICATION 1: water suppression in MRSI





Frequency domain Model

$$S(f) = \sum_{r=1}^{R} \frac{a_r e^{j\phi_r}/2\pi}{d_r + j2\pi(f - f_r)} + \eta(f)$$

$$S = {\color{red}W} H^T$$

Spectra from Voxels

Source abundancies in the grid

Spectra of sources

Time domain Model

$$S(t) = \sum_{r=1}^{R} a_r e^{j\phi_r} e^{(-d_r + j2\pi f_r)} + \eta(t)$$

HSVD based water suppression

Aim: Suppress the large water peak from all the voxels

Löwner based water suppression- Löwner matrix

- For a function $S(t)$ evaluated at $T = \{t_1, t_2, \dots., t_N\}$. Partition T into two disjoint point sets $X = \{x_1, x_2, \dots., x_I\}$ and $y = \{y_1, y_2, \dots., y_J\}$, then Löwner matrix is given by:

$$L = \begin{bmatrix} \frac{S(x_1) - S(y_1)}{x_1 - y_1} & \cdots & \frac{S(x_1) - S(y_J)}{x_1 - y_J} \\ \vdots & \ddots & \vdots \\ \frac{S(x_I) - S(y_1)}{x_I - y_1} & \cdots & \frac{S(x_I) - S(y_J)}{x_I - y_J} \end{bmatrix}$$

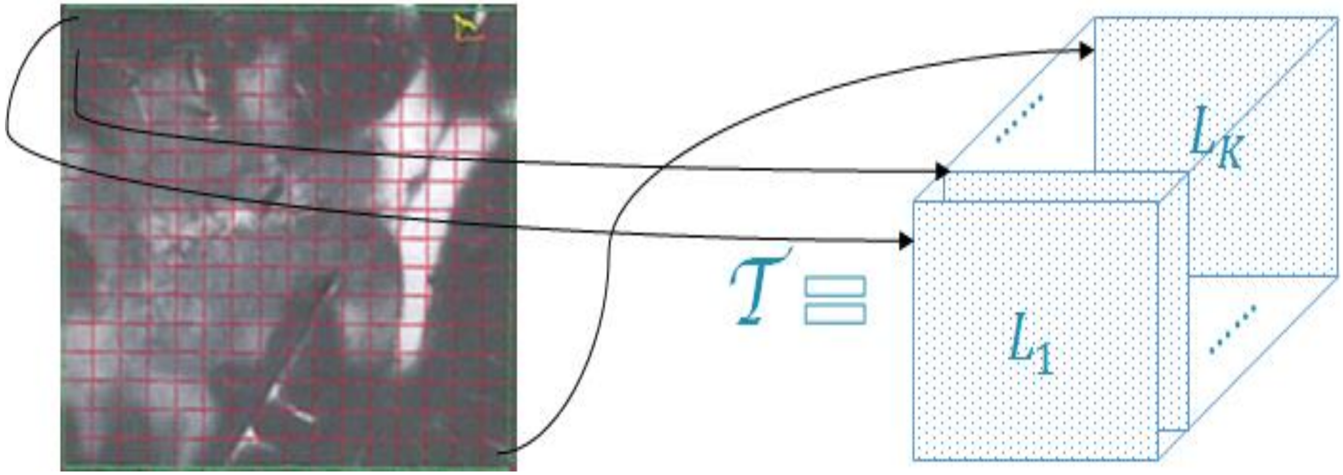
- A Löwner matrix constructed by a rational function of degree-R will have a rank-R.
- The BSS problem $S = WH^T$ can be formulated using Löwner matrix/tensor*.

$$\mathcal{L}_s = \sum_{r=1}^{R} L_{W_r} \otimes h_r$$

*O. Debals, M. Van Barel, and L. De Lathauwer, "Löwner-Based Blind Signal Separation of Rational Functions With Applications," Signal Processing, IEEE Transactions on, vol. 64, no. 8, pp. 1909–1918, April 2016.

Löwner based water suppression*- CPD

- For each voxel in the MRSI signal construct a Löwner matrix from the spectra and stack then to form a tensor.



- Each individual component can be well approximated by a degree-1 rational function, BSS reduces to CPD.

$$\mathcal{L}_s \approx \sum_{r=1}^{R} a_r \otimes b_r \otimes h_r$$

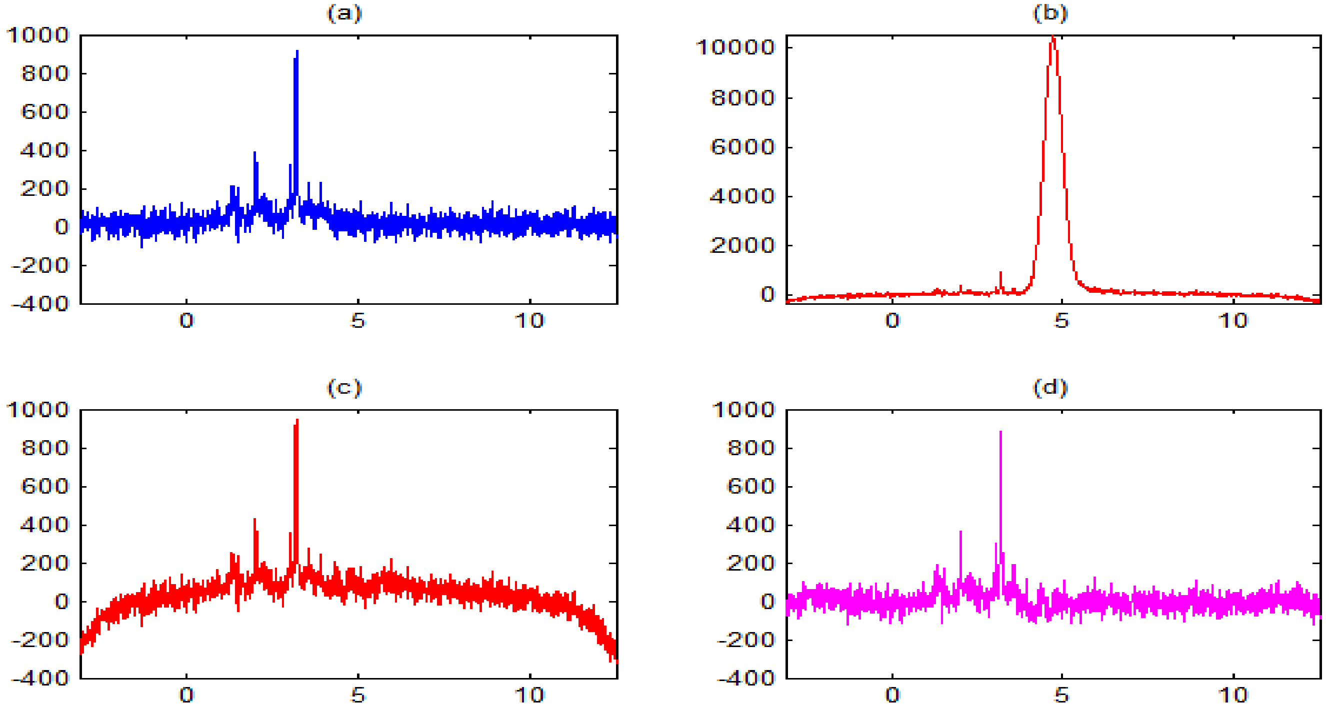
*H. N. Bharath, O. Debals, D. M. Sima, U. Himmelreich, L. De Lathauwer, S. Van Huffel, “Löwner Based Method for Residual Water Suppression in [1]H Magnetic Resonance Spectroscopic Imaging ”, Submitted to IEEE transactions on biomedical engineering.

Löwner based water suppression – Method

- Estimate the Rational function parameters from mode-1 and mode-2 factor matrices using Least squares.
- Extend the sources outside the region of interest using the estimated parameters.
- Calculate the abundancies h_k from extended sources and measured spectra using least squares.
- Water component is estimated using only the sources and amplitudes that are in the water frequency range (4.2-6 ppm).
- Finally the water component is suppressed by subtracting the estimated signal from the measured signal.

Löwner based water suppression- Baseline

- Problem: In some voxels, water suppression will result in a baseline at the edges of the spectra.



- Model the baseline using polynomial function by adding it to the source matrix W.

$$W_{poly} = \begin{bmatrix} w_{11} & \cdots & w_{1R} & 1 & \cdots & f_1^d \\ \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ w_{N1} & \cdots & w_{NR} & 1 & \cdots & f_N^d \end{bmatrix}$$

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Löwner based water suppression- Results

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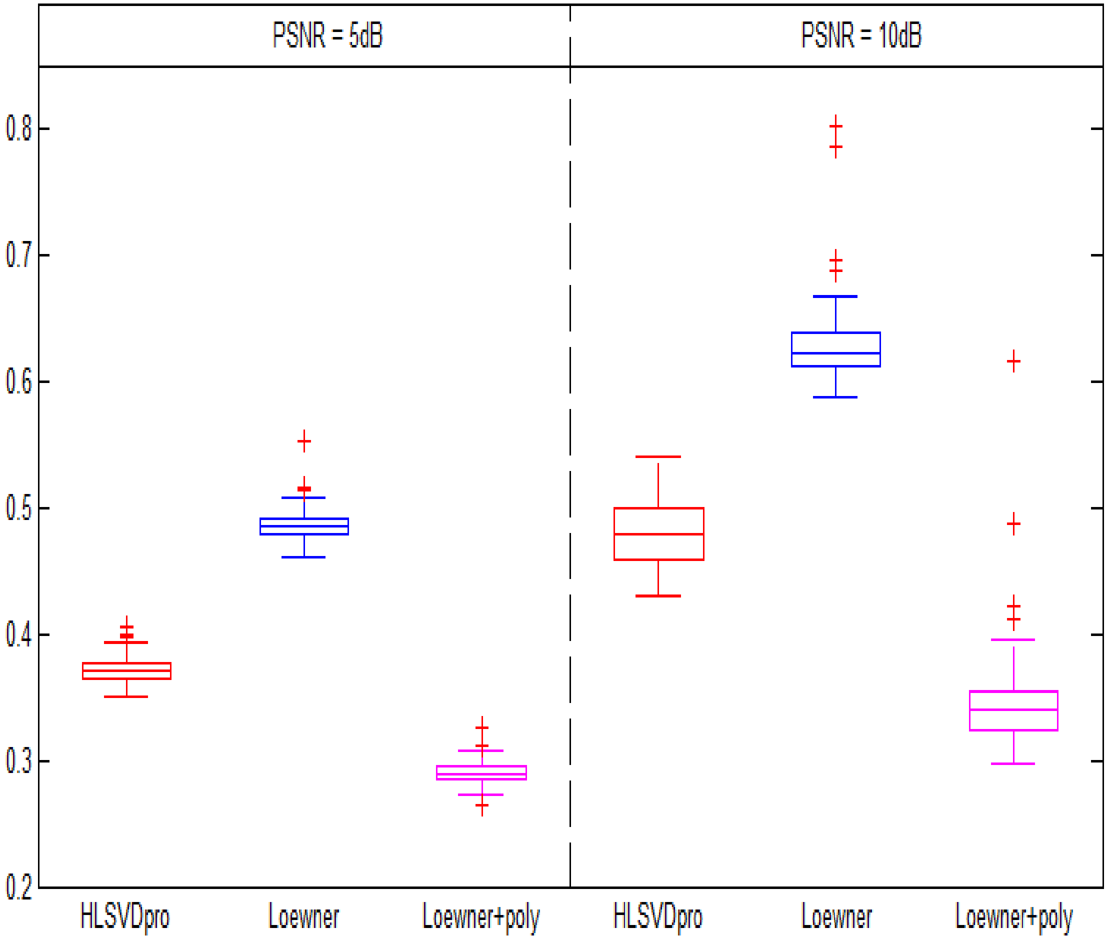
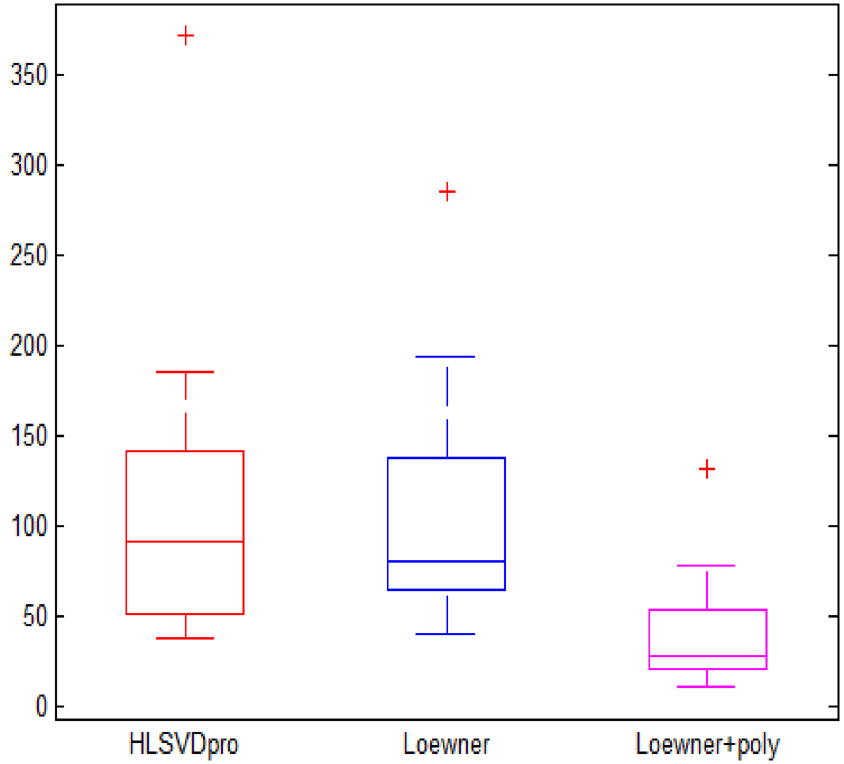
Box-plot of error on simulated MRSI data



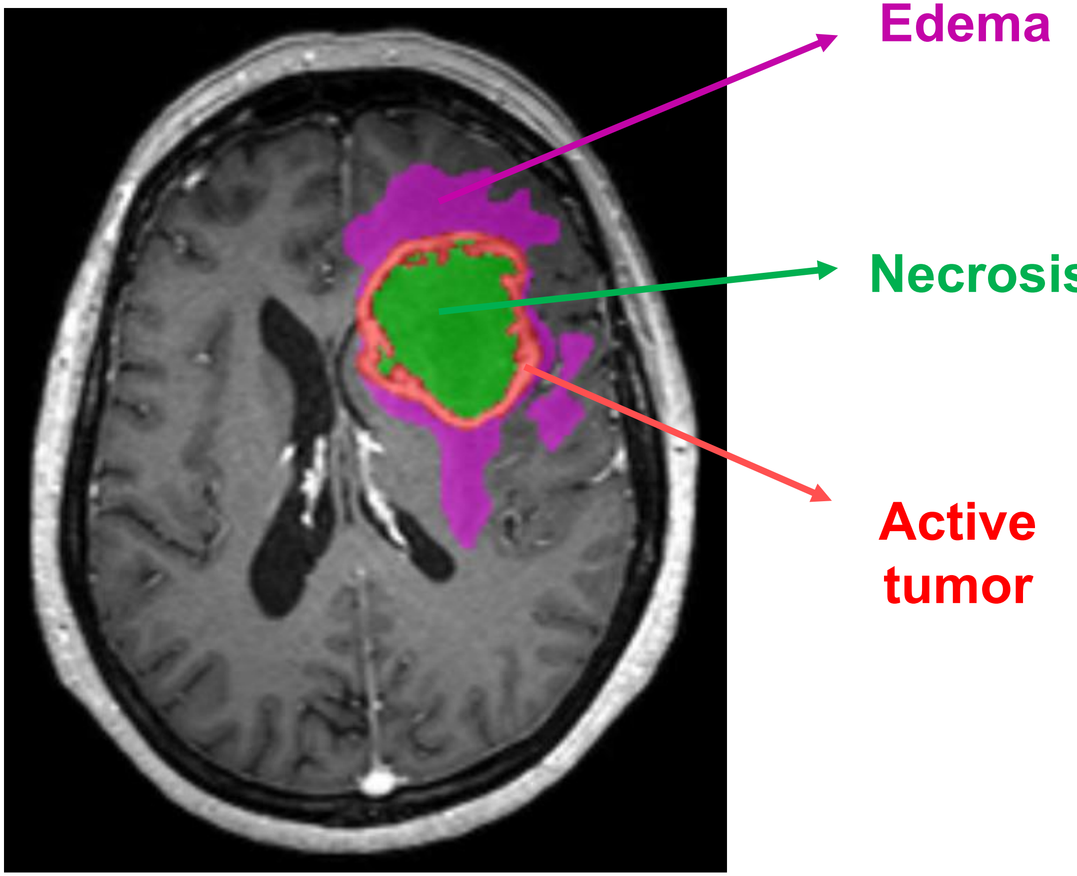
Box-plot of difference in variance on in-vivo MRSI data



APPLICATION 2: Tissue type differentiation of Gliomas

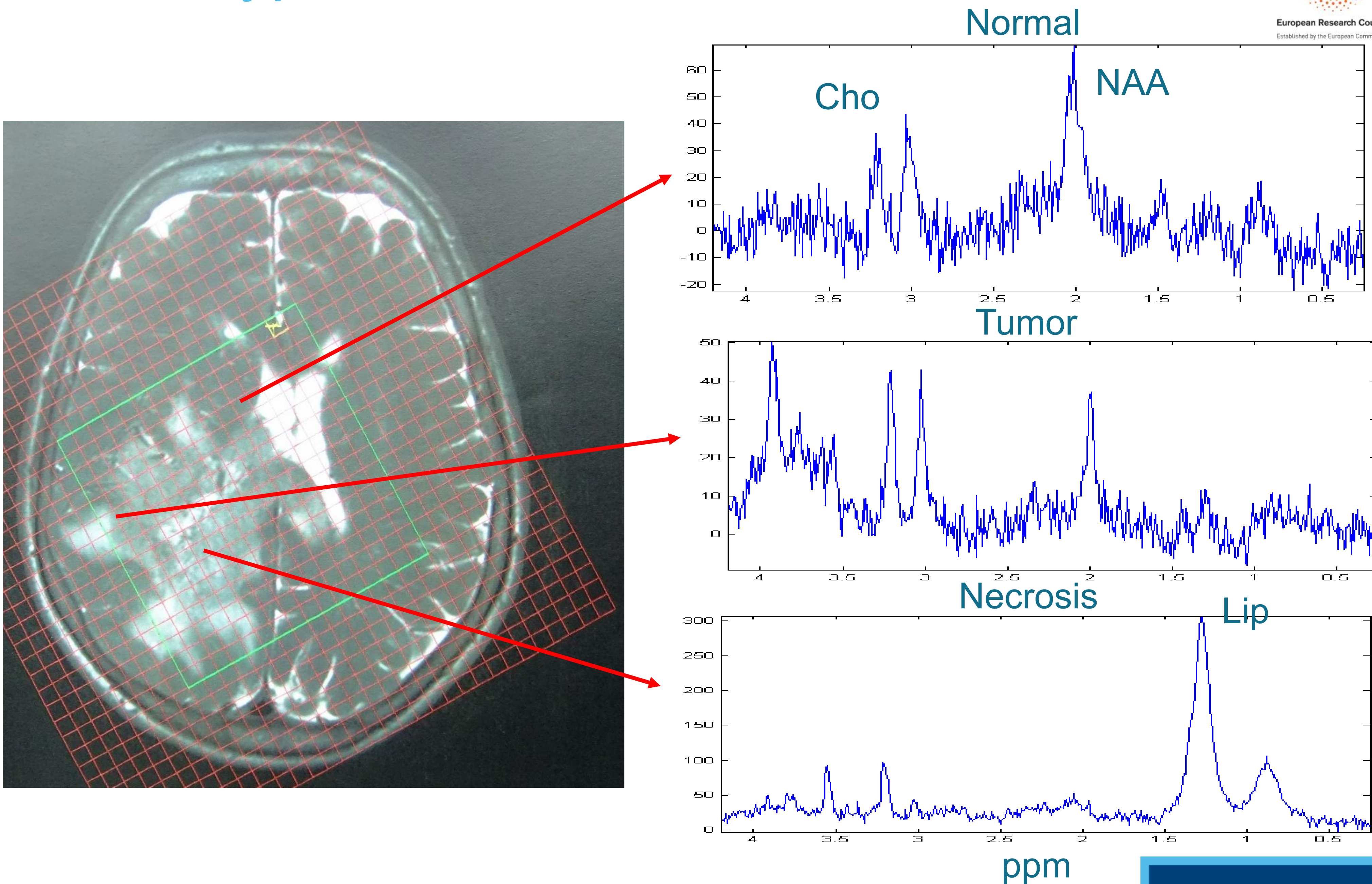
- Gliomas: 30% of all primary brain tumors and 80% of the malignant brain tumors.
- WHO grade of malignancy: grade I-IV.
- 5-year survival rates:
  - Anaplastic astrocytoma (grade III): 26%
  - Glioblastoma multiforme (grade IV): 5%

Grade IV Glioblastoma patient:

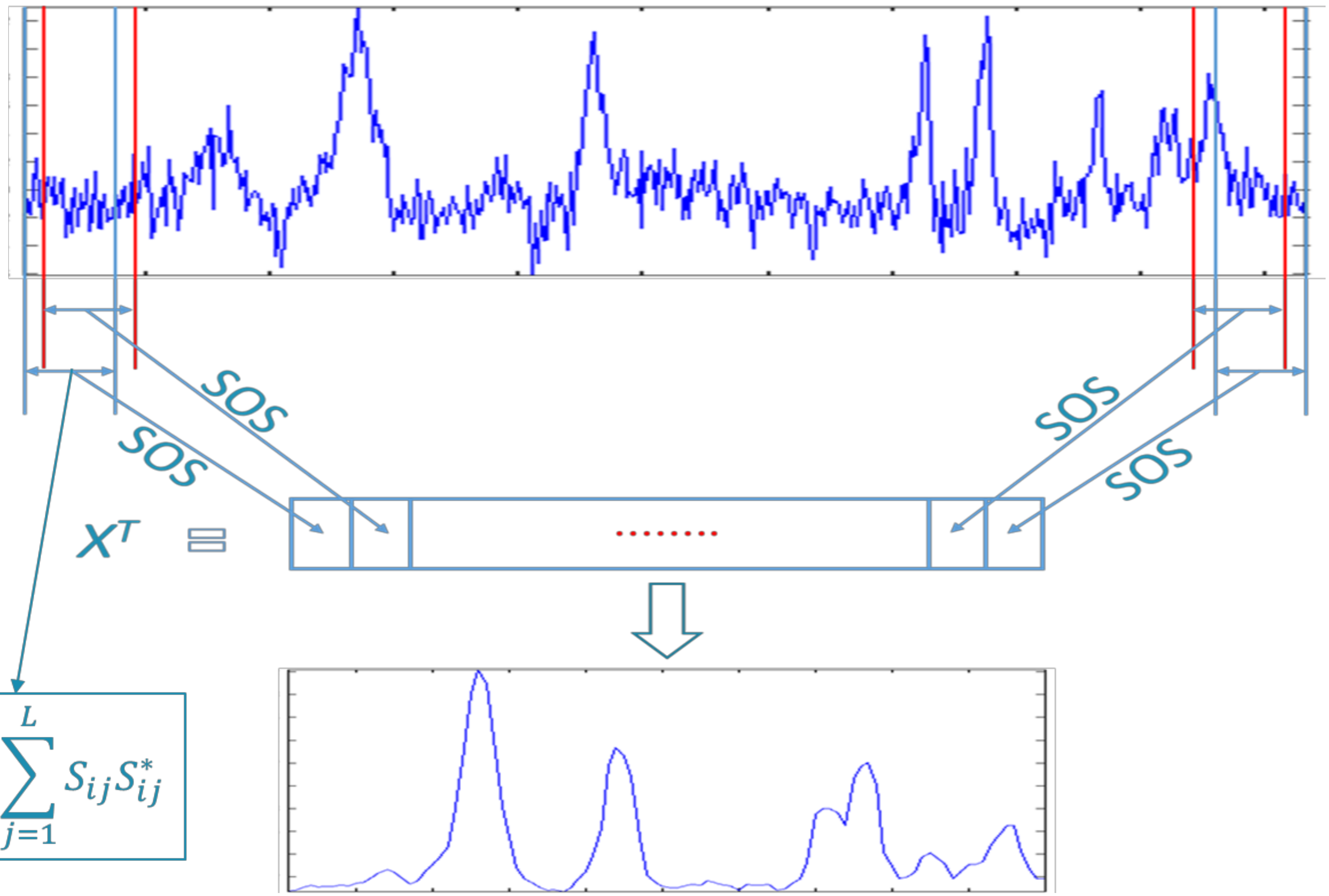


Aim: To identify active tumor and tumor core pathological region

Tissue type differentiation of Gliomas



Method 1: NCPD applied to MRSI*

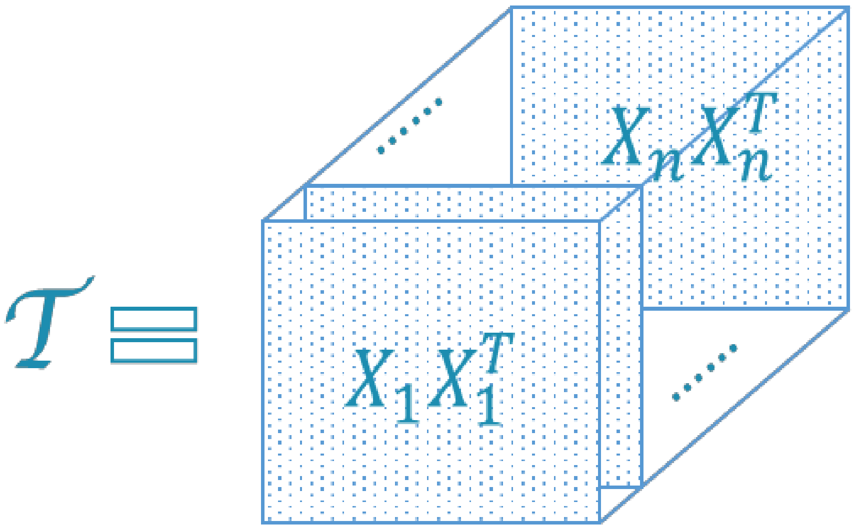


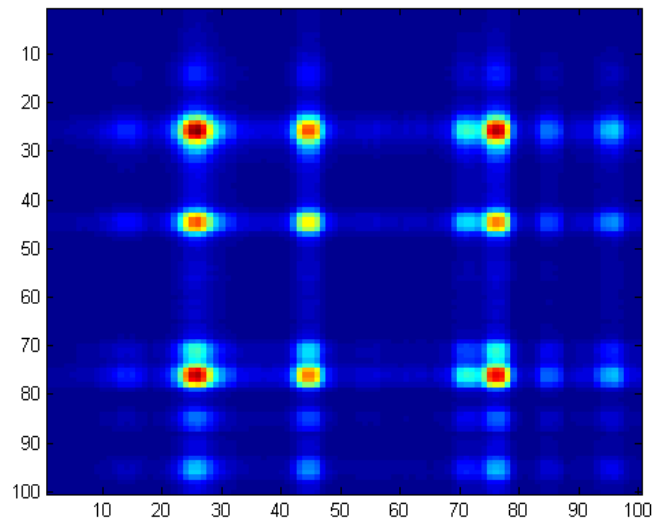
$$X(i) = \sum_{j=1}^{L} S_{ij} S_{ij}^{*}$$

- It reduces the length of spectra without losing vital information required for tumor tissue type differentiation.

*H. N. Bharath, D. M. Sima, N. Sauwen, U. Himmelreich, L. D. Lathauwer, and S. V. Huffel, "Non-negative canonical polyadic decomposition for tissue type differentiation in gliomas," IEEE Journal of Biomedical and Health Informatics, vol. PP, no. 99, pp. 1–1, 2016

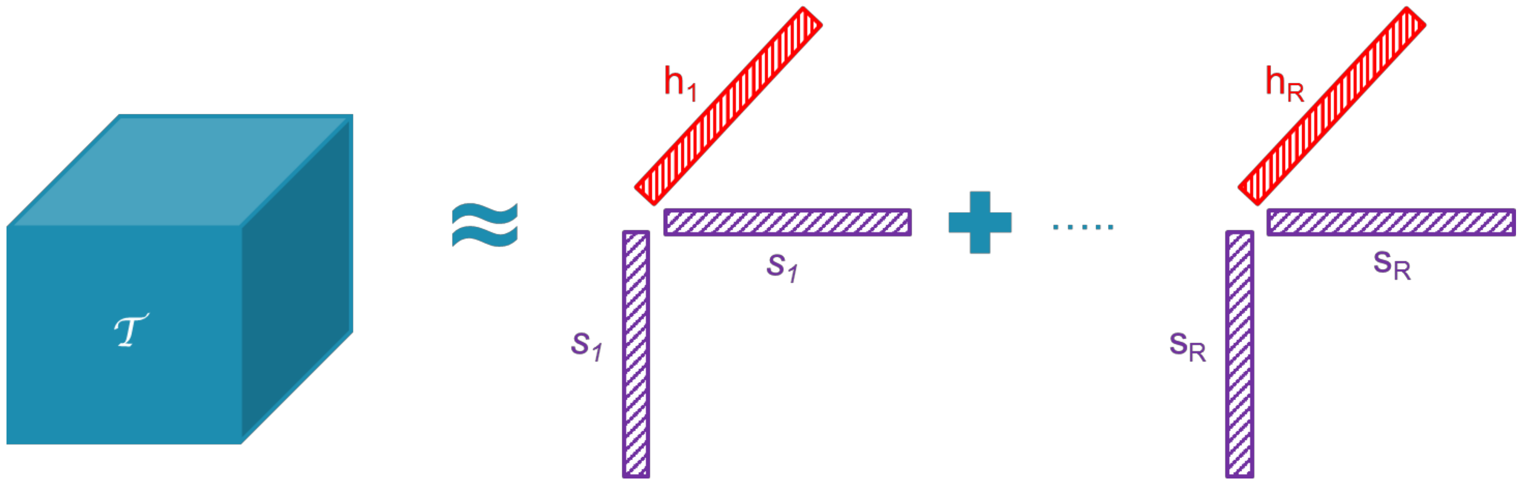
Method 1: NCPD applied to MRSI- XX^T tensor





- Construct a 3-D tensor by stacking XX^T from each voxel.
- It gives more weight to the peaks and makes the signal smoother.
- MRSI tensor couples the peaks in the spectra because of the XX^T in the frontal slices.

Method 1: NCPD applied to MRSI- NCPD



- Non-negative constraint is applied on all 3-modes.
- To maintain symmetry in frontal slices common factor (S) is used in both mode 1 and mode 2.

$$T \approx [S, S, H] = \sum_{r=1}^{K} S(:,r) \circ S(:,r) \circ H(:,r)$$

- Non-negative CPD is performed in Tensorlab* toolbox using structured data fusion.

* Vervliet N., Debals O., Sorber L., Van Barel M. and De Lathauwer L. *Tensorlab 3.0*, Available online, Mar. 2016. URL: http://www.tensorlab.net/

Method 1: NCPD applied to MRSI:- NCPD-l_1

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- Here, we assume that spectra corresponding to each voxel belong to a particular tissue type, therefore the factor matrix H will be sparse.
- Non-negative CPD with l_1 regularization on the abundances H.

$$[S^*, H^*] = \min_{S,H} \left\| T - \sum_{r=1}^{K} S(:,r) \circ S(:,r) \circ H(:,r), \right\|_2^2 + \lambda |Vec(H)|_1$$

Where λ controls the sparsity in H.

- Use more sources (higher rank) to accommodate for artifacts and variations within tissue types.
- Source Spectra are recovered from least squares:

$$S = (H^\dagger Y^T)^T$$

$H^\dagger$ is the pseudo inverse of *H* obtained from Non-negative CPD.

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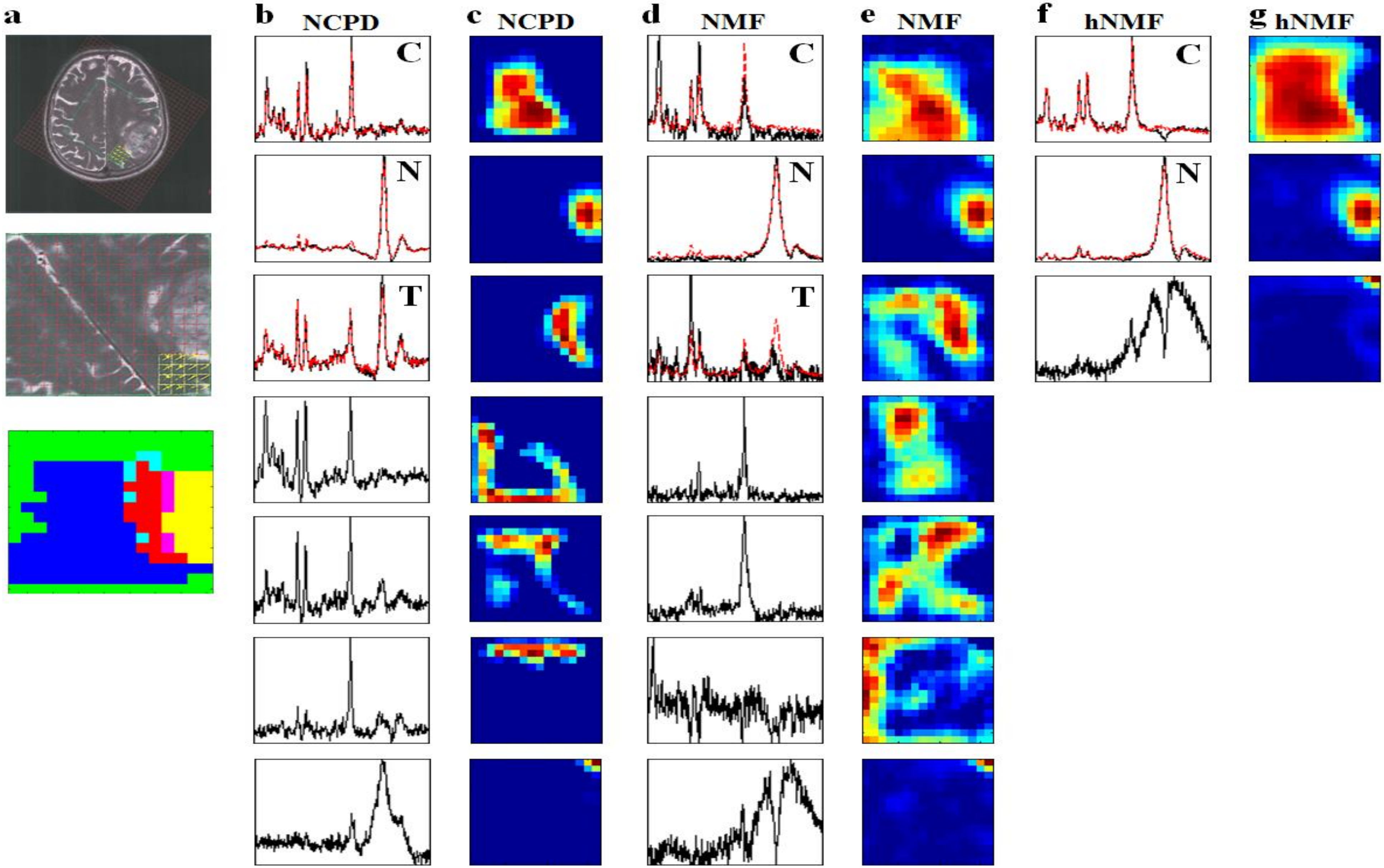
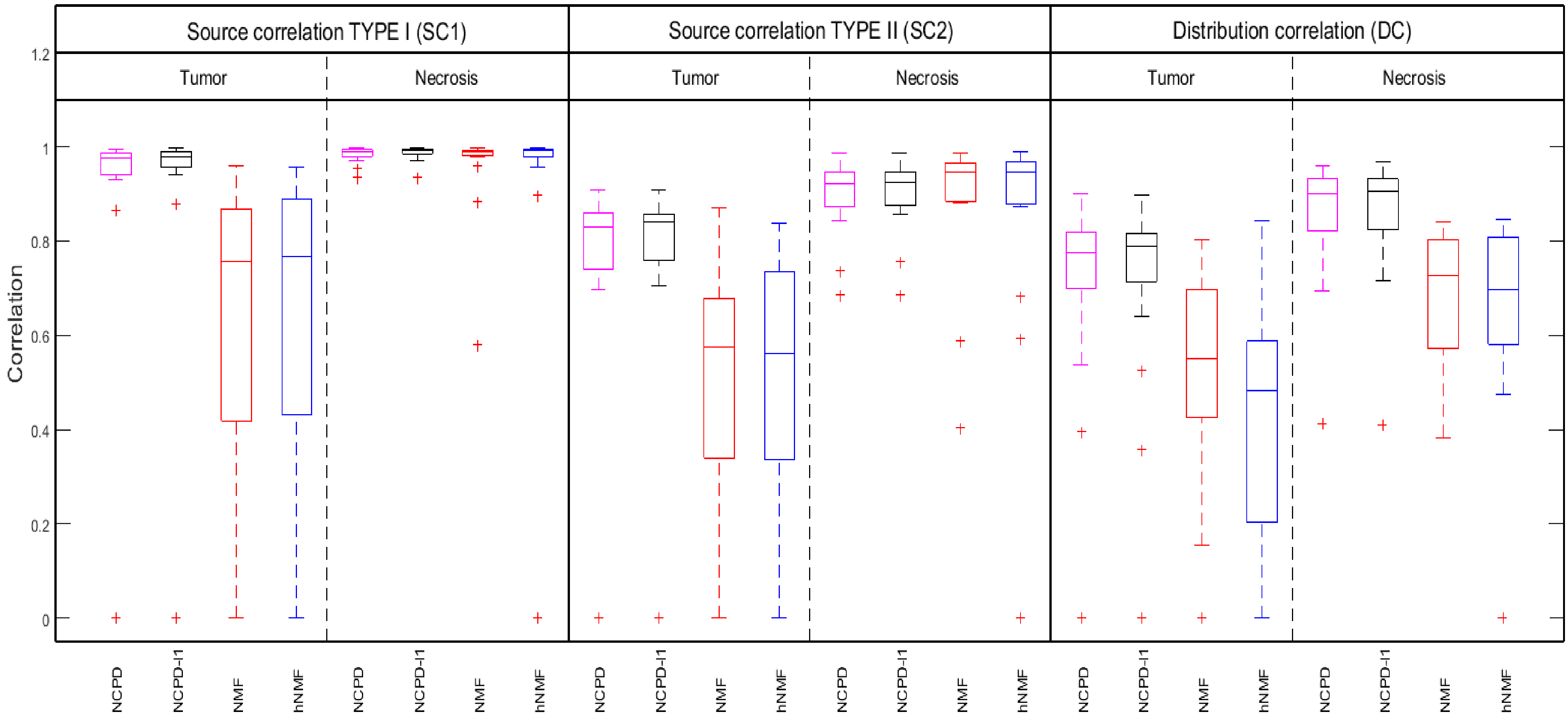
Method 1: NCPD applied to MRSI- Results

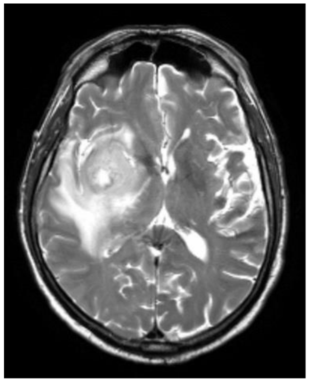


Method 1: NCPD applied to MRSI- Results

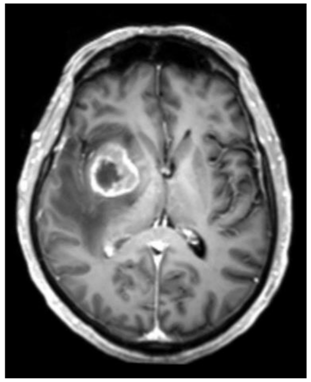


Method 2: NCPD applied to multiparametric MRI*

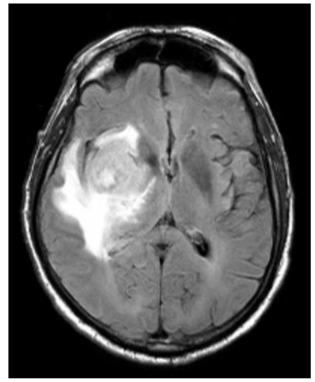
Conventional MRI



T2-weighted
(water)

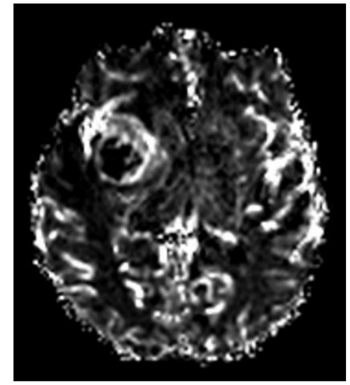


T1-weighted
(contrast-enhanced)



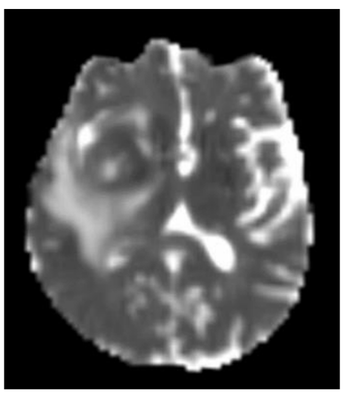
FLAIR
(fluid attenuation)

PWI

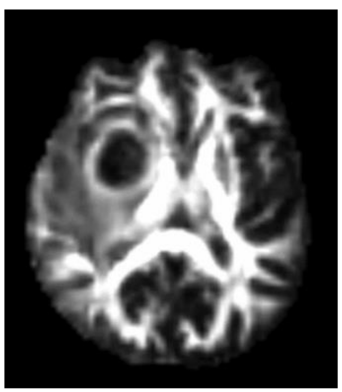


Cerebral blood
volume (CBV)

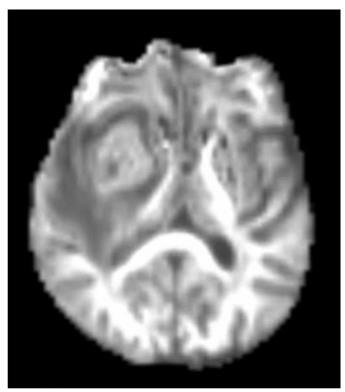
DWI



Mean diffusivity
(MD)

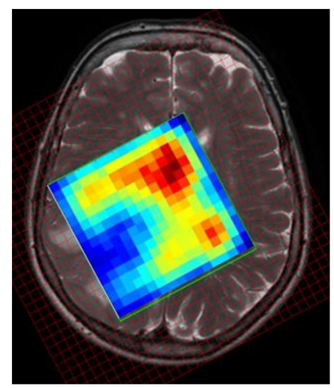


Fractional
anisotropy (FA)

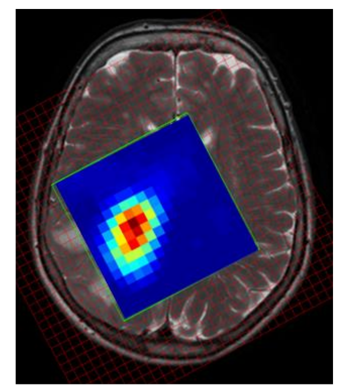


Mean kurtosis
(MK)

MRSI



NAA



Lip

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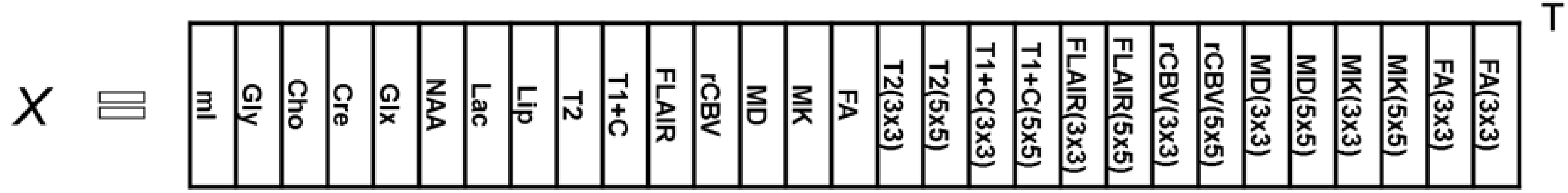
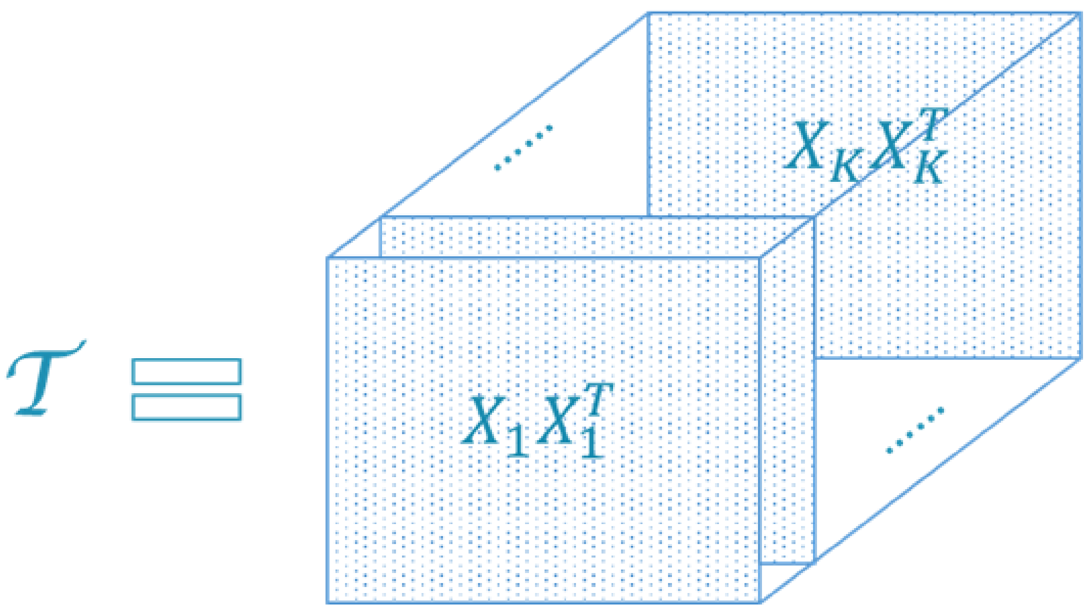
*H. N. Bharath, N. Sauwen, D. M. Sima, U. Himmelreich, L. De Lathauwer and S. Van Huffel, "Canonical polyadic decomposition for tissue type differentiation using multi-parametric MRI in high-grade gliomas," 2016 24th European Signal Processing Conference (EUSIPCO), Budapest, 2016, pp. 547-551.

Method 2: NCPD applied to MP-MRI:-XX^T tensor

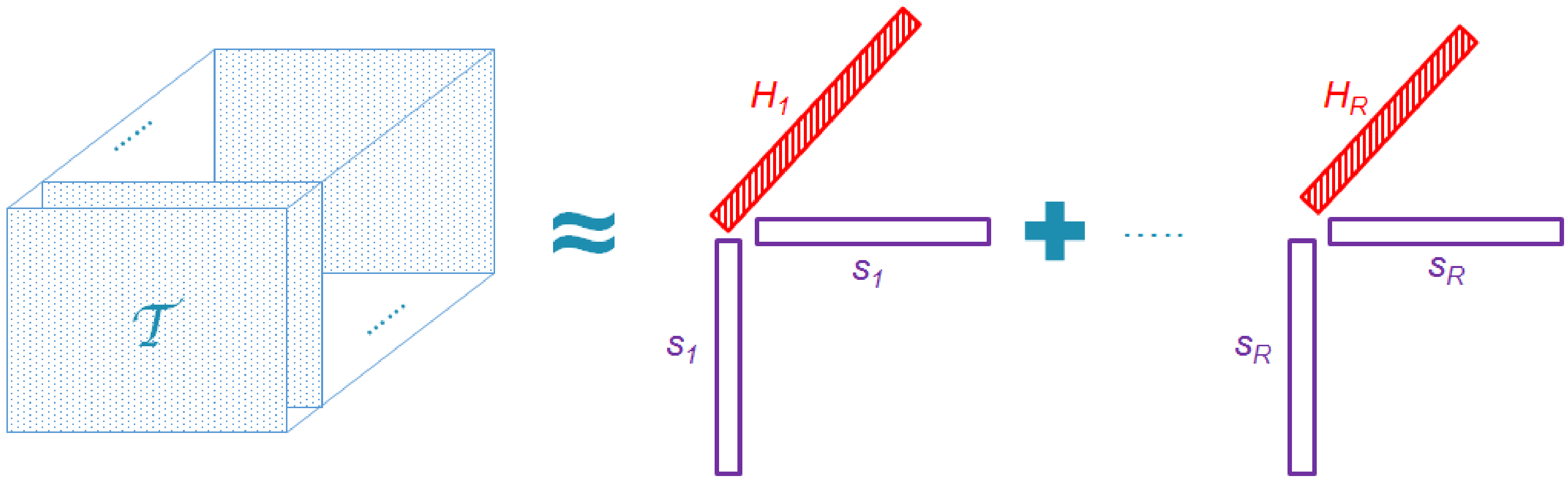
(a)



(b)



Method 2: NCPD applied to MP-MRI:- CPD



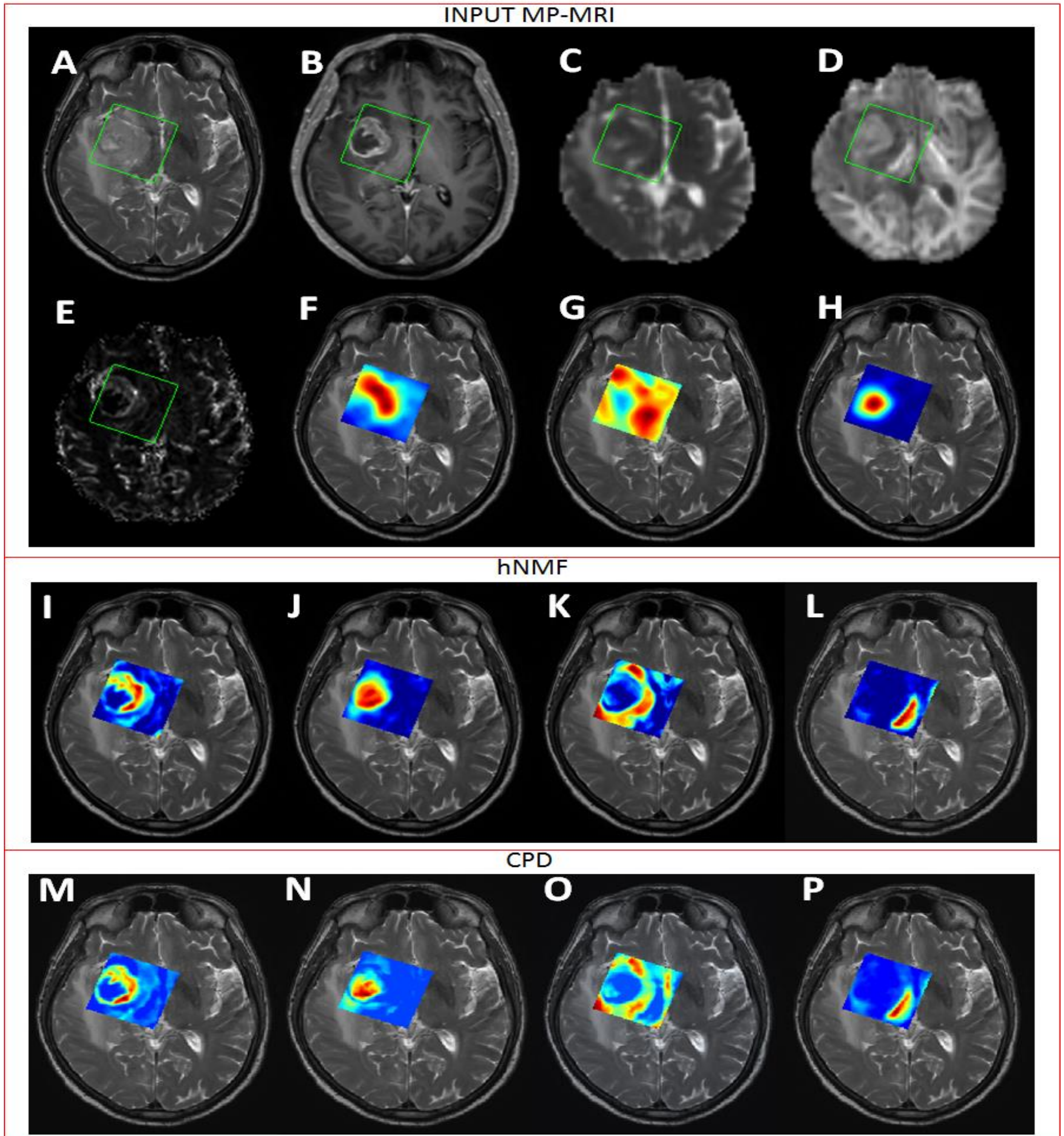
- To maintain symmetry in frontal slices common factor (*S*) is used in both mode-1 and mode-2.
- Non-negative constraint is applied on mode-3, *H*.
- Also, l_1 regularization in applied on the abundances *H*.

$$[S^*, H^*] = \underset{S,H \geq 0}{\arg\min} \left\| \mathcal{T} - \sum_{i=1}^{R} S(:,i) \, o \, S(:,i) \, o \, H(:,i) \right\|_2^2 + \lambda \| Vec(H) \|_1$$

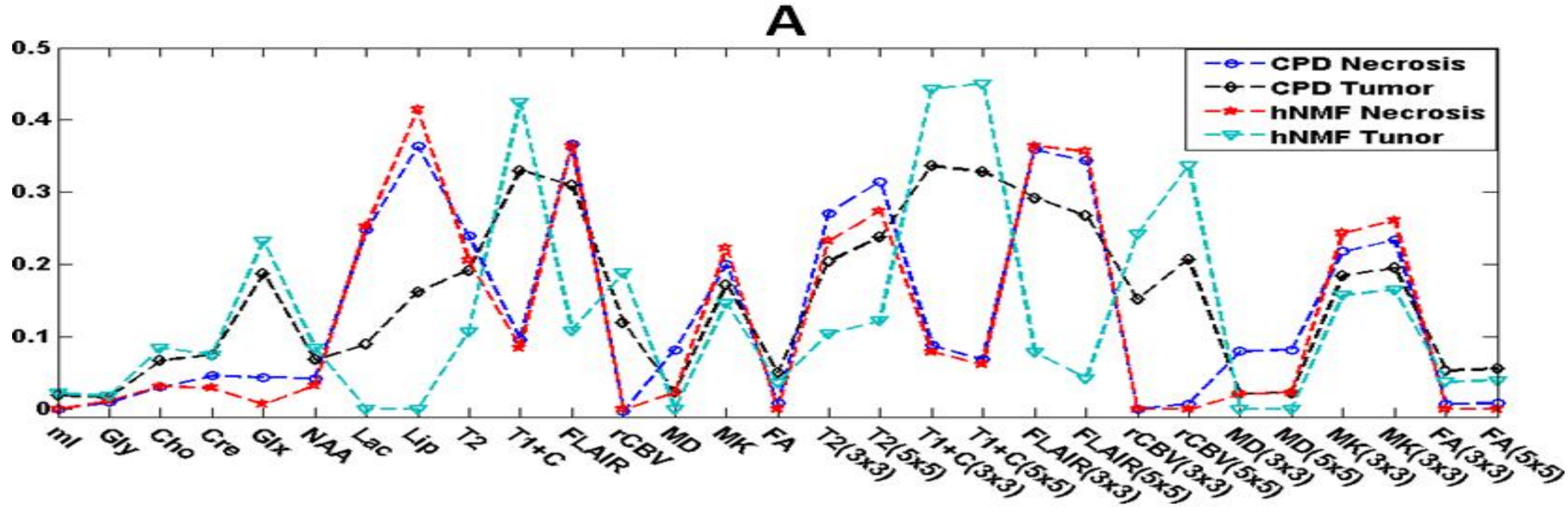
- Solved using structured data fusion method in Tensorlab*.

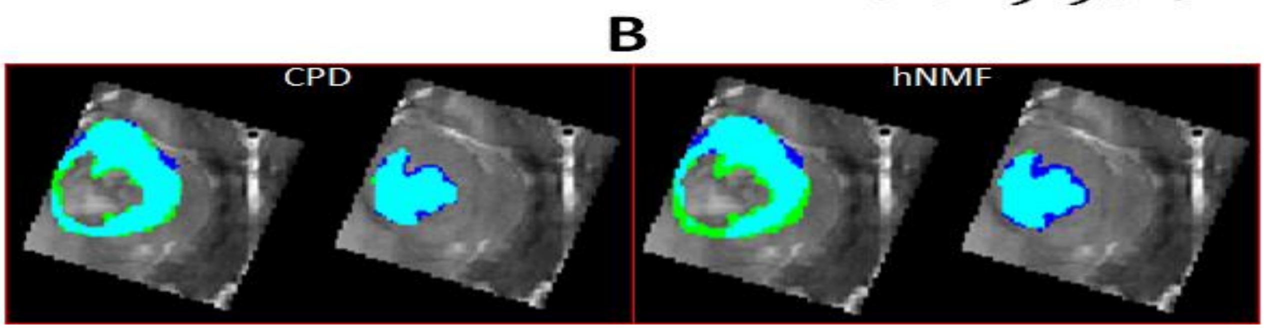
* Vervliet N., Debals O., Sorber L., Van Barel M. and De Lathauwer L. *Tensorlab 3.0*, Available online, Mar. 2016. URL: http://www.tensorlab.net/

Method 2: NCPD applied to MP-MRI:- Results



Method 2: NCPD applied to MP-MRI:- results





	Constrained CPD-l_1			hNMF		
	Dice Tumor	Dice Core	Tumor source Correlation	Dice Tumor	Dice Core	Tumor source Correlation
Mean	0.83	0.87	0.95	0.78	0.85	0.81
Standard deviation	0.07	0.1	0.05	0.09	0.13	0.19

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