

# Fast Double-coupled Nonnegative Tensor Decomposition

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## Introduction

### background

- Coupled tensor decomposition has become a popular technique for the simultaneous analysis of multi-block tensors [1].
- Simultaneous extraction of common components and individual components.
- It is reasonable to expect identical elicited information among subjects since ongoing EEG are collected under the same stimulus.
- Time consumption would go extremely heavy due to the high-dimensional and non-negative nature of ongoing EEG.

### Objective

To develop an efficient data-driven coupled tensor decomposition algorithm.

## Proposed algorithm

### Coupled tensor decomposition model

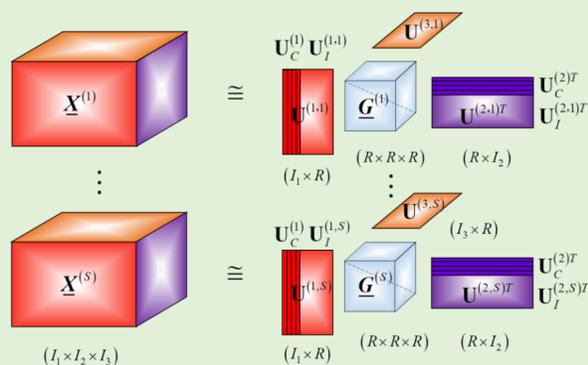


Fig.1 Conceptual illustration of dual-coupled LCPTD model [2]

### Realization of FDC-NCPD

- Squared Euclidean Divergence minimization
- Fast Hierarchical Alternating Least Squares (Fast HALS [3])
- The object function can be expressed as:

$$\text{minimize } \sum_{s=1}^S \left\| \underline{\mathbf{X}}^{(s)} - \sum_{r=1}^R \lambda_r^{(s)} \mathbf{u}_r^{(1,s)} \circ \mathbf{u}_r^{(2,s)} \circ \dots \circ \mathbf{u}_r^{(N,s)} \right\|_F^2$$

$$\text{s. t. } \mathbf{u}_r^{(n,1)} = \dots = \mathbf{u}_r^{(n,S)} \text{ for } r \leq L_n,$$

$$\|\mathbf{u}_r^{(n,s)}\| = 1, n = 1 \dots N, r = 1 \dots R, s = 1 \dots S$$

## Experiments and Results

### Exp1. Validation of synthetic data

- NTF-HALS, NTF-FastHALS, LCPTD-HALS and FDC-NCPD
- Convergence speed: Execution time, 30 runs  
SNR = 20 dB,  $I_{1,2,3} = \{7n, 8n, 9n\}$ ,  $R = 4n$ ,  $L_{1,2} = 2n$ ,  $S = 10$
- Decomposition quality: Performance Index, 20 runs  
SNR = -5~20 dB,  $I_{1,2,3} = \{40,50,60\}$ ,  $R = 30$ ,  $L_{1,2} = 20$ ,  $S = 10$

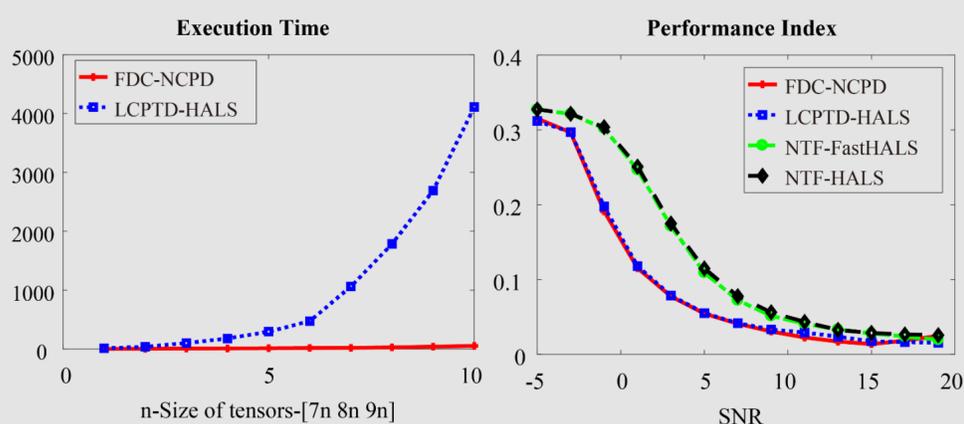


Fig 2. Results of Synthetic data

### Exp2. Application of multi-subject ongoing EEG data

- Data collection, data preprocessing can be found in [4]
- Tensors (14): 64 channels  $\times$  146 frequency bins  $\times$  510 samples
- Coupling information exists on the first two modes.
- DIFFIT suggested  $R = 36$ .  $L_{1,2} = 20$
- Running time : LCPTD-HALS - **76442.65 s** ; FDC-NCPD - **350.97 s**
- Tensor fitting : LCPTD-HALS - **0.7360** ; FDC-NCPD - **0.7353**

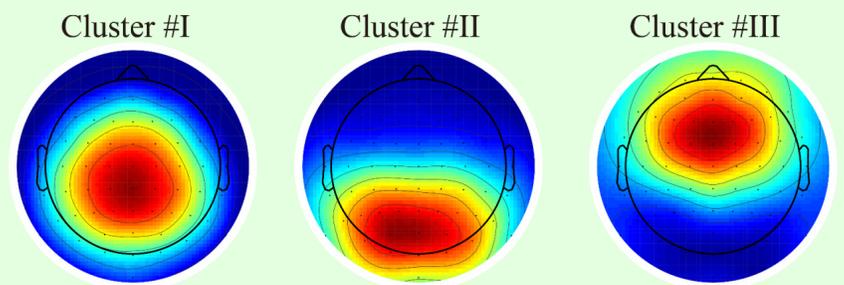


Fig 3. Averaged topographies of interest clusters from 10 runs.

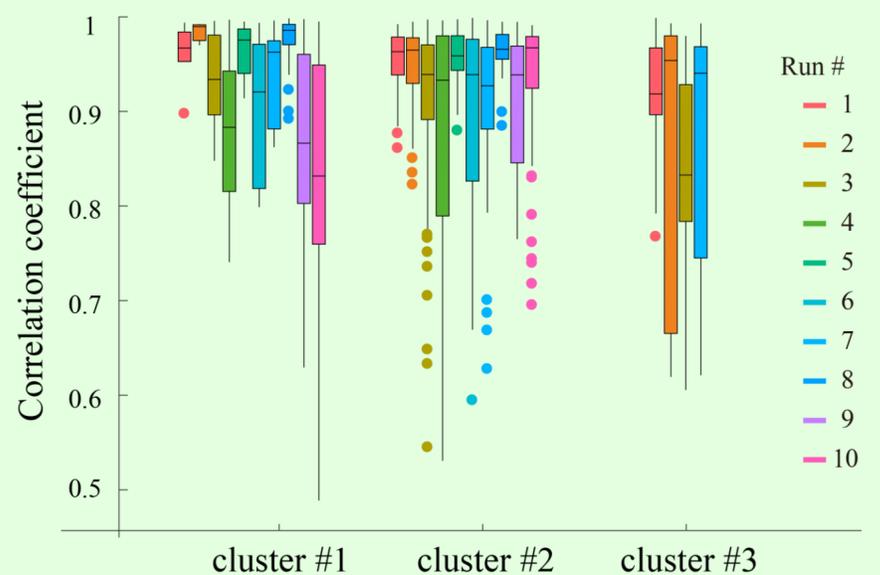


Fig 4. Correlation coefficients of internal components of clusters in 10 runs

## Conclusion

Double-coupled nonnegative tensor decomposition algorithm based on LCPTD model and Fast-HALS strategy greatly reduces the computational complexity without compromising the decomposition quality.

## References

- [1] G. X. Zhou et al., "Linked component analysis from matrices to high-order tensors: Applications to biomedical data," Proceedings of the IEEE, 2016.
- [2] T. Yokota et al., "Linked PARAFAC / CP Tensor Decomposition and Its Fast Implementation for Multi-block," ICONIP2012.
- [3] A. Cichocki et al., "Fast local algorithms for large scale nonnegative matrix and tensor factorizations," IEICE T FUND ELECTR, 2009.
- [4] F. Y. Cong et al., "Linking brain responses to naturalistic music through analysis of ongoing eeg and stimulus features," IEEE Transactions on Multimedia, 2013.

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