Multimodal ICA

Week 13 - Advanced Topic 4

Introduction

Definition of MICA[1]

- Modality: type of data that captures different aspects of a system or subject

- Separate and analyze independent components from multiple sources (modalities)

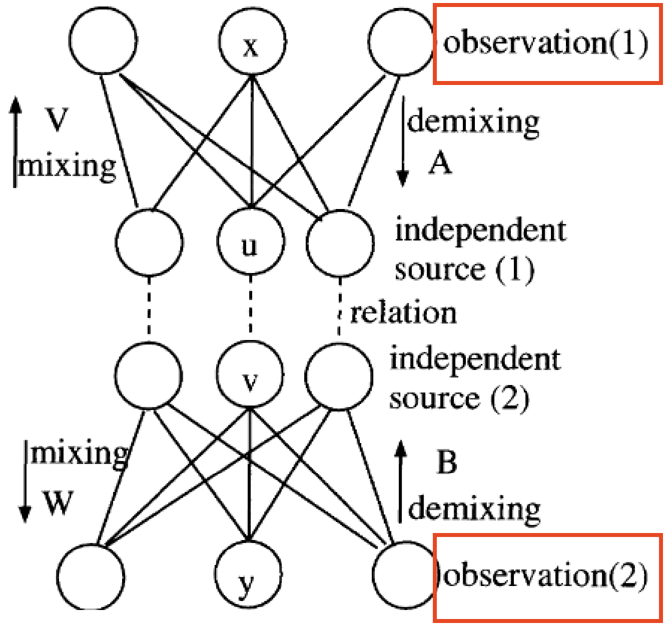


Fig. 1. Concept of MICA.

Features of MICA[1]

- Features are:
  - (u_i, v_i) are statistically dependent
  - (u_i, v_i) and (u_j, v_j) are independent, $i \neq j$ (mutually independent)

- Maximizes mutual information (MI) among modalities (or sources)
  - MI: shared information between two random variables
  - Cost function

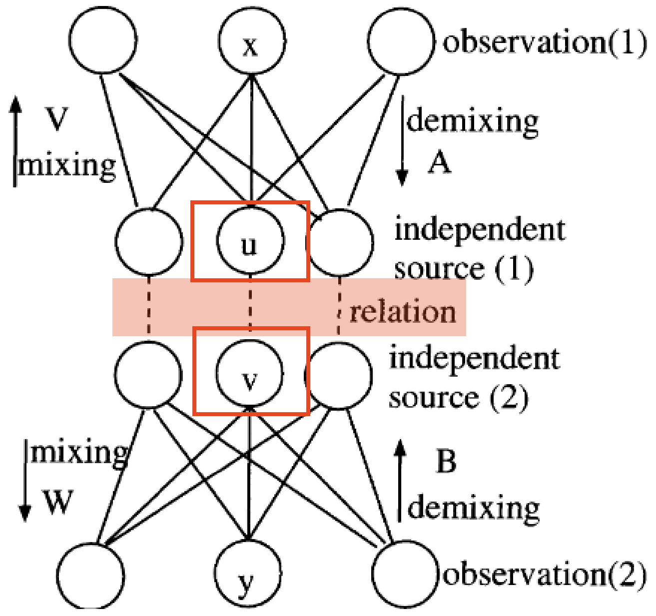


Fig. 1. Concept of MICA.

Purpose of MICA[1]

- Feature vectors demixing (extraction):

$$\begin{cases} \boldsymbol{u} = \boldsymbol{A}\boldsymbol{x} \\ \boldsymbol{v} = \boldsymbol{B}\boldsymbol{y} \end{cases}$$

- Purpose: choose A, B matrices such that MI is maximized
- **NOTE**: features can have nonlinear relations! 😎
- **NOTEx2**: It can be extended to more than two modalities! 😎

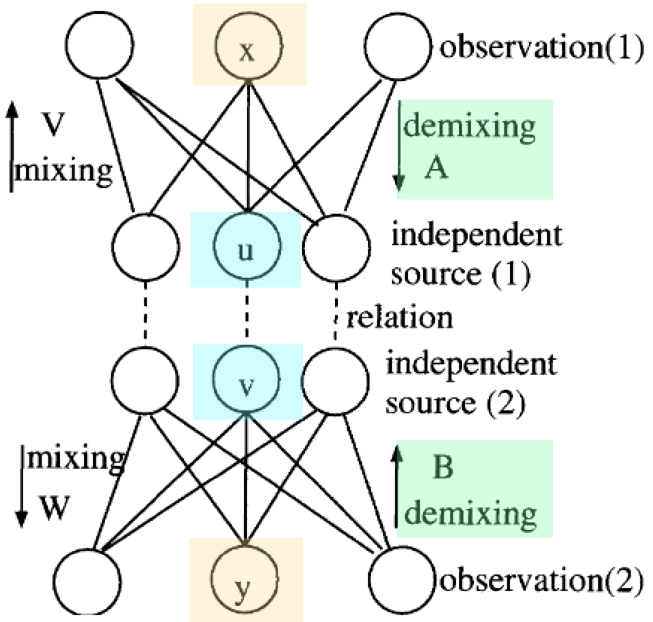
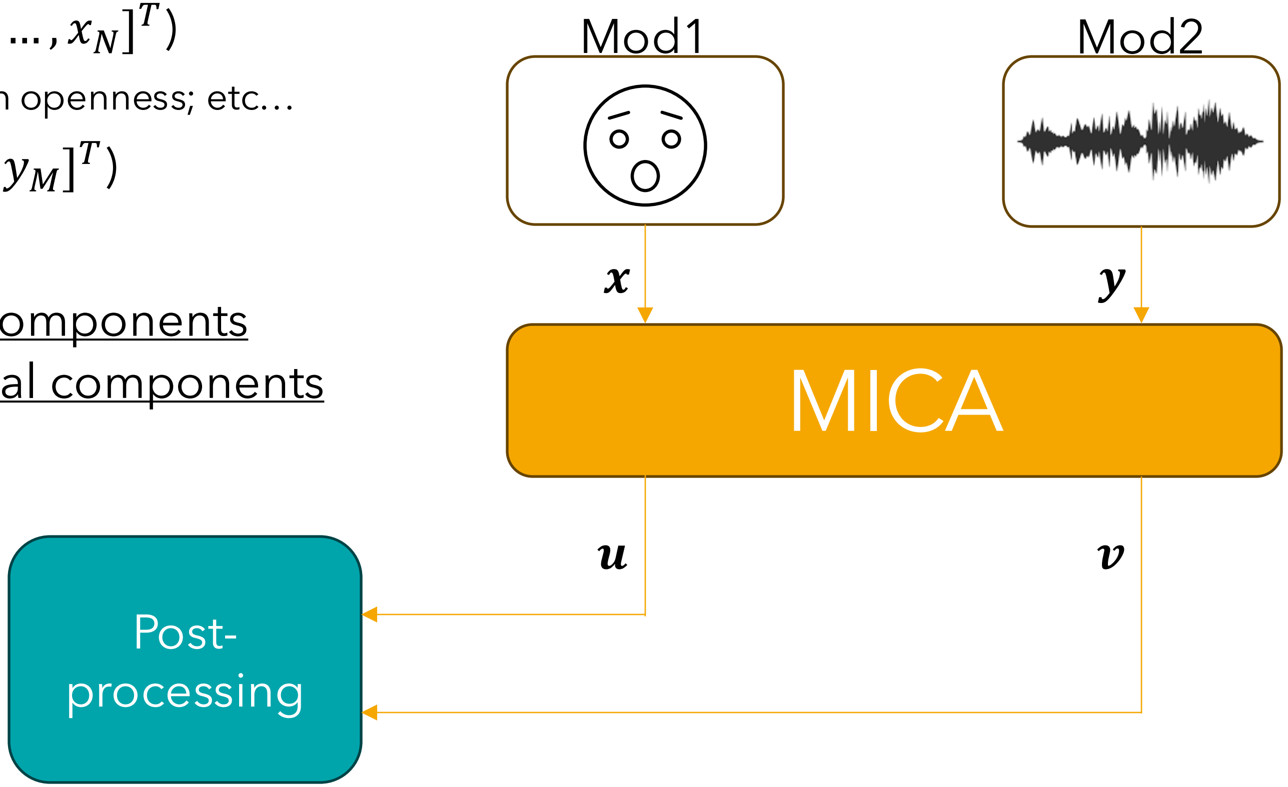


Fig. 1. Concept of MICA.

Very simple example

- Two modalities:
  - Mod1 : Facial Expressions ($\boldsymbol{x} = [x_1, \ldots, x_N]^T$)
    - E.g./ x_1: eyebrow movement; x_2: mouth openness; etc…
  - Mod2 : Speech Signals ($\mathbf{y} = [y_1, \ldots, y_M]^T$)
    - E.g./ y: pitch; y_2: speaking rate; etc…
- MICA decomposes the data into joint components (shared across modalities) and individual components (specific to one modality).



Applications

- Sensor fusion in general
- Neuroscience (EEG + fMRI, brain-computer interface)
- Telecommunications (MIMO, multisensor systems)
- Etc…

Variants of MICA

- Joint ICA
  - Fusion of multiple simultaneous modalities by finding **spatially** independent maps
  - Assumes that two or more modalities have **identical** mixing matrix
  - Used for image-based modalities
- Parallel ICA
  - Finds the independent components from both modalities in **parallel**
  - Assumes that two or more modalities have **similar** mixing matrix
  - Used for image and genetic modalities

Mohammed, A. N., Taha, T. E., & Faragallah, O. S. (2014). A comparison of joint ICA and parallel ICA multimodal fusion methods in schizophrenia. *International Journal of Computer Applications*, *95*(9).

Variants of MICA

- Linked ICA
  - Finds independent components from completely **different** modalities having:
    - different units, signal-and contrast-to-noise ratios, voxel counts, spatial smoothnesses and intensity distributions
  - Supports **tensor** ICA and **spatially-concatinated** ICA
  - Used for **image**-based modalities
- Fast ICA
  - Fast and reliable estimation of the **transformation** given by linear ICA
  - Proposed algorithms for optimizing the **contrast** functions
  - Generally applicable to single as well as **multiple** modalities

- Adrian R. Groves, Christian F. Beckmann, Steve M. Smith, Mark W. Woolrich, Linked independent component analysis for multimodal data fusion, NeuroImage, Volume 54, Issue 3, 2011, Pages 2198-2217, ISSN 1053-8119.
- Hyvarinen, A. (1999). Fast and robust fixed-point algorithms for independent component analysis. IEEE transactions on Neural Networks, 10(3), 626-634.
- Naqvi, S. M., Zhang, Y., Tsalaile, T., Sanei, S., & Chambers, J. A. (2008, August). A multimodal approach for frequency domain independent component analysis with geometrically-based initialization. In *2008 16th European Signal Processing Conference* (pp. 1-5). IEEE.

Why MICA?

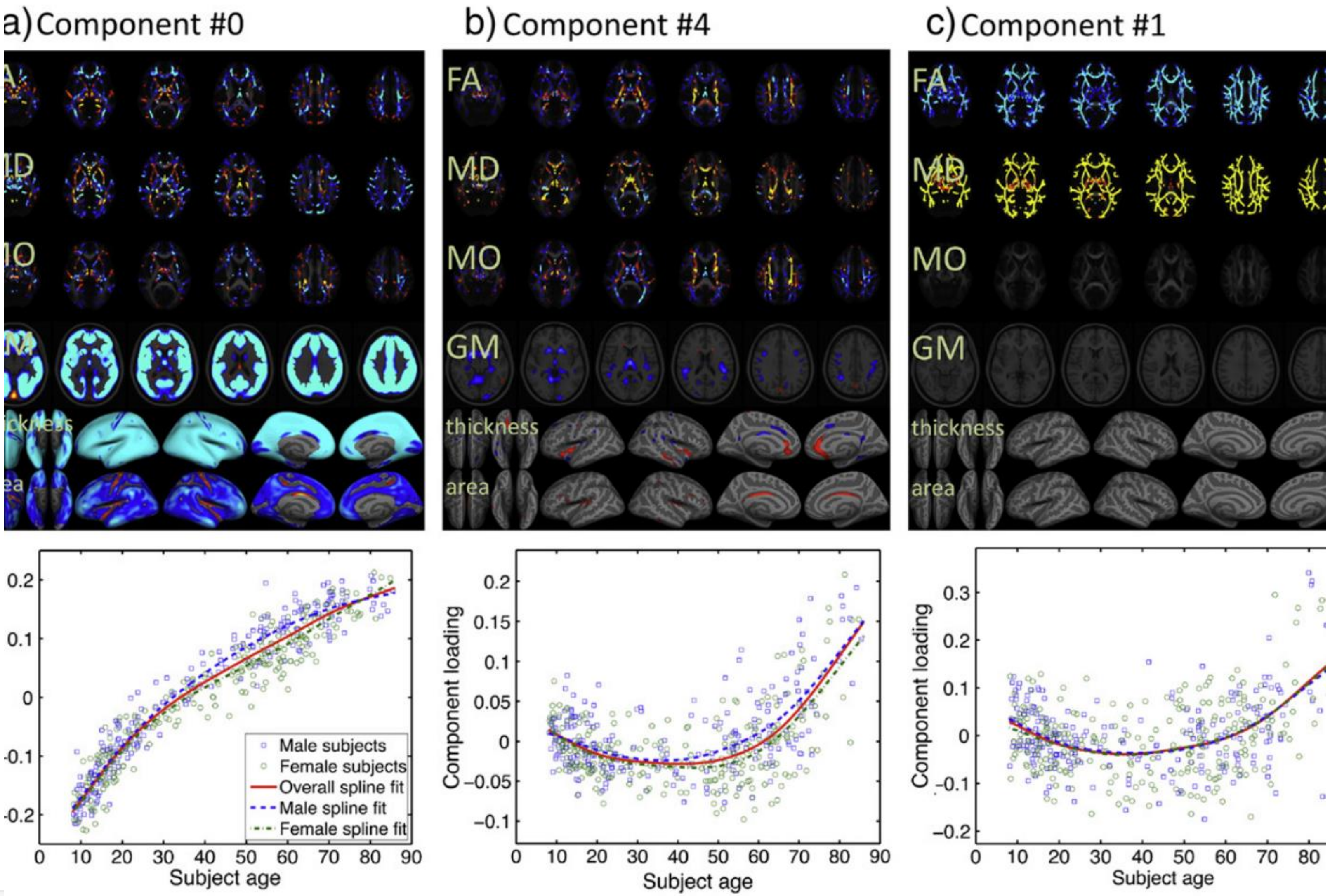
	ICA	MICA
Objective	Extract statistically independent components from a single dataset.	Maximize mutual information between features from two datasets while ensuring statistical independence within each dataset.
Assumptions	Non-Gaussian data and statistical independence between components.	Non-Gaussian data, statistical independence within modalities, nonlinear relationships across modalities.
Data Type	Multivariate, single dataset (unimodal).	Multivariate, two or more datasets (multimodal).
Dependency Captured	No dependency between modalities, only within.	Both linear and nonlinear dependencies between modalities.
Strengths	Effective for separating independent sources.	- Captures shared and unique features across modalities. - Handles nonlinear dependencies.

Example applications

MRI imaging

MRI images include different modalities

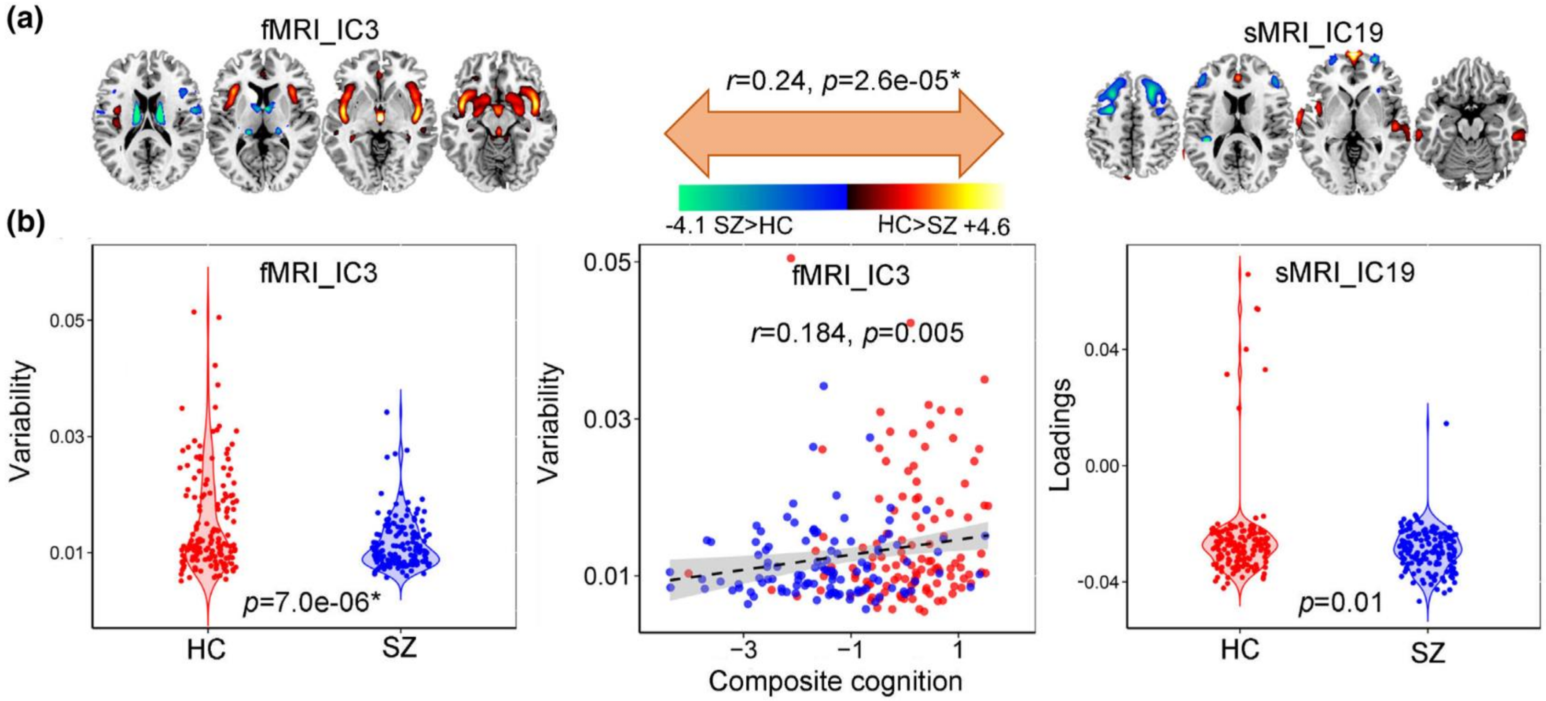
Linked ICA allows finding common components across modes



Groves, A. R., Smith, S. M., Fjell, A. M., Tamnes, C. K., Walhovd, K. B., Douaud, G., ... & Westlye, L. T. (2012). Benefits of multi-modal fusion analysis on a large-scale dataset: life-span patterns of inter-subject variability in cortical morphometry and white matter microstructure. *Neuroimage*, *63*(1), 365-380.

Detect schizophrenia?

- Uses Parallel Group ICA+ICA
- fMRI and sMRI



Qi, S., Sui, J., Chen, J., Liu, J., Jiang, R., Silva, R., ... & Calhoun, V. D. (2019). Parallel group ICA+ ICA: Joint estimation of linked functional network variability and structural covariation with application to schizophrenia. *Human brain mapping*, *40*(13), 3795-3809.

Conclusions

- Multimodal version of ICA
- Identifies shared patterns across modalities
- Applications in neuroscience, telecommunications, sensor fusion etc.

Sources

1. Akaho, S., & Umeyama, S. (2001). **Multimodal independent component analysis: A method of feature extraction from multiple information sources**. *Electronics and Communications in Japan, Part 3*, *84*(11), 21–28. https://doi.org/10.1002/ecjc.1045
2. Groves, A. R., Smith, S. M., Fjell, A. M., Tamnes, C. K., Walhovd, K. B., Douaud, G., ... & Westlye, L. T. (2012). Benefits of multi-modal fusion analysis on a large-scale dataset: life-span patterns of inter-subject variability in cortical morphometry and white matter microstructure. *Neuroimage*, *63*(1), 365-380.
3. Qi, S., Sui, J., Chen, J., Liu, J., Jiang, R., Silva, R., ... & Calhoun, V. D. (2019). Parallel group ICA+ ICA: Joint estimation of linked functional network variability and structural covariation with application to schizophrenia. *Human brain mapping*, *40*(13), 3795-3809.