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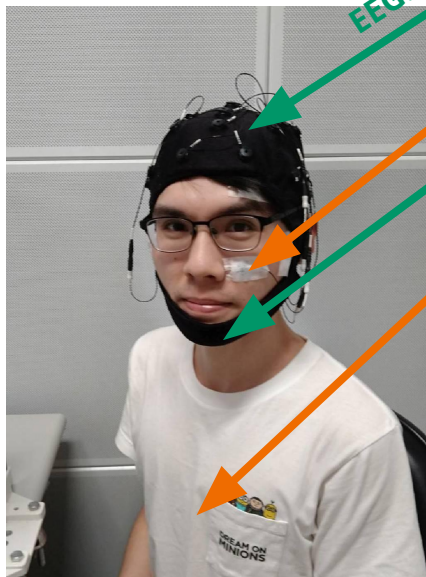
# Sleep Stages Prediction via Fusion Signals

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# Goal: Why fusion?

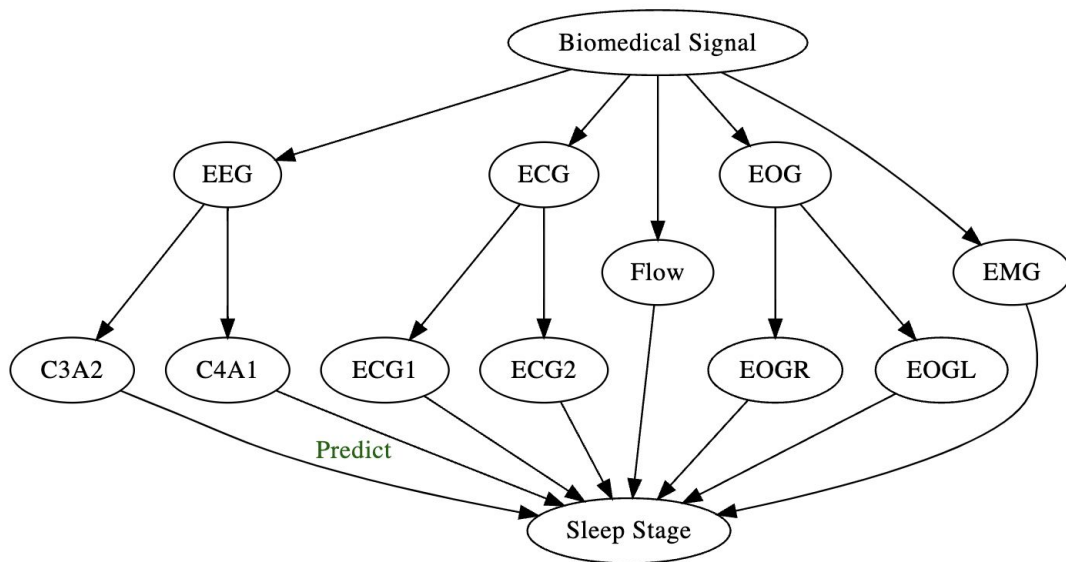
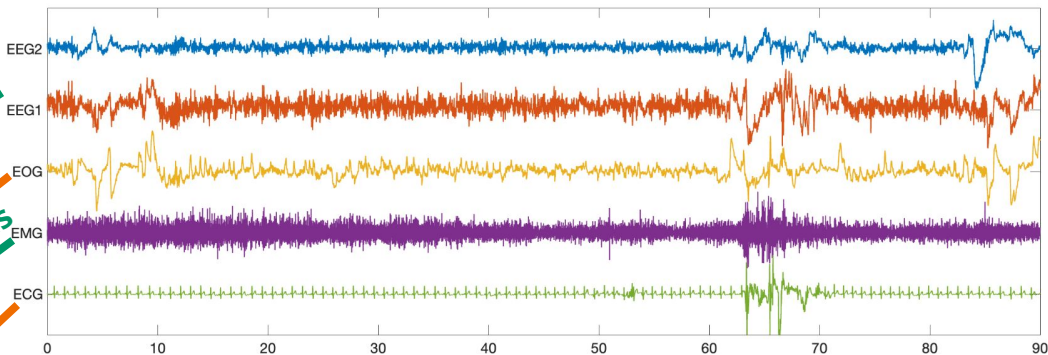


EEG: brain

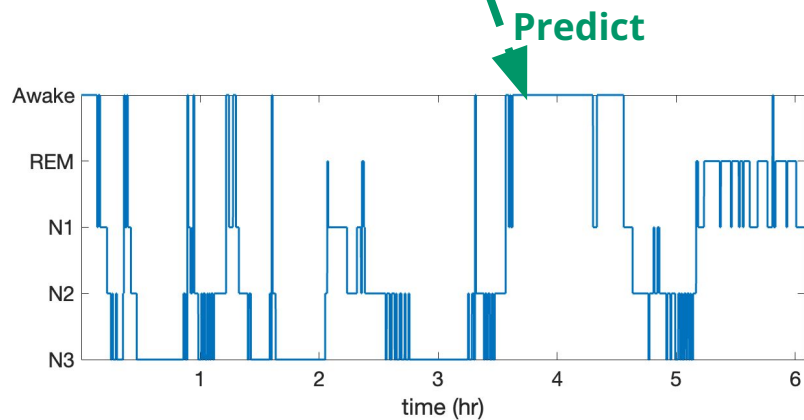
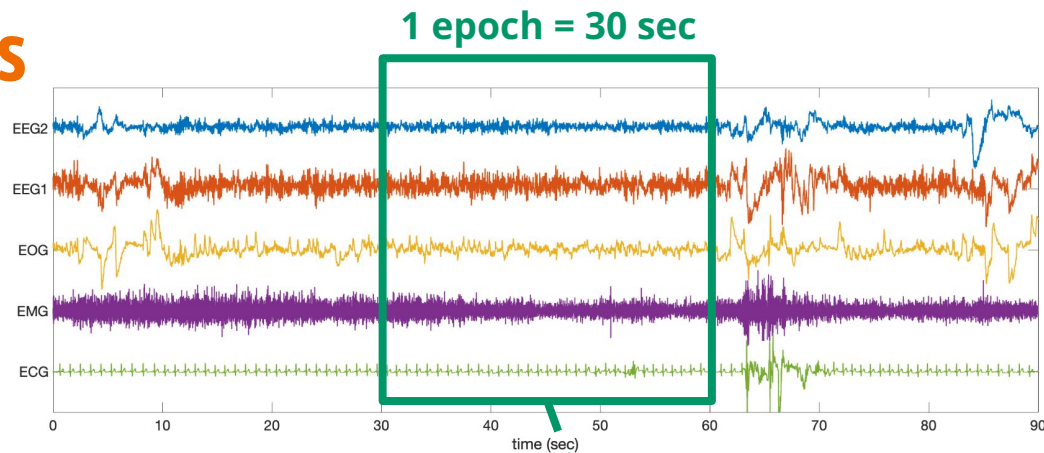
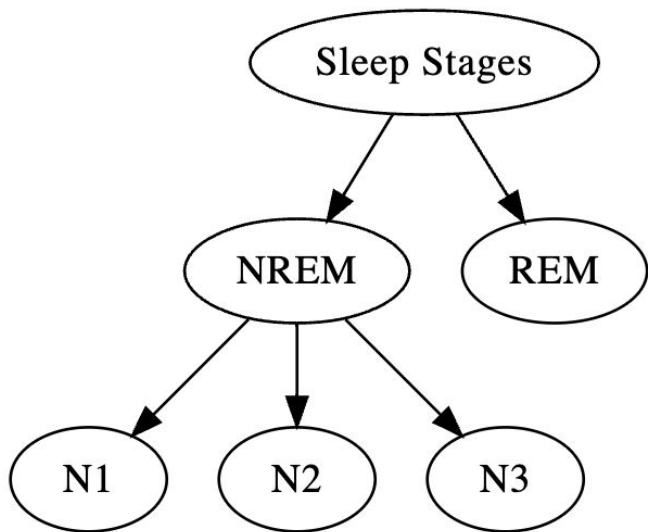
EOG: eyes

EMG: muscles

ECG: heart

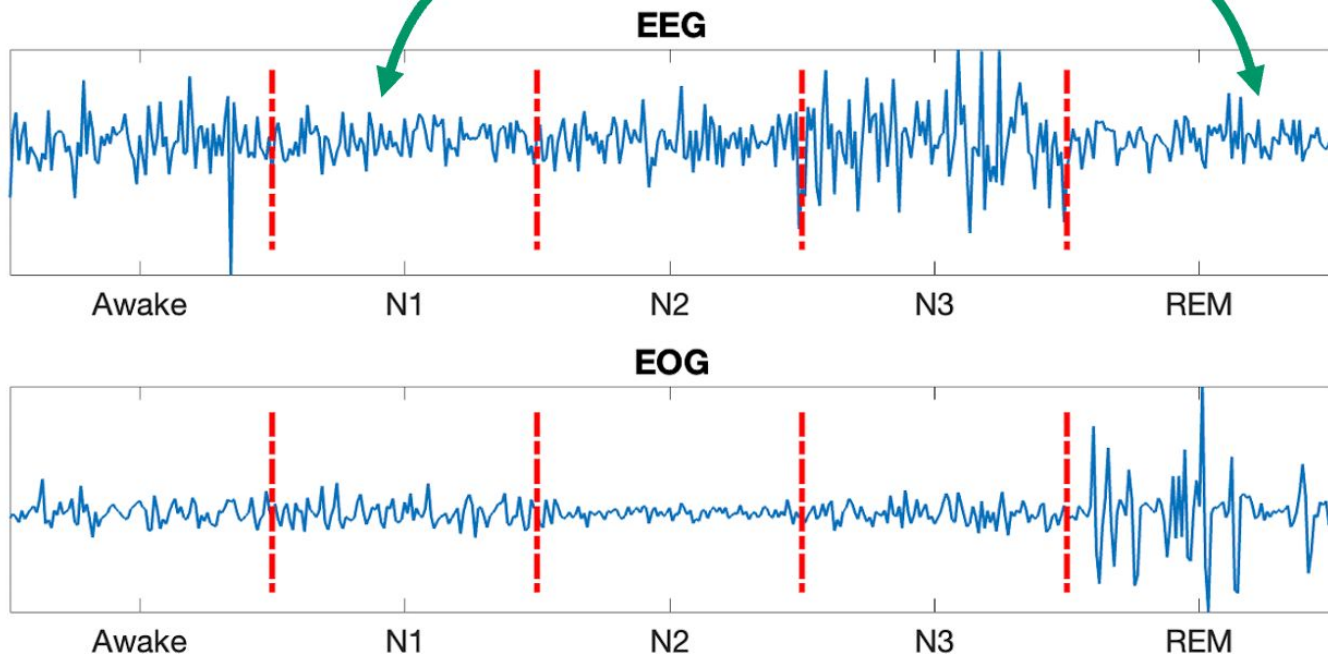


# Task: Predict sleep stages

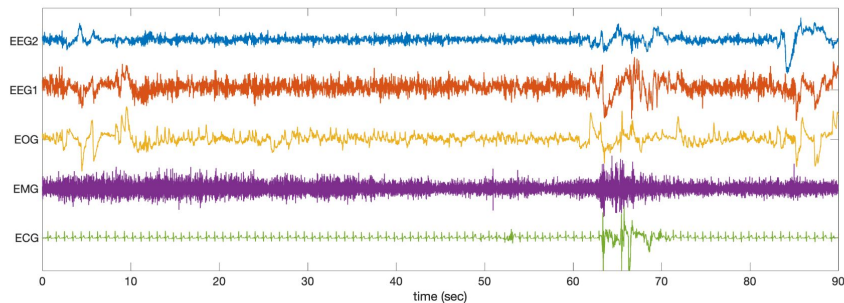


# Why fusion?

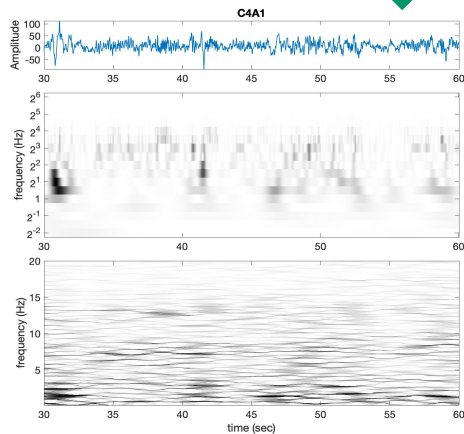
hard to distinguish



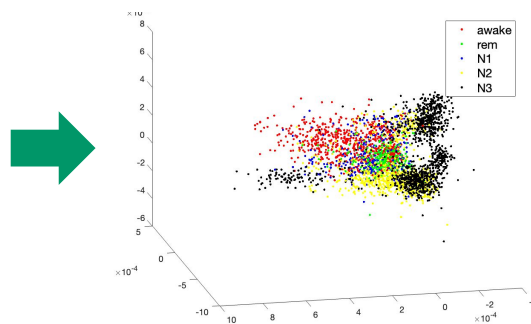
# Methodology



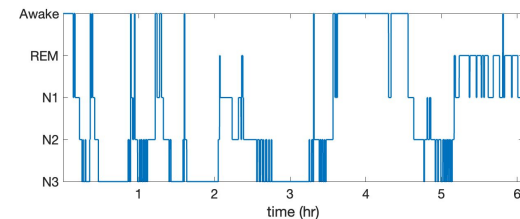
Signal collection: EEG & EOG & EMG



Feature extraction: TFA



Dimension reduction



Predict sleep stages

Please refer to G.-R. Liu, Y.-L. Lo, J Malik, Y.-C. Sheu, H.-T. Wu, Diffuse to fuse EEG spectra -- intrinsic geometry of sleep dynamics for classification, (2018).

# Data source

41 patients

29332 epochs

Total: 240+ hours



TIDIS



台灣智慧睡眠醫學整合資料庫

Taiwan Integrated Database for Intelligent Sleep

# Basic diffusion map (DM)

Let  $\{x_i\}_{i=1}^n \subset \mathcal{M}^d$  be a dataset, where  $\mathcal{M}^d \subset \mathbb{R}^p$ . Given a Gaussian kernel  $k_\epsilon$  with bandwidth  $\epsilon$ . Let the affinity matrix  $W_{ij} = k_\epsilon(x_i, x_j)$ . The degree matrix is defined as  $D_{ii} = \sum_{j=1}^n W_{ij}$ .

Then, the (negative) graph Laplacian operator is defined as

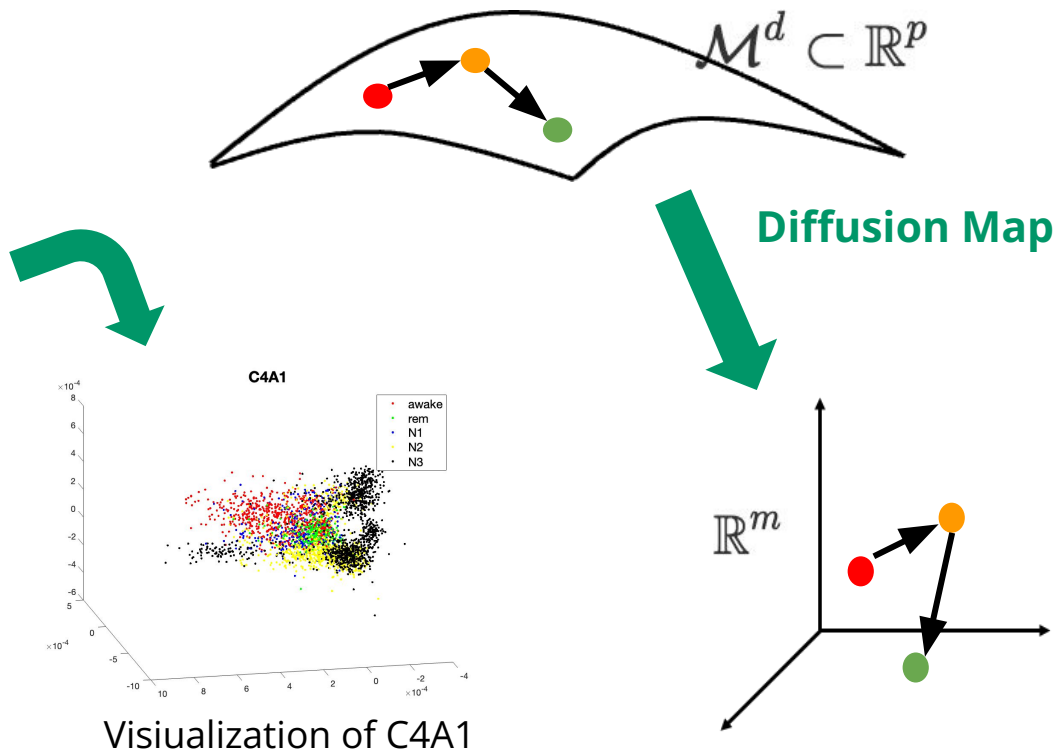
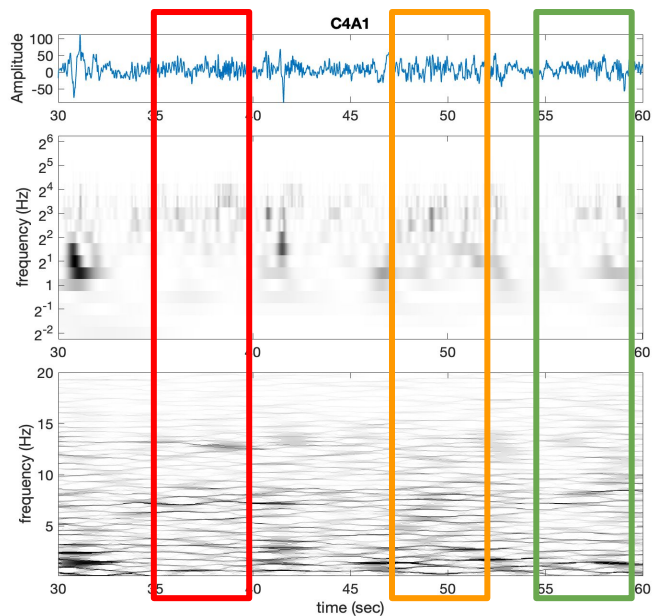
$$L = D^{-1}W - I$$

where  $K = D^{-1}W$  is transition matrix

The first  $m$  eigenvectors of  $K$  are our interests, which embedding the data into lower dimensional space,  $\mathbb{R}^m$ .

Please refer to R.Coifman & S. Lafon, *Diffusion maps*, (2006).

# Recover underlying manifold





# Fusion: S+A method

Consider two signals from two sensors. Let degree matrix and affinity matrix  $D^{(\ell)}$ ,  $W^{(\ell)}$  define as mentioned where  $\ell = 1, 2$  two signals. Define transition matrices  $K^{(\ell)} = (D^{(\ell)})^{-1}W^{(\ell)}$

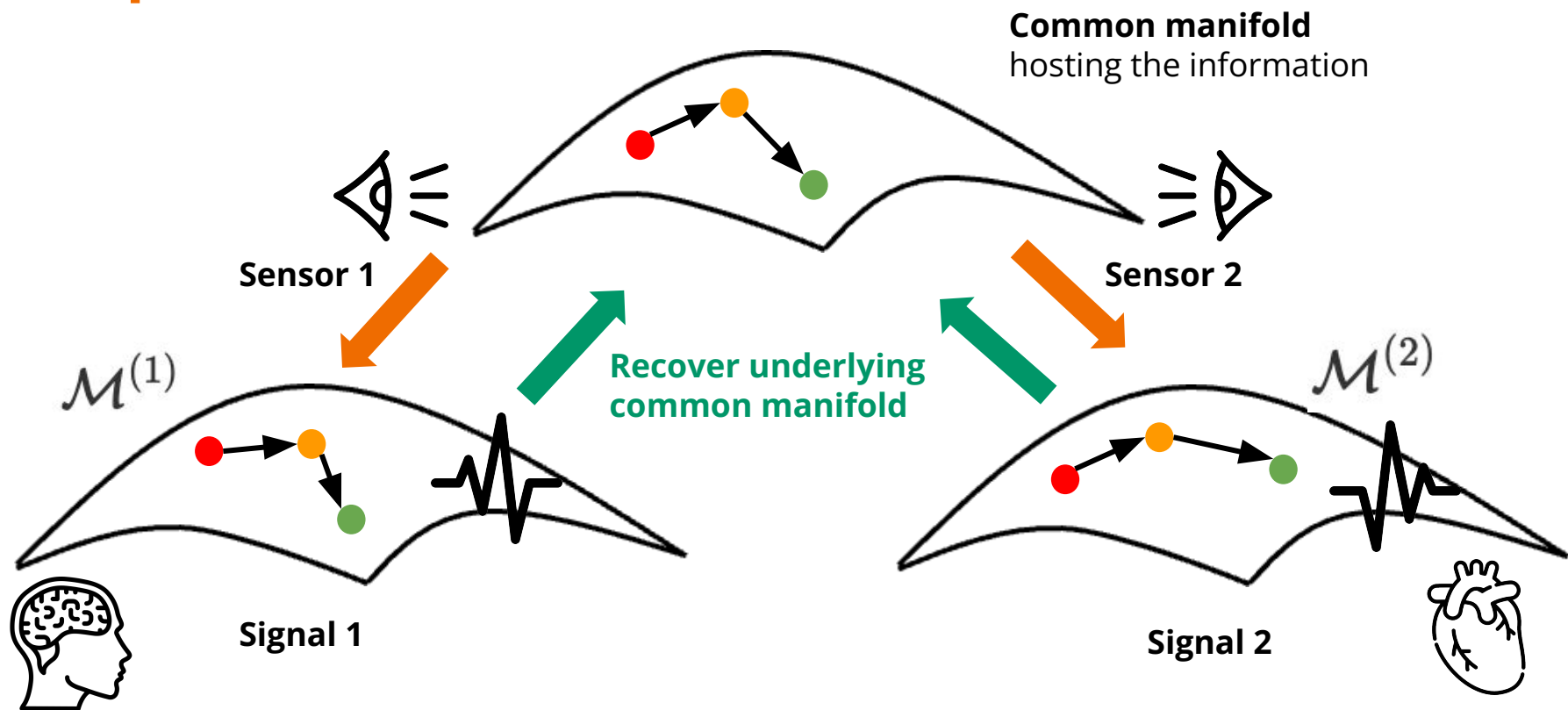
Let  $G = K^{(2)}K^{(1)T}$  and  $H = K^{(1)}K^{(2)T}$ . Define two  $n \times n$  matrices

$$S = G + H$$

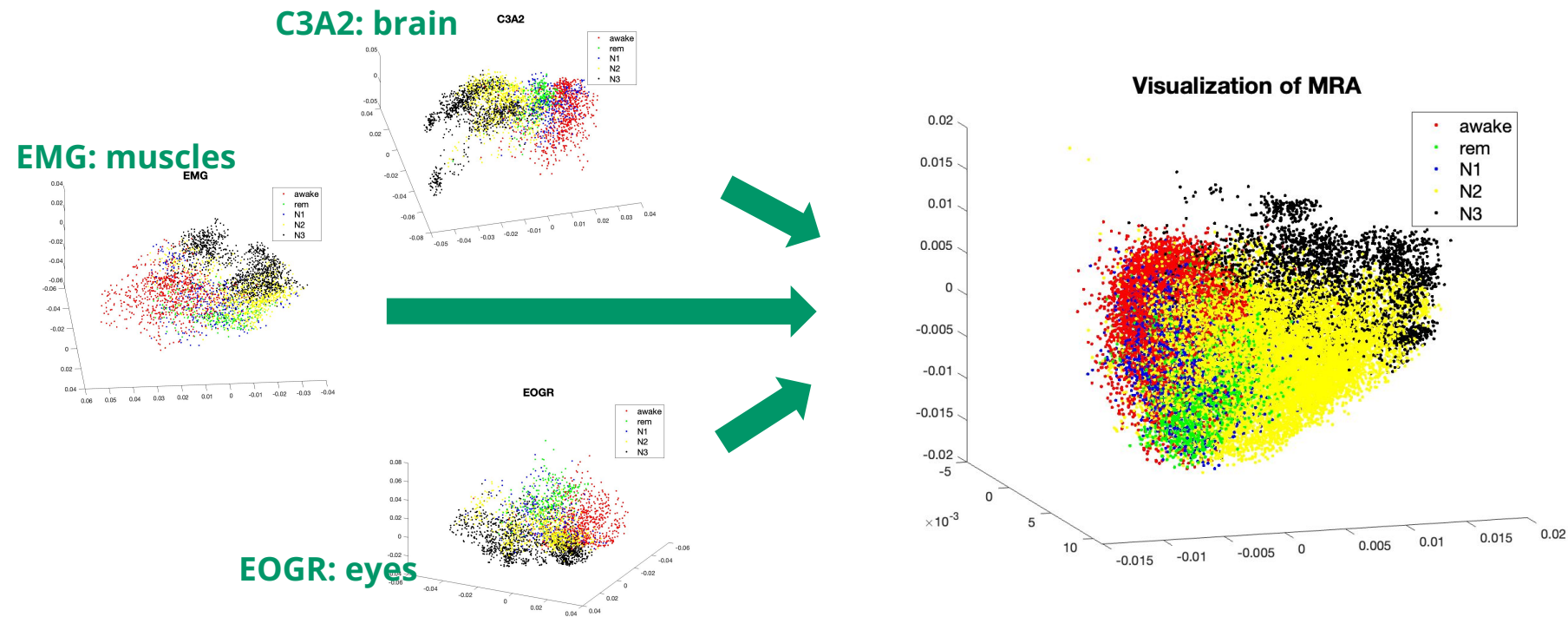
$$A = G - H.$$

In fact,  $S$  reveal common structures, and  $A$  reveal differences.

# Interpret S+A method



# How to fuse 3+ channels



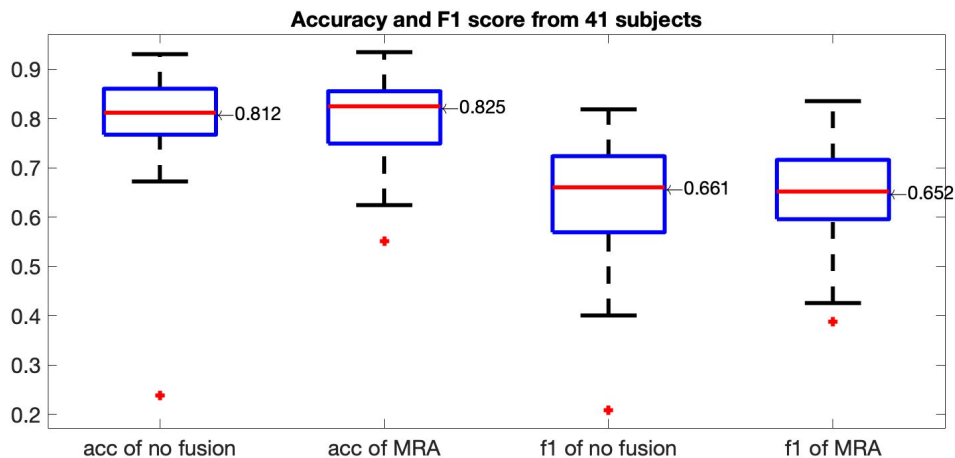
# Multi-resolution analysis (MRA)

Please feel free to contact me, if you are interested in this method!

# Results

metric: leave one subject out cross validation

	median of acc	median of macro f1	std of acc
No fusion	81.2%	66.1%	0.108
Fusion by MRA	82.5%	65.2%	0.078



No Fusion

		Predict				
		Aw	REM	N1	N2	N3
Target	Aw	82%	4%	9%	5%	1%
	REM	5%	79%	7%	8%	0%
	N1	21%	12%	44%	22%	0%
	N2	4%	2%	4%	86%	4%
	N3	1%	0%	0%	25%	74%

Fusion by MRA

		Predict				
		Aw	REM	N1	N2	N3
Target	Aw	80%	2%	10%	8%	0%
	REM	4%	75%	10%	10%	0%
	N1	20%	9%	49%	22%	0%
	N2	1%	2%	4%	90%	3%
	N3	0%	0%	0%	34%	65%

# References

- [1] R.Coifman & S. Lafon, *Diffusion maps*, [\(2006\)](#).
- [2] G.-R. Liu, Y.-L. Lo, J Malik, Y.-C. Sheu, H.-T. Wu, *Diffuse to fuse EEG spectra -- intrinsic geometry of sleep dynamics for classification*, [\(2018\)](#).
- [3] T. Shnitzer, M. Ben-Chen, L. Guibas, R. Talmon, H.-T. Wu, *Recovering Hidden Components in Multimodal Data with Composite Diffusion Operators*, [\(2018\)](#).
- [4] A. Singer, H.-T. Wu, *Vector Diffusion Maps and the Connection Laplacian*, [\(2011\)](#).
- [5] A. Singer, *From graph to manifold Laplacian: The convergence rate*, [\(2006\)](#).

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**Thank You**

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