

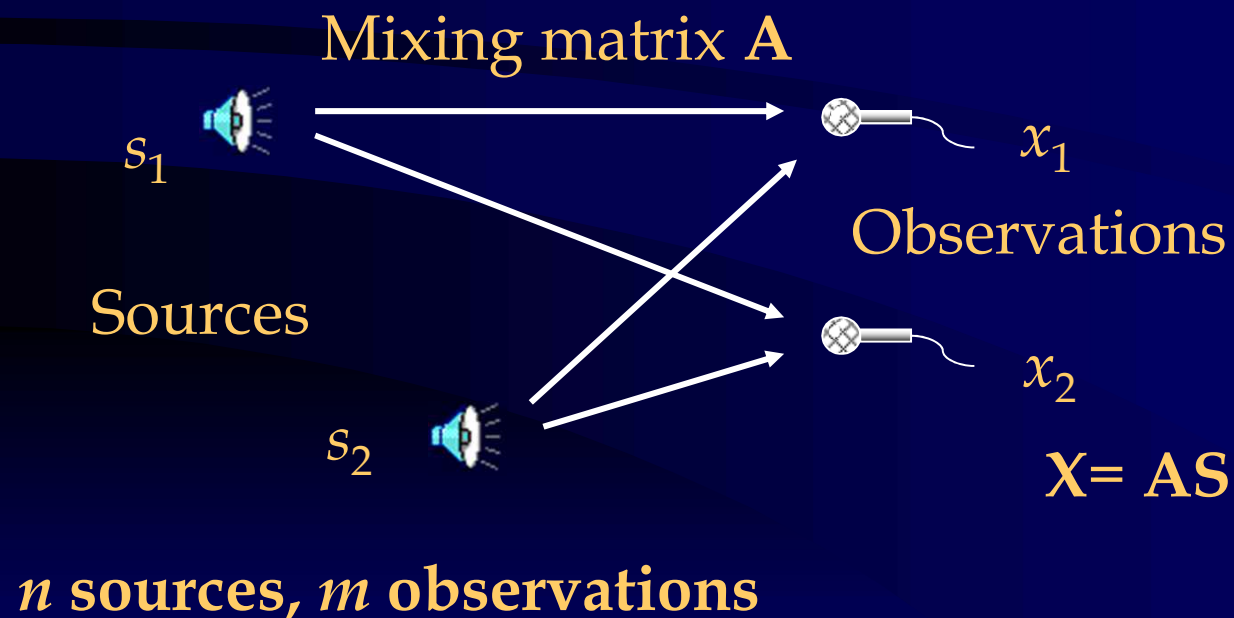
# ICA for Multi-channel Signals and Images

# What is ICA?

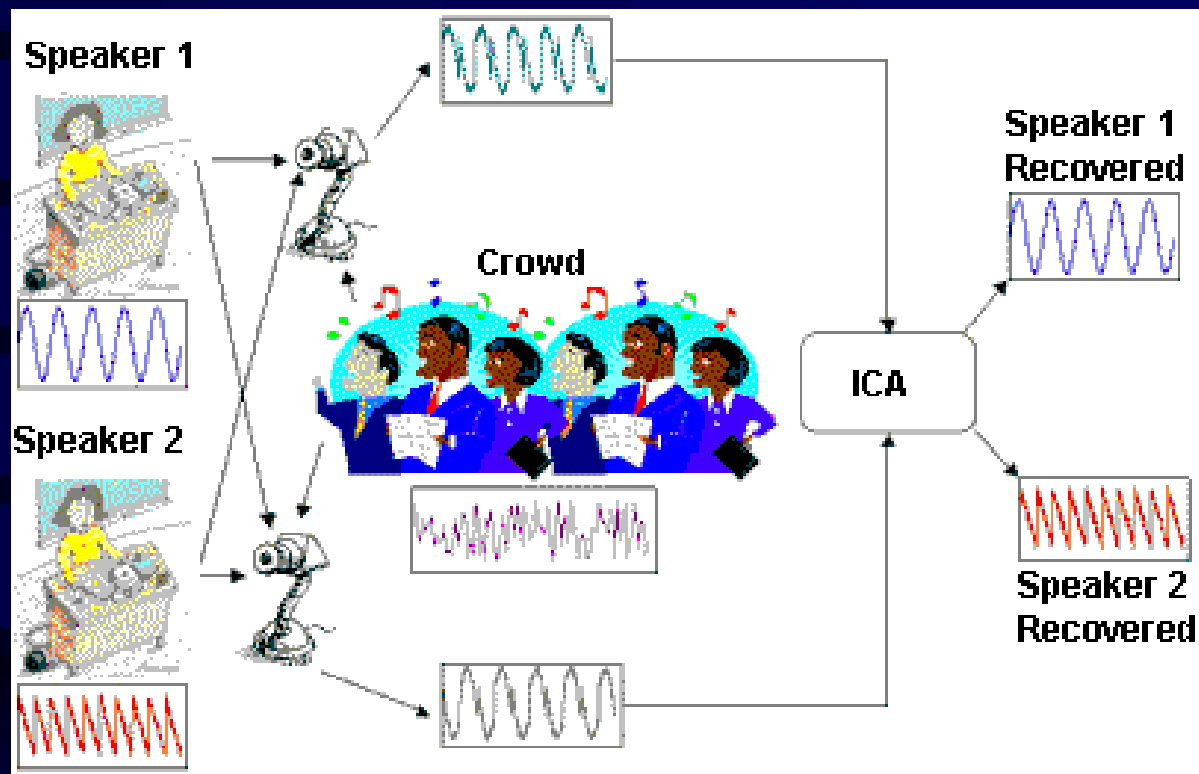
- **Blind Source Separation:**

$$\mathbf{X} = \mathbf{AS}$$

- Unknown sources  $\mathbf{S}$  as latent variables and unknown mixing matrix  $\mathbf{A}$
- Estimate  $\mathbf{S}$  and unmixing matrix  $\mathbf{W}=\mathbf{A}^{-1}$  from only  $\mathbf{X}$  (observations).



- The cocktail party problem: based only on  $x_1$  and  $x_2$  we need to recover  $s_1$  and  $s_2$ .



# Independent Component Analysis (ICA)

- The goal of blind source separation in signal processing is to **recover independent source signals** (e.g., different people speaking, music etc.) after they are linearly mixed by an unknown medium, and recorded at  $N$  sensors (e.g., microphones).
- The concept of independent component analysis (ICA) as **maximizing the degree of statistical independence** among outputs using contrast functions. In contrast with decorrelation techniques such as Principal Component Analysis (PCA), which ensures that output pairs are uncorrelated. ICA imposes the much stronger criterion that the multivariate probability density function (p.d.f.) of output variables
- Finding such a factorization requires that the **mutual information** between all variable pairs go to zero. Mutual information depends on all **higher-order statistics** of the output variables while decorrelation only takes account of 2nd-order statistics.

# Basics of ICA

- Blind Source Separation Problem

- Data Model

$$X = AS$$

X=observed data, A=mixing matrix, S=sources

- Assumptions

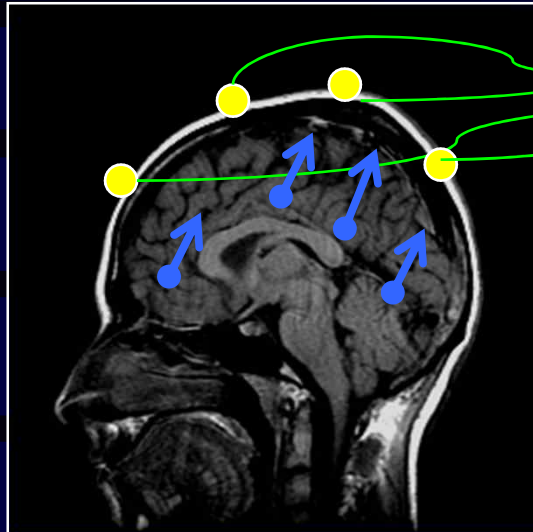
- Source density is NOT Gaussian
- Linear Mixing

- Find an **unmixing matrix** W by making components of S sparse, nongaussian and independent, such that

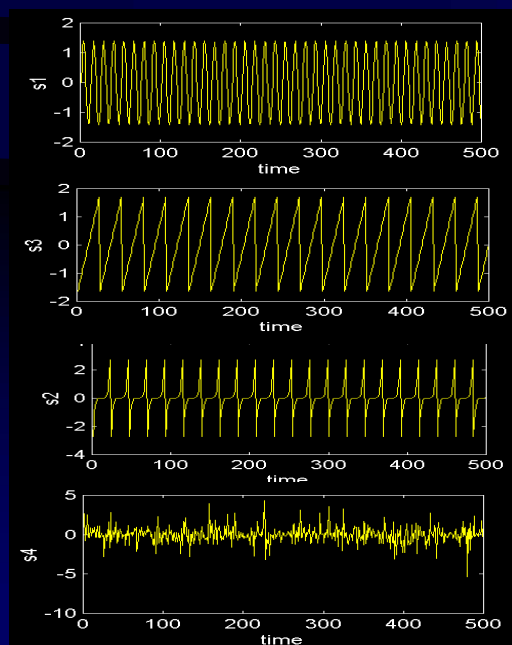
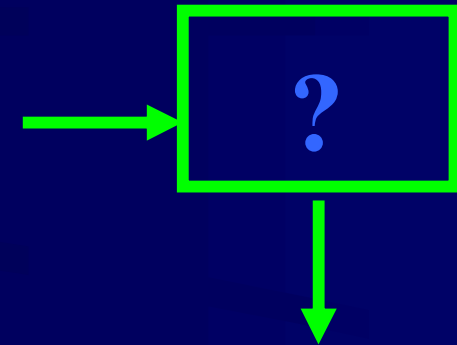
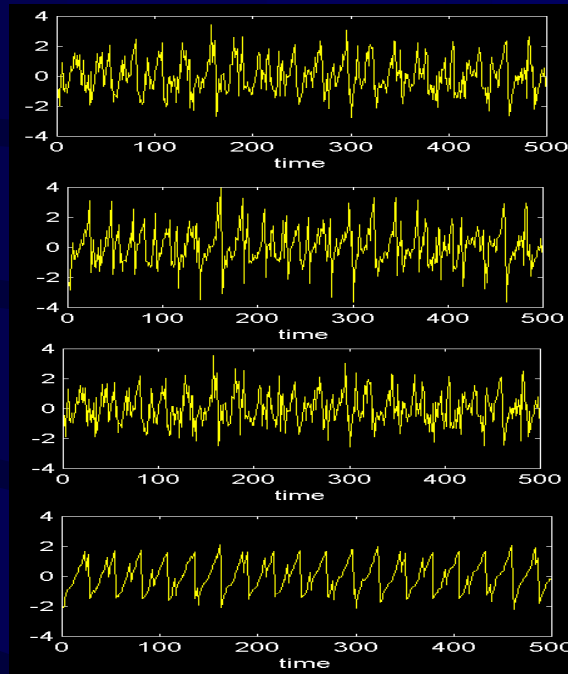
$$S = WX \quad A=W^{-1}$$

- Study Sources, S and mixing matrix, A to find hidden components in measurements

# Signal Mixing & Unmixing Example

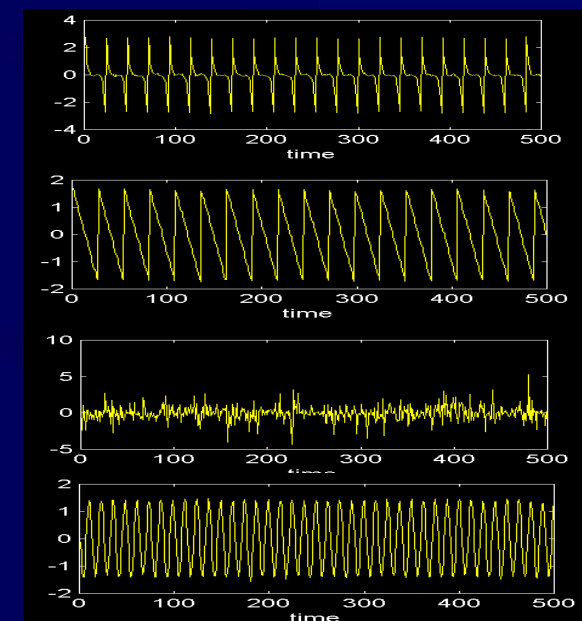


Mixed  
Sources



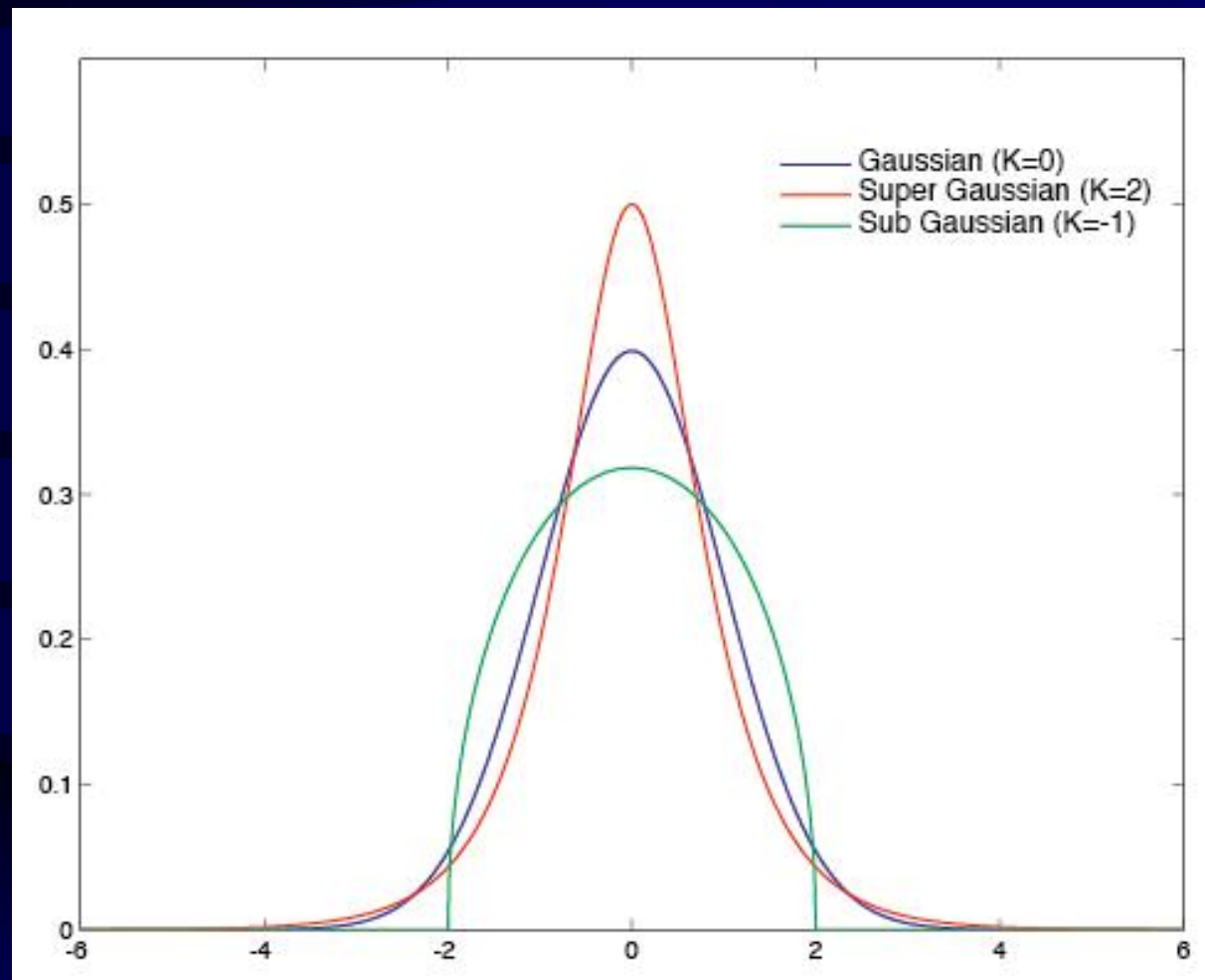
Sources

Unmixed  
Sources



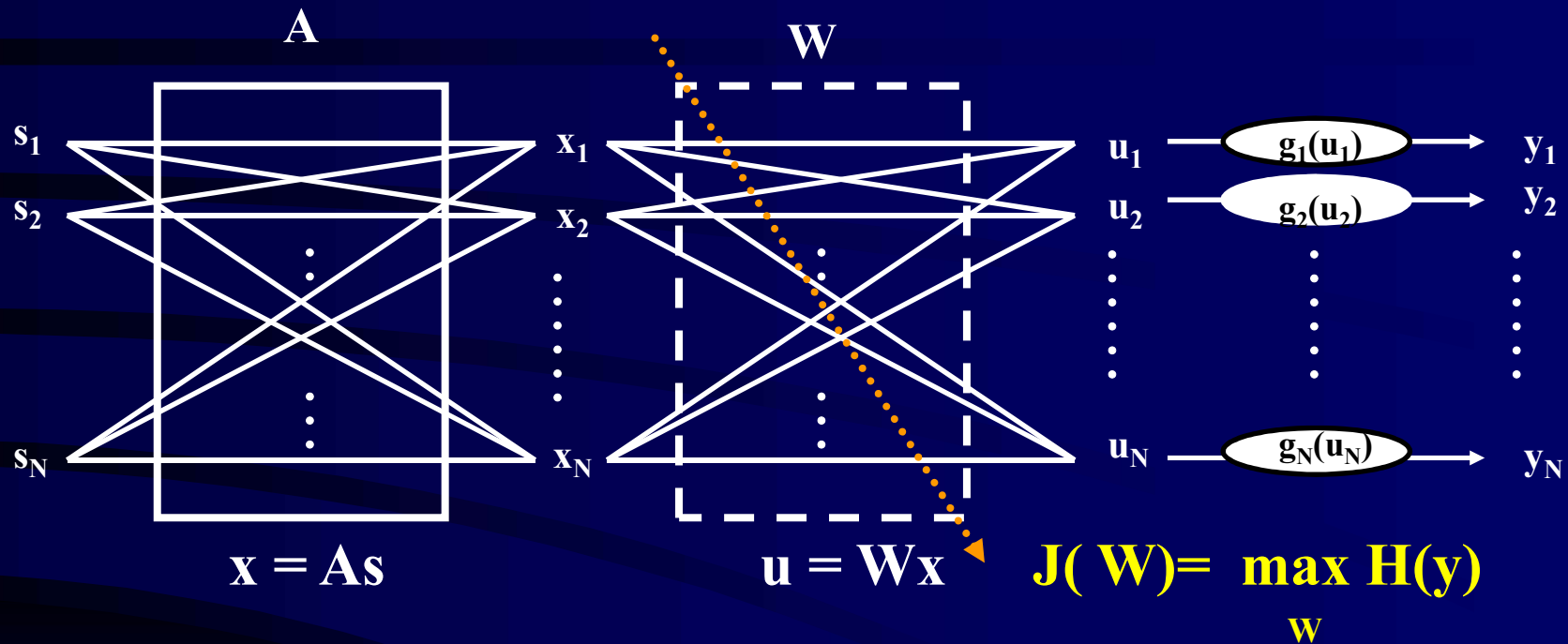
# ICA Estimation Principles

- Two ICA Estimation Principles
  - **Nonlinear Decorrelation**: Find  $W$  such that components of  $S$  and their non-linear transformed components are uncorrelated.
  - **Maximum Nongaussianity**: Find  $W$  such that components are the maximally nongaussian.
- ICA Limitations
  - Logistic BS Infomax: handles only super-gaussian
  - Extended Infomax: handles both sub- and super-gaussian
  - FastICA: handles both sub- and super-gaussian
  - Mixture Density: handles any different types of density with parameterized nonlinearity functions.



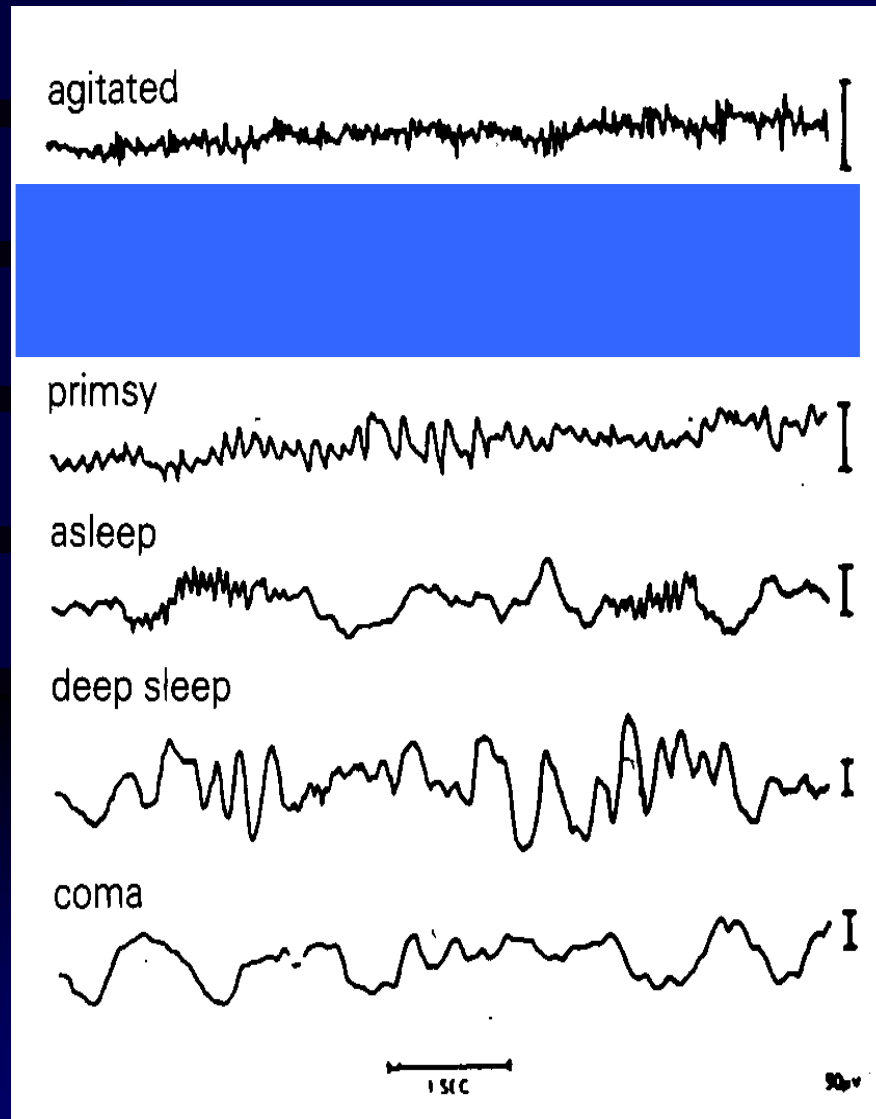


# Independent Component Analysis



- Original ICA(Bell,1996): preselected  $g_i(\cdot)$  for supergaussian
- Extended ICA(Lee,1998): preselected  $g_i(\cdot)$  for super or subgaussian
- FastICA(1999): for super and sub gaussian
- ICA with mixture density model(2000): **Adjustable**  $g_i(\cdot)$  for any density

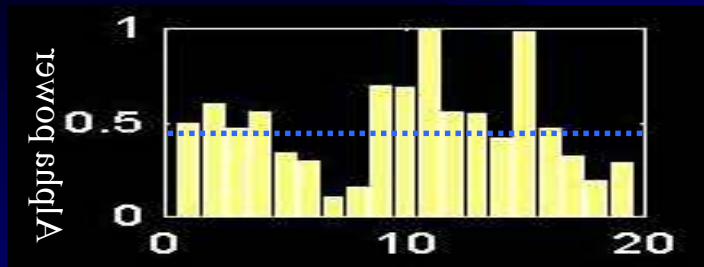
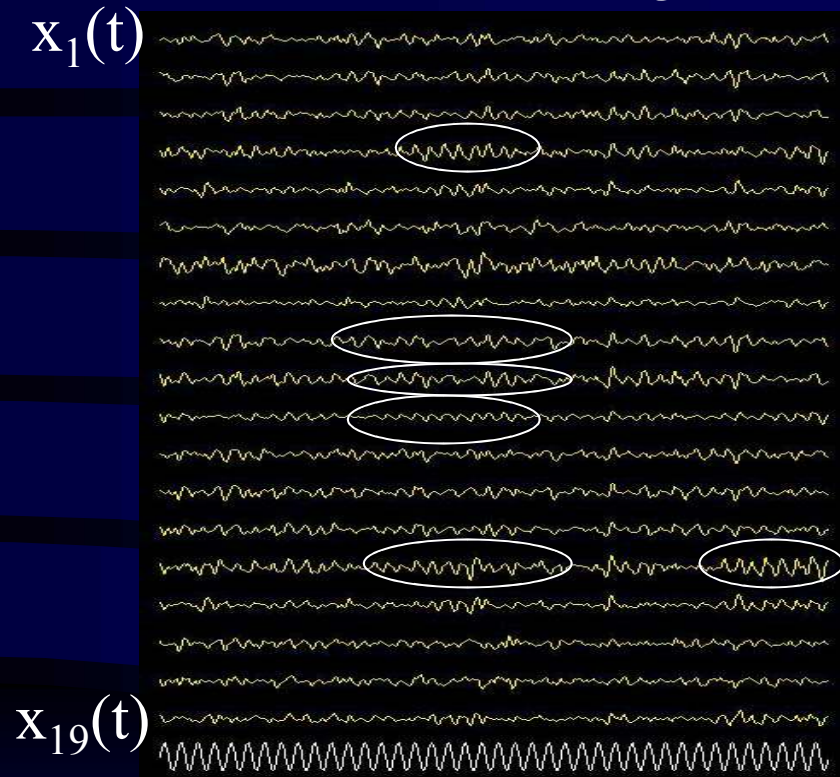
# What is Alpha Activity?



- Rhythmic (8-10 Hz in EEG)
- Produced during awake and relaxed state
- Intermittent burst
- Unknown hemodynamics response in fMRI
- Sources ?

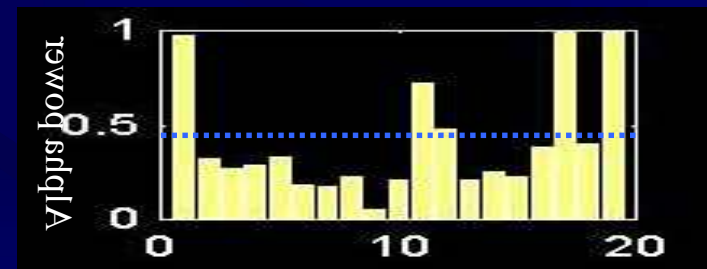
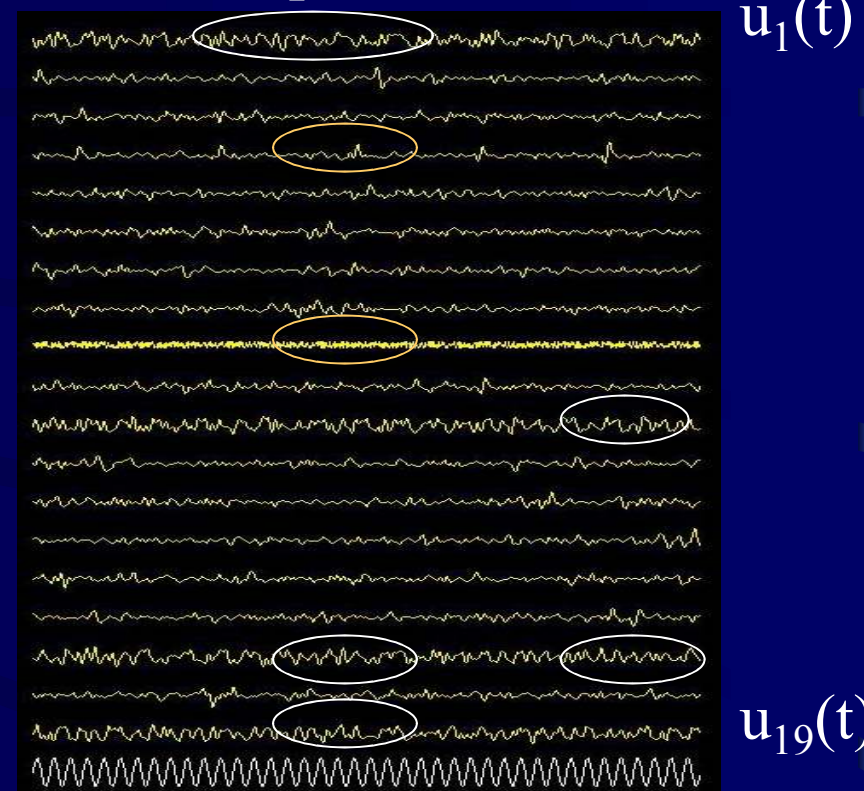
# Results of ICA in EEG

## Measured EEG Signals



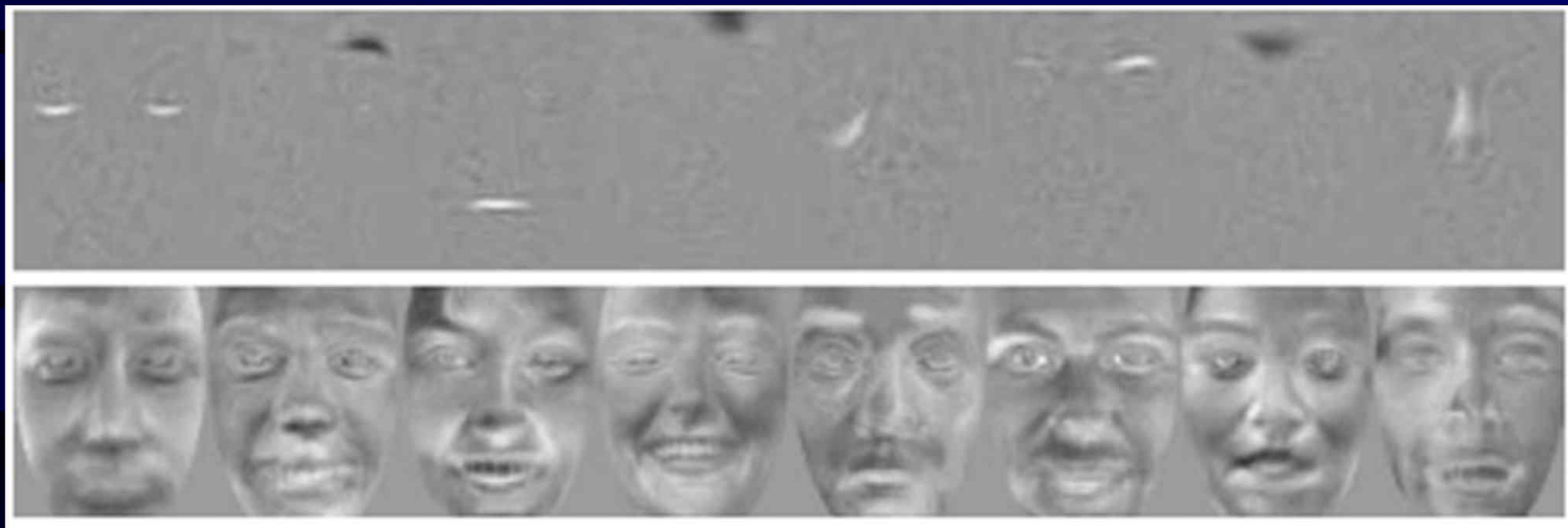
index of electrode

## Temporal IC's



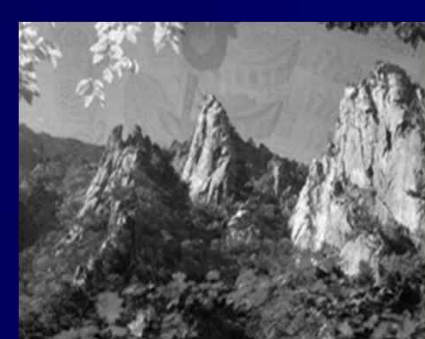
index of component.

# PCA & ICA Faces





# Image Mixing & Unmixing Example

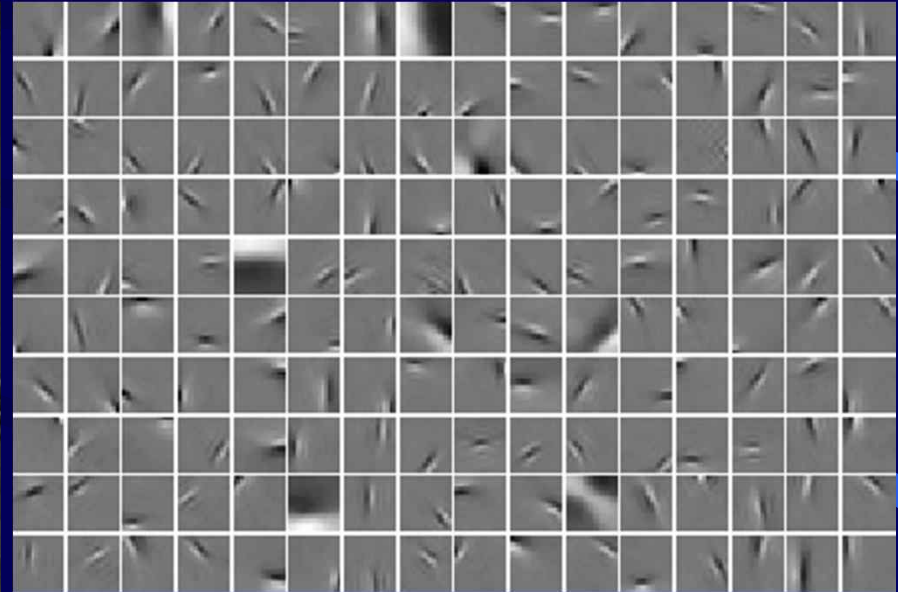


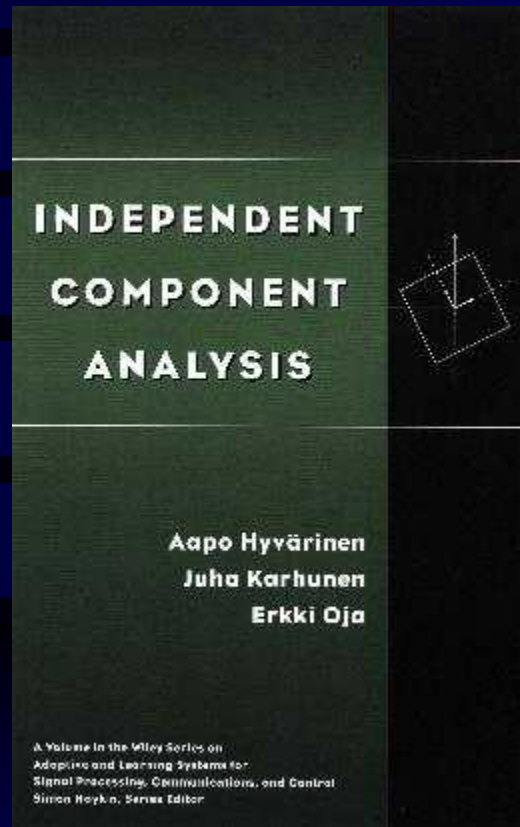
Source Images

Mixed Images

Unmixed Images

# Natural Image Statistics and the Visual Cortex





- Fast ICA
- <https://research.ics.aalto.fi/ica/fastica/>