

# ID Image Characterization by Entropic Biometric Decomposition

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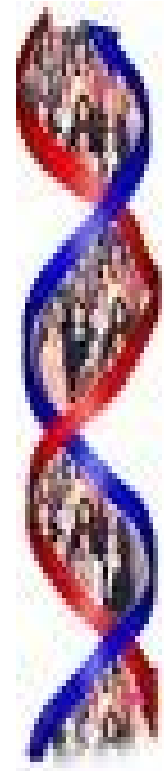
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# Introduction

Person's identity helpful in human behavior or required in biometry.

Identification technologies:

- non-invasive
- **invasive**



Face recognition remains of main interest.

**Particular case: identity image recognition**

- **robustness to print/scan**
- **simple & fast algorithm**

# ID image recognition

Faces with neutral frontal expression.

Difficulties in recognition caused by

**Print/scan process**



**Aging**



**Our goal: 100% recognition rate**

# Outlines

**1 – Tools**

**2 – Methodology**

**3 – Subspace selection**

**4 – Experimental results**

**5 – Conclusion**

# 1. Tools for image recognition

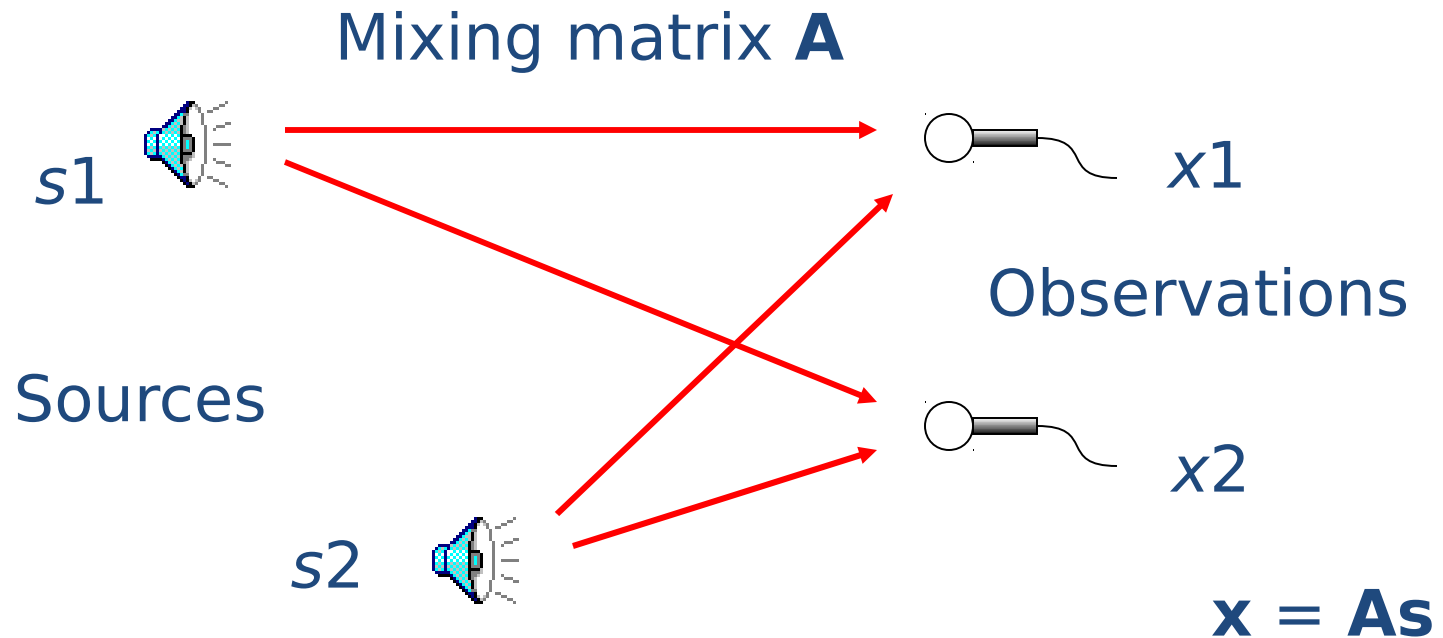
**Second  
order  
statics**

**Principal Component Analysis (PCA)**  
– the subspace basis vectors are eigenfaces related to the spectrum of the covariance matrix.

**Higher  
order  
statics**

**Independent Component Analysis (ICA)**  
– the sources are independent.

# The simple «Cocktail Party» Problem



$n$  sources,  $m=n$  observations

# Independent Component Analysis

**Objective:** maximize the statistical independence of the outputs.

## Algorithm:

1. Preprocessing:
  - a) centering
  - b) whitening
2.  $X = A * s$

$$\begin{pmatrix} x_{11} & x_{12} & x_{13} \\ x_{21} & x_{22} & x_{23} \\ \dots & \dots & \dots \end{pmatrix} = \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \\ \dots & \dots \\ a_{n1} & a_{n2} \end{pmatrix} \begin{pmatrix} s_{11} & s_{12} & s_{13} \\ s_{21} & s_{22} & s_{23} \\ \dots & \dots & \dots \end{pmatrix}$$

The columns of A constitute the vector bases of ICA

The particular realizations are on the rows of x

The ICs are on the rows of s.

# Algorithms

## **FastICA (Fast Independent Component Analysis)**

∅ maximizes the non-Gaussianity by fixed-point iteration scheme.

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## **InfoMax**

∅ maximizes the entropy of the estimated independent vectors.



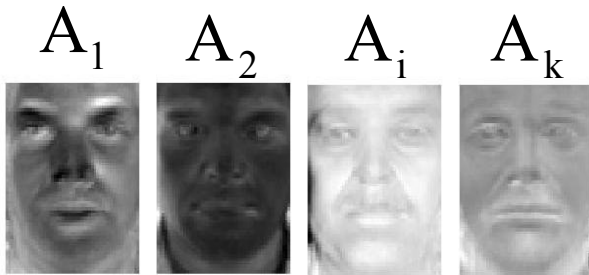
# Independent Component Analysis

Two types of architectures.



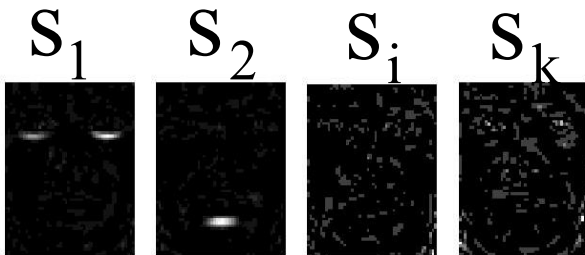
$x = [ \dots ]$

**Architecture II** – global features as columns of matrix  $X$ .



$$X = \begin{pmatrix} - & - & - & - \\ - & - & - & - \\ - & - & - & - \\ - & - & - & - \end{pmatrix}$$

**Architecture I** – local features as rows of matrix  $X$ .



$$X = \begin{pmatrix} \dots & \dots & \dots & \dots \\ \dots & \dots & \dots & \dots \\ \dots & \dots & \dots & \dots \\ \dots & \dots & \dots & \dots \end{pmatrix}$$

# ICA-Architecture I

Our approach for ID image characterization is based on biometric features.



ICA – Architecture I

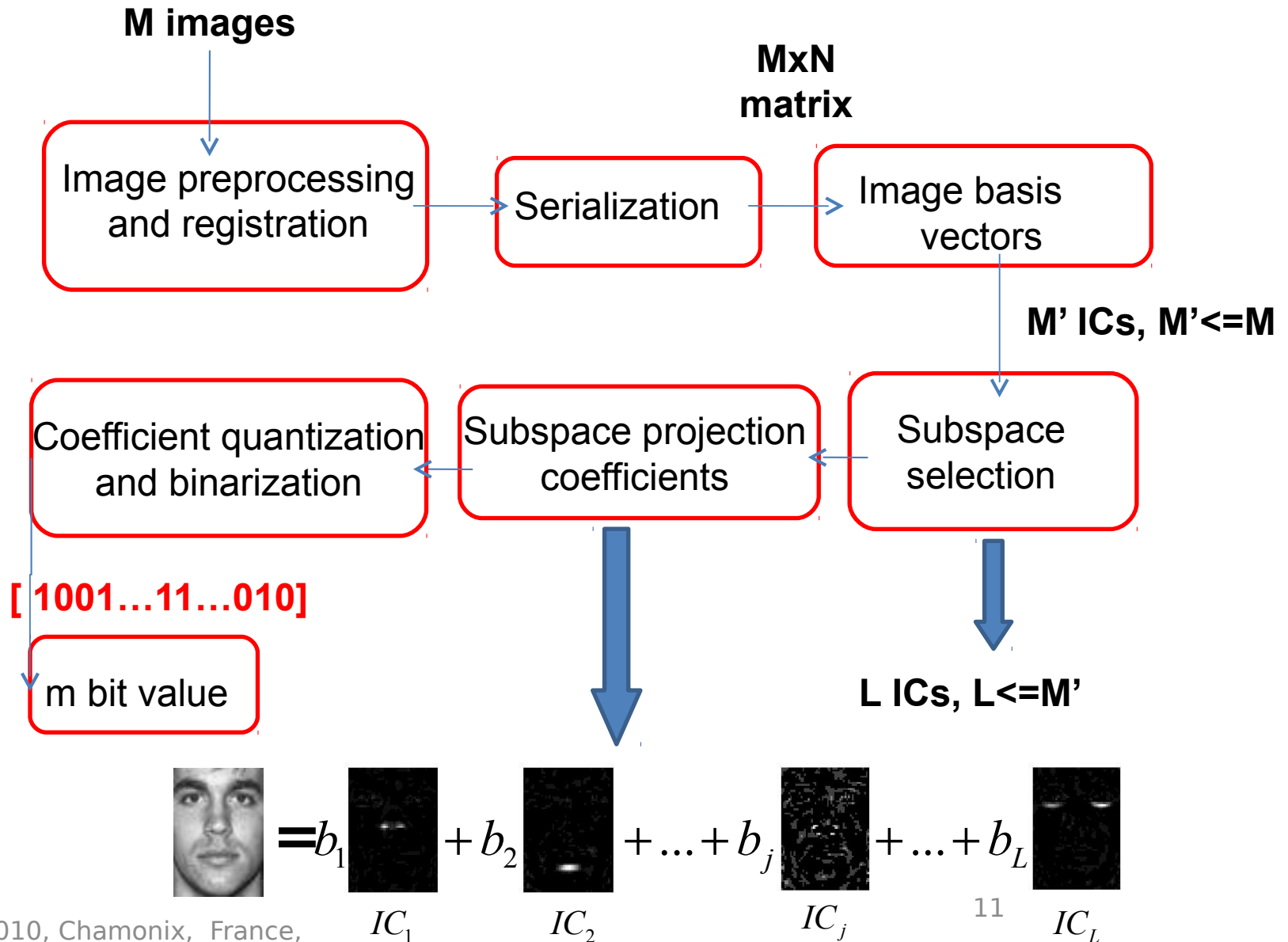


[ 1001...11...010 ]  
m bit

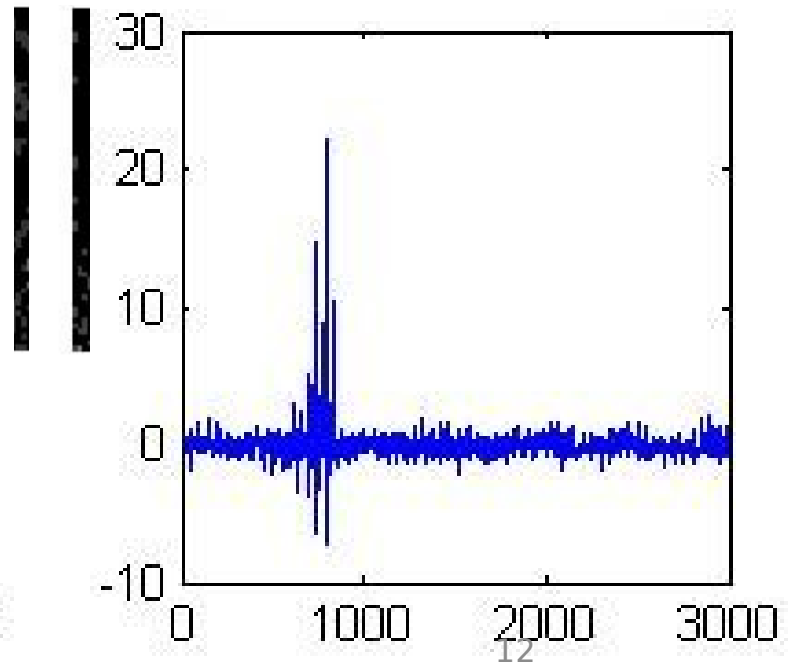
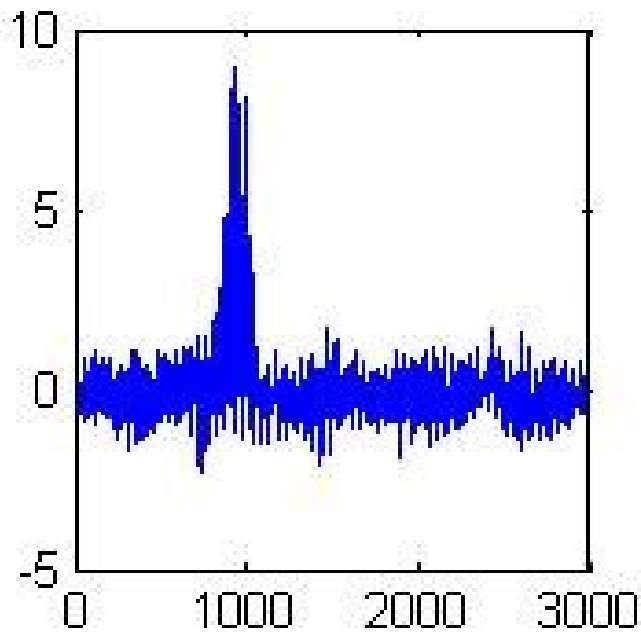
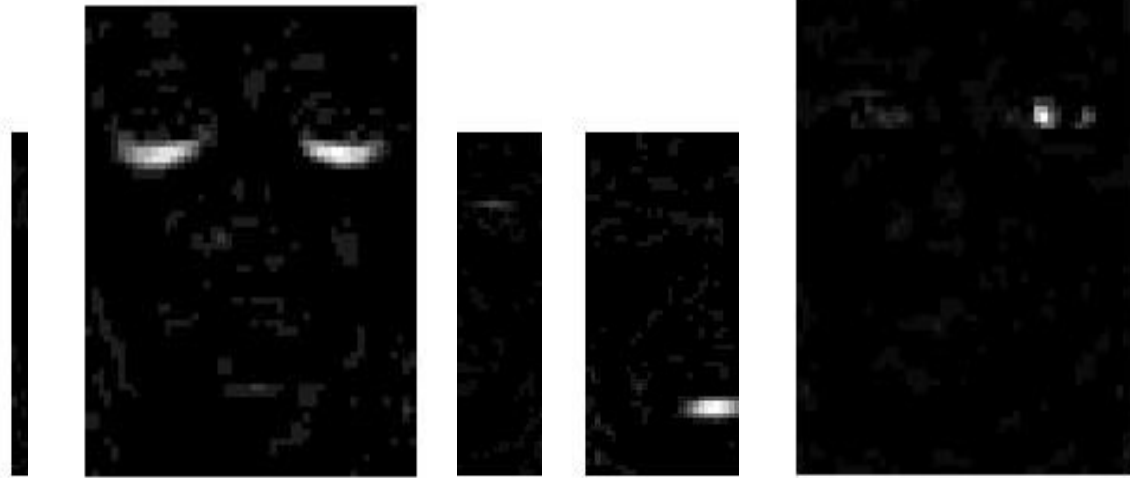
Formalized goal:

- Each image represented as a m-bit value signature.
- Recognition rate 100%.
- High discrimination power.

# 2. Methodology



# 3. Subspace selection



# Subspace selection

## Strategies for subspace selection:

- **PCA by filtering the spectrum before ICA.**
- **ICA by using a global entropic criterion.**
- **ICA by using a local entropic criterion.**
- **Combination of the above two.**

# Subspace selection

PCA selection to retain only the highest variance coefficients.

ICA selection by entropic criterion

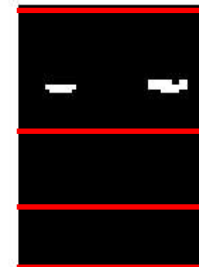
**Global criterion  
(minimal entropy)**



small area

high area

**Local criterion  
(maximal/minimal  
entropy)**

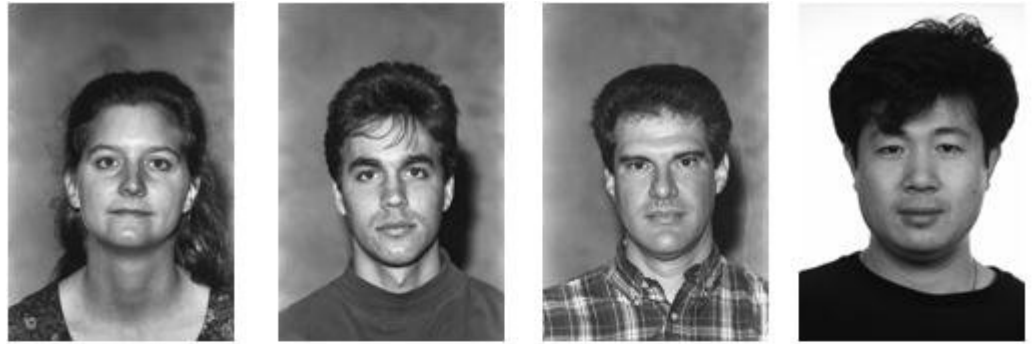


High area

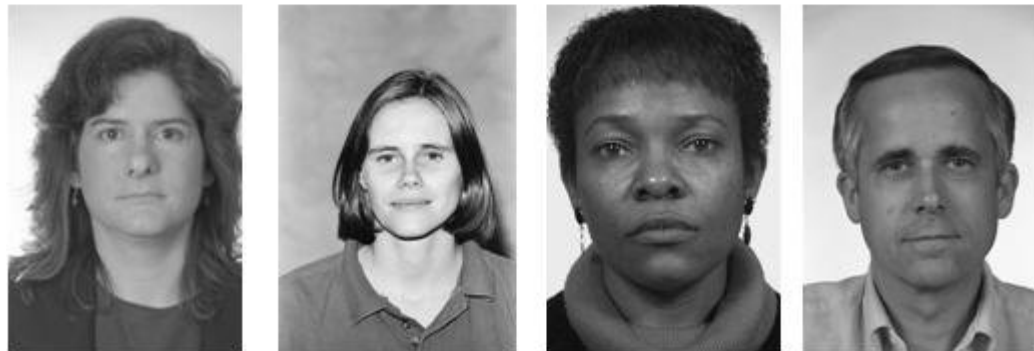
Small area

14

# 4. Experimental results



## FERET Database

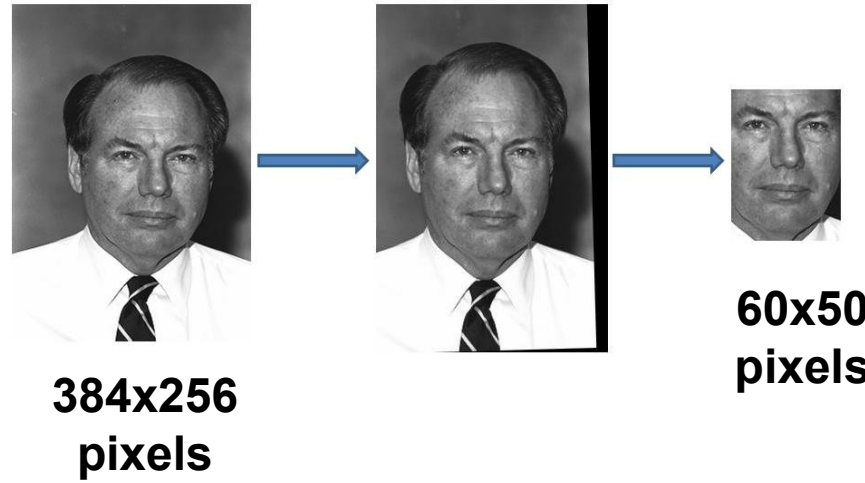


# Experimental results

**Gray level images of 384x256 pixels.**

**300 images for the training set.**

**210 images for the test set.**



**Affine transformation**



**Median filter**



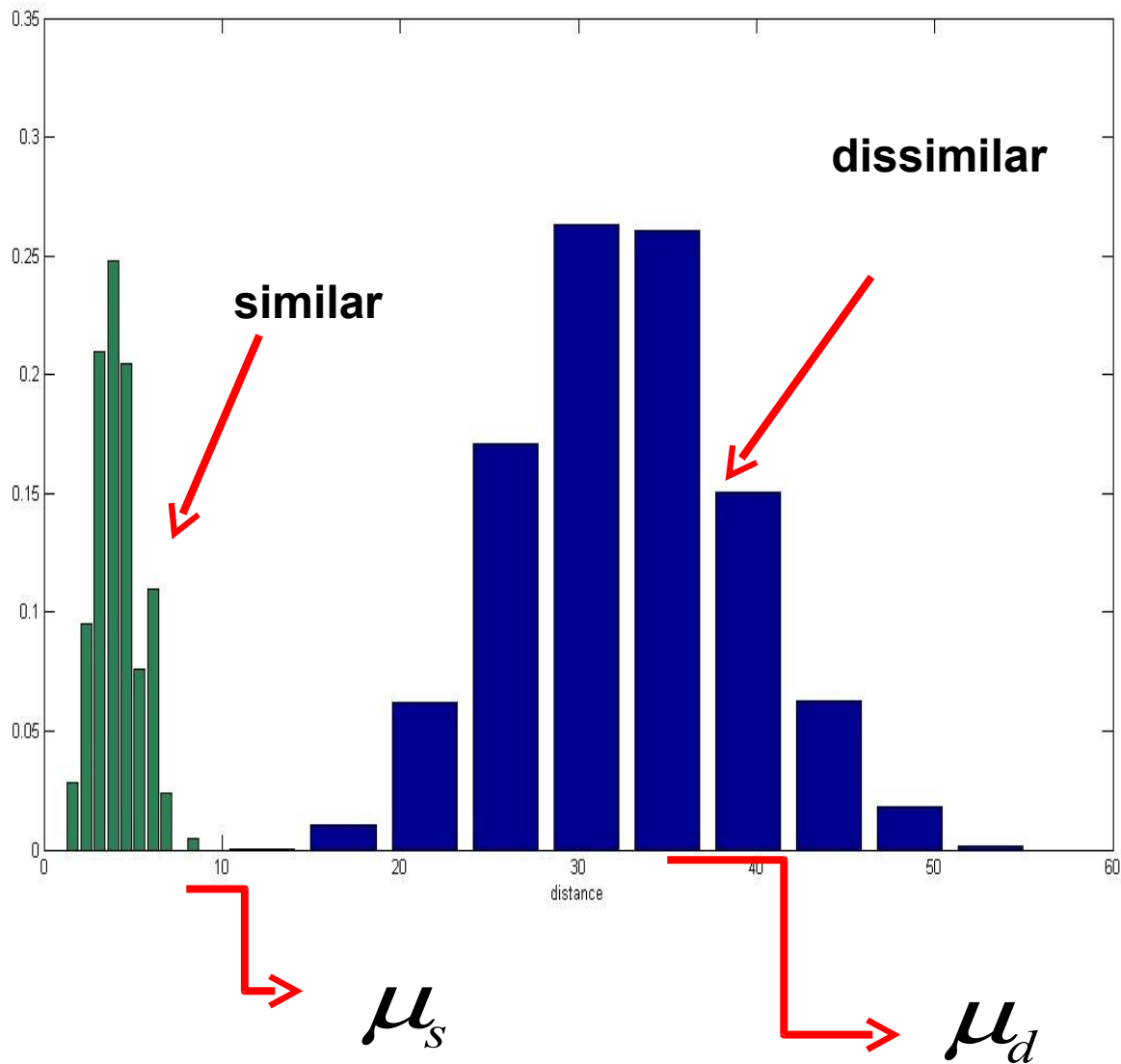
**Noise addition**





# Experimental results

## Discrimination power

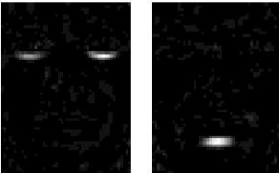


### Discrimination measure

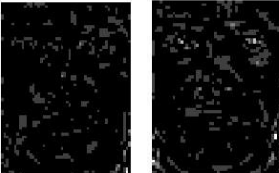
$$r = \frac{|\mu_s - \mu_d|}{\sigma_s + \sigma_d}$$

# Experimental results Importance of selection

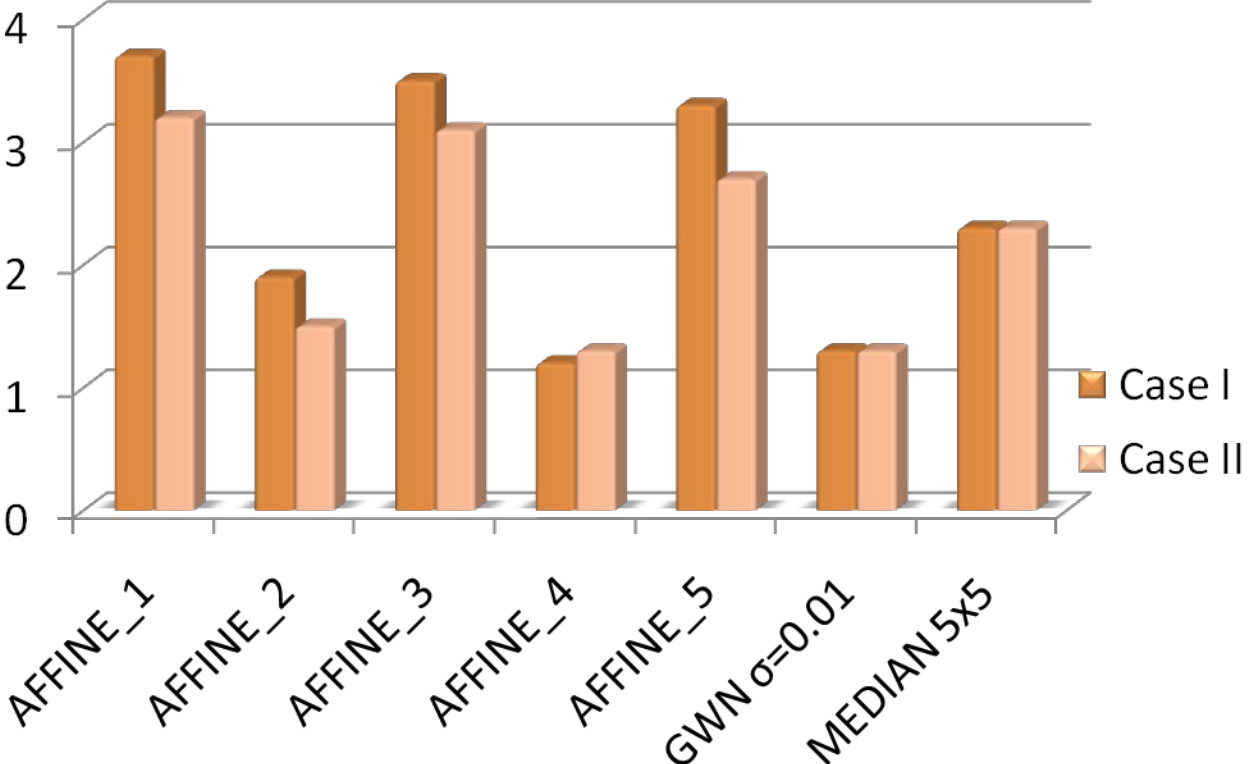
Case I



Case II

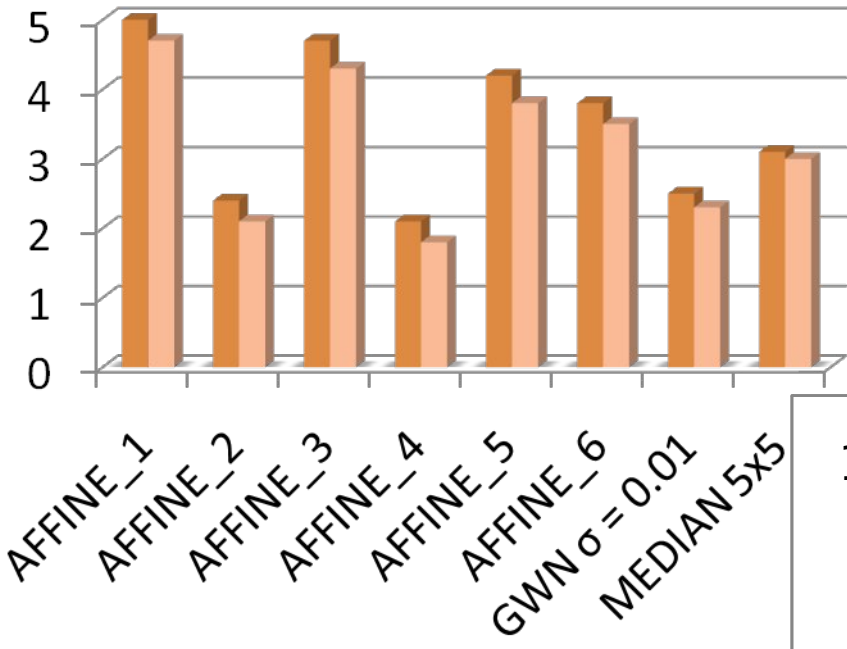


Discrimination measure



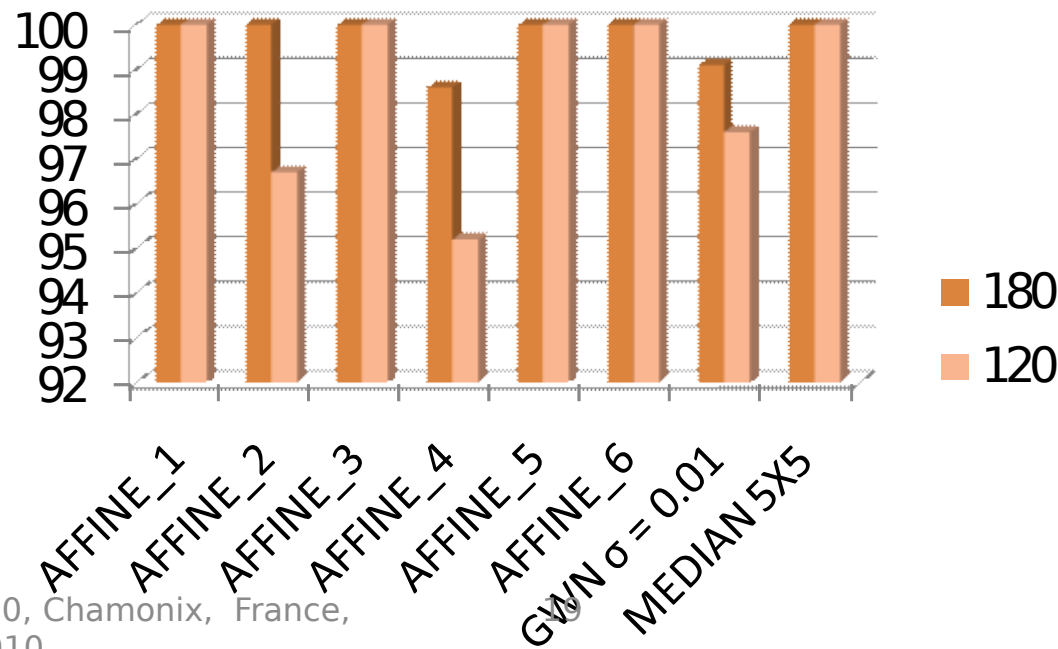
# Experimental results

Tuning the number of ICs.



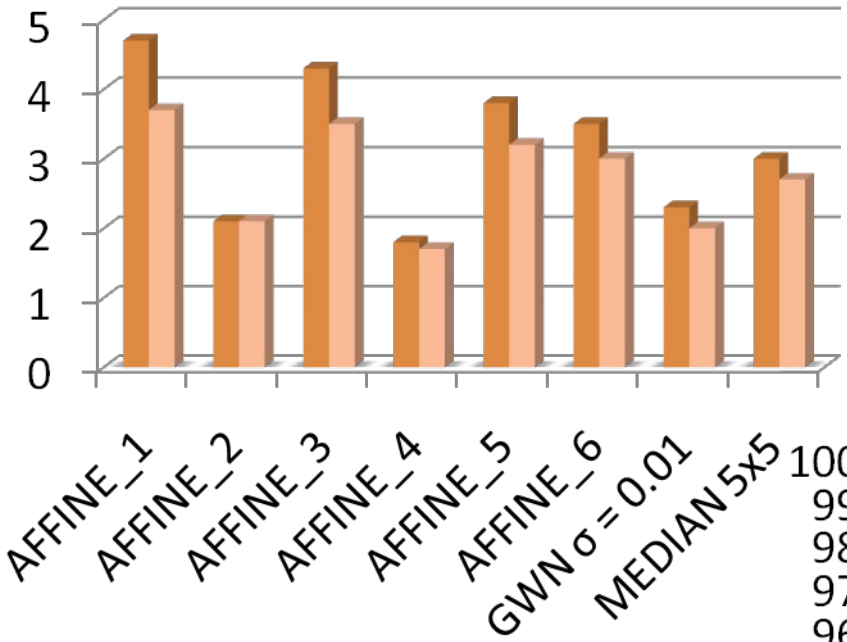
Discrimination measure

Recognition rate

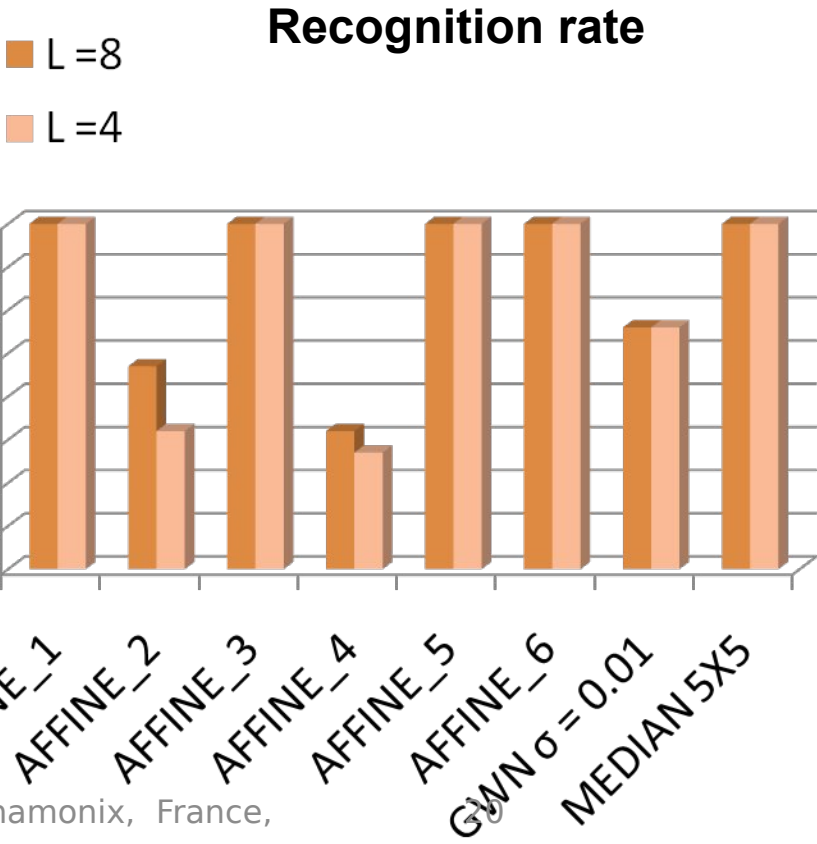


# Experimental results

Tuning the number of quantization levels.



Discrimination measure

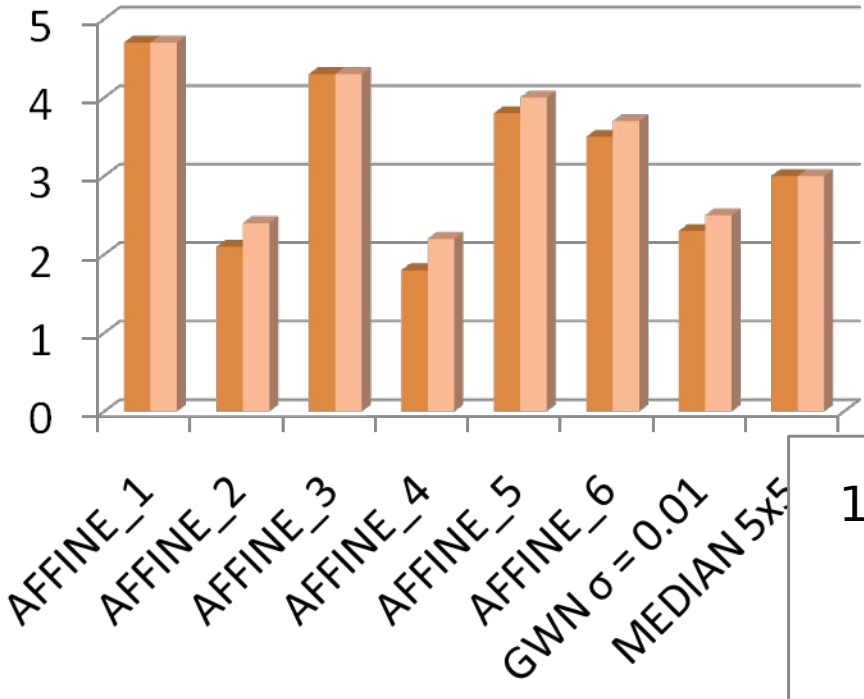


Recognition rate

# Experimental results

Different strategies.

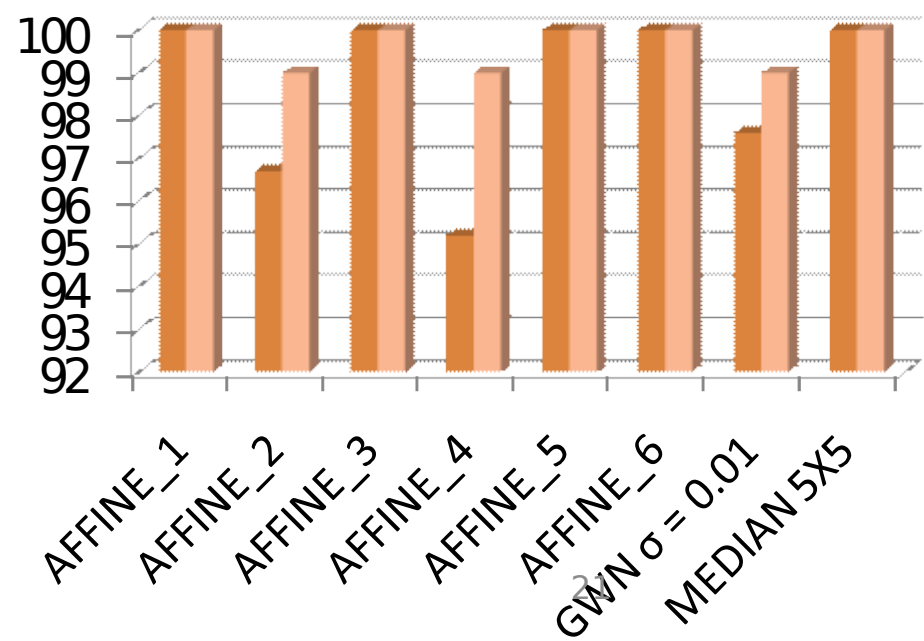
Number of ICs and quantization levels are constant.



Discrimination measure

PCA (PCA before ICA)  
LE (ICA with LE)

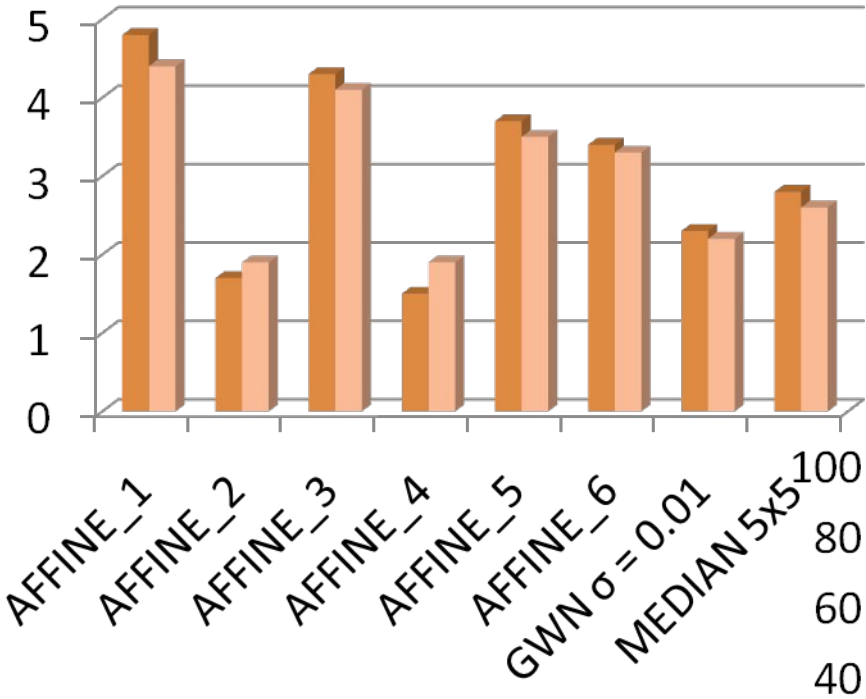
Recognition rate



PCA  
LE

# Experimental results

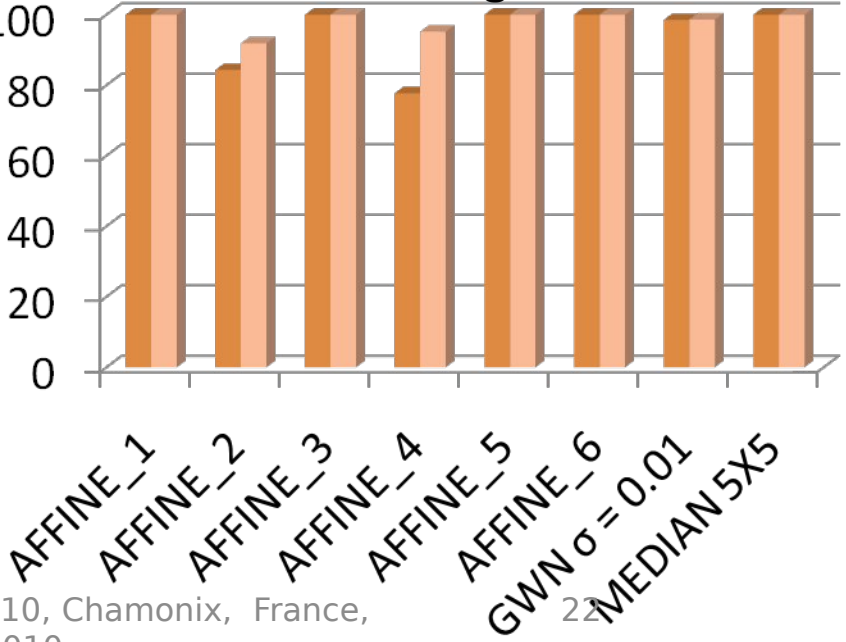
Strategies combination.



Number of ICs and quantization levels are constant.

PCA  
LE-GE

## Recognition rate



PCA  
LE-GE

Discrimination measure

# 5. Conclusions

**High recognition rate: 100% in almost all studied cases.**

**For a higher number of ICs and quantization levels the recognition rate and the gap between similar and dissimilar distributions is higher.**

**Local entropy maximization corresponds to the most suitable strategy for subspace selection.**

**Thank you!**