Robust Face Recognition under Varying Illumination and Occlusion Considering Structured Sparsity

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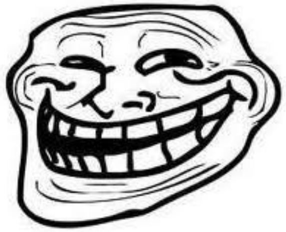
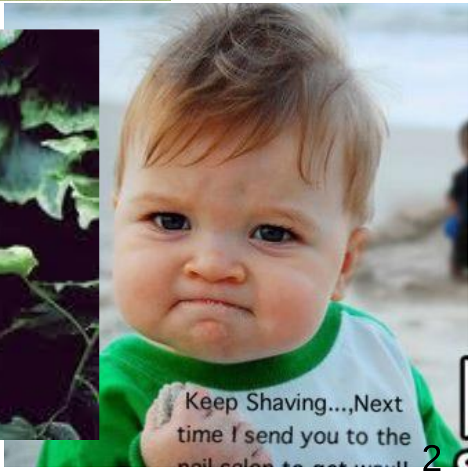
Face



- People love faces !
  - Biological nature
  - Sensitive to the face pattern

A house with a Hitler face



Face Recognition

- Uncontrolled conditions: large changes in pose, illumination, expression and occlusion, aging… Still challenging

Motivation

- Face recognition in real-world environments often has to confront with uncontrolled and uncooperative conditions
  - illumination changes, occlusion
- Uncontrolled variations are usually coupled
- Less work focuses on simultaneously handling them

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Our Method

- Our work deals with the illumination changes and occlusion simultaneously considering $\boxed{\text{structured sparsity}}$

represents a test image using the minimal number of ***clusters***

Sparse Representation

flat sparsity

represents a test image using minimal number of training images from ***all classes***

Our Method

- Our work deals with the illumination changes and occlusion simultaneously considering structured sparsity aided with:
  - **Structural occlusion dictionary**: better modelling contiguous occlusion

contiguous occlusion also forms a ***cluster*** structure

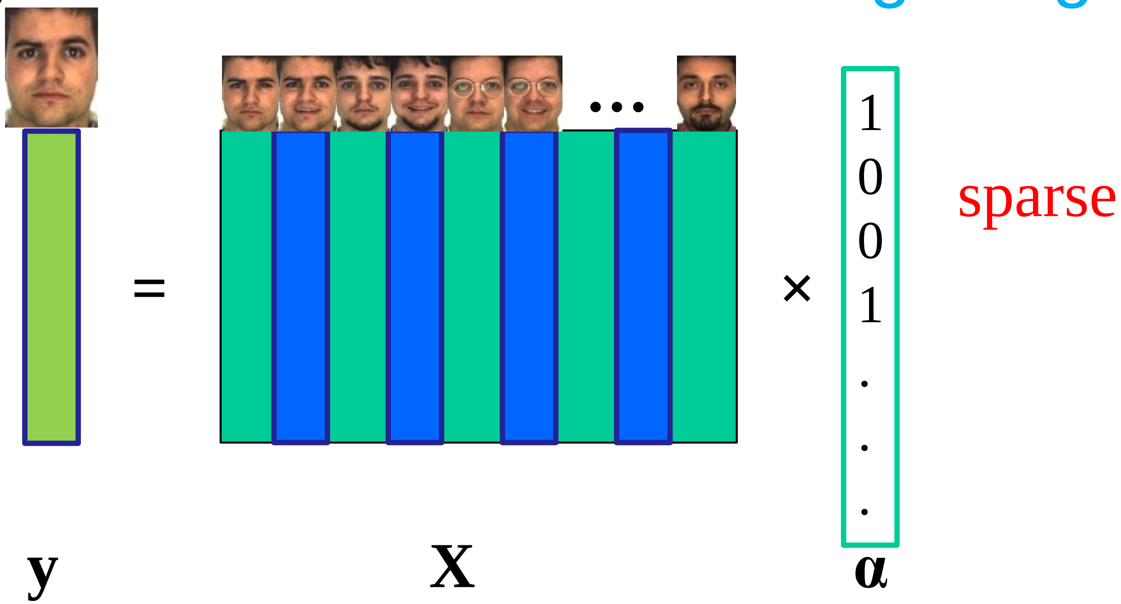
Our Method

- Our work deals with the illumination changes and occlusion simultaneously considering structured sparsity aided with:
  - **Structural occlusion dictionary**: better modelling contiguous occlusion
  - **WLD feature**: robust to illumination changes, remove shadows

Inspired by the psychophysical
Weber's Law

Sparse Representation

- Models a test image as a linear combination of training images
  - Using minimal number of training images

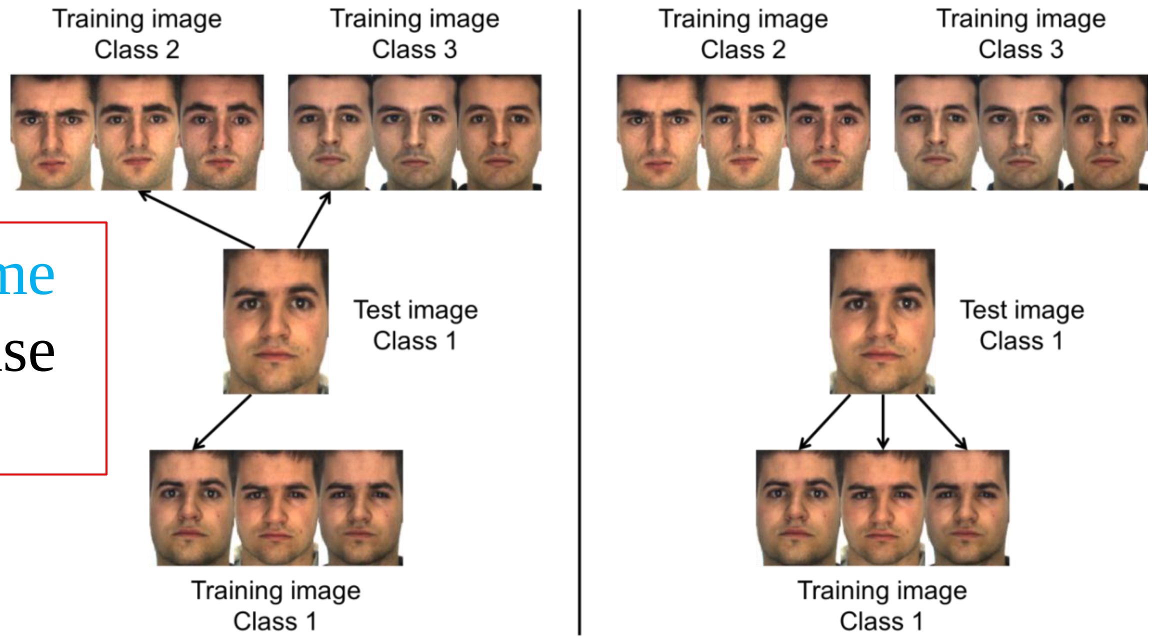


$$\hat{\boldsymbol{\alpha}} = \arg\min_{\alpha} \|\boldsymbol{\alpha}\|_1 \quad \text{subject to} \quad \boldsymbol{y} = \boldsymbol{X}\boldsymbol{\alpha}$$

Sparse Representation

- Involves training images from all classes
  - Optimal for reconstruction but not necessary for classification

Using the same number of base vectors



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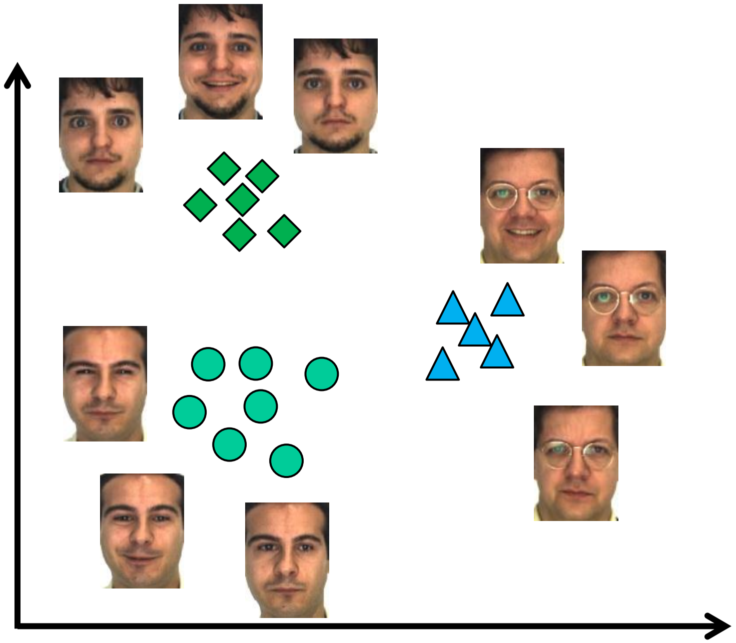
Our Method

- Structured Sparsity
  - Each class form a cluster



$$\boldsymbol{X} = [\underbrace{\boldsymbol{x}_1, \ldots, \boldsymbol{x}_d}_{\boldsymbol{X}[1]}, \ldots, \underbrace{\boldsymbol{x}_{n-d+1}, \ldots, \boldsymbol{x}_n}_{\boldsymbol{X}[s]}]$$

$$\boldsymbol{\alpha} = [\underbrace{\alpha_1, \ldots, \alpha_d}_{\boldsymbol{\alpha}[1]}, \ldots, \underbrace{\alpha_{n-d+1}, \ldots, \alpha_n}_{\boldsymbol{\alpha}[s]}]^T$$

cluster structure

$$y = X\alpha$$

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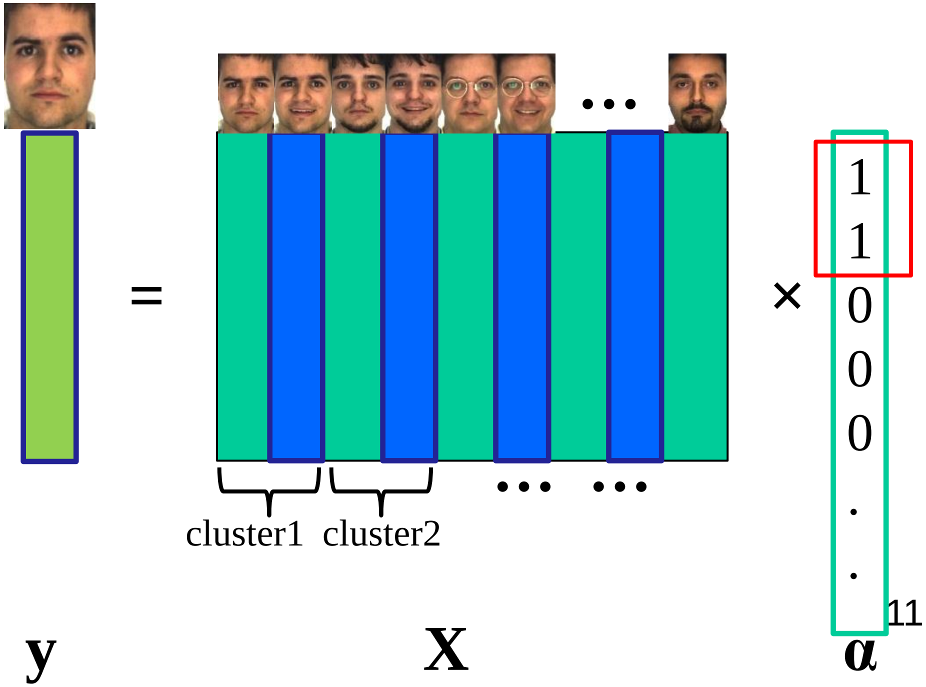
Our Method

- Structured Sparsity
  - Represents a test image using the minimum number of clusters

$$\hat{\boldsymbol{\alpha}} = \arg\min_{\alpha} \|\boldsymbol{\alpha}\|_{2,1}$$

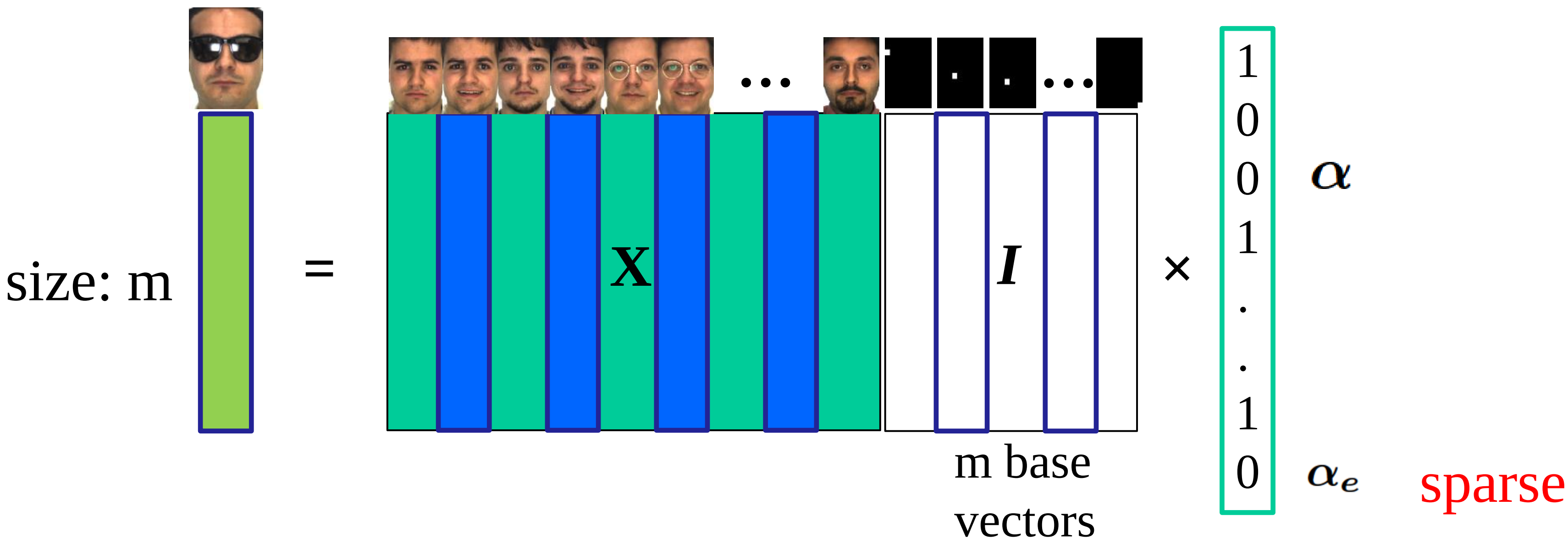
$$= \arg\min_{\alpha} \sum_{i=1}^{s} \sqrt{\sum_{j=1}^{d} \alpha_j^2[i]}$$

$$\text{subject to} \quad \boldsymbol{y} = \boldsymbol{X}\boldsymbol{\alpha}$$



Sparse Representation

- Occlusion modelling: identity matrix $\boldsymbol{I} \in \mathbb{R}^{m \times m}$

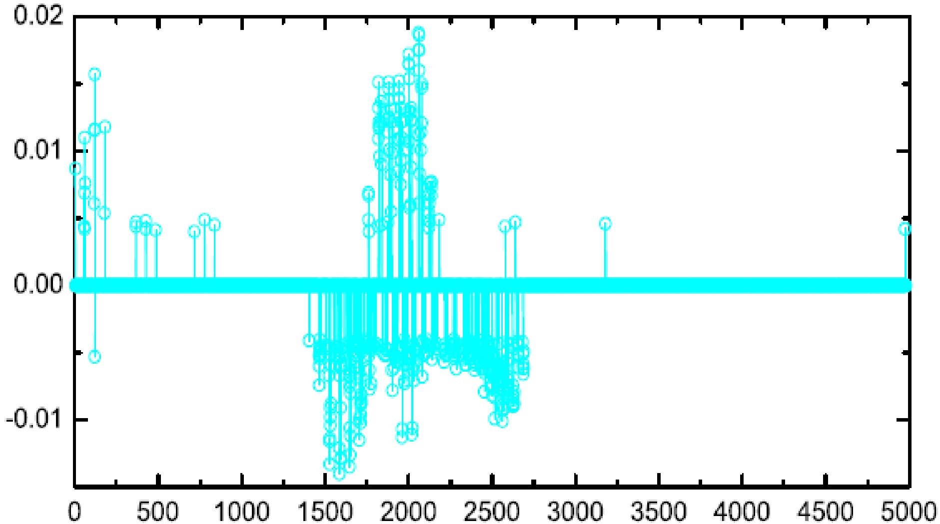


  – limitation: $\boldsymbol{I} \in \mathbb{R}^{m \times m}$ is able to represent any image of size *m*

Our method

- Contiguous occlusion: the nonzeros entries are likely to be spatially continuous, are aligned to clusters

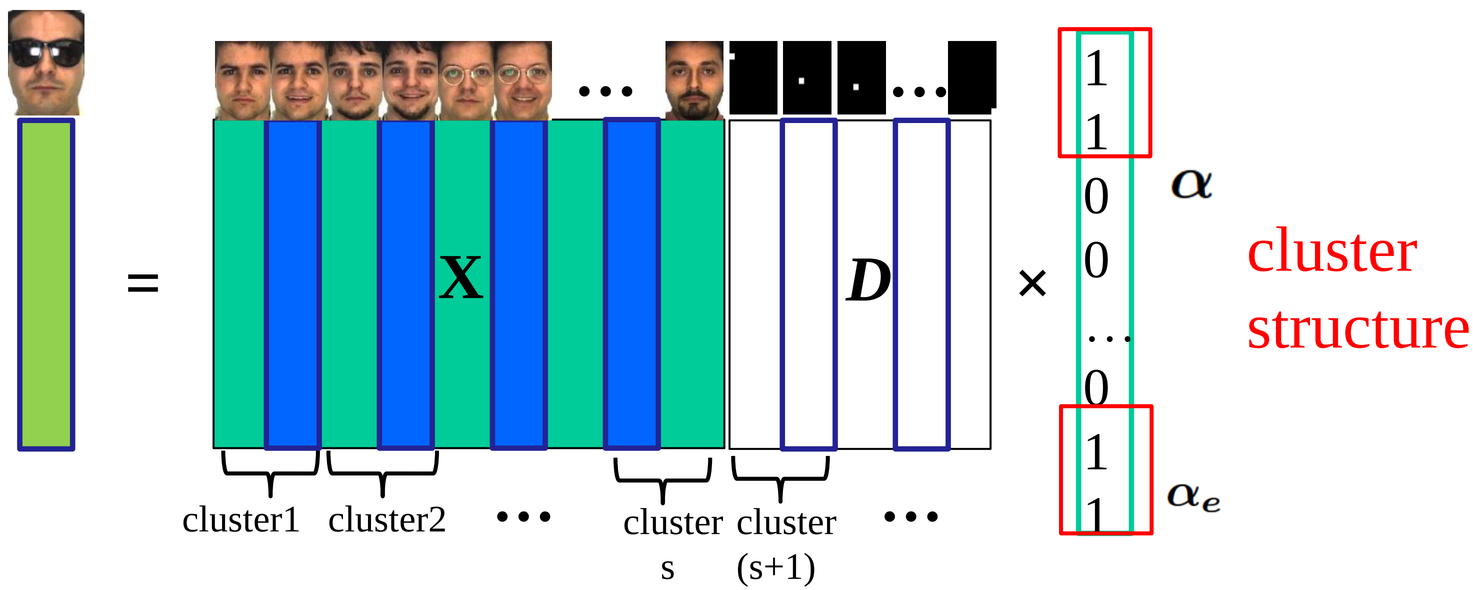
size: 83*60=4980



index of occlusion base vectors

Our method

- Structural occlusion dictionary
  - uses the cluster occlusion dictionary to replace the identity matrix ***I***



Our Method

- Extreme illumination + occlusion:
  - coupled occlusion takes up a large ratio of the image
  - not "*sparse*" error

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Our Method

- A different view: extract relevant features that reduce the difference
- Using WLD feature
  - ✓ Maintain most salient facial features
  - ✓ Insensitive to illumination changes
  - ✓ Can correct shadow effects

Original image

$$\begin{bmatrix} +1 & +1 & +1 \\ +1 & -8 & +1 \\ +1 & +1 & +1 \end{bmatrix} \qquad \begin{bmatrix} 0 & 0 & 0 \\ 0 & +1 & 0 \\ 0 & 0 & 0 \end{bmatrix}$$

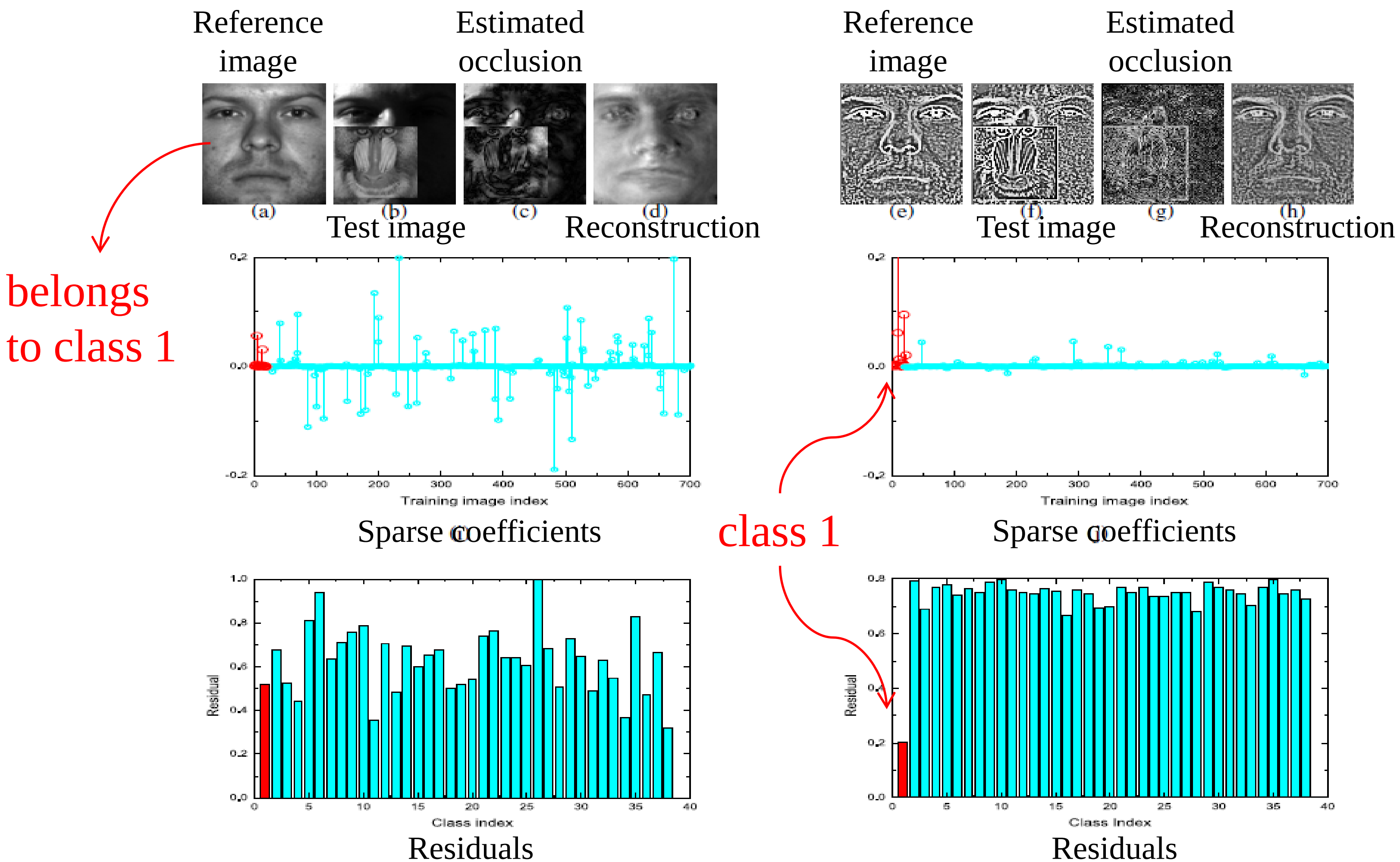
Filtering

WLD feature

$$WLD(p) = \arctan\left(\sum_{i=1}^{l} \frac{p_i - p}{p}\right)$$

Chen et al, *Wld: A robust local image descriptor*, PAMI, 2010

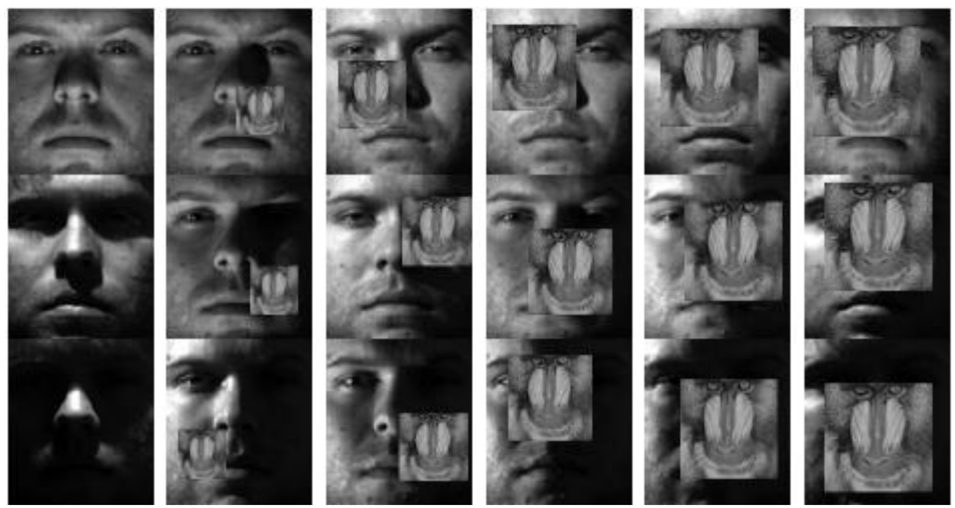
Illustrative Example



Experiments

- Synthetic Occlusion with Extreme Illumination
  - Extended Yale B database
  - Occlusion levels: 0% ~ 50% of the image

Training set



Testing set

Experiments

- Synthetic Occlusion with Extreme Illumination
  - – using only the raw pixel intensity as feature

TABLE I
RECOGNITION RATES (%) ON THE SUBSET 3 OF THE EXTENDED YALE B DATABASE

Occlusion	0%	10%	20%	30%	40%	50%
SR-P[15]	**100**	**100**	99.8	98.5	90.3	65.3
CRC-RLS[17]	**100**	**100**	95.8	85.7	72.8	59.2
R-CRC[17]	**100**	**100**	**100**	97.1	92.3	82.3
Proposed SSR-P	**100**	**100**	**100**	**100**	**97.8**	**85.4**

[15] Wright et al, TPAMI, 2009. [17] Zhang et al, ICCV, 2011

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Experiments

- Synthetic Occlusion with Extreme Illumination
  – using WLD feature

TABLE II
RECOGNITION RATES(%) ON THE SUBSET 4 AND SUBSET 5 OF THE EXTENDED YALE B DATABASE

	Occlusion	0%	10%	20%	30%	40%	50%
Subset 4	SR-P[15]	86.3	78.5	70.0	53.2	36.7	28.1
	Proposed SSR-P	97.2	93.4	84.8	68.4	53.4	39.9
	SR-G[16]	95.3	88.8	84.2	76.4	66.5	54.7
	SR-W	99.4	99.6	**99.4**	99.1	99.1	96.6
	Proposed SSR-W	**99.6**	**99.8**	**99.4**	**99.4**	**99.6**	**98.1**
Subset 5	SR-P[15]	37.5	26.9	14.3	9.0	7.9	7.3
	Proposed SSR-P	42.6	31.6	23.4	15.3	11.5	10.9
	SR-G[16]	44.2	31.7	32.0	23.8	21.5	17.5
	SR-W	98.0	97.5	96.9	**96.9**	91.9	83.0
	Proposed SSR-W	**98.3**	**98.0**	**97.3**	95.8	**95.4**	**88.6**

[15] Wright et al, TPAMI, 2009. [16] Yang et al, ECCV, 2010

Experiments

- Synthetic Occlusion with Extreme Illumination
  - using WLD feature

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	SR-W	99.4	99.6	**99.4**	99.1	99.1	96.6
	Proposed SSR-W	**99.6**	**99.8**	**99.4**	**99.4**	**99.6**	**98.1**
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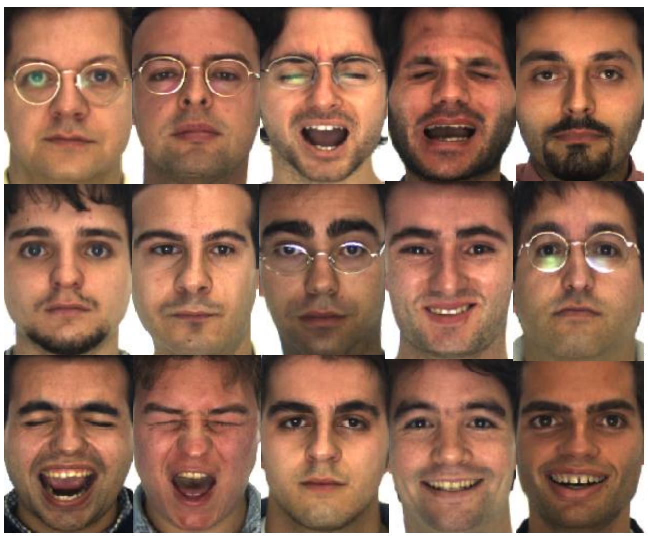
Experiments

- Disguise with Non-uniform Illumination
  - The AR Database
  - Real occlusion, 2 sessions



Training set

Testing set

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Experiments

- Disguise with Non-uniform Illumination

TABLE III
RECOGNITION RATES (%) ON THE AR DATABASE

	Sunglasses	Scarves
SR-P[15]	42.5	29.8
Proposed SSR-P	43.5	31.8
SR-G[16]	74.8	76.0
SR-W	85.0	89.5
Proposed SSR-W	**87.5**	**92.0**

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Thank you

- Questions ?

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