Close the loop: Joint Blind Image Restoration and Recognition with Sparse Representation Prior

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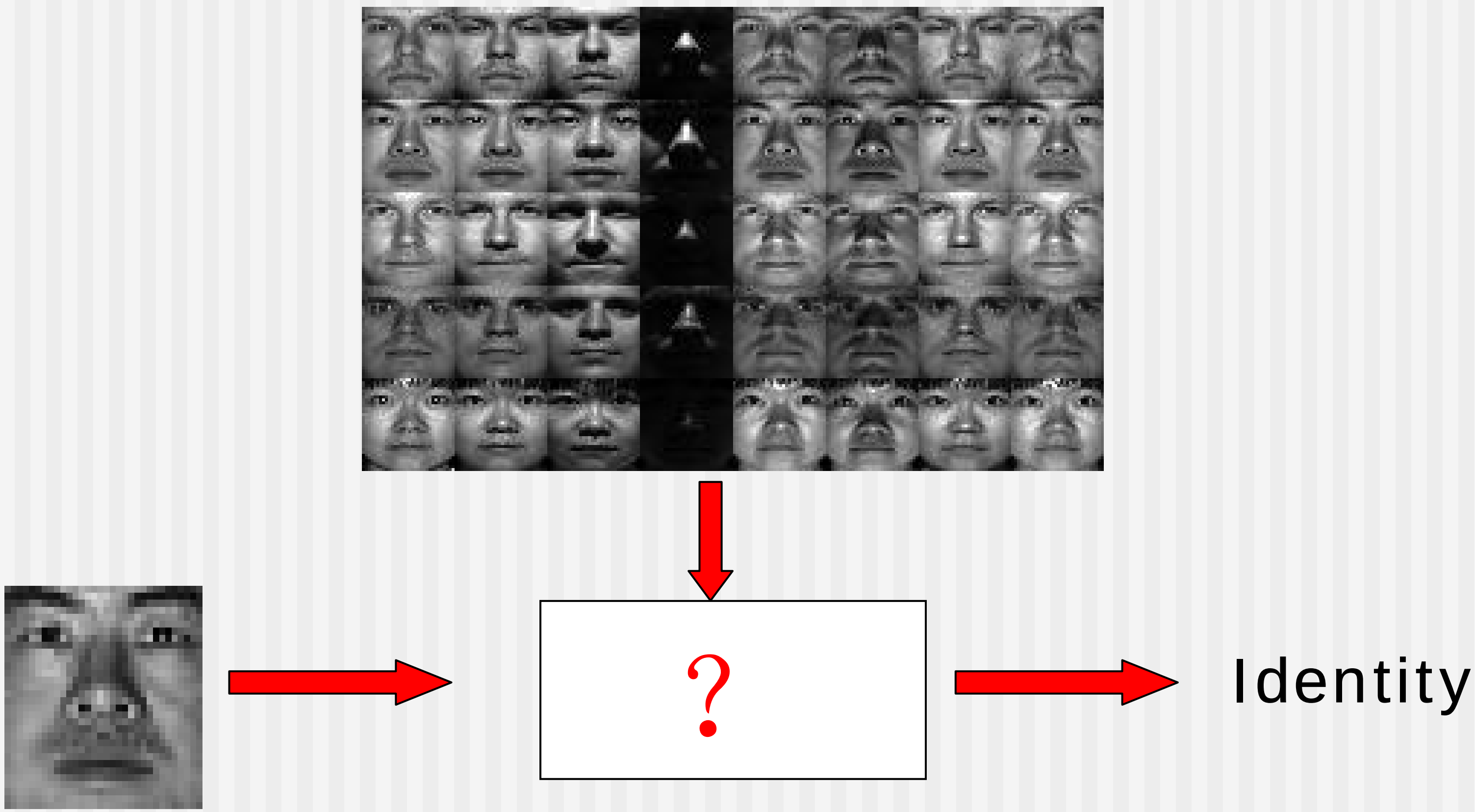
- Title: Close the loop: Joint Blind Image Restoration and Recognition with Sparse Representation Prior
- Authors: Haichao Zhang, Jianchao Yang, Yanning Zhang, Nasser M. Nasrabadi and Thomas S. Huang
- ICCV 2011
- Prize: Best Student Paper

Goal and Motivation

- Image restoration

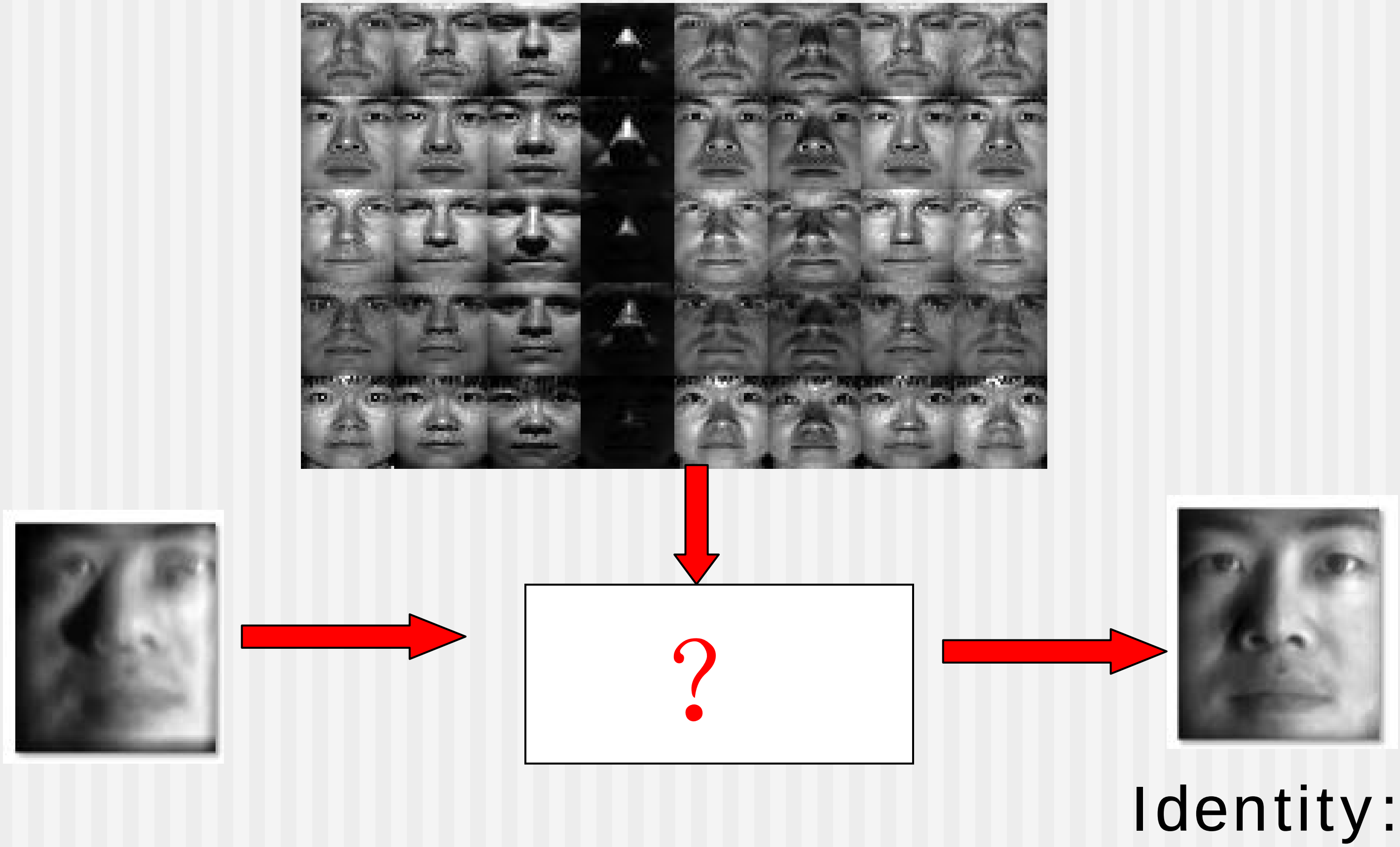
Goal and Motivation

- Recognition

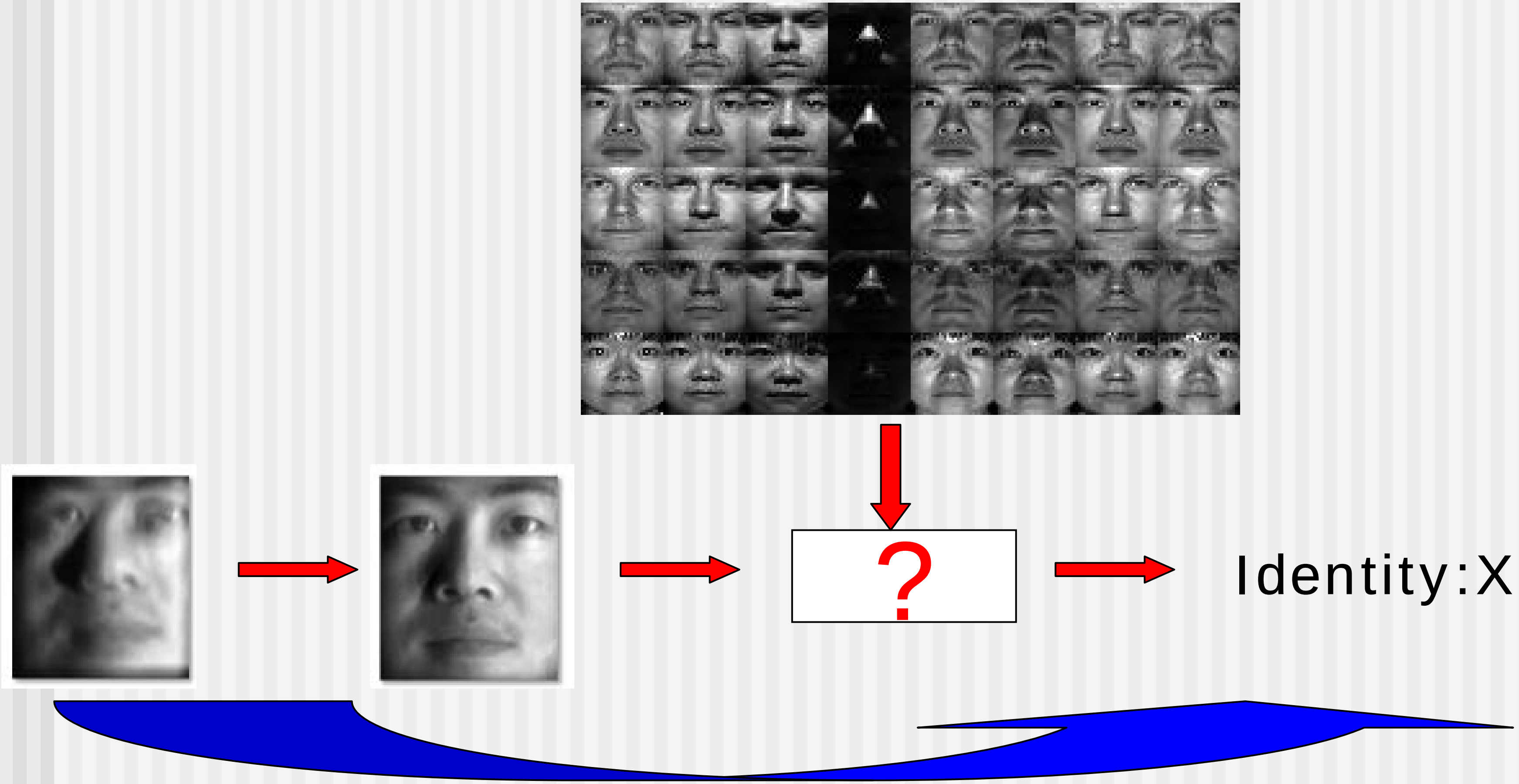


Goal and Motivation

- image restoration and recognition

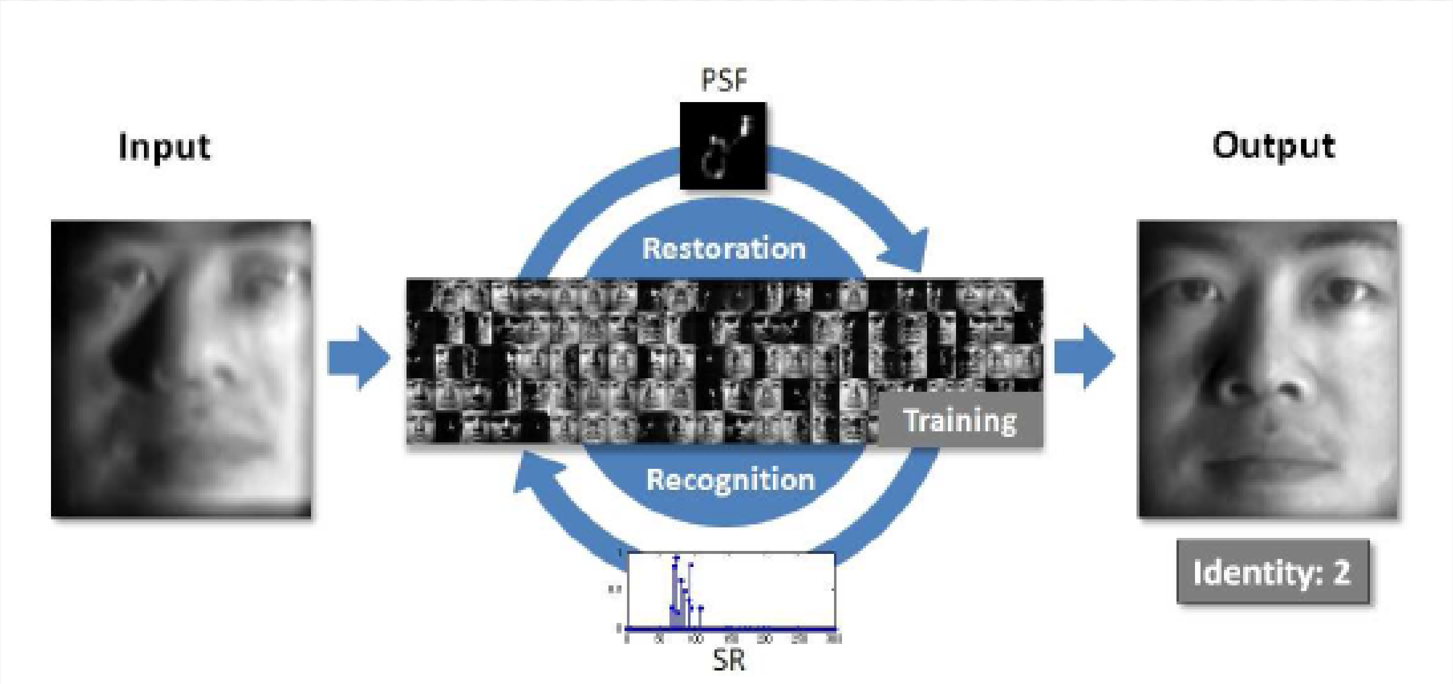


Straightforward idea



Goal and Motivation

- Simultaneous image restoration and recognition



Close the loop: Joint Blind Image Restoration and Recognition with Sparse Representation Prior

A detailed review

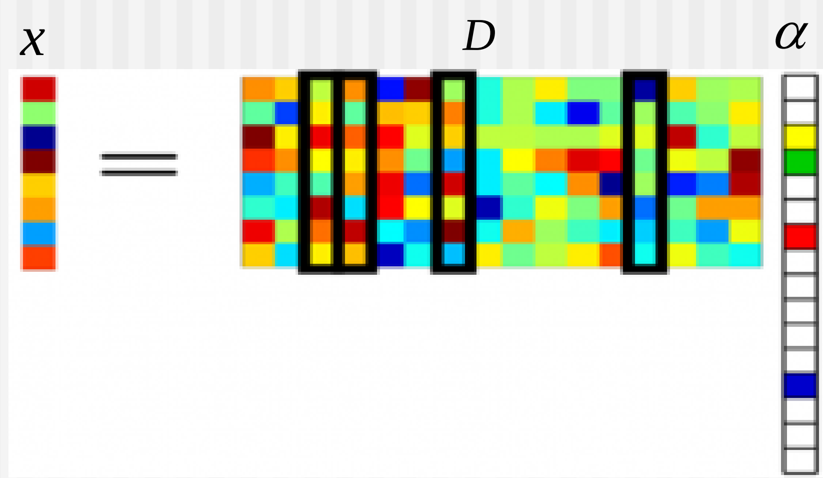
- Sparse representation
- Sparsity in image restoration
- Sparse representation for recognition

Sparse representation--what

- Original problem: Given $x \in R^m$, $D = [d_1, d_1, \ldots, d_n] \in R^{m \times n} (m \leq n)$ how to solve

$$x = D\alpha$$

- Sparse representations are the representations that account for most or all information of a signal with a linear combination of a small number of elementary signals.



Sparse representation-why

- Physiological phenomena: mammalian primary visual cortex (Olshausen and Field,1996)

- Sparsity constraint: The number of the non-zero entries of α are constrained to be as small as possible.

$$\min_{\alpha} \|\alpha\|_0$$
$$s.t. \quad x = D\alpha$$

Olshausen BA, and Field DJ. (1996). "Emergence of Simple-Cell Receptive Field Properties by Learning a Sparse Code for Natural Images." Nature, 381: 607-609

Sparse representation-how

- The constrained problem:

$$\min_{\alpha} \|\alpha\|_0$$
$$s.t. \quad x = D\alpha$$

NP hard

- Donoho(Stanford) and Elad: there exists a unique solution under some condition.

Sparse representation-how

- Candes (Stanford) and Tao(UCLA): Under the RIP(Restricted Isometry Property) condition, the solution to the original L0-norm problem is the same as the one to the corresponding L1-norm problem:

$$\min_{\alpha} \|\alpha\|_0 \quad s.t. \quad x = D\alpha \qquad \Rightarrow \qquad \min_{\alpha} \|\alpha\|_1 \quad s.t. \quad x = D\alpha$$

Convex!

Sparse representation-how

I. There exists a unique solution to the original L0-norm problem under some condition.
II. Under the RIP(Restricted Isometry Property) condition, the solution to the original L0-norm problem is the same as the one to the corresponding L1-norm problem,
III. The L1-norm problem is a convex problem, which has a unique solution.

Sparse representation

- The L1-norm problem with noise

$$\min_{\alpha} \|\alpha\|_0 \quad s.t. \quad x = D\alpha \quad \Rightarrow \quad \min_{\alpha} \|\alpha\|_1 \quad s.t. \|x - D\alpha\|_2^2 \le \varepsilon$$

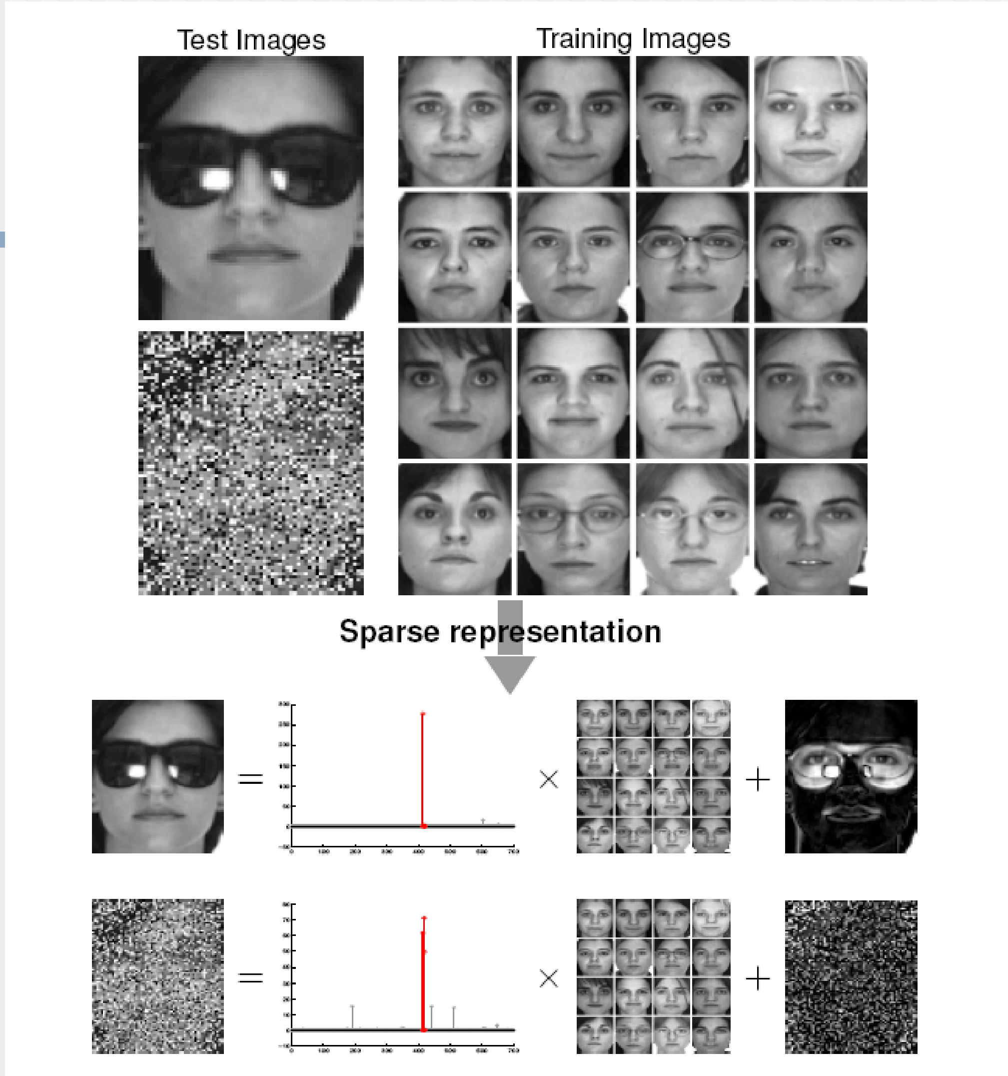
- Algorithms: many

$$\min_{\alpha} \underline{\|x - D\alpha\|_2^2} + \lambda \|\alpha\|_1$$

$$+ more \quad regularizations$$

$$\min_{\alpha} \| \alpha \|_1$$

$$s.t. \| x - D\alpha \|_2^2 \leq \varepsilon$$



John Wright, Allen Y. Yang, Arvind Ganesh, S. Shankar Sastry, and Yi Ma. Robust Face Recognition via Sparse Representation. PAMI. 31(2) , 210-227, 2009.

A brief review

- Sparse representation
- Sparsity in image restoration
- Sparse representation for recognition

Sparsity in Image Restoration

- Image restoration

observation model

Sparsity in Image Restoration

- Low quality image observation model:

$$y = k * x + \varepsilon$$

where y is the observation, x is the real image, k is the PSF (blur kernel) and $*$ denotes the convolution operator.

- The corresponding optimization problem:

$$\arg\min_{x,k} \| k * x - y \|_2^2 + \lambda P(x) + \gamma Q(k)$$

where P(x) and Q(k) are two regularization terms.

Sparsity in Image Restoration

- The corresponding optimization problem:

$$\arg\min \| k * x - y \|_2^2 + \lambda P(x) + \gamma Q(k)$$

- The corresponding optimization problem with the sparsity prior

$$\arg\min \| k * x - y \|_2^2 + \lambda \| S^T x \|_1 + \gamma \| k \|_2^2$$

where S is a sparse transformation.

S. Cho and S. Lee. Fast motion deblurring. In SIGGRAPH ASIA, 2009.

Sparsity in Image Restoration

$$(x,k) = \arg\min_{x,k} \| k * x - y \|_2^2 + \lambda \sum_{l=1}^{L} | e_l * x |^s$$

where e1=[1,-1], e2=e1’, s=0.5 (0.5-0.8).

D. Krishnan and R. Fergus. Fast image deconvolution using hyperlaplacian priors. In NIPS, 2009.

A brief review

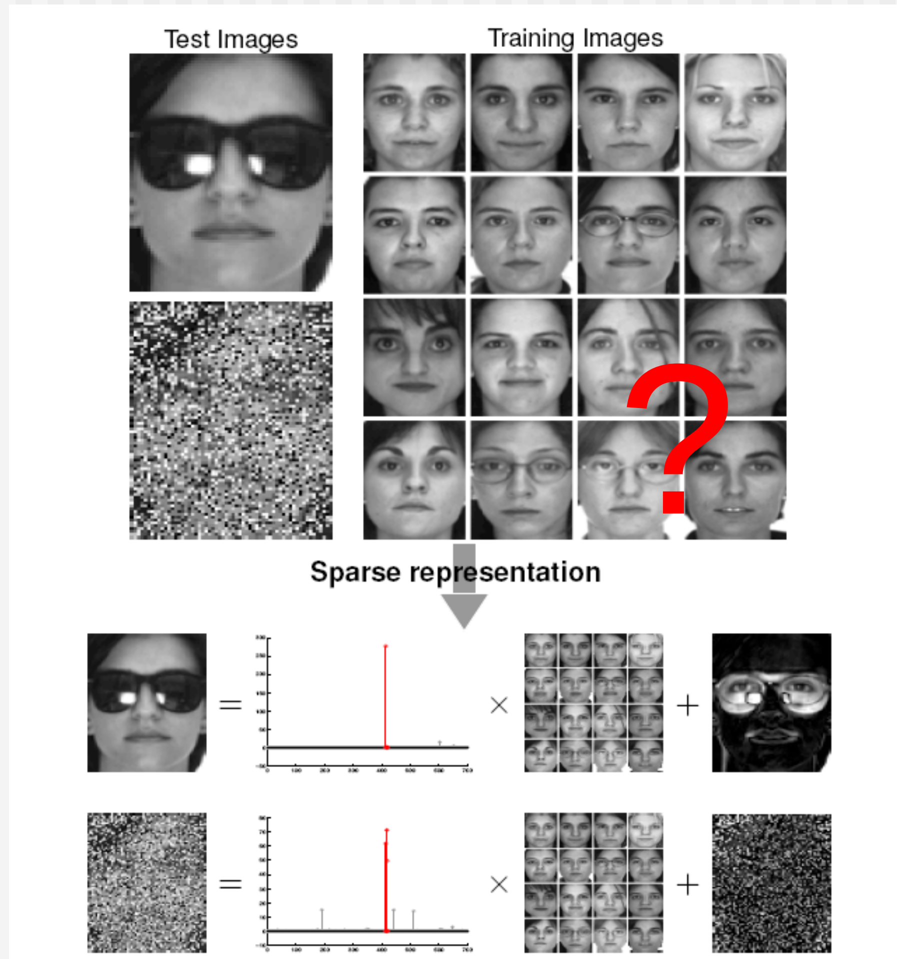
- Sparse representation
- Sparsity in image restoration
- Sparse representation for recognition

Sparse Representation for Recognition

$$\hat{\alpha} = \arg\min_{\alpha} \| \alpha \|_1$$

$$s.t. \| x - D\alpha \|_2^2 \leq \varepsilon$$

$$\min_{\alpha} \| x - D\alpha \|_2^2 + \lambda \| \alpha \|_1$$

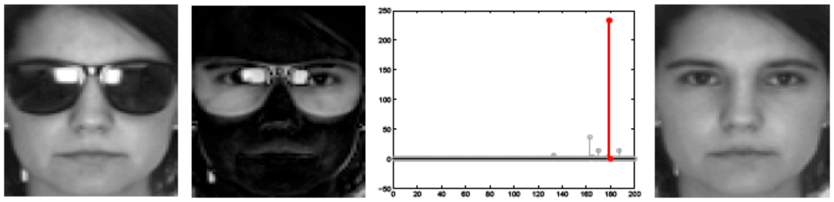


Sparse Representation for Recognition

- Assumption: a test sample can be represented by the training samples of the same class.
- Given a set of training samples D(c classes)

$$\hat{\alpha} = \arg\min_{\alpha} \| \alpha \|_1$$

$$s.t. \| x - D\alpha \|_2^2 \leq \varepsilon$$



(a) (b) (c) (d)

- The label for x is determined by the minimum reconstruction error:

$$\hat{c} = \arg\min_{c} \|\mathrm{D}\delta_c(\hat{\alpha}) - \mathrm{x}\|_2^2 = \arg\min_{c} \|\mathrm{D}_c\hat{\alpha}_c - \mathrm{x}\|_2^2.$$

Problem formulation(1)

- Sparsity in Image Restoration

$$(x,k) = \arg\min_{x,k} \| k * x - y \|_2^2 + \lambda P(x) + \gamma Q(k)$$

- Sparse Representation for Recognition

$$\alpha = \arg\min_{\alpha} \| x - D\alpha \|_2^2 + \tau \| \alpha \|_1$$

- Joint Blind Image Restoration and Recognition

$$(x,k,c) = \arg\min_{x,k,c} \| k * x - y \|_2^2 + \lambda P(x) + \gamma Q(k) + \eta \| x - D\alpha \|_2^2 + \tau \| \alpha \|_1$$

Problem formulation(2)

- Sparsity in Image Restoration

$$(x,k) = \arg\min_{x,k} \| k * x - y \|_2^2 + \lambda \sum_{l=1}^{L} | e_l * x |^s \quad + \gamma \| k \|_2^2$$

- Sparse Representation for Recognition

$$\alpha = \arg\min_{\alpha} \| x - D\alpha \|_2^2 + \tau \| \alpha \|_1$$

- Joint Blind Image Restoration and Recognition

$$(x,k,c) = \arg\min_{x,k,c} \| k * x - y \|_2^2 + \lambda \sum_{l=1}^{L} | e_l * x |^s + \gamma \| k \|_2^2 + \eta \| x - D\alpha \|_2^2 + \tau \| \alpha \|_1$$

where e1=[1,-1], e2=e1', s=0.5 (0.5-0.8).

Optimization Procedure

- The problem is solved in an alternated way.

$$(x,k,c) = \arg\min_{x,k,c} \| k * x - y \|_2^2 + \lambda \sum_{l=1}^{L} | e_l * x |^s + \gamma \| k \|_2^2 + \eta \| x - D\alpha \|_2^2 + \tau \| \alpha \|_1$$

- 1. k-estimation
- 2. x-estimation
- 3. alpha-estimation
- 4. classification

Experimental results

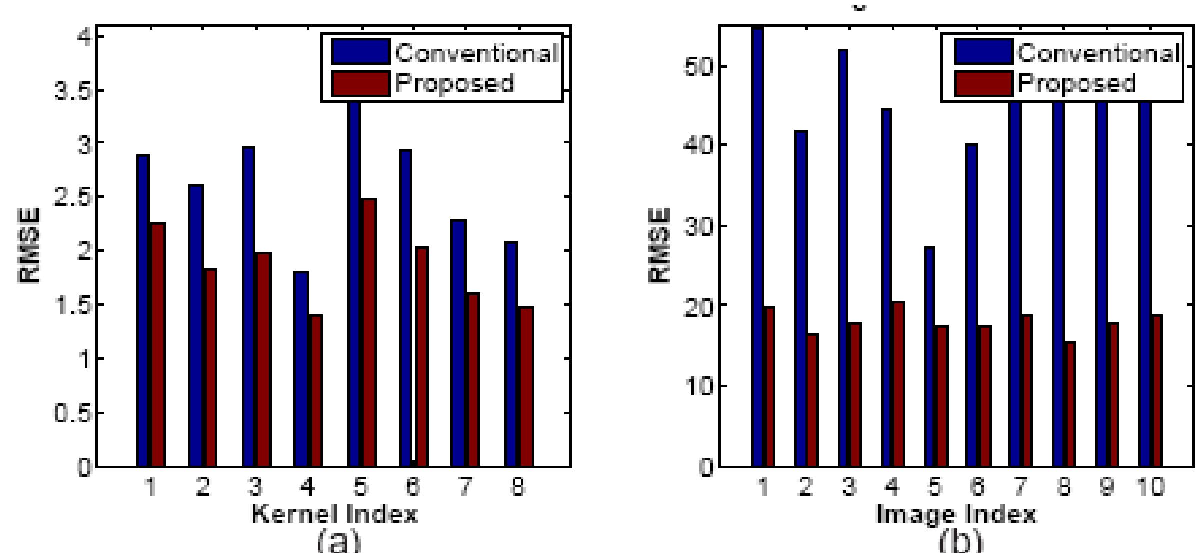


Figure 3. Restoration results comparison in terms of RMSE. (a) kernel estimation; (b) image estimation.

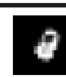
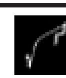
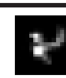
S. Cho and S. Lee. Fast motion deblurring. In SIGGRAPH ASIA, 2009.

Experimental results

Table 1. Recognition rate (%) on Extend Yale B under simple parametric blur kernels.

Kernel Type	SVM	SRC	SRC-B	JRR
Motion	40.0	68.7	85.3	**86.0**
Gaussian	29.9	57.7	**84.8**	**84.8**

Table 2. Recognition accuracy (%) on Extend Yale B set under complex non-parametric blur kernels.

Kernels								
Sizes	19	17	15	27	13	21	23	23
SVM	45.9	27.2	45.8	11.2	43.5	48.4	20.9	16.9
SRC	79.8	54.1	74.9	21.3	65.5	83.5	36.6	30.3
SRC-B	80.6	**79.3**	73.4	33.0	70.1	76.8	51.9	51.9
JRR	**86.2**	**79.3**	**85.7**	**43.1**	**81.9**	**86.4**	**64.7**	**54.8**

John Wright, Allen Y. Yang, Arvind Ganesh, S. Shankar Sastry, and Yi Ma. Robust Face Recognition via Sparse Representation. PAMI. 31(2) , 210-227, 2009.

Experimental results

Table 3. Recognition rate (%) on Multi-PIE with the third complex blur kernel.

Algorithm	SVM	SRC	SRC-B	JRR
Accuracy	84.8	85.2	79.1	**91.4**

Table 4. Recognition rate (%) with randomly blur kernels on both Extended Yale B and Multi-PIE.

Algorithm	SVM	SRC	SRC-B	JRR
Extended Yale B	57.0	68.8	66.3	**73.7**
Multi-PIE	49.4	53.6	54.9	**61.3**

John Wright, Allen Y. Yang, Arvind Ganesh, S. Shankar Sastry, and Yi Ma. Robust Face Recognition via Sparse Representation. PAMI. 31(2) , 210-227, 2009.

Experimental results

- A challenging situation is when the blurry test image suffers from extreme illuminations.

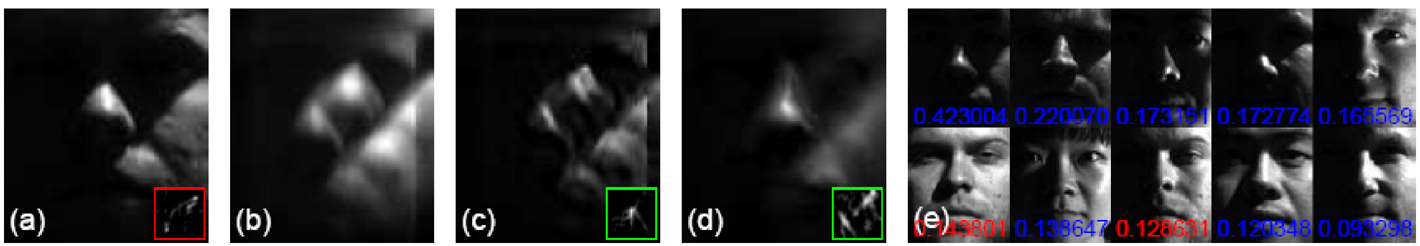


Figure 5. Failure case analysis. (a) ground truth image and kernel; (b) blurry input; estimated image and kernel using (c) conventional deblurring method [2] and (d) the proposed JRR method; (e) top-10 selected atoms with the JRR method. Kernel estimation is very challenging due to the extreme illumination.

Comments

- Novelty: By combining two interactive tasks, this algorithm demonstrates significant improvements over that of treating them separately.

Restoration VS Recognition!

deblur

representation

$$(x,k,\alpha)=\arg\min_{x,k,\alpha} \| k*x-y \|_2^2 + \lambda \sum_{l=1}^{L} | e_l * x |^s + \gamma \| k \|_2^2 + \eta \| x - D\alpha \|_2^2 + \tau \| \alpha \|_1$$

Comments

- Problems:
  - How to learn these tuning parameters;

deblur representation

$$(x,k,\alpha)=\arg\min_{x,k,\alpha}\|k*x-y\|_2^2+\lambda\sum_{l=1}^{L}|e_l*x|^s+\gamma\|k\|_2^2+\eta\|x-D\alpha\|_2^2+\tau\|\alpha\|_1$$

Some comments about sparse representation

- R. Rigamonti, M. Brown and V. Lepetit, Are Sparse Representation Really Relevant for Image Classification？ CVPR, 2011.

- Qinfeng Shi, Anders Eriksson, Anton van den Hengel, Chunhua Shen, Is face recognition really a Compressive Sensing problem？ CVPR, 2011.

- L. Zhang, M. Yang and X. Feng, Sparse Representation or Collaborative Representation: Which Helps Face Recognition？ ICCV, 2011

Summary

- What I have said does not mean that the sparsity has no place in computer vision and pattern recognition, but rather that we should use it more carefully.
- The real “sparsity” may be sparsely distributed in the complex problem space.

Thanks!