Computer vision winter class 2013

# Object Representation I

Nov. 20. 2013
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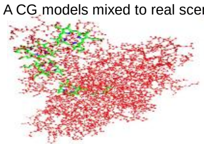
## Representing an object


## Objective in other fields

- **Computer Graphics (CG) or Virtual Reality (VR)**
  - how to realistically render a synthetic image
- **Computer Visualization**
  - how to make a visual form enabling the user to observe the invisible information


A CG models mixed to real scene


bacterial protein

## Computer vision system

**(what is where)**

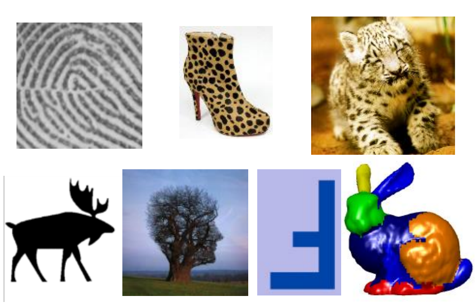
Data acquisition → Ex. 2D/3D Images

Our interest: Object representation → Ex. Characterize objects with features (feature detection and description)

Internal processing → Ex. Object Recognition, Tracking, Retrieval an object from DB…

High-level processing → Ex. Face Recognition, tracking a car in road scene, retrieval a location by a picture …

## These objects are recognized by…



pixels? Color? Texture? Shape (silhouette)?
Feature points? Image patches? …

## Outline

- 2D representation (for RGB image)
  - basics
  - research in the state of arts
- Sparse representation
  - basics
  - research in the state of arts

} Today

- 3D representation
  - basics
  - research in the state of arts
- Future study in 3D vision

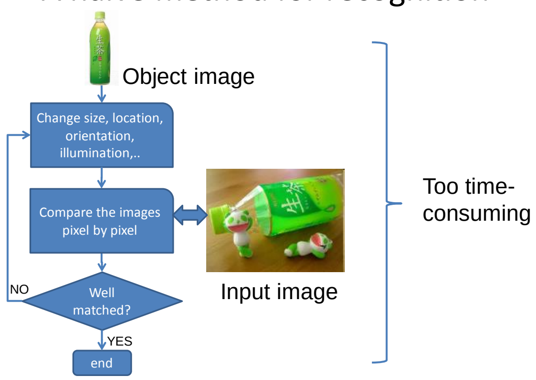
} Next week (Nov. 27)

Part I
Basics on 2D representation

## Problems on 2D representation

- Object changes at different location and orientation
- Object changes in scale or viewpoint
- Often with noises and occlusions
- Object captured in different illuminant conditions

## A naive method for recognition

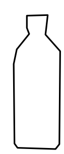



## A efficient way: using the visual features

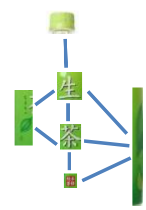
- Local representation

- Appearance at each local part

- Global representation



The shape of whole object

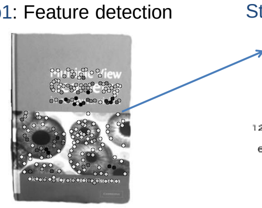


Structure (relations) of local features

## Local representation

## Local feature representation

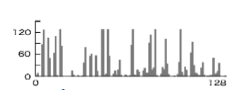
Step1: Feature detection



finding the special points or areas

Step2: Feature description

Interest point



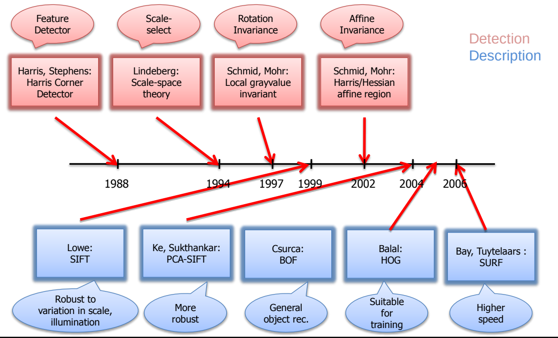

feature vector

Characterizing each interest point with digital numbers (feature vector)

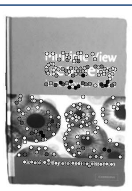
# Example: template matching

[M. Özuysal, PAMI'10]

# The history of contribution

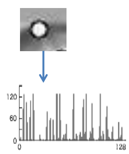



# First step



Step1: feature detection

finding the special local areas




Step2: feature description

Characterizing each area with digital numbers

# Image Feature Detection

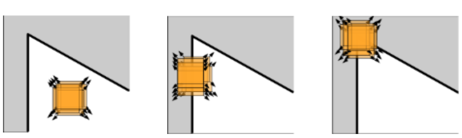
Goal: finding interest points or areas on an image invariant to image size, orientation, view point, illumination…

Approaches:

- corner detection
- Scale invariant detection
- Rotation/orientation invariant detection
- Affine invariant detection

# Corner definition

At a corner, the image intensity will change largely in multiple directions.



"flat" region: no change in all directions

"edge": no change along the edge direction

"corner": significant change in all directions

# Harris: how to determine a corner

Algorithm:

Autocorrelation matrix of the image I(x,y);

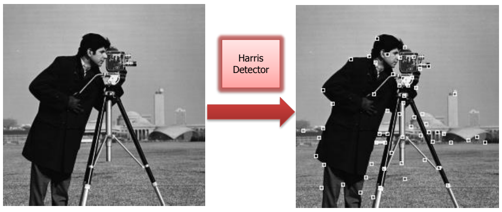
$$M = G(s) \otimes \begin{bmatrix} I_x^2 & I_x I_y \\ I_x I_y & I_y^2 \end{bmatrix}$$

Two eigenvalues ($\lambda_1, \lambda_2$) of M : principal curvatures of the point.

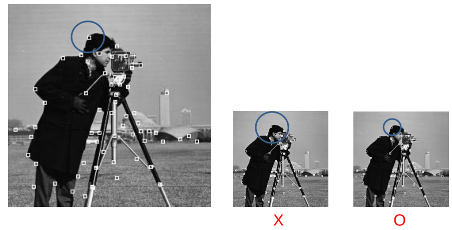
| | | |
|---|---|---|
| $\lambda_1 \approx 0$ | and $\lambda_2 \approx 0$: | "Flat" (No feature) |
| $\lambda_1 \approx 0$ | and $\lambda_2 >> 0$: | "Edge" |
| $\lambda_1 >> 0$ | and $\lambda_2 >> 0$: | "Corner" |

## Harris Corner

(Harris, AVC1988)




## Problem arise when image size changes

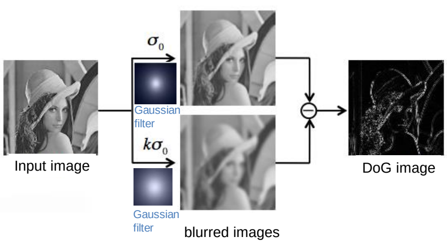



We want to know the relative scale (size) of the region around the interest point, when images are zoomed in/out?

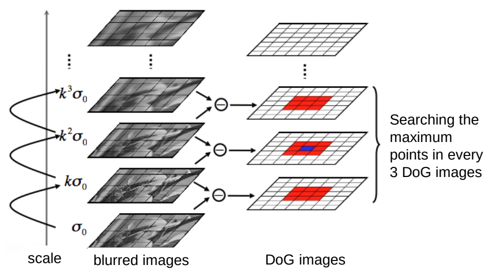
## A solution: Detecting scale invariant interest points

[Lowe, IJCV'04]

Difference-of-Gaussian (DoG):

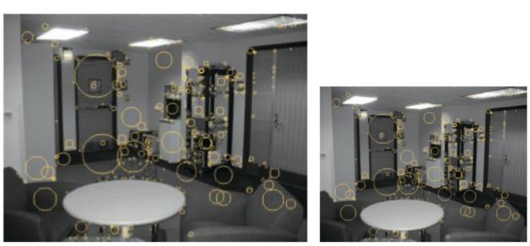



## Constructing the scale (σ) space




## The result:

finding the relative scale for each interest point

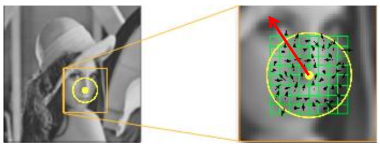


## Problem arise when the images are captured in different orientation

We need to know the orientation of each interest point!

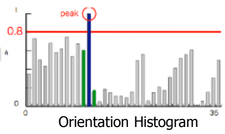
## Orientation detection (in SIFT)

[Lowe, IJCV'04]



Gradients (Ix, Iy)

**Count the numbers of gradients in all directions**




Orientation Histogram

**Orientation of the peak bin** → **Orientation of the Keypoint**

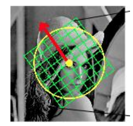
## Orientation detection (in SURF)

[H. Bay et al. ECCV06]

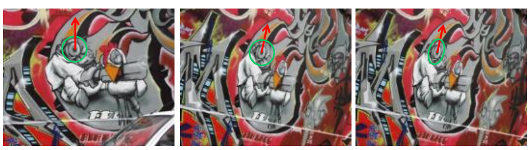
1, sliding the sector around center of feature.
2, sum up the harr filter responses in each sector.
3, finding the maximum summation.

Main Orientation

Rotate the Axis



## Problem arise if the pictures are taken in different view points?

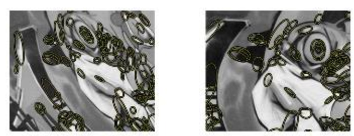



We need to know the affine-transformed information of each interest point.

## Harris/Hessian Affine Region

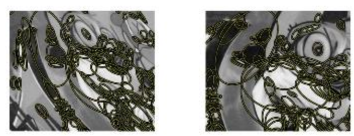
[Mikolajczyk and Schmid, IJCV'04]

Harris Affine:



(a) Harris-Affine

Hessian Affine:

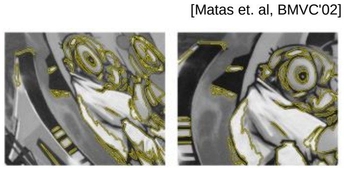


(b) Hessian-Affine

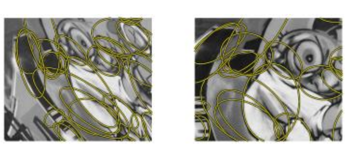
## Others

[Matas et. al, BMVC'02]

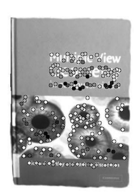
MSER (Maximally stable extremal region):



EBR (Edge-based region):

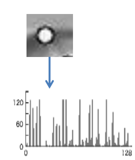


## Second step



Step1: feature detection

finding the special local areas



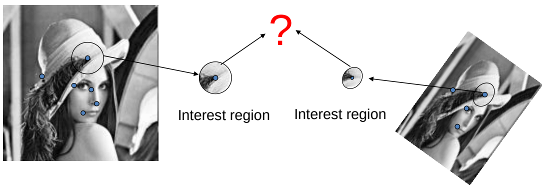

Step2: feature description

Characterizing each area with digital numbers

## Feature-Based Descriptors

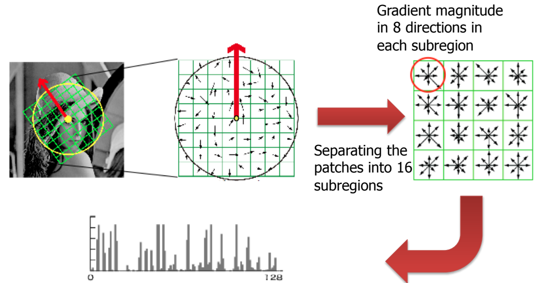
Goal: to characterize local regions with some digital numbers (feature vector) for the image matching.

Popular Approaches: SIFT, SURF…




## Gradients Descriptor (SIFT)

[Lowe, IJCV'04]

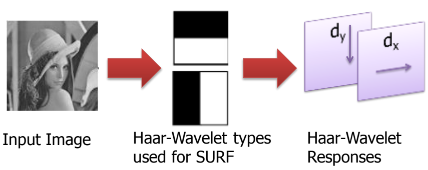



**Feature Vector (8*16=128 Dimensions)**

## Speeded Up Robust Feature (SURF)

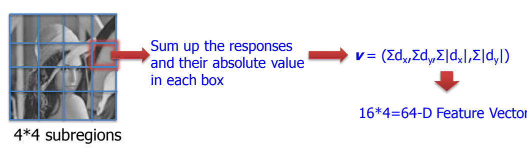
[Bay, ECCV2006]

- Approach: use Haar-Wavelet Responses to characterize the keypoints.




## Speeded Up Robust Feature (SURF)

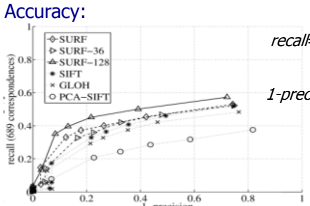
[Bay, ECCV2006]




## Comparison of SIFT and SURF

(Bay, ECCV2006)

Accuracy:




$$recall = \frac{\text{number of } \textit{true-matched}}{\text{total number of } \textit{correspondences}}$$

$$1\text{-}precision = \frac{\text{number of } \textit{false-matched}}{\text{total number of } \textit{matched}}$$

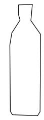
Speed:

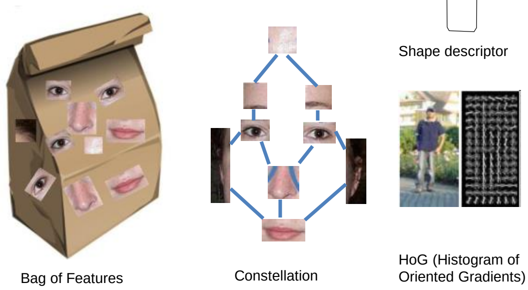
| | U-SURF | SURF | SURF-128 | SIFT |
|---|---|---|---|---|
| time (ms): | 255 | 354 | 391 | 1036 |

Computation Time on an example image (800*640)

## Global Descriptor

## Global representation



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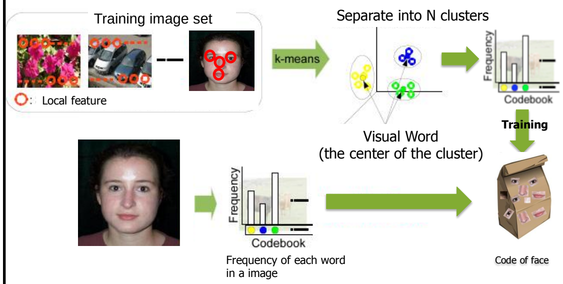
## Example: Bag Of Features（BOF） for image understanding

(Csurka, 2004)

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## Part II
## Research in the state of art

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## Critical Nets and Beta-Stable Features for Image Matching

ECCV 2010, oral

Steve Gu, Ying Zheng and Carlo Tomasi

Department of Computer Science

Duke University

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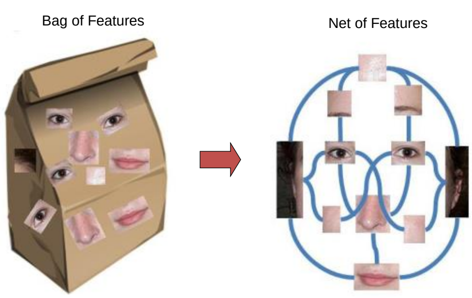
## idea

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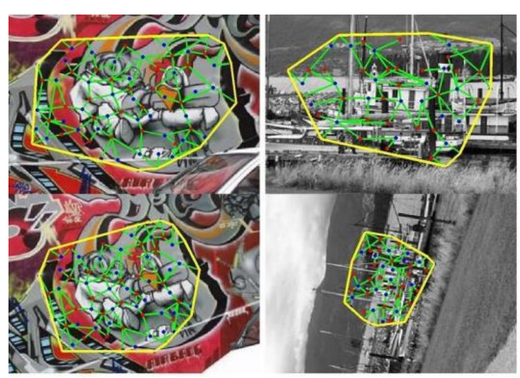


# Outline

- Beta-stable features detection
- Critical nets construction
- Application to Image matching

# Scale space revisited

approximate Laplacian (DoG) images changed in different scales

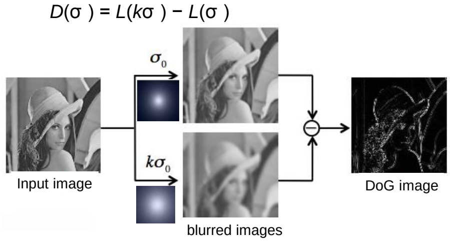
# Review of DoG

[Lowe, IJCV'04]

Difference-of-Gaussian (DoG):

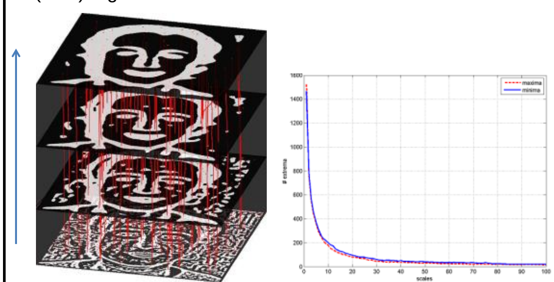
$L(\sigma) = G(\sigma) * I(x, y)$

$D(\sigma) = L(k\sigma) - L(\sigma)$

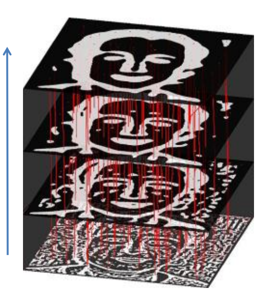



# Scale space revisited

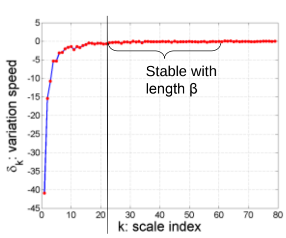
Compute the number of ``convex'' (bright) and ``concave'' (dark) regions



# Scale space revisited



The variation speed of the DoG over scale




# Beta-stable scale

- Scale k is called ``beta-stable'' if : the number of convex regions remains a constant within a scale interval of length beta.

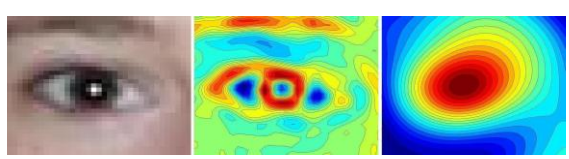


Fig. 3. From left to right: An image patch of a human eye and its DoG at scales 2 (middle) and 25 (right). Scale k = 25 is 10-stable.

## Beta-stable features

- The extrema of the DoG function computed at the smallest beta-stable scale

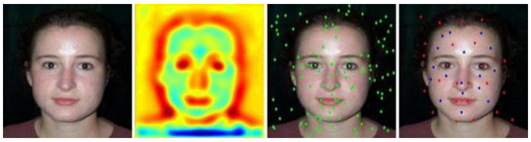


Fig. 4. From left to right: Original image; The 10-stable DoG image; SIFT features (green); 10-stable features. Red and blue dots are maxima and minima of L10.

## Critical Nets

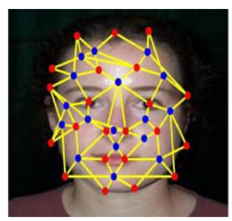
## Ascending paths

- Define practically repeatable connections between beta-stable features
- Connection:

| | | | | |
|---|---|---|---|---|
| 17 | 24 | 1 | 8 | 15 |
| 23 | 5 | 7 | 14 | 16 |
| 4 | 6 | 13 | 20 | 22 |
| 10 | 12 | 19 | 21 | 3 |
| 11 | 18 | 25 | 2 | 9 |

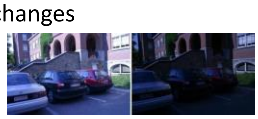
## Definition of Critical Nets

- A minimum A is connected to a maximum B if an ascending path goes from A to B
- Such a graph is called a **critical net**



## Critical Nets

- **Observation 1**: ascending paths are invariant under ``monotonic'' changes



- **Observation 2**:

  the higher the values of a point, the lower the probability this point can expand further

## Image Matching

## Example of dual SIFT descriptors

Note: using the edge information, no need to detect the scale and orientation

## Matching results Comparison

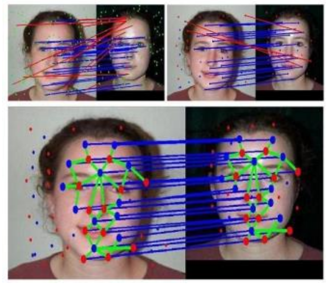
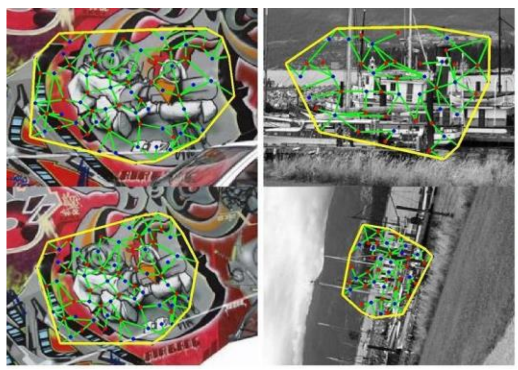
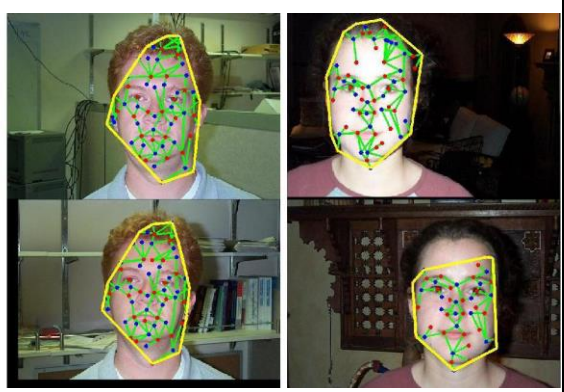


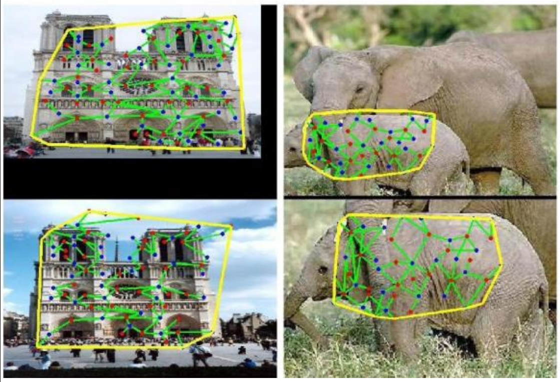
Fig. 7. Top left: SIFT; Top right: the 10-stable features and the matching result without using the critical net connections; Bottom: same 10-stable features, but with matching based on the critical net where dual SIFT descriptors are used.

## Compared to SIFT

- Reduce the number of parameters
  - –No need to determine orientation
- Richer local descriptor ( pair wised points )
- And better repeatability in matching







## Other Contributions

- Critical nets are simple graphs that are invariant under affine and monotonic changes
- A more reliable geometrical reference: rotation and scale

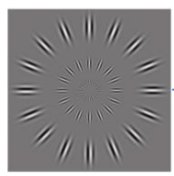
**Homepage of this research:**

http://www.cs.duke.edu/~steve/cnet.html

**Download**
1) Papers
2) Matlab code

Part II
Sparse representation

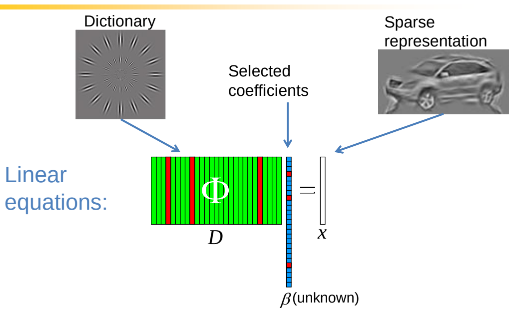
## An Example: sparse representation



Selecting a small number of the elements for representing an object

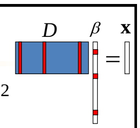
Elements in dictionary
[Wu, IJCV'09]

## Sparse coding




$$\min_{\beta} \|\beta\|_0 \quad s.t. \quad \|D\beta - x\|_2^2 \le \varepsilon^2$$

## How to solve the problem

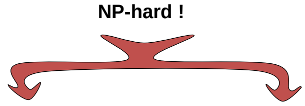



$$\min_{\beta} \|\beta\|_0 \quad s.t. \quad \|D\beta - x\|_2^2 \le \varepsilon^2$$

finding a representation with the smallest number of bases from an dictionary

↓

**NP-hard !**



Greedy methods

build up the approximation coefficients one by one

Relaxation methods

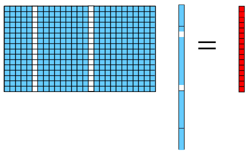
process all the coefficients simultaneously

## Greedy methods

$$\min_{\beta} \|\beta\|_0 \quad s.t. \quad \|D\beta - x\|_2^2 \le \varepsilon^2$$

Solve Instead

$$\min_{\beta} \|D\beta - x\|_2$$



**Greedy methods**

- Matching Pursuit (MP) [Mallat et al, Signal Pro. 1993]
- OMP [Mallat et al, constructive approximation, 1997]
- OMP [Tropp Info. T. 2006]
- StOMP, SP, CoSaMP…

## Relaxation methods

Ex. **Basis Pursuit**
[Chen, Donoho, Saunders ('95)]

$$\min_{\beta} \|\beta\|_0 \quad s.t. \quad \|D\beta - x\|_2^2 \le \varepsilon^2$$

Solve Instead

$$\min_{\beta} \|\beta\|_1 \quad s.t. \quad \|D\beta - x\|_2^2 \le \varepsilon^2$$

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

**Linear programming or interior point methods**

- BP [Donoho, Info. Theory 2006]
- l1 minimization [Candes et al, Info. Theory 2006]
- an interior method for l1-regularized least squares [Kim et al., Signal Pro.]

Why sparse is good?

Briefly review applications

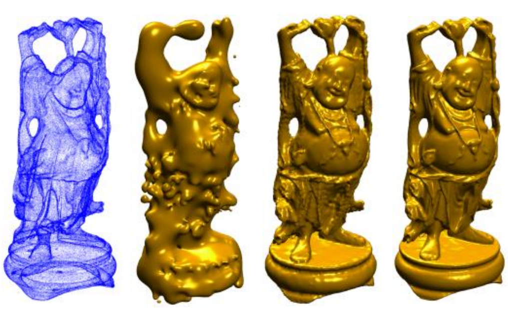
## Image representation- Gabor wavelets

[Mendels et al. ('06)]

20 bases 200 bases

## Shape representation- using RBF basis

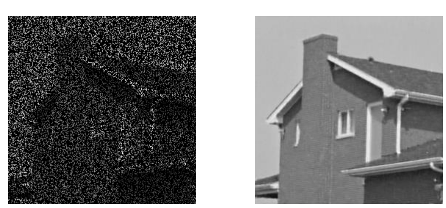
[Carr et al. (SIGGRAPH 01)]



544,000 point cloud → 8000 control points

## Image completion

[Mairal, Elad & Sapiro, ('08)]



30% pixels removed recovered image

## Inpainting – using learned dictionary

[Mairal, Bach, Ponce, Sapiro & Zisserman, ('09)]

Image with overlapped texts

## Inpainting – using learned dictionary

[Mairal, Bach, Ponce, Sapiro & Zisserman, ('09)]

Inpainting result

## Object Tracking

[X. Mei and H. Ling, ICCV09]

## More recently

- Matrix factorization
  - Low rank minimization
  - Sparse PCA
  - Robust PCA

  …

## Research in the state of arts

Journal paper

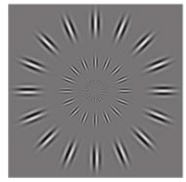
Y. N. Wu, Z.Z. Si, H. Gong and S.-C. Zhu (UCLA)
International Conference on Computer Vision (ICCV) 2007
International Journal of computer vision (IJCV) 2009

**Learning Active Basis Model for Object Detection and Recognition**

## Motivation

- Design a deformable template to model a set of images of a certain object category.
- The template can be learned from example images.

## Dictionary construction using Gabor wavelets

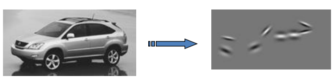


$\{B_{x,y,s,\alpha}\}$ — location, scale, orientation

Each element can be formed by a Gabor wavelet:

$$G(x,y) \propto \exp\{-\frac{1}{2}[\frac{x^2}{\sigma_x^2}+\frac{y^2}{\sigma_y^2}]\}e^{ix}$$

## Linear additive image model



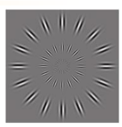


Image reconstruction by matching pursuit.

$$I = \sum_{i=1}^{n} c_i B_i + \varepsilon, \quad \{B_i, i=1,\ldots,n\}$$

selected from a dictionary of Gabor wavelet elements $\{B_{x,y,s,\alpha}\}$ — location, scale, orientation

**Two extensions**:

1. Encoding a single image → Simultaneously encoding a set of images;
2. Allow each Gabor wavelet element $B_i$ to locally perturb.

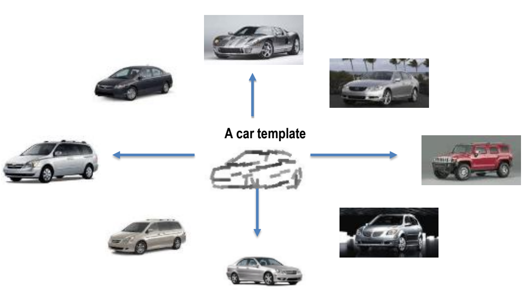
## Deformable template using active basis

**A car template**

(Gabor elements represented by bar)

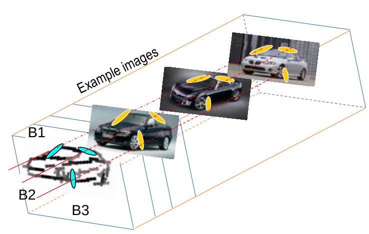
An incoming car image

## Deformable template using active basis




**Deformed to fit many car instances**

## Learning the template: pursuing the active basis



## Learning the template: pursuing the active basis

A car template consisting of 60 Gabor elements

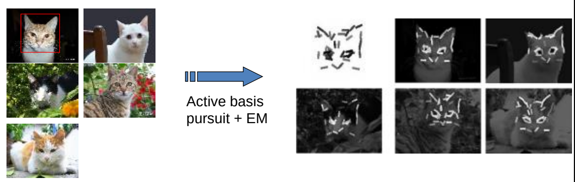
Car instances

## Experimental results

## Experiment 1: learning an active basis model of vehicle


- 37 training images, listed in the descending order of log-likelihood ratio
- 4.3 seconds (Core 2 Duo 2.4GHz) , after convolution

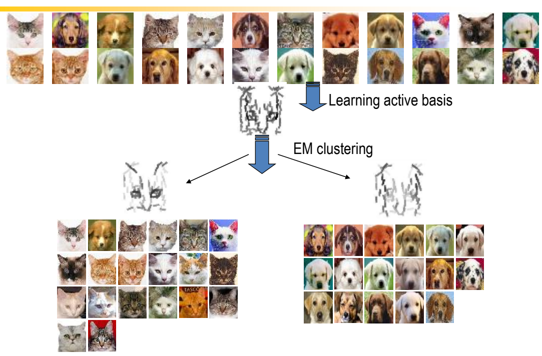
## Experiment 2: learning without alignment




Given bounding box for the first example for initialization.

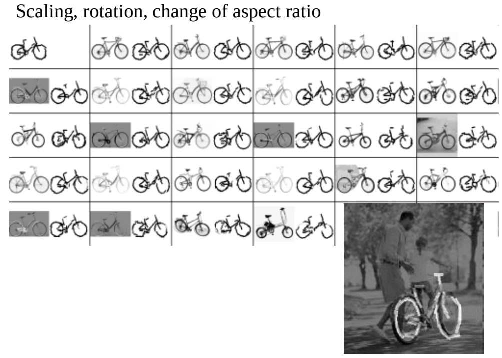
**Iterate:**
- Estimate the bounding boxes using current model.
- Re-learn the model from estimated bounding boxes.

## Experiment 3: learning and clustering

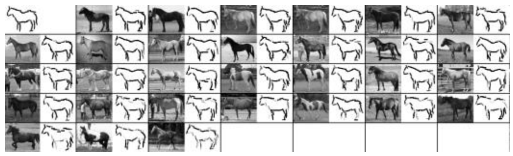



## Geometric transformation

Scaling, rotation, change of aspect ratio



## Geometric transformation



## Main contributions

1. An **active basis model** as deformable template.
2. An **active bases pursuit algorithm** for fast learning.
3. Robust for template matching

**Homepage of this research:**

**http://www.stat.ucla.edu/~ywu/ActiveBasis.html**

**Download**

1) Training and testing images
2) Matlab and mex-C source codes

## RASL: Robust Alignment by Sparse and Low-rank Decomposition for Linearly Correlated Images

CVPR 2010, oral

Yigang Peng[1], Arvind Ganesh[2], John Wright[3], Wenli Xu[1] and Yi Ma [2,3]

1 TNLIST and Dept. of Automation, Tsinghua Univ.

2 Dept. of Electrical and Computer Engg., UIUC

3 Visual Computing Group, MSRA

## Background

- Increasing data set from internet: Facebook, Flickr, You Tube…

Large amount

unconstraint

Difficult for object recognition or classification

## Challenges for recognition algorithms

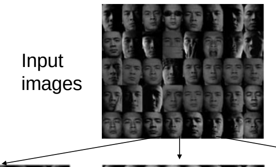
- illumination variation, partial occulusion, no alignment

Problem:

Can we recover the faces, despite corruptions or occlusions (shadow, sunglasses, hat, and scarves) ?

**Difficult for measuring the image similarity**

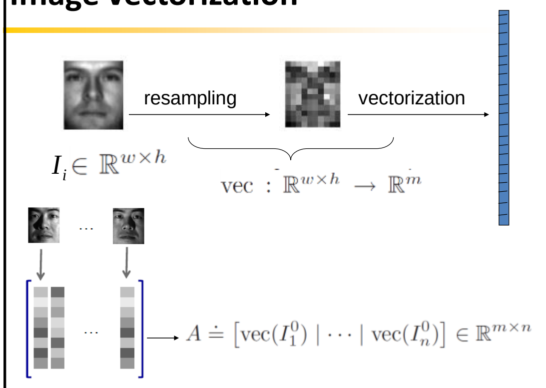
## Idea




simultaneously

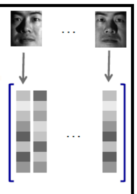
Method

## Image vectorization



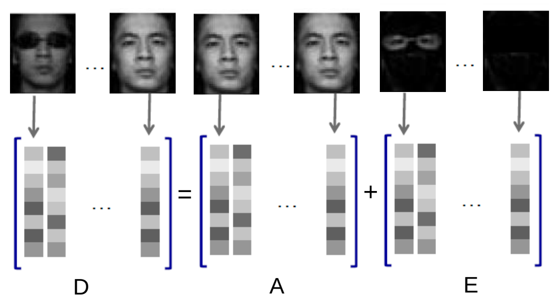

## Assumption

$$A \doteq [\mathrm{vec}(I_1^0) \mid \cdots \mid \mathrm{vec}(I_n^0)] \in \mathbb{R}^{m \times n}$$

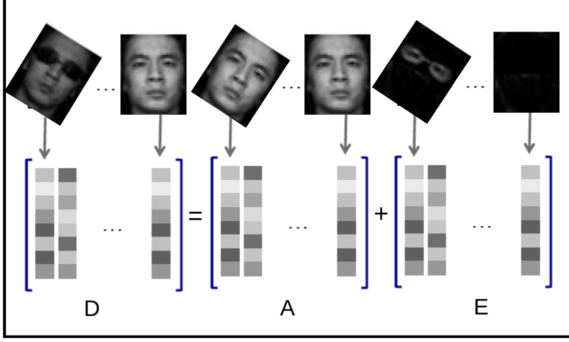


If $I_1^0, \ldots, I_n^0$ are taken from same object, well-aligned and without corruption, they are linearly correlated. Then $A$ should be low-rank.

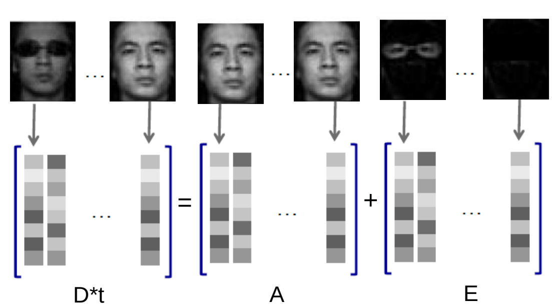
## Challenge 1: corruption




## Challenge 2: misalignment




## Challenge 2: misalignment



## Problem definition

$D$ corrupted & misaligned observation — $A$ – aligned low-rank signals — $E$ – sparse errors

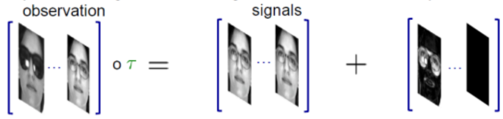

**Problem**: Given $D \circ \tau = A + E$, recover $\tau$, $A_0$ and $E_0$.

Parametric deformations (rigid, affine, projective…) — Low-rank component — Sparse component

**Solution**: Robust Alignment via Low-rank and Sparse (**RASL**) Decomposition

## Formulation

$D$ corrupted & misaligned observation — $A$ – aligned low-rank signals — $E$ – sparse errors




**Problem**: Given $D \circ \tau = A + E$, recover $\tau$, $A_0$ and $E_0$.

Parametric deformations (rigid, affine, projective…) — Low-rank component — Sparse component

$$\min_{A,E,\tau} \ \mathrm{rank}(A) + \gamma \|E\|_0 \quad \text{s.t.} \quad D \circ \tau = A + E.$$

The number of nonzeros

## The problem is N-P hard

$$\min_{A,E,\tau} \ \mathrm{rank}(A) + \gamma \|E\|_0 \quad \text{s.t.} \quad D \circ \tau = A + E.$$

$\gamma > 0$

The number of nonzeros

Optimization problem:

Both the low-rank and $\ell^0$-norm minimizations are nonconvex and discontinuous!

↓

N-P problem

## Convex relaxation

$$\min_{A,E,\tau} \ \mathrm{rank}(A) + \gamma \|E\|_0 \quad \text{s.t.} \quad D \circ \tau = A + E.$$

Instead they optimize the problem as:

$$\min_{A,E,\tau} \ \|A\|_* + \lambda \|E\|_1 \quad \text{s.t.} \quad D \circ \tau = A + E$$

$\|A\|_* \doteq \sum_{i=1}^{m} \sigma_i(A)$ $\qquad$ $\sum_{ij} |E_{ij}|$

## Transformation linearization

The current problem:

$$\min_{A,E,\tau} \ \|A\|_* + \lambda \|E\|_1 \quad \text{s.t.} \quad D \circ \tau = A + E$$

The constraint is nonlinear, due to the dependence of the transformations.

⬇

Solution:

*When the change in tau is small, we can approximate this constraint by linearizing about the current estimate of tau.*

## Transformation linearization

$$\min_{A,E,\tau} \ \|A\|_* + \lambda \|E\|_1 \quad \text{s.t.} \quad D \circ \tau = A + E$$

$$D \circ (\tau + \Delta\tau) \approx D \circ \tau + \sum_{i=1}^{n} J_i \Delta\tau_i \epsilon_i^T$$

$$J_i \doteq \frac{\partial}{\partial \zeta} \mathrm{vec}(I_i \circ \zeta)|_{\zeta = \tau_i} \in \mathbb{R}^{m \times p}$$

## Transformation linearization

$$J_i = \begin{bmatrix} \frac{\partial I_{i1}}{\partial \tau_i^1} & \frac{\partial I_{i1}}{\partial \tau_i^2} & \frac{\partial I_{i1}}{\partial \tau_i^p} \\ \frac{\partial I_{i2}}{\partial \tau_i^1} & \frac{\partial I_{i2}}{\partial \tau_i^2} & \frac{\partial I_{i2}}{\partial \tau_i^p} \\ \frac{\partial I_{im}}{\partial \tau_i^1} & \frac{\partial I_{im}}{\partial \tau_i^2} & \frac{\partial I_{im}}{\partial \tau_i^p} \end{bmatrix} \in \mathbb{R}^{m \times p}$$

$\Delta\tau_i \in R^{p\times 1}$ ⟶ Difference of transformation parameter

$\varepsilon_i \in R^{n\times 1}$ ⟶ The *i*-th Standard basis

## Transformation linearization

$$\min_{A,E,\tau} \|A\|_* + \lambda \|E\|_1 \quad \text{s.t.}$$

$$D \circ \tau + \sum_{i=1}^n J_i \Delta\tau_i \epsilon_i^T = A + E$$

⇩

Solvable problem: by convex programming

**Algorithm 1 (Outer loop of RASL)**

**INPUT:** Images $I_1, \ldots, I_n \in \mathbb{R}^{w \times h}$, initial transformations $\tau_1, \ldots, \tau_n$ in certain parametric group $\mathbb{G}$, weight $\lambda > 0$.

**WHILE** not converged **DO**

**step 1:** compute Jacobian matrices w.r.t. transformation:

$$J_i \leftarrow \frac{\partial}{\partial \zeta} \left( \frac{\text{vec}(I_i \circ \zeta)}{\|\text{vec}(I_i \circ \zeta)\|_2} \right) \Big|_{\zeta = \tau_i}, \quad i = 1, \ldots, n;$$

**step 2:** warp and normalize the images: transform images

$$D \circ \tau \leftarrow \left[ \frac{\text{vec}(I_1 \circ \tau_1)}{\|\text{vec}(I_1 \circ \tau_1)\|_2} \Big| \cdots \Big| \frac{\text{vec}(I_n \circ \tau_n)}{\|\text{vec}(I_n \circ \tau_n)\|_2} \right];$$

**step 3:** solve the linearized convex optimization:

$$(A^*, E^*, \Delta\tau^*) \leftarrow \arg\min_{A,E,\Delta\tau} \|A\|_* + \lambda \|E\|_1$$

$$\text{s.t. } D \circ \tau + \sum_{i=1}^n J_i \Delta\tau_i \epsilon_i^T = A + E;$$

**step 4:** update transformations: $\tau \leftarrow \tau + \Delta\tau^*$;

**END WHILE**

**OUTPUT:** solution $A^*, E^*, \tau$ to problem (5).

## Next problem

$\tau_1, \ldots, \tau_n$ in certain parametric group $\mathbb{G}$, weight $\lambda > 0$.

**WHILE** not converged **DO**

**step 1:** compute Jacobian matrices w.r.t. transformation:

$$J_i \leftarrow \frac{\partial}{\partial \zeta} \left( \frac{\text{vec}(I_i \circ \zeta)}{\|\text{vec}(I_i \circ \zeta)\|_2} \right) \Big|_{\zeta = \tau_i}, \quad i = 1, \ldots, n;$$

**step 2:** warp and normalize the images:

$$D \circ \tau \leftarrow \left[ \frac{\text{vec}(I_1 \circ \tau_1)}{\|\text{vec}(I_1 \circ \tau_1)\|_2} \Big| \cdots \Big| \frac{\text{vec}(I_n \circ \tau_n)}{\|\text{vec}(I_n \circ \tau_n)\|_2} \right];$$

**step 3:** solve the linearized convex optimization:

$$(A^*, E^*, \Delta\tau^*) \leftarrow \arg\min_{A,E,\Delta\tau} \|A\|_* + \lambda \|E\|_1$$

$$\text{s.t. } D \circ \tau + \sum_{i=1}^n J_i \Delta\tau_i \epsilon_i^T = A + E;$$

- **Semi-definite program**
- **Thousands or millions of variables**

**step 4:** update transformations: $\tau \leftarrow \tau + \Delta\tau^*$;

**END WHILE**

**OUTPUT:** solution $A^*, E^*, \tau$ to problem (5).

## Using APG (accelerated proximal gradient) algorithm [2,22,17]

$$\min_{A,E,\Delta\tau} \|A\|_* + \lambda \|E\|_1 \text{ s.t. } D \circ \tau + \sum_{i=1}^n J_i \Delta\tau_i \epsilon_i^T = A + E$$

$$f(A, E, \Delta\tau) \doteq \frac{1}{2} \left\| A + E - D \circ \tau - \sum_{i=1}^n J_i \Delta\tau_i \epsilon_i^T \right\|_F^2$$

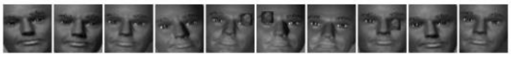
⇩

$$\min_{A,E,\Delta\tau} \|A\|_* + \lambda \|E\|_1 + \frac{1}{\mu} f(A, E, \Delta\tau)$$

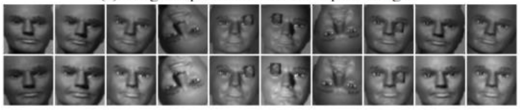
Fast solved by Accelerated Proximal Gradient (APG) [1,22,17]

## Experimental results

## Result 1 synthesized image



(a) Original perturbed and corrupted images



(b) Alignment results by [23] (Top: direct; Bottom: gradient)

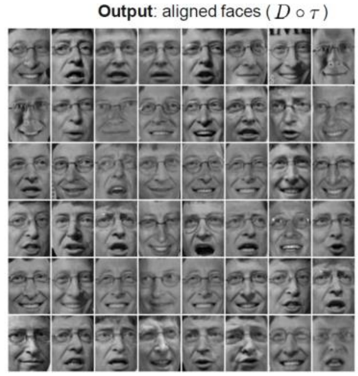
(c) Alignment results by RASL

## Nature image

**Input**: faces detected by a face detector ($D$)

Average

**Output**: aligned faces ( $D \circ \tau$ )



Average

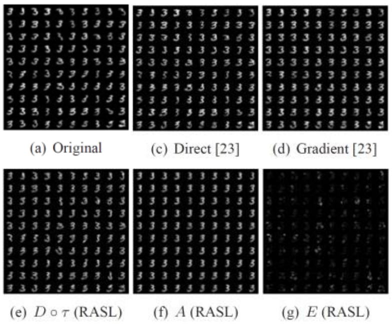
**Output**: clean low-rank faces ( $A$ )

Average

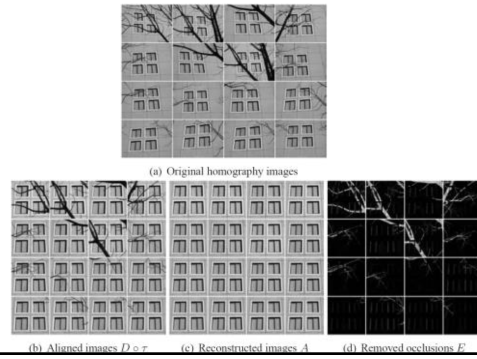
## Average image

(a) Average faces from face detector (b) Average faces after alignment

## Aligning handwritten digits




## Aligning planar surfaces




## Contributions

- Robustness to corruption and occlusion
- Robustness to misalignment

**Homepage of this research:**

http://perception.csl.illinois.edu/matrix-rank/rasl.html

**Download**
1) Papers
2) Sample code in Matlab

## Readings

1. David G. Lowe, "Distinctive image features from scale-invariant keypoints," International Journal of Computer Vision, 60, 2 (2004), pp. 91-110
2. H. Bay, T. Tuytelaars, L. V. Gool, "SURF: Speeded Up Robust Features," ECCV 2006
3. S. Gu, Y. Zheng and C. Tomasi, "Critical Nets and Beta-Stable Features for Image Matching," ECCV2010
4. Y. N. Wu, Z.Z. Si, H.f. Gong and S.-C. Zhu: Learning Active Basis Model for Object Detection and Recognition. International Journal of Computer Vision 90(2): 198-235 (2010)
5. Y.G. Peng, A. Ganesh, J. Wright, W. Xu and Y. Ma, "RASL: Robust Alignment via Sparse and Low-Rank Decomposition for Linearly Correlated Images," CVPR 2010.
6. J.P. Shi, X. Ren, G. Dai, J.D. Wang, Z.H. Zhang: "A non-convex relaxation approach to sparse dictionary learning," CVPR 2011.

Thank you for your attention!