

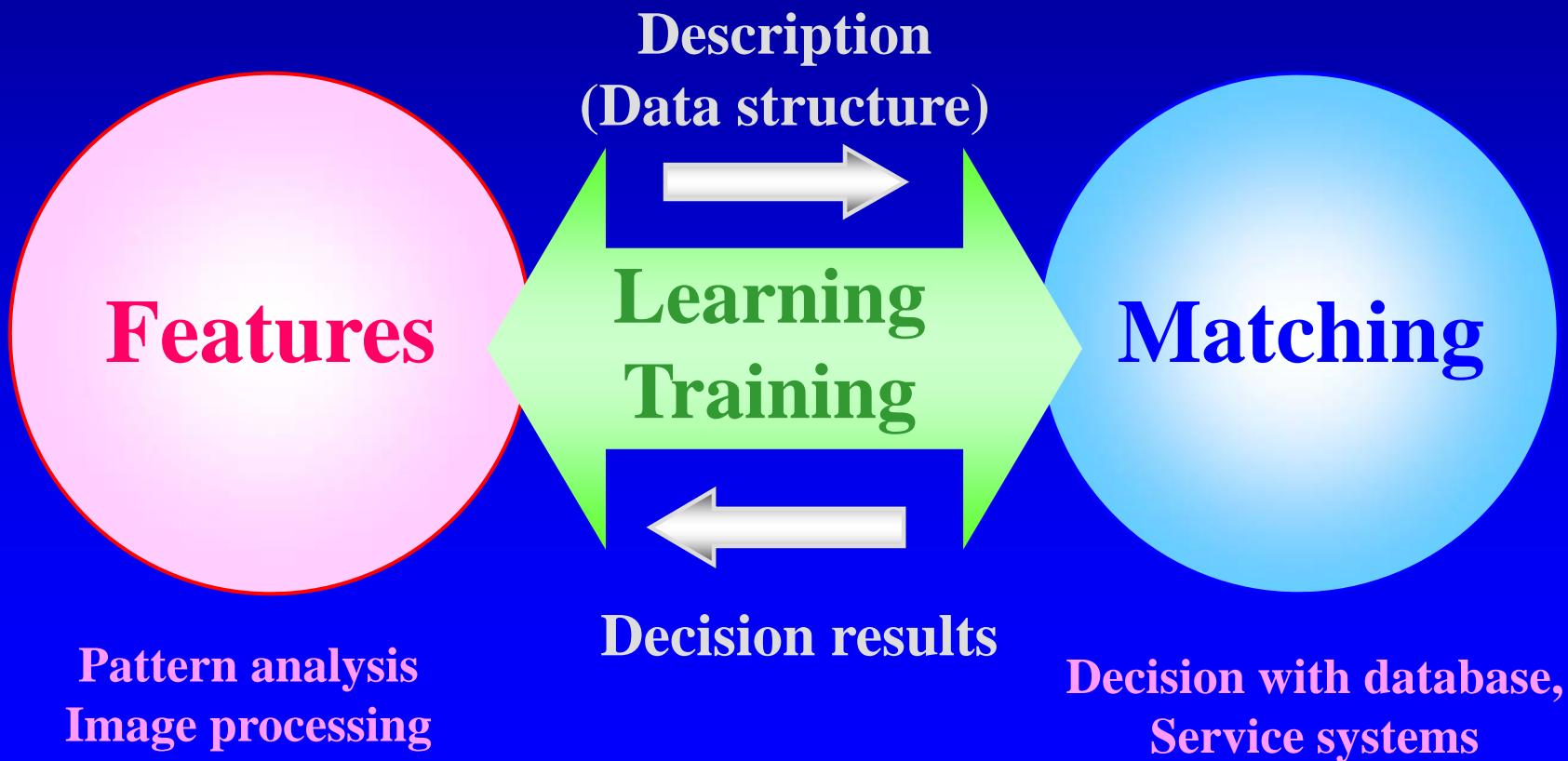
1

SIFT

Lecturer: Sang Hwa Lee

Introduction (I)

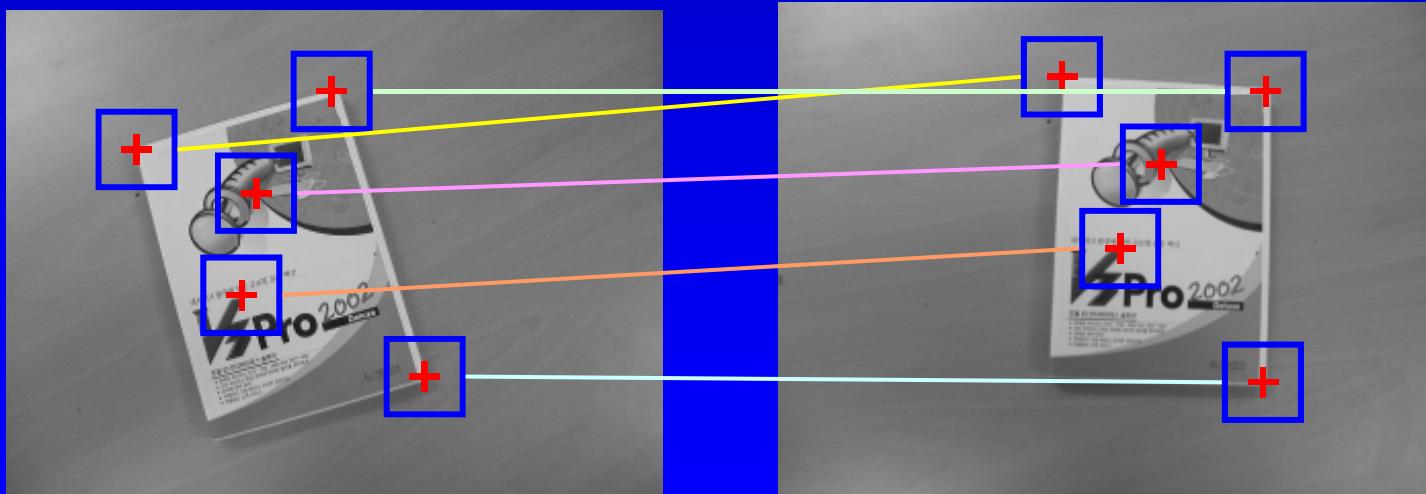
□ Elements of feature-based pattern recognition



Introduction (II)

□ Feature-based pattern recognition

- Finding interest points
- Analyzing features around the points
- Comparing the features with those in database





Introduction (III)

- **Variation of features**

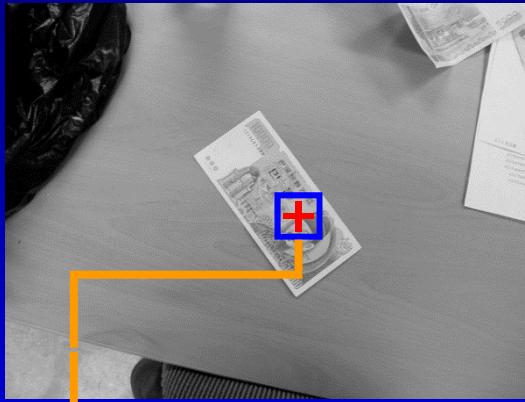
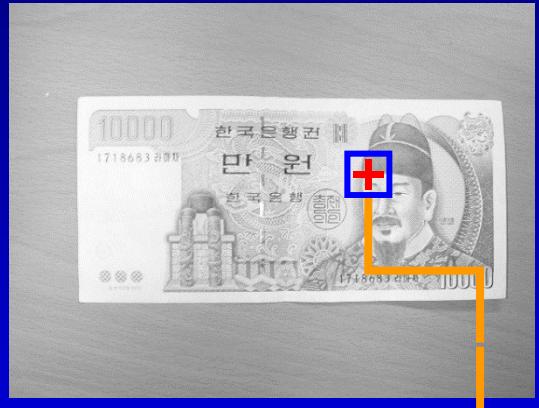
- Noise
- Image scale and resolution
- Rotation
- 2D/3D projective transformation
- Illumination change

- **We have to normalize the features with respect to the variations**

- **We need the invariant features for robust pattern matching**

- SIFT (Scale Invariant Feature Transform)

How to make invariant feature?

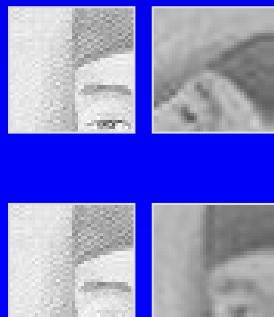


Scale
normalization



Scale & Rotation
Variation

Scale & rotation
normalization

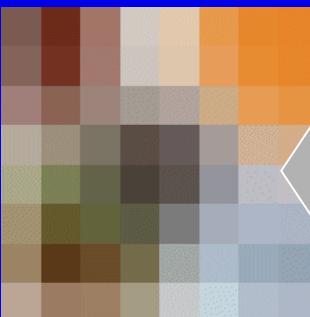
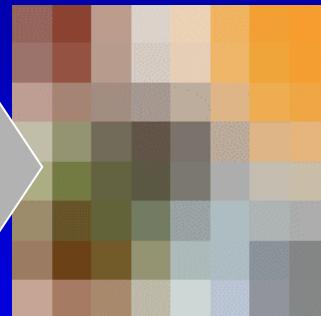
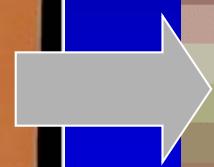
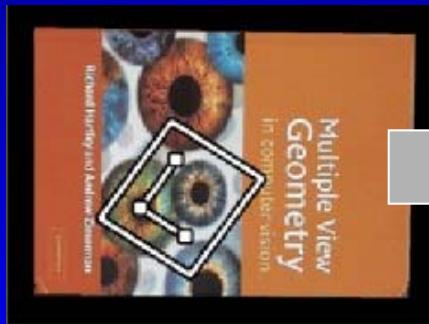


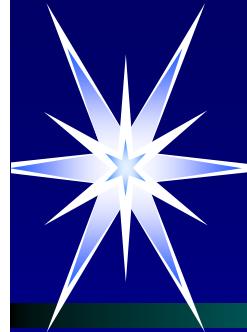
~~Scale~~ & Rotation
Variation

~~Scale & Rotation~~
Variation

What is the Invariant Feature ?

Invariant to
scale, resolution, rotation, illumination, perspective distortion, ...





SIFT-Overview (I)

□ References

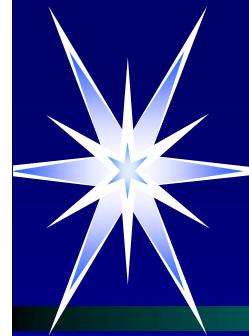
- D. Lowe, “Distinctive image features from scale-invariant keypoints”, *IJCV*, vol. 60, no. 2, pp. 91–110, 2004.

□ Scale Invariant Feature Transform (SIFT)

- Invariant to scales, rotations, perspective distortion, illumination change

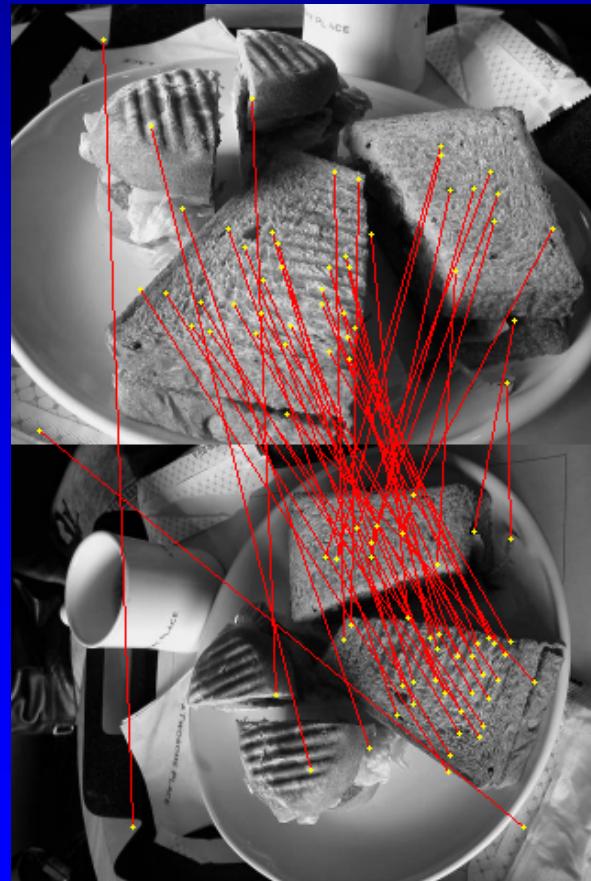
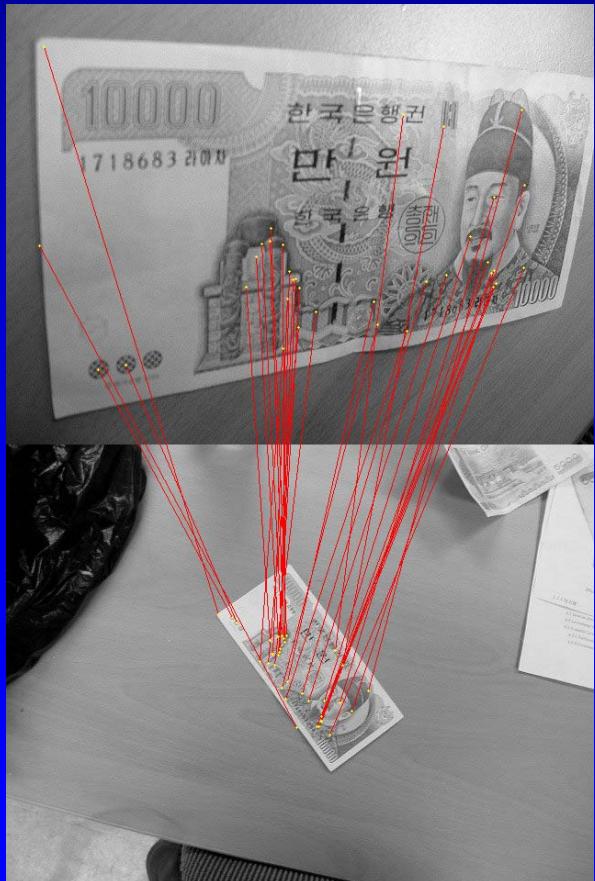
□ Additional advantages using SIFT

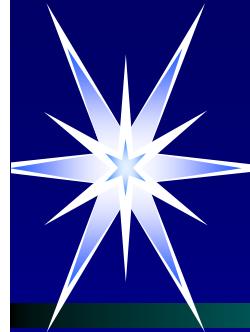
- A few features are enough for pattern matching
 - Occluded patterns are also recognized.
- Learning method is usually simple
 - Nearest neighbor matching
- Real time implementation



SIFT-Overview (II)

□ SIFT examples





SIFT-Overview (III)

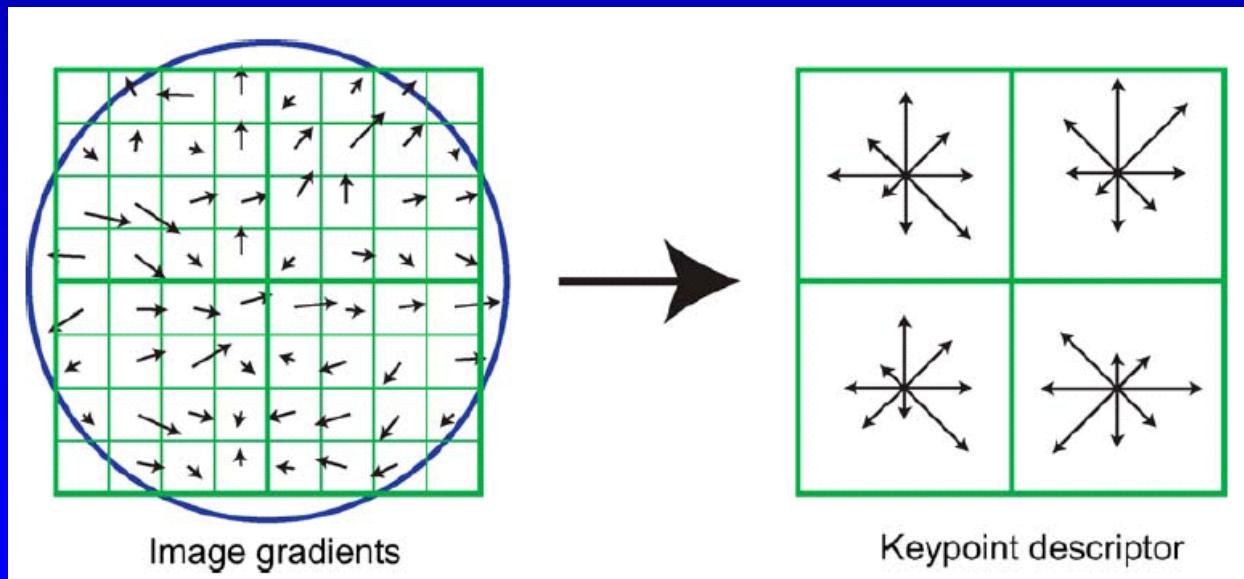
□ Procedure of SIFT

- Scale-space extreme point detection
 - ↗ Difference of Gaussian (DOG)
- Keypoint localization
 - ↗ Ratio of principal curvature
- Orientation assignment
 - ↗ Direction of local gradient at a keypoint
- Keypoint descriptor
 - ↗ Orientation representation in a region around the keypoint

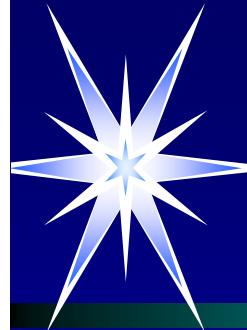
SIFT-Overview (IV)

□ Keypoint descriptor ($4 \times 4 \times 8$)

- Orientation histogram in a 16×16 block
- 128 dimensional vector: SIFT feature



SIFT feature vector in an 8×8 block



SIFT: Scale-Space Extrema Detection (I)

- Identification of candidate locations for keypoints
- Gaussian convolution with variable variances

- Pyramid structure
- Scale space with variable σ

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

$$G(x, y, \sigma) = \frac{1}{2\pi\sigma^2} e^{-(x^2+y^2)/2\sigma^2}.$$

- Difference of Gaussian (DOG)

- Similar properties of Laplacian of Gaussian (LOG)
 - ↗ LOG produced the most stable scale-invariant features

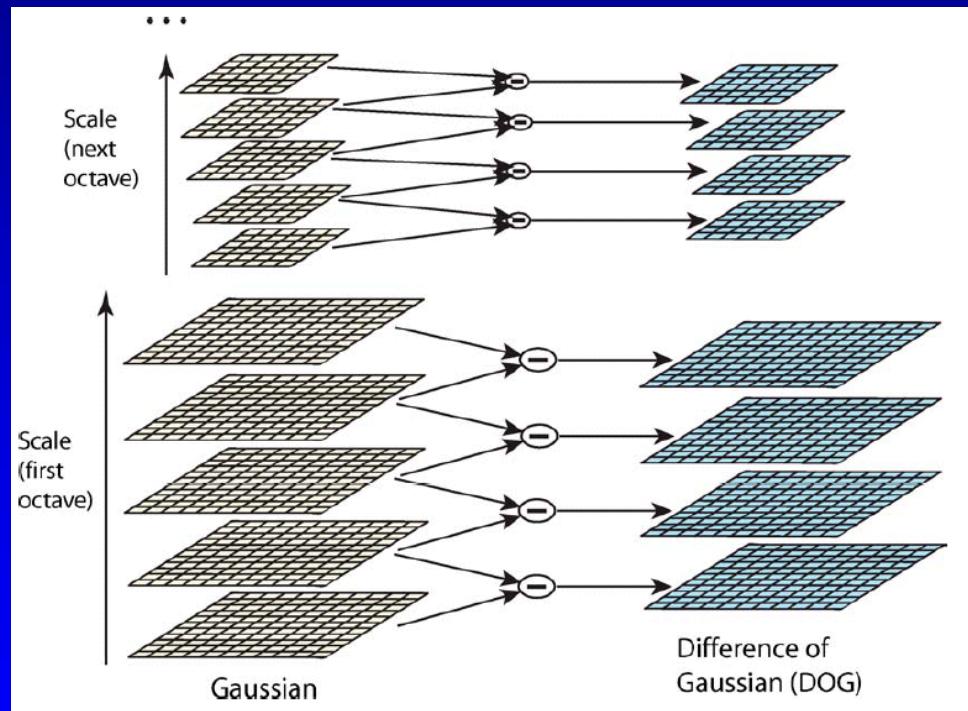
$$\begin{aligned} D(x, y, \sigma) &= (G(x, y, k\sigma) - G(x, y, \sigma)) * I(x, y) \\ &= L(x, y, k\sigma) - L(x, y, \sigma). \end{aligned} \quad (1)$$

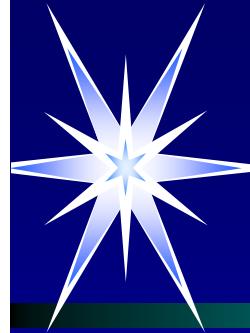
$$G(x, y, k\sigma) - G(x, y, \sigma) \approx (k - 1)\sigma^2 \nabla^2 G.$$

SIFT: Scale-Space Extrema Detection (II)

□ DOG Pyramid

- Incremental convolution with varying variance, $k\sigma$
 - ↗ Scale-space function
 - ↗ $\mathbf{x} (x,y,\sigma)$
- 2:1 subsampling
- Experimentally decided
 - ↗ $k: \sqrt{2}$
 - ↗ 3 scales per octave

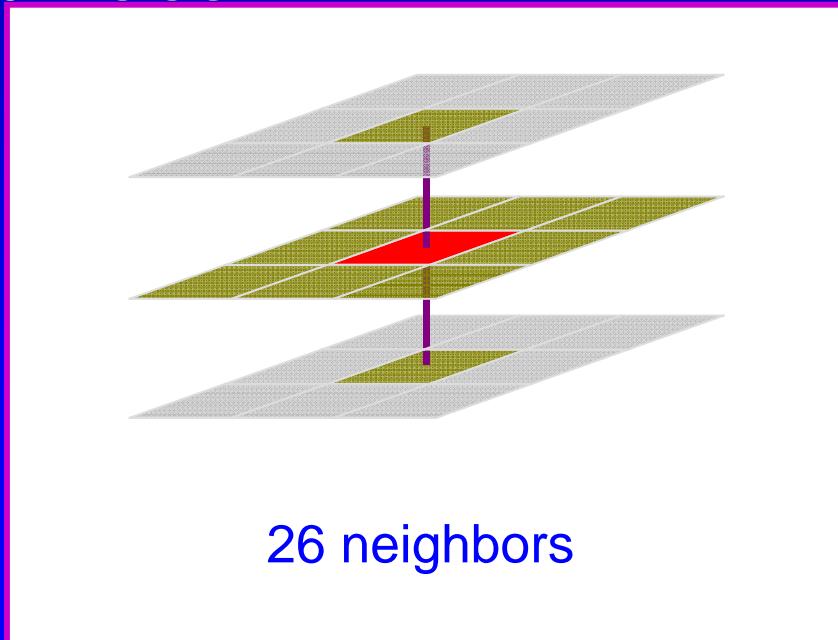




SIFT: Scale-Space Extrema Detection (III)

□ Local extrema detection of DOG

- Decide when DOG at the location is maximum or minimum compared with 26 neighbors in the layered DOGs



SIFT: Accurate Keypoint Localization (I)

□ Rejection of extrema locations

- Noisy
- Along an edge

□ Interpolation of extrema location

- Accurate location of extreme
- Quadratic function with Taylor expansion

$$D(\mathbf{x}) = D + \frac{\partial D^T}{\partial \mathbf{x}} \mathbf{x} + \frac{1}{2} \mathbf{x}^T \frac{\partial^2 D}{\partial \mathbf{x}^2} \mathbf{x}$$

$$\hat{\mathbf{x}} = -\frac{\partial^2 D}{\partial \mathbf{x}^2}^{-1} \frac{\partial D}{\partial \mathbf{x}}.$$

- Thresholding low extreme value ($T=0.03$ for $[0, 1]$)

$$D(\hat{\mathbf{x}}) = D + \frac{1}{2} \frac{\partial D^T}{\partial \mathbf{x}} \hat{\mathbf{x}}.$$

SIFT: Accurate Keypoint Localization (II)

□ Eliminating edge response

- Keypoints along the edge in the DOG have large principal curvature ratio
- The principal curvatures are proportional to eigenvalue of Hessian matrix at the location
- Thresholding the ratio of principal curvature, $\kappa < 10$

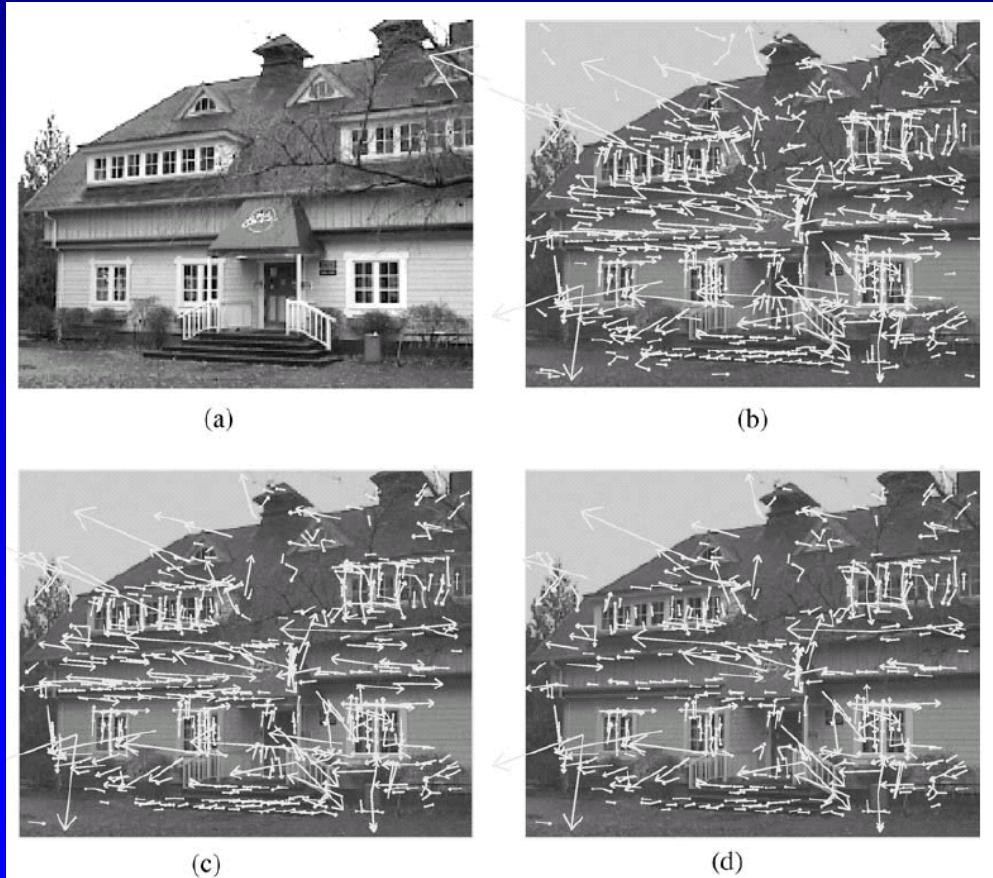
$$\mathbf{H} = \begin{bmatrix} D_{xx} & D_{xy} \\ D_{xy} & D_{yy} \end{bmatrix}$$

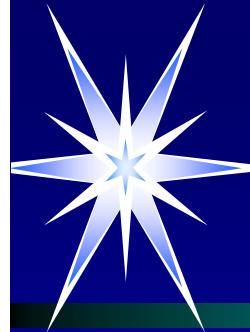
$$\begin{aligned} \text{Tr}(\mathbf{H}) &= D_{xx} + D_{yy} = \alpha + \beta, \\ \text{Det}(\mathbf{H}) &= D_{xx}D_{yy} - (D_{xy})^2 = \alpha\beta \\ \frac{\text{Tr}(\mathbf{H})^2}{\text{Det}(\mathbf{H})} &= \frac{(\alpha + \beta)^2}{\alpha\beta} = \frac{(r\beta + \beta)^2}{r\beta^2} = \frac{(r + 1)^2}{r}. \end{aligned}$$

SIFT: Accurate Keypoint Localization (III)

□ Results

- (a) original image
- (b) extreme points (832)
- (c) low extreme threshold (729)
- (d) large ratio of principal curvature threshold (536)





SIFT: Orientation Assignment (I)

□ Dominant direction of the keypoint

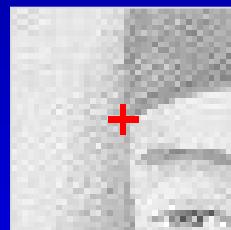
- Histogram of orientation in a region around the keypoint

$$dx = L_{x+1,y} - L_{x-1,y}$$

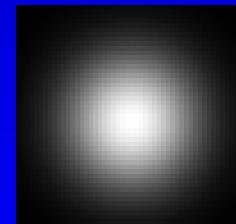
$$dy = L_{x,y+1} - L_{x,y-1}$$

$$m = \sqrt{dx^2 + dy^2}$$

$$\theta = \tan^{-1}(dy / dx)$$



Gaussian Weight



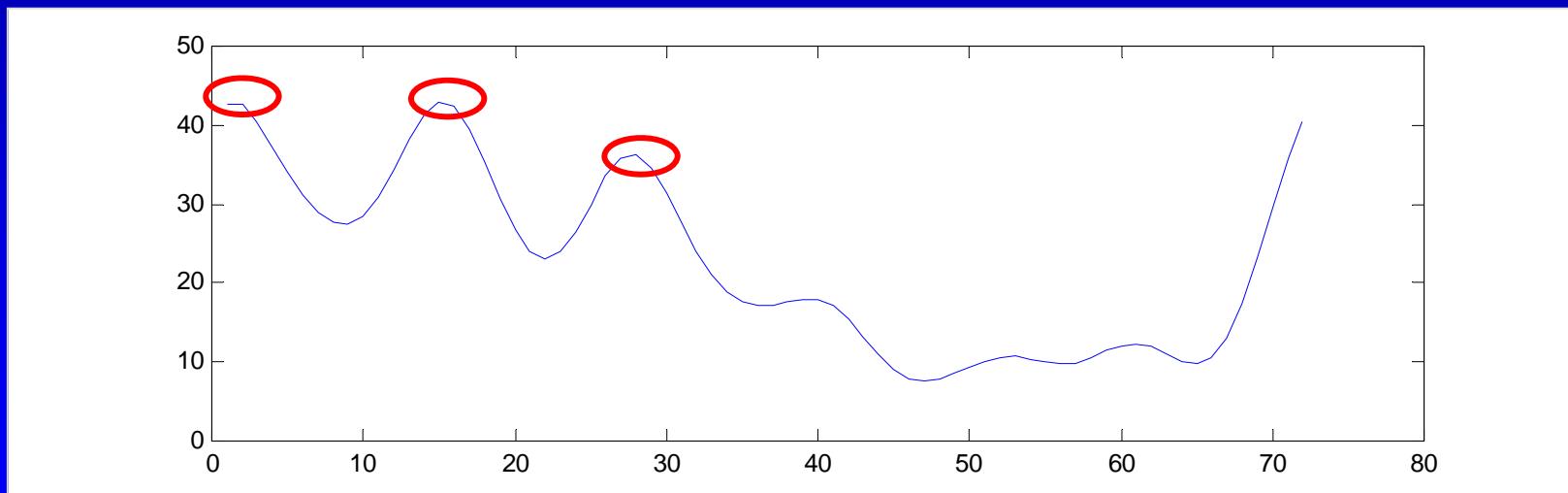
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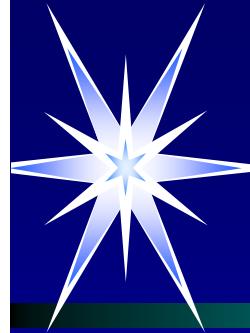
Orientation Histogram

SIFT: Orientation Assignment (II)

- ❑ 3 peaks in histogram

- Quadratic function fitting for accurate orientation

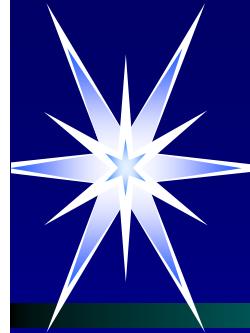




SIFT: Orientation Assignment (III)

□ Experiment





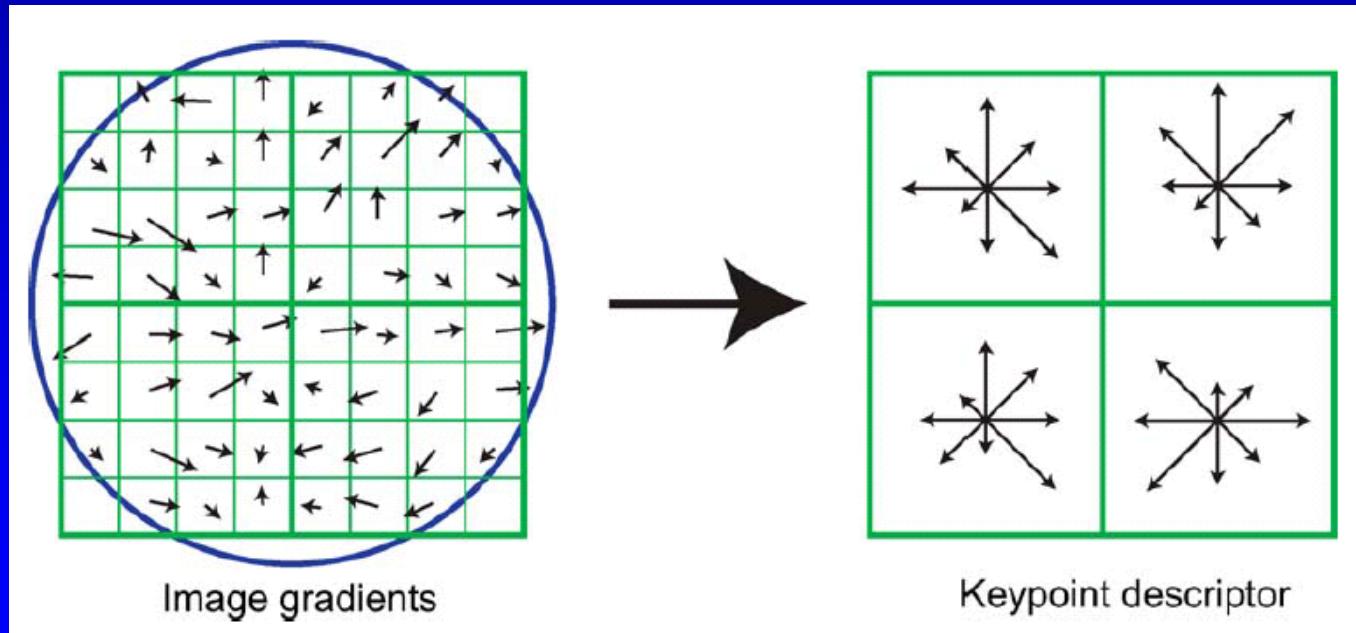
SIFT: Local Image Descriptor (I)

- **Local region description around keypoint location**
 - Real data structure to be stored and matched
 - keypoint location and scale
 - Local orientation histogram
- **Normalized orientation histogram**
 - Gradient pattern is distinctive in HVS
 - Invariant to illumination change
 - 8 directions (histogram bins) are optimal
- **Sensitivity of affine transformation**
 - 3D rotation up to 50° for reliable matching

SIFT: Local Image Descriptor (II)

□ Keypoint descriptor ($2 \times 2 \times 8$)

- 8x8 sample array



SIFT: Local Image Descriptor (III)

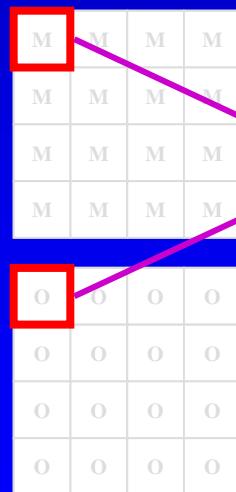
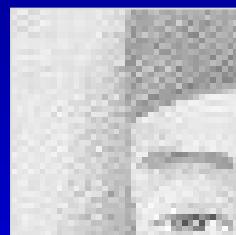
□ Histogram of orientation

$$dx = L_{x+1,y} - L_{x-1,y}$$

$$dy = L_{x,y+1} - L_{x,y-1}$$

$$m = \sqrt{dx^2 + dy^2}$$

$$\theta = \tan^{-1}(dy / dx)$$

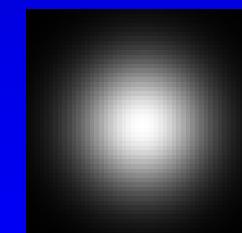


*4x4x8=128 Dimension
Feature Vector*

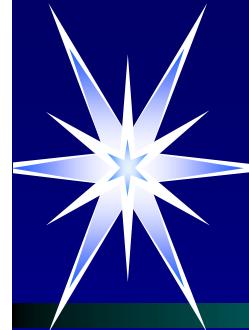
8 Orientation

*Orientation
Histogram*

\times



*Gaussian
Weight*

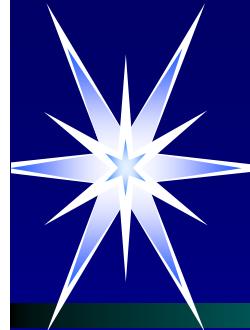


SIFT-Experiments (I)

□ Object recognition

- Occluded (partially visible) objects recognition
- Under varying illuminations



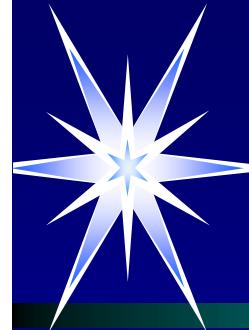


SIFT-Experiments (II)

□ Place identification

- Indoor/outdoor
- SLAMB
 - ↗ Simultaneous Localization And Map Building

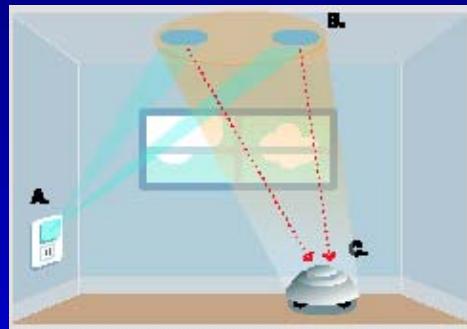




Applications Using SIFT (I)

□ Evolution Robotics

- Northstar
 - ↗ Self localization
- Robotics software

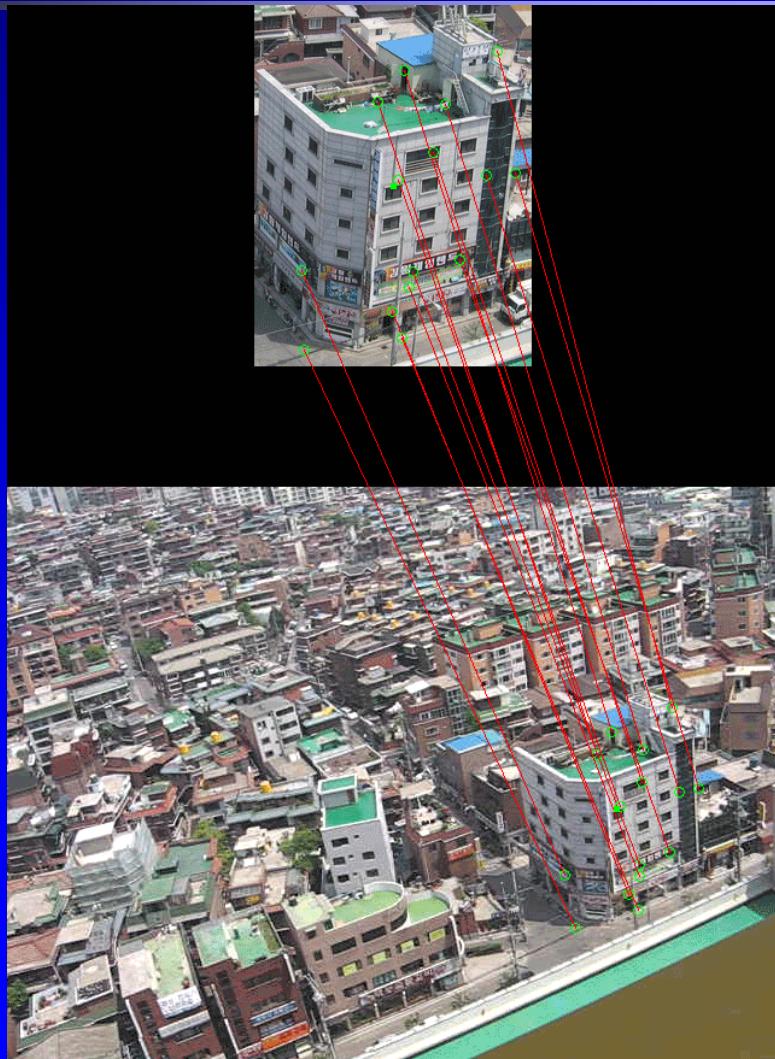


□ SONY

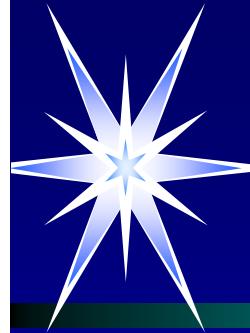
- AIBO



Applications Using SIFT (II)



- Target detection and recognition:
 - Position, pose
 - Sensor error compensation



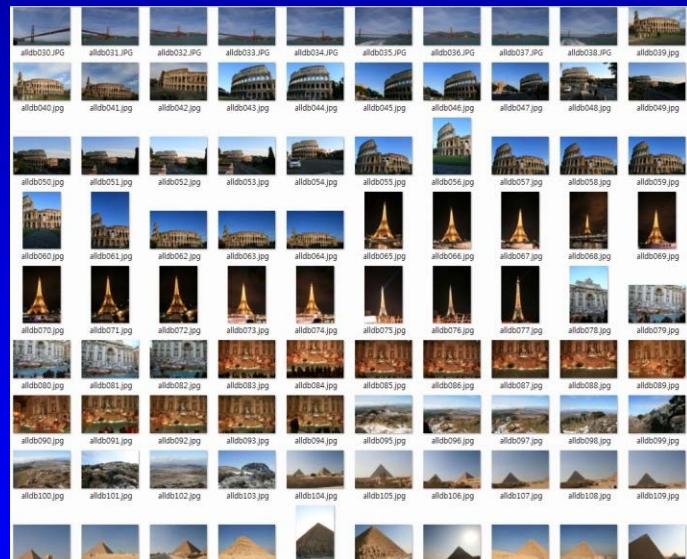
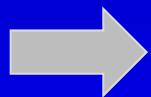
Applications Using SIFT (III)

- Building recognition in broadcasting contents



Applications Using SIFT (IV)

□ Image retrieval



Query

Database, BOF models

Result