Local Feature Extraction

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SIFT, SURF and LBP

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March 18, 2016

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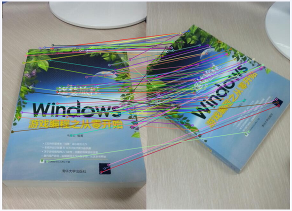
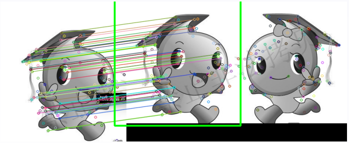
Introduction



SURF match



SIFT match

SIFT

SIFT(Scale Invariant Feature Transform):

- An algorithm in computer vision to detect and describe local features in images.
- Published by David Lowe in 1999.
- Accuracy, stability, scale and rotational invariance.

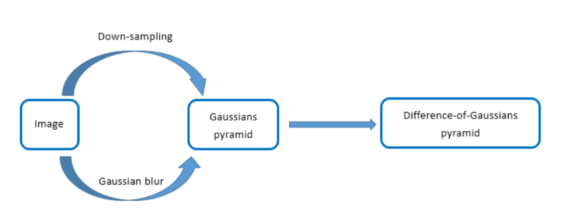
Steps

Steps:

1. Construct scale-space.
2. Detect scale-invariant interest points from scale-space extrema.
3. Orientation match.
4. Compute descriptor.
5. Match image descriptors.

Construct scale-space

Interest points are obtained from a difference-of-Gaussians pyramid.



Construct scale-space

Smoothed image values:

$$L(x, y, \sigma) = G(x, y, \sigma) * I(x, y) \tag{1}$$

Construct scale-space

Gaussian kernels:

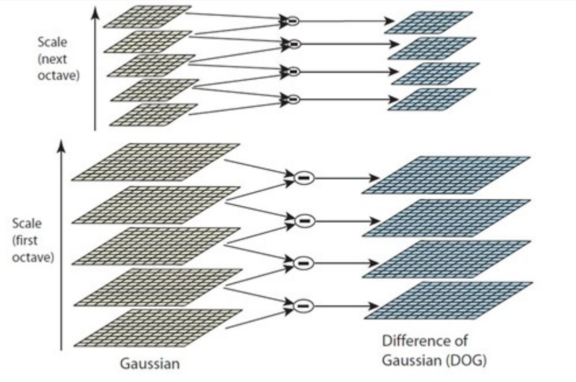
$$G(x, y, \sigma) = \frac{1}{2\pi\sigma^2} e^{-\frac{(x-m/2)^2+(y-n/2)^2}{2\sigma^2}} \tag{2}$$

The difference-of-Gaussians operator:

$$\begin{aligned} D(x, y, \sigma) &= (G(x, y, k\sigma) - G(x, y, \sigma)) * I(x, y) \\ &= L(x, y, k\sigma) - L(x, y, \sigma) \end{aligned} \tag{3}$$

In fact, we obtained the difference-of-Gaussians pyramid by taking subtraction between the adjacent two layers.

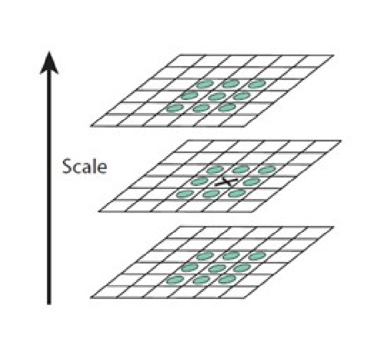
Construct scale-space



Contrust difference-of-Gaussians pyramid

Detect scale-space extrema

Compare the detecting point with other points in a $3*3*3$ neighbourhood.



Extrema detection

Detect scale-invariant interest points from scale-space extrema

The scale coordinate of keypoints:

$$\sigma(o,s) = \sigma_0 2^{o+\frac{s}{S}} \quad o = 0,1,\ldots,O-1, s = 0,\ldots,S+2 \tag{4}$$

The scale of a particular layer:

$$\sigma_{oct}(s) = \sigma_0 2^{\frac{s}{S}} \quad s = 0,\ldots,S+2 \tag{5}$$

Detect scale-invariant interest points from scale-space extrema

The Taylor expansion of D(X) is as follows:

$$D(X) = D(X) + \frac{\partial D^T}{\partial X} X + \frac{1}{2} X^T \frac{\partial^2 D}{\partial X^2} X \quad X = (x, y, \sigma)^T \tag{6}$$

Deal with the derivative and let it eqaual 0. We can obtain the offset of extrema:

$$X_1 = -\frac{\partial^2 D^{-1}}{\partial X_1^2} \frac{\partial D}{\partial X_1} \tag{7}$$

and

$$D(X_1) = D + \frac{\partial D^T}{\partial X_1} X_1 \tag{8}$$

If $|D(X_1)| < 0.3$, throw it.

Detect scale-invariant interest points from scale-space extrema

To suppress such points, which will be less useful for matching. We formulate the Hessian matrix:

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

$$Tr(H) = D_{xx} + D_{yy} = \alpha + \beta \tag{9}$$

$$Det(H) = D_{xx}D_{yy} - (D_{xy})^2 = \alpha\beta \tag{10}$$

Detect scale-invariant interest points from scale-space extrema

Assume that α is bigger than β, and $\alpha = r\beta$.

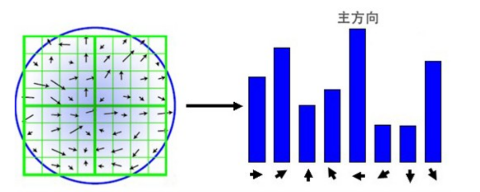
$$\frac{Tr(H)^2}{Det(H)} = \frac{(\alpha_+\beta)^2}{\alpha\beta} = \frac{(r\beta + \beta)^2}{r\beta^2} = \frac{(r+1)^2}{r} \tag{11}$$

If $\frac{Tr(H)^2}{Det(H)} > \frac{(r+1)^2}{r}$, throw it.

(Lowe recommended $r = 10$)

Orientation match

Select a window($r = 3 * 1.5\sigma_{oct}$) around the interest point.



Orientation histogram

With 36 bins in the histogram.

Orientation match

Using

$$m(x, y) = \sqrt{(L(x+1, y) - L(x-1, y))^2 + (L(x, y+1) - L(x, y-1))^2} \tag{12}$$

$$\theta = \tan^{-1}((L(x, y+1) - L(x, y-1))/(L(x+1, y) - L(x-1, y))) \tag{13}$$

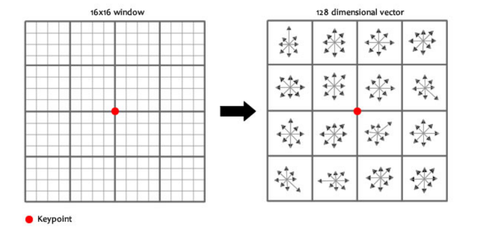
to find the dominant orientation.
Compute the orientation histogram based on every gradient direction $\theta(x, y)$.
Peak is the orientation.

Orientation match

Multiple peaks are accepted if the height of secondary peaks is above 80 % of the height of the highest peak. Express it approximately as the quadratic function curve to find actual location (the highest point).

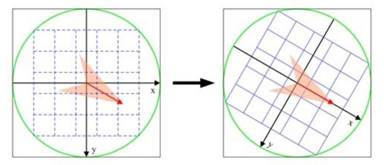
Determine the local image region

Divide the neighborhood into $4 * 4$ regions. Every region is a seed point.



Orientation histogram

Rotate the coordinate



The new coordinate is based on the orientation of interset point.

$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}$$

Allocate sampling points

Rotated sampling points was allocated to $4 * 4$ regions. The new coordinate is:

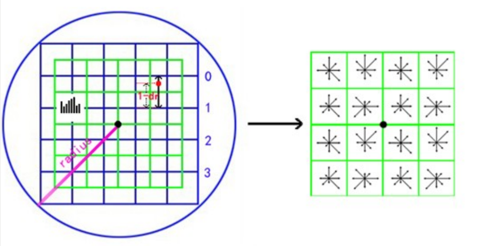
$$\begin{bmatrix} x'' \\ y'' \end{bmatrix} = \frac{1}{3\sigma\_oct} \begin{bmatrix} x' \\ y' \end{bmatrix} + \frac{d}{2}$$

The gradient can be computed by Gaussian weighted model as $\sigma = 0.5d$:

$$w = m(a + x, b + y) e^{-\frac{(x')^2 + (y')^2}{2x(0.5d)^2}} \tag{14}$$

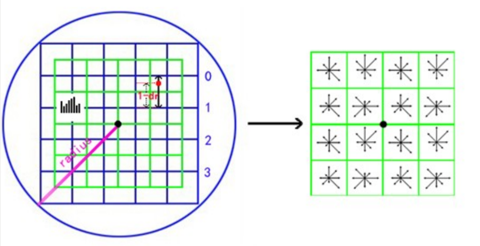
a, b is the coordinate in Gaussian pyramid.

Compute the gradient of 8 directions by interpolation



Linear interpolation is used on (x'', y'')(the red points) for computing its contribution to every seed point.

Compute the gradient of 8 directions by interpolation



Its contributions to

[0,3]: dr [1,3]: $1 - dr$

Column 2: dc Column 3: $1 - dc$

Neighbor directions: do and $1 - do$.

Compute the gradient of 8 directions by interpolation

The eventual gradient magnitude added on every direction is:

$$weight = w * dr^k * (1 - dr)^{1-k} * dc^m * (1 - dc)^{1-m} * do(1 - do)^{1-n} \tag{15}$$

$k, m, n = 0$ or 1.

Normalize

Taken together, the local histograms computed at all the 4×4 grid points and with 8 quantized directions lead to an image descriptor $H = (h_1, h_2, \ldots, h_{128})$ with 4×4×8=128 dimensions for each interest point.
Normalize H to avoid the effect of illumination:

$$l_i = \frac{h_i}{\sqrt{\sum_{j=1}^{128} h_j}} \tag{16}$$

Match image descriptors

$R_i = (r_{i1}, r_{i2}, \ldots, r_{i128})$: Descriptors from model image.

$S_i = (s_{i1}, s_{i2}, \ldots, s_{i128})$: Descriptors from another image.

$d(R_i, S_i) = \sqrt{\sum_{j=1}^{128} (r_{ij} - s_{ij})^2}$: Distance between R_i and S_i.

If $\frac{d_{min}(R_i,S_i)}{d_{the\_second\_min}(R_i,S_j)} < Threshold$, they matched.

SURF

SURF(Speeded Up Robust Features):

- An algorithm in computer vision to detect and describe local features in images.
- First presrnted by Herbert Bayet al. in 2006.
- Fast than SIFT, accuracy, stability, scale and rotational invariance.

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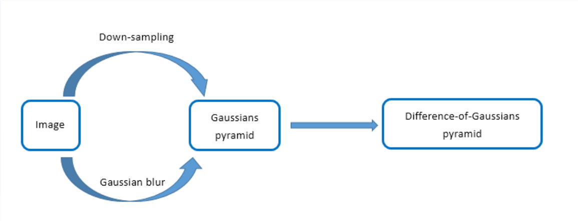
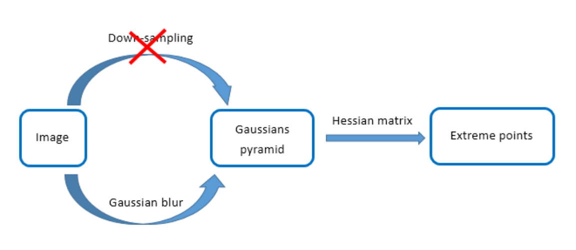


Construct scale-space

Construct scale-space



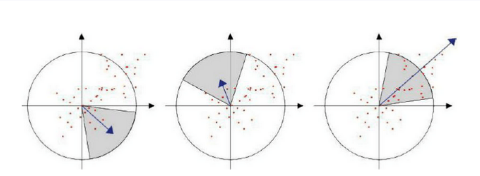
Construct scale-space

The discriminant of Hessian matrix to detect extrema can be approximated as follows:

$$Det(Happrox) = D_{xx}D_{yy} - (0.9D_{xy})^2 \tag{17}$$

D_{xx}, D_{xy}, D_{yy} are the convolution results of Gaussian kernels and original image.

Orientation match

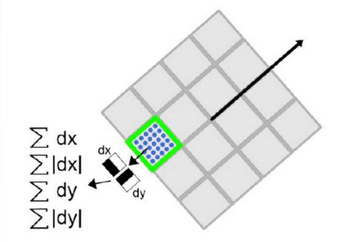


Estimate the dominant orientation

Angle: $\frac{\pi}{3}$.
Radius: 6s (s is the scale at which the interest pointwas detected).
Calculate the Haar-wavelet responses in x and y direction.
The maximum sum of all responses is the dominant orientation.

Compute descriptor

Construct a square region (20s) aligned to the selected orientation. $4 * 4$ square sub-regions, $5 * 5$ regularly spaced sample points.



Compute descriptor

We call dx the Haar wavelet response in horizontal direction and dy the Haar wavelet response in vertical direction.

Vector $\mathbf{v} = (\sum dx, \sum |dx|, \sum dy, \sum |dy|)$

LBP

LBP(Local Binary Pattern):

- One of the method about local information extraction. It reflects the gray value relationship between the pixel and points around it.
- Proposed by Ojala et al.
- LBP operator has significant effect in the description of texture feature extraction.

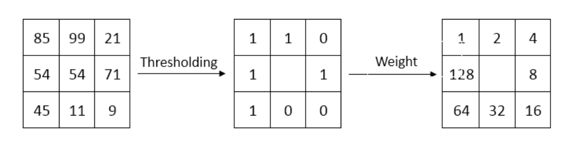
Encoding formula

The encoding formula for any LBP operator is:

$$LBP_{P,R} = \sum_{i=0}^{p-1} s(g_i - g_c)2^i, s(x) = \begin{cases} 1 & x \geqslant 0 \\ 0 & x < 0 \end{cases} \tag{18}$$

P: The number of pixels in the (P, R) neighborhood.
R: The neighborhood radius.
$g_i(i = 1, 2 \ldots P - 1)$: The pixel values in the neighborhood with a threhold g_c.

Calculation process

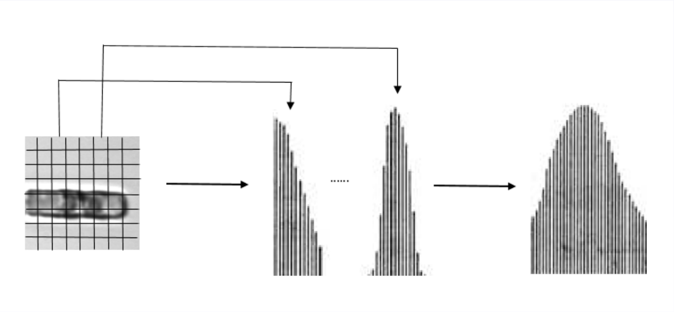


Basic LBP operator $(P = 8 \text{ and } R = 1)$

The LBP operator$= 1 + 2 + 8 + 64 + 128 = 203$
Count the ratio of LBP opetator between 0 and 255 to a histogram.
Obtain a data with 256-dimensional features.

Calculation process

Convert all the images size into $64 * 64$ and each image is divided into $8 * 8$ local regions.



Global image description based on LBP

Concatenate the regional histograms to build a global histogram.