

Machine Visions and Digital Image Analysis

Scale Invariant Feature Transform

developed by David Lowe University of British Columbia Initial paper ICCV 1999 Newer journal paper IJCV 2004



Hani M. A. Fahmi

Introduction



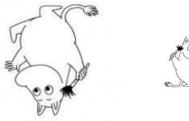
Scale-Invariant Feature Transform (SIFT) [1][2]

- by David G. Lowe, 1999,2004
- Feature detection algorithm
- Feature usefull for: Image matching, object or scene recognition, solving for 3D structure from multiple images, stereo correspondence and motion tracking,...
- > Features properties (invariance):
 - Scale
 - Rotation
 - Affine transform
 - 3D viewpoint
 - Illumination changes
 - Occlusion

Features invariance





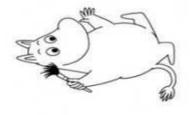










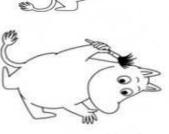


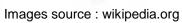














Sift Method Steps [1]



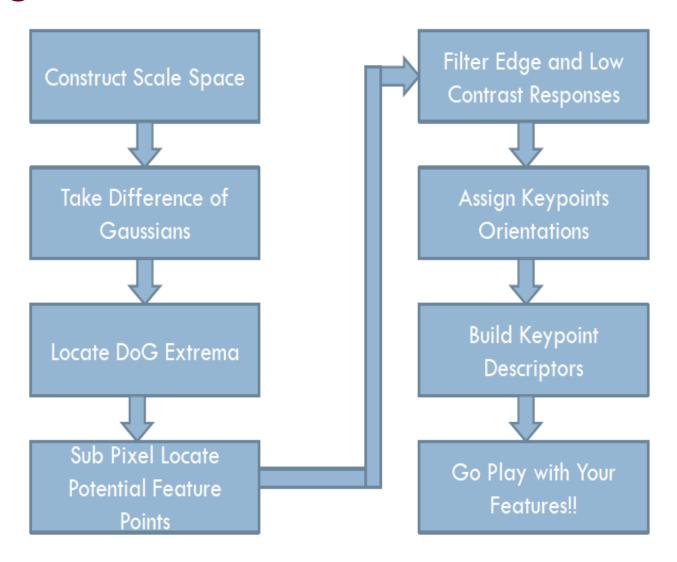
SIFT algorithm:

- 1. Scale-space extrema detection
- 2. Keypoint localization.
- 3. Orientation assignment.
- 4. Keypoint descriptor.

Output : feature descriptors

Sift Algorithm overview [1][4]





Images source: Jason Clemons presentation [4]

Scale Space Construction [1][4][15]



- >Gaussian kernel used to create scale space
- >Only possible scale space kernel (Lindberg, 94)

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

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

Scale Space representation [1][15]





Scale-space representation L(x,y;t) at scale t=0, corresponding to the original image f



Scale-space representation L(x,y;t) at scale t=1



Scale-space representation L(x,y;t) at scale t=4



Scale-space representation L(x,y;t) at scale t=16



Scale-space representation L(x,y;t) at scale t=64



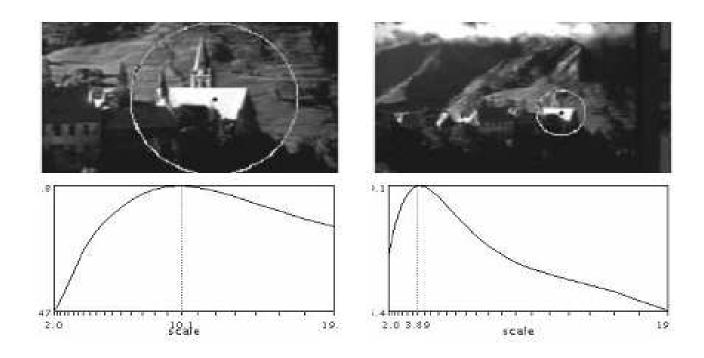
Scale-space representation L(x,y;t) at scale t=256

Images source : wikipedia.org [15]

Scale Space extrema [1][3][12][15]



Mikolajczyk (2002): Experimentally, extrema of LoG gives best notion of scale



Scale Space extrema localization



>Approximation of Laplacian of Gaussians

$$\frac{\partial G}{\partial \sigma} = \sigma \nabla^2 G.$$

$$\sigma \nabla^2 G = \frac{\partial G}{\partial \sigma} \approx \frac{G(x, y, k\sigma) - G(x, y, \sigma)}{k\sigma - \sigma}$$

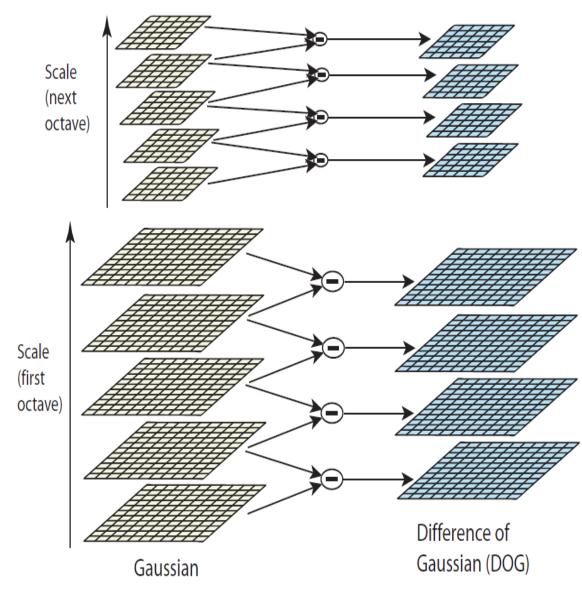
$$G(x, y, k\sigma) - G(x, y, \sigma) \approx (k-1)\sigma^2 \nabla^2 G$$

$$D(x, y, \sigma) = (G(x, y, k\sigma) - G(x, y, \sigma)) * I(x, y)$$
$$= L(x, y, k\sigma) - L(x, y, \sigma).$$

$$s = 3$$
 and $k = 2^{1/s}$.

Scale Space extrema localization (keypoint) overview [1].

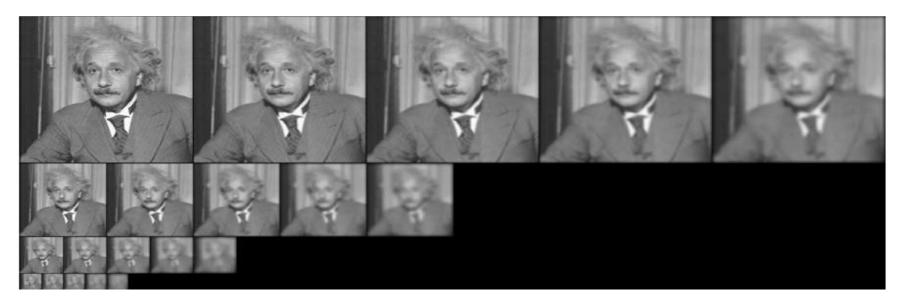




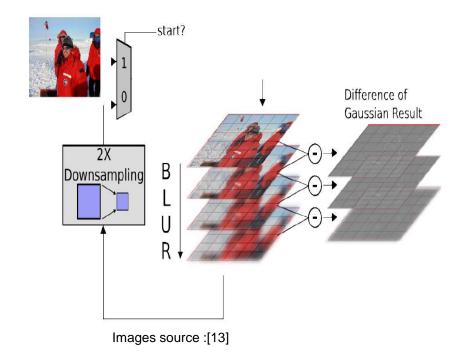
Images source :Lowe 2004 [1] 10/26

Example of DOG 1/2 [1][8][13]

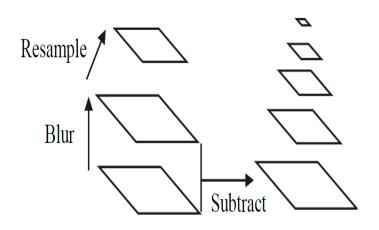




Images source :Allan Jepson [8]



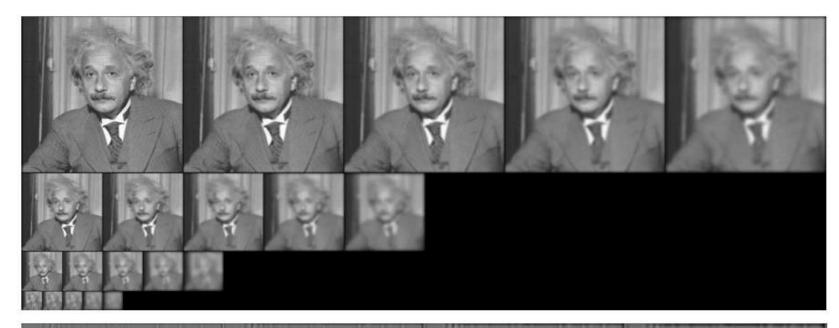
DOG pyramid (Burt & Adelson, 1983)



Images source : [13]

Example of DOG 2/2 [1][8]







Range: [-0.11, 0.131] Dims: [959, 2044]

DOG exterma localization [1][4]

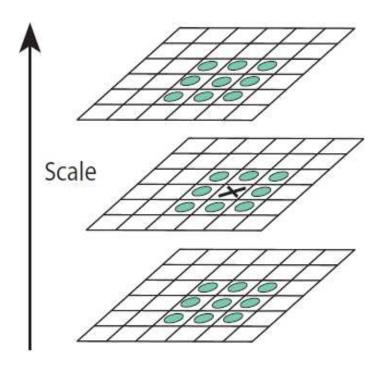


Scan each DOG image

Look at all neighboring points (including scale)

Identify Min and Max

26 Comparisons



Slide credit: Jason clemons [4]

Images source :Lowe 2004 [1]

Extra keypoints elimination 1/2 [1]



3D Curve Fitting for localization : Taylor Series Expansion + differentiation

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

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

Low Contrast Points Filter

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

Extra keypoints elimination 2/2 [1]



Edge Response Elimination:

Hessian

Eigenvalues Proportional to principle

CurvaturesTrace and Determinant

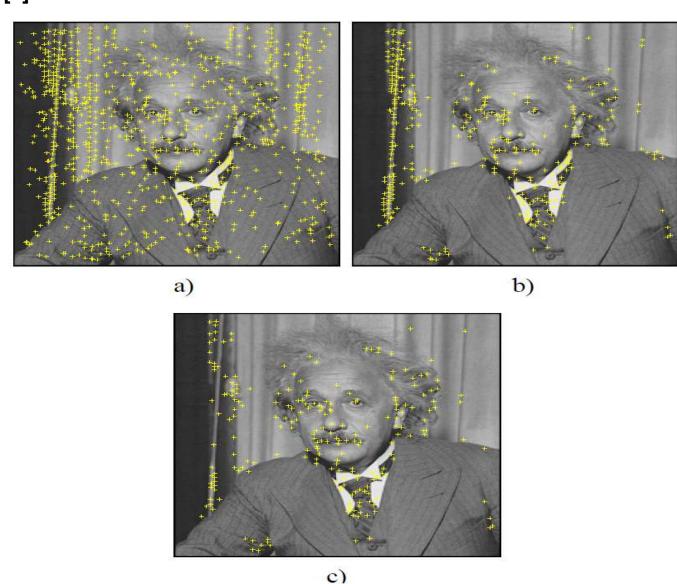
$$H = \begin{bmatrix} D_{xx} D_{xy} \\ D_{xy} D_{yy} \end{bmatrix}$$

$$\frac{Tr(H)^{2}}{Det(H)} < \frac{(r+1)^{2}}{r}$$

$$Tr(H) = D_{xx} + D_{yy}$$
$$Det(H) = D_{xx}D_{yy} - (D_{xy})^{2}$$

Extra keypoints elimination example [8]





Images source :Allan Jepson [8] 16/26

Orientation and feature descriptor [1][4][6]



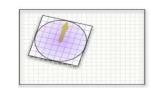
Compute Gradient for each blurred image

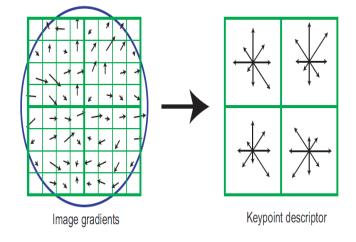
$$L(x, y) = G(x, y, \sigma) * I(x, y)$$

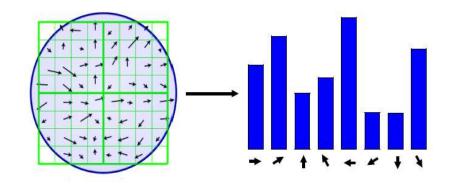
$$m(x, y) = \sqrt{(L(x+1, y) - L(x-1, y))^{2} + (L(x, y+1) - L(x, y-1))^{2}}$$

$$\theta(x, y) = \tan^{-1} \left(\frac{(L(x, y+1) - L(x, y-1))}{(L(x+1, y) - L(x-1, y))} \right)$$

Implementation uses 4x4 descriptors from 16x16 which leads to a 4x4x8=128 element vector



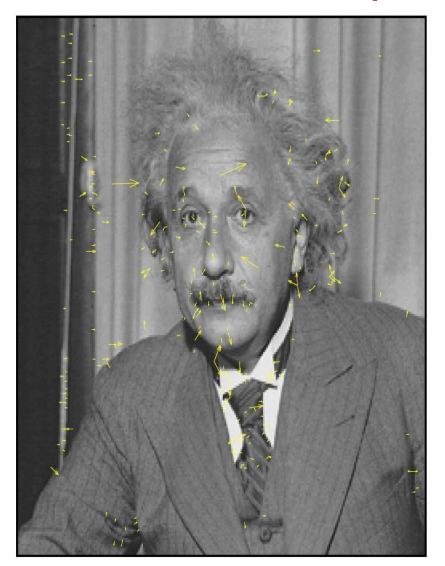




Images source :Lowe 2004 [1] 17/26 Images source: Ofir Pele [6] Slide credit: Jason clemons [4]

Orientation example [8]





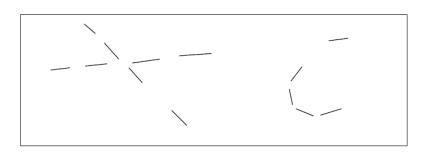


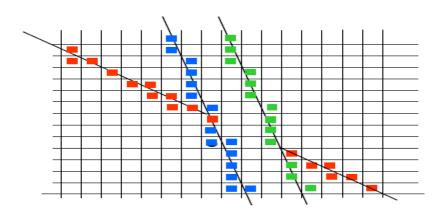
Images source :Allan Jepson [8]

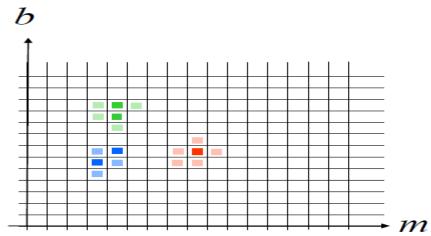
Hough transform : Global features [1][13]











SIFT example: Find the cellphone?

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[8]

Image Model Location Range: [-0.986, 0.765] Range: [0, 1] Range: [0, 1] Dims: [480, 640] Dims: [480, 640] Dims: [480, 640] Image Model Location Range: [0, 1] Range: [0, 1] Range: [-1.05, 0.866] Dims: [480, 640] Dims: [480, 640] Dims: [480, 640] Model Location Image Range: [0, 1] Range: [0, 1] Range: [-1.07, 1.01] Dims: [480, 640] Dims: [480, 640] Dims: [480, 640]

Images source : Allan jepson [8]

SIFT, Features database [13]





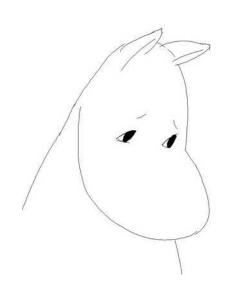
Images source :[13] 21/26

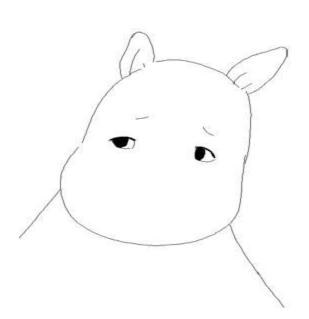
SIFT limitation [6]



Large illumination change

Non rigid deformations





SIFT Application [5]

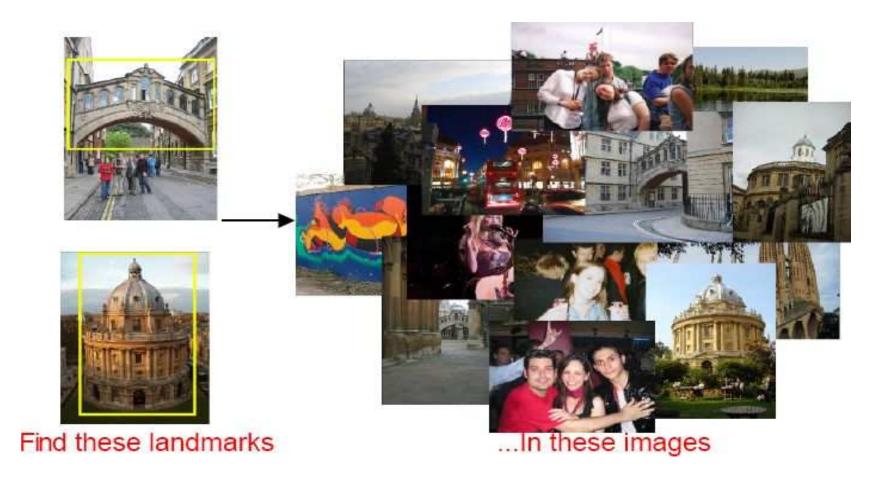


- Object recognition using SIFT features
- Robot localization and mapping
- Panorama stitching
- 3D scene modeling, recognition and tracking
- Others, (human action recognition)





http://www.robots.ox.ac.uk/~vgg/research/oxbuildings/index.html



Images source :Visual. Geometry Group[7]

Conclusion [6]



- In wide use both in academia and industry
- Many available implementations:
 - Binaries available at Lowe's website
 - C/C++ open source by A. Vedaldi (UCLA)
 - C# library by S. Nowozin (Tu-Berlin)
- Protected by a patent

Slide credit : Ofir Pele [6]

References



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