The **SIFT** (Scale Invariant Feature Transform) **Detector and Descriptor**

developed by David Lowe
University of British Columbia
Initial paper ICCV 1999
Newer journal paper IJCV 2004
Review: Matt Brown’s Canonical Frames
Multi-Scale Oriented Patches

- Extract oriented patches at multiple scales

[ Brown, Szeliski, Winder CVPR 2005 ]
Application: Image Stitching
Ideas from Matt’s Multi-Scale Oriented Patches

1. Detect an interesting patch with an interest operator. Patches are translation invariant.
2. Determine its dominant orientation.
3. Rotate the patch so that the dominant orientation points upward. This makes the patches rotation invariant.
4. Do this at multiple scales, converting them all to one scale through sampling.
5. Convert to illumination “invariant” form
Implementation Concern: How do you rotate a patch?

- Start with an “empty” patch whose dominant direction is “up”.
- For each pixel in your patch, compute the position in the detected image patch. It will be in floating point and will fall between the image pixels.
- Interpolate the values of the 4 closest pixels in the image, to get a value for the pixel in your patch.
Rotating a Patch

empty canonical patch

$T$

$x' = x \cos \theta - y \sin \theta$

$y' = x \sin \theta + y \cos \theta$

counterclockwise rotation

patch detected in the image

What’s the problem?
Using Bilinear Interpolation

- Use all 4 adjacent samples
SIFT: Motivation

- The Harris operator is not invariant to scale and correlation is not invariant to rotation.\(^1\)

- For better image matching, Lowe’s goal was to develop an interest operator that is invariant to scale and rotation.

- Also, Lowe aimed to create a descriptor that was robust to the variations corresponding to typical viewing conditions. The descriptor is the most-used part of SIFT.

\(^1\text{But Schmid and Mohr developed a rotation invariant descriptor for it in 1997.}\)
Idea of SIFT

- Image content is transformed into local feature coordinates that are invariant to translation, rotation, scale, and other imaging parameters.
Claimed Advantages of SIFT

- **Locality**: features are local, so robust to occlusion and clutter (no prior segmentation)

- **Distinctiveness**: individual features can be matched to a large database of objects

- **Quantity**: many features can be generated for even small objects

- **Efficiency**: close to real-time performance

- **Extensibility**: can easily be extended to wide range of differing feature types, with each adding robustness
Overall Procedure at a High Level

1. Scale-space extrema detection
   Search over multiple scales and image locations.

2. Keypoint localization
   Fit a model to determine location and scale.
   Select keypoints based on a measure of stability.

3. Orientation assignment
   Compute best orientation(s) for each keypoint region.

4. Keypoint description
   Use local image gradients at selected scale and rotation to describe each keypoint region.
1. Scale-space extrema detection

- **Goal:** Identify locations and scales that can be repeatably assigned under different views of the same scene or object.

- **Method:** search for stable features across multiple scales using a continuous function of scale.

- **Prior work** has shown that under a variety of assumptions, the best function is a Gaussian function.

- The scale space of an image is a function $L(x, y, \sigma)$ that is produced from the convolution of a Gaussian kernel (at different scales) with the input image.
Aside: Image Pyramids

And so on.

3\textsuperscript{rd} level is derived from the 2\textsuperscript{nd} level according to the same function

2\textsuperscript{nd} level is derived from the original image according to some function

Bottom level is the original image.
Aside: Mean Pyramid

Bottom level is the original image.

At 2\textsuperscript{nd} level, each pixel is the mean of 4 pixels in the original image.

At 3\textsuperscript{rd} level, each pixel is the mean of 4 pixels in the 2\textsuperscript{nd} level.

And so on.
Aside: Gaussian Pyramid
At each level, image is smoothed and reduced in size.

And so on.

At 2nd level, each pixel is the result of applying a Gaussian mask to the first level and then subsampling to reduce the size.

Bottom level is the original image.
Example: Subsampling with Gaussian pre-filtering

Gaussian 1/2

G 1/4

G 1/8
Lowe’s Scale-space Interest Points

- **Laplacian of Gaussian kernel**
  - Scale normalised (x by scale\(^2\))
  - Proposed by Lindeberg

- **Scale-space detection**
  - Find local maxima across scale/space
  - A good “blob” detector

\[ G(x, y, \sigma) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{1}{2} \frac{x^2 + y^2}{\sigma^2}} \]

\[ \nabla^2 G(x, y, \sigma) = \frac{\partial^2 G}{\partial x^2} + \frac{\partial^2 G}{\partial y^2} \]

[ T. Lindeberg IJCV 1998 ]
Lowe’s Scale-space Interest Points: Difference of Gaussians

- Gaussian is an ad hoc solution of heat diffusion equation

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

- Hence

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

- \( k \) is not necessarily very small in practice
Lowe’s Pyramid Scheme

- Scale space is separated into octaves:
  - Octave 1 uses scale $\sigma$
  - Octave 2 uses scale $2\sigma$
  - etc.

- In each octave, the initial image is repeatedly convolved with Gaussians to produce a set of scale space images.

- Adjacent Gaussians are subtracted to produce the DOG

- After each octave, the Gaussian image is down-sampled by a factor of 2 to produce an image $\frac{1}{4}$ the size to start the next level.
Lowe’s Pyramid Scheme

\[ \sigma_{s+1} = 2^{(s+1)/s}\sigma_0 \]

\[ \sigma_i = 2^{i/s}\sigma_0 \]

The parameter \( s \) determines the number of images per octave.

s+2 filters

s+3 images including original

Difference of Gaussian (DOG)

s+2 difference images
Key point localization

- Detect maxima and minima of difference-of-Gaussian in scale space.

- Each point is compared to its 8 neighbors in the current image and 9 neighbors each in the scales above and below.

For each max or min found, output is the location and the scale.

s+2 difference images, top and bottom ignored. s planes searched.
Scale-space extrema detection: experimental results over 32 images that were synthetically transformed and noise added.

- **Stability**
  - **Sampling in scale for efficiency**
    - **How many scales should be used per octave?** \( S = ? \)
      - More scales evaluated, more keypoints found
      - \( S < 3 \), stable keypoints increased too
      - \( S > 3 \), stable keypoints decreased
      - \( S = 3 \), maximum stable keypoints found

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Graphs showing:
- % detected
- % correctly matched
- Average no. detected
- Average no. matched
- Number of keypoints vs. number of scales sampled per octave
Keypoint localization

- Once a keypoint candidate is found, perform a detailed fit to nearby data to determine location, scale, and ratio of principal curvatures.
- In initial work keypoints were found at location and scale of a central sample point.
- In newer work, they fit a 3D quadratic function to improve interpolation accuracy.
- The Hessian matrix was used to eliminate edge responses.
Eliminating the Edge Response

- Reject flats:
  - $|D(\hat{x})| < 0.03$
- Reject edges:
  \[
  H = \begin{bmatrix}
  D_{xx} & D_{xy} \\
  D_{xy} & D_{yy}
  \end{bmatrix}
  \]
  \[
  \text{Tr}(H) = D_{xx} + D_{yy} = \alpha + \beta,
  \]
  \[
  \text{Det}(H) = D_{xx}D_{yy} - (D_{xy})^2 = \alpha \beta.
  \]
  Let $r = \alpha/\beta$. So $\alpha = r\beta$
  - $r < 10$

Let $\alpha$ be the eigenvalue with larger magnitude and $\beta$ the smaller.

$\frac{\text{Tr}(H)^2}{\text{Det}(H)} = \frac{(\alpha + \beta)^2}{\alpha \beta} = \frac{(r\beta + \beta)^2}{r \beta^2} = \frac{(r + 1)^2}{r}$, 

$(r+1)^2/r$ is at a min when the 2 eigenvalues are equal.
3. Orientation assignment

- Create histogram of local gradient directions at selected scale
- Assign canonical orientation at peak of smoothed histogram
- Each key specifies stable 2D coordinates (x, y, scale, orientation)

If 2 major orientations, use both.
Keypoint localization with orientation

233x189

(a) initial keypoints

729

keypoints after gradient threshold

(b) keypoints after ratio threshold

832

536
4. Keypoint Descriptors

- At this point, each keypoint has
  - location
  - scale
  - orientation

- Next is to compute a descriptor for the local image region about each keypoint that is
  - highly distinctive
  - invariant as possible to variations such as changes in viewpoint and illumination
Normalization

- Rotate the window to standard orientation

- Scale the window size based on the scale at which the point was found.
Lowe’s Keypoint Descriptor
(shown with 2 X 2 descriptors over 8 X 8)

gradient magnitude and orientation at each point weighted by a Gaussian

In experiments, 4x4 arrays of 8 bin histogram is used, a total of 128 features for one keypoint
Biological Motivation

- Mimic complex cells in primary visual cortex
- Hubel & Wiesel found that cells are sensitive to orientation of edges, but insensitive to their position
- This justifies spatial pooling of edge responses

[ “Eye, Brain and Vision” – Hubel and Wiesel 1988 ]
Lowe’s Keypoint Descriptor

- use the **normalized** region about the keypoint
- compute gradient magnitude and orientation at each point in the region
- **weight them by a Gaussian** window overlaid on the circle
- create an **orientation histogram** over the 4 X 4 subregions of the window
- 4 X 4 descriptors over 16 X 16 sample array were used in practice. 4 X 4 times 8 directions gives a vector of **128 values**.
Using SIFT for Matching “Objects”
Uses for SIFT

- Feature points are used also for:
  - Image alignment (homography, fundamental matrix)
  - 3D reconstruction (e.g. Photo Tourism)
  - Motion tracking
  - Object recognition
  - Indexing and database retrieval
  - Robot navigation
  - ... many others

[ Photo Tourism: Snavely et al. SIGGRAPH 2006 ]