Deep Learning for Computer Vision

Feature Detectors: SIFT and Variants

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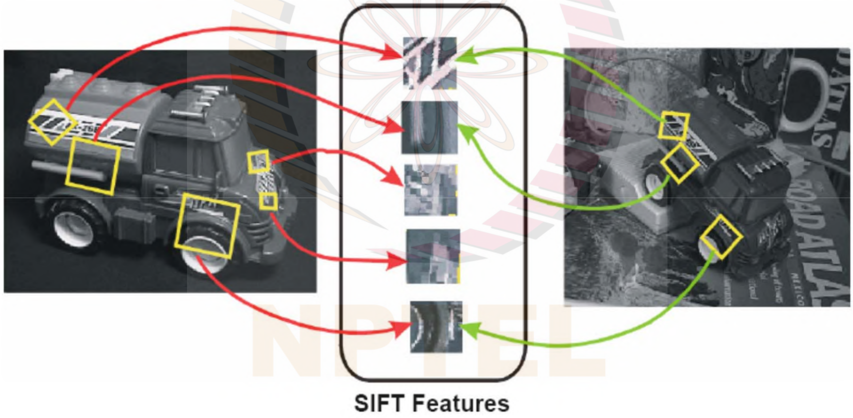
SIFT: Scale Invariant Feature Transform

- David G. Lowe, *Distinctive Image Features from Scale-invariant Keypoints*, IJCV 2004
  - Over 50000 citations
- Transforms image data into scale-invariant coordinates
- Fundamental to many core vision problems/applications:
  - Recognition, Motion tracking, Multiview geometry

SIFT: Invariant Local Features

Image content is transformed into local feature coordinates that are invariant to translation, rotation, scale, shear.



Credit: Mubarak Shah, University of Central Florida

SIFT

- **Step 1: Scale-space Extrema Detection** - Detect interesting points (invariant to scale and orientation) using DOG.
- **Step 2: Keypoint Localization** - Determine location and scale at each candidate location, and select them based on stability.
- **Step 3: Orientation Estimation** - Use local image gradients to assign orientation to each localized keypoint. Preserve orientation, scale and location for each feature.
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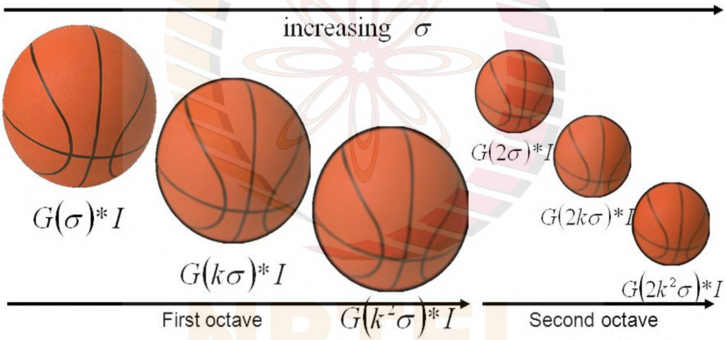
SIFT: Scale-space Extrema Detection

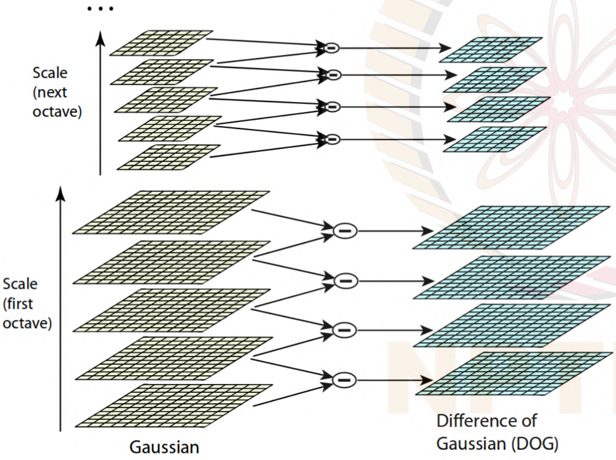
Constructing Scale Space



Credit: Ofir Pele

SIFT: Scale-space Extrema Detection

Difference of Gaussians



SIFT: Scale-space Extrema Detection

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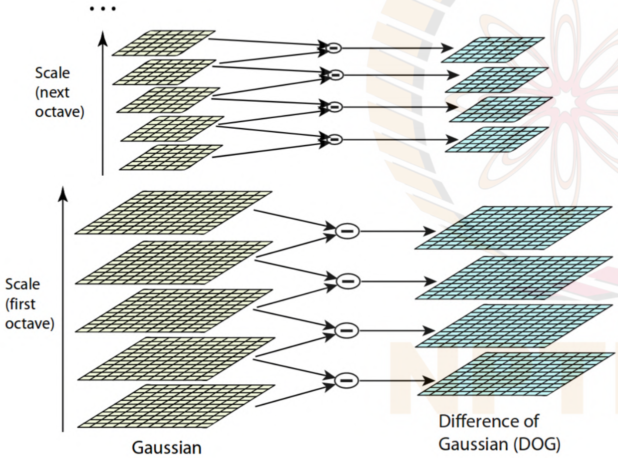
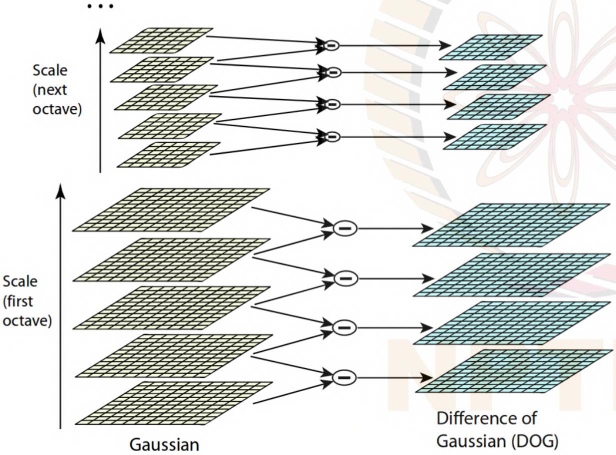


$$D(x, y, \sigma) = \hat{I}(x, y, \sigma) - \hat{I}(x, y, k\sigma)$$

where $\hat{I}(x, y, \sigma) = G(x, y, \sigma) * I(x, y)$

SIFT: Scale-space Extrema Detection

Difference of Gaussians



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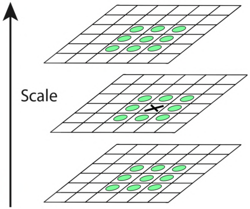

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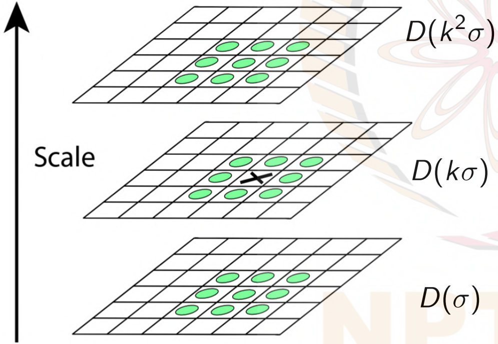
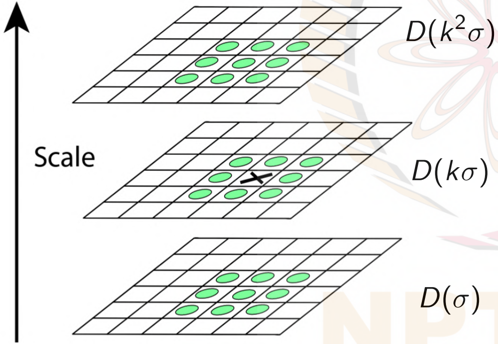
SIFT: Scale-space Extrema Detection



- Compare a pixel (X) with 26 pixels in current and adjacent scales (Green Circles)
- Select a pixel (X) if it is larger/smaller than all 26 pixels

Credit: *"Distinctive Image Features from Scale-Invariant Points", IJCV 2004*

SIFT: Scale-space Extrema Detection



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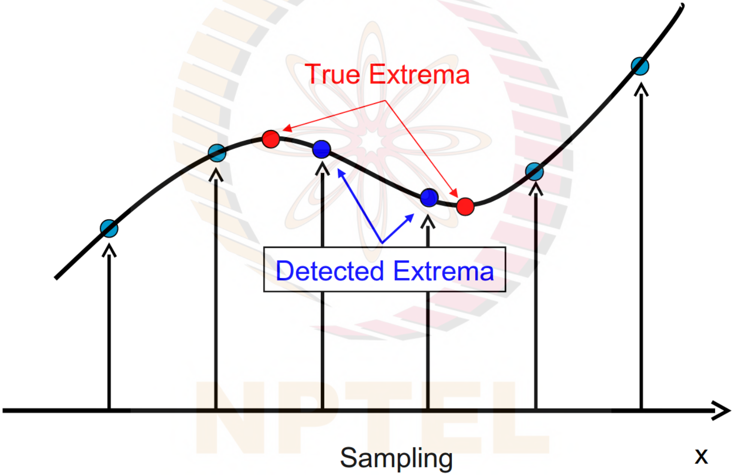
SIFT: Keypoint Localization

The Problem:



Credit: Ofir Pele

SIFT: Keypoint Localization

The Solution:

- Use Taylor series expansion of the scale-space function:

$$D(\mathbf{s}_0 + \Delta\mathbf{s}) = D(\mathbf{s}_0) + \frac{\partial D}{\partial \mathbf{s}}^T\bigg|_{\mathbf{s}_0} \Delta\mathbf{s} + \frac{1}{2}\Delta\mathbf{s}^T \frac{\partial^2 D}{\partial \mathbf{s}^2}\bigg|_{\mathbf{s}_0} \Delta\mathbf{s}$$

where $\mathbf{s}_0 = (x_0, y_0, \sigma_0)^T$ and $\Delta\mathbf{s} = (\delta x, \delta y, \delta\sigma)^T$

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- The location of the extremum, $\hat{\mathbf{s}}$, is determined by taking the derivative of this function with respect to $\mathbf{s}$ and setting it to zero:

$$\hat{\mathbf{s}} = -\left(\frac{\partial^2 D}{\partial \mathbf{s}^2}\bigg|_{\mathbf{s}_0}\right)^{-1} \frac{\partial D}{\partial \mathbf{s}}\bigg|_{\mathbf{s}_0}$$

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- Low contrast points elimination:
  - Reject keypoint if $D(\hat{\mathbf{s}})$ is smaller than 0.03 (assuming image values are normalized in [0,1])

SIFT: Keypoint Localization

- Reject points with strong edge response in one direction only
- Edge Elimination - How?

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- Edge Elimination - How?
  - Similar to Harris corner detector!
  - SIFT instead uses Hessian
- Compute Hessian of D (principal curvature)

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

α : largest eigenvalue(λ_{max})

β : smallest eigenvalue(λ_{min})

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

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

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- Evaluate ratio

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

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

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- This quantity is minimum when r $= 1$ (eigenvalues are equal)
- Reject keypoint if: $\frac{Tr(H)^2}{Det(H)} >$ a threshold (Original SIFT uses r $= 10$)

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SIFT: Orientation Estimation

- Why?

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- Why? To achieve rotation invariance

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- Why? To achieve rotation invariance
- Use scale of point to choose correct image:

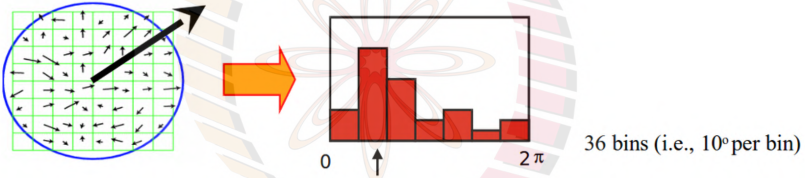
$$\hat{I}(x,y) = G(x,y,\sigma) * I(x,y)$$

- Compute gradient magnitude and orientation using finite differences:

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

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

- Create histogram of gradient directions, within a region around the keypoint, at selected scale:



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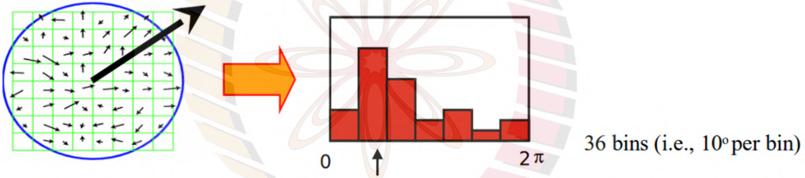

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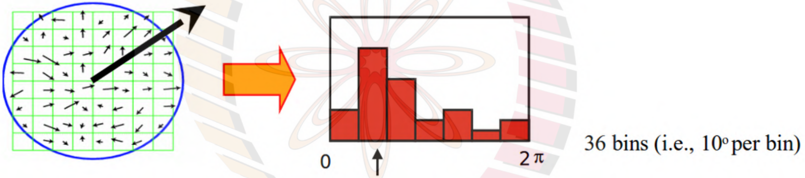

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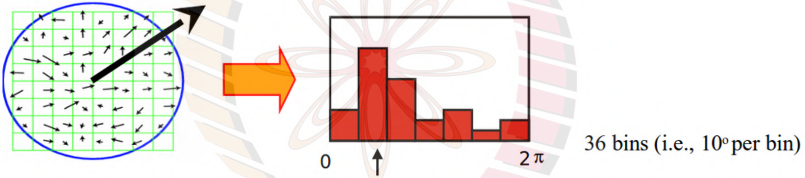
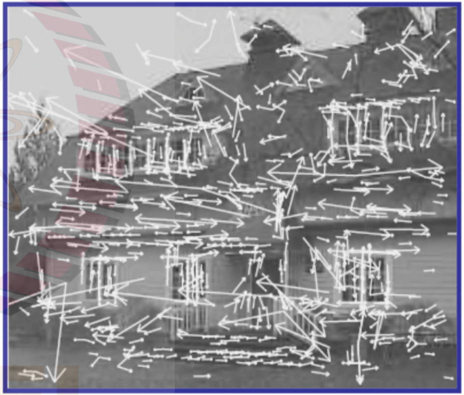


- Histogram entries are weighted by:
  - gradient magnitude, and
  - a Gaussian function with σ equal to 1.5 times scale of the keypoint
- Select **the peak as direction of keypoint**
- Introduce additional key points at same location if another peak is within 80% of max peak of histogram with different direction

Credit: Svetlana Lazebnik, UIUC

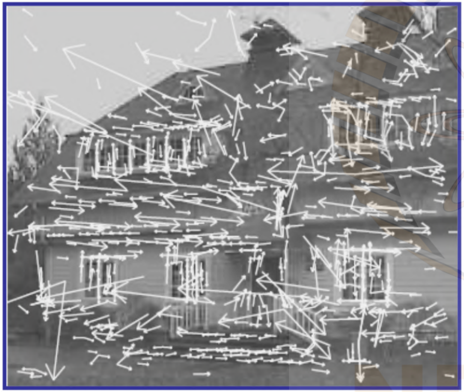
SIFT



From 233x189 original image to 832 DoG Extrema

Credit: Mubarak Shah, University of Central Florida

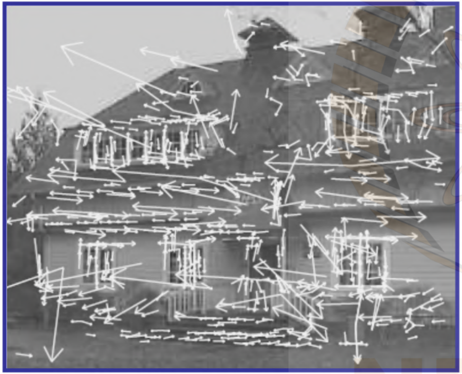
SIFT



From 832 DoG Extrema to 729 keypoints after low contrast threshold

Credit: Mubarak Shah, University of Central Florida

SIFT

From 729 keypoints to 536 keypoints after testing ratio based on Hessian

Credit: Mubarak Shah, University of Central Florida

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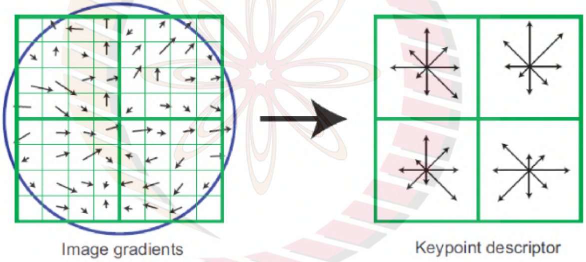
- Compute gradient at each pixel in a 16×16 window around the detected keypoint, using the appropriate leve as detected.



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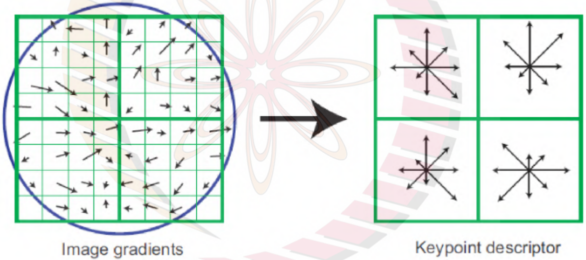

- Downweight gradients by a Gaussian fall-off function (blue circle) to reduce the influence of gradients far from the center.

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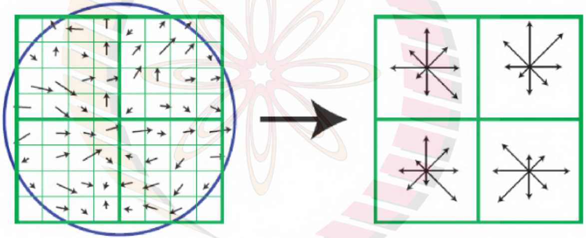


Image gradients

Keypoint descriptor

- Downweight gradients by a Gaussian fall-off function (blue circle) to reduce the influence of gradients far from the center.
- In each 4×4 quadrant, compute a gradient orientation histogram using 8 orientation histogram bins.

Credit: Raquel Urtasun, Szeliski

SIFT: Keypoint Descriptor

- The resulting 128 non-negative values form a raw version of the SIFT descriptor vector.
- To reduce the effects of contrast or gain (additive variations are already removed by the gradient), the 128-D vector is normalized to unit length.
- To further make the descriptor robust to other photometric variations, values are clipped to 0.2 and the resulting vector is once again renormalized to unit length.

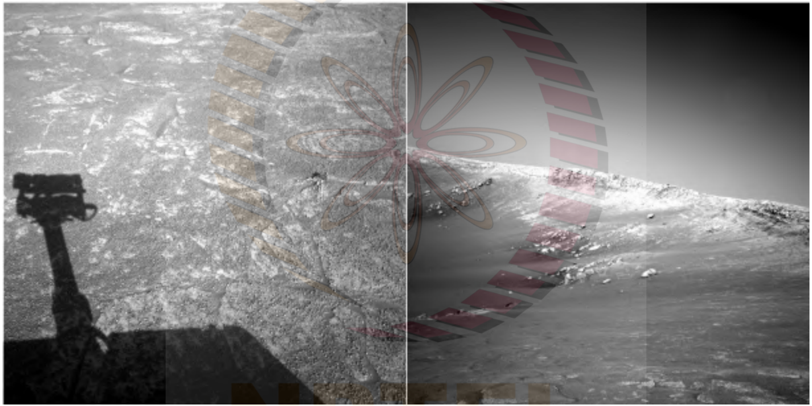
Credit: Raquel Urtasun, Szeliski

SIFT

- Extraordinarily robust feature detection
- Changes in viewpoint: up to about 60 degree out of plane rotation
- Changes in illumination: sometimes even day vs night (below)
- Fast and efficient – can run in real-time

Credit: Raquel Urtasun, Szeliski

SIFT: Example



Mars Rover images

Credit: Raquel Urtasun, N Snavely

SIFT: Example

Maybe, look for tiny squares. . . ?

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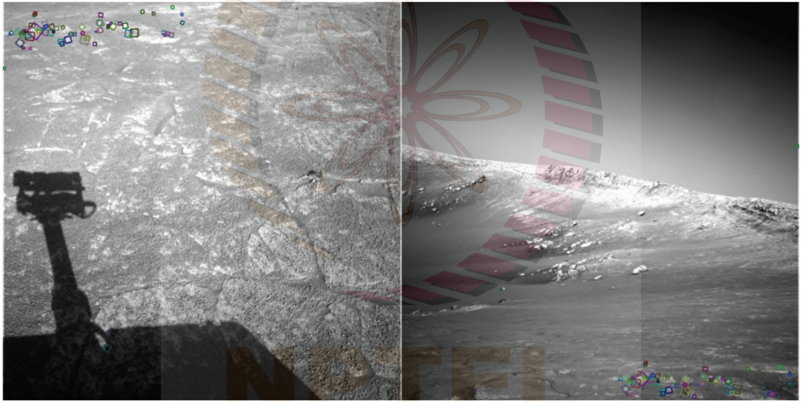

Mars Rover images with SIFT feature matches

Credit: Raquel Urtasun, N Snavely

SIFT: Invariances(Geometric Transformations)

e.g. scale, translation, rotation

Credit: Raquel Urtasun, Tinne Tuytelaars

SIFT: Invariances(Photometric Transformations)

Credit: Raquel Urtasun, Tinne Tuytelaars

SIFT Applications: Image Stitching

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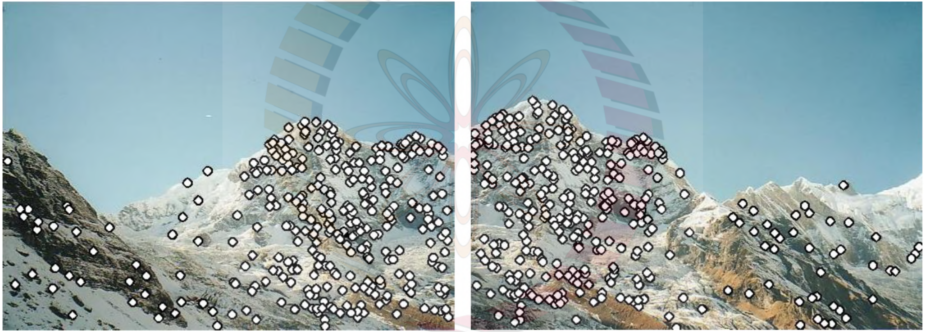
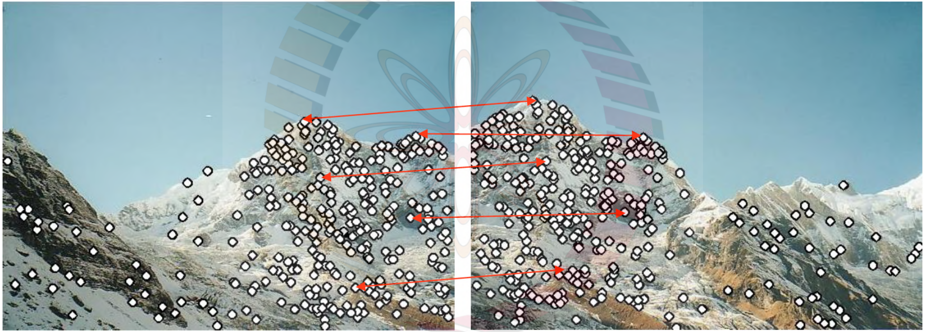


- Detect feature points in both images.

SIFT Applications: Image Stitching



- Detect feature points in both images.
- Find corresponding pairs of feature points.

SIFT Applications: Image Stitching

- Detect feature points in both images.
- Find corresponding pairs of feature points.
- Use the pairs the align the images.

Credit: Raquel Urtasun

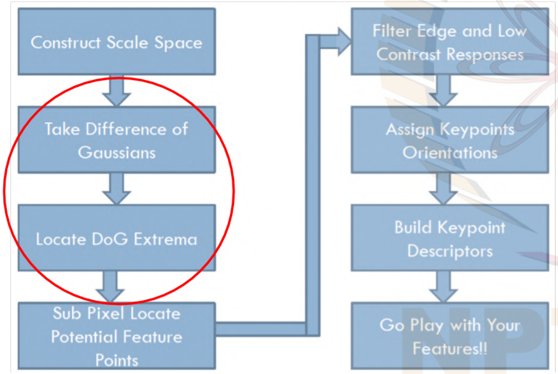
More Resources

If you want to learn more on SIFT

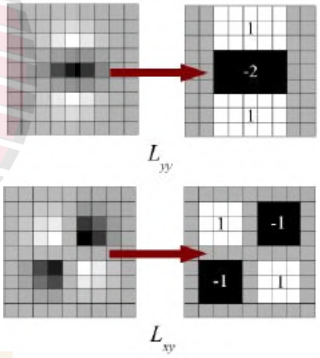
- The SIFT Keypoint Detector by David Lowe
- Tutorial: SIFT (Scale-invariant feature transform)
- OpenCV-Python Tutorials: Introduction to SIFT
- Wikipedia: Scale-invariant feature transform
- OpenSIFT: An Open-Source SIFT Library

SURF: Speeded Up Robust Features

SIFT

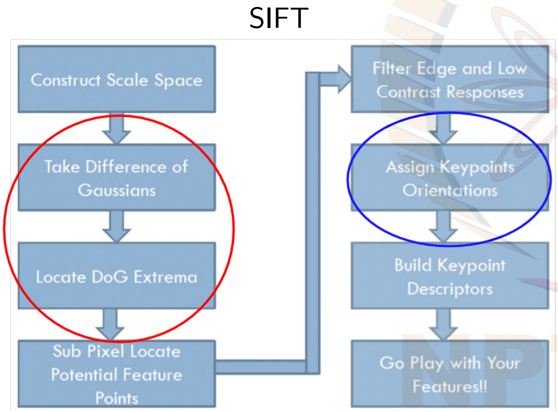


- Uses box filters instead of Gaussians to approximate Laplacians



- Uses Haar wavelets to get keypoint orientations

SURF: Speeded Up Robust Features

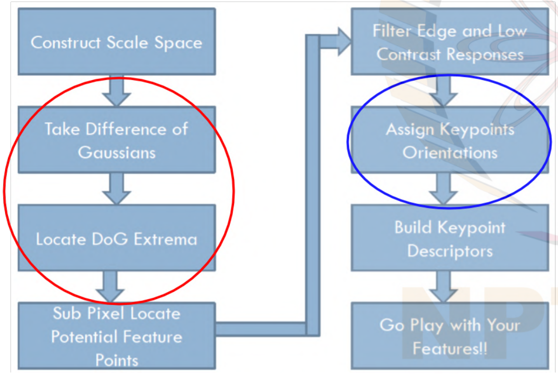


- Uses box filters instead of Gaussians to approximate Laplacians
- Uses Haar wavelets to get keypoint orientations
  - Haar wavelets are simple filters which can be used to find gradients in the x and y directions

- SURF is good at handling blur and rotation variations
- SURF is not as good as SIFT on

SURF: Speeded Up Robust Features

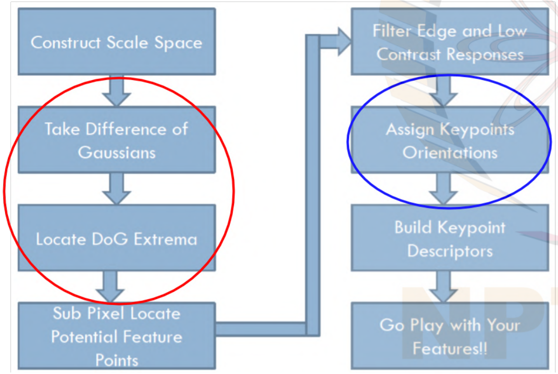
SIFT



- Uses box filters instead of Gaussians to approximate Laplacians
- Uses Haar wavelets to get keypoint orientations
- SURF is good at handling blur and rotation variations
- SURF is not as good as SIFT on invariance to illumination and viewpoint changes
- SURF is ~ 3 times faster than SIFT

SURF: Speeded Up Robust Features

SIFT



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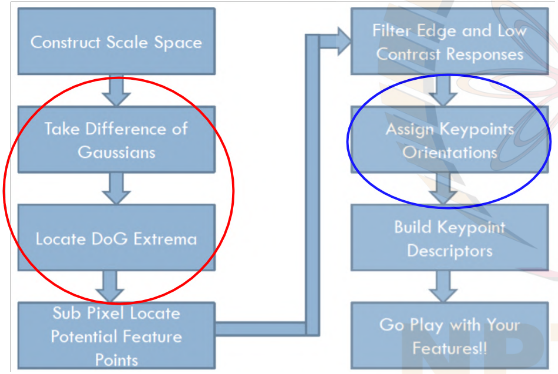

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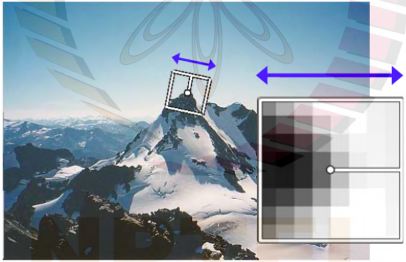
For more information:

- https://medium.com/data-breach/introduction-to-surf-speeded-up-robust-features-c7396d6e7c4e
- http://www.vision.ee.ethz.ch/~surf/

MOPS: Making Descriptor Rotation-invariant

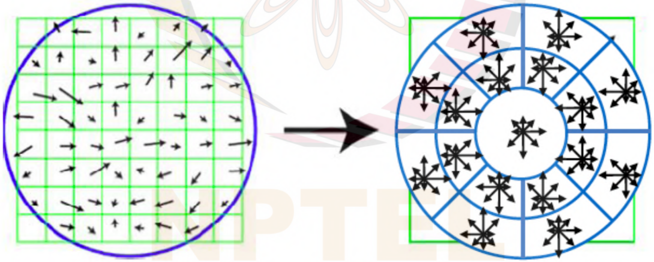
- **M**ultiscale **O**riented **P**atche**S** descriptor
- Rotate patch according to its dominant gradient orientation.
- This puts the patches into a canonical orientation



Credit: Matthew Brown, Kristen Grauman, Raquel Urtasun

Gradient Location-Orientation Histogram (GLOH)

- Variant of SIFT that uses a log-polar binning structure instead of four quadrants.
- Uses 17 spatial bins and 16 orientation bins.
- The 272D histogram is then projected onto a 128D descriptor using PCA trained on a large dataset.



Credit: Matthew Brown, Kristen Grauman, Raquel Urtasun

Homework

Readings

- Section 3.5, Szeliski, *Computer Vision: Algorithms and Applications*
- For more information on SURF:
  - OpenCV-Python Tutorials : Introduction to SURF
  - Wikipedia: Speeded up robust features
- Multi-Scale Oriented Patches
- Other links provided on respective slides

Questions

- Which descriptor performs better? SIFT or MOPS?
- Why is SIFT descriptor better than Harris Corner Detector?

References

- David G. Lowe. "Distinctive Image Features from Scale-Invariant Keypoints". In: *Int. J. Comput. Vision* 60.2 (Nov. 2004), 91–110.
- Richard Szeliski. *Computer Vision: Algorithms and Applications*. Texts in Computer Science. London: Springer-Verlag, 2011.
- David Forsyth and Jean Ponce. *Computer Vision: A Modern Approach*. 2 edition. Boston: Pearson Education India, 2015.
- *Lazebnik, Svetlana, CS 543 Computer Vision (Spring 2019)*. URL: https://slazebni.cs.illinois.edu/spring19/ (visited on 06/01/2020).
- *Shah, Mubarak, CAP 5415 - Computer Vision (Fall 2014)*. URL: https://www.crcv.ucf.edu/courses/cap5415-fall-2014/ (visited on 06/01/2020).
- *Urtasun, Raquel, Computer Vision (Winter 2013)*. URL: https://www.cs.toronto.edu/~urtasun/courses/CV/cv.html (visited on 06/01/2020).