SIFT: SCALE INVARIANT FEATURE TRANSFORM BY DAVID LOWE

Overview

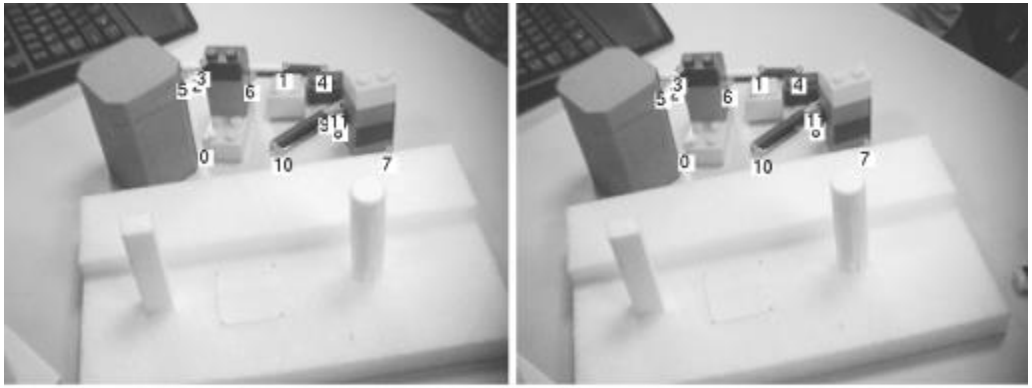
- Motivation of Work
- Overview of Algorithm
- Scale Space and Difference of Gaussian
- Keypoint Localization
- Orientation Assignment
- Descriptor Building
- Application

Motivation of Work

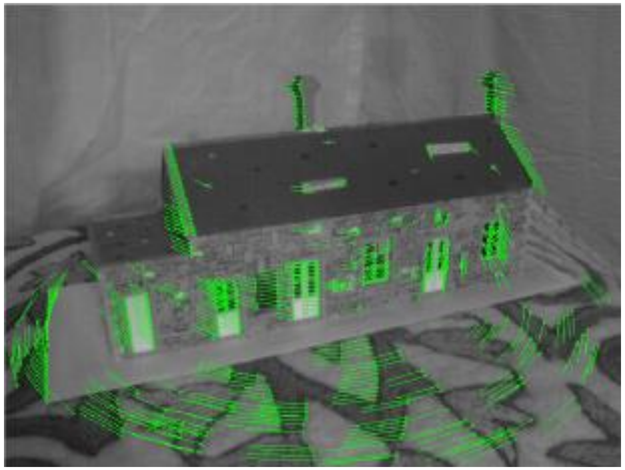
- Image Matching
- Correspondence Problem
- Desirable Feature Characteristics
- Scale Invariance
- Rotation Invariance
- Illumination invariance
- Viewpoint invariance

Why do we care about matching features?

- Object Recognition
- Tracking/SFM



(a) (b)



We want invariance!!!

- Good features should be robust to all sorts of nastiness that can occur between images.

Types of invariance

- Illumination

Types of invariance

- Illumination
- Scale

Types of invariance

- Illumination
- Scale
- Rotation

Types of invariance

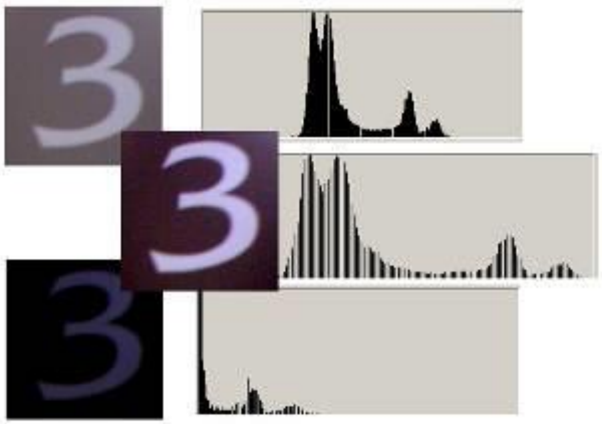
- Illumination
- Scale
- Rotation
- Affine

Types of invariance

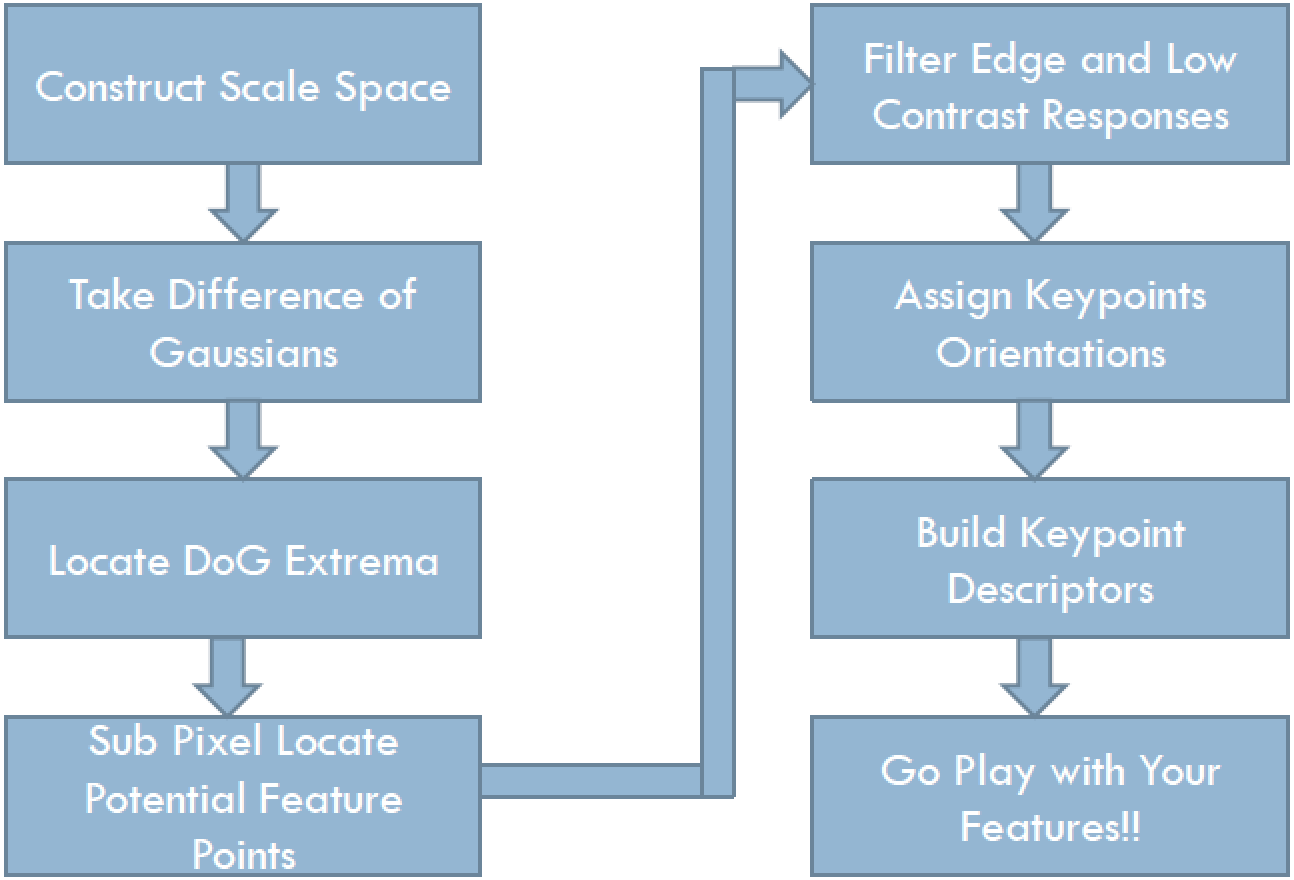
- Illumination
- Scale
- Rotation
- Affine
- Full Perspective

How to achieve illumination invariance

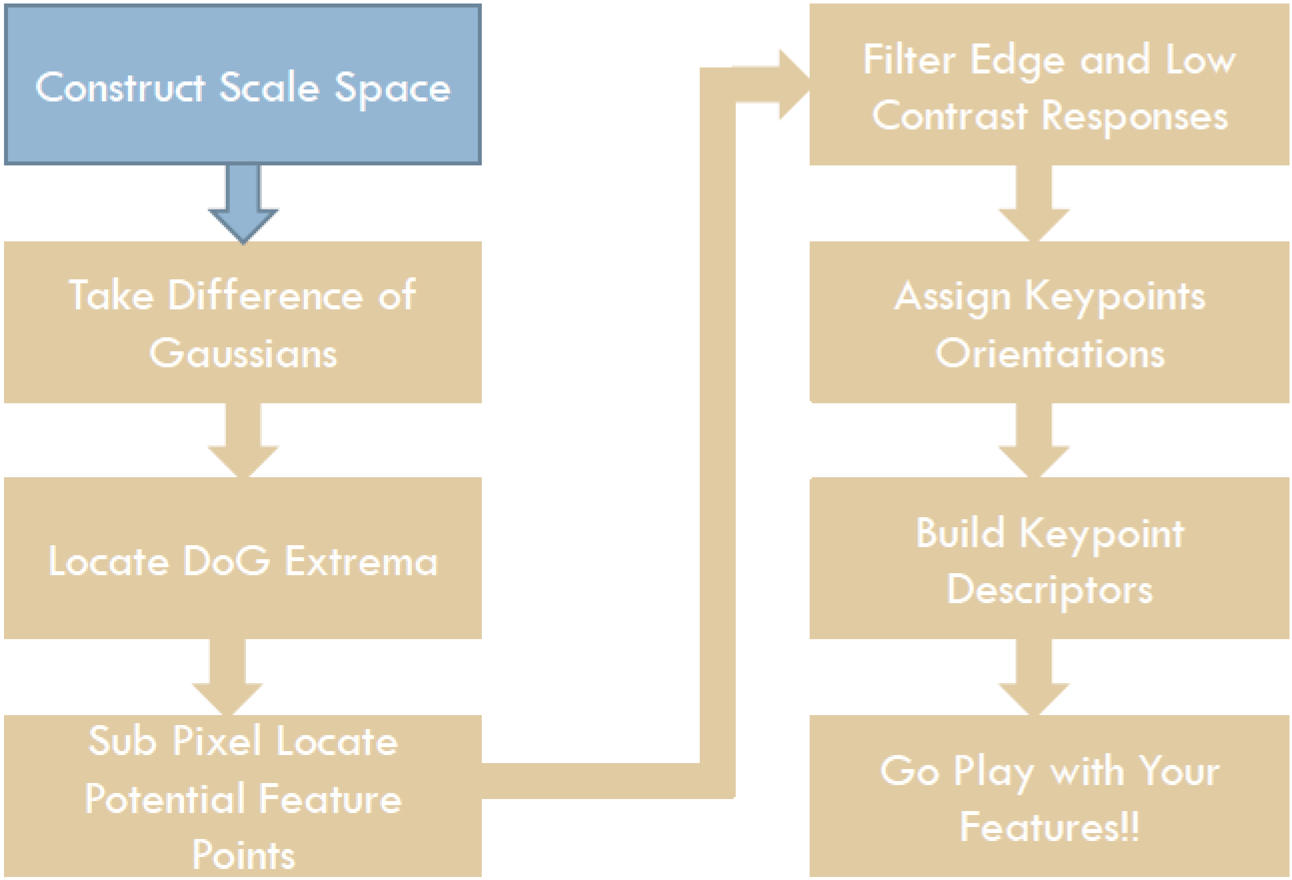
- The easy way (normalized)
- Difference based metrics (random tree, Haar, and sift)



Algorithm Overview



Constructing Scale Space

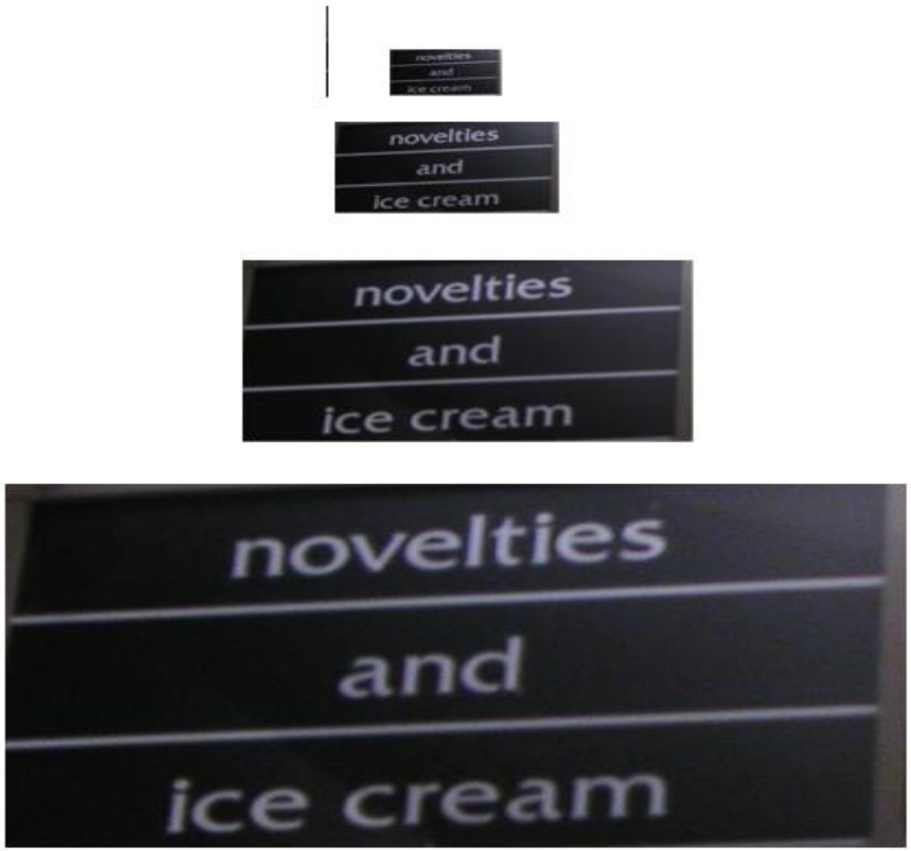


How to achieve scale invariance

- Pyramids
  - Divide width and height by 2
  - Take average of 4 pixels for each pixel (or Gaussian blur)
  - Repeat until image is tiny
  - Run filter over each size image and hope its robust

- Scale Space (DOG method)

Pyramids


novelties
and
ice cream
novelties
and
ice cream
novelties
and
ice cream

How to achieve scale invariance

- Pyramids
- Scale Space (DOG method)
  - Like having a nice linear scaling without the expense
  - Take features from differences of these images
  - If the feature is repeatably present in between Difference of Gaussians it is Scale Invariant and we should keep it.

Constructing Scale Space

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

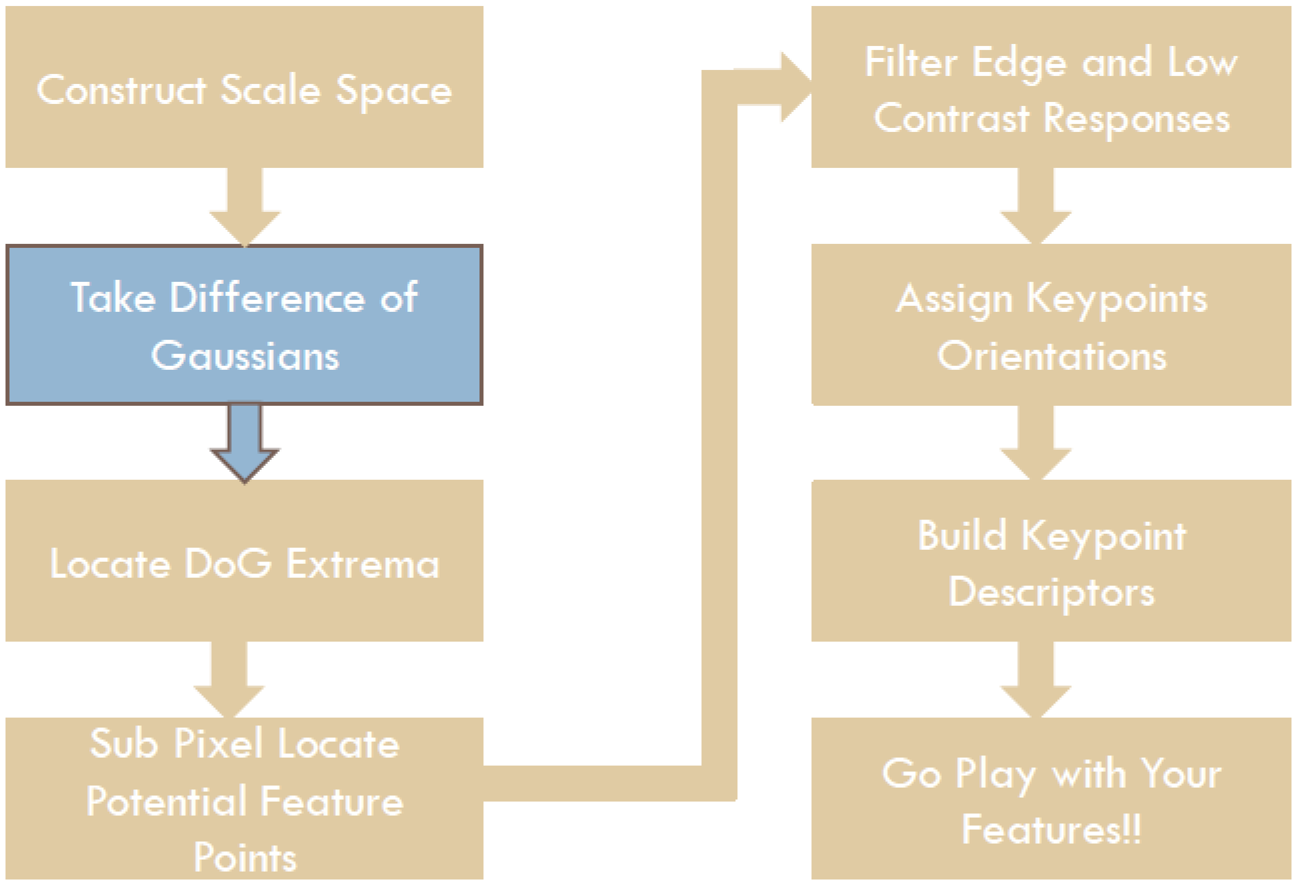
$$L(x, y, \sigma) = G(x, y, \sigma) * I(x, y),$$

where

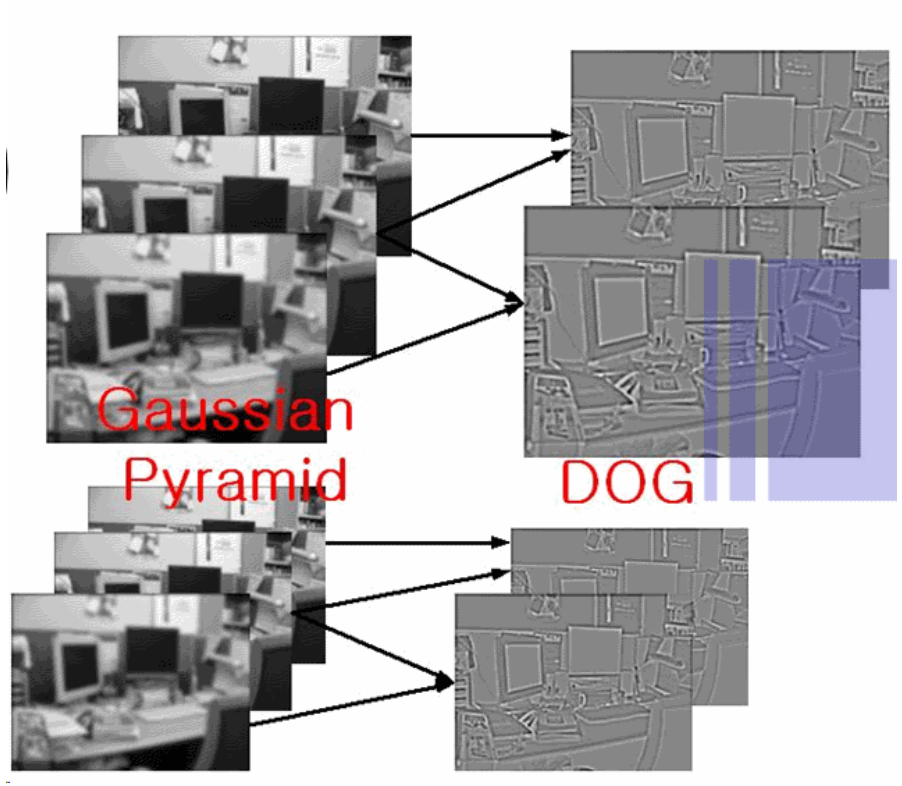
$$G(x, y, \sigma) = \frac{1}{2\pi\sigma^2} e^{-(x^2+y^2)/2\sigma^2}.$$

Laplacian of Gaussians

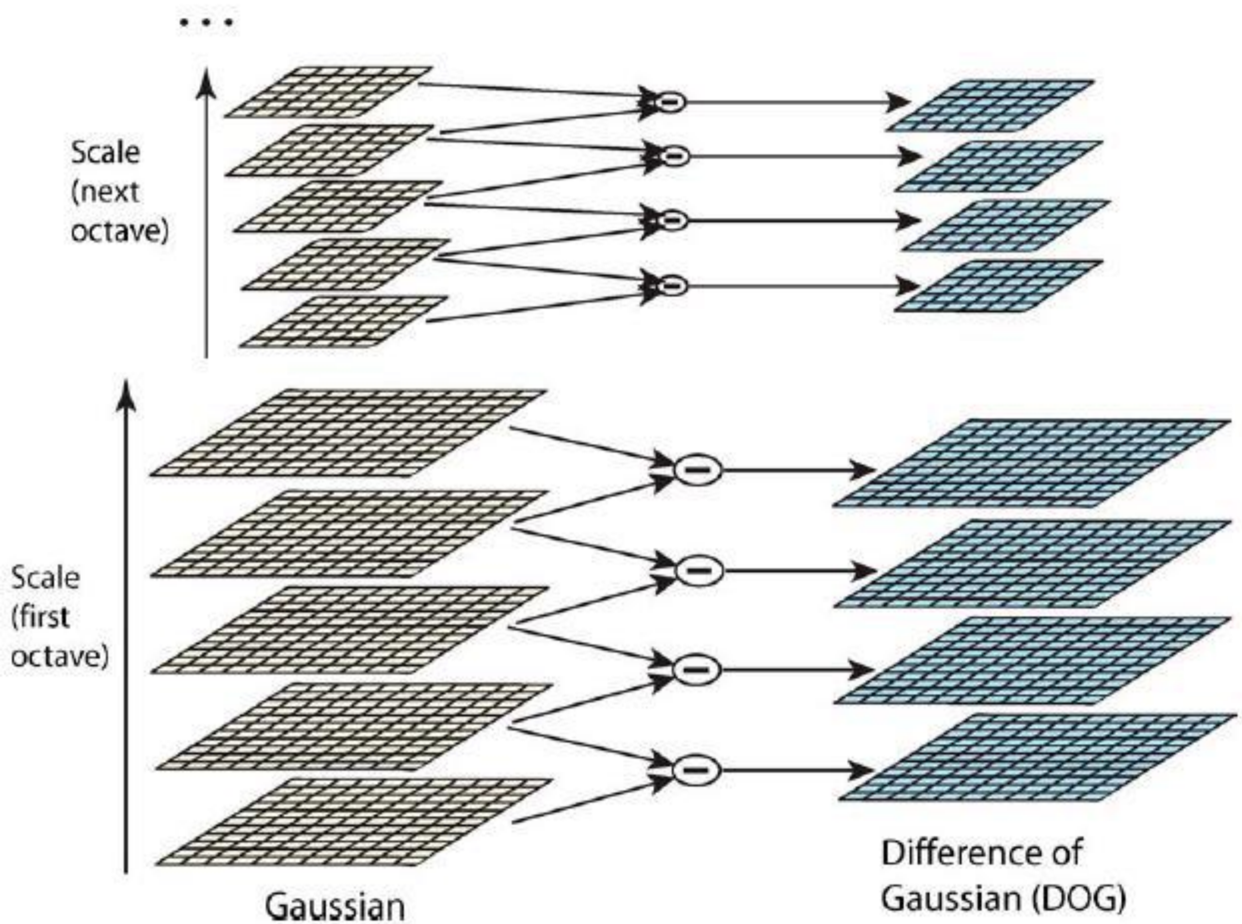
- LoG - σ2Δ2G
- Extrema Useful
  - Found to be stable features
  - Gives Excellent notion of scale
- Calculation costly so instead….


Construct Scale Space
Take Difference of Gaussians
Locate DoG Extrema
Sub Pixel Locate Potential Feature Points
Filter Edge and Low Contrast Responses
Assign Keypoints Orientations
Build Keypoint Descriptors
Go Play with Your Features!!

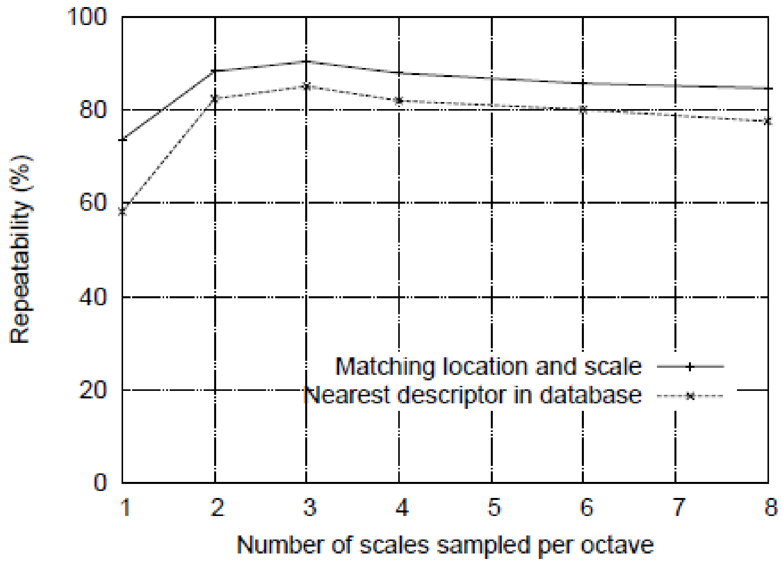
Differences Of Gaussians

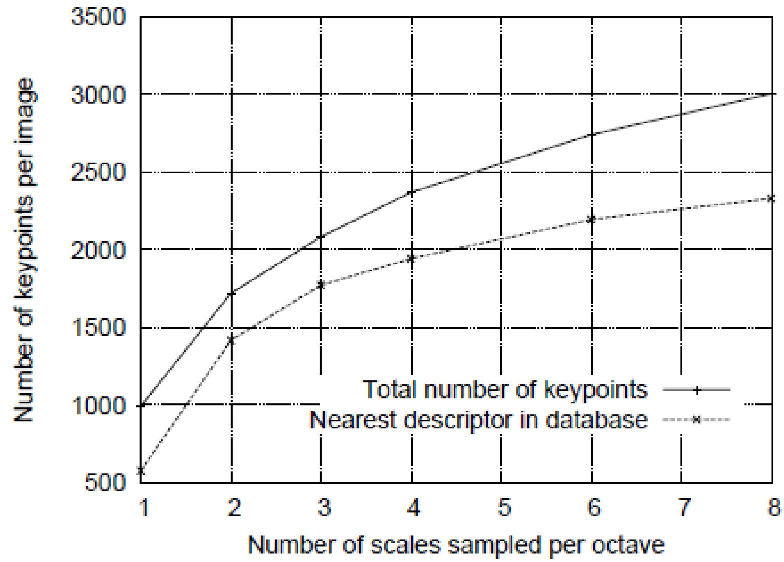


DoG Pyramid

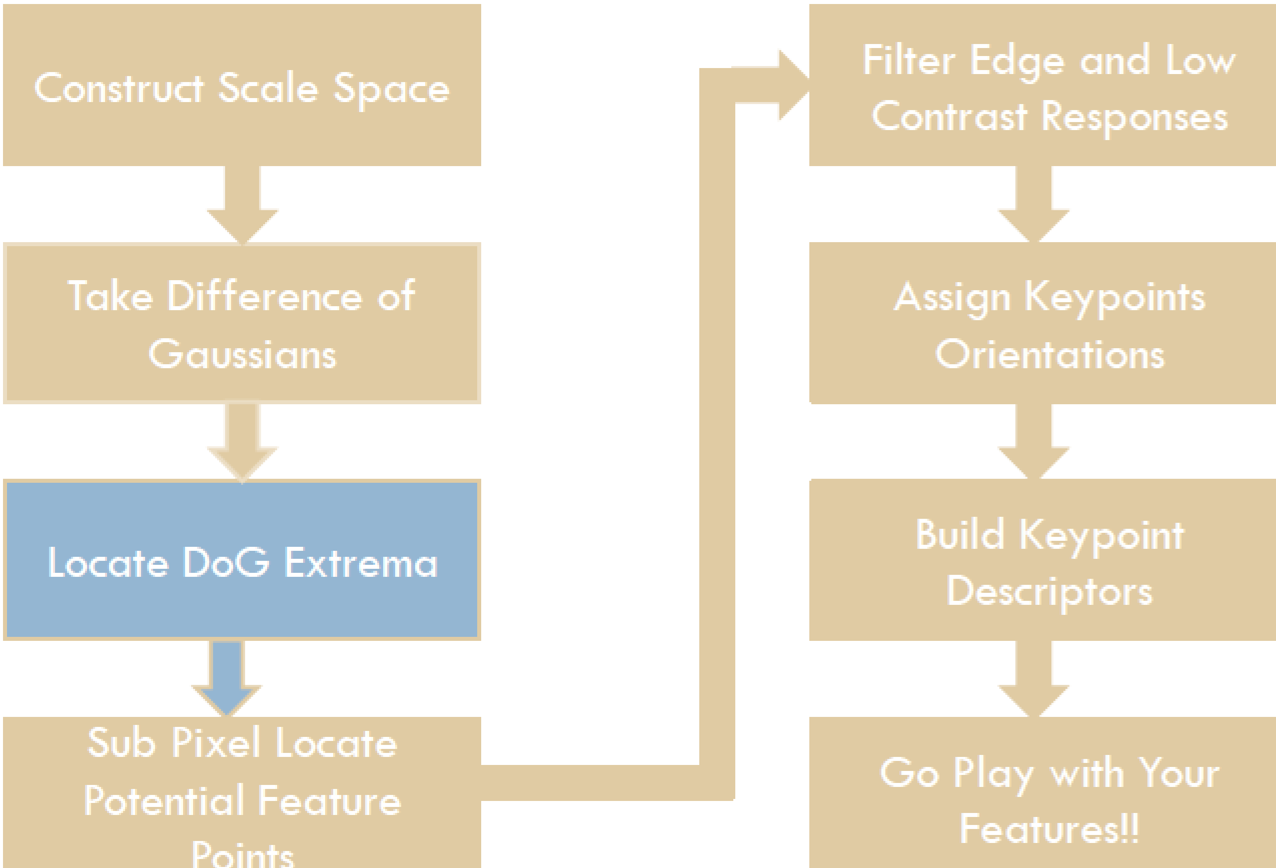


. . .
Scale
(next
octave)
Scale
(first
octave)
Gaussian
Difference of
Gaussian (DOG)





- The top line of the first graph shows the percent of keypoints that are repeatably detected at the same location and scale in a transformed image as a function of the number of scales sampled per octave. The lower line shows the percent of keypoints that have their descriptors correctly matched to a large database. The second graph shows the total number of keypoints detected in a typical image as a function of the number of scale samples.



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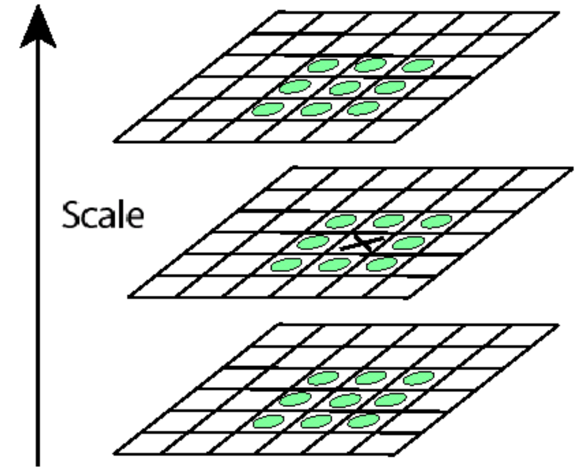
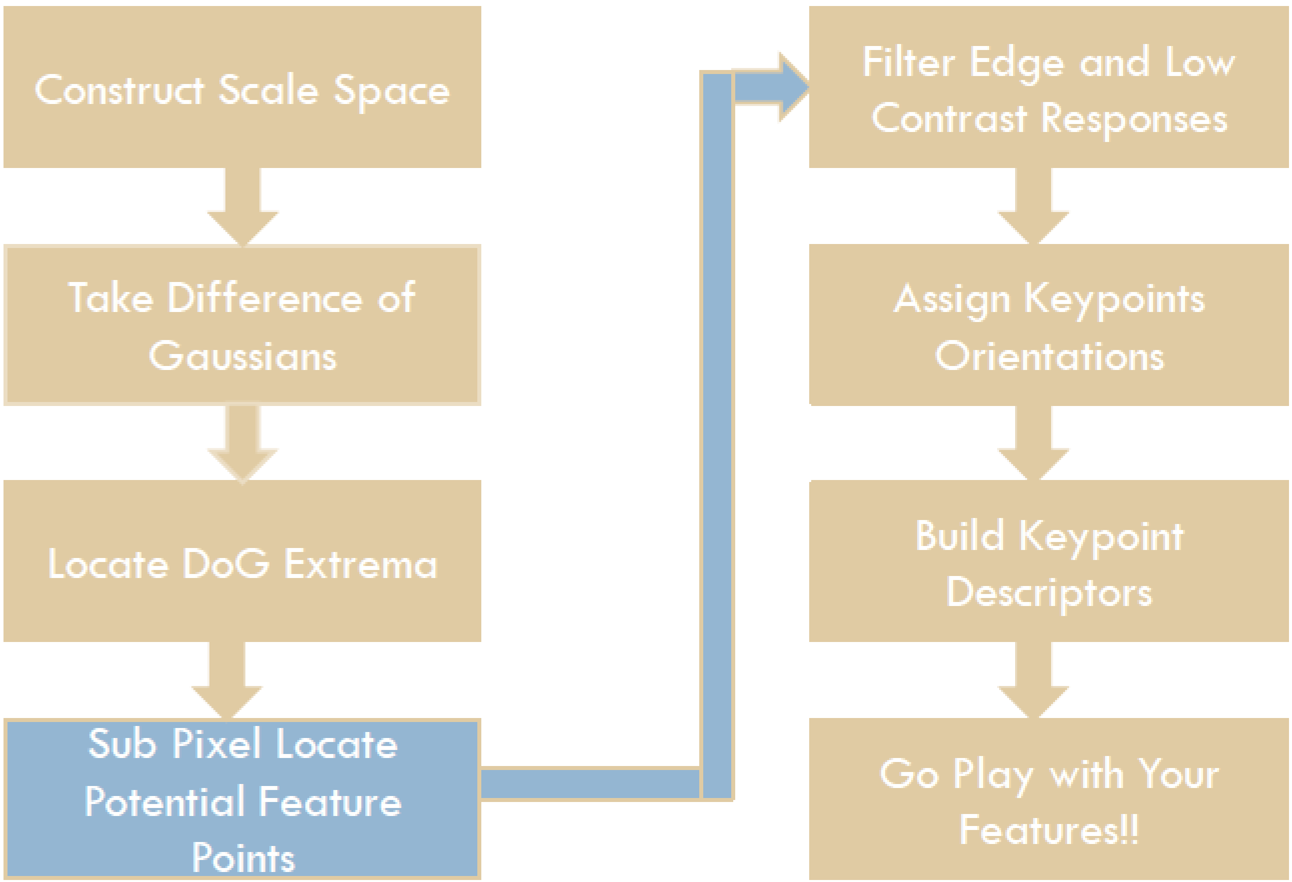
Locate the Extrema of the DoG

- Scan each DOG image
- Look at all neighboring points (including scale)
- Identify Min and Max



Sub pixel Localization



Sub pixel Localization

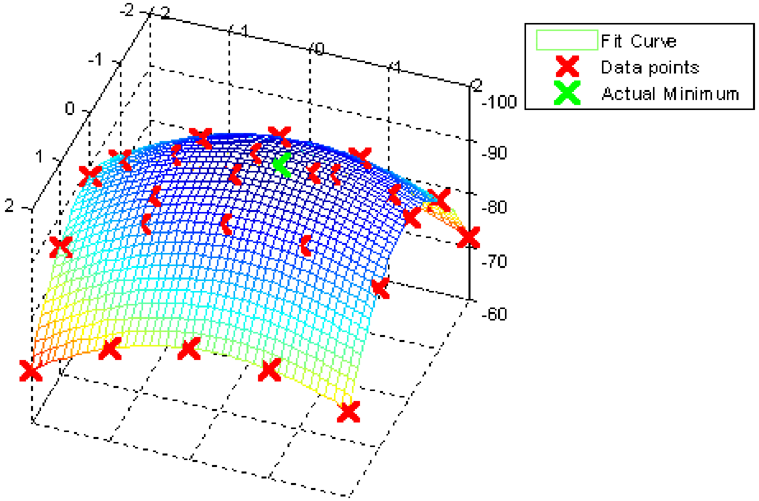
- 3D Curve Fitting
- Taylor Series Expansion

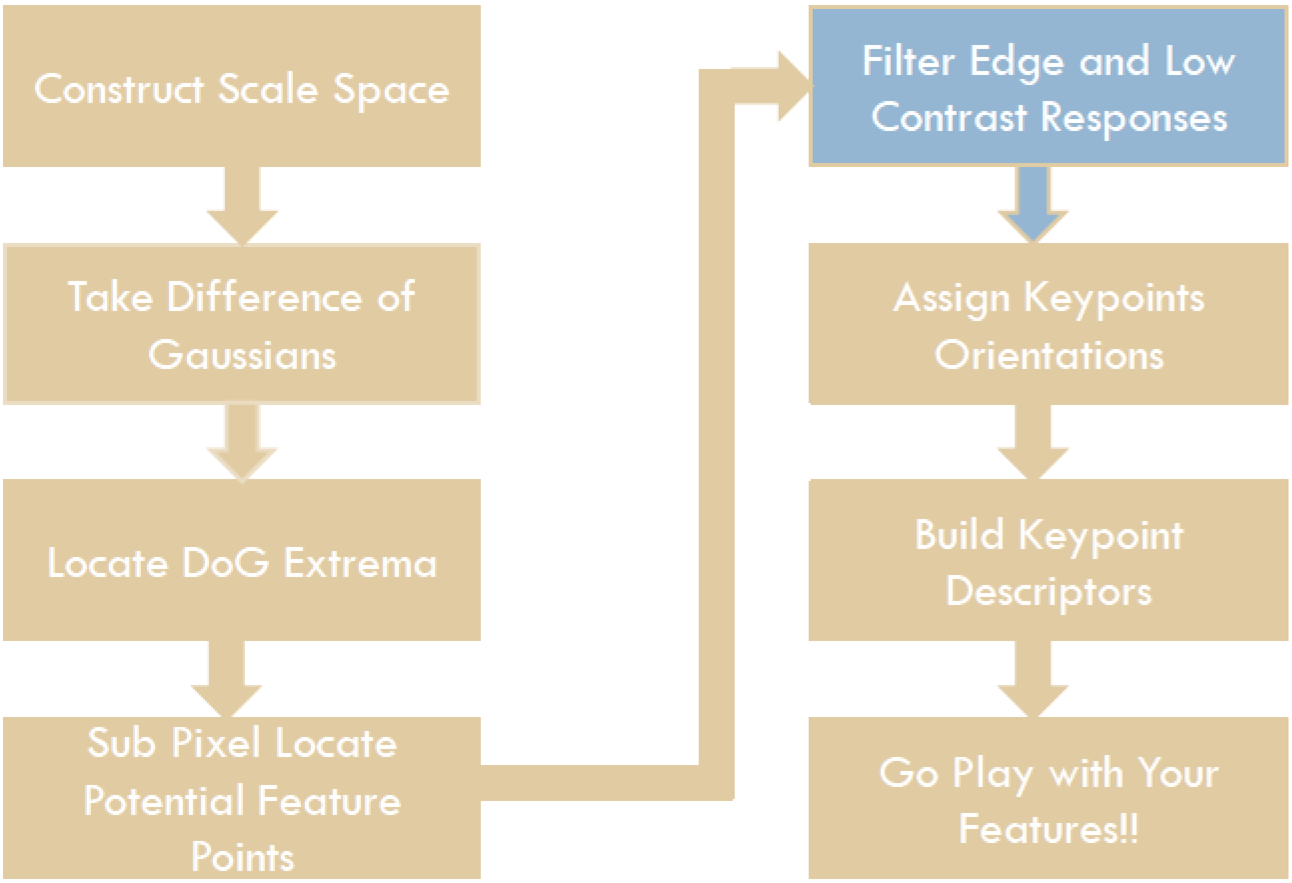
$$D(\mathbf{x}) = D + \frac{\partial D}{\partial \mathbf{x}}^T \mathbf{x} + \frac{1}{2}\mathbf{x}^T \frac{\partial^2 D}{\partial \mathbf{x}^2}\mathbf{x}$$

- Differentiate and set to 0

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

- to get location in terms of (x,y,σ)

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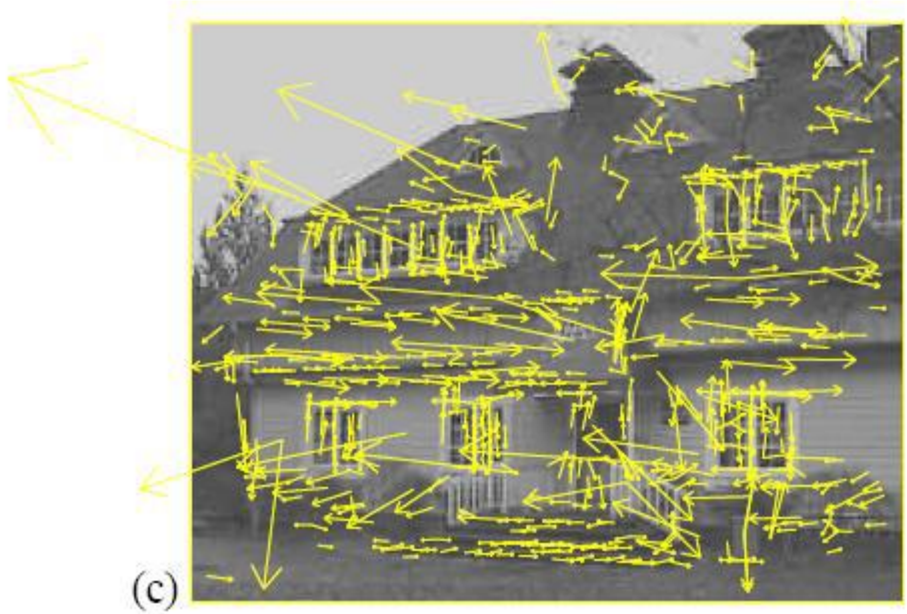
Filter Low Contrast Points

- Low Contrast Points Filter
- Use Scale Space value at previously found location

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

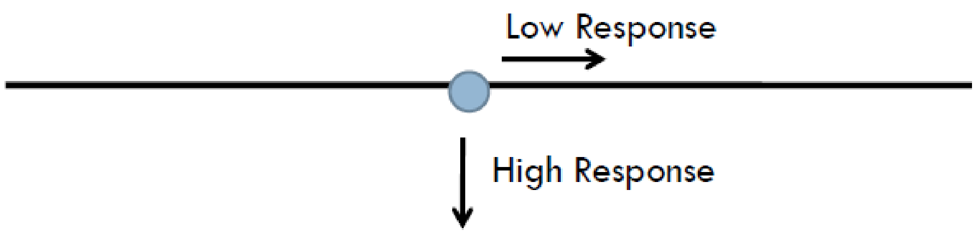
The House With Contrast Elimination



(c)

Edge Response Elimination

- Peak has high response along edge, poor other direction

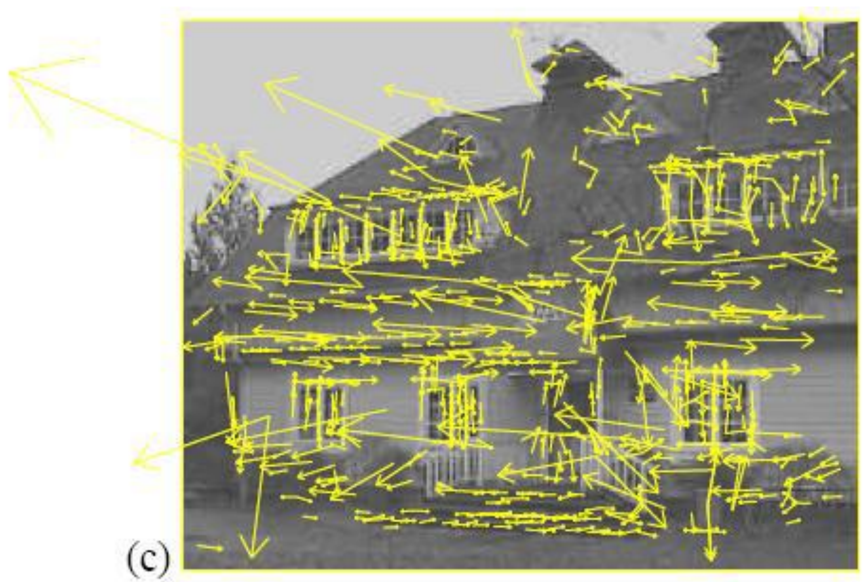


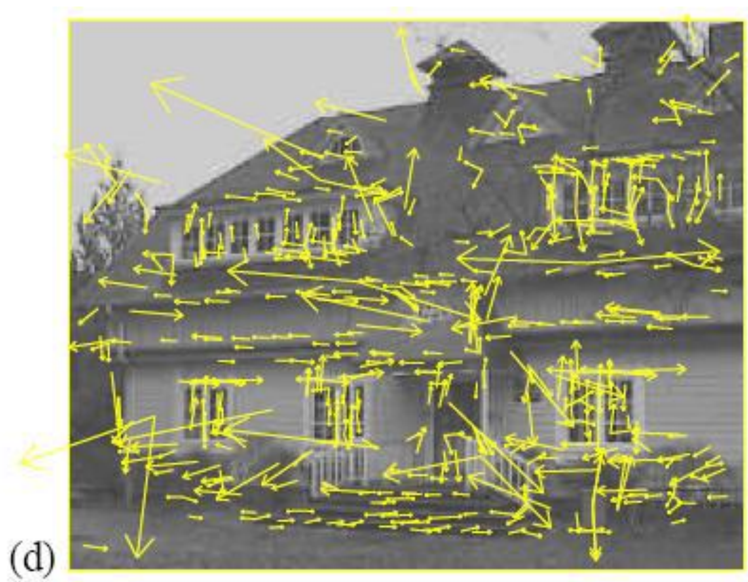
- A poorly defined peak in the difference-of-Gaussian function will have a large principal curvature across the edge but a small one in the perpendicular direction. The principal curvatures can be computed from a 2x2 Hessian matrix
- Use Hessian
  - Eigenvalues Proportional to principle Curvatures
  - Use Trace and Determinant

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

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

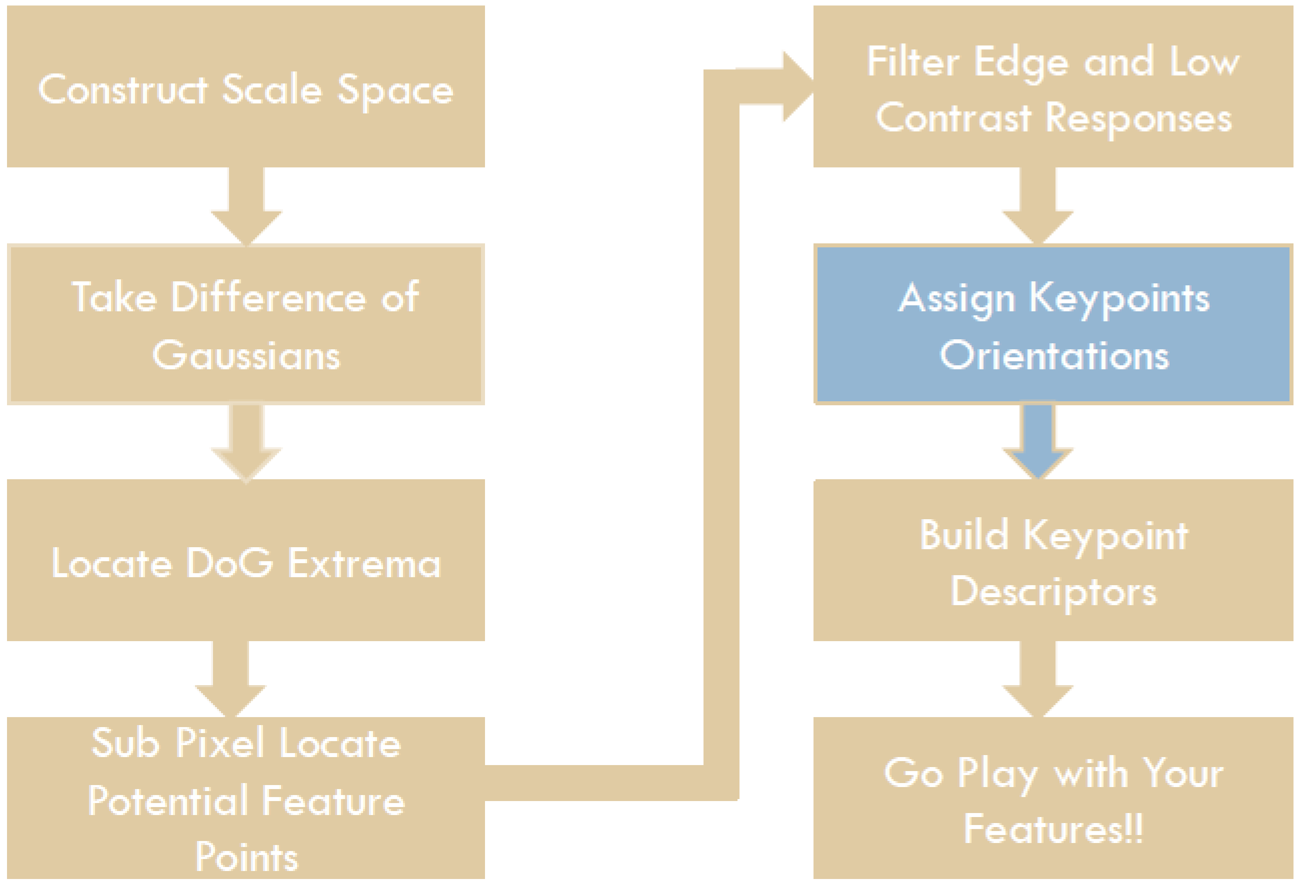
Results On The House





Apply Contrast Limit

Apply Contrast and Edge Response Elimination



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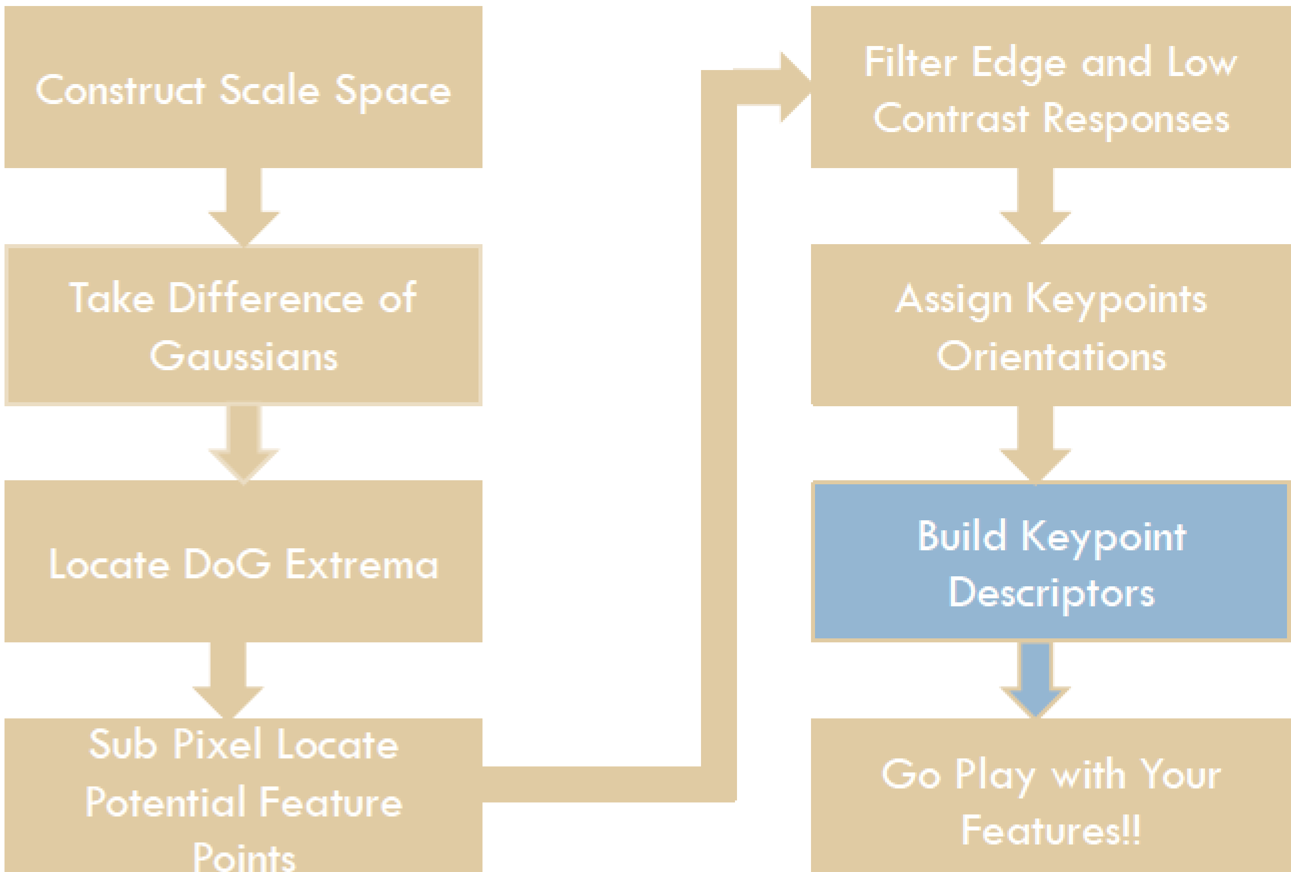
Orientation Assignment

- Compute Gradient for each blurred image

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

- For region around keypoint
  - Create Histogram with 36 bins for orientation
  - Weight each point with Gaussian window of 1.5σ
  - Create keypoint for all peaks with value>=.8 max bin



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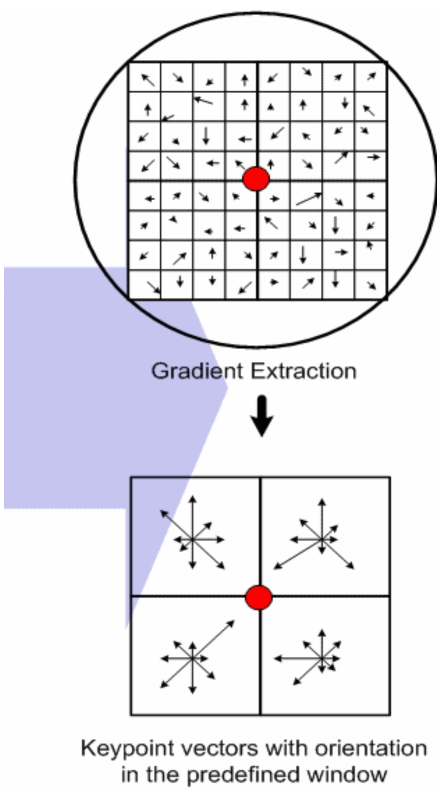
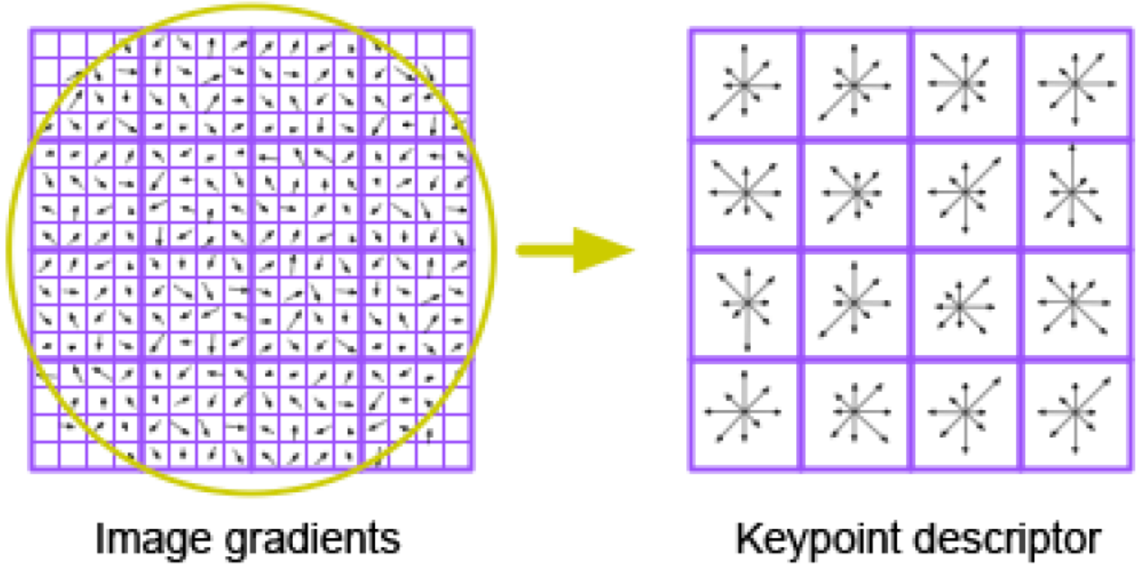
Building the Descriptor

- Find the blurred image of closest scale
- Sample the points around the keypoint
- Rotate the gradients and coordinates by the previously computer orientation
- Separate the region in to sub regions
- Create histogram for each sub region with 8 bins
  - Weight the samples with $N(\sigma) = 1.5$ Region width



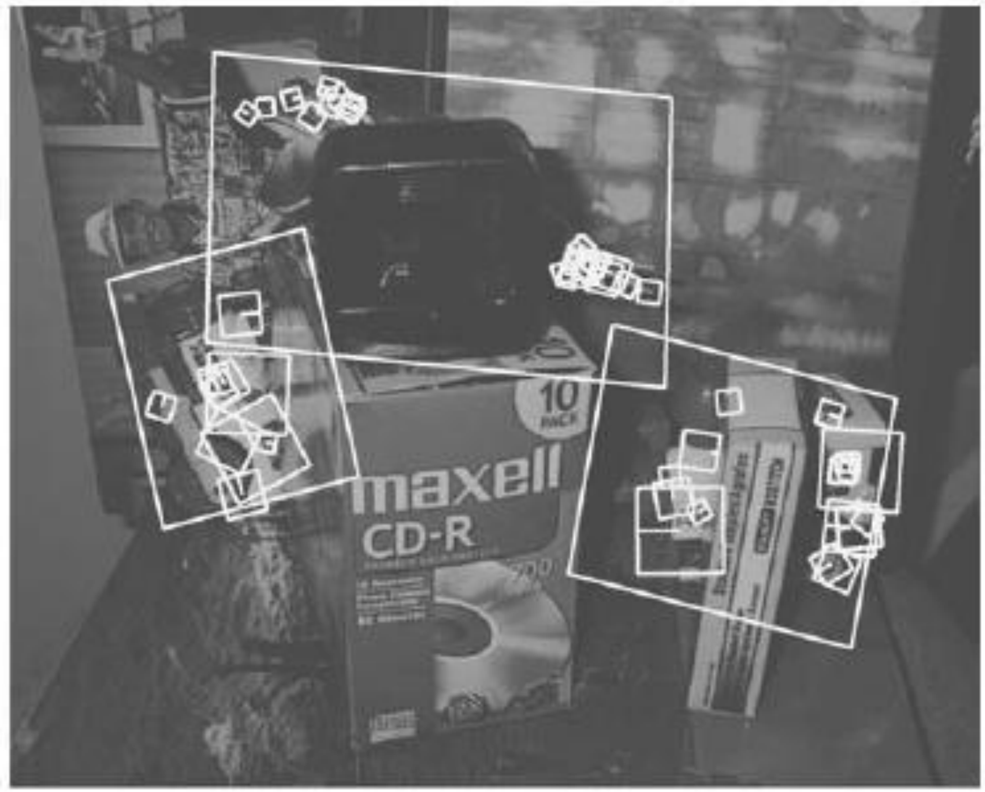


Actual implementation uses 4x4 descriptors from 16x16 which leads to a 4x4x8=128 element vector

Results check

- Scale Invariance
- Scale Space usage –Check
- Rotation Invariance
- Align with largest gradient –Check
- Illumination Invariance
- Normalization –Check
- Viewpoint Invariance
- For small viewpoint changes –Check (mostly)

Results



Results

Questions?

Credits

- Lowe, D. "Distinctive image features from scale-invariant keypoints" International Journal of Computer Vision, 60, 2 (2004), pp. 91-110
- Pele, Ofir. SIFT: Scale Invariant Feature Transform. Sift.ppt
- Lee, David. Object Recognition from Local Scale-Invariant Features (SIFT). O319.Sift.ppt