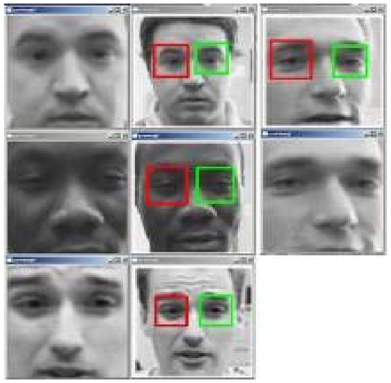
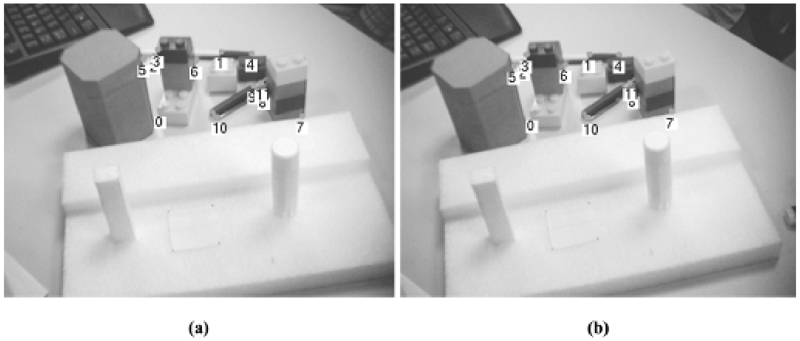
Scale Invariant Feature Transform (SIFT)

Why do we care about matching features?

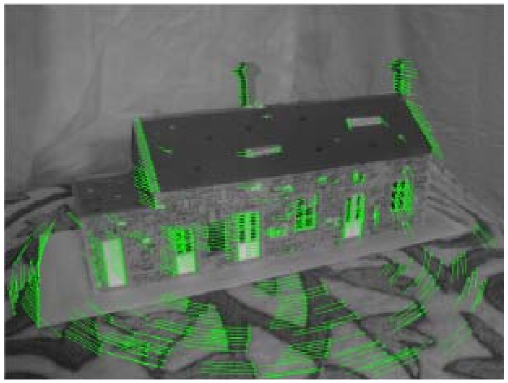
- Camera calibration
- Stereo
- Tracking/SFM
- Image moiaicing
- Object/activity Recognition
- …





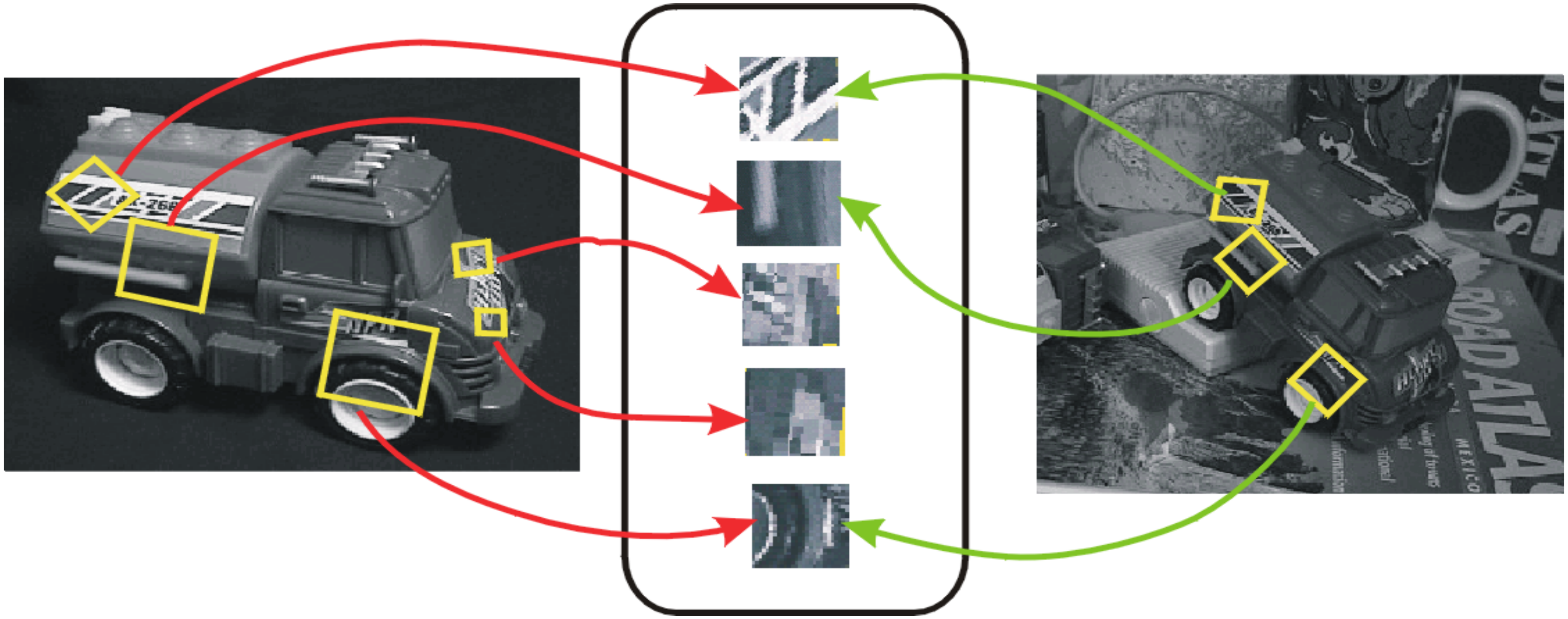
(a)

(b)

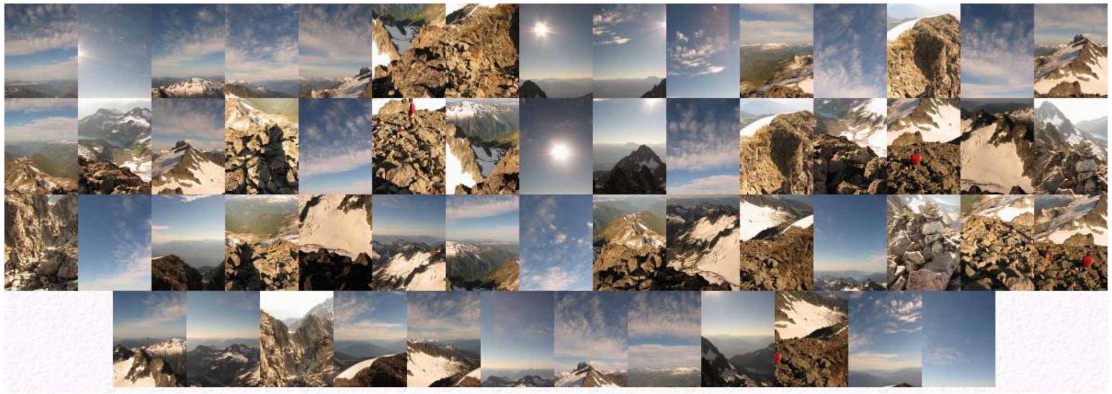


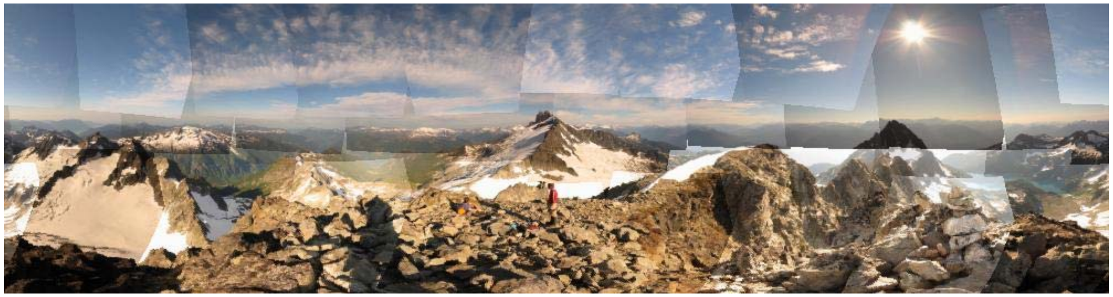
Objection representation and recognition

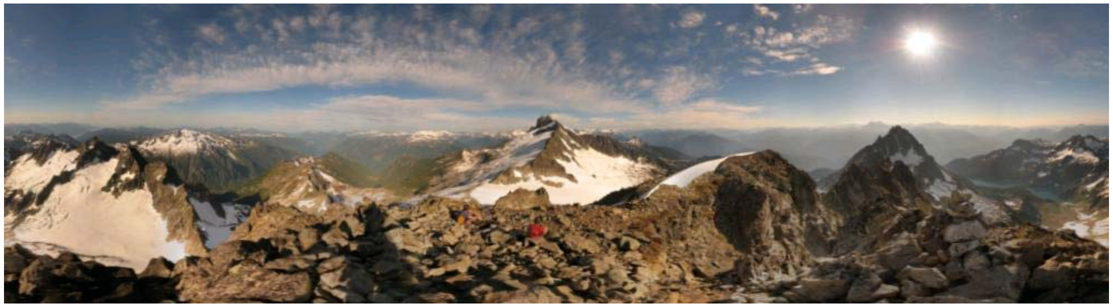
- Image content is transformed into local feature coordinates that are invariant to translation, rotation, scale, and other imaging parameters



- Automatic Mosaicing
- http://www.cs.ubc.ca/~mbrown/autostitch/autostitch.html





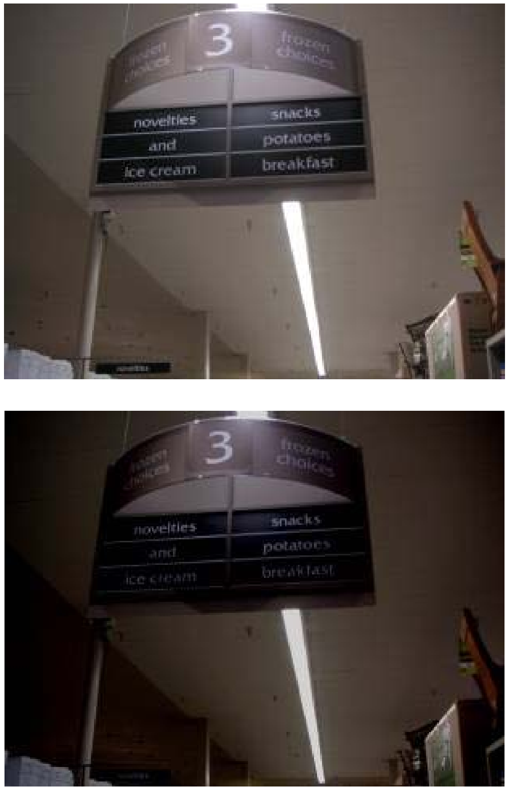


We want invariance!!!

- To illumination
- To scale
- To rotation
- To affine
- To perspective projection

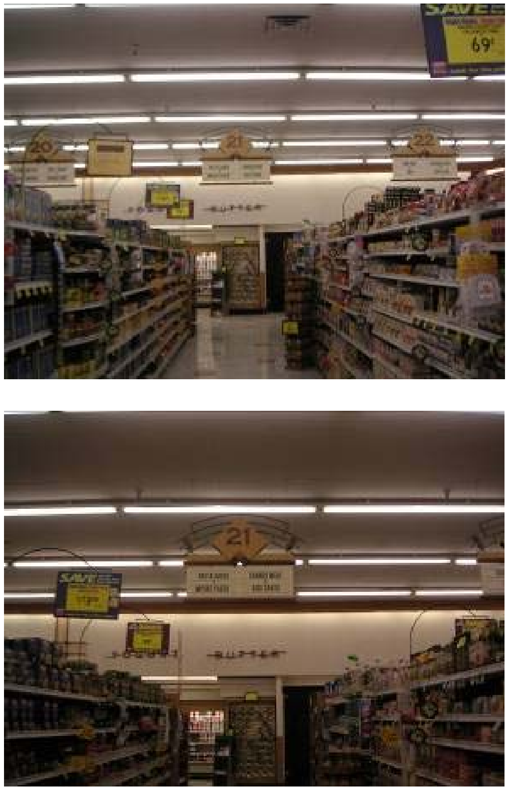
Types of invariance

- Illumination



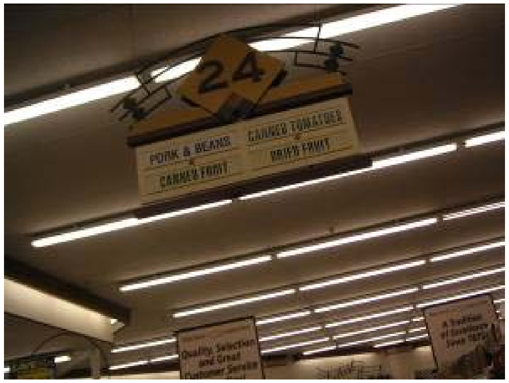
Types of invariance

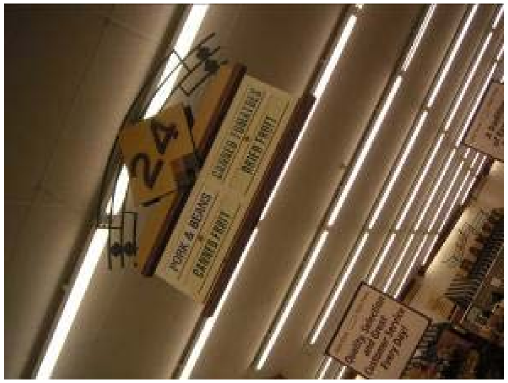
- Illumination
- Scale



Types of invariance

- Illumination
- Scale
- Rotation



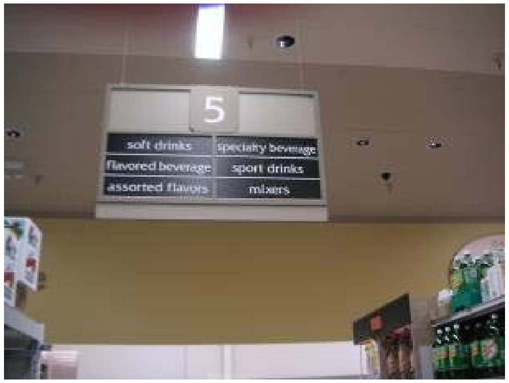


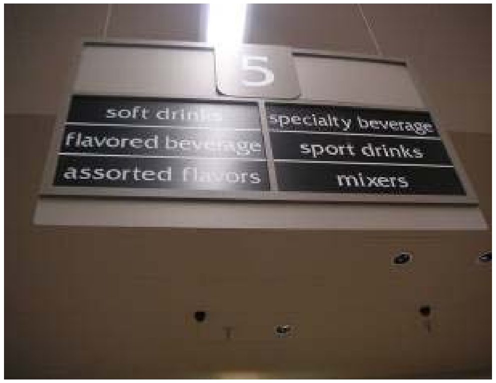
Types of invariance

- Illumination
- Scale
- Rotation
- Affine (view point change)

Types of invariance

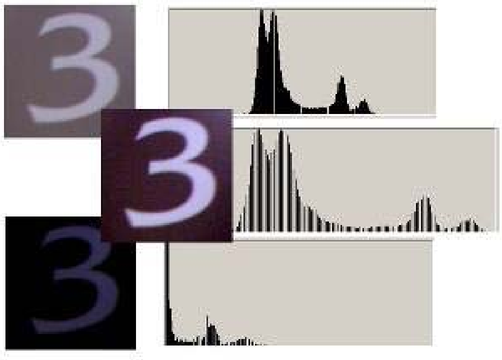
- Illumination
- Scale
- Rotation
- Affine
- Full Perspective





How to achieve illumination invariance

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



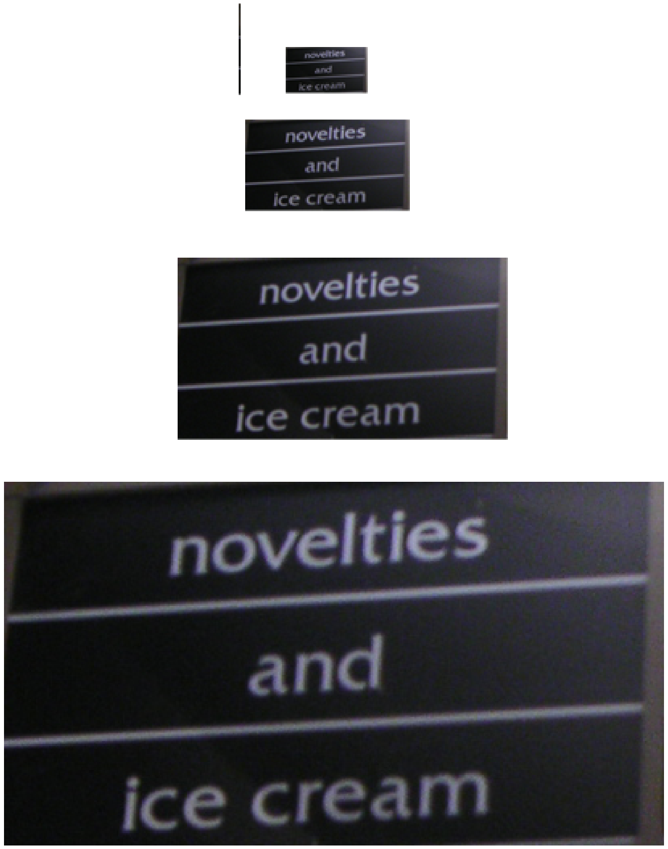
How to achieve scale invariance

- Pyramids

- Scale Space (DOG method)

Pyramids

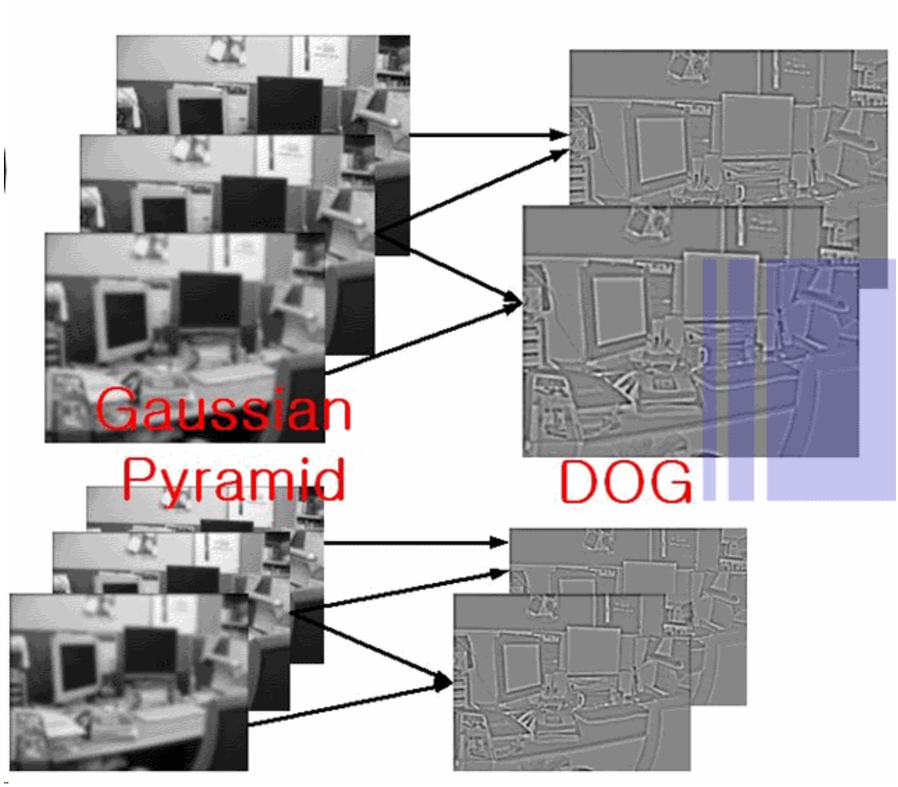
- Divide width and height by 2
- Take average of 4 pixels for each pixel (or Gaussian blur with different σ)
- Repeat until image is tiny
- Run filter over each size image and hope its robust



How to achieve scale invariance

- Scale Space: Difference of Gaussian (DOG)
  - Take DOG features from differences of these images-producing the gradient image at different scales.
  - If the feature is repeatedly present in between Difference of Gaussians, it is Scale Invariant and should be kept.

Differences Of Gaussians

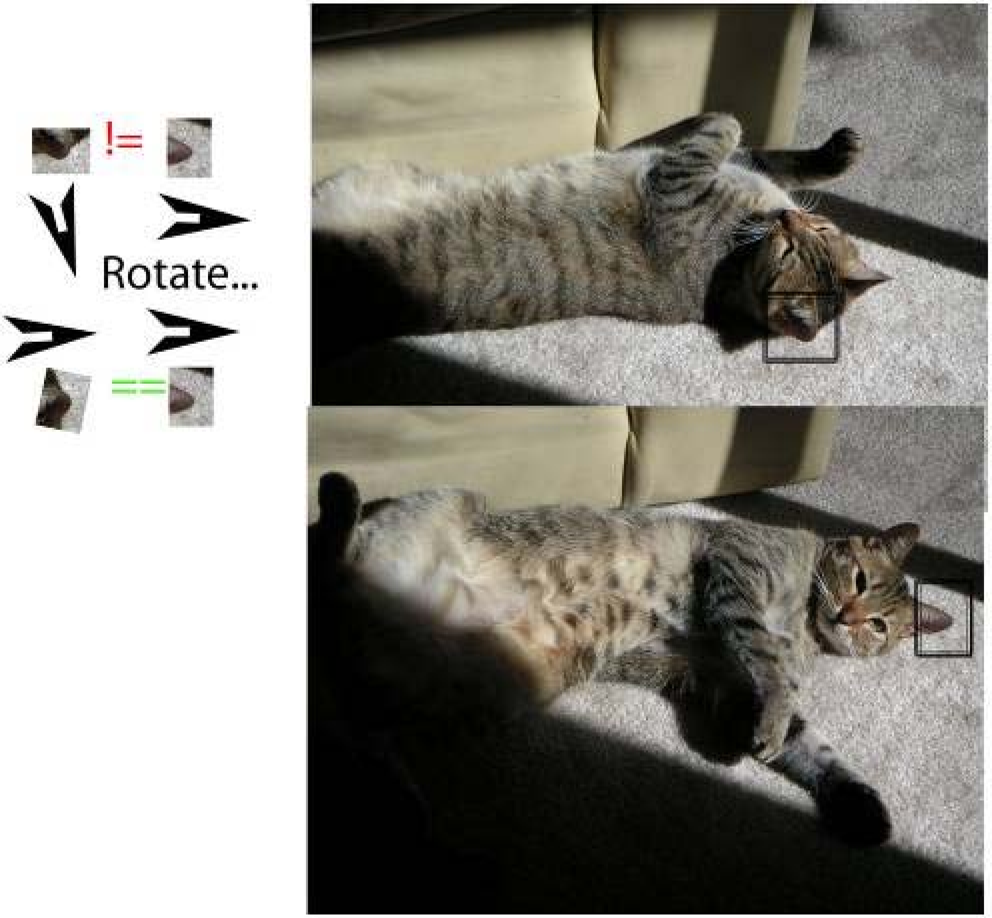


Rotation Invariance

- Compute histogram of gradient directions to identify the most dominant direction. Rotate image to the most dominant direction.

- Rotate all features to go the same way in a determined manner

Rotation Invariance



SIFT algorithm overview

- Scale-space extrema detection
  - Get tons of points from maxima+minima of DOGS
- Keypoint localization
  - Threshold on simple contrast (low contrast is generally less reliable than high for feature points)
  - Threshold based on principal curvatures to remove linear features such as edges
  - Orientation assignment
- Keypoint descriptor
  - Construct histograms of gradients (HOG)

Scale-space extrema detection

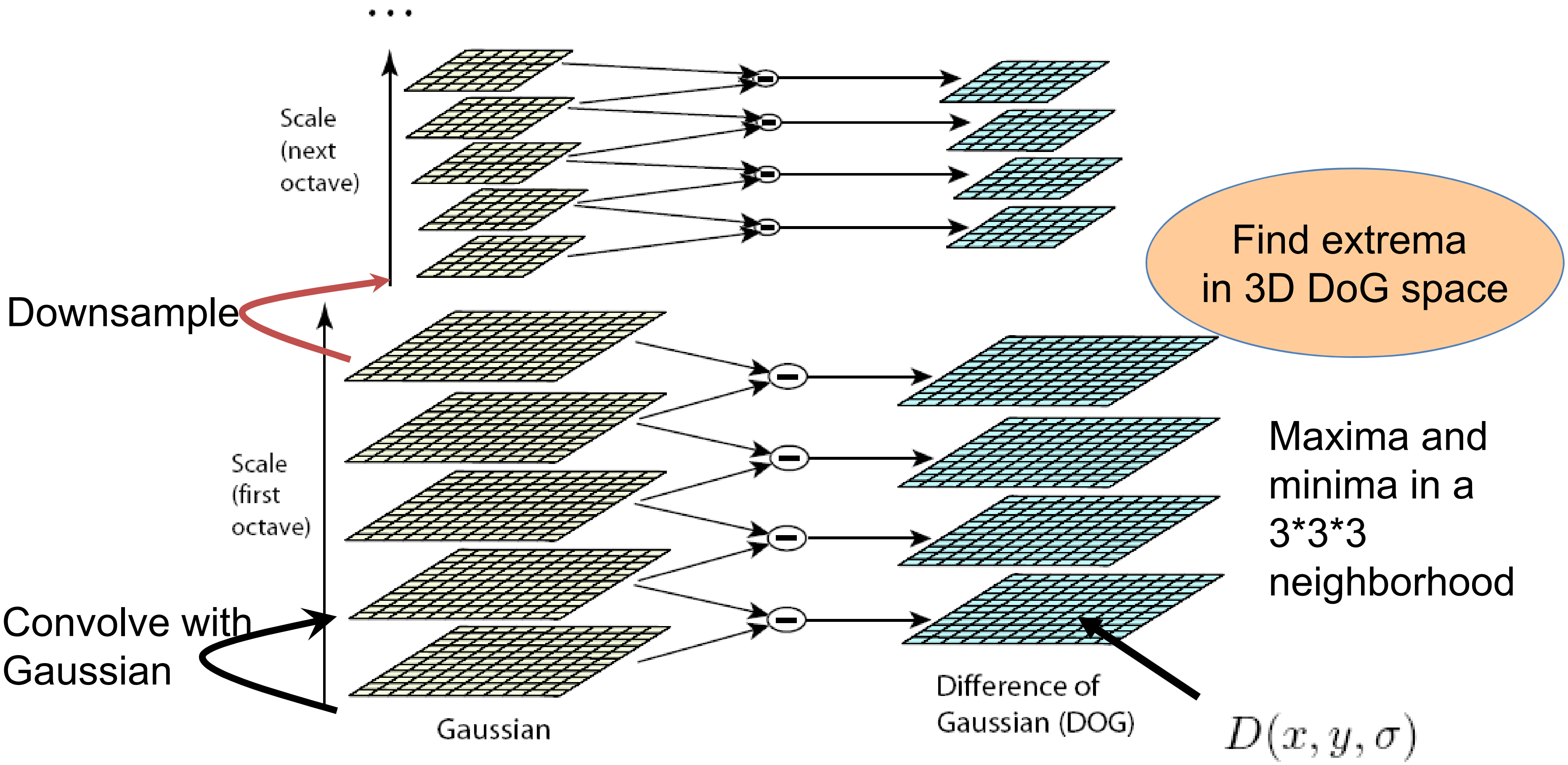
- Find the points, whose surrounding patches (with some scale) are distinctive
- An approximation to the scale-normalized Difference of Gaussian

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

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

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

Extreme Point Detection



Downsample

Convolve with Gaussian

Find extrema in 3D DoG space

Maxima and minima in a 3*3*3 neighborhood

$D(x, y, \sigma)$

At each image size, convolve with DoG of different scales.

Keypoint localization

- Eliminating extreme points with local contrast

- Eliminating edge points
  - Similar to Harris corner detector

Eliminating edge points

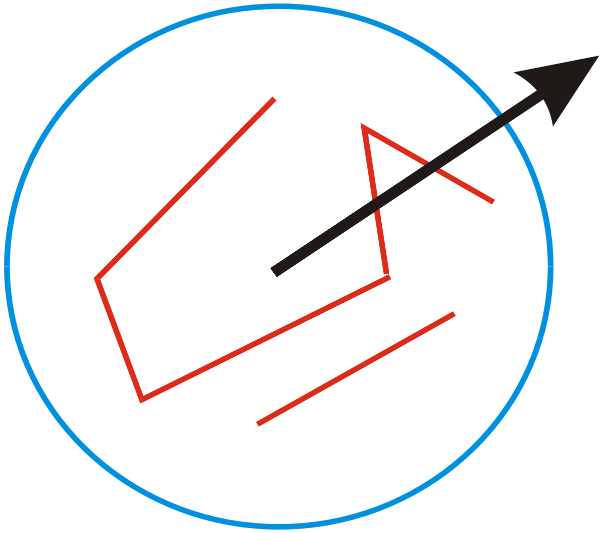
- Such a point has large principal curvature across the edge but a small one in the perpendicular direction
- The principal curvatures can be calculated from a Hessian function or covariance matrix of gradient (Harris detector)

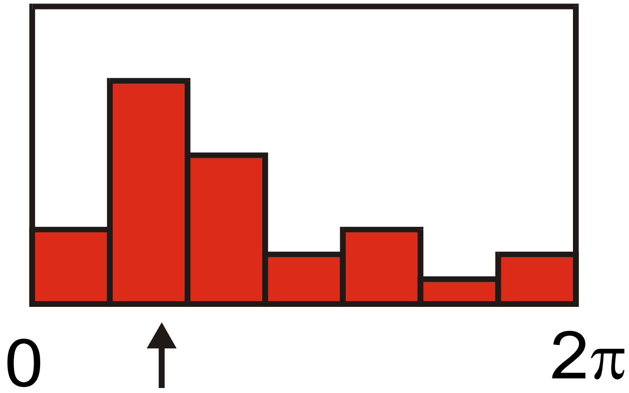
$$\mathbf{H} = \begin{bmatrix} D_{xx} & D_{xy} \\ D_{xy} & D_{yy} \end{bmatrix} \qquad C = \begin{bmatrix} \sum I_c^2 & \sum I_c I_r \\ \sum I_c I_r & \sum I_r^2 \end{bmatrix}$$

- The eigenvalues of H or C are proportional to the principal curvatures, so two eigenvalues shouldn’t differ too much.

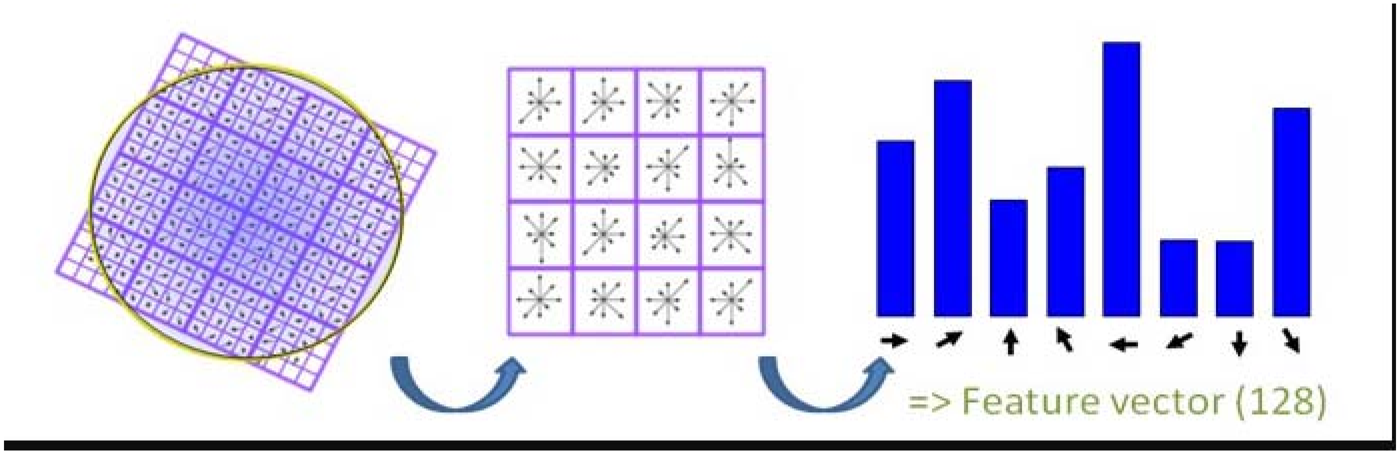
Finding Keypoints – Orientation

- Create histogram of local gradient directions computed at selected scale
- Assign canonical orientation at peak of smoothed histogram, achieving invariance to image rotation
- Each key point specifies stable 2D coordinates (x, y, scale, orientation)





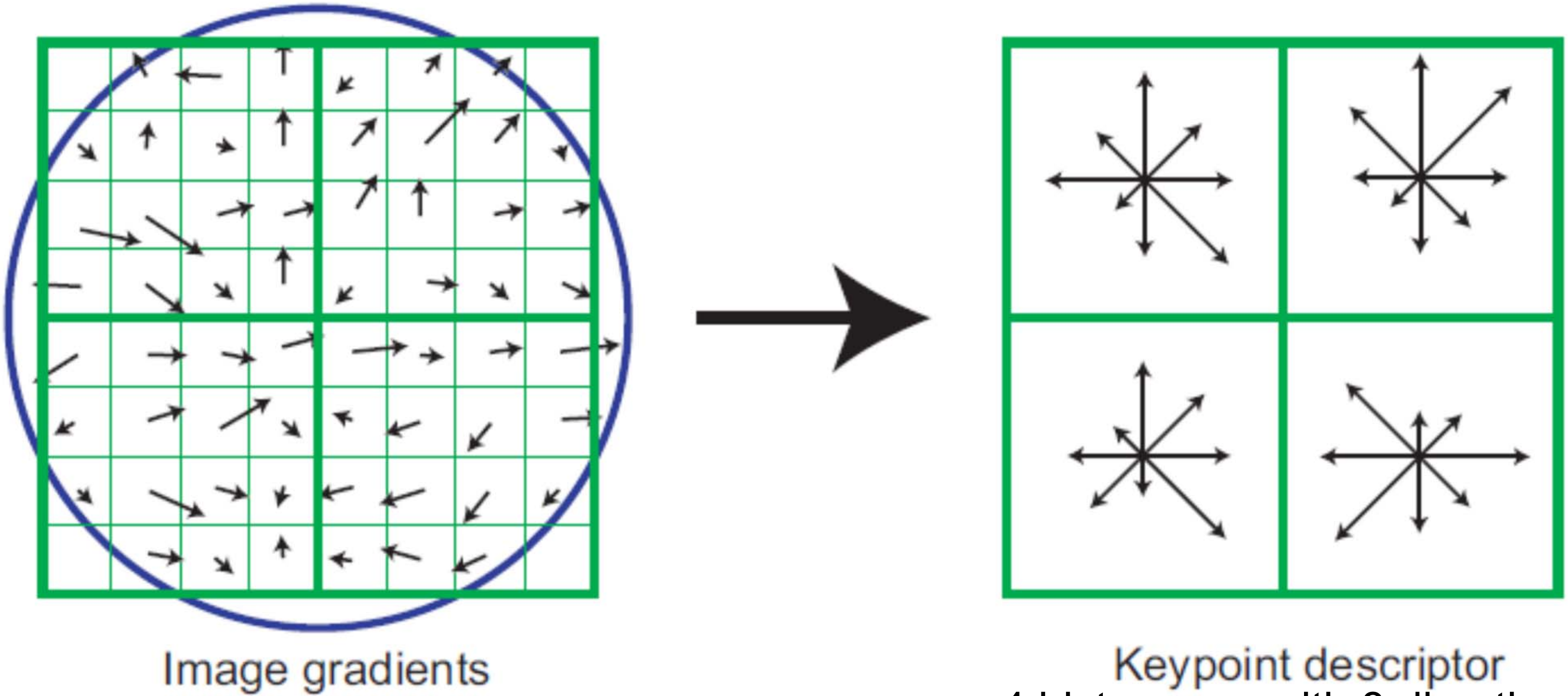
SIFT Key Feature descriptor



Take a 16x16 window of "in-between" pixels around the key point. Split that window into sixteen 4x4 windows. From each 4x4 window, generate a histogram of 8 bins, producing a total of 4x4x8=128 feature vector.

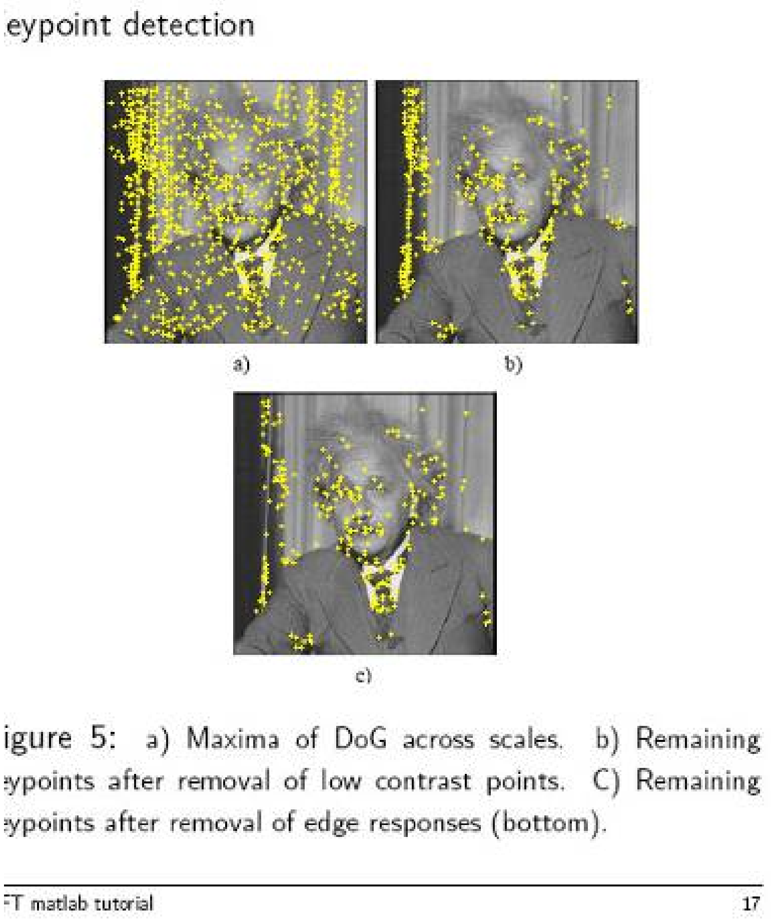
SIFT Key Feature descriptor

Create the features for each SIFT key point. Given 8 orientations and 4x4 histograms, each SIFT key is described by a vector of 128 (8x4x4) as shown below.



4 histograms with 8 direction bins for each histogram

Actual SIFT stage output



eypoint detection

igure 5: a) Maxima of DoG across scales. b) Remaining ypoints after removal of low contrast points. C) Remaining ypoints after removal of edge responses (bottom).

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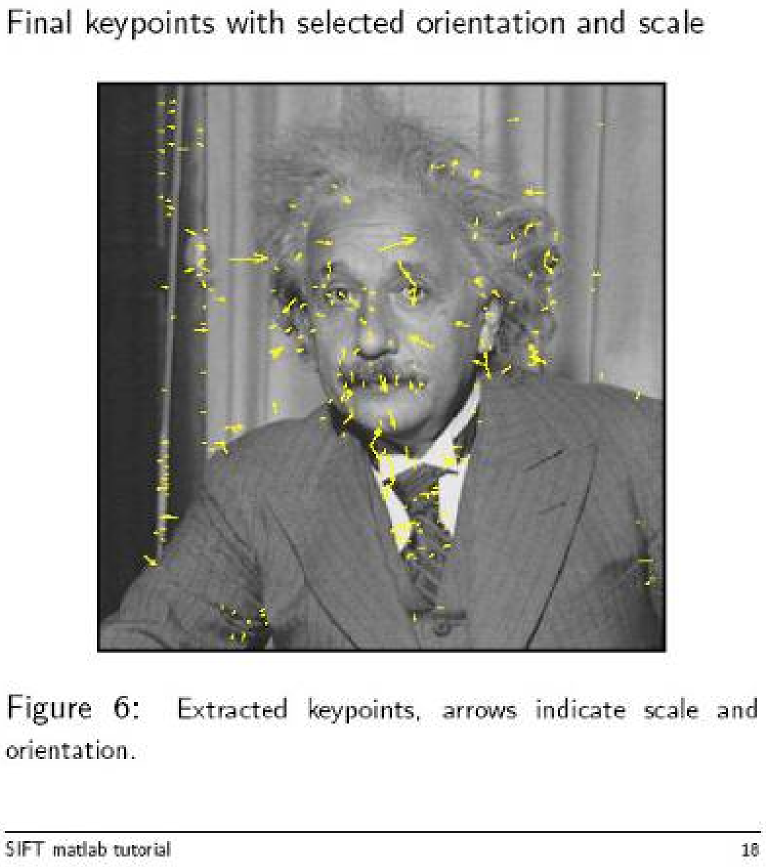

Final keypoints with selected orientation and scale

Figure 6: Extracted keypoints, arrows indicate scale and orientation.

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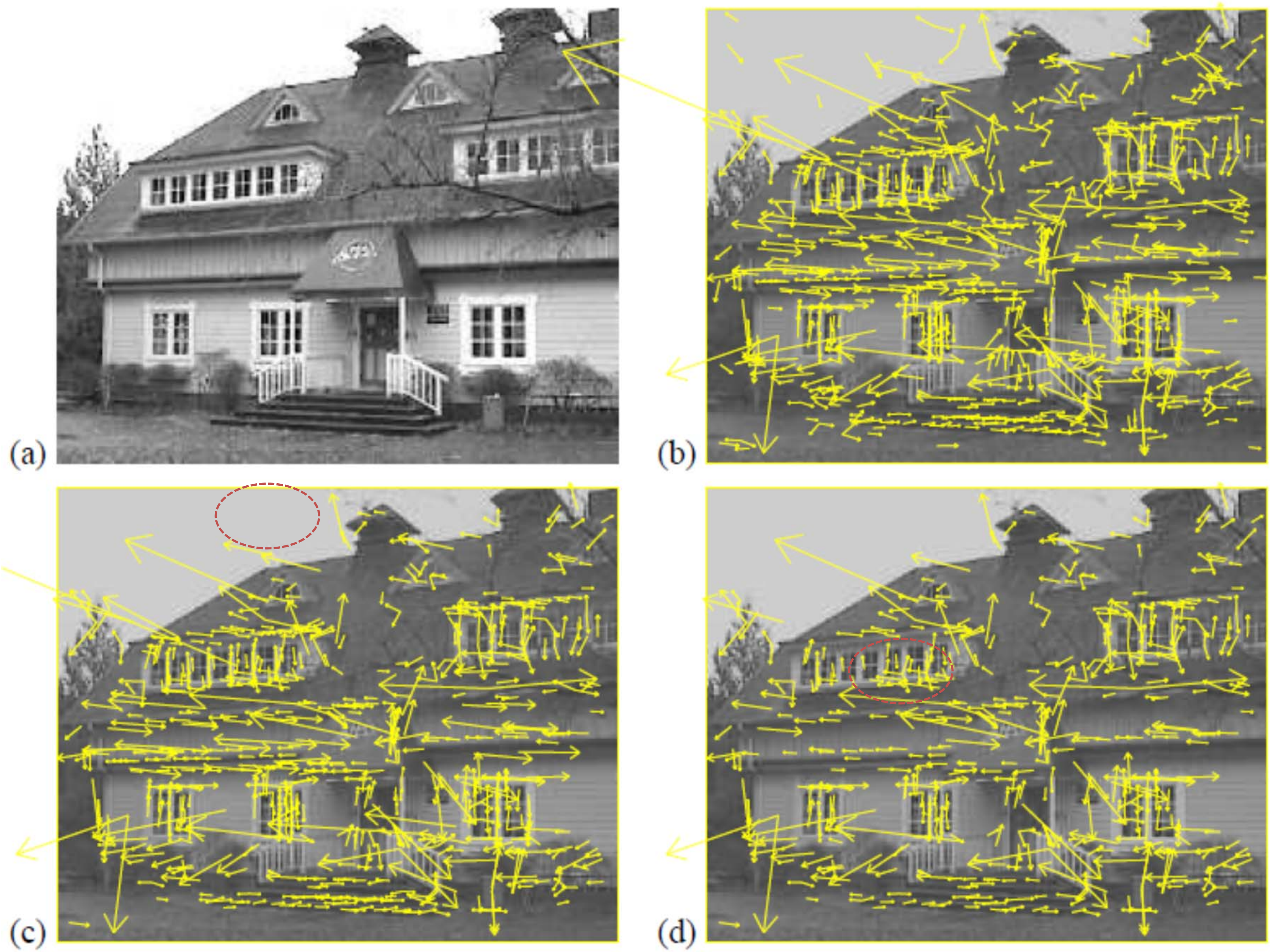

After remove low contrast features
e.g. in the sky region

After removing linear features (e.g. window edges)

Image matching with SIFT features

- Nearest neighbor matching
  - Distance could be L2 norm on histograms
  - Match by (nearest neighbor distance)/(2nd nearest neighbor distance) ratio
- Use Hough transform like voting: each SIFT key point votes for an object and the object receives the most votes is the recognized object

Application: object recognition

- The SIFT key features of training images are extracted and stored
- For a query image

1. Extract SIFT key points and their features
2. Nearest neighbor matching or HT voting

Conclusion

- A novel method for detecting interest points. The most successful feature in computer vision
- Histogram of Oriented Gradients are becoming more popular
- SIFT may not be optimal for general object classification