Computational Vision

Lecture 2.1.2: Scale Invariant Feature Transform (SIFT)

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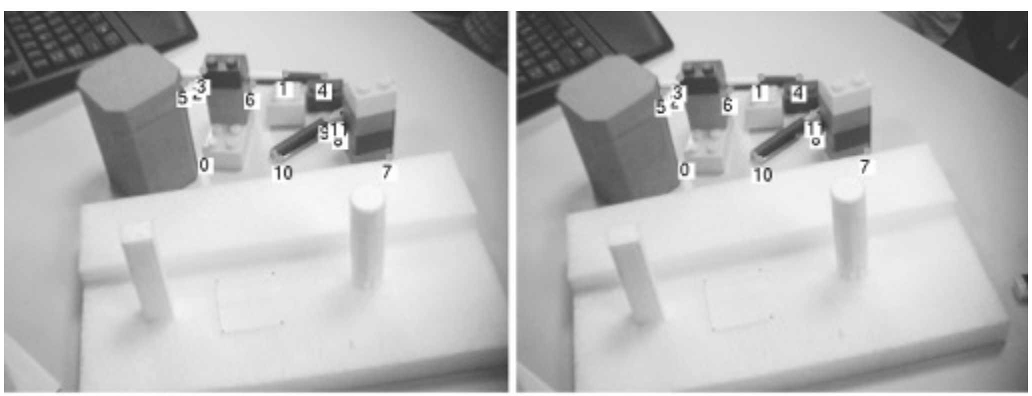
Why do we care about matching features?

- Object Recognition
- Wide baseline matching
  - Given any two images, estimate the fundamental matrix and a set of matched interest points.
- Tracking



(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

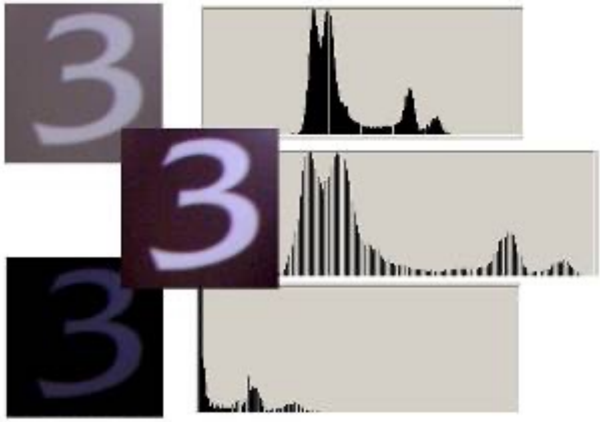
- Illumination
- Scale
- Rotation
- Affine

Types of invariance

- Illumination
- Scale
- Rotation
- Affine
- Full Perspective

How to achieve illumination invariance

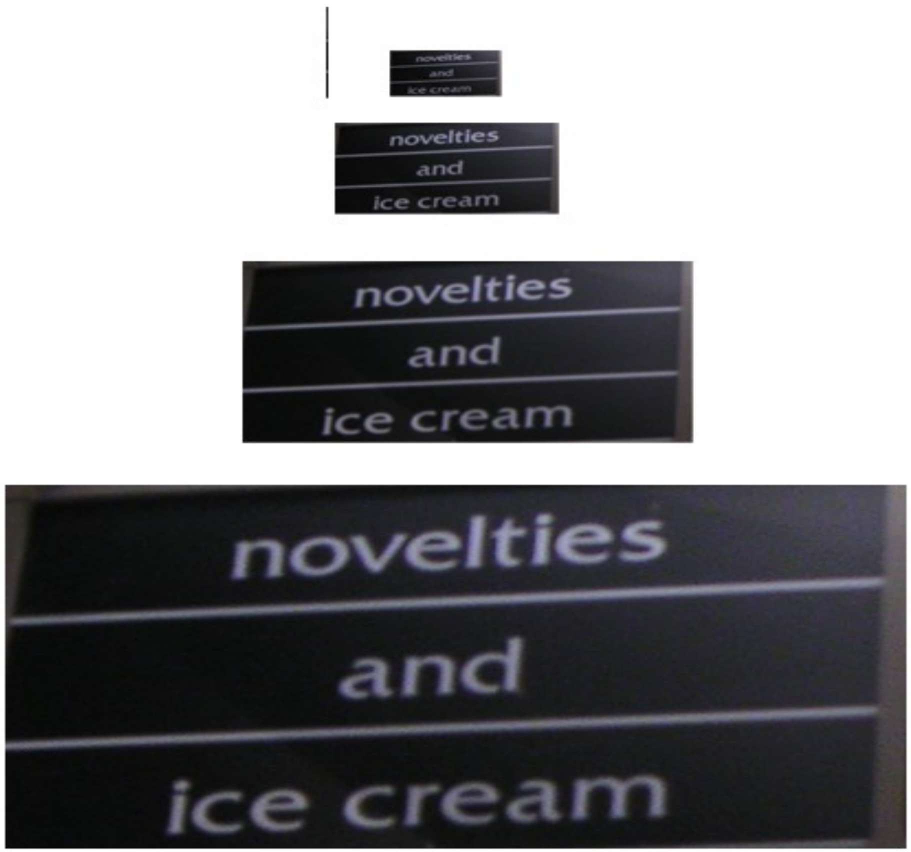
- The easy way (normalized)
- Difference based metrics (sift)



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)

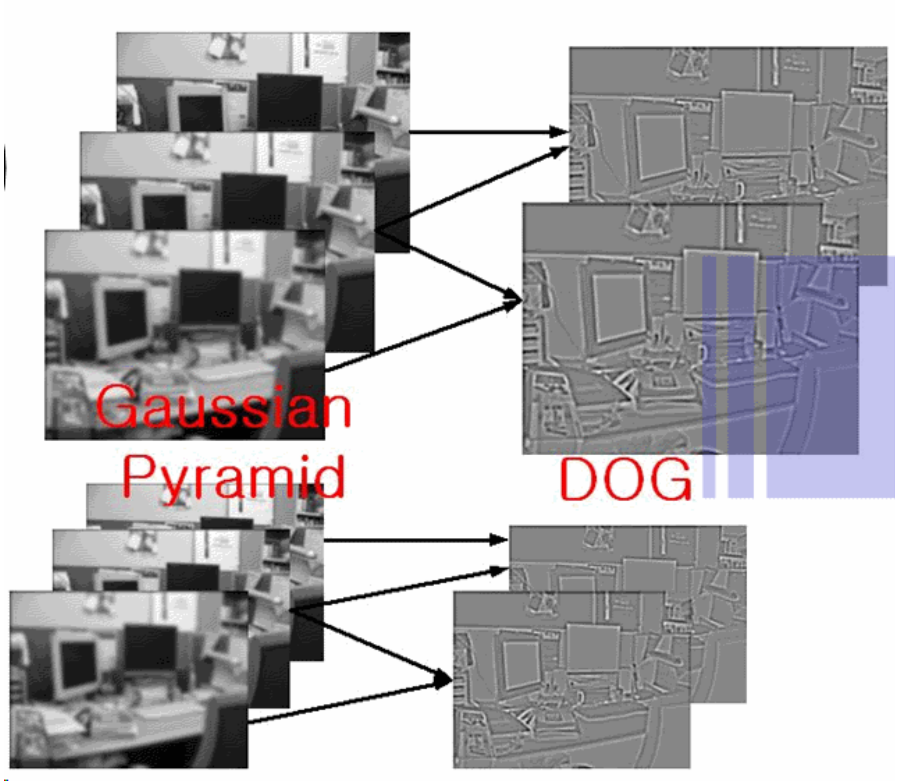
Pyramids


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

How to achieve scale invariance

- Pyramids
- Scale Space (DOG method)
  - Pyramid but fill gaps with blurred images
  - 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.

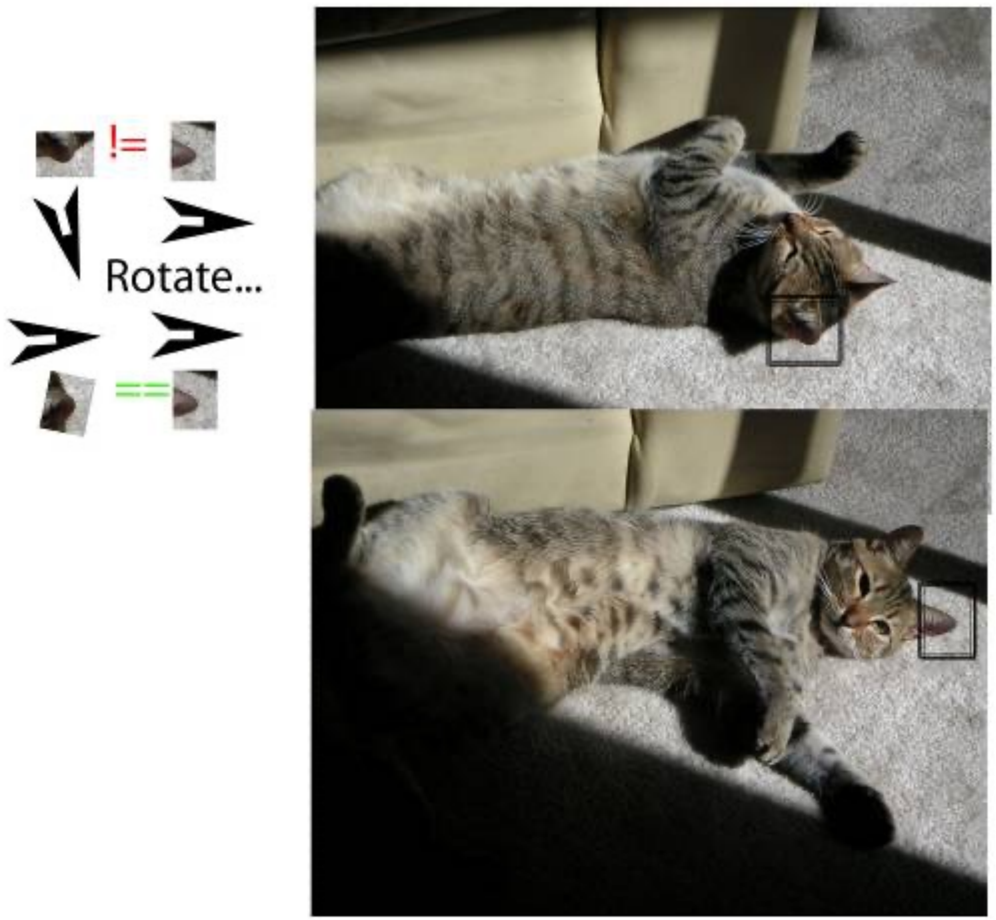
Differences Of Gaussians



Rotation Invariance

- Rotate all features to go the same way in a determined manner
- Take histogram of Gradient directions
- Rotate to most dominant (maybe second if its good enough)

Rotation Invariance



Labs!

- See announcement on canvas