PS3 Review Session

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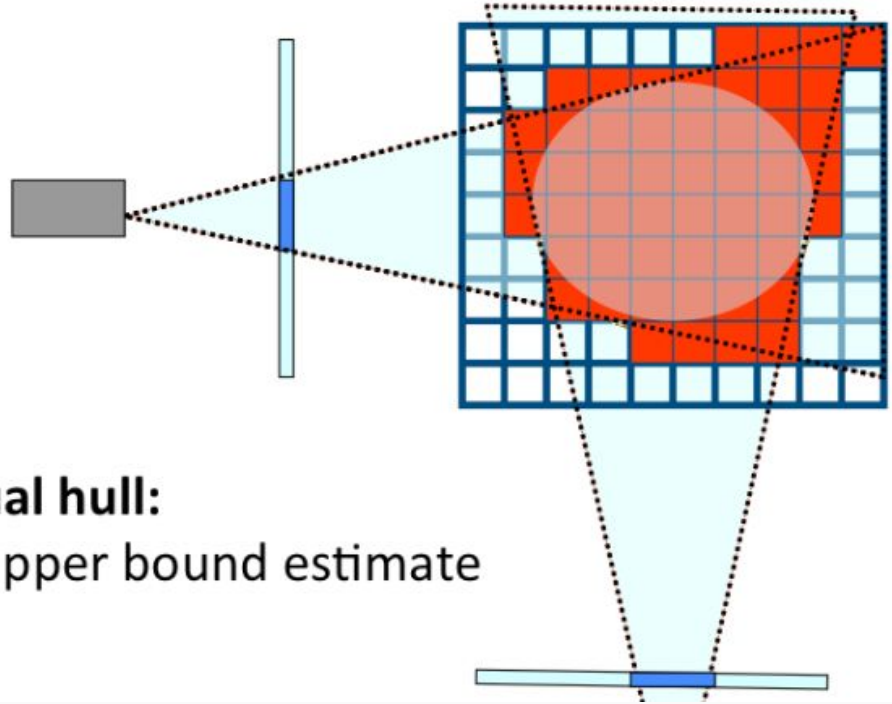
Overview

Space carving

Single Object Recognition via SIFT

Histogram of Oriented Gradient (HOG)

Space carving - overview

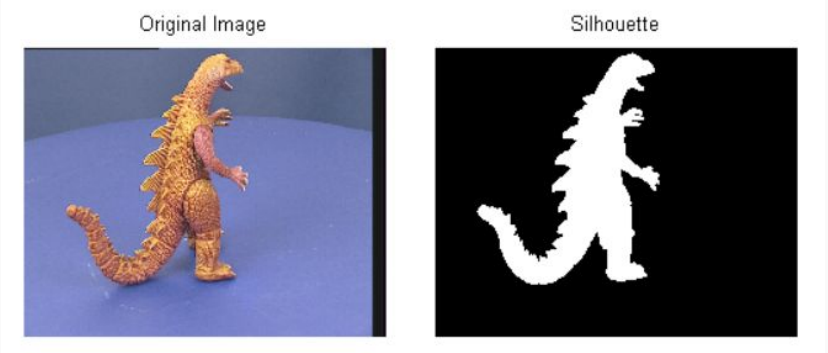


Visual hull:
an upper bound estimate

Space carving - overview

Steps:

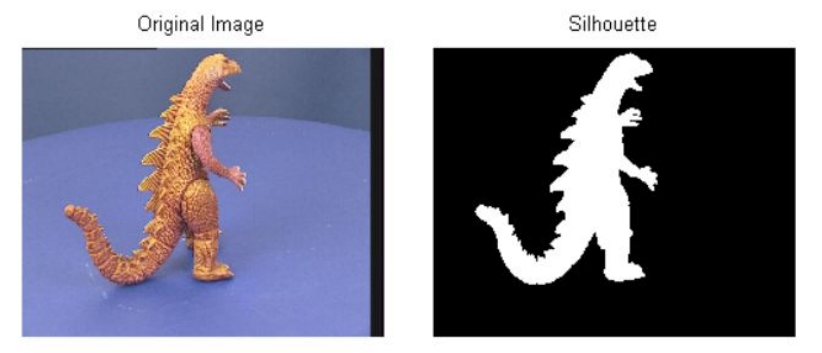
- Estimate silhouettes of images (could be based on some heuristics, e.g. color)
- Form the initial voxels as a cuboid
- Iterate over cameras and remove the voxels which project to the dark part of each silhouette



Space carving - (a) (b) (c)

Steps:

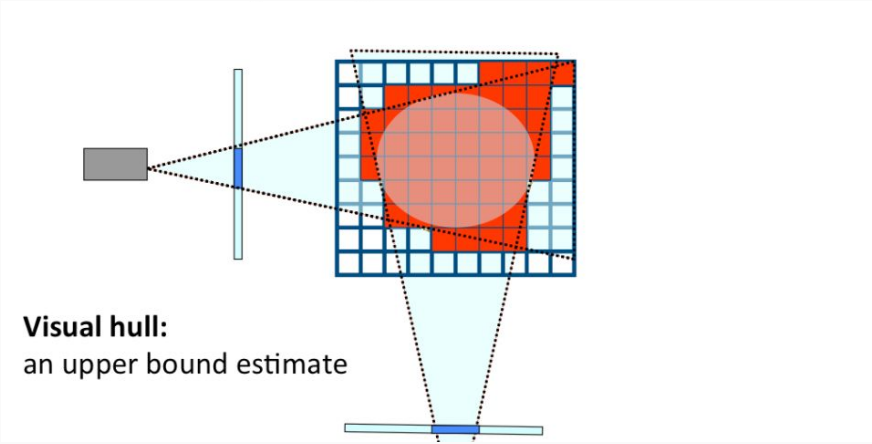
- Estimate silhouettes of images (could be based on some heuristics, e.g. color)
- Form the initial voxels as a cuboid #TODO
- Iterate over cameras and remove the voxels which project to the dark part of each silhouette #TODO



Space carving - (a) (b) (c)

Steps:

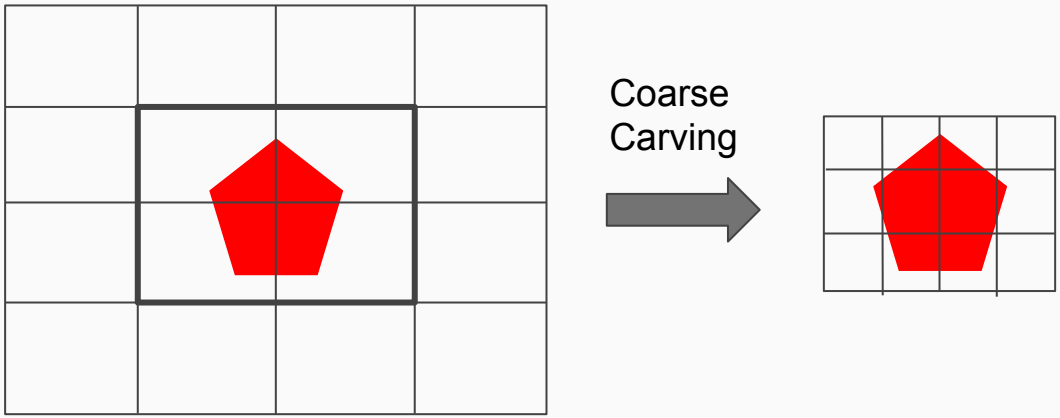
- Estimate silhouettes of images (could be based on some heuristics, e.g. color)
- Form the initial voxels as a cuboid
  - Try not just do for loops, too slow
  - Probably useful functions: np.meshgrid, np.repeat, np.tile
- Iterate over cameras and remove the voxels which project to the dark part of each silhouette
  - Critical step: project 3D voxel into 2D
  - Remember using homogenous coordinates for projection
  - Also, better no for loops...



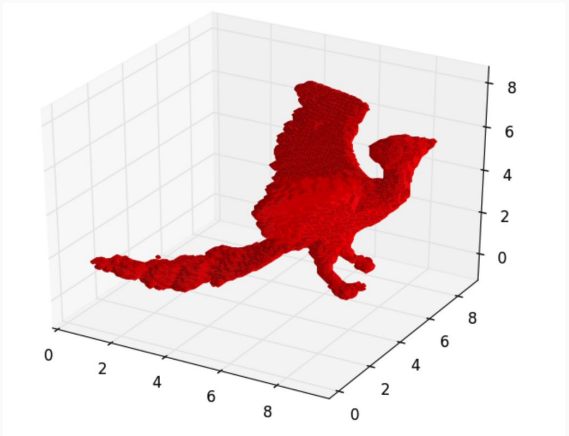
Space carving - (d)

Steps:

- Estimate silhouettes of images (could be based on some heuristics, e.g. color)
- Form the initial voxels as a cuboid
  - Improvement: tighter bounded cuboid
  - How: do a coarse carving first (we use num_voxels = 4000)
- Iterate over cameras and remove the voxels which project to the dark part of each silhouette



Final Output



Space carving - (e)

Steps:

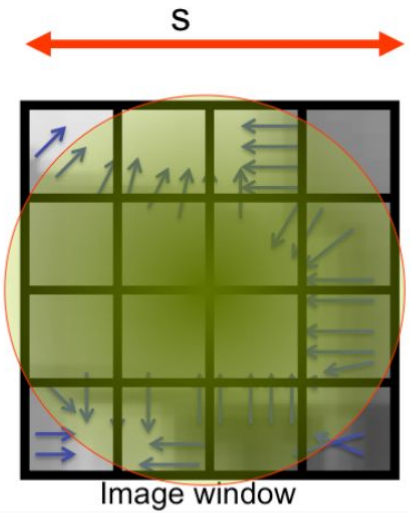
- Estimate silhouettes of images (could be based on some heuristics, e.g. color)
  - Issues: the quality of silhouettes
  - The silhouette from each camera is not perfect, but the result is ok. Why?
  - Experiment: use only a few of the silhouettes
- Form the initial voxels as a cuboid
- Iterate over cameras and remove the voxels which project to the dark part of each silhouette

Single Object Recognition Via SIFT - overview

SIFT descriptor

David G. Lowe. "Distinctive image features from scale-invariant keypoints." *IJCV* 60 (2), 04

- Alternative representation for image regions
- Location and characteristic scale s given by DoG detector



1 Compute gradient at each pixel

2 N x N spatial bins

3 Compute an histogram h_i of M orientations for each bin i

4 Concatenate h_i for i=1 to N^2 to form a 1xMN^2 vector H

5 Gaussian center-weighting

6 Normalize to unit norm

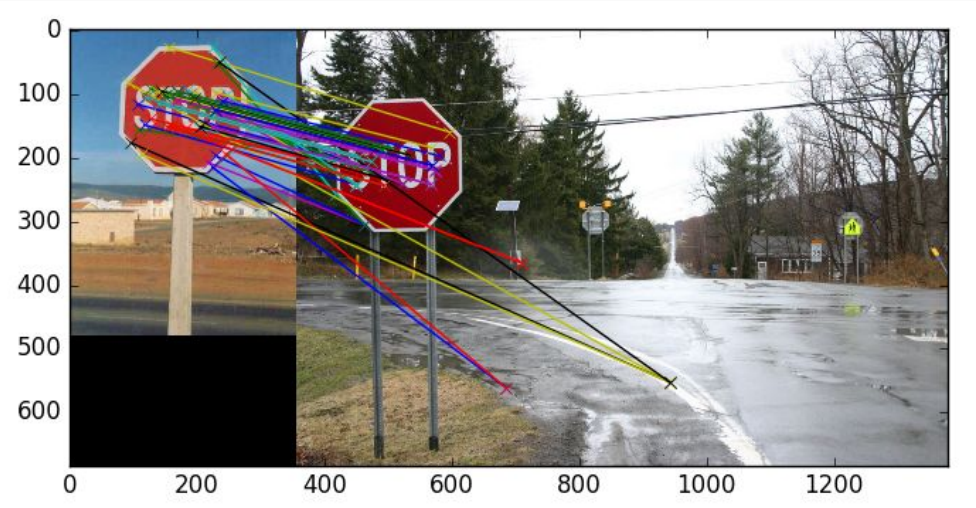
Typically M = 8; N= 4
H = 1 x 128 descriptor

Single Object Recognition Via SIFT - (a)

We've implemented SIFT descriptor for you, and your task is using it for object recognition.

Read: **Section 7. Application to object recognition** in Lowe's SIFT paper
http://www.cs.ubc.ca/~lowe/papers/ijcv04.pdf

Be sure to understand why is there a threshold and how to use it.

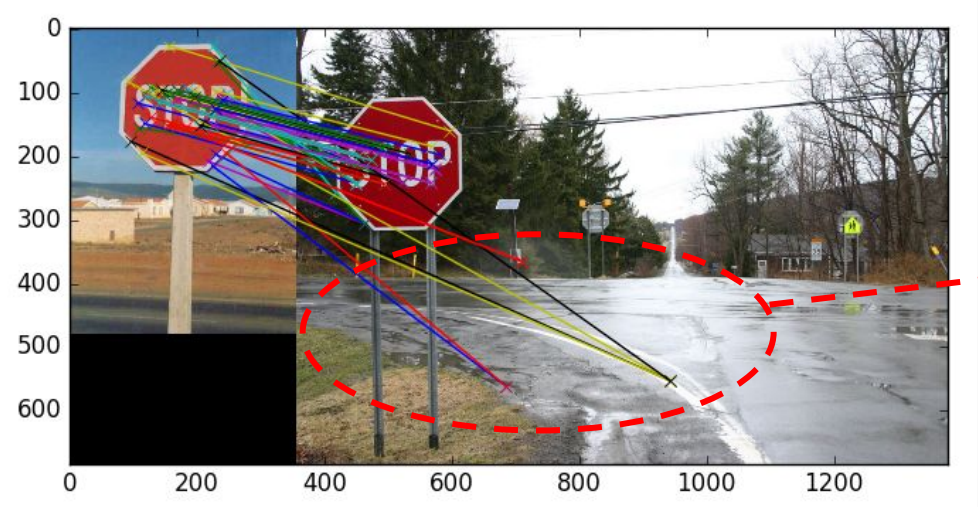


Single Object Recognition Via SIFT - (b)

RANSAC to refine matching

Basic idea: use RANSAC to fit a homography matrix *H* between two set of key points. Only keep the inliers for matching, remove the outliers.

Think: how many pairs of correspondence do we need in each iteration?



Single Object Recognition Via SIFT - (c)

More about RANSAC

Theoretical properties: see lecture notes / slides, figuring out the relations between

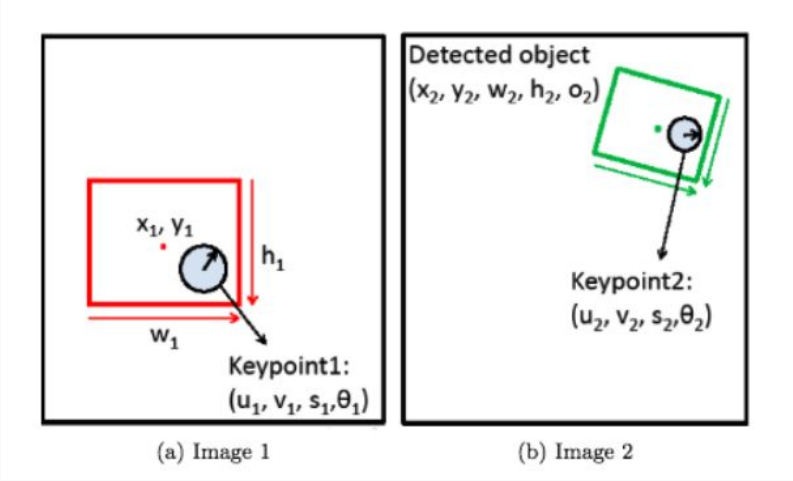
- N: number of samples
- e: outlier ratio
- s: minimum number of data points to fit the model
- p: probability guaranteed

Single Object Recognition Via SIFT - (d) (e)

Find quantitative relation between two bounding boxes

Input (u1, v1, s1, theta1; u2, v2, s2, theta2; x1, y1, w1, h1), find (x2, y2, w2, h2, o2)

Keypoint1 Keypoint2 Bbx1 Bbx2 & Orientation

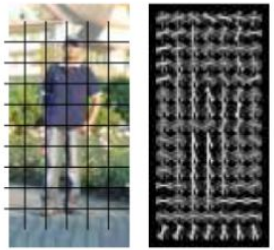


Histogram of Oriented Gradients (HOG) - Overview

HoG = Histogram of Oriented Gradients

Navneet Dalal and Bill Triggs, Histograms of Oriented Gradients for Human Detection, CVPR05

- Like SIFT, but…
  - Sampled on a dense, regular grid around the object
  - Gradients are contrast normalized in overlapping blocks



Histogram of Oriented Gradients (HOG) - Overview

Three levels of abstraction:

1. pixel-wise gradients (angle, magnitude) -> histogram in cell
2. histogram in cell -> HoG feature in the block
3. HoG feature in the block -> total HoG feature in the image

See whiteboard

Histogram of Oriented Gradients (HOG) - Overview

- Compute the gradients of image (angles, magnitudes)
- Divide the image into blocks with overlapping, each image contains many blocks
- Divide blocks into cells, each block contains several cells, and each cell contains several pixels.
- Generate the histogram (of shape (nbins,)) of each cell, the concatenation of histograms of cells in a block serves as the feature vector of this block
- Output feature: (H_blocks, W_blocks, cells_in_block ** 2 * nbins)

Histogram of Oriented Gradients (HOG) - (a)

See whiteboard

- Compute the gradients of image (angles, magnitudes)
- Divide the image into blocks with overlapping, each image contains many blocks
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Histogram of Oriented Gradients (HOG) - (a)

Compute the gradients of image (angles, magnitudes)

```
The way that the angles and magnitude per pixel are computed as follows:
Given the following pixel grid

    P1 P2 P3
    P4 P5 P6
    P7 P8 P9

We compute the angle on P5 as arctan(dy/dx) = arctan(P2-P8 / P4-P6).
```

```
The magnitude is simply sqrt((P4-P6)^2 + (P2-P8)^2)
```

Histogram of Oriented Gradients (HOG) - (b)

- Compute the gradients of image (angles, magnitudes)
- Divide the image into blocks with overlapping, each image contains many blocks
- Divide blocks into cells, each block contains several cells, and each cell contains several pixels.
- Generate the histogram (of shape (nbins,)) of each cell, the concatenation of histograms of cells in a block serves as the feature vector of this block
- Output feature: (H_blocks, W_blocks, cells_in_block ** 2 * nbins)

Histogram of Oriented Gradients (HOG) - (b)

```
def generate_histogram(angles, magnitudes, nbins = 9):
```

Binning the angles with magnitudes as weights

Be careful about the edge cases: what if the angle is close to 0 or 180 degrees?

Histogram of Oriented Gradients (HOG) - (c)

- Compute the gradients of image (angles, magnitudes)
- Divide the image into blocks with overlapping, each image contains many blocks
- Divide blocks into cells, each block contains several cells, and each cell contains several pixels.
- Generate the histogram (of shape (nbins,)) of each cell, the concatenation of histograms of cells in a block serves as the feature vector of this block
- Output feature: (H_blocks, W_blocks, cells_in_block ** 2 * nbins)