Robotic 3D Vision

Lecture 15: 3D Object Detection 1 – Introduction, Pose Alignment and Grouping

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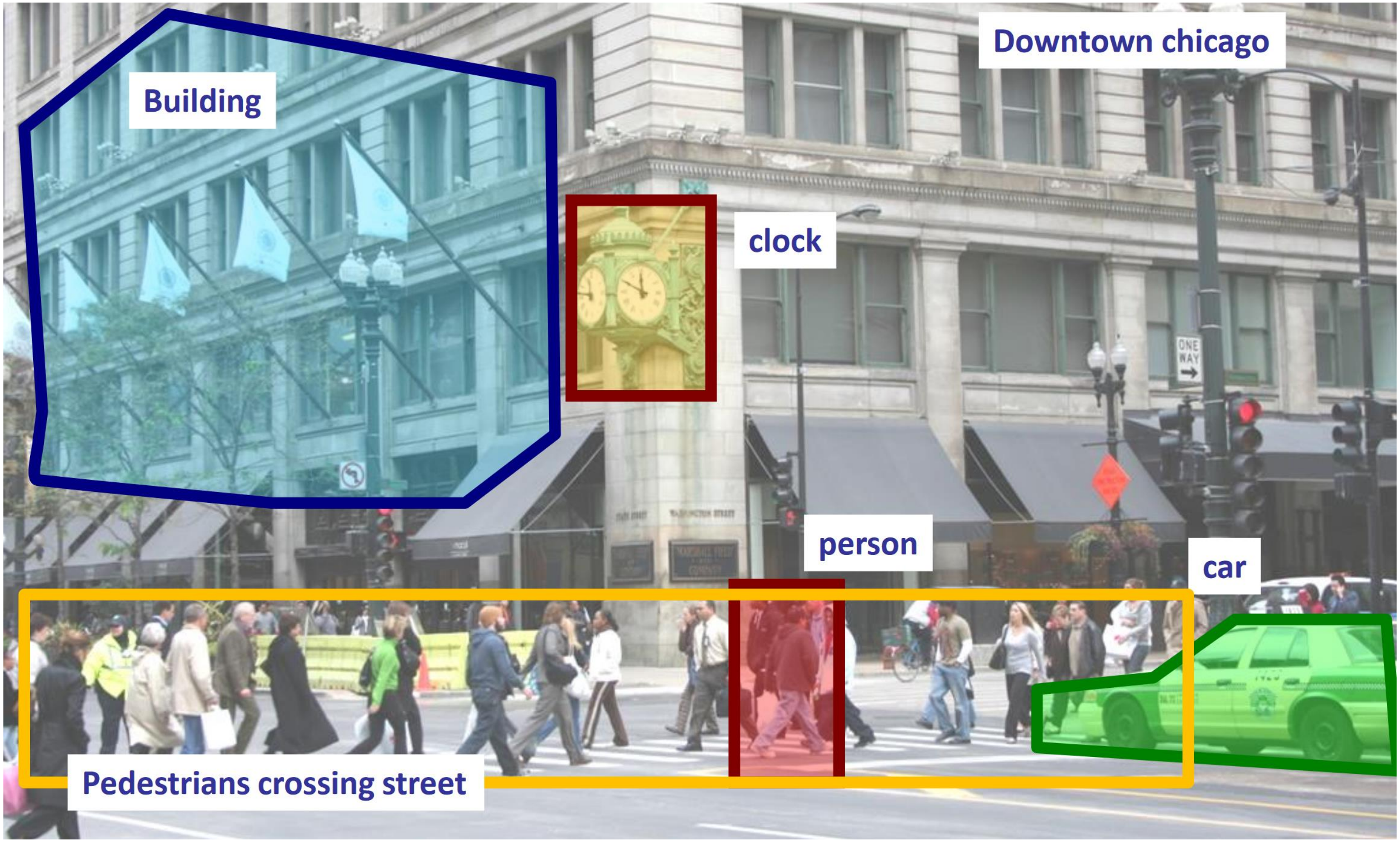
What We Will Cover Today

- Introduction to 3D object detection
- Challenges
- Object detection and pose estimation with local image features
  - Affine transformations
  - Homographies
- Correspondence grouping and robust alignment
  - Hough transform

Object Detection and Recognition



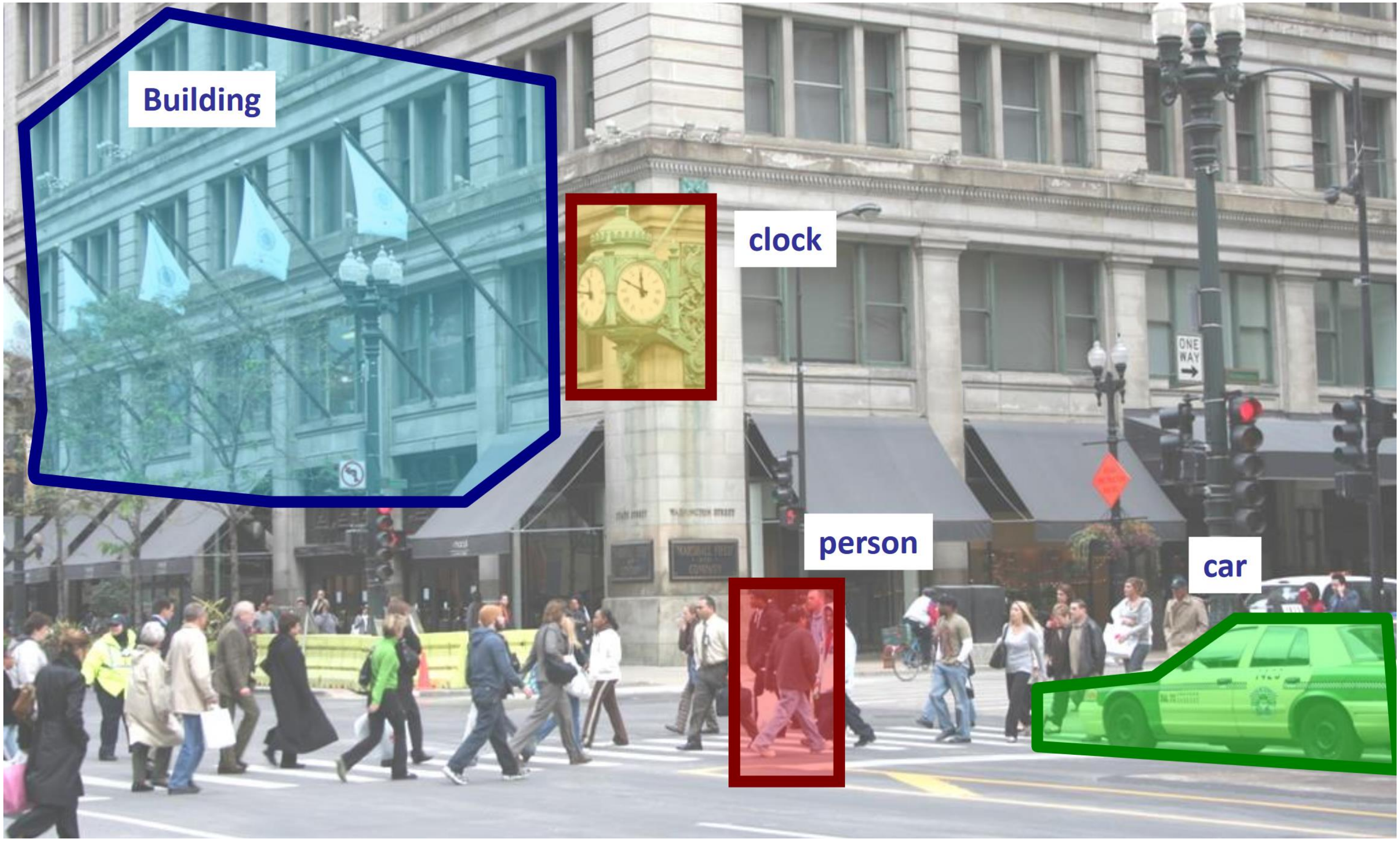
Slide adapted from S. Savarese

Object Detection and Recognition

Detection: does this image contain a car and where is it?

Slide adapted from S. Savarese

Object Detection and Recognition



Detection: which objects does this image contain and where are they?

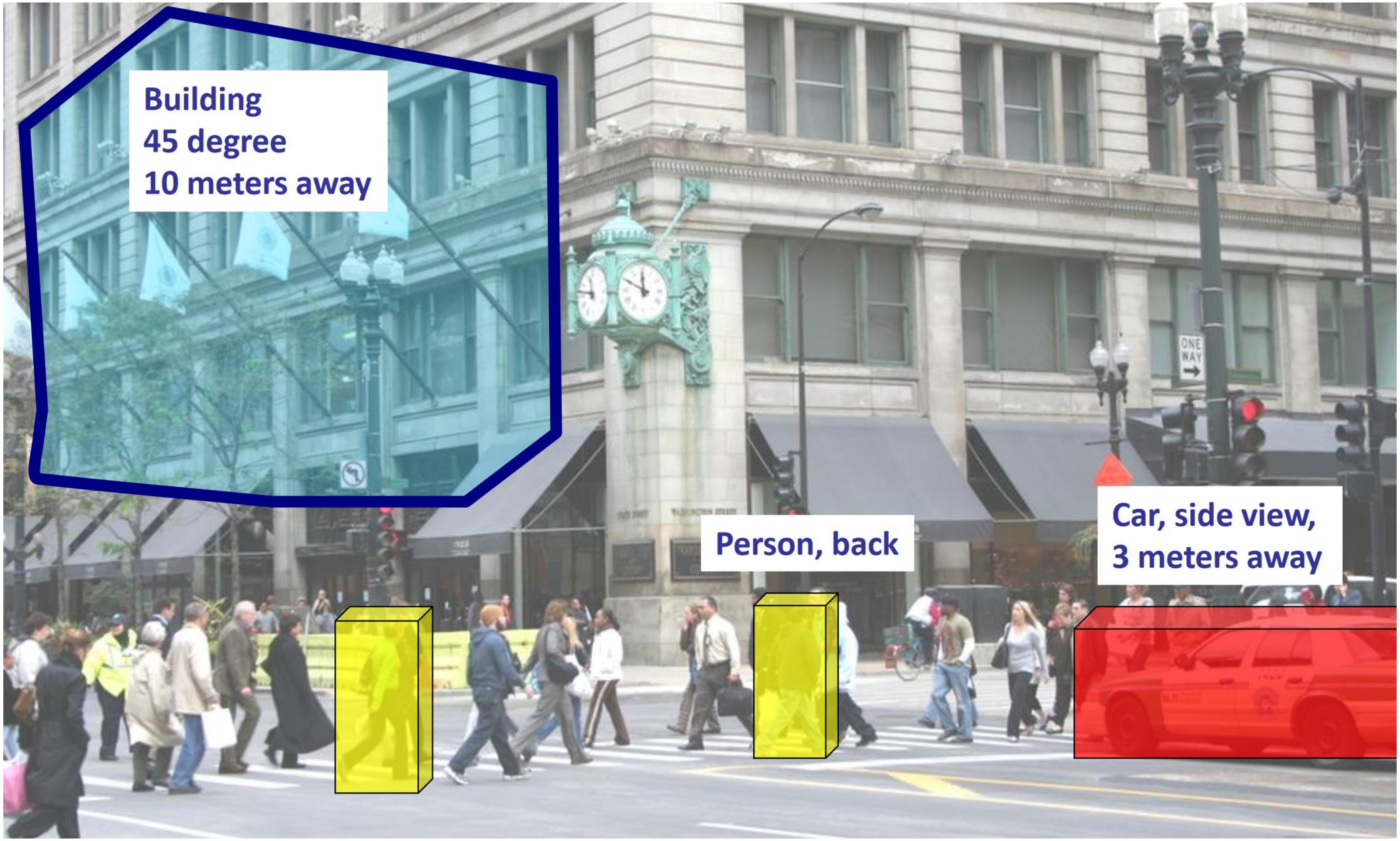
Slide adapted from S. Savarese

Object Detection and Recognition

Detection: instance segmentation

Slide adapted from S. Savarese

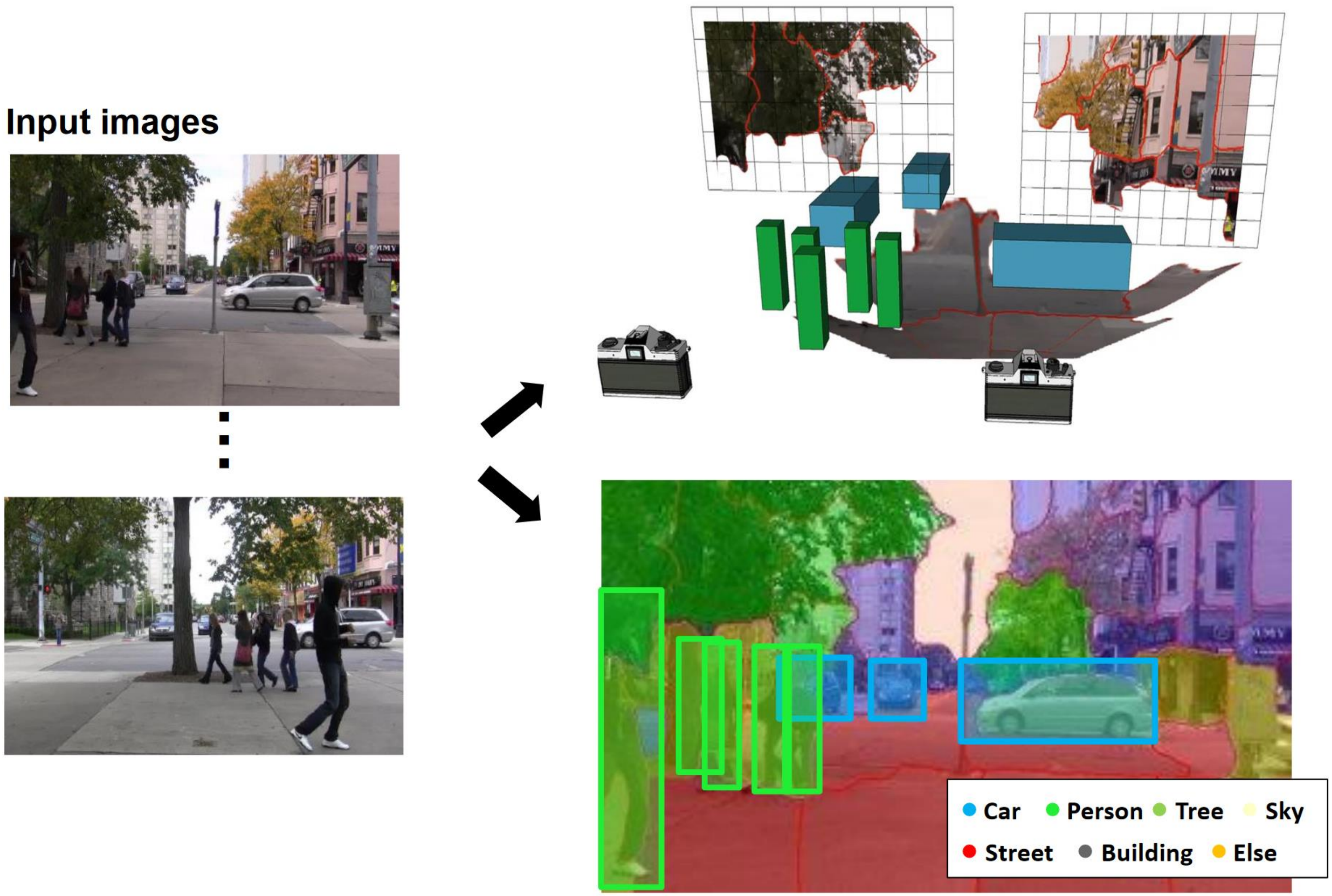
Object Detection and Recognition



Detection: where are the objects in 3D?

Slide adapted from S. Savarese

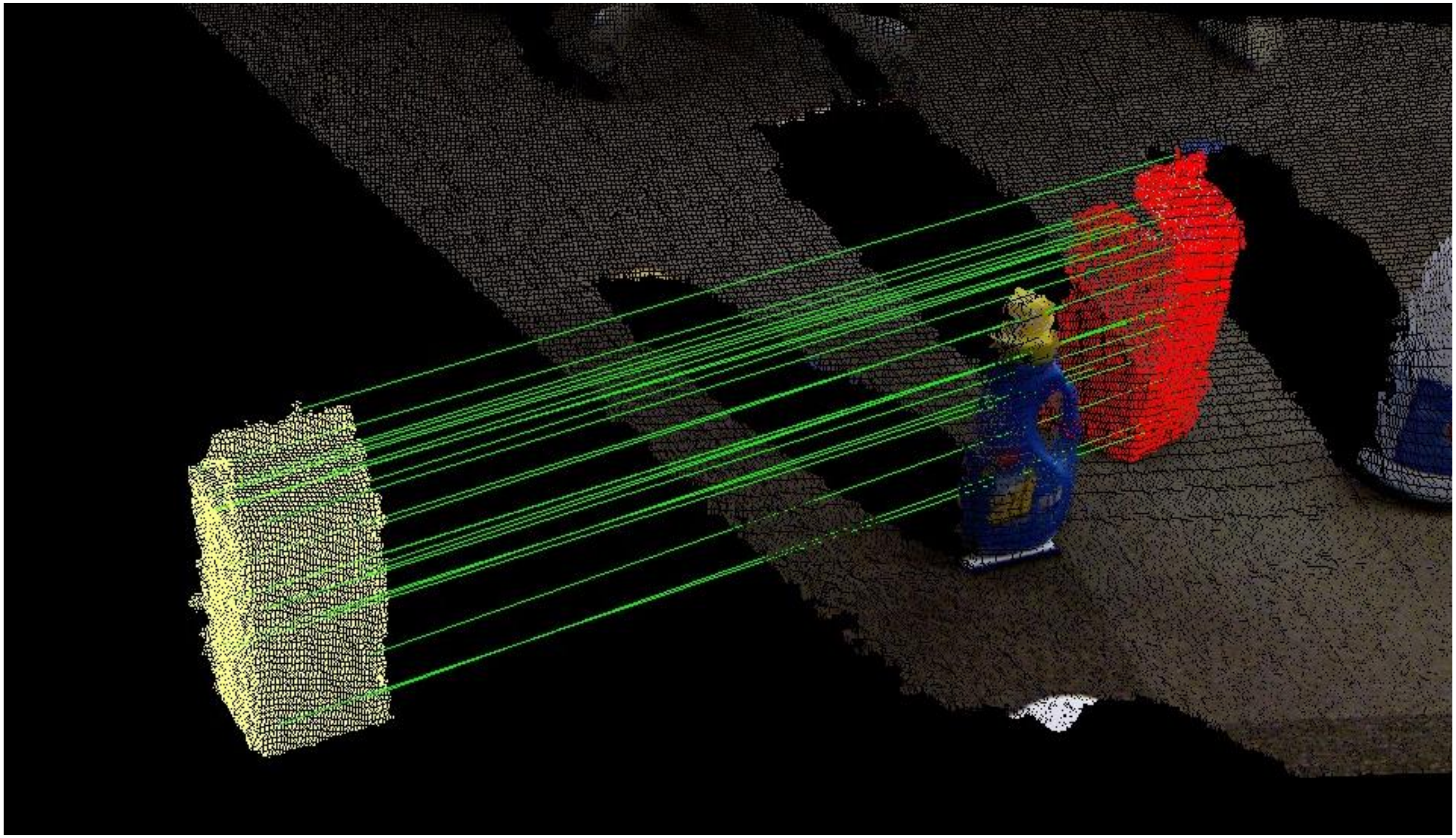
Joint Detection and Reconstruction



Detection: where are the objects in 3D?

Slide adapted from S. Savarese

3D Object Detection



Detection: where are the objects in 3D ?

Image from pointclouds.org

3D Object Detection for Robotic Grasping

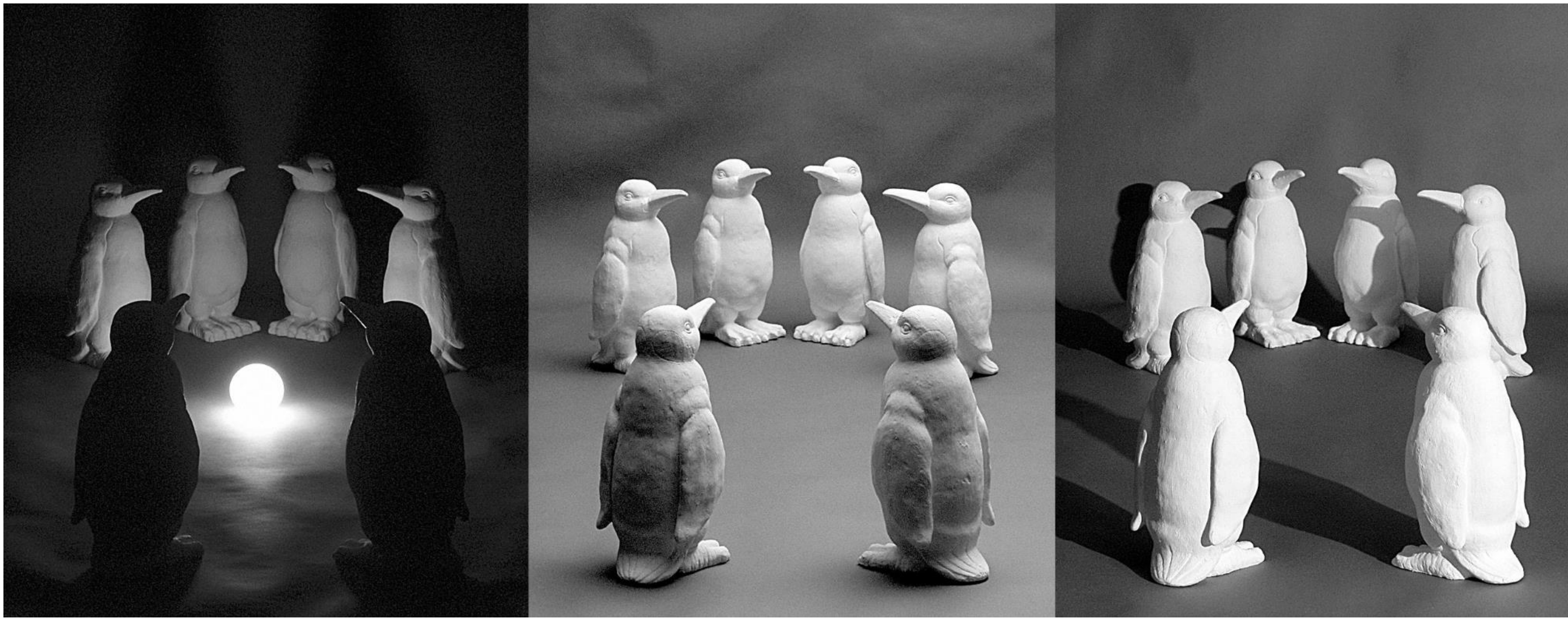
Papazov et al., IJRR 2012, video from youtube/qlt1os_WJRs

Challenges in Object Detection

View-point variation

Slide adapted from F. Li, A. Torralba

Challenges in Object Detection



Illumination variation

Image credit: J. Koenderink

Challenges in Object Detection

Scale

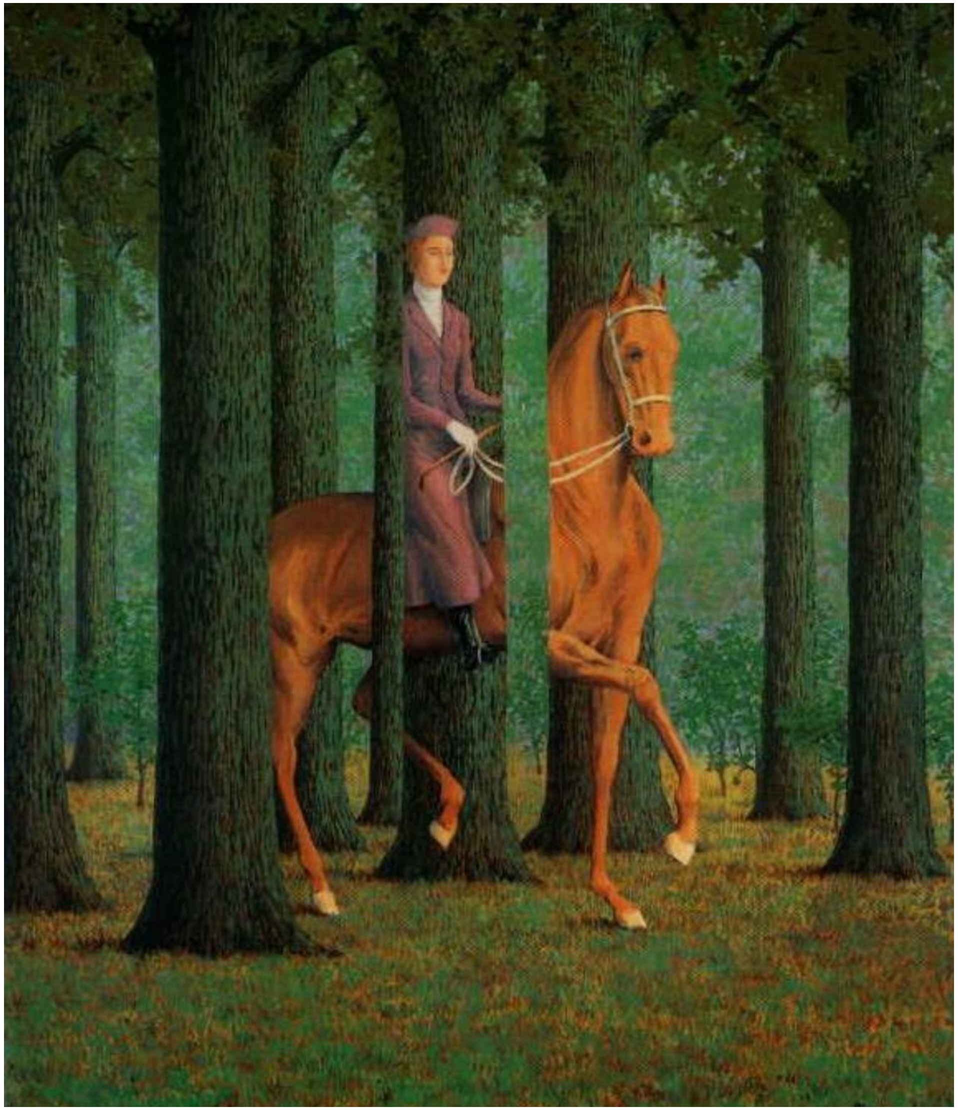
Slide adapted from F. Li, A. Torralba

Challenges in Object Detection

Deformation

Slide adapted from S. Savarese

Challenges in Object Detection



Occlusions

Slide adapted from F. Li and A. Torralba

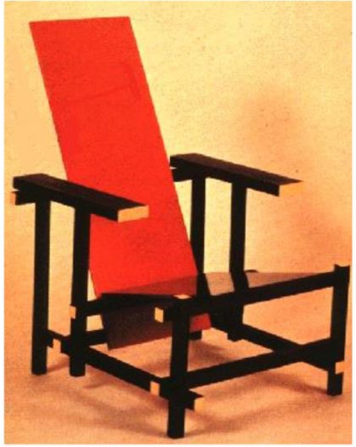
Challenges in Object Detection

Background clutter

Image: Kilmeny Niland, 1995
Slide adapted from S. Savarese

Challenges in Object Detection



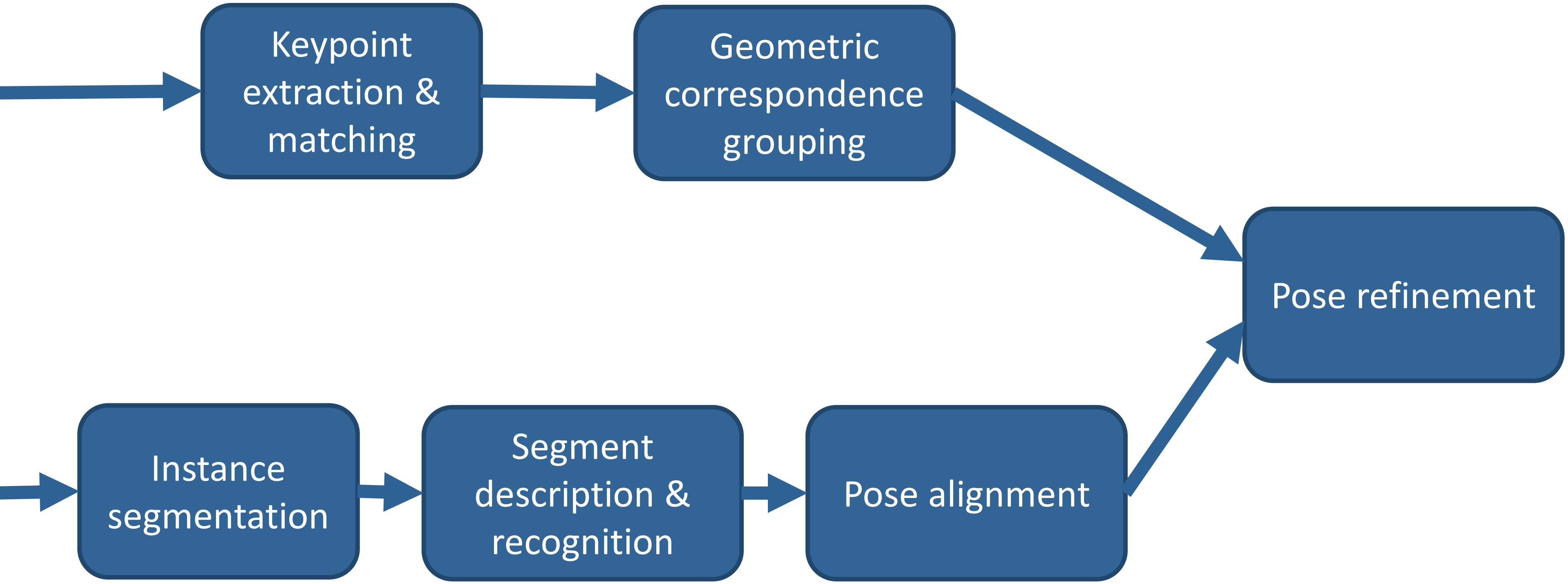



Intra-class variation vs. specific object detection

Slide adapted from F. Li and A. Torralba

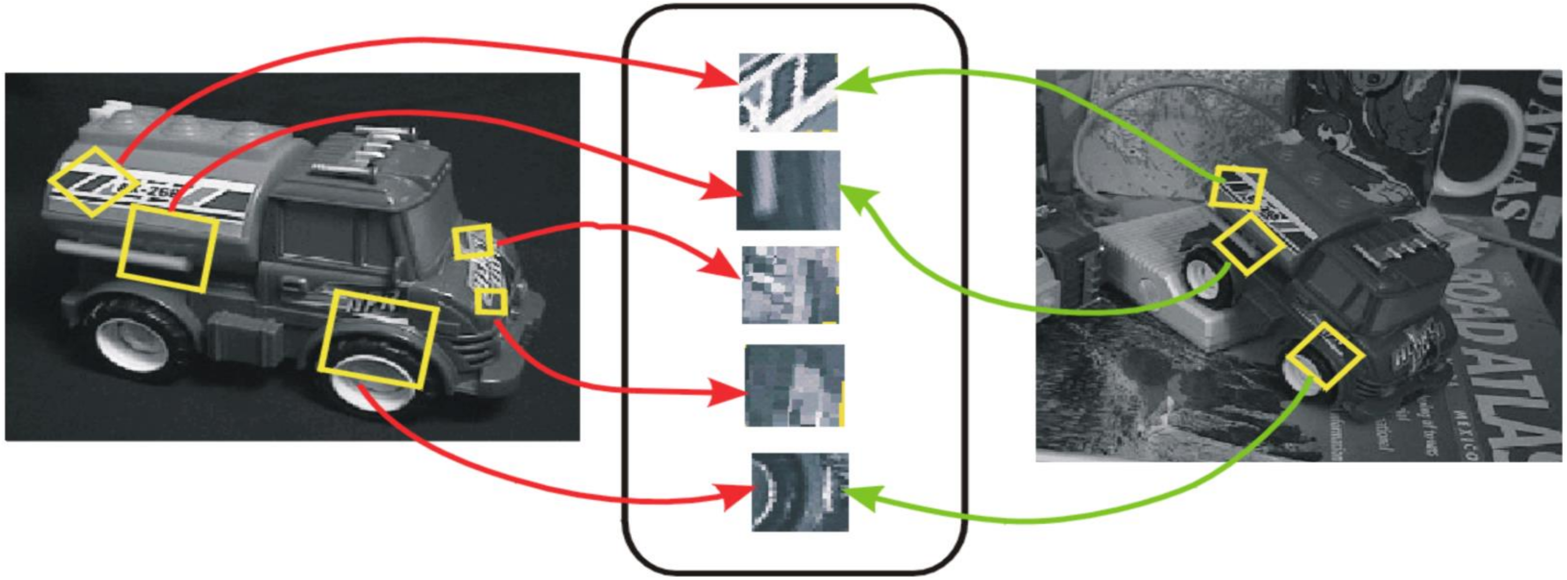
3D Object Detection Pipelines

- Local vs. global object description



Object Detection with Local Features

- Find a consistent geometric configuration of local features (keypoints)



Keypoints e.g. SIFT

Image from D. Lowe

Object Detection with Local Features

- Which transformations can we estimate, if we are only given 2D views on an object with 2D image locations of keypoints?
  - Affine transformations
  - Projective transformations (homography)

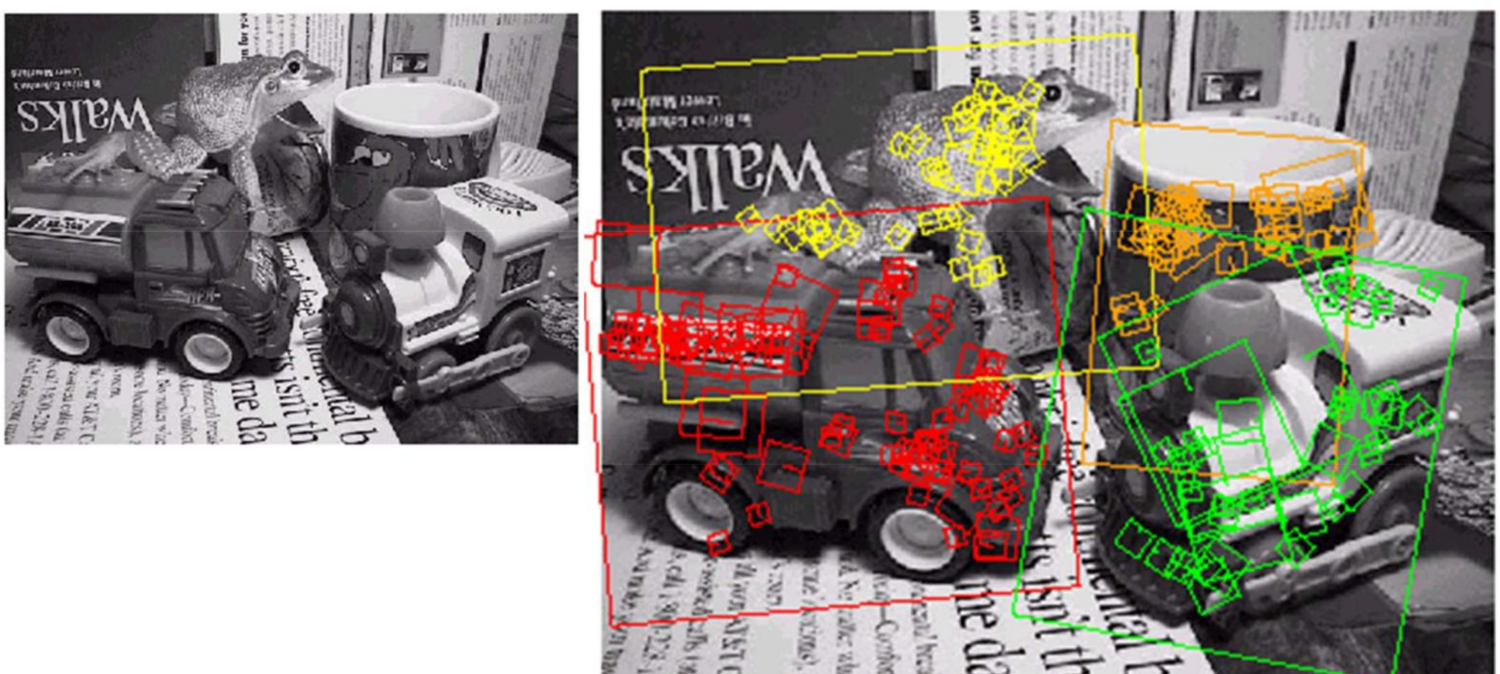
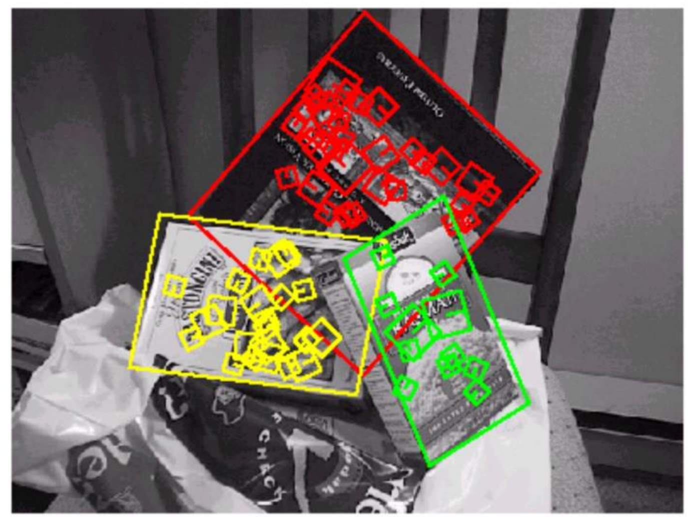


Image from D. Lowe

2D Affine Transformations

- 2D affine transformations approximate perspective projection of planar objects



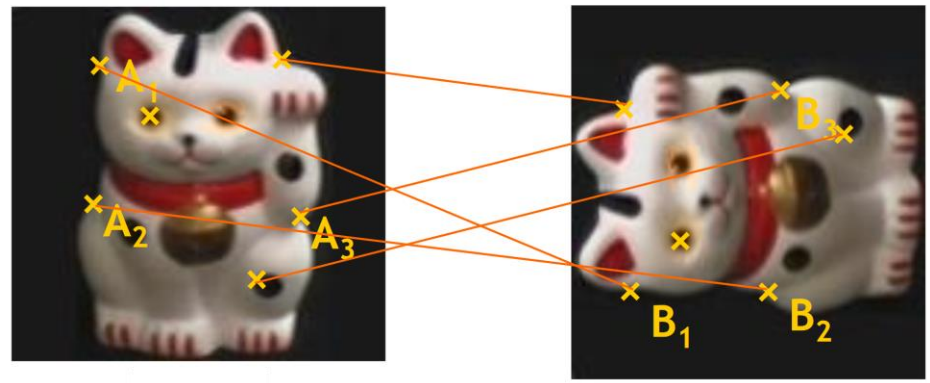
- Can work well for (almost) planar objects and (almost) orthographic camera

Image from D. Lowe

2D Affine Transformations

- 2D affine transformations approximate perspective projection of planar objects

$$\bar{\mathbf{y}}' = \begin{pmatrix} m_{11} & m_{12} & t_1 \\ m_{21} & m_{22} & t_2 \\ 0 & 0 & 1 \end{pmatrix} \bar{\mathbf{y}}$$



$\mathbf{y}$ $\mathbf{y}'$

- Parallel lines remain parallel

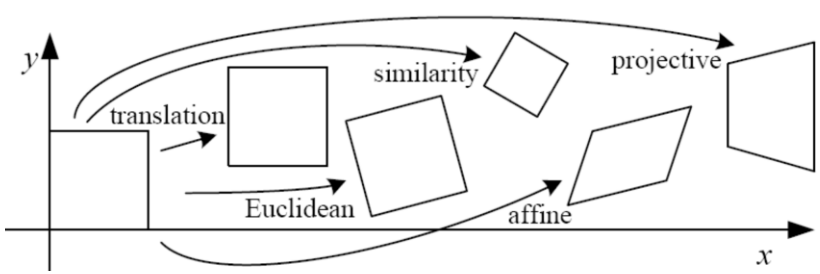


Image from A. Efros

Image from D. Lowe

2D Affine Transformations

- Which basic transformations can we represent with affine transformations?

$$\overline{\mathbf{y}}' = \begin{pmatrix} \cos\theta & -\sin\theta & 0 \\ \sin\theta & \cos\theta & 0 \\ 0 & 0 & 1 \end{pmatrix} \overline{\mathbf{y}}$$

2D rotation

$$\overline{\mathbf{y}}' = \begin{pmatrix} 1 & 0 & t_1 \\ 0 & 1 & t_2 \\ 0 & 0 & 1 \end{pmatrix} \overline{\mathbf{y}}$$

2D translation

$$\overline{\mathbf{y}}' = \begin{pmatrix} s_1 & 0 & 0 \\ 0 & s_2 & 0 \\ 0 & 0 & 1 \end{pmatrix} \overline{\mathbf{y}}$$

2D scaling

$$\overline{\mathbf{y}}' = \begin{pmatrix} 1 & sh_1 & 0 \\ sh_2 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix} \overline{\mathbf{y}}$$

2D shearing

Estimating 2D Affine Transformations

- Write constraints on affine transformation from multiple 2D point correspondences as

$$\underbrace{\begin{pmatrix} \vdots \\ x_i' \\ y_i' \\ \vdots \end{pmatrix}}_{\mathbf{b}} = \underbrace{\begin{pmatrix} \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ x_i & y_i & 0 & 0 & 1 & 0 \\ 0 & 0 & x_i & y_i & 0 & 1 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \end{pmatrix}}_{\mathbf{A}} \underbrace{\begin{pmatrix} m_{11} \\ m_{12} \\ m_{21} \\ m_{22} \\ t_1 \\ t_2 \end{pmatrix}}_{\boldsymbol{\theta}}$$

- Linear least squares estimation $\boldsymbol{\theta} = \mathbf{A}^{\dagger}\mathbf{b}$

Projective Transformations/Homographies

- Under a pinhole projection model, images of points on a 3D plane taken from different views are related by a homography

$$\tilde{\mathbf{y}}' = \underbrace{\begin{pmatrix} h_{11} & h_{12} & h_{13} \\ h_{21} & h_{22} & h_{23} \\ h_{31} & h_{32} & h_{33} \end{pmatrix}}_{\mathbf{H}} \bar{\mathbf{y}}$$

due to scale ambiguity we can set $h_{33} = 1$

- Parallel lines in 3D do not remain parallel in the image
- Straight lines are preserved
- Rectangle maps to quadrilateral

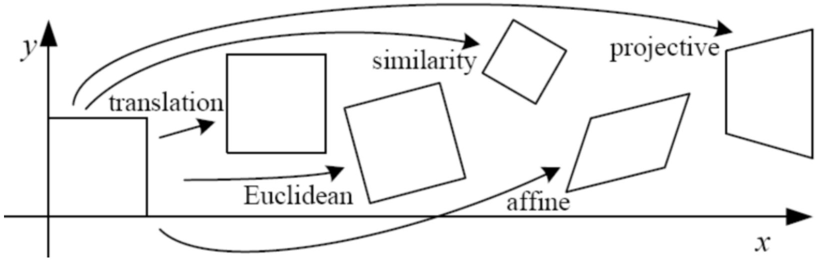
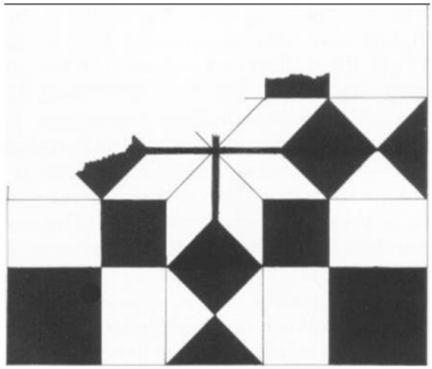


Image from A. Efros

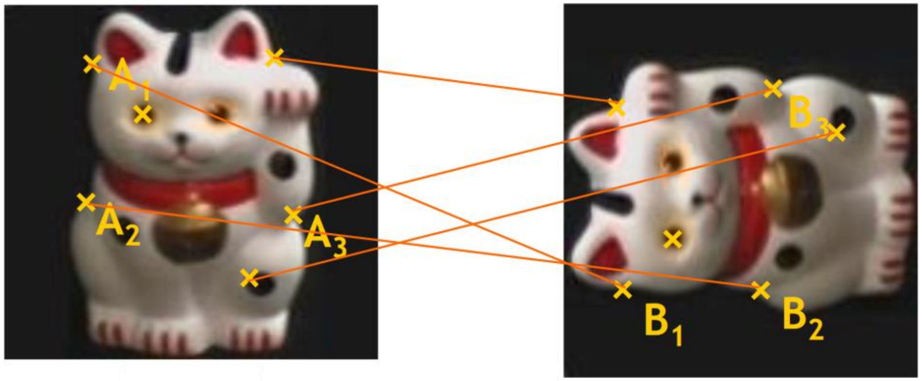
Homography Example

Image from A. Criminisi



Manual reconstruction by Martin Kemp, The Science of Art

Estimating Homographies



- Each 2D point correspondence provides the constraints

$$\tilde{\mathbf{y}}' = \mathbf{H}\bar{\mathbf{y}} \qquad \bar{\mathbf{y}}' = \frac{1}{\tilde{w}'}\tilde{\mathbf{y}}'$$

$$x' = \frac{h_{11}x + h_{12}y + h_{13}}{h_{31}x + h_{32}y + 1}$$

$$y' = \frac{h_{21}x + h_{22}y + h_{23}}{h_{31}x + h_{32}y + 1}$$

- Constraints can be written as

$$x'h_{31}x + x'h_{32}y + x' - h_{11}x - h_{12}y - h_{13} = 0$$
$$y'h_{31}x + y'h_{32}y + y' - h_{21}x - h_{22}y - h_{23} = 0$$

Estimating Homographies

- Leads to homogeneous set of linear equations

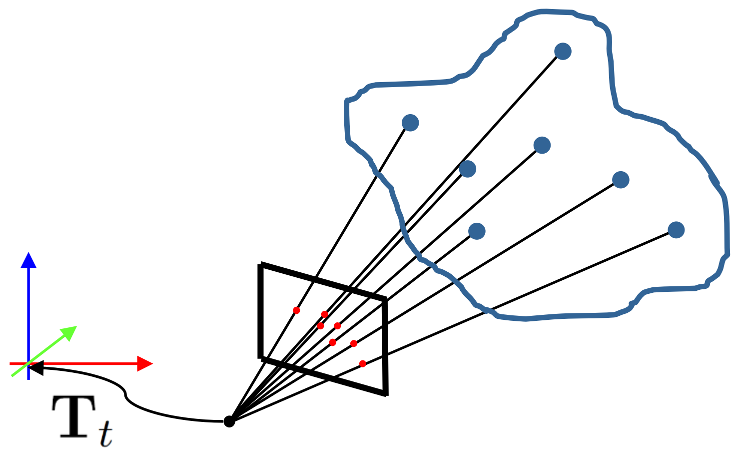
$$\underbrace{\begin{pmatrix} \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ x & y & 1 & 0 & 0 & 0 & -x'x & -x'y & -x' \\ 0 & 0 & 0 & x & y & 1 & -y'x & -y'y & -y' \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \end{pmatrix}}_{\mathbf{A}} \underbrace{\begin{pmatrix} h_{11} \\ h_{12} \\ h_{13} \\ h_{21} \\ h_{22} \\ h_{23} \\ h_{31} \\ h_{32} \\ 1 \end{pmatrix}}_{\mathbf{h}} = \mathbf{0}$$

- Find norm 1 solution in nullspace of A as singular vector of A corresponding to smallest singular value

$$\mathbf{A} = \mathbf{U}\mathbf{D}\mathbf{V}^\top \qquad \mathbf{h} = \left(v_{19} \cdots v_{99}\right)^\top / v_{99}$$

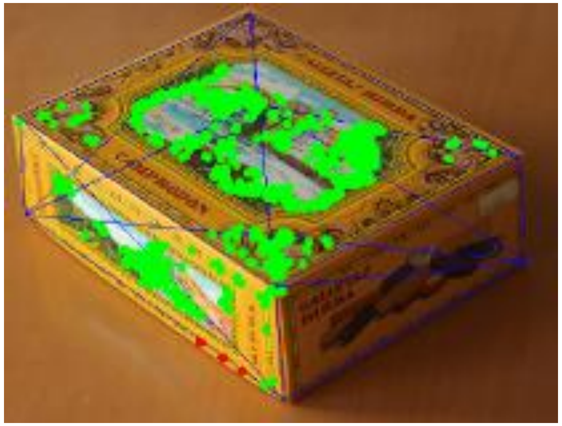
Monocular 3D Object Pose Estimation

- If we have a 3D model of keypoints on the object available, we can use PnP algorithms (see Lec. 6) to determine 3D rotation and translation of the object from 2D-to-3D keypoint matches



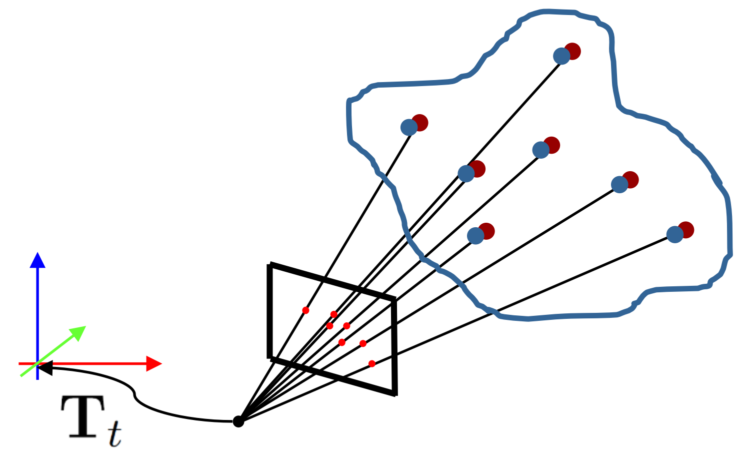
- How do we get the 3D model?

- Example: Render textured CAD model from different viewpoints and generate keypoint database with 3D coordinates in object coordinate frame

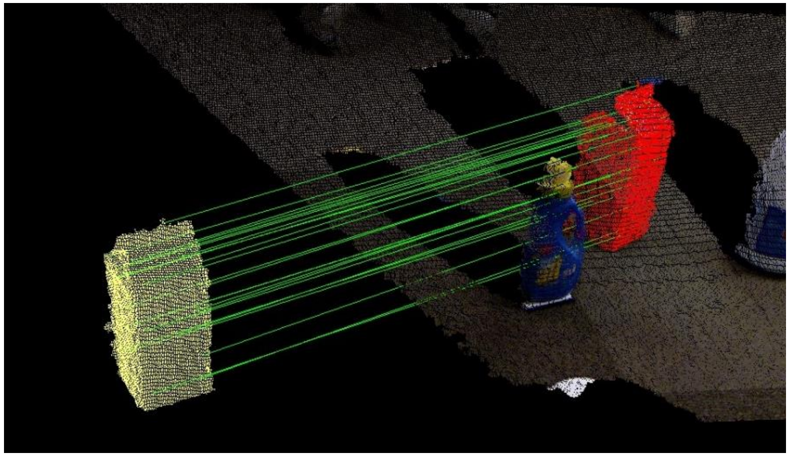


3D Object Pose Estimation in RGB-D Images

- With RGB-D images, we can also perform 3D-to-3D alignment of matched keypoints between model and image



- Alternatively to 2D image points in RGB images, 3D shape keypoints and global shape descriptors of object segments have been proposed that can be extracted from the depth images

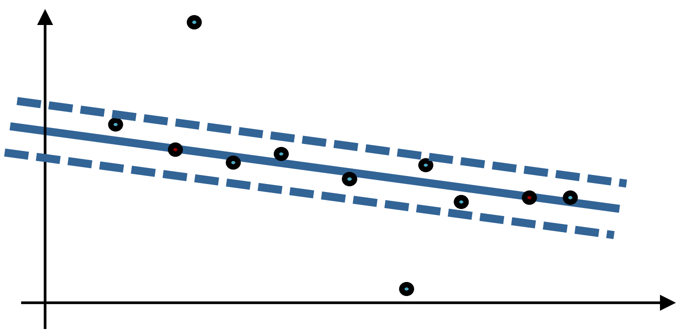


- Examples: FPFH, SHOT, Spin Images, CVFH, PPF… (details later)

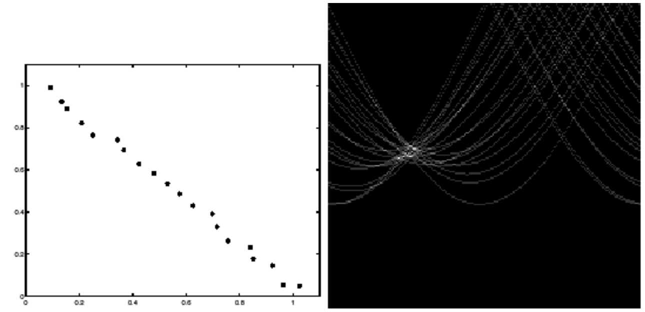
Correspondence Grouping and Robust Alignment

- If multiple objects are present in a scene, we need a process to group correspondences of each single object before alignment
- Keypoint matches can be erroneous, direct LS fitting not possible

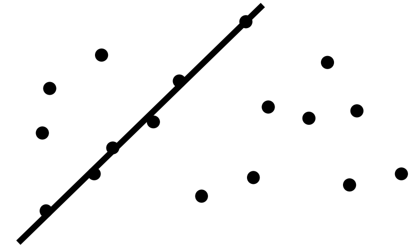
- Approach 1: RANSAC (see Lec. 7)
  - Sample minimal tuples of matches to perform alignment and determine LS fit to best inlier set
  - Remove inliers and fit next object

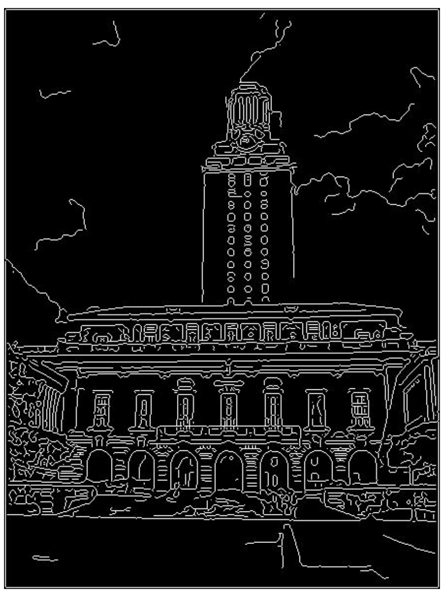


- Approach 2: Generalized Hough Transform (this lecture)
  - Each minimal tuple of matches needed for alignment votes in pose parameter space (using a discretization/histogram)
  - Object poses correspond to maxima in pose parameter histogram with sufficient number of votes



Example: Line Fitting





- Extra edge points (clutter), multiple models:
  - Which points go with which line, if any?
- Only some parts of each line detected, and some parts are missing:
  - How to find a line that bridges missing evidence?
- Noise in measured edge points, orientations:
  - How to detect true underlying parameters?

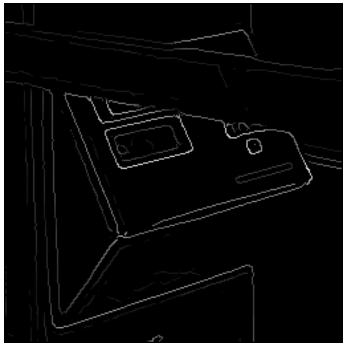
Slide adapted from K. Grauman

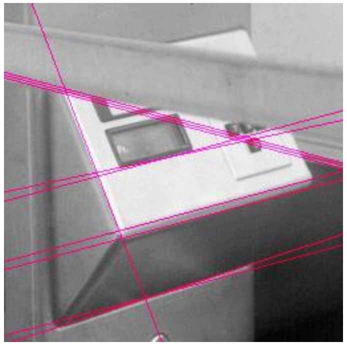
Fitting Lines with the Hough Transform

- Given points that belong to a line, what is the line?
- How many lines are there?
- Which points belong to which lines?

- Hough Transform is a voting technique that can be used to answer all of these questions.

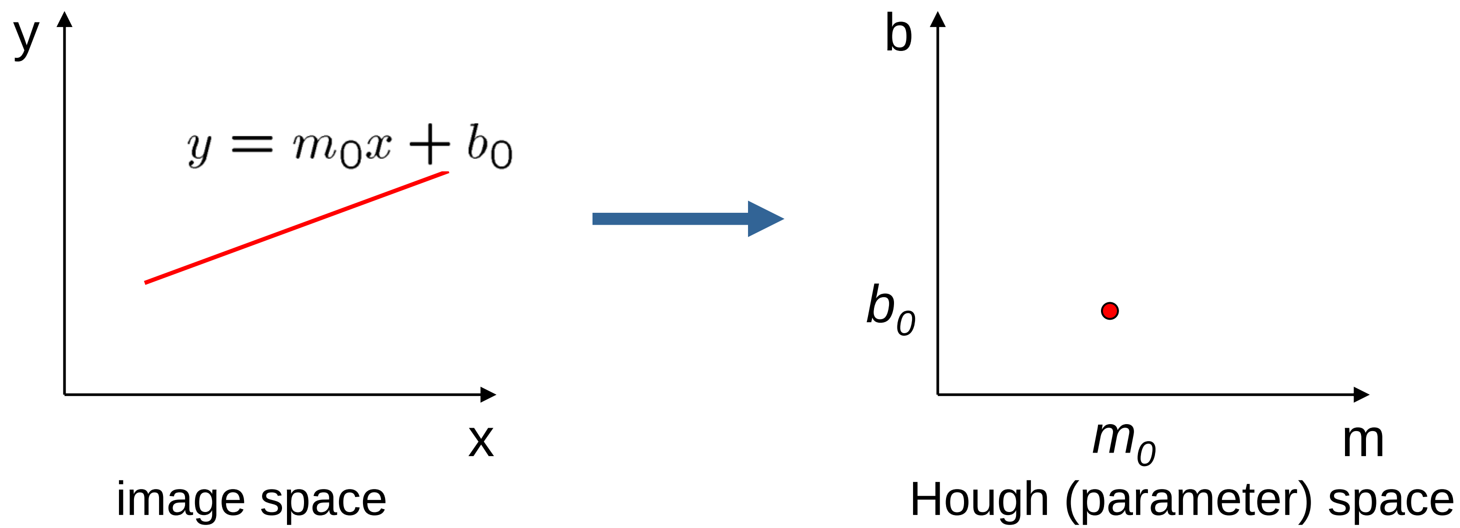
- Main idea:
  - 1. Record vote for each possible line on which each edge point lies
  - 2. Look for lines that get many votes





Slide adapted from K. Grauman

Fitting Lines with the Hough Transform

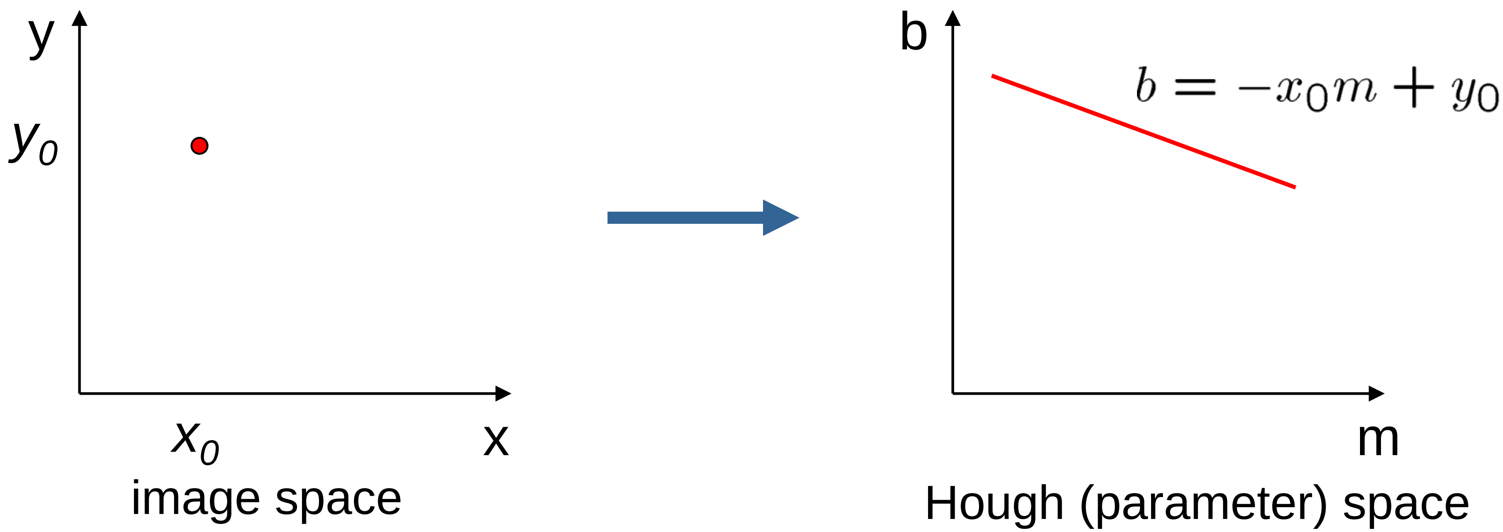


Connection between image (x,y) and Hough (m,b) spaces

- A line in the image corresponds to a point in Hough space
- To go from image space to Hough space:
  - given a set of points (x,y), find all (m,b) such that y = mx + b

Slide adapted from S. Seitz

Fitting Lines with the Hough Transform

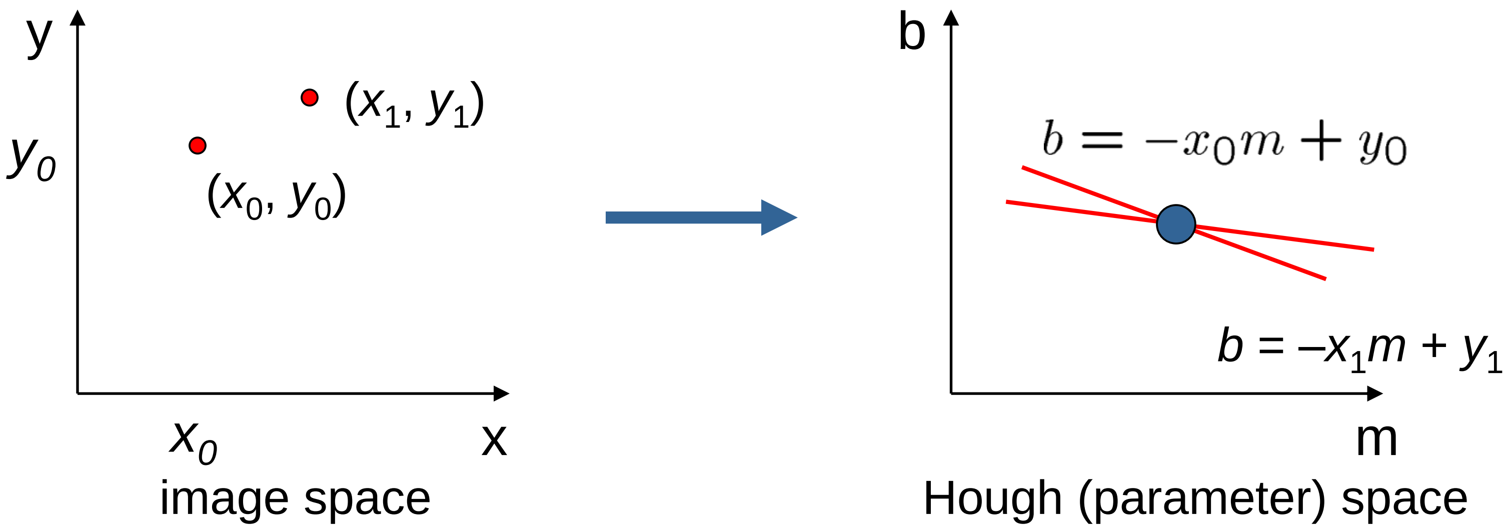


Connection between image (x,y) and Hough (m,b) spaces

- A line in the image corresponds to a point in Hough space
- To go from image space to Hough space:
  - given a set of points (x,y), find all (m,b) such that y = mx + b
- What does a point (x_0, y_0) in the image space map to?
  - Answer: the solutions of $b = -x_0 m + y_0$
  - this is a line in Hough space

Slide adapted from S. Seitz

Fitting Lines with the Hough Transform

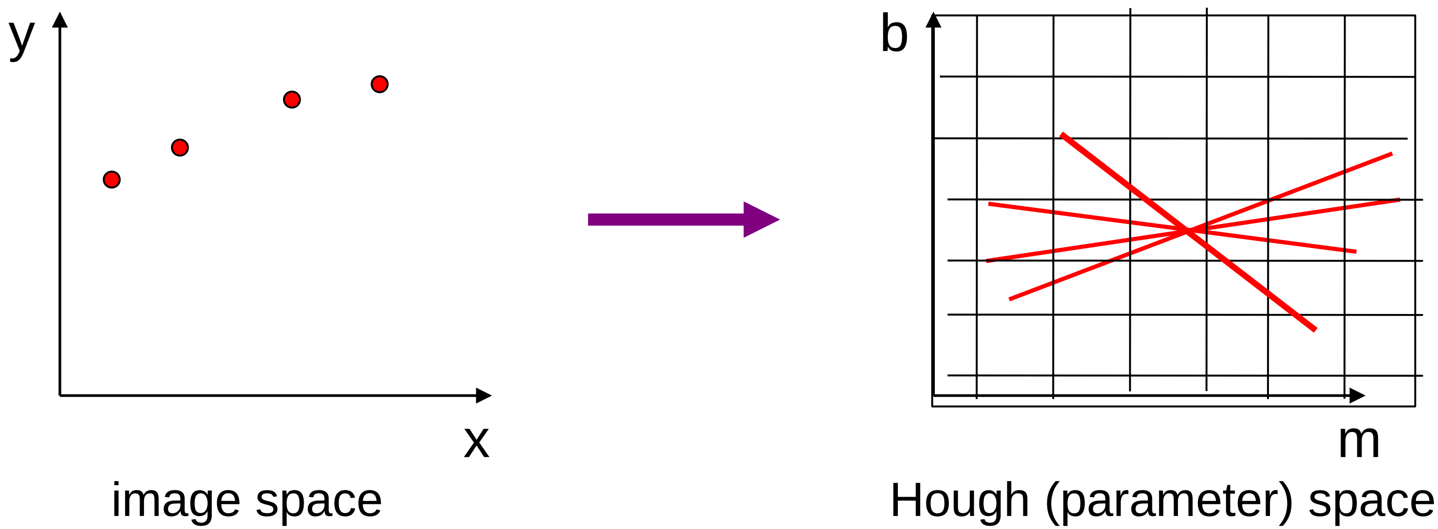


What are the line parameters for the line that contains both (x_0, y_0) and (x_1, y_1)?

- It is the intersection of the lines $b = -x_0 m + y_0$ and $b = -x_1 m + y_1$

Slide adapted from K. Grauman

Fitting Lines with the Hough Transform

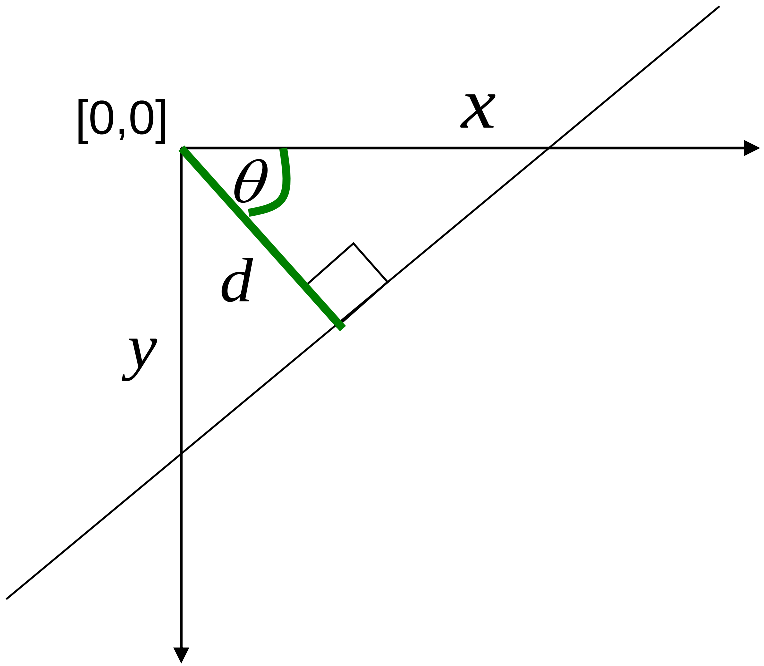


How can we use this to find the most likely parameters (m,b) for the most prominent line in the image space?

- Let each edge point in image space *vote* for a set of possible parameters in Hough space
- Accumulate votes in discrete set of bins; parameters with the most votes indicate line in image space

Slide adapted from K. Grauman

Polar Line Representation



d : perpendicular distance from line to origin

θ : angle the perpendicular makes with the x-axis

$$x\cos\theta - y\sin\theta = d$$

- Issues with usual (*m*,*b*) parameter space: can take on infinite values, undefined for vertical lines.
- Use polar representation of lines
- Point in image space → sinusoid segment in Hough space

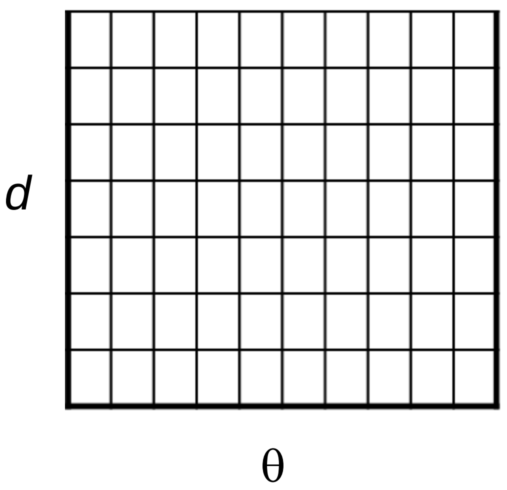
Slide adapted from K. Grauman

Hough Transform Algorithm (for Lines)

Using the polar parameterization:

$$x\cos\theta - y\sin\theta = d$$

H: accumulator array (votes)



Basic Hough transform algorithm

1. Initialize H[d, θ]=0
2. for each edge point I[x,y] in the image

   for θ = [θ_{min} to θ_{max}] // some quantization

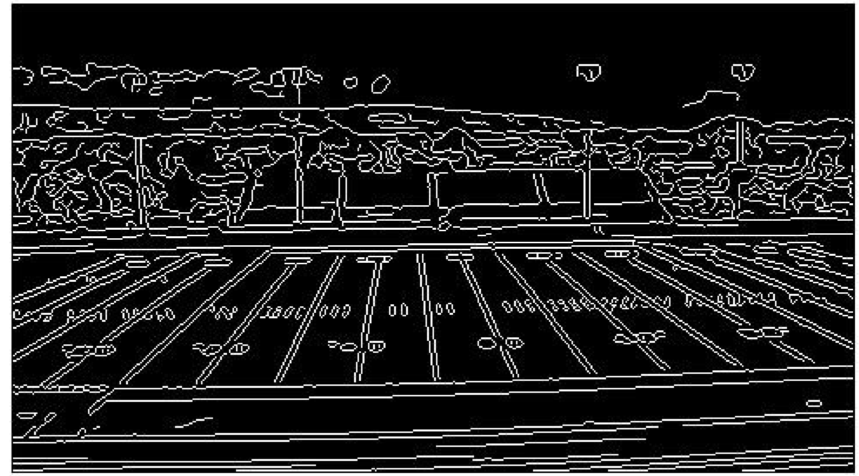
   $$d = x\cos\theta - y\sin\theta$$

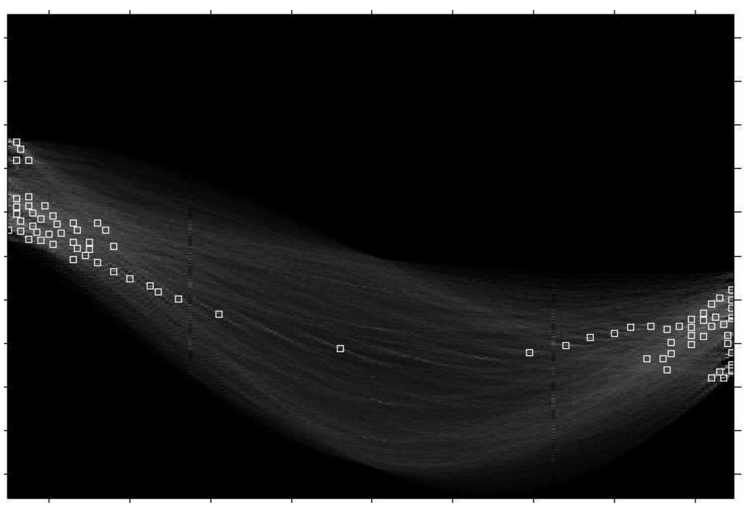
   H[d, θ] += 1
3. Find the value(s) of (d, θ) where H[d, θ] is maximum
4. The detected line in the image is given by $d = x\cos\theta - y\sin\theta$

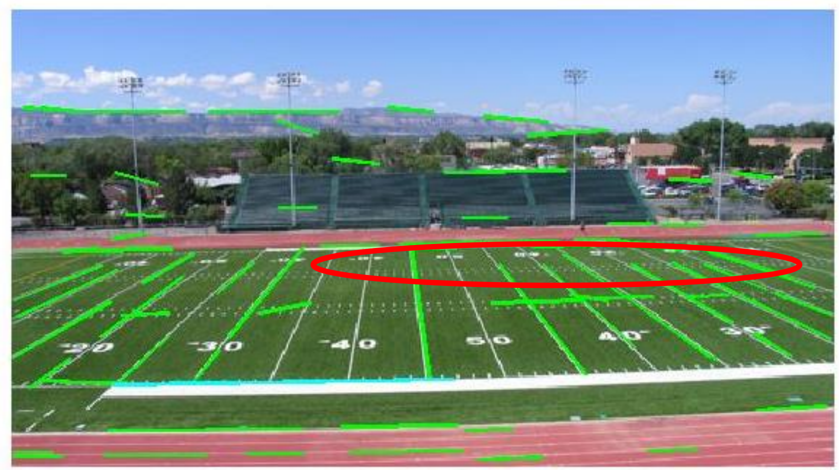
Time complexity (in terms of number of votes per pt)?

Slide adapted from K. Grauman

Fitting Lines with the Hough Transform







Showing longest segments found

Slide adapted from K. Grauman

Impact of Noise on the Hough Transform

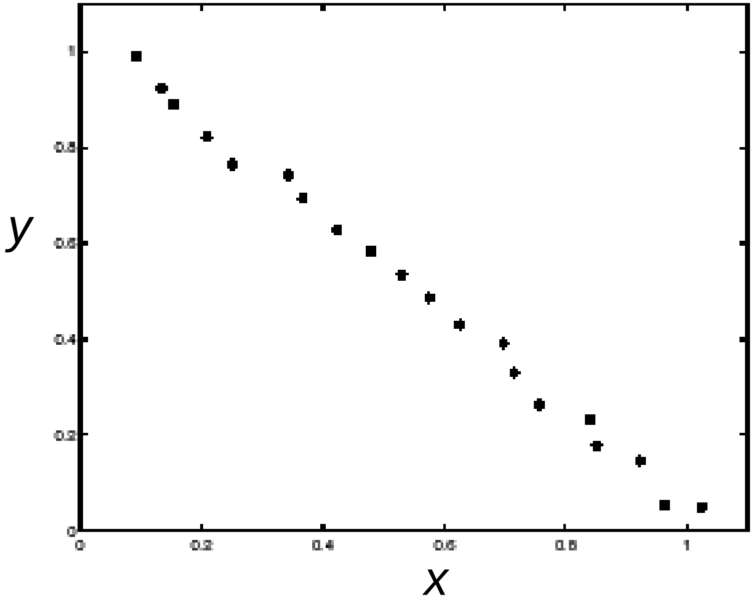
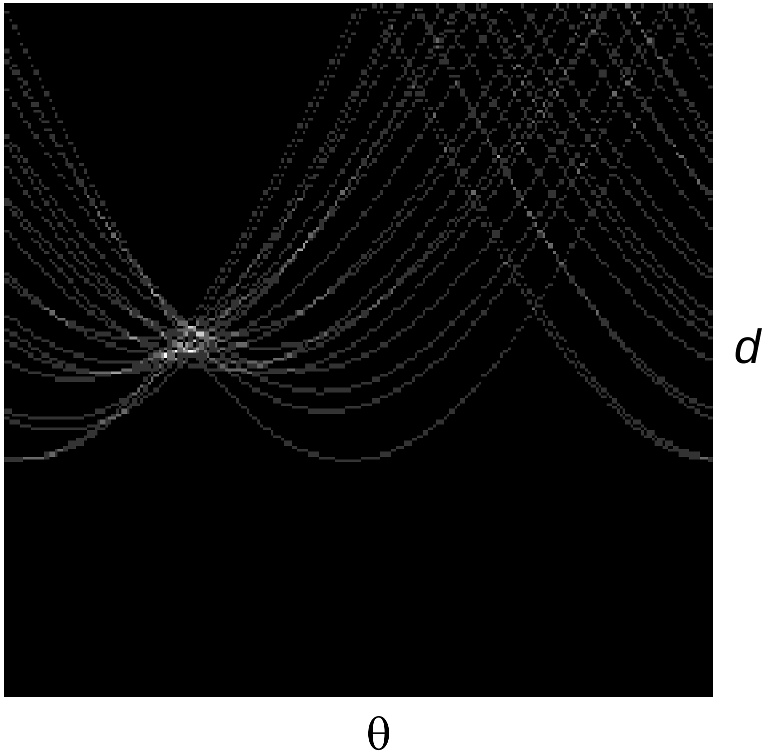


Image space
edge coordinates



Votes

Slide adapted from K. Grauman

Impact of Noise on the Hough Transform

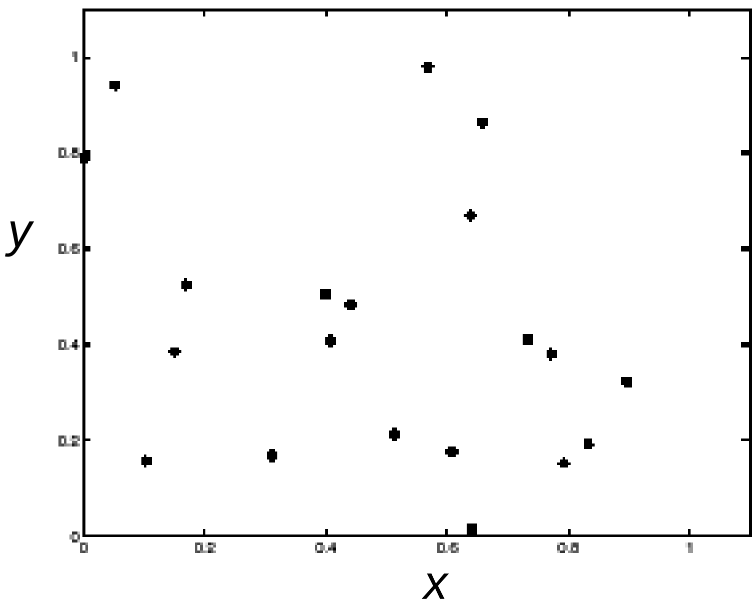
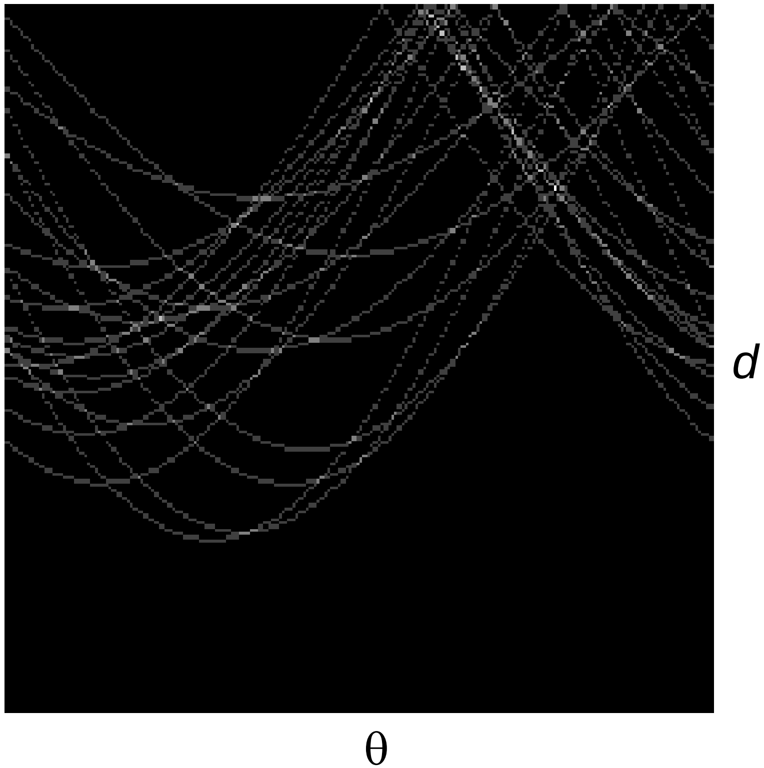


Image space
edge coordinates



Votes

Slide adapted from K. Grauman

Extensions

Extension 1: Use the image gradient

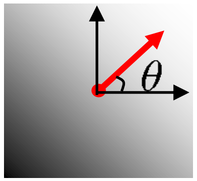
1. same
2. for each edge point I[x,y] in the image

   θ = gradient angle at (x,y)

   $d = x\cos\theta - y\sin\theta$

   H[d, θ] += 1
3. same
4. same

(Reduces degrees of freedom)



$$\nabla f = \left[\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y}\right]$$

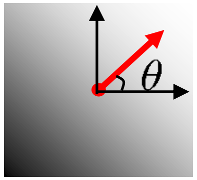
$$\theta = \tan^{-1}\left(\frac{\partial f}{\partial y} / \frac{\partial f}{\partial x}\right)$$

Slide adapted from K. Grauman

Extensions

Extension 1

- Use the image gradient



$$\nabla f = \left[\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y}\right]$$

$$\theta = \tan^{-1}\left(\frac{\partial f}{\partial y} / \frac{\partial f}{\partial x}\right)$$

Extension 2

- Give more votes for stronger edges (use magnitude of gradient)

Extension 3

- Change the sampling of (d, θ) to give more/less resolution

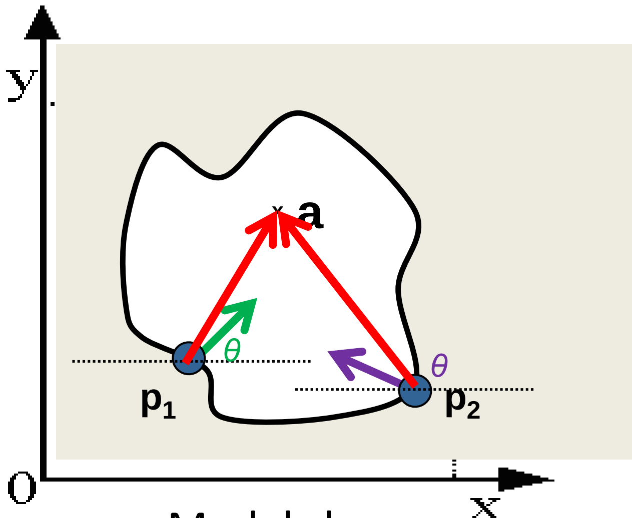
Extension 4

- The same procedure can be used with circles, squares, or any other shape…

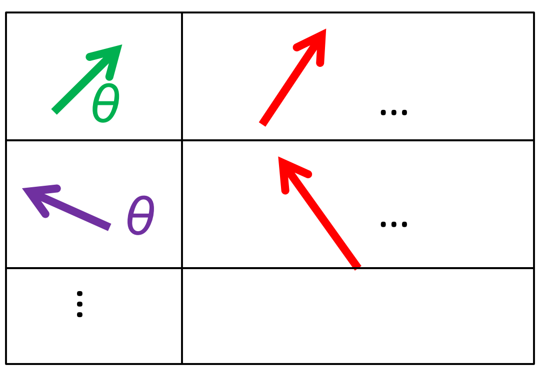
Slide adapted from K. Grauman

Generalized Hough Transform

- Define a model shape by its boundary points and a reference point



Model shape



<u>Offline procedure:</u>

At each boundary point, compute displacement vector: $\mathbf{r} = \mathbf{a} - \mathbf{p}_i$

Store these vectors in a table indexed by gradient orientation θ

(Dana H. Ballard, Generalizing the Hough Transform to Detect Arbitrary Shapes, 1980)

Slide adapted from K. Grauman

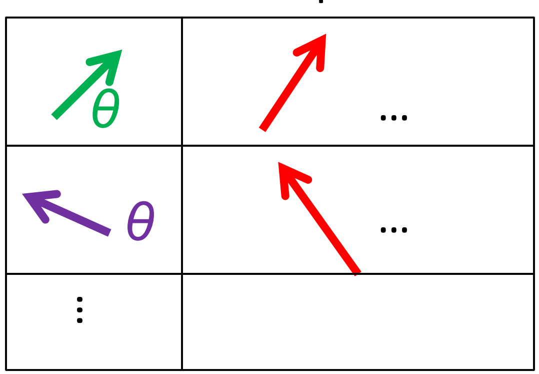
Generalized Hough Transform

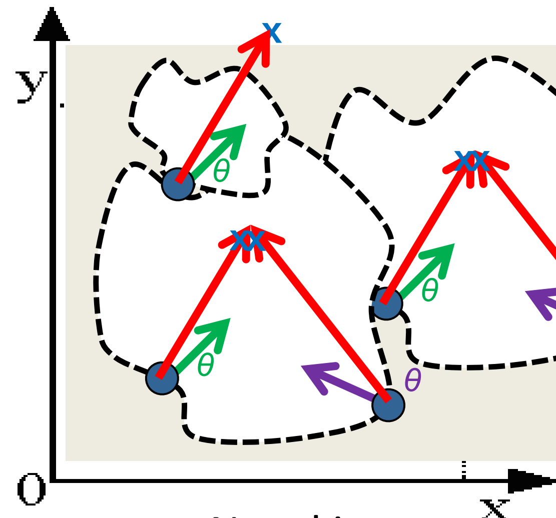
<u>Detection procedure:</u>

For each edge point:

- Use its gradient orientation to index into stored table
- Use retrieved **r** vectors to vote for reference point

Model shape





Novel image

[Dana H. Ballard, Generalizing the Hough Transform to Detect Arbitrary Shapes, 1980]

Slide adapted from K. Grauman

Generalized Hough Transform

- Instead of indexing displacements by gradient orientation, index by "visual codeword"

B. Leibe, A. Leonardis, and B. Schiele, [Combined Object Categorization and Segmentation with an Implicit Shape Model](), ECCV Workshop on Statistical Learning in Computer Vision 2004

Slide adapted from K. Grauman

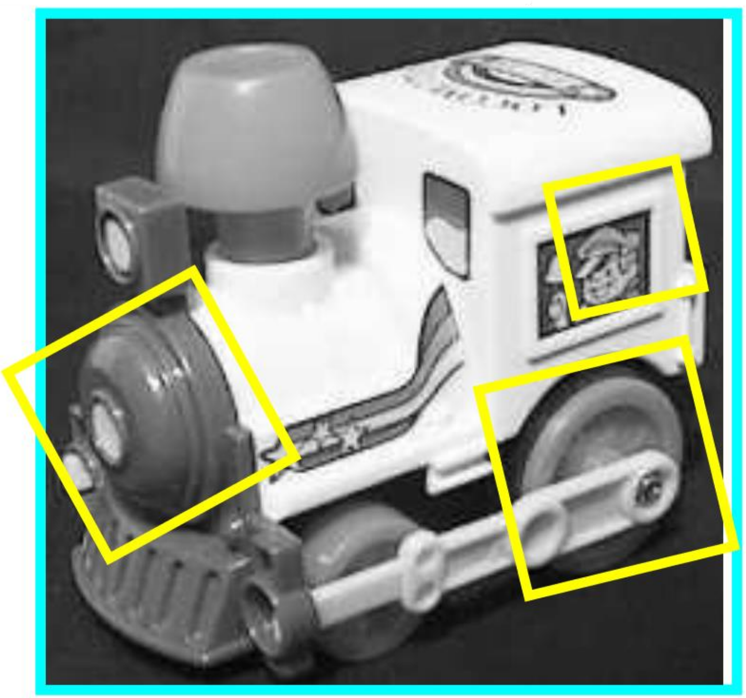
Hough Voting: Practical Tips

- Minimize irrelevant tokens first (take edge points with significant gradient magnitude)
- Choose a good grid / discretization
  - Too coarse: large votes obtained when too many different lines correspond to a single bucket
  - Too fine: miss lines because some points that are not exactly collinear cast votes for different buckets
- Vote for neighbors, also (smoothing in accumulator array)
- Utilize direction of edge to reduce free parameters by 1

Slide adapted from K. Grauman

Hough Voting: 2D-to-2D Matching

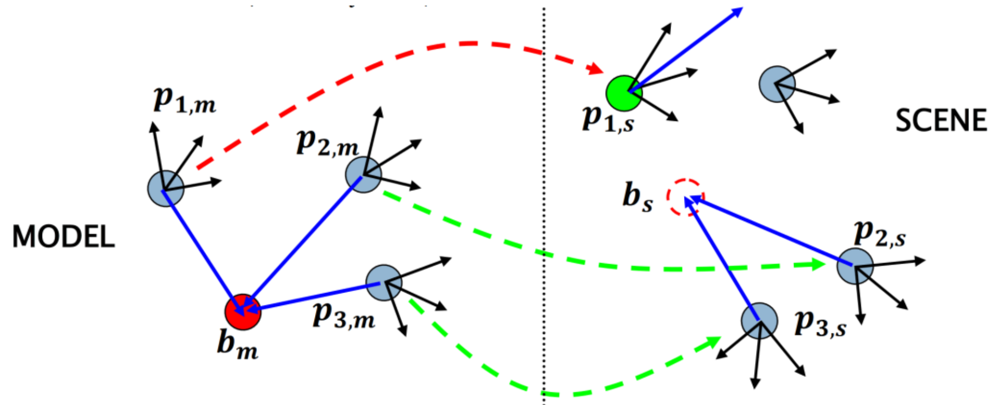
- Oriented local 2D keypoint matches cast votes for affine transformations (f.e. 2D translation, scale & 2D rotation)



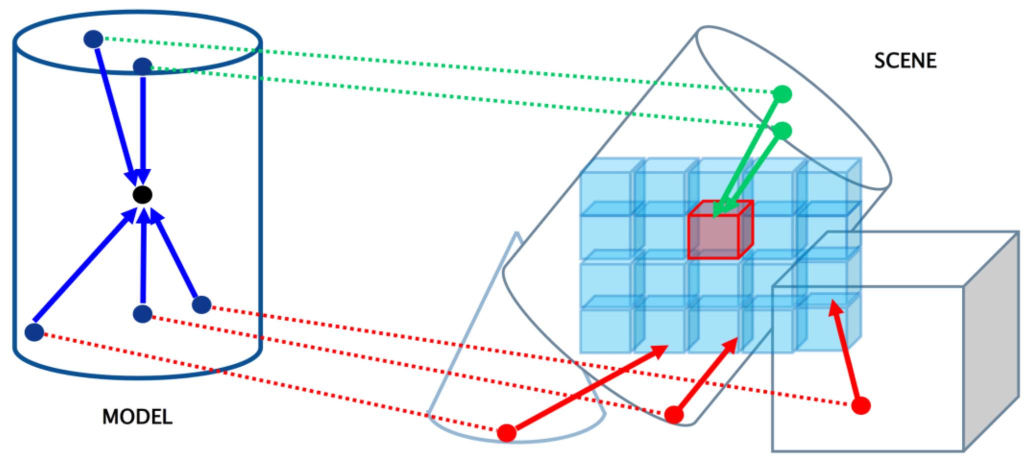
Slide adapted from S. Lazebnik

Hough Voting: 3D-to-3D Matching

- Oriented local 3D keypoint matches cast votes for Euclidean transformations (f.e. 3D translation & 3D rotation)



- Requires repeatable extraction of reference frame at each keypoint
  - Can be difficult to obtain reliably

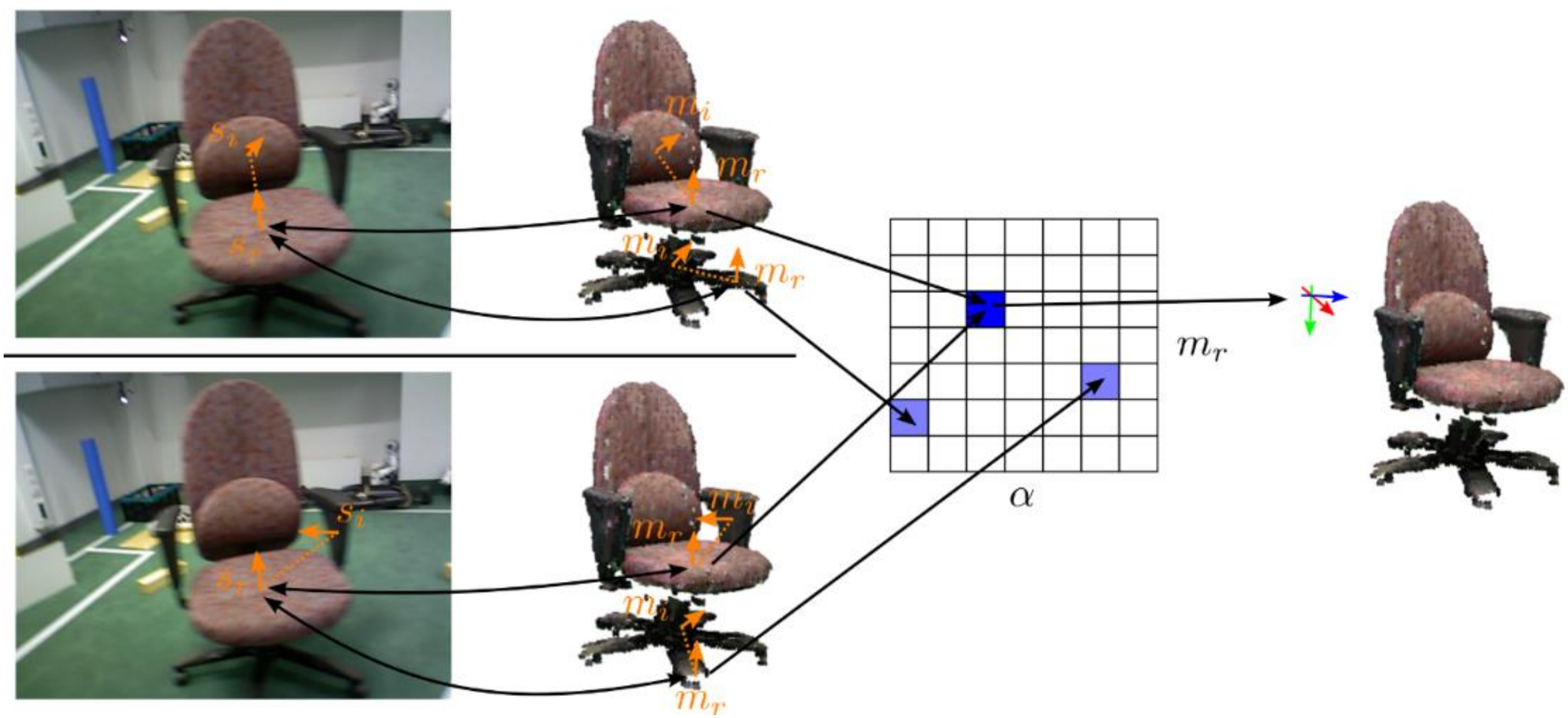


(F. Tombari and L. Stefano, Hough Voting for 3D Object Recognition under Occlusion and Clutter, 2012)

Images from F. Tombari

Hough Voting: Surfel-Pair Matching

- Surfel pairs cast votes for Euclidean transformations (f.e. 3D translation & 3D rotation)
- Details see next lecture



Lessons Learned Today

- Object detection is about localization and recognition of objects in images
- 3D object detection:
  - pose estimation of specific objects
  - From 2D-to-2D keypoint correspondences to an object model we can estimate affine and projective transformations
  - If we have 3D position of keypoints in a model available, we can apply PnP algorithms to estimate 6-DoF pose
- Generalized Hough transform as alternative to RANSAC for correspondence grouping and robust alignment

Thanks for your attention!