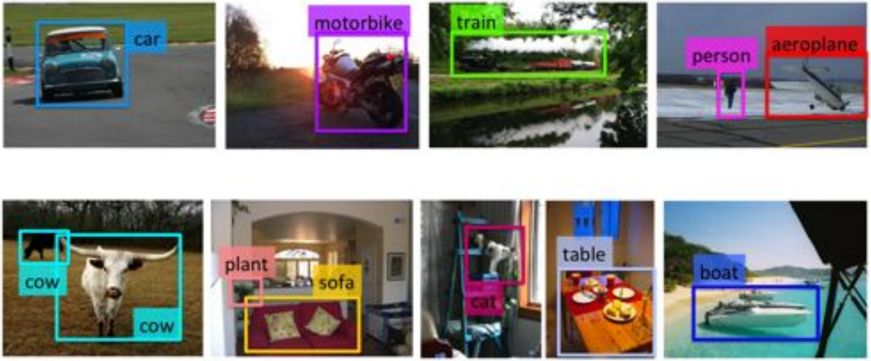
Object Detection

Object Detection

- The goal of object detection is to localize objects in an image and tell their class
- Localization: **place a tight bounding box around object**
- Most approaches find only objects of one or a few specific classes, e.g. car or cow



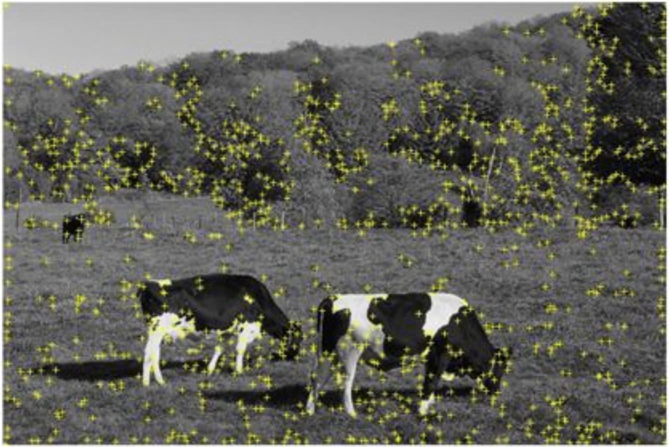
Type of Approaches

Different approaches tackle detection differently. They can roughly be categorized into three main types:

- Find **interest points**, followed by Hough voting

Interest Point Based Approaches

- Compute interest points (e.g., Harris corner detector is a popular choice)
- Vote for where the object could be given the content around interest points



Interest points

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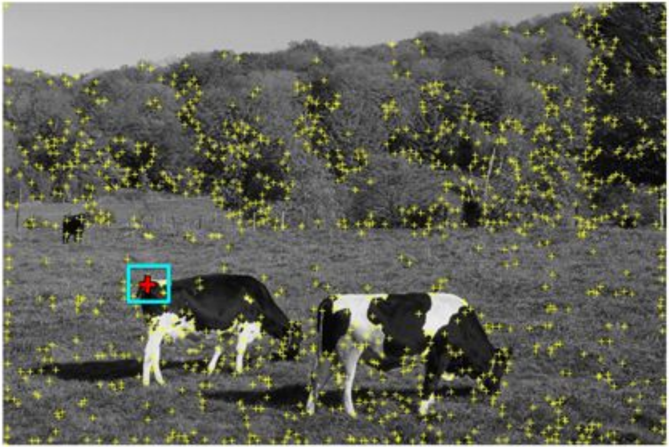

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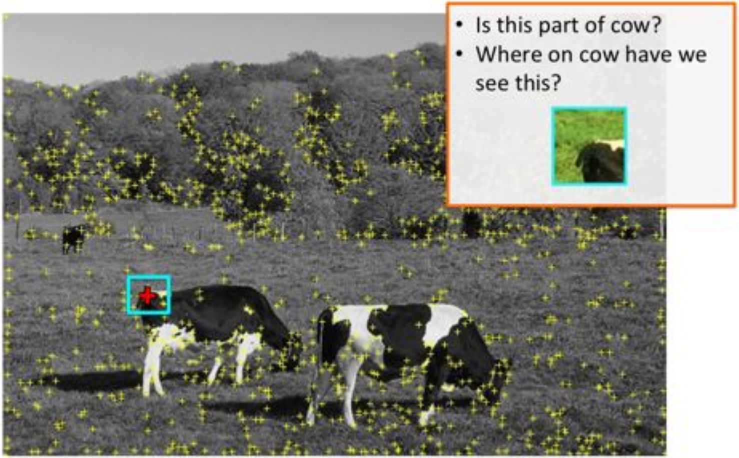

- Is this part of cow?
- Where on cow have we see this?

Interest points

Interest Point Based Approaches

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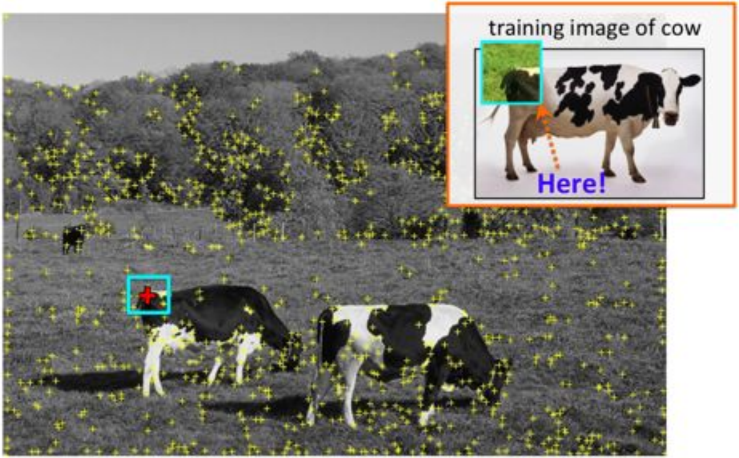

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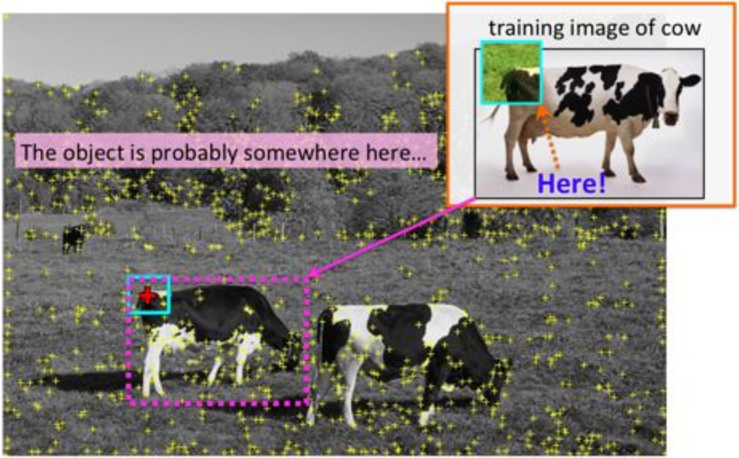


Interest points

Type of Approaches

Different approaches tackle detection differently. They can roughly be categorized into three main types:

- Find **interest points**, followed by Hough voting
- **Sliding windows: "slide" a box around image and classify each image crop** inside a box (contains object or not?)
- Generate **region (object) proposals**, and classify each region

Type of Approaches

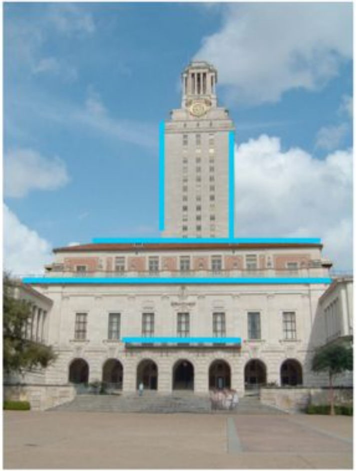
Different approaches tackle detection differently. They can roughly be categorized into three main types:

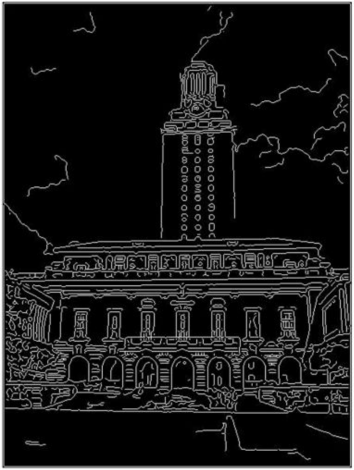
- Find **interest points**, followed by Hough voting ← **Let's first look at one example method for this**
- **Sliding windows**: "slide" a box around image and classify each image crop inside a box (contains object or not?)
- Generate **region (object) proposals**, and classify each region

Object Detection via Hough Voting:

Start with Simple: Line Detection

- How can I find lines in this image?



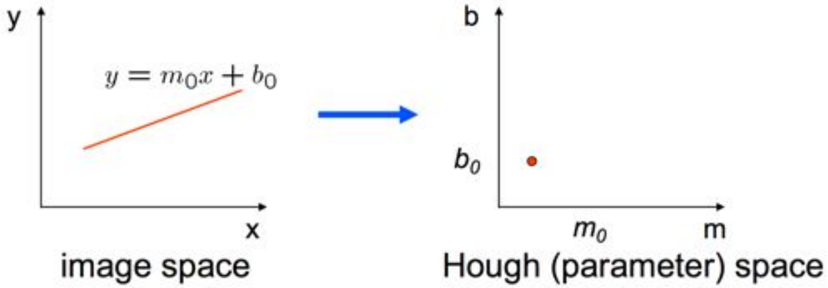


Hough Transform

- Idea: Voting (Hough Transform)
- Voting is a general technique where we let the features vote for all models that are compatible with it.
    - Cycle through features, cast votes for model parameters.
    - Look for model parameters that receive a lot of votes.

Hough Transform: Line Detection

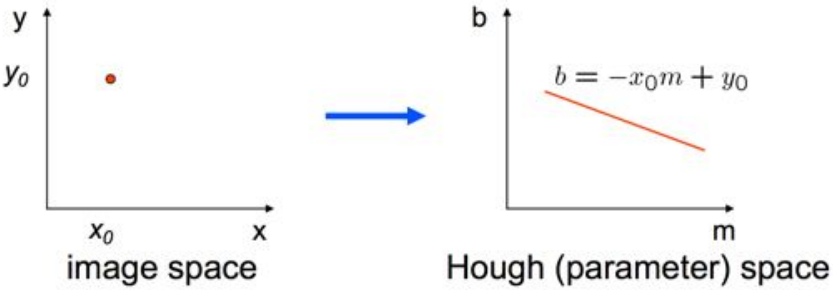
- Hough space: parameter space



- Connection between image (x, y) and Hough (m, b) spaces
  - A line in the image corresponds to a point in Hough space
  - What does a point (x_0, y_0) in the image space map to in Hough space?

Hough Transform: Line Detection

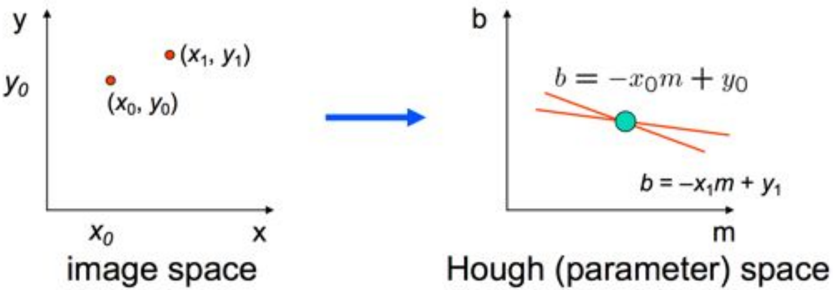
- Hough space: parameter space



- Connection between image (x, y) and Hough (m, b) spaces
  - A line in the image corresponds to a point in Hough space
  - A point in image space votes for all the lines that go through this point. This votes are a line in the Hough space.

Hough Transform: Line Detection

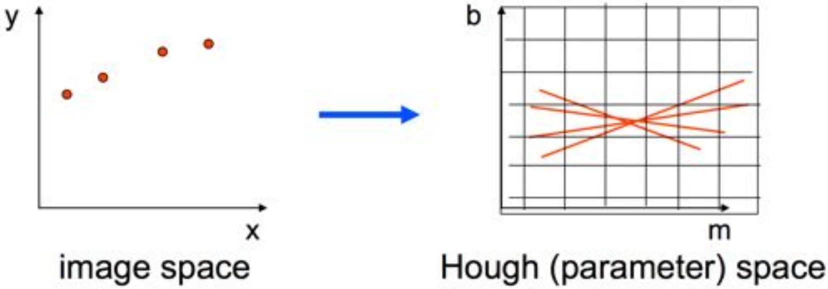
- Hough space: parameter space



- Two points: Each point corresponds to a line in the Hough space
- A point where these two lines meet defines a line in the image!

Hough Transform: Line Detection

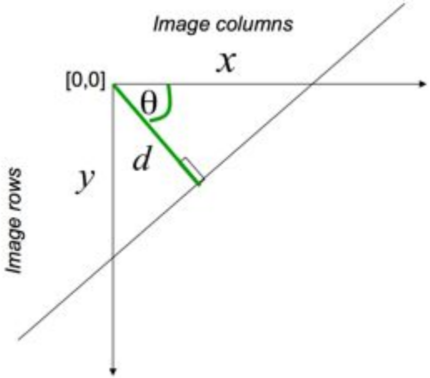
- Hough space: parameter space



- Vote with each image point
- Find peaks in Hough space. Each peak is a line in the image.

Hough Transform: Line Detection

- Issues with usual (m, b) parameter space: undefined for vertical lines
- A better representation is a polar representation of lines



d: perpendicular distance from line to origin

θ: angle the perpendicular makes with the x-axis

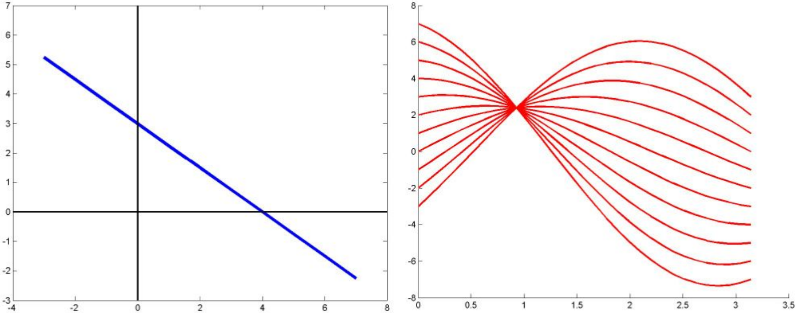
$$x\cos\theta - y\sin\theta = d$$

Point in image space → sinusoid segment in Hough space

Example Hough Transform

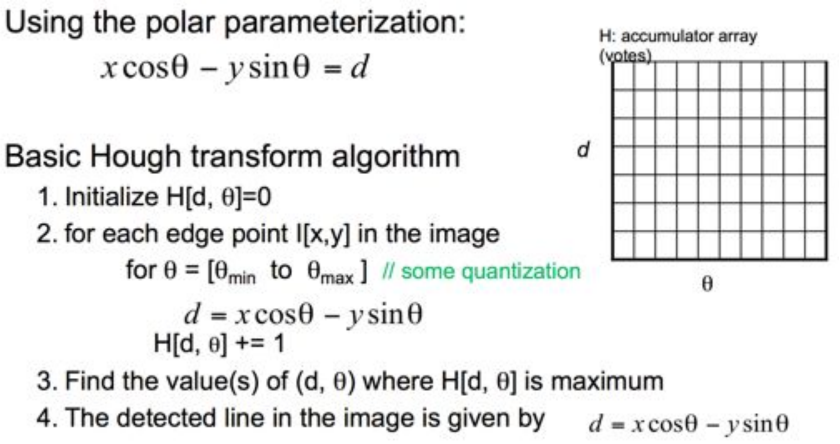
With the parameterization $x\cos\theta + y\sin\theta = d$

- Points in picture represent sinusoids in parameter space
- Points in parameter space represent lines in picture
- Example $0.6x + 0.4y = 2.4$, Sinusoids intersect at $d = 2.4$, $\theta = 0.9273$



Hough Transform: Line Detection

- **Hough Voting algorithm**



Using the polar parameterization:

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

Basic Hough transform algorithm

```
1. Initialize H[d, θ]=0
2. for each edge point I[x,y] in the image
        for θ = [$\theta_{min}$ to $\theta_{max}$ ]  // 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   $d = x\cos\theta - y\sin\theta$
```

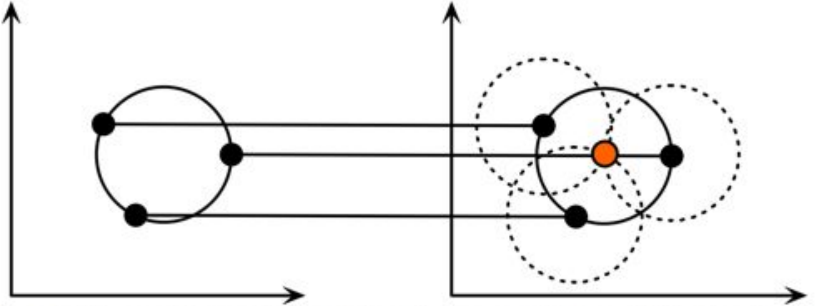
Hough Transform: Circle Detection

- What about circles? How can I fit circles around these coins?

Hough Transform: Circle Detection

Assume we are looking for a circle of known radius r

- Circle: $(x - a)^2 + (y - b)^2 = r^2$
- Hough space (a, b): A point (x_0, y_0) maps to $(a - x_0)^2 + (b - y_0)^2 = r^2 \;\rightarrow\;$ a circle around (x_0, y_0) with radius r
- Each image point votes for a circle in Hough space

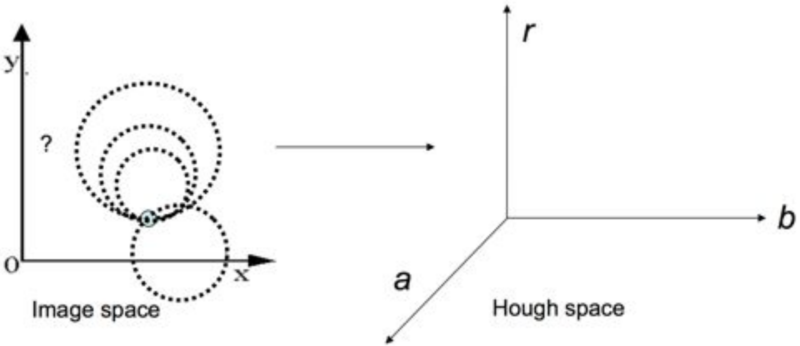


Each point in geometric space (left) generates a circle in parameter space (right). The circles in parameter space intersect at the (a, b) that is the center in geometric space.

Hough Transform: Circle Detection

What if we don't know *r*?

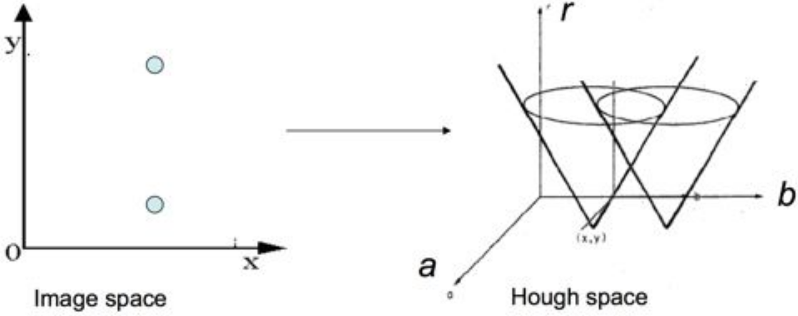
- Hough space: ?



Hough Transform: Circle Detection

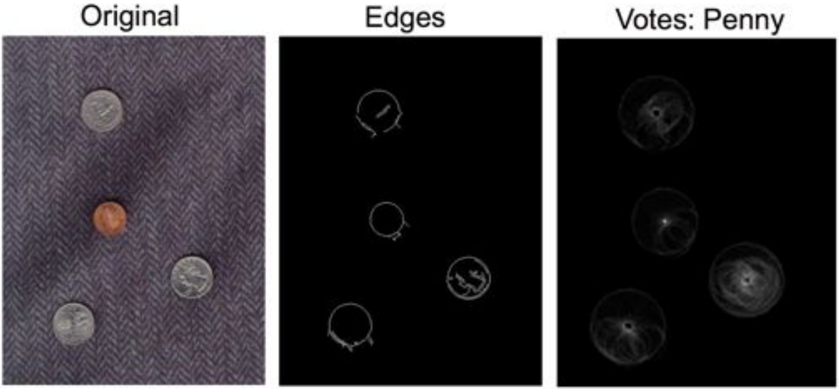
What if we don't know r?

- Hough space: conics



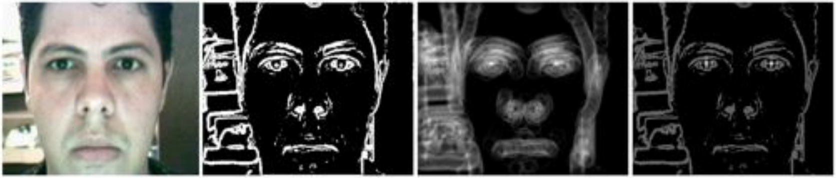
Hough Transform: Circle Detection

- Find the coins



Hough Transform: Circle Detection

- Iris detection



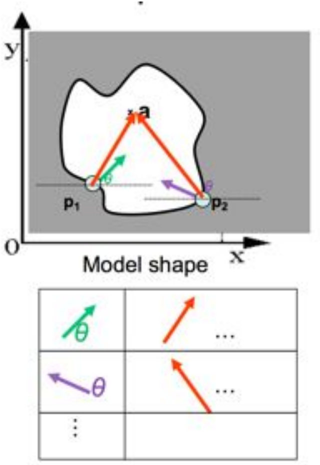
Gradient+threshold

Hough space
(fixed radius)

Max detections

Generalized Hough Voting

- Hough Voting for general shapes



<u>Offline procedure:</u>

At each boundary point, compute displacement vector: **r = a – p**$_i$.

Store these vectors in a table indexed by gradient orientation θ.

Implicit Shape Model

- Implicit Shape Model adopts the idea of voting
- Basic idea:
    - Find interest points in an image
    - Match patch around each interest point to a training patch
    - Vote for object center given that training instance

Scale Invariant Voting

Scale-invariant feature selection

- Scale-invariant interest points
- Rescale extracted patches
- Match to constant-size codebook

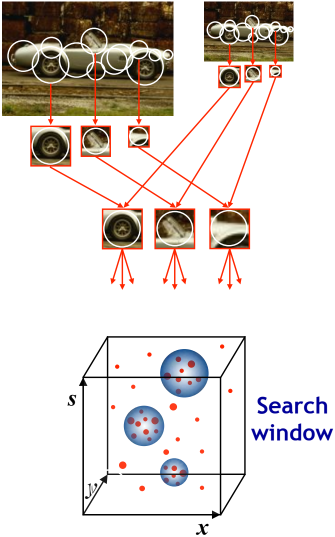
Generate scale votes

- Scale as 3rd dimension in voting space

$$\begin{aligned} x_{vote} &= x_{img} - x_{occ}(s_{img}/s_{occ}) \\ y_{vote} &= y_{img} - y_{occ}(s_{img}/s_{occ}) \\ s_{vote} &= s_{img}/s_{occ} \end{aligned}$$

- Search for maxima in 3D voting space

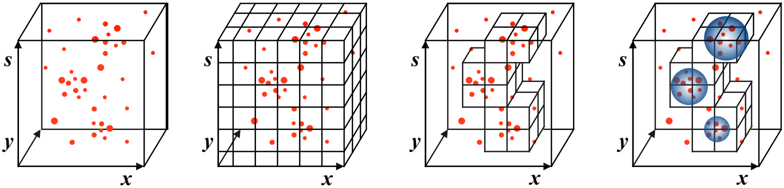
Scale Invariant Voting



Scale Voting: Efficient Computation

Continuous Generalized Hough Transform

- Binned accumulator array similar to standard Gen. Hough Transf.
- Quickly identify candidate maxima locations
- Refine locations by Mean-Shift search only around those points
- Avoid quantization effects by keeping exact vote locations.



Scale votes

Binned accum. array

Candidate maxima

Refinement (Mean-Shift)

Conclusion

- Exploits a lot of parts (as many as interest points)
- Very simple Voting scheme: Generalized Hough Transform
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