

Hough Transform

600.658 - Seminar on Shape Analysis and Retrieval

Detection of arbitrary shapes

- Partial shape matching can also be viewed as detecting arbitrary shapes
- **Hough transform** is a method for estimating the parameters of a shape from its boundary points
- The idea can be generalized to estimate “parameters” of arbitrary shapes

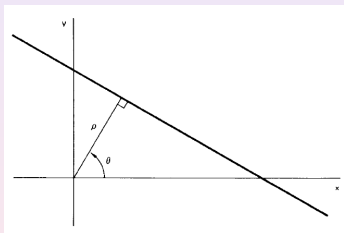
- 1 Hough Transform for Analytical Shapes
 - Voting in Parameter Space
 - Using Directional Information
 - Error Compensation: Smoothing

- 2 Generalizing to Non-Analytical Shapes

Outline

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Straight line



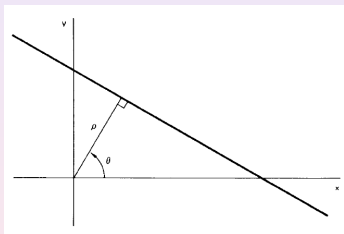
▶ [2]

- Normal parameterization:
 $x \cos \theta + y \sin \theta = \rho$
- Points in picture \leftrightarrow sinusoids in parameter space
- Points in parameter space \leftrightarrow lines in picture
- Sinusoids corresponding to co-linear points intersect at a unique point

Example

Line: $0.6x + 0.4y = 2.4$ Sinusoids intersect at: $\rho = 2.4, \theta = 0.9273$

Straight line



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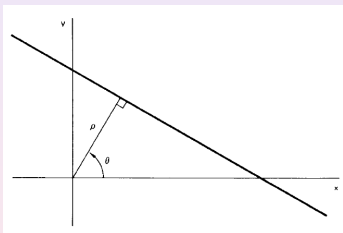
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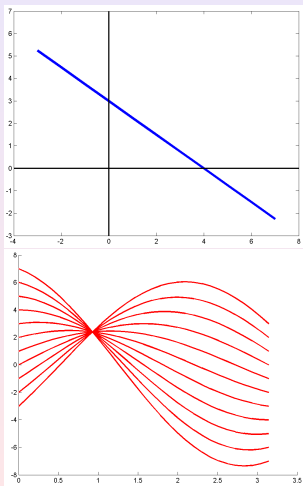
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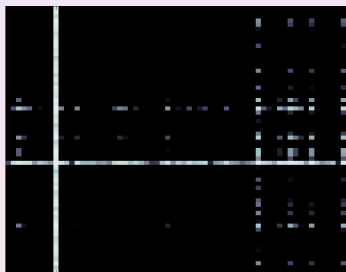
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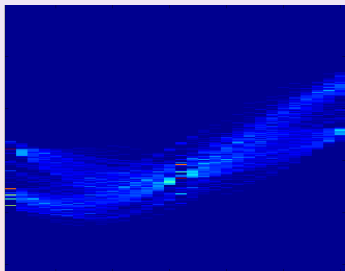
Quantize parameter space and vote into bins



- Let $\rho \in [-R, R]$ and $\theta \in [0, \pi)$
- For each edge point (x_i, y_i) , calculate:
$$\hat{\rho} = x_i \cos \hat{\theta} + y_i \sin \hat{\theta} \quad \forall \hat{\theta} \in [0, \pi)$$
- Accumulator: $\mathcal{A}(\hat{\rho}, \hat{\theta}) = \mathcal{A}(\hat{\rho}, \hat{\theta}) + 1$
- Threshold the accumulator values to get parameters for detected lines
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- Same general idea applies to other analytical shapes

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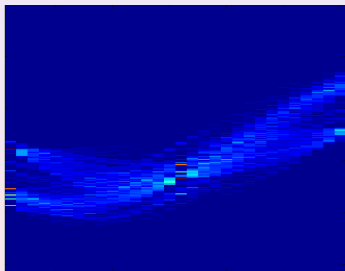
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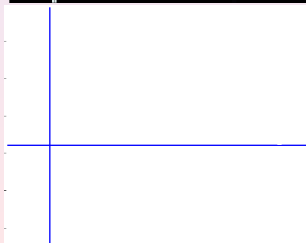
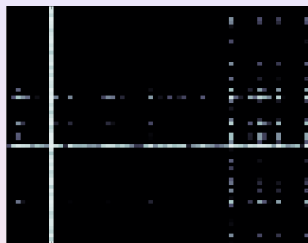
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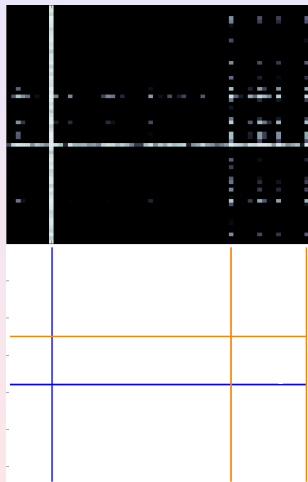
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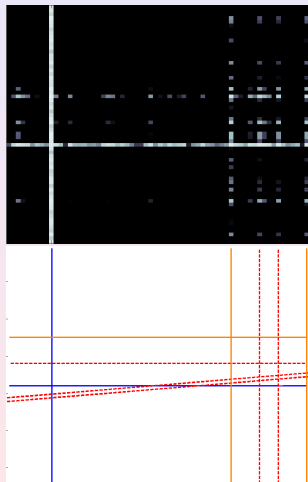
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- Accumulator: $\mathcal{A}(\hat{\rho}, \hat{\theta}) = \mathcal{A}(\hat{\rho}, \hat{\theta}) + 1$
- Threshold the accumulator values to get parameters for detected lines
 - Threshold at $\mathcal{A}(\hat{\rho}, \hat{\theta}) = 30$
- Same general idea applies to other analytical shapes

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- Threshold the accumulator values to get parameters for detected lines
 - Threshold at $\mathcal{A}(\hat{\rho}, \hat{\theta}) = 20$
- Same general idea applies to other analytical shapes

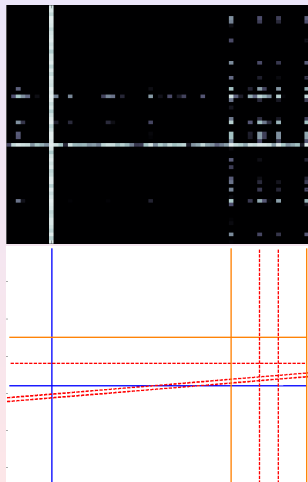
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- Accumulator: $\mathcal{A}(\hat{\rho}, \hat{\theta}) = \mathcal{A}(\hat{\rho}, \hat{\theta}) + 1$
- Threshold the accumulator values to get parameters for detected lines
 - Threshold at $\mathcal{A}(\hat{\rho}, \hat{\theta}) = 15$
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- Gradient computation, instead of edge detection
- Gradient smoothing

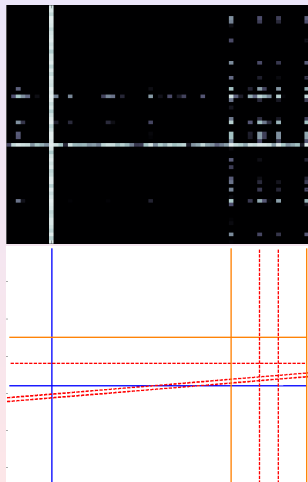
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- $O(nd_i)$ computation, instead of $O(n^2)$
- Can we do better?

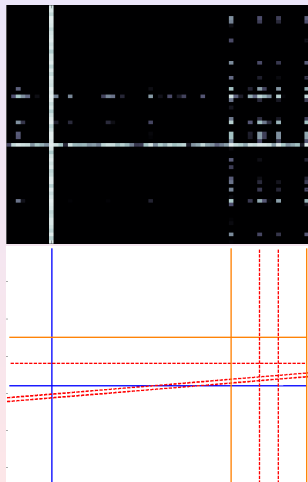
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Use what you have already got!

- More parameters \Rightarrow More computation and storage
- Gradient information reduces one more free parameter
- For circle: center lies r units along the gradient
- Rotation affects the gradient direction only

- $f(\mathbf{x}, \mathbf{p}) = (x - a)^2 + (y - b)^2 - r^2 = 0$ $\mathbf{p} = (a, b, r)$,
 $\mathbf{x} = (x, y)$

- $\frac{df}{dx}(\mathbf{x}, \mathbf{p}) = 0$

- $\frac{dy}{dx} = \tan \left[\phi(\mathbf{x}) - \frac{\pi}{2} \right]$ $\phi(\mathbf{x})$ is the gradient direction

- Update $\mathcal{A}(\mathbf{p})$ if $f(\mathbf{x}, \mathbf{p}) = 0$ and $\frac{df}{dx}(\mathbf{x}, \mathbf{p}) = 0$

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Compensating for errors

- Errors can cause $\mathcal{A}(\mathbf{p}')$ to be incremented, where \mathbf{p}' is close to the actual parameter \mathbf{p}
- Compensate for the uncertainty of measurement in parameter space
- Smooth the accumulator by incrementing counts of nearby cells according to some point-spread function h
- Equivalent to convolving $\mathcal{A} * h$

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The R -table

- Any shape is specified by the set of boundary points $B = \{\mathbf{x}_B\}$
- For a shape, define \mathbf{p} as: $\mathbf{p} = \{\mathbf{x}^0, s, \theta\}$
- For each \mathbf{x}_B , compute $\mathbf{r} = \mathbf{x}^0 - \mathbf{x}_B$, and store as function of ϕ
- For each edge pixel \mathbf{x} (with gradient direction $\phi(\mathbf{x})$) in an image, obtain \mathbf{r} from the table and update $\mathcal{A}(\mathbf{x} + \mathbf{r})$

i	ϕ_i	R_{ϕ_i}
0	0	$\{\mathbf{r} \mathbf{x}^0 - \mathbf{r} = \mathbf{x}_B, \mathbf{x}_B \in B, \phi(\mathbf{x}_B) = 0\}$
1	$\Delta\phi$	$\{\mathbf{r} \mathbf{x}^0 - \mathbf{r} = \mathbf{x}_B, \mathbf{x}_B \in B, \phi(\mathbf{x}_B) = \Delta\phi\}$
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Transformations of the R -table

- Let $R(\phi)$ be the R -table for a shape S
- Scale: $T_s[R(\phi)] = sR(\phi)$
 - Scale all the vectors \mathbf{r} by s
- Rotation: $T_\theta[R(\phi)] = \text{Rot}\{R[(\phi - \theta) \bmod 2\pi], \theta\}$
 - Change the indices ϕ to $(\phi - \theta) \bmod 2\pi$, find corresponding vectors \mathbf{r} and rotate them by θ

Hough transform for composite shapes

- Let a shape S have two subparts S_1 and S_2 with respective reference points \mathbf{x}^0 , \mathbf{x}_1^0 , and \mathbf{x}_2^0
- Compute $\mathbf{r}_1 = \mathbf{x}^0 - \mathbf{x}_1^0$ and $\mathbf{r}_2 = \mathbf{x}^0 - \mathbf{x}_2^0$
- R -table for composite shape:
$$R_S(\phi) = [R_{S_1}(\phi) + \mathbf{r}_1] \cup [R_{S_2}(\phi) + \mathbf{r}_2]$$

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Incrementation Strategies

- Increment the accumulator by a value depending on the gradient: $\mathcal{A}(\mathbf{p}) = \mathcal{A}(\mathbf{p}) + g(\nabla \mathbf{x})$
- Increment by larger values if neighbouring points are incrementing the same reference point
- Try to find progressively longer connected segments using dynamic programming
- Weigh different parts of a composite object differently

References



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Generalizing the Hough Transform to Detect Arbitrary Shapes
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