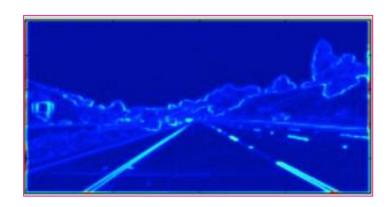
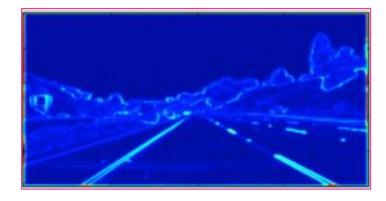
Edge: Hough transform

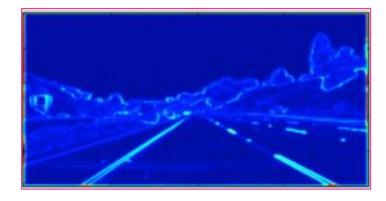
Dr. Tushar Sandhan



- Edges so far (operators, Canny)
 - o consider prior info about gradient behaviour
 - o do not consider anything about object shape, structure
 - o how did we get clear boundary edges previously?

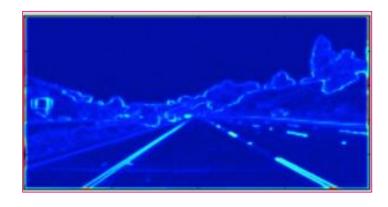


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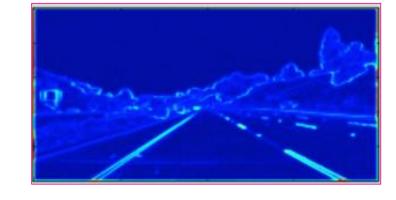
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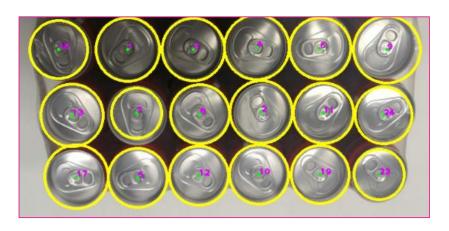
J•Linking



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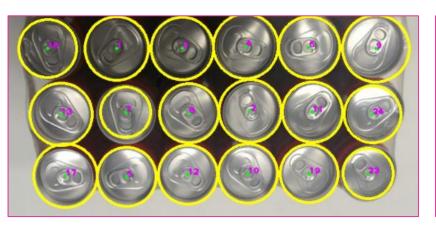
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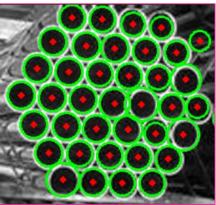


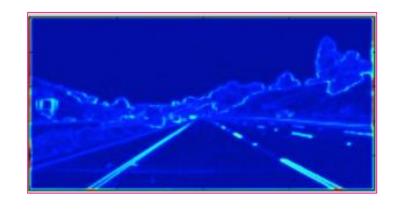


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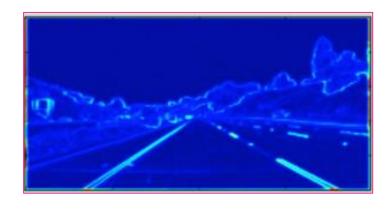


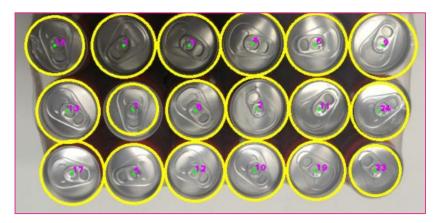


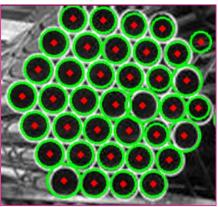


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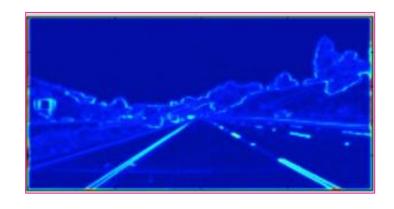


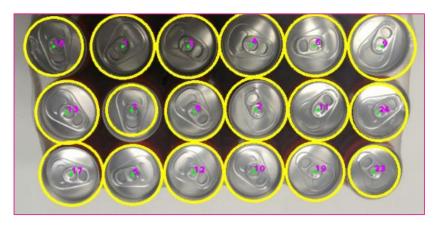


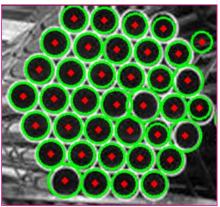


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J•Linking











- Image derivatives
 - o input image f(x, y)
 - o (optional) smoothed $f_s(x, y)$
 - o get the gradients $g_x(x,y)$, $g_y(x,y)$
 - \circ get thresholded edge map M_T

$$G(x,y) = e^{-\frac{x^2 + y^2}{2\sigma^2}}$$

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$$g_x(x,y) = \partial f_s(x,y)/\partial x$$
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$$\alpha(x,y) = \tan^{-1} \left[\frac{g_y(x,y)}{g_x(x,y)} \right]$$

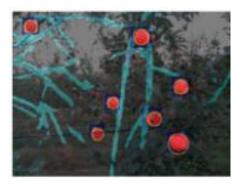
- Hough transform (HT)
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 - o shape is defined as a function and parametrized

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- Shape detection
 - plat fruits
 plucking
 autonomous
 robots

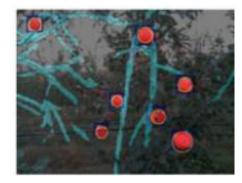
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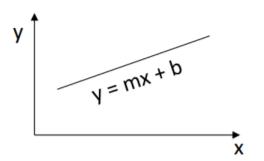


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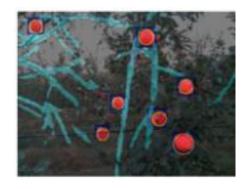


Lines

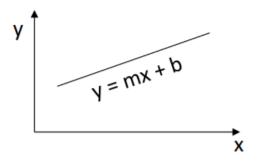


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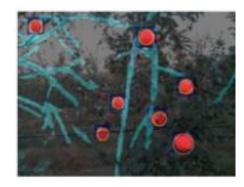
Lines



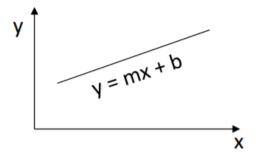
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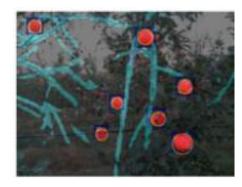
Lines



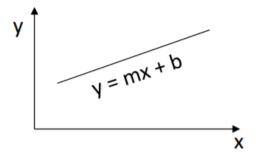
- Hough Transform
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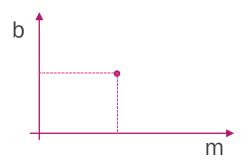
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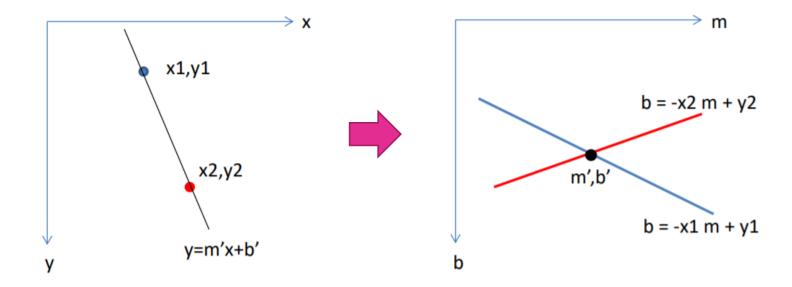


- Hough Transform
 - a space of parameters



- Hough transform duality
 - Lines in the image space becomes a point in the Hough space
 - A point in the image space becomes _____ in the Hough space

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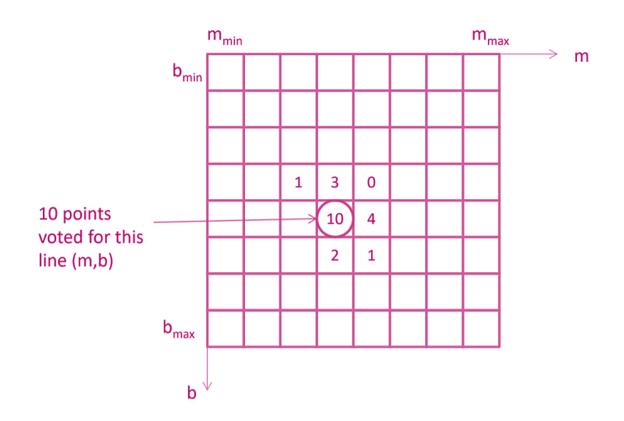


Hough space voting

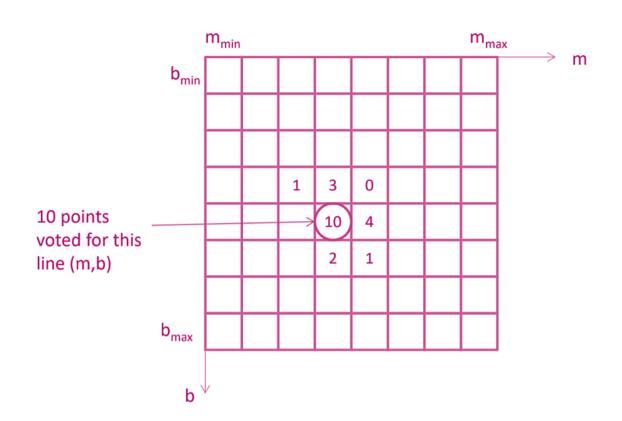
courtesy: W. Hoff

- Hough space voting
 - o initialize accumulator A(m,b) → 0

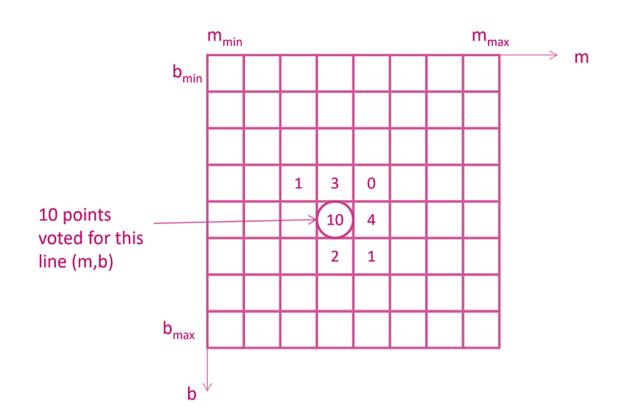
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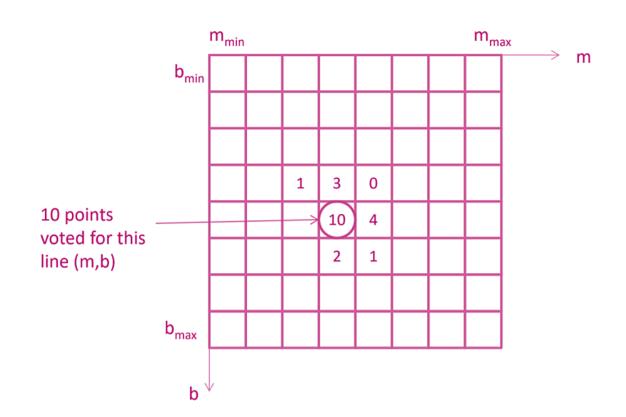
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- Hough space voting
 - o initialize accumulator $A(m,b) \rightarrow 0$
 - o for each edge element, increment all cells that satisfy b = -xm + y
 - o local maxima in A(m,b) correspond to lines



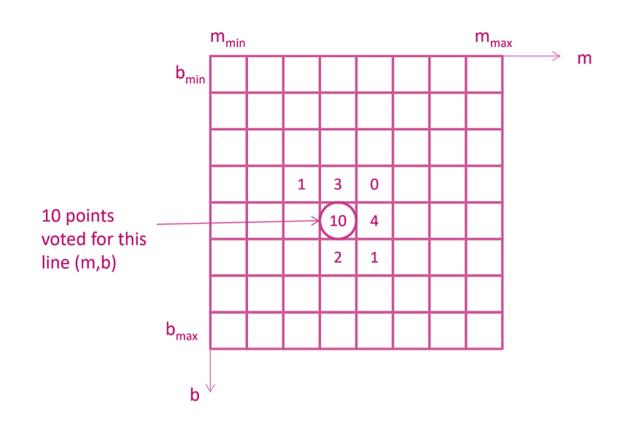
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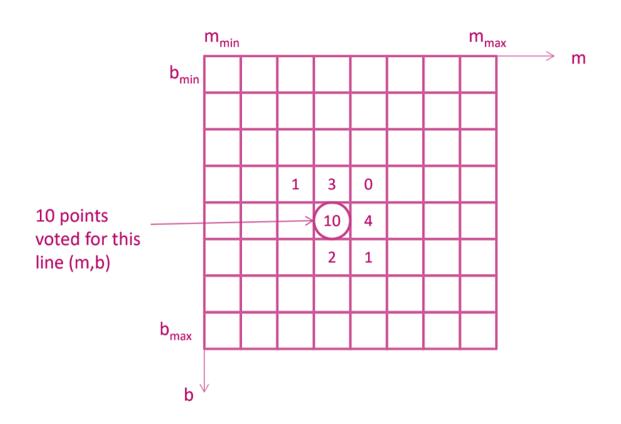
ï



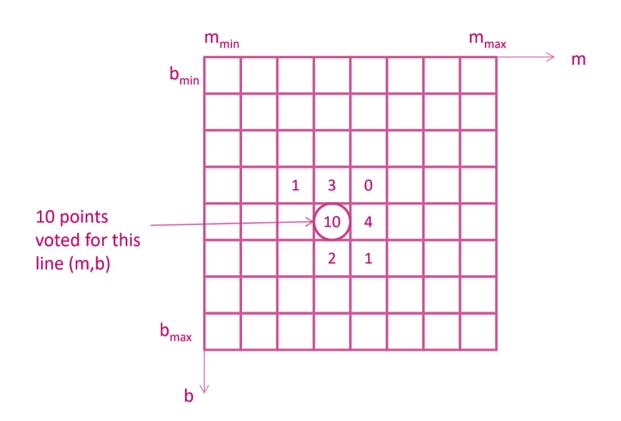
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 - o for each edge element, increment all cells that satisfy b = -xm + y
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 - is there any issue here?
 - for vertical lines

1



- Hough space voting
 - o initialize accumulator $A(m,b) \rightarrow 0$
 - o for each edge element, increment all cells that satisfy b = -xm + y
 - o local maxima in A(m,b) correspond to lines
 - is there any issue here?
 - for vertical lines
 - $I m \rightarrow \infty$

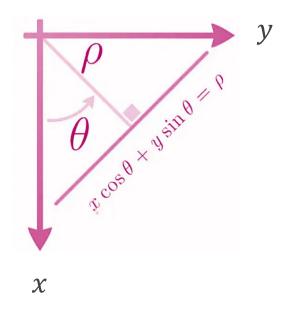


Horizontal lines

$$\theta = 0^{o}$$

Horizontal lines

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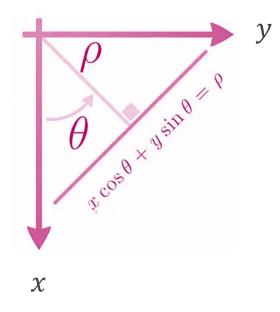


Horizontal lines

$$\theta = 0^{o}$$

Vertical lines

$$\theta = 90^{\circ}$$



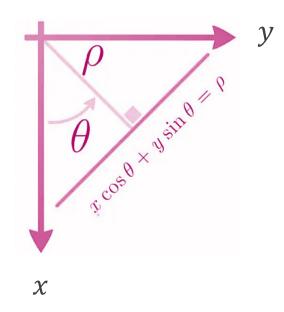
Horizontal lines

$$\theta = 0^{o}$$

Vertical lines

$$\theta = 90^{\circ}$$

- Ranges:
 - θ ∈ [−90°, 90)
 - $\rho \in [-dmax, +dmax]$
 - o dmax?



Horizontal lines

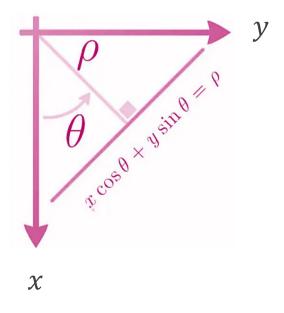
$$\theta = 0^{o}$$

Vertical lines

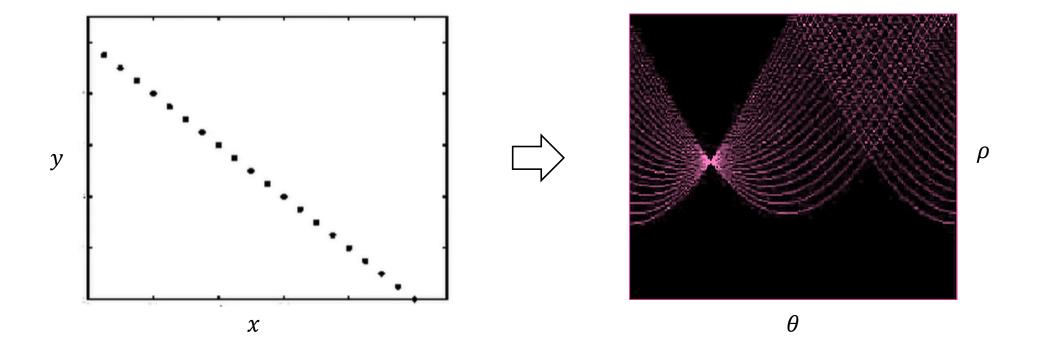
$$\theta = 90^{\circ}$$

- Ranges:
 - $\theta \in [-90^{\circ}, 90)$
 - $\rho \in [-dmax, +dmax]$
 - o dmax?

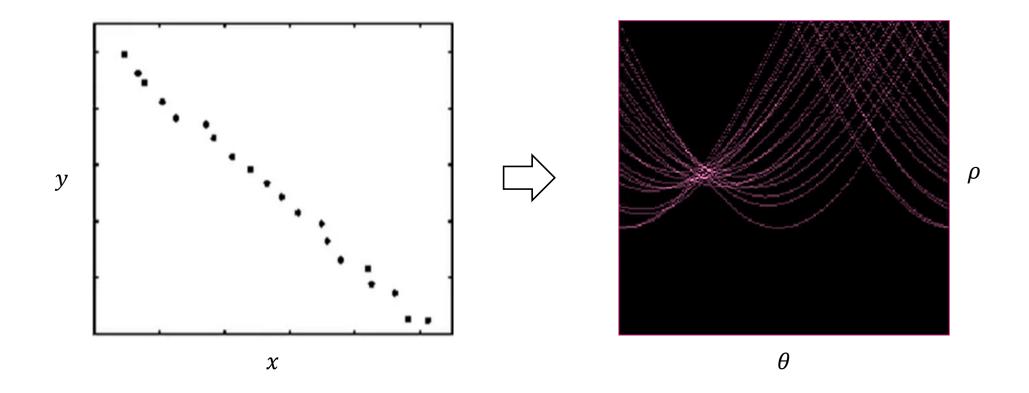




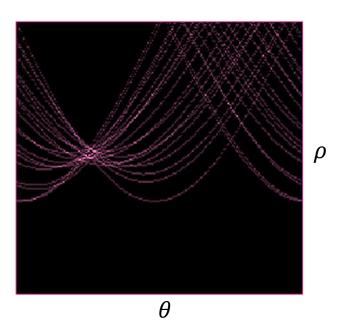
HT example:



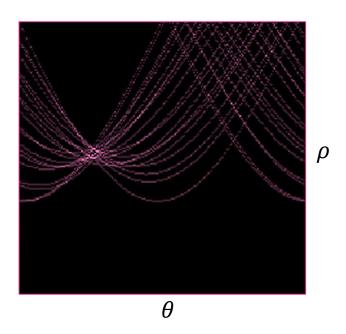
HT example: with a greater noise



- HT example: with a greater noise
 - tackling the noise

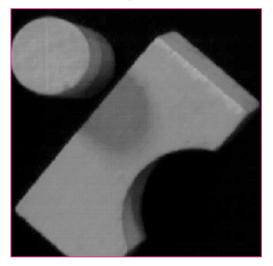


- HT example: with a greater noise
 - tackling the noise

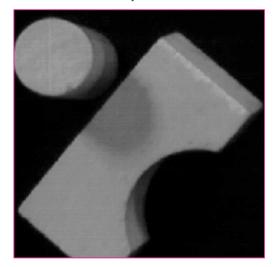


- Image processing in the Hough space
 - smoothing
 - thresholding
 - zoom in the space
 - re-quantize zoomed space
 - redo HT in zoomed space

input



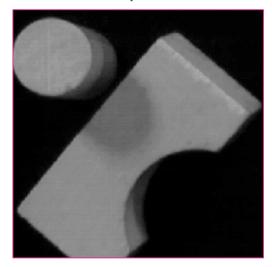
input







input



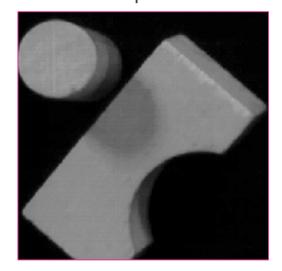


Hough transform



bright spot in HT corresponds to?

input



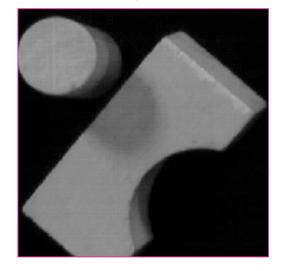


Hough transform



- bright spot in HT corresponds to?
- can circles be detected?

input



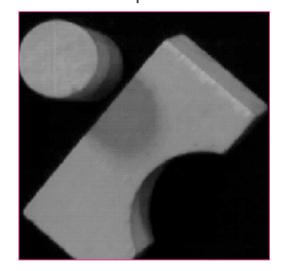


Hough transform



- bright spot in HT corresponds to?
- can circles be detected?
- why does Hough image is not the same size as input?

input





Hough transform



Input



Input

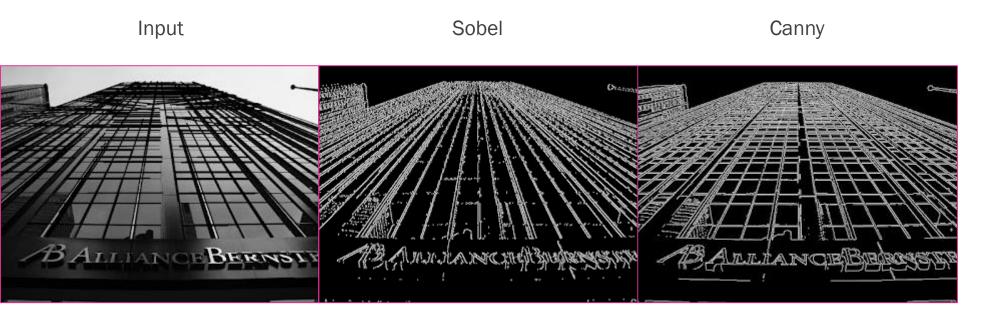


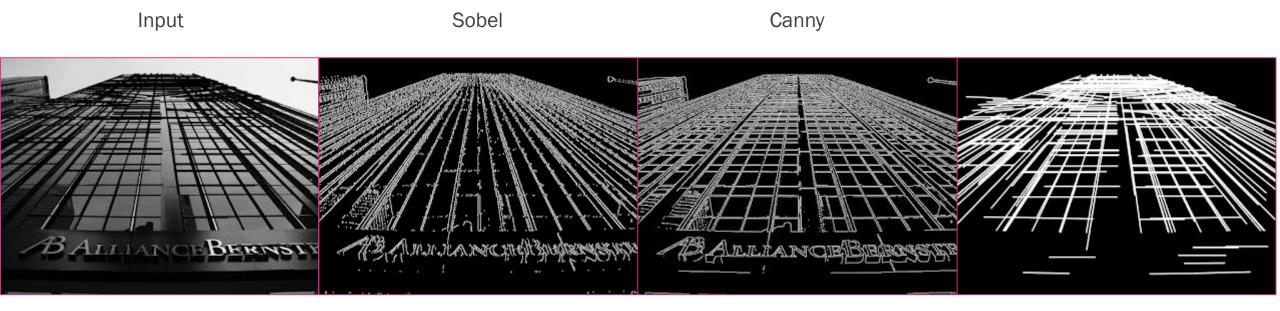
Input Sobel

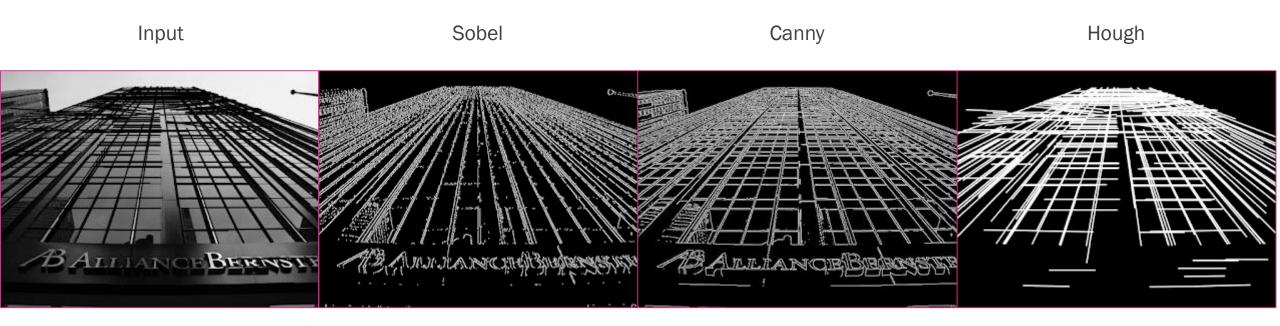


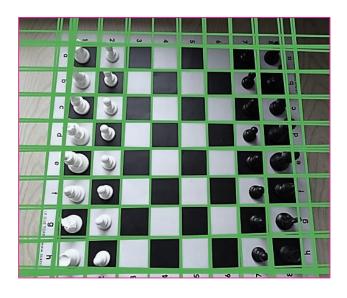
Input Sobel

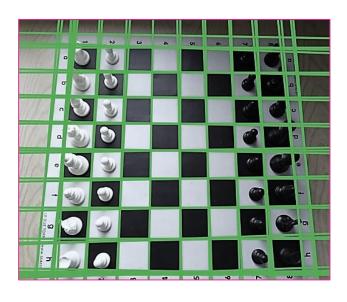




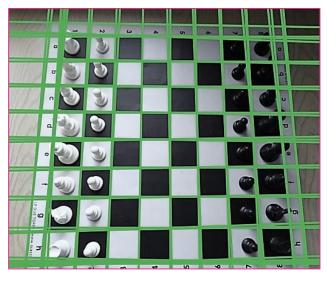






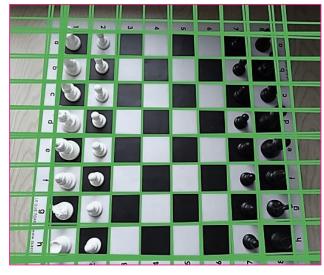










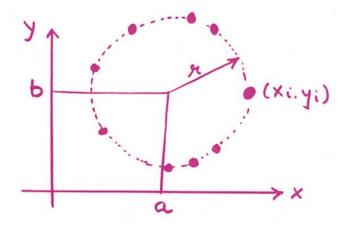








Equation of circle

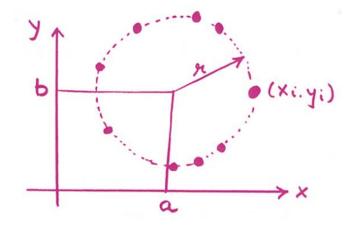


Equation of circle

$$(x_i - a)^2 + (y_i - b)^2 = r^2$$

If radius is known: (2D Hough Space)

Accumulator Array A(a,b)

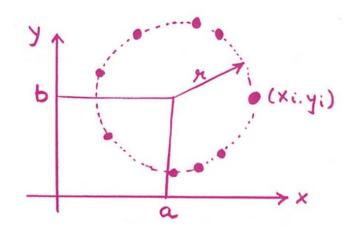


Equation of circle

$$(x_i - a)^2 + (y_i - b)^2 = r^2$$

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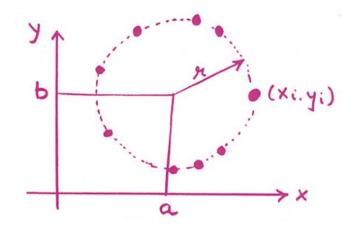
- Approx. object's size are known
 - o radius is known

Equation of circle

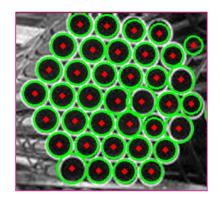
$$(x_i - a)^2 + (y_i - b)^2 = r^2$$

If radius is known: (2D Hough Space)

Accumulator Array A(a,b)



- Approx. object's size are known
 - o radius is known



- If radii are not known, exhaustively search all possibilities
- Pseudocode:

```
: A( ) = 0

: \forall (x,y)

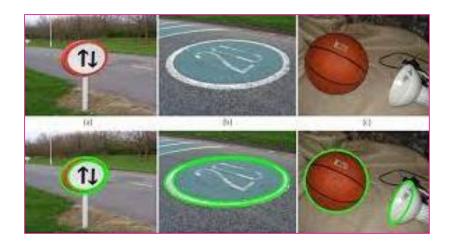
: if M_T(x,y)

: \forall (a,b)

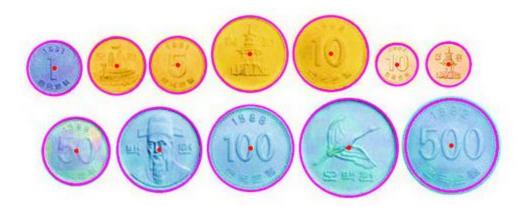
: r = sqrt\{ (x-a)^2 + (y-b)^2 \}

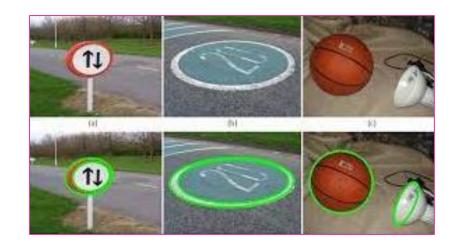
: A(a,b,r) + +

: find \ maximas \ in \ A( )
```

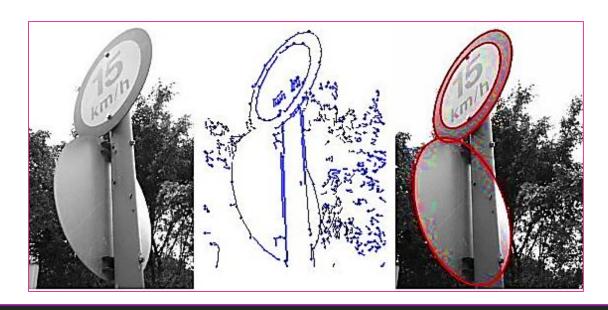


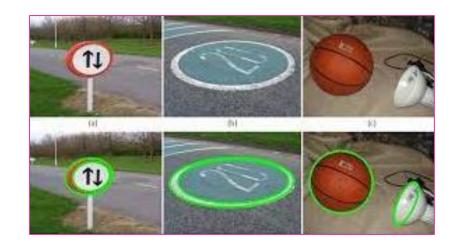






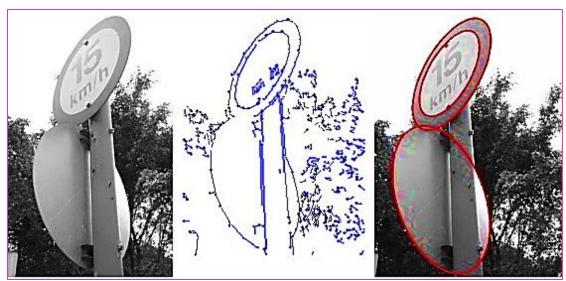












Space complexity

- Space complexity
 - With k quantized bins, it exponentially increases with number of parameters $n \rightarrow k^n$

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 - Separate quantization for each dimension can be performed

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Time complexity

- Space complexity
 - With k quantized bins, it exponentially increases with number of parameters $n \rightarrow k^n$
 - Separate quantization for each dimension can be performed

- Time complexity
 - Voting is linearly proportional to # of edge points
 - Time complexity is constant in # of edge points detected

Hough transform: other shapes

	parameters	
Line	ρ, θ	xcosθ+ysinθ=ρ
Circle	x ₀ , y ₀ , ρ	$(x-x_0)^2+(y-y_0)^2=r^2$
Parabola	x ₀ , y ₀ , ρ, θ	$(y-y_0)^2=4\rho(x-x_0)$
Ellipse	x_0, y_0, a, b, θ	$(x-x_0)^2/a^2+(y-y_0)^2/b^2=1$

Conclusion

- Hough Transform

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- Hough Transform

- ☐ It's tolerant to noise in some extent and highly tolerant to the missing points in an edge
- ☐ Space complexity increases with the number of parameters
- ☐ Hough space is quantized
 - finer the quantization,
 - more accurate the edge det. will be,
 - but slower will be the procc. speed

Conclusion

- Hough Transform

- ☐ It's tolerant to noise in some extent and highly tolerant to the missing points in an edge
- ☐ Space complexity increases with the number of parameters
- ☐ Hough space is quantized
 - finer the quantization,
 - more accurate the edge det. will be,
 - but slower will be the procc. speed

