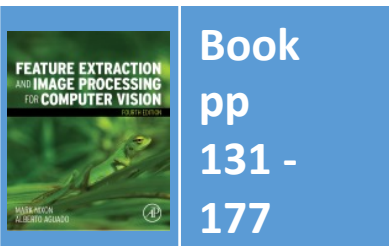


Lecture 7 Further Edge Detection

COMP6223 Computer Vision (MSc)

What better ways are there to detect edges?



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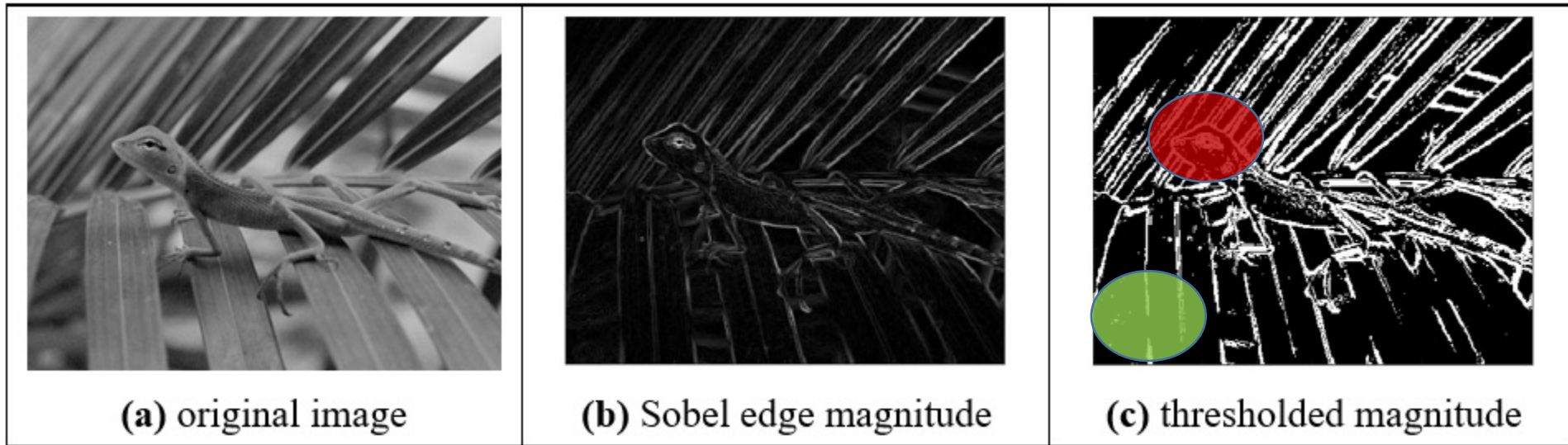
Content

1. How can we improve first-order edge detection?
2. How can we detect edges using second order differentiation/
differencing

Applying Sobel operator

Sobel is a good basic operator

Blurred edges



Noisy edges



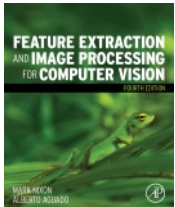
Canny edge detection operator

Formulated with three main objectives:

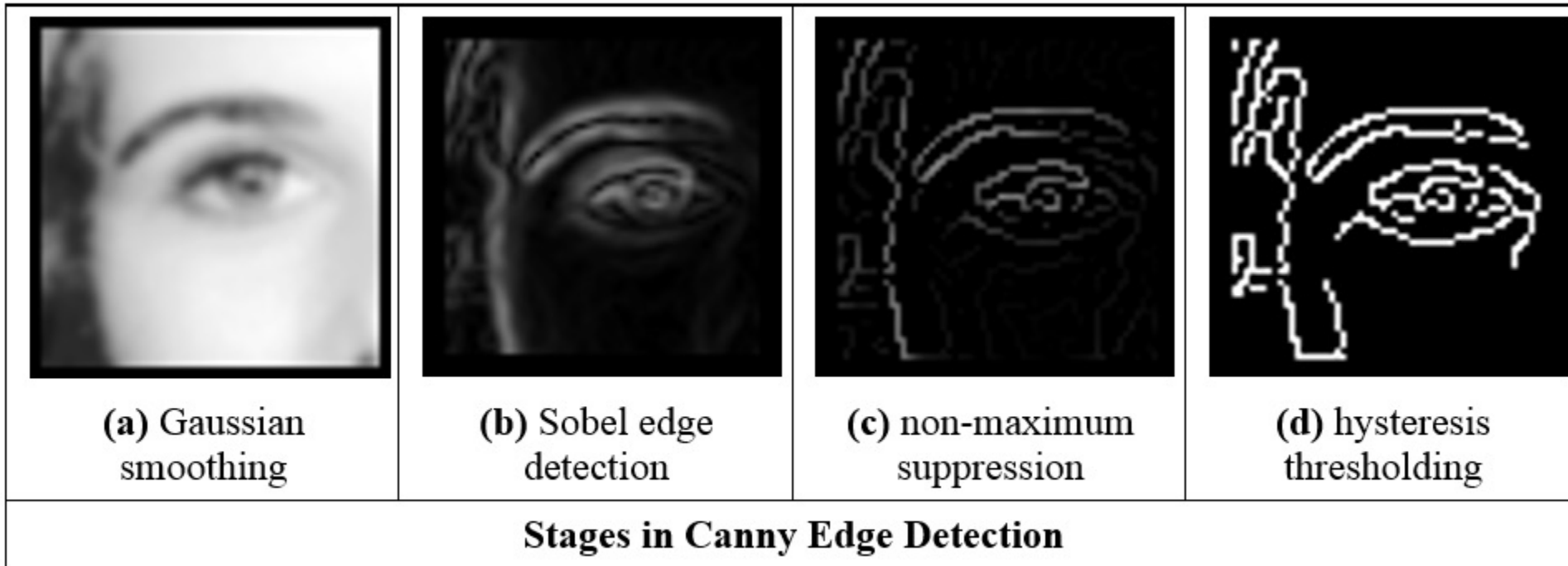
- optimal detection with **no spurious responses**;
- good localisation with **minimal distance** between detected and true edge position; and
- **single response** to eliminate multiple responses to a single edge.

Approximation

1. use **Gaussian smoothing**;
2. use the **Sobel** operator;) **combine?**
3. use **non-maximum suppression**; and
4. **threshold** with **hysteresis** to connect edge points.



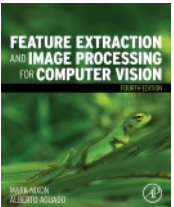
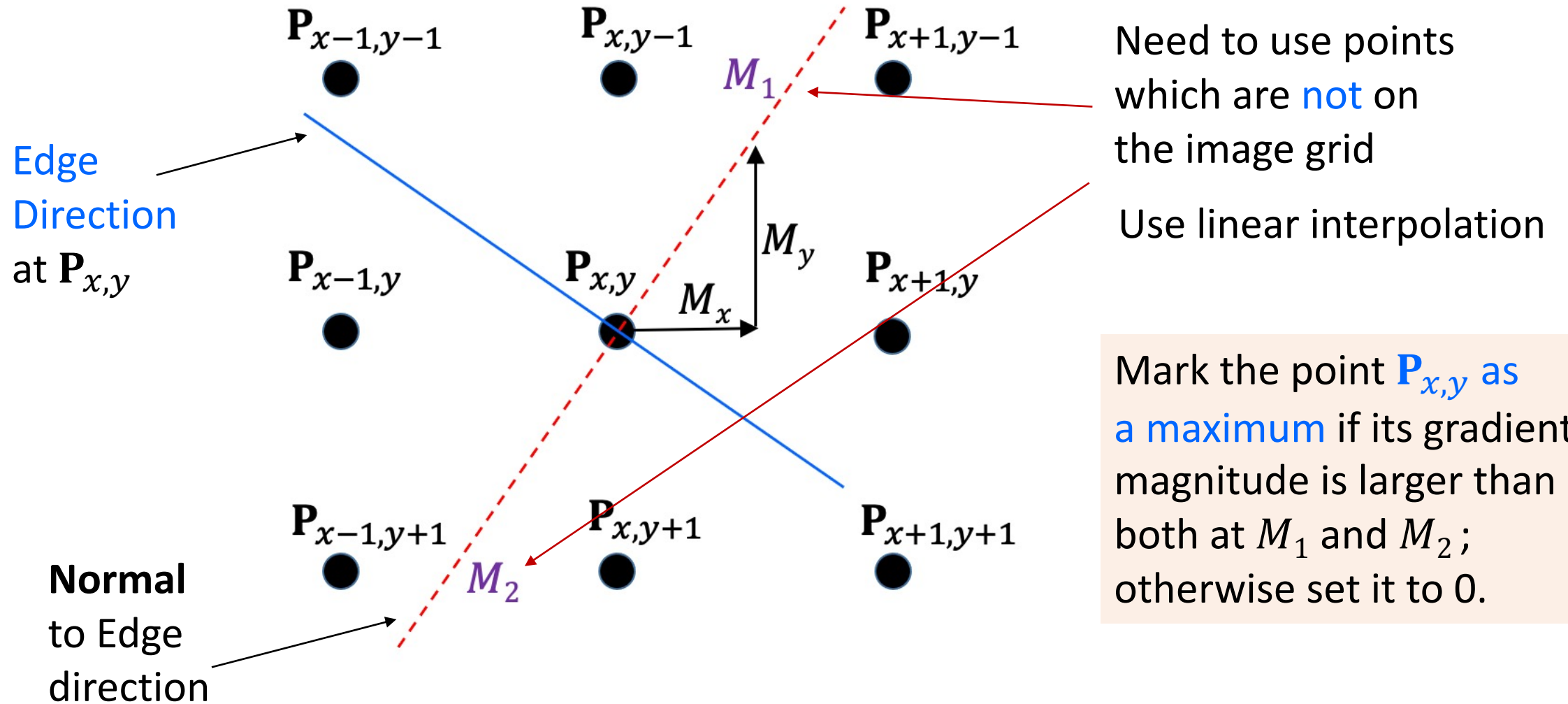
Stages in Canny edge detection operator



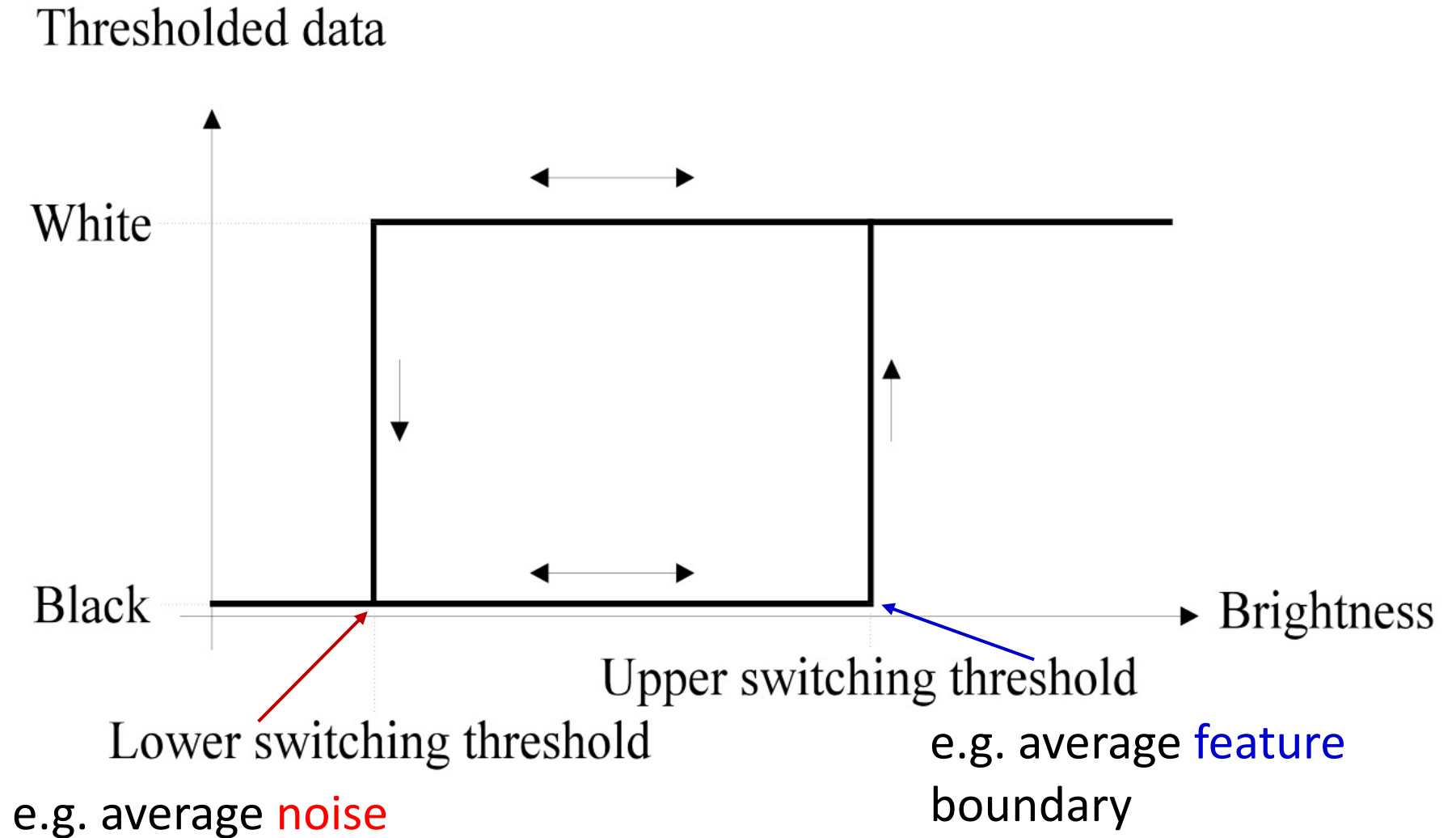
Canny gives thin edges in the right place,
but is more complex



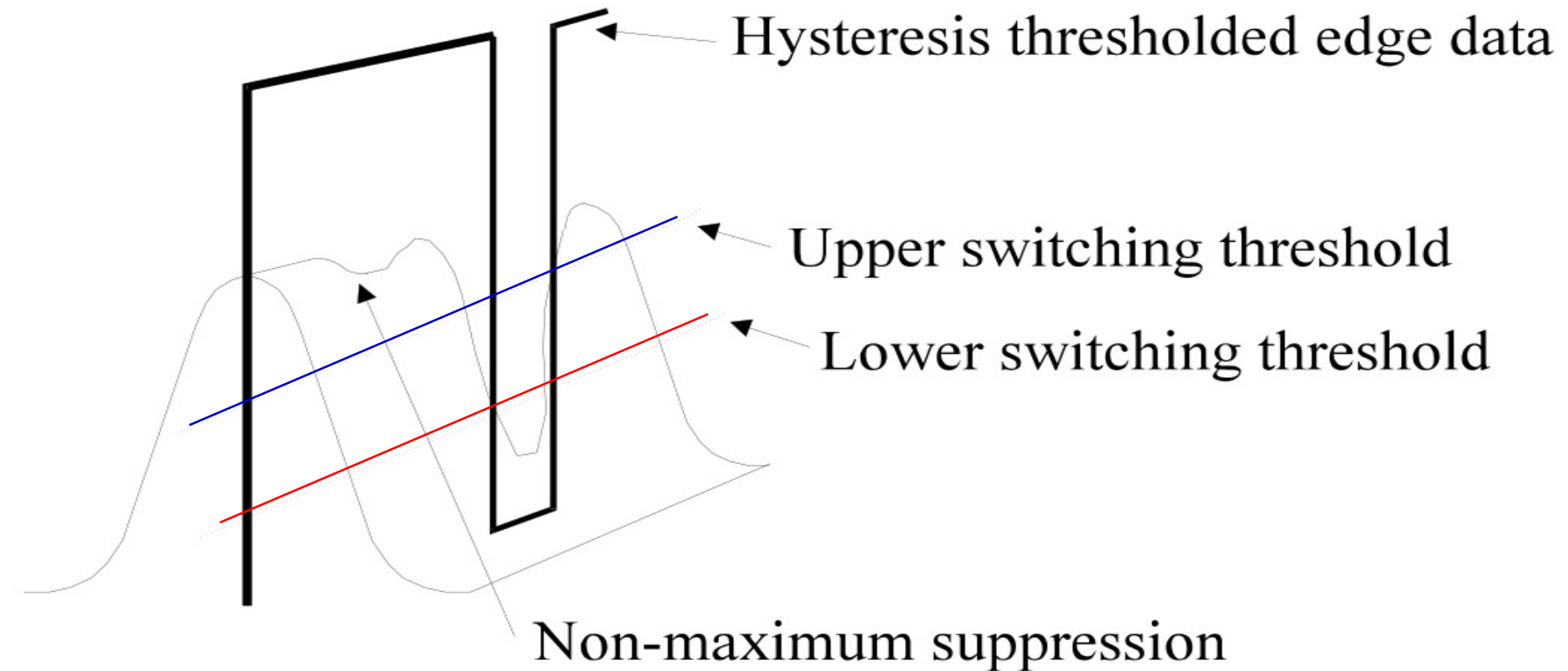
Interpolation in Non-maximum Suppression



Hysteresis thresholding transfer function



Action of non-maximum suppression and hysteresis thresholding

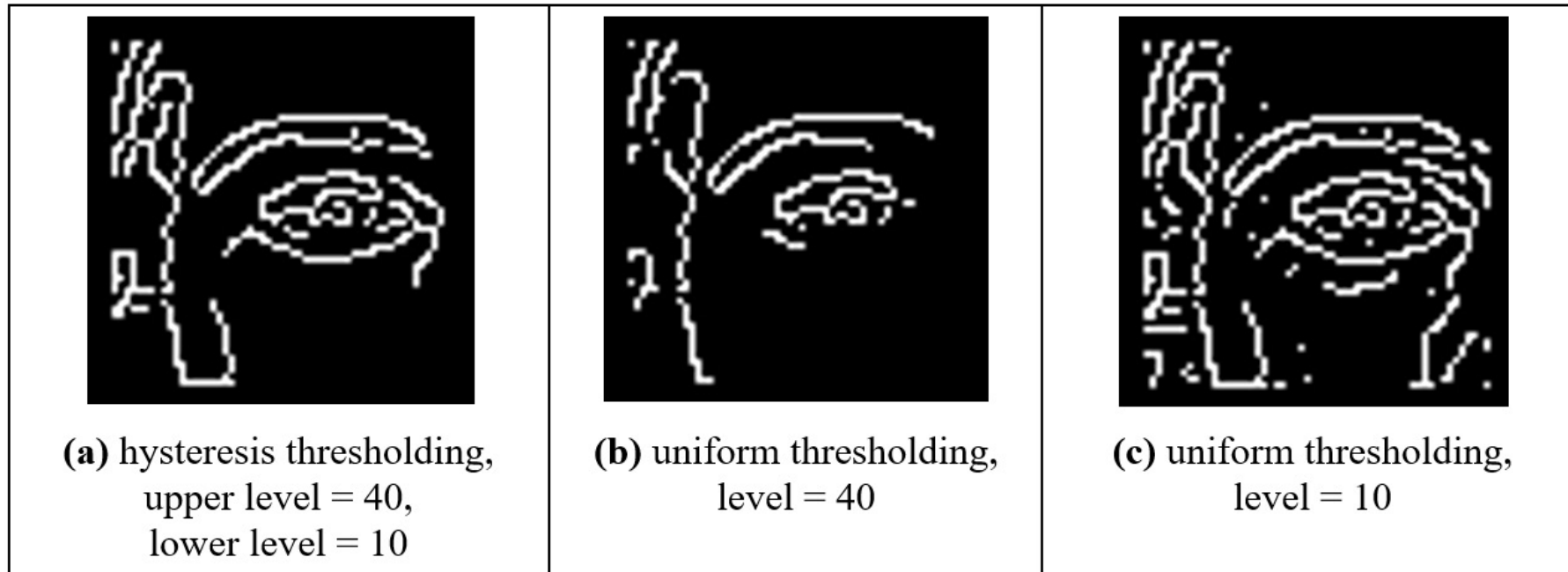


Walk along **top** of ridge

Gives thin edges in the **right** place



Comparing hysteresis thresholding with uniform thresholding

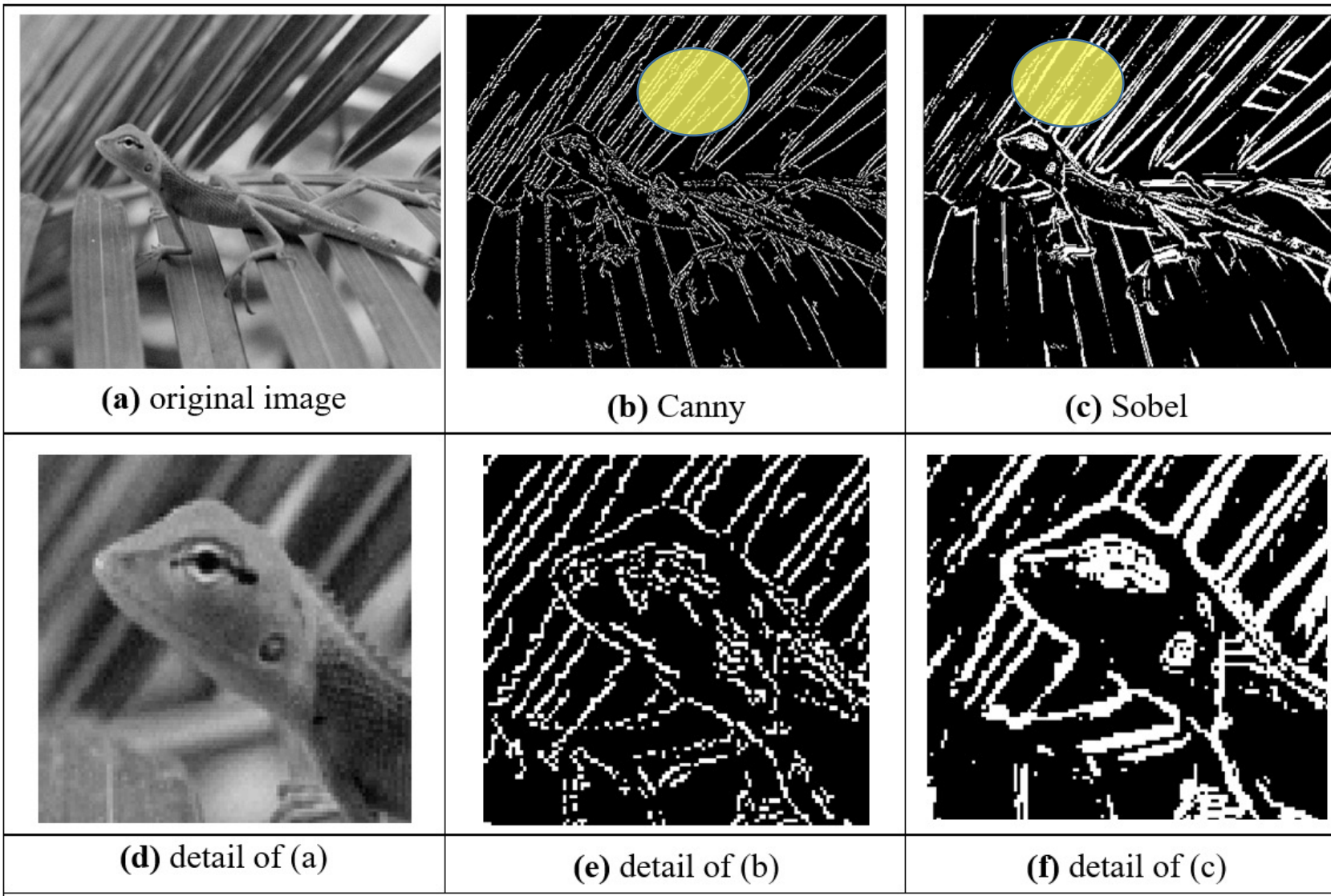


Hysteresis thresholding gives **all** points $>$ upper threshold
plus **any** connected points $>$ lower threshold

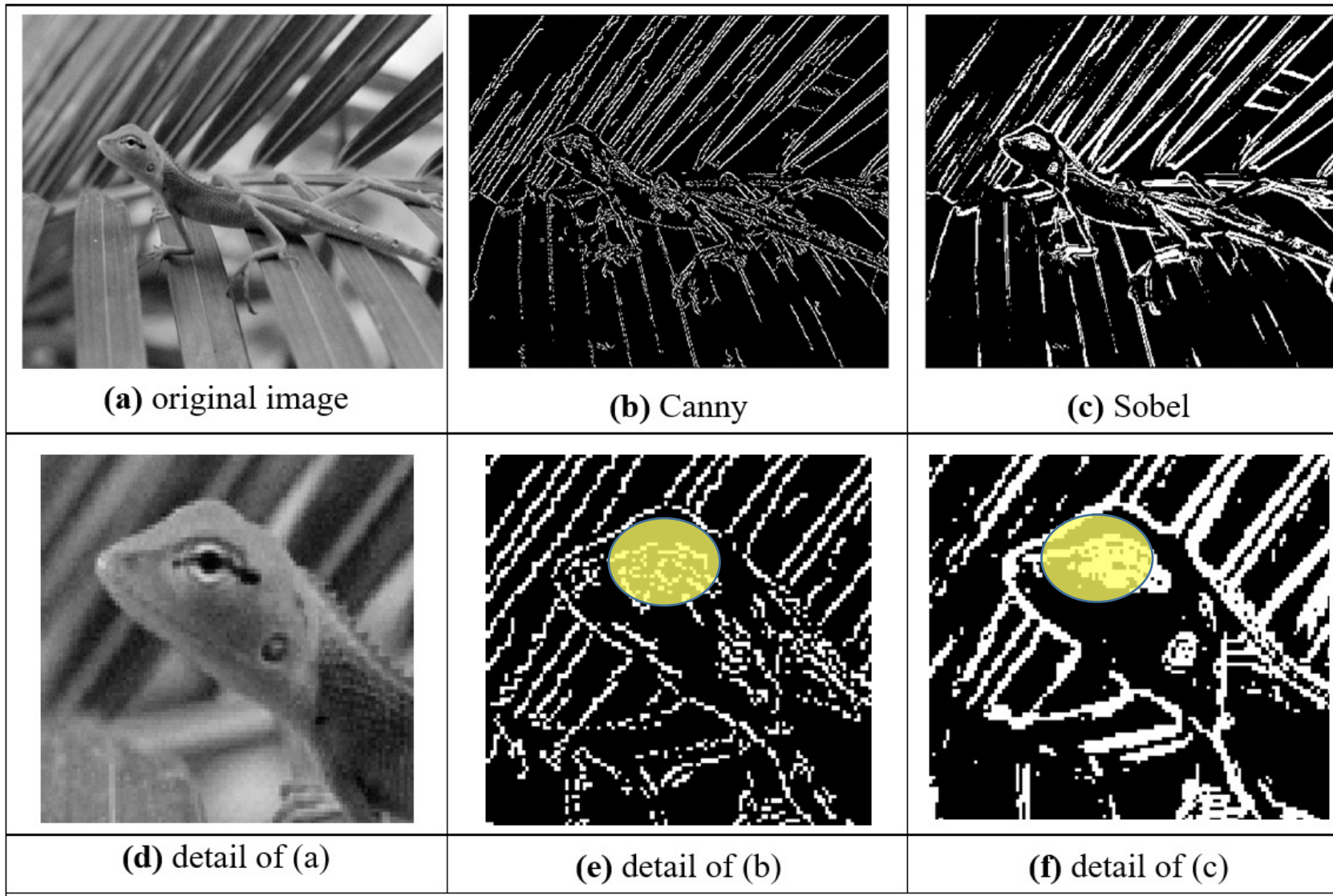


Comparing Canny with Sobel

The lines are thinner here, making Sobel look better!



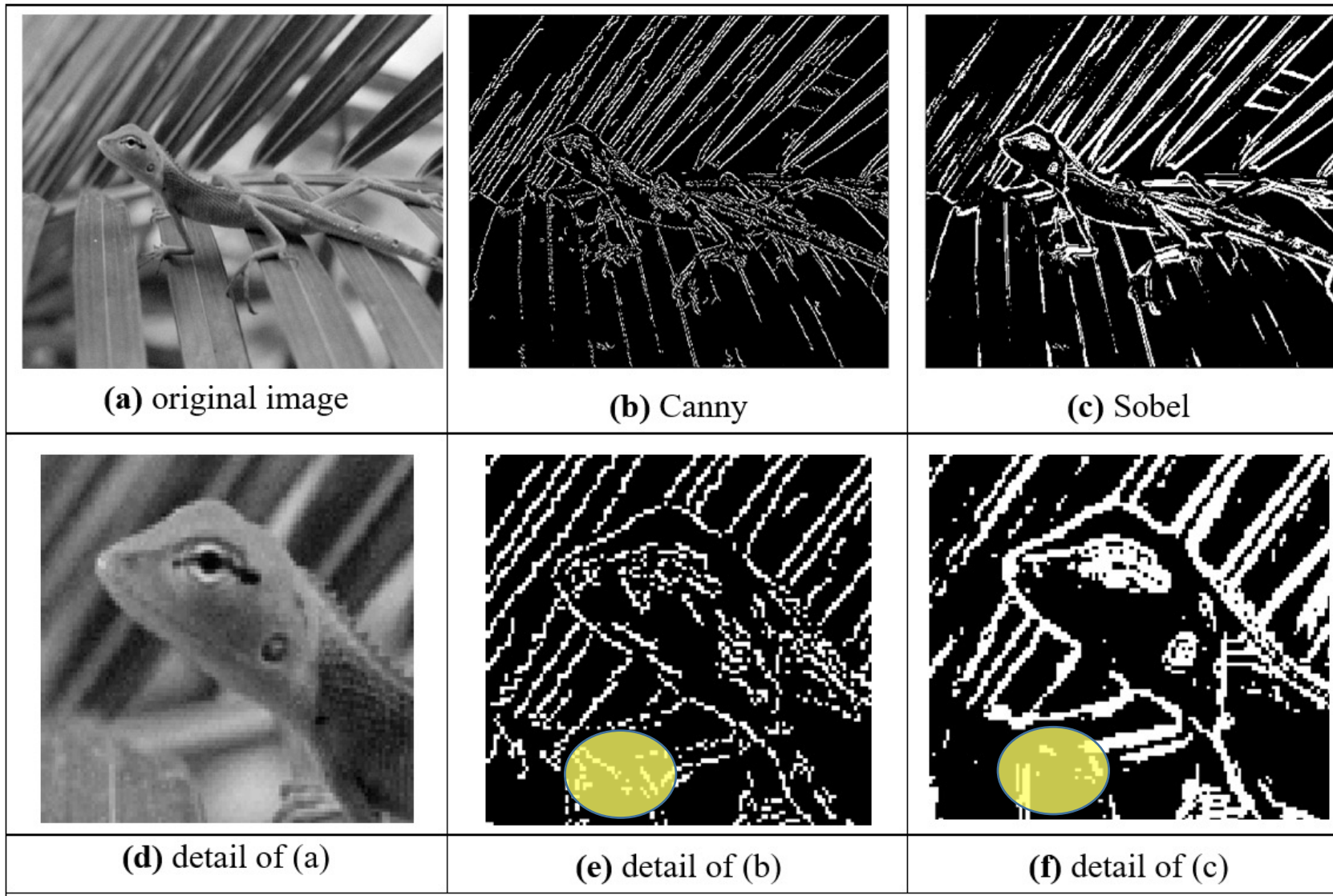
Comparing Canny with Sobel



The lines
are
indeed
thinner



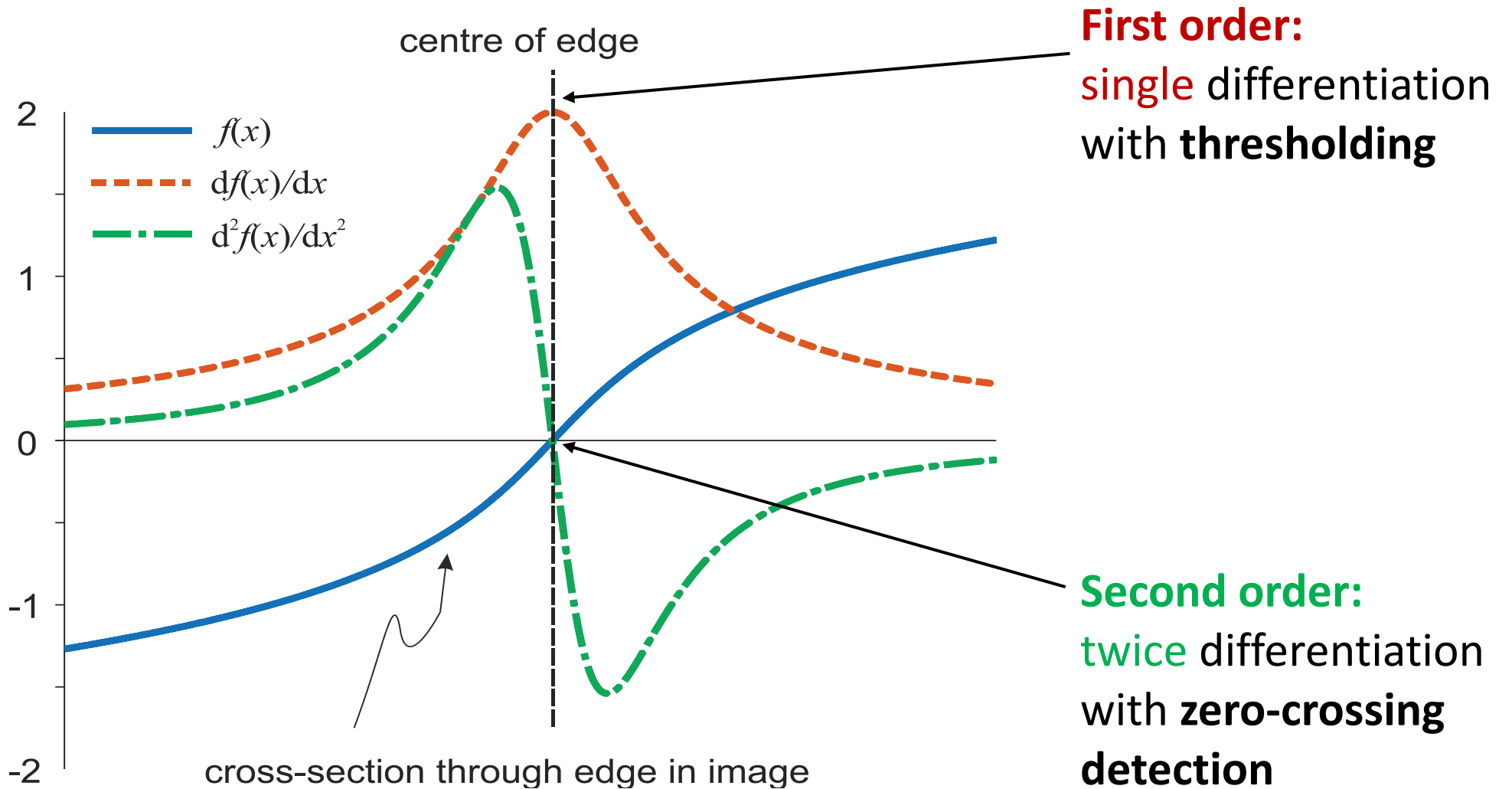
Comparing Canny with Sobel



The noise
is less



First and second order edge detection



Edge detection via the Laplacian operator

0	-1	0
-1	4	-1
0	-1	0

$$f'(x) = (f(x + \Delta x) - f(x)) / \Delta x$$

$$f'(x + \Delta x) = (f(x + 2\Delta x) - f(x + \Delta x)) / \Delta x$$

$$f''(x + \Delta x) = (f'(x + \Delta x) - f'(x)) / \Delta x$$

$$= (f(x + 2\Delta x) - 2f(x + \Delta x) + f(x)) / \Delta x$$

1	2	3	4	1	1	2	1	0	0	0	0	0	0	0	0	0
2	2	3	0	1	2	2	1	0	1	-31	-47	-36	-32	0	0	0
3	0	38	39	37	36	3	0	0	-44	70	37	31	60	-28	0	0
4	1	40	44	41	42	2	1	0	-42	34	12	1	50	-41	0	0
1	2	43	44	40	39	3	1	0	-37	47	8	-6	31	-32	0	0
2	0	39	41	42	40	2	0	0	-45	72	37	45	74	-36	0	0
0	2	0	2	2	3	1	1	0	6	-44	-38	-40	-31	-6	0	0
0	2	1	3	1	0	4	2	0	0	0	0	0	0	0	0	0
(a) image data								(b) result of the Laplacian operator								

Simple, but sensitive to noise!



Edge detection is about differentiation

Gaussian function has the smoothing effect

Can also add a constant: $\frac{1}{2\pi\sigma^2}$

Take a Gaussian function:

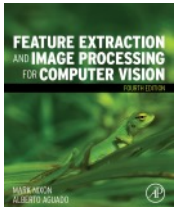
$$g(x, y, \sigma) = e^{\frac{-(x^2+y^2)}{2\sigma^2}}$$

Differentiate **once**:

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

And **again**:

$$\frac{\partial^2 g(x, y, \sigma)}{\partial x^2} = \left(\frac{x^2}{\sigma^2} - 1 \right) \frac{e^{\frac{-(x^2+y^2)}{2\sigma^2}}}{\sigma^2}$$

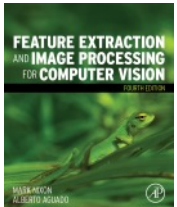


Mathbelts on...

Second order in x and y is:

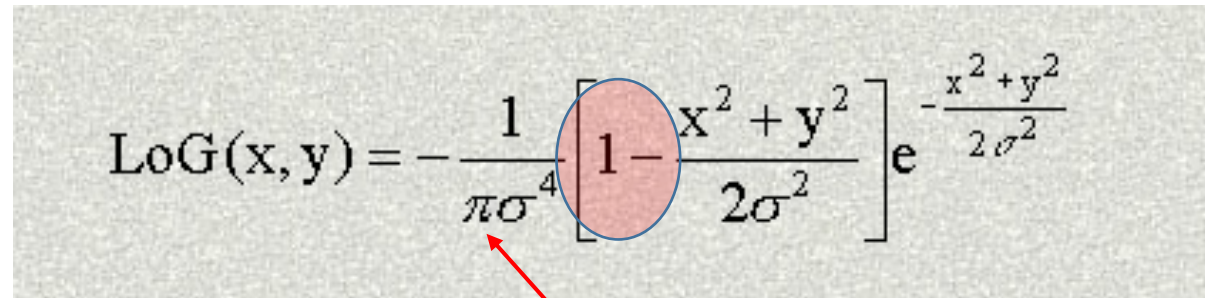
$$\begin{aligned}\nabla^2 g(x, y, \sigma) &= \frac{\partial^2 g(x, y, \sigma)}{\partial x^2} U_x + \frac{\partial^2 g(x, y, \sigma)}{\partial y^2} U_y \\ &= \left(\frac{x^2}{\sigma^2} - 1 \right) \frac{e^{\frac{-(x^2+y^2)}{2\sigma^2}}}{\sigma^2} + \left(\frac{y^2}{\sigma^2} - 1 \right) \frac{e^{\frac{-(x^2+y^2)}{2\sigma^2}}}{\sigma^2} \\ &= \frac{1}{\sigma^2} \left(\frac{x^2 + y^2}{\sigma^2} - 2 \right) e^{\frac{-(x^2+y^2)}{\sigma^2}}\end{aligned}$$

Second order = Laplacian of Gaussian = Marr Hildreth



Google: “Laplacian of Gaussian”

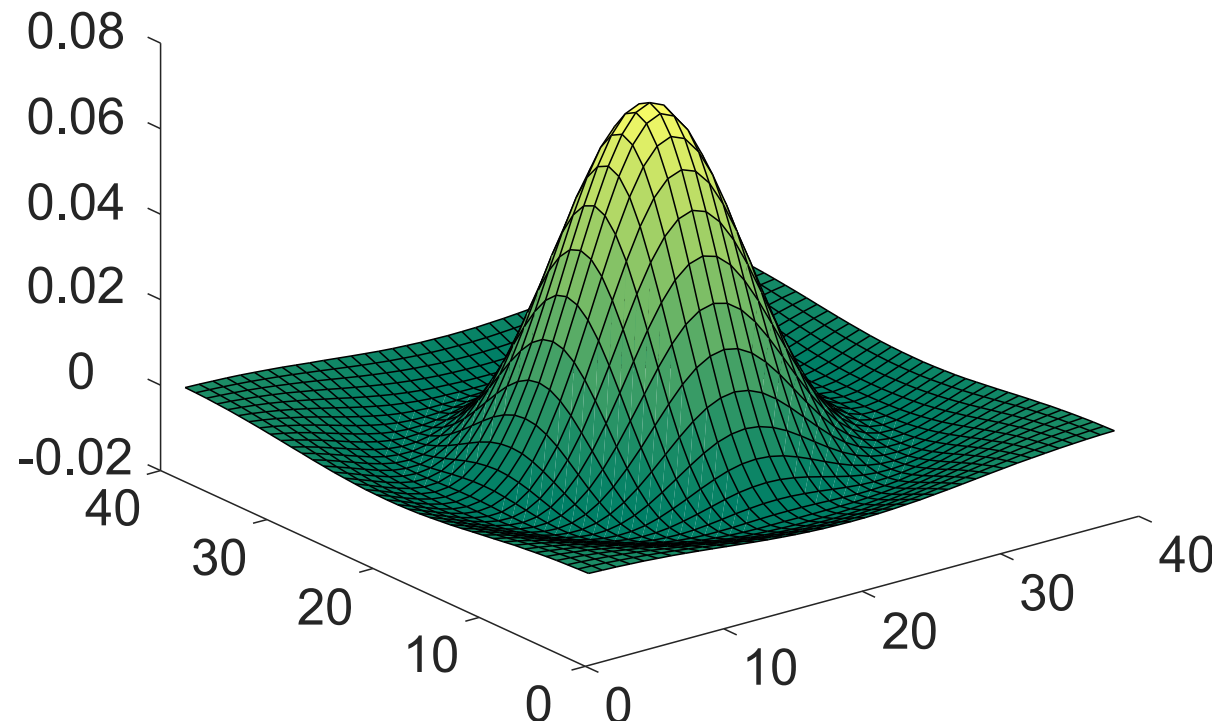
$$LoG \triangleq \Delta G_{\sigma}(x, y) = \frac{\partial^2}{\partial x^2} G_{\sigma}(x, y) + \frac{\partial^2}{\partial y^2} G_{\sigma}(x, y) = \frac{x^2 + y^2 - 2\sigma^2}{\sigma^4} e^{-(x^2+y^2)/2\sigma^2}$$


$$LoG(x, y) = -\frac{1}{\pi\sigma^4} \left[1 - \frac{x^2 + y^2}{2\sigma^2} \right] e^{-\frac{x^2 + y^2}{2\sigma^2}}$$

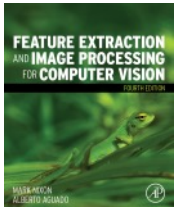
<http://homepages.inf.ed.ac.uk/rbf/HIPR2/log.htm>;
<http://fourier.eng.hmc.edu/e161/lectures/gradient/node8.html> ;
<http://academic.mu.edu/phys/matthysd/web226/Lab02.htm>

Difference comes from
the constant: $\frac{1}{2\pi\sigma^2}$
in front of the Gaussian
function.

Shape of Laplacian of Gaussian operator

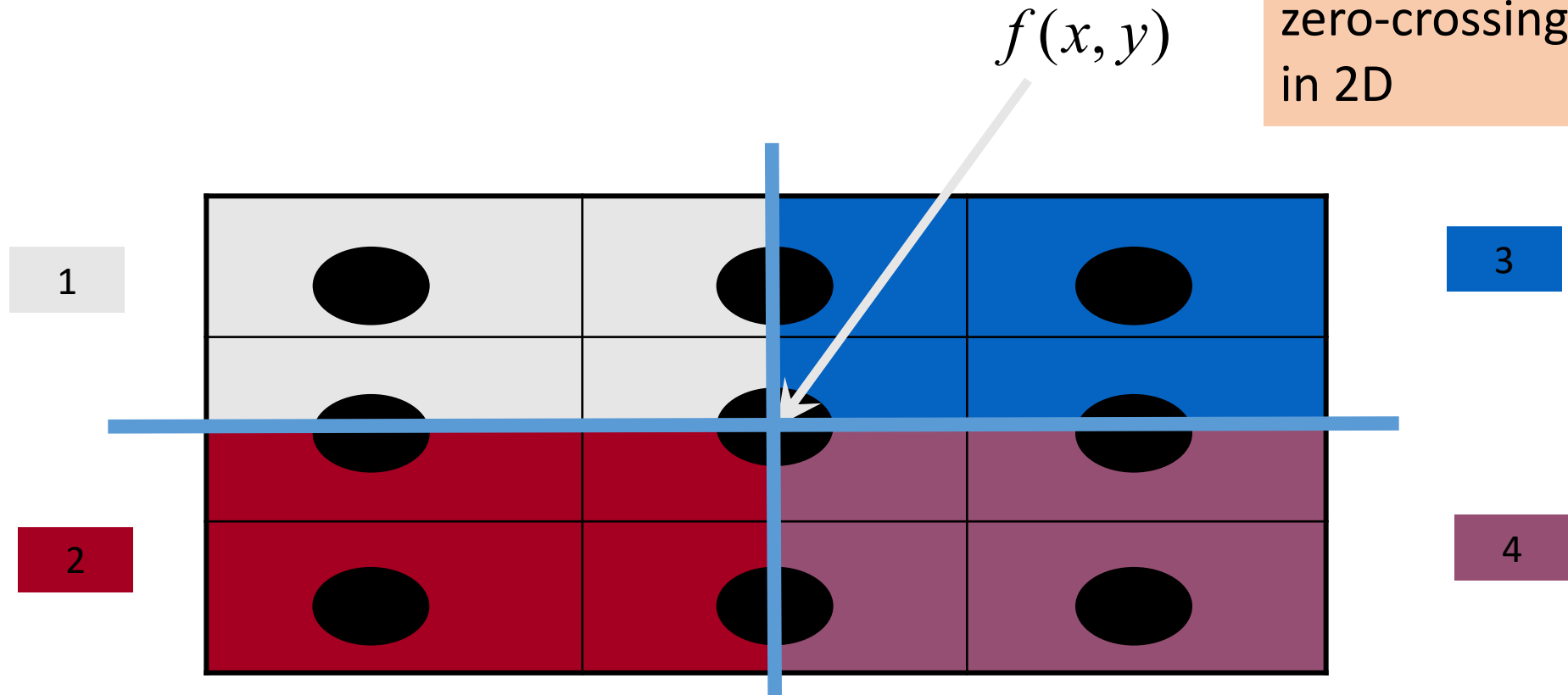


It's called the 'Mexican hat operator'



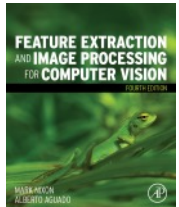
Zero crossing detection

Need to find
zero-crossings
in 2D

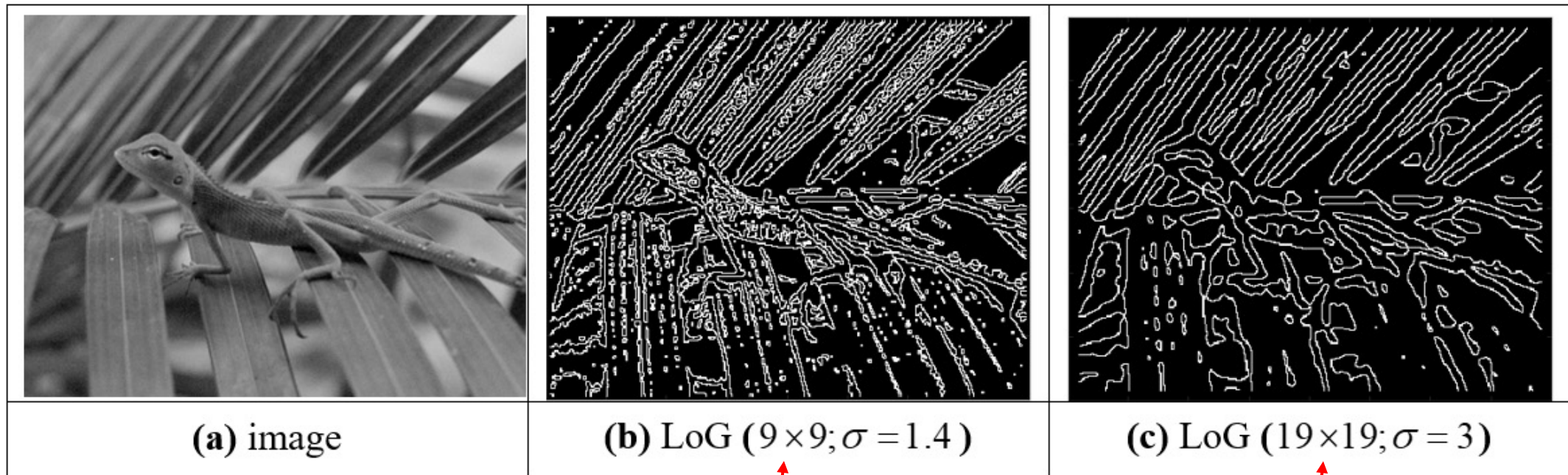


Using e.g.: straight comparison

$$IF (\max(1, 2, 3, 4) > 0 \wedge \min(1, 2, 3, 4) < 0) \quad THEN \quad f(x, y) = \text{edge}$$



Marr-Hildreth edge detection

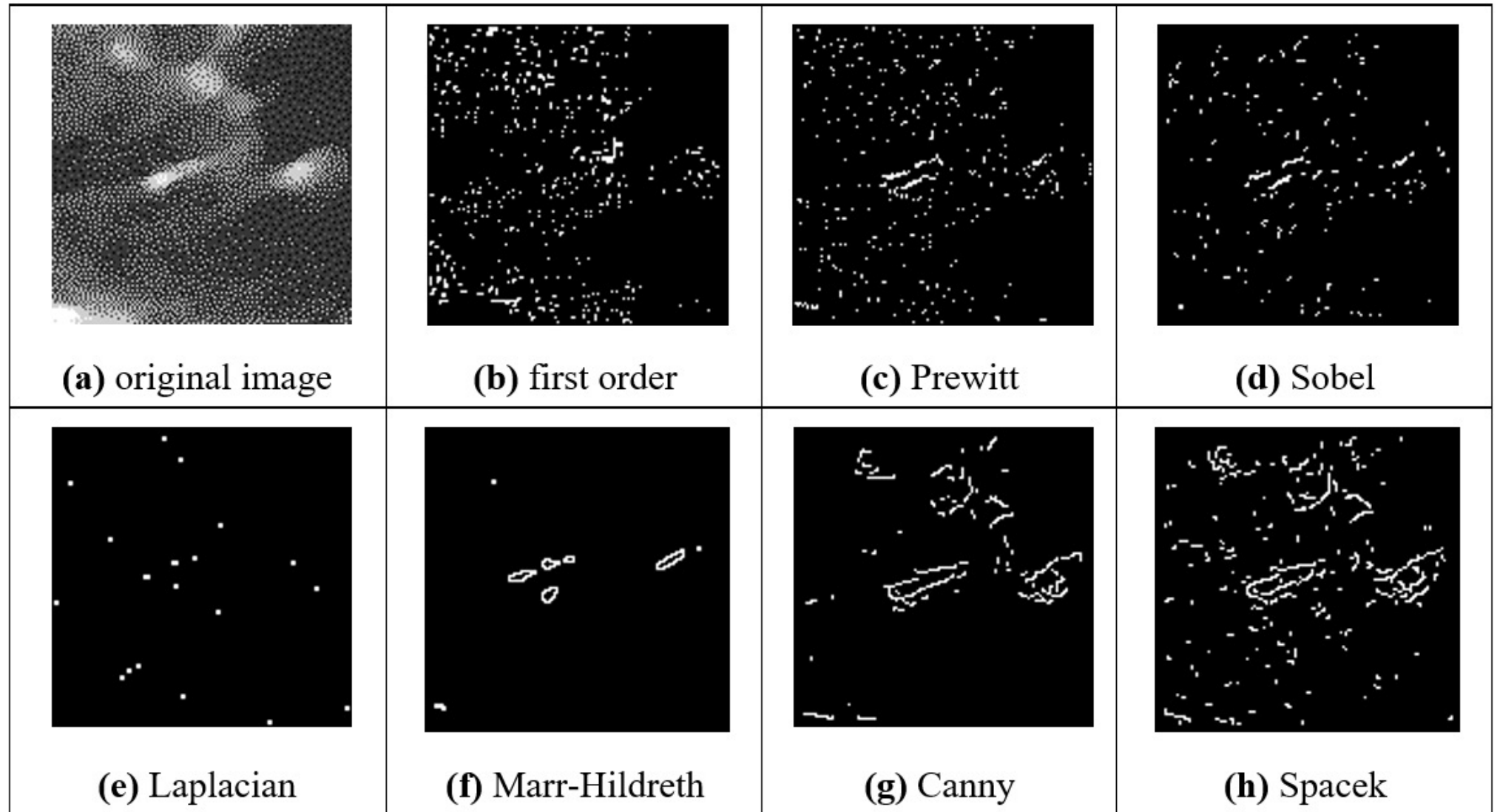


Small template, small σ
for local features

Large template, large σ
for global features



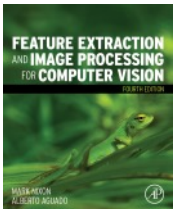
Comparison of edge detection operators



Main points so far

- 1 – **Canny** provides thin edges in the right place
- 2 – **second order** (Marr-Hildreth) requires zero-crossing detection
- 3 – the results by Marr-Hildreth and Canny are well worth the extra computation

Now we need to collect the edges to find shape.
Coming next...



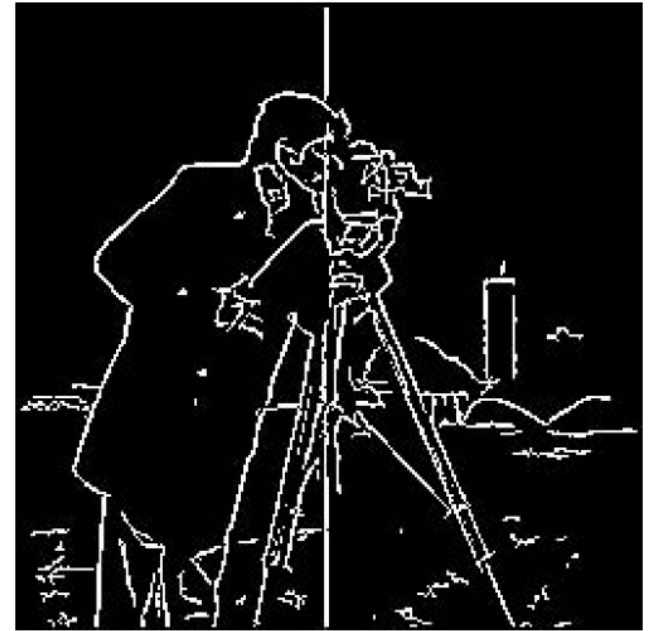
Advanced: Phase Congruency



(a) modified cameraman image



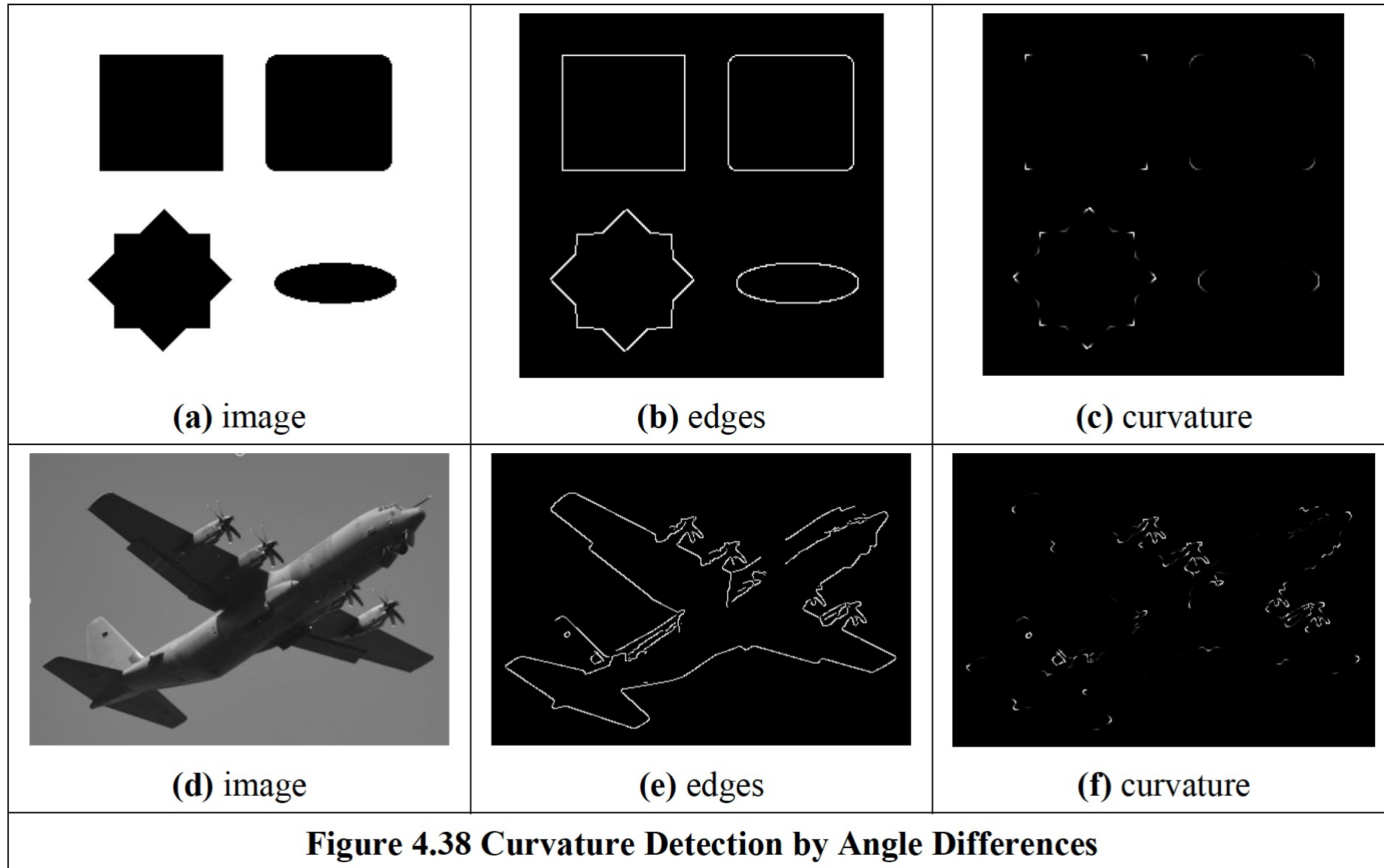
(b) edges by the Canny operator



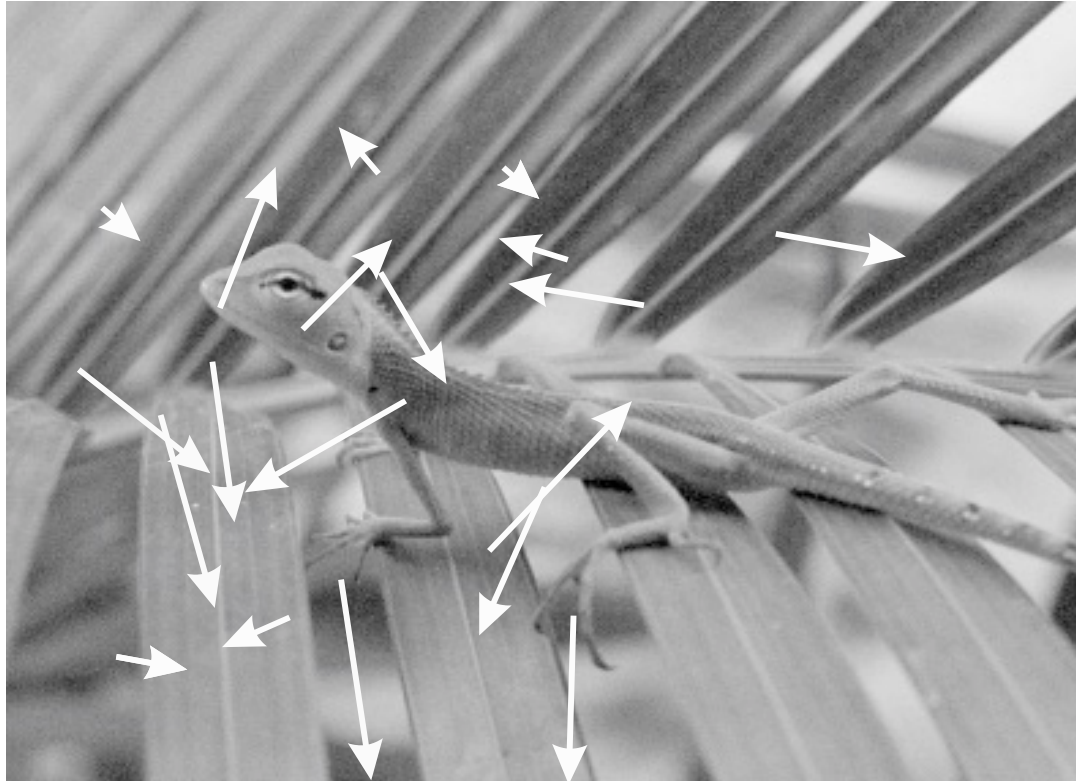
(c) phase congruency

Figure 4.34 Edge Detection by Canny and by Phase Congruency

Advanced: localised feature extraction



Advanced: localised feature extraction



SIFT (mega famous) feature points

Others: SURF, FAST, ORB, FREAK, LOCKY, etc.

