

# EPL668: COMPUTER VISION

## LECTURE 3: EDGE DETECTION I

Dr Paris Kaimakis

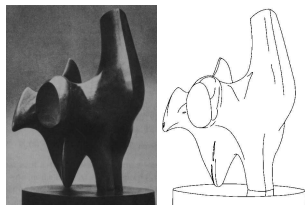
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# MOTIVATION

## SALIENT FEATURES

It is evident that the human visual system is able to interpret images using a small amount of **edge** and **corner** data. This should be also possible in computer vision.

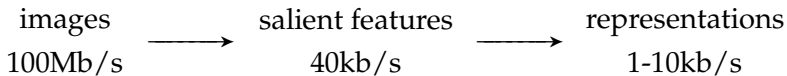


Edges and corners can be matched in stereo views or tracked over time to deduce the scene's shape. Single images can also be interpreted if adequate assumptions about the scene are made.

# MOTIVATION

## DATA REDUCTION

With current computer technology, it is necessary to discard most of the data coming from the camera before any attempt is made at real-time image interpretation.



All subsequent interpretation is performed on the generic representation, not the original image.

# MOTIVATION

## DATA REDUCTION

With data reduction we aim to:

- Discard the redundant information in the images (such as the lighting conditions)
- Preserve the useful information in the images (such as the projected shape of objects in the scene)

# IMAGE STRUCTURE

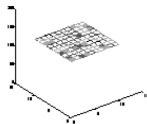
In this photo we will examine the pixel data around 3 patches: a featureless region, an edge and a corner.



The featureless region is characterized by a smooth variation of intensities.



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140 141 141 140 141 141 140 141 141 141 139
140 141 141 139 140 140 140 140 140 140 140
139 140 139 139 140 139 139 138 139 140 140
140 140 139 139 140 140 138 140 140 140 140
140 140 141 139 141 141 140 140 139 139 138
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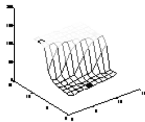


# IMAGE STRUCTURE

The patch containing the edge reveals an intensity discontinuity in one direction.



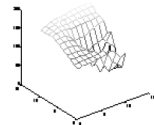
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54 52 60 88 114 127 133 134 132 133 132
49 48 50 53 56 76 99 117 130 133 135
46 45 45 48 50 53 55 57 77 99 118
44 44 45 46 45 47 50 52 54 49 54
42 43 43 44 46 47 50 51 50 52 55
41 40 44 44 44 46 49 48 50 51 56
```



The patch containing the corner reveals an intensity discontinuity in two directions.



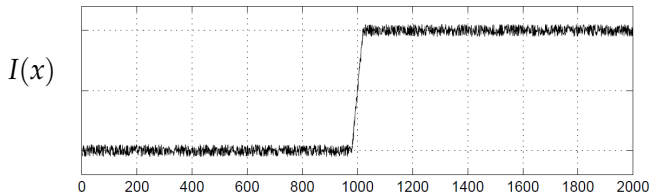
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158 160 160 154 133 113 111 123 127 131 143
163 165 166 158 145 146 147 155 160 166 171
168 171 174 173 169 171 172 173 173 176 176
167 171 176 177 176 178 180 181 181 180 179
166 173 179 182 182 184 185 187 188 189 190
166 173 179 183 183 185 189 191 191 194 194
```



# 1D EDGE DETECTION

## A NAÏVE STRATEGY

Real-world images always contain **noise**. Consider this signal  $I(x)$  with an obvious edge:

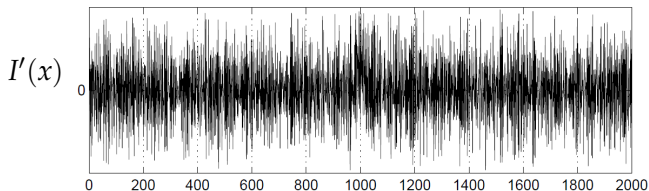


An intuitive approach to detect edges could be to look for maxima and minima in  $I'(x)$ ...

# 1D EDGE DETECTION

## A NAÏVE STRATEGY

Real-world images always contain **noise**. Consider this signal  $I(x)$  with an obvious edge:



...but this simple strategy is defeated by noise. For this reason, all edge detectors start by **smoothing** the signal to suppress noise. This is done by **convolution** with a Gaussian kernel.



# 1D EDGE DETECTION

## A BETTER STRATEGY

- 1 Construct a Gaussian kernel:

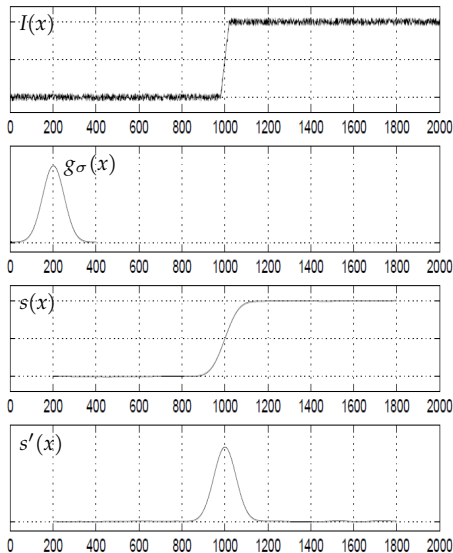
$$g_{\sigma}(x) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{x^2}{2\sigma^2}\right)$$

- 2 Convolve  $I(x)$  with  $g_{\sigma}(x)$  to produce a smoothed signal  $s(x)$ .

- 3 Compute  $s'(x)$ , the derivative of  $s(x)$ .

- 4 Find maxima and minima of  $s'(x)$ .

- 5 Use thresholding on the magnitude of the extrema to mark edges.



# 1D EDGE DETECTION

## A BETTER STRATEGY

The smoothing in **step 2** is performed by a 1D convolution:

$$\begin{aligned} s(x) = g_{\sigma}(x) * I(x) &= \int_{-\infty}^{+\infty} g_{\sigma}(X) I(x - X) dX \\ &= \int_{-\infty}^{+\infty} g_{\sigma}(x - X) I(X) dX \end{aligned}$$

The differentiation in **step 3** is also performed by a 1D convolution.

So *at first glance*, edge detection appears to require **two** convolutions, which is quite computationally expensive.

# 1D EDGE DETECTION

## A BETTER STRATEGY

However, it can be shown that

$$\frac{d}{dx} \left[ g_{\sigma}(x) * I(x) \right] = g'_{\sigma}(x) * I(x)$$

so we can compute  $s'(x)$  directly from  $I(x)$  by convolving only **once** — a considerable computational saving.

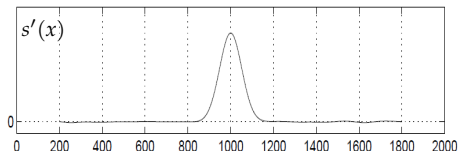
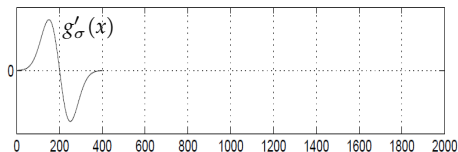
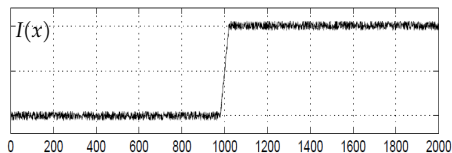
# 1D EDGE DETECTION

## AN EVEN BETTER STRATEGY

- 1 Construct the derivative of a Gaussian:

$$g'_\sigma(x) = -\frac{x}{\sigma^3\sqrt{2\pi}} \exp\left(-\frac{x^2}{2\sigma^2}\right)$$

- 2 Convolve  $I(x)$  with  $g'_\sigma(x)$  to directly produce  $s'(x)$ .
- 3 Find maxima and minima of  $s'(x)$ .
- 4 Use thresholding on the magnitude of the extrema to mark edges.

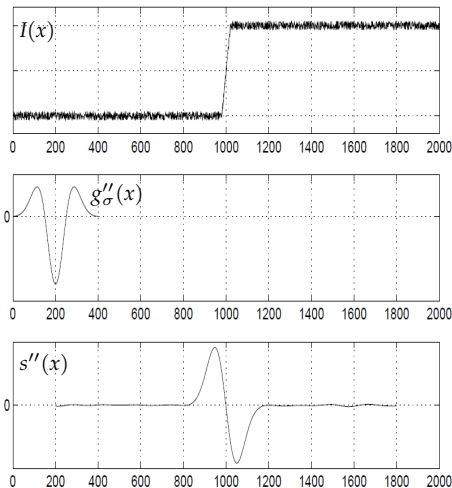


# 1D EDGE DETECTION

## AND AN ALTERNATIVE STRATEGY

Looking for maxima and minima of  $s'(x)$  is the same as looking for zero-crossings of  $s''(x)$ . In some variants of the edge detection algorithm, the signal is convolved with the **Laplacian** of a Gaussian,  $g''_{\sigma}(x)$ :

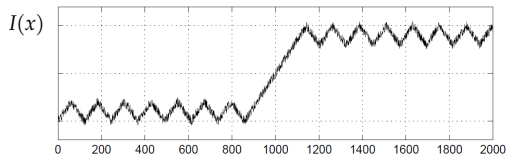
$$s''(x) = g''_{\sigma}(x) * I(x)$$



# 1D EDGE DETECTION

## MULTISCALE EDGE DETECTION

We have not yet addressed the issue of what value of  $\sigma$  to use.  
Consider this signal:

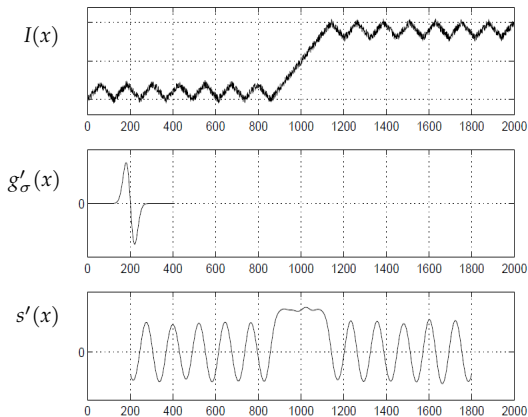


Does the signal have one positive edge, or a number of positive and negative edges?

# 1D EDGE DETECTION

## MULTISCALE EDGE DETECTION

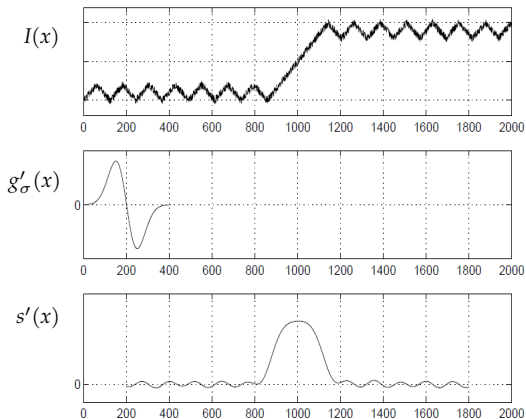
Using a small  $\sigma$  brings out all the edges.



# 1D EDGE DETECTION

## MULTISCALE EDGE DETECTION

As  $\sigma$  increases, the signal is smoothed more and more, and only the central edge survives.





# 1D EDGE DETECTION

## MULTISCALE EDGE DETECTION

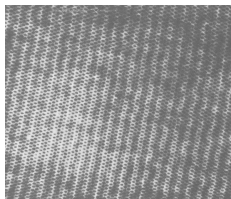
The amount of smoothing controls the **scale** at which we analyze the image. There is no right or wrong size for the Gaussian kernel, it all depends on the scale we are interested in.

Modest smoothing (a Gaussian kernel with small  $\sigma$ ) brings out edges at a fine scale. More smoothing (larger  $\sigma$ ) identifies edges at larger scales, suppressing the finer detail.

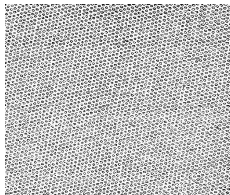
# 1D EDGE DETECTION

## MULTISCALE EDGE DETECTION: 2D EXAMPLE

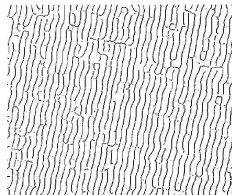
On the left is an image of a dish cloth. After edge detection, we see different features at different scales  $\sigma$ .



raw



$\sigma = 1$



$\sigma = 5$