CSCI435 / CSCI935 – Computer Vision

Lecture 5

Edge Detection

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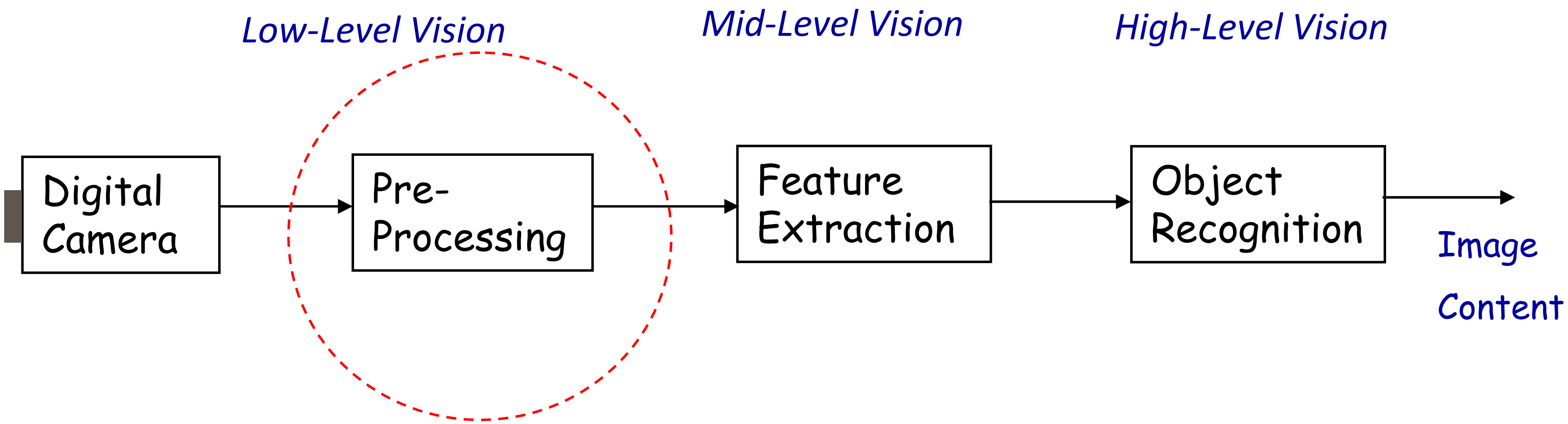
Machine Vision Concept (review)

- Machine Vision is a multistage process where each previous stage affects performance of all following stages



Visual Image Analysis

We isolate objects by analysing sudden variations of brightness or colour

- Image content is analysed through analysis of individual objects, their composition and interaction
- To analyse objects, the objects must be separated from the background

Separation of Objects

- Object separation is a complex process, but it is based on two basic principles:

  - detection of discontinuities (luminance or colour) ← The scope of this lecture

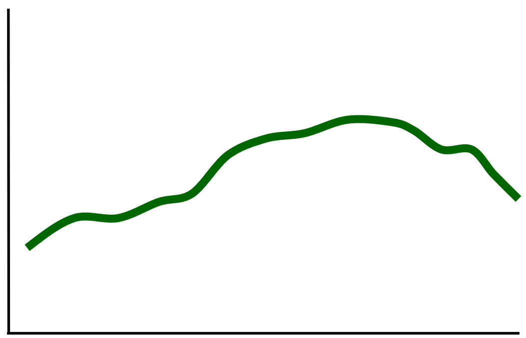
  - identification of similarity

Continuous Functions

- In mathematics, function `f(x)` is said to be continuous at the point `c`, if for any small ε there is Δ, that

$$c-\Delta < x < c+\Delta \quad \Rightarrow \quad f(c)-\varepsilon < f(x) < f(c)+\varepsilon$$

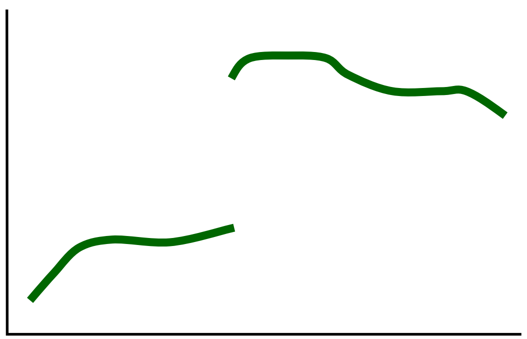
f(x)



x

Continuous Function

f(x)

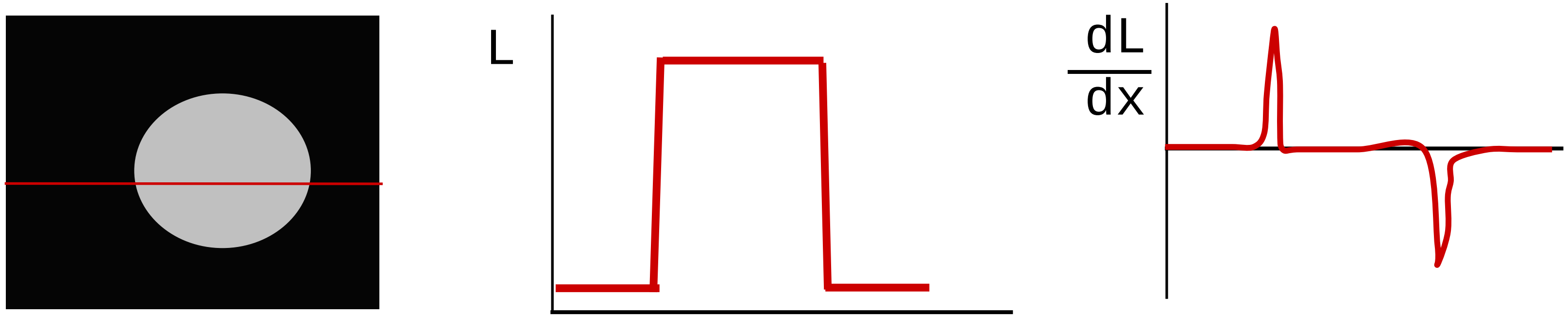


x

Discontinuity

Object Edges

- Object Edges are areas in the image where image luminance has discontinuity



Image

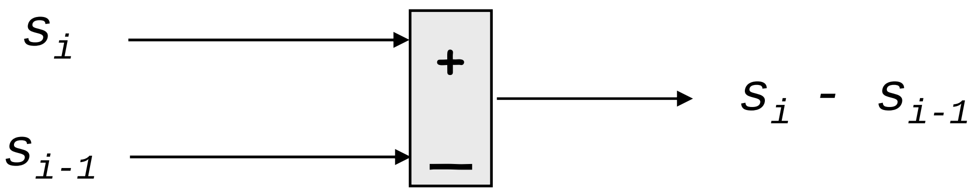
Luminance variation along a image row

- Areas with sudden change of luminance have large magnitude of the gradient in horizontal, or vertical direction (or both)

$$|g_x| > \varepsilon, \quad |g_y| > \varepsilon \quad \text{where} \quad g_x = \frac{dL}{dx} \quad g_y = \frac{dL}{dy}$$

Detection of Discountinuities

- Areas of discontinuities can be detected by measuring gradients and comparing against a predefined threshold value ε
- Gradient is essentially a derivative calculated in one of the directions
- As images are digitised sequences the derivative can be calculated by the commonly used digital differentiator



An example of the 1D differentiator

Detection of Discountinuities

- As images are 2D sequences, the gradients can be measured by 2D differentiators

-1	0	1
-1	0	1
-1	0	1

g_x

3x3 Prewitt kernels

-1	-1	-1
0	0	0
1	1	1

g_y

- Each gradient operator produces produces output that at each location is proportional to the derivative at that location
- Diagonal gradients affect both operators, but to a smaller degree
- Outputs from both operators are combined into a single magnitude

$$g = |g_x| + |g_y|$$

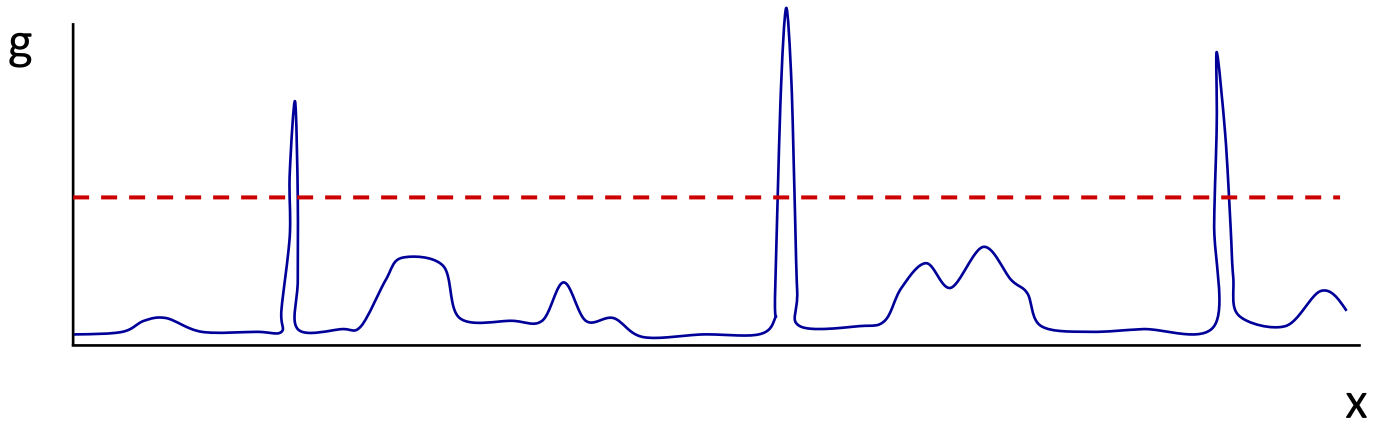
Example

Luminance component of a colour image

Magnitude of the gradient

Sharpness

- The magnitude has largest values at object edges
- Areas with uniform luminance (regardless its absolute value) result in very low values of the magnitude
- Luminance variation inside objects can also produce large magnitudes which can be mistaken for object edges
- High magnitudes created by object luminance variation can be discarded by properly selected thresholds



Example

Magnitude of the gradient

Threshold = 200

Influence of Noise

- White noise causes random sadden variation of image luminance in smooth areas producing false dots and disconnected lines

If images are affected by noise, it should be suppressed before edge detection is carried out

Influence of Noise

- Some operators larger kernels that combine differentiation with smoothing to reduce influence of noise

-2	-1	0	-1	-2
-2	-1	0	-1	-2
-2	-1	0	-1	-2
-2	-1	0	-1	-2
-2	-1	0	-1	-2

5x5 Prewitt kernel for g_x

Other Operators

-1	0	1
-2	0	2
-1	0	1

-1	-2	-1
0	0	0
1	2	1

3x3 Sobel kernels

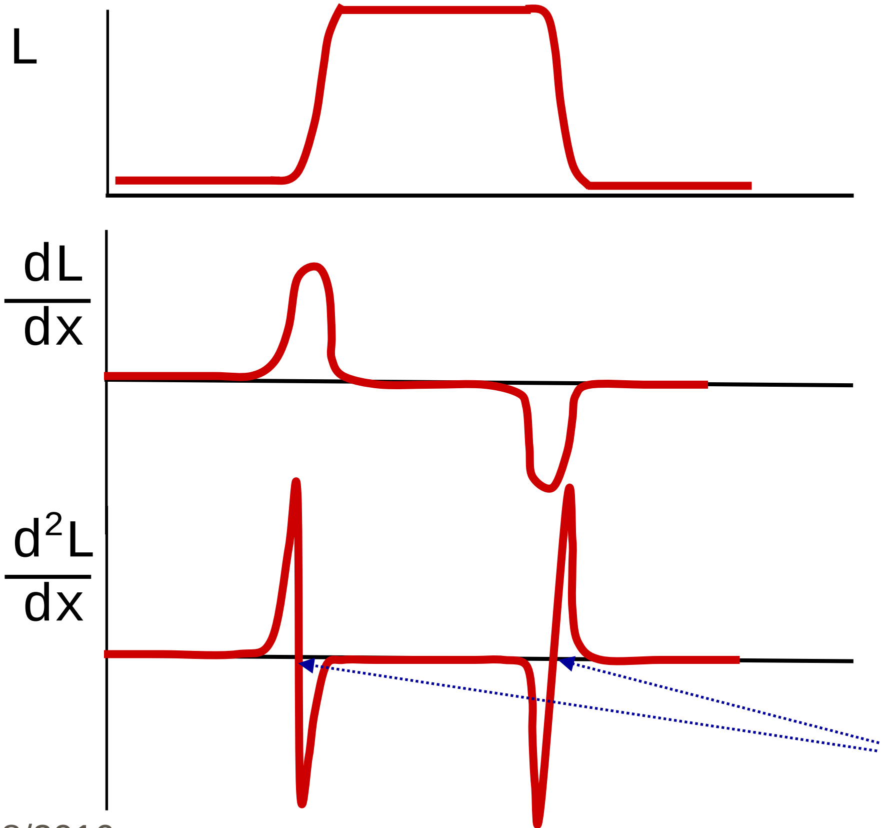
- Some research results suggest using diagonal edge detection kernels together with the vertical and horizontal ones

0	1	1
-1	0	1
-1	-1	0

-1	-1	0
-1	0	1
0	1	1

Higher Order Derivatives

- Some operators combine differentiation with smoothing to reduce influence of noise



The second derivative has a zero crossing at the location of each edge

Higher Order Derivatives

- The second-order derivative can be approximated by the Laplacian kernel

-1	2	-1
2	-4	2
-1	2	-1

Laplacian kernel

- After Laplacian filtering, zero crossings located between double picks have to be detected
- Laplacian kernel is unacceptably sensitive to noise
- Laplacian kernel is not sensitive to edge directions

Binary Image Processing

- After applying the threshold operation images have only two quantisation levels

  0 - below the threshold

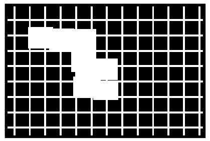
  1 - above the threshold

The detected boundary has an irregular shape with several discontinuities

- If binary images need to be further processed, application of linear filters (LPF , HPF, etc) is not efficient
- Another basis is required for binary image processing

Binary Morphology

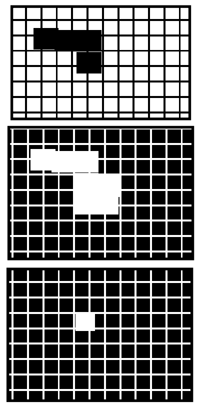
- Binary Image Processing is based on Morphology which in turn is based on Set Theory
- Binary Images are represented as sets of ordered coordinate pairs



A = {(1,1), (1,2), (1,3), (2,3)}

B = {(2,3), (2,4), (3,3), (3,4)}

- There is a set of basic operations



- A^c – the complement of the image A (inversion)
- $A \cup B$ – the union of images A and B
- $A \cap B$ – the intersection of images A and B
- $A - B = A \cap B^c$ – the difference between A and B

Binary Morphology

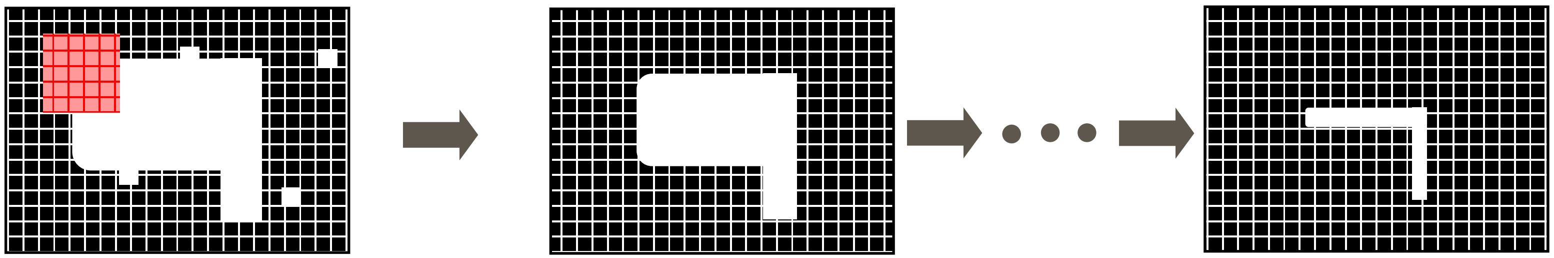
- If image B corresponds to a morphological filter kernel the basic operations can be used to define binary image processing algorithms

1. Erosion $A \Theta B$

where B :

1	1	1
1	1	1
1	1	1

Each output pixel is equal to 1 if all 9 pixels under the mask are equal to 1 (pixel-based AND)



All pixels produced by noise are removed

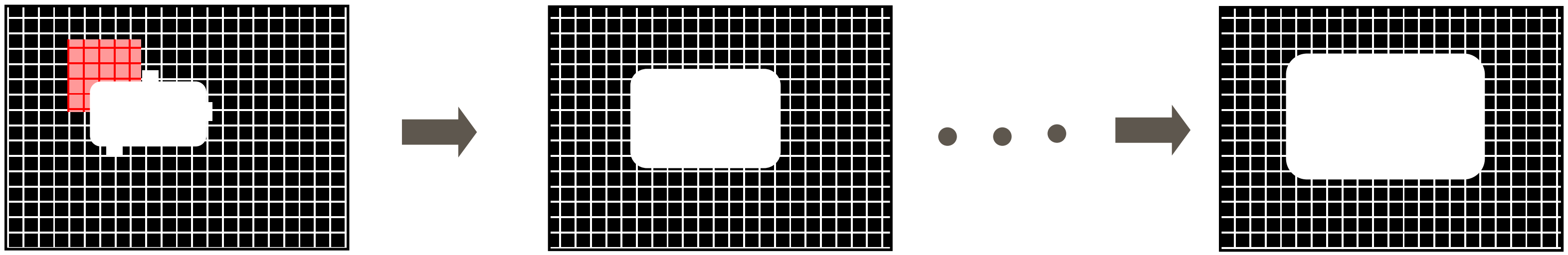
Object Skeleton

Binary Morphology

2. Dilation $A \oplus B$ where B :

$$\begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix}$$

Each output pixel is equal to 1 if at least one of the 9 pixels under the mask are equal to 1 (pixel-based OR)

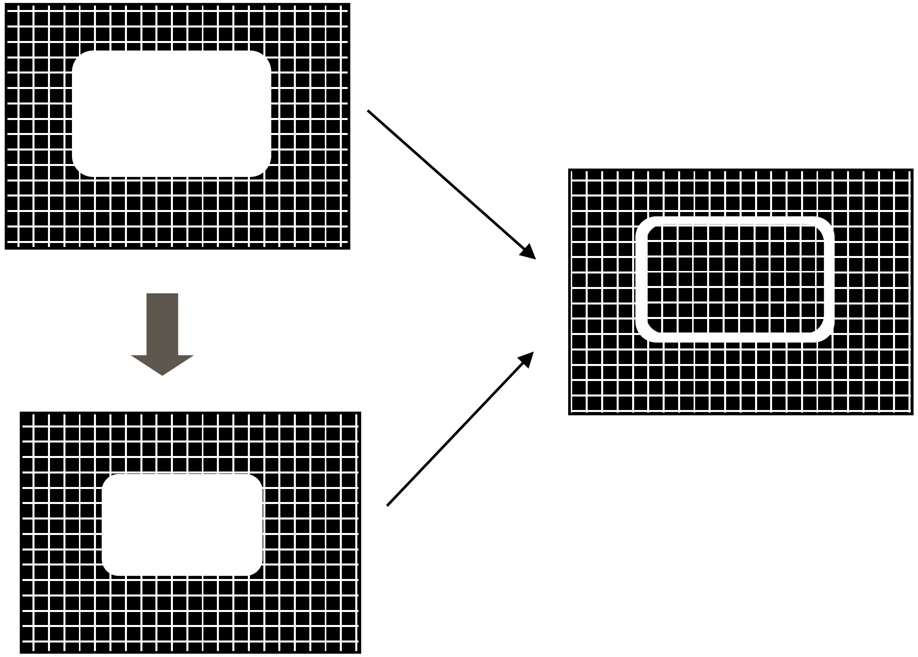


All boundaries are smoothed

Binary Morphology

3. Boundary Extraction $A - (A \; \Theta \; B)$

A

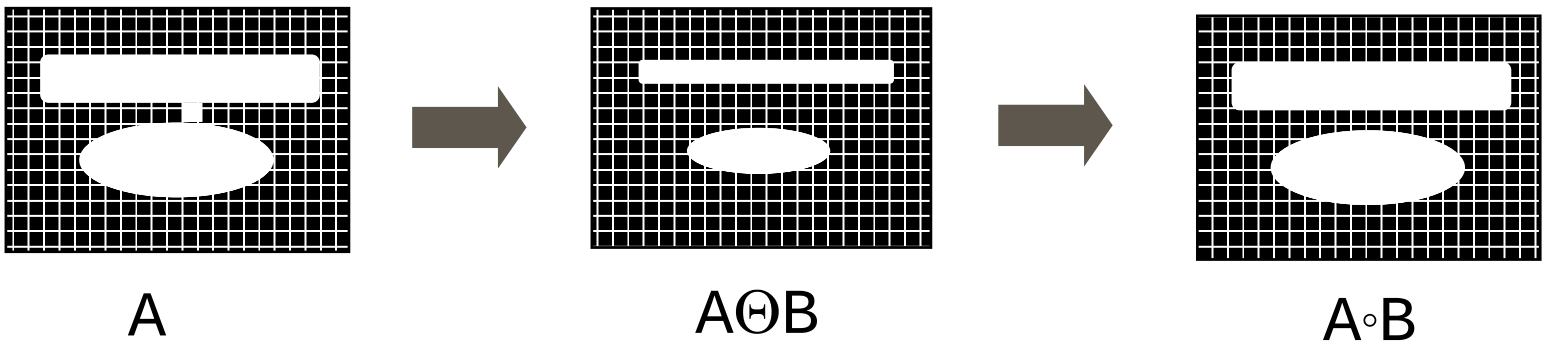


$A \; \Theta \; B$

This approach may be more computationally efficient than Edge Detection when images with few simple objects can be easily binarized

Binary Morphology

4. Opening $A \circ B = (A \Theta B) \oplus B$



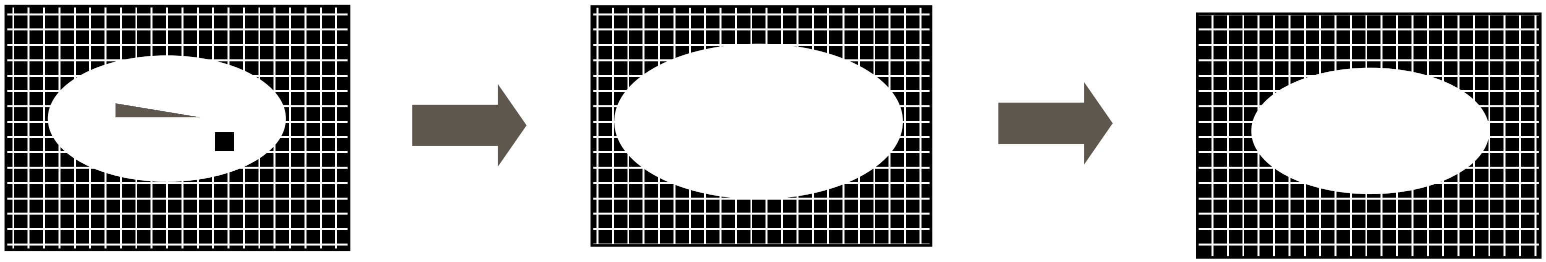
Opening can be used to eliminate false connectivity between separate objects produced by noise

$A - A \circ B$ Indicates what was removed from the original image

The result can be used for automatic inspection in manufacturing process (inspection of PCB traces, etc)

Binary Morphology

5. Closing $A \bullet B = (A \oplus B) \ominus B$



A $\quad$ $A \oplus B$ $\quad$ $A \bullet B$

Closing can be used to eliminate separate noise samples inside objects and thin lines

$A - A \bullet B$ Indicates what was removed from the original image

The result can be used for automatic inspection in manufacturing process (small cracks, scratches, etc)

Suggested Reading

- D Forsyth, Computer Vision. A Modern Approach
  - Chapter 8: Edge Detection
- G. Bradski, A. Kaehler, *Learning OpenCV*

  Chapter 5 Image Processing
  - Image Morphology
  - Threshold

  Chapter 6 Image Transforms
  - Convolution
  - Gradients and Sobel Derivatives
  - Laplace