# EECS 4422/5323 Computer Vision

## Feature Detection Lecture 3

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25 September, 2019

# Announcments

- Bring your Python questions to office hours or labs
  - Recommendation for your own machine: Anaconda
  - Installing OpenCV through `conda`: link
  - Note that `matplotlib` works differently in Jupyter than in standard Python, requires `matplotlib.pyplot.show()` to display figure windows

# Outline

- Linking Edge Elements
- Parametric Fitting
- Contour Voting
- Gestalt Principles

# Review of Edge Elements

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- For many applications, it is better to have a localized edge line rather than a gradient map
- One way to better localize edges is through a Laplacian
- The individual localized points responding to the Laplacian are *edge elements*
- Let's demo the behaviour of a Laplacian filter...

# The Canny Edge Detector

A classic and still popular approach to edge detection was formalized by Canny (1986), which is now known as the Canny edge detector.

The Canny detector is based on many of the principles which we have already discussed, but also includes slightly more sophisticated localization techniques.

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3. Apply non-maximum suppression along the gradient
4. Double-threshold - employ hysteresis when eliminating weak edges

# Hysteresis

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Let's look at a Canny demo.

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The most general structure formed by stringing together edge elements is often referred to as a *contour*.

Contours are formed by taking edge elements and grouping them, usually through connected components with added rules. We can see an example with OpenCV's `findContours()` function.

# Reasoning with Contours

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- Compute bounding boxes over objects with closed contours
- Encode additional logical steps to manipulate contours based on whole contour attributes, rather than kernel neighbourhoods
  - Link contour segments even across gaps
  - Eliminate isolated or topologically unsatisfying contour segments

# Parametric Segments

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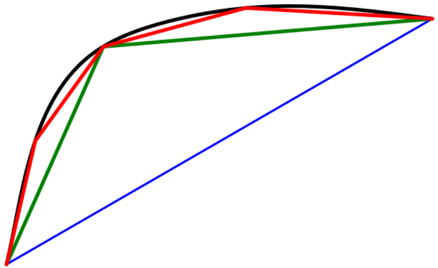
- More compact representations
- Allows straightforward applications of algebraic operations (*e.g.* calculate intersections)
- Can sometimes eliminate small quantities of noise

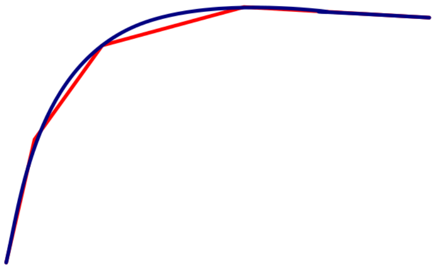
# Piecewise Linear Fitting

Approximating a curve with an increasing number of small linear segments (each increase is done by finding points on the curve furthest from the current approximation).



# Splines

Instead of piece-wise linear approximations, we can instead utilize piecewise polynomial fitting (splines).



# Linking Contour Segments

As we saw with our example penguin, often we must deal with missing "chunks" of an edge, and it would be beneficial to link together contour segments which follow the same overall curve even if they have a gap in the edge image.

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- Random sample consensus (RANSAC)
- Hough Transform

# The Challenge of Outliers

When trying to link up disparate contour segments, we often face the challenge of spurious segments (either because they more properly belong to another grouping, or because they are an edge element based on noise).

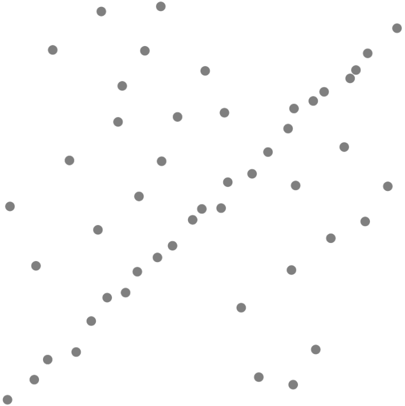


Image source: Wikipedia

# Random Sampling

RANSAC runs a number of trials, each time sampling a minimal set of data to fit a parametric model (such as a line).

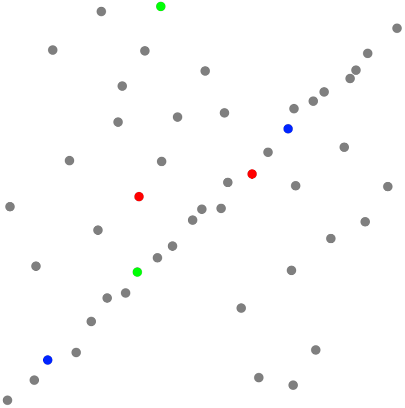
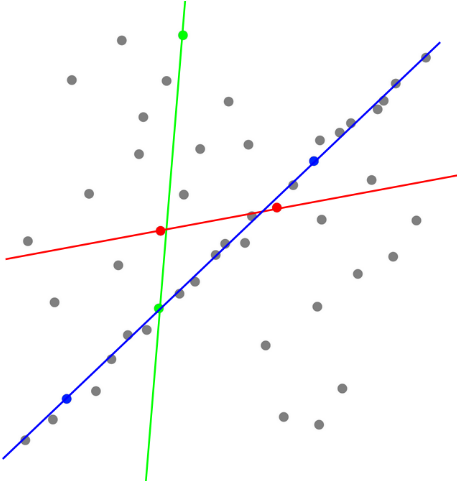


Image source: Modified from Wikipedia

# Sample Voting

For each random sample, the fitted model is tested to see how much of the data it explains.



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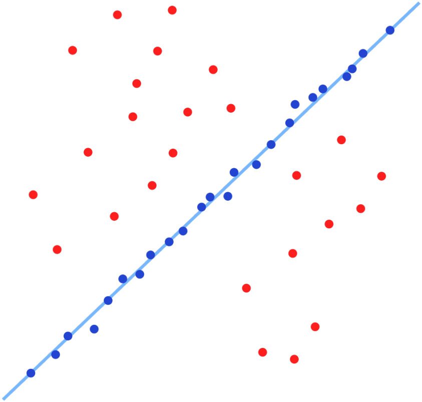
# Fit Selection

The fit which best explains the majority of data is accepted. Only data which is consistent with this fit (within an allowable error threshold) is considered part of the final fit; all other data is considered an outlier.



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# Fair Voting

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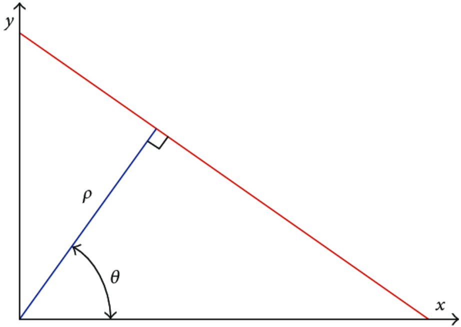
In the Hough Transform, edge elements vote for the lines which they provide evidence for, and these votes are tallied in an *accumulator space*.

If gradient information is retained to assign an orientation to a given edge element, then voting can be restricted to elements in accumulator space which are consistent with a given orientation. Without orientation, edge elements typically vote for all possible oriented lines passing through them, leading to a significant increase in computational requirements.

# Accumulator Space

Typically, the accumulator space is a large array corresponding to parameter values characterizing instances of the target shape.

- For lines, this is typically implemented in $\rho$-$\theta$ coordinates

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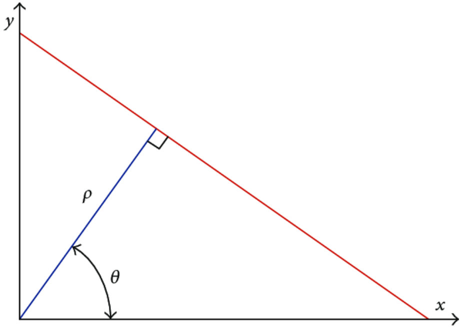

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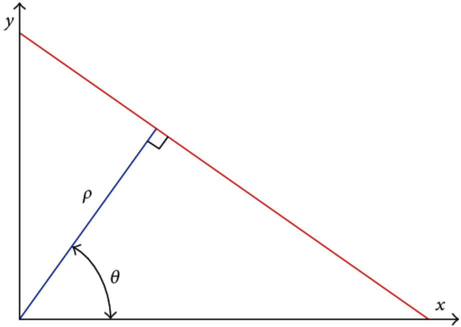
- Often accumulator space is implemented over a coarse spatial scale, and then fit is refined

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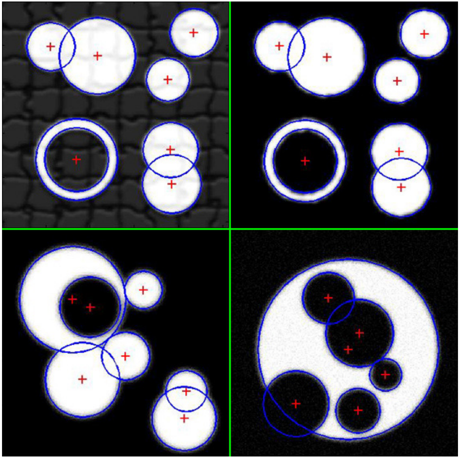
# Hough Transforms for All

Although originally developed for line detection, Hough transforms can be readily adapted to arbitrary parametric shapes, and are particularly popular for circles and ellipses.



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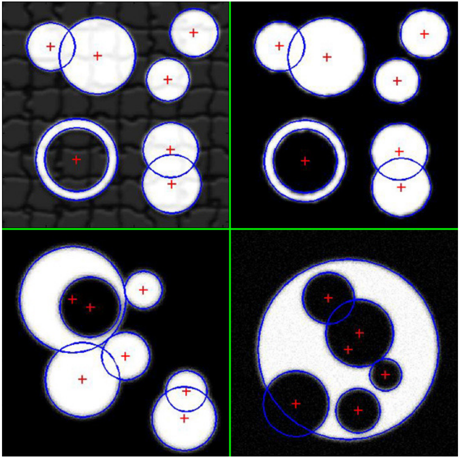

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What changes about the accumulator space for a circle transform instead of a line?

# Hough Transforms Example

Go to Hough Transform example.

# Useful Tool for Constrained Applications

If you know what sorts of curves and lines you should find in an image, these tools can be very straightforward to implement and execute while still achieving satisfactory results. Examples of applications for which these would be well suited include, especially for situations with minimal training data:

- Scanned form analysis

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- Scanned form analysis
- Counting repetitive objects
- Detecting reliable structures (field lines in sports, windows or building contours)

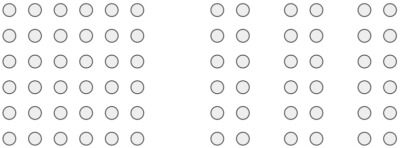
# Overarching Principles

The heuristics and rules we have covered so far for how to select and group contours and fit lines and curves to those contours are drawn from a set of psychological principles known as *Gestalt Principles* (or *Gestalt Laws* or *principles of grouping*).

These general rules do not fit all possible situations in visual perception, but they do give us a nice starting point when reasoning over lines, curves, and contours (or even other features, like patches).

# Proximity

- Items which are close by tend to be interpreted as forming a group



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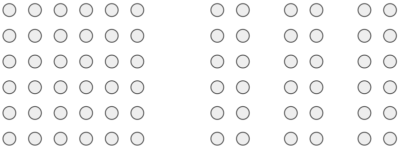

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# Proximity

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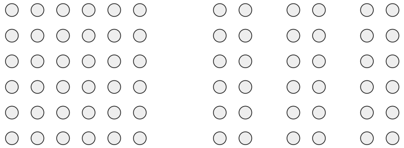
- Grouped elements can create the illusion of shapes, even when not touching



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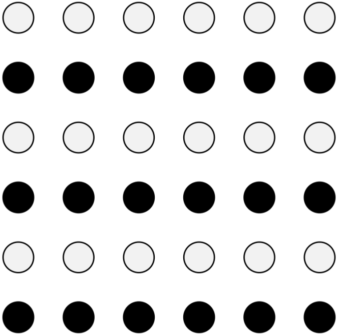

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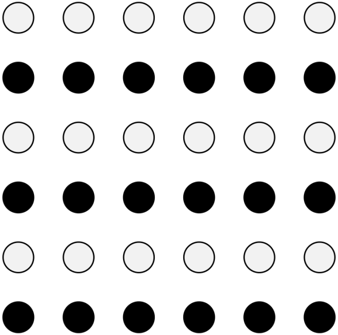

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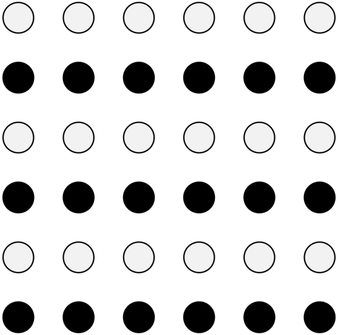
- Can operate along disparate feature channels (*e.g.* colour, texture, shape)



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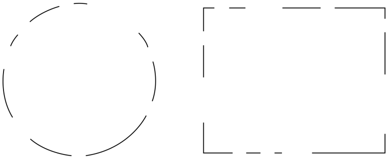
# Closure

- Despite gaps, we tend to group edges into complete, closed contours



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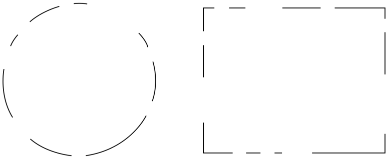

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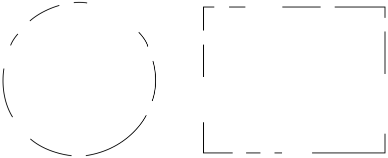
# Closure

- Despite gaps, we tend to group edges into complete, closed contours
- Heavily informed by *border ownership*, which will be discussed later
- Influenced by surrounding context, semantic knowledge, strength of existing edges, and size of the gaps



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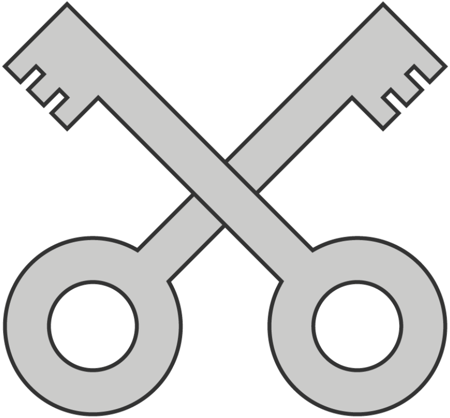
# Continuation

- Perceptual preference is given to items being uninterrupted, cohesive objects



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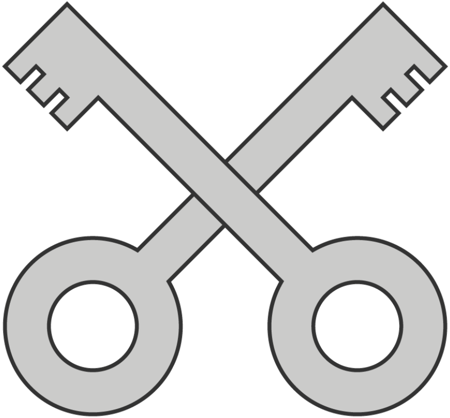

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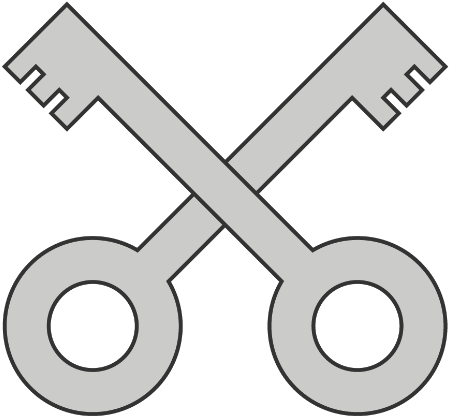
# Continuation

- Perceptual preference is given to items being uninterrupted, cohesive objects
- Curves and lines tend to follow an established direction, rather than sharp or abrupt changes
- When abrupt changes do occur, they tend to indicate occlusions or boundaries



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