EECS 4422/5323 Computer Vision

Feature Detection Lecture 2

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23 September, 2019

Announcments

- White papers are due today
- Reminder: When you submit, follow instructions. PDF filenames must start with your last name.
- Assignment 1 is out
  - You can download the assignment PDF from the link in the course schedule
  - Files for the programming components can be found at the bottom of the schedule page under "Assignment Downloads"
- This weeks' labs are dedicated time for you to work on the assignment and get help or clarifications from the TA
  - Please don't ask "Is this the right answer?" - this is not what the time is for
  - Use this time to make sure you understand what is being asked, and get any help you might need with software requirements or syntax

Computing Resources - The GPUs in the Room

A number of you are looking into projects which will be easier to complete with GPU resources, and so I wanted to mention available options.

- There are ten machines in the lab with GPUs
- There are options for cloud-based computing resources (an example link here), but I can't vouch for them

Outline

- Historical Patterns
- Semantic Features Overview
- Patches
- Edges

Research Often Follows Patterns

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  - Lack of realistic noise might lead to overfitting of features

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- Can lead to false confidence in the degree of data representation (*e.g.* see the Training Humans project)

Patterns in Features

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Patterns in Features

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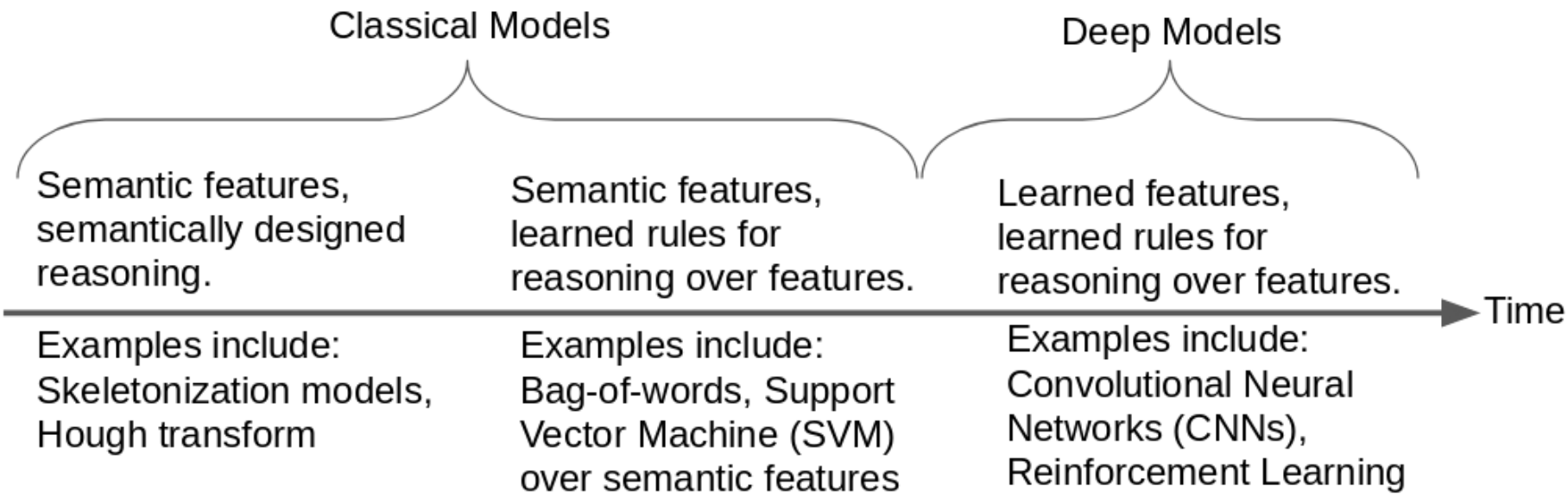
- We say that a feature or process is *semantic* if we can ascribe interpretable meaning to the specific activity along its dimension
  - Semantic features are typically carefully designed
  - Examples include edges and corners
- We say that a feature or process is *learned* if it has been set based on some pattern in a set of training data
  - Learned features often are difficult to interpret on their own
  - Examples include features based on PCA and the features found in deep networks

The Learning Creep

A very prevalent pattern in computer vision is in the balance between semantic and learned design.



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If it's possible to learn features and then learn the rules to reason over those features, why bother studying semantic feature design?

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- Some applications require explanatory traceback
- Understanding how to handle features, whether learned or semantic, is important for many fields of artificial intelligence, and semantic features are in many ways easier to visualize and intuit

Image Patch Features

Image patch feature detectors are sometimes also known as *keypoint detectors*, and the the primary goal for these methods is to find local patches of an image which are distinctive and which can be matched to corresponding patches in other images.

Applications of Keypoints

Image stitching for panoramas.

Image source: Wloka Farms fruitstand

Applications of Keypoints

Object detection and localization.

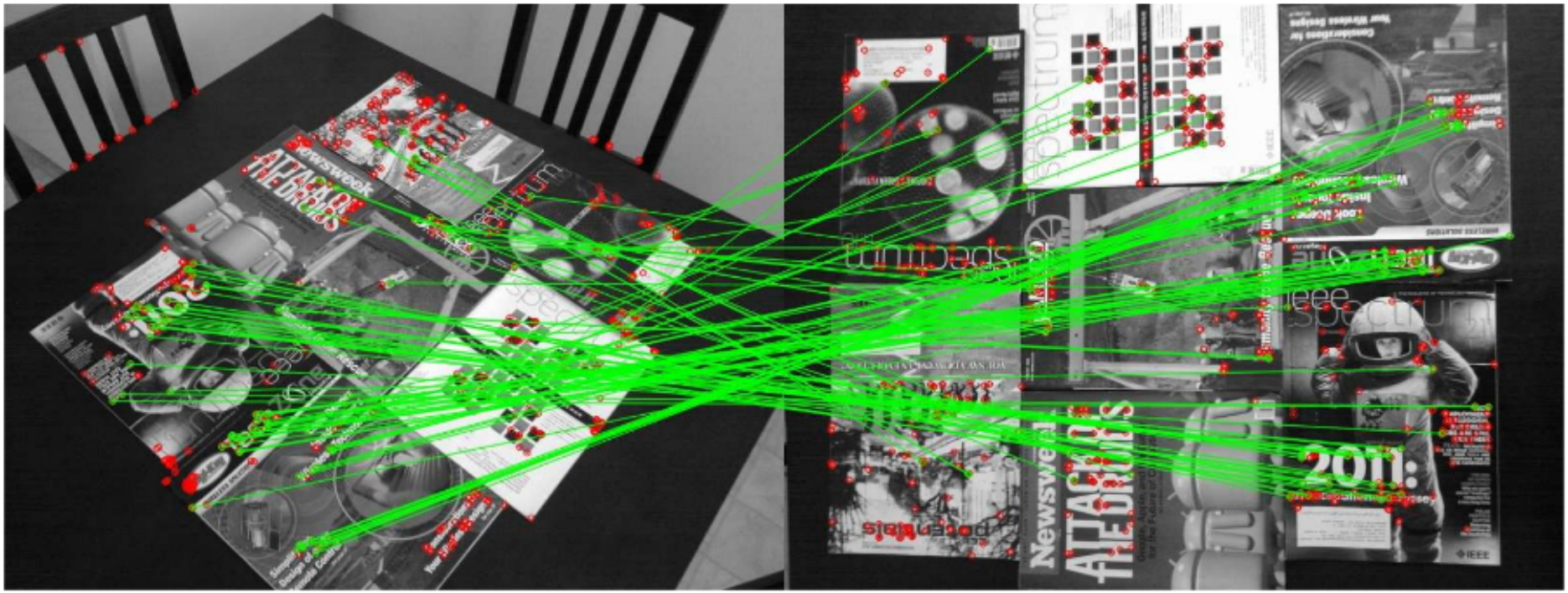


Image source: Rublee *et al.*, 2011

Applications of Keypoints

As a basis for stereo or temporal correspondence, or any other application in which correspondence between frames is desired.

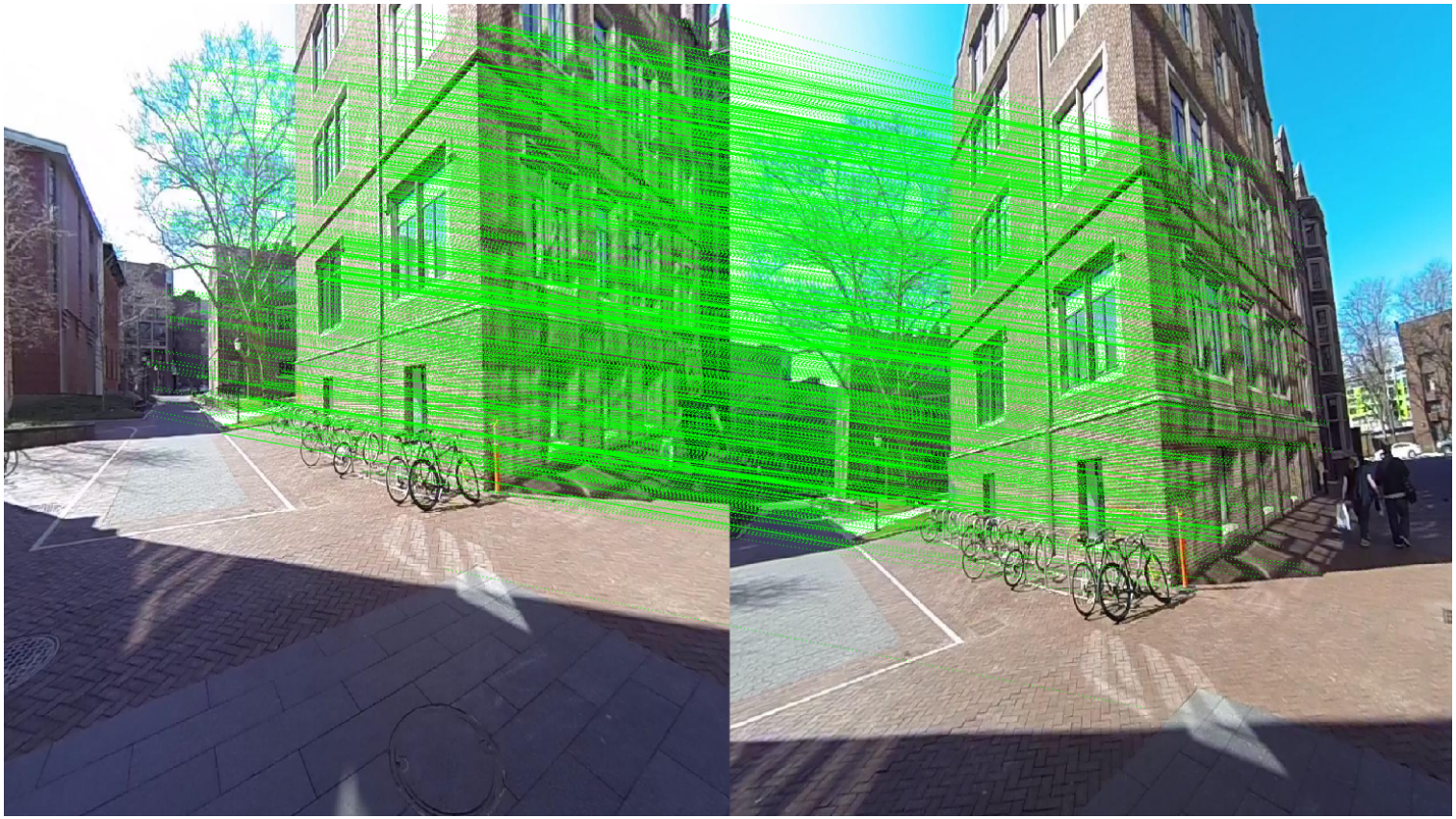


Image source: Singh, Structure from Motion course material

What Makes a Good Patch?

Patch features tend to be sparsely assigned over an image, because not all patches are equivalently good for matching.

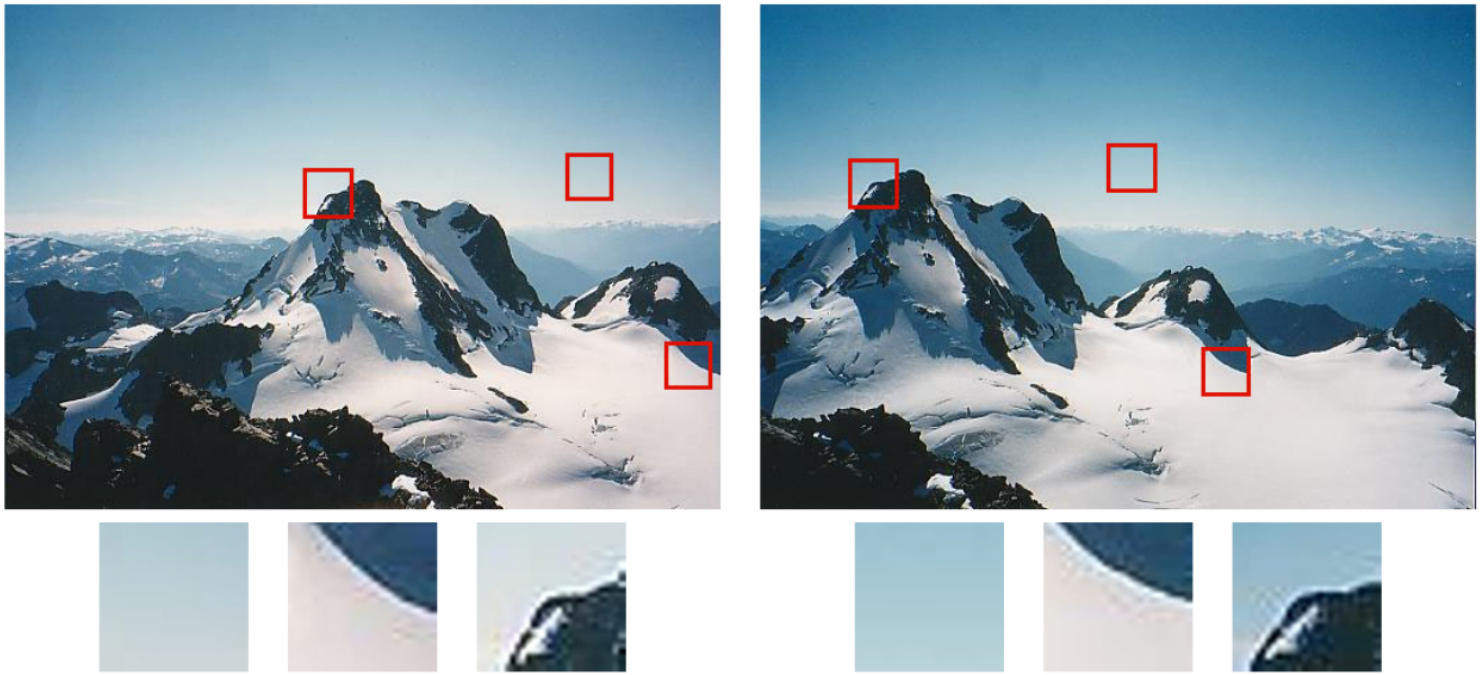
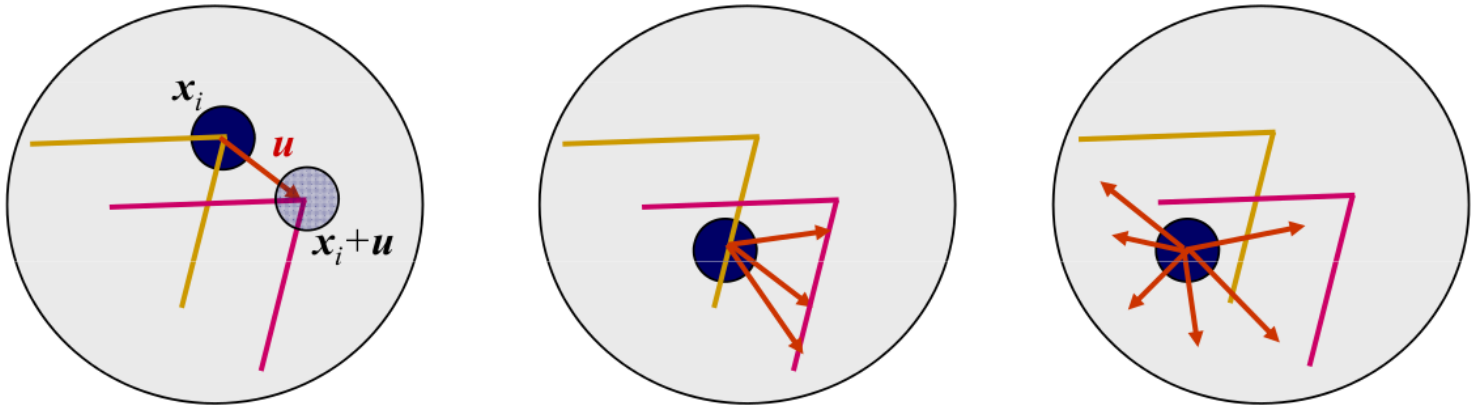


Image source: Szeliski, 2011

What Makes a Good Patch?

A schematic overview of patch suitability.



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a) The dark patch contains two uniquely angled segments and their intersection, so may be matched to the light patch

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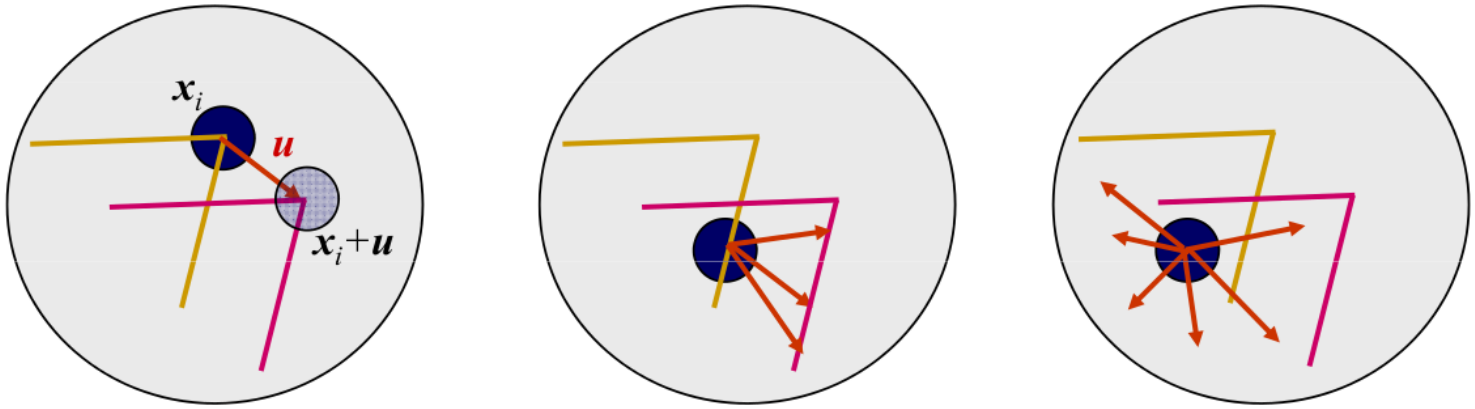

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b) The dark patch only has enough information to be matched somewhere along the corresponding line segment (aperture problem or barber pole illusion)

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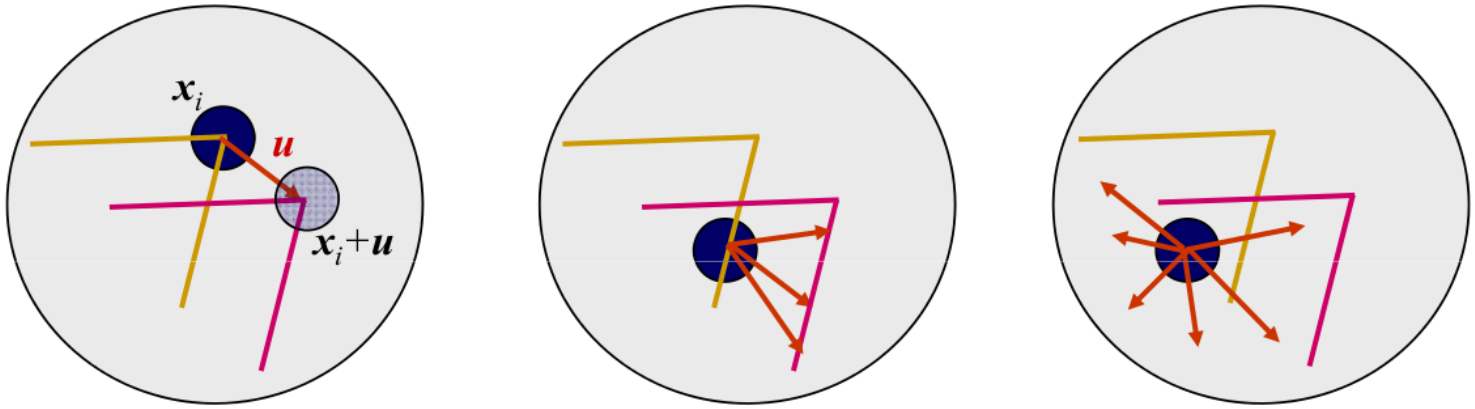

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a) The dark patch contains two uniquely angled segments and their intersection, so may be matched to the light patch
b) The dark patch only has enough information to be matched somewhere along the corresponding line segment (aperture problem or barber pole illusion)
c) The dark patch has no useful information, and could be conceivably matched to any background patch

What Makes a Good Patch?

An example in a real image.

- Top image: input
- Middle row: patches extracted
- Bottom row: autocorrelation surfaces

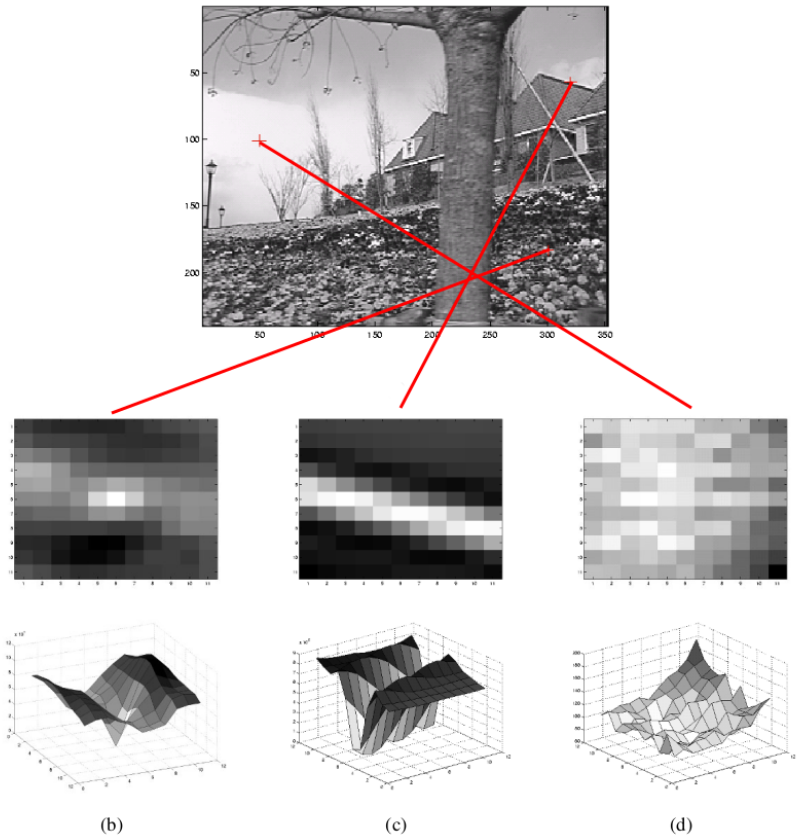

Image source: Modified from Szeliski, 2011

Patch cross-correlation is brittle

For some applications (such as panoramic image stitching), we can assume minimal changes to spatial scale and object orientation while performing patch matching.

However, as we saw in lab, template matching under even very small changes in size or orientation often fails. We therefore would like to find approaches to patch matching which are more robust.

Feature Matching Method Steps

Most feature matching algorithms include two distinct steps:

1. Candidate keypoint detection
2. Keypoint descriptor calculation

Keypoint Detection

There are a number of different ways to do this, including:

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- Harris corner detection (Harris and Stephens, 1988)
- FAST (Rosten and Drummond, 2006)

Keypoint Selection

Once the keypoint detector has run, we need to decide which keypoints to keep. Common approaches include:

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- Adaptive non-maximal suppression (ANMS - Brown, Szeliski, and Winder, 2005)
- Threshold or soft-weighting from an additional value (*e.g.* saliency)

Keypoint Description

Once keypoints are found, they can be made more effective by computing a *descriptor*. This is typically a high-demonsional feature vector computed at each keypoint. The goal of a keypoint descriptor is typically to be robust to an *affine* transformation (*i.e.*, scale, rotation, reflection, and shear), and as such includes the following aims:

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- High discriminability between keypoints
- Rotational invariance (often done by computing a canonical orientation for a given keypoint)
- Scale invariance (often done by computing descriptor features over an image pyramid)

Comparing Keypoints

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For large numbers of keypoints, it is often beneficial to use data representations like a k-d tree to more efficient calculations.

Keypoint Models

For many years keypoint detectors dominated a broad range of applications in computer vision, and still prove useful for a number of specific roles and areas today. Examples of keypoint detection methods which see high use include:

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- Gradient Location-Orientation Histogram (GLOH - Mikolajczyk and Schmid, 2005)
- Oriented FAST and Rotated BRIEF (ORB - Rublee *et al.*, 2011)

Edges

We have already talked about gradients and edge detection filters, including steerable Gaussian derivative kernels. This section will expand upon this topic, particularly with respect to the interpretation and characterization of edges.

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- Object boundary
- Internal structure or components
- Symbolic meaning (*e.g.* text)
- Distinctive texture or patterns for recognition

Semantic Edges

Some edges are more meaningful than others.

Image source: Shi *et al.*, 2013

Illusory Contours

Sometimes an "edge" is missing local contrast.

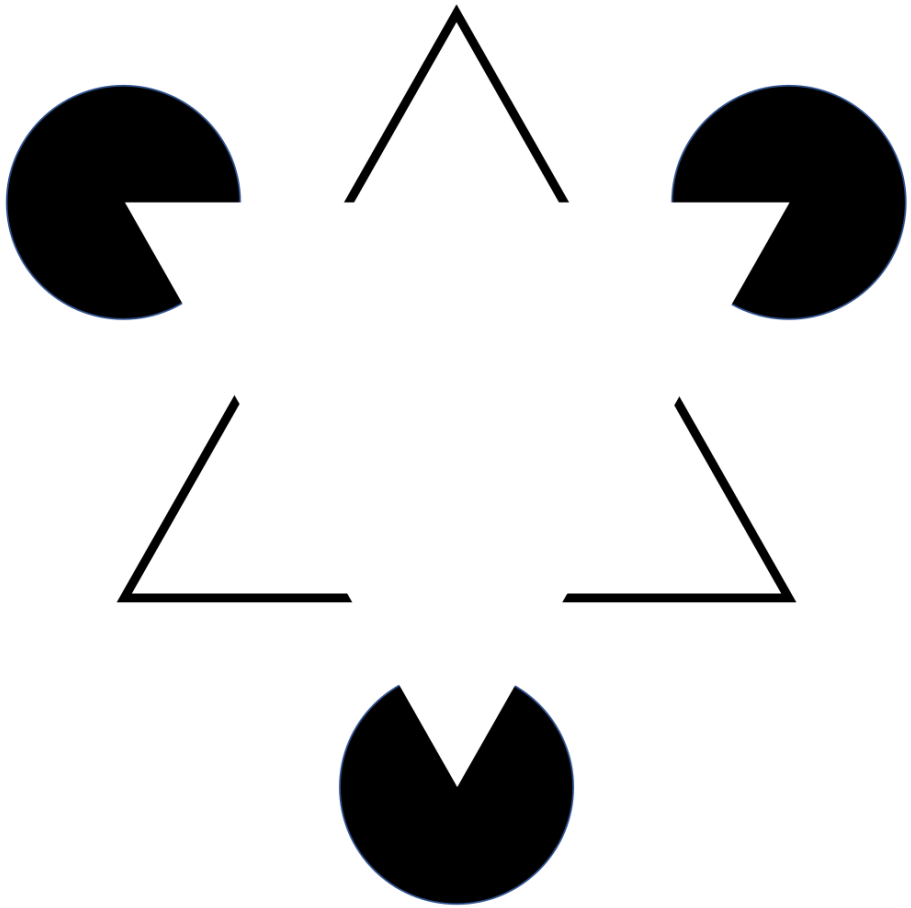


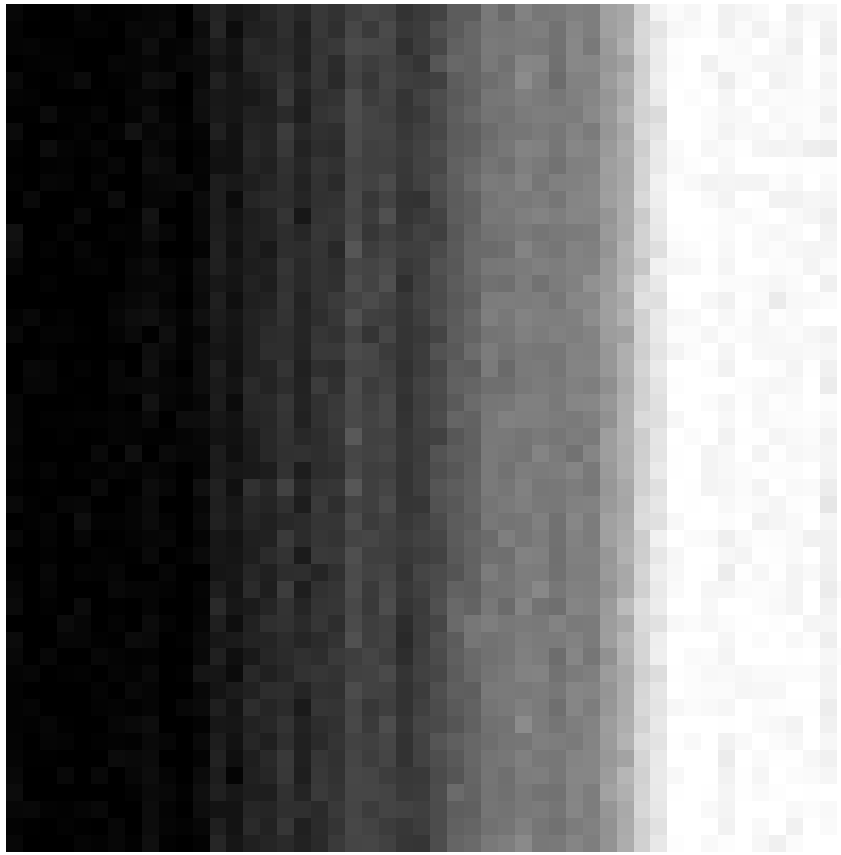
Image source: Kanizsa's Triangle

The Challenge of Shadows

Image source: Steinmetz, National Geographic, 2005

Edge vs. Gradient

Where is the edge in this picture?



Localizing an Edge

As we saw in the Image Representation 2 lecture, we can detect edges with the spatial derivative of the image surface, and can define the direction of that edge by the gradient:

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To localize the edge explicitly, we can calculate the extrema of the derivative, which we can find by taking the second derivative:

$$\nabla \cdot \nabla f = \nabla^2 f$$

This operation is known as the *Laplacian*.

Laplacian of Gaussians

As we saw previously, it is helpful to combine a Gaussian kernel with the derivative to better incorporate local context and reduce the impact of noise on edge detection. This approach remains valid for the Laplacian, and taking the Laplacian of a Gaussian is sometimes referred to as a LoG filter.

As before, this can be equivalently computed using separable filters.

$$\nabla^2 G_\sigma(x,y) = \frac{1}{\sigma^3}\left(1-\frac{x^2}{2\sigma^2}\right)G_\sigma(x)G_\sigma(y) + \frac{1}{\sigma^3}\left(1-\frac{y^2}{2\sigma^2}\right)G_\sigma(x)G_\sigma(y)$$

Localized Edges and Further Reasoning

Once we have localized edge information, we can begin trying to link those edge elements (sometimes referred to as *edgels*) into more complete contours.

This will be explored more next class with a look at the subtopic *Lines*.