15-780 – Computer Vision

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Outline

Basics of computer images

Image processing

Image features

Object recognition

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Image features

Object recognition

Computer images

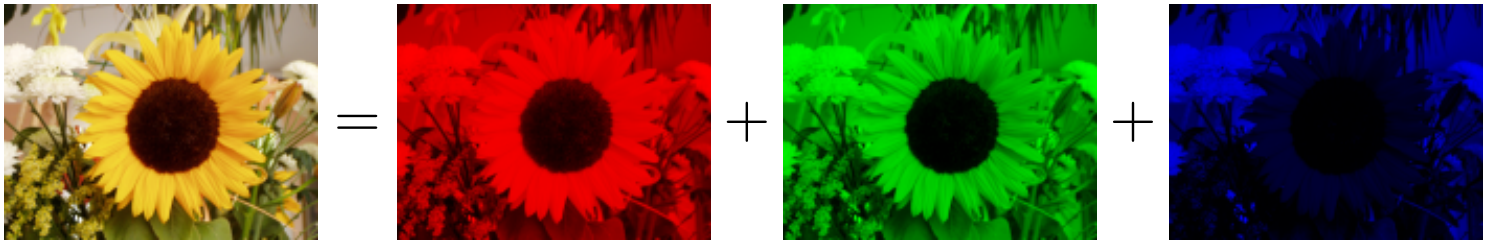
What you see

What computer sees

156	159	158	155	$\cdots$
160	154	157	158	$\cdots$
156	159	158	155	$\cdots$
160	154	157	158	$\cdots$
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\ddots$

- Images represented as matrices of intensity values (already seen this in the digit classification problem)

- For color images, image just contains three intensity matrices, one for red, green, and blue channels



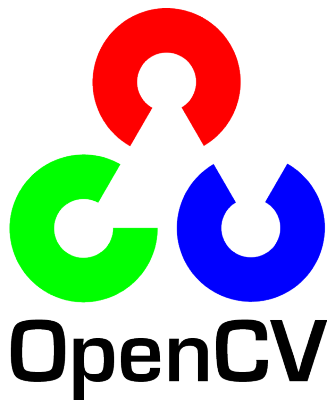
- Almost all the techniques presented here could be applied to color images by applying them to their individual channels, but it's more common to just use grayscale images

- When we write mathematical forms, we'll think of image pixels being real-valued entries, even though they are typically e.g. 8 bit quantities in the images themselves

This lecture

- This lecture will be about some basic methods that practitioners use to "understand" images on a computer

- It will also be a (very brief) introduction to a tool used for computer vision applications: OpenCV



http://opencv.org

OpenCV basics

- Open/save/display an image

```
import numpy
import cv2

img = cv2.imread('camera.png',cv2.IMREAD_GRAYSCALE)
img = cv2.imwrite('camera2.png',img)
cv2.imshow('image',img)
cv2.waitKey(0)
cv2.destroyAllWindows()
```

- Images are stored as normal numpy arrays

```
img[10:15,10:15] # returns 5x5 numpy array of uint8
```

- Display video from camera

```
import numpy
import cv2

cap = cv2.VideoCapture(0)
while(True):
    ret, frame = cap.read()
    cv2.imshow('frame',frame)
    if cv2.waitKey(1) > 0:
        break
cap.release()
cv2.destroyAllWindows()
```

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Color to grayscale

- Because we typically work in grayscale, one of the more basic image processing options to convert images from color to grayscale

- A simple approach, averaging

$$Y = (R + G + B)/3$$

- However, there are alternatives

$$\text{Lightness: } Y = (\max\{R, G, B\} + \min\{R, G, B\})/2,$$
$$\text{Luminosity: } Y = 0.21R + 0.72G + 0.07B$$

(where exact constants are subject to change, these ones and following images are from GIMP documentation)

- Average, lightness, luminosity for sunflower

Original **Average** **Lightness** **Luminosity**




- OpenCV command

```
gray = cv2.cvtColor(frame, cv2.COLOR_BGR2GRAY)
```

(uses luminosity transformation but with slightly different weights)

Convolutions

- Convolutions are one of the most basic image operations, and form the foundation for many more involved approaches

- Written e.g. as the following

$$\begin{bmatrix} -1 & 0 & 1 \\ -1 & 0 & 1 \\ -1 & 0 & 1 \end{bmatrix} * Y$$

- The operation "slides" the left matrix over the entire image $Y \in \mathbb{R}^{m \times n}$, sums the product of corresponding entries for each position

H_{11}	H_{12}	H_{13}
H_{21}	H_{22}	H_{23}
H_{31}	H_{32}	H_{33}

$*$

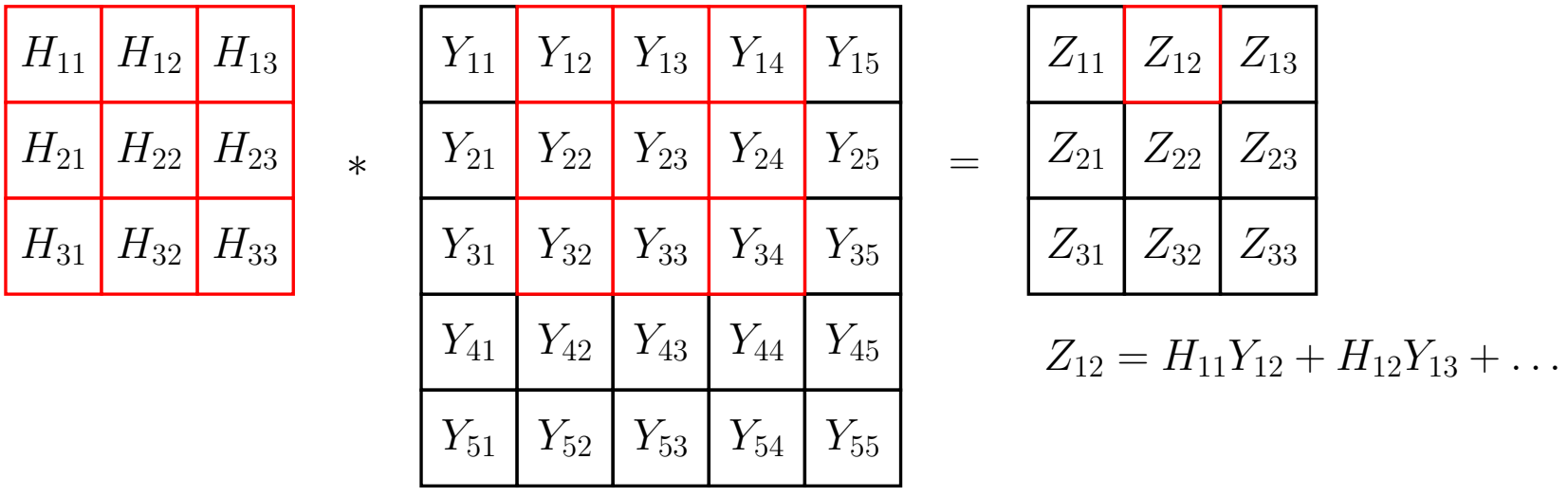
Y_{11}	Y_{12}	Y_{13}	Y_{14}	Y_{15}
Y_{21}	Y_{22}	Y_{23}	Y_{24}	Y_{25}
Y_{31}	Y_{32}	Y_{33}	Y_{34}	Y_{35}
Y_{41}	Y_{42}	Y_{43}	Y_{44}	Y_{45}
Y_{51}	Y_{52}	Y_{53}	Y_{54}	Y_{55}

$=$

Z_{11}	Z_{12}	Z_{13}
Z_{21}	Z_{22}	Z_{23}
Z_{31}	Z_{32}	Z_{33}

$$\begin{array}{|c|c|c|}\hline H_{11} & H_{12} & H_{13} \\ \hline H_{21} & H_{22} & H_{23} \\ \hline H_{31} & H_{32} & H_{33} \\ \hline \end{array} * \begin{array}{|c|c|c|c|c|}\hline Y_{11} & Y_{12} & Y_{13} & Y_{14} & Y_{15} \\ \hline Y_{21} & Y_{22} & Y_{23} & Y_{24} & Y_{25} \\ \hline Y_{31} & Y_{32} & Y_{33} & Y_{34} & Y_{35} \\ \hline Y_{41} & Y_{42} & Y_{43} & Y_{44} & Y_{45} \\ \hline Y_{51} & Y_{52} & Y_{53} & Y_{54} & Y_{55} \\ \hline \end{array} = \begin{array}{|c|c|c|}\hline Z_{11} & Z_{12} & Z_{13} \\ \hline Z_{21} & Z_{22} & Z_{23} \\ \hline Z_{31} & Z_{32} & Z_{33} \\ \hline \end{array}$$

$$Z_{11} = H_{11}Y_{11} + H_{12}Y_{12} + \ldots$$



$$\begin{bmatrix} H_{11} & H_{12} & H_{13} \\ H_{21} & H_{22} & H_{23} \\ H_{31} & H_{32} & H_{33} \end{bmatrix} * \begin{bmatrix} Y_{11} & Y_{12} & Y_{13} & Y_{14} & Y_{15} \\ Y_{21} & Y_{22} & Y_{23} & Y_{24} & Y_{25} \\ Y_{31} & Y_{32} & Y_{33} & Y_{34} & Y_{35} \\ Y_{41} & Y_{42} & Y_{43} & Y_{44} & Y_{45} \\ Y_{51} & Y_{52} & Y_{53} & Y_{54} & Y_{55} \end{bmatrix} = \begin{bmatrix} Z_{11} & Z_{12} & Z_{13} \\ Z_{21} & Z_{22} & Z_{23} \\ Z_{31} & Z_{32} & Z_{33} \end{bmatrix}$$

$$Z_{12} = H_{11}Y_{12} + H_{12}Y_{13} + \dots$$

H_{11}	H_{12}	H_{13}
H_{21}	H_{22}	H_{23}
H_{31}	H_{32}	H_{33}

$*$

Y_{11}	Y_{12}	Y_{13}	Y_{14}	Y_{15}
Y_{21}	Y_{22}	Y_{23}	Y_{24}	Y_{25}
Y_{31}	Y_{32}	Y_{33}	Y_{34}	Y_{35}
Y_{41}	Y_{42}	Y_{43}	Y_{44}	Y_{45}
Y_{51}	Y_{52}	Y_{53}	Y_{54}	Y_{55}

$=$

Z_{11}	Z_{12}	Z_{13}
Z_{21}	Z_{22}	Z_{23}
Z_{31}	Z_{32}	Z_{33}

$$Z_{12} = H_{11}Y_{12} + H_{12}Y_{13} + \ldots$$

- Typically, separate operations for image "borders" so that convolved image is the same size as original
- Usually use odd-sized convolutions, so that "center" pixels correspond

- Example: average pixels (blur)

$$H = \frac{1}{9}\begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix}$$

- Example: Gaussian blur

$$H = \begin{bmatrix} G_\sigma(-1,-1) & G_\sigma(-1,0) & G_\sigma(-1,1) \\ G_\sigma(0,-1) & G_\sigma(0,0) & G_\sigma(0,1) \\ G_\sigma(1,-1) & G_\sigma(1,0) & G_\sigma(1,1) \end{bmatrix}$$

where

$$G_\sigma(x,y) = \frac{1}{\sqrt{2\pi}\sigma}\exp\{-(x^2+y^2)/(2\sigma^2)\}$$

Example: blur

Original image

5x5 averaging

Example: Gaussian blur

Original image

7x7 Gaussian blur

- As you would expect, OpenCV has built-in methods for general convolution, blur and Gaussian blur

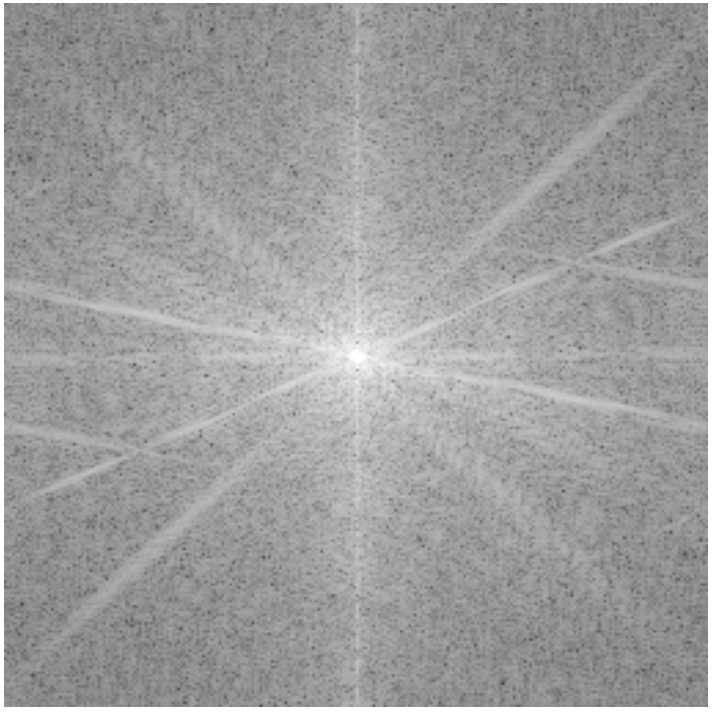
```
H = np.ones((5,5)/25.0
blurred1 = cv2.filter2D(gray, cv2.CV_8U, H);
blurred2 = cv2.blur(img,(5,5)))
gaussian_blurred = cv2.GaussianBlur(img,(7,7),0))
```

Aside: Fourier transform

- Fourier transform expresses image in terms of "frequencies"

Original image

Log frequency magnitudes



- A very nice property: convolution in image space is equivalent to (elementwise) multiplication in frequency space

- Leads to procedure: apply FFT to convert image and filter to frequency space, multiply, then apply inverse FFT to convert to image space

- When filter is large, can be a big benefit, but for small filters, better to just do convolution manually

Image gradients and edge detection

- "Edges" in images represent one of the more interesting properties we could extract

- Informally, we expect an edge to occur when there is a sudden change in image intensity

- If we think of images as two-dimensional functions $f(x, y)$, then we can think about the gradients of this function

$$\frac{\partial f}{\partial x}, \quad \frac{\partial f}{\partial y}$$

- In practice, since images are discrete, we could approximate these just using differences, i.e. to compute all x and y gradients respectively, we could use the convolutions

$$H_x = \begin{bmatrix} -1 & 1 \end{bmatrix}, \quad H_y = \begin{bmatrix} -1 \\ 1 \end{bmatrix}$$

- In practice, this simple difference is too noisy, a better alternative is to first (Gaussian) blur the image, then take differences

- We can do both of these using a single convolution: Sobel filters

3x3: $H_x = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix}$, $H_x = \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{bmatrix}$

5x5: $H_x = \begin{bmatrix} -1 & -2 & 0 & 2 & 1 \\ -2 & -3 & 0 & 3 & 2 \\ -3 & -5 & 0 & 5 & 3 \\ -2 & -3 & 0 & 3 & 2 \\ -1 & -2 & 0 & 2 & 1 \end{bmatrix}$, $H_y = \begin{bmatrix} -1 & -2 & -3 & -2 & -1 \\ -2 & -3 & -5 & -3 & -2 \\ 0 & 0 & 0 & 0 & 0 \\ 2 & 3 & 5 & 3 & 2 \\ 1 & 2 & 3 & 2 & 1 \end{bmatrix}$

Original image

Magnitude of gradient

$$\sqrt{\left(\frac{\partial f}{\partial x}\right)^2 + \left(\frac{\partial f}{\partial y}\right)^2}$$

- OpenCV calls:

```
dfdx = cv2.Sobel(img, cv2.CV_64F, 1, 0, ksize=3)
dfdy = cv2.Sobel(img, cv2.CV_64F, 0, 1, ksize=3)
```

Canny edge detector

- Extremely popular edge detection algorithm, compute image gradients and then

  1. Non-maximal suppression: only keep "ridges" of the gradient magnitude

  2. Ignore edges that are too small

  3. Ignore edges that never reach high enough magnitude

```
edges = cv2.Canny(img, 100, 200)
```

Original image

Canny edges

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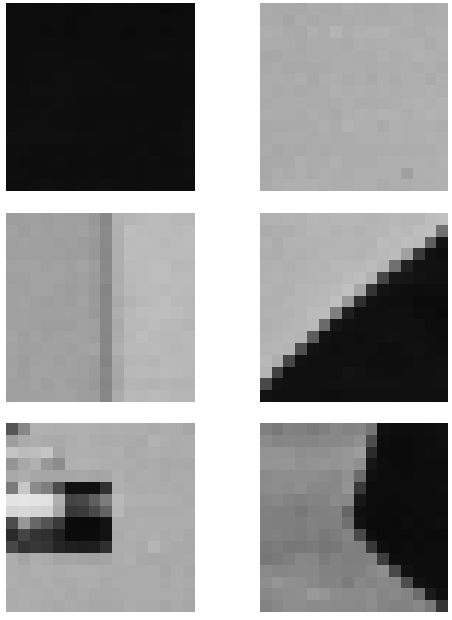
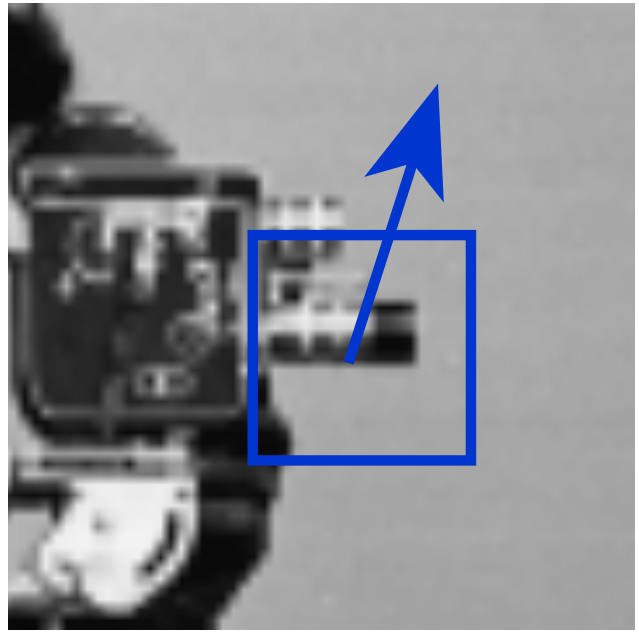
- In computer vision "features" correspond to patches of the image that are "easy to identify"

Can you find these patches in the image?



- What makes a "good" feature?

- One possible answer: if we shift the window for an image patch in any direction, it should look different from the original patch



- Mathematically, let's consider our image as a function again, and look at all pixels inside some window W

- Define the function

$$E_W(\Delta x, \Delta y) = \sum_{x,y \in W} (f(x,y) - f(x+\Delta x, y+\Delta y))^2 \qquad (1)$$

- If $E_W(\Delta x, \Delta y)$ is big for small displacements $\Delta x, \Delta y$ in *any* direction, the window is a good feature

- For small displacements

$$f(x+\Delta x, y+\Delta y) \approx f(x,y) + \frac{\partial f(x,y)}{\partial x}\Delta x + \frac{\partial f(x,y)}{\partial y}\Delta y$$

so

$$\begin{aligned} E_W(\Delta x, \Delta y) &= \sum_{x,y\in W} (f(x,y) - f(x+\Delta x, y+\Delta y))^2 \\ &\approx \sum_{x,y\in W} \left(\frac{\partial f(x,y)}{\partial x}\Delta x + \frac{\partial f(x,y)}{\partial y}\Delta y \right)^2 \\ &= \begin{bmatrix} \Delta x & \Delta y \end{bmatrix} M_W \begin{bmatrix} \Delta x \\ \Delta y \end{bmatrix} \end{aligned}$$

where

$$M_W = \sum_{x,y\in W} \begin{bmatrix} \left(\frac{\partial f(x,y)}{\partial x}\right)^2 & \frac{\partial f(x,y)}{\partial x} \cdot \frac{\partial f(x,y)}{\partial y} \\ \frac{\partial f(x,y)}{\partial x} \cdot \frac{\partial f(x,y)}{\partial y} & \left(\frac{\partial f(x,y)}{\partial y}\right)^2 \end{bmatrix}$$

- Again, want to find patches W where

$$E_W(\Delta x, \Delta y) \approx \begin{bmatrix} \Delta x & \Delta y \end{bmatrix} M_W \begin{bmatrix} \Delta x \\ \Delta y \end{bmatrix}$$

  is big for inputs in any direction $\Delta x, \Delta y$

- Look at eigenvalues λ_1, λ_2 of M_W; if they are both large, displaement in any direction will cause increase in E

  – Harris corner detector: good feature if $\det(M_W) - k(\mathrm{trace}(M_W))^2$ is above some threshold

  – Shi-Tomasi corner detector: good feature if $\min(\lambda_1, \lambda_2)$ is above some threshold

Original image

50 Shi-Tomasi Features

- In OpenCV:

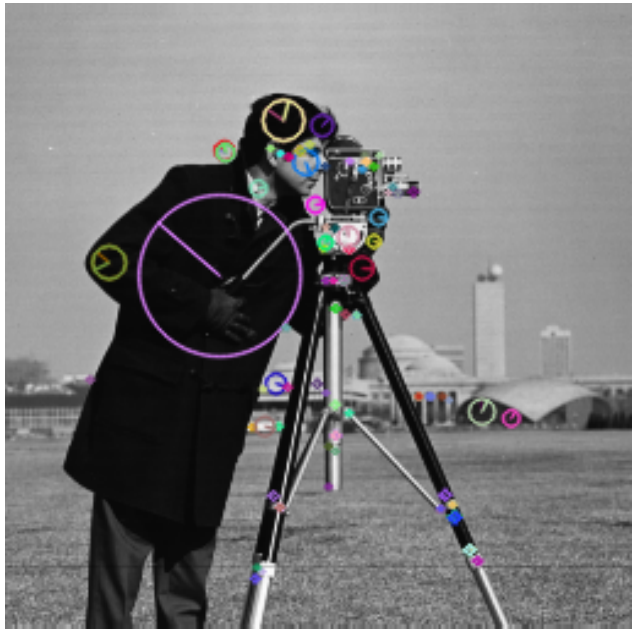
```
corners = cv2.goodFeaturesToTrack(gray,50,0.01,10)
```

SIFT features (very briefly)

- Downside of Harris/Shi-Tomasi features is that they are not invariant to recsaling

- Scale Invariant Feature Transform, (Lowe 2004): compute (something similar to) these features, but at multiple image scales

- Also computes feature *descriptors*, a 128-dimensional vector describing histogram of image gradients at feature points/scales



Tracking features over time

- One of the most common tasks in images/video is to track how features move across multiple images
- Consider image (video) now also as function of time $f(x, y, t)$
- For some point x, y (e.g., an image features) find displacement $\Delta x, \Delta y$ such that

$$f(x, y, t) = f(x + \Delta x, y + \Delta y, t + \Delta t)$$

- By first order expansion,

$$f(x+\Delta x, y+\Delta y, t+\Delta t) \approx$$
$$f(x,y,z) + \frac{\partial f(x,y,t)}{\partial x}\Delta x + \frac{\partial f(x,y,t)}{\partial y}\Delta y + \frac{\partial f(x,y,t)}{\partial t}\Delta t$$

  so we want to find $\Delta x, \Delta y$ such that

$$\frac{\partial f(x,y,t)}{\partial x}\Delta x + \frac{\partial f(x,y,t)}{\partial y}\Delta y + \frac{\partial f(x,y,t)}{\partial t}\Delta t = 0$$

- Written a bit more compactly

$$\frac{\partial f(x,y,t)}{\partial x}u + \frac{\partial f(x,y,t)}{\partial y}v = -\frac{\partial f(x,y,t)}{\partial t}$$

  where $u = \Delta x/\Delta t$, $v = \Delta y/\Delta t$

- One equation and two unknowns

Lucas-Kanade optical flow

- Assume that flow field is the same over small patch W (say, centered around the feature) in an image

- Find u, v that solve optimization problem

$$\underset{u,v}{\text{minimize}} \sum_{x,y \in W} \left(\frac{\partial f(x,y,t)}{\partial x} u + \frac{\partial f(x,y,t)}{\partial y} v + \frac{\partial f(x,y,t)}{\partial t} \right)^2$$

- This is a least-squares problem, can be solved using a matrix inverse

- In fact, quadratic term in u, v is the exact same M_W matrix as in feature detection: good features to track also give "good" least-squares problems

- Some tricks are needed to make this robust:
  - Compute multiple optimal flow fields at different scalings of the image (track larger differences)
  - Track features/points across multiple frames
  - Add/remove new features as necessary
- As usual, OpenCV has a fast method for doing this

```
corners = cv2.calcOpticalFlowPyrLK(img1, img2, points)
```

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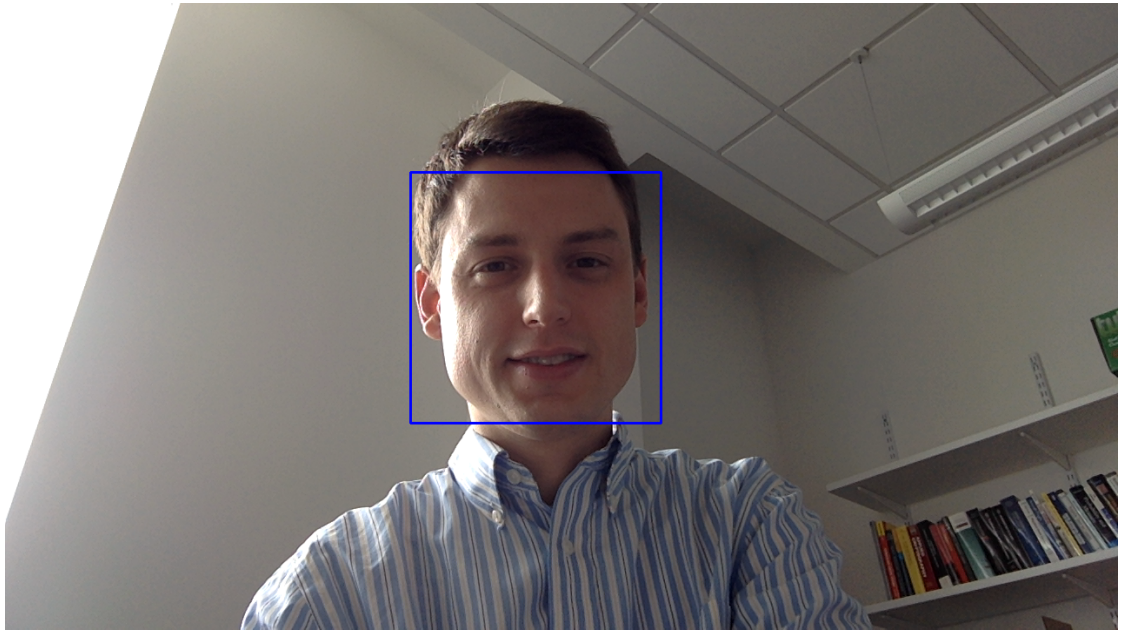
Example: face detection

- How can we detect all the faces in an image?



- Seems less impressive than 10 years ago (our phones all do this now), but here we'll see how it's done

- Conceptually, this is a simple machine learning task
  - Collect many images of faces and non-faces, scaled to some small but reasonable size (24x24 is common)
  - Use machine learning to learn a classifier for face/not-face
  - Given new image, create new images at many different scales, look at all 24x24 windows and classify each as face/not-face, add non-maximal suppression
- What could possibly go wrong?

- We need extremely high accuracy (very low false positive rate), computed very quickly
- Linear classifier? (like you used for digit classification)
  - Fast, but 90% accuracy isn't going to cut it
- SIFT features and descriptors
  - Very accurate, but much too slow

Viola-Jones object detection

- (Viola and Jones, CVPR 2001)

Rapid Object Detection using a Boosted Cascade of Simple Features

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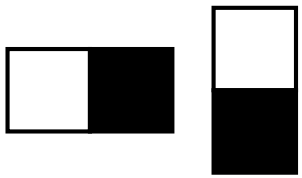
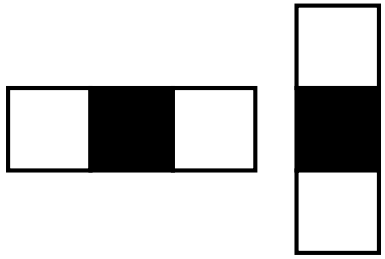
- "Just" a set of good features and ways to speed up ML algorithms for face detection (9,000+ citations)

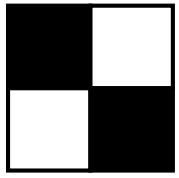
- ... like SIFT was "just" a set of good images features and descriptions (27,000+ citations)

Haar features

- A type of feature that is good at capturing relevant characteristics and easy to compute

Edge Features: 

Line Features: 

Rectangle Features: 

- These features take the sum of all pixels in white area, minus sum of all pixels in black area

- Quickly compute Haar features (at any image scale) through *integral image*

$$\bar{f}(x,y) = \sum_{\substack{x' \le x \\ y' \le y}} f(x',y')$$

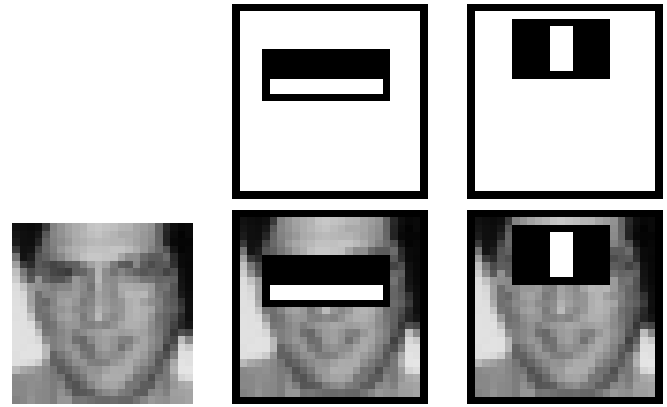
- Then

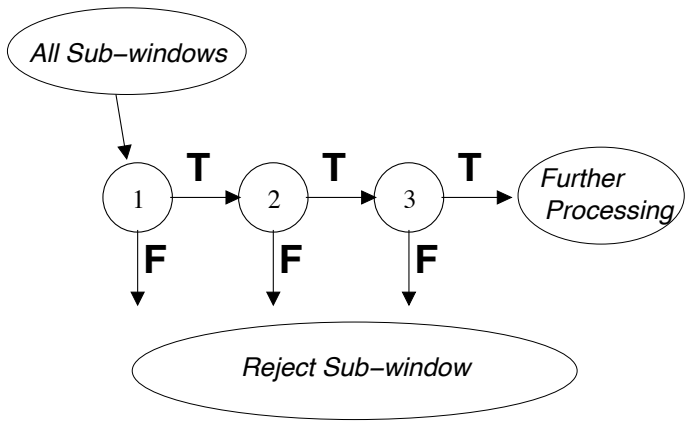
$$\sum_{\substack{x_1 \le x' \le x_2 \\ y_1 \le x' \le y_2}} f(x',y') = \bar{f}(x_2,y_2) + \bar{f}(x_1,y_1) - \bar{f}(x_1,y_2) - \bar{f}(x_2,y_1)$$

- Upshot: any Haar feature at any scale can be computed in a constant number of operations

Fast classification

- Still have 180,000+ Haar features for each 24x24 region (most of these are uninteresting)
- Use boosted decision stumps to extract 5,000 most relevant features
- Use "cascade" of classifiers that can quickly reject many regions using far fewer features





Figures: (Viola and Jones, 2001)

Take home points

- Computer vision studies how computers can "understand" the content of images
- The "general" vision problem is extremely challenging, but many "simple" operations can reveal a surprisingly large amount of information about images
- Lots of these items have been implemented already, a good idea to use existing software package