EE482/682 DSP APPLICATIONS

CLASSICAL DETECTION
These slides will follow parts of Szeliski’s Computer Vision book (available online)

Most of the lecture content comes from specific research papers
OVERVIEW

- Recognition Overview
  - Instance Recognition, Image Classification, Object Detection, Semantic Segmentation [Szeliski]
  - Performance Characterization

- Classical Detection [read papers]
  - Viola and Jones
  - Histogram of Oriented Gradients
  - Deformable Parts Model
RECOGNITION OVERVIEW
SZELISKI 2E CHAPTER6
Undergone largest changes and fastest developments in the last decade
- Availability of larger labeled datasets
- Breakthroughs in deep learning

Historically, recognition was a “high-level task” built on top of lower-level components (e.g. feature detection and matching)

With deep learning, there is little distinction between high- and low-level tasks \(\rightarrow\) end-to-end learning
RECOGNITION TASKS

- Instance recognition – find specific objects (exemplars, e.g. a stop-sign)
- Class/category recognition – recognize members of highly variable categories (e.g. any dog)
- Object detection – classify and localize objects
- Segmentation – pixel-level annotation of images into objects/class
Re-recognize a known 2D/3D rigid object (exemplar)

Potentially with novel viewpoint, cluttered background, and partial occlusion

Figure 6.3  3D object recognition with affine regions (Rothganger, Lazebnik et al. 2006) © 2006 Springer: (a) sample input image; (b) five of the recognized (reprojected) objects along with their bounding boxes; (c) a few of the local affine regions; (d) local affine region (patch) reprojected into a canonical (square) frame, along with its geometric affine transformations.
General approach:
- Find distinctive features while dealing with local appearance variation
- Check for co-occurrence and relative positions (e.g. affine transformation)

More challenging version: instance retrieval (content-based image retrieval) where the number of images to search is very large
- Also known as category/class recognition
  - Must recognize members of highly variable categories
- Much more challenging than instance recognition
  - Same challenges but without known object
- Extensively studied area of CV
  - Where CNNs have dominated
- Note this is whole image classification
CLASSICAL APPROACHES: BOW

- Bag-of-words (features) – simple approach based co-occurrence of collected features
  - Detect features/keypoints
  - Describe keypoints = words
  - Compute histogram (distribution) of words
  - Compare histogram to database for matching
- Note: no geometric verification since not applicable to general objects

Figure 6.6 A typical processing pipeline for a bag-of-words category recognition system (Csurka, Dance et al. 2006) © 2007 Springer. Features are first extracted at keypoints and then quantized to get a distribution (histogram) over the learned visual words (feature cluster centers). The feature distribution histogram is used to learn a decision surface using a classification algorithm, such as a support vector machine.
Approach to find constituent parts and measuring geometric relationships
- Spring-like connections between subparts that have structure but allow variation
- Basic idea is to have an energy minimization function for subpart arrangements
- Common (graph) structures/topologies include threes and stars for efficiency
- Popular model: Deformable Part Model (DPM) of Felzenszwalb
  - Star model on HOG parts

Figure 6.7 Using pictorial structures to locate and track a person (Felzenszwalb and Huttenlocher 2005) © 2005 Springer. The structure consists of articulated rectangular body parts (torso, head, and limbs) connected in a tree topology that encodes relative part positions and orientations. To fit a pictorial structure model, a binary silhouette image is first computed using background subtraction.
Previous approaches were object-centric which limits recognition

- Scene context is very important for disambiguation (e.g. lemon vs. tennis ball)

- Context models combine objects into scenes
  - Number of constituent objects is not known a priori

- The idea of context has been important for deep techniques
SEGMENTATION

- CV task of segregating an image into multiple regions according to different properties of pixels (e.g. color, intensity, texture)
  - Typically a low-level task that relies on spatial information (neighborhood)
  - Pixel-level class label
- Semantic segmentation – associate a class label for every pixel in an image
- Instance segmentation – mask (segment) each instance of an object in an image independently
- Panoptic segmentation – combination of semantic segmentation and instance segmentation
  - Label both class and separate instances (detection)
Confusion matrix-based metrics
- Binary \{1,0\} classification tasks

<table>
<thead>
<tr>
<th>Predicted outcome</th>
<th>Actual value</th>
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- True positives (TP) - # correct matches
- False negatives (FN) - # of missed matches
- False positives (FP) - # of incorrect matches
- True negatives (TN) - # of non-matches that are correctly rejected

A wide range of metrics can be defined

- True positive rate (TPR) (sensitivity)
  \[ TPR = \frac{TP}{TP+FN} = \frac{TP}{P} \]
- Document retrieval \(\rightarrow\) recall – fraction of relevant documents found

- False positive rate (FPR)
  \[ FPR = \frac{FP}{FP+TN} = \frac{FP}{N} \]

- Positive predicted value (PPV)
  \[ PPV = \frac{TP}{TP+FP} = \frac{TP}{P'} \]
- Document retrieval \(\rightarrow\) precision – number of relevant documents are returned

- Accuracy (ACC)
  \[ ACC = \frac{TP+TN}{P+N} \]
RECEIVER OPERATING CHARACTERISTIC (ROC)

- Evaluate matching performance based on threshold
  - Examine all thresholds $\theta$ to map out performance curve
- Best performance in upper left corner
  - Area under the curve (AUC) is a ROC performance metric
OUTLINE

- Motivation
- Contributions
- Integral Image Features
- Boosted Feature Selection
- Attentional Cascade
- Results
- Summary
FACE DETECTION

• Basic idea: slide a window across image and evaluate a face model at every location
Sliding window detector must evaluate tens of thousands of locations/scale combinations
- Computationally expensive → worse for complex models
- Faces are rare → usually only a few per image
  - 1M pixel image has 1M candidate face locations (ignoring scale)
- For computational efficiency, need to minimize time spent evaluating non-face windows
- False positive rate (mistakenly detecting a face) must be very low ($< 10^{-6}$) otherwise the system will have false faces in every image tested
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CONTRIBUTIONS

- Robust
  - Very high detection rate and low false positive rate
- Real-time
  - Training is slow, but detection very fast

- Key Ideas
  - Integral images for fast feature evaluation
  - Boosting for intelligent feature selection
  - Attentional cascade for fast rejection of non-face windows
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Want to use simple features rather than pixels to encode domain knowledge

Haar-like features
- Encode differences between two, three, or four rectangles
- Reflect similar properties of a face
  - Eyes darker than upper cheeks
  - Nose lighter than eyes

Believe that these simple intensity differences can encode face structure
Simple feature
- \( val = \sum \text{(pixels in black area)} - \sum \text{(pixels in white area)} \)

Computed over two-, three-, and four-rectangles
- Each feature is represented by a specific sub-window location and size

Over 180k features for a 24 × 24 image patch
- Lots of computation
INTEGRAL IMAGE

- Need efficient method to compute these rectangle differences
- Define the integral image as the sum of all pixels above and left of pixel \((x, y)\)

\[
ii(x, y) = \sum_{x' < x, y' < y} i(x', y')
\]

- Can be computed in a single pass over the image
- Area of a rectangle from four array references
  - \(D = ii(4) + ii(1) - ii(2) - ii(3)\)
  - Constant time computation

- Integral image

- Rectangle calculation
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There are many possible features to compute
- Individually, each is a “weak” classifier
- Computationally expensive to compute all
- Not all will be useful for face detection

Use AdaBoost algorithm to intelligently select a small subset of features which can be combined to form an effective “strong” classifier
ADABOOST (ADAPTIVE BOOST) ALGORITHM

- Adaptive Boost algorithm
  - Iterative process to build a complex classifier in an efficient manner
- Construct a “strong” classifier as a linear combination of weighted “weak” classifiers
  - Adaptive: subsequent weak classifiers are designed to favor misclassifications of previous ones

\[ F(x) = \alpha_1 f_1(x) + \alpha_2 f_2(x) + \alpha_3 f_3(x) + ... \]
**IMPLEMENTED ALGORITHM**

- Initialize
  - All training samples weighted equally
- Repeat for each training round
  - Select most effective weak classifier (single Haar-like feature)
    - Based on weighted error
  - Update training weights to emphasize incorrectly classified examples
    - Next weak classifier will focus on “harder” examples
- Construct final strong classifier as linear combination of weak learners
  - Weighted according to accuracy

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- Given example images \((x_1, y_1), \ldots, (x_n, y_n)\) where \(y_i = 0, 1\) for negative and positive examples respectively.
- Initialize weights \(w_{1,j} = \frac{1}{2n}, \frac{1}{2}\) for \(y_i = 0, 1\) respectively, where \(n\) and \(l\) are the number of negatives and positives respectively.
- For \(t = 1, \ldots, T\):
  1. Normalize the weights,
     \[
     w_{t+1,j} = \frac{w_{t,j}}{\sum_{j=1}^{m} w_{t,j}}
     \]
     so that \(w_t\) is a probability distribution.
  2. For each feature \(j\), train a classifier \(h_j\) which is restricted to using a single feature. The error is evaluated with respect to \(w_t\), \(e_j = \sum_i w_t |h_j(x_i) - y_i|\).
  3. Choose the classifier, \(h_t\), with the lowest error \(e_t\).
  4. Update the weights:
     \[
     w_{t+1,j} = w_{t,j} \beta_t^{1-e_t}
     \]
     where \(e_t = 0\) if example \(x_i\) is classified correctly, \(e_t = 1\) otherwise, and \(\beta_t = \frac{1}{1-e_t}\).
- The final strong classifier is:
  \[
  h(x) = \begin{cases} 
  1 & \sum_{t=1}^{T} \alpha_t h_t(x) \geq \frac{1}{2} \sum_{t=1}^{T} \alpha_t \\
  0 & \text{otherwise}
  \end{cases}
  \]
  where \(\alpha_t = \log \frac{1}{\beta_t}\).
AdaBoost starts with a uniform distribution of “weights” over training examples.

Select the classifier with the lowest weighted error (i.e. a “weak” classifier).

Increase the weights on the training examples that were misclassified.

(Repeat)

At the end, carefully make a linear combination of the weak classifiers obtained at all iterations.

\[
h_{\text{strong}}(x) = \begin{cases} 
1 & \alpha_1h_1(x) + \ldots + \alpha_nh_n(x) \geq \frac{1}{2}(\alpha_1 + \ldots + \alpha_n) \\
0 & \text{otherwise}
\end{cases}
\]
BOOSTED FACE DETECTOR

- Build effective 200-feature classifier
- 95% detection rate
- $0.14 \times 10^{-3}$ FPR (1 in 14084 windows)
- 0.7 sec / frame
- Not yet real-time
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Boosted strong classifier is still too slow
- Spends equal amount of time on both face and non-face image patches
- Need to minimize time spent on non-face patches

Use cascade structure of gradually more complex classifiers
- Early stages use only a few features but can filter out many non-face patches
- Later stages solves “harder” problems
- Face detected after going through all stages

**ATTENTIONAL CASCADE**
**ATTENTIONAL CASCADE**

- Much fewer features computed per sub-window
  - Dramatic speed-up in computation
- See IJCV paper for details
  - \#stages and \#features/stage
- Chain classifiers that are progressively more complex and have lower false positive rates
FACE CASCADE EXAMPLE

- Visualized
  - https://vimeo.com/12774628
RESULTS

- Training data
  - 4916 labeled faces
  - 9544 non-face images → 350M non-face sub-windows
  - 24 × 24 pixel size
- Cascade layout
  - 38 layer cascade classifier
  - 6061 total features
  - S1: 1, S2: 10, S3: 25, S4: 25, S5: 50, ...
- Evaluation
  - Avg. 10/6061 features evaluated per sub-window
  - 0.067 sec/image
    - 700 MHz PIII
    - 384 × 388 image size
    - With various scale
  - Much faster than existing algorithms

Similar performance between cascade and big classifier, but cascade is ~10x faster
MIT+CMU FACE TEST

- Real-world face test set
- 130 images with 507 frontal faces
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SUMMARY

- **Pros**
  - Extremely fast feature computation
  - Efficient feature selection
  - Scale and location invariant detector
    - Scale features not image (e.g. image pyramid)
  - Generic detection scheme → can train other objects

- **Cons**
  - Detector only works on frontal faces (< 45°)
  - Sensitive to lighting conditions
  - Multiple detections to same face due to overlapping sub-windows
HOG DETECTOR
DALAL AND TRIGGS, CVPR2005
Want descriptor for a full object rather than keypoints
- Geared toward detection/classification rather than matching
- Designed by Dalal and Triggs for pedestrian detection
- Must handle various pose, variable appearance, complex background, and unconstrained illumination
HOG STEPS I

- Compute horizontal and vertical gradients (with no smoothing)
- Compute gradient orientation and magnitude
- Divide image into $16 \times 16$ blocks of 50% overlap
  - For $64 \times 128$ image $\Rightarrow 7 \times 15 = 105$ blocks
  - Each block consists of $2 \times 2$ cells of size $8 \times 8$ pixels
- Histogram of gradient orientation of cells
  - 9 bins between 0-180 degrees
  - Bin vote is gradient magnitude
  - Interpolate vote between bins
HOG STEPS II

- Group cells into large blocks and normalize
- Concatenate histograms into large feature vector
  - \#features = (15*7)*9*4 = 3780
    - 15*7 blocks
    - 9 orientation bins
    - 4 cells per block
- Use SVM to train classifier
  - Unique feature signature for different objects
  - Computed on dense grids at single scale and without orientation alignment
Note: emphasizes contours/silhouette of object so robust to illumination

Figure 6. Our HOG detectors cue mainly on silhouette contours (especially the head, shoulders and feet). The most active blocks are centred on the image background just outside the contour. (a) The average gradient image over the training examples. (b) Each “pixel” shows the maximum positive SVM weight in the block centred on the pixel. (c) Likewise for the negative SVM weights. (d) A test image. (e) It’s computed R-HOG descriptor. (f,g) The R-HOG descriptor weighted by respectively the positive and the negative SVM weights.
DPM DETECTOR

FELZENSZWALB, PAMI2010
Want to detect all objects of the same category within in image

Must account for dramatic appearance differences

Object is composed of parts in different positions

Non-rigid objects
DPM COMPONENTS

- Root – rough appearance of object
- Part – local appearance of object
- Spring – spatial connection between parts
- Use HOG descriptors
DPM SEARCH

- Use pyramid to view image at different scale
  - Coarse level (low resolution) used for root filter (general object outline)
  - Fine level (high resolution) used for parts
- Use a mixture of models to handle wide variation in appearance
  - E.g. model for front and side view of a person/horse/bike

Fig. 3. A feature pyramid and an instantiation of a person model within that pyramid. The part filters are placed at twice the spatial resolution of the placement of the root.
SIFT FEATURES

LOWE, IJCV 1999
SCALE IN Variant FEATURE TRANSFORM (SIFT)

- One of the most popular feature descriptors [Lowe 2004]
  - Many variants have been developed

- Descriptor is invariant to uniform scaling, orientation, and partially invariant to affine distortion and illumination changes

- Used for matching between images
SIFT STEPS I

- Identify keypoints
  - Use difference of Gaussians for scale space representation
  - Identify “stable” regions
    - Location, scale, orientation
- Compute gradient $16 \times 16$ grid around keypoint
  - Keep orientation and down-weight magnitude by a Gaussian fall off function
    - Avoid sudden changes in descriptor with small position changes
    - Give less emphasis to gradients far from center
- Form a gradient orientation histogram in each $4 \times 4$ quadrant
  - 8 bin orientations
  - Trilinear interpolation of gradient magnitude to neighboring orientation bins
  - Gives 4 pixel shift robustness and orientation invariance

Figure 4.18 A schematic representation of Lowe’s (2004) scale invariant feature transform (SIFT): (a) Gradient orientations and magnitudes are computed at each pixel and weighted by a Gaussian fall-off function (blue circle). (b) A weighted gradient orientation histogram is then computed in each subregion, using trilinear interpolation. While this figure shows an $8 \times 8$ pixel patch and a $2 \times 2$ descriptor array, Lowe’s actual implementation uses $16 \times 16$ patches and a $4 \times 4$ array of eight-bin histograms.
Final descriptor is $4 \times 4 \times 8 = 128$ dimension vector
- Normalize vector to unit length for contrast/gain invariance
- Values clipped to 0.2 and renormalized to remove emphasis of large gradients (orientation is most important)
- Descriptor used for object recognition
  - Match keypoints
  - Hough transform used to “vote” for 2D location, scale, orientation
  - Estimate affine transformation
OTHER SIFT VARIANTS

- Speeded up robust features (SURF) [Bay 2008]
  - Faster computation by using integral images (Szeliski 3.2.3 and later for object detection)
  - Popularized because it is free for non-commercial use
    - SIFT is patented
- OpenCV implements many
  - FAST, ORB, BRISK, FREAK

- OpenCV is a standard in vision research community
  - Emphasis on fast descriptors for real-time applications
| SIFT VS HOG | Powerful orientation-based descriptors  
| Robust to changes in brightness |

**SIFT**
- 128 dimensional vector
- 16x16 window
- 4x4 sub-window (16 total)
- 8 bin histogram (360 degree)

- Computed at sparse, scale-invariant keypoints of image
- Rotated and aligned for orientation
- Good for matching

**HOG**
- 3780 dimensional vector
- 64x128 window
- 16x16 blocks with overlap
- Each block in 2x2 cells of 8x8 pixels
- 9 bin histogram (180 degree)

- Appears similar in spirit to SIFT
- Computed at dense grid at single scale
- No orientation alignment
- Good for detection
Questions?
REFERENCES

- **Reading**
  - P. Viola and M. Jones, Rapid object detection using a boosted cascade of simple features, CVPR 2001
  - P. Viola and M. Jones, Robust real-time face detection, IJCV 57(2), 2004
  - Dalal and Triggs, "Histogram of Oriented Gradients for Human Detection", CVPR 2005
  - Lowe, "Distinctive Image Features from Scale-Invariant Keypoints", IJCV 60(2) 1999

- **Code**
  - OpenCV has implementations [cascade classifier][HOG][SIFT-like]