Object Detection, Method of Viola and Jones

Integral Image, Boosting, and Cascade

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Detection Based On Rectangle Feature

- Rather than use pixels directly, form rectangles inside a 24 x 24 window

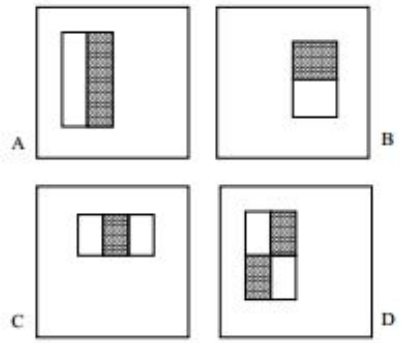
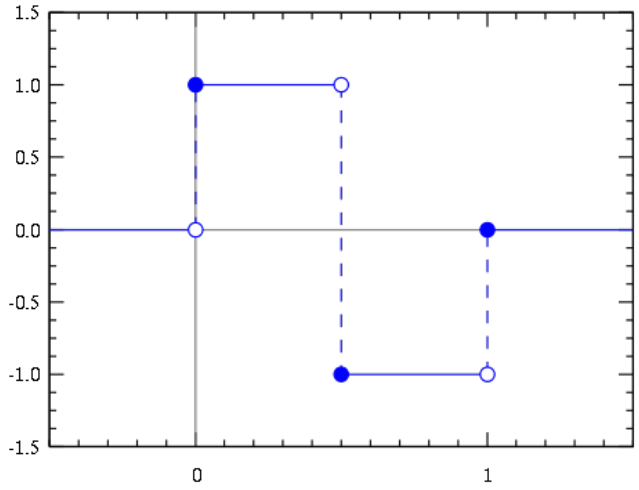


Figure 1: Example rectangle features shown relative to the enclosing detection window. The sum of the pixels which lie within the white rectangles are subtracted from the sum of pixels in the grey rectangles. Two-rectangle features are shown in (A) and (B). Figure (C) shows a three-rectangle feature, and (D) a four-rectangle feature.

- Motivation comes from Haar basis functions

Haar Basis Function

- Haar Wavelet



$$\psi(t) = \begin{cases} 1 & 0 \leq t < 1/2, \\ -1 & 1/2 \leq t < 1, \\ 0 & \text{otherwise.} \end{cases}$$

- So Viola and Jones are sort of using a 2D Haar Basis

Haar-like Feature

- So the rectangles are the basis
  - The set of overall rectangles containing smaller rectangles is the “function" being represented
  - The coefficients in the basis are the sums of the individual rectangles
- The classifier is based on forming simple “features" out of the rectangles
  - *Two-rectangle feature* is difference between sum of pixels within two rectangles
  - *Three-rectangle feature* is sum within two outside rectangles subtracted from sum in center rectangle
  - *Four-rectangle feature* is difference between diagonal pairs of rectangles
  - They claim features better capture particular domain knowledge and is faster than pixel-based
  - Since window is 24 x 24, must compute 45,396 features

Integral Image

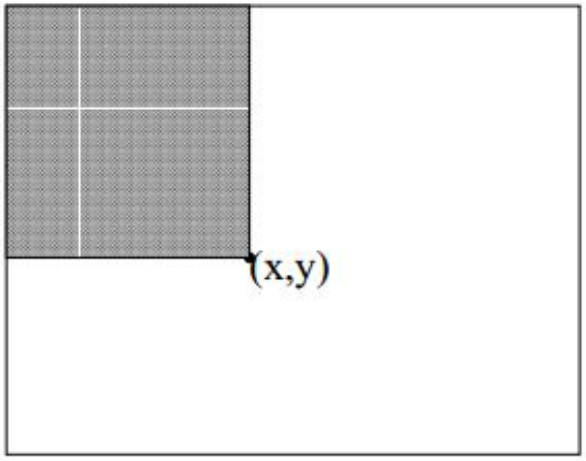


Figure 2: The value of the integral image at point (x, y) is the sum of all the pixels above and to the left.

- Rather than compute the sum of all possible rectangles, use integral image

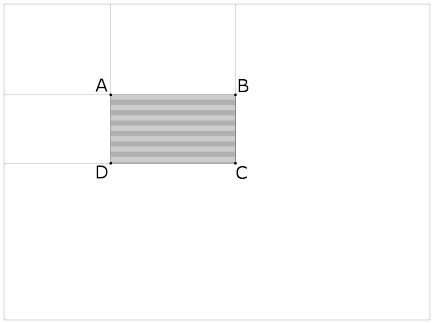
$$I(x, y) = \sum_{\substack{x' \leq x \\ y' \leq y}} i(x', y')$$

Integral Image

- Can be computed in one pass:

$$I(x, y) = i(x, y) + I(x - 1, y) + I(x, y - 1) - I(x - 1, y - 1)$$

- Any rectangle can be computed with four array references:



Suppose,
$A = (x_0, y_1), B = (x_1, y_1), C = (x_1, y_0), D = (x_0, y_0)$,
Then,

$$\sum_{\substack{x0 \le x \le x1 \\ y0 \le y \le y1}} i(x, y) = I(C) + I(A) - I(B) - I(D).$$

The Method of Viola and Jones

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2. Construct cascade of classifiers to make detection more efficient

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Training Classification Function

1. Start with weak classifiers based only on one feature:

$$h_j(x) = \begin{cases} 1 & \text{if } p_j f_j(x) < p_j \theta_j \\ 0 & \text{otherwise.} \end{cases}$$

   where $h_j(x)$ is weak classifier, f_j is feature, θ_j is threshold, p_j is parity (direction of inequality), and x is 24 x 24 sub-window
2. Use AdaBoost to determine small set of good classification features
3. Combine into large classification function function using a weighted majority vote

The Training Algorithm

- 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 $w_{1,i} = \frac{1}{2m}, \frac{1}{2l}$ for $y_i = 0, 1$ respectively, where m and l are the number of negatives and positives respectively.
- For $t = 1, \ldots, T$:
  1. Normalize the weights,
  $$w_{t,i} \leftarrow \frac{w_{t,i}}{\sum_{j=1}^{n} w_{t,j}}$$
  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, $\epsilon_j = \sum_i w_i \left| h_j(x_i) - y_i \right|$.
  3. Choose the classifier, h_t, with the lowest error ϵ_t.
  4. Update the weights:
  $$w_{t+1,i} = w_{t,i} \beta_t^{1-e_i}$$
  where $e_i = 0$ if example x_i is classified correctly, $e_i = 1$ otherwise, and $\beta_t = \frac{\epsilon_t}{1-\epsilon_t}$.
- 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 $\alpha_t = \log \frac{1}{\beta_t}$

Table 1: The boosting algorithm for learning a query online. T hypotheses are constructed each using a single feature. The final hypothesis is a weighted linear combination of the T hypotheses where the weights are inversely proportional to the training errors.

Note that as $\epsilon_t \to 0$, $\beta_t \to 0$ which implies $\alpha_t \to \infty$

The Cascade

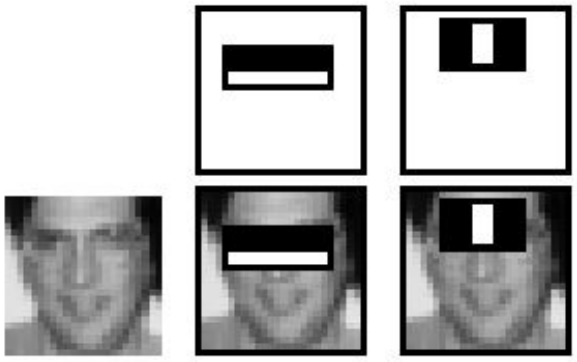

Figure 5: The first and second features selected by AdaBoost. The two features are shown in the top row and then overlayed on a typical training face in the bottom row. The first feature measures the difference in intensity between the region of the eyes and a region across the upper cheeks. The feature capitalizes on the observation that the eye region is often darker than the cheeks. The second feature compares the intensities in the eye regions to the intensity across the bridge of the nose.

- AdaBoost selected two strong features in face detection but not good enough
- Correctly detects about 100% of faces but only rejects 60% non-faces
- Use as a first classifier in a cascade where each subsequent one has more features and has high detection still but less false-positives

The Cascade Problem

- Design cascade detector that has good detection rate, 85-95% for faces and low false positive rates (10^{-5} or 10^{-6})
- It also must minimize computations
- False positive rate of cascade is

$$F = \prod_{i=1}^{K} f_i$$

where F is false positive rate, K is number of classifiers, and f_i is false positive rate of *ith* classifier

- Detection rate of cascade is

$$D = \prod_{i=1}^{K} d_i$$

where d_i is detection rate of *ith* classifier

The Cascade Problem

- Given expression for detection rate, it must be kept high since it is the product of numbers < 1 and goal is high
  - 10 stage classifier with each stage 0.99 detection rate has overall 0.9 detection rate
- But false positive rate only needs to be 0.3
- Most image sub-windows should fail early but only rare ones make it to classifier with most features
- Number of expected features which are evaluated is:

$$N = n_0 + \sum_{i=1}^{K} \left(n_i \prod_{j<i} p_j \right)$$

where N is expected number of features evaluated, p_i is positive rate of *ith* classifier, and n_i are number of features in *ith* classifier

The Cascade Algorithm

- User selects values for f, the maximum acceptable false positive rate per layer and d, the minimum acceptable detection rate per layer.
- User selects target overall false positive rate, F_{target}.
- P = set of positive examples
- N = set of negative examples
- $F_0 = 1.0$; $D_0 = 1.0$
- $i = 0$
- while $F_i > F_{target}$
  - $i \leftarrow i + 1$
  - $n_i = 0$; $F_i = F_{i-1}$
  - while $F_i > f \times F_{i-1}$
    - $n_i \leftarrow n_i + 1$
    - Use P and N to train a classifier with n_i features using AdaBoost
    - Evaluate current cascaded classifier on validation set to determine F_i and D_i.
    - Decrease threshold for the ith classifier until the current cascaded classifier has a detection rate of at least $d \times D_{i-1}$ (this also affects F_i)
  - $N \leftarrow \emptyset$
  - If $F_i > F_{target}$ then evaluate the current cascaded detector on the set of non-face images and put any false dectections into the set N

Table 2: The training algorithm for building a cascaded detector.

- Hard to optimize
- Another step in algorithm to check whether a stage can be removed or combine subsets?

Performance of Viola and Jones method

- They created a 32 layer cascade of classifiers which had 4297 features
- Classifiers trained with 4916 faces and 10,000 non-face sub-windows using Adaboost
- Training time was weeks (computer from years ago)
- On MIT+CMU test set, 8 features out of 4297 are evaluated on average per sub-window
- On old computer, detector processes 384 x 288 image in .067 seconds

ROC curve

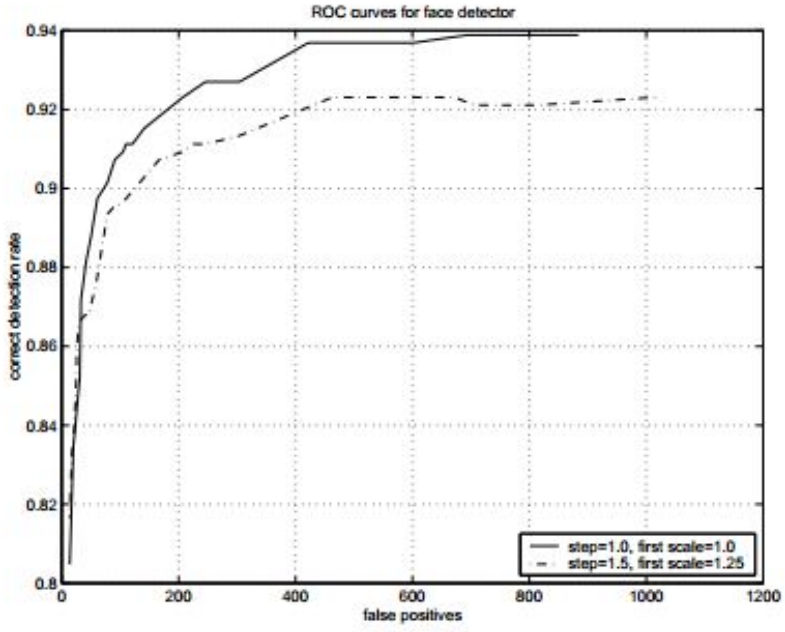

Figure 9: ROC curves for our face detector on the MIT+CMU test set. The detector was run once using a step size of 1.0 and starting scale of 1.0 (75,081,800 sub-windows scanned) and then again using a step size of 1.5 and starting scale of 1.25 (18,901,947 sub-windows scanned). In both cases a scale factor of 1.25 was used.

Other Notes

- They needed to do pre-processing to minimize effect of different lighting conditions
  - Normalized variance
  - They were able to compute variance from integral images
  - Could normalize by operating on feature values rather than pixels
- Needed to scale detector
- Shifting detector across locations more than one pixel at a time decreases detection rate
- Had multiple detections around each face
  - Simply paritioned set of detections into disjoint subsets
  - Two detections were in same subset if bounding regions overlap
  - Each partition is one detection and corners are averaged between all detections

Summary

- Classify objects based on “Haar-like" features
- Train classifiers based on AdaBoost algorithm
- Use cascading to make detector more efficient