Object Detection

Computer Vision CMP-6035B

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- Sliding Window
- Detecting Faces
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Object Detection

What is object detection?

Object Detection

Image classification methods can detect an object in the image if there is just a **single** object in the scene and it clearly dominates the image.

If this constraint is not met, we are in the **object detection** scenario.

Object Detection

We can use similar techniques we have learnt in Image Classification to detect objects in an image.

Here we apply these techniques to **sub-windows** of the image.

This approach is called a *sliding window* method.

Sliding Window

Sliding window is a *meta* algorithm - a concept found in many machine learning algorithms.

Sliding Window

First, let's assume our objects have relatively similar size and fit into $n \times m$ pixel windows.

Sliding Window

Build the dataset of positive and negative instances and train the classifier.

We could then *slide* the classification window over the image to **search** for the object location.

Sliding Window

But, there are problems:

- Objects may be of significantly *different sizes*.
- Some windows will overlap - how do we avoid counting objects *multiple times*?

Sliding Window

We tackle the first problem by searching over scale as well.

- We build the **Gaussian pyramid** of our image.

Gaussian Pyramid

Each layer of a pyramid is obtained by *smoothing* a previous layer with a Gaussian filter and *subsampling* it.

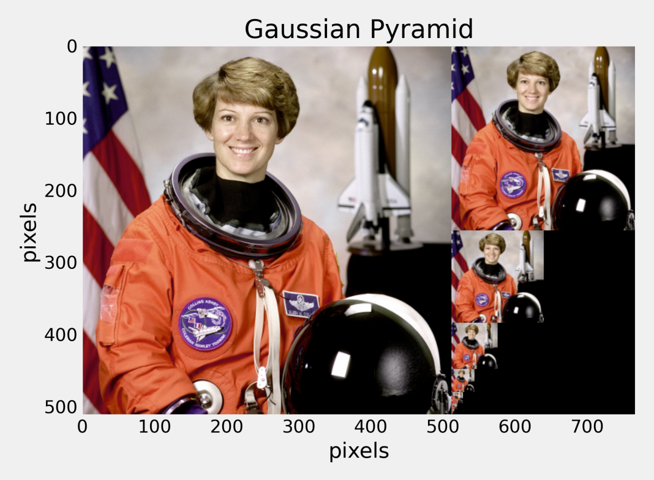


Figure 1: Gaussian Pyramid

Gaussian Pyramid

We search using our $n \times m$ window in each **layer** of the pyramid.

Sliding Window

The second problem is usually solved using **non-maximum suppression**.

Non-Maximum Suppression

Windows with a local maximum of *classifier confidence* **suppress** nearby windows.

Sliding Window

Train the classifier on $n \times m$ windows.

Choose a threshold t and Δx and Δy, where:

- t is a threshold for the classifier confidence.
- Δx and Δy are the step distance for each direction.

Sliding Window

Construct an Image Pyramid.

For each level:

- Apply the classifier to each $n \times m$ window, stepping by Δx and Δy in this level to get a classifier confidence c.
- If c is above t, insert a pointer to the window into a list L, *ranked* by c.

Sliding Window

For each window w in L, from highest confidence:

- remove all windows $u \neq w$ that overlap w *significantly*
- overlap is calculated in the *original* image, by expanding coarser scales

Detection Applications

Now we know *how* to detect objects in an image, **what** can be detected?

Face Detection

We will mostly discuss the classic *Viola-Jones* algorithm for face detection.

Face Detection

Another classic method in face classification is *Eigenfaces*.

- Eigenfaces use PCA on an aligned set of face images.
- *Fisherfaces* extends Eigenfaces to use Fisher LDA.
- There is a document on Blackboard for you to read on these methods.

Viola-Jones object detection

P. Viola, and M. Jones,

Rapid Object Detection using a Boosted Cascade of Simple Features.

International Conference on Computer Vision and Pattern Recognition, pp. 511-518, 2001.

Viola-Jones object detection framework

A fast and robust method for face detection.

- Can be used for detection of other objects, not only faces.
- Robust - high detection rate and low false-positive rate.
- Detection only - not recognition.

Viola-Jones object detection framework

The method comprises four stages:

- feature detection
- integral image
- learning algorithm using modified AdaBoost
- *cascade* of classifiers

Viola-Jones Feature Extraction

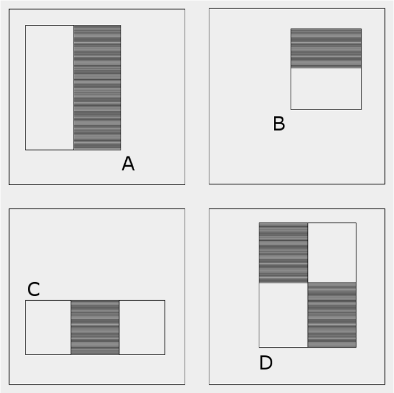


Figure 2: Haar features

Features need to be calculated **fast**!

- Use a simple set of *Haar-like* features.
- add light rectangle and subtract dark rectangle
- features are translated within a sub-window

Viola-Jones Feature Extraction

Features can be calculated very quickly by pre-calculating the **integral** image.

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

i.e. the sum of pixels to the left and above a given pixel.

Viola-Jones Feature Extraction

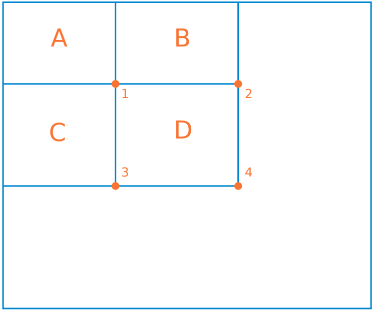


Figure 3: Integral Image

Sum of pixels under a rectangle:

- Value at pixel 1 is *sum* of rectangle A.
- Value at 2 is A + B.
- Value at 3 is A + C.
- at 4 is A + B + C + D.
- D = 4 + 1 - (2 + 3)

Viola-Jones Feature Extraction

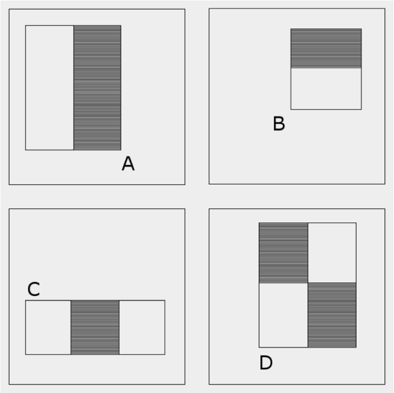


Figure 4: Haar features

Each of these 4 features can be scaled and shifted in a 24×24 pixel sub-window.

– giving a total of approx 160,000 features.

Viola-Jones Feature Learning

The number of features extracted from an image is very large.

- We need a way to select the *subset* of features, which are the most *important* from the point of object **detection**.
- We also need a **fast** classifier.
- Solution: modified **AdaBoost**.

Viola-Jones Feature Learning

Modified Adaboost algorithm.

- Each *weak* learner operates on only **one** feature.
- Thus, Adaboost acts as a feature *selector*.
- Can significantly reduce the initial number of 160,000 features.
- e.g. 200 features can provide 95% detection rate with 1 in 14000 false positives.

Viola-Jones Features

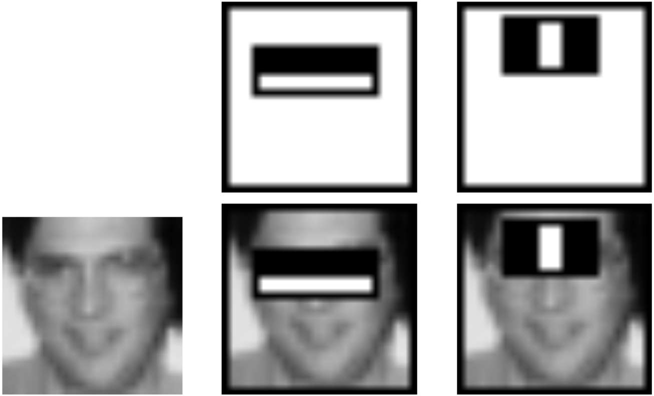


Figure 5: Image from original paper

Viola-Jones Learning

Attentional cascade of boosted classifiers.

We can train a simple boosted classifier on a very low number of features and adjust its threshold to guarantee 100% detection rate.

Viola-Jones Learning

Many false positives, but we can easily **reject** most sub-windows.

- Sub-windows classified as positives are passed to the next stage of the cascade.
- Additional features are used in a more complex classifier.
- ...and so on, to reduce the number of false positives.

Viola-Jones Learning

Attentional cascade of boosted classifiers.

- 38 layers with 6061 features
- Majority of sub-windows will be rejected in the early layers of the cascade where few features are needed.

Viola-Jones Multiple Detections

The image is scanned with sub-windows at different *scales* and different *locations*.

- Results from individual sub-windows are combined for the final result.
- Detected sub-windows are divided into disjoint sets.
- In each disjoint set we calculate the mean of four corners.

Viola-Jones

MATLAB has an implementation of the algorithm.

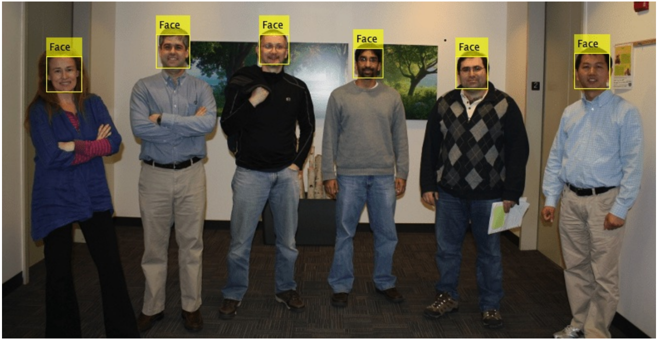


Figure 6: Viola Jones Face Detection

Viola-Jones

Very slow to train. The original paper reports *weeks* of training for the training set they used (5k faces, 9.5k non-faces).

Very fast to execute. On 700 MHz processor, it takes 0.067s to analyse 384x288 image.

Detecting Humans

The original HOG paper also proposed detection of humans in the sliding window.

Detecting Humans

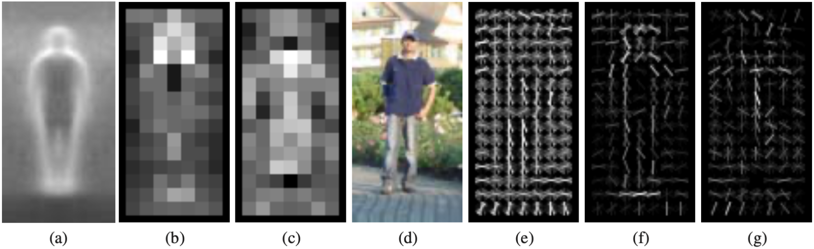


Figure 7: HOG - from original paper

Dalal and Triggs used a linear SVM classifier.

Detecting Humans

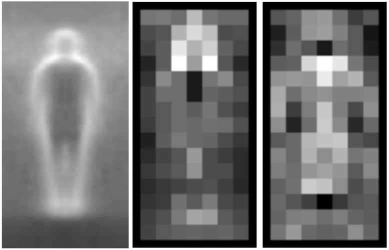
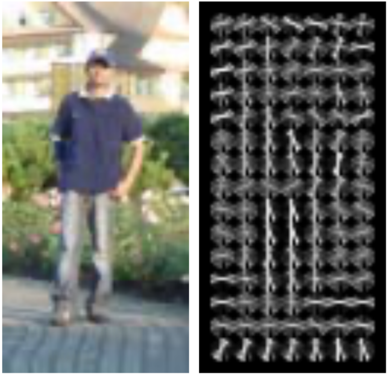

(a) (b) (c)

Figure 8: mean gradients and SVM weights

a. The mean gradient image for all data.
b. The maximum positive SVM weights.
c. The maximum negative SVM weights.

The SVM weights provide a nice visualisation of the decision boundary.

Detecting Humans



(d) (e)

Figure 9: hog test image

d. An example 64×128 test image.
e. The computed HOG descriptor.

Performance was reduced with less margin around the subject in the test images.

Detecting Humans

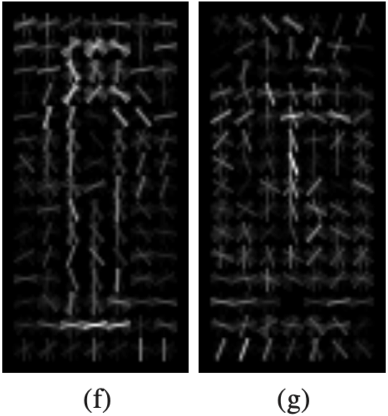


Figure 10: hog weighted

f. Positively weighted HOG descriptor.
g. Negatively weighted HOG descriptor.

Showing that the detector cues mainly on the contrast of silhouette contours and gradients inside the person typically count as negative cues.

Detecting Boundaries

Object detection through segmentation using *boundary detection*.

Edges are **not** the same as object contours or occluding contours.

- Some edges are irrelevant or confusing for object detection.
- Solution: use a *sliding window* to detect boundaries.

Detecting Boundaries

At each window we extract features that will decide whether the centre pixel in the window is an occluding contour or not.

- Each pixel is assigned a *probability* of boundary.
- Circular windows often used as boundaries are oriented.
- A boundary splits the circular window into two halves.

Detecting Boundaries

Features could be *histograms* produced from image intensity, oriented energy, brightness gradient, colour gradient etc.

The histograms are extracted from two halves of the window, and the distance between them is calculated. E.g. χ^2

This distance is mapped to probability using *logistic regression*.

Detecting Boundaries

Training and test data require *annotations*.

Figure 11: test image

Detecting Boundaries

Annotations are performed by different subjects.

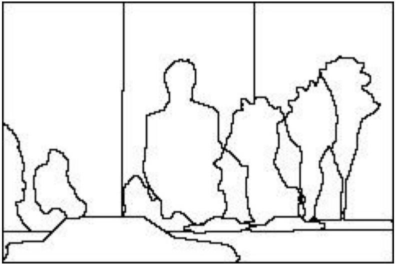


Figure 12: annotation 1

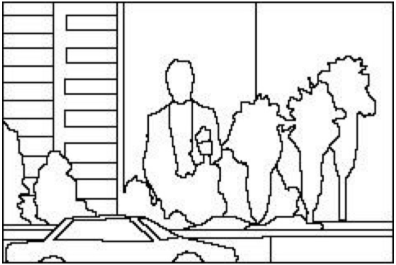


Figure 13: annotation 2

Detecting Boundaries

Inconsistent annotations are averaged.

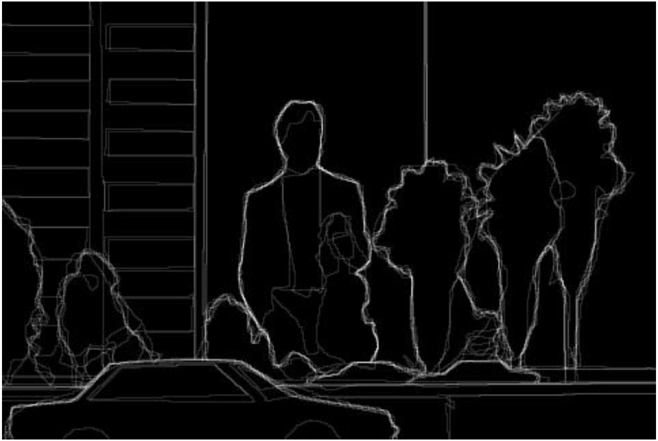


Figure 14: test image

Detecting Boundaries

$$P_b(x, y, \theta)$$

The probability that the pixel is a boundary for some orientation.

$$P_b(x, y) = \max(\theta) P_b(x, y, \theta)$$

The maximum probability that the pixel is a boundary for all orientations.

Detecting Boundaries

Solution: weighted matching between the machine and human generated boundaries.

- Predicted boundary point too far away from any annotation is considered a false positive.
- If there are no predicted points close to the annotation, then this pixel is considered a false negative.
- Probability boundary map can then be thresholded which allows us to calculate precision-recall curves.

Detecting Boundaries

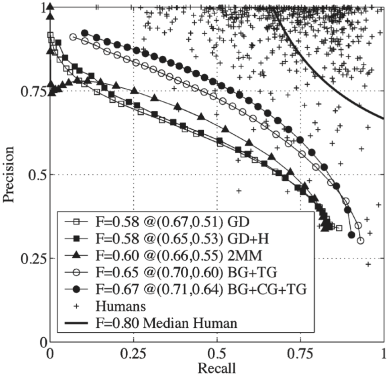


Figure 15: precision-recall curve

GD+H - Canny
BG+CG+TG - Martin et al.
Ground Truth

Detecting Boundaries

Figure 16: results

Martin, Fowlkes and Malik. Learning to Detect Natural Image Boundaries Using Local Brightness, Color and Texture Cues (2004).

Summary

- Classification or Object Detection
- Sliding Window
- Detecting Faces
- Detecting Humans and other applications

Reading:

- Forsyth, Ponce; Computer Vision: A modern approach, 2nd ed., Chapters 16,17 and 5.
- Sonka et al., Image Processing, Analysis and Machine Vision, 4th ed., Chapter 10
- Papers mentioned in the slides!