ICS2207 Report

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Viola-Jones Object Detection/Haar Cascade Technical Overview

Viola-Jones Object Detection is a technique used to detect objects using a sliding window over an image. It was developed in 2001 by Paul Viola and Michael Jones. Haar features are used to recognize certain patterns commonly found in objects, (like how the nose is usually brighter than the eyes given a picture of a face).

To achieve object detection with Viola-Jones Object Detection Framework, means to train a Cascade Classifier for a face. A cascading classifier is a collection of weak classifiers which sequentially feed into each other. A weak classifier is composed of one Haar Feature and is able to detect small patterns of an object in an image, but not the whole object.Hence, when these weak classifiers are chained together the whole image can be detected.

A Haar Feature is a rectangular template for the brightness of pixels. In Voila-Jones when an area of pixels, has its average pixel brightness arranged in one of the following forms (where white mean bright, and black means dark), we say that a feature was recognized. A trained cascade classifier will detect objects by sliding a window across the image, with Haar Features in a certain position inside the window. If all the features sequentially fire for the image, the object was detected.

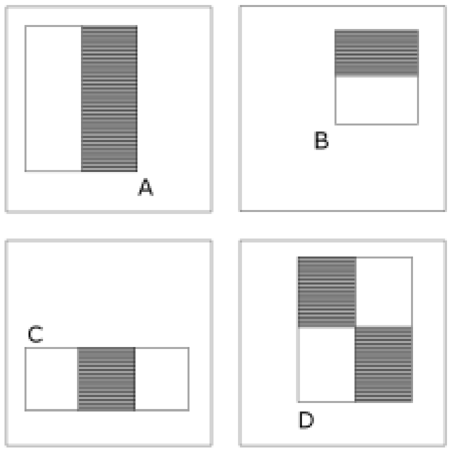


Figure 1: Different possible Haar Features. [1]

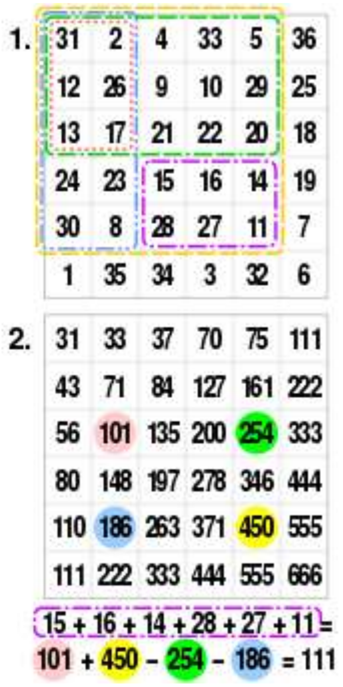
The certainty of a given feature is the sum of the brightness of the pixels within white rectangles subtracted from the sum of the brightness of the pixels within black rectangles.

If a given weak classifier fails to find the Haar Feature in a given part of the image, the image is discarded as not being an object. Hence only when an image passes through all the weak classifiers, is the object detected.

Therefore to detect an object using a Cascading Classifier, which is the concatenation of several weak classifiers, each individual Haar features of that cascading classifier must be detected across the image.

In order for the cascading classifiers to find which features are the best in which position and size, the algorithm has to exhaustively search each possible configuration. These features can be of varying sizes, each rectangle could represent one pixel or half the image. Hence it becomes quite expensive to sum up every possible pixel brightness in a white rectangle subtracted from the sum of the brightness of the pixels within black rectangles for every possible different variation of a Haar Feature. To make the process faster an *integral image* is generated from the image being trained on.

An integral image is composed of values each corresponding to a pixel on the original image. A value in the integral image is the (inclusive) sum of all pixel values to the left and up of the corresponding pixel in the original image. This integral image is then used to calculate the sum over an area of pixels in the original image. The calculation will use the precomputed values in the integral image to determine the sum over an area of pixels, instead of linearly summing each pixel. This technique is much faster.


1.

31	2	4	33	5	36
12	26	9	10	29	25
13	17	21	22	20	18
24	23	15	16	14	19
30	8	28	27	11	7
1	35	34	3	32	6

2.

31	33	37	70	75	111
43	71	84	127	161	222
56	101	135	200	254	333
80	148	197	278	346	444
110	186	263	371	450	555
111	222	333	444	555	666

$15 + 16 + 14 + 28 + 27 + 11 = 101 + 450 - 254 - 186 = 111$

Figure 2: An example of an integral image being generated. [2]

So given an input's integral image, how does the Cascading Classifier learn that object's features? Given a 24x24 image, there are 180,000+ possible feature configurations, as we have to consider the object can be of different sizes and position across the image. Only a small sample of these are actually useful. For example, the feature which says the eye region is darker than the forehead is useful while the one that says the forehead is darker than the inside of the mouth should not be considered, as generally this is not the case.

An exhaustive search for every combinations of features is infeasible. Viola-Jones uses a variant of the learning algorithm AdaBoost in order to detect the best features in a positive sample and add them to cascading classifier.

AdaBoost assigns a coefficient to every possible weak classifiers such that the sum training error of all the weak classifiers is as small as possible. To do this, this coefficient, or weight, is initially the same for all possible weak classifiers. For all weak classifiers, a strong classifier with only the weak classifier's single feature is trained, and the error is computed for every image passed, (if the feature fires on a negative sample then the error is increased, otherwise it's decreased). After this process, the weights of the weak classifiers are updated. The lower the error, the higher this coefficient is, meaning that this feature will be more significant. This process will repeat until the sum of the weighted features is higher than half of the sum of the weights.

So after performing AdaBoost, we have obtained many different features, each with a value corresponding to how significant they are. Features with negligible values are discarded. Given an image that we wish to classify, the image will be passed through each of these features sequentially, starting with the highest significant one. If at any given moment, a feature does not fire on an image, we can immediately discard this image as not having our object. This greatly reduces the time for detection, as once a feature fails to fire on an image, since it is of higher significance than all the features coming after it, we know that it's redundant to try the rest. This is why it is called a *cascading* classifier, as there are multiple small classifiers each feeding into each other.

Hence after training a cascading classifier using the Viola-Jones algorithm, given a trained cascading classifier and an input image, the integral image of the input image is computed. Then a sliding window of variant size which encapsulates any size the object can be in, is slid over the integral image. For every sliding window, the image encapsulated by this window is passed through the cascading classifier, and if the image passes through all of the features, the object is detected, and we can extract the bounding box of the object, since we know the position of our sliding window with respect to the image. If a feature fails to fire given an image, the image is discarded and the computation starts again for the next sliding window.

Viola-Jones Object Detection algorithm has seen a number of use-cases, specifically in the field of real-time facial detection. The algorithm is computationally cheap and is still the standard for facial detection despite the boom of deep learning and the fact that the algorithm is over 20 years old. Since the algorithm is fast, manufacturers do not have to increase hardware specifications for the devices running the algorithm which saves companies money. Moreover, it does not consume a lot of power due to it being computationally inexpensive, hence it is suitable for portable devices.

Digital Cameras use the Viola-Jones algorithm in-order to focus the lens of the camera on faces. Since the algorithm is fast, the camera's display's framerate remains real-time and power consumption is low. Smile detection is often a feature in digital cameras where smiling can make the camera take a photo. Moreover, Snapchat uses a variant of the Viola-Jones algorithm to apply face filters. Viola-Jones algorithm is also used in biometrics (usually paired with a facial recognition technique) and has other applications such as emotional inference and lip reading.

Developing Artifact 1

Databases

For the positive samples, I used CelebA, a dataset consisting of 200,000 celebrity faces. The images were of size 178x218 and the face's eyes were fixed to an absolute position.

For the negative samples, I used Caltech101 and Caltech256, a dataset of objects from 101 and 256 categories respectively.

Cleaning

I flattened both the directories of CelebA and Caltech using a shell script and placed them in a folder named *pos* and *neg* respectively. I manually looked through the negative dataset and removed any images with faces. Finally I created a shell script to rename all the images in the respective folder to a sequential index.

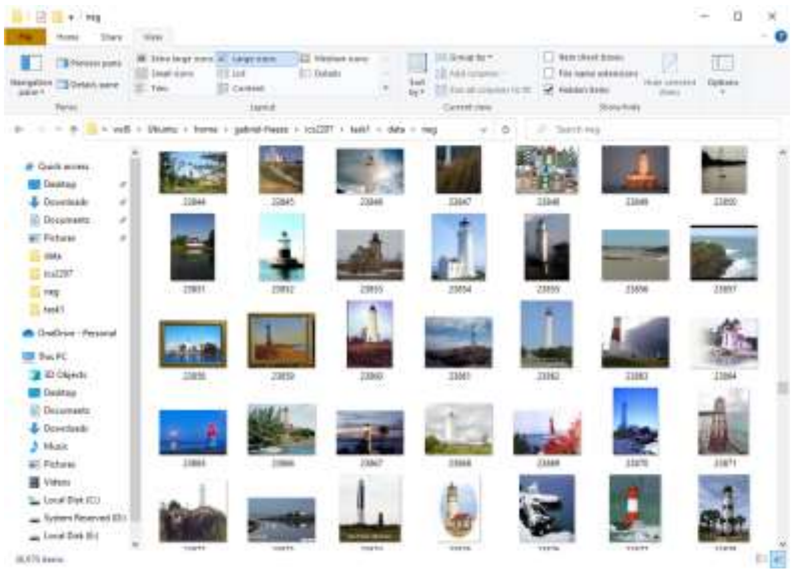
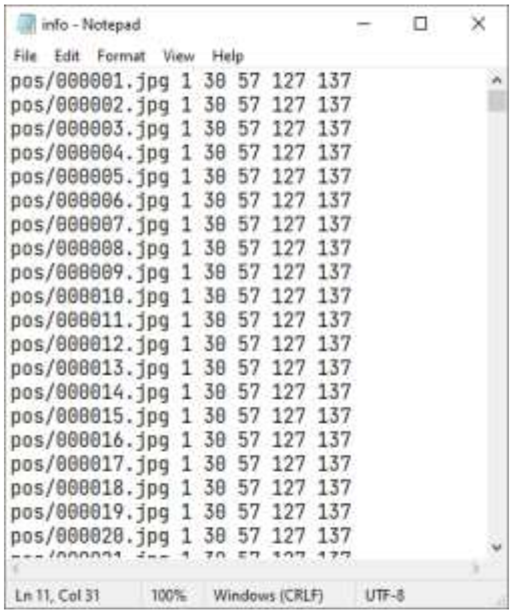


Figure 3: A snapshot of the *neg* folder.

Preparation

I created a file called *info.dat* using a shell script which lists every positive image's relative directory path and the bounding boxes for the face. A few images were cherry-picked to be used as the validation set. Since the faces were all aligned by the position of the eyes, I overlayed some hundred faces on each other and took the average bounding box to be the bounding box for all the images, which I settled to be (x,y,w,h) = (30,57,127,137).



```
pos/000001.jpg 1 30 57 127 137
pos/000002.jpg 1 30 57 127 137
pos/000003.jpg 1 30 57 127 137
pos/000004.jpg 1 30 57 127 137
pos/000005.jpg 1 30 57 127 137
pos/000006.jpg 1 30 57 127 137
pos/000007.jpg 1 30 57 127 137
pos/000008.jpg 1 30 57 127 137
pos/000009.jpg 1 30 57 127 137
pos/000010.jpg 1 30 57 127 137
pos/000011.jpg 1 30 57 127 137
pos/000012.jpg 1 30 57 127 137
pos/000013.jpg 1 30 57 127 137
pos/000014.jpg 1 30 57 127 137
pos/000015.jpg 1 30 57 127 137
pos/000016.jpg 1 30 57 127 137
pos/000017.jpg 1 30 57 127 137
pos/000018.jpg 1 30 57 127 137
pos/000019.jpg 1 30 57 127 137
pos/000020.jpg 1 30 57 127 137
```

Figure 3: A snapshot of the *info.dat*

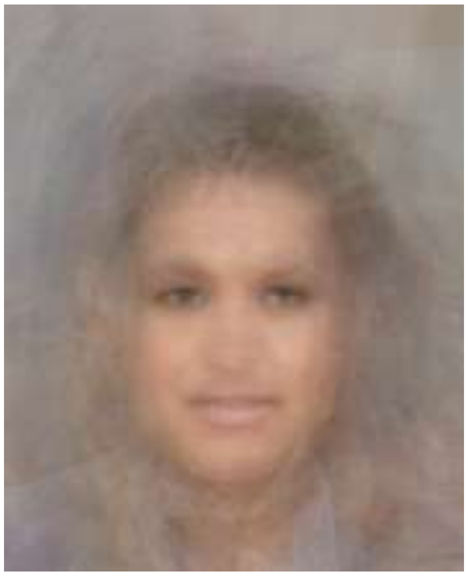


Figure 4: Overlay of several face images.

I created a file called *bg.txt* using a shell script which lists every negative images relative path directory. Both *bg.txt* and *info.dat* are needed to train the cascading classifier.

Using **OpenCV 3.4.3**, I had to transform the positive images into the binary format needed for OpenCV to process them. Using OpenCV's *opencv_createsamples* application I created a file called *pos.vec*. This file will be passed to the cascading classifier for training.

Training

I used OpenCV's *opencv_traincascade* application to train the cascading classifier. I trained a number of different classifiers and chose the best one. I then passed them into a script, which performs the cascading classifier on each frame of a webcam and attempts to draw the bounding boxes across a face.

Machine on which the cascading classifiers were trained:

Processor: AMD Ryzen 5 3600 6-Core Processor 3.59 GHz

RAM: 16GB

GPU: GTX 1050 2GB

OS: Windows 10 Home 21H1

Index	**Positive Samples**	**Negative Samples**	**Acceptance Ratio Break Value**	**Max Number of Stages**	**Width and Height of Training Window**	**Remarks**
1	2,000	1,000	10e-5	3	(24,24)	My face and other faces were not being detected at all. I figured much would be so since the algorithm only took about 5 minutes to train and the False Alarm rate was well over 0.5.
2	2,000	1,000	10e-5	12	(24,24)	I increased the number of stages to 12 as I thought 3 stages were little. Performance increased and the False Alarm rate was now hovering about 0.4
3	70,000	35,000	10e-5	12	(24,24)	I was only using a small sample of my data before. I read that a 2:1 ratio for positive is to negative is the best approach, so I used all the negative images. The model took 5 hours to train and the False Alarm Rate had started increasing again after stage 6 of training. Performance was worse.

4	5,000	2,500	10e-5	20	(24,24)	I decreased the dataset from fear of overfitting. I decided to increase the number of stages instead. The algorithm did not take a long time to train and the False Alarm rate was around 0.3. Only 14 stages were used as on stage 14 the acceptance ratio had fallen below the threshold. This classifier performed the best so far
5	5,000	2,500	NULL	38	(24,24)	I decided to increase the number of stages and remove the acceptance ratio break value. The algorithm took a longer time to train than before and the false alarm rate was more or less the same.
6	10,000	5,000	10e-5	20	(24,24)	Classifier 4 had since performed the best so far, so I decided to train with the same parameters but more training data.

Evaluation

In the end I chose **Classifier 6** as it had performed the best. It outperformed the other classifiers in false positive rates, jitteriness while tracking a face and performance in noisy conditions. Classifier 4 was also good but it had a large false positive rate from testing. Classifier 6 could detect my face under a variety of different backgrounds. It detects my face both with and without glasses however it has a slight boost in performance without glasses. My guess is it’s because the training set was of celebrities, and when their photo is being taken they’re like at a public event and hence they do not wear glasses. Classifier 6 could also detect faces slightly rotated the best, albeit both eyes still had to be visible. Bright direct light in the background of a face would cause the face to not be detected. The face cannot be in a background that is brightly lit in order to accurately detect it.

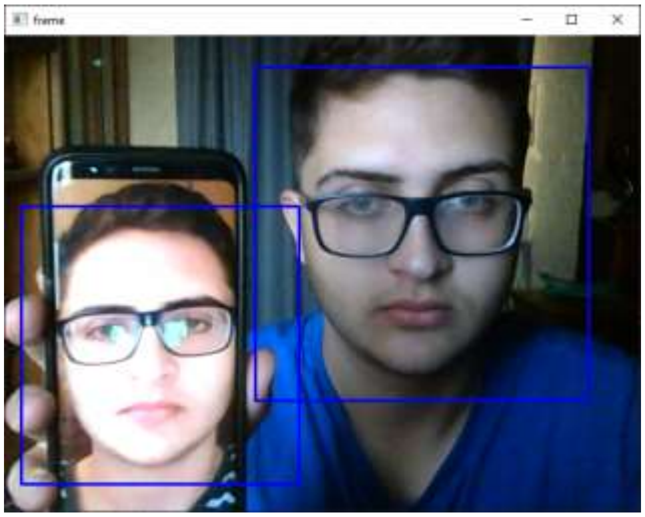
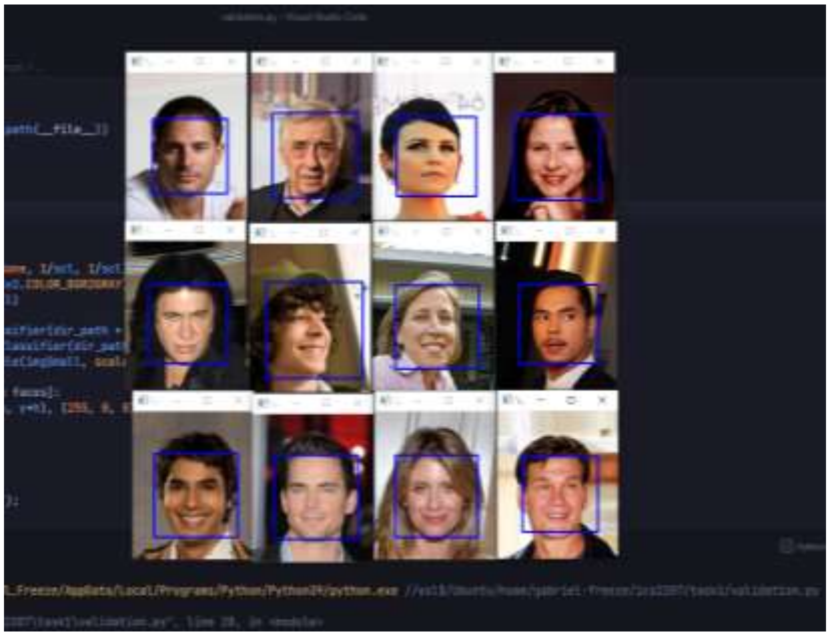


Figure 5: Multiple faces being detected using my cascade classifier.

I wrote a script to test the classifiers. First I scale the current frame of the webcam by a factor of 1/4, grayscale it and equalize the brightness histogram. I detect faces across the processed face with parameters *scaleFactor=1.05* and *minNeighbours=3*. For each face detected, I draw the bounding boxes on the original frame. The testing script is *task1/face-recognition.py*

My webcam feeding the input to the script is a *Logitech C270* webcam which is placed perpendicular to eye level. I test if the classifier can detect faces from different distances from the webcam, different backgrounds and different lighting conditions. A sample run of the webcam feed *sample-run.mp4* is provided in the directory.

The validation set was used to further test the classifier. The script *validation.py* is provided. All images were correctly recognized. Below are a few instances.



Developing Artifact 2

I downloaded a frontal face cascade and an eye cascade. I then wrote a script that runs the face cascade on every frame of a webcam. Every section of the frame with a face is passed to the eye cascade. Then all bounding boxes are drawn. The script is *task2/face-eye-detection.py*

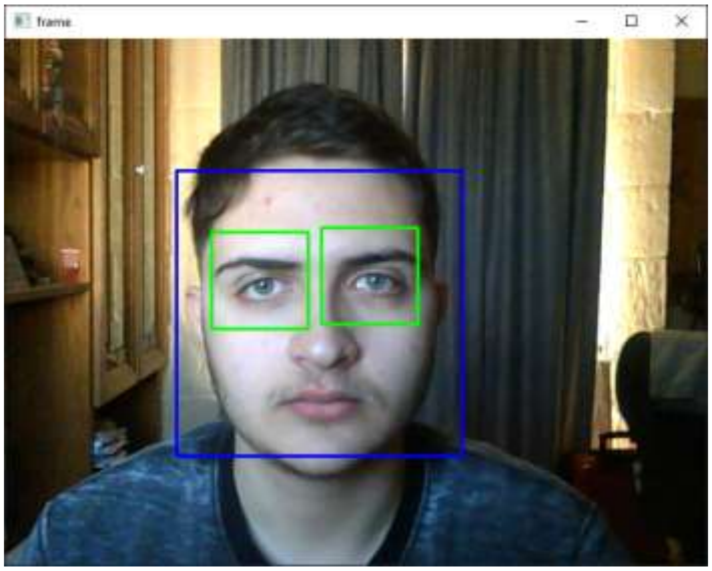


Figure 6: Facial and Eye Detection using a Cascade Classifier for each

Alternative Facial Detection Techniques

Deep Learning techniques may be used to solve the facial detection problem, namely a MultiTask Cascaded Convolutional Network (MTCNN) by Kaipeng Zhang, et al. in 2016. This MTCNN has three separate convolutional neural networks that both feed as inputs into each other.

The first network is called a *Proposal Network*, which given an input image proposes possible bounding boxes for faces. The image is scaled to multiple sizes and is called an *image pyramid*. This image pyramid is passed to the Proposal Network which gives *candidate windows and their bounding box regression vectors.* Non-Maximum Suppression (NMS) is then applied to merge overlapping bounding boxes.

These bounding boxes are then passed to the *Refinement Network* which chooses the best ones. It performs further calibration and filtering of the bounding box regression vectors as well as using NMS candidate merge.

Finally the filtered bounding boxes are passed to the *Output Network*. Five facial landmarks, the two eyes, tip of the nose and the two corners of the mouth are outputted. A definitive final bounding box for the face is also outputted.

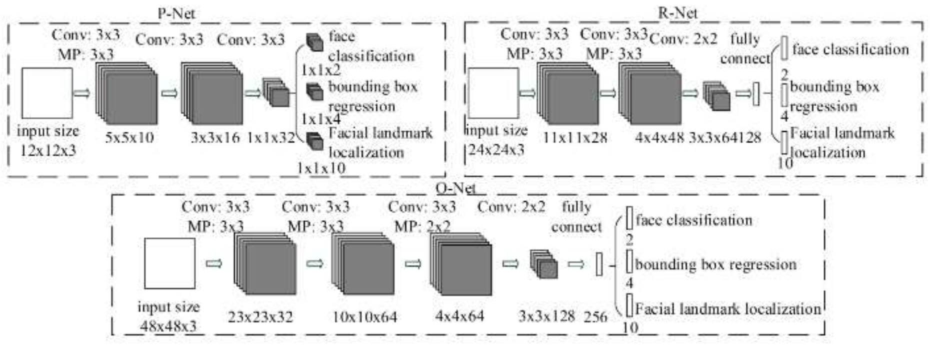


Figure 7: The Architecture of MTCNN. [3]

MTCNN uses deep learning techniques while Viola-Jones does not. It follows that MTCNN is more computationally expensive to train, store and use, as opposed to Viola-Jones. However MTCNN is more robust, as it can detect distorted faces, partially covered faces and faces in poor light conditions. Since Viola-Jones relies on a set of features which it assumes to be common on every face, it only succeeds in detecting faces in a specific orientation (such as frontal) and in good light conditions. Moreover MTCNN can detect facial landmarks while Viola-Jones cannot.

References

[1] en.wikipedia.org. 2021. *Viola–Jones object detection framework - Wikipedia*. [online] Available at: <https://en.wikipedia.org/wiki/Viola%E2%80%93Jones_object_detection_framework#/media/File:Prm_VJ_fig1_featureTypesWithAlpha.png> [Accessed 26 November 2021].

[2] en.wikipedia.org. 2021. *Summed-area table - Wikipedia*. [online] Available at: <https://en.wikipedia.org/wiki/Summed-area_table#/media/File:Integral_image_application_example.svg> [Accessed 26 November 2021].

[3] Zhang, K., Zhang, Z., Li, Z. and Qiao, Y., 2016. *Joint Face Detection and Alignment using Multi-task Cascaded Convolutional Networks*. [online] Arxiv.org. Available at: <https://arxiv.org/ftp/arxiv/papers/1604/1604.02878.pdf> [Accessed 26 November 2021].