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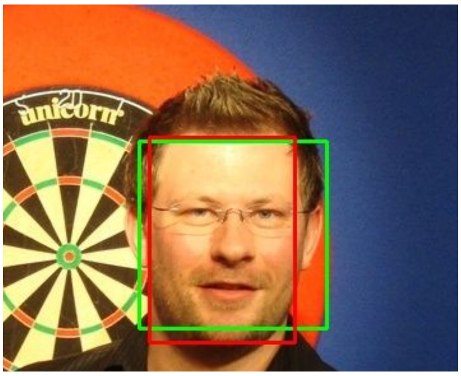
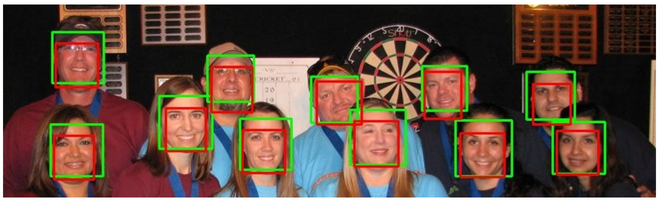
Image Processing and Computer Vision Report

Task 1: Face Detection with the Viola-Jones Object Detector

Ground Truth and Visualisations





IOU, TPR, F1-SCORE

Image	dart4	dart5	dart13	dart14	dart15
True Positive Rate	100%	100%	100%	100%	67%
F-1 Score	1	0.88	0.667	0.5	0.286

A difficulty we found when analysing the TPR was that for most of the images, the rate was 100%. This was good in the sense that it shows that the detector is working properly; for any detection task this rate is achievable because it is possible to make the threshold for detection low enough so that any object that remotely “looks” like the desired object is detected as one. However, as can be seen in some of the images, the TPR does not represent to us the false positive detections, i.e. objects that are not faces that are detected as such. Therefore, an F-1 score is a much better representation of how effective the detector is, as it takes into account these false positive identifications.

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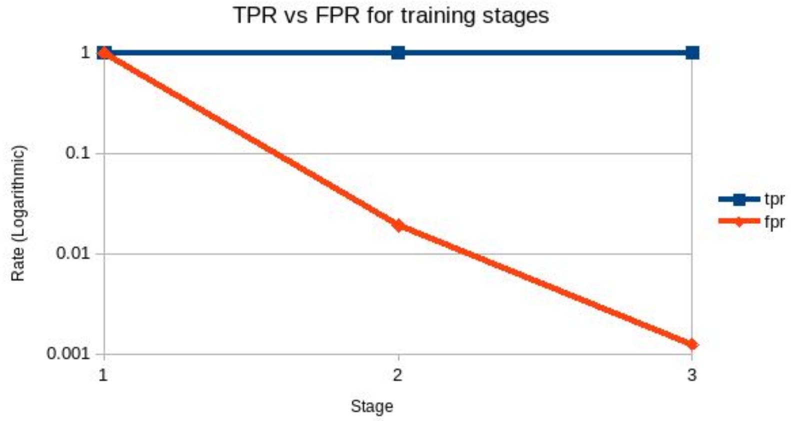
Task 2: Dartboard Detection with the Viola-Jones Object Detector

Training Performance

Stage 0: TPR =1, FPR = 1
Stage 1: TPR=1, FPR = 0.0190643
Stage 2: TPR=1, FPR = 0.00125023



The training performance shows that as the classifier progresses through the different stages, the TPR stays constant at 1. Meanwhile, the FPR reduces to around 2% after stage 1, and even further to 0.1% after stage 2. The logarithmic graph to the right shows the consistent reduction in false positive detections which supports the idea that adding more feature classifications is crucial to the process of lowering the FPR; without it the TPR could not be trusted to represent the precision of the classifier.

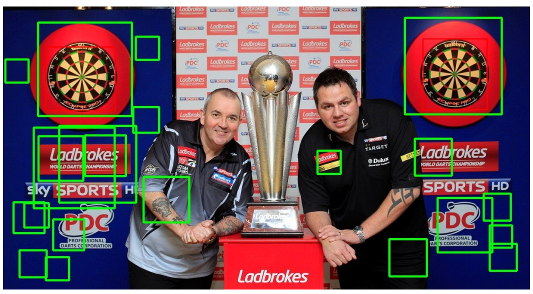
Testing Performance

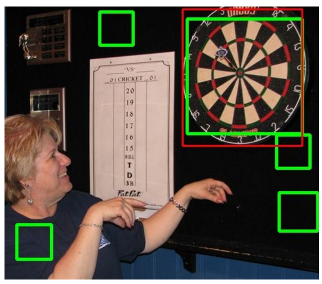
The table on the right shows our results after testing the performance of the classifier. Again, the TPR for most of the images was at 100% and overall had a pretty high average of 81%. However, this time for a couple of the images the TPR was unfortunately 0% as the Viola-Jones classifier was not effective enough in recognising smaller dart boards, some partially covered dart boards and ones at an angle away from the camera. The F1 score was more mixed. Only on the dart9, dart13 and dart15 images did the classifier perfectly detect dart boards without any false positive detections. However, for cases 4, 5 and especially 14 we can see a fall in the F-1 score, which is most likely due to overfitting from the classifier.

Testing Performance Table

Image	TPR	F1-score
dart0	100%	0.333
dart1	100%	0.667
dart2	100%	0.667
dart3	100%	0.5
dart4	100%	0.5
dart5	100%	0.667
dart6	0%	0
dart7	100%	0.667
dart8	50%	0.333
dart9	100%	1
dart10	67%	0.5
dart11	0%	0
dart12	100%	0.667
dart13	100%	1
dart14	100%	0.167
dart15	100%	1
Average	81%	0.541

The TPR here is less than in the Training Performance because in the training stage, it wants to detect as many dart boards as possible and then tune away the incorrect data. Whereas in the testing stage new images are provided for the classifier to test itself on. Some features or variations of dartboards in the testing data it wouldn't have seen and therefore may not be able to classify them correctly.





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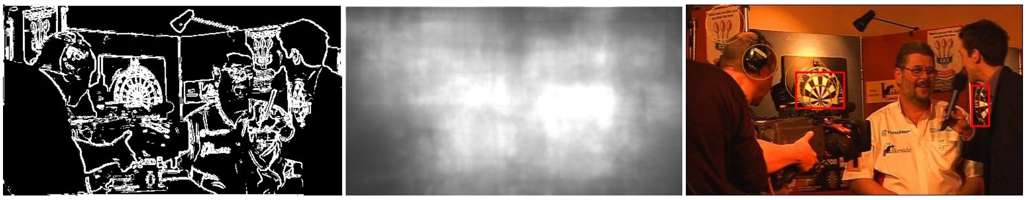
Integration with Shape Detectors

Hough Details - Dart11:



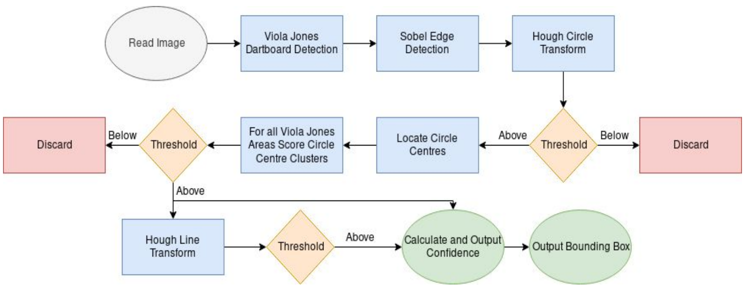
Dart14:

Evaluation - As we can see in the Hough space for the dart14 image, our enhanced detector can clearly identify the two dart boards after considering all of the thresholds. After implementing the Hough circle transform especially (seen in orange in the image above), our detector reduces the amount of false positives being found. We also made our line detector consider objects found within the green bounding boxes, and ignore all other noise.

However, as for examples such as dart11, our detector struggles finding more obscured dartboards, and the Hough space for this image shows that it doesn't actually find any points or objects of interest. This is partly due to the weakness of the Viola Jones detector preventing the Hough line transform being able to be used.

Image	TPR	F1-Score	F-1 score difference from Viola-Jones
0	100%	1	+0.667
1	100%	1	+0.333
2	100%	1	+0.333
3	0%	0	-0.5
4	100%	1	+0.5
5	100%	1	+0.333
6	0%	0	+0
7	100%	1	+0.333
8	50%	0.667	+0.333
9	100%	1	+0
10	67%	0.8	+0.3
11	0%	0	+0
12	0%	0	-0.667
13	100%	1	+0
14	100%	1	+0.833
15	100%	1	+0
Average	69.8%	0.72	+0.175

Detection Pipeline



For each Viola Jones area count up the score from the circle centres. If these are above a certain threshold then classify the area as a dartboard.

We chose this way because the Viola Jones has a high true positive rate so detects almost all dartboards. However there are lots of things it detects as darboards which are not. Therefore using the Hough Circle Transform in each area then finds many circles and classifies an area as a dartboard if its been detected by Viola Jones and has many circles. This removes all these extra Viola Jones areas which are clearly not circles.

A downside to this is that if Viola Jones doesn't detect a dartboard, it will not be detected using the Hough Transform. However this would classify more things incorrectly as dart boards rather than correctly classify the few that Viola Jones doesn't detect because there can be circles in an image which isn't a dartboard.

Extra additions:

The detector finds the intersection over union between each pair of detected dartboards and uses it to determine if there are multiple detections for the same dartboard. If the IOU is above a certain threshold, then it considers this as both detections detecting one dartboard. This happened a few times, however now after this implementation it combines all the detections and outputs just one detection, for all cases in which this previously was a problem, using averaging.

Final Results

After implementing our Hough transforms, the results changed. On a positive note, our F1-score increased by almost 0.2, which demonstrates the need for a combination of different identification techniques to effectively sort between true and false positives. On the other hand, our TPR score actually went down by around 11%; which is because some of the dartboards are at too much of an angle to have circles detected and then does not pass the circle thresholds. This shows how in our case we have had to compromise our TPR and F1 score. Even though we are disappointed that our TPR could have been higher, we think that having less false positives is important. However, we are aware that real world applications it may be better to have more false positives due to safety reasons, for example in automated cars identifying pedestrians. Overall, we agree that if we could have added more detection techniques, like analysing ellipses in the Hough space, our detector would be better. Also more data for the Viola-Jones detector, such as more dartboard images and more negative images would have improved it. This would then help with detecting the less obvious dartboards that it cannot currently detect.

Contributions: Roberto = 1, Tommy = 1

Signatures: