

Image Processing Report

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Introduction

This report examines the performance of a dartboard detector for any given image. Firstly, we were given the Viola-Jones detector for faces and asked to evaluate its performance. We then trained the Viola-Jones detector to work for dartboards and combined this with our implemented Hough circle and line transforms in order to improve its performance. Our Hough Transform considers both circle centres and line intersections and we used this data to help remove the false positives output by the Viola-Jones detector.

| File name | TPR | F1-Score |
|------------|----------|----------|
| dart0.jpg | 0 | 0 |
| dart1.jpg | n/a | n/a |
| dart2.jpg | n/a | n/a |
| dart3.jpg | n/a | n/a |
| dart4.jpg | 1 | 1 |
| dart5.jpg | 1 | 0.88 |
| dart6.jpg | 0 | 0 |
| dart7.jpg | 1 | 1 |
| dart8.jpg | 0 | 0 |
| dart9.jpg | 1 | 0.4 |
| dart10.jpg | n/a | n/a |
| dart11.jpg | 1 | 1 |
| dart12.jpg | n/a | n/a |
| dart13.jpg | 1 | 0.67 |
| dart14.jpg | 1 | 0.5 |
| dart15.jpg | 0.33 | 0.29 |
| averages | 0.666364 | 0.521818 |

Table 1: Performance Results for face detector. n/a means that the image did not contain a face

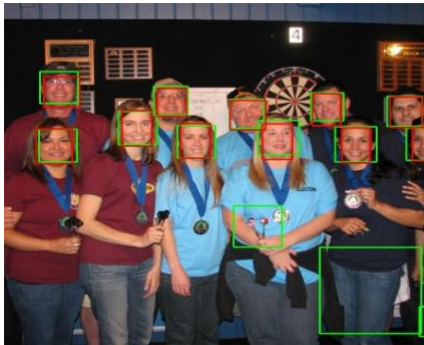


Figure 2: dart5.jpg



Figure 1: dart4.jpg

Viola-Jones Face Detector Performance

We evaluated the detector's performance by annotating the valid faces on the image with red boxes. A valid face was determined if a Viola-Jones box and ground truth box had an IOU (Intersection over Union) score of 0.5. This is defined as the intersection area of the 2 boxes over the union area. The number of valid faces detected divided by the number of valid faces gave us the true positive rate as seen on Table 1.

However, the TPR alone is not robust enough to measure performance as it tells us nothing of how precise the detector was (defined by the number of valid faces detected/ number of detections made) since it does not consider false positives. An example of this is shown in figure 1 as although the detector has managed to detect both faces, it has also detected the trophy and part of the man's shirt as faces. For this reason, it is always possible to get a true positive rate of 1 if your predictions contain all the faces.

To make use of both precision and the true positive rate, we calculated the F1-Score for every image as seen in Table 1. The average TPR score was 0.66 while the average F1 Score for faces was 0.52. After this was done, we then trained the viola jones-detector to work for dartboards as discussed on the next page



Figure 4 dart14.jpg



Figure 3: dart13.jpg

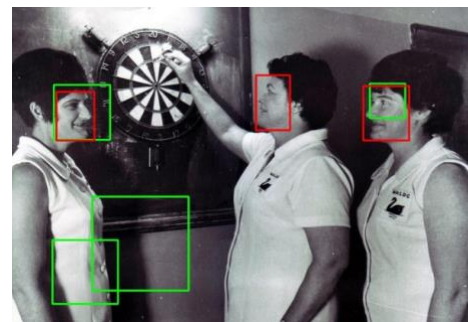


Figure 5: dart15.jpg

Viola-Jones Dartboard Detector Performance

Figure 6: TPR vs FPR for each stage



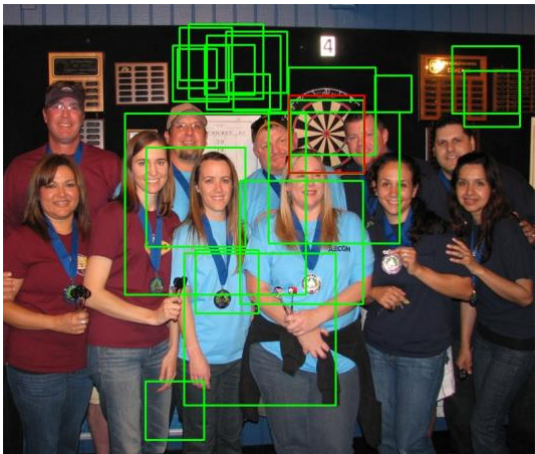
A feature cascade was trained via AdaBoost using true positive samples generated by OpenCV and true negative samples given by us. AdaBoost works by combining weak classifiers at every stage in order to build a strong classifier. In figure 6, a graph of the true positive rate against the false positive rate can be seen. From the graph, we show that the true positive rate stays the same while the false positive rate reduces every stage. In stage 0, the false positive rate is 1. This could be interpreted as the detector making random guesses as to what a dartboard is as it is along the diagonal. As the classifier becomes stronger and more refined every stage, the false positive rate reduces.

We annotated the valid dartboards and calculated the TPR and F1 scores for the dartboard classifier using an IOU score of 0.4 which can be seen in Table 2.

Figure 7: dart14.jpg



Figure 8: dart5.jpg



Although, the average TPR score is 0.88, the average F1 score is 0.16. This is due to the classifier being very imprecise as seen in all the figures 7-9. This imprecision may be due the classifier not being as well trained as the face classifier. For example, the face classifier goes through 25 stages while the dartboard classifier only goes through 3. This may result in a weak set of features that many objects share. Also, OpenCV may not create as varied a set of samples for true positives compared to if the training set was manually obtained.

The average TPR value is lower than in the training process. This is due to AdaBoost overfitting to the training set and thus it may not be as accurate to images it has never seen before.

| File name | TPR | F1-Score |
|------------|------|----------|
| dart0.jpg | 1 | 0.12 |
| dart1.jpg | 1 | 0.33 |
| dart2.jpg | 1 | 0.29 |
| dart3.jpg | 1 | 0.18 |
| dart4.jpg | 1 | 0.11 |
| dart5.jpg | 1 | 0.1 |
| dart6.jpg | 1 | 0.13 |
| dart7.jpg | 1 | 0.06 |
| dart8.jpg | 0.5 | 0.05 |
| dart9.jpg | 1 | 0.2 |
| dart10.jpg | 0.67 | 0.06 |
| dart11.jpg | 1 | 0.33 |
| dart12.jpg | 1 | 0.33 |
| dart13.jpg | 0 | 0 |
| dart14.jpg | 1 | 0.07 |
| dart15.jpg | 1 | 0.22 |

Table 2: Performance Results for Dart Detector

Figure 9: dart9.jpg

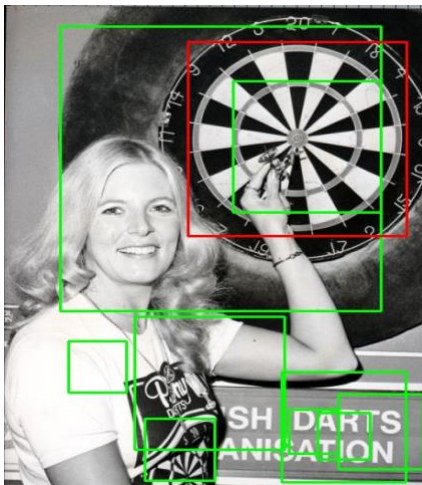


Figure 10: Thresholded gradient magnitude image of dart3.jpg

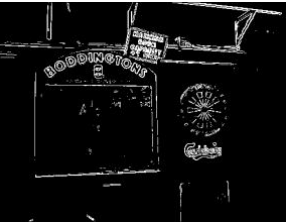


Figure 11: Hough circle space of dart3.jpg

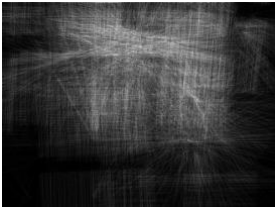


Figure 13: Hough line intersection space for dart3.jpg

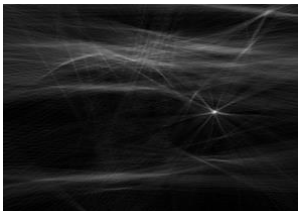


Figure 12: dart3.jpg detection



Performance of Viola-Jones Detector with Hough Transform

We combined the AdaBoost detector with our implementation of the Hough transform in order to detect both circle centres and line intersections. The method we used to do this is detailed in Figure 18. Our rationale for combining it this way was as follows:

- We generated circles in the centre of the Viola-Jones Rectangles to aid with our detection.
- The line intersections on the intersection Hough space are fixed in size so we used a constant circle size for line detection.
- The circle centres on the circle Hough space scale with their size from observation, so we scaled the circle with the rectangle size.
- If a good portion of circle centres or line intersections are concentrated in a specific area, then that means it's a valid prediction.
- Therefore, we use the ratio of centres in the rectangle area over centres in the entire image as a means of checking if it's a valid prediction.

- One Hough transform may not detect the dartboard centre but the other may, causing it to be detected such as how for dart3.jpg, the circle space does not detect the dartboard but the line space does.

Table 3 shows that our combined detector produces more accurate results. The key merits of our implementation are:

- The average F1-score for the combined detector was 0.82. This was an improvement from the Viola-Jones detector by 412%.
- This was due to us removing false positives detected by the Viola -Jones detector.
- However, for certain images we stopped detecting dartboards that were previously detected such as dart4.jpg and dart10.jpg.
- This is because we expected the Viola-Jones detector to produce at least 1 valid detection where the circle centre is at the centre of the rectangle.
- We are also limited by the how good the Hough transforms were at detecting circle centres and line intersections.
- For example, for dart10.jpg, neither the Hough circle transform and the Hough line transform can detect the dartboard on the far end.

Figure 14: Thresholded gradient magnitude image of dart10.jpg

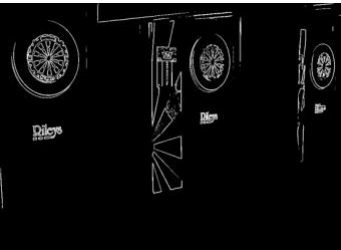


Figure 15: Hough circle space of dart10.jpg

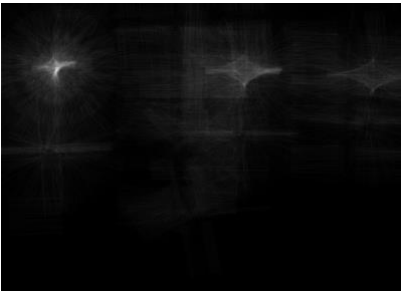


Figure 16: Hough line intersection space for dart10.jpg



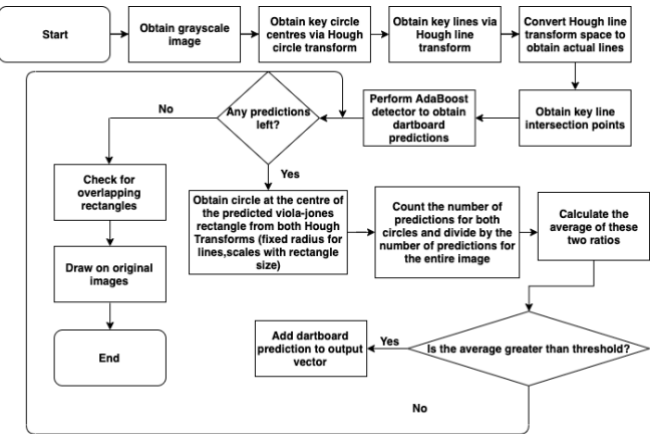
Figure 17: dart10.jpg detection



Table 3: Performance results for new detector with IOU 0.4

| File name | TPR | F1 - Score | TPR % Increase | F1 - Score % Increase |
|------------|------|------------|----------------|-----------------------|
| dart0.jpg | 1 | 1 | 0 | 733.33 |
| dart1.jpg | 1 | 1 | 0 | 203.03 |
| dart2.jpg | 1 | 1 | 0 | 244.83 |
| dart3.jpg | 1 | 1 | 0 | 455.56 |
| dart4.jpg | 0 | 0 | -100 | -100 |
| dart5.jpg | 1 | 1 | 0 | 900 |
| dart6.jpg | 1 | 1 | 0 | 669.23 |
| dart7.jpg | 1 | 1 | 0 | 1566.67 |
| dart8.jpg | 0.5 | 0.67 | 0 | 1240 |
| dart9.jpg | 1 | 1 | 0 | 400 |
| dart10.jpg | 0.33 | 0.5 | -50.75 | 733.33 |
| dart11.jpg | 1 | 1 | 0 | 203.03 |
| dart12.jpg | 1 | 1 | 0 | 203.03 |
| dart13.jpg | 0 | 0 | 0 | 0 |
| dart14.jpg | 1 | 1 | 0 | 1328.57 |
| dart15.jpg | 1 | 1 | 0 | 354.55 |

Figure 18: Flowchart of our combined classifier



Further Improvements

- We considered detecting ellipses by using OpenCV's findContours function.
- This detected dartboards where none were being detected such as in Figures 19 and 20 as it now detects all dartboards.
- To combine this with the previous detector, the same method is used with a greater weighting being placed for a prediction if it contained an ellipse centre.
- However, this method still fell into the same problems as detailed above and as such did not make any noticeable improvement.
- We also used unsharp masking before applying the Hough line transform to make the lines more noticeable and thus aid our line detection.
- We also considered using Histogram Equalization as a way of pre-processing our image for line detection as it removes effects of bright light and increases contrast.
- However, this only gave a slight improvement in the Hough line intersection space for dart8.jpg while it performed worse for others as it added noise.

To conclude, we employed a variety of Computer Vision techniques and succeeded in creating a working dartboard detector.

| File name | TPR | F1-Score |
|------------|-----|----------|
| dart0.jpg | 1 | 1 |
| dart1.jpg | 1 | 1 |
| dart2.jpg | 1 | 1 |
| dart3.jpg | 1 | 1 |
| dart4.jpg | 0 | 0 |
| dart5.jpg | 1 | 1 |
| dart6.jpg | 1 | 1 |
| dart7.jpg | 1 | 1 |
| dart8.jpg | 0.5 | 0.67 |
| dart9.jpg | 1 | 1 |
| dart10.jpg | 0.3 | 0.5 |
| dart11.jpg | 1 | 1 |
| dart12.jpg | 1 | 1 |
| dart13.jpg | 0 | 0 |
| dart14.jpg | 1 | 1 |
| dart15.jpg | 1 | 1 |

Table 4: results for the detector with it now detecting ellipses. No improvements compared to Table 3.

Figure 19: dart10.jpg with the ellipses drawn.



Figure 20: dart8.jpg with the ellipses drawn. As you can see this detects both dartboards.



Figure 21: Improved Hough line intersection space after using histogram equalization

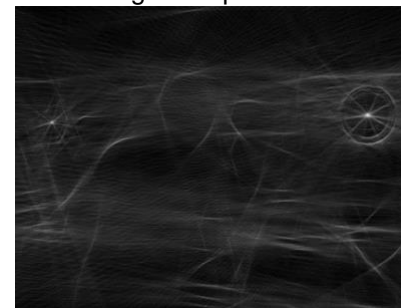


Figure 22: Contribution Agreement

| Name | Contribution | Signature |
|--------------------|--------------|-----------|
| Michael Mapeni | 1 | Michael |
| Ainesh Sevellaraja | 1 | Ain |