Dartboard Detection

Martin Dimitrov, Antonio Gugin
md16024, ag17174

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Abstract. This report explains and provides supporting data regarding our approach, results and gained knowledge over the course of the Dartboard Detection Challenge.

1 Viola-Jones Detector

1.1 Ground Truth and visualisation

We were given a pre-built off the shelf Viola-Jones model for frontal face recognition. Using it, we were tasked to visualise and compare its detections to the manually annotated Ground-Truths [fig. 1].

(a) face4.jpg (b) face5.jpg (c) face13.jpg (d) face14.jpg (e) face15.jpg

Figure 1: Comparison between the Viola-Jones face detections (green) and ground truth (red)

1.2 Face detector evaluation

The locations of the predicted faces can be used to mathematically express the correctness of the Viola-Jones algorithm. Calculating the ground truth's maximum *Intersection Over Union* (*IOU*) and applying a threshold gives the total number of successfully detected faces. Table 1 displays the *True Positive Rate* (*TPR*) and *F1 score* for each image.

Table 1: (Face Recognition) TPR and F1 score for each image enumerated by their index. F1 calculated $\beta = 0.5$

	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
TPR	0%	100%	100%	100%	100%	100%	0%	100%	0%	100%	100%	100%	100%	100%	100%	33%
F1	0%	100%	100%	100%	100%	85%	0%	100%	0%	40%	0%	100%	100%	66%	44%	29%

The *TPR* (recall) measures the percentage of ground truths that were classified as positive. Although this proves useful, it should not be used to assess the accuracy of a classifier as it does not take into consideration *False Positives* (*FP*). For instance, any classifier that detects everything as positive will have 100% TPR. The *F1 score* on the other hand, accounts for FP by using recall as well as the precision of the detector. Taking image *face5* [fig. 1-b] as an example, the classifier has detected all of the actual faces giving it 100% TPR, however, because it has also detected 4 additional false faces, the F1 score equates to roughly 85%.

2 Building a Dartboard Detector

2.1 Training performance

By training the Viola-Jones framework on a dartboard object class, we built a Dartboard Detector. The training procedure is split into stages where each stage accumulates more Haar-like features.

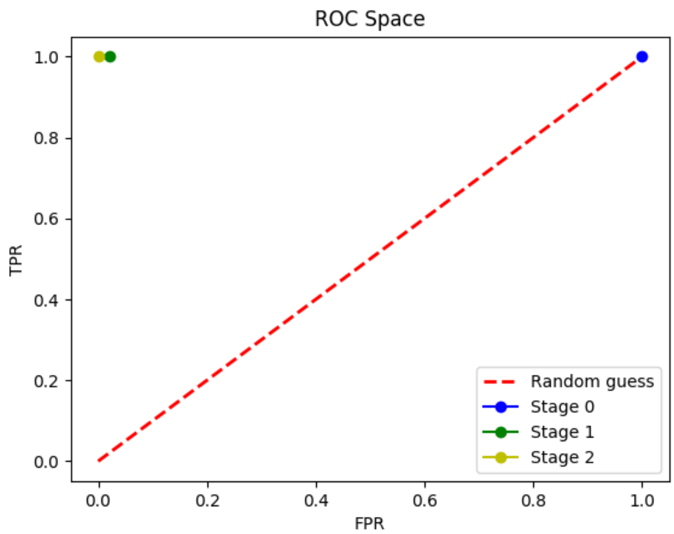


Figure 2: The TPR and FPR for each training stage. $numStages = 3$

As seen in [fig. 2], the procedure keeps the TPR equal to 100% whilst trying to minimise the FPR. At the end of *stage 2*, the classifier has such a combination of soft features that it has near-perfect classification for the given training data with an overall F1 = 100% (rounded by 0.001).

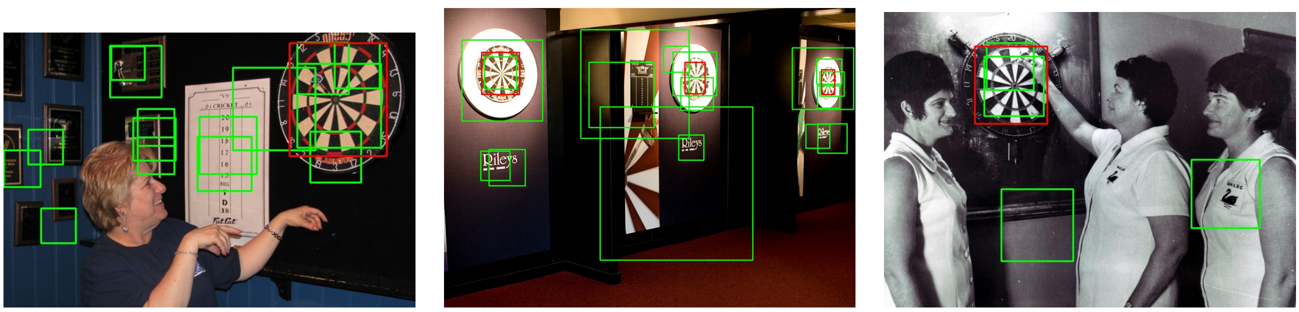
2.2 Testing performance

We tested the now trained dartboard classifier using the same set of images with manually annotated ground truths for the dartboards [fig. 3].

Table 2: (Dartboard Recognition) TPR and F1 score for each image enumerated by their index. F1 calculated $\beta = 0.5$

	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
TPR	100%	100%	100%	100%	100%	100%	0%	100%	100%	100%	66%	100%	100%	100%	100%	100%
F1	12%	18%	18%	15%	25%	18%	0%	9%	15%	22%	20%	22%	29%	15%	12%	40%

This resulted in an overall $TPR = 91\%$ and $F1 = 18\%$ [table 2]. The significant difference between the training and test F1 scores shows that the classifier is over-fitting. Doubling the training set leads to an almost linear increase: $F1 = 33\%$, which means that the accuracy of the classifier scales accordingly to the training data.



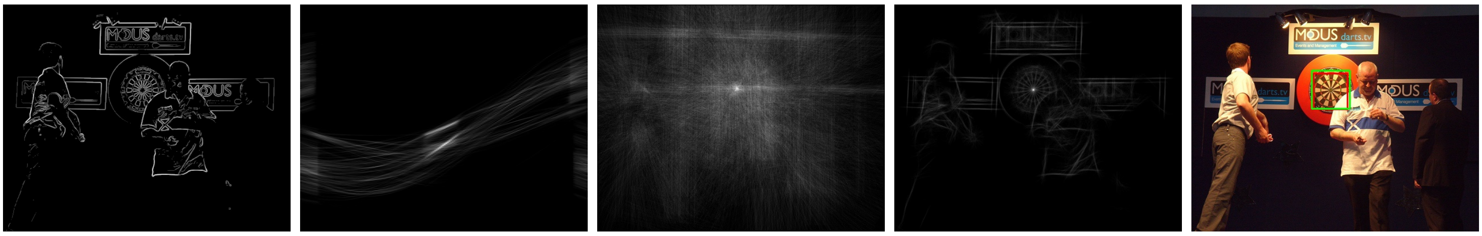
(a) dart0.jpg (b) dart10.jpg (c) dart15.jpg

Figure 3: Comparison between the Dartboard Hard Classifier (green) and ground truth (red)

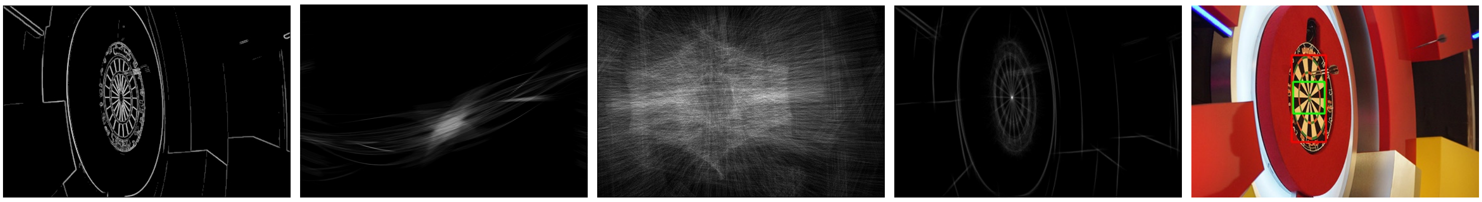
3 Integration with Shape Detectors

3.1 Hough Details

To improve the accuracy of the classifier we introduced three Hough Spaces: Lines, Circles and Line intersections [fig. 4].



(a) Image: dart6.jpg



(b) Image: dart12.jpg

Figure 4: The thresholded magnitude, Line, Circle and Line intersection Hough spaces and final detection

3.2 Evaluation

Table 3 displays the performance of the final dartboard classifier. Compared to the vanilla Viola-Jones detector, it is making fewer but more precise predictions. This leads to a greatly reduced FP at the cost of a slight TPR decrease. The overall F1 score is 90%, compared to the original 18%.

Table 3: (Final Recognition) TPR and F1 score for each image enumerated by their index and an overall average.

	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	Avg
TPR	100%	100%	100%	100%	100%	100%	100%	100%	50%	100%	66%	100%	0%	100%	100%	100%	88.5%
F1	100%	100%	100%	100%	100%	100%	100%	100%	66%	100%	80%	100%	0%	100%	100%	100%	90.4%

To classify, we use the following workflow [fig. 5]. The dartboard center is computed by the linear combination of our Circle and Intersection Hough Spaces. This gives us a better estimate when the dartboard is ellipsoidal. For the width and height, we take the radii of some of the highest voted circles for that center point in our Circle Hough space and average it with the size given by the best matching Viola-Jones detection.

fig. 4 is a good representation of the strengths and weaknesses of this implementation. It exceeds in locating the dartboard centers but sometimes fails to calculate the correct width and height as shown on fig. 4b.

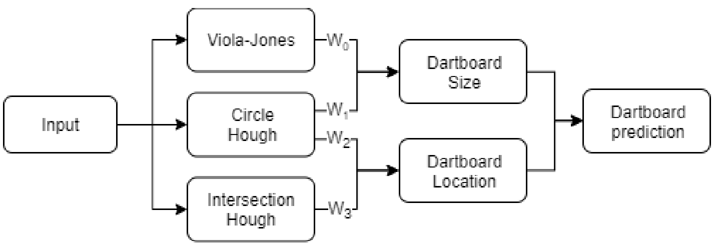


Figure 5: Flow diagram of the final classifier.

4 Improvements

4.1 Line intersection

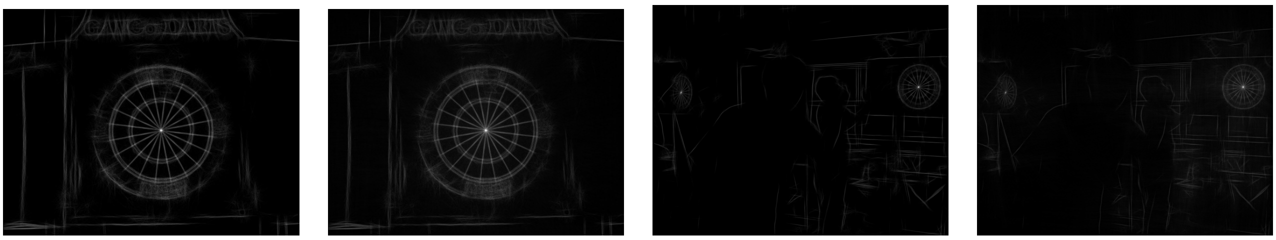
Thus far our Circle Hough Space was performing great at detecting and displaying center points of perfect/almost perfect circles. However, this introduced some challenges which we needed to deal with:

- It was also detecting Circles which were not Dartboards.
- It failed to detect Dartboards which appeared ellipsoidal.

We devised an idea about creating our own Hough Space. It serves as a line intersection detector which pinpoints the center points of the dartboard. It uses the location of a pixel and its direction to vote on neighbouring pixels along that line within a range(offset).

$$x* = x + offset * cos(thetha) \qquad y* = y + offset * sin(thetha)$$

We combined this 2D representation with the Circle Hough Space flattened into 2D in order to deal with both Circle Hough Space and regular Line Hough Space disadvantages. This resulted in a 30% F1 increase giving us a total F1 score of 90% [table 3].



(a) Intersection Hough for dart1 (b) Combined Hough for dart1 (c) Intersection Hough for dart8 (d) Combined Hough for dart8

Figure 6: Images representing the line intersection Hough space.

4.2 Average radii

We encountered the problem of determining the size of the bounding box when detecting a Dartboard. Our approach was relying on the average of the classifier's width and height and the radius with the highest amount of votes in the Circle Hough Space for the given point. This method performed well, however, for some pictures, the radius we took into account was one of the inner dartboard circles. This reduced the average size and made the IOU drop below the accepted threshold. We devised a new method which would take more than one of the highest voted radii into account and average them to get the best prediction.

4.3 Other

Some of the other improvements about:

- Replacing the Circle Hough to an Ellipse. As we wanted to avoid the computational heavy 5D Ellipse Hough space we found Yonghong's paper[1] on efficient Ellipse Detection. It states that it can accurately compute the Hough Space in a manner of O(n^3). Unfortunately, we were unable to replicate it.
- Hough Spaces highly rely on efficient gradient magnitudes. We experimented with different kernels like Scharr and Canny, but ultimately Sobel's kernel gave us the best result.

[1] A New Efficient Ellipse Detection Method (2002) by Yonghong Xie Qiang , Qiang Ji

5 Sign off

	Antonio Gugin = 1	Martin Dimitrov = 1
Signatures: