COMS30121 - Image Processing and Computer Vision

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1 Face Detection

1.1 Images

For each of the images below, on the left is the result of the face detector and on the right is the ground truth.

Figure 1: Dart4.jpg

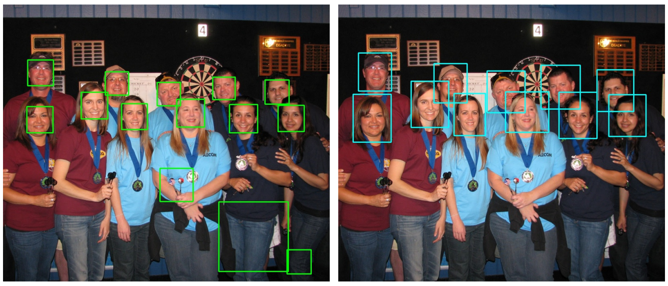

Figure 2: Dart5.jpg

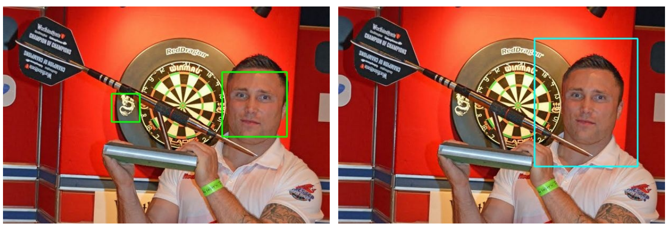

Figure 3: Dart13.jpg

Figure 4: Dart14.jpg

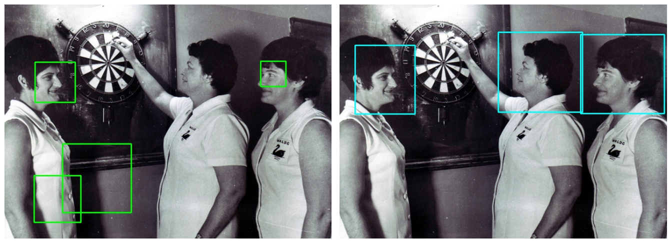

Figure 5: Dart15.jpg

1.2 Discussion

For Dart5.jpg, the True Positive Rate (TPR) is 100%, as all 11 faces are correctly identified by the algorithm (albeit with a number of false positives as well). For Dart15.jpg, depending on whether or not we classify the partial identification of the right-most face as a success, our TPR is either 33% (one face is correctly classified) or 66% (two faces are correctly classified) of the ground truth of 3 faces. From this point onward we will consider the rightmost face to be correctly classified when discussing Dart15.jpg.

One practical difficulty is in deciding whether something has been correctly classified. For example, in the output of Dart15.jpg, we see that the right-most face has been partially classified, likely due to the fact that this face is not facing the camera. Whether we decide this face has been correctly classified or not has a big effect on the True Positive Rate.

It is always possible to achieve a TPR of 100% because at the extreme we can design a classification algorithm that classifies every possible combination of pixels in the image as the shape we are looking for. This will classify all shapes correctly, therefore achieving a TPR of 100%, however it will also give us a vast number of False Positives to go alongside them. The difficulty with classification is designing an algorithm which correctly classifies all the shapes we are looking for, and nothing else.

Image	True +	False +	False -	F1 Score
Dart4	1	0	0	1
Dart5	11	3	0	0.88
Dart13	1	1	0	0.67
Dart14	2	4	0	0.5
Dart15	2	2	1	0.57

2 Viola Jones Detection

2.1 Training Tool

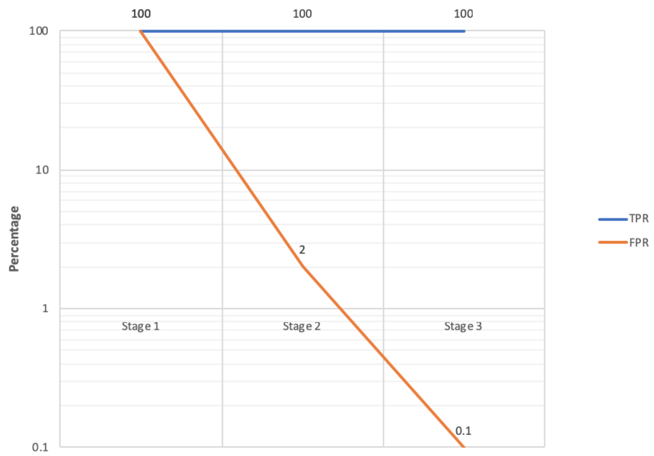

Figure 6: TPR vs FPR

As can be seen clearly from our graph above, at each stage in the process the False Positive Rate decreases exponentially, from initially 100% to 0.1% in Stage 3. It retains a 100% True Positive Rate throughout as it always successfully classifies correct images, but its accuracy at identifying false images improves exponentially as it proceeds through each stage.

2.2 Using the Classifier

Figure 7: Dart1.jpg

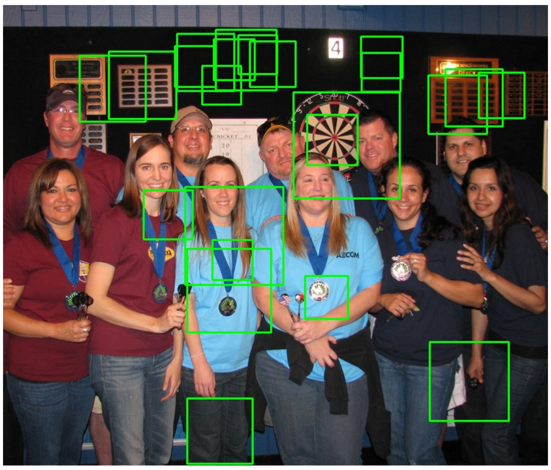

Figure 8: Dart5.jpg

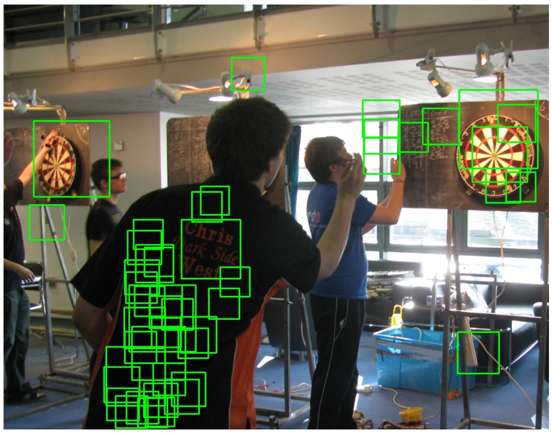

Figure 9: Dart8.jpg

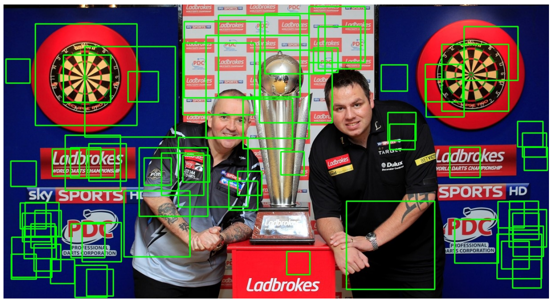

Figure 10: Dart14.jpg

2.3 Results

Image	True +	False +	False -	F1 Score
Dart0	1	19	0	0.095
Dart1	1	4	0	0.333
Dart2	1	9	0	0.182
Dart3	1	9	0	0.182
Dart4	1	16	0	0.111
Dart5	1	22	0	0.083
Dart6	1	16	0	0.111
Dart7	1	46	0	0.042
Dart8	1	46	1	0.041
Dart9	1	11	0	0.167
Dart10	3	56	0	0.097
Dart11	1	5	0	0.286
Dart12	1	8	0	0.200
Dart13	1	10	0	0.167
Dart14	2	64	0	0.059
Dart15	1	4	0	0.333

The average F1 Score when detecting Dartboards is **0.156**. The average F1 Score for the 3 stages when training the detector was **0.885**.

Our detection in real images is much worse than the in the training environment by a factor of 5.67. This may be due to the artificial nature of the training environment, and the fact that the classifier was trained only on a single, albeit altered, image of a dartboard. This would mean that the classifier becomes highly trained in detecting the one specific dartboard used in the training data, leading to its high F1 score during that stage. However the lower F1 score when used on real images suggests overfitting, which could be remedied by using different images of dartboards in training.

3 Combined Detector

3.1 Images

To showcase the merits and limitations of our combined Viola Jones and Hough Transform detector we chose the images dart5.jpg (left) and dart8.jpg (right).

Figure 11: Thresholded Gradient Magnitudes

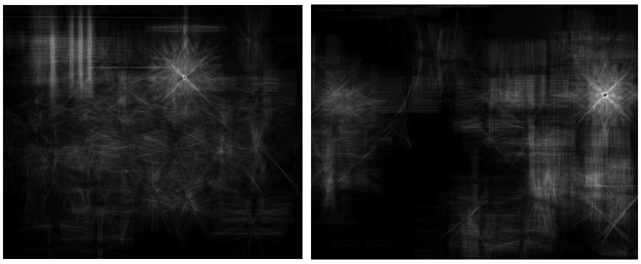

Figure 12: Circle 2D Hough Spaces

Figure 13: Bounding Boxes for Detected Dartboards

3.2 Results & Discussion

Image	True +	False +	False -	F1 Score
Dart0	1	3	0	0.500
Dart1	1	1	0	0.667
Dart2	1	1	0	0.667
Dart3	0	0	1	0.000
Dart4	1	5	0	0.286
Dart5	1	2	0	0.500
Dart6	1	2	0	0.500
Dart7	1	5	0	0.286
Dart8	1	3	1	0.333
Dart9	1	7	0	0.222
Dart10	2	4	1	0.444
Dart11	0	0	1	0.000
Dart12	1	1	0	0.667
Dart13	0	5	1	0.000
Dart14	2	15	0	0.211
Dart15	1	2	0	0.500

3.2.1 Merits

- Accurately detects the concentric circles which comprise the structure of the dartboard, with an average F1 score of **0.361**, more than double the score of Viola Jones alone.
- Correctly removes almost all False Positives from the output of the Viola Jones detection. We found in Subtask 2 that large numbers of False Positives were the main limitation of using V.J. alone. This is best exemplified by dart8, where 47 classifications, with 46 False Positives, were reduced to 4 classifications, with 3 False Positives.
- Simple method is regardless highly effective at detecting dartboards without the need for extra complexity, such as using multiple Hough Transforms; classifier is effective as well as computationally efficient.

3.2.2 Limitations

- Classifier struggles to detect skewed dartboards as it can only detect circles not ellipses. This is shown in dart8, where the rightmost of the two dartboards is successfully classified, as it is more circular, but the leftmost is not.
- Available detection limited by output from Viola Jones as our combined detector returns a subset of bounding boxes that also match with our Hough Transform.
- Detector tends towards giving False Positive results as any bounding box which contains the central point of detected concentric circles from the Hough Transform is classified as a dartboard even if it contains other things too. This is exemplified by dart5, where two faces are included in the larger bounding box alonsgide the dartboard.

3.3 Methodology

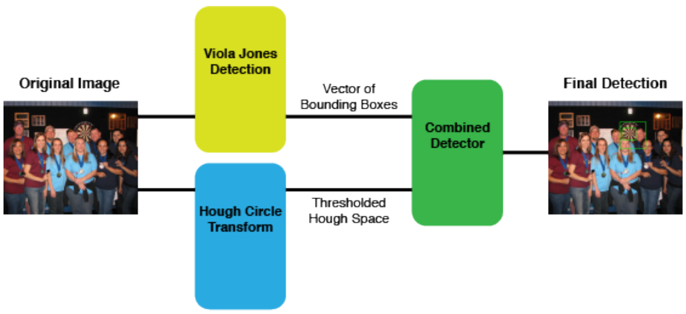

Figure 14: Flowchart for Combined Detector

- Results from Hough Transform are used to find subset of bounding boxes given as output from Viola Jones
- Viola Jones results had large number of False Positives, generally finding all dartboards alongside other random items, so utilising the Hough Transform as a secondary discriminator reduces number of FPs while retaining those which satisfy the H.T. criteria.

4 Probabilistic Transform

4.1 Discussion

- Our combined detector is often slow at detecting dartboards in larger images.
- In order to improve efficiency of our algorithm we implemented a Probabilistic Hough Transform similar to *Kiryati et al*[1].
- This improved the efficiency of the detector as with only a small fraction of the pixels we can still get good results. We used a random sample of 20% of edge pixels.
- Utilising subset m from M edge points reduces computational load from $O(M, N_\theta)$ to $O(m, N_\theta)$ where $m < M$.

4.2 Visualisation

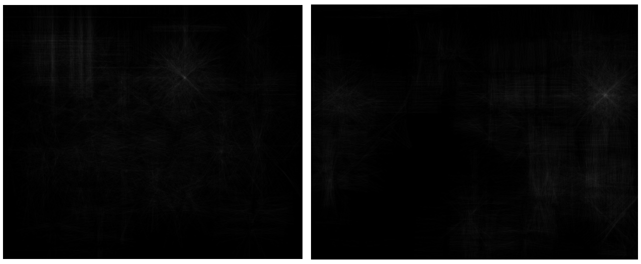

Figure 15: Circular Hough Spaces

Figure 16: Bounding Boxes for Detected Dartboards

4.3 Results

Image	F1 Score	Time0 /ms	Time1 /ms
Dart0	1.000	6150	5800
Dart1	0.667	4650	4400
Dart2	0.000	4320	4180
Dart3	0.000	2930	2560
Dart4	0.333	17960	17820
Dart5	0.667	21690	21170
Dart6	0.000	3200	3010
Dart7	0.667	15830	15330
Dart8	0.500	44180	42970
Dart9	0.400	6770	6140
Dart10	0.333	39750	39270
Dart11	0.000	1810	1790
Dart12	0.000	1510	1390
Dart13	0.000	5450	5180
Dart14	0.444	48490	46960
Dart15	0.667	9900	9520

Our average F1 score was 0.355. This is a less than 2% decrease in performance from our previous method where we used every edge pixel.

We timed how long the detection process took, from reading in the image to writing out the final image with drawn bounding boxes around the detected dartboards.

Our average time (Time0) for our detector before our improvements was 14662 ms. Our average time (Time1) for our detector after our improvements was 14218 ms. This is a 3% decrease in the time taken.

Therefore our efficiency increase outweighs the slight drop in efficacy.

4.3.1 Merits

- Increases F1 score for those dartboards which the detector is best at recognising: those which are facing forwards. This is best exemplified by Dart0, where the F1 score increases from 0.5 to 1!
- Slight decrease in time taken to identify dartboards in image.
- Detector is better at removing False Positive identifications of dartboards, well exemplified by dart5 where the 3rd bounding box has been removed.
- Efficacy of detection suffers only a slight drop despite using only 20% of the edge pixels for the Hough Transform.

4.3.2 Limitations

- Performance still bottlenecked by other parts of the detection process, even if the Hough transform is faster.
- Improved detector exaggerates merits and limitations of previous detector, where it is even better at detecting face forward dartboards and worse at detecting skewed, occluded or small dartboards.

5 Conclusion

Overall, we have found through this process that there is a trade off in image processing between creating detectors which have broad scope and can detect objects with a large potential for False Positives and specialised detectors which are very good at detecting objects that appear in a specific way but cannot recognise the more general idea of that same object if it is distorted in some way.

6 References

1. N. Kiryati, Y. Eldar, A.M. Bruckstein, A probabilistic Hough transform , Pattern Recognition, Volume 24, Issue 4, 1991, Pages 303 - 316, ISSN 0031 - 3203, DOI: 10.1016/0031 - 3203(91)90073 - E.