Report: Image Processing and Computer Vision 2018

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I. Subtask 1

A. Result Images

Fig. 1. Image face4.jpg — $F1 = 100\%$

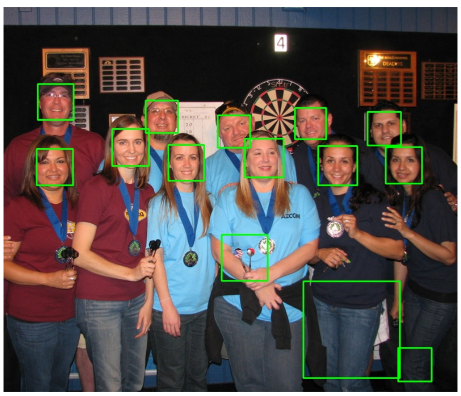


Fig. 2. Image face5.jpg — $F1 = 88\%$

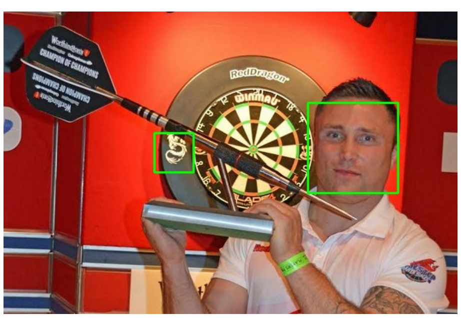


Fig. 3. Image face13.jpg — $F1 = 66.67\%$

B. TPR and F1-score calculation

Calculating the true positive rate:

$$TPR = \frac{TP}{P} = \frac{TP}{TP + FN}$$

where :
TPR = True positive rate

Fig. 4. Image face14.jpg — $F1 = 50\%$

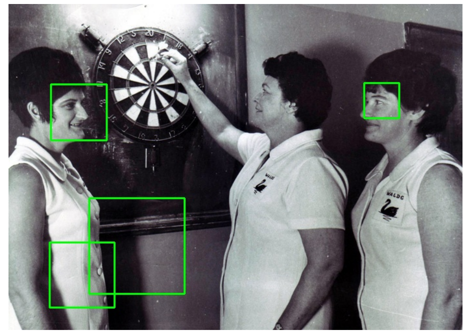


Fig. 5. Image face15.jpg — $F1 = 57.14\%$

TP = The number of cases correctly recognised
P = The number of actual positive cases in the data
FN = The number of false negatives, or the number of actual true cases not recognised

dart5.jpg TPR =

$$\frac{11}{11+0} = 1 \therefore 100\%$$

dart15.jpg TPR =

$$\frac{2}{2+1} = 0.\dot{6} \therefore 66.\dot{6}\%$$

The TPR is independent of the false positive rate. Consider a face detection task where we have x faces to detect $(A = \{face_1 \ldots face_x\}$ and a hypothetical model that produces a set of detected faces B comprised of all y possible contiguous combinations of pixel areas. $A \subset B$, however it also contains $y - x$ false positive detections. In this case the model has a TPR of 100%, however a potentially much lower precision. This hypothetical model is always possible, regardless of input, therefore a TPR of 100% is always possible.

$$F_1 = \left(\frac{TPR{-}1 \cdot PRECISION^{-1}}{2}\right)^{-1}$$

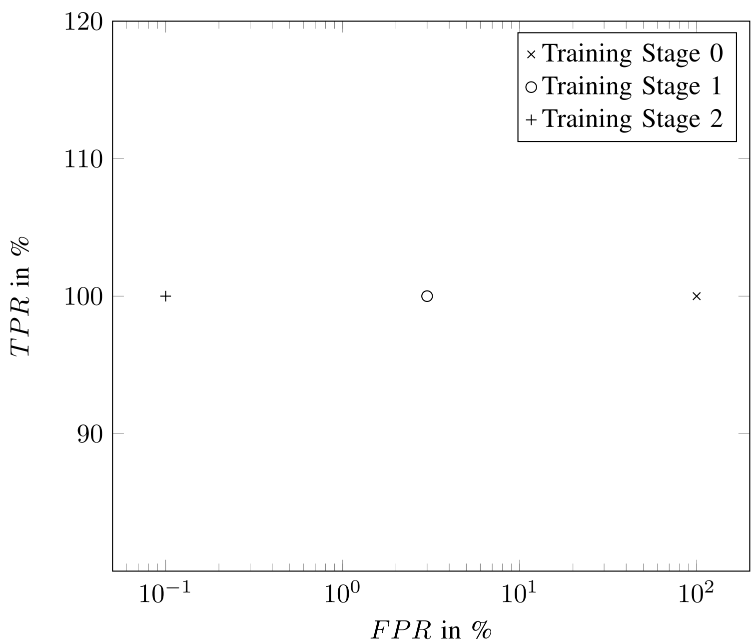
$$= 2 \cdot \frac{PRECISION \cdot TPR}{PRECISION + TPR}$$

$$PRECISION = \frac{TP}{TP + FP}$$

where : FP = False positive rate

II. Subtask 2

A. TPR vs FPR Scatter Plot



As training progresses from stage 0 to 2 we see that the *true positive rate* (TPR) appears to remain constant. This is due to being parametrised with a minimum hit rate of 0.999, essentially ensuring that all dartboards are detected while the algorithm attempts to reduce the number of false positives. We can see that *false positive rate* decreases at an exponential rate between each of the training stages.

B. F1-Scores for Dartboards

Fig. 6. Image dart1.jpg

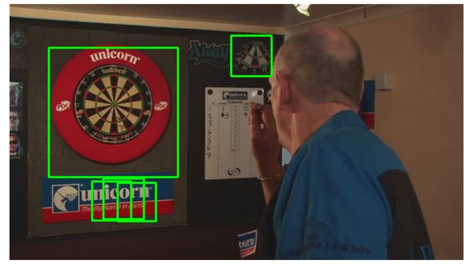


Fig. 7. Image dart2.jpg

Fig. 8. Image dart5.jpg

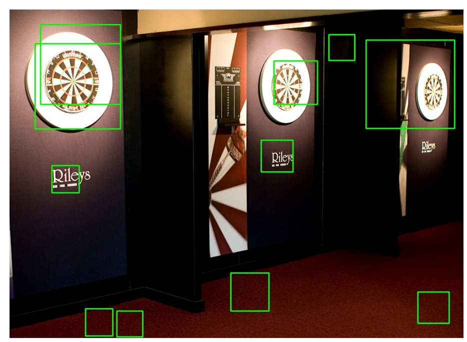


Fig. 9. Image dart10.jpg

Image	F1-Score
0	100%
1	100%
2	33.33%
3	50%
4	50%
5	100%
6	66.67%
7	28.57%
8	66.67%
9	66.67%
10	42.86%
11	0%
12	66.67%
13	66.67%
14	44.44%
15	100%
average	61.32%

TODO: DISCUSSION OF PERFORMANCE ACHIEVED

III. Subtask 3

A. Images for Hough Space, Gradient Magnitude, and Final Result

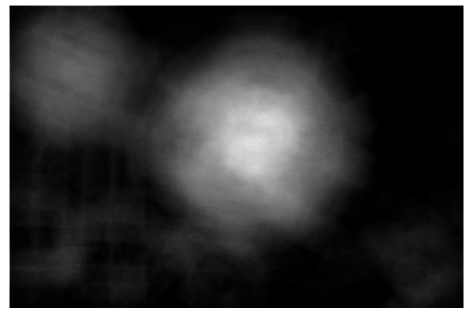


Fig. 10. Hough Space for image dart13.jpg

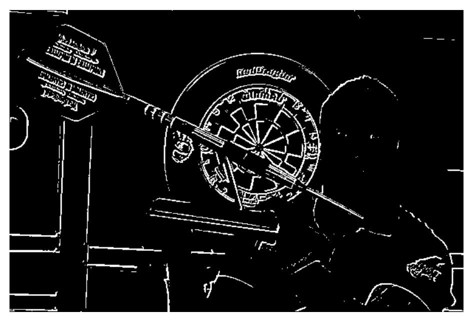


Fig. 11. Thresholded Gradient Magnitude for image dart13.jpg

Fig. 12. Hough Space for image dart10.jpg

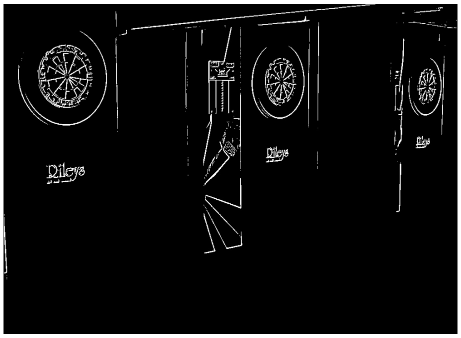


Fig. 13. Thresholded Gradient Magnitude for image dart10.jpg

Fig. 14. Final Detections for image dart13.jpg

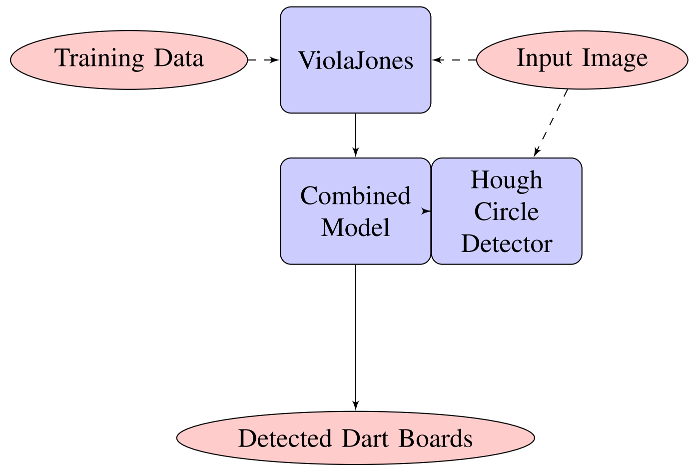
Fig. 15. Final Detections for image dart10.jpg

B. Evaluation of Detector

Image	F1-Score	Precision	Recall
0	100%	100%	100%
1	100%	100%	100%
2	100%	100%	100%
3	0%	0%	0%
4	66.67%	50%	100%
5	100%	100%	100%
6	100%	100%	100%
7	50%	33.33%	100%
8	100%	100%	100%
9	100%	100%	100%
10	85.71%	75%	100%
11	0%	0%	0%
12	100%	100%	100%
13	66.67%	50%	100%
14	57.14%	40%	100%
15	100%	100%	100%
average	76.60%	71.77%	87.5%

+ False positive rate strongly decreases due to a requirement of a positive from both **Viola-Jones**, and **Hough Circle Detection**
+ There is an improvement of 16 percentage points over regular Viola-Jones (A ~25% improvement).
- A small number of false negatives was introduced (Viola-Jones produced 0 false negatives)
- Like Viola-Jones, overlapping detection rectangles result in an increase in the false positive rate.

C. Evidence of Combined Hough Transform and Viola-Jones



- Viola-Jones is first trained using the training data as input.
- Viola-Jones receives an test image as input and returns detected dart boards.
- The Hough Circle Detector receives the same input image and returns detected circles.
- All detected dart boards are cross referenced against the Hough Detector's circles.
- If a Viola-Jones detected board contains no circle it is disregarded as a false positive.
- Conversely, if the board contains one or more circles the Viola-Jones prediction is considered to have been confirmed.
- The decision to confirm Viola-Jones using detected Hough circles and not vice versa is due to the following:
  - Viola-Jones has a comparatively lower false positive rate.
  - Viola-Jones has a near 100% true positive rate

IV. Subtask 4

The Forth Page of your Report (strict limit):
a) In bullet points, explain briefly your rationale behind selecting the approach you have taken.
b) Visualize important aspects of your technique in two of the given example dart images selected to best exhibit the merit of your approach.
c) Evaluate your final detector on all of the example images, show the improvements in F1-score. Document your overall detection results and briefly note in bullet points the key merits and shortcomings of your final implementation.

A. Rationale

- In order to avoid false positives produced by dartboards being detected multiple times with Viola-Jones overlapping boards have been consolidated into one.
- This works due to the assumption that boards would not be expected to overlap or lie within the edge of another in reality due to their positioning being mounted typically on solid walls, and being of fixed size.

Future Improvements

- Add an implementation of a Hough Lines detector detecting line intersections.
- Any point at or near which multiple lines intersect is potentially the centre of a dart board.
- The efficacy of this method is largely independent of the angle at which the dartboard is viewed.
- Adding this detection of potential dartboard centres to the combined model can be done in a similar way to the addition of the circle detector.

B. Images showing aspects of the final technique

C. Final F1-Scores

Image	F1-Score	Precision	Recall
0	100%	100%	100%
1	100%	100%	100%
2	100%	100%	100%
3	0%	0%	0%
4	100%	100%	100%
5	100%	100%	100%
6	100%	100%	100%
7	100%	100%	100%
8	100%	100%	100%
9	66.67%	50%	100%
10	100%	100%	100%
11	0%	0%	0%
12	100%	100%	100%
13	100%	100%	100%
14	66.67%	50%	100%
15	100%	100%	100%
average	83.33%	81.25%	87.5%