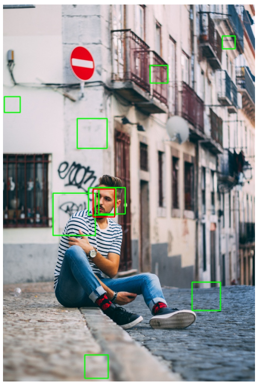
No Entry Sign Challenge Report

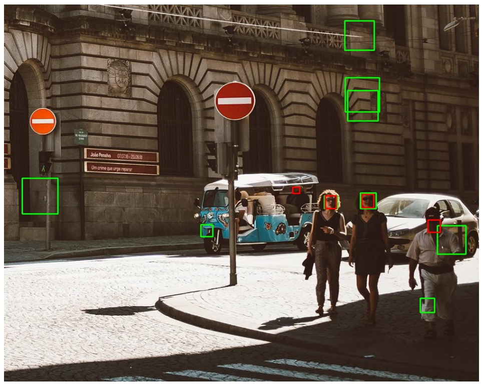
1 The Viola-Jones object detector

1.1 Ground truth and visualisation



(a) NoEntry1.jpg

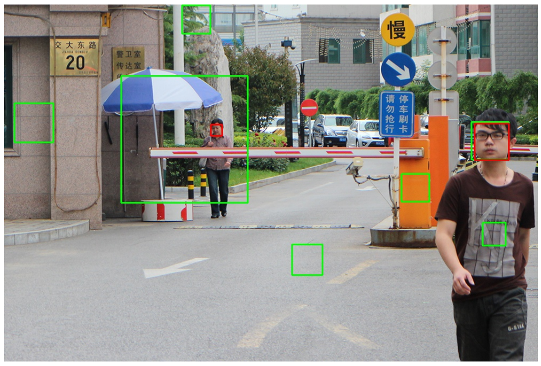
(b) NoEntry5.jpg



(c) NoEntry11.jpg

(d) NoEntry2.jpg

(e) NoEntry4.jpg



(f) NoEntry7.jpg

Figure 1: Six images with the bounding boxes of the ground truths (in red) and actually detected instances (in green) from the frontal face detector

1.2 Intersection-over-union, true positve rate and F_1 score

In an object detection task, the true positive rate (TPR) is the probability that an object will be positively detected. However, the first practical difficulty that arises in calculating the TPR is whether or not to define a predicted bounding box as a being a true positive or a false positive. I opted to define a detected bounding box as being a true positive if it had an intersection-over-union (IoU) value greater than 0.5 with a ground truth bounding box, as this is considered a good score [1]. Moreover, for each ground truth bounding box, I only defined the detected bounding box with the largest IoU value as being a true positive if there was more than one intersecting detected bounding box.

In any detection task, TPR can be a flawed metric to use to define how well a given model performs. This is because, it is possible to achieve a TPR of 100% by detecting every possible pixel region as being the object being detected, despite having a large number of false positives. As a result of this, the F_1 score is often used as a measure of a model's accuracy. F_1 score is the harmonic mean of sensitivity (i.e. TPR) and precision. Table 1 displays the F_1 score and TPR that 'face.cpp' achieved on each of the NoEntry$*$.jpg images

Table 1: TPR and F_1 score of the frontal face detector on each image

Image	TPR	F_1 score
NoEntry0.jpg	Undefined	0.00
NoEntry1.jpg	1.00	0.20
NoEntry2.jpg	0.25	0.18
NoEntry3.jpg	Undefined	Undefined
NoEntry4.jpg	1.00	0.28
NoEntry5.jpg	Undefined	0.00
NoEntry6.jpg	Undefined	0.00
NoEntry7.jpg	0.50	0.22
NoEntry8.jpg	Undefined	0.00
NoEntry9.jpg	Undefined	0.00
NoEntry10.jpg	Undefined	0.00
NoEntry11.jpg	0.50	0.31
NoEntry12.jpg	0.00	0.00
NoEntry13.jpg	Undefined	0.00
NoEntry14.jpg	Undefined	0.00
NoEntry15.jpg	Undefined	0.00

2 Building and testing my own detector

2.1 Training performance

ROC graph

2.2 Testing performance

3 Integration with shape detectors

3.1 Hough details

3.2 Evaluation

3.3 Detection pipeline

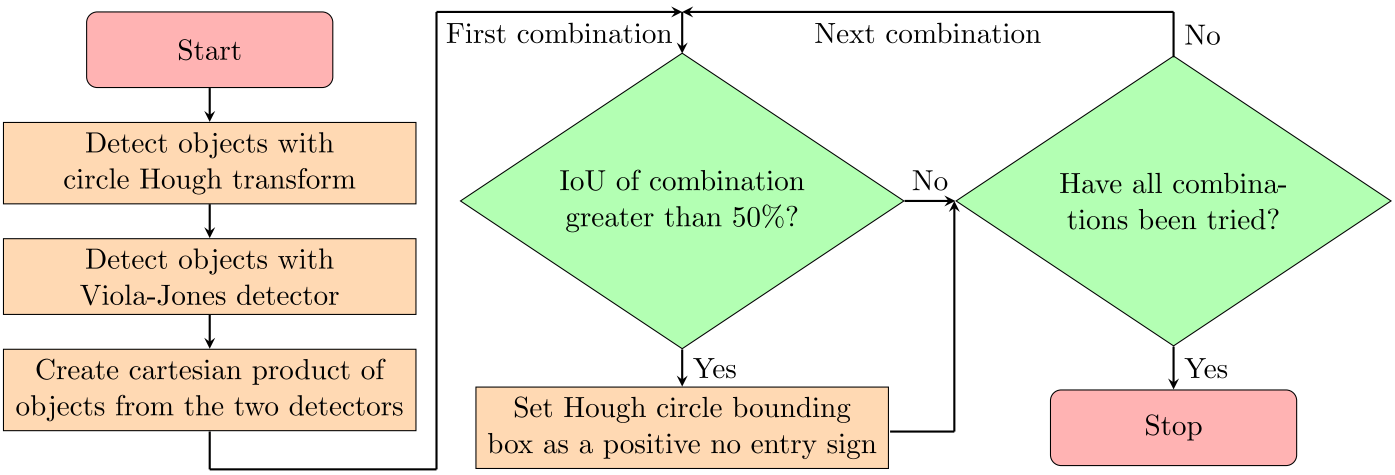


Figure 2: Flow chart detailing my algorithm that integrates Viola-Jones with the circle Hough transform

The rationale behind combining evidence in this way was as follows:

- The Viola-Jones detector was approximately 50% effective at detecting no entry signs, but had a large number of false positives
- Upon inspection of the detected bounding boxes, it became clear the Viola-Jones detector appeared to be detecting regions with a lighter area horizontally between two darker areas
- Since no entry signs are circles, we could choose to keep only the detected boxes from the Viola-Jones detector that also coincide with a circle

4 Improving my detector

References

[1] Adrian Rosebrock. *Intersection over Union (IoU) for object detection.* URL: https://www.pyimagesearch.com/2016/11/07/intersection-over-union-iou-for-object-detection/.