Car Detection with Yolo Toolset

ENCE 688V Project II

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1. Introduction

The scope of this research is to process the video from a highway and detect the number of cars in each second, which can be classified as a computer vision problem. Computer Vision is comprised of many tasks in real-world scenarios such as recognition, object detection or localization. Object detection is an important subdomain of computer vision and advanced form of image classification where a neural network predicts objects in an image and points them out in the form of bounding boxes.

Object Detection can be done in one-stage, which is proposal free and two-staged (proposal). In two-staged object detection after detecting possible object regions, the classification of the image into object classes is performed. Popular two-step algorithms like Fast-RCNN and Faster-RCNN are usually used for the two-staged object detection.

For one-staged object detection the most popular algorithms to use are YOLO (You Only Look Once) and Single-Shot-Detector (SSD). YOLO proposes the use of an end-to-end neural network that makes predictions of bounding boxes and class probabilities all at once.

2. OpenCV and Yolo

OpenCV (Open-Source Computer Vision Library) is an open-source computer vision and machine learning software library. One of the 2500 algorithms used for object detection and similar tasks in this package is YOLO. The algorithm works by dividing the captured image into N number of grids, which have same dimension of SxS. Each of these *N* grids is responsible for the detection and localization of the object it contains. Therefore, grids are used to predict B bounding box coordinates relative to their cell coordinates and the label of the object, by calculating the probability, that there is an object in cell. However, there can be several duplicate predictions, because the same object can be predicted with different box cells. Figure 1 illustrates this algorithm.

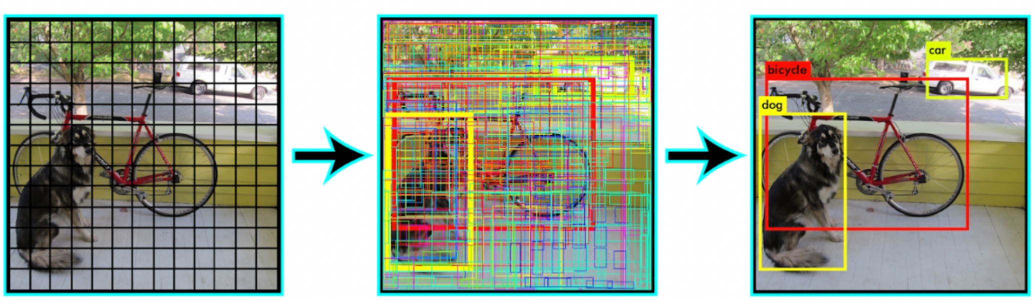

Figure 1. Yolo algorithm

The major limitations of YOLO include its ineffectiveness in the detection of small objects which appear in groups, because each grid is constrained to detect only a single object. YOLO is also less accurate compared to much slower object detection algorithms like Fast RCNN.

3. Results

Results from processing 60 second video through the algorithm is presented in Table 1 as well as processed video result. The detection accuracy was calculated by manually calculating the number of cars in each second, which can be the reason for discrepancy. As it can be noticed, the algorithm performs better in after the 25-30 seconds of processing the video, by resulting in accuracy of 95% or higher, which could be the result of training. It is also possible to get the classification probability of each of the car in a video as mentioned before, however due to large number of cars it is not presented in this report.

Overall, as it is expected it was more challenging for the YOLO toolset to detect small cars, which appear in groups. Also, there were some discrepancies such as detecting the grass as a car object or signs on the road. Although, the model performed satisfactorily since it resulted in 87% accuracy in average.

Table 1. Results of Car Detection from Surveillance Video

Time (s)	Cars Detected	Detection Accuracy (%)	Time (s)	Cars Detected	Detection Accuracy (%)	Time (s)	Cars Detected	Detection Accuracy (%)
1	5/20	25.00	21	73/78	93.59	41	134/135	99.26
2	13/25	52.00	22	79/80	98.75	42	137136	99.26
3	14/26	53.85	23	86/84	97.62	43	137/137	100.00
4	14/32	43.75	24	89/88	98.86	44	143/138	96.38
5	16/35	45.71	25	90/89	98.88	45	143/139	97.12
6	17/37	45.95	26	91/91	100.00	46	144/140	97.14
7	18/42	42.86	27	95/95	100.00	47	145/145	100.00
8	27/45	60.00	28	95/101	94.06	48	146/146	100.00
9	28/47	59.57	29	95/104	91.35	49	147/148	99.32
10	30/50	60.00	30	100/107	93.46	50	152/150	98.67
11	32/51	62.75	31	101/112	90.18	51	152/155	98.06
12	38/56	67.86	32	102/113	89.38	52	154/159	96.86
13	45/57	78.95	33	108/116	93.10	53	159/161	98.76
14	52/62	83.87	34	114/119	95.80	54	159/163	97.55
15	52/66	78.79	35	115/122	94.26	55	163/164	99.39
16	61/67	91.04	36	115/125	92.00	56	164/166	98.80
17	62/70	88.57	37	120/126	95.24	57	165/170	97.06
18	64/71	90.14	38	122/129	94.57			
19	66/74	89.19	39	128/131	97.71			
20	70/76	92.10	40	133/134	99.25			