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Band Traffic Light Scheduling for Waiting time Reduction

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ABSTRACT

Economic and social impacts are significant when there are traffic emergencies and delays as a result. Managing traffic infrastructure and planning traffic times are both early steps in urban planning. Traffic times were traditionally measured using inductive loops underground, pneumatic tubes on the roads, and manual counts will be used in the interim. Despite their advantages, Due to their high costs, degradation of the road surface, and difficulties in implementation, these approaches cannot be used in large areas. Detection and classification of vehicles has been made possible by recent advancements in computer vision methods through conjunction with available for free Closed-Circuit Television (CCTV) datasets. Based on video data from surveillance cameras, this study attempts to estimate traffic time. In order to improve the YOLOv3 algorithm, we have trained it on five different objects (cars, trucks, vans, bikes, and buses). A Signal Switching Algorithm is also proposed, timers also control the cyclical switching between signals. A simulation of real-life traffic was created using Pygame from scratch. Among the four traffic signals it contains, there is a four-way intersection. A timer is displayed at the top of each signal to make the simulation more realistic.

Keywords: *Fixed-Cycle Traffic Light (FCTL), Bounding Boxes, Object Detection, YOLOv3, Signal, Vehicles, Closed-circuit television (CCTV)*

INTRODUCTION:

With today's rapid development because of urban sprawl, the amount of automobiles on a city's road system has managed to grow dramatically. Understanding road traffic behavior is an important part of developing an emergency traffic response plan. Estimating traffic flow is the first step in identifying road traffic patterns, which helps with traffic modling, urban sprawl planning, and design development for all aspects of a road transport network. Yolov3 is a popular tool for gathering traffic data. Closed-circuit television (CCTV) systems are becoming more popular and are being installed in an increasing number of public spaces to provide real-time surveillance. Because all of these systems are constantly operational, tremendous quantities of information are generated, which makes a contribution to big data. Significant challenges have been identified in terms of transferring, stashing, processing, and continuing to develop efficient algorithms for CCTV data analysis.

Traffic congestion will harm human health in addition to being an economic issue. resulting in the emission of nitrogen oxides and large amounts of particulate matter. Because many tall buildings cannot dissipate polluted air and heavy traffic, these pollutants are easily trapped in cities. As a result, poor air quality will cause a great deal of illness, particularly in the respiratory system.

Pedestrians and vehicles are usually competing for space on the crosswalk, so dangerous situations are common because neither wants to wait at a junction. You and Hsieh proposed an idea for managing visitor routines in museum exhibition rooms using an evolutionary algorithm. Flow management was successfully implemented in the museum as part of the scheme to provide the finest possible experience for all visitors. Vehicles can be compared to visitors entering the exhibition room, and intersections to the best traffic management rooms. An ITLS was developed to reduce traffic congestion by utilizing object detection and an evolutionary algorithm. Real-time situations captured on camera at intersections were classified and determined using object detection. The evolutionary algorithm was used to create a strategic traffic light arrangement with the goal of lowering vehicle traffic and pedestrian waiting time at intersections and increasing road usage efficiency.

1. METHODOLOGY:

2.1. Input - Video
2.2. Non-Maximum Suppression and YOLOv3
2.3. Vehicle Counting
2.4. Signal Switching Algorithm

2.1. Input - Video

Steps to Follow:
Trying to import Libraries and Path
-Using the Video Capture function in CV2, import the video in which the objects and labels are to be recognized.
-i : argument for the path to the input video.
-o : argument for the path to the output video.
-yolo: argument for the base path to the YOLO directory.
-confidence: a non-mandatory argument with a default value of 0.5 for the minimum probability to filter weak detections.
-threshold: a supplementary argument with the value 0.3 by default for the threshold when applying non-maxima suppression.

2.2. Non-Maximum Suppression and YOLOv3

Getting Bounding Boxes:-"bicycle", "car", "motorbike", "bus", "truck".

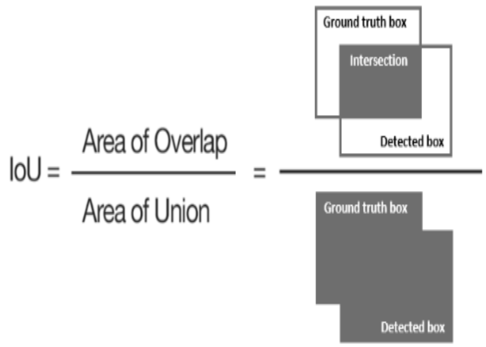
In YOLO v3, a bounding box in an image is a rectangular region that surrounds an object.

The bounding box formula is used in image processing to locate and identify objects. The model makes predictions for bounding boxes, object class probabilities, and confidence scores for each bounding box based on their class. These predictions are then used to determine which bounding boxes best enclose the objects in an image and to assign class labels to those objects. The use of bounding boxes in YOLO v3 helps to accurately locate objects in an image, even if they are partially occluded or overlapping with other objects. This is achieved by predicting multiple bounding boxes for each object, and using non-maximal suppression to eliminate bounding boxes with low confidence scores. Despite the removal of the low confidence bounding boxes, it is possible that duplicate detections will still occur around an object. The object detection algorithms' final step is non-max suppression, which is used to select the most appropriate bounding box for an object. From among the multiple predicted bounding boxes, these object detection algorithms use non-max suppression to choose the best bounding box. The purpose of this method is to ensure that only the best bounding boxes are retained, and to remove less likely ones. To select one bounding box, we use the confidence threshold value and the NMS threshold value as parameters. In YOLO v3, the NMS formula is used to perform the following steps:

- For each bounding box, the intersection over union (IoU) between the bounding boxes is computed.

- For each bounding box, keep it if its best bounding box IoU which is below a predefined threshold (e.g., 0.5).
- Repeat step 2 until no bounding box can be suppressed.

In summary, the NMS formula in YOLO v3 is used by removing redundant or low-confidence predictions; we can reduce the number of bounding boxes and improve object detection accuracy.



Formula for IOU (1)

2.3. Vehicle Counting

"boxes" is an image's bounding boxes contain objects.
"classIDs" is a list of class IDs for each bounding box, indicating the type of object it contains.
"classname" is a list of class names for each bounding box, representing the type of object it contains (e.g., car, truck, bus, etc.).
The function "get_vehicle_count" takes the boxes and classnames as inputs and returns the total number of vehicles in the image and the count of each type of vehicle.
"cv2.dnn.NMSBoxes" is used to perform non-maximum suppression (NMS), where overlapping or weak bounding boxes are eliminated to keep only the most confident predictions for each object.
"idxs" is a list of indices of the remaining bounding boxes after NMS has been applied.

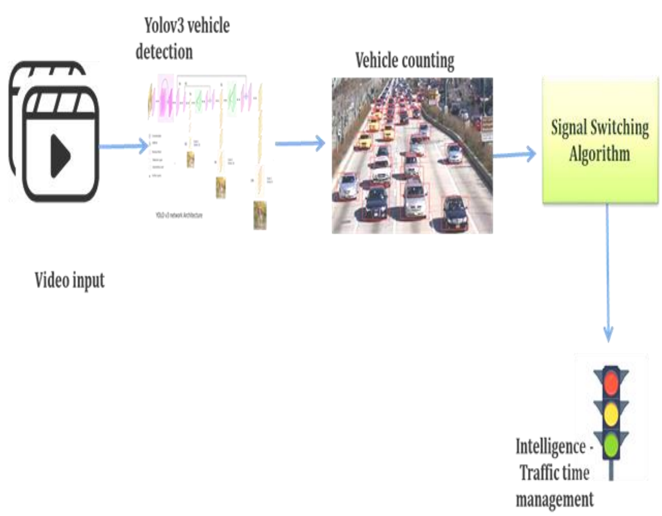


Figure 1: Traffic time Intelligence Using Signal Swithching Algorithm

YOLOv3 takes an input video and applies non-max suppression to eliminate redundant boxes and keep only the most probable ones to detect the vehicle. Implement a counting algorithm that tracks the number of vehicles detected over time.Signal Switching Algorithm Implement a control system to switch the signal based on the output of the YOLOv3 algorithm as shown in above figure 1.

2.4 Signal Switching Algorithm

During the creation of the algorithm, the following factors were considered:

1. When acquiring the image, the duration of the image is determined by the processing time of the algorithm to calculate traffic density, followed by the length of the green light.
2. Lane count.
3. The maximum quantity of vehicles from each class (i.e., cars, trucks, and motorcycles).
4. Determined traffic density according to the previously mentioned factors.
5. Additional time due to each vehicle's start-up lag, as well as the non-linear increase in delay experienced by vehicles in the rear.
6. As a result of the green light turning on, the average time it takes each vehicle class to cross the signal is based on the actual speed of each class of vehicles.

2.5.1 Working of the Algorithm

Whenever the algorithm will be first run, it determines how long it will take to generate the initial signal of the first cycle, as well as how long it will take to generate each additional All signals from the first cycle, as well as all signals from subsequent cycles. A separate thread is started to handle both directions of vehicle detection, while the main thread is in charge of the current signal's timer. The detection threads take a picture of the next direction when the current signal's green light timer (or the next green signal's red light timer) reaches zero seconds. The result is then parsed, and the timer for the next green signal is set. All of this takes place in the background while the main thread counts down the timer for the current green signal. This allows for timer assignment with no lag. The next signal turns green for the prescribed time, when the green timer on the signal generator reaches zero. The image is captured when the next signal to turn green is 0 seconds away. The average speeds and acceleration times of vehicles at start-up were used to estimate the average amount of time it takes each vehicle type to cross an intersection in order to determine the optimal green traffic signal time based on the number of vehicles of each class at a signal.

To improve traffic management, the average time it takes each vehicle class to cross an intersection can be set based on location, i.e., region-wise, city-wise, locality-wise, or even intersection-wise based on the intersection's characteristics. This can be accomplished by analysing data from the respective transportation authorities. Rather than switching in the direction with the highest density first, the signals are switched cyclically. This is consistent with the current system, in which the signals turn green in a predictable pattern way one after the other, requiring no changes in people's habits or causing confusion. The signal sequence also remains the same as it is in the current system, and the yellow signals have been added. This gives the algorithm a total of 5 seconds (the value of the yellow signal timer) to perform the image, recognize the number of vehicles in each class in the image, evaluate the green signal time, and adjust the times of this signal and the following signal accordingly.

Order of signals: Red → Green, Green → Yellow,
Yellow → Red.

3. RESULT AND DISCUSSION

The majority of the models used for Vehicle Detection are variations of YOLO. For object detection, I've gone with YOLOv3. It employs Darknet-53 as a backbone, and three outputs are drawn from different residual blocks before being concatenated and convolved to yield three predictions, which are then subjected to non-maximum suppression to yield the final predicted bounding box. Deep Sort Algorithm uses Kalman Filters to track objects for better predictions. As a result, we were able to train the novel YOLOv3 algorithm for five different object classes (car, truck, van, bike, and bus). There is also a four-way stop with four traffic lights. A timer is displayed on top of each signal, indicating how long it will be until the signal changes to yellow, red, or green.

YOLOv3 takes an input video and it's divided into a grid of cells. Each grid cell forecasts a set of bounding boxes each with its own confidence score and class probabilities. YOLOv3 applies non-max suppression to eliminate redundant boxes and keep only the most probable ones. Then, YOLOv3 generates output in a list of detected objects, along with their class and location in the video. Implement a counting algorithm that tracks the number of vehicles detected over time. Finally, integrate the YOLOv3 detection output into your traffic signal control system. Then an interface like OpenCV to display the video feed and draw bounding boxes around the detected vehicles. Then, we can use the Signal Switching Algorithm to manage the traffic time in figure 2.

• Here are some examples of the Signal Switching Algorithm's output:

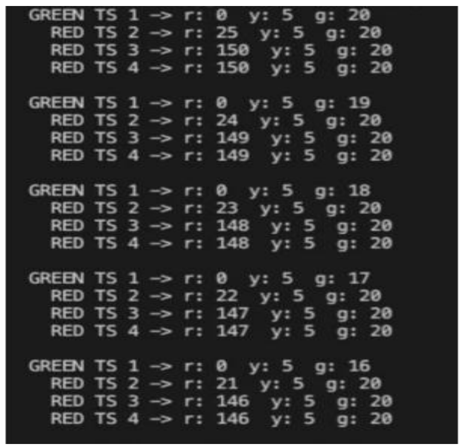


Figure 2: Output vehicle counting

With the exception of the second signal's red signal time, which is determined by the first signal's green and yellow times, all signals are initially loaded with default values.

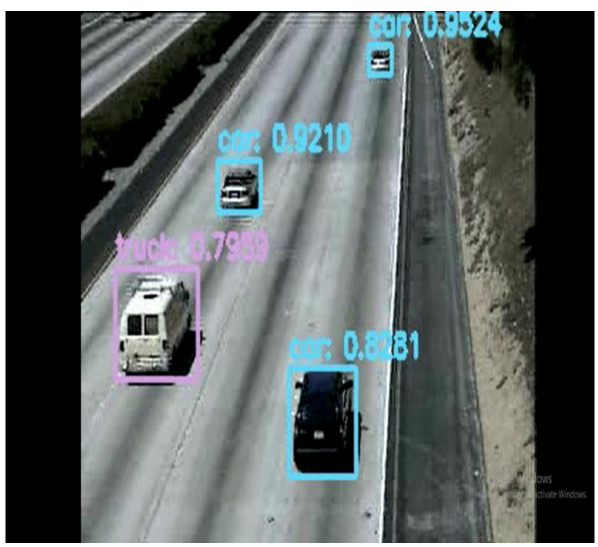


Figure 3: output vehicle counting

Once the vehicles are detected, they need to be tracked across different frames of the video to count them. This can be done using tracking algorithms that can track the location and movement of objects over time. The final step is to count the number of vehicles in the video. This can be done by analyzing the tracked vehicle trajectories and using threshold-based or machine learning-based classification methods to distinguish between different types of vehicles as seen in figure 3.

Figure 4: The simulation begins with red and green lights, with the green signal timer having By default, the red signal timer is blank and the countdown starts at 20. We display an empty value for 10 seconds when the signal is red. The count of vehicles that have passed through the signal can be seen next to it, which is initially all zero. On the top right, you can see how long has it been since the simulation started?

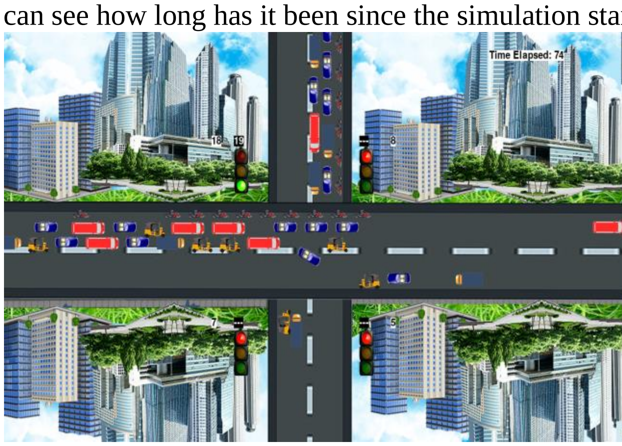


Figure 5: Based on the simulation shows there is an 18-second green signal period set for vehicles moving left.

4. CONCLUSION

YOLOv3 is a powerful object detection algorithm that can be applied to vehicles detection and traffic management in various settings. By training the algorithm on a large dataset of images, YOLOv3 can accurately detect vehicles and count their number in real-time. This information can be used to manage traffic signal timing and improve traffic flow, reducing congestion and improving overall safety on the roads. While YOLOv3 has many potential applications in traffic management, its effectiveness ultimately depends on factors such as camera placement, image quality, and the specific needs of the traffic system in question.

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CONFLICT OF INTEREST

The authors declare no conflict of interest.

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