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TITLE-Car detection and Velocity Calculator using OpenCV.

ABSTRACT

In recent times, there has been a drastic change in people's lifestyles and with an increase in incomes and lower cost of automobiles there is a huge increment in the number of cars on the roads which has led to traffic and commotion. The manual efforts to keep people from breaking traffic rules such as the speed limit are not enough. There is not enough police and man force available to track the traffic and vehicles on roads and check them for speed control. Hence, we require technologically advanced speed calculators installed that effectively detect cars on the road and calculate their speeds.

To implement the above idea two basic requirements, need to be met which are the effective detection of the cars on roads and their velocity measurement. For this purpose, we can use OpenCV software which uses the Haar cascade to train our machine to detect the object, in this case the car.

Using OpenCV we can develop either a Haar cascade or a Hough cascade, but for our use we have developed a Haar cascade to detect cars on the roads, whose velocities are then measured using a python script. The real-time application of this project proves to be much useful as it is easy to implement, fast to process and efficient with low cost development. Also, the tool might be useful to apply in simulation tools to measure velocities of cars. This can be further developed to identify all kinds of vehicles as well as to check anyone who breaks a traffic light.

The improvements in the project can be done by creating a bigger haar cascade since bigger the haar cascade developed, more the number of vehicles that can be detected on the roads. Better search algorithms can allow a faster search and better detection of these vehicles for better efficiency.

INTRODUCTION

In picture handling, Viola-Jones question identifier is a standout amongst the best and broadly utilized question finders. A prominent usage utilized by most picture handling analysts and implementers is the one actualized in OpenCV. The locator demonstrates its solid power in recognizing faces, however we thought that it was difficult to be stretched out to different sorts of items. The meeting of the preparation period of this calculation depends a ton on the preparation information. Also, the expectation exactness remains low. In this paper, we have concocted new thoughts to enhance its execution for differing object classes.

The Haar-like components are predefined and registered straightforwardly on the indispensable picture of the dark picture. So, the to start with commitment of this paper is that we have brought various element pictures into preparing the arrange classifier rather than just the dark picture. For one arrange, a few phase classifiers are prepared on these highlight pictures separately. The one gives out the greatest separation between the question and nonobject picture patches win and will then be chosen as the stage classifier for the present stage.

Detector is most effective only on frontal images of faces. It can hardly cope with 45° face rotation both around the vertical and horizontal axis. Sensitive to lighting conditions, we might get multiple detections of the same face, due to overlapping sub-windows. This is the biggest disadvantage of the Voila-Jones algorithm that we have attempted to overcome. Here we introduce a new stopping criterion to terminate the training of the stage classifier, the maximum variance ratio between score of positive image patches and score of the negative ones.

The third contribution of the paper is to develop an algorithm to calculate the speed of the object(vehicle) detected. We have implemented the algorithm using Python Script.

LITERATURE SURVEY

Introduction

The exploration led so far for question discovery and following articles in video reconnaissance framework are discussed in this area. The arrangement of difficulties plot above traverse a few areas of research and the larger part of important work. In this segment, just the delegate video reconnaissance frameworks are talked about for better comprehension of the major idea. Following is the procedure of object detection of enthusiasm inside a grouping of frames, from its first appearance to its last. The kind of object and its depiction inside the framework relies on upon the application. Amid the time that it is available in the scene it might be blocked by different objects of intrigue or settled obstructions inside the scene. A following framework ought to have the capacity to foresee the position of any impeded articles.

- “Real-Time Object Detection and Tracking on a Moving Camera Platform”. This paper proposed a real-time visual tracking system on a controlled pan-tilt camera. The input/output HMM is employed to model the overall visual tracking system in the spherical camera platform coordinate. In order to fast detecting and tracking targets on a moving camera at the same time, we adopt the optical flow to observe the different displacement in the image sequence. A two layer visual tracking architecture is proposed to improve the tracking robustness. The bottom level uses the optical flow estimation again for tracking the feature points across image frames. The top level utilizes the tracking result of bottom level and applies the particle filter for estimating the target state.
- “A Moving Articles Location Calculation In light of Enhanced Foundation Subtraction.”
In this material, another proficient moving target recognition strategy which is an enhanced foundation subtraction was proposed to recognize moving items, I summed up two noteworthy focal points, one of them is enhanced the foundation subtraction and expanded calculation's running effectiveness. Another is to counterbalance delicate insufficiency of the light changes.
- "Free Part Examination Based Foundation Subtraction for Indoor Observation" Foundation subtraction is a generally utilized approach for distinguishing frontal area protests in recordings from a static camera. Indoor observation applications, for example, home-care and social

insurance checking, an unmoving individual ought not be a piece of the foundation. A reference foundation picture without moving articles is, in this manner, required for such applications. In this paper, we have introduced an ICA-based foundation subtraction plot for frontal area division. The proposed ICA model depends on the immediate estimation of measurable independency that limits the contrast between the joint PDF and the result of minimal PDFs, in which the probabilities are basically assessed from the relative recurrence dispersions. The proposed ICA display well plays out the partition of profoundly associated signals

- Felzenszwalb et al. [1] portrayed a protest discovery framework in light of blends of multiscale deformable part models. Their framework could speak to profoundly factor question classes and accomplishes best in class brings about the PASCAL protest recognition challenges. They consolidated an edge touchy approach for information mining hard negative cases with a formalism we call idle SVM. This prompted an iterative preparing calculation that exchanges between settling dormant qualities for positive illustrations and advancing the inert SVM target work. Their framework depended vigorously on new techniques for discriminative preparing of classifiers that make utilization of inactive data. It likewise depended vigorously on effective strategies for coordinating deformable models to pictures. The depicted system takes into account investigation of extra inactive structure. For instance, one can consider further part orders (parts with parts) or blend models with numerous segments.
- Leibe et al. [2] in 2007, exhibited a novel strategy for recognizing and limiting objects of a visual classification in jumbled genuine scenes. Their approach considered protest classification and figure-ground division as two interleaved forms that intently team up towards a shared objective. The tight coupling between those two procedures enables them to profit by each other and enhance the joined execution. The center some portion of their approach was a profoundly adaptable educated portrayal for question shape that could consolidate the data seen on various preparing cases in a probabilistic expansion of the summed-up Hough Transform.
- Zhang et al. [3] in 2006, introduced a substantial scale assessment of an approach that spoke to pictures as circulations (marks or histograms) of components separated from an inadequate arrangement of key-point areas and learnt a Bolster Vector Machine classifier with bits in light of two viable measures for looking at dispersions. They first assessed the

execution of the proposed approach with various key-point locators and descriptors, and in addition distinctive bits and classifiers. At that point, they directed a similar assessment with a few present day acknowledgment strategies on 4 surface and 5 question databases.

- In 2001, Viola and Jones [4] in a meeting on example acknowledgment depicted a machine learning approach for visual protest location which was fit for preparing pictures to a great degree quickly and accomplishing high identification rates. Their work was recognized by three key commitments. The first was the presentation of another picture portrayal called the "necessary picture" which permitted the components utilized by their identifier to be figured rapidly. The second was a learning calculation, in view of AdaBoost, which used to choose few basic visual elements from a bigger set what's more, yield to a great degree proficient classifiers.
- In 2000, Weber et al. [5] proposed a strategy to learn heterogeneous models of question classes for visual acknowledgment. The preparation pictures, that they utilized, contained a prevalence of messiness and the learning was unsupervised. Their models spoke to objects as probabilistic heavenly bodies of inflexible parts (highlights). The inconstancy inside a class was spoken to by a join likelihood thickness work on the state of the heavenly body and the presence of the parts.

Methodology

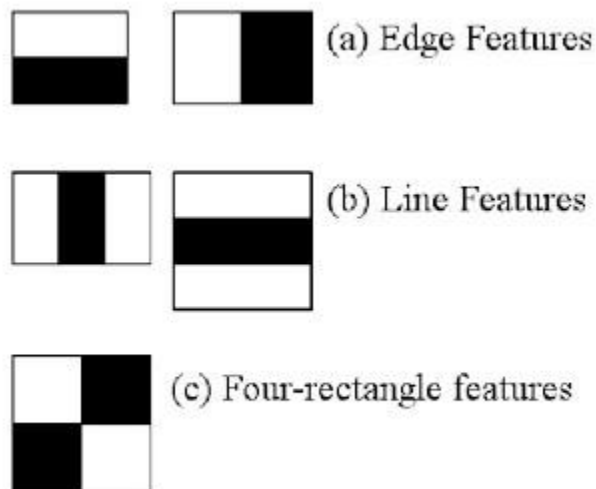
The complete implementation uses two basic processes: -

1. Car detection using Haar cascades in OpenCV
2. Measurement of velocity of detected cars using python script.

Car Detection

Object Location utilizing Haar highlight based course classifiers is a compelling item discovery strategy that uses a machine learning based approach where a course capacity is prepared from a considerable measure of positive and negative pictures. It is then used to recognize protests in different pictures.

- Initially, the calculation needs a considerable measure of positive (pictures of autos) and negative (pictures without autos) to prepare the classifier. At that point, we have to concentrate highlights from it. For this, haar highlights appeared in beneath picture are utilized. They are much the same as our convolutional part. Each component is a solitary esteem acquired by subtracting total of pixels under white rectangle from aggregate of pixels under dark rectangle.



- Now every single conceivable size and areas of every part is utilized to ascertain a lot of components. (Simply envision what amount of calculation it needs? Indeed, even a 24x24 window comes about more than 160000

components). For each component computation, we have to discover whole of pixels under white and dark rectangles. To tackle this, they presented the necessary pictures.

- Now, we apply each component on all the preparation pictures. For each component, it finds the best limit which will characterize the countenances to positive and negative. Be that as it may, clearly, there will be blunders or misclassifications. We select the elements with least mistake rate, which implies they are the elements that best orders the auto and non-auto pictures.
- So now you take a picture. Take each 24x24 window. Apply 6000 elements to it. Check on the off chance that it is auto or not.

Speed Calculation

- Once a car is detected, using the `cascadeClassifier()` function on the haar cascade developed.
- Now the time is started which was initialized to 0.
- Using the ratio in the image for each cm travelled by the detected image and real-time distance in meters, the actual distance covered by the car is calculated.
- As soon as the car reaches the center of the detection window whose distance is already known to us the time is stopped.
- Now the actual distance calculated is divided by the time calculated and velocity is obtained.
- This velocity and the distance of the camera in feet from the car (i.e. the height of camera above the car) is printed on the output screen.

For this use multiple object detection algorithms could have been used but the algorithm of developing the Haar cascade and its implementation proves to be the best since it is the least time consuming, most efficient and highly reliable. Also, it is easy to implement for real time application of the concept.

Framework Architecture

Image Detection

Right off the bat, the locator would stack the classifier what's more, decide it is not unfilled. On the off chance that it is, at that point it just exits with a mistake message. At that point, the picture being referred to is stacked and same system is taken after.

Background Subtraction

To limit the false positive rate beginning from the defects of the classifier, an extra layer was added to the calculation, before the classifier is connected to the picture. This layer has extra information of the finish foundation. This information can be connected to endeavor the separating of the foundation from the picture from which we might want to distinguish vehicles.

Background Subtraction Augmentation

This process uses the erosion and dilation procedure. Dilation is an approach to make the splendid districts of a picture to "develop". As the portion (little lattice utilized for picture handling) is looked over the picture, the maximal pixel esteem covered by the portion is ascertained and the picture pixel in the grapple purpose of the part (for the most part at the focal point of the picture) is supplanted by the maximal esteem.

Erosion works comparably to expansion, however rather than the maximal, it registers the nearby least over the region of the piece, in this way making the dim territories of the picture bigger.

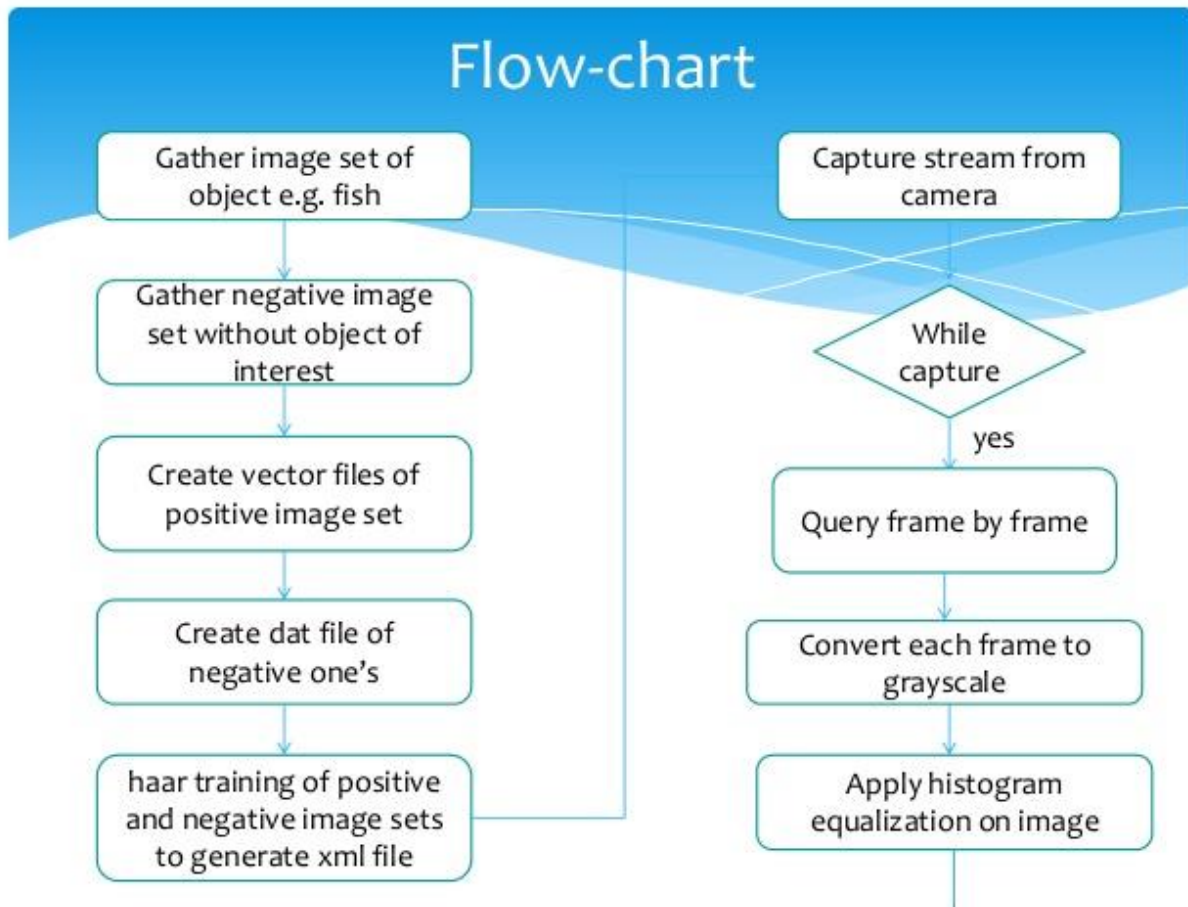
Region Merging

This layer was added after the Haar-cascade has done its work. Since it is possible for the classifier to detect many parts of a car as several distinct cars, the results of the classifier regions must be merged. The merge cannot however just detect whether the two regions have an overlap of any size, because the overlap can simply be the result of two adjacent cars, which would thereby be merged into one result.

Training Cascade

The principal fundamental piece was to assemble the pictures, then make tests in view of them lastly beginning the preparation procedure. The OpenCV train cascade utility is an change over its forerunner in a few viewpoints, one of them

being that train cascade permits the preparation procedure to be multithreaded, which lessens the time it takes to complete the preparing of the classifier. This multithreaded approach is just connected amid the pre-calculation step be that as it may, so the general time to prepare is still very critical, bringing about hours, days and weeks of preparing time.



Results and Analysis

Results

To check the implementation and obtain meaningful outcomes, we used a video file with a busy road which had cars running on it. The following observations were made which show car detection in image1 and the speed and distance of camera from car calculation in image 2.

The green boundary on the car shows the matching of features in the current image to that available in the cascade and therefore identifies it as a car and when the python program is run the time is started henceforth. The blue line represents the center of the image in the frame.

Image 2 is the output screen of the python program which shows the speed calculated of the detected car and the distance of the camera from the car in feet.

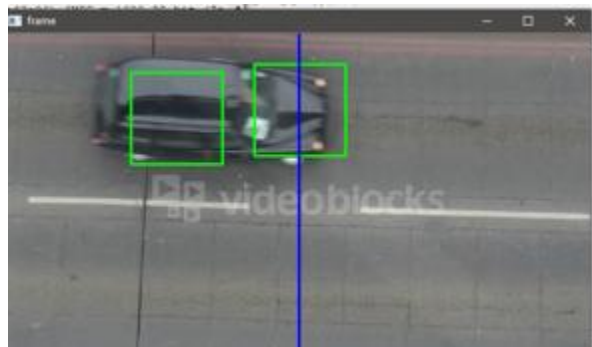
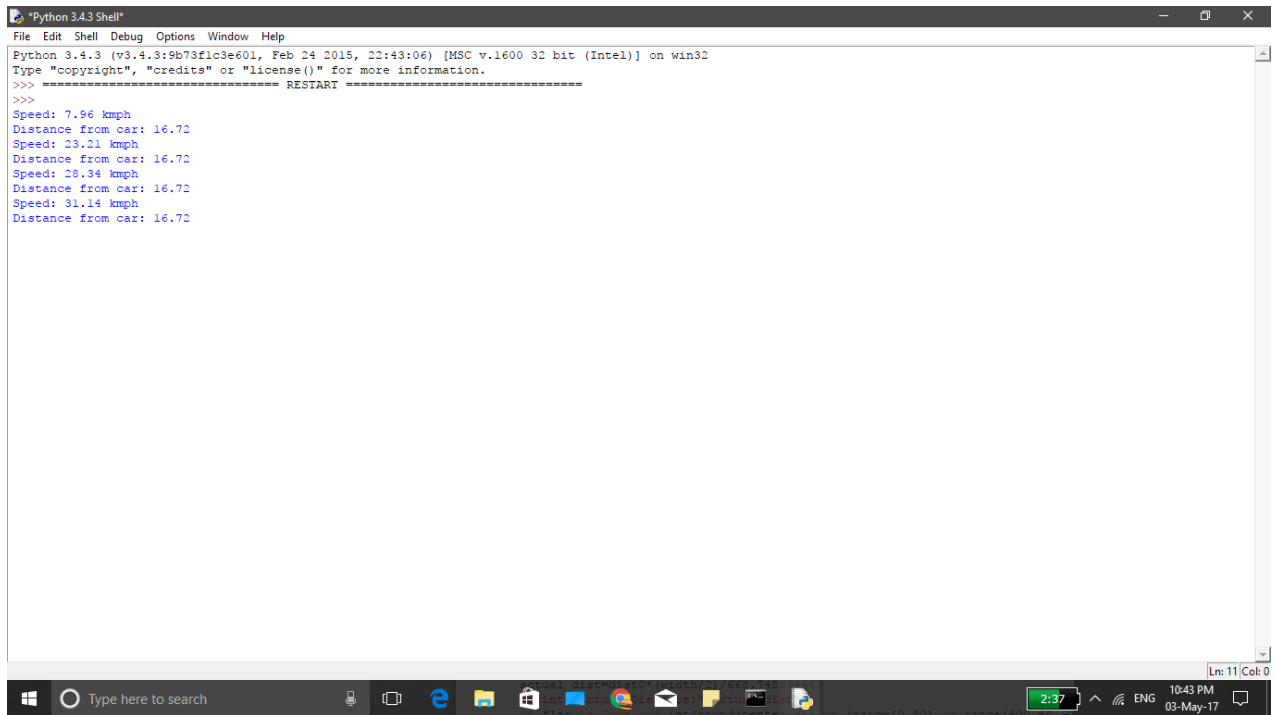


Image 1



```
Python 3.4.3 Shell
File Edit Shell Debug Options Window Help
Python 3.4.3 (v3.4.3:9b73f1c3e601, Feb 24 2015, 22:43:06) [MSC v.1600 32 bit (Intel)] on win32
Type "copyright", "credits" or "license()" for more information.
>>> ===== RESTART =====
>>>
Speed: 7.96 kmph
Distance from car: 16.72
Speed: 23.21 kmph
Distance from car: 16.72
Speed: 28.34 kmph
Distance from car: 16.72
Speed: 31.14 kmph
Distance from car: 16.72
```

The screenshot shows a Windows taskbar at the bottom with the system clock at 10:43 PM on 03-May-17. The Python Shell window title bar includes standard Windows window controls and a menu bar with File, Edit, Shell, Debug, Options, Window, and Help. The main text area displays the Python version and environment information, followed by a restart command and a series of speed and distance measurements.

Image 2

Analysis

For the algorithm used five video files were taken and time for detection as well as velocity calculation was determined and compared to available algorithms for the purpose.

The following graph shows the observations made.

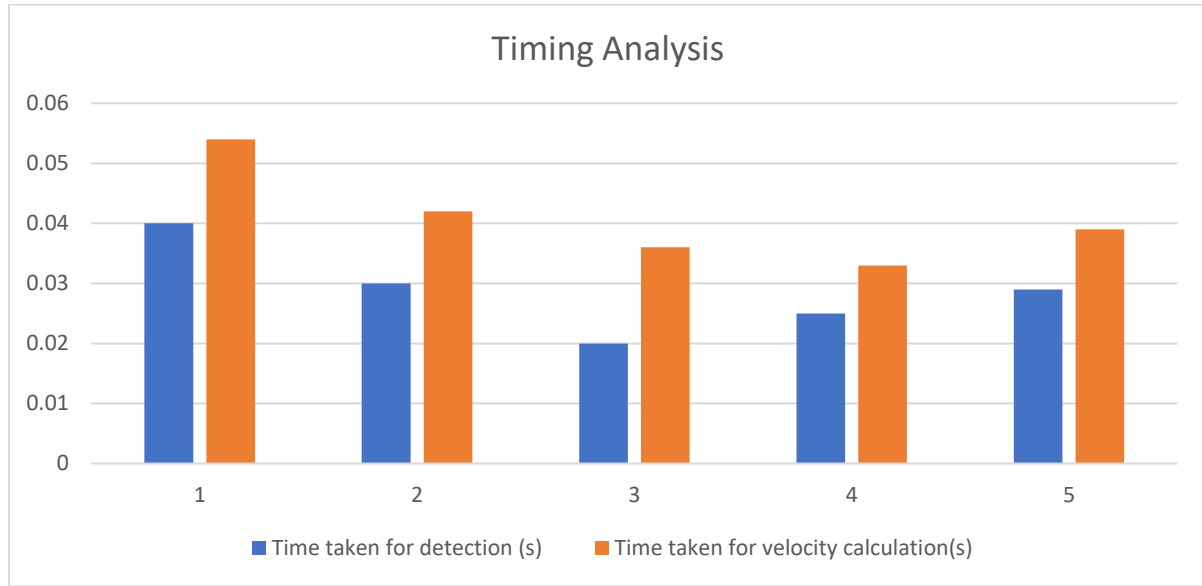


Image	Time taken for detection (s)	Time taken for velocity calculation(s)
1	0.04	0.054
2	0.03	0.042
3	0.02	0.036
4	0.025	0.033
5	0.029	0.039

Table 1

Performance Analysis

Since the detection rate of the next stage is greater or equal to the previous stage rate and only the false detection rate decreases (i.e. every stage corrects the number of false images), we propose to build our own stage by stage measured ROC curve for classifiers comparison (Table 2 and Image 3). We consider that this curve is more suitable for the comparison of classifiers.

We can conclude from the mentioned table (Table 2), that our classifier presents a lower false detection rate, beginning from the earlier stages. This result is due to the proposed algorithm.

stage no.	10	11	12	13	14	15	16	17	18	19	20
hit rate	91,84	94,29	96,1	95,9	96,1	95,6	94,5	94	93,4	93,75	94,3
no.false det	4458	3412	2805	2157	1685	1199	832	598	346	219	143

stage no.	6	7	8	9	10	11	12	13	14	15	16
hit rate	85	89,4	89,9	90,4	88,85	87,8	85,32	83,96	80,16	75,8	75,5
no.false det	4661	3588	2646	2230	1722	1363	1188	846	390	168	150

Table. 2 Stage by stage measurements for FA2 and Class_05

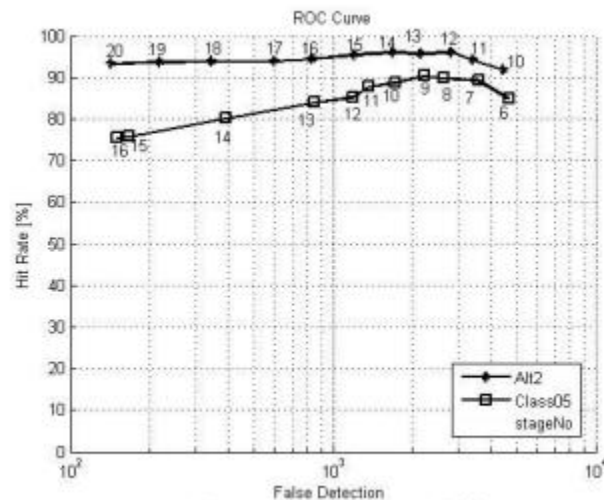


Figure. 3 Stage by stage ROC curve

Hit rate: - It is the ratio of the number of objects detected correctly to the number of objects in the image. The higher the hit rate, better the classifier developed and its working.

No. of false detection: - It is the number of false objects detected while matching features with those trained by the classifier. These should be minimum for the classifier to work better.

Stage no.: - This is the stage of the haar classifier. Here, we have developed a Haar classifier with 20 stages and the hit rate as well as the number of false detection for each stage has been calculated.

CONCLUSION

Hence, we have obtained a 20 stage Haar classifier with a high hit rate and a low number of false detections which shows that the algorithm works fine for detecting cars on the roads. It was developed in a time span of about 5 days using OpenCV.

The classifier matches about 16000 features in an image and identifies the object as a car or not. Also, the algorithm takes very little time to do so, is free of errors and efficient with lesser false detections.

We have also successfully developed an algorithm to measure the velocities of the detected cars on the roads in kms/hour along with the distance of the camera from the car in feet using Python Script.

Both stages of algorithm development were completed well in time limits and work fine for real time implementation which is clear from the multiple test runs and observations made on these test runs that allow us to infer that the algorithm can be used commercially as it is cost effective and efficient.

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