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Distance Estimation by using Camera

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Abstract*— Road accidents are increasing rapidly throughout the world. In India where road traffic is already heterogenic in nature, incidents of road accidents are more frequent. Various reasons behind it are increasing number of vehicles, improper road and traffic infrastructure etc. vehicular speed is also a major reason behind accidents. To overcome this and to take preventative actions, a better infrastructure and use of intelligent traffic system tools should be used. traffic surveillance system is one such a tool but some techniques of it are quite expensive and need high support and some are less precise.to overcome the problem, a new mechanism is needed to be proposed which should be precise and cost efficient. Advance Driver Assistance System (ADAS) requires a distance estimation which is useful in various functions like accident prevention, tailgating detecting and hurdle/obstacle avoidance. Presently RADAR and LIDAR are primarily used in distance estimation which are either quite expensive or gives poor resolution. Present techniques require huge data. Therefore, we propose a system using OpenCV to calculate the distance between cars.

***Index Terms*— Camera, Distance Estimation, Image processing, OpenCV, Python**

I. INTRODUCTION

India is one amongst a busiest nation within the world when it comes about road traffic. The vehicle business over the land was 4 largest within the world up to 2017 [1]. In 2019, there have been as regards to three million additional automobile enrollments within the country. The web of Indian roads is very vast and almost crossed a mark of more than five million. Fast increment within the range of vehicles and relatively slow development within the needed infrastructure resulted as brutally blocked Indian roads [2]. Thus, infrastructure of road use and safety provisions became prior importance of governing bodies and of vehicle users also. Accidents on road may it be pedestrians or drivers, became a major appertain of people still as for the govt. Nearly, 1,51,000 mortalities happened in road accidents in 2018 itself in India [3]. ITS with proper hardware infrastructure including use of artificial intelligence and use of information technology is the only solution or we can say is the closest option towards the solution to mitigate the problem or to reduce the intensity at least. In addition to that equal inputs are needed from vehicle manufacture companies such as to equip their models with latest technologies considering human safety and comfort as a first priority [4]. In each facet, traffic management authority wants a much better closed-circuit television to beat many traffic connected issues. Considering individual driver's purpose of read, an economical system or infrastructure ought to be obtainable at their finish to boost the security [5]. So, it's necessary to propose some mechanisms to beat such issues. Therefore, we have a tendency to planned the system that calculate the space between vehicle to avoid the accidents [6].

There have been a lot of experiments done on symmetrical distance measurement using visual sensors [7]. Depending on the characteristics of the vision sensor, there are several ways that image processing may be used. Multiple pieces of information about the identified vehicle may be gathered by utilizing image processing to identify the vehicle on the input image [8]. The majority of vehicle distance estimating techniques are based on information about the identified vehicle shape [9]. Despite the reasonably precise results of the distance estimate based on the stereo camera, the stereo camera is more costly, and its calculation throughput is less compared to a single camera.

In order to determine the distance between the present vehicle and the observed vehicle, a system is presented in this study to identify a forward moving vehicle using a single camera [10]. The input road picture was divided into multiple-resolution pictures to save computing costs while also ensuring symmetrical real-time computation [11]. Vehicle recognition was then carried out for a low-resolution image. To learn vehicle pictures and produce vehicle detectors, the suggested technique employed a cascade classifier utilizing aggregated channel information [12].

II. LITERATURE SURVEY

Kim et al. [13] noticed automobiles using edge orientation information and Haar-like choices, and they estimated the distance between vehicles using the observed vehicle dimensions. For training, a huge amount of automobile images is required in order to develop a classifier that can detect cars. To solve this problem, they noticed the car using the patterns of the vehicle's back half on the roadway. Misdetection, however, may happen if the vehicle's surface reflects light or if the road picture includes objects that don't appear to be linked to the vehicle (like lanes or pollutions in roads). To use the dimension of the observed car for the determination of the distance of the vehicle, it's needed to precisely notice the form of the vehicle.

In order to determine the spacing towards the vehicle observed inside the image that was non-heritable from the camera, Bertozzi et al. [14] proposed a 2-dimensional image over to a 3-dimensional space using calculation of inverse perspective transformation. Data processing is challenging when projecting a 2-dimensional picture onto a 3-dimensional structure because more computations are required for each ingredient to put into action a safe ADAS.

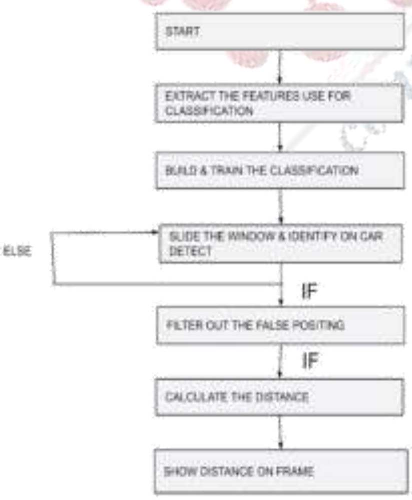
A technique for assessing a driver's motion while driving which is focused on the driving job was introduced by Lee et al. [15]. The probability level might be calculated using the motive force's hand movement data according to their proposed approach. While their methods are focused on the driver's careless driving, the proposed approach suggests a strategy that is interested in the motion of other cars.

A strategy for achieving the motor speed estimate approach was provided by Leite A.V. et al. [16] and focuses on a lower order expand Kalman filter. A lower order state house system which is unique in a very specific and creative way is benefited by rule. But this approach also requires expensive installation and maintenance costs, and it doesn't provide adequate information on devices attached to vehicles.

An optimized fuzzy-set platform for enhancing driving safety in autonomous cars was presented by Yin et al. [17]. In order to increase driving safety by warning drivers of risk, the idea of hazardous driving intensity (DDI) is estimated. Fuzzy sets and particle swarm optimization (PSO) are used to model vehicle, driver, and lane features in order to predict the DDI. The fuzzy sets are optimized using PSO. The experiment's findings show that integrating the vehicle, driver, and lane contexts to estimate the DDI could efficiently increase driving safety by identifying if a driver is engaged in a hazardous driving condition.

III. METHODOLOGY

A. Working



In the developed model using Opencv, the frmework which helps to avoid the accident distance between the vehicles is developed. In this project firstly extract the features used for classification then build and train the classifier. After training of files camera turns on and identify car in captured video if car found then filter out the false positives and calculate the distance of car from capture camera and then print distance on this car frame and this process will continue while we stop. Else work of identification of cars continues while we stop code execution.

B. Algorithm

The ML algorithm used for detecting cars and bounding boxes coordinates is a pre trained cascade model Haar cascade car. Machine learning algorithms create it potential for self-driving cars to exist. they permit a automobile to gather knowledge on the adjoining from cameras and different sensors, clarify it, and choose what actions to require. Machine learning direct permits cars to be told the way to execute these work (or bigger than) humans.

Haar Cascade

Haar Cascade is used for identifying objects in an image or video and it's a machine learning object detection only.

Steps:

Step 1: Import python library

Open Computer vision ::: import Computer vision2

Step 2: Capturing video in the form of frames

Use the ## Video Capture of cv2 and store the value in cap.

cap = cv2.VideoCapture('cars.mp4')

Step 3: Create our body classifier

Trained XML classifiers describing some features of object we should to detect Car_cascade is equal to cv2. cascade classifier(‘cars.xml’)

Using triangle similarity, calculate the distance among the known item and the camera.

The triangle similarity works in the following way,

- Suppose we've a marker or object with a far-famed breadth W.
- After that this marker we have to place a ways D from our camera.
- We have a tendency to capture an image of our object exploitation our camera and so live the evident breadth in pixels P.

This enables United States of America to derive the recognize distance F of our camera given in eqn. (1).

$$\text{Focal length} = (P \times D) / \text{width} \quad (1)$$

For example, suppose I have placed a typical piece of eight point six multiply by eleven in piece of paper (horizontally; W = 12) D is equal to twenty-four inches (D=24) ahead of my camera and take a photograph. When I live the breadth of the piece of paper within the image, I seen that the recognized breadth of the paper is P is two hundred and forty-eight pixels

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(P=248).

My focal length is F is equal to two hundred and forty-eight pixels multiply twenty-four inches divided by twelve after calculation of the value is four hundred and ninety-six (Eqn. (2)).

$$\text{i.e., } F = \frac{(248 \times 24)}{12} \rightarrow F = 496 \tag{2}$$

Still as I move my camera each nearer and farther removed from the object/marker, I will make use of the triangle similarity to identify the gap of the object to the camera: D' is equal to P multiply D divided by W.

Again and again, to form this a lot of concrete, like considered, I move my camera three foot (or thirty-six inches) distant from marker and capture a photograph of a similar piece of paper. Through automatic image process I can confirm that the recognized breadth of the piece of paper is currently one hundred and seventy pixels. Inserting this into the equation we have a tendency to currently get: D' is equal to twelve inches multiply four hundred and ninety-six divided by one hundred and seventy after calculation it is thirty-five inches, like 3 feet (Eqn. (3)).

$$D = \left(\frac{12 \times 496}{170}\right) = 35\ inches \tag{3}$$

IV. RESULTS

In this project, Identify the car in video capture if the car is detected then calculate the distance and print on the frame of that car else identification process will be continuous.

In the first image,

Distance of imaginary image car is = 76.2 cm

focal_length_value is equal to width in rf image multiplied by measured distance divided by real width

#return focal_length.

return value of focal_length

Focal_Length` is focal length, out of multiply Focal Length in to finder function.

define focal_length (measured_distance, real_width, width_in_rf_image):

focal_length_value = (rf_image width×distance measured)/real_width

#return focal_length.

return value of focal_length

And the width is 14.3 cm`real_face_width` the common measure width of real-world object, at this time the face width was measured in real world that was `Known_ Width is equal to 14.3.

frames	xmin	ymin	xmax	ymax
1	656	234	862	330
2	627	234	870	332
3	626	233	869	332
4	627	232	869	330
5	623	230	867	329
6	624	229	868	327
7	626	229	870	325
8	626	244	748	323
9	628	227	872	323
10	645	226	872	321

frames	Scaled_xmin	Scaled_ymin	Scaled_xmax	Scaled_xmax
1	636.525	121.875	836.4037	171.875
2	608.3859	121.875	844.1718	172.916
3	607.4156	121.354	843.2015	172.9166
4	608.3859	120.833	843.2015	171.875
5	604.5046	119.7916	841.2609	171.354
6	605.475	119.2708	842.2312	170.312
7	607.415	119.2708	844.1718	169.270
8	607.415	127.0833	725.79	168.2708
9	609.3562	118.229	846.1125	168.229
10	625.8515	117.708	84.1125	167.1875

#centimeter` of car.

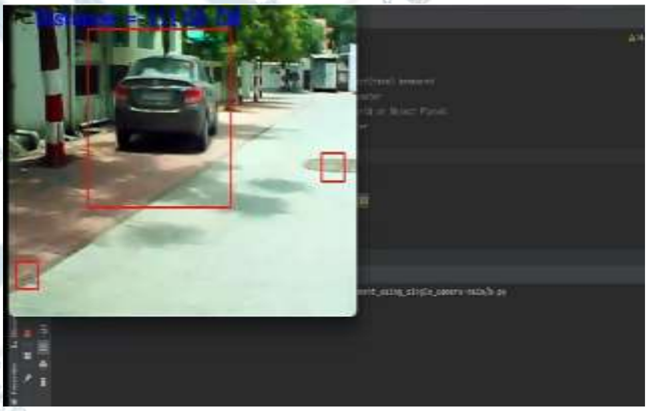

Fig. 1. Distance

Above fig. 1 shows the distance

By using the formula,

Distance is equal to real_face_width multiply focal_length divided by face_width_in_frame

return distance

Distance is equal to 111.55cm

Fig. 2. Distance between the car and the object

In above image we calculate the distance of car from another by image processing. Here we capture the live video and calculate distance. The performance evaluation of distance resolution and accuracy is represented in figure 3 & 4.

By using same formula i.e.,

Distance is equal to real width of face multiplied by focal_length divided by face width in frame return distance.

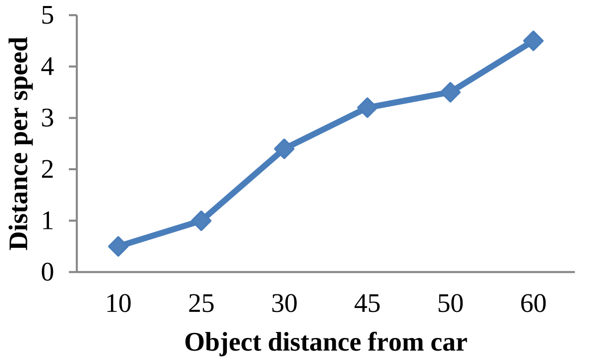

Figure 3: Performance evaluation of distance resolution

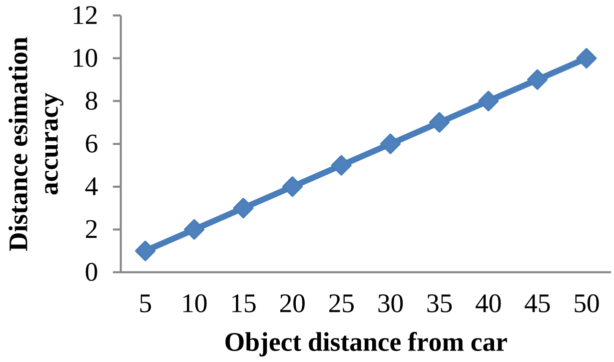

Figure 4: Distance resolution evaluation in terms of accuracy

V. CONCLUSION

The projected approach includes the assessment of the speed of the vehicle which is finished by utilizing the picture strategies. Vehicle distance assessment methods are done utilizing open cv moving multi-motor identification, that recognized motor which brings about greater exactness. the proposed framework diminishes the mishap by knowing the distance between the vehicle or any vehicle. The speed is the most significant thing in venturing to every part of the vehicle. By knowing the speed, we control the mishap which is created by the uncontrolled speed of the vehicle. It is a programming-based framework where no man energy is expected to calculate the distance. So, it's required less time for measuring distance and gives the output fastly as compared to other existing techniques.

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