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Simulation of Collision Avoidance for Autonomous Vehicle

Manjunath R, M S Imran, N P Hemchand,
Department of Computer Science and Engineering, Dayananda Sagar University, Karnataka, India.
Department of Computer Science and Engineering, Dayananda Sagar University, Karnataka, India.
Department of Computer Science and Engineering, Dayananda Sagar University, Karnataka, India.

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ABSTRACT
Self-driving technology presents a rare opportunity to improve the quality of life in many of our communities. Avoidable collisions, single-occupant commuters and vehicle emissions are choking cities, while infrastructure strains under rapid urban growth.Autonomous vehicles are expected to redefine transportation and unlock a myriad of societal, environmental and economic benefits. We apply our analysis skills in this competition to advance the state of self-driving technology vehicles, or cars, that are driverless and autonomous. They have no driver manually to steer. The autonomous car performs these activities without human input. These cars use various technologies like RADAR and LIDAR for detecting the surroundings. They also have controlled systems which analyze the collected data. This analysis is useful in planning a path a vehicle should take in order to reach the desired location. For performing these analytical tasks, i.e in order to process data and produce required output, car controlled systems use various machine learning algorithms. Machine learning algorithms train the system to behave in a certain way.

Keywords:Autonomous Vehicle; Collision Avoidance; Controlled Systems; Obstacle;

I. INTRODUCTION

Collision avoidance is a crucial issue since most of the accidents are due to human errors such as delayed reaction, misestimating the time to collision or the misjudgement of the overtaking maneuver risk. Thus, autonomous driving has witnessed strong progress in the last decade since it aims to omit human intervention on driving by creating fully automated vehicles able to interact with the environment and to react properly and efficiently to the driving situation while guaranteeing safety and comfort.

Collision avoidance on the highway is a challenging task due to the short reaction time, the safety lane constraints, the high impact of coupled lateral and longitudinal vehicle dynamics.For these reasons, safe trajectory generation and guidance to overtake the obstacle have gained much attention in recent years. Moreover, we observed that autonomous vehicles learn their surrounding environment and optimal driving strategies through a large number of onboard sensors, such as lidar, radar and acceleration sensors. However, because of the limited communication range of the vehicles, the collected information from one vehicle is not sufficient to fulfill large-scale road safety requirements and improve the collision performance efficiently. It is extremely difficult for the driver to precisely recognize the situation and immediately decide to act in a way of avoiding the collision or minimizing the damage to his or her body. For collision detection and avoidance, the proposed steps to formulate the proposed model is: 1) Classification of object types using neural network model 2) Determining distance from the autonomous car using data set 3) Comparing the speeds of both obstacle and autonomous car, determine if collision will occur based on relative speeds 4) Apply a collision avoidance algorithm and guide the car.

Problem Definition

Autonomous driving is one of the major problems arising in the emerging technologies.The main challenge in the existing system is to detect signs on the pathway, obstacles and interact accordingly. Our ideology emphasizes the concept of simulation. By performing safe autonomous driving simulation to avoid collisions.

Objectives

The safety verification module that is described in this paper requires the description of a traffic situation containing the following information gathered by the perception module: 1) the planned trajectory of the autonomous car; 2) the geometric description of the relevant road sections; 3) the position and geometry of static obstacles; 4) the position, velocity, and classification of dynamic obstacles.

II. METHODOLOGY

You Only Look Once (YOLO) is a network that uses Deep Learning (DL) algorithms for object detection. YOLO performs object detection by classifying certain objects within the image and determining where they are located on it. For example, if you input an image of a herd of sheep into a YOLO network, it will generate an output of a vector of bounding boxes for each individual sheep and classify it as such. Previous object detection methods like Region-Convolutional Neural Networks (R-CNN), including other variations of it like fast R-CNN, performed object detection tasks in a pipeline of multi-step series. R-CNN focuses on a specific region within the image and trains each individual component separately.This process requires the R-CNN to classify 2000 regions per image, which makes it very time-consuming (47 seconds per individual test image). Thus it cannot be implemented in real-time. Additionally, R-CNN uses a fixed selective algorithm, which means no learning process occurs during this stage so the network might generate an inferior region proposal.This makes object detection networks such as R-CNN harder to optimize and slower compared to YOLO. YOLO is much faster (45 frames per second) and easier to optimize than previous algorithms, as it is based on an algorithm that uses only one neural network to run all components of the task.To gain a better understanding of what YOLO is, we first have to explore its architecture and algorithm.

YOLO Algorithm

Once you input an image into a YOLO algorithm, it splits the images into an SxS grid that it uses to predict whether the specific bounding box contains the object (or parts of it) and then uses this information to predict a class for the object.Before we can go into details and explain how the algorithm functions, we need to understand how the algorithm builds and specifies each bounding box. The YOLO algorithm uses four components and additional values to predict an output:The center of a bounding box (bx by); Width (bw); Height (bh); The Class of the object (c).

YOLO V3

YOLO V3 is an incremental upgrade over YOLO V2, which uses another variant of Dark net. This YOLO V3 architecture consists of 53 layers trained on Image net and another 53 tasked with object detection which amounts to 106 layers. While this has dramatically improved the accuracy of the network, it has also reduced the speed from 45 fps to 30 fps.Dark net is a little awesome open source neural network written in C. Is fast, slim and friendly to use.

III. PROJECT DESCRIPTION

We should enter their details login and register We can enter their details using login and register with their personal details is used for register for login register using login and register we can enter their details for login register with their personal details Vehicle speed count using yolo based algorithm is used for pre trained model for recognize the vehicle and recognition of vehicle and analysis the speed of the vehicle, YOLO based algorithm is implemented for vehicle speed counting to use YOLO for vehicle speed detection, you would need to do the following: Detect the vehicles in the video frame using YOLO. Track the vehicles across multiple frames to determine their speed. Calculate the speed of each vehicle by measuring the distance, it has travelled over time. yolo based algorithm to track the vehicles across multiple frames, you can use a tracking algorithm such as Kalman filter or Hungarian algorithm. these algorithms can track the movement of objects across frames and predict the future positions.

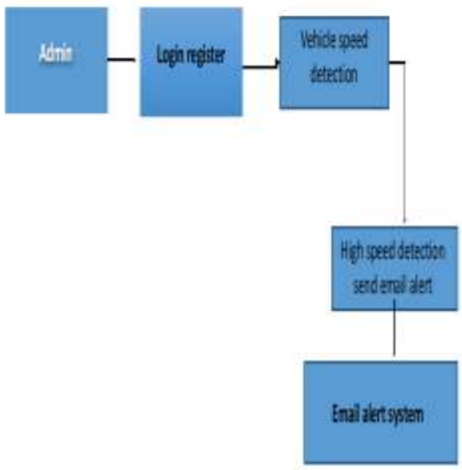

FIGURE 1. Block dig

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FIGURE 2. Flowchart Trajectory analysis

The object detection methods used in this study. The implementation of the highway vehicle detection framework used the YOLOv3 network. The YOLOv3 algorithm continues the basic idea of the first two generations of YOLO algorithms. The convolutional neural network is used to extract the features of the input image. According to the size of the feature map, such as 13*13, the input image is divided into 13*13 grids. The centre of the object label box is in a grid unit, and the grid unit is responsible for predicting the object. The network structures adopted by YOLOv3 is called Darknet-53. This structure adopts the full convolution method and replaces the previous version of the direct-connected convolutional neural network with the residual structure. The branch is used to directly connect the input to the deep layer of the network. Direct learning of residuals ensures the integrity of image feature information, simplifies the complexity of training, and improves the overall detection accuracy of the network. In YOLOv3, each grid unit will have three bounding boxes of different scales for one object. The candidate box that has the largest overlapping area with the annotated box will be the final prediction result. Additionally, the YOLOv3 network has three output scales, and the three scale branches are eventually merged. Shallow features are used to detect small objects, and deep features are used to detect large objects; the network can thus detect objects with scale changes

IV. CONCLUSION

Thus, the project the rapid growth witnessed in urban infrastructure gave tremendous rise to the need to improve road traffic management. Several techniques have been presented and discussed in the literature. In this project, we present a real-time road traffic management approach using an improved YOLOv3. By using online available datasets, we trained our neural-network and applied the proposed solution to improve vehicle detection. We used a convolution neural network for the traffic analysis system. The evaluation results showed that the proposed system achieved satisfactory performance. In addition, it does not need large scale construction or installation work

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