Artificial Intelligence Based on Self Driving Cars with Safety Algorithm

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Abstract- The auto industry is going through a radical transformation with the introduction of self-driving cars, which offer safer and more effective transportation systems. An extensive analysis of the most recent developments in autonomous vehicle technology is given in this research report. It examines the different parts and mechanisms such as perception, decision-making, and control that are essential for autonomous functioning. The study also explores the benefits and problems that come with self-driving automobiles, including ethical issues, legal barriers, and public acceptance.

This study contributes to the continuing discussion on the future of transportation by providing insightful information about the existing and potential states of autonomous cars through a synthesis of recent academic findings and industry advances.

Keywords-- Self-driving Cars, Road Safety, Autonomous Vehicles, Decision Making, Safety Algorithm.

I. INTRODUCTION

Autonomous vehicles are a revolutionary technological development at the nexus of robotics, artificial intelligence, and transportation engineering. These cars have the power to completely change the way we travel, providing a host of advantages like improved mobility, decreased traffic, and increased safety. These cars will represent the first widespread integration of personal robots into human society, despite the fact that the adoption and domestication of technology may encounter immediate or ongoing resistance. In the past ten years, there has been an increase in research interest in using AI to drive automobiles. Cars are ultimately positioned to develop into autonomous robots entrusted with human lives, and this will have a diverse socio-economic impact due to the rapid advancements in artificial intelligence and related technologies. However, in order for these vehicles to work in the real world, they must be endowed with the perceptual and cognitive abilities necessary to handle stressful situations, make wise choices, and always act in the most secure manner.

Visual recognition systems (VRS), including image classification, object detection for segmentation and localization for basic visual functionality are integrated into self-driving car AI [6]. A subfield of computer vision called object recognition using deep learning (DL) approaches especially convolutional neural networks (CNNs) has gained popularity recently. DL is also used to interpret complex vision, improve perception and control kinematic maneuvers in these vehicles. This paper presents techniques that can customize DL for item recognition and scene understanding on autonomous vehicles. But for them to work in the real world, they need to perceive their environment, make good decisions, and always act safely: fundamentally dependent on an advanced network of sensors, actuators, and AI algorithms. Among the essential parts of autonomous driving systems are:

1.1 Sensor Systems:

Lidar (Light Detection and Ranging), radar, cameras, and ultrasonic sensors are just a few of the sensors that self-driving cars are outfitted with. Real-time information about the environment around the car, such as details about other cars, pedestrians, traffic signals, and road signs are provided by these sensors.

1.2 Artificial Intelligence:

AI algorithms are essential for processing sensor data and making intricate decisions instantly. Deep learning and other machine learning techniques allow self-driving cars to learn from their past experiences, anticipate behavior, and identify patterns to enhance their driving capabilities.

1.3. Control Systems:

In order to perform driving functions like steering, braking and acceleration, autonomous cars need highly developed control systems. These systems maintain safe trajectories and prevent collisions by using AI algorithms and sensor feedback.

1.4. Communication Technologies:

Through vehicle-to-vehicle and vehicle to infrastructure communication systems, self-driving cars can interact with infrastructure elements like traffic lights and road signs as well as with each other. This improves general traffic flow, safety, and the ability for cooperative driving behaviors.

The advancement of technology, scientific discoveries, and calculated financial commitments from both established corporations and start-ups have all contributed to the development of self-driving cars. Leading the charge in the development and testing of autonomous vehicle technologies are businesses like Waymo, Tesla, Uber, and conventional automakers like Ford and GM.

In summary, AI-powered self-driving cars have the potential to drastically change the transportation landscape by providing easier, safer, and more convenient mobility options. Even though there are still a lot of obstacles to overcome, continuous research and development work is moving us closer to a time when autonomous cars are a regular sight on the roads.

2.Related Work of Self Driving Cars

2.1 What is AI?

Although technology adoption and domestication may face immediate or continued resistance, these cars will be the first wide-scale integration of personal robots into human society. In the past decade, there has been a surge in research interest in AI driving cars. Eventually, cars will become autonomous robots that drive humans around, leading to a diverse socio-economic impact due to rapid advancements in AI and related technologies.

2.2 What is Self-driven car?

Self-driving cars are fundamentally reliant on an advanced network of sensors, actuators, and AI algorithms to perceive their surroundings, make decisions and navigate routes without human intervention. Some essential components of autonomous driving systems include: Radar, Cameras, Ultrasonic sensors, Numerous businesses, including Audi, BMW, Ford, Google, Tesla, and Volvo, are creating and testing autonomous vehicles. Numerous businesses, including Audi, BMW, Ford, Google, Tesla, and Volvo, are creating and testing autonomous vehicles.

2.3 How self-driving cars work?

Self-driving cars are fundamentally reliant on an advanced network of sensors, actuators, and AI algorithms to perceive their surroundings, Data patterns are found by the neutral network and input into machine learning algorithms. It recognizes street signs, pedestrians, curbs, trees, traffic signals, and other elements of a particular driving situation.

A driver is not necessary for self-driving automobiles to go from point A to point B. The driver of a car is its technology. Numerous sensors, including radar, lidar, and ultrasonic sensors, are part of the technology. Both the front and rear of the vehicle have sensors. Lidar sensors usually include cameras mounted on the roof; without them, the car would be essentially blind.

A vital part of many cars is lidar. It functions similarly to radar. Instead of using radio waves, it makes use of many libraries that are picked up by the lidar sensor through reflections from nearby objects. In this way a point car is generated from the environment. Road signs are not recognized by lidar, though.

Artificial intelligence is used by cameras to identify street signs. In addition, cameras are employed for lane maintenance and obstacle detection. In this case, radar is required for collision warning and avoidance because lidar and cameras are unable to manage the fog.

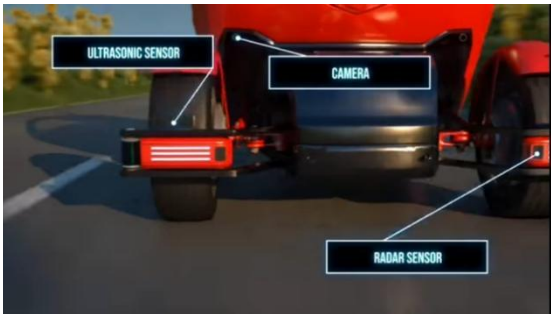

Fig 1. Radar Sensor

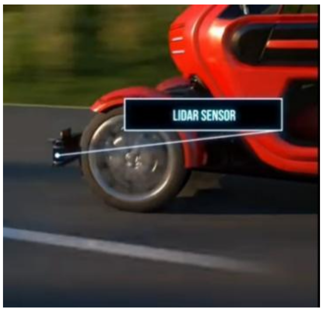

Fig 2. Lidar Sensor

The requirement that the object be large enough to be noticed is one of radar's main drawbacks. This could mean that the radar does not recognize bikes or pedestrians. GPS and incredibly precise digital maps pinpoint the precise location of the car. Speed restrictions and junction signs are only two examples of the vast amount of information that can be found on digital maps. Given that GPS cannot always be relied upon. For instance, in street canes and tunnels.

For instance, the wheel diameter and wheel speed can be utilized to predict the vehicle's future location.

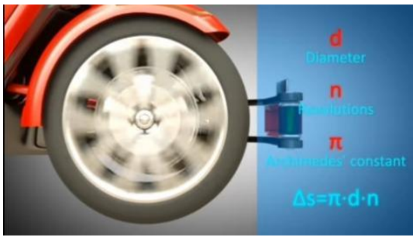

Fig 3. Wheel diameter and speed

Fig 4. Sensor

Every sensor's data is collected, aggregated, and processed by one or more processors.

2.4 Cars with self-driving features:

The car has hands-free steering at the center, meaning you can take your hand off the wheel, but it still requires an attentive driver. Adaptive cruise control (ACC) keeps the driver's car and a vehicle in front of it automatically at a safe distance. When a driver crosses lane markings, lane-centering steering automatically steers the car toward the opposite lane marking.

2.5 Safety Measures of self-driving cars:

Autonomous vehicles have many objects to recognize in their path, ranging from people and animals to branches and rubbish. Other roadside obstacles include tunnels that obstruct GPS construction projects, resulting in lane shifts or difficult decision-making. The system must decide quickly whether to swerve, slow down, or resume regular acceleration.

3.Features of Self driving cars

3.1. Foundations of Technology:

Self-driving car sensor systems (e.g., Lidar, radar, cameras). Machine learning and artificial intelligence algorithms for perception, control, and decision-making. Technology related to vehicle-to-everything and communication systems. Over the past ten years, the Defense Advanced Research Projects Agency

(DARPA) has held three challenges to advance the technology needed for the creation of self-driving cars. The first, known as the DARPA Grand Challenge, took place in the Mojave Desert in the United States in 2004 and required self-driving automobiles to complete a 142-mile course along desert trails in under ten hours. Within the first several miles, all of the rival cars broke down.

In the rerun of the DARPA Grand Challenge (Buehler et al., 2007), autonomous vehicles had to travel 132 miles across flatlands, arid lakebeds, and mountain ranges, with three winding tunnels and over a hundred sharp turns to the left and right. There were twenty-three finalists in this competition, and four cars finished the course in the allocated time. The automobiles Sandstorm and H1ghlander from Carnegie Mellon University came in second and third, respectively, while Stanley from Stanford University took first prize (Thrun et al., 2006).

The third contest, dubbed the DARPA Urban Challenge (Buehler et al., 2009), took place in 2007 at the former George Air Force Base in California, USA. Its objective was for autonomous vehicles to travel a 60-mile course through a fictitious urban setting in six hours, competing against other autonomous and human-driven vehicles. California traffic laws had to be followed by the autos. Six of the eleven cars that competed finished the course in the allocated time. Boss (Urmson et al., 2008) from Carnegie Mellon University took first prize, Junior (Montemerlo et al., 2008) from Stanford University placed in second place, and Odin (Bacha et al., 2008) from Virginia Tech took third place. Despite the difficulties these contests provided. They're being heralded as significant advancements in the field of self-driving cars, while being far more basic than those usually seen in regular traffic.

With an autonomy system that may be classified as SAE level 3 or higher, the research on self-driving cars developed since the DARPA challenges is the focus of this paper's survey of published research on the subject (SAE, 2018).

3.2. Decision Making and Control:

Lidar, radar, cameras. Control algorithms and machine learning. The tech behind vehicle-to-everything communications and related systems. In the past decade, researchers have made huge strides in building self-driving cars, which come equipped with a host of sensors for monitoring their surroundings and algorithms that help them make decisions about what to do next.

But from a technological standpoint, such cars are nothing new: In 2004, the Defense Advanced Research Projects Agency (DARPA) — an agency of the U.S. Department of Defense — launched the first-ever competition for self-driving vehicles. The DARPA Grand Challenge required teams to build autonomous vehicles that could complete a 142-mile course along desert trails in under 10hours. Not one competitor made it more than several-miles before breaking down.

In a revised version of the challenge three years later (Buehler et al., 2007), vehicles had to travel through three tunnels, up and down over 100 sharp turns to the left and right, across flatlands and arid lakebeds, and over mountain ranges for a total distance of 132 miles. Twenty-three finalists competed in this race, with four finishing on time; second place went to Carnegie Mellon University's Sandstorm; third went to its H1ghlander; and Stanford University's Stanley took top honors (Thrun et al., 2006).

3.3. Safety and Reliability:

Standards and frameworks for autonomous vehicle safety are examined. Techniques for evaluating and reducing risk in self-driving systems. Redundancy and fail-safe features in software and hardware design. We observe notably divergent social evaluations of acceptable risk when it comes to transportation. Although most people are aware of the risks associated with numerous transportation systems, the development of legislation, The third installment in DARPA's series — known as the DARPA Urban Challenge (Buehler et al., 2009) — was held at California's former George Air Force Base in 2007. For that competition, autonomous vehicles were given six hours to travel through an imaginary city spanning 60 miles while competing against other autonomously driven machines as well as human drivers. The robot cars were required to follow California traffic laws during the drive. Of the 11 finishers out of a field of more than two dozen, six made it on time; Carnegie Mellon's Boss (Urmson et al., 2008) took first place; Stanford's Junior (Montemerlo et al., 2008) placed second; and Virginia Tech's Odin (Bacha et al., 2008) came in third.

In an era of social and technological uncertainty, all sorts of groups have their own way to put a damper on new things. Those who advocate for precautionary regulation emphasize the novelty and uncertainties that loom over innovators. On the other hand, those in favor of genetically modified crops claim that it's not much different from conventionally bred equivalents. For these people, the tactic is to make it seem 'substantially equivalent' (Millstone et al., 1999). A good innovator knows how to strike a balance between assurances that their technology isn't something we need to freak out about, but also has many benefits (Rayner, 2004).

3.4. Use cases and applications:

An overview of the sectors and industries (such as transportation, logistics, and agriculture) that stand to gain from autonomous driving technology. Case studies of pilot projects and successful deployments.

The regulatory landscape provides an overview of the laws that control the use and deployment of driverless cars.

Obstacle detection is one of the most basic and important technical issues in self-driving systems. There are many sensors used for obstacle detection and recognition, such as visual, ultrasonic, radar, lidar, etc. The advantage of vision sensor-based detection technology over other sensor-based technology is that it has a huge amount of information, high sampling speed and relatively low cost. The two main types of vision sensors based on obstacle detection technology are: binocular vision and monocular vision.

Lane detection is an important feature of self-driving cars. Accurate lane detection can lay a solid foundation for functions such as path planning, collision prevention, deviation warning and so on. The baseline of lane detection refers to the definition of lanes in terms of line segments, point sets or occurrences (the continuation or discontinuation of lanes). The lane identification techniques described in this paper do not limit themselves to any kind of lane detection technique. Conventional image processing algorithm is used to extract potential lane area in conventional lane detection approach , enhance edges , get lane lines features and then obtain lane lines through tracking . However, these traditional image processing methods require more training for specific objects like lanes and are more susceptible to the interference from light, shade and other external conditions.

Path planning has been widely studied for many years and plays a very important role in autonomous driving research. Genetic Algorithm (GA), Particle Swarm Optimization (PSO), etc., which have been widely used in path planning researches also have their own limitations when applied for autonomous vehicle planning tasks under complex situations. Deep learning holds great promise for overcoming the limitations of traditional planning algorithms and learning to plan pathways for self-driving automobiles in an effective manner under a variety of scenarios because of its remarkable advantages in feature extraction. For instance, a deep reinforcement learning-based path planning technique. The issue of training a model with continuous input and output can be resolved with this technique.

4.Algorithms used in self-driven cars

In order to process the information from its camera and sensors and make driving decisions in real time, some of the algorithms that are employed are:

4.1. CNN:

CNN stands for Convolutional Neural Networks, which are designed to process large amounts of data in real time and are used in image recognition and classification. For example, a CNN can achieve 100% classification accuracy on datasets such as ImageNet [180]. In the CNN architecture, the last layer represents the output image categories. The previous layers learn increasingly complex features by backpropagating classification errors, supervised by class labels. There is no separate module for feature extraction or classification; therefore, there is no need for manual feature description and feature extraction. Instead, raw data is input directly into the system and final object categories are learned by extracting features based on pixel values. CNNs have been used in self-driving cars to analyze driver behavior (e.g., gaze direction) [30], details about the driver (e.g., emotional state) [31], mental workload [32], estimated body posture [33], level of drowsiness [34], etc. Since knowledge generation is a prerequisite for full autonomy in self-driving vehicles, we are investigating what intelligence is and how AI systems should be organized. CNNs can be fed with data of various types: photos, videos, text, audio — one-to-one relationship between input and output classes or one-to-many / many-to-many — depending on the type of data you use. Depth is determined by the number of layers in a CNN; similarly to features where all features produced by filters of different sizes are combined and those that work better during backpropagation prevail. Instead of training from scratch new architectures such as GoogLeNet, ResNet, VGGNet use transfer learning from old ones as a predesigned sequence remains but fully-connected layers change. A driving picture convolved with activation functions creates feature maps that can be reduced in size multiple times to focus attention on patterns inside signal or image.

4.2. Object Detection:

This feature helps cars identify items that cross their field of vision, like pedestrians and traffic signals. Finding the cat's precise location is just as important as determining whether or not it is present in the picture. In addition to labeling an object's class, Bounding box techniques are usually used in object localization to identify an objects position. It's a method that supplements the output layer with four additional numbers, and then you can find position again. However, what about finding every single thing? That would be called multiple object detection and localization. You need to apply principles from both image categorization and object localization if you want to detect every different type of item in an image. The algorithm needs all this capability in order to do its job properly. So it has to classify and localize every object somehow. One common way of doing this is feeding the whole image through a ConvNet, along with a sliding window algorithm. What happens is the sliding window moves through the image little by little, and each time it goes over something there will be a clipped section produced with an item, class, and bounding box attached to it . This method is simple but crude. Because of this lots of methods have been developed for this problem alone.

4.3. Optical Flow:

This function helps the system to assess the movement of objects within the vehicle's field of view in order to direct it properly. Optical flow has been used extensively in many applications, including autonomous vehicles. The optical flow was computed from a front-view camera. With the camera motion estimated by a deep network, the flow was divided into an image velocity component and an object motion component. Hou et al argued that two pre-trained auxiliary networks are needed to guide the primary encoder network: one for image segmentation and another for optical flow prediction, so as to provide low-dimensional deep features that can be fed into an LSTM module to predict control signals. We find that since optical flow features can well represent the motion feature along time axis, it is unnecessary to exploit LSTM module to model temporal information. Thus we present that control signals can be directly predicted with optical flow as input. Furthermore, instead of predicting steering angle and speed in one layer like did, we propose a multi-task structure that uses two sub-branches to predict these two independent control signals separately.With separate sub-branches for each of them, our system is more likely generalize well on those control signals where angle and speed have some unusual combinations.

5. Experimental Environment:

The track size in our self-driving car environment is two meters wide and four meters long. The dimensions of the car hardware platform are twenty-one centimeters in length, seventeen centimeters in width, and twelve centimeters in height. To practice and test the car's ability to swerve across each lane, the track is split into two lanes. Also, in figure 3, you can see that we used white tape to draw those curves and lines. Trying not to use the same curve as before is why the angle is about forty-five degrees. We will use oval-shaped lines with more curves than the track for this experiment because they have a significant effect on it. You'll find that bump height is roughly four centimeters as shown.

FIG.3

frames or data readings from cameras and other sensors attached to the Raspberry Pi. SD card is also a component of Stereo pi as it contains Raspbian operating system of Raspberry pi.

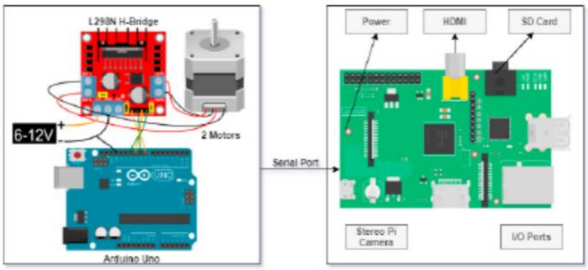

Fig 8. Hardware Implementation

5.2. Dataset:

To collect the dataset, we manually drove a vehicle on the road built by us to get information about the anomaly in the road through its sensors using Bluetooth and mobile. The conditions were made that way so it was easier to gather data. Higher Accuracy in using multiple-axis classification of their sensor data when they used more axis classifications of their sensor data. It has three thousand records of accelerometer data combined with gyroscope data. Dataset comprises GX, GY, and GZ, representing Gyroscope data and AX, AY, and AZ representing Accelerometer data. Two classes are included in the dataset. We labeled initial class labelled as "0" are the normal road's data and second-class label is "1" for anomalous road's data.

5.1. Hardware Environment:

The hardware platform overview is provided here. The car has two motors, an Arduino UNO for its movement and an L298N H-Bridge motor driver to control both motors. The main part of the system is the Raspberry Pi, which connects to a MPU unit, Wi-Fi dongle and stereo vision cameras. All these hardware can allow the system to identify accurately all things in its surrounding space. Two motors are handled by L298N motor driver that receives signals from Arduino while it is powered by external 9V battery. It gives those signals utilizing serials from Raspberry Pi which it received earlier. The path between Arduino and Raspberry Pi through this serials is a Serial Path. Also, Algorithm input may be either video

6 Conclusion

As technology progresses on a global scale, self-driving cars are going to take over as the primary mode of transportation. The concepts of accountability, efficiency and culpability are critical in the legal, moral and societal consequences that will follow. Fuel efficiency boosts the economy and allows less carbon emissions into the environment which will result in many people being very happy with them. Advances in security technology will help to avoid hackers and improve internal systems accuracy. It'll also be crucial in stopping accidents from happening. When all of these technologies reach their peak, we'll be one step closer to achieving flying cars — something many people dreamed of when they were children. CNNs are exceptional at extracting features which is why it made sense for us to analyze popular deep learning architectures, frameworks and models for object detection. We found that both CNN by itself and RNN mixed with CNN are commonly used techniques currently employed. They're able to recognize small patterns within images while resisting rotational or translational changes with ease. Utilizing DL for real-time object detection is expected by researchers who test self-driving vehicles so we discussed their current efforts here. By using GPU tech and cloud computing to speed up processing, DL was able to examine information in real-time before sharing it with other vehicles and the cloud operating around them within a meaningful area

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