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A Review on Self Driving Cars based on ML Algorithm and Artificial Intelligence

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Abstract— *The idea of a self-driving car has become increasingly prevalent in recent years, despite the widespread integration of driver assistance technologies into high-end automobiles. The self-driving car, also known as the wheeled mobile robot, is a type of intelligent car that, using data from automotive sensors, including perception of the path environment, route information, and car control, travels to a destination. Transporting people or items to a predefined target without human drivers is the core feature of self-driving cars. Automatic control, architecture, artificial intelligence, computer vision and many other technologies are integrated into the self-driving car, which is a product of the highly developed computer science, pattern recognition and intelligent control technology. From a different viewpoint, the technology of self-driving cars represents the level of scientific research and industrial strength of a country.*

Keywords— Machine learning, Artificial Intelligence, automatic control, self-driving, computer vision

I. INTRODUCTION: -

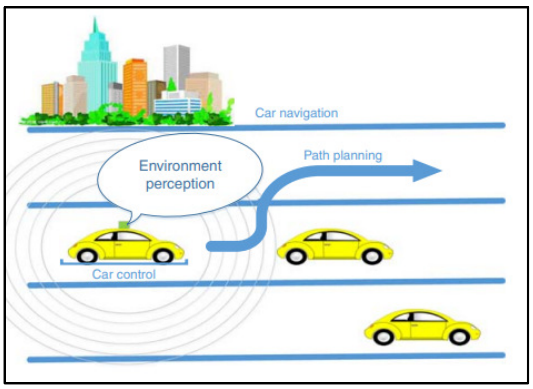
The self-driving car, also known as the wheeled mobile robot, is a type of intelligent car that, using data from automotive sensors, including perception of the path environment, route information, and car control, travels to a destination. Transporting people or items to a predefined target without the need for a human driver is the primary feature of self-driving cars. The self-driving automobile, a creation of very advanced computer science, pattern recognition, and intelligent control technology, incorporates automatic control, architecture, artificial intelligence, computer vision, and many other technologies. From a different angle, a nation's capacity for scientific research and industrial development can be gauged by the technology of its self-driving cars. Due to its complexity, the technology behind a self-driving car has only been examined in a small number of studies. This study proposed a new classification for the self-driving car's core technology based on how the function is implemented in order to simplify and clarify the description. The primary distinction between self-driving cars and manual cars is that the human driver is replaced with automation equipment. The basic technology of a self-driving car is divided into four major components known as the car navigation system, path planning, environment perception, and car control based on this characteristic and functional requirement on driving and on-board equipment modules.

In contrast to the approach of classification based on automotive level, this study suggests a new classification based on the self-driving car's function realization. This classification is able to concisely express the technical specifications for a self-driving car, assisting researchers and pertinent businesses in comprehending the technical implementation of the self-driving car. It is also able to succinctly describe the key technologies of the self-driving car's implementation and its most recent advancements. According to the role of a self-driving automobile, this study divides the core technology into four categories: environment perception, vehicle navigation, path planning, and vehicle control. Each component is independent from the others, with no coverage overlap. This classification is inspired by the operation steps of human driving vehicles and is easy for researchers to understand.

II. DESCRIPTION:

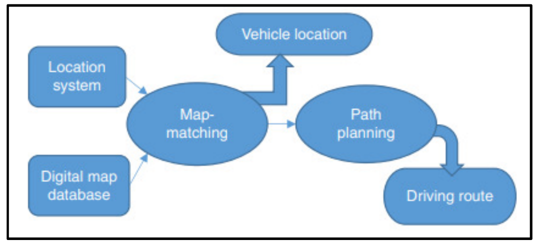
A. *Car navigation system*

The current location of the car and how to get from the location to the destination must be determined during self-driving. Undoubtedly, a human's understanding of driving can be used to resolve the two problems mentioned above. However, for self-driving to work, the vehicle must be able to autonomously and intelligently determine its location and design a route to the desired location. The self-driving car's on-board navigation system is used to achieve this goal. The global positioning system (GPS) and geographic information system (GIS) in the car navigation system are set up to receive location data from the satellite, such as longitude and latitude. These data serve as the source data inputted into the map-matching model, where the intelligent path planning algorithms (i.e. Dijkstra algorithm, Bellman-Ford algorithm) are used to enable the path planning calculation. These data are combined with the road information generated by the location system and digital map database. The self-driving automobile can locate itself after some calculation. The path planning model can also be used to programme and compute the driving route using the location and destination information for the self-driving automobile.



B. Location system

The primary goal of the location system is to pinpoint the location of the vehicle, which can be divided into relative, absolute, and hybrid locations. The car's relative course angle and speed can be computed by integrating these data (such as angular velocity and accelerated velocity). By incorporating the course angle and speed once more, it is possible to determine the car's direction and distance. The current car location can be determined by adding the previous vehicle location. However, the difference between the predicted location and actual location will inevitably occur owing to vehicle vibration when it is driving. The position of the vehicle is determined using the absolute location approach using data from the positioning system. The satellite-based systems, including GPS, GLONASS, Galileo, Beidou, and others, are a common type of positioning system. The measured absolute position is not exact because the satellite signal is susceptible to interference from the weather and urban environment, including buildings and mountains, which introduce inaccuracy and noise into the location signal. The most popular technique for finding the position of a self-driving automobile is the hybrid location, which combines the advantages of the previous two locating approaches.



C. Electronic map (EM)

EM is used to store digital map data, which mostly consists of geographic information, traffic data, building data, traffic signs, road facilities, etc. The majority of the EMs utilised in self-driving cars today are human-designed EMs. In the future, it's anticipated that customised EMs for self-driving vehicles will be developed, including ones that automatically recognise road signs and interact among themselves. The self-driving car EM, known as HD map, has now surfaced. On the one hand, an HD map has higher absolute coordinate precision than a regular map. For instance, it is stated that its upcoming drawing apps will be centimeter-accurate, while the parts of road traffic information are richer and more detailed. The nature of computer vision, consideration of 3D modelling technology, the development of cloud computing technology based on the deep-learning environment perception and end-closed loop real-time update will allow for the gradual development of highly automated driving levels in HD maps in the future. This study predicts that once the 5 G standard is implemented and artificial intelligence enters its mature stage, HD maps will steadily mature and become one of the most important technologies to enable intelligent driving networks.

D. Map matching

Map matching, the cornerstone of path planning, determines the location of the car by combining the geographic data from GPS/INS and the map data from EM. The advanced fusing approach is used during the calculation to fuse the longitude, attitude, or other coordinates information into the EM. The output of the car location should be precise and timely from a practical perspective. Finding an effective mechanism to combine the data from GPS and INS is crucial in this regard. In fact, the INS or GPS satellite signal could occasionally be lost, therefore a good data fusion approach that can incorporate the data from the current location and route situation will significantly improve the accuracy, resilience, and reliability

E. Global Path Planning

The best route between the start and destination points is chosen using global path planning. To combine the EM information and determine the best way, common path planning techniques including the Dijkstra algorithm, Bellman-Ford algorithm, Floyd algorithm, and heuristic algorithm are typically used (Seshan and Maitra, 2014).

F. The next step of navigation system

The position module must incorporate the data from EM during path planning. Even while the location-based technologies that are essential to self-driving cars—the EM and positioning system—have developed and been commercially adopted, there are still numerous obstacles to overcome.

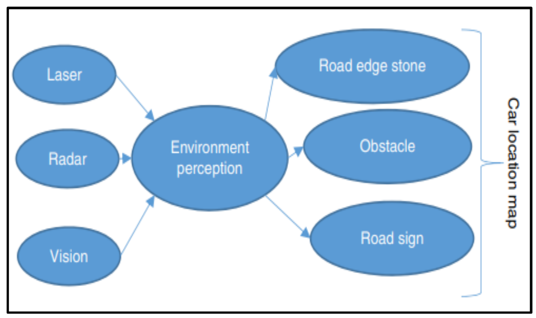
(1) The trade-off between price and accuracy: The current location system in a self-driving car primarily relies on the satellite location system; however, high-accuracy location information extraction is necessary to achieve the stability and accuracy of satellite signal, and high cost is then required to spend on the additional equipment. Therefore, it is essential to lower the cost while preserving location accuracy in large-scale commercial applications in the future.

(2) The compromise between speed and location accuracy: Even in a case where the self-driving car is going at a high speed, it is still important to find it precisely; yet, higher speeds cause the position information to update more quickly, necessitating the integration of additional data. However, because of the equipment's limited computational power and processing speed (i.e., CPU), it is unable to calculate location data in real time, which results in inaccurate position. Therefore, a future study focus will be on getting high-accuracy location under high-speed conditions.

(3) The specific EM for self-driving cars: While the general EM is now used in self-driving cars, it is important to build a special EM for a self-driving car to take into account the human identity, such as a person's interest or career, in order to speed up the EM's response time.

G. Environment perception

A self-driving car's second module is environment perception. The car must independently perceive its surroundings in order to supply the data required for the control decision. Laser navigation, optical navigation, and radar navigation are the three main techniques for detecting the surroundings. Multi-sensors (such as laser sensors and radar sensors) are used to gather detailed information about the environment, which is then combined to create an impression of the environment. The radar sensor is used for distance perception, the vision sensor is used to recognise traffic signs, and the laser sensor is used to bridge the gap between the actual world and the data world. The self-driving automobile combines input from visual, radar, and laser sensors to create a perception of its surroundings, including the road.



III. IMPLEMENTATION:

Nowadays, a lot of different problems are solved using machine learning algorithms, from self-driving cars to financial market predictions. It is critical to improve the usage of machine learning for new tasks as sensor data processing is integrated into a centralised electronic control unit (ECU) in an automobile. Applications could include categorising driving situations or assessing driver fitness using data fusion from various internal and external sensors, including cameras, radars, lidar, and the Internet of Things.

Applications that control a car's entertainment system can get data from sensor data fusion systems and, for instance, can steer the car to a hospital if it detects a problem with the driver. The driver's gesture, speech, and language recognition capabilities can all be included in this machine learning-based application. Both supervised and unsupervised algorithms can be used to describe

the methods. How kids learn makes a distinction between the two.
Using a training data set, supervised algorithms learn, and they keep learning until they attain the target degree of confidence (minimization of probability error). Anomaly detection, regression, and dimension reduction are three subcategories that they might be categorised under.

Unsupervised algorithms attempt to interpret the information at hand. In order to find patterns, an algorithm creates a relationship within the set of data that is accessible, or it splits the data set into subgroups based on how similar they are to one another. Unsupervised algorithms can be broadly divided into two categories: association rule learning and clustering.

Reinforcement algorithms are a new class of machine learning algorithms that sit between supervised and unsupervised learning. For every training example, there is a goal label in supervised learning; there are no labels at all in unsupervised learning; and the labels in reinforcement learning are sparse and time-delayed—they represent the future rewards.

(i) MACHINE LEARNING:

Continuous depiction of the surrounding environment and the prediction of potential changes to those surroundings are two of the primary duties of any machine learning system in the self-driving car. Four sub-tasks make up the majority of these tasks:

- Detecting objects
- Identification or recognition of an object Classification of objects
- Object localization and movement prediction

Regression algorithms, pattern recognition algorithms, cluster algorithms, and decision matrix algorithms are the four broad categories into which machine learning algorithms can be categorised. There are multiple subtasks that can be carried out by a single category of machine learning algorithms. Regression techniques, for instance, can be utilised for object localisation, movement prediction, and object detection.

a. Regression Algorithm:

This kind of algorithm is effective in forecasting outcomes. Regression analysis calculates the relationship between two or more variables, compares the impact of variables assessed on various scales, and is primarily motivated by three metrics:

i. how many independent variables there there

ii. dependent variables' nature

iii. The regression line's form.

The development of an image-based model for prediction and feature selection is the biggest problem for any algorithm. In ADAS, pictures (radar or camera) play a very essential role in localization and actuation.

Regression techniques use the environment's repeatability to build a statistical model of how an image and a specific object's position relate to one another. By permitting picture sampling, the statistical model may be learned offline and offers quick online detection. Additionally, it doesn't necessitate intensive human modelling in order to be expanded to other objects. The method provides the online stage with an object position and a confidence in the object's presence as outputs.

Long learning and short prediction can both be done using these techniques. Regression algorithms of the Bayesian, neural network, and decision forest types are among those that can be applied to self-driving cars.

b. Pattern Recognition Algorithms (Classification)

To distinguish instances of an item category by excluding the unnecessary data points, filtering of the images is necessary in ADAS. Images collected by sensors contain all forms of environmental data. Algorithms for pattern recognition are effective at excluding these anomalous data points. Prior to classifying the items, it is crucial to identify patterns in a data collection. These formulas might also be referred to as data reduction formulas.

By locating object edges and fitting line segments (polylines) and circular arcs to the edges, these methods aid in the reduction of the data set. A new line segment is initiated once a line segment has been aligned to edges up to a corner. Sequences of line segments that closely resemble an arc are fitted with circular arcs. Line segments and circular arcs from the image are combined in different ways to create the features that are needed to identify an object.

c. Clustering

The system's visuals might occasionally be blurry, making it challenging to identify and find items. It's also feasible that the object will go unclassified and not be reported to the system by the classification algorithms. Low-resolution photos, a dearth of data points, or inconsistent data may be at blame. Discovering structure from data points is a strong suit of this kind of algorithm. Similar to regression, it describes the class of problem and the class of methods. Modeling strategies like centroid--based and hierarchical modelling are usually used to group clustering techniques. The goal of all methods is to use the data's natural structures to group the data into sets that have the most things in common. K-means and Multi-class Neural Network algorithms are the most popular types of algorithms.

d. Decision Matrix Algorithm

This kind of algorithm excels at methodically locating, examining, and rating the effectiveness of relationships between collections of values and data. The main application of these algorithms is decision-making. Depending on how confident the algorithms are in the classification, recognition, and forecast of an object's next movement, an automobile may need to make a left turn or brake. These algorithms are models made up of numerous decision models that were independently trained, and whose predictions were then integrated in some fashion to produce the overall forecast while lowering the likelihood of decisional errors. Gradient boosting (GDM) and AdaBoosting are the most widely utilised algorithms.

(ii) CNN

A Convolutional Neural Network (ConvNet/CNN) is a Deep Learning method that can take in an input image, give various elements and objects in the image importance (learnable weights and biases), and be able to distinguish between them. Comparatively speaking, a ConvNet requires substantially less preparation than other classification techniques. ConvNets have the capacity to learn these filters and properties, whereas in primitive techniques filters are hand-engineered.

Through the use of pertinent filters, a ConvNet may effectively capture the spatial and temporal dependencies in a picture. Because there are fewer factors to consider and the weights can be reused, the architecture provides a better fitting to the picture dataset. To put it another way, the network can be instructed to understand the sophistication of the image better. Technically, deep learning uses CNN models to train and test, each input image will pass it through a series of convolution layers with filters (Kernels), Pooling, fully connected layers and apply Softmax function to classify an object with probabilistic values between 0 and 1.

IV. CONCLUSION:

The future of the auto industry is autonomous vehicles. Self-driving vehicles represent a significant advancement both technologically and practically. You see, these cars are equipped with everything necessary to facilitate and speed up our daily work. Companies that operate self-driving cars can save time and money (drivers can concentrate on more difficult jobs, for example) and even run around-the-clock, all year round. Less accidents occur overall (AI algorithms are never tired, intoxicated, or sleepy)

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