International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

Designing An Autonomous Vehicle Through The Image Processing And Machine Learning

Sandeep. M[1], Vijay Kumar. P[2], Kalpana. P[3], Kavitha. P[4], Manasa. Ch[5], Chandra Sekhar. V[6], Praveen. Y[7]

[1,2,3,4,5,6,7] Student, GMR Institute of Technology, Rajam, India

ABSTRACT :

The advent of image processing and machine learning techniques has revolutionized the development of autonomous vehicles, offering promising avenues for enhancing safety, efficiency, and adaptability. This paper presents a comprehensive framework for designing an autonomous vehicle system leveraging advanced image processing algorithms and machine learning models. The proposed system integrates various components, including sensors, cameras, actuators, and onboard processors, to enable real-time perception of the vehicle's surroundings. Image processing algorithms are employed for tasks such as object detection, lane recognition, traffic sign recognition, and pedestrian detection, providing crucial inputs for decision-making. Machine learning algorithms play a pivotal role in analyzing and interpreting the vast amounts of visual data collected by the vehicle's sensors. Deep learning models, such as convolutional neural networks (CNNs), are utilized for tasks like semantic segmentation, object classification, and trajectory prediction, enabling the vehicle to understand its environment and make informed navigation decisions. Furthermore, the autonomous vehicle system incorporates robust control algorithms for trajectory planning, obstacle avoidance, and path following, ensuring smooth and safe operation in diverse road conditions. Real-world testing and validation are conducted to assess the performance and reliability of the proposed system under various scenarios and environmental factors. Overall, the integration of image processing and machine learning techniques offers a promising pathway towards the development of highly capable and intelligent autonomous vehicles, poised to revolutionize transportation systems and redefine mobility in the future.

Keywords: Driverless cars, Arduino, Sensors, Real- time data, Actuators, MATLAB.

INTRODUCTION :

The autonomous car has received a lot of attention during the past decade and prototype versions have been developed by different vendors. However, the commercial realization of autonomous vehicles remains a significant challenge. At the very basic level, the autonomous car is equipped with a myriad of sensors and actuators that generate a lot of data in real-time that must be processed and analyzed for timely decisions to be made. Therefore, the design of an autonomous car must consider the volume, speed, quality, heterogeneity, and real-time nature of data. It is worth noting that different auto manufacturers leverage onboard sensor and actuator technologies for different types of optimized applications. However, at the core of the autonomous car design is the major requirement of being able to function autonomously. Vehicles were once considered the realm of mechanical engineers. However, the unprecedented advancements in automobiles and information technology have transformed the traditional vehicle from an old-fashioned source of the commute into a full-scale, smart, and infotainment-rich computing and commuting machine on the move. If we take a close look at recent advances of the afore-mentioned technologies, we find that the features and characteristics offered by both cutting edge communication and computing technologies along with the emergence of high-end cars provide the foundation for the realization of smart vehicles. These smart cars are autonomous in that they support features such as sensing the surrounding environment, making quick and timely decisions, navigating without human input on the road, maintaining safe mobility patterns, performing all kinds of maneuvers, and cruise control, to name a few.

1.INTRODUCTION TO MACHINE LEARNING :

The term Machine Learning was coined by Arthur Samuel in 1959, an American pioneer in the field of computer gaming and artificial intelligence, and stated that it gives computers the ability to learn without being explicitly programmed. Machine learning is a subfield of artificial intelligence (AI). The goal of machine learning generally is to understand the structure of data and fit that data into models that can be understood and utilized by people.In short, Machine Learning is a modeling technique that involves data. This definition may be too short for first-timers to capture what it means. So, let me elaborate on this a little bit. Machine Learning is a technique that figures out the model out of data. Here the data means information such as documents, audio, images, etc. The model's final product of Machine Learning. Before we go further into the model, let me deviate a bit. Isn't it strange that the definition of Machine Learning only addresses the concepts of data and model and has nothing to do with "learning"? The name itself reflects that the technique analyzes the data and finds the model by itself rather than having a human do it. We call it "learning" because the process resembles being trained with the data to solve the problem of finding a model. Therefore, the data that Machine Learning uses in the modeling process is called "training" data.

1.1 Types of machine learning

Many different types of Machine Learning techniques have been developed to solve problems in various fields. These Machine Learning techniques can be classified into two types depending on the training method.

• Supervised learning

• Unsupervised learning

Supervised Learning ;

Supervised learning is very similar to the process in which a human learns things. Consider that humans obtain new knowledge as we solve exercise problems.

To solve a given problem of supervised learning, one has to perform the following steps:

1. Determine the type of training examples. Before doing anything else, the user should decide what kind of data is to be used as a training set for example, this might be a picture or any voice note.
2. Gather a training set. The training set needs to be representative of the real-world use of the function. Thus, a set of input objects is gathered and corresponding outputs are also gathered, either from human experts or from measurements.
3. Determine the input feature representation of the learned function. The accuracy of the learned function depends strongly on how the input object is represented. Typically, the input object is transformed into a feature vector, which contains several features that are descriptive of the object. The number of features should not be too large but should contain enough information to accurately predict the output.
4. Determine the structure of the learned function and corresponding learning algorithm. For example, the engineer may choose to use support vector Machines or Decision trees.
5. Complete the design. Run the learning algorithm on the gathered training set. Some supervised learning algorithms require the user to determine certain control parameters. These parameters may be adjusted by optimizing performance on a subset (called a validation set) of the training set.
6. Evaluate the accuracy of the learned function. After parameter adjustment and learning, the performance of the resulting function should be measured on a test set that is separate from the training set. Training data already trained.
   Ex: { input, correct output }

Unsupervised learning:

Learning in unsupervised learning is the series of revisions of a model to reduce the difference between the correct output and the output from the model for the same input. If a model is perfectly trained, it will produce a correct output that corresponds to the input from the training data. In contrast, the training data of the unsupervised learning contains only inputs without correct outputs.

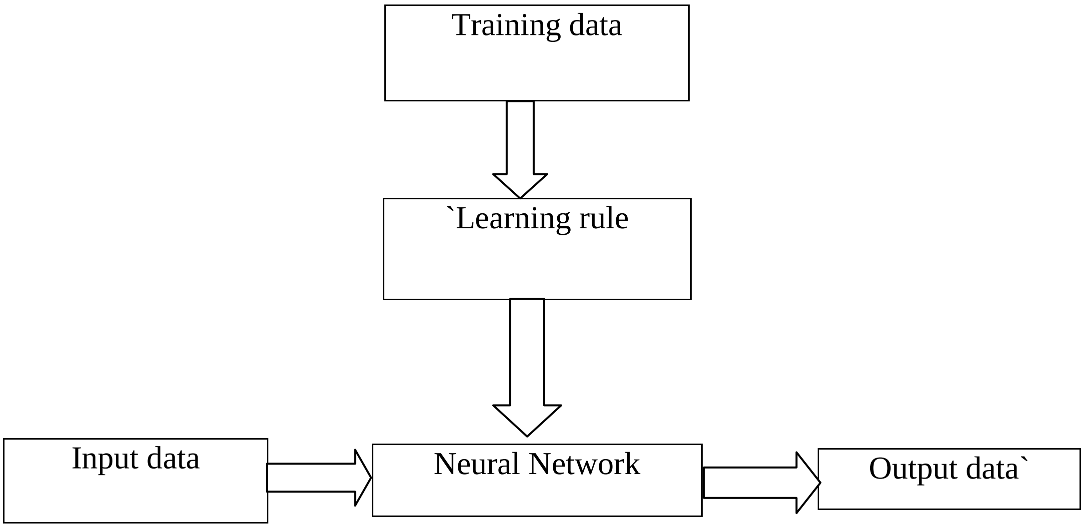
Ex:{ input }

At first glance, it may seem difficult to understand how to train without correct outputs. However, many methods of this type have been developed already. Unsupervised learning is generally used for investigating the characteristics of the data and preprocessing the data. This concept is similar to a student who just sorts out the problems by construction and attributes and doesn't learn how to solve them because there are no known correct outputs.

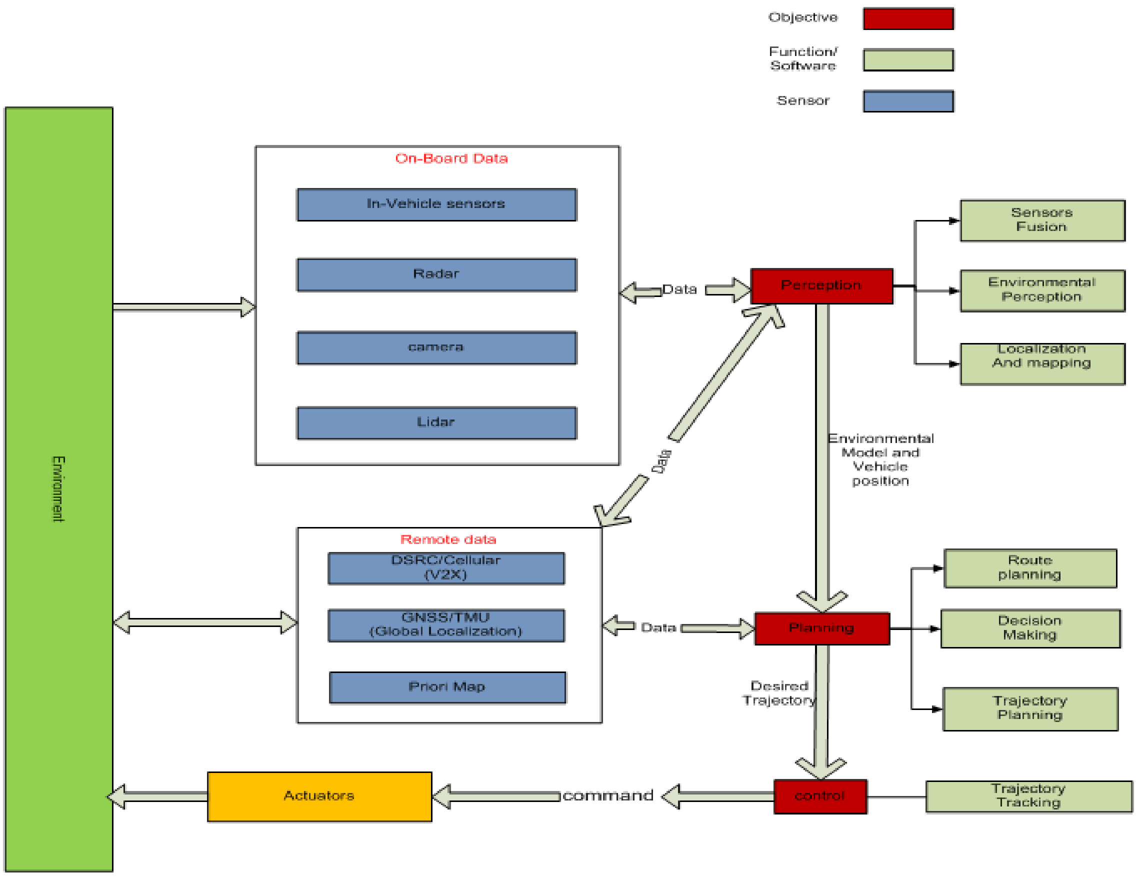
Neural Network:

This Module introduces the neural network, which is widely used as the model for Machine Learning. The neural network has a long history of development and a vast amount of achievement from research works. There are many books available that purely focus on the neural network. Along with the recent growth in interest for Deep Learning, the importance of the neural network has increased significantly as well. We will briefly review the relevant and practical techniques to better understand Deep Learning. For those who are new to the concept of the neural network, we start with the fundamentals.

The models of Machine Learning can be implemented in various forms. The neural network is one of them. Simple isn't it? Figure 2-1illustrates the relationship between Machine Learning and the neural network. Note that we have the neural network in place of the model and the learning rule in place of machine learning. In the context of the neural network, the process of determining the model (neural network) is called the learning rule. This Module explains the learning rules for a single-layer neural network.



2. METHODOLOGY FOR AN AUTONOMOUS VEHICLE TO HAVE IMAGE PROCESSING AND MOVE IN A COMPLEX ENVIRONMENT



In the domain of Connected Autonomous Vehicles (CAV), there exist three core functions: perception, planning, and control, as illustrated in Figure. The perception component gathers a variety of environmental data from different sensors. By either utilizing raw sensor data or employing fused sensor techniques, this layer determines the vehicle's global and local positioning while generating a map of the environment. The planning aspect establishes the most efficient route from the vehicle's current position to the desired destination by leveraging external map data containing information about road layouts and traffic conditions. Following this, taking into account real-time vehicle status and current environmental factors (such as lane markings, nearby vehicles, pedestrians, and road signs) provided by the perception layer, the planning layer devises a local trajectory through dynamic decision-making and trajectory planning. Finally, to adhere to the designated trajectory, the control layer calculates the necessary commands to control the vehicle's actuators (such as steering, acceleration, and braking). Through vehicle connectivity, the perception layer can exchange environmental data with other road users, facilitating collaborative driving capabilities within the planning layer.

Planning involves employing decision-making algorithms within a hierarchical control structure, where decisions made at a higher level influence the servo control mechanisms at a lower level to effectively steer or operate the vehicle. Moreover, beyond the challenges posed by individual vehicle autonomy, the interconnectivity among vehicles, as well as between vehicles and infrastructure or other road users, along with the collaborative perception and control mechanisms involved, contribute significantly to the intricacy of Connected and Autonomous Vehicles (CAVs).

- On-Board Data: This section refers to the data that is collected by the car's sensors
- Sensor: This section refers to the devices that collect data about the car's surroundings.
- Data: This section refers to the raw information that is collected by the car's sensors.
- Fusion: This section refers to the process of combining data from multiple sensors to create a more complete picture of the car's surroundings.
- Perception: This section refers to the process of understanding the car's surroundings using the data from the sensors.
- Environmental Model: This section refers to a digital representation of the car's surroundings that is created using the data from the sensors .
- Route Planning: This section refers to the process of planning a safe path for the car to follow.
- Decision Making: This section refers to the process of choosing the best course of action for the car to take.
- Desired Trajectory: This section refers to the planned path that the car should follow.
- Command: This section refers to the signals that are sent to the car's actuators to control its movement.
- Control: This section refers to the process of keeping the car on the desired trajectory.
- In-Vehicle Sensors: These are sensors that are mounted inside the car. Examples of in-vehicle sensors include accelerometers, gyroscopes, wheel speed sensors, and steering wheel angle sensors.
- Remote Data: This data is collected from sources outside of the car. Examples of remote data include data from other vehicles, traffic signals, and high-definition maps.
- DSRC/Cellular (V2X): This refers to Dedicated Short-Range Communication/Cellular Vehicle to Everything, which is a type of communication technology that allows vehicles to communicate with each other and with roadside infrastructure.
- GNSS/IMU (Global Navigation Localization System/Inertial Measurement Unit): This refers to a combination of GPS and inertial measurement sensors that are used to determine the car's location and position.
- Priori Map: This refers to a high-definition map that is stored in the car's memory. This map can be used to help the car localize it and plan its route.

3. PROCESS OF LANE DETECTION IN MATLAB

1. Capture Image from Camera via IP Address using TCP Client: This involves accessing a camera's feed by providing its IP address.
2. Convert Image to Detect Lanes: The image is processed to highlight lane markings, typically through techniques like edge detection and filtering.
3. Convert Image to Grayscale: Grayscale conversion simplifies subsequent processing steps by reducing color information to a single intensity value per pixel.
4. Noise Reduction: Various techniques such as Gaussian blurring can be applied to smooth out the image and reduce noise, making subsequent edge detection more effective.
5. Edge Detection using Canny Edge Detector: Canny edge detection algorithm identifies edges in the image by detecting areas of significant intensity changes.
6. Define Region of Interest (ROI): Specify a specific area in the image where lanes are expected to be located. This helps in focusing the analysis and reducing computational load.
7. Apply ROI Mask: This step involves masking out areas outside the defined ROI to ignore irrelevant information.
8. Exclude Border Lines: Lines detected near the borders of the image, which are likely not part of the lanes, are filtered out to improve accuracy.
9. Hough Transform for Line Detection: The Hough transform is applied to identify lines within the ROI, which represent the lane markings.
10. Detect One Peak per Lane: This ensures that only one line (representing each lane) is detected, helping in simplifying the subsequent processing.
11. Plot Detected Lane Lines: The detected lane lines are overlaid on the original image to visualize the result.
12. Calculate Line Angles: The angles of the detected lines are calculated, typically with respect to a reference axis.
13. Find Average Angle: The average angle of the detected lines is computed to provide a measure of the overall orientation of the lanes.
14. Send Command to TCP Client: Finally, the relevant information, such as lane angles or other data, is sent to a TCP client for further processing or action.

4. FUTURE SCOPE

The future of autonomous vehicles holds immense potential across various sectors and industries. Here are some key areas where we can expect significant developments:

1. Transportation and Mobility: Autonomous vehicles have the potential to revolutionize transportation and mobility, making it safer, more efficient, and convenient. They can reduce traffic congestion, lower emissions, and provide mobility solutions for people who cannot drive, such as the elderly and individuals with disabilities.
2. Logistics and Delivery: Autonomous vehicles can optimize logistics and delivery operations by enabling round-the-clock transportation without the need for human drivers. This can lead to faster and more cost-effective delivery of goods, particularly in e-commerce and supply chain management.
3. Public Transportation: Autonomous buses and shuttles can enhance public transportation systems, offering flexible and on-demand services while reducing the need for large-scale infrastructure investments. This can improve access to transportation in urban and rural areas alike.

4. Ride-Hailing and Shared Mobility: Companies like Uber and Lyft are already exploring autonomous ride-hailing services, which could significantly reduce the cost of transportation for consumers. Shared autonomous vehicles can also promote carpooling and reduce the number of vehicles on the road.
5. Smart Cities and Infrastructure: Autonomous vehicles rely heavily on advanced infrastructure, including sensors, communication networks, and smart traffic management systems. The development of smart cities and infrastructure will be crucial to support the widespread adoption of autonomous vehicles.
6. Safety and Accident Reduction: Autonomous vehicles have the potential to significantly reduce the number of accidents caused by human error, which is currently a leading cause of traffic fatalities worldwide. Advanced sensors, real-time data analysis, and machine learning algorithms can help vehicles anticipate and respond to potential hazards more effectively.
7. Economic Impact: The adoption of autonomous vehicles is expected to have far-reaching economic implications, affecting industries such as automotive manufacturing, insurance, and urban planning. It could also create new job opportunities in areas such as software development, data analysis, and maintenance.
8. Regulatory and Legal Considerations: As autonomous vehicles become more prevalent, policymakers will need to address various regulatory and legal challenges, including safety standards, liability issues, data privacy concerns, and ethical considerations. Clear and consistent regulations will be essential to ensure the safe and responsible deployment of autonomous vehicles.

5. CONCLUSION

Automated track guided vehicle is one of material handling equipment that has been widely used in most manufacturing industry today as it provides more flexibility to the systems.The concept of this type of vehicles involves driverless vehicles with programming capabilities for path selection and positioning. These type of vehicles can be easily modified and expanded for different type of techniques used for path guiding system. These vehicles are the future smart vehicles anticipated to driverless, efficient and crash avoiding ideal urban vehicle to future. A driving algorithm is designed using deep learning and a type of reinforcement learning and the performance of driving algorithm is tested for perfect knowledge regarding surrounding vehicles. Autonomous vehicles are the type of vehicles that arecapable of sensing their environment and navigating without human input. Autonomous vehicles are very closely associated with industrial IOT. One of the main tasks of any machine learning algorithm in self-driving car is a continuous rendering of surrounding environment and the prediction of possible changes to those surroundings. Artificial intelligence based decision making has become increasingly more successful as they are capable of handling different complex calculations and have good results in those type of situations. The development of image processing based implementations for the navigation track guided vehicles. A mobile video camera is used as sensor to gather the necessary data. Algorithms will be implemented on a PC in MATLAB environment. The navigation of autonomous vehicles in complex environments remains a significant challenge. While significant progress has been made on well-defined highways, navigating unpredictable situations like busy intersections, construction zones, and adverse weather conditions requires robust solutions. Researchers are actively developing advanced sensor technologies to provide a 360-degree perception of the surroundings. High-definition maps and improved localization techniques are crucial for pinpointing the vehicle's location within the environment. Furthermore, sophisticated decision-making algorithms are being explored to enable real-time path planning, obstacle avoidance, and safe navigation in these dynamic scenarios. As these technologies mature and integrate seamlessly, autonomous vehicles will be better equipped to handle the complexities of the real world, paving the way for a future of safer and more efficient transportation.

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