Asian Journal of Applied Science and Technology (AJAST)
Volume 7, Issue 3, Pages 28-32, July-September 2023

Advanced Self Driving Car Using Machine Learning

Shakeel Ashraf[1] & Dr. Vivek Kumar[2]

[1]*Research Scholar,* [2]*Professor,* [1,2]*Department of Electronics and Communication Engineering, Ganga Institute of Technology and Management, Maharshi Dayanand University, Rohtak, Haryana, India.*

DOI: https://doi.org/10.38177/ajast.2023.7303

Article Received: 17 May 2023 *Article Accepted: 09 July 2023* *Article Published: 15 July 2023*

ABSTRACT

There are surprisingly innovative approaches to develop AI systems for self-driving cars, many of which require advanced and high-end hardware. However, this paper proposes a simple AI-based system with low hardware requirements. The proposed system comprises a simple three-layer fully connected neural network that can interpret images captured by a forward-facing QVGA camera and generate corresponding steering commands. When presented with an input image, the neural network selects one of four available commands: forward, left, right, or stop. Surprisingly, the system successfully learns to navigate the road and stay within its lane using only a limited amount of training data (just 250 images). Notably, the system acquires knowledge of crucial road features solely based on the steering angle provided by the human driver, without explicit training for road line detection. In comparison to more intricate approaches like Nvidia's convolutional neural network-based lane detection and management, this method demonstrates remarkable robustness and cost-effectiveness. The aim is to showcase that this approach can lead to enhanced performance and reduced hardware requirements, thereby facilitating the development of more accessible and affordable self-driving vehicles. The described paper highlights that a simple artificial neural network, like the one discussed, is sufficient for accomplishing relatively complex tasks such as lane keeping.

Keywords: AI-based system; Neural network; Autonomous driving; Driverless vehicle; Object recognition; Computer vision; Robotics.

1. Introduction

In the United States, approximately 37,000 individuals lose their lives in car accidents each year, representing a 5.8% increase since 2014. The majority of these accidents, up to 90%, are caused by human errors. Autonomous vehicles have the potential to significantly reduce this high number of fatalities. One of the most important and widely adopted technologies in this field is line detection and lane keeping, which has been continuously improved since the 1980s. The desire to enhance road safety has led to the development of various systems that are integrated into vehicles.

However, each new system adds complexity to the mathematical model and requires additional data representation to make accurate decisions. To address this, the goal is to create a system that mimics human driving based on predetermined rules, using artificial intelligence. As computer science progresses, one of its fundamental sub-branches, autonomous vehicles, becomes closely associated with computer vision. The primary objective of this technology is to design a system that can perform steering, braking, and acceleration independently. In this task, computer vision assists the system in detecting and identifying objects, while other algorithms handle the decision-making process.

2. Related Work

There are various anticipated solutions for the problem at hand, including numerical methods, neural networks, reinforcement learning, convolutional neural networks (CNNs), and Q-learning. The two most significant approaches are numerical methods and CNNs, each with their own advantages and disadvantages. This paper introduces a simple, fast, and effective approach to address the problem. The numerical approach involves a meticulous analysis of the problem and can utilize either monocular or stereo vision. Many of these techniques

Asian Journal of Applied Science and Technology (AJAST)
Volume 7, Issue 3, Pages 28-32, July-September 2023

focus on identifying lane markers on the road, which are comparatively easier to detect. Typically, a reference point is necessary, such as a horizontal line in the image parallel to the x-axis. The lines should have sufficient thickness and form a shape resembling a parallelogram or approximation. Once the boundaries of the road are identified, the position of the vehicle can be determined using predefined camera calibration data. By accurately establishing the vehicle's position and employing advanced algorithms, the required steering angle can be computed. However, alternative methods similar in nature necessitate a level road, substantial distance, optical focus, pitch point, yaw angle, and height above the ground to perform intricate mathematical transformations.

Another approach involves using CNNs, which require substantial data collection. This is done by recording commands given by human drivers and capturing images from onboard cameras. CNNs have revolutionized pattern recognition and can make accurate decisions based on past data. However, due to the high quality of CNNs, they require powerful hardware to run efficiently. Many solutions of this kind use multiple graphics processing units (GPUs) or dedicated hardware like the NVIDIA DRIVE platform, which significantly accelerates the learning rate and performance of a trained network. These solutions, however, often suffer from issues such as large size, complexity, high cost, and high-power consumption.

One notable CNN solution is the end-to-end learning approach developed by nVidia, where the system learns to drive a car with minimal training data from a human driver, similar to the approach presented in this paper. However, a major drawback of this approach is the use of expensive hardware, such as the Nvidia Devbox and DRIVE platform, which can cost thousands of dollars.

The objective of this paper's proposed solution is to create a more economical implementation of an autonomous driving AI system. This approach avoids the necessity for complex mathematical modeling and analysis of the problem. Additionally, it eliminates the requirement for power-intensive, high-end, and costly hardware for operation. The system can be trained with a limited amount of past data due to its straightforwardness.

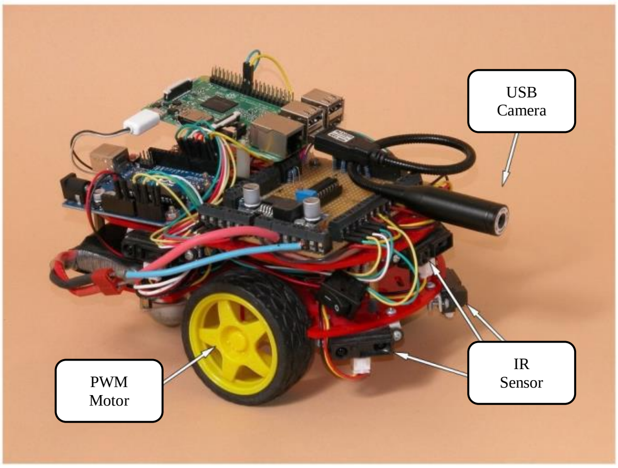

Figure 1. Overview of the robot

3. System Overview

For this experiment, a specially constructed machine was utilized, incorporating Raspberry Pi and Arduino computers as the primary control units. The task of controlling the robot was performed by a separate computer,

Asian Journal of Applied Science and Technology (AJAST)
Volume 7, Issue 3, Pages 28-32, July-September 2023

with communication between the two systems established through a TCP/IP network. The robot was propelled by two wheels powered by steam and featured an additional independent wheel. It was equipped with five IR proximity sensors, with three facing forward and two positioned at the edges, along with a front-facing camera. The IR sensors were employed for detecting obstacles, while the camera was used to identify signs and traffic signals. The robot's appearance is depicted in Figure 1.

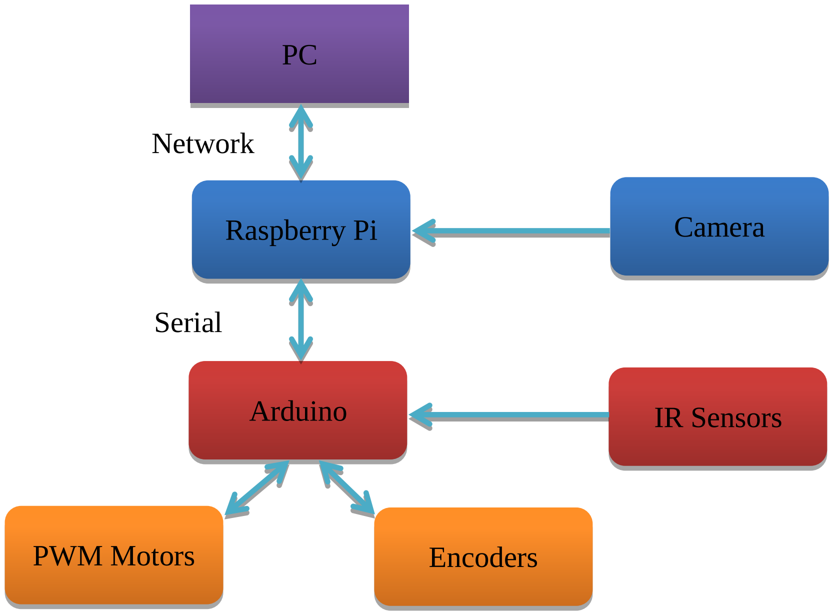

Figure 2. Connections of the electrical components of the system

Effective communication between all modules is facilitated by clearly defined protocols, allowing for seamless updates and scalability when required. The system has been designed to handle a multitude of vehicles, diverse users, and numerous AI agents. This is achieved by implementing a concurrent and stateless configuration, enabling vehicles to be controlled by multiple instances of the AI agent concurrently. Furthermore, the utilization of a load balancer between these instances ensures efficient scalability of the system.

4. Data Collection

The training data was acquired through manual driving of the vehicle on a simulated road. Along with the usual road configuration featuring dark asphalt and white lines, the vehicle was also trained and evaluated on a darker road with white lines. The training data exclusively consisted of images captured from the front-facing camera while operating in manual mode.

The collected data was stored as a set of attributes, with one parameter representing the command (direction of movement) sent to the vehicle, and the other parameter representing a video frame at the precise moment the command was given.

5. Artificial Intelligence System

The AI system functions as several state machines and has the task of issuing instructions to govern the vehicle. It employs a three-tier arrangement consisting of an input layer (camera image), a hidden layer, and an output layer (steering command). This configuration represents a basic fully connected neural network. The system's output encompasses four potential options: three directions (forward, forward-left, forward-right), as well as a stop command. This design allows for seamless incorporation of forthcoming updates and alterations to particular algorithms. The implementation outlined in this paper operates in three distinct modes, as depicted in Figure 3. Initially, the vehicle operates in "Manual control" mode and can transition to other modes based on user input.

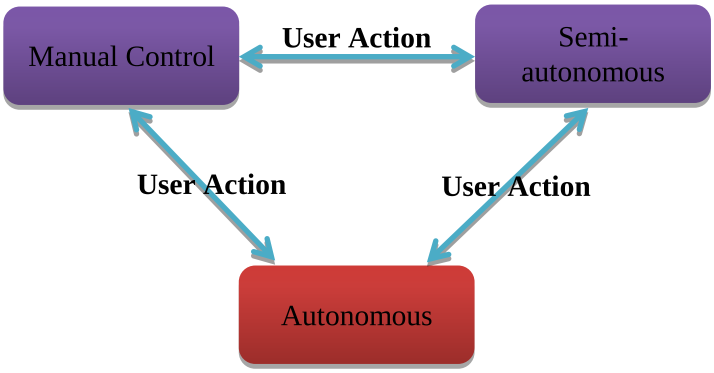

Figure 3. Autonomous vehicle operation modes

In the "Semi-autonomous" mode, the state machine is straightforward, consisting of only two possible states. However, the more intriguing state machine is observed in the "Self-governing" mode, similar to autopilot, as depicted in Figure 4. It comprises four states, with "Free drive" serving as the initial and final state. In this state, the Artificial Neural Network (ANN) takes control of the vehicle. It continuously analyzes the input data and sensor readings for obstacle detection. Based on the identified objects or information from IR sensors, it determines whether to transition to the next state.

If a directional signal is detected, the state machine switches to the "Course sign" state. In this state, the vehicle first checks for approaching traffic on the intersecting road. If the intersection is clear, the vehicle executes the appropriate command, such as making a turn in the desired direction. After completing this action, the state machine transitions back to the "Free drive" mode, returning control to the ANN.

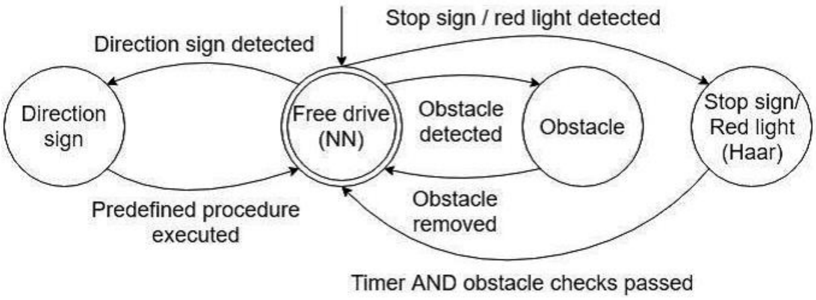

Figure 4. Autonomous mode finite state machine

6. Sign Detection

The identification and recognition of traffic signs are crucial for self-driving vehicles. The OpenCV library offers the necessary tools for this task, including a trainer and a detector. In this case, classifiers were specifically implemented for stop signs, traffic lights, and directional signs (left, right, forward, and U-turn). Given the limitations of this approach, where each object requires its own classifier and scaling issues make it challenging to obtain sufficient training data, it was deemed suitable for proof of concept.

The behavior of the vehicle once a sign is detected is hard-coded. The distance to the object is measured for all types of signs, including stoplights.

7. Conclusion

One drawback of any AI system is its unpredictable behavior. However, this experiment demonstrated that the development of such systems can be relatively easy, especially for non-critical applications. Real-world implementation would require additional testing and safety protocols. Nevertheless, the demonstrated system was able to achieve all of this using minimal data and modest hardware. It successfully trained the system to drive in various conditions, including different times of day, urban and highway roads, and adapting to traffic regulations despite the presence of multiple vehicles.

Declarations

Source of Funding

The study has not received any funds from any organization.

Competing Interests Statement

The authors have declared no competing interests.

Consent for Publication

The authors declare that they consented to the publication of this study.

Authors' Contributions

Both the authors took part in literature review, research and manuscript writing equally.

References

[1] U.S. Department of Transportation's National Highway Traffic Safety Administration (2016). Retrieved from United States Department of Transportation: crashstats.nhtsa.dot.gov/Api/Public/Publication/812456.

[2] Tan, B., Xu, N., & Kong, A.B. (2018). Autonomous Driving in Reality with Reinforcement Learning and Image. AreXiv preprint arXiv:1801.05299. Retrieved from https://arxiv.org/pdf/1801.05299.

[3] Massimo, B., & Broggi, A. (1996). Real-time lane and obstacle detection on the GOLD system. Intelligent Vehicles Symposium, Pages 213-218.

[4] Bertozzi, M., Broggi, A., Conte, G., & Fasciola, A. (1997). Obstacle and lane detection on ARGO. IEEE Conference on Intelligent Transportation System, Pages 1010-1015.

[5] Wang, H., & Chen, Q. (2016). Real-time lane detection in various conditions and night cases. Intelligent Transportation Systems Conference, Pages 1226-1231.

[6] Aly, M. (2008). Real time detection of lane markers in urban streets. Intel. Vehicles Symposium, Pages 7-12.

[7] Bojarski, M., Del Testa, D., Dworakowski, D., Firner, B., Flepp, B., Goyal, P., Jackel, L.D., Monfort, M., Muller, U., Zhang, J., Zhang, X. (2016). End to end learning for self-driving cars. arXiv preprint arXiv: 1604.07316.

[8] Krizhevsky, A., Sutskever, I. and Hinton, G.E. (2012). ImageNet Classification with Deep Convolutional. Advances in Neural Information Processing Systems, Pages 1097-1105.