SteerBrains : Moving towards Vehicular Autonomy

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Abstract - *The concept of autonomous driving represents a significant advancement in transportation, where artificial intelligence (AI) assumes the role of the driver, navigating vehicles on the road. This paper, titled "SteerBrains: Moving towards Vehicular Autonomy," serves as a platform to discuss the design and development of autonomous systems, drawing insights from personal experiences and partial results obtained. While not presenting comprehensive results for the entire autonomous driving scenario, the paper provides a structured framework for designing such systems, which may serve as a foundation for further research endeavors. Beginning with an overview of the evolution of autonomous driving, the paper examines fundamental principles underlying the concept and explores challenges and considerations in system design. It delves into the potential implications of AI-driven autonomy for road safety, efficiency, and accessibility. Through this exploration, the paper aims to offer valuable insights into the transformative impact of autonomous driving on the future of transportation. Despite presenting partial results, the paper contributes to the broader understanding of autonomous systems' design and lays the groundwork for future advancements in the field.*

Key Words: Autonomous Vehicles, Autonomous Systems, Driving Automation, Vehicle Control, Self driving cars, Supervised learning, SteerBrains, Localization, Simulator, Carla.

1. Introduction

In recent years, the automotive industry has witnessed a paradigm shift with the emergence of autonomous driving technology. This groundbreaking advancement holds the promise of transforming the way we perceive and interact with transportation, offering unprecedented levels of safety, efficiency, and convenience on our roads. As such, our research endeavors to contribute to this transformative field by developing an innovative autonomous driving system that embodies the latest advancements in technology and methodology.

Our research represents a comprehensive exploration of autonomous driving, capable of navigating complex environments autonomously. Through meticulous design and implementation, we aim to address the challenges associated with autonomous driving, from perception and decision-making to control and execution. By leveraging state-of-the-art methodologies and cutting-edge technologies, our system aims to push the boundaries of what is possible in autonomous transportation.

1.1 Background

Our system is built upon a foundation of cutting-edge methodologies, including computer vision for visual perception, Kalman filters for state estimation, and finite state machines for behavior planning. Through the integration of these techniques, we aim to address the multifaceted challenges inherent in autonomous driving, from perception and decision-making to control and execution.

1.2 Tools and Technologies

Central to our research is the utilization of the Carla Simulator, a state-of-the-art simulation platform that enables us to replicate real-world driving scenarios in a virtual environment. By leveraging the capabilities of the Carla Simulator, we can evaluate the performance of our autonomous driving algorithms under various conditions, from inclement weather to heavy traffic.

Additionally, our system is implemented and programmed entirely in Python, harnessing the flexibility and versatility of this programming language for the design and development of complex autonomous systems. Operating on a Windows system, our development environment provides the necessary resources and support for software development, testing, and validation.

In the following sections, we delve deeper into the intricacies of our autonomous driving system, detailing the methodologies, algorithms, and experiments conducted. Through empirical evaluation and analysis, we seek to demonstrate the effectiveness and reliability of our system in navigating urban environments autonomously.

2. Literature Review

Sr .No.	Title	Objectives	Findings
1	**Autonomous vehicles: theoretical and practical challenges**	The Paper aims to offer insights into the theoretical and practical challenges associated with AVs, including their impact on traffic efficiency, mobility patterns, and ethical considerations.	The paper explains how AVs could contribute to making future mobility more efficient, safer, cleaner and more inclusive. However, it also highlights that several conditions must be fulfilled to achieve this goal.
2	**Autonomous driving in urban environments :approaches, lessons and challenges**	Aims to highlight major research challenges and opportunities for application of autonomous driving in urban environments.	Authors explore the AVs in urban environments highlighting the need for the environments to have a smart infrastructure.
3	**Reliable Decision-Making in Autonomous Vehicles**	The paper aims to investigate the high-level decision-making process in autonomous vehicles (AVs) by modeling an intelligent agent responsible for determining actions in various levels of emergency situations	The paper exemplifies decision making approaches in a basic urban traffic environment with different levels of emergency, paving the way for potential extensions to address real-world scenarios, such as the integration of road traffic laws and regulations into the decision-making process.
4	**End to End Learning for Self-Driving Cars**	The paper aims to develop a convolutional neural network (CNN) that learns the entire processing pipeline required for steering an automobile.	CNN demonstrated the ability to operate in diverse conditions, including highways, local and residential roads, in various weather conditions.
5	**Survey of Deep Reinforcement Learning for Motion Planning of Autonomous Vehicles**	The paper aims to devise a survey of advancements in motion planning for autonomous vehicles, focusing specifically on the application of Deep Reinforcement Learning (DRL) approach to address the complexity of various motion planning problems.	The findings indicate that different deep reinforcement learning techniques are promising, but, challenges remain in ensuring safety and robustness. Safety concerns include the amount of training data needed, verification, and validation, particularly in complex scenarios.
6	**Challenges in Autonomous Vehicle Testing and Validation**	The objectives of the paper are to explore the challenges faced by developers in qualifying fully autonomous vehicles for large-scale deployment, specifically focusing on National Highway Traffic Safety Administration (NHTSA) Level 4 vehicles and their validation within the ISO 26262 V framework to ensure safety and reliability.	Suggests adopting a phased deployment approach, tied to well-specified operational concepts and requirements, which appears promising for ensuring safety while making progress towards full autonomy.

3. Algorithms/Techniques

3.1 Random Sample Consensus (RANSAC)

RANSAC is an iterative method to estimate parameters of a mathematical model from a set of observed data that contains outliers, when outliers are to be accorded no influence on the values of the estimates. Therefore, it also can be interpreted as an outlier detection method.[1]

$$1 - p = (1 - w^n)^k$$
$$k = \frac{\log(1 - p)}{\log(1 - w^n)}$$

Figure 3.1(A) RANSAC

Where,

w= probability of choosing an inlier each time a single data point is selected.

p = desired probability that the RANSAC algorithm provides at least one useful result after running.

n = points from the data set from which the model parameters are estimated.

k = number of iterations in running the algorithm.

In the context of self-driving cars, drivable space includes any space that the car is physically capable of traversing in 3D. The task of estimating the drivable space is equivalent to estimating pixels belonging to the ground plane in the scene. We have used the RANSAC algorithm to estimate the Drivable Space i.e. The ground plane from the x.y and z coordinates obtained from each pixel of the image.

Figure 3.1 (B)

In fig. 3.1(B), the image on the left is the original image taken by the camera, the image in the middle contains x, y, and z coordinates of pixels in the road mask obtained from segmentation output. The image to the right contains x, y, and z coordinates of pixels belonging to the road to estimate the ground plane.

3.2 Kalman Filter

For statistics and control theory, Kalman filtering, also known as linear quadratic estimation (LQE), is an algorithm that uses a series of measurements observed over time, including statistical noise and other inaccuracies, and produces estimates of unknown variables that tend to be more accurate than those based on a single measurement alone, by estimating a joint probability distribution over the variables for each timeframe.[2]

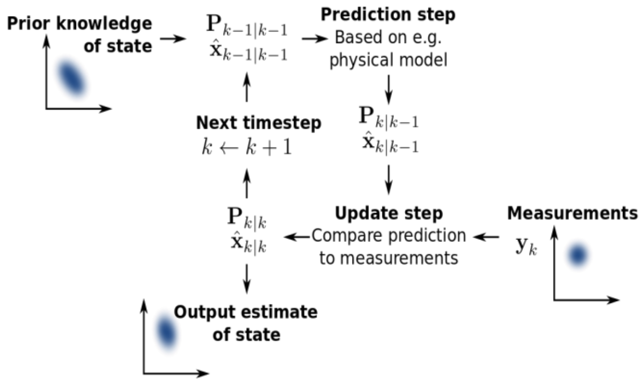

Figure 3.2(A) Kalman Filter

The estimate is updated using a state transition model and measurements.

$\hat{x}_{k|k-1}$ = estimate of the system's state at time step k before the k-th measurement yk has been taken into account

$P_{k|k-1}$ = corresponding uncertainty.

The Error State Extended Kalman Filter (EKF) is a widely-used technique for state estimation in autonomous navigation systems, particularly in the context of self-driving cars. The EKF extends the traditional Kalman Filter framework to handle nonlinear systems by linearizing the system dynamics around an estimated state. We employed the Error State Kalman Filter (EKF) to estimate the vehicle's state variables, including position, velocity, orientation, and sensor biases, based on sensor measurements collected from onboard sensors such as GNSS, IMU, and LiDAR.

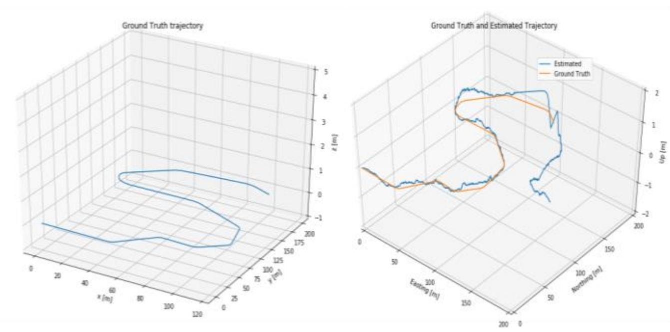

Figure 3.2(B) EKF (Estimated Trajectory)

In fig. 3.2(B), the image on the left is a 3D representation of the Ground Truth Trajectory and is plotted in Blue color. The image on the right side is the representation of the states estimated i.e. the estimated trajectory using the Error State Extended Kalman Filter. The plotted curve in Blue color represents the estimated Trajectory and Orange is the truth.

3.3 Finite State Machines

A finite state machine (FSM), also known as a finite state automaton, is a mathematical model used to represent and control the behavior of systems with discrete states. It consists of a finite number of states, along with transitions between these states triggered by input events. FSMs are widely used in various fields, including computer science, engineering, and artificial intelligence, for modeling and controlling systems with finite and discrete behaviors.[3]

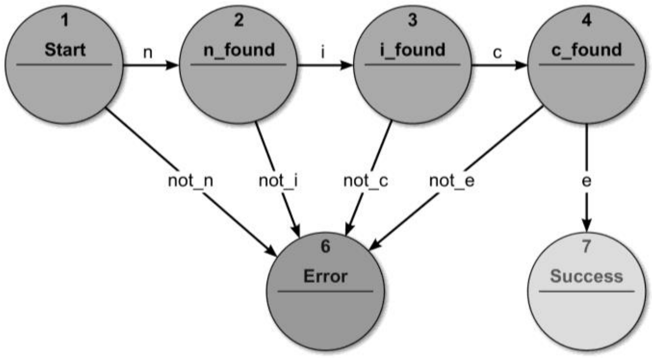

Figure 3.3(A) FSM (Parsing the String "nice")

In our development, we have employed Hierarchical Finite State Machine (HFSM). A Hierarchical Finite State Machine introduces additional levels of abstraction to the FSM model by organizing states into hierarchical layers or levels. Each layer represents a different level of granularity, with higher-level states encapsulating lower-level states and transitions. This hierarchical structure allows for the modularization and composition of complex behaviors, making it easier to design, understand, and manage the autonomous driving system.[4]

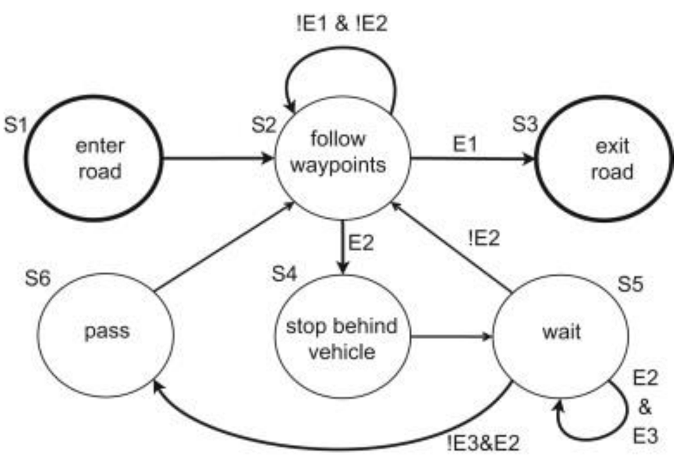

Figure 3.3(B) HFSM

4. Design and Methodology

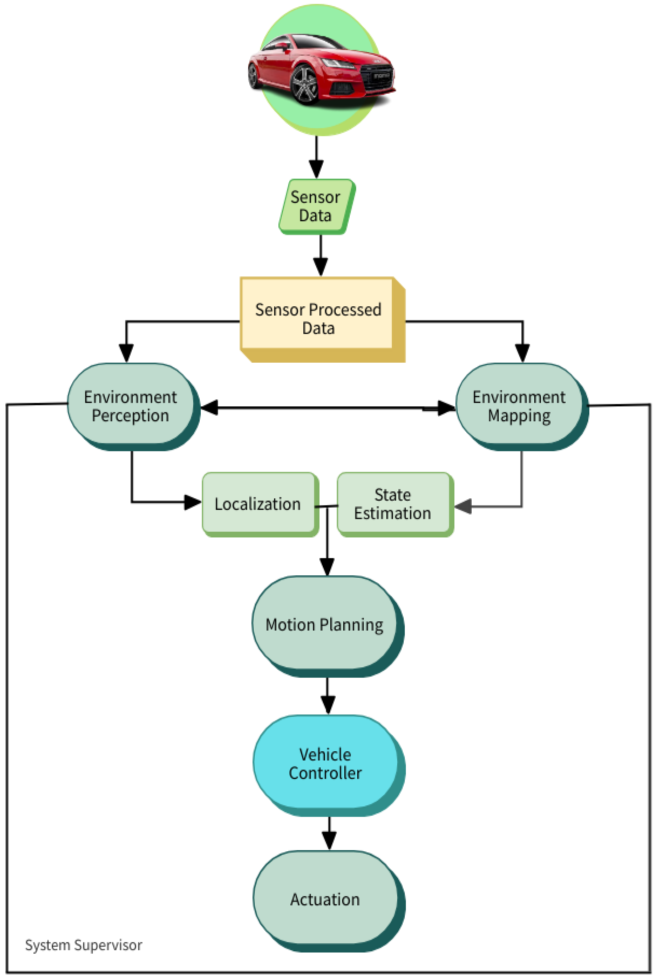

Figure 4.1(A) High Level System Design

Our autonomous vehicle system design features a hierarchical structure comprising six main components. At the top level, the car is equipped with an array of sensors for comprehensive environmental perception. In the second level, the processed sensor data undergoes preprocessing and filtering to extract relevant information. Subsequently, the system branches into two modules at the third level: environment perception and environment mapping. Utilizing computer vision techniques including object detection, recognition, depth estimation, and occupancy grid creation, these modules work in tandem to facilitate localization and state estimation processes. Specifically, the Random Sample Consensus (RANSAC) algorithm is employed for robust state estimation, ensuring accurate positioning within the environment.

Moving down the hierarchy, at the fourth level, motion planning is executed through the utilization of Hierarchical Finite State Machines. This approach enables the system to efficiently generate optimal trajectories and paths based on the processed sensor data and environmental information. Subsequently, the resulting plans are transmitted to the vehicle controller module at the fifth level. Here, control commands are translated into physical actions such as steering, acceleration, and braking. Throughout the entire hierarchical structure, from level two to level six, all processes are continuously monitored and supervised by a dedicated system supervisor to ensure the safe and efficient operation of the autonomous vehicle system.

5. Results

The implemented environment perception and mapping module has demonstrated robust performance across various scenarios. It accurately estimates states, localizes the vehicle, and effectively detects both static and dynamic obstacles. Notably, the system successfully detects and recognizes traffic lights, as well as identifies lanes for navigation. Although not tested extensively with pedestrians, the capability to recognize dynamic obstacles positions it well for future pedestrian detection tasks.

The Hierarchical Finite State Machines (HFSM) employed for motion planning have exhibited commendable performance in diverse test cases. The system effectively maintains lane keeping, avoids static obstacles, executes turns, applies braking maneuvers, accelerates smoothly, and adjusts steering as required. These results underscore the efficacy of the HFSM approach in achieving complex driving maneuvers.

Simultaneously, the velocity profile and trajectory tracking module have demonstrated precision in tracking the vehicle's movement. By dynamically adjusting the velocity profile based on the planned trajectory, the system ensures smooth and accurate tracking.

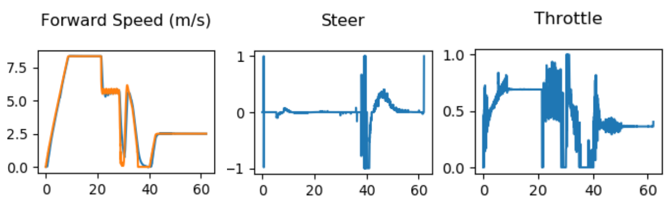

Figure 5.1 Resulting Graph

6. Conclusions

In conclusion, our system showcases promising results in both environment perception and vehicle control aspects, paving the way for the development of robust autonomous driving systems. The successful implementation of environment perception techniques, coupled with efficient motion planning and control strategies, underscores the potential of our approach in achieving safe and reliable autonomous navigation in complex urban environments.

7. Future Scope

In addressing the identified limitations and exploring future avenues for enhancement, it is evident that our system's performance, while strong within the confines of the test cases conducted, is constrained by several factors. First and foremost, the limited scope of test cases poses a challenge, as our system's capabilities have yet to be fully tested across a diverse range of real-world scenarios. Expanding the testing regime to encompass a broader spectrum of conditions and edge cases will provide a more comprehensive assessment of the system's robustness and identify areas requiring further refinement. Additionally, resource constraints, particularly in terms of computational capacity, present a significant hurdle, limiting the number of iterations and explorations feasible during development and testing phases.

Looking towards the future, there are promising avenues for addressing these limitations and advancing the capabilities of our system. One such avenue involves the integration of reinforcement learning techniques, which can empower the system to autonomously learn and adapt its decision-making strategies based on feedback from the environment. By leveraging reinforcement learning algorithms, our system can navigate complex scenarios more effectively and respond dynamically to changing conditions in real-time. Furthermore, the exploration of imitation learning methodologies holds considerable potential for accelerating the system's learning process. By training the system to mimic expert behaviors through observation and imitation of human or expert demonstrations, imitation learning can facilitate rapid knowledge transfer and enhance the system's performance in diverse scenarios. Ultimately, by addressing the identified limitations and embracing these future-oriented approaches, we can propel our system towards greater adaptability, robustness, and efficacy in autonomous navigation tasks.

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