# Autonomous vehicle navigation methods in dynamic environments: A review

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***Abstract*—Autonomous vehicles (AV) must constantly assess the area around them using their onboard sensors to predict an optimal path to navigate to the desired destination. Currently, autonomous navigation systems seldom generate the required path optimality due to the complexity of various environments such as densely populated areas, traffic junctions etc. In real world scenarios just the path planning algorithms alone are not sufficient to guide the vehicle in a dynamic environment. This paper investigates the different state-of-the-art path optimization algorithms like RRT, ATMC, sparrow search algorithm, and real time trajectory prediction algorithms of dynamic road agents like StopNet, MotionCNN. These methods further assist the path planning algorithms to determine a safe and optimal path for the vehicle. A smarter system can be derived by integrating these methods effectively into a control architecture which can navigate the autonomous vehicle through any kind of dynamic environment reliably and efficiently.**

***Key Words*—Autonomous vehicles, Path planning, trajectory prediction, control systems.**

## I. INTRODUCTION

Navigation is a central aptness of mobile robots and considerable progress has been made in the realm of Autonomous Navigation in the past [1]. Proportionally few Robotic systems have been developed for autonomous navigation in city centers. The Autonomous City Explorer project [2] primarily focuses on human-robot interaction, in contrast to our system, which runs entirely independently. In contemporary civilization, automated automobiles are more prevalent. Automated prototype vehicles have already been tested in real-world driving situations and found to be trustworthy enough to operate autonomously. There are many different vehicles that can be automated outside just cars, and for each type of vehicle, there are established common standards that help to uniformly create autonomous vehicles. To choose where to proceed next, the robot interacts with pedestrians [3,4]. It creates local maps rather than planning its own route from its current place to the ultimate objective location. From [5] navigation and path planning by robotic systems can be widely classified into Deliberative path planning and Reactive object avoidance. The Deliberative path planning system considers a fixed map and discovers the optimal path between start and end positions, whereas in Reactive object avoidance system, a vessel is considered which quickly evaluates its location relative to known close-aboard obstacles and ensures choices of heading and thrust will avoid them. One of the main areas of Robotic Navigation research is the capacity of robots to recognize objects or obstacles in the moving path. In few applications, frequent employment of deep learning object detection techniques like You Only Look Once (YOLO) [6], Single Shot Detector [7], Faster R-CNN [8] are implemented. To improvise the robotic capabilities, pre-trained Convolutional Neural Networks (CNNs) [9] are combined with visual Simultaneous localization and mapping (SLAM) in object detection With the help of Networking algorithms such as A* algorithm for global route planning and the Dynamic Window Approach (DWA) [10] for local path planning is implemented and the map created by the SLAM algorithm is evaluated. The main focus of this paper is to not only represent the pertinent elements but also to highlight the potential that can be attained with such a system. The paper persuades the design decisions, discusses critical aspects as well as limitations of the contemporary system.

## II. AUTONOMOUS NAVIGATION SYSTEM

The self-steering of a mobile robot during autonomous navigation entails using the computational capabilities onboard the robot to move the robot from one location to . There are numerous approaches to mobile robot navigation, with path planning and obstacle avoidance being crucial components. By combining technologies or strategies, it is possible to create a system that is more reliable and can be used to perform autonomous navigation in any environment. This paper discusses such approaches to achieve autonomous navigation in the following sections.

### 1. Navigation in uncertain environment:

The system proposed in [11] is designed to identify obstacles in a sliding window using the adaptive threshold clustering algorithm (ATCM), which categorizes the identified obstructions using a decision tree, heuristically anticipates potential collisions, and finds the best route using a condensed version of the Morphin algorithm. The robot initially positions a sliding window with itself in its center. The robot's laser scanner is used to gather environmental data, the adaptive-threshold clustering technique is used to recognize static or moving impediments in the environment using the data within the window. The types of obstacles (new, dynamic, or static) are determined by a straightforward decision tree learned from experienced parameters; the movement of dynamic obstacles is computed in terms of their speed and direction and the relationship between the robot and the detected obstacles, and the potential for conflict is predicted; the Morphin algorithm is then applied to avoid obstacles if a potential collision in front of the robot is not avoidable; and finally, the robot updates its stats. The experimental results show that the suggested navigation method enables a mobile robot to effectively and efficiently avoid any static and dynamic impediments on the path the robot travels through. The shortest length of the navigation path was obtained by ATCM when compared to other path planning techniques. The six-step navigation system for mobile robots' modular design offers a framework for additional study and development.

### 2. Navigation using Improved Informed-RRT* Algorithm and DWA:

Informed-RRT*, an algorithm for path planning in autonomous navigation proposed in [12], is enhanced in this study in order to address several of its prior versions' flaws. The RRT algorithm departs from the ideal path as a result of the production of numerous nodes. The RRT* algorithm, created by Karaman et al., reroutes additional nodes in the direction of the ideal path in order to overcome this deviation. Gammell et al. developed the Informed-RRT* algorithm, which does sample space optimization to improve path efficiency, in response to the persistent issue of low path efficiency. By omitting explicit sample space, this approach further cuts down on search time, but it was unable to improve path efficiency. Additionally, it addresses the issue of local optimization that the dynamic window technique addresses (DWA). The path planning technique first introduces the greedy algorithm. It is determined whether a node can be directly connected to the target point when a new sampling point that can be added to the node tree is discovered. When the prerequisite is met, path planning is put on hold while the current course is optimized; if not, sampling keeps going. The created node tree containing the path is then used as the search object to replace the prospective ideal parent node in order to shorten the path optimization process' search duration. On the ROS platform, simulations have been run. This advancement of the RRT algorithm suggests that path planning and optimization have been enhanced. While the previously mentioned method is effective for the problem of global path planning, dynamic obstacle avoidance (DWA) is necessary to further optimize the path while avoiding the obstacle.

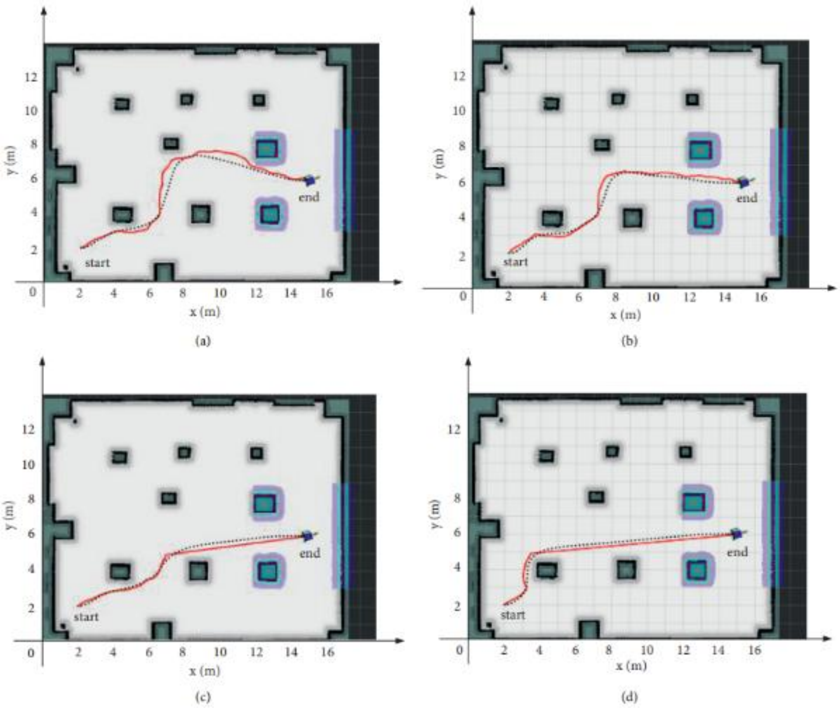


Figure 1:Autonomous navigation maps based on the two Informed-RRT* algorithms before and after improvement [12]

### 3. CNN based trajectory and occupancy prediction

The research [13] suggests a unique motion forecasting (behavior prediction) technique called StopNet that, while maintaining accuracy, satisfies the latency requirements for autonomous driving in congested urban contexts. To maintain a safe and efficient motion plan for itself, autonomous vehicles (AV) must constantly assess the area for any potential future motions from other road agents. As a result, a brand-new whole-scene sparse input representation is created that can simultaneously encode scene inputs for all agents. They have created a scene encoder that is inspired by PointPillars to handle sparse points sampled from all agents concurrently. This results in a highly quick trajectory prediction model whose latency is mostly independent of the number of agents. The AV frequently views the anticipated trajectories and uncertainties as planning limitations, therefore in crowded scenarios the planning algorithm's latency also rises.

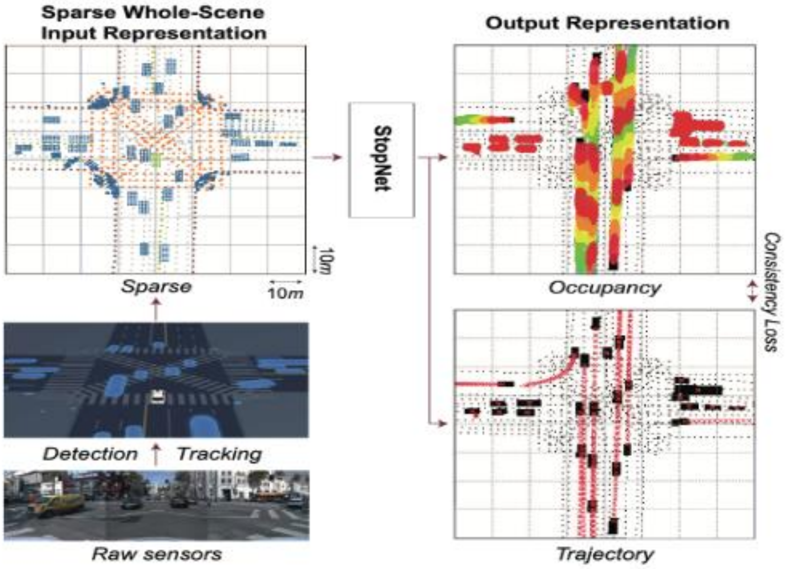


Figure 2:StopNet uses a whole-scene sparse input representation, supporting a scalable motion forecasting model that unifies occupancy grids and trajectories [13]

### 4. MotionCNN: A Strong Baseline for Motion Prediction in Autonomous Driving

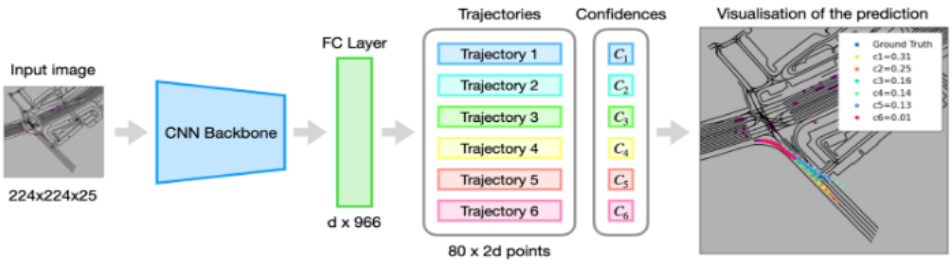


Figure 3:Overview of the architecture [14]

This paper [14] provides a convolutional neural network-only baseline for multimodal motion prediction that is both straightforward and extremely robust. Reliable projection of the future trajectories of other traffic agents, such as vehicles, cyclists, and pedestrians, is essential for an autonomous vehicle (AV). It is assumed that some sort of vision system is responsible for providing object tracks. The created model explicitly predicts a set of potential trajectories together with their confidences given a raster image with a target agent in the centre as input. Based on the confidence levels, a set of trajectories is chosen for the final prediction.

### 5. Bioinspired path planning and navigation using sparrow search algorithm

Traditional algorithms have some benefits, like simple principles, but they also have some drawbacks. It is important to remember that certain traditional approaches are deterministic algorithms that, in challenging circumstances, are readily stuck in local optimal solutions. In addition, the algorithm from [15] may not reach the end point in a complex environment. The path generated may be too rough, which would cause collisions between robots and obstacles. A cutting-edge method of swarm intelligence optimization is the sparrow search algorithm (SSA). We have taken into account both the producer and the scrounger types of captive house sparrows in the SSA method. While the scroungers rely on the producers to provide them with food, the producers actively seek for sources of food. The population is initialized with specific parameters using a random approach as the first stage in this algorithm. The current best and worst sparrows are then determined by rating the sparrows according to fitness values. Locations of the sparrows for producers and scavengers in the search space have been updated. Alarm value and safety threshold are defined as two values, R2 and ST, respectively. The producer switches to wide search mode when R2 ST, which indicates that there are no nearby predators. If R2 ST, then the producers have found the predator and are guiding the scavengers to safety. Scroungers' fitness value is based on how much energy they can consume. It is considered that only 10% to 20% of the population is aware of risk when the initial population value is produced at random. If a sparrow's fitness value is higher than the world's best fitness value, it indicates that it is at the edge of the population; if it is equal to the world's best fitness value, it indicates that it is in the middle and is aware of the threat and needs to migrate closer to other sparrows for safety.

**6. Autonomous navigation system based on a dynamic access control architecture for the internet of vehicles**

An autonomous mobile robot can develop basic characteristics, such as avoiding obstacles and establishing a trajectory toward a certain target point, by examining the control architectures. The design mentioned in this paper [16] features a top-down approach to the planning unit in which high-level restrictions are broken down into lower-level instructions.

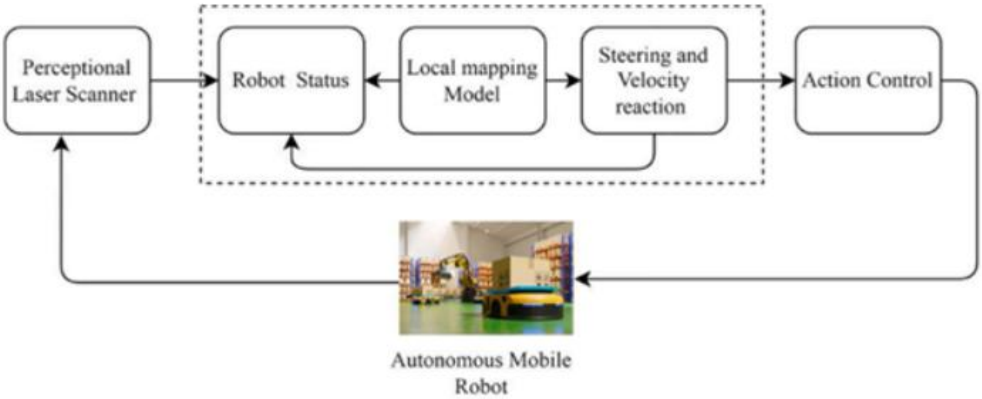


Figure 4:Autonomous robot control architecture [16]

In a novel presenting method, the problem was broken down into behaviours such as obstacle avoidance, exploration, wall-following, and target-seeking rather than function elements, and a set of behaviours was given in layers. Evaluating the control architecture is a major contribution to effective navigation of autonomous mobile robots in real time environment conditions. The autonomous mobile robot can develop basic characteristics, such as avoiding obstacles and establishing a trajectory toward a certain target point, by examining the control architectures. The three main components to architecture are perceiving, planning, and responding. The "sense-plan-act" framework of a control strategy for autonomous robotic systems involves a number of subsystems. Among these are environment analysis, task planning, task execution, and motor control.

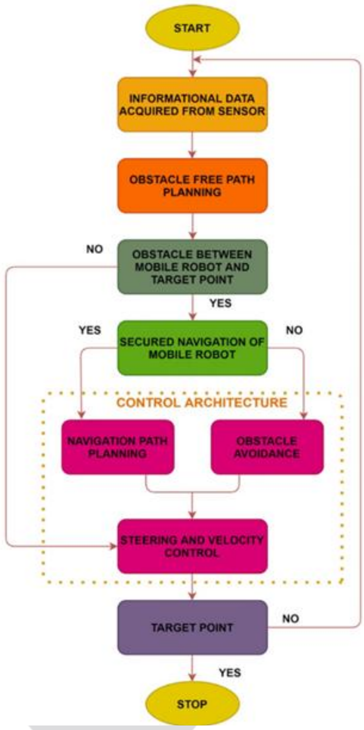


Figure 5:Navigation control system [16]

Figure 5 depicts the schematic representation of the navigation control system with dynamic access for an autonomous mobile robot. Control architecture 1 offers a reactive framework that can produce the two unique behaviours of attachment to the objective and repulsion of the barriers depending on the potential field approach. To prevent running into other objects, the robot's movement planning incorporates several steps. Using a vector sum, this composition has been created. Control architecture 2 uses adaptive fusion of reactive behaviours (AFREB) as its basis along with neural network algorithms. By using Giraa 02 robotic mobile platform to conduct experiments using these two control architectures, it was observed that control architecture 2 showed better results even in complex situations whereas control architecture 1 appeared to create secured trajectories in only some cases.

**7. Local Path Planning of the Autonomous Vehicle Based on Adaptive Improved RRT Algorithm in Certain Lane Environments**

Algorithms such as RRT-connect algorithm [28], quadruple tree mechanism and guidance improved RRT-connect algorithm etc, have improved the quality of the path and reduced computation time, but rarely take into consideration the various factors of structured road environments. In this paper, an improved RRT algorithm is proposed in order to obtain a path which considers vehicle constraints and is applied to structured road environments.

In the proposed algorithm, the random tree is made to grow more directionally using the sample node approach based on heuristic knowledge and its convergence is sped up using adaptive sampling space and adaptive step size. In order to travel smoothly and cheaply, the heuristic node selection technique is used to choose the closest tree node. The resulting path is optimized using post-processing techniques like the pruning method and the cubic B-spline to ensure that it satisfies the requirements of autonomous vehicle driving. The RRT algorithm iteratively adds additional randomly selected nodes as leaf nodes in the direction of the target point by searching the feasible region space from the starting point, which is regarded as the root node of the random tree, to the target point.

This work suggests an alternative RRT version that can be applied to the local path planning of the autonomous vehicle on the basis of the analysis of vehicle path planning issues produced by employing the basic RRT method provided above. The adaptive improved RRT algorithm seeks to swiftly produce an initial path and then enhance the original path's quality within the allotted time to satisfy the needs of vehicle driving. A high-quality path can be planned using the adaptive improved RRT algorithm in a specific lane environment, according to simulation results.

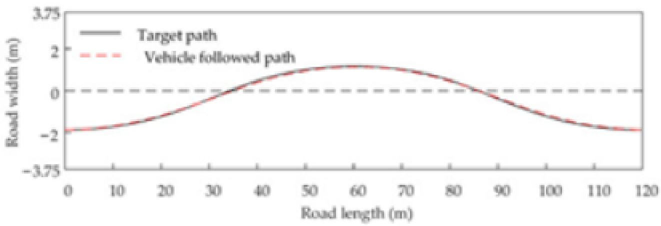


Figure 6: Path followed on straight road [28]

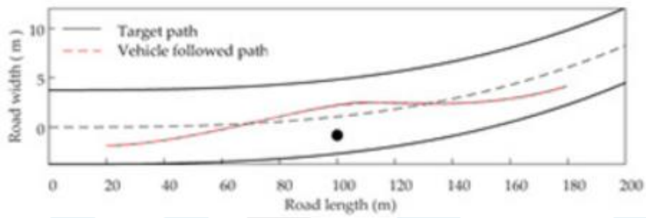


Figure 7:Path followed on curved road [28]

**8. Autonomous Navigation System of Greenhouse Mobile Robot Based on 3D Lidar and 2D Lidar SLAM**

With the world moving swiftly towards warehouse automation, this paper [27] focuses on one particular application under this domain i.e., intelligent greenhouses. The complex environment makes navigation one of the major existing issues. The development of SLAM in recent years has proven to provide a solution to a similar issue in other applications of autonomous navigation. However in similar cases to the one focussed on in this paper, SLAM based on a three-dimensional LiDAR is believed to solve the levelling issue of the same based on a 2D LiDAR. However, 3D mapping comes with a much higher computation cost which goes way beyond the capabilities of standard industry computers. This study is purely focused on developing a workaround that reduces these exorbitant computational requirements to a certain extent. Initial mapping done by the 3D system is filtered by the navigation control system and fused with the same obtained from 2D mapping. Thus, the greenhouse environment is mapped by a mobile robot using a 2D LiDAR SLAM algorithm in Cartographer which works on the basis of robot odometers and inertial measurement unit information. The algorithm has achieved the required mapping accuracy with reduced computational dependencies.

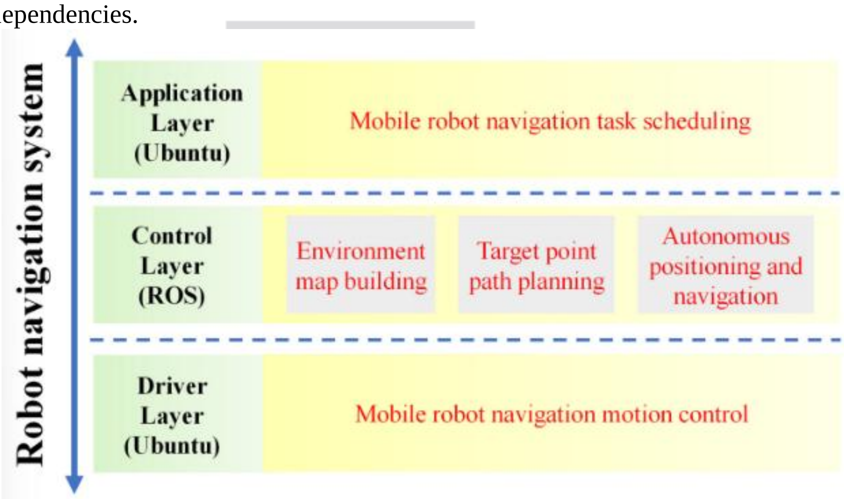


Figure 8: Software structure diagram of the robot [27]

The hardware components used include a 3D LiDAR , IMU, odometer and an encoder. The entire software control system is developed using ROS. Through navigation testing, positioning and navigation accuracy is studied. Navigational accuracy stays within 10cm of the actual target point while heading deviation does not exceed 3 degrees, thereby meeting the mobility requirements of the robots.

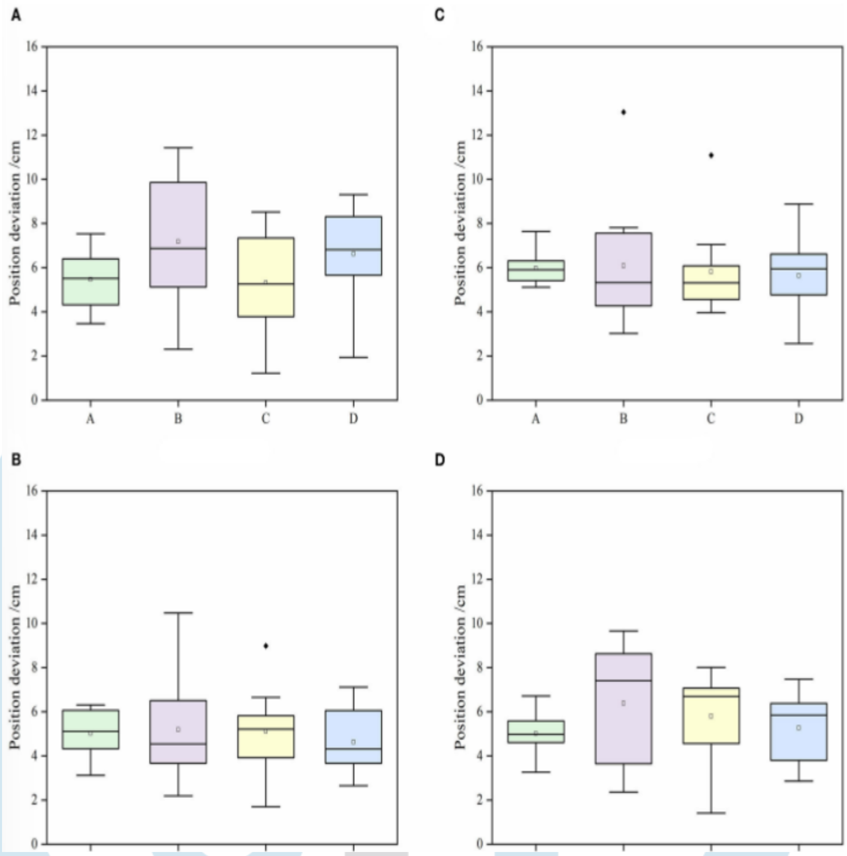


Figure 9:Positioning deviation of the robot at each target point [27]

## III. Applications

Autonomous vehicles are emerging applications in automobile industries or automotive technologies. These vehicles can perceive the segments [18], plan the path and control the motion [19] by themselves while interacting with the vehicle user. Whilst these vehicles can secure appreciable attention, components of autonomous vehicles are insurmountable to the public but instead are developed as proprietary assets. New vehicle models progressively include features such as Adaptive cruise control and parking assist systems that allow cars to steer themselves into parking lots. Autonomous cars [20] and trucks [21] have the capabilities to fundamentally amend transportation systems by precluding deadly crashes, providing critical mobility to the elderly and disabled, expanding road dimensions, saving fuel and lessening emissions. However, it is far from certain that autonomous vehicles will proliferate. The large-scale production and availability for mass consumers are hampered by the high costs. The explicit roadway map is an essential information for driving autonomous vehicles. This information is the foundation for many for many activities that work in autonomous vehicle driving systems. In this context, a localization algorithm [22,23]can improve the accuracy and dependability of position impressions through the employment of antecedent road geometry. Typically, the data from the on-board sensors will be combined with the GPS measurements [24,25] using the fixed-interval optimal smoothing algorithm to increase the accuracy, consistency, and dependability of road geometry estimation. The optimal smoother [26] which has a fixed-intervals will estimate each time state. Forward-backward approach and Raunch-Tung-Striebel (RTS) smoother are the two main types of fixed-interval optimal smoothers. The forward-backward smoothing approach makes it simpler to comprehend the optimal smoothing principle than the RTS smoother. However, because it is more computationally effective and simpler to use, the RTS smoother is chosen as the best smoothing technique in this study.

## IV. Conclusion

In this work, most popular and widely used path planning working algorithms and techniques are summarized for autonomous vehicles in the literature. The design of a trajectory involves more than just creating a path from one point to another and it also involves ensuring that the chosen path is smooth and optimal in a variety of local and global contexts by considering all the literary works. The three main technologies for self-driving obstacle avoidance are decision making, path planning, and path tracking. So, future research will concentrate on path tracking and motion control. Additionally, even though many techniques have been made public, certain options are still available, and different viewpoints are considered to improve the suggested procedures.

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