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# Robust Control Strategies for Autonomous Vehicles in Varied Traffic Conditions

**Nurul binti Ismail**
Department of Civil Engineering, Universiti Malaysia Terengganu (UMT), Mengabang Telipot Campus, Terengganu.

**Wong Yee Chong**
Department of Computer Engineering, Universiti Malaysia Sabah (UMS), Sandakan Campus, Sabah.

## Abstract

The advancement of autonomous vehicles (AVs) is largely reliant on robust control strategies capable of managing diverse and unpredictable traffic situations. This study discusses six key strategies commonly used in the design and operation of AVs: Model Predictive Control (MPC), Reinforcement Learning (RL), Fuzzy Logic, Sliding Mode Control (SMC), Genetic Algorithms, and Neural Networks. MPC offers a method of predicting and optimizing system behavior over time, a valuable tool for handling changing traffic conditions. RL provides a mechanism for learning from the environment and adjusting vehicle behavior accordingly, using a reward system. Fuzzy Logic, with its basis in human-like reasoning, adapts well to unpredictable traffic situations. SMC is advantageous in its robustness to uncertainties and nonlinearities in traffic conditions. Genetic Algorithms offer an approach for evolving resilient control strategies by simulating traffic conditions and selecting the highest-performing strategies. Finally, Neural Networks, especially Convolutional Neural Networks (CNNs), process sensor data for perception tasks such as object detection and depth estimation. However, the effectiveness of these control strategies is dependent on accurate environmental perception and prediction, which remain significant research challenges. This involves the use of advanced sensing technology and sophisticated algorithms to interpret the sensor data accurately. Ultimately, the study emphasizes the need for these control strategies to account for a broad spectrum of potential traffic scenarios, underscoring the complexity and breadth of ongoing research in this field.

**Keywords:** *Autonomous Vehicles, Model Predictive Control, Reinforcement Learning, Fuzzy Logic, Sliding Mode Control, Genetic Algorithms, Neural Networks*

## Introduction

Autonomous vehicles, also known as self-driving cars, are vehicles that are capable of navigating and operating without any direct human input. They use a combination of advanced sensors (like lidar and radar), computer systems, artificial intelligence, and machine learning algorithms to understand their environment and make decisions about driving actions. Essentially, these vehicles incorporate technologies that perceive the surroundings, identify paths for safe travel, and control the vehicle accordingly. The aim is to perform all these tasks as accurately as, if not more than, a human driver. These vehicles range from semi-autonomous, where they can control certain aspects of driving but still require human supervision, to fully autonomous, where they can operate independently under all conditions [1].

The ability of autonomous vehicles to operate is made possible through various components working together to mimic the cognitive functions of a human driver. The sensors, which act like the car's eyes and ears, continuously gather data about the surrounding environment. This data can include information about nearby vehicles, pedestrians, road signs, and obstacles. It is then processed by the onboard computers, much like the brain of a car. The artificial intelligence and machine learning algorithms analyze this data, make decisions on how the car should respond, and then send commands to the car's systems to execute those decisions. For instance, if a pedestrian were to suddenly step out into the road, the car's sensors would detect this, the AI would process it, decide to apply the brakes, and then send a command to the car's braking system to do so [2].

Despite the significant advancements, autonomous vehicles still face a series of challenges that need to be addressed. These include technical issues, such as how to make the AI capable of handling every possible driving situation, and ethical dilemmas, such as how the AI should decide in life-or-death situations. Additionally, there are legal and regulatory issues, such as who would be held responsible in the event of an accident. Nonetheless, the potential benefits of autonomous vehicles are compelling. They can potentially reduce traffic accidents caused by human error, provide mobility for those who cannot drive, and even free up time for passengers.

As research and development continue to progress, it is expected that these challenges will be gradually addressed, and autonomous vehicles will become a common sight on our roads.

Varied traffic conditions present some of the most significant challenges for autonomous vehicles. These include inclement weather, traffic congestion, varying road conditions, and unpredictable human behavior. Bad weather, like heavy rain or snow, can hinder sensor perception and degrade the performance of the vehicle's radar, lidar, and camera systems. Similarly, fog can reduce visibility and the vehicle's ability to accurately perceive its surroundings. Complex traffic conditions, such as congested roads or unpredictable maneuvers by other road users, can also pose significant challenges. Furthermore, road conditions that change due to construction, potholes, or detours necessitate advanced understanding and decision-making capabilities from the autonomous vehicle. The unpredictable nature of human drivers and pedestrians, who may not always follow traffic rules, adds another layer of complexity for these vehicles to handle [3].

These challenges impact the performance of autonomous vehicles by complicating the decision-making process. In essence, autonomous vehicles operate optimally in predictable environments where they can make decisions based on pre-programmed scenarios. However, unpredictable and varied traffic conditions can create scenarios that the vehicle's artificial intelligence might not have been trained to handle. This results in increased uncertainty in decision-making and, potentially, decreased safety. For example, in heavy traffic, the vehicle might struggle to merge lanes if it is programmed to always maintain a safe distance from other vehicles. Similarly, in the case of a sudden downpour, the vehicle's perception system might become less accurate, and the vehicle might react in a way that is either overly cautious, causing traffic delays, or not cautious enough, leading to safety risks.

Overcoming these challenges necessitates advances in both hardware and software. Hardware, such as sensors and perception systems, needs to be robust enough to function reliably under diverse weather and traffic conditions. Software, on the other hand, including AI and machine learning algorithms, needs to be trained on a vast range of scenarios, including those that are rare or hard to predict. Moreover, it must be capable of making complex, ethical decisions when faced with unprecedented situations. Addressing these challenges is vital to the broader acceptance and deployment of autonomous vehicles. By doing so, it will increase their reliability and performance, which in turn will enhance their safety and the public's confidence in this technology.

## Robust Control Strategies

*Model Predictive Control (MPC):*

Model Predictive Control (MPC) is an advanced control strategy that uses mathematical models and optimization algorithms to predict and optimize system behavior over a defined future horizon. The foundation of MPC lies in the principle of making real-time predictions about future system behavior and using these predictions to influence current actions to achieve optimized operation.

At the heart of MPC is the concept of prediction. It uses a system model that can represent complex interactions between different variables. These models could be linear or non-linear, and they could be discrete or continuous. For example, in an automated driving system, the model could represent the dynamics of the vehicle, the behavior of other vehicles, and the physical constraints of the road [4]. These models are then used to predict the future system state based on the current system state and possible control inputs [5].

The second important concept in MPC is optimization. MPC is an optimal control technique where the control actions are chosen to minimize a certain cost function. The cost function is a mathematical representation of the system's objectives. It quantifies the deviation from the desired system behavior, such as deviations from the desired speed, trajectory, or fuel consumption. In real-time, the controller minimizes this cost function by selecting the most suitable control inputs. The choice of cost function is crucial as it reflects the control priorities. It is often designed to balance multiple conflicting objectives [6].

For example, in the context of autonomous driving, the cost function could reflect safety requirements (like maintaining a safe distance from other vehicles), traffic rules (like speed limits), passenger comfort (like avoiding abrupt braking or accelerating), and energy efficiency (like minimizing fuel consumption). The optimization problem then becomes to select the vehicle's control inputs (like acceleration, braking, and steering) that minimize this cost function over the prediction horizon [7].

MPC's real power comes from its ability to handle multivariable control systems and manage constraints. Traditional control strategies often struggle when multiple control variables interact with each other and have to adhere to physical or operational constraints. MPC, on the other hand, can systematically handle such interactions and constraints within its optimization framework.

For instance, in autonomous driving, the control variables, such as the vehicle's speed and direction, are influenced by each other and have to adhere to physical constraints like the vehicle's maximum acceleration and operational constraints like traffic rules. MPC can handle these interactions and constraints effectively by incorporating them into its optimization problem, ensuring that the selected control actions are always feasible and safe [8].

MPC is a model-based strategy, implying that its performance depends on the accuracy of the system model. In practical applications, the system model might not perfectly represent the real-world system due to various uncertainties and disturbances. Therefore, it is common to couple MPC with robust or adaptive control strategies to improve its robustness to model uncertainties.

Another defining feature of MPC is its ability to adapt to changing operating conditions. Traditional control strategies often need manual tuning when the operating conditions change. MPC, in contrast, continuously re-evaluates the future prediction and optimization based on the current data. This makes it highly suitable for applications with variable operating conditions, such as autonomous driving in variable traffic conditions [9].

However, the extensive computational requirements are one of the main challenges of MPC. Solving the optimization problem in real-time can be computationally intensive, especially for large-scale systems or long prediction horizons. Therefore, the practical application of MPC often requires a trade-off between the prediction horizon, the model complexity, and the computational resources.

Despite these challenges, MPC has become a popular control strategy in various applications, including process control, energy systems, robotics, and autonomous driving [10]. It has demonstrated its ability to handle complex system dynamics, manage operational and physical constraints, and adapt to changing conditions, making it a powerful tool for designing advanced control systems [11].

### *Reinforcement Learning (RL):*

Reinforcement Learning (RL) is a subfield of machine learning that allows machines, including autonomous vehicles (AVs), to learn from their interactions with their environment. It operates on the principle of a reward and penalty system, encouraging positive actions and discouraging negative ones. Modern advancements in RL have led to deep reinforcement learning, integrating deep learning into RL to enable understanding and responding to complex scenarios [12].

The cornerstone of RL is the concept of agents interacting with an environment. In the context of AVs, the vehicle acts as the agent, and the environment comprises the road, other vehicles, pedestrians, and traffic signals, among other elements [13]–[15]. The agent, in this case, the AV, takes actions based on its current state and the environment's condition, transitioning to the next state and receiving a corresponding reward or penalty [16].

The reward system is a fundamental aspect of RL. It quantifies the success of an action, providing positive feedback for beneficial actions and negative feedback for undesirable actions. In the case of AVs, positive actions could include maintaining lane discipline, avoiding collisions, following traffic signals, while negative actions might entail erratic driving, speeding, or traffic rule violations. The objective of the AV, as the agent, is to learn the optimal policy, which is the sequence of actions that maximizes the cumulative reward over time.

In an RL paradigm, the agent does not have prior knowledge of the environment. It learns the optimal policy through exploration and exploitation. Exploration allows the agent to try new actions and discover their outcomes, leading to new knowledge about the environment. Exploitation, on the other hand, leverages this learned knowledge to make decisions that maximize the reward. Balancing exploration and exploitation is a central challenge in RL, known as the exploration-exploitation dilemma.

RL has shown significant promise in dealing with dynamic and uncertain environments, such as traffic scenarios faced by AVs. The adaptability of RL makes it suitable for AVs, which must operate under diverse traffic conditions and make real-time decisions to ensure safe and efficient operation.

A significant advancement in RL is the incorporation of deep learning, leading to Deep Reinforcement Learning (DRL). DRL combines the decision-making capabilities of RL with the representational power of deep learning. Deep learning, a subset of machine learning, uses neural networks with several hidden layers (hence, 'deep') to learn representations of data with multiple levels of abstraction. This enables DRL to handle high-dimensional state spaces and understand complex scenarios, which are common in autonomous driving.

For example, a DRL-based AV controller could use a deep neural network to process visual inputs from on-board cameras and LiDAR data to understand the current traffic situation. The controller could then use an RL algorithm to select the optimal driving action based on this understanding [17]–[19].

### *Fuzzy Logic:*

Fuzzy logic is a unique computational approach to reasoning that closely mimics human thinking. Unlike classical binary logic, which deals in strict true or false values, fuzzy logic operates on degrees of truth. This characteristic makes it well-suited for dealing with uncertainty and vagueness, commonly encountered in real-world scenarios like autonomous vehicle operation [20], [21].

The crux of fuzzy logic lies in the concept of 'fuzzy sets', which are mathematical representations of vague concepts. For example, in the context of autonomous vehicles, consider the concept of speed. In classical logic, a vehicle would be classified as either 'fast' or 'slow' based on a strict cutoff. However, fuzzy logic allows a more nuanced understanding, assigning a degree of membership to the 'fast' and 'slow' categories [22]. So, a vehicle could be 'somewhat fast' or 'mostly slow', mirroring human intuition.

Fuzzy logic systems include four main components: fuzzification, knowledge base, inference engine, and defuzzification. Fuzzification involves converting crisp inputs, such as sensor readings, into fuzzy sets. The knowledge base contains the fuzzy rules, representing human expert knowledge. The inference engine applies these rules to the fuzzy inputs to generate fuzzy outputs. Finally, defuzzification converts these fuzzy outputs back into crisp values, usable for decision-making or control [23].

The application of fuzzy logic in autonomous vehicles can greatly enhance their adaptability to various traffic conditions. The traffic environment is highly dynamic and full of uncertainties. Unpredictable human drivers, diverse weather conditions, and varying road surfaces are just some of the challenges that AVs face.

Fuzzy logic can help manage these uncertainties effectively. For instance, consider an AV interacting with a human-driven vehicle. Human drivers may not always follow traffic rules strictly, making their behavior difficult to predict. A fuzzy logic controller can interpret such uncertain behaviors in a flexible and nuanced way, enabling the AV to react appropriately [24].

In varied weather conditions, fuzzy logic can also be invaluable. For example, consider an AV operating in foggy conditions where sensor readings could be less reliable. A fuzzy logic system could interpret these uncertain readings and adjust the vehicle's speed and following distance to ensure safe operation.

Moreover, the flexibility of fuzzy logic allows it to adapt to different road surfaces. For example, an AV might need to adjust its braking or steering depending on whether the road is dry, wet, or icy. A fuzzy logic controller can handle such variations effectively, providing a smooth and safe driving experience [25], [26]e.

Despite its strengths, fuzzy logic does have limitations. It is highly dependent on expert knowledge to formulate the fuzzy rules, making it potentially subjective and imprecise. Furthermore, while it excels in handling uncertainty, it may not be the best choice for problems where precise quantitative results are needed [27], [28].

### *Sliding Mode Control (SMC):*

Sliding Mode Control (SMC) is a robust control methodology that has proven to be effective for systems characterized by nonlinearities, uncertainties, and disturbances [29], [30]. Predicated on the unique concept of "sliding" along a predetermined surface, or "sliding mode", SMC reduces deviations from the desired path, providing a high degree of robustness. This property is especially advantageous in various traffic conditions where uncertainties are rife, as in the case of autonomous vehicles. At the core of SMC is the idea of a sliding surface or a sliding mode [31]. This is essentially a mathematical construct that is defined in the state space of the system. When the system reaches this sliding mode, it slides along it towards the origin, which is typically defined as the desired state [32]. Thus, by forcing the system to reach and stay on the sliding surface, SMC ensures that the system converges to the desired state, regardless of any disturbances or uncertainties [33], [34].

SMC employs a two-phase control strategy. In the reaching phase, the controller drives the system state towards the sliding surface. Once on the surface, during the sliding phase, the controller ensures that the system state slides along the surface towards the origin. This switching between the reaching and sliding phases occurs at a high frequency, giving the appearance of a continuous control action.

A critical feature of SMC is its robustness to uncertainties. This robustness arises from the discontinuous control action in the vicinity of the sliding surface, which can counteract the effects of uncertainties and disturbances. This makes SMC a potent control strategy for systems where the model is not completely known or where the system is subject to external disturbances [35].

For instance, in the context of autonomous vehicles, consider a scenario where the vehicle is navigating through a crowded urban environment. Here, the vehicle dynamics might be uncertain due to variations in road conditions, and the vehicle may also encounter unpredictable disturbances from other vehicles or pedestrians. An SMC-based controller could effectively handle these uncertainties and disturbances, ensuring that the vehicle stays on its desired path [36].

Moreover, the nature of the control action in SMC lends itself well to systems with nonlinearities. Traditional linear control methods often struggle with nonlinear system dynamics, while SMC can handle them more effectively due to its non-linear control law. This is another advantage of SMC in autonomous driving, where the vehicle dynamics and the driving environment can often exhibit nonlinear characteristics [37].

Despite its advantages, SMC does come with its challenges. The discontinuous control action can lead to chattering, a phenomenon where the control input rapidly oscillates, potentially causing wear and tear in physical systems. Modern variations of SMC, such as higher-order SMC and continuous approximations of SMC, have been developed to mitigate this issue.

### *Genetic Algorithms:*

Genetic algorithms are a form of evolutionary computation that emulate the process of natural selection, the fundamental mechanism of evolution in biological species [38]–[40]. These algorithms have proven to be powerful optimization tools, capable of finding high-quality solutions to complex problems by iteratively refining a population of candidate solutions. In the realm of autonomous vehicles (AVs), genetic algorithms can be harnessed to evolve robust control strategies by simulating a variety of traffic scenarios and optimizing the control strategies for the best performance [41].

The basic workings of a genetic algorithm involve several stages: selection, crossover (or recombination), and mutation. The algorithm begins with an initial population of candidate solutions, represented as 'chromosomes'—sequences of 'genes', which are fundamental decision variables in the optimization problem.

The 'fitness' of each solution is evaluated based on a pre-defined fitness function, which quantifies the quality of a solution. For instance, in the context of AV control strategies, the fitness function might consider factors like safety, efficiency, comfort, and adherence to traffic rules. The higher the fitness score, the better the control strategy.

During the selection phase, solutions are chosen for reproduction, with preference given to those with higher fitness scores, reflecting the survival of the fittest in natural selection. This process often uses methods such as tournament selection or roulette wheel selection [42].

The selected solutions then undergo crossover, where pairs of 'parent' solutions are combined to create 'offspring' solutions. This process mirrors biological recombination, where offspring inherit traits from both parents. In the crossover phase, genes from parent chromosomes are mixed to form new offspring chromosomes, potentially combining the strengths of both parents [31].

Finally, mutation introduces small random changes in the offspring, analogous to genetic mutation in biology. This process helps maintain diversity in the population and prevent premature convergence to suboptimal solutions [43].

Over successive generations, the population evolves towards better solutions, with unfit strategies gradually phased out and more effective ones proliferating. In the context of AVs, this means that control strategies that result in safer, more efficient, and more comfortable driving would be more likely to be selected and refined over time [44], [45].

Using genetic algorithms to evolve AV control strategies has several advantages. Firstly, they can handle large, complex search spaces, making them suitable for complex problems like AV control. Secondly, they are robust to changes in the problem environment, as the population-based approach provides a diverse set of solutions. Lastly, they can find global optima without requiring gradient information, making them suitable for non-differentiable, non-convex, and discontinuous optimization problems .

However, genetic algorithms do come with certain limitations. They can be computationally expensive, especially for large populations or complex fitness functions. They also do not guarantee finding the absolute global optimum, and the quality of the solution can depend on the choice of parameters like mutation rate and crossover rate.

### *Neural Networks:*

Neural networks, and in particular Convolutional Neural Networks (CNNs), have revolutionized the field of computer vision, bringing significant advancements in perception tasks such as object detection, segmentation, and depth estimation. These capabilities make them a cornerstone technology in autonomous vehicles (AVs), where understanding the vehicle's environment through sensory data is crucial for safe and efficient operation.

Neural networks are machine learning models inspired by the human brain's structure. They consist of interconnected layers of nodes, or 'neurons', which can learn complex patterns in data. These networks learn by adjusting the weights of the connections through a process called backpropagation, optimizing the weights to minimize the difference between the network's predictions and the actual values.

Convolutional Neural Networks (CNNs) are a specialized type of neural network designed to process grid-like data, such as images. They are composed of convolutional layers, pooling layers, and fully connected layers. The convolutional layers apply filters to the input data, identifying local patterns such as edges or textures. The pooling layers then reduce the dimensionality of the data, keeping the most important information. Finally, the fully connected layers generate the output predictions.

In the context of AVs, CNNs can process input data from sensors like cameras or LiDAR (Light Detection and Ranging) to detect and classify objects, segment images, and estimate depth. For instance, a CNN might take as input an image from a front-facing camera and output bounding boxes around detected cars, pedestrians, and other relevant objects (object detection). Or, it could classify each pixel in the image as belonging to a particular class (e.g., road, car, pedestrian), providing a detailed understanding of the scene (segmentation).

CNNs can also estimate depth from images, a process called depth estimation. By understanding how far away objects are, an AV can make informed decisions about how to navigate its environment. Depth can be estimated from a single image, from a sequence of images, or from stereo images. CNNs can be trained to perform this task, enabling AVs to understand the 3D structure of the scene. However, CNNs are not without their challenges. They require large amounts of labeled training data and significant computational resources, which can be prohibitive. Furthermore, they may not perform well in conditions that differ from those in the training data, making them susceptible to adverse weather conditions or unexpected situations [46]. Additionally, they operate as "black boxes," making their decision-making process hard to interpret, which can be a concern for safety-critical applications like autonomous driving.

## Conclusion

Robust control strategies are methods used in autonomous vehicles to ensure their optimal operation under a wide variety of conditions, and especially in the presence of uncertainties or disturbances. Essentially, the aim of robust control is to make the autonomous vehicle's performance less sensitive to changing conditions by having it adapt to different scenarios that it may encounter. These strategies are crucial in autonomous vehicle design as they enable the system to manage varied and unpredictable situations such as different road conditions, weather conditions, and driver behaviors.

There are several types of robust control strategies utilized in autonomous vehicles, including Model Predictive Control (MPC), Linear Quadratic Gaussian (LQG) Control, and H-Infinity Control, among others. Model Predictive Control (MPC) is a popular method due to its ability to handle multivariable control problems and constraints. It uses a model of the system to predict future outcomes and makes decisions based on minimizing a cost function over a given horizon. Linear Quadratic Gaussian (LQG) Control is a strategy that combines optimal control (based on minimizing a quadratic cost function) with state estimation (using a Kalman filter) under the assumption of Gaussian noise. H-Infinity Control is a method that aims to minimize the maximum gain from disturbance to output across all frequencies, providing a strong level of robustness against uncertainties.

Model Predictive Control (MPC) is an advanced method of process control that is used to solve control problems involving constraints and multivariable systems. In autonomous vehicles, MPC uses a model of the system to predict future outcomes based on current states, control inputs, and a defined cost function. This cost function typically includes factors such as safety, energy efficiency, passenger comfort, and adherence to traffic rules . By continuously updating and optimizing this prediction, MPC provides a robust control strategy that can effectively navigate varied and unpredictable traffic conditions.

Reinforcement Learning (RL) is a type of machine learning that trains algorithms using a system of reward and punishment. This strategy is especially effective in training autonomous vehicles, as it allows them to learn from their environment and adapt to new situations. By assigning rewards for desirable actions (such as maintaining the correct lane or avoiding collisions) and penalties for undesirable actions (like erratic driving or breaking traffic rules), RL can teach autonomous vehicles to operate safely and efficiently under a variety of traffic conditions. More advanced methods, like deep reinforcement learning, even use deep learning architectures to understand complex driving scenarios.

Fuzzy Logic is a form of many-valued logic in which the truth values of variables may be any real number between 0 and 1, and not just strictly 0 or 1 as in traditional binary logic [47]. This approach enables autonomous vehicles to handle ambiguous and complex situations much like a human driver would. By accounting for various levels of truth, fuzzy logic allows for more nuanced decision-making, making it particularly useful in dealing with unpredictable human drivers, diverse weather conditions, and changing road conditions.

Sliding Mode Control (SMC) is a robust control strategy that's designed to cope with systems affected by nonlinearities, uncertainties, and disturbances. It works by forcing the system to operate in a 'sliding mode', reducing the effects of system deviations and leading to an invariant system behavior [48], [49]. This characteristic makes SMC exceptionally useful in varied traffic conditions, as it can maintain stable and predictable operation despite changing and unpredictable circumstances.

Genetic Algorithms are optimization methods that simulate natural selection, where the most successful individuals are chosen for reproduction to produce the offspring of the next generation. This method can be used to optimize the control strategies in autonomous vehicles by simulating a variety of traffic conditions and selecting the control strategies that yield the best performance.

Neural Networks, particularly Convolutional Neural Networks (CNNs), are widely used in perception tasks for autonomous vehicles, including object detection, segmentation, and depth estimation. These networks process input data from various sensors like cameras or LiDARs and extract meaningful information for the vehicle to make informed decisions. This is particularly beneficial in varied traffic conditions, as it allows the autonomous vehicle to accurately perceive its environment and respond accordingly.

Robust control strategies offer numerous benefits in helping autonomous vehicles navigate varied traffic conditions. Firstly, they improve the adaptability of the autonomous vehicles, allowing them to handle a broad range of scenarios. This makes them more reliable in unpredictable environments, enhancing their overall performance and safety. Secondly, these strategies provide a systematic approach to handle uncertainties, which can result from sensor noise, changes in vehicle dynamics due to varying load or road conditions, or unforeseen actions from other road users. Lastly, robust control strategies can help optimize the vehicle's responses, enhancing efficiency and comfort. For instance, a robust control strategy could ensure smooth braking despite changes in road friction, leading to a more comfortable ride. The development and implementation of robust control strategies are crucial for the wider adoption of autonomous vehicles, as they significantly increase their performance, safety, and reliability under diverse traffic conditions.

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