Autonomous Vehicle Overtaking: A Comprehensive Review of Decision-Making, Learning, Control, and Trajectory Planning Approaches

Hriday Parikh
Navrachana Higher Secondary School, Sama

Abstract
Autonomous vehicle overtaking presents a complex challenge in the development of self-driving technology, with significant implications for road safety, traffic efficiency, and user acceptance. The global autonomous vehicle market is projected to grow rapidly, with overtaking capabilities being a crucial component of this technology. This has generated significant interest in developing robust and efficient overtaking systems for autonomous vehicles. Autonomous overtaking systems offer several advantages over human-controlled overtaking, including improved safety, enhanced decision-making, and optimized trajectory planning. These systems have the potential to revolutionize traffic flow and reduce accidents caused by human error during overtaking manoeuvres. This paper reviews various approaches to autonomous vehicle overtaking, including rule-based systems, reinforcement learning methods, model predictive control strategies, and trajectory optimization techniques. It also discusses decision-making processes, learning approaches, control strategies, and trajectory planning methods for autonomous overtaking. Challenges, economic implications, and future prospects of autonomous overtaking technology in the context of the broader autonomous vehicle industry are also explored.

Keywords: *Autonomous vehicles, Overtaking manoeuvres, Reinforcement learning, Model predictive control, Trajectory optimization*

Introduction

Autonomous vehicles (AVs) have emerged as a transformative technology in the automotive industry, promising to revolutionize transportation systems worldwide. As AVs continue to evolve, one of the most challenging manoeuvres they must master is overtaking. Overtaking in autonomous vehicles is a complex interplay of perception, decision-making, planning, and control, requiring the vehicle to safely and efficiently pass slower-moving vehicles while following traffic rules and considering the dynamic nature of road environments.

The evolution of overtaking systems for AVs has been marked by significant advancements in various technological domains. Early approaches relied heavily on rule-based systems and simplified models of vehicle dynamics. However, as sensing technologies improved and computational power increased, more sophisticated methods emerged. These include the integration of machine learning algorithms, advanced control techniques, and optimization strategies to handle the complexities of real-world traffic scenarios.

Numerous studies have contributed to the development of overtaking systems for AVs, each presenting innovative approaches to address specific challenges. For example, Ngai and Yung (2011) proposed a multiple-goal reinforcement learning method for complex vehicle overtaking manoeuvres. Murgovski and Sjoberg (2015) used convex modelling in a Model Predictive Control (MPC) framework to create safe overtaking trajectories, highlighting the importance of predictive control in handling the uncertainties associated with overtaking. Yu et al. (2017) explored the use of deep Q-learning for autonomous overtaking decisions, demonstrating the suitability of deep learning techniques.

Other notable innovations include the development of potential-field-based methods for trajectory optimization, the application of fuzzy logic systems for lane-keeping during overtaking, and the integration of reachability analysis for ensuring safety guarantees. These diverse approaches reflect the multifaceted nature of the overtaking problem and the need for interdisciplinary solutions.

Despite the wealth of research in this area, there is a notable lack of comprehensive reviews that collate and analyze the various approaches to autonomous vehicle overtaking. This gap in the literature hinders the ability of researchers and practitioners to gain a holistic understanding of the most recent advancements in overtaking systems for AVs. Therefore, this review paper aims to fill this gap by providing a systematic overview of the existing research, synthesizing key findings, and identifying trends and challenges in the field.

The primary research questions addressed in this review are:

RQ1: What are the main approaches and technologies used in developing overtaking systems for autonomous vehicles?

RQ2: What are the key challenges and open problems in autonomous vehicle overtaking that require further research?

This paper is organized as follows: The next section discusses the decision-making processes involved in autonomous overtaking, including both rule-based and learning-based approaches. The third section explores various learning techniques applied to overtaking, with a focus on reinforcement learning and deep learning methods, followed by control strategies for overtaking, including Model Predictive Control and other adaptive techniques. The fifth section discusses trajectory planning and optimization methods for executing safe and efficient overtaking manoeuvres. Finally, the last section concludes the paper with a summary of findings, limitations of current approaches, implications for the field, and directions for future research.

The Rise of Autonomous Vehicles

AVs have seen a surge of interest in recent years, driven by their potential advantages (Fagnant & Kockelman, 2015). As we move towards an increasingly automated transportation landscape, one of the critical challenges lies in replicating and improving upon complex driving manoeuvres traditionally performed by human drivers. Among these, overtaking stands out as a particularly complex and safety-critical operation.

Automation involves "the replacement of human activities by machine activities" (Satchell, 1998). In the context of autonomous driving, this means transferring the cognitive and physical tasks of driving from humans to sophisticated computer systems. However, the successful implementation of autonomous overtaking requires not just a simple transfer of control, but a complete understanding of its nuances and the development of advanced algorithms capable of making split-second decisions in dynamic traffic environments.

The Complexity of Overtaking

Overtaking is a fundamental driving task that will remain essential even in an increasingly automated environment, especially in mixed traffic conditions involving vehicles with different speeds and behaviours (Sourelli et al., 2023). The overtaking manoeuvre can be broken down into three main phases (Naranjo et al., 2008). The process begins with the pull-out phase, where the vehicle initiates the manoeuvre by moving into the overtaking lane. This is followed by the passing phase, during which the vehicle accelerates past the slower vehicle(s). Finally, the cut-in phase involves the vehicle returning to its original lane, completing the overtaking manoeuvre.

However, this simplified model belies the complexity of real-world overtaking scenarios. Depending on the driving context, the manoeuvre may involve additional steps or variations to ensure safety and efficiency (Bellem et al., 2016). For instance, the overtaking vehicle might need to adjust its speed multiple times, account for other vehicles in adjacent lanes, or abort the manoeuvre if conditions change unexpectedly. These nuances highlight the intricate nature of overtaking and the challenges involved in automating this process.

Challenges in Autonomous Overtaking

Implementing effective overtaking strategies in autonomous vehicles presents several significant challenges. One of the primary concerns is speed and trajectory planning. As Jung et al. (2023) point out, there is often a time constraint for occupying the overtaking lane. The AV must balance energy efficiency with the need to complete the manoeuvre within a safe time frame, determining the optimal velocity profile for overtaking.

Decision-making is another crucial aspect of autonomous overtaking. The AV must decide when it is appropriate to initiate an overtaking manoeuvre, which involves assessing the speed differential with the leading vehicle, available gaps in traffic, and potential risks (Wang et al., 2009). This decision-making process is closely tied to environmental perception, as accurate sensing and interpretation of the surrounding environment, including other vehicles, road markings, and potential obstacles, is critical for safe overtaking (Milanés et al., 2012).

Furthermore, the ability to predict the behaviour of other road users adds another layer of complexity to autonomous overtaking. Anticipating the actions of other vehicles, especially in mixed traffic scenarios with human drivers, is a challenging task that requires sophisticated algorithms and extensive training data (Okamoto et al., 2017).

Ethical considerations also come into play in autonomous overtaking scenarios. In some situations, the AV may need to make complex ethical decisions, weighing factors such as safety, efficiency, and fairness to other road users (Goodall, 2014). These ethical dilemmas further complicate the development of strong autonomous overtaking systems.

Lastly, user acceptance is a critical factor in the widespread adoption of autonomous overtaking technology. As Abe et al. (2018) highlight, driver trust in automated driving systems, particularly for complex manoeuvres like overtaking, is crucial. Ensuring that human passengers feel comfortable and confident during autonomous overtaking manoeuvres is an important consideration in the development of these systems.

Developing Efficient Overtaking in AVs

As research in autonomous overtaking progresses, several key areas are emerging as focal points for future development. Advanced AI and machine learning techniques, such as reinforcement learning, are being explored to develop more adaptive and efficient overtaking strategies (Li et al., 2015; Yu et al., 2017). These approaches point towards autonomous systems that can learn from experience and improve their performance over time.
Improved sensor technologies are another critical area of development. Enhancing the AV's ability to perceive its environment accurately, even in challenging weather or lighting conditions, is crucial for safe overtaking (Shen & Yan, 2018). This includes advancements in cameras, lidar, radar, and other sensing technologies that can provide a comprehensive and reliable view of the vehicle's surroundings.
Vehicle-to-Vehicle (V2V) and Vehicle-to-Infrastructure (V2I) communication technologies are also being researched as potential enablers of safer and more efficient autonomous overtaking. These technologies could provide AVs with additional information to make more informed overtaking decisions, improving overall traffic flow and safety (Luo et al., 2016).
Finally, as Kyriakidis et al. (2019) emphasize, focusing on user-centred design for complex manoeuvres like overtaking will be crucial for public acceptance and trust. This involves not only technical development but also careful consideration of human factors, user interface design, and clear communication of the system's capabilities and limitations to users.

Overtaking Decision-making in Autonomous Vehicles

Overtaking involves a sophisticated combination of mental processing and accurate vehicle manipulation (Liu et al., 2023). The intricacy of this manoeuvre makes it a significant contributor to traffic violations and accidents, particularly when drivers disregard safety regulations (Lodhi et al., 2021; Mocsári, 2009).
For an overtaking manoeuvre to be initiated, specific conditions must be met: an empty lane ahead, no oncoming traffic, and a slower-moving vehicle in front. Once these conditions are satisfied, the overtaking process typically involves three main phases: a lane change to the passing lane, acceleration past the slower vehicle, and a return to the original lane (Mocsári, 2009). This sequence of actions presents a significant challenge for AVs, especially when multiple actions need to be combined seamlessly.

Approaches to Autonomous Overtaking

Researchers have proposed various approaches to address the challenge of overtaking manoeuvres in AVs. These methods can be broadly categorized into theoretical and artificial intelligence (AI)-based approaches (Lodhi et al., 2021). However, it is important to note that most evaluations of these methods have been conducted in simulated environments, highlighting the need for more real-world testing.

The complexity of real-world overtaking scenarios far exceeds that of simulations due to factors such as variable speeds, traffic density, and the need for real-time decision-making. While longitudinal and lateral controllers can handle basic acceleration and lane changes, these tasks become more complex for AVs in dynamic real-world traffic environments (Lodhi et al., 2021; Atagoziyev et al., 2016).

Vehicle Motion Prediction and Behaviour Modelling

Accurate vehicle motion prediction is crucial for AVs to safely execute overtaking manoeuvres. Researchers have explored various methods to predict human driver behaviour, including probabilistic approaches like Dynamic Bayesian Networks and methods based on past driving patterns (Carvalho et al., 2015; Gindele et al., 2010; Okamoto et al., 2017). Some studies have also considered factors such as driver aggression and unorganized traffic patterns when planning overtaking manoeuvres (Kala & Warwick, 2013).
Milanés et al. (2012) took this a step further by factoring in the behaviour of surrounding drivers, detected using stereo vision, to adjust control strategies and generate safe overtaking trajectories.

Rule-Based Decision-Making

Rule-based methods have shown effectiveness in controlled environments, such as the DARPA Urban Challenge, where driving scenarios are pre-defined (Leonard et al., 2008; Montemerlo et al., 2008; Urmson et al., 2008). These methods excel at tasks like lane changes, intersections, and recoveries from contingencies by using techniques such as decision trees or finite state machines. However, their reliance on pre-programmed rules makes them struggle to adapt to the uncertainties of real-world driving situations (Liu et al., 2019).
An interesting application of rule-based decision-making is the formalization of traffic rules using logical frameworks. For example, researchers have used Defeasible Deontic Logic (DDL) to create a machine-understandable format of Queensland's (Australia) overtaking rules (Bhuiyan et al., 2023). This approach allows an AV's reasoning engine to

make overtaking decisions based on both the formalized rules and real-time sensor data.

Learning-Based Approaches

Learning-based approaches, such as reinforcement learning, offer more flexibility in handling diverse scenarios but raise concerns about safety during training and deployment due to the vast number of possible situations (Yu et al., 2017; Li et al., 2015). Some learning-based methods divide overtaking into distinct stages with corresponding rewards (Ngai & Yung, 2011). Other approaches incorporate elements like graph-based motion prediction or dynamic potential fields to enhance safety considerations (Hegedüs et al., 2019; Huang et al., 2021).

Event-Driven and Multi-Layer Decision-Making

Recent research has proposed more sophisticated decision-making strategies. For example, Huang et al. (2023) introduced an event-driven decision-making strategy for AV overtaking manoeuvres that optimizes resource allocation. This approach focuses on making key decisions only when specific events occur, minimizing computational burden while adapting to varying traffic conditions.

Ji et al. (2023) proposed a two-layer decision-making system for connected and autonomous vehicles (CAVs) during overtaking scenarios. This system leverages Vehicle-to-Everything (V2X) communication to assess the "aggressiveness" of surrounding vehicles, allowing the CAV to plan a high-level trajectory and determine if overtaking is safe or beneficial before refining the plan at a lower level.

Factors Influencing Overtaking Decisions

Several factors influence overtaking decisions in both human drivers and AVs:

Traffic Density

Studies have shown that traffic density significantly impacts overtaking behaviour. Drivers tend to make more frequent lane changes and take greater risks when traffic is congested (Yang et al., 2018; Bella, 2011; Younsi et al., 2011). This results in higher average speeds with more variation, most likely due to drivers being more impatient and stressed in heavy traffic (Liu et al., 2023).

Speed Advantage

Research by Kan et al. (2009) focused on mathematically quantifying the speed advantage that motivates drivers to change lanes for overtaking manoeuvres. They proposed a comprehensive approach that incorporates the vehicle's acceleration rate, surrounding vehicle distances, and potentially remaining travel time, building upon existing models that considered speed and distance (Jin et al., 2019; Balal et al., 2016) and speed differences (Zhou et al., 2019).

Time Pressure and Situational Factors

Time pressure can lead to faster, potentially riskier choices due to limited situation awareness (Hwang, 1994). Situational criticality, measured by time-to-collision with oncoming traffic, also plays a major role in overtaking decisions (Miller et al., 2022; Stoll et al., 2020). As criticality increases, drivers may choose smaller safety margins or even abandon the overtake altogether (Bianchi Piccinini et al., 2018; Yan et al., 2019).

Automation Level

Studies have examined how driver behaviour changes with varying levels of vehicle automation (manual, partially automated, and conditionally automated). Research suggests that vehicle automation may lead to improved driver control, with drivers exhibiting calmer eye movements and lower speed variations during automated driving (Madigan et al., 2018; Goncalves et al., 2020; Chen et al., 2015).

User Preferences and Acceptance

Some studies indicate a preference for cautious overtaking manoeuvres in AVs compared to human driving (Basu et al., 2017; TRL, 2017). People generally favour AVs maintaining larger distances from vulnerable road users and initiating overtaking only after clear opportunities arise (Abe et al., 2018). This suggests a general aversion to risk-taking by AVs during overtaking.

Learning Overtaking

The complexity of overtaking manoeuvres in autonomous vehicles has led researchers to explore various machine learning approaches, with a particular focus on reinforcement learning (RL) techniques. RL has shown promise in handling the sequential decision-making nature of overtaking, allowing vehicles to learn optimal behaviours through environmental interaction (Liu et al., 2017).

Reinforcement Learning Approaches

Reinforcement learning is considered effective in autonomous vehicle decision-making due to its ability to handle unpredictable driving scenarios. Unlike supervised and unsupervised learning methods, RL allows the vehicle to continuously learn and adapt its behaviour based on environmental feedback (Du et al., 2019). This approach has been successfully applied to various aspects of autonomous driving, including driver activity recognition (Xing et al., 2019), lane changing, and car-following control (Wang et al., 2018).

Zheng et al. (2013) demonstrated the effectiveness of RL in overtaking scenarios by using the Least Squares Policy Iteration (LSPI) algorithm to model overtaking decisions as a Markov Decision Process (MDP). Their simulations in a highway environment showed promising results for safe overtaking manoeuvres.

Building on this work, Yu et al. (2017) proposed a deep Q-learning method for overtaking decisions, which considers the velocities of surrounding vehicles in various situations. Their model focused on training for high-speed overtaking scenarios, further advancing the application of RL in complex driving situations.

Multi-Objective Approaches

Recognizing the multi-faceted nature of overtaking decisions, researchers have developed multi-objective RL approaches. Ngai and Yung (2011) proposed a multiple-goal RL method for complex vehicle overtaking manoeuvres. Similarly, Xu et al. (2018) modelled overtaking as a sequential decision process using an MDP with multiple goals, developing a multi-objective algorithm to address these complex decisions effectively.

Fuzzy Logic Integration

To handle real-world uncertainties in overtaking scenarios, some researchers have proposed integrating fuzzy logic with RL. Wu et al. (2021) introduced a fuzzy logic-enhanced reinforcement learning (FIRL) approach that considers safety, comfort, and efficiency in overtaking decisions. This method combines fuzzy logic for uncertainty handling with a RL technique (DF-TDL) for optimal decision-making, enabling autonomous vehicles to navigate overtaking manoeuvres more effectively.

Hierarchical Reinforcement Learning

Recent research has explored hierarchical reinforcement learning (HRL) approaches to overtaking. Yu et al. (2020) proposed a two-module system that considers the social preferences of overtaken vehicles. The first module uses an MDP-based approach for high-level decision-making, analyzing the behaviour of overtaken vehicles and generating appropriate overtaking manoeuvres. The second module acts as a low-level controller, handling the execution of the overtaking manoeuvre. This hierarchical approach combines technical aspects with social etiquette considerations on the road.

Deep Learning and V2I Communication

Several studies have proposed deep learning approaches assisted by Vehicle-to-Infrastructure (V2I) communication for crash detection and avoidance in overtaking scenarios. Abdou et al. (2019), Gumaei et al. (2020), and Alamri et al. (2020) developed systems that leverage V2I to share real-time accident information with nearby vehicles, allowing them to adjust their routes and avoid potential collisions during overtaking.

Shen and Yan (2018) addressed blind spot monitoring using a deep learning model that predicts the likelihood of accidents and estimates the number of vehicles present, triggering driver alarms when necessary during overtaking.

Thus, learning-based approaches, particularly reinforcement learning and its variants, offer the flexibility and adaptability required to handle the unpredictable nature of real-world driving scenarios.

Control of Overtaking

The control of overtaking manoeuvres in autonomous vehicles presents a complex challenge that requires sophisticated approaches to ensure safety, efficiency, and smooth execution. This section explores various control strategies and methodologies used in autonomous overtaking.

Traditional automated vehicle control systems typically follow a hierarchical structure consisting of four layers (Paden et al., 2016; Pereira et al., 2017):

Route Planning. Generates the optimal path between start and destination points.

Behavioral Layer. Determines appropriate actions based on the vehicle's current state and environment.

Motion Planning. Formulates safe and feasible trajectories to execute the desired behaviour.

Control Layer. Directly controls the vehicle's steering and acceleration to follow the planned trajectory.

The last three layers play the most crucial role in the on-board automated driving control system, particularly for overtaking.

Unified Control Approaches

The complexity of real-world traffic scenarios has led researchers to explore unified control methods that can directly translate traffic situations into control commands. This approach aims to bypass the need for separate decision-making and trajectory planning modules, addressing issues such as potential loss of crucial commands during inter-module communication.

MPC-Based Overtaking Control

Model Predictive Control (MPC) has emerged as a popular unified control method for autonomous vehicles (Camacho & Alba, 2013; Mayne, 2014). By treating roads, lanes, and obstacles as virtual potential fields (Volpe & Khosla, 1990; Wolf & Burdick, 2008), MPC-based systems can comprehensively handle dynamic traffic scenarios while incorporating vehicle limitations and safety distances as constraints.

Several researchers have explored MPC-based methods for autonomous vehicle control, particularly for overtaking. Murgovski and Sjoberg (2015) used convex modelling to generate safe overtaking trajectories. Chandru et al. (2017) employed MPC to determine safe lane changes during overtaking. Gray et al. (2012) and Nilsson et al. (2013) focused on collision avoidance during overtaking using MPC for trajectory planning and control. Qian (2016) formulated motion planning as a mixed-integer optimization problem within the MPC framework for obstacle avoidance during overtaking. Wang et al. (2009) utilized MPC to estimate conflict probability during overtaking manoeuvres.

MPC offers several advantages for overtaking control, including the ability to integrate various constraints (obstacle avoidance, path following, speed limits), enforce safety with hard control and state limitations, and adapt quickly to changing environments due to its receding horizon nature (Vu et al., 2021).

Reachability Analysis for Safe Overtaking

Reachability analysis is being adapted to guarantee safety in autonomous overtaking (Scott & Barton, 2013). This approach predicts all possible future states a vehicle can reach, accounting for external disruptions. Two main approaches exist:

1. Robust methods: Offer strong safety guarantees but require precise vehicle and environment models (Bertsekas & Rhodes, 1971).
2. Stochastic methods: Account for uncertainties using probability (Abate et al., 2008).

Recent research has explored the use of martingales as a less restrictive model for human drivers, reducing the data needed for safe overtaking (Sadigh et al., 2018; Gao et al., 2019).

Fuzzy Logic Control

Fuzzy logic systems have been proposed for autonomous overtaking control. One approach aims to keep the vehicle centred in its lane during normal driving, with slight deviations allowed for overtaking. This system tolerates small lateral and angular deviations to ensure smooth operation and prevent lane departure, with specific thresholds determined through real-world driving experiments.

Overtaking-Enabled Eco-Approach Control (OEAC)

A novel strategy called Overtaking-Enabled Eco-Approach Control (OEAC) has been proposed for autonomous vehicles at traffic lights. OEAC prioritizes both fuel efficiency and reduced travel time by allowing overtaking under specific conditions. It employs a two-stage receding horizon control approach:

1. Markov Decision Process (MDP) to determine optimal lane and speed trajectories.
2. Pontryagin's Minimum Principle (PMP) for real-time speed optimization.

This approach balances energy usage and traffic flow while considering traffic lights, preceding vehicles, and potential disruptions.

Nonlinear Adaptive Control

Recent research has proposed a nonlinear adaptive controller specifically designed for autonomous overtaking. This approach addresses the complexities of overtaking, which requires a sequence of lane changes, trajectory tracking, and another lane change. The proposed method builds upon existing research on overtaking control, including two-layer fuzzy logic controllers (Naranjo et al., 2008) and real-time trajectory planning (Resende & Nashashibi, 2010).

Trajectory Planning and Optimization

Trajectory planning and optimization play a crucial role in ensuring safe and efficient overtaking manoeuvres for autonomous vehicles. This section explores various approaches to designing and optimizing overtaking trajectories.

Potential-Field-Based Method

A promising approach for designing overtaking trajectories involves the use of potential-field-based methods. This technique optimizes multiple performance criteria by assigning a potential value to each feasible trajectory, thereby simplifying the search process. The primary goal is to identify a collision-free trajectory that aligns with desired performance specifications.

Key features of this method include:

1. Multi-criteria optimization: Considers various factors such as safety, efficiency, and comfort.
2. Simplified search process: Potential values guide the selection of optimal trajectories.
3. Neural network integration: Complex calculations are estimated using neural networks, enhancing computational efficiency.

Comprehensive Trajectory Planning

Effective overtaking requires precise execution of lane change manoeuvres while avoiding collisions with other vehicles. To achieve this, autonomous vehicles must plan trajectories that consider both longitudinal and lateral movement. A comprehensive trajectory planning approach typically involves:

1. Longitudinal planning: Determining the appropriate speed profile for overtaking.
2. Lateral planning: Calculating the optimal path for changing lanes safely.
3. Obstacle avoidance: Incorporating real-time sensor data to avoid potential collisions.
4. Vehicle dynamics: Considering the physical limitations and capabilities of the autonomous vehicle.

Importance of Robust Trajectory Planning

Developing a robust autonomous overtaking system is essential for improving the overall safety and performance of self-driving cars. Key benefits of advanced trajectory planning and optimization include:

1. Enhanced safety: Minimizing the risk of collisions during overtaking manoeuvres.
2. Improved efficiency: Optimizing the overtaking process to reduce travel time and energy consumption.
3. Smoother operation: Ensuring comfortable and natural-feeling manoeuvres for passengers.
4. Adaptability: Enabling the vehicle to handle diverse traffic scenarios and unexpected obstacles.

Conclusion

This comprehensive review has explored the various aspects of autonomous vehicle overtaking, including decision-making processes, learning approaches, control strategies, and trajectory planning techniques. The findings reveal a complex landscape of interdisciplinary research aimed at developing safe, efficient, and adaptable overtaking systems for autonomous vehicles.

Key insights from this review include the growing prominence of reinforcement learning and deep learning techniques in decision-making and control, the potential of MPC for unified vehicle control during overtaking manoeuvres, and the importance of advanced trajectory planning methods that consider multiple performance criteria. The integration of fuzzy logic systems and the application of reachability analysis for safety guarantees highlight the multifaceted approach required to address the challenges of autonomous overtaking.

Despite the significant progress in this field, several limitations and challenges remain. First, the complexity of real-world traffic scenarios makes it difficult to develop universally applicable overtaking strategies. Second, the balance between safety and efficiency in overtaking decisions continues to be a critical concern. Third, the transition from simulation-based research to real-world implementation presents significant hurdles, particularly in terms of sensor accuracy, computational efficiency, and robustness to unexpected situations.

The implications of this research are far-reaching for the automotive industry and transportation infrastructure. As autonomous overtaking capabilities improve, we can expect enhanced road safety, improved traffic flow, and increased public acceptance of self-driving vehicles. However, these advancements also require updates to traffic regulations and infrastructure to accommodate the unique behaviour of autonomous vehicles during overtaking manoeuvres.

Future research in this field should focus on improved integration of machine learning techniques with traditional control methods to leverage the strengths of both approaches. It should also aim for development of more sophisticated sensor fusion algorithms to enhance situational awareness during overtaking. It is also important to research into human factors and user acceptance of autonomous overtaking behaviours.

Thus, while significant strides have been made in autonomous vehicle overtaking, continued interdisciplinary research and development are crucial to overcome existing challenges and realize the full potential of this technology. As autonomous vehicles become increasingly prevalent on our roads, the ability to perform safe and efficient overtaking manoeuvres will be a key factor in their successful integration into our transportation systems.

References

[1]. Abate, M. Prandini, J. Lygeros, and S. Sastry, “Automatica probabilistic reachability and safety for controlled discrete time stochastic,” Automatica, vol. 44, no. 11, pp. 2724–2734, 2008.

[2]. Abdou, M., Mohammed, R., Hosny, Z., Essam, M., Zaki, M., Hassan, M., Eid, M., & Mostafa, H. (2019). End-to-end crash avoidance deep IoT-based solution. In 2019 31st International Conference on Microelectronics (ICM) (pp. 103-107). IEEE.

[3]. Abe, G., Sato, K., & Itoh, M. (2018). Driver trust in automated driving systems: The case

of overtaking and passing. IEEE Transactions on Human-Machine Systems, 48(1), 85-94.

[4]. Alamri, A., Gumaei, A., Al-Rakhami, M., Hassan, M. M., Alhussein, M., & Fortino, G. (2020). An effective bio-signal-based driver behavior monitoring system using a generalized deep learning approach. IEEE Access, 8, 135037-135049.

[5]. Atagoziyev, M., Schmidt, K. W., & Schmidt, E. G. (2016). Lane change scheduling for autonomous vehicles. IFAC-PapersOnLine, 49(3), 61-66.

[6]. Balal, E., Cheu, R. L., & Sarkodie-Gyan, T. (2016). A binary decision model for discretionary lane changing move based on fuzzy inference system. Transportation Research Part C: Emerging Technologies, 67, 47-61.

[7]. Basu, C., Yang, Q., Hungerman, D., Singhal, M., & Dragan, A. D. (2017). Do you want your autonomous car to drive like you? In Proceedings of the 2017 ACM/IEEE International Conference on Human-Robot Interaction (pp. 417-425).

[8]. Bella, F. (2011). How traffic conditions affect driver behavior in passing maneuver. Advances in Transportation Studies, (SPEC), 113-126.

[9]. Bellem, H., Schönenberg, T., Krems, J. F., & Schrauf, M. (2016). Objective metrics of comfort: Developing a driving style for highly automated vehicles. Transportation Research Part F: Traffic Psychology and Behaviour, 41, 45-54.

[10]. Bhuiyan, H., Governatori, G., Rakotonirainy, A., Bond, A., & Demmel, S. (2023). Formalization of overtaking rules for autonomous vehicles using defeasible deontic logic. Artificial Intelligence and Law, 31(1), 65-105.

[11]. Bianchi Piccinini, G. F., Moretto, C., Zhou, H., & Itoh, M. (2018). Influence of oncoming traffic on drivers' overtaking of cyclists. Transportation Research Part F: Traffic Psychology and Behaviour, 59, 378-388.

[12]. Camacho, E.F., Alba, C.B.: 'Model predictive control' (Springer Science & Business Media, London, UK, 2013)

[13]. Carvalho, A., Lefévre, S., Schildbach, G., Kong, J., & Borrelli, F. (2015). Automated driving: The role of forecasts and uncertainty—A control perspective. European Journal of Control, 24, 14-32.

[14]. Chandru, R., Y. Selvaraj, M. Bra¨nnstro¨m, R. Kianfar, and N. Murgovski. Safe Autonomous Lane Changes in Dense Traffic. Proc., IEEE 20th International Conference on Intelligent Transportation Systems (ITSC), Yokohama, Japan, IEEE, New York, 2017, pp. 1–6.

[15]. Chen, R., Kusano, K. D., & Gabler, H. C. (2015). Driver behavior during overtaking maneuvers from the 100-Car Naturalistic Driving Study. Traffic Injury Prevention, 16(sup2), S176-S181.

[16]. D. P. Bertsekas and I. B. Rhodes, "On the minimax reachability of target sets and target tubes," Automatica, vol. 7, no. 2, pp. 233–247, Mar. 1971.

[17]. D. Sadigh, N. Landolfi, S. S. Sastry, S. A. Seshia, and A. D. Dragan, "Planning for cars that coordinate with people: Leveraging effects on human actions for planning and active information gathering over human internal state," Auton. Robots, vol. 42, no. 7, pp. 1405–1426, Oct. 2018

[18]. D. Sadigh, N. Landolfi, S. S. Sastry, S. A. Seshia, and A. D. Dragan, "Planning for cars that coordinate with people: Leveraging effects on human actions for planning and active information gathering over human internal state," Auton. Robots, vol. 42, no. 7, pp. 1405–1426, Oct. 2018

[19]. Du, Y., Zhang, Y., & Yang, X. (2019). A reinforcement learning approach for autonomous decision making in lane changing. IEEE Access, 7, 65562-65570.

[20]. Fagnant, D. J., & Kockelman, K. (2015). Preparing a nation for autonomous vehicles: Opportunities, barriers and policy recommendations. Transportation Research Part A: Policy and Practice, 77, 167-181.

[21]. Gindele, T., Brechtel, S., & Dillmann, R. (2010). A probabilistic model for estimating driver behaviors and vehicle trajectories in traffic environments. In 13th International IEEE Conference on Intelligent Transportation Systems (pp. 1625-1631). IEEE.

[22]. Goncalves, R. C., Louw, T., Quaresma, M., Madigan, R., & Merat, N. (2020). The effect of motor control requirements on drivers' eye-gaze pattern during automated driving. Accident Analysis & Prevention, 148, 105788.

[23]. Goodall, N. J. (2014). Ethical decision making during automated vehicle crashes. Transportation Research Record, 2424(1), 58-65.

[24]. Gray, A., Y. Gao, T. Lin, J. K. Hedrick, H. E. Tseng, and F. Borrelli. Predictive Control for Agile Semi-Autonomous Ground Vehicles Using Motion Primitives. Proc., American Control Conference (ACC), Montreal, QC, Canada, IEEE, New York, 2012, pp. 4239–4244.

[25]. Gumaei, A., Al-Rakhami, M., Hassan, M. M., Alamri, A., Alhussein, M., Razzaque, M. A., & Fortino, G. (2020). A deep learning-based driver distraction identification framework over edge cloud. Neural Computing and Applications, 14, 1-6.

[26]. Hegedüs, T., Németh, B., & Gáspár, P. (2019). Graph-based multi-vehicle overtaking strategy for autonomous vehicles. IFAC-PapersOnLine, 52(5), 372-377.

[27]. Huang, C., Lv, C., Hang, P., Xing, Y., & Hu, C. (2021). Toward safe and personalized autonomous driving: Decision-making and motion control with DPF and CDT techniques. IEEE/ASME Transactions on Mechatronics, 26(2), 611-620.

[28]. Huang, P., Pi, J., & Xu, P. (2023). Event-driven decision-making strategy for autonomous vehicle overtaking maneuvers. IEEE Transactions on Intelligent Transportation Systems, 24(5), 5181-5191.

[29]. Hwang, M. I. (1994). Decision making under time pressure: A model for information systems research. Information & Management, 27(4), 197-203.

[30]. J. K. Scott and P. I. Barton, "Bounds on the reachable sets of nonlinear control systems," Automatica, vol. 49, no. 1, pp. 93–100, Jan. 2013.

[31]. J. Zhou, P. Tkachenko, L. Del Re, Gap acceptance based safety assessment of autonomous overtaking function, in: 2019 IEEE Intelligent Vehicles Symposium (IV), IEEE, June 2019, pp. 2113–2118.

[32]. Ji, K., Jiang, Y., Tao, P., & Zhu, F. (2023). Two-layer decision-making framework for CAV overtaking maneuvers considering V2X communications. IEEE Transactions on Intelligent Transportation Systems, 24(5), 5192-5204.

[33]. Jin, C. J., Knoop, V. L., Li, D., & Wang, H. (2019). Discretionary lane-changing behavior: Empirical validation for one realistic rule-based model. Transportmetrica A: Transport Science, 15(2), 244-262.

[34]. Jung, M. J., Kim, J., Lee, S. G., & Baek, D. (2023). Energy-efficient driving scheduling for heterogeneous electric vehicles with consideration of overtaking. Applied Energy, 329, 120218.

[35]. Kala, R., & Warwick, K. (2013). Motion planning of autonomous vehicles in a non-autonomous vehicle environment without speed lanes. Engineering Applications of Artificial Intelligence, 26(5-6), 1588-1601.

[36]. Kan, S., Sun, L., & Zhang, X. (2009). Analysis of drivers' motivations during discretionary lane changes on a multi-lane freeway. In Logistics: The Emerging Frontiers of Transportation and Development in China (pp. 4482-4488).

[37]. Kyriakidis, M., de Winter, J. C., Stanton, N., Bellet, T., van Arem, B., Brookhuis, K., Martens, M. H., Bengler, K., Andersson, J., Merat, N., Reed, N., Flament, M., Hagenzieker, M., & Happee, R. (2019). A human factors perspective on automated driving. Theoretical Issues in Ergonomics Science, 20(3), 223-249.

[38]. Leonard, J., How, J., Teller, S., Berger, M., Campbell, S., Fiore, G., Fletcher, L., Frazzoli, E., Huang, A., Karaman, S., Koch, O., Kuwata, Y., Moore, D., Olson, E., Peters, S., Teo, J., Truax, R., Walter, M., Barrett, D., ... Williams, J. (2008). A perception-driven autonomous urban vehicle. Journal of Field Robotics, 25(10), 727-774.

[39]. Li, X., Xu, X., & Zuo, L. (2015). Reinforcement learning based overtaking decision-making for highway autonomous driving. In 2015 Sixth International Conference on Intelligent Control and Information Processing (ICICIP) (pp. 336-342). IEEE.

[40]. Liu, T., Hu, X., Li, S. E., & Wu, D. (2017). Reinforcement learning optimized look-ahead energy management of a parallel hybrid electric vehicle. IEEE/ASME Transactions on Mechatronics, 22(4), 1497-1507.

[41]. Liu, T., Tang, X., Zhang, J., & Zeng, W. (2019). Reinforcement learning-enabled decision-making strategies for a vehicle cyber physical system in connected environment. In 2019 IEEE Vehicle Power and Propulsion Conference (VPPC) (pp. 1-5). IEEE.

[42]. Liu, Y., Zhao, R., & Li, Y. (2023). The impact of traffic density and automation level on drivers' overtaking behavior: A driving simulator study. Transportation Research Part F: Traffic Psychology and Behaviour, 94, 305-324.

[43]. Lodhi, S. S., Kumar, N., & Pandey, P. K. (2021). A comprehensive review of overtaking maneuvers for autonomous vehicles. IEEE Access, 9, 114564-114581.

[44]. Luo, Y., Xiang, Y., Cao, K., & Li, K. (2016). A dynamic automated lane change maneuver based on vehicle-to-vehicle communication. Transportation Research Part C: Emerging Technologies, 62, 87-102.

[45]. Madigan, R., Louw, T., & Merat, N. (2018). The effect of varying levels of vehicle automation on drivers' lane changing behaviour. PLoS One, 13(2), e0192190.

[46]. Mayne, D.Q.: 'Model predictive control: recent developments and future promise', Automatica, 2014, 50, (12), pp. 2967–2986
[47]. Milanés, V., Llorca, D. F., Villagrá, J., Pérez, J., Fernández, C., Parra, I., González, C., & Sotelo, M. A. (2012). Intelligent automatic overtaking system using vision for vehicle detection. Expert Systems with Applications, 39(3), 3362-3373.
[48]. Miller, L., Leitner, J., Kraus, J., Lee, J., Daimon, T., Kitazaki, S., & Baumann, M. (2022). Time to arrival as predictor for uncertainty and cooperative driving decisions in highly automated driving. In 2022 IEEE Intelligent Vehicles Symposium (IV) (pp. 1048-1053). IEEE.
[49]. Mocsári, T. (2009). Analysis of the overtaking behaviour of motor vehicle drivers. Acta Technica Jaurinensis, 2(1), 97-106.
[50]. Montemerlo, M., Becker, J., Bhat, S., Dahlkamp, H., Dolgov, D., Ettinger, S., Haehnel, D., Hilden, T., Hoffmann, G., Huhnke, B., Johnston, D., Klumpp, S., Langer, D., Levandowski, A., Levinson, J., Marcil, J., Orenstein, D., Paefgen, J., Penny, I., ... Thrun, S. (2008). Junior: The Stanford entry in the urban challenge. Journal of Field Robotics, 25(9), 569-597.
[51]. Murgovski, N., and J Sjo¨berg. Predictive Cruise Control With Autonomous Overtaking. Proc., 54th IEEE Conference on Decision and Control (CDC), Osaka, Japan, IEEE, New York, 2015, pp. 644–649.
[52]. Naranjo, J. E., Gonzalez, C., Garcia, R., & De Pedro, T. (2008). Lane-change fuzzy control in autonomous vehicles for the overtaking maneuver. IEEE Transactions on Intelligent Transportation Systems, 9(3), 438-450.
[53]. Ngai, D. C., & Yung, N. H. (2011). A multiple-goal reinforcement learning method for complex vehicle overtaking maneuvers. IEEE Transactions on Intelligent Transportation Systems, 12(2), 509-522.
[54]. Nilsson, J., M. Ali, P. Falcone, and J. Sjo¨berg. Predictive Manoeuvre Generation for Automated Driving. Proc., 16th International IEEE Conference on Intelligent Transportation Systems (ITSC 2013), The Hague, Netherlands, IEEE, New York, 2013, pp. 418–423.
[55]. Okamoto, K., Berntorp, K., & Di Cairano, S. (2017). Similarity-based vehicle-motion prediction. In 2017 American Control Conference (ACC) (pp. 303-308). IEEE.
[56]. P. Resende and F. Nashashibi, "Real-time dynamic trajectory planning for highly automated driving in highways," in IEEE Conf. Intel. Transp. Systems, 2010, pp. 653-658.
[57]. Paden, B., Čáp, M., Yong, S.Z., et al.: 'A survey of motion planning and control techniques for self-driving urban vehicles', IEEE Trans. Intell. Veh., 2016, 1, (1), pp. 33–55
[58]. Pereira, A.M., Anany, H., Přibyl, O., et al.: 'Automated vehicles in smart urban environment: A review'. 2017 Smart City Symp. Prague (SCSP), Prague, Czech Republic, 2017, pp. 1–8
[59]. Qian, X. Model Predictive Control for Autonomous and Cooperative Driving. PhD thesis. PSL Research University, France, 2016.
[60]. Satchell, P. (1998). Innovation and automation. Ashgate.
[61]. Shen, Y., & Yan, W. Q. (2018). Blind spot monitoring using deep learning. In 2018 International Conference on Image and Vision Computing New Zealand (IVCNZ) (pp. 1-6). IEEE.
[62]. Sourelli, A. M., Welsh, R., & Thomas, P. (2023). User preferences, driving context or manoeuvre characteristics? Exploring parameters affecting the acceptability of automated overtaking. Transportation Research Part F: Traffic Psychology and Behaviour, 94, 305-324.
[63]. Stoll, T., Lanzer, M., & Baumann, M. (2020). Situational influencing factors on understanding cooperative actions in automated driving. Transportation Research Part F: Traffic Psychology and Behaviour, 70, 223–234. https://doi.org/10.1016/j.trf.2020.03.006
[64]. Urmson, C., Anhalt, J., Bagnell, D., et al.: Autonomous driving in urban environments: Boss and the urban challenge. J. Field Robot 25(8), 425–466 (2008)
[65]. Volpe, R., Khosla, P.: 'Manipulator control with superquadric artificial potential functions: theory and experiments', IEEE Trans. Syst., Man, Cybern., 1990, 20, (6), pp. 1423–1436
[66]. Vu, T. M., R. Moezzi, J. Cyrus, and J. Hlava. Model Predictive Control for Autonomous Driving Vehicles. Electronics, Vol. 10, No. 21, p. 2593.
[67]. Wang, F., Yang, M., & Yang, R. (2009). Conflict-probability-estimation-based overtaking for intelligent vehicles. IEEE Transactions on Intelligent Transportation Systems, 10(2), 366-370.
[68]. Wang, X., Jiang, R., Li, L., Lin, Y., Zheng, X., & Wang, F. Y. (2018). Capturing car-following behaviors by deep learning. IEEE

Transactions on Intelligent Transportation Systems, 19(3), 910-920.
[69]. Wolf, M.T., Burdick, J.W.: 'Artificial potential functions for highway driving with collision avoidance'. 2008 IEEE Int. Conf. on Robotics and Automation, (ICRA), Pasadena, CA, USA, 2008, pp. 3731–3736
[70]. Wu, Q., Cheng, S., Li, L., Chen, H., & Xu, H. (2021). A fuzzy-inference-based reinforcement learning method of overtaking decision making for automated vehicles. Proceedings of the Institution of Mechanical Engineers, Part D: Journal of Automobile Engineering, 235(10-11), 2851-2866.
[71]. Xing, Y., Lv, C., Wang, H., Wang, H., Ai, Y., Cao, D., Velenis, E., & Wang, F. Y. (2019). Driver activity recognition for intelligent vehicles: A deep learning approach. IEEE Transactions on Vehicular Technology, 68(6), 5379-5390.
[72]. Xu, X., Zuo, L., Li, X., Qian, L., Ren, J., & Sun, Z. (2018). A reinforcement learning approach to autonomous decision making of intelligent vehicles on highways. IEEE Transactions on Systems, Man, and Cybernetics: Systems, 50(10), 3884-3897.
[73]. Yan, F., Eilers, M., Weber, L., & Baumann, M. (2019). Investigating initial driver intention on overtaking on rural roads. In The 2019 IEEE Intelligent Transportation Systems Conference (pp. 4354–4359). IEEE. https://doi.org/10.1109/ITSC.2019.8917324.
[74]. Yang, L., Li, X., Guan, W., Zhang, H. M., & Fan, L. (2018). Effect of traffic density on drivers' lane change and overtaking maneuvers in freeway situation—A driving simulator–based study. Traffic Injury Prevention, 19(6), 594–600. https://doi.org/10.1080/15389588.2018.1471470.
[75]. Younsi, K., Floris, J., Rajaonah, B., Simon, P., Loslever, P., & Popieul, J.-C. (2011). Study of driver's behavior during overtaking situations. Advances in Transportation Studies, 25, 29–38. https://doi.org/10.4399/97888548430803
[76]. Yu, L., Shao, X., & Yan, X. (2017). Autonomous overtaking decision making of driverless bus based on deep Q-learning method. In 2017 IEEE International Conference on Robotics and Biomimetics (ROBIO) (pp. 2267-2272). IEEE.
[77]. Yu, Y., Lu, C., Yang, L., Li, Z., Hu, F., & Gong, J. (2020). Hierarchical reinforcement learning combined with motion primitives for automated overtaking. In 2020 IEEE Intelligent Vehicles Symposium (IV) (pp. 1-6). IEEE.
[78]. Zheng, R., Liu, C., & Guo, Q. (2013). A decision-making method for autonomous vehicles based on simulation and reinforcement learning. In Proceedings of the 2013 International Conference on Machine Learning and Cybernetics (pp. 362-369). IEEE.