Navigating Mixed Traffic: Current State and Future Challenges in Integrating Autonomous and Human-Driven Vehicles

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***Abstract*—As autonomous vehicles (AVs) become increasingly prevalent in our society, it is crucial to address the technical challenges coexisting with human-driven vehicles (HVs) on the roads. Transportation administrators and constructors must be poised to harness the controllability and potential offered by these innovative vehicles when they gradually penetrate the roads in the near future. However, existing studies often focus on either the safe autonomous driving technology of single AVs alongside HVs or on collective coordination among AVs exclusively, neglecting the challenges inherent in heterogeneous multi-agent transportation systems. These challenges encompass critical aspects such as safety, human-robot interactions, and infrastructure adaptation, which Requires detailed exploration. This paper aims to explore the current state and future challenges in mixed traffic scenarios that lie at the intersection of artificial intelligence, multi-agent systems, safe control, and intelligent systems design in the context of advancing AV technology while ensuring safety and effective interaction between human, robot, and road infrastructure. We examine the current state-of-the-art of AV technology, identify key challenges for integrating human-centric approaches into the design, development, and deployment of AVs. Drawing upon insights from safety standards, human-robot interaction, and road infrastructure design frameworks, we highlight the importance aspects surrounding AV and HV designs to enhance user trust, acceptance, and overall societal impact.**

***Index Terms*—Autonomous vehicles, safety, human vehicle Interaction, road infrastructure, intelligent transportation systems**

I. Introduction

The rapid development of communication, perception, and automation technologies has facilitated the production and emergence of autonomous vehicles (AVs). With the expected benefits of AVs, many countries are supporting the development and commercialization of AVs. For example, the UK government is keen to roll out AVs on roads by 2025 with massive regulatory and financial support [1]. Countless efforts and resources in academia and industry have been put into realizing the autonomy of vehicles. Millions and billions of miles are autonomously driven on public roads and in simulation, respectively [2], and increasingly more commercial vehicles are embedded with autonomous driving features [3]. It is unsurprising that AVs will become prevalent in the future. Since the penetration of AV will be gradually increased, there must be a transition phase leading to a system mixed with AVs and human-driven vehicles (HVs). Moreover, most of the road infrastructure is designed for HVs only without considering AVs. Intelligent road infrastructure designs, such as dynamic reversible lanes [4] and autonomous intersection management [5], are being actively studied primarily for AVs. However, the use and impact of these intelligent components, as AVs are adopted progressively, is not well explored. The transportation system mixed with AVs, HVs, and intelligent road infrastructure forms a heterogeneous multi-agent system with many challenges.

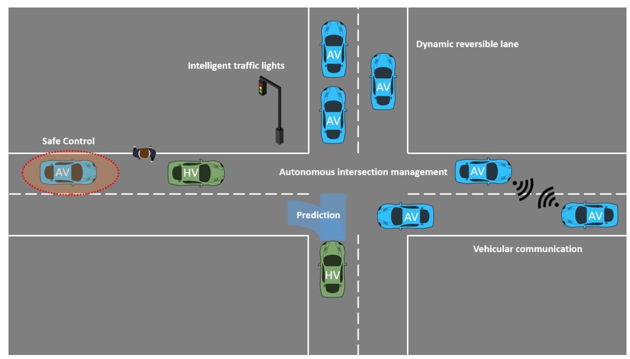

Fig. 1. Interaction between AVs, HVs, and intelligent systems.

The successful integration of AVs poses numerous challenges, particularly in heterogeneous multi-agent environments where AVs coexist with HVs and other road infrastructure. One of the critical considerations is the interaction between AVs and HVs, which introduces complexities beyond technical capabilities. While AVs adhere to precise algorithms and protocols, human drivers often operate based on intuition, experience, and social norms. This raises questions about how

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effectively AVs and human drivers can coexist on roadways governed by abstract traffic rules and conventions. Furthermore, human drivers' attitudes and behaviors towards AVs can significantly impact the safety and efficacy of autonomous transportation systems. Concerns about AV reliability, trust, and perceived safety may influence human drivers' interactions with AVs, potentially leading to unpredictable or even adversarial behaviors. Instances of aggression, skepticism, or non-compliance with AV protocols could impede the realization of AVs' purported safety benefits and hinder their widespread adoption. For example, human drivers may have a greater intention to bully AVs than to bully other human drivers [6].

In parallel with the advancements in AV technology, there has been considerable progress in enhancing the intelligence and adaptability of road infrastructure. Innovations such as dynamic reversible lanes [4], autonomous intersection management [5], and intelligent traffic signal control systems [7] represent promising solutions to increase traffic throughput, reduce congestion, and optimize resource utilization for AVs. Dynamic reversible lanes, for instance, offer the flexibility to adjust lane direction based on real-time traffic demands, effectively maximizing roadway capacity. Similarly, intelligent traffic signal control systems leverage sensor data and predictive algorithms to optimize signal timing and coordination, minimizing delays and improving overall traffic efficiency at road intersections. To push it one step forward, autonomous intersection management gets rid of the traffic light and coordinating AVs wireless signaling and coordination algorithm. However, while these intelligent infrastructure solutions hold great potential for enhancing transportation systems' performance, their effectiveness in facilitating the integration of AVs and HVs remains a subject of inquiry. The interaction between AVs, HVs, and road infrastructure elements introduces new challenges and considerations. For example, how do HVs perceive and adapt to dynamically changing lane configurations in reversible lane systems? Can HVs effectively communicate with traffic control systems to optimize their movement through intersections like an AV? Moreover, how do human drivers respond to changes in infrastructure behavior induced by AVs, and how does this impact overall traffic flow and safety? In light of these challenges, this paper seeks to pose three inter-related research questions:

1. How can we ensure the safe integration of AVs and HVs within heterogeneous multi-agent transportation systems, considering factors such as human-robot interaction, partial controllability, and mixed traffic dynamics?
2. What strategies can be employed to facilitate effective cooperation between AVs, HVs, and road infrastructure, thereby enhancing overall traffic safety and efficiency?
3. How can road infrastructure be adapted to accommodate the diverse needs of AVs and HVs, including the implementation of intelligent infrastructure, while optimizing safety and traffic flow?

Towards research question 1, we will explore safety considerations in integrating AVs and HVs, including human-robot interaction, partial controllability, and mixed traffic dynamics. It will discuss strategies to mitigate safety hazards and develop robust safety protocols. Towards research question 2, we will focus on enhancing cooperation between AVs, HVs, and road infrastructure to improve traffic safety and efficiency. It will address design strategies for interfaces and public acceptance of AV technology. Towards research question 3, we will discuss intelligent road infrastructure to support AVs and HVs, covering topics of AV lane, dynamic reversible lane, autonomous intersection management, and intelligent traffic signal control. It will highlight successful case studies and innovative solutions to optimize safety and traffic efficiency. By addressing these research questions, we aim to provide insights into the development of robust, human-centric approaches to AV deployment, ensuring the seamless integration of AVs into our transportation systems while prioritizing safety and efficiency. Through interdisciplinary collaboration and innovative solutions, we can pave the way for a safer, more sustainable future of mobility.

II. Safe Coordination Between AVs and HVs

With all the heterogeneous agents interacting in the system in the context of mixed traffic, ensuring safety is the most crucial consideration, as traffic accidents may cause serious damage to humans, vehicles, and infrastructure. Leveraging sensor-based perception systems, such as online motion prediction, real-time gesture recognition and safe control, facilitates the seamless integration of AVs with HVs.

A. Motion Prediction

Motion prediction is a pivotal component facilitating the safe interaction between AVs and HVs, particularly during merging and unprotected turning maneuvers. The ability to anticipate the future behaviors of surrounding vehicles empowers AVs to execute informed decisions, including timing maneuvers appropriately to avoid collisions. Schwarting et al. [8] proposed a comprehensive framework that incorporates social psychology principles into autonomous controller design. This integration enables AVs to discern human drivers' behaviors and predict their forthcoming actions based on their social value orientation. Such an approach enables AVs to model interactions within a multi-agent system and formulate autonomous control policies customized to the unique driving behavior of each individual HV. Consequently, this framework contributes to enhancing safety in mixed traffic environments.

Additionally, for effective cooperation in mixed traffic, AVs must emulate HVs' driving behaviors to ensure seamless interaction. Gu et al. [9] presented a framework to generate human-like driving parameters and speed trajectories for AVs, based on the driving data of human drivers. Aligning AV behaviors with those of HVs not only improves road safety but also enhances the effectiveness of online motion prediction systems, as human drivers find it challenging to distinguish between AVs and HVs.

B. Gesture Recognition

Gesture recognition plays a crucial role in facilitating safe cooperation between AVs and HVs, particularly at dynamic intersections where human drivers commonly employ hand gestures and eye contact to convey intentions. Deo et al. [10] developed an in-vehicle hand gesture recognition system using motion tracking and temporal state models, allowing AVs to interpret gestures of surrounding human drivers and pedestrians in real-time. Similarly, Smith et al. [11] developed a gesture recognition system capable of detecting precise features of hand gestures and signals. These gesture recognition systems enable AVs to understand and respond to human drivers' gestures effectively, enhancing communication and cooperation in mixed traffic environments.

C. Safe Control

Safe control of AVs and HVs driving aims to develop control policies that confine their motions within safe regions. Current studies on safe control often integrate safety constraints through reachability analysis [12]. They leverage the concept of reachable sets, wherein vehicle motion is controlled to remain within a set derived from safety constraints, such as collision or obstacle avoidance, and practical security limits. For individual vehicles, the control barrier function method [13] and the Hamilton-Jacobi reachability method [14] are commonly employed to devise safe control policies while ensuring the ego motion of vehicles remains safe. The control barrier function method is particularly effective in identifying an approximate invariant set, while the Hamilton-Jacobi reachability method utilizes optimal control principles to estimate the reachable set. Apart from ensuring the safe control of individual vehicles, interactions between multiple AVs and HVs should not be neglected. By appropriately modeling these scenarios as heterogeneous multi-agent systems, cooperative safe control policies should be established by taking vehicles as agents and incorporating communication protocols to address interactions among them.

By integrating motion prediction, gesture recognition, safe control technologies, AVs can safely and seamlessly interact with HVs, facilitating efficient traffic and enhancing road safety in mixed traffic environments.

III. Interaction Between AVs and HVs

The interaction between humans and AVs is a rapidly developing field with the potential to revolutionize transportation. Unlike traditional vehicles, AVs possess the ability to perceive their surroundings, make decisions, and execute maneuvers autonomously. However, the interaction between AVs and human drivers, pedestrians, and cyclists introduces unique challenges and considerations that extend beyond technical capabilities. There are several significant challenges that need to be addressed before AVs can become a widespread reality.

A. Mixed Traffic Scenario

The vast majority of the existing research focused on either a single AV with HVs, or interactions among AVs only. The feasibility of using an AV to mitigate the stop-and-go waves has been studied [15]. In those preliminary research, single agent-based control is considered, which is inadequate for understanding the potential of AV when it is gradually penetrated on the roads. For collective control, the fleet of AVs is usually assigned with a common goal to be accomplished collaboratively. Cooperative vehicle platooning control, which minimizes the distance between vehicles, and its impact on traffic flow characteristics have been studied [16]. However, not all vehicles on the roads are controllable AVs in the near future. The model and control are much more complex for a system mixed with AVs and HVs. The study [17] has investigated the control and effect of the mixed system in simplified road lanes and intersections.

B. Driver State and Intent Recognition

Accurately recognizing the driver's state and intent is essential for safe human-AV interaction. Recognizing driver intentions, also referred to as understanding driver behavior, has emerged as a crucial concern due to the reasons outlined. This recognition involves identifying the objectives of observed agents in the immediate future based on the type of maneuvers and the driving scene [18]. Being able to recognize a driver's intention allows for proactive engagement and behavioral adjustments to prevent accidents or address cooperative challenges. Driver intention recognition typically employs prediction-based approaches, such as probabilistic graphical models [19], [20], to illustrate relationships among modeled variables, as well as artificial neural networks [21], which can capture correlations between input and target data with relatively low accuracy. For example, Jain et al. [22] used in-car video cameras to predict driver intent 3.5 seconds before maneuvers, but this system was only tested in a simulated environment and may not be reliable in real-world conditions. Current systems for driver state and intention recognition are still in their early stages of development and thus need to be improved.

C. Factors Influencing Human Driving Behavior

Human drivers' perceptions, attitudes, and behaviors towards AVs play a crucial role in shaping the dynamics. Various factors, such as the driver's level of fatigue, distraction, and emotional state, influence driving behavior, encompassing driver state, acceleration dynamics, braking patterns, headway gap management, and cornering maneuvers. These driving behaviors are not solely determined by individual traits but are also influenced by environmental conditions, external road factors, and different driving styles. For instance, drivers may experience distraction due to fatigue, stress, or long trips, leading to unreliable maneuvers and reduced alertness [23]. To address this, methods such as physiological analysis and visual feature detection are proposed for detecting signs of drowsiness or fatigue, including monitoring heart rate, eye position, and skin conductance [24]. Similarly, computer vision techniques are utilized to monitor eye-lid position and mouth opening, assessing indicators of sleepiness or yawning [25].

However, challenges exist in these methods due to potential errors and false detections.

Moreover, environmental factors, including traffic lights, road complexity, and weather conditions, significantly influence driving patterns and decision-making. For instance, complex traffic signage or frequent signals can lead to driver frustration and distraction, contributing to traffic violations [26]. Similarly, adverse weather conditions such as rain or fog present challenges in maintaining appropriate speeds and headway gaps, requiring heightened situational awareness and adaptability [27]. Intelligent systems play a crucial role in monitoring driver situation awareness, predicting road-agent behaviors, and allocating attention effectively to accomplish driving tasks [28].

D. Communication and Cooperation Between AVs and HVs

Effective communication and cooperation between humans and AVs is necessary to avoid misunderstandings and accidents. This includes both verbal and non-verbal communication, as well as the ability to share information and intentions. Current communication systems between AVs and humans are limited and need to be more intuitive and natural.

Recent advancements aim to enhance the communication efficiency. Vehicular communication technologies, including Vehicle-to-Vehicle (V2V) and Vehicle-to-Infrastructure (V2I) communication [29], serve as the backbone for enabling interaction between AVs and HVs. V2V communication allows vehicles to exchange real-time data, such as position, speed, and trajectory, fostering situational awareness and facilitating cooperative maneuvers [30]. On the other hand, V2I communication enables vehicles to interact with roadside infrastructure, access traffic information, receive safety alerts, and coordinate with traffic management systems [31]. For example, Chu et al. [32] presented a system for sharing road map data between autonomous vehicles and roadside infrastructure using index coding, which minimizes transmissions and prioritizes data based on demand, reducing redundancy and enhancing efficiency by a 30% reduction in transmissions compared to traditional methods.

There is research on other types of communication besides digital ones. For instance, studies have explored tactile and multisensory interfaces to convey information effectively to human drivers [33]. Additionally, research has focused on developing natural language processing algorithms to enable seamless verbal communication between humans and driving assistants, allowing drivers to issue commands and receive responses in a conversational manner [34].

By prioritizing effective human-robot interaction strategies, we can foster trust, acceptance, and cooperation between AVs, HVs, and pedestrians, ultimately enhancing safety and efficiency on our roadways. Through further research work, we can develop innovative solutions to navigate the complex dynamics of human-robot interaction and pave the way for the successful integration of AVs into our transportation systems.

IV. INFRASTRUCTURE ADAPTATION

This section will discuss how road infrastructure can be used to accommodate the diverse needs of AVs and HVs while optimizing safety and traffic. Specific topics may include the design and implementation of dynamic reversible lanes, AV lane, autonomous intersection management, and intelligent traffic signal control mechanisms. This section may also examine studies that have demonstrated innovative infrastructure solutions to accommodate AVs and improve overall transportation efficiency.

A. AV Lane

AVs may provide much more benefits if they are properly controlled. Platooning is one of the formation examples [35]. AVs and HVs can be cooperatively controlled for a mixed flow platoon [36], which could be a solution in the mixed traffic scenario despite the fact that this might sacrifice the capability of AVs. Another possible solution is to deploy the AV lane, which is dedicated to AVs. According to the study [37], benefits such as reduced travel cost can be obtained from AV lanes deployment. However, AV lanes should be implemented gradually rather than abruptly, and wide deployment of AV lanes should be postponed until the market penetration of AVs reaches a significant level, such as over 20%. Yu et al. [38] discerned between the behaviors exhibited by HVs and AVs by analyzing factors such as reaction time, desired speed, and car-following models. Their findings indicate that as the market penetration rate of AVs increases, there is a notable improvement in efficiency, particularly evident in the increased highway throughput, which can rise by up to 84% in mixed traffic scenarios. However, safety metrics show a decline when the market penetration of autonomous vehicles is below 40%. An alternative to AV lane is AV/toll lanes, which grant free access to AVs while allowing HVs to access the lanes by paying a toll. Liu et al. [39] investigated the optimal deployment of dedicated AV lanes and AVT lanes in transportation networks with mixed AV and HV flows, which demonstrated that AV and AV/toll lanes provide a promising alternative to improve system performance compared to dedicated AV lanes when AV flows are low.

B. Dynamic Reversible Lane

A reversible lane that allows vehicles to enter either direction depending on the demand or at regular hours has been reported in [40]. Although it can increase traffic throughput and has been deployed in many countries for years, the temporal and spatial granularity is low, resulting in limited improvement. Therefore, the feasibility of a dynamic reversible lane, which alternates the lane direction on the scale of minutes or even seconds, has been studied [41]. However, it requires a short reaction time, and thus it is AV-exclusive. Such a high temporal and spatial granularity design can further increase road throughput to a level that could not reached by existing HV-related infrastructure. Furthermore, as AVs provide control capabilities on routing and scheduling, Chu et al. proposed to jointly optimize both the lane direction of the dynamic reversible lane and the routing and scheduling of the AVs [42], which can reduce roughly 38% travel time according to the simulation results. With these designs working exclusively for AVs, how the reversible lanes can evolve for traffic mixed with AVs and HVs is still an unresolved challenge.

C. Autonomous Intersection Management

Control strategies have the capacity to coordinate the seamless passage of AVs through intersections, effectively negating the presence of the intersection itself. Each AV is allocated a precise temporal and spatial slot to navigate the intersection without encountering interference, thereby substantially mitigating traffic congestion at these junctions. Similar to dynamic reversible lanes, this system is primarily designed for AVs. The efficacy of autonomous intersection management is marginal or nonexistent when the proportion of autonomous vehicles falls below 90%. Consequently, during a substantial portion of the transitional phase in mixed traffic scenarios, autonomous intersection management proves ineffectual [5]. In response, a hybrid autonomous intersection management protocol for managing mixed traffic intersections was proposed, viable as long as autonomous intersection management remains applicable and the infrastructure possesses the capability to detect approaching vehicles. Experimental results indicate that this protocol can alleviate traffic delays for AVs even at a technology penetration rate as low as 1% [43]. However, a drawback of this approach is that hybrid autonomous intersection management fails to exhibit superiority to the baseline until the AV technology penetration level exceeds 10%, particularly concerning congestion reduction. Hence, it is imperative to explore a viable and efficient control system for traffic integration involving both AVs and HVs across varying penetration rates.

D. Intelligent Traffic Signal Control

Intelligent traffic signal control systems have been extensively researched over several decades [7] as a potential alternative to traditional pre-timed controllers, which operate on fixed cycle lengths, fixed durations for each stage, and fixed sequences. Instead, fully actuated controllers can dynamically adjust the duration of each stage based on traffic demand. Decades ago, Chiu et al. [44] pioneered the development of fuzzy decision rules for traffic signal timing control, considering parameters such as cycle time, phase split, and offset. Integration of future traffic flow prediction into traffic signal control has been explored to enhance control performance [45]. Another approach, known as Max Pressure Control, aims to minimize intersection "pressure", defined as the difference between queuing vehicles entering and exiting lanes, thereby maximizing intersection throughput [46]. Traffic signal control methods have also ventured into learning-based approaches. Chu et al. [47] proposed a camera video-based signaling control system, eliminating the need for extra on-road sensors and vehicle communication. Such learning-based strategies can be extended to multi-agent control at the city level [48]. Nonetheless, conventional vehicles present performance limitations due to the reaction time of human drivers, mirroring concerns observed in autonomous intersection management.

V. Conclusion and Discussion

The integration of AVs into our transportation systems presents a multitude of technical, social, and infrastructural challenges. As AV technology continues to advance, it is imperative to address these challenges to ensure the safe and effective coexistence of AVs with HVs and road infrastructure. This paper has explored the current state and future challenges in mixed traffic scenarios.

The safe coordination between AVs and HVs is paramount to ensuring the safety of all road users. Leveraging motion prediction, gesture recognition, and safe control technologies enables AVs to interact safely with HVs, minimizing the risk of accidents and enhancing traffic efficiency. However, challenges remain in accurately predicting human driver behavior and ensuring seamless cooperation between AVs and HVs in dynamic traffic environments.

Human-robot interaction plays a crucial role in shaping the dynamics of mixed traffic scenarios. Understanding human drivers' perceptions, attitudes, and behaviors towards AVs is essential for fostering trust, acceptance, and cooperation. Effective communication and cooperation strategies between AVs and HVs, including V2V and V2I communication and non-digital interfaces, are vital for enhancing safety and efficiency on our roadways.

Infrastructure adaptation is essential to accommodate the diverse needs of AVs and HVs while optimizing safety and traffic. Innovative solutions such as AV lanes, dynamic reversible lanes, autonomous intersection management, and intelligent traffic signal control mechanisms offer promising avenues for enhancing transportation systems' performance. However, further research is needed to explore how these infrastructure solutions can be effectively integrated into mixed traffic environments and how they interact with AVs and HVs.

In conclusion, addressing the technical, social, and infrastructural challenges associated with integrating AVs into our transportation systems requires interdisciplinary collaboration and innovative solutions. By prioritizing safety, cooperation, and infrastructure adaptation, we can pave the way for a safer, more efficient future of mobility. Through further research and development, we can overcome the challenges posed by mixed traffic scenarios and realize the full potential of autonomous transportation systems.

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