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Review

Model-Based Control and Model-Free Control Techniques for Autonomous Vehicles: A Technical Survey

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Abstract: Autonomous driving has the potential to revolutionize mobility and transportation by reducing road accidents, alleviating traffic congestion, and mitigating air pollution. This transformation can result in energy efficiency, enhanced convenience, and increased productivity, as valuable driving time can be repurposed for other activities. The main objective of this paper is to provide a comprehensive technical survey of the latest research in the field of lateral, longitudinal, and integrated control techniques for autonomous vehicles. The survey aims to explore a wide range of techniques and methodologies employed to achieve precise steering control while also considering longitudinal aspects. Model-based control techniques form the foundation for control, utilizing mathematical models of vehicle dynamics to design controllers that effectively track desired speeds and/or steering behavior. Unlike model-free control techniques such as reinforcement learning and deep learning algorithms facilitate the integration of longitudinal and lateral control by learning control policies directly from data and without explicit knowledge of the underlying dynamics. Through this survey, the paper delves into the strengths, limitations, and advancements in both model-based and model-free control approaches for autonomous vehicles. It investigates their performance in real-world scenarios and addresses the technical challenges associated with their implementation. These challenges may include uncertainties in the environment, adaptability to dynamic conditions, robustness, safety considerations, and computational complexity.

Keywords: autonomous vehicles; lateral control; longitudinal control; model-based control techniques; model-free control techniques

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1. Introduction

Autonomous vehicles (AVs) have garnered increasing interest in recent decades due to advancements in computing devices and sensor technology, leading to numerous research programs involving the car manufacturing industry and academic laboratories [1]. The objective of this paper is to survey the current state-of-the-art on recent control methodologies applied to AVs. We start by presenting lateral, longitudinal, as well as the integrated lateral and longitudinal control of AVs. These methodologies form a base for the surveyed recent motion-control algorithms, and both the model-based control techniques as well as model-free control techniques are investigated. The self-driving concept has various socioeconomic benefits and impacts public transportation systems, including reducing accidents, improving passenger comfort, and optimizing fuel consumption [2,3]. According to the World Health Organization (WHO), approximately 1.35 million people die each year from traffic-related accidents or injuries [4]. Adopting technologies such as advanced driver-assistance systems (ADAS) and automated driving systems (ADS) can significantly reduce over 80% of accidents caused by human error [4]. AVs can also reduce travel time, positively impacting passengers' mental and physical health, and provide economic benefits. They are also a viable mobility option for elderly and disabled individuals. In

Australia, for example, 79% of 9.2 million daily commuters spend an average of 25 min commuting to work [5]. Table 1 shows the list of acronyms and their definition.

Table 1. List of acronyms and their definition.

Acronyms	Definition
AVs	Autonomous vehicles
RNNs	Recurrent neural networks
DN	Deep network
EN	Evolutionary network
MPC	Model predictive control
ML	Machine learning
RL	Reinforcement learning
WHO	World Health Organization
RADAR	Radio detection and ranging
DNN	Deep neural networks
DDPG	Deep deterministic policy gradient
MCTS	Monte Carlo tree search
DQN	Deep Q network
TORCS	The open racing car simulator
CNNs	Convolutional neural network
LSTM	Long short-term memory
AI	Artificial intelligence
DL	Deep learning
LIDAR	Light detection and ranging
MFCN	Motion-aid feature calibration network
NN	Neural networks
MDP	Markov decision process
DVSL	Differential variable speed limit
DoF	Degrees of freedom
GAN	Generative adversarial network
PID	Proportional integral derivative
OEM	Original equipment manufacturer
PPC	Pure pursuit controller

However, AVs present several social and technological challenges encountered in passenger and vehicle safety, efficient maneuvering on different terrains and environments, and fuel efficiency [6]. The complexity of ADS depends on the required level of autonomy, which consists of six levels (levels 0–5) ranging from "no autonomy" to "fully autonomous", according to the Society of Automotive Engineers' standard (SAE-J3016) [7]. The level of autonomy increases with the human subject's responsibility in the driving task, the complexity of driving assistance systems, and the operating conditions of the vehicles.

The comparison presented in this survey helps provide insight into the strengths and limitations of recent control approaches for autonomous driving to tackle these challenges and assist with design choices. This paper focuses on the advanced control methodologies applicable to AVs that ensure the stability and safety of the vehicle system. Section 2 presents lateral, longitudinal, and integrated lateral and longitudinal control of AVs, while Section 3 discusses the control techniques used in autonomous vehicles. Finally, Section 4 offers concluding remarks and prospects for future research.

2. Control of Autonomous Vehicle

The key technologies for autonomous vehicles are structured into three distinct layers, as illustrated in Figure 1 [8], with each layer fulfilling a crucial role.

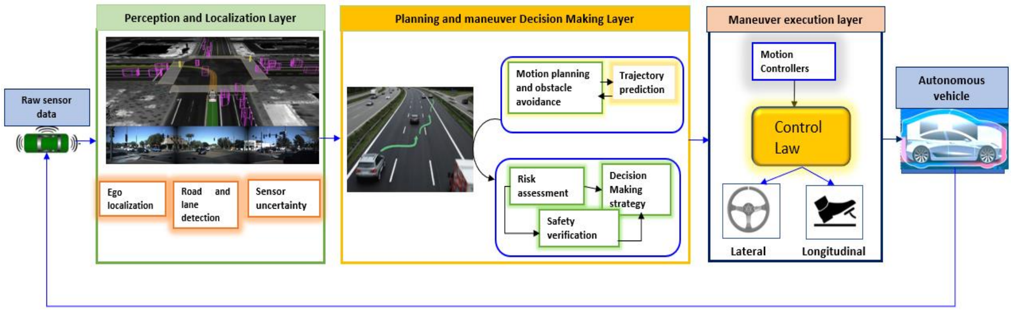

Figure 1. Key technologies for an autonomous driving.

The first layer, known as perception and localization, involves the interpretation and understanding of the surrounding environment. It encompasses the utilization of sensor data from various sources to detect and identify objects, analyze their positions and movements, and accurately determine the vehicle's own location in relation to its surroundings.

The second layer, referred to as planning and maneuver decision making, focuses on generating optimal paths and making informed decisions regarding the vehicle's movements. This involves advanced algorithms and techniques that consider factors such as traffic rules, road conditions, and potential obstacles. Path-planning algorithms determine the safest and most efficient routes, while maneuver decision-making algorithms select appropriate actions, such as lane changes, overtaking, or merging, to navigate the vehicle through its intended trajectory.

The third layer, known as decision making, involves higher-level cognitive processes that integrate information from perception, planning, and other sources to make intelligent decisions. This includes evaluating potential risks, predicting the behavior of other vehicles and pedestrians, and selecting the most suitable course of action in complex driving scenarios. Decision-making algorithms ensure that the autonomous vehicle can respond effectively to changing situations and prioritize safety at all times.

The function of longitudinal control is to regulate the vehicle's speed and maintain a safe distance from the preceding vehicle by using acceleration or braking actions. On the other hand, the primary objective of lateral control is to minimize the vehicle's lateral displacement and heading error. This is achieved by precisely adjusting the steering wheel angle, enabling the vehicle to follow a desired trajectory. Both longitudinal and lateral control play essential roles in the foundation of an autonomous vehicle's control system.

2.1. Lateral Control of Autonomous Vehicles

2.1.1. Lateral Model-Based Control Techniques

In the environment for a lane-change maneuver, similar to vehicle dynamics, a vehicle's presence in the current and adjacent lane is evaluated using the strategic level. Minimizing overall braking induced by lane changes (MOBIL) is a model of strategic level that minimizes the overall lane changes induced by braking. This model can deduct the rules of lane changing for mandatory and optional lane changes in different following models of a car [9]. The challenges of lane keeping, lane changing, safety, and achieving the desired lateral position are dealt with in lateral control [10,11]. The complicated lateral dynamics make the lateral control of autonomous vehicles a challenging task. There are several studies in the literature that designed different control methodologies for the lateral dynamics of autonomous vehicles, involving proportional integral derivative (PID) [12], backstepping [13,14], LQR [15], and feedback linearization [16]; sliding mode control (SMC) and backstepping control were designed in [17], a higher sliding mode control technique was developed with experiment validation [18], gain scheduling was proposed and compared with LQR and MPC approaches [19], and fuzzy logic was also tested [20,21]. To improve the transient performance and ensure the normal path-tracking maneuver, a novel approach based on a fuzzy-observer-based composite nonlinear feedback (CNF) controller was proposed [21]. This controller was designed to effectively deal with system disturbances and uncertainties that may affect the vehicle's performance. By including a fuzzy observer, the CNF controller is able to estimate the vehicle's lateral states accurately. The proposed technique was formulated using linear matrix inequalities (LMIs) to implement an observer-based controller aimed at enhancing the tracking performance under challenging conditions such as input saturation and disturbances in GPS-denied environments. To validate the effectiveness of the approach, high-fidelity simulations were conducted using CarSim-Matlab/Simulink, and the results demonstrate the validity of the proposed methodology. A novel Lyapunov-based robust control for lateral control of an autonomous vehicle utilizing meta-heuristic optimization algorithm is presented in [17]. First, a double-lane-change path was developed utilizing a fifth-degree polynomial (quantic) function and dynamic constraints. The double-lane-change maneuver was designed using a lane-changing path-planning strategy. Then, a two-degree-of-freedom vehicle bicycle model was used to extract the position and orientation errors. Integration of backstepping control and sliding mode control (SMC) was applied for steering control. The overall stability of the proposed control was analytically demonstrated using the Lyapunov stability theorem. Additionally, a particle swarm optimization algorithm was proposed to determine the optimal parameters of the combined controller. Simulation studies were carried out using CarSim software and Matlab/Simulink, and the proposed controller showed superior performance compared to the backstepping controller in low road friction scenarios.

A 3 (DOF) nonlinear vehicle model was developed in [22], which accounts for yaw, lateral, and roll motions, and chaotic behavior was then simulated using the Lyapunov exponent method. To control this chaotic behavior, a sliding mode variable structure control (SM-VSC) was designed. To further improve lateral vehicle stability and reduce chattering under maximum operating conditions, a fuzzy control technique was used to realize an adaptive power-reaching law. The SM-VSC system performance was simulated using Matlab/Simulink. The results of the simulation showed that the adaptive-reaching SM-VSC control approach was effective in quelling the chaotic phase of the vehicle's lateral motion. Overall, the study demonstrated the usefulness of combining SM-VSC with fuzzy control techniques to control chaotic behavior and enhance the stability of lateral vehicle motion under challenging operating conditions.

A novel and efficient control strategy for the path following of autonomous vehicles was proposed in [23]. The control strategy was designed to handle uncertainties and mismatched disturbances in the system. The sliding mode control (SMC) was used in combination with a radial basis function neural network (RBFNN), gain scheduling with fuzzy system, and disturbance observer (DOB). The RBFNN estimates uncertainties, the fuzzy system compensates for changes in system parameters, and DOB estimates mismatched disturbances. The stability of the closed-loop system was guaranteed using the Lyapunov stability theorem. The proposed control was tested for path-following tasks of autonomous vehicles under different road adhesion conditions and at high speeds in hard driving conditions. Simulation results demonstrated that the proposed control is more efficient than other robust strategies such as $\mathbf{H}_\infty$ and the principle of immersion and invariance. The proposed control strategy has potential for use in real-world applications of autonomous vehicle control. A block diagram of the lateral control scheme is depicted in Figure 2.

A technical survey on the latest research on lateral control techniques applied for autonomous vehicles and the path-tracking task was proposed in [24]. Many concepts of control formulation are demonstrated and discussed, and the challenges and strengths of each control technique are mentioned and compared. Model predictive control (MPC) is one of the best control techniques for the task of path tracking because of its capability to ensure input and state constraints and its challenge is the stability analysis. SMC, $\mathbf{H}_\infty$, and back-stepping control are great control approaches to deal with disturbances, parameter uncertainties, and nonlinearities on account of complex design techniques and theoretical derivations. LQR, geometry-based, and PID controllers are appropriate for the applications of low-speed and simple models with negligible uncertainties and disturbances. Most model-based controllers except MPC cannot impose constraints on system states, inputs, and outputs. This is a crucial quality for comfort and safety insurance in automated guidance for imposing actuator limits and maintaining stability conditions. Otherwise, model-free controllers are a crucial solution when modeling becomes a challenging task. These techniques are useful in the case of available sufficient data and can guarantee multitasking without being affected by the system nonlinearities. AI-based techniques can be utilized to improve model-based controllers by learning control algorithms and complex models. The drawbacks of these techniques are the difficulty of interpretability and the nature of black box, which cannot ensure some physical properties and stability. Generally, in spite of the great progress in the field of autonomous driving, many problems such as steering systems, unmeasurable parameters, and discontinuous data still continue and need great efforts to be solved.

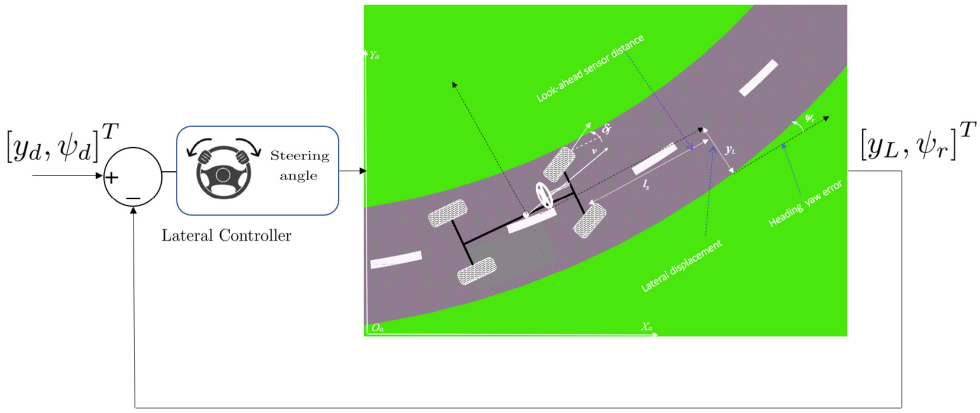

Figure 2. Block diagram of lateral control.

A detailed overview and comparison of different control methods that can be utilized for the purpose of path tracking in autonomous ground vehicles (AGVs), with a focus on car-like autonomous vehicles, was presented in [25]. It covers several control techniques, including feedback linearization (FL), $\mathbf{H}_\infty$ controller, sliding mode controller (SMC), Lyapunov's direct method (LDM), Stanley controller, pure pursuit controller (PPC), neural network (NN) controller, model predictive control (MPC), and linear quadratic regulator (LQR). The performance of each technique was evaluated through a simulation study in urban path tracking. The simulation results and pros and cons of each technique were presented in detail, with nonlinear model predictive control (NMPC) being the most appropriate technique for highway driving. The article concluded that geometric control techniques (i.e., PPC and Stanley) are not suitable for highway driving due to their low performance at higher speeds, while robust control techniques (i.e., SMC) have lower-quality performance for external disturbances and may cause discomfort to passengers due to chattering. The optimization-based control techniques, such as NMPC and LQR, have been shown to achieve minimum lateral and orientation errors with disturbance compared to the other control techniques. In uncertain environments, the stability and safety of the autonomous vehicles are important prospects. The operating range of the vehicles can be unsafe due to the nonlinear tire–terrain dynamics and saturation. The states of the system should be restricted within certain bounds to solve this problem.

A multi-input multi-output (MIMO) model reference adaptive control (MRAC) approach was designed in [26]. The purpose was to improve vehicle stability by acting as an advanced driver-assistance system (ADAS). This approach enhances the yaw and handling stability of the vehicle's lateral dynamics. A nonlinear integrated adaptive control strategy was proposed, using a constraint optimization algorithm. The efficiency of the proposed control technique was compared with a linear time-varying MRAC and a nonlinear integrated adaptive controller. Simulation results for the double-lane-change (DLC) and

J-turn maneuvers at low tire–road friction coefficients and high speeds demonstrated the superiority of the proposed controller over the conventional MRAC in terms of the handling of sideslip limitation and yaw rate tracking.

Despite the existence of several studies that have utilized the barrier function approach in autonomous vehicle research [27,28], there is currently no significant body of research that addresses the control of lateral dynamics in autonomous vehicles using the barrier function approach in combination with sliding mode control (SMC) in the presence of curvature angle, nonlinear tire-forces, and parametric uncertainties.

In addition to addressing the challenges posed by road curvature angle, unknown lateral tire forces, and parametric uncertainties, the sliding mode control (SMC) approach with barrier Lyapunov function implemented in [29] was also designed to keep the system outputs of the autonomous vehicle's lateral dynamics within realistic bounds. This further enhances the effectiveness and practicality of the control approach. The paper [30] introduced a new approach called Type-II zeroing control barrier function (ZCBF), which was designed to ensure both the robustness and forward invariance of a constraint set. Unlike the original ZCBF formulation, Type-II ZCBF is more general and allows for the accommodation of multiple Type-II ZCBFs, which have non-intersecting boundaries for the constraint set. This property ensures that input constraints are respected. The proposed method was applied to a classical unicycle system. Furthermore, this approach can be extended to handle non-intersecting constraint set boundaries. The authors in [31] present a system that utilized a finite state machine (FSM) to automatically switch between different states based on input from the traffic environment and driver. The system's optimal inputs were calculated using a quadratic program (QP)-based optimization problem. The QP was solved by employing rule-based control strategies that leverage control barrier functions and control Lyapunov functions (CBF-CLF). The system's safety was ensured by using a convex quadratic program to perform high-frequency updates, ensuring that the system operates in a safe and collision-free manner, especially during lane-change maneuvers.

A novel approach utilizing a fractional-order PID control algorithm based on data-driven control was proposed to enhance tracking precision in autonomous driving [32]. The algorithm's parameters were optimized using the particle swarm optimization (PSO) algorithm. Comparative analysis against PID control and linear quadratic regulator (LQR) was performed using MATLAB/CarSim. Experimental results showed that the fractional-order PID control effectively reduces tracking error caused by path curvature changes while maintaining comfort, stability, and safety.

In [33], a control algorithm based on a lateral dynamic model was introduced for path tracking in autonomous vehicles. To enhance stability at high speeds, an improved model predictive control (MPC) controller was proposed. By combining the steady-state response and MPC, the lateral motion of the vehicle can be controlled smoothly, ensuring accurate path tracking at high speeds. Simulation results obtained using MATLAB were presented to validate the effectiveness of this approach.

An efficient model predictive control (MPC) approach for lateral control (LC) in autonomous vehicles was presented in [34]. To address computational time limitations, a proposed approximate explicit model predictive control (AEMPC) scheme utilized pre-computed control gains and eliminated the need for online quadratic programming. The suitability of AEMPC for real-time implementation on automotive electronic control units (ECUs) was emphasized, and the usefulness of AEMPC in lateral control was demonstrated through computational experiments.

A lateral control for autonomous vehicles aiming to compare the performance of three controllers (PID, Stanley, and sliding mode control) across multiple environments was investigated in [35]. By evaluating their performance in seven environments, the study identified the controllers that excel in each specific setting. These findings enable the design of an efficient controller suitable for diverse environments. Table 2 summarizes the lateral model-based control techniques existing in the literature.

Table 2. Lateral model-based control techniques.

Papers	Publication Year	Control Technique	Vehicle Model/Vehicle Type Modeling	Output/Primary Objective	Validation	Advantages	Disadvantages
[12]	2011	Nested PID	Simplified single track vehicle model	Steering control and lane keeping	Simulation and real	– Performs path following for roads of an uncertain curvature; – Robust against uncertain vehicle physical parameters and speed variations.	Does not consider the interactions between the proposed controller and the driver both in normal driving and during emergency conditions.
[13,14]	2018, 2019	Backstepping	Reduced second-order model of lateral vehicle motion and a vehicle–road system model	Lane keeping and steering control	Simulation and real	– The proposed approach is robust to disturbances, including external disturbances and modeling uncertainties; – The control structure is simple. & – Good real-time performance, tracking accuracy, and robustness against vehicular velocity.	There is no guarantee of the boundedness of the lateral offset in transient response.
[15]	2018	Hierarchical vision-based lateral control	The vehicle lateral model	Steering angle control	Simulation	– The introduced control scheme balances well between the predicted performance and the amount of online calculation; – Provides a potential low-cost solution for lateral control of autonomous vehicle.	
[17,18]	2019, 2013	Backstepping controller and sliding mode control (SMC)	Two-degree-of-freedom vehicle bicycle model and dynamic bicycle model	Steering control/angle and trajectory tracking	Simulation	– The accurate tracking in low (0.3) and high (0.9) frictions and also in different maneuver durations. & – The robustness of the sliding mode controller against nonlinearities and parametric uncertainties in the vehicle model while reducing chattering of first-order sliding mode; – Achieves robust lateral path tracking at high speed.	– The long running time of the proposed control law. & – There is no robustness against uncertainties and noisy measurements; – the control law does not consider the cant and the slope of the road.
[19]	2021	Gain scheduling	Two-degree-of-freedom (2-DOF) lateral vehicle model	Tracking references of lateral position and heading angle	Simulation	– Robustness against time-varying system parameters.	
[20,21]	2015, 2020	Fuzzy logic	Lateral kinematic model of an autonomous vehicle and Takagi-Sugeno (T-S) vehicle lateral dynamic model	Steering control and path-tracking control	Simulation	– Ensures the safety and stability of autonomous vehicles. & – Lowers the oscillations and overshoots, saves the control energy, and improves the transient performance of the controlled output.	
[22]	2019	Sliding mode variable structure	Three-degree-of-freedom (DOF) nonlinear model	Improved a vehicle's lateral stability under extreme operating conditions	Simulation	– The adaptive-reaching SM-VSC control approach is more efficient in eliminating the chaotic phase of the lateral motion of the vehicle and significantly ameliorates a vehicle's lateral stability under extreme operating conditions.	

Table 2. *Cont.*

Papers	Publication Year	Control Technique	Vehicle Model/Vehicle Type Modeling	Output/Primary Objective	Validation	Advantages	Disadvantages
[23]	2020	SMC in conjunction with disturbance observer and gain scheduling	The model of the vehicle lateral dynamics, including the modeling of the external disturbances	Path-following control	Simulation	– Chattering is completely removed; – Can treat all perturbations; – Has greater robustness against parameters variation; – Stability is robust.	– Requires bounded disturbances.
[25]	2021	Feedback linearization (FL); two most common robust controllers: H_∞ controller and sliding mode controller (SMC), the Lyapunov's direct method (LDM); two geometry-based controllers: Stanley controller and pure pursuit controller (PPC); neural network (NN) controller; and two optimization-based controllers: model predictive control (MPC) and linear quadratic regulator (LQR)	Kinematic and dynamic vehicle model	Path-following task of autonomous ground vehicles (AGVs)	Simulation	(FL) – Allows use of well-defined linear control techniques. & (LDM) – Is stable for a large range of gain values. & (Stanley) – Easy to implement; – Low computational cost; – No look-ahead distance requirement; – Performs well at varying path conditions. & (PPC) – Easy to implement; – Low computational cost; – Good performance at lower vehicle speeds; – Good tracking performance when starting on the reference path (low lateral and heading error). & (Adaptive) – Good performance with parametric uncertainty; – No prior information about dynamic parameter if an intelligent algorithm (NN, FLS) is used. & (MPC) – Ability to handle multiple variables; – Constraints can be included in states and control; – Optimized performance based on a cost function. & (LQR) – Control effort and system response can be optimized.	(FL) – Lacks robustness – Presence of internal dynamics (for input-output linearization). & (LDM) – Lyapunov candidate function is not easy to construct. & (Stanley) – Performance depends on proper tuning of parameters; – Does not perform well in case of path discontinuity; – Less robust than PPC. & (PPC) – Does not consider the orientation of the vehicle at the target point; -Does not perform well in case of large initial lateral and heading error; – Performance depends on the proper tuning of look-ahead distance, which may vary for different trajectories; – Performance degrades at higher vehicle speeds. & (Adaptive) – Not robust against non-parametric uncertainty; – Parameter drifting problem. & (MPC) – Solves online optimization problem, which is computationally expensive. & (LQR) – Use of linear model increases uncertainty; – Not robust in the presence of uncertainty.

Table 2. *Cont.*

Papers	Publication Year	Control Technique	Vehicle Model/Vehicle Type Modeling	Output/Primary Objective	Validation	Advantages	Disadvantages
[26]	2021	Multi-input multi-output (MIMO) model reference adaptive control (MRAC) strategy	Single-track (ST) 2-degree-of-freedom (DOF) vehicle model	Yaw rate tracking and handling of sideslip limitation	Simulation	Improves the handling and yaw stability of the lateral dynamics of the vehicle.	
[29]	2021	A sliding mode control (SMC) with barrier Lyapunov function	Nonlinear second-order system—following the model reduction approach in the literature, the slow and fast system dynamics are separately controlled	Tracking the system's desired outputs while restricting the output in certain bounds	Simulation	– SMC with barrier function is used to track the system's desired outputs while restricting the output in certain bounds; – SMC with barrier function provides better tracking performance than the conventional SMC.	
[30]	2021	Type-II ZCBF	Nonlinear affine system	Ensuring forward invariance and robustness of a constraint set.	Simulation	– Can be applied for a larger class of systems (e.g., passivity-based) while still ensuring robustness.	– Does not address non-intersecting constraint set boundaries.
[31]	2021	CBF-CLF	Kinematic bicycle mode	Guaranteeing a vehicle's safety during lane-change maneuvers in a complex traffic environment.	Simulation	– Guarantees a vehicle's safety in a complex traffic environment during lane-change maneuvers; – Ensures the system's safety at a high update frequency.	– The zero slip angle assumption limits the ego vehicle's lateral acceleration and the controller's performance; – The small angle assumption also creates a mismatch between the real dynamics model and the used approximated nonlinear affine dynamics model.
[36]	2018	Hierarchical controllers	Two-DOF bicycle model/ SIMO system	Guaranteeing the stability and robustness under various environments	Simulation	– The vehicle can track any "feasible" references with the designed controller at a constant speed, and the lateral deviation converges to zero within a short period.	– Does not consider the presence of uncertainties and disturbances.
[37]	2013	A distributed model predictive control approach	Model of lateral inter-vehicle dynamics between two adjacent vehicles	Steering control	Simulation	The proposed approach can deal with the actuator, comfort, and safety constraints.	

2.1.2. Lateral Model-Free Control techniques

There are complex road situations such as crosswalks, dense traffic, intersections, etc. Due to these reasons, artificial intelligence (AI) techniques, reinforcement learning (RL), and deep learning (DL) learn from their environment to outperform the model-based control techniques to take accurate control command, such as steering [38].

A recent study proposed an end-to-end control system for steering autonomous vehicles using a convolutional neural network (CNN), referred to in [39]. The system does not rely on explicit hand-engineered algorithms for path planning, lane detection, or object detection and instead maps pixel data directly to steering commands using the trained neural net. This means that any other sensors are not required for the system to function. The performance of the controller was evaluated by comparing its steering behavior with that of a human driver.

In [40], the study detailed the training of an end-to-end model for controlling the lateral motion of autonomous vehicles (AVs). The authors demonstrated that CNNs can drive in similar but previously unseen scenarios. To train the network, a small amount of training data was used within a simulation to control the car. Furthermore, the study suggests that this approach can be extended to integrate longitudinal control of AVs by training the network to use both steering angles and vehicle speed to achieve the desired steering angles and vehicle speed.

An end-to-end autonomous driving system that combines long short-term memory (LSTM) and CNN architectures was proposed in [41]. The integration of LSTM and CNN allowed the system to extract both spatial and temporal features, and changes in the steering-wheel angle of the vehicle were considered over time. However, data collection from real-world vehicles was limited due to the challenges in processing vehicle data. To overcome this issue, the authors used a driving simulator to train the proposed approach for the steering wheel angle. The study suggests that a complete end-to-end driving system could be constructed using large-scale vehicle data, provided solutions to the limitations in vehicle data collection are found.

In [42], a deep neural network technique was proposed to explore the potential of event cameras in predicting the steering angle of a vehicle, which is a challenging task in motion estimation. The performance of this approach was evaluated on a publicly available dataset of large-scale event-camera data. The simulation results demonstrated that the proposed approach performs well using event cameras under different conditions, including challenging illumination and fast motion, compared to traditional standard cameras.

In [43], a novel network architecture was developed to enhance the end-to-end learning of the steering angle based on baseline vision using auxiliary tasks. The architecture incorporated vehicle kinematics, recurrence modules, segmentation of auxiliary image, introduction of optical flow, and transfer from existing tasks as distinct auxiliary tasks. The Imagenet recognition task was used to learn features that were useful for on-road driving in the steering task. By enhancing the mask of the pre-trained segmentation with more information, a more accurate prediction could be obtained. Additionally, the precise addition of vehicle kinematics led to a more concrete representation of the state and boosted performance. The proposed approach was evaluated using the Comma.ai dataset and Udacity simulator, demonstrating its effectiveness in improving end-to-end learning of the steering angle.

An advanced chauffeur hybrid method was utilized to steer autonomous vehicles in various situations, including changing from one road to another, lane changes, traffic signs, and traffic lights [44]. CNNs were used to extract data features from the Udacity simulator, and both recurrent neural networks (RNNs) and CNNs were employed. However, one limitation of this method is that it does not consider other road users or obstacles, which can pose significant challenges for autonomous vehicles in real-world driving scenarios.

Three major architectural parameters of CNN were evaluated and compared in [45] to demonstrate their impact on the overall performance of the network. An optimal design of deep networks and the best performance of the network were achieved based on this comparison. The performance of CNN models was further enhanced by a new MSE-based ensemble approach, which was used for regression problems. A bagging method was utilized to demonstrate the superior performance of this new approach.

A vision-based lateral control approach for autonomous driving using reinforcement learning and deep learning methods was proposed in [46]. The approach consists of a perception module and a control module. The perception module takes a driver-view image as input and predicts track features using a neural network of multi-task learning. The control module generates control decisions based on these features using reinforcement learning. The approach was evaluated using Visual TORCS (VTORCS) and a deep reinforcement learning environment based on the open racing car simulator (TORCS) to improve data efficiency. The trained reinforcement learning controller outperformed the model predictive control (MPC) and linear quadratic regulator (LQR) controllers on various tracks. The experiments showed that the perception module performs well, and the controller can effectively steer the vehicle along the center of the track using visual input.

A data-driven simulator and an engine for training are proposed in [47] to learn control policies for end-to-end autonomous vehicles using sparse rewards. The simulator allows the policies learned to be generalized for navigating previously unseen real-world roads without the need for human-labeled training data. The effectiveness of the learned policies was demonstrated through experiments conducted on a full-scale autonomous vehicle in complex and novel scenarios, such as near-crash situations and new roads. The proposed approach leverages scalable reinforcement learning techniques and can be applied to achieve robust operation and efficient perception of autonomous vehicles in the physical world. Additionally, the approach enables autonomous vehicles to detect and avoid obstacles, including pedestrians, other vehicles, and trees, on the road.

In [48], a deep Monte Carlo tree search (MCTS) algorithm based on reinforcement learning for vision-based control of autonomous driving was introduced. The algorithm uses driver-view images as input, captured by a camera mounted on the vehicle, and does not require human knowledge for vehicle control. The deep-MCTS algorithm performed virtual simulations of driving to predict maneuvers and enhance the stability of driving trajectory and steering control. Compared to current approaches, the proposed technique shows a significant improvement in the training efficiency, stability of driving trajectory, and stability of steering control, with 50.0%, 59.06%, and 66.30% improvement, respectively. The technique has the potential to be applied in real-life scenarios.

A reinforcement learning (RL) approach for training a vehicle agent to perform automated lane changes in various scenarios was proposed in [49]. The RL algorithm uses a Q-function approximator to compute a closed-form greedy policy, enabling efficient computation of deep Q-learning with continuous action and state spaces. The simulation results demonstrated the effectiveness of the vehicle agent in learning efficient and smooth driving policies for lane changing. Furthermore, the adaptability and robustness of the RL agent were improved by testing in different traffic flow conditions and road geometries, making it suitable for complex driving scenarios.

A novel model-free adaptive control (MFAC) algorithm called the dual successive projection (DuSP)-MFAC method was proposed and analyzed in [50]. The DuSP method is used for analysis, examining the MFAC controller and its parameter estimator. The DuSP-MFAC scheme was successfully implemented in the autonomous car “Ruilong” to address lateral tracking control. By utilizing the proposed preview-deviation-yaw angle, trajectory tracking was transformed into stabilization. Real road tests in Fengtai, Beijing, China, and participation in the Chinese Smart Car Future Challenge Competition demonstrated the satisfactory performance of the MFAC-based lateral tracking control method.

A neural-network-based robust lateral control strategy was proposed for an autonomous vehicle (AV) in [51]. A radial basis function neural network (RBFNN) was used to decrease the effect of unknown external disturbances for inaccurate model information and tackle the problem of chattering, which is faced by the conventional sliding mode controller (SMC), by estimating the equivalent control. Further, a switching control based on higher-order sliding mode (HOSM) was developed to compensate the external disturbances effect. The simulation results demonstrate the effectiveness of the proposed control in terms of lateral stability and lane keeping in the high-fidelity environment of Carsim-Matlab Simulink in diverse road and environmental conditions.

In [52], a speed-adaptive model-free lateral control strategy was developed with a wide range of operation in order to increase the situations where the autonomous vehicles steer without intervention. A minimum level of comfort and safety were considered. A systematic procedure was used to test the performance of controllers on trajectories with different dynamic constraints and shapes. The simulation and real-world tests explained that the speed-adaptive model-free Control (MFC) has a superior performance compared to other controllers with the same structure, such as a MFC and a PID. The simulation and real vehicle results demonstrated that the proposed control strategy has a high degree of accuracy, comfort, and safety.

The necessity of accurate vehicle models in traditional automated vehicle path-tracking algorithms, which are challenging to obtain due to complex interactions and unknown disturbances, was emphasized by the aim of this work [53]. Furthermore, the popularity of path tracking using data-driven controllers such as model-free control (MFC) was highlighted. The objective of addressing the trial-and-error nature of control gain tuning in MFC and the potential issues associated with existing adaptive gain-tuning methods, such as chattering or unbounded control gains, was pursued. To improve the performance of MFC, the integration of MFC with extremum-seeking control (ESC) was proposed, aiming to enable real-time updates of the control gain. The effectiveness of this adaptive model-free controller was demonstrated through simulations and field tests conducted in Simulink-CarSim.

2.2. Longitudinal Control of Autonomous Vehicles

2.2.1. Longitudinal Model-Based Control Techniques

To ensure proper longitudinal control, four types of information are required: the speed and acceleration of the ego vehicle, the speed and acceleration of the preceding vehicle, the distance to the preceding vehicle, and the speed and acceleration of the leader vehicle in a platoon scenario. The OEM speed sensors and accelerometers can measure the speed and acceleration of the ego vehicle, as shown in Figure 3. Range sensors such as vision, ultrasonic, LIDAR, and radar can measure the distance to the preceding vehicle, with radar being the most common sensor used. The physical principle of automotive radar is the main reason for its success and provides unique characteristics of performance at a reasonable cost. These characteristics include design compatibility, vehicle integration independent of environmental conditions (weather and light), multiple fields-of-view capability, Doppler velocity, and directly measured spatial parameters. Radar works in case of the failure of other sensors. This radar can virtually observe the perspective effect of vehicles by utilizing the reflection between the vehicle floor and the road surface to make invisible objects visible. Mutual interference between vehicle radars represents a challenging problem that must be considered. For example, the consequences can be unimaginable, and the radar can misjudge the surrounding environment when the speed is high, when two autonomous vehicles are driving beside each other, and when the radars affect each other [54].

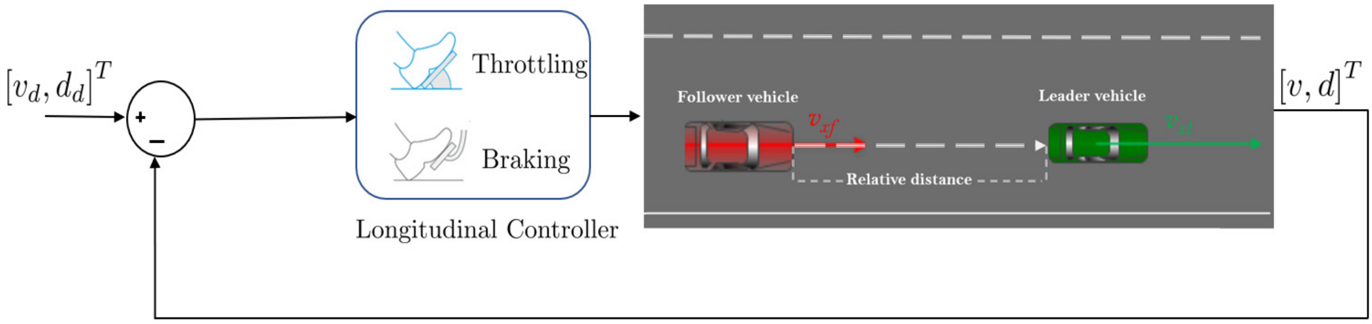

Figure 3. Schematic of longitudinal control system.

The speed and acceleration of the preceding vehicle can be measured in two ways: by using range sensors and deriving the information from the ego vehicle or by communicating the information between the vehicles. In a platoon scenario, the lead vehicle's speed and acceleration can be obtained through communication. However, the reliability of communication cannot be fully trusted.

The autonomous vehicle Leonie utilizes the adaptive longitudinal control system described as [55]. This system was designed to respond to changing weather and road conditions through a calculation known as the grip value. The grip value influences several key factors, including the safe time headway, the magnitude of acceleration demands, and the maximum allowable vehicle speed for both the longitudinal controller and the entire vehicle-guidance system. By incorporating the grip value calculation, the results of test drives demonstrated a smoother acceleration profile and reduced interference from electronic stability control (ESC) and automatic traction control (ATC) systems.

In [56], a comparison was made between four different longitudinal controllers. The first was a classical proportional-integral (PI) control, which is a well-established control method. The second was an advanced i-PI control, which incorporates an intelligent component into the traditional PI control. The third was a fuzzy control system based on human experience, and the fourth was a neuro-fuzzy control system. The aim of the comparison was to evaluate the performance of these controllers under various driving conditions and identify the most suitable control method for autonomous vehicles. The proposed control techniques were validated by numerical simulations in first step, and experiment results were highlighted on a real vehicle in the second one.

A longitudinal controller for an automated driving bus was developed in [57]. A linear longitudinal model was presented by approximating a rolling resistance force and an aerodynamic drag force in a low speed range. Then, the feedback gains of a proportional integral (PI) control were determined using a root locus method to consider the longitudinal grade of the road with a constraint derived from the Chien–Hrones–Reswick (CHR) method. The vehicle predicts the traffic light for the smooth passing of a signalized intersection. Further, the novel adaptive cruise control (ACC) was proposed for the automated driving bus for the acceleration reduction of the vehicle. Pilot tests were used to validate the controller's performance on public roads.

A methodology was proposed in [58] for selecting a longitudinal model and improving velocity control in an autonomous car. The inverse model compensates for nonlinear dynamics in the transmission system and engine. The modeling method works for any automated car with actuated throttle and braking, relying on data without prior knowledge. The control system uses two loops for throttle and braking, achieving good performance on uneven surfaces. It maintained acceleration around 2.5 m/s^2 in the 0–40 km/h speed range, which is suitable for passenger comfort. The methodology was validated through simulations and experiments, proving its effectiveness in enhancing safety and performance. A controller for a longitudinal ADAS system of a test vehicle was designed in [59]. A robust H_∞ cruise control based on a feedforward and a feedback control design was proposed to ensure a precise velocity tracking and robustness against longitudinal disturbance effects such as aerodynamic forces, mass parameter variations, rolling resistance, and road slopes of the vehicle. The parameter variation (dynamics) of the actuator was considered in a simplified form in the control formulation. The proposed control algorithm was implemented in CarSim. The method efficiency was illustrated during simulation scenarios on the Mulhouse-Belfort highway section. The introduced control design will be applied to various vehicles because it needs a small number of vehicle parameters.

An MRAC approach for ACC systems in vehicles, which is capable of effectively managing uncertainties in low-level dynamics, was introduced by the authors of [60]. The linear longitudinal dynamic model incorporates uncertainties in the state and input matrices, and the system was designed based on error dynamics. The velocity of the lead vehicle was considered an exogenous disturbance, and the uncertainties were addressed by the control structure to maintain the desired distance. Despite model uncertainties, the proposed control demonstrated superior performance compared to a linear-state feedback control in MATLAB/Simulink. This controller is suitable for practical implementation, as it only requires a sensor in addition to vehicle velocity to measure the relative distance between the lead and controlled vehicle. In [61], a longitudinal control algorithm was developed for an autonomous vehicle without the need for vehicle parameter identification. The modified MRAC approach was studied with appropriate initial conditions, ignoring powertrain dynamics and road slope changes. Despite these simplifications, the adaptive algorithm effectively tracks speed profiles with comfortable acceleration and robustness to environmental variations. The control architecture is suitable for vehicles with approximately known parameters. Simulation using a CarSim-Simulink setup demonstrated the feasibility of the approach, evaluating vehicle performance under different dynamic conditions.

In [62], a novel longitudinal control method for autonomous vehicles was presented. The approach utilizes the reverse plant model of the vehicle to address non-linearity in the powertrain at low speeds and rapid acceleration/deceleration caused by surrounding vehicles. The parameters known to original equipment manufacturers (OEMs) were used to design the complete controller, incorporating an inner controller for brake requests and accelerator pedal percentage, and an outer controller for desired speed based on the lead vehicle's speed. The inner controller employs a reverse plant model with a virtual load sensor and follows a PI control strategy, enabling the control of vehicles with non-linear powertrain dynamics. The performance of the controller was validated on a city bus with automatic transmission and a diesel engine, demonstrating its capability to effectively control autonomous vehicles with non-linear powertrain dynamics at low speed. Table 3 summarizes the longitudinal model-based control techniques existing in the literature.

2.2.2. Longitudinal Model-Free Control Techniques

The function of longitudinal control is the automated guidance. Therefore, the longitudinal control regulates the autonomous vehicle (AV) speed to ensure comfort and safety. The labeled training data are collected in simulation environments or the real world to estimate the right speed using DL as a longitudinal control technique.

Table 3. Longitudinal model-based control techniques.

Papers	Publication Year	Control Technique	Vehicle Model/Vehicle Type Modeling	Output/Primary Objective	Validation	Advantages	Disadvantages
[57]	2020	Adaptive cruise control	A linear longitudinal model	Reducing the acceleration of the vehicle	Simulation	Improved ride comfort in urban areas.	The maximum delay from reference and the maximum overshooting rate are especially large in rural areas, which affects the ride comfort.
[58]	2014	Model identification and velocity control	Model of longitudinal dynamics of a commercial car	Velocity control	Simulation and real	– The proposed strategy improves the velocity control of the vehicle; – The controller utilizes the inverse model of the vehicle to compensate for the nonlinear dynamics resulting from the transmission system and the engine of the car; – The control architecture is simple, can be implemented on a real-time system, and can control the vehicle in non-flat and uneven surfaces with a good performance; – Proposes low-speed longitudinal control methodology for autonomous vehicles built without manufacturer support.	
[59]	2015	Optimal/ robust H_∞ control	Simplified longitudinal model deals with = structured uncertainties such as mass variations and road slope	Precise velocity tracking at varying vehicle mass and road inclinations	Simulation	– The introduced control design needs a low number of vehicle parameters, and thus, the approach can be applied to various vehicles; – Provides precise velocity tracking at varying road inclinations and vehicle mass; – The system is robust against disturbances and takes into account actuator dynamics.	
[61]	2017	Model reference adaptive control (MRAC)	Longitudinal vehicle model with approximately known parameters	Tracking the speed profile with comfort acceleration	Simulation	– The introduced control can track the speed profile with comfort acceleration; – The proposed architecture can control a vehicle whose parameters are known approximately.	The initial condition of the adaptive parameters has to be properly chosen to guarantee an effective implementation.
[62]	2021	This control methodology combines an inner controller and an outer controller	Reverse plant model of the vehicle	Controlling an autonomous vehicle with nonlinear power-train dynamics	Simulation and real	– The designed control can control an autonomous vehicle with nonlinear power-train dynamics even at low speeds with onboard computational capacity; – The proposed control is realistic and can easily be applied by the industry to any vehicle.	The control design is limited to the parameters known to OEMs (original equipment manufacturer).
[63]	2018	Longitudinal control based on cloud model	Cloud model for Mengshi AV	Ensuring the dynamic stability and tracking performance of Mengshi AV	Simulation	Guarantees the tracking performance and dynamic stability of Mengshi autonomous vehicle.	The speed and acceleration of the cloud model are classified according to experience without certification.

Table 3. *Cont.*

Papers	Publication Year	Control Technique	Vehicle Model/Vehicle Type Modeling	Output/Primary Objective	Validation	Advantages	Disadvantages
[64]	2011	Distributed receding horizon control	Platoon of vehicles with nonlinear dynamics	Ensuring asymptotic stability, leader–follower string stability, and predecessor–follower string stability, following a step speed change in the platoon	Simulation	– Ensures predecessor–follower string stability, leader–follower string stability, and asymptotic stability; – Conjectural tradeoffs between lead car and following car control flexibility; – The proposed string-stable controller does not require any continuous information from the lead car to cars down the string, nor does it require acceleration information from the lead car.	The platoon size depends on the individual choices and the behavior of the constituent vehicles.
[65]	2010	Vehicular adaptive cruise control (ACC) (a hierarchical control architecture composed of a lower controller used to compensate for nonlinear vehicle dynamics and to track the desired acceleration and upper controller designed in the framework of MPC)	Model of nonlinear vehicle dynamics	Compensating for nonlinear vehicle dynamics and tracking the desired acceleration	Simulation	– Provides tracking capability and fuel economy; – Satisfies driver's desired car-following characteristics; – Ensures driver's longitudinal ride comfort.	

In [66], a neural network-based control was developed for intersections in autonomous vehicles, aiming to reduce computational complexity in motion optimization. The neural network was trained using an offline solution, and a robustness analysis examined the impact of speed and position estimation errors. CarSim simulations demonstrated the design and analysis, highlighting the trade-off between robust scenarios, position estimation error, and the need to balance energy loss and sensor network costs. In [67], a sensorless state estimation approach was presented for brake pressure in vehicles using deep learning, with the goal of achieving high autonomy and safe driving. The structured deep neural network (DNN) was trained using techniques such as rectified and dropout units, yielding a highly accurate model for brake-pressure state estimation. Training and validation were performed using experimental data collected from a real test vehicle connected to a chassis dynamometer. The effectiveness and applicability of the proposed technique were demonstrated, with a root mean square error (RMSE) of 0.048 MPa achieved for brake-pressure state estimation. In [68], an RL model was introduced for optimizing car-following performance by integrating comfort, efficiency, and safety factors. The RL agent learned vehicle speed control through simulations using a reward function derived from human driving data. Collision avoidance was incorporated for safety. Comparative evaluations with MPC-based ACC and empirical data showed that the proposed RL model outperforms in terms of time-to-collision values, headways, and comfortable following with smooth acceleration. It demonstrates potential for advanced autonomous driving systems. In [69], DRL and MPC were compared for ACC in car-following scenarios. A COM approximates vehicle dynamics. DRL (trained with DDPG) equals MPC with a long prediction horizon within the training data range and no modeling errors. DRL's episode cost is 5.8% higher than IPO-optimized benchmark. DRL's performance degrades outside training data range, indicating poor generalization. DRL matches MPC with small modeling errors and outperforms with large errors, disturbances, control delays, and high-fidelity models. Integration of DRL and MPC can leverage strengths and mitigate drawbacks.

In [70], a multi-agent reinforcement learning approach for cooperative adaptive cruise control (CACC) in platooning vehicles was presented. The LSTM was trained with policy gradient for ACC implementation, allowing the LSTM to be adapted for information exchange and driving coordination. Simulations were conducted with two platoons of three and five vehicles, evaluating the CACC with the learned communication protocol against various communication baselines and a jamming attack. The approach incorporates local and global reward systems, demonstrating faster convergence and higher performance when utilizing the learned communication protocol and individual rewards.

In [71], a method for predicting nearby vehicles' paths and controlling autonomous vehicles (AVs) in urban road conditions was introduced. The trajectory prediction was performed using a deep learning model based on long short-term memory (LSTM), incorporating the historical relationship between a target vehicle and lanes. The interaction among adjacent vehicles was captured through a graph convolutional network (GCN) with self-attention. The prediction model utilizes sensor data locally acquired from AVs. The determination of acceleration inputs is done by model predictive control (MPC), with a focus on prioritizing safety and ride quality. Comparative studies showed improved accuracy compared to baseline approaches, and automated driving tests confirmed the safety and comfort achieved by the proposed control algorithm with the LSTM-based prediction model. A safe velocity control method for autonomous vehicles (AVs) was proposed in [72], considering the following vehicle in car-following models. Trajectories of leading and following vehicles were extracted from driving data. The soft actor-critic (SAC) algorithm was used for velocity control, enabling AVs to learn collision avoidance Zero collisions were observed as the test result of the trained model, demonstrating the SAC agent's ability to achieve complete collision avoidance. Furthermore, the driving performance of the SAC agent and human driving was compared and analyzed to enhance safety and efficiency, aiming to improve the car-following process.

2.3. Integrated Lateral and Longitudinal Control of Autonomous Vehicles

2.3.1. Integrated Lateral and Longitudinal Model-Based Control Techniques

Great attention towards the autonomous vehicles' development has appeared in the last decades in the academic, research, military, and industry fields. The guarantee of secure and reliable navigation of vehicles even in critical situations of driving is the main motivation. The perception and localization, the planning of trajectory, and the control of the vehicle are the three main steps to achieve vehicle autonomy. Lateral control [37,73] and longitudinal control [74,75] for the dynamics of vehicles are separately addressed in most control techniques in the literature, and the control of longitudinal and lateral vehicle dynamics could be separated or coupled, as shown in Figure 4, depending on the control methodology, the dynamics model used, the assumptions, considered uncertainties and parameter variation, and the applications for both dynamics.

The coupling of vehicle dynamics must be considered in the vehicle control design for the vehicle control and to handle its stability and safety, as shown in Figure 5. The lateral and longitudinal control problem of vehicle dynamics was recently addressed in a coupled way by some research groups.

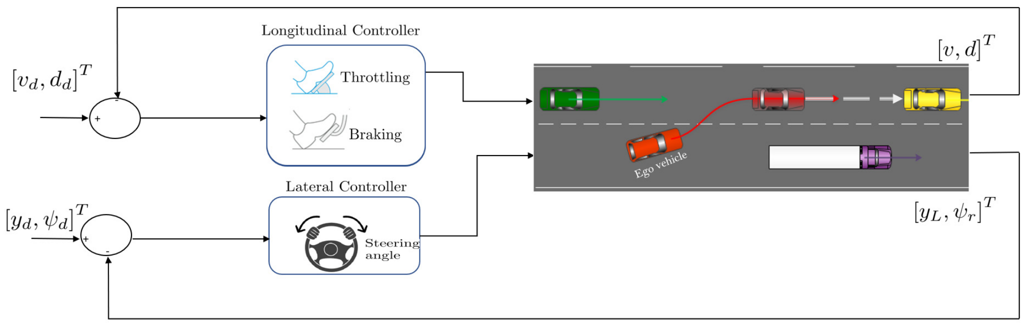

Figure 4. Block diagram of integrated longitudinal and lateral control.

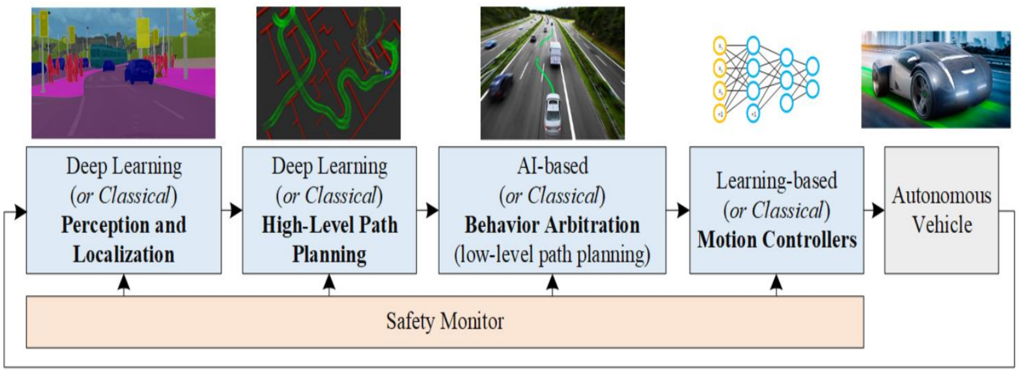

Figure 5. Deep-learning-based autonomous vehicle.

Control algorithms for autonomous vehicles operating at tire adhesion limits are presented in [76]. The algorithms include feedforward and feedback components that replicate the actions of a skilled racecar driver in managing throttle, brakes, and steering. In terms of ensuring safe and efficient vehicle operation at the limits, the feedback control, specifically heading error feedback, surpassed lookahead error feedback. This approach minimizes tracking errors, enhances stability, and guarantees precise trajectory following. In [77], a nonlinear cascade control system was developed for longitudinal control, ensuring torque control and reference speed tracking. The longitudinal control is interconnected with a model predictive control (MPC)-based lateral control for full autonomous driving. Simulations demonstrated the effectiveness of the longitudinal controller in tracking time-varying reference speeds. Real-world trajectory data validated the promising performance of the automated guidance strategy.

A method for platoon control was proposed in [78], where longitudinal and lateral control were combined to ensure the vehicle remains within a lane. The integration of frequency and time domain methods in the longitudinal control allows for consideration of safety, performance, comfort, and actuator limitations, thereby ensuring string stability. The lateral control, employing LPV-MPC and convex optimization, was utilized to address speed changes resulting from longitudinal control and attain global optimality. With this method, the vehicle is maintained within the lane with minimal tracking errors, even when longitudinal velocities vary. The control strategy for fully automated guidance in an automotive vehicle, with a focus on longitudinal and lateral control, was discussed in [79]. Simultaneous utilization of both control types effectively handles the vehicle's complex dynamics. Nonlinear model predictive control (NLMPC) achieves steering automation, while a nonlinear longitudinal control strategy addresses speed tracking and powertrain dynamics. Simulations validated the approach, demonstrating efficient path tracking, acceptable lateral errors, and accurate longitudinal speed tracking. Overcoming the challenge of strong coupling between lateral and longitudinal dynamics in the design of robust, real-time controllers for real vehicle implementation remains a key consideration. In [80], two coupled controllers were proposed: one utilizing Lyapunov control techniques and the other employing immersion and invariance with a sliding mode approach. These controllers guarantee robust tracking of the reference trajectory and desired speed while considering the strong coupling between the vehicle's lateral and longitudinal dynamics. Validation was conducted via simulation in Matlab/Simulink and experimental tests using a robotized vehicle (Renault-ZOE).

The proposed approach by [81] for autonomous driving involves coordinated longitudinal and lateral control, prioritizing stability and comfort. It introduced an enhanced particle swarm optimized proportional-integral-derivative (PSO-PID) method for speed tracking and an improved linear parameter varying model predictive controller (LPV-MPC) for lateral dynamics control. The LPV-MPC incorporates an adaptive LPV model and an enhanced cost function to enhance performance and stability. Matlab/Carsim co-simulations validated the controllers for general trajectory tracking and double-lane-change scenarios, demonstrating reasonable performance and robustness against wind disturbances.

A control framework that improves lateral stability and trajectory tracking accuracy by jointly estimating multiple parameters using an adaptive unscented Kalman filter was developed in [82]. This estimation was used to design a lateral control system focusing on large lateral acceleration and a longitudinal control system for accurate speed tracking, including compensation for drive and brake forces using road slope estimation. The proposed framework was validated through co-simulation and experimental tests on a hybrid LincolnMKZ autonomous vehicle platform, showing excellent performance in enhancing lateral stability and tracking accuracy. Wireless communication-based platoon control for vehicles was investigated in this paper. An integrated approach for longitudinal and lateral control within a designated lane was proposed in [83]. The follower vehicle speed is regulated, and the inter-distance is maintained proportionally to the vehicle speed through longitudinal control. Stability conditions were formulated using a Lyapunov candidate function and BMIs. String stability and robust platoon control were ensured through additional conditions. Constraints such as actuator saturation and limited controller information were taken into account. Vehicle lateral control was achieved using a multi-model fuzzy controller, which maintains road position. The design conditions were expressed as LMIs solvable with numerical solvers. The effectiveness of the proposed control method was validated using the CarSim software package. Table 4 summarizes the integrated lateral and longitudinal model-based control techniques.existing in the literature.

Table 4. Integrated lateral and longitudinal model-based control techniques.

Papers	Publication Year	Control Technique	Vehicle Model/Vehicle Type Modeling	Output/Primary Objective	Validation	Advantages	Disadvantages
[79]	2014	Nonlinear model predictive control (NLMPC) for lateral control and Lyapunov theory for longitudinal control	Nonlinear bicycle model and Longitudinal synthesis model	Path tracking at variable speeds and correctly tracking longitudinal speed reference	Simulation and real	– Guarantees the simultaneous control of longitudinal and lateral motions; – Can decouple the problems of speed and path tracking; – Enhances the lateral stability level and improves the autonomous guidance safety.	Does not consider the road slope in the trajectory generation to ameliorate the reference generation.
[80]	2019	The first controller used Lyapunov control techniques, and the second controller used invariance and immersion with sliding mode control technique	Four-wheel vehicle model	Trajectory tracking and robust speed tracking	Simulation and real	Guarantees a robust tracking of the desired speed and the reference trajectory.	– The tire model is linear and does not consider the non-linearity of the tire/ground contact forces such as piece-wise linear model, Dugoff's model, and others; – The used simplifications affect the performance of the controllers and reduce their robustness; – The lateral controllers/actuators cause delay with respect to the reference trajectory curvature and the vehicle speed; – The tuning of the parameter L_s is not at all a simple task; – Does not consider stronger non-linearity and higher speeds conditions that affect the controllers' robustness at the stability limits of the vehicle.
[81]	2022	PSO-PID for longitudinal control and LPV-MPC for lateral control	A vehicle consists of several subsystems for longitudinal dynamics and an LPV version of the standard bicycle model for lateral dynamics	Lateral and longitudinal tracking with robustness against wind disturbances	Simulation	– Ensures accurate speed tracking; – Provides better performance and stability.	Does not handle both lateral and longitudinal control simultaneously.
[82]	2022	Lateral and longitudinal control of AVs based on multi-parameter joint estimation	Longitudinal model for longitudinal dynamics and 3-DOF vehicle model for lateral dynamics	Improving the trajectory-tracking accuracy and vehicle lateral stability	Simulation and real	Provides excellent performance and enhances the lateral stability and tracking accuracy.	The parameters need to be estimated, and the control structure is not simple.

2.3.2. Integrated Lateral and Longitudinal Model-Free Control Techniques

By employing both lateral and longitudinal controls in conjunction, we can enhance both acceleration and steering performance. To this end, various artificial intelligence (AI) techniques have been developed that allow the estimation of control commands (e.g., steering, braking, and acceleration) in real time. These approaches leverage the power of AI to optimize vehicle handling and responsiveness, leading to safer and more efficient driving experiences.

In [84], a multi-task learning framework was proposed in an end-to-end manner to simultaneously predict speed control and steering angle. The network utilized image sequences to predict steering angles and discrete commands of speed because visual inputs alone were not sufficient to predict accurate speed. To address this, a multi-modal multi-task network was used, which incorporated both visual recordings and previous feedback speeds as inputs to predict steering angles and speed values. The proposed approach was evaluated on a newly collected SAIC dataset and a public Udacity dataset, and the results demonstrated the accuracy of speed value and steering angle predictions. The problem of error accumulation was addressed using methods of failure data synthesis in real road tests.

An investigation of the effect of connected and autonomous vehicles (CAVs) on traffic flow in mixed traffic scenarios, with a focus on on-ramp merging and off-ramp diverging of vehicles, was presented in [85]. The study explored the impact of increasing market-penetration rates of CAVs and proposed a lane-changing cooperative strategy based on reinforcement learning to enable CAVs to make farsighted lane changes and improve traffic efficiency. Simulation results showed that incorporating CAVs can improve traffic capacity, flow, and mean speed, with significant impacts on the processes of lane changes at on/off-ramps. This study highlighted the mixed dynamics of traffic networks and the potential of CAVs for future mobility.

In [86], a new approach was developed, referred to as "implicit affordances", for applying reinforcement learning to urban driving tasks such as vehicle and pedestrian avoidance, traffic light detection, and lane keeping. Ablation studies were conducted to confirm the design choices, and the proposed method demonstrated high performance by winning the camera only track in the CARLA challenge.

In [87], a dynamic obstacle avoidance model predictive control (MPC) framework was proposed for autonomous driving, which incorporates deep learning techniques to achieve velocity-based collision avoidance in unknown environments. The main goal of this approach was to enable the autonomous vehicle to perform various safe traffic maneuvers in the shortest possible time and with maximum passenger comfort while considering the vehicle's dynamics and maneuvering capabilities as well as road boundaries, traffic rules, and static/dynamic unknown obstacles. To address the dynamic collision avoidance problem, the authors defined local coordinates and collision regions, which allowed them to convert it into a static collision avoidance problem. This conversion simplifies the optimization process, and the authors used an ensemble of deep neural networks to estimate collision probabilities and prioritize between safety and mission using an uncertainty-based collision cost. The MPC generates a predicted trajectory by leveraging a learning procedure that predicts collisions in advance using labeled data. The proposed method was tested in different simulation environments and scenarios, and the results demonstrated its safety, good performance, and adaptability to unknown environments.

In [88], an overview of deep learning techniques applied in the context of autonomous driving was presented. The survey covered recurrent and convolutional neural networks, deep reinforcement learning, and AI-based self-driving architectures. These methodologies are crucial for driving scene perception, path planning, arbitration of behavior, and motion control algorithms. The article discussed both modular perception-planning-action pipelines and end-to-end systems that use deep learning methods to build each module. However, the current challenges in designing AI architectures for autonomous driving include ensuring safety, addressing computational hardware limitations, and obtaining adequate training data sources. The survey provided a comparison of the features and limitations of AI and deep learning techniques in autonomous driving, which can assist in making informed design choices. A block diagram of the deep-learning-based autonomous vehicle is shown in Figure 5 [88] and the schematic diagram of a vehicle control system using RL is depicted in Figure 6.

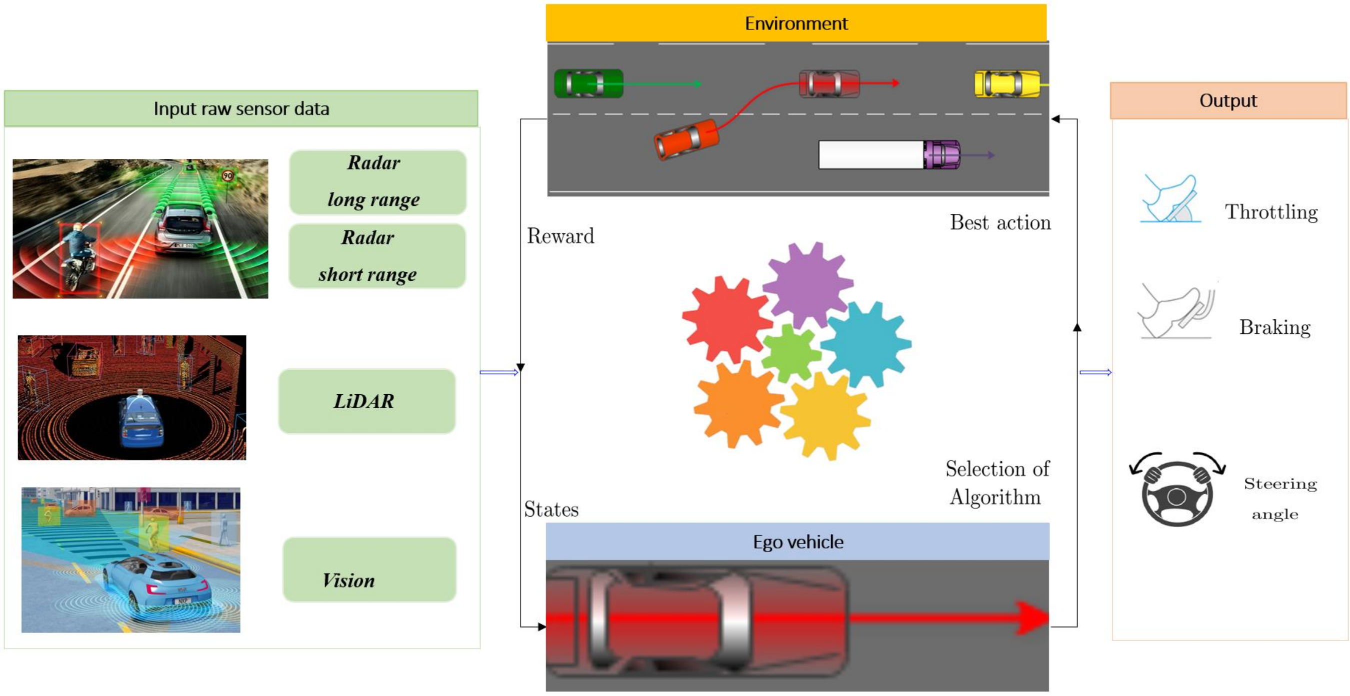

Figure 6. Vehicle control system using RL.

The complex and nonlinear system of an autonomous vehicle was successfully subjected to simultaneous longitudinal and lateral control [89]. This was achieved through a series of steps including selecting an appropriate adaptive neural network that can generate both linear and complex mappings, developing an adaptive lateral control, and evaluating its robustness and precision against parametric uncertainty. Additionally, an adaptive longitudinal control was developed, and its performance was compared with that of a sliding-mode-based longitudinal control and a simple neural-network-based longitudinal control. A simultaneous combined control was proposed for the longitudinal and lateral dynamics of the autonomous vehicle, which outperformed the other control approaches in achieving simultaneous speed-tracking and path-following objectives, as demonstrated through simulation results. In [90], lateral and longitudinal control of autonomous vehicles (AVs) motion was designed utilizing deep learning. The control implementation was developed and tested utilizing the open racing car simulator (TORCS). The vehicle steering and speed were predicted by training two separate neural networks based on the road trajectory. A system that uses artificial intelligence was built, using such an approach to determine the value of the vehicle speed rather than respecting a set of predetermined rules and analyzing the environment.

The existing vehicle lateral and longitudinal control techniques using DL and RL are compared in Tables 5 and 6, respectively.

Table 5. Integrated lateral and longitudinal control techniques using DL.

Papers	Publication Year	Sensor Input	Dataset	Output	Neural Network Architecture	DL Framework	Hardware	Validation	Advantages	Disadvantages
[84]	2018	Cameras	Udacity and SAIC	Steering angle and speed command	CNNs and LSTM	Not reported	GPUs	Real	– Predicts steering angles and speed values accurately; – Predicts the steering angle and speed control simultaneously in an end-to-end manner.	
[90]	2019	Camera	TORCS data	Steering angle and vehicle speed	CNNs	Not reported	NVIDIA GeForce GTX	Simulation and real	– Predicts the vehicle steering and speed based on the road trajectory; – Determines the value of vehicle speed rather than following a set of predetermined rules.	The system performs well only on the two testing tracks due to the limited training data.
[91]	2015	Camera LIDAR	KITTI	Steering and acceleration and brake	CNNs	Caffe	NVIDIA	Simulation and real	– Drives a car in a very diverse set of virtual environments; – Performs well in both virtual and real environments.	
[92]	2018	-	Nine-DoF data	Steering angle	CNNs	Not reported	Not reported	Simulation	– Handles situations with strongly coupled longitudinal and lateral dynamics in a very short time.	The proposed controller is a black-box and cannot be used in standalone.

Table 6. Integrated lateral and longitudinal control techniques using RL.

Papers	Publication Year	Contributions	Output	RL Technique	Scenarios	Validation
[93]	2017	Modeling of driver and vehicle interactions using game theoretic and RL	Decelerate and hard decelerate and maintain	MDP	Multi-lane highways	Simulation
[94]	2018	Controllable imitative reinforcement learning to achieve higher success	Steering and brake and acceleration	DDPG	Urban traffic	Simulation
[95]	2020	RL model for differential variable speed limit control	Speed limits	DDPG	Freeway with five-lane	Simulation
[96]	2020	Model-based RL of the complex driving environment methodology	Steering and acceleration and brake	RNNs and EN and DN	Urban driving	Simulation
[97]	2020	Combination of RL and game theory to learn merging behaviors	Steering and velocity	DQN	Urban traffic	Simulation
[98]	2020	Automated lane-change strategy using proximal policy optimization-based RL	Lane change and acceleration	NN	Highways	Simulation and real

3. Discussion

The most common control techniques utilized in autonomous vehicles are model-based control techniques, such as lateral, longitudinal, and integrated lateral and longitudinal model-based control techniques, and model-free control techniques, such as artificial intelligence (AI)-based lateral, longitudinal, and integrated lateral and longitudinal control techniques. These techniques rely on mathematical models of the system being controlled, which can be used to predict the behavior of the system and optimize control inputs. Furthermore, they are typically more efficient and accurate than model-free techniques, but they require accurate models of the system, which may not always be available. On other hand, the model-free control techniques do not rely on explicit models of the system but instead learn control policies from data through trial and error. These approaches are often used in situations where the system is highly complex, poorly understood, or changing rapidly. Model-based control techniques and model-free control techniques are two approaches to control system design that have their own strengths and weaknesses. Furthermore, there are some key differences between these two techniques that show the advantages and disadvantages of both of them, which are as follows:

Model-based control techniques are as follows:

- Require a mathematical model of the system being controlled;
- Use the model to predict the behavior of the system and optimize control inputs;
- Are often more efficient and accurate than model-free techniques when the model is accurate;
- May be limited by the accuracy and completeness of the model;
- Are typically designed by control engineers who have expertise in modeling and system identification.
- Model-free control techniques are as follows:
- Do not require an explicit model of the system being controlled;
- Learn control policies from data through trial and error;
- Can be used when the system is highly complex, poorly understood, or changing rapidly;
- Are often more robust to model uncertainties than model-based techniques;
- May require a large amount of data and time to learn a control policy;
- Are typically designed by machine learning experts who have expertise in reinforcement learning or other model-free techniques.

We suggest combining model-based and model-free techniques to leverage the strengths, avoid the limitations, improve the performance, and show the effectiveness of both approaches. For example, one approach to combine these techniques is to use reinforcement learning (RL) and deep learning (DL). RL is a type of model-free control that learns from experience to improve control decisions. RL can be used to learn a control policy that optimizes a performance metric, while a model-based controller can be used to provide stability guarantees and constraints. Another approach is to use a hybrid controller that switches between model-based and model-free models depending on the situation. For example, a model-based controller could be used when the system is in a known operating regime, while a model-free controller could be used when the system enters an unknown or highly dynamic regime. Model-based control techniques are commonly used in autonomous vehicles to model the dynamics of the vehicle and its environment and to design control laws that optimize safety, efficiency, and other performance criteria. For example, model-based controllers can be used to regulate the vehicle's speed, steering, and braking and to ensure that the vehicle stays within its lane and avoids collisions with other objects. However, model-based control techniques can be limited by the accuracy and completeness of the model and by the complexity of the system being controlled. This is where model-free control techniques can be useful, as they can learn control policies directly from data without requiring a model of the system.

4. Concluding Remarks and Future Works

This paper proposes a review on recent advanced control methodologies applied for autonomous vehicles (AVs), which can be generally classified into lateral, longitudinal, and integrated lateral and longitudinal model-based and model-free control schemes. Because the development of AVs is driven by recent advances in methodologies of vehicle control, intelligent transportation systems, artificial intelligence (AI) techniques such as deep learning (DL) and reinforcement learning (RL), and computational systems, this progress has led to intelligent vehicles, smart roads, intelligent traffic safety, and improved passenger comfort.

Current research work is focused on handling the main issues related to AVs, such as model-based and model-free control techniques. Model-based control approaches are accurate and efficient for an accurate system model but are limited by model uncertainties. Model-free control approaches are robust against model uncertainties but need more data and time to learn the control policy, which represent the control issues of intelligent connected vehicles developed on the basis of intelligent vehicles. The choice between these two approaches relies on the experience of the control system designer, available data and computational resources, and specific requirements of the control problem. Autonomous vehicles use both model-based and model-free control techniques to obtain high performance and robustness. AVs can take advantage of the strengths of both control types and alleviate their weaknesses using these approaches.

The potential of recent control techniques in various fields of AVs is highlighted, with a focus on the objectives that can be achieved in these aspects. The improvements achieved by advanced control techniques, which overcome the limitations of traditional ones in autonomous driving, are also demonstrated.

Finally, the main existing research challenges are addressed, and future research areas in the direction of fully autonomous/driverless vehicles is identified as a vision and suggestions complementary to this work through the integration of different advanced control methodologies, with different vehicle models improving their performance under various assumptions in various driving scenarios and regions in different research areas. The literature survey presented in this paper will support future research initiatives as a guideline in autonomous vehicles.

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