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A Review on Driving Control Issues for Smart Electric Vehicles

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ABSTRACT Smart electric vehicles (EVs) are attractive because of their clean, zero-emission, low impact on the environment whilst providing a safer and smoother riding experience. To provide the latter, driving control requires appropriate systems and algorithms to optimize smart vehicle performance, maximize vehicle stability and protection, minimize accident probability, heighten driving comfort, and optimize transportation costs. Despite advancements in these areas, the realization of optimal smart EVs still requires considerable effort. This paper reviews driving control systems and algorithms for smart EVs, including the advanced driving assistant system, implementation of sensors, vehicle dynamics, and control algorithms. The major contribution of this review is to identify promising work to assist researchers with the most advanced trends in this area for prospective regulations.

INDEX TERMS Smart electric vehicles (EVs), driving control systems (DCS), advanced driving assistance system (ADAS), algorithms.

I. INTRODUCTION

Electric Vehicles (EV) show significant potential in the reduction of greenhouse gas (GHG) emissions [1] as well as offering other significant advantages. Unlike internal combustion engine vehicle, an EV operates each wheel using an individually mounted motor producing independent power output. This feature offers greater power density, greater safety stability, and improved dynamic efficiency [2]. Integration of EV technology and automatic control methodologies creates a smart EV possessing visual, auditory, olfactory, and tactile functions [3] allowing it to react faster and potentially more accurately than a human driver.

A smart EV is capable of intelligently identifying and evaluating a vehicle's running and driving condition [4]. The smart EV can also use a control system to automatically detect road conditions and receive road traffic guidance, resulting in environmentally friendly driving, efficient traffic flow, automated traffic condition monitoring, and safe control under erratic driving conditions, all of which reduce the likelihood and severity of traffic accidents. Yang *et al.* [5] presents several advanced control systems with control modules for traffic accident avoidance and minimisation. The Advanced Driving Assistance System (ADAS)is a convenient option to increase driving safety and includes control mechanisms such as adaptive headlights, blind-spot monitoring (BSM) [6], obstacles and accident Warning, fixed-lane driving, automatic emergency braking, and environmental driving comfort.

Figure 1 shows Driving Control Systems (DCS) and algorithms for a smart EV. DCS encompasses control methods and control modes based on ADAS [7], including Adaptive Cruise Control (ACC) [8], Automatic Emergency Braking System (AEBS) [9], Lane Departure Warning (LDW) [10], [11], Lane Change Assist (LCA) [12], Lane Keeping Assist (LKA) [13], Night Vision [14], Traffic Sign Recognition (TSR) [15], Pedestrian Detection [16], Automatic Parking [17], and Traction control [18]. Traffic flow parameters, driver behavior, and driving conditions

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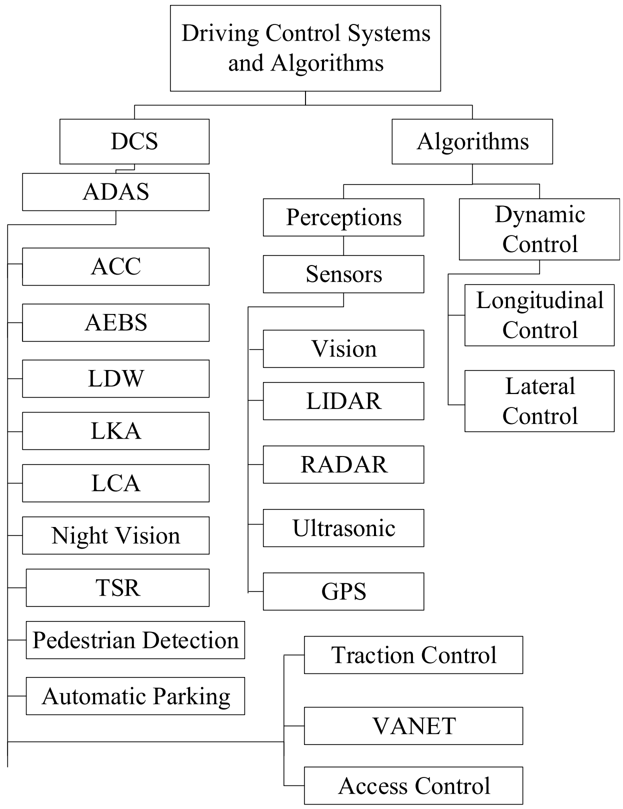

FIGURE 1. Driving control systems and algorithms.

can be detected and shared with vehicles within their vicinity. To share this information and increase the efficient communication between vehicles, vehicular ad hoc networks (VANETs) have been introduced [19], [20]. Multiple VANET surveys referring to security and privacy schemes have been developed in recent years [19]. To establish these security concerns, the smart EV requires some security mechanisms like Access Control [21]. The majority of those approaches are discussed in this review.

The control systems and algorithms depend on the information generated by relevant vehicle sensors to determine the vehicle's condition and position, the surroundings, and several other factors. Elementary sensors include Vision sensors, LiDAR, radar, Ultrasonic sensors, and Time of Flight (TOF). ADAS, for example, utilizes ambient sensors such as camera, radar, LiDAR, night vision, and ultrasonic sensors to track, sense, and evaluate the vehicle's position and surroundings [22]. The system fuses sensor information from multiple sensors to avoid the sensory drawbacks and inconsistencies of each individual sensor [23].

This review also discusses several kinematic and dynamic models used for longitudinal control and lateral control systems, which are the main control methods for smart EV. Longitudinal control is of acceleration and braking; lateral control is of the steering mechanism. Both are essential. Researchers have established several techniques to control longitudinal and lateral dynamics including Proportional Integral Derivative (PID), Model Predictive Control (MPC), Feed-forward, Pure-Pursuit, and Stanley [24]–[28].

The major aims of longitudinal control is to maintain a comfortable distance from the vehicle in front, to maintain a relatively constant velocity with minimum use of the brake, and to apply the brakes as quickly as possible in emergency situations. Thus, longitudinal control aids in accident prevention by providing sufficient time to apply breaking. Lateral control holds the vehicle in the middle of the lane and steers it into an adjacent lane while ensuring good comfort for passengers. Lateral control requires lane-holding, reversing, lane changing, and avoiding obstacles which might emerge in front of the vehicle. By implementing a lane departure warning system and advanced steering control, automatic steering will minimize road accidents [29].

Table 1 shows a comparison of the current study and previous surveys on DCSs and vehicle perception sensors. This article presents all of the DCSs and sensors for those control systems in Table 1. These control systems require control algorithms to provide control over all the previously mentioned systems; sensor performance; and longitudinal, lateral, and actuation systems [30]. Some of the popular algorithms researched in recent decades for precise and accurate driving control systems are: machine vision, machine learning, and deep learning [31].

Advanced vehicle control systems are of significant interest in the automobile industry–see Table 1 for a brief summary. In [32], a substantial variety of research papers have reviewed the use of deep learning techniques to control a vehicle, since vehicle control systems and perception are related. This paper focuses mainly on the control system aspect, offering a comparative analysis identifying the strength and limitations of available deep learning methods. Research challenges are also discussed in terms of computation, architecture selection, goal specification, generalization, verification, validation, and safety.

Path tracking control focuses on lateral and longitudinal vehicle control to follow a predetermined path or trajectory. In [33], This paper discusses path tracking control in terms of the primary vehicle model that is usually used, the control methods that are typically used in path tracking control, and the performance measures that are used to calculate the controller's output. A nonlinear vehicle model is used to construct an adaptive geometric controller, which is then validated with hardware-in-the-loop.

Many active and passive sensors (such as cameras, laser sensors, radars, ultrasonic sensors, and GPS sensors) can now be used in autonomous vehicles using various AI techniques. In [34], the authors provide a comprehensive overview of an artificially intelligent vehicle, including the various approaches used, such as neural networks and fuzzy logic, as well as the various modules and their benefits and drawbacks. The paper also discussed how to make an autonomous car more stable by using multiple sensors and creating maps.

TABLE 1. Survey of relevant literature.

Ref.	Driving Control Systems									Perception Sensors						Highlights
	ACC	AEBS	LKA	LCA	TSR	Padestrian Detection	Automatic Parking	VANET	Access Control	Vision	Lidar	Radar	Ultrasonic	Night Vision	Sensor Fusion	
[15]	×	×	×	×	✓	×	×	×	×	✓	×	✓	×	×	×	This paper discusses the difficulties of real-time traffic sign recognition.
[35]	✓	×	×	×	×	×	×	×	×	✓	×	×	×	×	×	The strengths and weaknesses of ACC techniques such as PID feedback/feedforward control, model predictive control (MPC), and fuzzy logic control are highlighted in this paper.
[36]	×	×	✓	✓	×	×	×	×	×	✓	×	×	×	×	×	This study describes various vision-based lane recognition and departure warning systems in depth.
[37]	×	✓	×	×	×	×	×	×	×	✓	×	✓	×	×	×	This paper is suggested that AEBSs be created with a camera as the distance measurement sensors.
[38]	×	×	×	×	×	✓	×	×	×	✓	✓	✓	✓	✓	×	This paper provides a thorough evaluation of faults, appropriate detection and recovery methods, and a classification schema for vehicle perception sensors.
[39]	×	×	×	×	×	×	×	✓	×	×	×	×	×	×	×	This paper also goes into a deep review of security systems and potential solutions for providing secure communication in VANETs.
Current Study	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	The study surveys ADAS and other significant types of methods applied in smart EVs. It also includes perform analysis of several driving control algorithms and the sensors.

Despite the existence of a number of surveys, most concentrate only on a single aspect of the vehicle control system [9], [35], [36] or a small number of aspects such as in [34] and [33], in which the authors discussed only sensor operation, path control and vehicle control systems. No review presents a holistic approach of smart EV technology.

The current state-of-the-art methods for improving the efficiency of smart EV systems in local area or urban vehicle environments are reviewed in this article. Indicatively, it discusses on recent research that employs machine learning techniques for vehicle perception, localization, and actuation control (i.e., vehicle lateral and longitudinal control). The main goal is to provide a detailed overview of the most effective machine learning and control techniques in the fields of DCSs, sensor technologies, and vehicle control for smart EV.

Smart EV technology is being gradually introduced into the current vehicles with leading automotive companies developing various control systems and algorithms for the advancement of autonomous vehicles. It is therefore timely to review the driving control issues for smart EV, including DCS and algorithms, to provide a survey, discussion, and comparisons. This review may help in terms of developing smart EV by surveying research that develops DCS, identifies appropriate sensors for perception, realizes vehicle dynamics control for vehicle actuation to improve the vehicle's stability, and reduces vehicular accidents. It should be noted, however, that there has recently been a significant increase in research in the automatic control of smart vehicles we do not pretend to have conducted a comprehensive review of the widely accessible driving control systems and algorithms in the literature–rather we have focused on presenting major work.

The remainder of the review is organized as follows: Section II describes the driving control systems. Section III presents a description of the control system algorithms. Section III(A) and III(B) respectively discuss perception and localization algorithms, and control algorithms. Section IV provides a summary and Section V concludes and presents the future scope of DCS.

II. OVERVIEW OF SMART EV

EV are based on an electric propulsion system and all power is based on electrical power, such as a battery, super-capacitor. There are two basic classifications of EV: Full Electric vehicle (FEV) and Hybrid Electric Vehicle (HEV). The main advantage of EV, through its electric motor system, is the high efficiency of electricity conversion. The driver simply turns on the power by choosing ''Forward'' or ''Reverse'' and steps on the throttle [40].

EV utilise several types of electric motors for EVs. Motors can be connected directly to the wheel shaft in order to reduce transmission loss and increase control ability. Hub motors can control each wheel independently in an all-wheel drive system, which reduces energy loss. Either approach can easily incorporate anti-lock braking and electronic brake distribution, so EV can incorporate several types of control systems such as traction control, brake control, and vehicle stability control. The implementation of these control methodologies can make EV a smart vehicle which can implement several DCS and several types of sensor to provide driving safety and driving comfort. Smart control systems include ACC, AEBS, LDW, automatic park parking, and several driving assistance systems [41].

Smart EVs also comprise of smart Battery Management System (BMS). The BMS system enhances the safety and reliability of batteries and reduces the stress due to charge and discharge. The system would help to avoid high discharge rates by preventing sudden current abruption. BMS also prevents single cells from overstressing by equalizing charge on all cells to extends battery pack life [42]. The BMS should cover important features like thermal management, electrical management, thermal management, safety management, and communication, driving range calculation. Smart energy demand management enhances parameters including the state of charge, the state of health, and the state of life. Several studies show that BMSs will be more efficient integrating on chips and will have capabilities to accurately estimate driving ranges and smart adapting to load changes for better power delivery. BMSs will also support: (i) different and adaptive charging protocols, (ii) any battery cell number, sizes, and configurations, and (iii) vehicle to grid capabilities, enabling charging transactions or booking charging slots [43].

The powertrain of the smart electric vehicle is a simpler and more efficient system, comprising far fewer components, which makes it more compact and convenient. It enhances the efficiency of power transmission of the system. There are multi-objective powertrain control strategies that accomplish operational objectives like energy consumption minimization or increasing battery life. The choice of a control system is always subject to certain constraints. These approaches acknowledge physical component properties, such as speed restrictions or battery state of charge limits. The practical implementation of these strategies considers driving comfort. So that large torque gradients, frequent gear changes, start and stop intervals can be avoided. Modern powertrain control systems include a large number of different control approaches and combinations of these [44].

III. DRIVING CONTROL SYSTEMS (DCS)

The driving control system (DCS) determines control methods and control modes based on the ADAS [7] which, in recent years, has received considerable interest from researchers and the automotive sector.

A. ADAS

ADAS is a well-known term in the vehicle industry for advanced technologies, the popularity of which as the most prominent road safety system is increasing day by day. ADAS takes precautions to avoid road collisions by providing supportive information on incoming traffic in a range of circumstances [45]. Johnson and Trivedi [46] notes that most

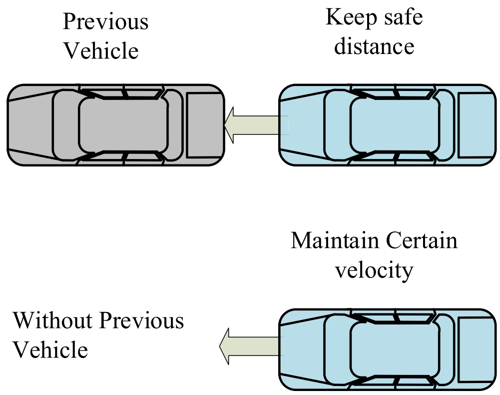

FIGURE 2. **Adaptive cruise control [51].**

vehicle drivers are more likely to commit potentially dangerous actions due to lack of attention. ADAS provides real-time observation and auditory risk warnings to improve the overall attentiveness of the driver and to optimize road safety [47]. ADAS is considered to be a prime characteristic of control and safety in modern vehicles and fundamental technology for the emergence of the autonomous vehicle [48].

ADAS was originally vision-based and GPS-based, but object detection and position measurement (radar, LiDAR, and Ultrasonic sensor), as well as other sophisticated-sensing technologies are increasingly incorporated [48]. By supplying additional knowledge from the vehicle's surrounding environment, ADAS assists a driver in taking important decisions. The systemic output of a number of ADAS applications depends on the combination of the driver's behavior and environmental data [49]. In order to gain a greater understanding of the applications and functionality of existing state-of-the-art sensors, this paper reviews ADAS currently available on the market. The following subsections review ten control systems of ADAS for smart EV: ACC [8], AEBS [9], LDW [10], [11], LKA [13], LCA [12], Night Vision [14], TSR [15], Pedestrian Detection [16], Automatic Parking [17], Traction control [18].

1) ADAPTIVE CRUISE CONTROL (ACC)

The ACC system for longitudinal monitoring of the vehicle offers improved driving comfort and convenience. It enables the cruise control option to function for prolonged periods, even during the presence of other traffic. Since human failure causes more than 90% of highway incidents [50], the ACC system promises improved highway protection.

ACC can replace Conventional Cruise Control (CCC). By automatically controlling the accelerator and the brake, ACC regulates vehicle speed velocity and contributes to safe driving with the least distance to the previous vehicle [51] aided by a range sensor (such as radar, lidar, or vision sensor) that measures the relative velocity and distance of the two successive vehicles [51]. See Figure 2 An ACC-equipped vehicle moves at a user-set velocity in the absence of any preceding vehicle. The system operates, just like CCC, by regulating the throttle position. In presence of a preceding vehicle, ACC determines and predicts whether or not the following vehicle can still drive safely at the fixed speed. When the preceding vehicle is slow or near, the ACC switches the power from the fixed speed control to the fixed forward velocity control by regulating both the throttle position and the braking pedal position [18]. ACC also has an extension system called Cooperative-ACC (CACC) which provides vehicle-to-vehicle (V2V) connectivity. Highway developers are interested in CACC as it has the potential of organizing cooperating vehicles to provide opportunities to enhance traffic efficiency [52].

In [53], the study demonstrated a practical process to allow ACC-CACC implemented vehicles to follow a preceding vehicle free of collisions. The work introduced various combined ACC-CACC systems to achieve longitudinal vehicular movement with driver actions. The study also showed through simulation that the suggested models were collision-free under standard traffic conditions and most security situations, testing the models for various vehicle states and for several conditions.

In [54], the authors presented an adaptive neuro-fuzzy predictor based control approach for cooperative ACC. That study also offered a preceding vehicle estimation system for future state prediction of the previous vehicle in which the system would predict the future state by employing the fuzzy model Takagi-Sugeno, depending on the vehicle information including sensor data of the previous vehicle state. It work also comprised the previous vehicle control law achieved via V2V communication.

Zhang and Zhutan [55] presented a control strategy on car following process for EV ACC. The analysis described the control structure for the ACC system, which includes the upper and the lower level controller. The upper controller, which optimizes the power consumption by implementing the model predictive control (MPC) process, contributes to safe driving, vehicle monitoring and comfortable ride. The lower controller is used to recover the energy during braking.

ACC has a number of types of control operations:

1) Speed Control: A standard ACC system can control the speed of the car at the desired level using throttling input. The upper and lower level controller constitute the centralized longitudinal control system architecture for the ACC. see figure 3 The upper level controller measures the predictive acceleration of the supported (host) vehicle and the lower level controller controls the input actuators to monitor the preceding vehicle [56].

   The upper level control model is:

$$p''(x) = \frac{1}{\tau s + 1} p''(x_{des}) \tag{1}$$

   where x denotes the vehicle's longitudinal position as determined by a reference line. $p''(x)$ defines the

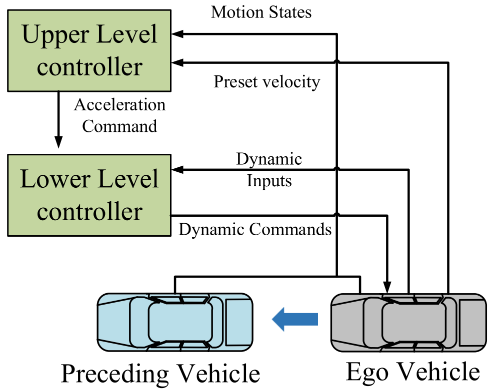

FIGURE 3. Speed control system design.

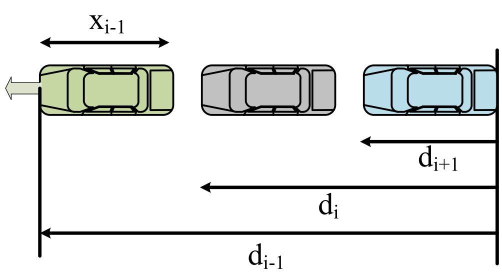

FIGURE 4. ACC vehicles string [59].

acceleration of the vehicle and $p''(x_{des})$ defines the desired acceleration of the vehicle according to the preceding vehicle dynamic states. The upper-level controller control input is therefore the desired acceleration from the MPC strategy [56]. It is assumed that the real velocity of the car would track the required velocity with the τ time constant which is ensured by the lower-level controller.

2) Vehicle Following: Vehicle following is part of the ACC's steady-state operation. The system includes two significant terms that must be satisfied including the stability of the single vehicle and the stability of the string.

a) Vehicle Stability: The stability of a single vehicle is provided by following the process of spacing control. In Figure 4, let the position of i th car be d_i, determined from the point of comparison. The i th vehicle's spacing error is then defined as $\delta_i = d_i - d_{i-1} + x_{des}$. The preceding vehicle runs at a steady velocity if the spacing error stabilizes to zero. The discrepancy between the previous vehicle's actual spacing and the intended spacing is the result of this spacing error. The spacing error should be negligible when the previous vehicle accelerates or slows down [57], [58].

The required space is x_{des} and the required length of the previous vehicle is x_{i-1}. Vehicle speed is denoted by $\dot{d}_i$ and the optimal spacing of x_{des} could be selected. If the following condition is met, the ACC control regulations enhance the safety of single vehicles.

$$\ddot{d}_{i-1} \rightarrow 0 \Longrightarrow \delta_i \rightarrow 0 \tag{2}$$

b) String Stability: The stability of the string of the group is a feature of the ACC vehicle. When errors propagate to the end of the group, the stability of the string constrains the spacing errors from diverging [60]. String stability describes the relationship of a vehicle in a group.

In [61], authors investigated the problems of *L2* string stochastic stability analysis. It also introduced a new algorithm for stabilizing Vehicular Network Systems (VNS). Feng *et al.* [62] defined the stability of the string and the applicable analytical techniques by which the appropriate features of string stability are obtained. The study addressed current issues and opportunities for research in this area, such as general topology string stability, lateral string stability, primary disturbance string stability, and nonlinear systems.

Spacing Policies for ACC. The Spacing Policy is of prime importance in an ACC system. The design of the ACC starts with the identification of an acceptable spacing policy [63] such that the design meets several criteria [59]:

- Individual Vehicle Stability is a fundamental prerequisite for the spacing policy and the principle of control associated with it.
- A conjunction ACC controller which maintains the stability of the string is needed for the selected spacing policy.
- The selected spacing policy should ensure the stability of traffic flow.
- The spacing policy must allow a host vehicle to avoid potential conflicts with the preceding vehicle.
- The spacing policy should have equivalent driving characteristics to human driving habits to prevent driver and passenger discomfort.

Wu *et al.* [59] discussed the primary spacing policies of the current ACC and also observed the advantages and disadvantages of the spacing policies with a comparison study. That survey reviewed five types of spacing policies and investigated their performances. These spacing policies cannot ensure stability, comfort, and safety at a time. The future of ACC systems demands the implementation of a coordination strategy and includes a real-world road network scenario for traffic grids.

2) ADVANCED EMERGENCY BRAKING SYSTEM (AEBS)

Autonomous Emergency Braking (AEB), also known as AEBS, is a road vehicle safety device. Sensors are used by AEBS to track the presence of vehicles in front of it. It also defines conditions such as an impending accident with relative motion and distance between host and target vehicles [64]. The system automatically applies emergency braking to prevent or mitigate the impact of a collision on an approaching vehicle or a pedestrian [65].

Yang *et al.* [66] presents the functional requirement of AEBS to avoid collision with a pedestrian (AEB-P) and to ensure the pedestrian's safety by determining TTC (Time To Collision) and to brake at a safe distance. This work presents a Fuzzy Neural Network (FNN) controller for a braking function to avoid collision with a pedestrian. The research also presented a PID controller for vehicle speed reduction. The control strategy efficiently distributes advanced warning and stopping periods to reduce pedestrian collisions.

AEBS systems are known as percipient assistance systems and uses ACC sensor technology to assist drivers in avoiding rear-end collisions with the approaching vehicle [67]. AEBS is divided into three types:

1) Forward Collision Warning Systems (FCW) monitor forward motion to identify and warn of approaching conflicts. Emergency warning signals are activated when the driver fails to act on the conflict warning.
2) Collision Mitigation Braking Systems (CMBS) are part of the FCW system. CMBS immediately deploys maximum braking when the conflict is imminent and, furthermore, tries to mitigate the effects of the crash.
3) Unlike the CMBS and FCW systems, the Collision Avoidance System (CAS) attempts to prevent an accident by employing the brakes until the impact is certain. The CMBS and FCW systems can prevent collisions below a particular speed but can only attenuate the effects of the crash during higher velocity movements.

Maximum Road accidents take place due to insufficient, late, or no application of brakes by drivers to avoid an collision. The AEBS is designed to work in a variety of road conditions [68]. When the driver fails to react on time, the AEB device can use an adaptive algorithm to apply various levels of pressure to the emergency brakes, based on speed, direction, momentum, and other variables, to prevent or mitigate the impact of the collision. Some models will also begin to tighten the restraint system ready for impact [9].

In [69], the study presents a new AEBS nonlinear MPC technique based on an algorithm with more reliable integrated performance in reducing collision uncertainty and riding convenience and energy efficiency improvisation of an intelligent vehicle similar to the current individual AEBS. The work also presents a hierarchical control structure for decoupling and coordinating the system in order to increase vehicle stability and comfort.

Coordination requires measurement of the distance between the host and the preceding vehicle and object, commonly employing a radar sensor placed behind the grille to calculate the distance from an object using radar reflections. Metallic substances such as cars partially reflect radar pulses and the system measures the return time of the radar echo by examining the Doppler shifts in reflections from moving objects [70] which allows the device to calculate the moving object's speed. Long-range sensing is also possible using radar [71]. Some of the devices have a sensor module to capture images in addition to radar tracking.

Kim and Song [72] presents a vehicle recognition technique based on the information of radar and camera sensors for AEBS. The commercial radar identifies the vehicles and road infrastructure and provides improved radar detection of the nearest preceding vehicle on the road. The work discussed a vehicle identification method for improvised detection based on structure and acceleration characteristics.

Hamid *et al.* [73] provides an improved AEBS with a potential field (PF) risk management approach that limits nearby incidents. In this process, the host vehicle produces the desired degree of braking actuation, in accordance with the risk measurement, that allows the vehicle to stop in time. The research also showed the efficient implementation of AEBS and PF, which aids the vehicle to moderate the effects of a impact and assists in providing a safe distance from the obstruction in front.

AEBS is bringing positive changes in collision avoidance as an ADAS that helps prevent and mitigate crashes. With continuous improvement in capability, studies anticipate that autonomous steering may prevent the effects of severe head-on collisions and "run-off-road" strikes in the future, resulting in lower road user deaths.

3) LANE DEPARTURE WARNING (LDW)

The LDW system [11] provides warning for drivers when the vehicle unintentionally leaves its present lane. During the process, the system follows lane markings with forward-looking vision systems, defining the area within the current route, providing appropriate warnings [10]. Lane detection is an essential component of LDW. Narote *et al.* [36] provides a detailed description of some of the vision-based lane detection and departure warning systems and highlighted the problem of lane detection under different complex environmental conditions.

Chen and Boukerche [11] presents an improvised novel LDWS model for image processing, lane detection, and lane departure recognition. The algorithm retains necessary portions of the road lane and removes useless details during the image processing stage, which minimizes the possibility of false warnings caused by false lane detection. Wang *et al.* [74] presents Time-to-lane-change (TLC) and Personalize driver model (PDM) methods to reduce the false warning rate of LDR systems.

The computer vision based LDW system consists essentially of a camera module, video recording device, computer CPU, warning module, monitor facilities and several supporting items [75]. Tan *et al.* [76] presents a vision-based LDW system with Deep Fourier Neural Network (DFNN) to assist in lane departure prediction using an image processing unit for making lane-departure decisions. For this purpose, the system utilizes a camera and video storage device for a high-speed running vehicle to provide photos of the road. The image processing segment produces digital photos in order to develop an understanding of left and right lanes in real environments. If the car diverges or tends to diverge from the initial lane, the device will transmit a warning message

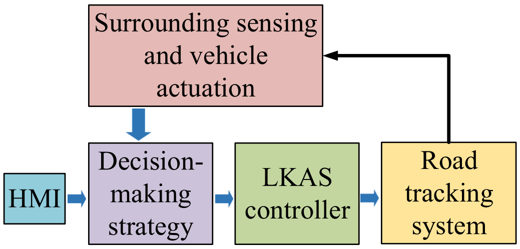

FIGURE 5. System structure for LKA [80].

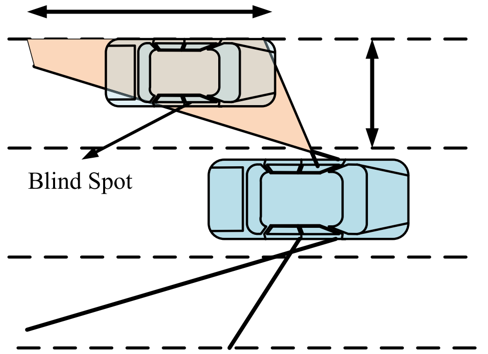

FIGURE 6. Blind spot area detection.

to the display and alarm system. This warning would signal the driver to take a different direction [11], [77].

4) LANE KEEPING ASSIST (LKA)

LKA, also known as lane departure prevention (LDP), is a type of ADAS as it aims to avoid unintentional lane departures [13]. Numerous LKA model approaches are proposed by the use of various types of actuators, such as electrical power steering, automatic braking, and hybrid solutions.

Hu *et al.* [78] addresses an integrated control method for LKA which also offers an improved Sliding mode control (SMC) for rollover prevention during the lane-keeping operation. Modern advancements in LKA also involve learning-based design approaches [74], [76] and dataset-based assessment and testing procedures [79]. Bian *et al.* [80] present an advanced LKA system utilizing self-learning MPC methods and also present two switchable control function assistance those are LDP function and lane-keeping co-pilot function.

Figure 5 provides a suggested LKA system structure which focuses on five sections [80].

The surrounding sensing and vehicle actuation section collects environmental data from on-board sensors and digital maps and also obtains the speed, steering angle, and lateral acceleration of the vehicle. The Human-machine interface (HMI) section assists the driver in selecting the initial assistance mode which implement different strategies and controller algorithms. The decision-making strategy section makes a decision if it is needed to provide assistance control. The decision-making strategy module commands the vehicle's LKA controller. The road tracking system section understands the dynamics of the vehicle relative to the road [80].

5) LANE CHANGE ASSIST (LCA)

Lane change is a dynamic process which simplifies the driving environment for the driver by allowing adjustable driving behavior. Zhu *et al.* [81] offers a personalized LCA framework for vehicles combined with a recognition strategy for driver actions. The framework utilizes a neural network of back-propagation (BP) optimized for driver behavior by a particle swarm optimization (PSO) algorithm. The driver's actions are stimulated with information obtained from the surroundings (including vehicle velocity, inter-vehicle space, and lane lines) essential for the integral monitoring of longitudinal and lateral movements of the vehicle [12].

The LCA system is a lateral control mode that engages the steering assistance system (SAS). Bujarbaruah *et al.* [82] approaches a predictive control mode implementation for SAS through both Active Front Steering (AFS) and Electric Power Assisted Steering (EPAS) systems. The system also utilizes a model-predictive controller (MPC) to follow the intended lateral path, maintaining the vehicle on track and improving lateral stability. The LCA system employs short-range radar sensors for improvised blind-spot detection [83].

LCA facilitates maneuverability of lane-change during execution. The system alerts the driver in a hazardous situation by scanning the neighboring lanes for vehicles in two broad ways:

1) Blind Spot Monitoring (BSM) devices detect the host driver's blind spots for the presence of an approaching vehicle and then propagates warning alerts to prevent collisions. Cameras and radar systems are used by the device to protect areas laterally and behind the side mirrors. [6], as illustrated in the Figure 6. Kwon *et al.* [84] presents an improved BSM system using radar and camera sensor on an IoT (Internet of Thing) based vehicle.
2) Lane Change Warning (LCW) is equivalent to Blind Spot Monitoring (BSM). However, LCW can also help with the traffic detection technique from behind. It incorporates the host vehicle's adjacent lanes from behind up to a predefined limit [10]. For tracking, the LCW system often makes use of a radar system. It also sends out warning signals if a potentially dangerous situation is observed [6].

Figure 7 depicts the entire design of the LCA scheme based on the proposed approach. This strategy includes two parts, one being the relative motion estimator and the other is the supervisor. To estimate and re-examine the data, the system employs an Extended Kalman Filter (EKF) as an estimator. The estimator deals with relative motion in the adjoining lane connecting the host vehicle and the approaching vehicle. The system includes the supervisor to evaluate protection

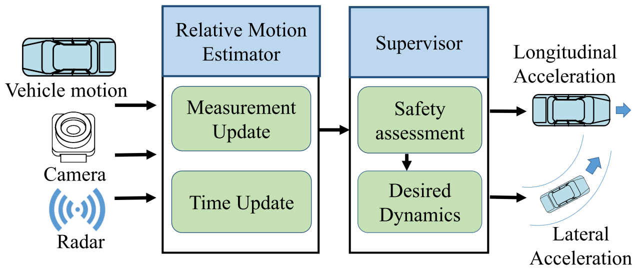

FIGURE 7. The overall design of the LCA system [85].

measures and estimate essential dynamics for lane change situations. The supervisor analyzed vehicle kinematics in both the longitudinal and lateral aspects. The analysis defines the initialization conditions of the LCA system. Then the supervisor will evaluate the safety measures and calculate an applicable longitudinal and lateral acceleration. The calculation is necessary for collision prevention between the host and threatening vehicle in adjoining paths [85].

6) NIGHT VISION

The Automotive night vision scheme uses the infrared spectrum to provide vision beyond the scope of the vehicle's headlights using a thermographic camera to improve the vision of a driver with an additional display in darkness or bad weather. This system uses image recognition algorithms to issue warnings whenever there are any pedestrians and animals in the path of the vehicle [14]. A comparative analysis was performed in [86] using a multi-resolution image fusion algorithm for night vision system enhancement.

The primary functions of the night vision system are pedestrian detection and crash warning, image view, and audio warning. The pedestrian detection and collision warning utilises image processing, called a pedestrian detection algorithm, to analyze pedestrian patterns to accurately detect pedestrian detection of adults, children, and animals [87], [88].

Image display is an essential function of pedestrian detection. Symbols are used for detection and warning: each time a pedestrian is detected, a yellow box symbol appears on screen around the figure; a warning symbol is placed in the upper part of the image when a pedestrian is detected in the estimated collision area; after which the warning symbol begins to flash when impact is imminent.

7) TRAFFIC SIGN RECOGNITION (TSR)

As part of ADAS, TSR enables a vehicle to identify and classify traffic signs (such as speed limits or children or turn ahead) with image processing techniques applied to camera data. Hatolkar *et al.* [89] offer a TSR system that employs pre-processing methods and a fuzzy classification module based on a Convolutional Neural Network (CNN) to improve image frame quality. Detection range and accuracy vary with the properties of the camera, and the algorithm [90]. A good number of automotive suppliers have developed this

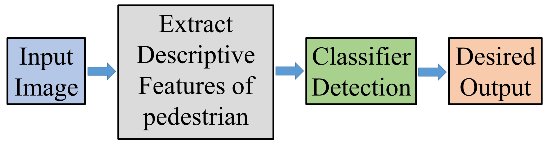

FIGURE 8. Pedestrian detection process.

technology over time using key detection techniques that are color-based, shape-based, and learning-based [15].

Image pre-processing is an essential part of TSR in order to prepare the image for detection by eliminating low-frequency ambient noise, simplifying the amplitude of individual particle images, removing reflections, and masking segments of images. The following section describes some techniques utilised in image pre-processing [90].

Shape Matching Based Identification: The general concept for shape matching based identification is to use color characteristics to detect the desired object, which accelerates detection as it doesn't require time-consuming processes such as those used by model-based classifiers. The features of the detected object are then filtered and analyzed and the appropriate traffic sign is chosen on the basis of shape matching [91].

In [92] presents a CNN for TSR that includes both text and symbol-based signs. Jung *et al.* [93] also offers the LeNet-5 CNN architecture that helps to recognize traffic signs through training. These machine learning-based methods play a vital role in automatic TSR.

8) PEDESTRIAN DETECTION

The Pedestrian Detection system detects pedestrians and estimates their risk. The PDS is an integral part of the AEBS system which also applies full braking to counteract or moderate possible collision with a pedestrian. This system generally utilizes a radar-fused vision system to detect and categorize objects to determine whether a pedestrian is present [94]. Various research shows that lidar-based systems are also useful for pedestrian detection [16], but lidars are not broadly used due to a shortage of those devices in the market. Night vision systems can also be beneficial for pedestrian detection in low-light conditions [14].

Traditional pedestrian detection methods are based on artificial feature extraction, which extract the main features that describe pedestrians and then use them to form instructions for classifiers to discriminate between pedestrians and other structures, therefore fulfilling the goal of pedestrian detection [95]. Figure 8 shows the procedure of pedestrian detection.

In [96], pedestrian detection systems are analyzed depending on their area of use, acquisition techniques, computer vision methods, and classification techniques. The paper also discussed Deep Learning methodologies, including CNNs for pedestrian detection and tracking. The integration of Deep Learning with classical Machine Learning models is the best way of high precision and simple calculation for pedestrian detection.

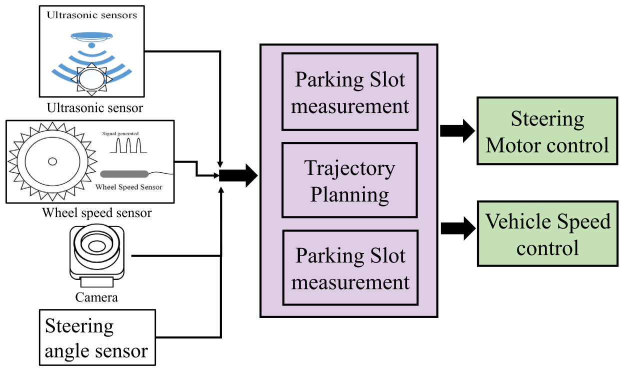

FIGURE 9. Automatic parking process.

In [97], [98], and [95], a pedestrian detection system is presented based on deep learning that Faster R-CNN obtains competitive output through multiple training on general object detection. The authors also proposed the Caltech and city persons method which collect data of city pedestrians. The CityPersons dataset is based on the data from Cityscapes to provide the pedestrian detection group with a new dataset of importance. This algorithm plays an important role in pedestrian detection.

9) AUTOMATIC PARKING

Automated parking assistance is needed to reduce the likelihood of frequent vehicle park collisions. The initial parking assist system assists the driver during parallel parking chores by utilizing beeping warning noises generated by side-mounted ultrasonic sensors that analyze the size of the parking space. It notifies the driver if the parking spot is broad enough and if the move is possible. It uses ultrasonic sensors on both the front and back of the host vehicle to determine the distance between it and other vehicles or obstacles. Some parking assistance systems additionally use backward-facing camera modules positioned at the rear end of the vehicle to offer a visual inspection of the area behind the host vehicle. The automated parking system enables the host car to park itself with little or no driver intervention [17]. The automatic car parking system is made possible by Android application commands [99], which control the steering wheel while the driver operates the throttle and brake pedal.

Figure 9 depicts the principal parking assistant system (PAS). To begin, the sensor takes data from the surroundings and analyses information such as obstacle distance, current vehicle speed, and parking space length. The next stage is to create a map based on the evidence and estimate the relative position of the vehicles. The algorithm produces a desired trajectory and then, if there is enough parking space, converts it to an intended steering angle principle. The steering angle sensor and the speed sensor of the wheel provide the desired data for position estimation. In the following phase, the vehicle position changes in response to steering angle changes, which are controlled by the steering motor. The tracking controller controls the action of the steering motor in accordance with the steering law's variables of direction, velocity, and time [100].

In [101], a literature review is conducted of automated parking systems, describing the recent progress including vision, ultrasonic and radar sensor technology, image processing, path and trajectory planning, control algorithms, and neural networks. In [102], proposes a technique for an automated parking system for a self-driving car based on lidar technology. The paper also discusses calculating the minimum distance between two vehicles in a parking area using dynamic theories of vehicles.

10) TRACTION CONTROL

Traction Control is the most important component of a control strategy because it regulates vehicle speed and can directly improve driving performance, protection, and stability [18]. The vehicular propulsive force is defined as traction which is the product of friction between the tire surface and the road surface. The friction is dependent on factors such as the type of tire, road surface, condition of the road surface, and wheel slip ratio. Maximal torque from the propulsion system is given by the slip ratio which makes it possible for the vehicle to move forward so the slip ratio providing the maximum coefficient of friction is required. Consequently, traction control aims to operate vehicles with an adequate wheel slip ratio. Compared with conventional internal combustion engines, electric motors produce rapid and accurate torques.

In [103], a maximum transmission torque estimation (MTTE) method is presented based an open-loop disturbance observer which requires input torque and wheel motion. In the control rule, the estimated maximum transmission torque was used as a limit to avoid the slip. A fault-tolerant solution is suggested in [104] dependent on MTTE to prevent the EV from sliding. To improve the steering efficiency of the MTTE solution, a PI-type observator is proposed which was expected to make a remarkable enhancement of the control system in robustness.

In [105], a sliding-mode investigator was applied to determine the skidding and vehicle speed of the EV. The observer is used to evaluate the average friction, dependent on the dynamic friction method of Lu Gre. The controller utilizes the calculated maximum friction to calculate the acceptable max torque for the tires. Sliding mode control (SMC) provides robustness, which is why it is widely used in the control of uncertain nonlinear systems. In [106], a PID sliding surface dependent SMC control approach is suggested for the tracking problem of nonlinear uncertain systems. Using the Lyapunov stability principle, the stability and robustness of the proposed control technique are proven.

For SMC, [107] suggested wheel slip control of EVs based on a sliding-mode system. An active braking controller configuration of a sliding-mode was presented in [108] who merged the regulated parameter with wheel deceleration and wheel slip. The existing traction control system discusses torque control and SMC. In [109], a smart traction control system is developed using acoustic road surface estimation

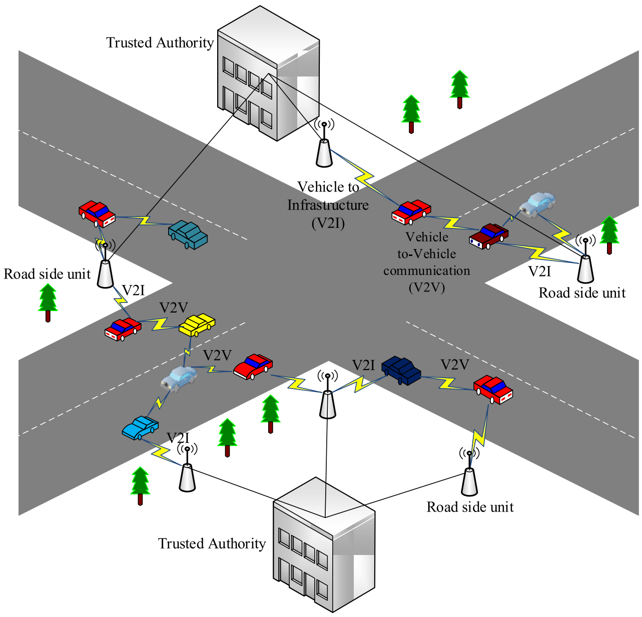

FIGURE 10. **VANET system.**

which includes friction co-efficient and slip-ratio which is important for input torque.

11) COMMUNICATION-VANETs

Information and communication technologies have influenced some of the most significant innovations in the automobile sector. Intelligent transportation systems (ITS) play a critical role in making citizens' lives more comfortable in every way in today's digital society. The vehicular communication network (VANET) is an integral feature of an ITS. It allows for vehicle-to-vehicle communication. A VANET is a type of Mobile Ad Hoc Network (MANET) in which vehicles equipped with wireless and computing capabilities can form a network on the fly as they travel down the road [39].

VANETs are categorized into two kinds: vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communications [110]. VANET facilitates V2V communications between neighboring vehicles and V2I and V2R communications from vehicles to other communication equipment. A VANET system is shown in Figure 10. The principal objective of VANETs is to facilitate successful communication. In general, nodes require specific qualities to acquire information, communicate with neighbors, and then make judgments based on the data collected via sensors, cameras, GPS receivers, and omnidirectional antennas [111]. Multiple VANET surveys referring to security and privacy schemes have been developed in recent years [19], [20]. These studies addressed the majority of the aspects of VANETs. However, it covers a small portion of VANET security services and contemporary state-of-the-art methods. C-V2X technology, a unified connectivity platform designed to support V2X communications, was recently introduced [112]. C-V2X is a robust communication technology that can conduct V2X communications. It is an establishment that is a part of the third generation partnership project (3GPP). It connects each vehicle, allowing cooperative intelligent transportation systems (C-ITS) to decrease traffic congestion and improve traffic efficiency [113].

VANET security assures that outsiders do not inject or corrupt the conveyed messages. In addition, the driver is accountable for accurately updating the traffic conditions within the time constraints. VANETs are more vulnerable to hacking because of their unique properties. In particular, security concerns need to be handled adequately. Otherwise, secure communication in VANETs will be relatively limited [114].

Comfort Applications: This VANET application is classified as a non-safety application that attempts to improve the comfort of drivers and passengers. It can deliver updated weather information, hotels, nearby restaurants, and petrol stations [115]. Safety Applications: The VANET's safety applications are used to improve security. Vehicle-to-vehicle and/or vehicle-to-infrastructure communications can be utilized in this application to develop traffic safety, lane change warning, emergency video streaming, collision avoidance, and accident evasion. The primary goal of this application is to ensure drivers, passengers, and pedestrians safe [115].

The fundamental issue with the VANET is communication security. Because of the rapid growth of topology, small-sized devices, and other factors, ad-hoc networks have more security challenges than regular wireless communication. Because of the dynamic nature of the topology, maintaining security is complicated because there is no pre-existing infrastructure for ad-hoc networks, such as the cellular framework, that can regulate the network's security [116]. VANET, like all other computing systems, confronts data security constraints such as integrity, confidentiality, authenticity, and availability [117].

Data Confidentiality in VANET: Confidentiality is known as privacy. Its purpose is to keep sensitive information from getting into the wrong hands. According to [118], there are several challenges to VANET data confidentiality.

Data Authentication in VANET: Data Authenticity is the process of confirming a person's identity, which can be performed using a user id and password. After passing through the identification procedure, authentication is the evaluation used to verify that only an authorized user enters the system. Furthermore, this procedure is regarded as the primary course of protection against illegitimate users [119].

Data Availability in VANET: Availability can be described as the system's ability to be used at all times. It is necessary to do regular hardware equipment maintenance and keep the system up to date with upgrades to avoid any ambivalence.

There are numerous hurdles concerning VANETs. The unique characteristics of VANETs require alternative communication paradigms, security, privacy techniques, and wireless communication technologies compared to MANETs [120]. Network connections, for example, may not be steady for an extended period. Researchers have looked to make the most from existing infrastructure, such as roadside units and cellular networks, to enhance communication performance. Although some specific VANET issues have been overcome, some significant research challenges remain partly resolved [120].

Though existing algorithms have implemented some resolutions to definite data dissemination difficulties in VANETs. Due to the unique characteristics of VANETs, it is still difficult to assess their performance and security. The end-to-end communication path, for example, may not exist due to non-persistent network connections. The authors of [121] propose that using the carry-forwarding pattern, the opportunistic routing algorithm can overcome this problem. As a result, advanced algorithms should be developed with a low communication delay, communication overhead, and time complexity in mind.

12) SECURITY AND ACCESS CONTROL

The Internet of Things has propagated to every domain from wearable mobile gadgets, smart homes, manufacturing units, and power grids. Artificially intelligent and connected automobiles are essential for smart city envisioning and providing users with a comfortable, safe, and pleasurable driving experience. These automobiles include sensors, electronic control units (ECUs), software with about 100 million lines of code, and internet connectivity. This ecosystem facilitates inter communications between vehicles (V2V), vehicles and infrastructure (V2I), vehicles and pedestrians (V2H), and, ultimately, anything associated.

Security and privacy are the principal concerns in Smart cars. These vehicles feature a large attack surface (TPMS, keyless entry, smartphone, engine ECU, OBD ports, etc.) also accessible external interfaces. As a result, attacks such as sending false and unauthorized basic safety messages (BSMs), controlling ECUs, accessing personal information, and sensor spoofing are possible, as documented in various publications [122]–[124]. To establish these security concerns, the smart EV requires some security mechanisms like Access Control.

Access Controls (ACs) are an essential security mechanism. It ensures only authorized users have access to resources. Smart automobiles also require similar controls for security purposes. It secures trust among entities that exchange BSM communications and also eliminates unauthorized system control. Outchakoucht *et al.* [125] develops a global framework to address policy management and AC models to achieve the fundamentals of Access Controls. It also profoundly discusses the mechanisms that allow them to fit so precisely. It leads to a smooth and uniform Machine Learning (ML) integration, also highlights the requisite ML algorithm and where they should perform.

Due to the fast growth of the smart automotive sectors, there's been a surge in interest in Internet of Vehicles (IoV) technology. IoV was developed to improve the experience of drivers and passengers by reducing traffic congestion, enhancing traffic management, and assuring road safety. Precise monitoring of the privacy of large data groups and vehicles in IoV is one of the critical challenges. In [126], This study performed a critical analysis using analytical modeling for offloading mobile edge-computing decisions based on machine learning and Deep Reinforcement Learning (DRL) techniques for IoV. The study estimates a Secure IoV edge-computing offloading paradigm with multiple data processing and traffic flow scenarios. In offloading the decision process of various task progress of the IoV network control cycle, the suggested analytical model acknowledges the Markov decision process (MDP) and machine learning (ML).

The automatic identification of vehicle license plates is a critical component of intelligent vehicle access control and monitoring systems. Islam *et al.* [127] offer a method for identifying license plates that aim to establish a balance between these two objectives. An ANN classifier trained on HOG characteristics identifies the segmented characters. There are two stages there in the proposed method: detection and identification. The image is evaluated in the detection step to determine a region of interest, with a 99.3 % prediction performance. In the identification step, the system uses the HOG technique to extract features from the range of interest, with a classification accuracy of 99.5%.

This study suggested an extended access control-oriented (E-ACO) [21] architecture that addresses the access control constraints in the smart car ecosystem and facilitates appropriate access control model selection at various layers. The E-ACO architecture consists of four layers [128]. Object Layer contains clustered objects (such as cars and traffic signals), each of these, holds numerous individual objects like sensors and in-vehicle applications. The Virtual Object Layer addresses the concerns of heterogeneity and connectivity by providing a cyber-twin of all physical items. In automobiles, as mobility and location do not always guarantee internet access, a virtual entity that maintains physical object status information is required. Cloud Services and Application layers provide cloud infrastructure for data storage and processing. The application layer contains end-user apps that utilize data in the cloud to offer services to users. Entities within and across neighboring levels interact with one another; for example, a car can 'speak' to other vehicles as well as its virtual object. Users can also use their phones or remote keys to issue commands to sensors within the car [128].

IV. ALGORITHMS

An algorithm is utilized to calculate a particular problem or to perform a number of calculations. This part of the article presents basic image analysis algorithms, information storage, and decision algorithms used in the prototype construction of autonomous systems. Smart EV Usually have three types of algorithms: perception, localization, and control.

- The sense of perception is used to perceive and re-imagine one's surroundings. It detects pedestrians,

TABLE 2. A summary of driving control systems.

Control systems	Ref.	Methods	Highlights	Performances	Limitations
ACC	[53]	Realistic and collision-free car-following model for ACC-CACC vehicles	• The model is for longitudinal vehicle motions. • It underwent several tests regarding model performance and collision possibilities.	Maximum deceleration time (MDT) is 1s	The author verified the model in simulation only.
	[54]	Adaptive neuro-fuzzy predictor for CACC	• Estimating the condition of the vehicle first and then following the vehicle controller. • The CACC method will help you save a lot of money on fuel.	Headway time 0.9s	The model was verified in simulation only
	[55]	Model predictive control	MPC optimizes various targets in the car-following system	Spacing margin 5m	The strategy for weight adjustment was quite effective
AEBS	[66]	Fuzzy neural network model with genetic algorithm	• The upper-layer fuzzy neural network controller of the AEB-P system was designed. • PID controller base AEB-P system uses for the expected speed reduction	Vehicle stopped within 3m at high speed	The research of AEBS is not applicable for complex scenarios
	[69]	Nonlinear Model Predictive Algorithm	• Considering the nonlinearities of vehicle dynamics • AEBS is designed based on the Non-singular Fast Terminal Sliding Mode (NFTSM) control theory for quick track control	AEBS function slows down after 2.5s.	The model was verified in simulation only
	[73]	Potential Field (PF) risk assessment strategy	• When the frontal obstacle risk PF threshold is exceeded, AEB provides active braking intervention. • The proposed design reduces the possibility of colliding with a stationary object.	Vehicle maintain the safe distance of 2 m	The proposed design can not mitigates the collision risk with a dynamic obstacle
LDW	[11]	Hough Transform (HT)	HT is applied to detect lane boundaries and with Euclidean-distance-related parameters it calculate vehicle's position and motion.	True Warning Rate is 94%.	It is not feasible in several real-time scenarios
	[74]	Gaussian mixture model and the hidden Markov model	Establishing lane-departure and lane-keeping behavior and predict preceding vehicle status	Reduce the false-warning rate to 3.13%	The driver's physiological state was not considered here.
LKA	[80]	Learning-based model predictive control (LBMPC)	Use extended Kalman filter to learn unmodeled dynamics.	0.5m space between vehicle trajectory and lane center	Results are not well defined.
LCA	[81]	Fuzzy c-means (FCM) clustering algorithm	Analysis driver's behavior	85% accuracy to predict the driving characteristics	The precision of driver behavior identification is not promising
	[92]	CNN	Extraction of traffic sign regions of interest (ROIs), ROI refinement and classification, and data marking were all lacking.	Recognition score of 86.75%	The system can't preprocess data at high speed.
Automatic Parking	[102]	Rapidly-exploring random tree algorithm (RRT) algorithm	Automatic Parking with Lidar, Camera and ultrasonic sensors and use fuzzy logic controller to control brake and accelerator	-	It can not add camera data for parking.
Traction control	[103]	Maximum transmissible torque estimation (MTTE)	This estimator provides a good foundation for anti-slip control	MTTE applied for slip prevention.	The vehicle is not calculated
	[106]	Dynamic PID sliding mode control technique	Eliminating tracking error with this controller technique and the system is robust and stable	Efficiency and feasibility	This technique is applied to an inverted pendulum system.

traffic signs/signals, and obstacles in the vehicle's immediate vicinity.

- The term "localization" refers to the process of mapping the surrounding area and determining the precise location of a vehicle.
- The control section deals with low-level activities that are driven by the perception algorithm's planning and sensor data. Low-level behaviors are determined by a vehicle's steering, acceleration, and braking systems.

Here, all the sensors used for perception and localization are reviewed.

A. PERCEPTION AND LOCALIZATION

The perception algorithm combines and integrates the information from the sensors using sensor-fusion algorithms that help to detect static and dynamic objects while driving. Sensors include ranging sensors (lidar, radar, Ultrasonic sensors) and vision sensors (camera and night vision). Sensor-fusion algorithms aids in overcoming the individual limitations of ranging sensors and vision sensors. Goelles *et al.* [38] reviewed limitations of perceptions sensors, and also discussed fault detection and recovery. Fayyad *et al.* [129] presents a review of sensor fusion algorithms using deep learning for vehicle perception and localization.

Localization algorithms predict and determine the location and behavior of the host vehicle on the map monitor display using GPS or Vehicle on-board sensors. A smart driving system demands an accurate determination of the vehicle's position and orientation requiring precise, effective and stable localization techniques to support maneuvering, prevent collisions and enforce the necessary driving actions. Furthermore, the method of localization must be robust in handling variant complex environments and a wide range of weather conditions. In addition to supporting perception, sensor fusion is also used for localization [129]. This paper describes the sensors and sensor fusion used in perception and localization. Table 3 summarizes the relevant algorithms.

This section discusses the sensors available for use in automobiles, with a focus on those that detect and deal with objects. Along with the calculations to condition the necessity of a sensor set, they will also be addressed in relation to the important prospects of autonomous driving. Finally, the definition of sensor fusion is discussed including the improvements over use of data from individual sensors.

1) VISION

A vision system forms image of the surroundings with a light-sensitive sensors. Since only a few sensors can pick up sections of the infrared spectrum that allow for night vision, the vision system relies on the benefits of the visual light spectrum to function [130]. It requires an unobstructed sightline, which means the system needs to be mounted on the windshield in the open air or on a clear surface.

Two types of vision systems are primarily available: monoscopic and stereoscopic. The monoscopic vision system uses one optical sensor, while the stereoscopic one uses two with a distance in between. Stereoscopic vision provides benefits equivalent to a pair of human eyes allowing the ability to measure differences in range. The accuracy varies with range, as the difference is relatively smaller for points further from the sensor [131].

To detect and classify images, the camera system depends on image processing techniques for multiple functions, such as positioning and routing, object identification, collision avoidance, and to collect and extract data from images [131].

Borkar *et al.* [132] presents a lane detection algorithm for street lane detection based on the Kalman filter, which is also used in [133] for precise lane detection on the highly curved road applying parabolic and circular equations with a Kalman filter.

In [134], a histogram of oriented gradient (HOG) features and support vector machines (SVM) methods were utilized for road surface detection. A CNN and supervised learning were also used for road surface detection in [135]. In [136], HOG features and SVM-based techniques were also proposed to detect the shadow of the preceding vehicle (in daylight) with a camera module. The HOG and SVM qualified vehicle classifier has good generalization ability and can effectively exclude non-vehicle objects such as houses, trees, flowers, fence, and pedestrians.

Vision systems are passive because they rely on external lighting conditions. Incidents at night with inadequate light can reduce a sensor's functionality which may also be blinded by light sources with sharp rays of high intensity (sun or bright headlights). For vision sensors, environmental conditions often play a prime role such that the effective range of the image processing algorithm is also limited by heavy rain, snow, and foggy conditions. Multi-purpose units have the maximum number of sensors available at the current time and come with a built-in image processor. The units typically contain algorithms for various forms of detection and classification purposes such as for pedestrian detection, road surface detection, general object detection, traffic sign recognition.

2) LiDAR

Laser scanners, also known as lidar, are active sensors that serve many applications such as blockage identification, pedestrian and vehicle identification [137], host vehicle lane detection [138], and describing the precise location of a vehicle [139]. Using a laser, the lidar emits high-frequency pulses. The amount of reflected light is determined by whether the projected light reaches and reflects from an object in its path. The delay between transmission and reception determines the distance between the lidar and the subject. However, lasers can only identify a single isolated spot, so scanning at a high rate is required in order to develop a high-resolution depth image. Scanning is achieved by reflection from rotating mirrors or by rotating the whole sensor unit. Lidar primarily scans horizontally in layers. A larger number of layers compensates the pitch angle of the vehicle [140] and minimizes the effects of blockades [141].

The lidar produces a point cloud, where a single distance measurement is described by each and every point. The point cloud must be analyzed to collect object data. Classification techniques may be utilized to categories the objects identified [142]. At least two lidar reflections from each object are required to detect the object reliably [143]. The space between the lidar positions d in Figure 11 can

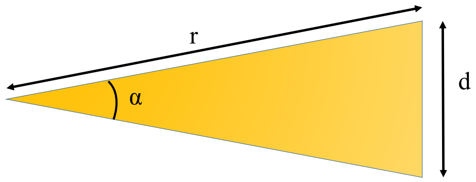

FIGURE 11. Low lidar point at given range.

be determined utilizing the following formula, including the angular resolution α and the range r:

$$d = 2rsin(\frac{\alpha}{2}) \tag{3}$$

Since $r \gg d$, so equation is:

$$d = \alpha r \tag{4}$$

To guarantee two outputs from the lidar, an object must be at least 2d wide to be seen from range r if a single layer scanning is assumed. Lidar primarily has a high angular resolution that helps in the detection of smaller objects. For an object of size x from the range r, the equation for necessary angular resolution is (5) [143]:

$$\alpha = \frac{x}{2r} \tag{5}$$

As it requires significant amounts of computation, lidar sensors do not instantaneously output velocity data as a tracking algorithm is required to provide velocity estimation [144] relying on two or more lidar readouts to be compared. Ch Fuerstenberg [140] discusses a filtering method called gating which minimizes the area linked between data readings and thus eliminates unnecessary calculation steps. However, it also implies that a quickly moving object might be regarded as a new object as it could end up extending beyond the gated area.

The quality of lidar data is based on algorithms for object recognition–a supervised 3d CNN has been created in [145]. A CNN-based 3D object classification system in [146] uses the lidar point cloud Hough space to resolve the computation of a large volume of data and unstructured point cloud. Initially, a Hough transform is used to transform the object point clouds to Hough space. Then the CNN classifier is trained to identify four types of artifacts: walls, bushes, pedestrians, and trees.

There are some difficulties with using lidar. Lidar lasers are harmful to the eyes of humans and animals and are therefore subjected to regulations defined by the laser safety standard IEC 60825-1 [147]. During unfavorable weather and lighting conditions, lidars are affected like vision systems [148]. An NIR gated imaging system was used in [148] to cope with poor weather conditions such as fog. The gated camera exhibits much greater contrast and it is possible to detect higher viewing distances. Table 3 summarises methods for detecting an object using lidar.

3) RADAR

Radar operates using high-frequency radio waves transmission and receives the reflected signals from any object within the Field of View (FOV) of the sensor. Radar sensors will automatically define the relative motion of the object which is detected. Although radar systems may provide a wide range of FOVs, a trade-off is required [149].

Automotive radar sensors primarily use two frequency bands around 24 gigahertz and 77-81 gigahertz. 24 gigahertz was once very common due to its rady the availability in industry [150], however automotive radar requirements have moved towards 77-81 gigahertz with many innovations due to the shorter wavelength at that frequency, which improves range, resolution, and precision. 77-81 gigahertz is therefore more appropriate for pedestrian detection and vehicle detection [151].

A radar sensor's detection area is separated into resolution cells. The detection area of a RADAR sensor is divided into resolution cells. The size of a resolution cell is determined by the angular resolution and the range resolution. A cell's length remains the same but with range, the width increases since the width ω of a radar cell is the multiplication of angular resolution α and range r which can be defined by the equation (6) [152].

$$\omega = \alpha * r \tag{6}$$

Elimination of Ghost target generation is another promising issue for the radar sensor. If the radar signal reflects from several objects before the sensor device is received, it can lead to false identification at random locations of non-existing targets [153]. In order to eliminate a shadow objective that is not a real entity, an artificial neural network (ANN) is suggested in [154].

Reference [155] proposes a deep-learning approach for the identification of vehicles running on an image-like tensor where the radar data consists of a 3D tensor which is typically processed by utilizing a Constant False-Alarm Rate (CFAR) technique to obtain a sparse 2D point-cloud that separates the targets of interest from the surrounding clutter. The paper also suggested a new way to manage the 3D radar signal and the Doppler dimension, which could enhance the accuracy of detection. In addition, [156] designed a Doppler radar-based vehicle detection and parking space detection system.

In [157], a radar-based pedestrian detection system is built using the SVM and Micro-Doppler effects. SVM is designed for pedestrian short-range detection and speed resolution enhancement for micro-Doppler effects extraction. In [158], a pedestrian detection system for the clutter area is also built using a 2D range-Doppler Frequency Modulated Continuous Wave (FMCW) radar. A 2D Fast Fourier Transform (FFT) with Fast-ramp based FMCW radar is a very helpful algorithm for detecting slow-moving targets from unwanted clutter.

Using ground penetrating radar (GPR), an automated road surface crack detection method was built in [159]. GPR detects cracks on the road by electromagnetic reflection.

TABLE 3. Algorithms for environmental recognition with camera and sensors.

Sensors	Methods	Reference	Highlights	Performance
Lidar	Edge Based	[180], [181]	Artificial edge features for road line detection.	96% accuracy
	Region Based	[182]	Self-adaptive Euclidean clustering for road surface detection.	Error rate of 0.674%
		[183]	Plane fitting and RANSAC techniques for ground detection and voxel-grid Model for identification of stationary and moving road objects.	94% accuracy
	Model Based	[146]	CNN based object classification algorithm using Hough space.	93.3% accuracy
	Graph Based	[184]	For segmenting ground road and objects, a graph-based technique is used with CNN.	94% accuracy
	Detection Based	[185]	SVM classification Clusters are classified into vehicles, ground, pedestrians, buildings, power lines.	86% overall accuracy
		[145]	VoxNet implements 3D CNN to characterize the 3D point cloud.	
		[186]	Volumetric based 3D CNN has been enhanced through the implementation of auxiliary learning process on vehicle detection.	95% maximum recall
Vision	Lane Line Marking Detection	[132], [133]	A lane detection algorithm is presented for street lane detection based on the Kalman filter.	96% Overall accuracy
	Road Surface detection	[134]	HOG and SVM	91% accuracy
		[135]	A CNN algorithm is used to identify if it was a road or not.	93.8% accuracy
	Vehicle Detection	[187]	Faster-RCNN	60.4% average precision
		[136]	HOG and SVM	96.87% accuracy
	Pedestrian Detection	[188]	Faster-RCNN	23% Miss Rate
Radar	vehicle detection	[155]	Deep learning on Doppler tensor.	95.46% precision
		[160]	CNN	F1 score 0.70
	Road Surface detection	[159]	Singular Value Decomposition (SVD)	Good accuracy
	Ghost target detection	[154]	Artificial neural network (ANN) (multilayer perceptron)	88% accurate
	Pedestrian Detection	[157]	SVM and Micro-Doppler effects	Improved Accuracy
		[158]	2D Fast Fourier Transform (FFT) with Fast-ramp based FMCW radar	From distance 15.82 m and velocity ´6.59 m/s
		[160]	CNN	94% accuracy
Ultrasonic	Parking space detection	[162]	Grid projection method	0.2m detection error
	Road Surface detection	[167]	Dynamic Time Warping (DTW) technique and HANUMAN algorithm	95.50% accuracy
	moving object detection	[165]	EKF and Unscented Kalman filter (UKF) tracking algorithms	speed error <0.2 m/s
		[166]	Using Bayesian Networks estimate the speed and size of the vehicle detected	99% accuracy
Time of Flight	Parking space detection	[172]	CC-RANSAC algorithm uses for restriction and ramp identification for Safe Parking.	Accurately measure curbs and ramps
	Pedestrian detection	[171]	SVM classifier	95% accuracy
Sensor Fusion	Parking space detection	[178]	Simultaneous localization and mapping (SLAM)	97% accuracy
	Road Surface detection	[179]	Fully CNN (FCN)	96.03% accuracy
	Vehicle detection	[137]	YOLO v3 deep learning algorithm	17% accuracy improvment
		[176]	Unscented Kalman filter (UKF)	-
		[177]	SVM	96.5% accuracy
	Pedestrian detection	[175]	FLDA, RBF-SVM, and MCI-NN vector classifier	82.9% accuracy
		[16]	Faster R-CNN architecture	99.16% accuracy

The Singular Value Decomposition (SVD) algorithm analyzes this GPR image to minimize noise from the image. A CNN was also developed in [160] for the detection of road users such as pedestrians, vehicles, bicycles using 3D radar cubes.

Radars are sensitive to interference by other surrounding radars since signals could be selected from another nearby radar which will trigger false detection and create noise. Noise Radar Technology proposed in [161] eliminates interference effectively.

4) ULTRASONIC

Ultrasonic sensor transmit high-frequency audio signals observing the time taken to receive the reflected signal to measure the distance between the object and the sensor. Ultrasonic sensors are now commonly used to assist in parking [162]. An automated parking system based on a grid projection to detect parking space is suggested in [162] using an ultrasonic signal with grid projection to detect the edges of the obstacle. A smart parking system is suggested in [163], using ultrasonic sensors to detect the parking slots in the parking area which are occupied by vehicles.

Like radars, ultrasonic sensors may suffer interference from signals in the same frequency range, possibly from other nearby ultrasonic sensors. A solution identical to that for the radar problem is suggested in [164]. Stochastic coding was used to distinguish the signal from other signals by the use of an adaptive filter, efficiently solving the interference problem.

A system for detecting and tracking moving objects is suggested in [165], using an ultrasonic sensor around the vehicle. EKF and Unscented Kalman filter (UKF) tracking algorithms are designed for precise dynamic object tracking using arrays of ultrasonic sensors which are cost-effective. In [166], Bayesian Networks are suggested to predict the velocity and size of the automobile detected by means of a passive infrared sensor and an ultrasonic sensor.

In [167], a road surface monitoring technique is developed using ultrasonic sensors and image processing. The paper uses a dynamic time warping (DTW) technique and proposes a HANUMAN algorithm for the ultrasonic sensor to enhance the detection process of road track surface, crack road and speed bumps.

A system for the identification of a vehicle road accident using an ultrasonic sensor is suggested in [168]. It is a good option to use an ultrasonic sensor for accident detection since it operates on the concept of reflection of sound waves that are capable of moving through all types of matter with less environmental effects and other considerations, such as the color of the colliding object.

5) NIGHT VISION

There are two types of night vision sensors: near-infrared (NIR) and far-infrared (FIR) sensors (FIR). NIR requires active IR sources that are mounted in the headlights, which implies that one NIR system in opposing traffic may be blinded by another NIR system from a car. Additionally, the NIR sensor could also be blinded by Xenon headlight bulbs, since it absorbs a broad spectrum of light. FIR systems are on the other hand, more passive taking advantage of the emission of natural thermal radiation. That is, FIR systems differentiate artifacts by temperature differences so that it is possible to use these systems to track cyclists, pedestrians and animals. However, the FIR device can not detect an object if the temperature difference with respect to the atmosphere or background is minimal [130], [169].

6) TIME-OF-FLIGHT

Lidar can also be implemented by a time-of-flight (ToF) sensor that utilizes photonic mixer devices (PMD). The amount of time between pulse firing, pulse reflection and reception at the sensor is calculated to determine the range to the reflecting point. A large scale single pulse is more effective that repetition of a small laser pulse because the reflection is measured at the same time for the whole field-of-view of the sensor instead of being measured for a particular point which enables smoother operation and avoids moving components [170].

Using the ToF camera, a pedestrian detection method is suggested in [171] using an SVM classifier including Scale Invariant Feature Transform (SIFT), Gradient Oriented Histogram (HOG), and Extractors with Holistic Shape Feature (GIST). Such extractors are used for the classification of pedestrians and non-pedestrians.

In [172], a restriction and ramp identification method was proposed for a smooth car park utilizing ToF. Ultrasonic sensors for detecting these curbs and ramps are not that useful, so this work introduces a robust algorithm for CC-RANSAC to precisely detect the location of curbs and ramps on the side of the road in a parking space.

ToF sensors are capable of detecting both light intensity and detail information. The stereo camera can read information in detail, but it requires heavy processing for analysis of data and image processing. A review paper for ToF is presented in [173] addressing ToF concepts, advantages and challenges. ToF sensors are good for the protection of humans and animals as they are safe for the eyes.

7) SENSOR FUSION

A combination of pieces of information gathered from various sensors is called sensor fusion which is used to improve the sensing capability of an automated vehicle. By integrating the output of a number of sensors, any individual sensor shortcoming or defect is offset by the strengths of one or more other sensors. The fusion of vision, radar, and lidar sensors therefore enhances the efficiency of pedestrian detection [16], [174] by utilising the strengths of each technique.

A pedestrian detection technique using lidar and single camera fusion is provided in [175] by merging lidar and vision spaces in a single vector classifier (FLDA, RBF-SVM, and MCI-NN) improving detection efficiency. A pedestrian detection system using Lidar-Camera Fusion is also introduced in [16] and a faster R-CNN architecture was suggested for more accurate detection.

A vehicle detection process is suggested using vision and lidar sensor fusion in [137]. To accurately identify the vehicle, the proposed technique is the YOLO v3 deep learning algorithm. In [176], based on UKF using Sensor fusion, a similar vehicle detection approach is suggested. In another study [177], classifier-based vehicle detection is proposed using SVM by radar and vision sensor fusion.

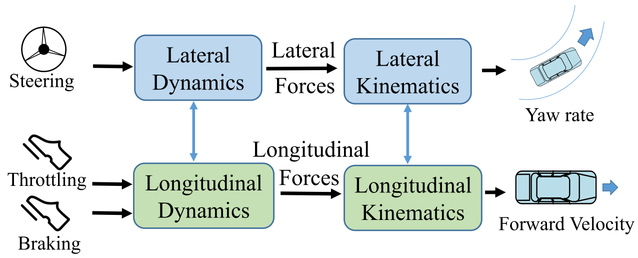

FIGURE 12. Combination of both Lateral and Longitudinal dynamics.

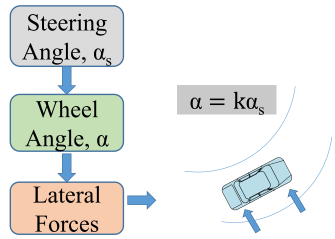

FIGURE 13. Steering system.

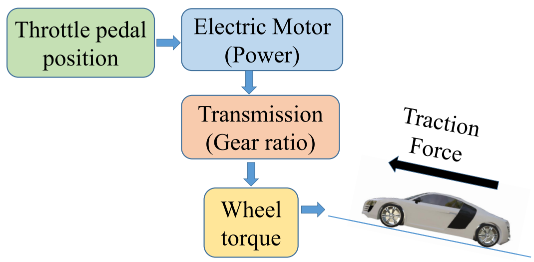

FIGURE 14. Throttle system.

A parking space detection and safe parking method are proposed in [178] using AVM and lidar sensor fusion. The proposed method is simultaneous localization and mapping (SLAM) through the suggested parked line, which can identify an empty parking space. For road detection, a fully CNN (FCN) architecture is developed in [179] using lidar camera sensor fusion. This FCN performs good and provides an accurate road image.

B. VEHICLE CONTROL ALGORITHM

Vehicle control algorithms follow perception algorithms by actuating the acceleration, braking and steering systems for comfort and safe driving according to the DCS previously discussed.

The factors related to longitudinal vehicle control are discussed here to understand speed regulation of smart EV, including classical linear time-invariant control, development of PID control law for a longitudinal vehicle model, and combined feed-forward and feedback control for improved desired speed tracking. Here the design of the longitudinal speed control includes everything about vehicle performance on the track, and is a key element of autonomous operation.

Lateral vehicle control is also discussed here including two geometric paths that pursue control strategies built on the no-slip assumption of kinematic modeling. Lastly, the review focuses on the model predictive control system, for example, an advanced control strategy in autonomous vehicles [189].

1) VEHICLE ACTUATION

Vehicle actuation of the vehicle involves steering, acceleration, and brake systems so the key objective of vehicle control is to provide appropriate accelerator, brake and steering commands to maintain the vehicle following a certain velocity profile on a targeted route.

Considering the figure 12, in the lateral vehicle dynamics system, the steering angle is the principal input. Similarly, in longitudinal vehicle dynamics, the key inputs are the throttle and the brake position.

The inputs include the friction forces operating on the vehicle which are fed into the ordinary differential equations that are used to regulate the condition of the car. The lateral forces and moments drive the lateral kinematics of the car inducing the optimal lateral velocity rate of the vehicle. The longitudinal forces drive the longitudinal kinematics. Both the resultant forward velocity and displacement are defined.

It should be noted that lateral dynamics and longitudinal dynamics impact one another.

- Steering
  The steering translates the driver input by changing the steering angle of the steered wheels. Here the driver input is the turning action practiced by the driver on the steering wheel. Simultaneously it provides hap-tic feedback as information for the diver informing them of the driving conditions and condition of the road.
  The steering model operates the vehicle by moving it to the right or left. The operation follows the driver input or autonomous system command and the steering angle is converted into a wheel angle. The lateral force provided by the intervening mechanisms and gear ratios maintains the vehicle while riding on a curved path. The wheel angle is considered proportional to the steering angle, according to the general steering model which is why the α_s steering angle is linearly proportional to the α steering angle, where k is the steering coefficient.
- Throttling
  The throttling system calculates the traction force required to move the vehicle in the desired direction.
- Braking
  The process of vehicle braking starts with a brake pedal position that is commanded by the driver. An electronic unit converts the position to brake pressure, the outcome of which is the braking force that acts on the brake disk or the brake drum. The braking forces are then convert into a braking wheel torque on the wheel which results in a reverse longitudinal force that slows down the vehicle.
  Basic Function of Brake system.
  1) To stop the vehicle within the desired distance while braking.

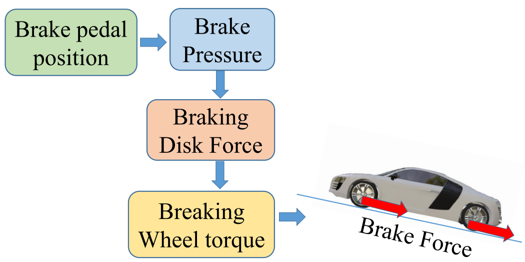

FIGURE 15. Brake system.

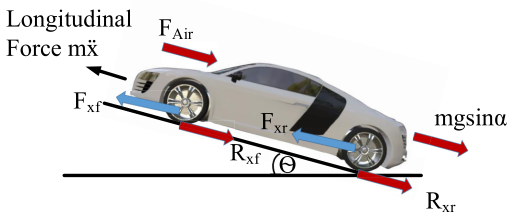

FIGURE 16. Longitudinal forces of vehicle on inclined road.

2) To maintain vehicle steerability while braking with ABS (Anti-lock Braking System).
3) To maintain vehicle stability while braking to prevent for overturning.

C. LONGITUDINAL CONTROL ALGORITHM

Vehicle and power-train dynamics are two main aspects of the longitudinal model. Forward tire force, rolling resistance, aerodynamic drag, and gravitational forces are all factors that affect the vehicle dynamics system. The electric motor, torque converter, transmission, and wheels are all part of the car's power-train dynamics system.

- Vehicle Dynamics:
  From Figure 16 Vehicle longitudinal forces Equation:

$$m\ddot{x_f} = F_{xr} + F_{xf} - F_{air} - R_{xr} - R_{xf} - mgsin\alpha \quad (7)$$

  Here, in equation (7) F_{xf} denotes the front tire forces, F_{xr} denotes the rear tire forces, F_{air} denotes the aerodynamic drag force, and the rolling resistance of front tires is R_{xf} and back tires is R_{xr}. The gravitational forces mgsinα act on the slope of the road.
  The combination of these forces determines the acceleration of the vehicle which is indicated by $\ddot{x_f}$. Let, F_x be the total longitudinal force that is:

$$F_x = F_{xr} + F_{xf} \quad (8)$$

  Let, R_x be the total rolling resistance that is:

$$R_x = R_{xr} + R_{xf} \quad (9)$$

  as α is small angle so:

$$sin\alpha = \alpha \quad (10)$$

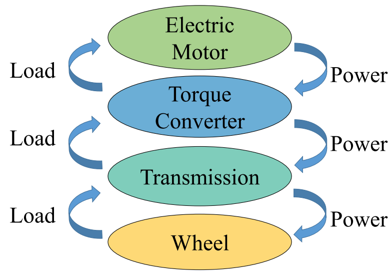

FIGURE 17. Power and load transmission in vehicle power-train.

  So, from equation (8),(9)and (10) we can find the simplified equation:

$$m\ddot{x_f} = F_x - R_x - mg\alpha - F_{air} \quad (11)$$

- Power-train Dynamics:
  The dynamic equations are constructed from power train elements. The vehicle wheel is the junction between the torques operating on the power train and the outer resistance forces. See Figure 17.
  Where from equation (12), we can say that R_x, $mg\alpha$ and F_{air} are the resistance load for a vehicle.

$$Resistantload = R_x + mg\alpha + F_{air} \quad (12)$$

  where from equation (13), we can say that F_x is the power that is generated by the EV's electric motor.

$$Power = F_x \quad (13)$$

  In longitudinal vehicle modelling, equation (11) states that, if a vehicle's power is greater than the vehicle's load, then the vehicle will move forward.

In [190], a Deep kinematic model(DKM) is introduced which estimates using convolutional neural networks (CNNs) accurate position and acceleration and deceleration of a vehicle. In [191], a connected and automated vehicle (CAV) longitudinal controller is developed for driver safety, comfort and operational efficiency of the vehicle. An information-aware driver model (IADM) is also developed in this paper, which provides local stability and string stability as well as driving comfort for a range of autonomous driving.

In [192], neural networks with various architectures are developed as methods for modeling the longitudinal dynamics of a vehicle. The difference in the modeling output of CNN and RNN reveals that the convolutive design is more accurate and stable for a comparable number of training parameters. In [193], a predictive controller is also developed based on the Deep Reinforcement Learning (RL) algorithm for the longitudinal motion dynamics of autonomous cars.

The vehicle's longitudinal control measures the vehicle's longitudinal velocity to govern the cruise velocity. This control system facilitates monitoring of the speed and acceleration, and to follow a vehicle while driving on a highway. Neural networks, PID, MPC, fuzzy control, and

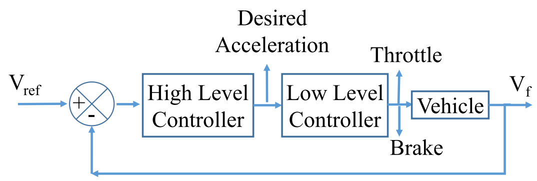

FIGURE 18. Close-loop system of cruise control.

feedforward control techniques have been commonly used in the longitudinal drive control system.

1) PID

PID control is expressed using three types of mathematical terminology, depending on the error function: proportional, integral, and derivative. Each one is proportional to the mistake e. To manage longitudinal speed and provide adaptive cruise control, a PID controller is used [24].

The cruise controller and plant vehicle model are shown as a closed-loop system in the block diagram in Figure 18. The goal of this system was to keep the vehicle velocity V_f constant and near to the reference velocity V_r. The controller has two levels: a high-level controller and a low-level controller (although the low-level controller is not an essential part of the control task). To reduce the disparity between the set point speed and the actual speed of the vehicle, the high-level controller provides vehicle acceleration.

With the vehicle acceleration, the low-level controller initiates a throttle or breaking actuation. This braking or throttle actuation aids in the monitoring of the reference acceleration. Each time, the top level controller calculates the required acceleration. The calculation is based on the velocity error as an input, with the required acceleration as the output. This controller makes use of PID [18]:

$$\ddot{x}_{ac} = K_P(\dot{x}_{ref} - \dot{x}) + K_I \int_0^t (\dot{x}_{ref} - \dot{x})\, dt + K_D \frac{d(\dot{x}_{ref} - \dot{x})}{dt} \tag{14}$$

where $\ddot{x}_{ac}$ is the desired acceleration, $\dot{x}_{ref}$ is the reference velocity, and $\dot{x}$ is the output velocity in equation (14). The error's current values are represented by K_P. The error's previous values are represented by K_I. According to the current rate of change, K_D represents the probable future values of the error [194].

In [195], a novel approach using a self-adapting radial-based function neural network PID (RBFNN-PID) was developed to improve longitudinal vehicle speed control with precision and robustness. In [196], a control strategy based on fuzzy adaptive control is proposed that can control PID gain parameters using a genetic algorithm in order to control brake actuators.

2) MPC

Model Predictive Control (MPC) focuses on optimal control theory, usually described as receding horizon function, where a plant model and a collection of predicted inputs are used to predict future system states. The methods are focused on the use of a model's mathematical representation to forecast a system's future behavior within a finite time horizon. The control action is obtained by minimizing a cost function that may involve constraints [197].

In [198], a simple MPC is proposed for longitudinal motion, considering a motion planner based on estimated curved path. In [25], a longitudinal collision avoidance control system is proposed based on MPC applied to control the desired deceleration and yaw moment for collision avoidance.

In [193], a predictive controller is presented on the basis of a Deep RL algorithm for the longitudinal motion dynamics of autonomous vehicles. Compared with a Nonlinear Model Predictive Controller, this paper also presents a Deep Reinforcement Learning based controller, once trained, with significantly low computation times, while achieving close-to-optimal efficiency.

3) FEED-FORWARD CONTROL

The combination of feed-forward and feedback loops improves controller performance. The main rationale for using both of these controllers in a control system is because feed-forward controllers give a predicted response by generating reference output in order to achieve the appropriate tracking response, which is especially important when the required inputs are non-zero. The feedback controllers' reactive response eliminates any control faults that may have happened as a result of the disruptions [201].

The feedback controller corrects mistakes caused by disturbances or inaccuracies, while feed-forward control supplies the required inputs as predicted to build a reference trajectory to keep the vehicle on track. Because the vehicle system requires a consistent radius turn, throttle and brake command, and steering angle while driving for a comfortable riding experience, the previously reported combination is widely employed in the advanced automobile industry. The feed-forward control and the feedback control must be coupled in order to develop the vehicle actuation system [201]. In Figure 19, the input of the feed-forward controller is reference velocity V_{ref} and the input of the feedback or PID controller is velocity error that is, $V_{ref} - V$. The throttle and braking commands are produced by these controllers. The feedback controller's primary function is to obtain the desired acceleration. A mapping from accelerations is used by the controller to build up the. The engine commands are then handled by the feed-forward block.

In [26], for a vehicle model, a feedback and feed-forward control technique is proposed. The vehicle's desired speed is maintained via the control algorithm. The throttle and braking pedals are controlled by the feedback section. The feed-forward section is in charge of the gear shift and clutch, as well as the feedback signals. In [202], feedback-feed-forward control architectures are also used for steering control systems.

TABLE 4. Longitudinal vehicle control system.

Control Functions	Sensor	Ref.	Highlights	Summary
Adaptive Cruise Control (ACC)	Vision sensor and Radar	[59]	ACC system with automatic throttle or brake adjustment, whether it sustains a particular cruising velocity or a targeted distance from the previous vehicle.	5 types of spacing policies are evaluated. among them CSF(Constant Safety Factor) is comparatively safe.
Traction Control System (TCS)	Wheel Speed sensor	[109]	TCS for EVs has great potential due to the simple application of torque control systems. To obtain excellent vehicle dynamics while ensuring vehicle stability, TCS is an active safety control system that avoids wheel skidding during driving.	Reducing the slip ratio by 75% while conserving energy by decreasing the applied torque and improving the TCS's robustness.
Automatic Emergency Braking System (AEBS)	Vision and Radar sensor	[67]	AEBS is a safety feature for vehicles which uses sensors to look at the proximity of previous vehicles. It detects hazardous situations as an imminent collision with relative speed and space between host and target vehicles.	Cost effective AEBS
Anti-lock Braking System (ABS)	wheel speed sensor or ABS brake sensor	[199]	ABS is used to avoid the loss of brake force cause of tire force drops at high slips and to leave some friction for steering and cornering.	The jerk RMS and the braking distance are reduced by 97.3% and 8.4%.
Electronic Brake Distribution (EBD)	Speed sensors, Steering wheel angle sensors and Yaw sensors	[200]	If the proportioning between the front and rear axle braking is divided, then there is a risk to the overbrake rear axle in high friction as the rear axle is unloaded. Previously, when the control wasn't available, hydraulic valves were used to solve the problem by limiting the brake pressure to the rear axle if the pedal force became too high. Modern cars provide electronic brake control due to the legislation of ABS. So the software base function EBD meets the requirements by balancing the amount of braking force on each wheel.	The positive consistency of the data between real and target pressures, indicating the efficiency of the compensation control for use in braking force distribution.

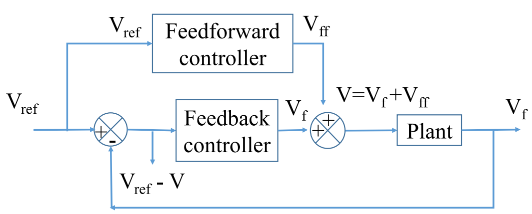

FIGURE 19. Combination of feedback and feed-forward controller.

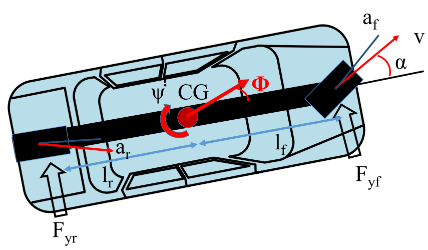

FIGURE 20. Lateral vehicle dynamics.

D. LATERAL CONTROL ALGORITHMS

This section discusses dynamic control modeling for a four-wheel vehicle. The model was created using the bicycle modeling method. Side slip, yaw rate, lateral acceleration, lateral speed, and lateral displacement are the key focuses of lateral dynamics [18].

The longitudinal velocity v is considered to be constant in lateral vehicle dynamics, as shown in Figure 20. The left and right axles are united into a single wheel, allowing the four-wheel vehicle to be classified as a bicycle. The debate also ignores the effects of road slope and aerodynamics.

The fundamental context of this lateral vehicle model methodology is the modeling of the vehicle's rotation rate. The simulation was based on the events that occur while the car is driving. During the development of the dynamic model in this part, the vehicle's center of gravity is used as a reference point. This was done to make Newton's second law easier to apply.

Lateral acceleration equation:

$$a_y = \ddot{y} + \omega^2 R \tag{15}$$

Here, the total acceleration in the inertial frame denotes as a_y, the lateral acceleration in the body frame denotes as $\ddot{y}$, and the centripetal acceleration from rotation of the vehicle denotes as $\omega^2 R$.

Equation (15) can be rewritten as equation (16), where $\dot{\phi}$ is the slip angle rate of change and $\dot{\psi}$ is the heading rate of change.

we know, $v = \omega R$ and $\omega = \dot{\psi}$. So, the lateral acceleration equation:

$$a_y = v\dot{\phi} + v\dot{\psi} \tag{16}$$

The lateral dynamic model equation is:

$$mv(\dot{\phi} + \dot{\psi}) = F_{yr} + F_{yf} \tag{17}$$

here in equation (17), mass of the vehicle is m, v is the vehicle longitudinal velocity. The lateral dynamic formula is formed with the lateral forces on the front and rear tires. F_{yr} is the rear tires force and F_{yf} is the front tires force.

The angular acceleration equation is:

$$I_v\ddot{\psi} = l_f F_{yr} - l_r F_{yf} \tag{18}$$

here in equation (18), $\ddot{\psi}$ is the angular acceleration of the vehicle and I_v is the vehicle inertia. l_f and l_r are the distance between the CG(Center of Gravity) and the front and rear axle.

Front and Rear tire forces Equations are:

$$F_{yf} = C_f a_f = C_f(\alpha - \phi - \frac{l_f\dot{\psi}}{v}) \tag{19}$$

$$F_{yr} = C_r a_r = C_r(-\phi + \frac{l_r\dot{\psi}}{v}) \tag{20}$$

In equation (19) and (20), a_f is front tire slip angle and a_r is rear tire slip angle. The linearized cornering stiffness for both front and rear wheels are C_f and C_r respectively. Cornering stiffness of a tire is its ability to resist deformation in the shape of a tire while the vehicle corners. α is the steering angle.

From equation (17), (18), (19) and (20) we can rearrange the equations:

$$\dot{\phi} = \frac{-(C_r + C_f)}{mv}\phi + (\frac{C_r l_r - C_f l_f}{mv^2} - 1)\psi + \frac{C_f}{mv}\alpha \tag{21}$$

$$\ddot{\psi} = \frac{C_r l_r - C_f l_f}{I_v}\phi - \frac{C_r l_r^2 + C_f l_f^2}{I_v v}\psi + \frac{C_f l_f}{I_v}\alpha \tag{22}$$

As the resultant lateral dynamic model is linear, we can define a state vector.

state vector:

$$X_{state} = \begin{bmatrix} y \\ \phi \\ \psi \\ \dot{\psi} \end{bmatrix} \tag{23}$$

In equation (23), y is the lateral position, ϕ is side slip angle, ψ is yaw angle and $Dot\psi$ is yaw rate.

Standard state space equation is:

$$\dot{X_{state}} = A_{state}X_{state} + B_{state}\alpha \tag{24}$$

The dynamics matrices in this system are A_{state} and B_{state}. If the forward speed (V) is kept constant, both of these are time-invariant. The main input of the system is α, which is defined as the driver steering angle command. While designing different control strategies, the state-space representation is predicted as a necessity. As an example, PID or MPC for lateral control. The model is suitable for state estimation with Kalman filters, as it provides linearity.

In [205], a deep reinforcement learning (RL) based vehicle lateral control model is proposed. This methodology developed a generalized RL model which is capable of controlling a host vehicle from the previously unseen vehicle in an unseen trajectory without additional training. In [204], an ML-based trajectory design technique is presented for the overtaking process on the road. The paper also proposed a method of neural network trajectory design to determine the desired trajectory.

The major goal of a smart vehicle is to ensure that the vehicle can follow a specific path. To follow that desired path, the vehicle must adjust the required steering angle to correct the errors that accumulate. We have to calculate the errors between position of vehicle and the co-ordinates of the desired following path. We should choose a control system that eliminates errors within steering angle limits. The control system must recognize the tire forces and not exceed the vehicle's capability while removing such errors. There are other options for reference paths, but you must choose the easiest and most consistent approach for smooth riding, which is continuous parameterized curves. These curves create a continuous variable speed and smooth derivatives to ensure error and error computation uniformity. The vehicle eliminates the offset of the vehicle using the lateral controller and aligns back to the reference path to follow the reference path [27]. Some lateral control approaches are presented in Table 5

There are two main controllers for lateral control:

1) Geometric Controller: This controller depends on the geometry and coordinates of the reference trajectory and the vehicle kinematic model.
2) Dynamic Controller: The most advanced type of controller is the Model Predictive Controller or MPC. MPC can identify the control commands that are applicable through finite-horizon optimization.

1) GEOMETRIC LATERAL CONTROL - PURE PURSUIT

Pure pursuit and Stanley are the two types of geometric lateral control. Geometric controller, also known as a geometric path tracking controller, can track the reference path using the reference trajectory's geometry and the vehicle's kinematic model. The reference point on the reference path was determined by the pure pursuit controller, whereas the Stanley controller derives the same reference point as is required for error computations. The pure pursuit method is discussed here.

The pure pursuit method's fundamental idea is to place a reference point on the reference path at a given distance, and then have the vehicle intercept the reference point using a determined constant steering angle. As the car approaches the point, the steering angle is reduced, and the vehicle arrives at the location gently [27], [206]. The reference point in Figure 21 is the vehicle's rear wheel axle center, and the distance between it and the targeted reference point highlighted in red is d, which is known as the look-ahead distance. The angle formed by the vehicle body and the look-ahead distance line is called *theta*. We examine an instantaneous centre of rotation in which the intended reference point and the rear axle's center form a triangle with

TABLE 5. Lateral vehicle control systems.

Control Functions	Sensor	Ref.	Highlights	Summary
Lane keeping assist	Radar and Vision	[80]	LKA system is used to prevent unwanted or unintended lane departures	Reduce driving burden.
LCA	Radar and Vision	[203]	LCA informs the driver of the nearby circumstances that the driver might miss around the vehicle. It provides the host vehicle with the capability of tracking other vehicles from behind and even within the blind spot for the driver.	80% detection rate
Pedestrian Detection	Vision sensor, radar	[95]	Pedestrian detection systems are subordinates of the AEBS system designed for pedestrian detection and risk evaluation.	Center and Scale Prediction (CSP) achieves MR^{-2} of 4.5%.
Automatic Parking	Ultrasonic sensor, Brake sensor	[100], [102]	During parallel parking activities, the initial parking assist system was designed to assist the driver by providing a beeping warning sound. To calculate the range from vehicles and objects, parking assist systems utilize ultrasonic sensors.	The error in the simulation and experimental results is around 5%, which is mainly due to hardware non-linearities.
Overtaking Technique	Vision sensors, Steering wheel sensor	[204]	Machine Learning based overtaking strategy is presented with accurate collision avoidance ability. This paper provide a design method for desired trajectory.	The proposed neural-network-based trajectory design method has been able to provide an appropriate trajectory

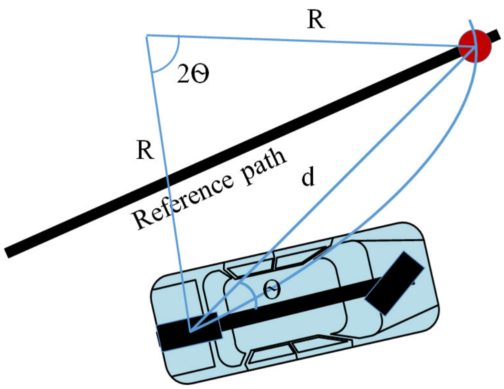

FIGURE 21. Pure pursuit geometry.

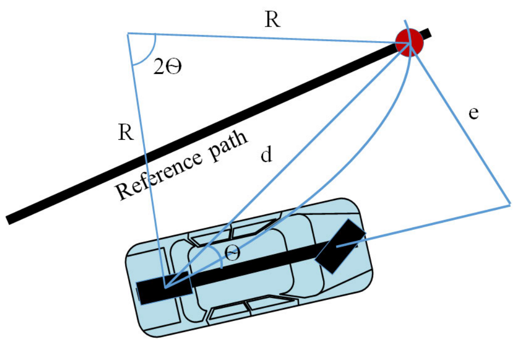

FIGURE 22. Pure pursuit geometry with cross-track error.

R and d as the lengths of the two sides. We'll draw a non-linear/circular line from the vehicle's reference point to the desired reference point. The angle formed on the center of the circle by the vehicle's reference point and the targeted reference point is called 2θ [28], [207]. Now from the sine formula we get:

$$\frac{d}{sin2\theta} = \frac{R}{sin(\frac{\pi}{2} - \theta)} \tag{25}$$

$$\frac{d}{2sin\theta cos\theta} = \frac{R}{cos(\theta)} \tag{26}$$

$$\frac{d}{sin\theta} = 2R \tag{27}$$

now the path curvature is $k_c = \frac{1}{R}$, so

$$k_c = \frac{2sin\theta}{d} \tag{28}$$

Now, from the bicycle model in figure 20 it can determine the steering angle α that is:

$$\alpha = tan^{-1}kL \tag{29}$$

$$\alpha = tan^{-1}\frac{2Lsin\theta}{d} \tag{30}$$

The equation (29), The length between the front and the back axle is L. This is how we can calculate the steering angle α.

However, the cross-track error (e) must be taken into account, which is the difference between the heading vector and the intended reference point, see Figure 22. From this Fig. 22:

$$sin\theta = \frac{e}{d} \tag{31}$$

so from the equation (28) and (31) we get:

$$k_c = \frac{2e}{d^2} \tag{32}$$

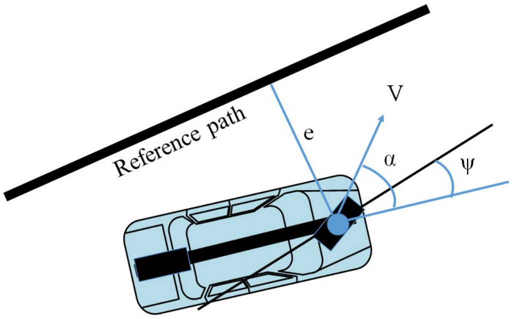

FIGURE 23. Stanley control geometry.

From equation (32), we can say that if the error decreases, the path curvature k_c will also decrease, which brings the vehicle smoothly to the target point.

We utilize a proportional controller with path curvature as the output to eliminate this inaccuracy. The proportional gain is $\frac{2}{d^2}$, as calculated by equation (32). The look-ahead distance is responsible for modifying the steering angle in this case, but vehicle speed must also be taken into account; otherwise, the steering angle will remain constant regardless of whether the vehicle is traveling at 10 km/h or 100 km/h. Because they are distinct lateral accelerations, we must take the vehicle's forward speed into account. To solve this issue, we'll change the controller.

We consider distance d is related with forward velocity v_f such that:

$$d = K_{pp}v_f \tag{33}$$

where K_{pp} is the pure pursuit proportional gain.

From the equation (30) and (34) we get:

$$\alpha = tan^{-1}\frac{2Lsin\theta}{K_{pp}v_f} \tag{34}$$

The controller chooses the steering angle that will produce a curvature to the chosen reference point, and the faster the vehicle goes, the faster the reference point changes and a new curvature is created. Controlling steering is how the car travels forward.

2) GEOMETRIC LATERAL CONTROL - STANLEY

In the DARPA Global Challenge, Gabe Hoffman at Stanford University designed the Stanley Controller, a geometric path tracking control. It is essential for autonomous robotics and cars, as it allows a car to maneuver at any speed while remaining independent. The reference point is switched to the front axle in this controller, and it considers both heading and position error while advancing towards the intended point, removing all mistakes without taking into account the look-ahead distance [28].

For correcting the heading error, the steering angle α is equal to the heading alignment ψ. see in equation (35)

$$\alpha(t) = \psi(t) \tag{35}$$

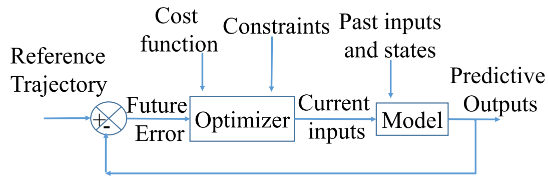

FIGURE 24. MPC structure.

For correcting the cross-track error, it uses a proportional controller whose gain is C:

$$\alpha(t) = tan^{-1}(\frac{Ce(t)}{v_s(t)}) \tag{36}$$

where, the cross-track error is e(t) and v_f is the forward velocity of the vehicle.

The final equation can now be derived from (35) and (36) for the steering angle $\alpha(t)\epsilon[\alpha_{min}, \alpha_{max}]$ which is:

$$\alpha(t) = \psi(t) + tan^{-1}(\frac{Ce(t)}{v_f(t)}) \tag{37}$$

The equation (38), if the vehicle speed is quite low, tending to zero, denominator value $v_f(t)$ will tend to zero. so to solve this problem we use a constant k_s to stabilize the system and maintain a non-zero denominator. So the resultant equation is:

$$\alpha(t) = \psi/(t) + tan^{-1}(\frac{Ce(t)}{k_s v_f(t)}) \tag{38}$$

This controller could be enhanced by adding a feed-forward controller to enhance the tracking of the reference path on the curve.

3) ADVANCED STEERING CONTROL - MPC

MPC is commonly used to find optimum solutions that take into account future prediction mistakes in addition to current errors, as well as its ability to operate with a wide range of disciplines. MPC may improve the performance and operating range of any controller, which is why it's utilized in traction control, steering control, speed control, and other automotive applications. This control system has a number of advantages, including the fact that it may be used for both linear and nonlinear vehicle control approaches. The controller, on the other hand, has a significant drawback in that it is extremely expensive and demands more control resources [208]. Here in Figure 24, the MPC structure consists of two blocks that form a closed-loop feedback controller. One is a dynamic model, which uses historical inputs and states to generate predicted outputs, which are then compared to the reference trajectory to generate a future error. The optimizer, the second block, takes the future error and gives the current inputs to the model while taking into account the cost function and a number of restrictions.

- Linear MPC control design process:
  Discrete State space formula:

$$x_{t+1} = Ax_t + Bw_t \tag{39}$$

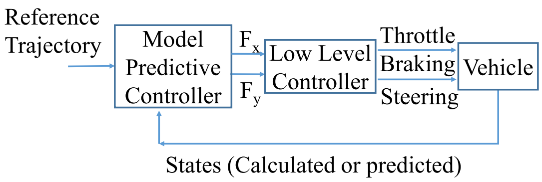

FIGURE 25. Vehicle lateral and longitudinal control with MPC controller.

where in (25), x_{t+1} is the future state, x_t is the current state and w_t is the actuation command. A and B are the time-invariant coefficient matrices.
Control policy is:

$$W = w_{t|t}, w_{t+}1_{|t}, w_{t+}2_{|t\ldots} \tag{40}$$

Optimize the cost function:

$$J(x(t), W) = \sum_{j=t}^{t+T-1} x_{j|t}^T Q x_{j|t} + w_{j|t}^T R w_{j|t} \tag{41}$$

Optimized cost function for desired trajectory:

$$\delta x_{j|t} = x_{j|t,des} - x_{j|t} \tag{42}$$

$$J(x(t), W) = \sum_{j=t}^{t+T-1} \delta x_{j|t}^T Q \delta x_{j|t} + w_{j|t}^T R w_{j|t} \tag{43}$$

where in equation (43), Q and R are the weight metrics of the cost function.
Now, Linear Quadratic regulator:

$$J(x(t), W) = x_{t+T|t}^T Q_f x_{t+T|t} + \sum_{j=t}^{t+T-1} x_{j|t}^T Q x_{j|t} + w_{j|t}^T R w_{j|t} \tag{44}$$

The state space solution is:

$$x_{j+1|t} = A x_{t|t} + B w_{t|t} \quad t \leq j \leq t+T-1 \tag{45}$$

The LQR solution specifies a control gain k, which is computed using the state space functions A and B, as well as the cost functions Q and R.

- Non-Linear MPC control:
  Non-linear MPC (NMPC) incorporates a repeated solution of the optimization problem at every sampling moment in the receding horizon method. The NMPC issue in terms of a non-linear optimization problem is convenient to solve by numerical optimization. The cost function and constraints set out the NMPC control features and dynamic performance requirements. The system utilizes these control methods in turning and for the stability of wheeling calculation steering angles [209].

Implementation of MPC controller for Vehicle lateral and Longitudinal Control:

As shown in Figure 25 MPC takes reference velocity, reference route, and heading angle as inputs. The longitudinal forces F_x and lateral forces F_y are outputs, and these forces are inputs to the low-level controller. As previously stated, the low-level controller's outputs are the accelerator and brake instructions for longitudinal control and the steering instruction for lateral control.

In [210], a NMPC is also developed for speed and steering control based on a genetic algorithm to construct the cost function and constraints in a more precise, meaningful and straightforward way. The vehicle under the guidance of the advanced NMPC is capable of accurately and reliably following the center line of the lane, even at sharp edges.

V. SUMMARY AND COMPARISON

There is a considerable amount of research on driving control system for smart EV, concerning ADAS. These studies survey and discuss ADAS and propose significant types of methods such as ACC, ABES, LCA, LKA, LDW, Night Vision, TSR, Automatic parking assistance, Pedestrian Detection, Traction control, Communication VANETs, and Security and access control. These systems are applied in a smart EV for safe driving and driving comfort.

A comparison between current study and existing surveys is shown in Table 1, on DCSs and vehicle perception sensors. From this Table 1, this paper present all the DCSs and sensor for those control system. Each of the control systems is important enough in terms of security, comfort and ease of implementation. The following systems of control are based on lateral and longitudinal control of the vehicle. Several types of control methods operate these control systems discussed in the ADAS section.

An analysis between the control systems of ADAS is shown in Table 2, on findings, performances, and disadvantages. In addition, this paper analyzed some research articles on various control approaches, which are summarized in Table 2. The extensive examination of driving control schemes as well as performance measures are discussed in order to identify the optimal control schemes in DCSs.

The investigation regarding algorithms is the key to DCS. Various algorithms have been used to rectify the performance of DCS, which are based on perception, localization, and vehicle control. For perception and localization algorithms this paper presents various types for sensor: Vision, lidar, radar, Ultrasonic, Night vision, Time of Flight. These sensors and sensor fusion are compared in Table 3 for road surface detection, object detection, vehicle detection, parking space detection, and so on.

We conduct a performance analysis of these sensors in terms of their accuracy when used with a certain detection method. From Table 3 we can understand that vision sensor works well for vehicle detection. Fusion of vision and radar sensor works well for road surface detection. The ultrasonic sensor is ideal for detecting moving objects. Furthermore, sensor fusion of camera and radar is the most effective for detecting pedestrians. In addition, the LIDAR sensor performs well in terms of detecting road lines but vision sensor has better accuracy. Figure 26 shows the performance comparison of sensors. The perception and

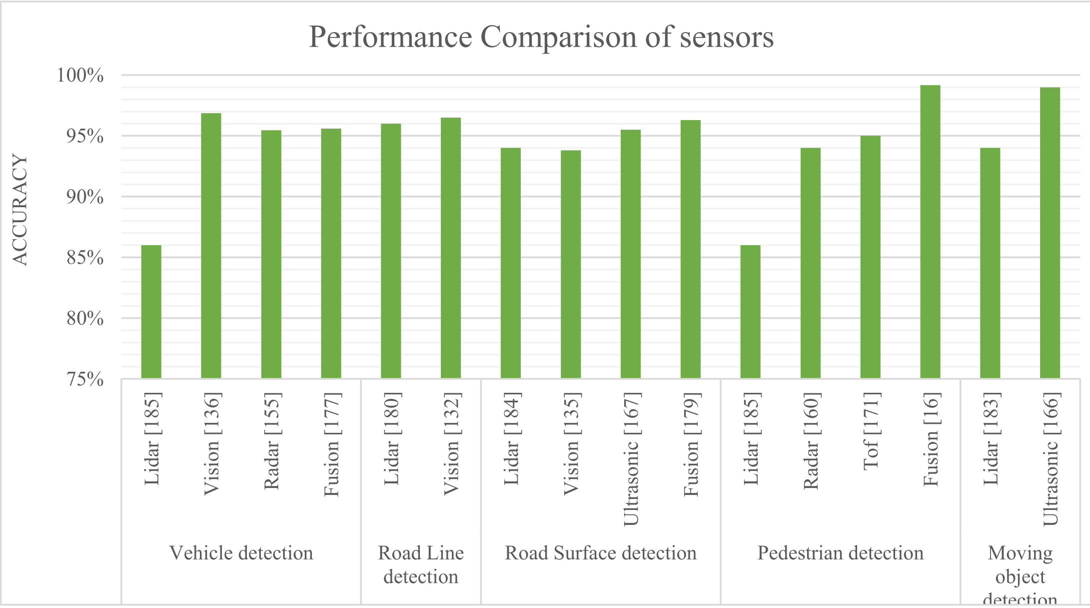

FIGURE 26. **Histogram of performance comparison of sensors.**

localization algorithms are used for understanding the vehicle environment and perform accordingly.

The vehicle control algorithms are presented to perform perception algorithms. To understand vehicle control, vehicle control dynamics and actuation are presented in this paper. Vehicle control dynamics are longitudinal and lateral dynamics are about acceleration, brake, and steering system. This paper presents a comparison of Longitudinal and Lateral vehicle control systems in Table 4, 5.

There are three controllers: PID, MPC, and feed-forward for longitudinal control. PID has a moderate performance for longitudinal control; MPC and feed-forward schemes show better performances. For lateral control, there are also two types of controller: geometric and dynamic. Geometric control has two forms of pure pursuit and Stanley. The geometric controller is a path tracking controller that uses the reference path geometry and the vehicle's kinematic model to map the reference route. The reference point on the reference path is derived from the pure pursuit controller, while the Stanley controller derives the same reference point as is used to measure errors. The MPC is the most advanced sort of controller, as it can use finite-horizon optimization to discover the control instructions that are appropriate.

All driving control systems and algorithms discussed earlier for driving safety and driving conformity of smart EVs need to be further enhanced with software that implements AI techniques [211], [212]. To improve these control systems, the accuracy of the sensors must also be improved. For vehicle longitudinal and lateral control, the emergence of further improvements is also required. However, to gain greater control, fault avoidance, and higher stability, all of these control systems and algorithms need to be improved.

VI. CONCLUSION AND FUTURE SCOPE

Control methodologies for improving the performances of smart EVs have been actively developed and implemented. Furthermore, one of the most notable areas of growth in the transportation business is road safety. As a result, automakers are developing a variety of driver aid technologies to make driving easier, reduce driver stress, and reduce the severity of accidents.

This paper provides an overview of many control systems and algorithms for control systems. Many of the control systems are used in the ADAS. Perception, localization, and vehicle control is covered in the algorithms section. Perception and localization include sensor metrics as well as the types of sensors used in smart EVs. Vehicle dynamics, longitudinal, and lateral control algorithms are among the vehicle control algorithms, and these control system algorithms and sensor styles are briefly discussed in a number of research papers. There are, however, several methods and algorithms that can be applied to smart EVs. For decades, the smart vehicle has been an active research field.

Moreover driving control system for smart EV has numerous research scopes including:

- The application of Big Data may entail interconnecting multiple smart vehicles, i.e. connecting vehicle to vehicle (V2V) and building the infrastructure.
- It is important to understand human behavior for perception, information processing and decision making. Human Machine Interaction (HMI) system can be improved to increase dynamic interaction between people and the controlled system.
- AI-driven algorithms for Vehicle-to-Everything (V2X) applications can be developed and improved for greater driving safety and vehicle stability.

We hope that this paper will provide some ground for researchers wishing to conduct research on Smart Electric Vehicle Technology.

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