Autonomous Vehicle Control Systems- State of the Art of Decision-Making and Maneuver execution

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Abstract: As self-driving cars perform more tasks, new challenges arise. One of these challenging tasks is autonomous driving decision-making due to the uncertainty of the vehicle's complex environment. This paper provides an overview of decision-making technology and trajectory control for autonomous vehicles. The main common goal in decision-making is to consider uncertainties, unpredictable situations, and driving tasks to propose a global and robust solution adapted to each situation. The main concern is safety. Decision-making falls into three categories. The first is the traditional approach, which often consists of building a rule system and deriving optimal operations. The advantages of such an approach are well known for being easy to understand and applicable to small problems. The second category of decision-making is based on a probabilistic process and, due to its efficiency, has several applications in this area. The third category is learning-based approaches. Once a decision has been made, manipulate the steering angle or accelerator/brake pedals to perform the appropriate action. Two approaches are existing to designing autonomous driving controllers. Either based on imitating human drivers that includes approaches based on the use of driver models such as AI, or the use of approach-based models.

Nomenclature

ACC	Adaptive Cruise Control
AI	Artificial Intelligence
ANN	Artificial Neural Networks
AV	Autonomous Vehicle
BN	Bayesian Network
CACC	Cooperative Adaptive Cruise Control
CC	Cruise Control
CBF	Control Barrier Function
DBN	Dynamic Bayesian Network
DFT	Decision Field Theory
DMS	Decision Making System
DN	Dynamic Network
DOF	Degree Of Freedom
DPN	Dynamic Probabilistic Network
Fuzzy-AHP	Fuzzy Analytic Hierarchy Process
FSM	Finite State Machine
HSSOR-RB	Half-Sweep Successive Over-Relaxation- Red-Black
MPC	Model Predictive Control
M2D	Model to Decision
PID	Proportional-Integral-Derivative
QL	Q-learning
RL	Reinforcement Learning
RSS	Responsibility Sensitive Safety
SMC	Sliding Mode Control

1. Introduction

Autonomous vehicles, or "AVs," are still favored and appealing due to their advantages in improving peoples' quality of life. The capability of an artificial agent to navigate (by itself) toward a chosen waypoint without colliding is known as autonomous vehicle navigation. This topic has drawn a large number of research interest in the previous two decades, which justifies the several strategies and approaches used to enhance safety and security. The requirements of such a moving task from one position to another must include techniques in perception, state estimation, path planning, and motion control. One of the main challenges in autonomous driving is the decision-making due to the uncertainty of the complex environment surrounding the vehicle. Nowadays, the primary goal of decision-making is to provide comprehensive, reliable, and robust solutions that are adapted to all conceivable circumstances while considering uncertainty and unpredictable situations. The crucial task is to ensure the safety of road users. Furthermore, the vehicle has to adapt its decisions to its environment using sensors and internal memory for analyzing and updating its representation of both, its inner state and the surrounding objects in the environment. Decision-making involves deciding the course of action to take in light of the vehicle's internal presentation. This method is applicable to a variety of fields and performed well for autonomous robots such as the humanoid robot [1].

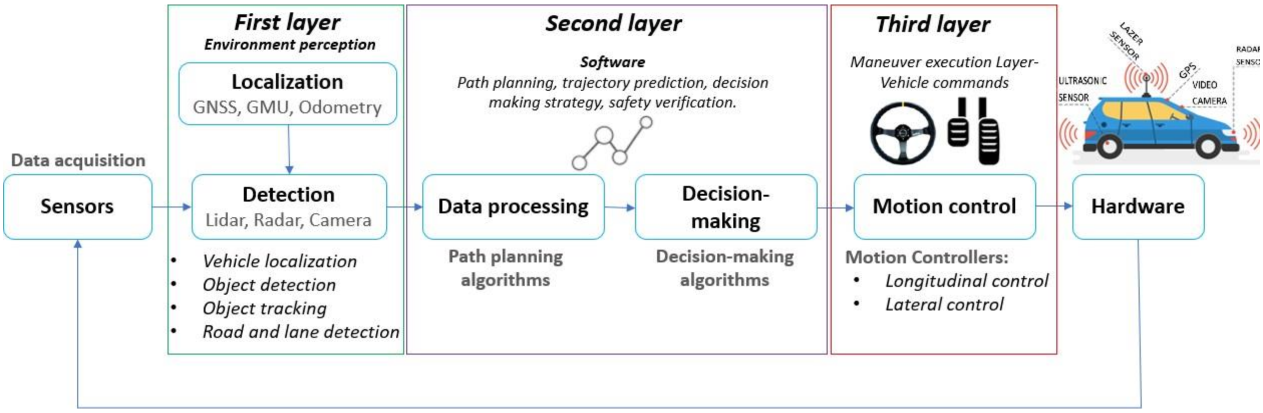

Fig. 1. *Standard components of an autonomous driving system architecture*

The prediction module involves estimating intentions and trajectories that the vehicle needs to perform for decision-making. The planning module finds out which trajectories are safe, while the control phase issues the commands needed to move the vehicle along such a trajectory. Fig. 1 represents the basic components of an autonomous vehicle. It consists of three Layers, the first one corresponds to the perception and localization layer, the second one is the planning maneuver decision-making layer, and the last one is the maneuver execution layer. However, fully autonomous driving remains a complex task that involves challenging aspects and requires skills indomains such as perception, vision and image processing, trajectory generation path planning, decision-making, modeling, and automatic control. In this paper, we will focus on the importance of the second and third layers of vehicle guidance.

The rest of the paper is organized as follows. Section 2 discusses some decision-making methods for autonomous driving. In section 3, we introduce vehicle control for path tracking which includes the lateral and longitudinal control design. In section 4, we formulate decision-making approaches and vehicle controllers respectively. Finally, the conclusion is drawn in Section 5.

2. Outline of Decision-Making for AVs

Decision-making corresponds to making a choice between several possible modes of action when confronted with a problem, the goal being to solve it by translating the choice made into a behavior. For the autonomous vehicle, it involves a certain number of distinct operations such as the definition of the object, the search, the analysis and the organization of useful information, the elaboration and the evaluation of hypotheses for decisions by taking in particular relying on prior knowledge and/or experience, the choice of a decision hypothesis and its implementation. Some decisions are simple to make, while others are much more complex, in the sense that they involve a number of variables more or less. Efficient path planning algorithms and decision control systems are crucial issues for the navigation of autonomous vehicles. Therefore, decision-making can be divided into three categories as shown in Fig. 2. The first one includes traditional approaches often consist of building a system of rules and deducing the most suitable maneuver. Traditional approaches' advantages are known by their ability to be easily comprehensible and traceable for small problems. However, the only shortcoming of these approaches is that uncertainties and partial observability cannot be considered correct in this type of approach. The second type of decision-making is based on a probabilistic process and it has several applications in this field due to its efficiency. The most used methods in probabilistic approaches are Markov Decision Processes, Bayesian Networks, and Monte Carlo Decision Maps The third and last is learning-based approaches. The biggest challenge for decision-making algorithms is to be fast enough to have a real-time decision.

2.1. Traditional Methods

Finite State Machine "FSM" is used as a decision-making strategy in the robotic field to rule vehicles' behavior and decision. The FSM is defined by a finite set of states in which the agent can be, and by the transitions between the states in response to some inputs. In general, the aim of the FSM strategy is to search for a suitable behavior such as changinglane or making a U-turn to allow the robot to reach the desired goal. Furthermore, it sends the chosen trajectory to the controller, which in return sends the steering and velocity commands, or sends a message to the planner that the final goalcannot be reached while operating [2].

Fuzzy Analytic hierarchy process "Fuzzy-AHP" based is proposed in [3], the method is considered powerful in multi-objective decision-making under the user's preference on objectives. It is applied to path planning to improve the performance of the AHP, which is responsible for decision-making. The proposed method takes into consideration three main objectives, which are the travel distance to the desired position, the robot's rotation, and safety against collision between obstacles. As AHP is inappropriate for making decisions under uncertain conditions, FAHP came to compensate for the weakness of AHP. The main advantage of FAHP is that it can be applied with a variety of objectives classified into three levels, the highest level being the goal, the middle level being the objectives, and the lowest level being the alternatives. However, AHP-based decision-making inevitably involves the decision-maker's subjectivity in determining the preference for evaluation objectives [4].

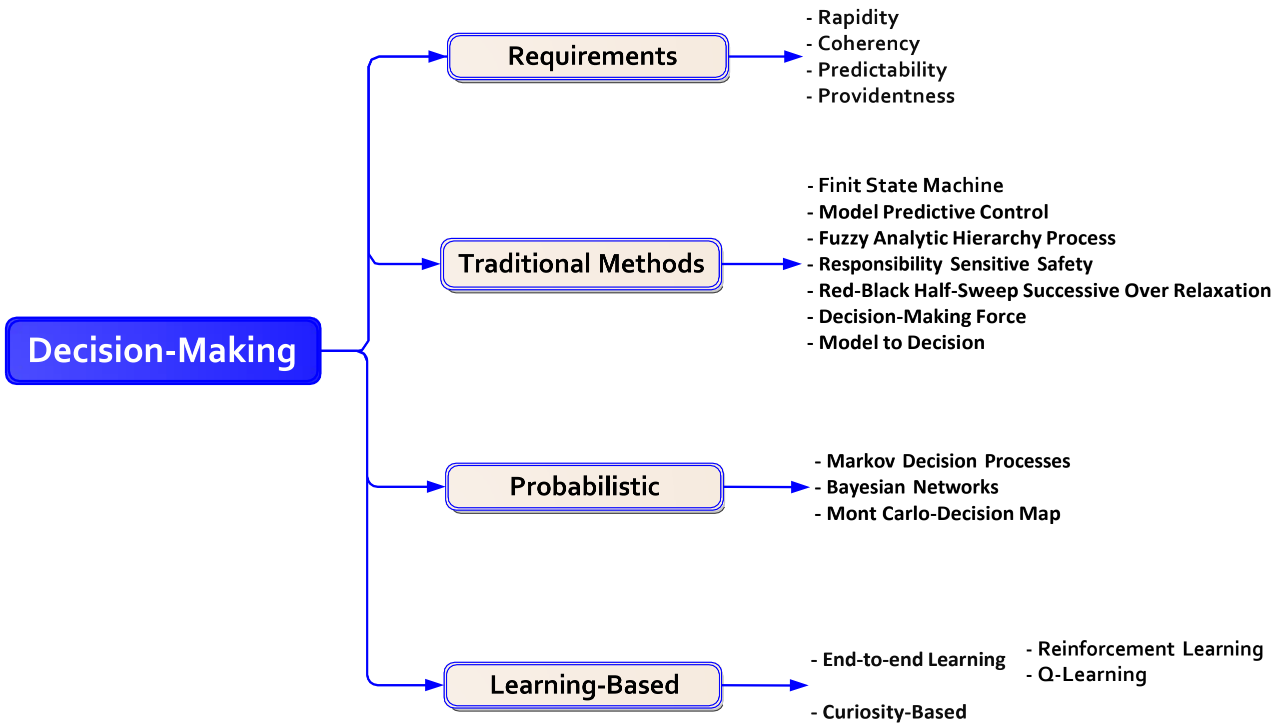

Fig. 2. *Flowchart of decision-making approaches and process*

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To solve this difficulty, fuzzy is addressed to deal with ambiguity and uncertainty resulting from AHP; thus providing robustness and flexibility; according to [5]. FAHP selects the optimal path from pre-planned paths considering safety, steepness, congestion, and roughness.

Responsibility Sensitive Safety ‘RSS’ is a mathematical method that represents a rigorous mathematical model formalizing an interpretation of the law that can be applicable to self-driving vehicles, thus guaranteeing that from a planning perspective there will be no accidents caused by the AV. RSS is widely used to control swerve maneuvers for autonomous driving. [6] Proposes a feasible solution using RSS to swerve maneuver boundary condition problems in addition to standard brake maneuvers. For that reason, they build both lateral and longitudinal safe distances between two vehicles. The longitudinal safe distance help to examine the swerving maneuver to be done while maintaining an appropriate lateral safe distance.

Red-Black Half-Sweep Successive Over-Relaxation ‘HSSOR-RB’ iterative method is a numerical technique. [7] Introduces a novel technique for mobile robot path planning based on potential field method and HSSOR-RB strategy. The work implements a numerical potential function in configuration space based on the theory of heat transfer. An environment is created by the heat transfer, modeled by using Laplace’s Equation, which will not only allow skipping the known problem of potential field method, which is local minima but also, favorable for robot navigation control, Laplace’s Equation is fast solved using HSSOR-RB.

The decision-Making force was inspired by Decision Field Theory ‘DFT’, which is a dynamic cognitive approach to human decision-making based on psychology. Researchers initially introduced it as a deterministic dynamic model of approach-avoidance conflict behavior.

So that the robot can neither, track the task trajectory smoothly, nor avoid obstacles in different possible configurations. The decision-making force will decide which direction is more suitable for obstacle avoidance. In [8], the authors presented a new method for obstacle avoidance by combining the closed-loop control system, dynamic repulsion field, and decision force. The decision-making force includes two forces that are repulsive force and the driving force. When an obstacle is detected, both the obstacle avoidance and decision-making force modules will output the repulsive and the decision-making forces to the closed-loop control system in order to track the suitable direction to a free obstacle. In this work, an algorithm for obstacle avoidance is proposed for a two-degree-of-freedom manipulator robot, which can also be applied to a mobile robot.

Model Predictive Control ‘MPC’ method sets the current control by anticipating future events using a mathematical model of the system dynamics. This method is originally used as a control method as developed in section 3, and has been extended in the literature for decision-making applications as reported in [9]. Two levels of decision-making exist in decision-making processes; Low level and high level. The most developed is the high level, which focuses on long-term driving planning, due to the fact that driving strategy majorly relates to the high-level decision-making process. Besides, the low-level decision-making process focuses on generating collected action patterns within 0.1s to several seconds. Recently, high-level driving schemes were applied for the whole decision process and all possible traffic scenarios as investigated in [10]. In [11], the authors introduce a curiosity-based method with mental energy function (bio-interpretable), which is designed to guide the learning direction of the robot in navigation tasks and re-learn the environment information. The experiences were done by changing the simulation environment so that the robot can reach the final goal through re-learning the current environment, which reflects the autonomous learning ability and the environmental adaptability of robots.

Furthermore, the Model to Decision 'M2D' method has been investigated in the literature and implemented for AV's decision-making. In [12], the authors present an ethical M2D approach for autonomous vehicles with full autonomy, which remain at level 5 and are able not only to recognize the type of obstacles ahead; but also to determine, estimate and predict all kinds of information needed in the decision-making process. The main idea of this work is to introduce M2D for making a decision between colliding into an immovable rigid barrier or a group of pedestrians. Ethical M2D involves the use of a mathematical model of the collision scenarios to make a decision; this model describes the key features of an autonomous vehicle.

2.2. Probabilistic Methods

Decision-making is widely used in robot soccer navigation in a probabilistic way to choose an appropriate kick for soccer. The work in [13] presents a probabilistic approach to decision-making based on maximizing a game situation score function. This approach takes into account only the uncertainty in the kicks; it will give better results if the method takes into account also the uncertainty in the perception in situations including localization, vision, and object tracking. Markov Decision Process is defined as a discrete-time stochastic state transition system. The Markov Decision Process-based approach is used in [14] for trajectory planning with the clothoid tentacles method that generates tentacles in an ego-centered grid, that represents feasible trajectories by the vehicle. Then the problem is formulated as Markov Decision Process so that the right trajectory can be chosen. The proposed Markov Decision-Making process for trajectory planning with tentacles is formulated with five components that allow the agent to drive toward the final goal while avoiding obstacles. The components are as follows: States, which is a set of states of the system. Actions: a set of actions allowed in each state where A is the set of all actions. Transition Probabilities: This defines the transition probabilities of the system. Rewards: Depending on the current state of the system and the action taken, then the agent will receive a reward drawn from this model. Discount Factor: the discount rate used to calculate the long-term attenuation.

Bayesian Networks are typically part of Directed Acyclic Graphs. In general, Decision Networks combine BNs with additional node types for actions and utilities, whereas Dynamic Networks 'DNs' allow to support of probabilistic reasoning, and decision-making under uncertainty for a given system and give the capacity to incorporate multiple decision criteriawhich are the most suitable in path planning. BNs can be designed in two levels, the situation assessment level to infer the current situation state based on the risk assessment and the decision-making strategy level to deduce the maneuvering decisions [15]. DBNs are widely used for maneuver intention, trajectory prediction, and modeling the interaction between traffic participants the fact that makes this technique very suitable for decision-making. In addition, Dynamic Probabilistic Networks have been used as a basis for three separate decision-making approaches. These approaches are as follows: dynamic decision networks, which are the DPN extended with actions node and utility function for each period. Hand-coded policy representations through a decision tree and supervised learning and reinforcement learning methods for solving the full Partially Observable Markov Decision Process, which is difficult to solve and which helps to find an optimal value (direct link with action for agent) thatmaximizes the expectation for the reward sum over the futuretime slice. This work [16] presents a decision-making framework for autonomous driving in highway environments, to determine an appropriate and desired maneuver to the trajectory generation module; in doing so, they used the Bayesian approach in decision-making calculations of threat levels at the car and lane level. The results of this study show that the performance of the decision-making framework of Co-Pilot is sufficiently reliable and robust for AVs in highway environments. Monte Carlo can also be chosen for path planning algorithms [17] in order to generate a probability distribution for the future motions of traffic scene participants. Each object is assigned a goal function, and self-adaptive Monte Carlo integration is used with LIDAR data to assess the probability that all objects will safely reach their goal.

2.3. Learning-based Methods

Most of nowadays strategies in this field are learning-based due to their possibility to deal with road conditions and risks, which are often unknown or uncertain, the purpose of having AVs that are characterized by an adaptive long-term high-level strategy besides the ability to adjust flexibly through interactive decision-making.

The paper [18] presents End-to-End learning which treats the entire pipeline as one learnable machine-learning task. Furthermore, end-to-end driving in the autonomous vehicles field is defined as a system where a neural network makes the main driving decisions, without forcing what the inputs/outputs of the network should be or in how many stages it is trained. In addition, Reinforcement Learning 'RL' is learning of decision-making through the ego vehicle's interaction with the environment. Using the known sensors (Lidar, Radar, Camera RGB…), the vehicle makes observations of the environment, the fact which makes the vehicle able to capture the current state which then enables an active decision to be made accordingly. In [19], authors propose a learning method to deal with obstacle avoidance problems for autonomous vehicles in a dynamically changing environment (multiple goals). The proposed method is based on a multiple goals reinforcement-learning framework while considering several goals and they employed Q-learning in order to determine action decisions based on the interaction of other vehicles with the agent with respect to its interesting goal. With this fusion of two methods Reinforcement, learning and Q learning, the authors succeeded to make corrective action decisions for the overtaking problem, avoiding collisionswith vehicles,

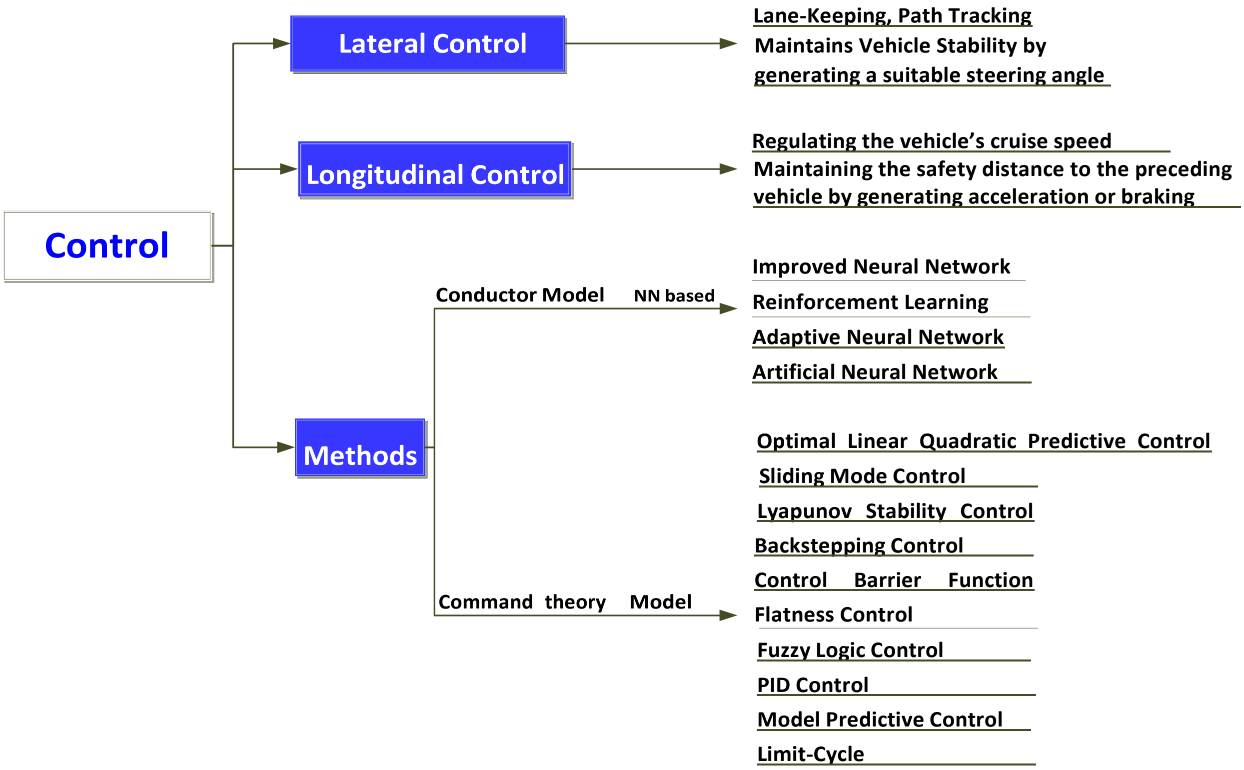

Fig. 3. *Flowchart of existing motion controllers for autonomous driving cars.*

reaching the final target, and keeping and maintaining almost the speed and the heading angle, respectively.

Inverse reinforcement learning is presented in [20]. The authors proposed this method to learn individual driving styles for self-driving cars from the demonstration. In [21], deep reinforcement learning for the decision-making of autonomous vehicles is proposed. By using a transfer reinforcement-learning framework in order to improve the control performance and learning efficiency for automated vehicles' decision-making problems. Another approach based on RL named Q-Learning algorithm 'QL', by definition is a reinforcement learning technique. This technique does not require any initial model of the environment. Q letter designates the function that measures the quality of an action performed in a given state of the system. By some researchers, QL is a simple model-free of RL method. QL is known for its simplicity but it is not very effective in handling a dynamically changing environment. The fact that many other QL extensions as an improved version of QL are developed to overcome the approach weakness. In [19], QL and DAQL are used to determine individual action decisions, for target seeking, it allows the vehicle to learn to achieve the goals. Deep learning-based decision-making system is proposed in [22] for autonomous vehicles for decision-making before entering a roundabout. The proposed approach helps vehicles make correct decisions, including decisions to enter or wait, when entering a roundabout. Curiosity based is a method inspired by psychology research. Authors in [23] proposed a curiosity-based mobile robot path planning method with a designed mental energy function to guide the Learning direction of the robot in navigation.

3. Vehicle Control for Path Tracking

By definition, vehicle control involves maneuvering the vehicle using actuators such as the steering wheel, brake, and accelerator to ensure the reference path following. There are two ways to design controllers for autonomous driving; either based on the imitation of the human driver, which includes approaches based on the use of driver models such as AI (Artificial Intelligence), or the use of approaches based on the theory command.

The vehicle control system is composed of longitudinal and lateral controllers or it can have a coupled controller for both of them as it is described in Fig. 3. Most of the control strategies proposed in the literature deal independently with longitudinal control or lateral control. Lateral control is responsible for lane keeping or lane changing for obstacle avoidance, whereas longitudinal control is designed for tracking (car following).

3.1. Lateral and Longitudinal Controllers

Lateral control focuses on adjusting the steering angle such that the vehicle follows the desired reference path. Wherein the complexity of the dynamic model of the vehicle, the environment, and driving situations make the transposition of the proposed solutions of path following problems into the context of the autonomous driving field quite difficult. It is considered the most challenging part of vehicle dynamics research while considering the nonlinearity of the system, uncertainty, and existing disturbancesin the environment. Therefore, designing robust control laws capable of considering these requirements; remains one of the main challenges today in the vehicle dynamics field.

To ensure such a maneuver, the vehicle must have longitudinal control as CACC (Cooperative Adaptive Cruise Control), ACC (Adaptive Cruise Control), and CC (Cruise Control) to provide robust and string stable car-following in urban environments [24]. However, the purpose of using longitudinal control is to control the longitudinal movement of the vehicle, such as longitudinal speed, acceleration, or longitudinal position of the vehicle, by operating on the engine torque. The most interesting part of Longitudinal control is how ACC regulates speed according to the driver's set point and maintains a safe distance from the vehicle in front. When a vehicle approaches another vehicle, the system immediately reduces or stops engine power and moves forward to maintain a safe following distance. This distance can be measured by a radar or camera or a combination of both that detects the obstacle. The fusion between multiple sensors is well recommended in this field in order to improve the control performance.

In the research that is detailed in the following paragraph, lateral and longitudinal control problems have been investigated in a decoupled way. In fact, numerous works dealing with the lateral guidance of AV are based on the assumption of a constant speed and low longitudinal dynamics. The development of intelligent systems requires efficient and coupled control of the longitudinal and lateral movements of the vehicle. In [25], the authors present a coupled non-linear control of the longitudinal and lateral modes of the vehicle, and an estimator of road deflection angle. As it has an important influence on vehicle lateral dynamics behavior and control vehicle systems, they used an algebraic estimation approach, which is employed in this work to estimate simultaneously the vehicle dynamic parameters such as lateral forces and deflection angle. For the coupled non-linear control, they consider a three degree-of-freedom 'DOF' nonlinear model of the vehicle describing the longitudinal, lateral, and yaw dynamics. The obtained experimental tests provide promising results on the joint approach of algebraic estimation and flatness control.

The core of a coupled longitudinal and lateral dynamic is the control design that is based on a complex mathematical model, which is a challenging task due to these couplings. However, we cannot deny the existence of strong couplings between the two dynamics at several levels: dynamic, kinematic, and tire-forces. Consequently, to improve performance guidance in a large operating range, the simultaneous inclusion of longitudinal and lateral control becomes unavoidable and necessary. Authors in [26] deal with the longitudinal and lateral control of autonomous driving. As the automated guidance must be simultaneously performed with longitudinal and lateral control, a combination of the steering and the longitudinal controllers; is introduced. The authors propose an automated steering strategy based on Nonlinear-MPC for lateral control, and the longitudinal control here is based on a direct Lyapunov approach. Moreover, this work adds a second contribution that consists of the use of heterogeneous criteria to update the longitudinal speed reference to improve the lateral stability level, thus increasing safety.

3.2. Control Methods

3.2.1 Model-based controllers: Numerous works on vehicle control are done using Optimal Linear Quadratic predictive control which provides optimal control [27]. H_∞ controller-based approaches are presented in [28,29]. It is a state-feedback controller that authors use for control design for ground vehicles processing steer-by-wire and drive/brake-by-wire functions, their experimental results show the effectiveness of the control algorithm in dealing with the steering system when tracking yaw rate references. Sliding Mode Control 'SMC' has been developed and implemented for several applications as provided in [30-32]. In [31], SMC is applied with Predictive Voltage for the innovative paradigm of path planning and control of autonomous driving vehicles lateral maneuvering. The proposed control assures smooth lateral vehicle motion to the target lane. Nevertheless, the steering command still suffers from chattering issues. In [32], Backstepping control method with Sliding Mode Observer is employed for an autonomous lane-keeping System. The proposed control has a relatively simple control law to implement. Besides, it pronounces robustness against parameter uncertainties and noises. The two basic functions of vehicle lateral control systems are lane keeping and lane changing. Lane-keeping system automatically controls the steering to not only keep the vehicle in its lane but also to follow the lane. Concerning lane changing system it steers the vehicle from the current lane to an adjacent lane. Both are concerned with using Fuzzy logic control as in [33, 34]. By considering the external disturbance and the parameters uncertainties, an adaptive robust controller based on Backstepping technology is widely used to improve the lateral dynamics stability as in [35,36]. Flatness control is presented in [37], authors used flatness-based and new algebraic estimation techniques for a combined longitudinal and lateral vehicle control. This nonlinear control is designed for automatic path tracking of straight or curved trajectories, and also it can be used to perform lane keeping and lane changing while avoiding obstacles. In [38], the authors integrate Lyapunov theory for the desired path-tracking system, thus guaranteeing global system stability. Model Predictive Control 'MPC' is designed for low-level control or cooperative driving applications. It is a method used in the trajectory tracking of autonomous vehicles, it deals with both linear and nonlinear systems, and requires online optimization problems to be solved at each prediction sampling time. The main disadvantage of this approach is the computation time of nonlinear MPC [39]. Proportional-Integral-Derivative 'PID' is a control loop mechanism that employs feedback control, which is widely used in industrial control systems [40]. Recently, the Limit Cycle controller has been investigated by many researchers and has been implemented for several issues mainly in the robotic field. It generates precisely the robot trajectories, which are defined according to a set of differential equations as developed in [21, 41 ,42]. This approach is known for this optimality and it uses specific reactive rules, which allows the robot to avoid deadlocks, local minima, and oscillations. The Limit Cycle control is presented by authors in [41] where they used a modified Limit Cycle Navigation method for the case of local sensing. In [42], a stable limit cycle has been proposed and designed for Nonlinear Time-delay Systems. This technique leads to achieving strong behavior for trajectory tracking in nonlinear dynamical systems. In the temporal domain, stable limit cycles are similar to stable oscillations. In this way, numerous real systems have been subjected to this behavior's analysis in an effort to create stable oscillations by modifying an appropriate limit cycle to correspond to the desired output's shape, amplitude, and frequency. In the limit cycle shaping technique, oscillatory behavior is a natural characteristic of solutions and is not dependent on a reference signal or on temporal derivatives either. As reported in previous research, the Lyapunov theorem is primarily used to characterize the stability of limit cycles and the candidate Lyapunov function is chosen based on the desired limit cycle's geometric shape.

3.2.2 Neural Network-based controllers: Artificial Neural Network 'ANN' is a popular form of approximate learning solution. The latter is based on the error backpropagation to adjust the weights of neural connections with different learning strategies. Nowadays, many works intend to use neural network approaches for autonomous driving where the vehicle can choose the correct motion and accomplish the task of reaching the final destination with collision-free according to the environment information perceived by the sensors. Behind an unknown and dynamic environment, this task proves to be difficult, which explains the need for a large time-life so that the proposed neural network method can learn and accumulate more about behavior knowledge. In addition, Fuzzy logic [43] is part of a neural network-based controller, reinforcement-learning algorithm [44] is suitable for the application of the control of intelligent robots, but it has some limitations as the problems of the delayed reward and temporal credit assignment. Adaptive neural network is presented in [45]. ANNs are widely used due to their good generalization performance and effectiveness in solving the problem of nonlinear mapping. Authors in [46], propose a multi-layer feedforward artificial neural network to develop a motion planning controller for a mobile robot. The multi-layer feedforward artificial neural network is a supervised learning technique that requires some training data. The authors gathered the training samples using Q-learning. They reduced the complexity of planning to five state actions: move forward, turn right, turn left, rotate 180 degrees, and stop action. The ability of the vehicle to learn and adapt is necessary for the creation of a self-driving automobile. To improve control outcomes and overcome the drawbacks of the already implemented control systems, it is advised to combine existing methods.

The previously discussed controllers in the literature have been developed for both decision-making and path control and tracking for autonomous vehicles. These proposed controllers have been implemented for precise obstacle avoidance thus trajectories tracking in time. Nevertheless, the overall stability of the vehicle and the passenger's safety neither were given sufficient consideration. Safety is equally paramount of importance and brought to the forefront of Autonomous vehicle design, especially for dynamic AVs when prone to a random and unknown environment. In this way, several studies have been investigated to ensure safety hence stability as well. Several authors have refocused on AV's safety by introducing Control Barrier Function 'CBF' approach [47-49]. It is considered the most effective algorithm to guarantee AV stability and safety, thus solving such AV problems as lane-keeping in [50], obstacle avoidance, and free-collisions in [51]. The CBF has been integrated with other controllers to achieve simultaneous decision-making, path tracking, and safety at the same time. In [52], a robust control for lateral dynamics of autonomous vehicles has been developed using Barrier Lyapunov-Function control. Furthermore, the CBF has been successfully combined with MPC and SMC for autonomous surface vehicles in presence of tire forces, road curvature, and parametric uncertainties as reported in [48] and [53] respectively. Due to recent activity in related fields and the necessity of safety associated with autonomous systems, the authors envision control gate functionality to become an integral part of modern control system design.

4. Discussions

The decision-making module is a fundamental component of autonomous driving since it has finite set of actions to perform. There will be no reasonable behavior without decision-making action. Different decision-making algorithms have been implemented in the past few years (see section 2) which focus on planning, predicting, reactivity, and so forth. The main task in decision-making algorithms is that it must be fast enough to have real-time. According to [15], decision-making systems for self-driving require four criteria, rapidity in the planned decision, coherency for avoiding unnecessary actions, and providentness which means that the module should foresee how the situation will evolve after some time/maneuvers and include it in the decision-making, and finally, the predictability.

The present paper discusses the state-of-the-artalgorithms in the domain of decision-making of autonomous driving. Table.1 summarizes the main advantages and drawbacks of the mentioned decision-making approaches. It illustrates a comparison between performances of the traditional, the probabilistic, and the learning-based approaches. The most important task in DMS (Decision-Making System) is the ability to solve any unexpected situation while considering uncertainty and finding the right balance between accuracy and computational complexities. For doing, the probabilistic approaches are recommended for such general decision-making in autonomous vehicles, because it has the potential to take into account the nature ofthe stochastic dynamics of a traffic environment, to be able to account for uncertainties thanks to well-known probabilistic algorithms and to take into account both of the present and future interactions between the participants.

The second part of this paper deals with control strategies for autonomous vehicles. Automatic control is the last part of the autonomous vehicle sequence and one of the most important tasks since it is responsible for ensuring its motion. The controllers vary depending on the chosen technique. In this paper, various vehicle control methods are presented. A summary of the discussed control algorithm in this review is listed in Table. 2. The main advantages and drawbacks are given for each proposed technique for AV system control.

For lateral control, several works used the dynamic bicycle model, which seems to be the most appropriate for high-speed

Table 1. Analysis of decision-making approaches for AVs.

Category	Method	Advantages	Drawbacks
Traditional	Finite State Machine [2]	Searches for a suitable behavior that makes the vehicle reach an objective checkpoint, online	Transitions are coded and tested by hand and thus prone to errors
	Fuzzy Analytic Hierarchy Process [3]	Handles the uncertainty, robustness and flexibility, powerful in multi-objective decision-making, online	------------
	Responsibility Sensitive Safety [6]	Guarantees safety	The lack of long-term decision-making, the sacrifice of traffic efficiency
	Red-Black Half Sweep Successive Over Relaxation [7]	Reduces computational complexity, fast iterative method, and solves path planning problems.	Static environment
	Decision-Making Force [8]	Brings great flexibility into the online adaption framework, and guarantees the endeffector and robot links' safety.	Less efficient.
Probabilistic	Markov Decision Process [14]	Dynamic environment with uncertain dynamics.	High complexity
	Bayesian Networks [15, 16]	Considers interaction between participants, flexible design.	Computationally expensive
	Monte Carlo Decision Map [17]	Used to either control the car, or to display warnings for the driver.	Exponential computational cost, short-term prediction
Learning-Based	End-to-End Learning [18]	Makes correct action decisions for overtaking problem.	Offline, Discrete space, unsafety of the decisions.
	Curiosity-Based [11, 23]	Re-learning of the environment.	Computational complexity.

autonomous driving. It is basically a non-linear and time-varying model. However, it is difficult to make a very objective comparison of the control techniques developed in the literature because they are generally used on different models and vehicles, with different assumptions. Many of them have only been validated in simulation using autonomous driving simulators as Carla, CarMaker, and so forth. However, we can deduct from the analysis that adaptive controllers are more efficient. Control laws such as Sliding Mode Control, MPC, and Predictive Linear Quadratic optimal control seem to be appropriate. In addition, the use of artificial intelligence techniques or even hybrid controllers is also recommended since neural network approaches can have unexpected behavior while running the network in real-time or giving some inexplicable outputs. On the contrary, longitudinal control is responsible for regulating the car's cruise velocity. Many researchers focus on classical controllers such as PID, which are widely used to provide longitudinal control in self-driving car applications. Furthermore, Fuzzy controllers and Sliding mode controllers in this field are still being developed and implemented due to their significant advantages and pronounce performance in following and keeping, respectively, the reference velocity.

5. Conclusion

In this paper, we have addressed the problem of decision making and command control in order to ensure safe and smooth trajectory tracking.

The first level is a scan of all decision-making methods for AVs. The second level is to discuss some vehicle control methods for path following for autonomous vehicle.

After having performed a large state-of-art, research on control and decision-making of autonomous vehicles, several contributions have been presented.

During the last few years, several challenges have stimulated research methods for the design of autonomous driving. Many researchers and developers as well as carmakers become more interested in the development of such applications. This is a fast-growing field of research,

Table 2. Analysis of system control algorithms for AVs.

Category	Method	Advantages	Drawbacks	Experimental Validation
Lateral and Longitudi-nal Control	Cooperative Adaptive Cruise Control [24]	Robust and string stable car-following in urban environments Speed regulation according to the driver's set point safe distance from the vehicle in front	Assumption of constant speed and low longitudinal dynamics	**V**
	CC (Cruise Control)	promising results on the joint approach of algebraic estimation and flatness control	Requirement of efficient and coupled control for vehicle movement	----------
Model based Control	Optimal Linear Quadratic predictive control [27]	Optimal control Vehicle stability and the trajectory improvement along the desired path	Limitation for multi-variable systems and systems with constraints	**NV**
	H_∞ State-Feedback Controller [28,29]	Dealing with steering system when tracking yaw rate reference	Difficulty to restrict the manipulated controlled variable.	**V**
	Sliding Mode Control with Backstepping [30]	Robust against parametric uncertainties and noises	Chattering phenomena	**V**
	Flatness control [37]	Perform lane keeping and lane changing while avoiding obstacle	Difficulties to use real measurements for reference signal generation for control application Required algebraic estimation of measurements	**V**
	Model Predictive Control [39]	Application for both of linear and nonlinear systems Less sensors are used High performance when tracking reference in the next step in sampling time	Computation time of nonlinear MPC Requires online optimization problem to be solved at each sampling time Limitations on steering angle and steering angle rate	**V**
	PID Controller [40]	Employ feedback control Industrial control systems applications	Saturation issues in time Tuning parameters problems	**NV**
	Limit cycle [21, 41, 42]	Optimal control based on differential equations Simple to implement High accuracy generation of the robot trajectories Strong behavior for trajectory tracking in nonlinear dynamical systems.	Combination of linearization methods Necessitate to add the avoidance trajectory equation to the controller Reference and trajectory error still exist	**NV**
	Lyapunov and Control Barrier Function [47-53]	Guarantee the system stability and safety of vehicle Candidate for nonlinear systems control	------------	**NV**

Table 2. Analysis of system control algorithms for AVs. (The following)

Category	Method	Advantages	Drawbacks	Experimental Validation
Neural Network-based controllers	Artificial Neural Networks 'ANN' [46]	Adjust the weights of neural connections	unexpected behavior while running the network in real time	**V**
	Fuzzy logic [43]	Suitable for control of intelligent robots.	Problems of the delayed reward and temporal credit assignment.	**NV**
	Adaptive neural network [45]	Good generalization performance Effective for solving the problem of nonlinear mapping	Requirement of own learning and adaptive abilities of the vehicle Combination of existing method to get better control	**V**

Securing autonomous driving in urban areas is one of the biggest issues facing the world today

Furthermore, these research works are interested in three key steps to achieve autonomous navigation: the planning of trajectories, the decision-making, and the development of robust control laws that will ensure, in real-time, trajectory tracking. A well-designed system for self-driving cars should ensure not only path tracking while avoiding obstacles, but also must take into account safety, and the ability to comfort in critical situations and it should have a strong positive impact on traffic safety.

By making the state-of-the-art, we have concluded the fact of using multiple complementary criteria, which allowed to have not only redundancy in the assessment but also to improve the accuracy of the acquired information. In addition, as each event on the road is distinct and a prompt response is necessary to handle any emergency or critical situation, the given methodologies and online verification of the safety of autonomous cars are essential.

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