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 SURVEY

Review of Decision-Making and Planning Approaches in Automated Driving

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ABSTRACT The number of research papers on decision-making systems in automated driving has increased significantly over the last few years. Decision-making for automated driving can be performed at different levels: (i) strategic level: generating the optimal route up to the destination; (ii) tactical level: identifying and ranking feasible high-level maneuvers that the vehicle can perform, considering the dynamic objects that are in the surroundings; (iii) operational level: generating a collision-free trajectory (path and speed profile) up to the planning horizon; (iv) stability level: computing the motion control commands for tracking the trajectory. Additionally, supervision can be understood as a combination of one or more decision-making levels. Previous reviews have focused either on one of the levels of decision-making or on a specific environment where the approaches are applied, without any distinction between the contexts in which they are applied (robotics, unmanned vehicles or automated driving). This review studies the state-of-the-art on the decision-making approaches applied specifically to automated driving, during the last lustrum.

INDEX TERMS Automated driving, strategic level, tactical level, operational level, stability level, route planning, maneuver planning, motion planning.

I. INTRODUCTION

A. CONTEXT

Decision-making and planning are common terms for both robotics and automated driving domains. Sometimes these terms are used interchangeably, other times a large variety of terms are used without unanimity. For the sake of clarity, we refer to decision-making as the *plan* primitive of the *sense-plan-act* [1] robotics primitives. In the automated driving domain, the authors consider that decision-making can be found in planning, supervision and control systems.

In this work we present the state-of-the-art on the planning approaches for decision-making, focusing on the automated driving application and not in the robotics domain. Thus, the related works during the last lustrum were studied in this article.

B. CLASSIFICATIONS OF DECISION-MAKING AND PLANNING APPROACHES

Different classifications of decision-making in general and planning approaches in particular have been presented in the

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automated driving field. In this chapter, first, a classification based on the type of planning task ordered by computation time is presented; and second, some of the most common classifications are presented.

1) CLASSIFICATION BASED ON PLANNING TASK TYPE AND COMPUTATIONAL TIME

Automated driving tasks in which decision-making can be found are planning tasks, control tasks and even supervision tasks. Planning tasks can be divided into route (or mission) planning, maneuver (or behavioral) planning, and motion (or trajectory) planning.

A classification of these decision-making tasks is presented in Figure 1. There, a pyramid where the different levels are increasingly ordered by the time consumption of the decision-making tasks performed on it, that is, from long-term to short-term. This pyramid is inspired by the classification of decision-making in management [2], which divides decision-making into strategic, tactical, and operational levels. In the proposed classification, the strategic level corresponds to route planning, the tactical level corresponds to maneuver planning, and the operational level corresponds

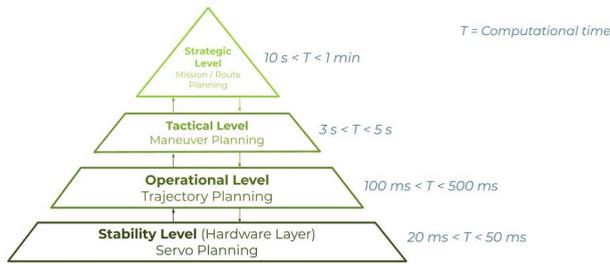


FIGURE 1. Levels of decision-making according to classification based on the planning task type and the computational time.

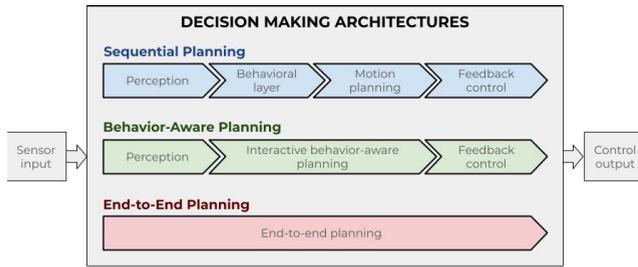


FIGURE 2. Architectures for decision-making based on the sequential or simultaneous execution of the planning tasks [3].

to motion planning. There is an additional level called the stability level, which corresponds to control tasks. The final level is supervision, which is the most reactive system. It is not presented in the pyramid since the functions presented here may override the tactical, operational or stability level if needed in case a fallback function is required, such as an emergency braking or a minimum risk maneuver.

2) CLASSIFICATION BASED ON THE COMPONENTS ARCHITECTURE

According to the architectures for decision-making presented in Figure 2 [3], the planning approaches can be divided into three different types depending on the architecture: sequential, behavior-aware or end-to-end planning, depending on the kind of architecture used for the planning modules.

Sequential planning (depicted in blue in Figure 2) consists of representing the driving tasks as individual elements performed consecutively in time: from the sensor inputs, passing through the perception stage, then maneuver planning as the first element of the planning stage, and motion planning as the second element of the planning stage, ending with the control stage.

Behavior-aware or interaction-aware planning (depicted in green in Figure 2) considers both maneuver and motion planning tasks are done in the same stage.

Finally, end-to-end planning (depicted in red in Figure 2) represents all the learning-based approaches. They can be divided into the following approaches: (i) End-to-end: A fully end-to-end approach where perception, planning and control tasks are all performed in the neural network, receiving the sensor data as input and generating the control data as output. (ii) End-to-mid: The neural network receives the sensor data

as input, performs the perception and planning tasks to generate the planned trajectories as output of the neural network. (iii) Mid-to-end: The neural network receives the data from the perception as input and both planning and control tasks are considered in the neural network, where the output are the control commands. (iv) Mid-to-mid: The neural network receives as input the perception data and generates as output the planned trajectories for the control stage.

The main contribution of this review is to present the most relevant works on decision-making for automated driving during the last lustrum, dividing the contributions into different planning levels according to the decision-making pyramid presented in Figure 1, which can be summarized in Table 1. The rest of the paper is organized as follows: Section II introduces the review of route planning approaches (strategic level), Section III presents the review of maneuver planning approaches (tactical level), Section IV shows the review of motion planning (operational level), Section V briefly describes the trajectory tracking stage or control (stability level), and finally Section VI summarizes the conclusions of this review and the trends of decision-making in automated driving.

II. STRATEGIC LEVEL (ROUTE PLANNING)

Route (or mission) planning corresponds to the strategic level, which is the higher level of the pyramid of decision-making presented in Figure 1. It computes the sequence of waypoints from an origin to a destination point. This process is also called global planning, since all information about the map is known in advance. Meanwhile, in local planning, most of the information about the map and environment is unknown before the vehicle starts moving. Therefore, in global planning the route or itinerary is planned until the destination; however, in local planning, the trajectory is computed until a time horizon (five seconds is the most common horizon for motion planning in the state-of-the-art).

The route or mission generated by the route planner is at the top of the planning levels since this route is further used by the maneuver planner (to plan the next sequences of maneuvers to perform) and by the motion planner (to plan the geometric path and speed profile to be tracked by the vehicle). That is, route planning is the less reactive stage of the planning architecture: the behavior of the surrounding vehicles in the short-term will have a lower impact on the route than on the trajectory. The latter may change to avoid collisions with other road users. For this reason, the route planning process does not need to be recomputed with a high frequency; a reasonable execution period is around a few seconds.

First section of Table 1 summarizes the most relevant route planning publications described below, which are classified in more detail in Table 2.

Route planning is one of the main tasks of the Vehicle Route Planning Problem (VRP), which consists of optimization problems found in the transportation, distribution, and logistics industries [51]. VRP is an NP-hard combinatorial optimization problem [52]. The main classification of VRP

TABLE 1. Classification of works in the SoA.

Planning Level	Testing Environment		Testing Platform	
	Urban	Highway	Vehicle	Simulation
Route Planning	[4]–[9], [10], [11]	[6], [9], [12]–[14], [10], [11]	[7], [12]	[4]–[6], [8], [12], [9], [13], [10], [11]
Maneuver Planning	[15], [16], [17], [18], [19], [20], [21], [22], [23]	[17], [24], [25], [26], [27], [28], [21], [29], [30], [31]	[17], [26], [27], [32], [23]	[15], [16], [17], [24], [25], [26], [18], [27], [28], [19], [20], [21], [30], [22], [31]
Motion Planning	[33], [34], [35], [36], [37], [38], [39], [16], [40], [41], [42], [43], [44], [45]	[35], [38], [42], [46], [47], [45]	[33], [34], [35], [36], [37], [38], [35], [48], [40], [42]	[35], [36], [37], [38], [49], [48], [39], [16], [40], [41], [50], [46], [47], [43], [44], [45]

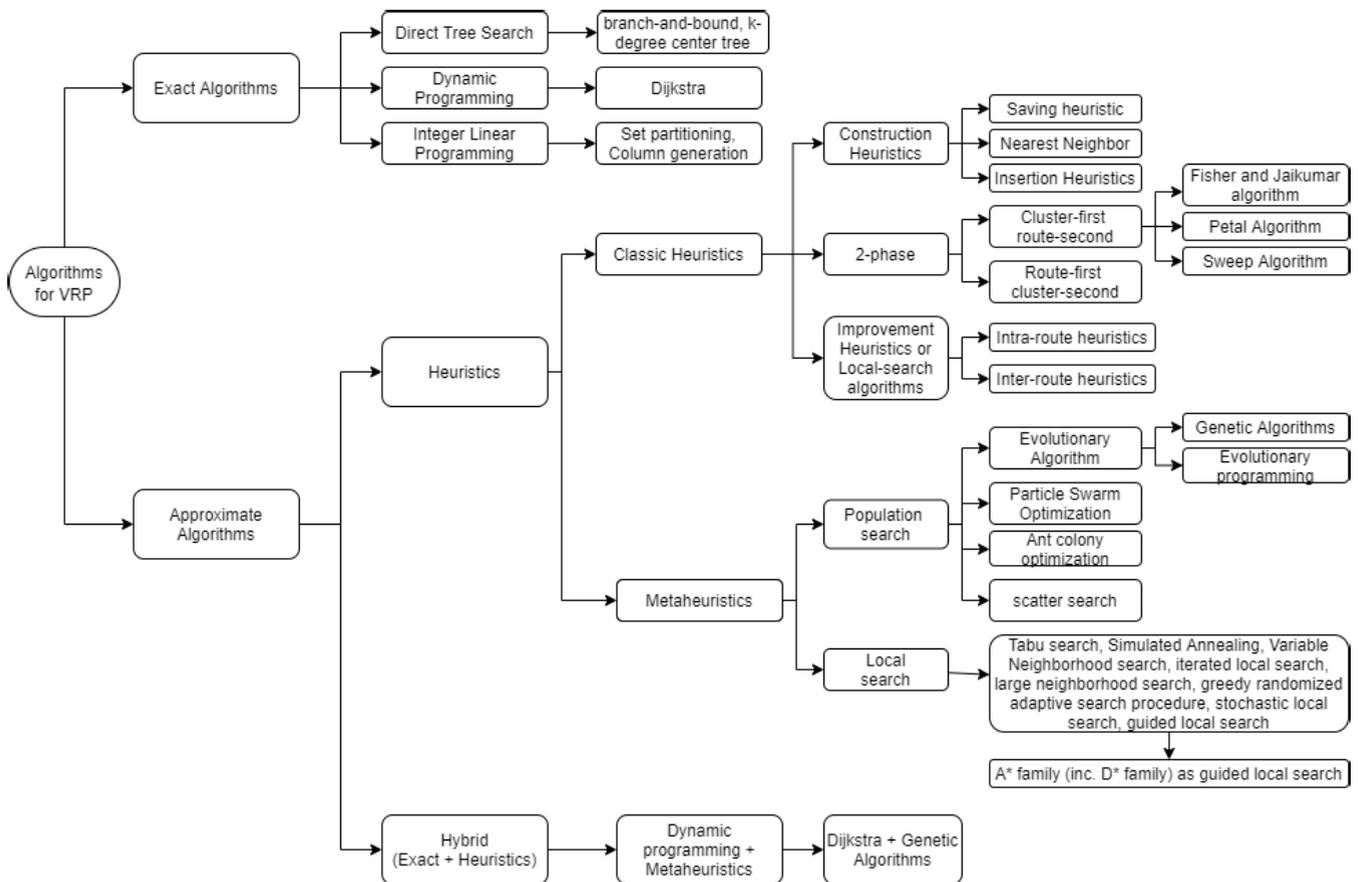


FIGURE 3. Classification of algorithms for VRP problem.

algorithms in the state-of-the-art is based on the method of solving this problem: either obtaining an optimal solution (exact algorithms) or a near-optimal solution (approximate algorithms) [53].

These articles propose the classification shown in Figure 3, where the algorithms are first divided into exact or approximate algorithms (heuristics or metaheuristics based) since we focus on the method of solving the VRP problem. This classification is detailed in further subsections, where the algorithms used in the automated driving domain are

classified. This can be considered an extension of the prior art. Some previous studies are as follows: [51], [52], [53], [54], [55], [56], [57].

A. EXACT ALGORITHMS

The exact algorithms aim to obtain an optimal solution for the VRP problem. The scope of these algorithms is small-scale problems, as they would not be efficient in large-scale problems, such as planning the route between different continents,

for example, where the representation of the road network would be too large.

These algorithms can be divided into the following subtypes according to [58]: direct tree search, dynamic programming, and linear programming.

1) DIRECT TREE SEARCH

Among the direct-tree search algorithms, we can highlight the branch-and-bound and k-degree center tree algorithms. The branch-and-bound algorithm breaks-up the solution space into several subsets or branches. The lower bounds for the objective functions are computed for discarding some of these subsets or branches, thereby minimizing the solution space. This algorithm was recently applied in [59] to solve the VRP problem with customer costs. Some more recent examples of tree search heuristics are the branch-and-cut [60] and branch-and-cut-and-price [61] algorithms.

2) DYNAMIC PROGRAMMING

Dynamic programming is an optimization method as well as a computer programming method that aims to simplify a complicated problem by splitting it into different sub-problems in a recursive manner.

Dijkstra is a graph-search based algorithm that can be considered a dynamic programming method because it is a deterministic optimization method that solves the shortest route problem. Söderberg [12] developed a bidirectional Dijkstra search approach for a rapid route planning using trucks and heavy vehicles. In the context of urban driving, a Dijkstra-based approach was used by Yu *et al.* [4] for the valet parking problem. The authors developed a solution combining a Dijkstra-based search with V2X communication for the parking problem. Liu *et al.* [5] also applied a Dijkstra-based approach to improve parking efficiency. Sun *et al.* [7] proposed a solution for multi objective route planning in parking scenarios. In addition to the parking problem, Dijkstra's algorithm has been used for route planning with temporary driving bans, road closures, and rated parking areas [6].

Apart from Dijkstra, we can highlight the following applications of Dynamic Programming algorithms in automated driving. Zeng and Wang [8] proposed an approach for time-optimal route planning, focusing on energy-efficient vehicle driving within a bounded period of time. For this purpose, they presented a dynamic programming based method where the following decision constraints were considered: stop signs, traffic lights, turns and curved segments, roads with different grades and speed limits and torque operation. Sever *et al.* [62] proposed a hybrid Approximate Dynamic Programming (ADP) approach with a deterministic look-ahead policy and value function approximation for the dynamic shortest path problem with travel time-dependent stochastic disruptions. The problem was formulated as a discrete-time finite-horizon Markov decision process.

3) INTEGER LINEAR PROGRAMMING (ILP)

Integer Linear Programming (ILP) is an optimization algorithm in which some variables are integers. The most common ILP algorithms for route planning are set partitioning and column generation algorithms. Angelelli *et al.* [9] proposed a linear programming model as a route planning approach to minimize both user travel inconvenience and traffic jams. Their approach consists of optimizing the travel-time instead of generating the shortest route in terms of distance. Rahmani *et al.* [13] studied the accuracy of the predicted travel times and proposed a solution based on a fixed-point formulation of the simultaneous path inference and travel time prediction problem. Lee *et al.* [14] focused on the evaluation of travel-time reliability and proposed a measurement method based on the Gini coefficient, which is a well-known measure of statistical dispersion.

B. APPROXIMATE ALGORITHMS

Approximate algorithms (bottom part of Figure 3 can be divided into two categories: fully heuristics-based or hybrid approaches, combining exact algorithms and heuristics.

Heuristics are basic approximate algorithms that find in a reasonable computation time a solution that is as good as possible, but not optimal.

The same way, heuristics can be divided into classical heuristics and metaheuristics.

1) CLASSICAL HEURISTICS

Classical heuristics can be classified into constructive heuristic, improvement heuristics and 2-phase heuristics. **Constructive heuristics** include the following types of heuristics: saving heuristic, route-first cluster-second, cluster-first route-second, and insertion heuristics. (i) Saving heuristic: This solves the problem in which the number of vehicles is not fixed. It generates n routes consisting of only one starting vertex and ending vertex. It then computes the saving cost for combining each of the two routes and sorting the values. (ii) Nearest neighbor method: starts from the starting vertex and searches for the nearest unvisited customer (destination vertex) as the next customer (destination). This procedure is repeated unless it exceeds the capacity limit until all customers (destination vertices) are visited. (iii) Insertion heuristics: This starts from a single node, which is usually called a seed node. This formed the initial route from the depot. Other nodes are inserted individually to evaluate certain parameters to select a node and the place in the route for insertion.

Two-phase heuristic algorithms consist of a cluster phase and a route construction phase. They can be considered as subtypes of constructive heuristics. One example of a two-phase heuristic is the Fisher-Jaikumar algorithm. First, clusters are created using a geometric method that partitions the plane into several cones, where the cone number is equal to the vehicle number. Then, in the route construction phase, customers are inserted into routes according to their increasing insertion cost, and a traveling salesman optimization

algorithm is applied to obtain the optimal travel cost. A two-phase heuristic based on the Fisher-Jaikumar algorithm was proposed in [63] to solve the Capacitated Vehicle Routing Problem, that is, route planning considering the capacity constraint, including the implementation of new costs such as delivery expenses for logistic activities. Another example of a cluster-first route-second is the sweep algorithm, where a set of feasible cluster is first formed by rotating a ray centered at the departure point based on their capacity. Second, the vehicle routing is obtained for each cluster.

Improvement heuristic: Most algorithms starting with a constructive heuristic phase are then followed by an improvement heuristic phase, which is typically based on neighborhood search operators, where the neighborhood is the set of feasible solutions similar to the given one. They start from any feasible route solution and improve it by successive small changes related to the neighborhood search. There are two groups of improvement heuristics based on local search: intra-route heuristics (such as $2 - opt$ search or $\lambda - interchange$) and inter-route heuristics (such as customer relocation, customer crossover and customer exchange).

2) METAHEURISTICS

Metaheuristics are higher-level procedures designed to find, generate or select a heuristic that may provide a sufficiently good solution to an optimization problem, particularly with incomplete or imperfect information. Their main goal is to guide the search process, and efficiently explore the search space to find the optimal solutions.

Metaheuristics can be classified into population search and local search algorithms, as depicted in the bottom-right part of Figure 3.

- (i) **Population search:** These algorithms maintain a proof of good parent solutions, by continually selecting parent solutions to produce promising offspring, by updating the pool, either by combining and pairing existing ones or by making them cooperate through a learning process. Among the most common population search metaheuristics we can find evolutionary algorithms (such as genetic algorithms or evolutionary programming and memetic algorithms), particle swarm optimization, ant colony optimization or scatter search. [11] proposed a real-time based optimization approach to solve the Vehicle Macroscopic Motion Planning (VMMP) problem. This consists of optimizing simultaneously a vehicle route and a speed using both traffic data and vehicle characteristics to improve the fuel consumption as well. Authors use a genetic algorithm based co-optimization method to solve the VMMP problem combined with an adaptive real time optimization process.
- (ii) **Local search:** These metaheuristic algorithms keep exploring the solution space by iteratively moving from the current solution to a promising solution in the neighbourhood. Most common local search metaheuristics are the tabu search, simulated annealing, variable

neighborhood search, iterated local search, large neighborhood search, greedy randomized adaptive search, stochastic local search and guided local search.

A* family of methods, that is, Dijkstra derived methods where a cost function guides the search, can be classified as local search metaheuristics. A method based on a variant of the hybrid-state A* search algorithm for global planning was proposed in [64], where the global path permits searching to generate steering actions.

A cluster-first route-second 2-phase heuristic-based approach was proposed in [65]. A variant of the Fisher-Jaikumar algorithm was investigated to solve Capacitated Vehicle Routing Problem. During the constructive phase, routes are created attempting to minimize the cost at the same time. On the other hand, during the route optimization phase, three metaheuristic methods are used: genetic algorithm, ant colony optimization and particle swarm optimization.

An approach to solving the shortest path problem using a hybrid metaheuristic was proposed in [10]. The authors combined the Variable Neighborhood search metaheuristic with genetic algorithms. Unlike standard methods such as Dijkstra, metaheuristics allow computing multi-objective routes that meet additional constraints even in large-scale road networks.

3) HYBRID (EXACT AND HEURISTICS)

Apart from the exact and approximate approaches, there exists a hybrid model in the state-of-the-art in which a heuristic is applied together with an exact algorithm.

Apart from the proposed architecture of route planning algorithms for solving the Vehicle Routing Problem (VPP), other classifications in the state-of-the-art divide the methods depending on the structure used for modeling the space: either graphs or trees. A common way of dividing these approaches is graph search-based or sampling-based [64], [66].

- **Graph search-based approaches:** These approaches model the road with graphs, where a sequence of configuration states (position and orientation) from the initial state of the vehicle up to the destination state is searched into the feasible space of the configuration space. The main graph-search algorithms used in the state-of-the-art for route planning are: Dijkstra and the A* family (A*, D*, Hybrid-A*, etc).
- **Sampling-based approaches:** These approaches consist of randomly sampling the configuration space to solve timing constraints, usually in high-dimensional spaces. The main sampling-based algorithms used for route planning are: Rapidly-Exploring Random Trees (RRT) and Enhanced Rapidly-Exploring Random Tree (RRT*).

A new trend in the study of route planning problems has arisen in recent years. The green Vehicle Routing Problem has been investigated since 2006 and has focused on the energy optimization in transportation [52]. Green VRP can be classified into: green-VRP, pollution routing problem and VRP in reverse logistics. First, it deals with the optimization

of energy consumption of transportation; second it focuses on the impact of transportation on the environment considering gas emissions; third focuses on the distribution aspects of reverse logistics.

Another trend in route planning is the application of traffic flow optimization. This branch is often referred to as intelligent route planning. For instance, the authors in [67] assumed that even if travel times are not precisely known beforehand, they are bounded both from below and above. They presented an approach focused on highly dynamic road environments combining traffic image processing with interval data for dynamic route optimization. Other authors such as [68] studied the problem of traffic congestion providing to the route planning system an equilibrium, aiming to enable future interactive transportation systems comprising urban planning applications under demand and with a real-time response. The authors stated that their approach accelerates the computation of traffic flow patterns, enabling interactive transportation. For instance, the authors claim that their approach is three times faster than that of the Dijkstra-based baseline.

III. TACTICAL LEVEL (MANEUVER PLANNING)

Maneuver planning corresponds to the tactical level of decision-making as presented in Figure 1, which is in charge of identifying and ranking the possible maneuver sequences to be performed by the vehicle. In the literature, maneuver planning can also be referred to as manoeuvre planning, behavioral planning, maneuver decision-making, behavior decision-making, or a combination of the previous. A maneuver is a high-level characterization of the motion of the vehicle regarding its behavior on the road in terms of direction and/or speed changes. Some examples of maneuvers are: go straight, turn, stop, overtake, turn around, park, keep lane, change lane, merge, wait or follow the leading vehicle. Certain maneuvers are combinations of other maneuvers. For instance, the overtake maneuver is an ordered sequence of three maneuvers: change lane, keep lane, and change lane.

Maneuver planning approaches commonly consist of the following tasks: 1) **scenario recognition**, comprising the identification of environmental constraints and motion prediction of the surrounding dynamic obstacles; and 2) **identification and ranking of feasible maneuvers**. These tasks represent most of the work in the state-of-the-art regarding decision-making. They define the criteria to determine which maneuvers can be performed by the vehicle, ranking them using evaluation criteria.

The following sections describe the algorithms and approaches used for obstacle motion prediction and for the identification and ranking of feasible maneuvers for automated driving used in the state-of-the-art during the last few years.

Second section of Table 1 summarizes the most relevant maneuver planning publications described below, which are classified in more detail in Table 3.

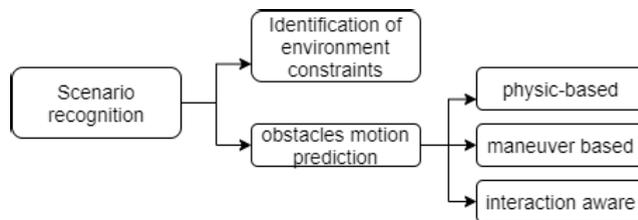


FIGURE 4. 1st stage of Maneuver Planning - Scenario recognition: comprising scenario identification and motion prediction.

A. OBSTACLES MOTION PREDICTION

Since motion prediction for obstacles also makes part of the trajectory planning tasks, this section is common to both chapters (Chapters III and IV).

Obstacles motion prediction consists of determining the future motion of dynamic obstacles in a short-term time horizon, where these obstacles may be pedestrians, bikes, motorbikes, cars, trucks, etc.

A common classification of motion prediction approaches was proposed in [70], where the authors classified them based on the kind of hypotheses they made about the modeled entities. Thus, they propose the following three-level classification with an increasing degree of abstraction:

- 1) **Physics-based motion models:** These models consider that the motion of obstacles depends only on the laws of physics. Two different evolution models can be applied: dynamics and kinematics.
- 2) **Maneuver-based motion models:** These models are more advanced since they consider that the future motion of a vehicle not only depends on the laws of physics but also on the maneuvers that the obstacles may perform, independent of the interaction with the other surrounding obstacles.
- 3) **Interaction-aware motion models:** These models are the most advanced since they take into account the interactions among obstacles including the ego-vehicle.

In the last few-years some reviews of motion prediction on automated vehicles have been published [71], where the authors present the trends in objects motion prediction and discuss the challenges and non-fulfilled gaps in the automated driving domain. In addition, research works such as [27] covered in his thesis work the state-of-the-art on motion prediction approaches.

Although the main scope of this paper is focused on decision-making and not on motion prediction, a few applications of these three motion prediction models can be found below.

1) APPLICATIONS OF PHYSICS-BASED MOTION MODELS

A tool-set for the prediction of traffic participants considering both physical constraints as traffic rules was proposed in [72]. This tool-set targets the motion prediction problem through a reachability analysis. The authors predicted both the future occupancy of other traffic participants and their maneuvers on arbitrary road networks. Hang *et al.* [21] used

TABLE 2. Mission planning works in the State-of-the-Art.

Mission Planning Algorithm	References	Description	Testing Environment		Testing Platform	
			Urban	Highway	Vehicle	Simulation
Exact algorithms:						
Dijkstra	[4]–[7], [12], [69]	Bidirectional Dijkstra for fast route planning; Valet-parking scenarios; parking; parking; Considering temporary driving restrictions; Multi-modal route planner framework;	[4]–[7]	[6], [12]	[7], [12]	[4]–[6], [12]
Dynamic Programming	[8], [62]	Time-optimal route planning; dynamic shortest path problem with travel time-dependent stochastic disruptions		[8]		[8]
Integer Linear Programming	[9], [13], [14]	Optimization for traffic jams and inconveniences; simultaneous path inference and the travel time prediction problem; evaluation of travel-time reliability	[9]	[9], [13], [14]		[9], [13]
Approximate algorithms:						
Classical Heuristics	[63]	Two-phase heuristic based Fisher and Jaikumar algorithm to solve the Capacitated Vehicle Routing Problem				
Metaheuristics	[10], [11], [69]	GA population combined with a Variable Neighborhood Search; reduction of fuel consumption optimizing both route and speed simultaneously; Multi-modal route planner framework;	[10], [11]	[10], [11]		[10], [11]

a motion prediction approach based on Model Predictive Control (MPC) for obstacle avoidance in lane change, merging and overtaking scenarios.

2) APPLICATIONS OF MANEUVER-BASED MOTION MODELS

Maneuver-based motion prediction approaches consist of two phases: first, the system predicts the maneuver being executed by moving objects; and second, the corresponding trajectory for this maneuver is calculated [27]. Izquierdo *et al.* [73] used a Support Vector Machine (SVM) classifier to predict the occurrence of a lane change three seconds before it actually occurs. Zyner *et al.* presented a supervised learning-based approach for predicting driver intentions at unsignalized intersections [74]. A prediction method based on Recurrent Neural Networks (RNNs) was used in a roundabout scenario.

3) APPLICATIONS OF INTERACTION-AWARE MOTION MODELS

A framework for motion prediction that integrates social psychology metrics was proposed in [29]. The authors used Social Value Orientation (SVO) to quantify the degree of selfishness or altruism of other drivers in order to enhance the prediction of their behavior. A probabilistic approach was presented in [18]. The authors formulated the motion prediction problem considering the uncertainty of the prediction system using a Partially Observable Markov Decision Process (POMDP) where the intended route of the surrounding vehicles are hidden variables. The proposed system determines the optimal acceleration of the ego-vehicle

along a pre-planned path. Besides predicting the motion of other vehicles, there are works such as [32] and [75] that propose an interaction-aware approach for predicting the decisions of multiple humans that interact with each other during navigation. For this purpose, the authors use the game-theory approach of Nash equilibrium to anticipate collisions with humans and propose several avoidance maneuvers. The behavior of pedestrians when negotiating the road crossings with motorized vehicles was studied in [76]. The authors presented the state-of-the-art in vehicle-pedestrian interaction and they provide an interaction process where this interaction can be divided into five different phases: monitoring of potential conflict zone, indication of pedestrian crossing intention, assessment of the environment, communication methods among them and decision of maneuver strategies for both vehicle and pedestrian. A motion prediction approach using a Long Short-Term Memory (LSTM)-based Recurrent Neural Network (RNN) for multi-lane turn intersection scenarios was proposed in [23]. The authors focused on improving the decision-making at intersections to achieve human-like accelerations with this learning approach, where the RNN is trained with data of surrounding objects and with the trajectories generated by an MPC-based motion planner for the ego-vehicle, reflecting the interactions among ego and objects. Apart from the previous methods, there is a branch of the interaction-aware motion prediction model called model-based motion prediction. This model assumes that drivers behave in a risk-averse manner, selecting the maneuvers that keep the vehicle away from collision-risk scenarios [27]. This model-based behavior is formulated using

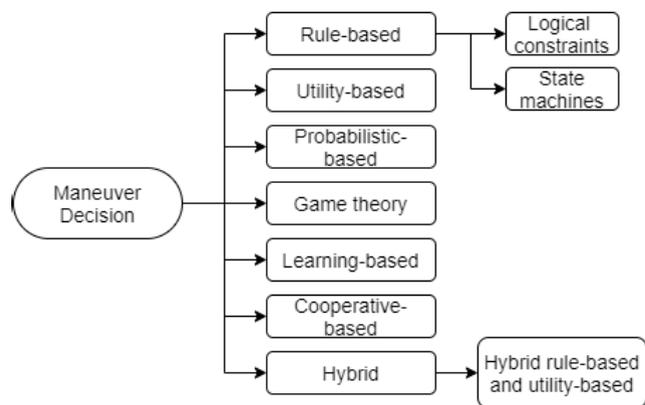


FIGURE 5. 2nd stage of Maneuver planning: Identification and ranking of feasible maneuvers: comprising decision-making.

a cost function that contains terms related to risk, comfort, or driving style.

Beyond using a single motion prediction model, some authors propose to use the most appropriate prediction model depending on a continuous evaluation of a group of motion models, searching the one that predicts better the dynamics of the object. This technique is known as Interacting Multiple Model (IMM) [77], [78]. The authors in [77] presented a unified vehicle tracking and behavior reasoning algorithm for simultaneously estimating the dynamic state of surrounding vehicles and classifying the behavior of the vehicle. Lefkopoulos et. al [78] propose an Interacting Multiple Model Kalman Filter (IMM-KF) capable of predicting collision-free trajectories of multiple traffic participants, combining the three basic motion models.

B. MANEUVER DECISION

The decision-making process in Maneuver Planning is responsible for the identification and ranking of the feasible maneuvers that the automated vehicle may perform. Figure 5 depicts a classification of the different approaches in the state-of-the-art, which are detailed below.

1) RULE BASED APPROACHES

Rule-based approaches consist of statements where there is first an observation of the environment and then the system acts consequently. The most common rule-based approaches can be divided into logical constraints and state machines.

- **Logical constraints:** Logical constraints can be understood as symbolic planning approaches, where systems are defined to solve complex tasks using inference rules, emulating logic and rational human reasoning. These logical constraints can be applied to select the maneuver that the vehicle should perform, for instance for planning lane change maneuvers as in [17].
- **State machines:** Finite State Machines (FSM) model the behavior of a system by representing the system states with actions or conditions, avoiding the declaration of a vast number of rules. Palatti *et al.* [24] targeted

safe overtaking trajectories by combining a rule-based maneuver planner using Finite State Machines and reachable sets. A predictive maneuver-planning method for navigation in public highway traffic was proposed in [25]. The proposed method integrates high-level discrete maneuver decisions, that is, lane and reference speed selection automata (state machine), using an MPC-based motion planning scheme. State machines were also used for maneuver planning in the 2016 Grand Cooperative Driving Challenge [26]. This state machine implemented the interaction protocols for the different scenarios (merging on highways, intersection crossing, and giving free passage to an emergency vehicle on highways). Recently, a maneuver planner based on finite state machines was used in [24] to seek safe overtaking maneuvers with aborting capabilities. A finite state machine based on heuristic rules is used to select an appropriate maneuver (lane keeping, overtaking or aborting), and a combination of reachable sets is used to generate intermediate reference targets based on the current maneuver.

2) UTILITY BASED APPROACHES

Utility-based approaches use heuristics to evaluate different candidate maneuvers with respect to specific objectives, that is, driving goals. These approaches use utility functions (or cost functions) to measure the level of achievement of each alternative maneuver.

Examples of utility-based approaches include optimization-based solutions such as those in [15]. The authors presented a time-optimal maneuver planning system for automatic parallel parking using a simultaneous dynamic optimization approach. A dynamic optimization method is proposed using the interior-point method which includes vehicle kinematics, physical restrictions, collision-avoidance constraints, and an optimization objective. In addition, online maneuver planning is performed via receding-horizon optimization.

A hybrid approach was presented in [16], in which a maneuver-based maneuver planner acts fused with a motion planner. After the first trajectory set is computed, the maneuver planner extracts tactical patterns depending on the spatial area where the trajectory terminates, how it gets there around the obstacles, and the overtaking order (if any) it follows.

3) PROBABILISTIC BASED APPROACHES

One of the well-known approaches to performing decision-making under uncertainty is the probabilistic-based family, where the uncertainty may be in the perception or in the non-deterministic decision effects. The decision-making process is represented as a graph. Four types of Markov models are used depending on the context: the Hidden Markov Model (HMM) and Partially Observable Markov Decision Process (POMDP) if the states are not completely observable. Meanwhile, if the states are completely observable, the

models used are the Markov chain and Markov Decision Process (MDP). However, since uncertainty is always present in automated driving, the first two models are the most commonly used. The difference between HMM and POMDP lies in the control over the state transitions: in the HMM model we do not have control over the transitions, whereas in POMDP we do have it.

A method for making automated longitudinal decisions along a predetermined path for automated driving in unsignalized urban scenarios was proposed in [19]. The author deals with this decision-making problem in dynamic and uncertain environments using a continuous POMDP with a discrete Bayesian Network to estimate the behavior of the surrounding traffic participants. By means of this probabilistic approach the author deals with uncertainty, anticipating the behavior of occluded vehicles and detecting possible collisions. The decision-making approach proposed in [20] uses an online POMDP to consider the interaction and uncertainty in the prediction on intersections. Another online decision-making approach for highway scenarios was proposed in [27]. The author aimed to provide human-like behavior to the system by means of a POMDP with a behavioral model learned from demonstrated driving data. Schmidt *et al.* presented a probabilistic approach for planning lane change maneuvers in highway driving scenarios, where the model quantifies the utility of lane changes [28].

4) GAME-THEORY BASED APPROACHES

Game-theoretic approaches for decision-making consist of building a tree for the decision-making process with discrete action primitives to model vehicle behavior to maximize the expected utility through a reward or utility function.

A game-theoretic approach for uncertain scenarios such as merging maneuvers in high-density traffic was presented in [30]. The authors propose an interactive, multi-player level-k model that uses cognitive hierarchy reasoning for decision-making, modeling human decisions in uncertain situations. In this way, they aimed to anticipate both the actions of the surrounding vehicles as their reactions to the automated ego-vehicle movement. A human-like decision-making framework based on game-theory was proposed in [21]. The Nash equilibrium and Stackelberg game-theory are applied to non-cooperative decision-making in intersections. The authors consider the acceleration and deceleration behaviors of obstacles in the modeling process to decide whether the automated vehicle has to change lanes or not, without considering the lane change intention of the moving obstacles in the scene. A game-theory based approach for decision-making in congested urban intersection was presented in [22]. The authors focused on deciding on the lane change maneuver, proposing a dynamic non-cooperative game that uses acceleration as part of the player set of strategies, aiming to allow lane changes even when the destination lane is occupied.

5) LEARNING-BASED APPROACHES

Learning-based approaches are based on a Neural Network trained for a specific purpose. An interaction-aware end-to-end deep reinforcement learning approach was proposed in [31]. This work focused on enhancing traffic flow and safety by inducing altruism in the decision-making process, focusing on merging scenarios such as the incorporation into highways. The automated vehicle learns if performing a lane change is more convenient for allowing the other vehicles to merge in the lane. Some specific reviews on the state of the art covering decision-making strategies including maneuver-planning approaches have been presented recently in [79] and [80].

6) COOPERATIVE BASED APPROACHES

Cooperative based approaches use V2V communications to reduce the uncertainty about the motion of the surrounding objects and therefore, solve conflict situations with multiple vehicles. Hess *et al.* proposed a cooperative maneuver planning approach for planning lane following and lane change maneuvers using V2V communication allowing to negotiate space-time reservations in conflict areas. This cooperation allows the cooperating vehicle to keep the lane decelerating and the requesting vehicle to change lane to the other vehicle's lane avoiding further collisions [81]. The authors in [82] discussed the challenges of cooperative driving and proposed a system called COMPACT to deal with maneuver planning. They focused on the overtaking scenario on secondary roads with traffic in front and compared their approach with elastic bands and tree search based algorithms, stating that their approach maximizes distances between objects as the two other vehicles yield, drive to their right road boundary and decelerate. A two-dimensional maneuver planner in a distributed predictive control framework was proposed in [83] to reduce energy consumption through traffic motion harmonization, thereby improving traffic flow and travel time. The approach includes explicit coordination constraints between the connected vehicles driving in mixed traffic on multi-lane roads.

IV. OPERATIONAL LEVEL (MOTION PLANNING)

Motion planning corresponds to the operational level of decision-making as presented in Figure 1. It is responsible for defining the sequence of vehicle configurations (position and orientation in time) that allow the vehicle to move from the current position up to the planning horizon, considering both vehicle and environment constraints. In the state-of-the-art, motion planning can be referred to as trajectory planning equivalently.

Motion planning consists of two tasks: path planning, searching the path in the vehicle's configuration space; and speed planning, generating a speed profile, that is, defining a speed (plan in time) per space configuration. These tasks can be performed either sequentially or simultaneously, as explained in the following subsections.

TABLE 3. Maneuver planning works in the SoA.

Maneuver Planning Algorithm	References	Description	Testing Environment		Testing Platform	
			Urban	Highway	Vehicle	Simulation
Rule-based approaches	[17], [24], [25], [26]	Logical-constraints for lane changes; Finite State Machines for overtaking maneuvers; predictive lane and reference speed selection state machine in highway traffic; state machine for merging on highway, intersection crossing and give free passage to emergency vehicles		[17], [24], [25], [26]	[17], [26]	[17], [24], [25], [26]
Utility-based approaches	[21], [15], [16]	Cost function for lane change decision making; receding-horizon multi-objective optimization for automatic parallel parking; fused decision making and trajectory planning with cost function deciding on maneuver-based tactical patterns; Utility function for mandatory, discretionary and anticipatory lane change decisions	[15], [16], [17]	[17]	[17]	[15], [16], [17]
Probabilistic-based approaches	[18], [27], [28], [19], [20]	POMDP for uncertain environments; POMDP based on Monte-Carlo tree search for decision-making in highways; probabilistic model for lane change maneuver in highways; POMDP with discrete Bayesian network for decision making in dynamic and uncertain unsignalized urban environments; online POMDP considering uncertainty on intersections.	[18], [19], [20]	[27], [28]	[27]	[18], [27], [28], [19], [20]
Game-theory based approaches	[21], [75], [30], [22]	Noncooperative game methods for decision making (Nash equilibrium, Stackelberg game); Nash-equilibrium based decision-making with Nash equilibrium and SVO; Nash-equilibrium interaction-aware decision making for human avoidance; multi-player model for merge maneuver in high traffic; decision-making for lane changes in congested urban scenarios.	[21], [22]	[21], [29], [30]	[32]	[21], [30], [22]
Learning-based approaches	[23], [31]	LSTM-RNN motion prediction model at multi-lane turn intersections; cooperative altruistic maneuver planning	[23]	[31]	[23]	[31]
Cooperative-based approaches	[81], [82], [83]	cooperative approach using V2V communication for lane following and lane change maneuvers; COMPACT system focused on overtaking scenario in secondary roads with in-front traffic; Two-dimensional maneuver planner into distributed predictive control framework to reduce energy consumption	[81]	[82], [83]	[81]	[81], [82], [83]

Motion planning allows the vehicle to adapt to uncertain and incomplete environments, both static and dynamic, where a real-time response is necessary to ensure harmless motion. It considers the vehicle, environment and time horizon constraints. As a result, the generated motion must be smooth not only for better tracking in the control stage, but also for increasing the passenger comfort and automated driving acceptance.

Motion planning approaches can be classified based on different criteria. In the following sections we present two different classifications: (i) Classification based on the vehicle architecture, (ii) Classification based on the spatio-temporal order in the trajectory generation.

Third section of Table 1 summarizes the most relevant motion planning publications described below, which are classified in more detail in Table 4.

A. CLASSIFICATION BASED ON THE VEHICLE ARCHITECTURE

According to the architectures for decision-making presented in Figure 2, planning approaches can be divided into three different types depending on the architecture: sequential, behavior-aware or end-to-end planning.

Motion planning in both sequential and parallel hierarchical approaches can be mostly found in the modules highlighted in green in Figure 6.

Sequential approaches (left part of Figure 6) are the most common method for representing motion planning in automated driving. The motion planner receives from the upper stage both the information from the perception as well as the ranked maneuvers from the behavioral planning (at the tactical level), and it generates the trajectory or trajectories that are sent to the control of the vehicle as output to the next stage.

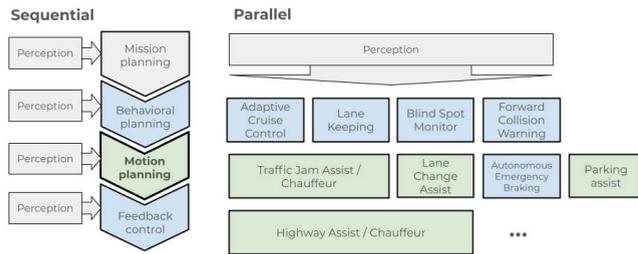


FIGURE 6. Hierarchical Planning: Sequential planning and Parallel planning.

Parallel approaches (right part of Figure 6) consist of grouping the different automated driving functions into Advanced Driving Assistance Systems (ADAS). These ADAS can be considered as individual functions or a combination of multiple functions that can be executed in an automated vehicle. For instance, the Traffic Jam Assist is formed by an Adaptive Cruise Control (ACC) module plus a Lane Keeping module. A few examples of modules (ADAS) where we can find motion planning algorithms are as follows: Traffic Jam Assist/Chauffeur, Lane Change Assist, Parking Assist, or Highway Assist. This is the most common way to represent functions when different levels of automated driving are presented.

The behavior-aware or interaction-aware approaches in Figure 2 consider that both maneuver and motion planning tasks are performed in the same stage. Since the maneuver planning approaches were already presented in the previous chapter, we only focused on motion planning algorithms. These are usually game-theoretic or probabilistic based approaches.

Finally, end-to-end planning approaches represent all learning-based approaches, as shown in Figure 2. Some relevant works are presented in the following sub-section, under the learning-based classification.

B. CLASSIFICATION BASED ON THE SPATIO-TEMPORAL ORDER IN THE TRAJECTORY GENERATION

As stated at the beginning of this chapter, motion planning consists of generating both the geometry path (planning in space) and the speed profile (planning in time) to be followed by the vehicle controller. These subtasks can be performed sequentially or simultaneously. On the one hand, in the sequential case the alternatives are: (i) generating the path and then the speed profile, or (ii) generating the speed profile and then finding a path to follow it. On the other hand, for simultaneous approaches both path and speed profile are generated at the same time.

These approaches can also be classified according to the algorithm used for the trajectory generation. Among them, we can distinguish the following approaches:

- (i) Interpolating-curve based: These methods are based on the interpolation of several curves forming the path or even the speed profile. According to [64], these methods

can also be called functional methods and can be divided into closed-form functional methods (methods whose coordinates have a closed-form expression) and parametric functional methods (methods whose curvature is defined as a parametric curve, which is a function of their arc length). The most common closed-form methods are polynomials, Bézier curves, splines and nurbs; and the most common parametric methods are Dubins path, clothoids, cubic spirals and quintic G^2 splines.

- (ii) Graph-search based: These methods aim to find the optimal route on a graph and are mostly used for route planning (as seen in Chapter II). However, some of these methods can also be applied for local planning (such as A^*) in static environments such as parking lots.
- (iii) Sampling-based: These methods explore the configuration space using either deterministic or probabilistic patterns to divide the vehicle-configuration search. Among these methods we can highlight Probabilistic Roadmaps (PRM), Rapidly-Exploring Random Trees (RRT), enhanced RRT (RRT*), and Artificial Potential Fields (APF).
- (iv) Optimization-based: These methods are based on mathematical optimization techniques for solving the motion planning problem. The most common optimization method used for automated driving is Model Predictive Control (MPC), which is used for motion planning, vehicle control, or both simultaneously.
- (v) Learning-based: These methods correspond to the end-to-end architectural model presented in Figure 2. These methods are based on artificial intelligence approaches aimed at mimicking the driving behavior of humans, as presented in Chapter I.

Prior surveys [84], [85], [86], [87] studied motion planning approaches up to 2017. Additionally, other surveys such as [88] focused on highway environments only. In this section we cover the work conducted during the last few years in the entire automated driving domain.

1) PATH PLANNING BEFORE SPEED PLANNING APPROACHES

A trajectory generation approach for urban environments based on interpolation of consecutive quintic Bézier curves was proposed in [33]. The authors used quintic Bézier curves since they ensure G^2 geometric continuity (the curves share the same tangent direction and curvature at the joint point) to provide comfort for motion. For this purpose, the authors used the Douglas-Peucker algorithm to compute the reference points for generating the set of quintic Bézier curves that will be interpolated to generate the path inside a corridor. They then evaluated the candidate paths and checked if there was a risk of collision with either static or dynamic obstacles. In case of collision risk with a static obstacle, a set of collision avoidance curves was generated by changing the position of the point perpendicular to the obstacle in the lane. In the case of collision risk with a dynamic obstacle, they analyzed

the type of scenario (perpendicular obstacle, obstacle moving in the same direction, or obstacle moving in the opposite direction to the vehicle). Additionally, the authors computed a speed profile for the generated path by first generating a speed limit curve that considered both the maximum road speed and the maximum curvature of the vehicle. Then, authors check the longitudinal acceleration assuming a uniform acceleration between consecutive points. Finally, the generated speed profile is under the speed limit curve while respecting the maximum lateral acceleration and maximum speed.

Quartic Bézier curves were used in [89] to generate a smooth path for optimizing consecutive curves ensuring a continuous transition between them by limiting the curvature derivative at the joint point. The author focuses on urban scenarios where several consecutive turns make the system adapt in real-time, proposing a virtual lane framework where the local path is generated into their limits, being recomputed for obstacle avoidance if needed.

B-spline curves were used in [34] to interpolate the centerline of the reference lane after optimization using the conjugate gradient nonlinear optimization algorithm. Subsequently, a set of path candidates is generated on the reference path using the curvilinear coordinate system (Frenet frame), and a hierarchical velocity profile strategy is defined to generate the speed profile according to the specific urban driving situation by using trapezoidal (S-shaped) ramp-up and ramp-down profiles employing cubic polynomial splines, considering the road speed limit constraint.

Clothoids were used in [35] as the primitive for generating a set of possible local paths (tentacles) in dynamic environments to follow a reference trajectory and avoid obstacles on it. The candidate paths are evaluated using the reward system of a Markov Decision Process model regarding several criteria, including the uncertainty represented by the evidential occupancy grid used for modeling the environment that includes the information of the surrounding obstacles.

A special geometric technique based on discrete shape patterns built by assembling circular arcs, line segments and clothoids was proposed in [36] for collision avoidance in real driving scenarios. The authors aimed to generate robust and rapid trajectories by discretizing continuous trajectories to polygonal chains via the deflection of their edges.

Although most graph-search based planning approaches in automated driving focus on the route planning problem, there are some works that combine graph-search methods for motion planning. State lattices allow the discretization of the configuration space of the vehicle as directed graphs, where a local path generation method can be applied to direct the search. For instance, a state-lattice based trajectory planner was proposed in [49] to precompute a set of paths using splines over the generated state lattice to generate fast real-time planning in semi-structured race environments. The A* graph-search method can also be applied to local planning. It was combined with RRT for the navigation of an automated vehicle through an unmapped road scenario in [38].

An evidential occupancy grid was used in [35] to model the environment and represent the uncertainty produced by surrounding obstacles. It serves to determine the path candidates (clothoid tentacles) that are navigable. Chebly also proposed a motion planning approach using the tentacles method with a clothoid form in [48]. The author combined navigation through clothoid tentacles selection with a high-level maneuver planner for the obstacle avoidance application. Yu *et al.* [39] proposed a layered motion planning framework that handles geometry, nonholonomic and dynamic constraints with distinct methods. After a global path modification layer is used to solve the geometric constraints, a multiple phase sampling layer is performed generating an occupancy grid map. The authors combined this occupancy-grid based discretization with an optimization based path generation to consider the nonholonomic constraints. Finally, they solved the speed planning over the path to solve the dynamic constraints as a convex optimization problem. Gu *et al.* proposed a sampling-based motion planner fused with a tactical maneuver discovery reasoning in [16]. Distinct tactical maneuver patterns are extracted from the set of feasible trajectories computed via path generation primitives such as splines (both for path and speed profile). A cost function is then used to choose the final trajectory into the more appropriate tactical pattern set.

Risk assessment is an important element in the evaluation of candidate paths using sampling-based approaches. Pierson *et al.* [90] applied risk level sets to measure driving congestion, learning the common risk thresholds from the NGSIM and highD driving datasets to classify risk situations into low, medium and high risk. Qin *et al.* [91] focused on the risk analysis. The authors formulated a safety assessment of the actions of a level 3 automated vehicle with respect to its environment as constrained optimization problems, solved using Dynamic Programming algorithms. For that purpose, they divided risk into longitudinal risk and lateral risk, regarding the collision risk with the intermediate front object and the risk of crossing the lane boundaries, respectively. A safety verification system for merge and crossing scenarios was presented in [92]. The authors present a Responsibility-Sensitive Safety (RSS) system and integrate the defined safety constraints into motion planning with reachable sets.

Baidu Apollo [40] presented a planning approach in which both path and speed profile were generated by solving optimization problems iteratively, combining dynamic programming with spline-based quadratic programming. The authors used the Expectation Maximization (EM) algorithm at the lane level for both the path and speed profile. A convex-optimization based approach was proposed in [41] to generate an optimal speed profile over a fixed path in both static and dynamic driving environments. This speed planner optimizes the performance from three aspects: smoothness, time efficiency and speed deviation. For this purpose, it considers three types of constraints: soft (smoothness, time efficiency, speed deviations), hard (friction circle, path constraints, time window and boundary condition) and semi-hard constraints

(comfort box). A speed planner based on an optimal control approach to enhance passenger comfort by minimizing the jerk was presented in [50]. The authors used the minimum time control method to generate a continuous and smooth speed profile. This method is equivalent to the well-known Jerk Limitation method when used under the same conditions. A game-theoretic based motion planner was presented in [46] combined with an online parameter estimator, called LUCIDGames. It estimates the objective function parameters of other objects, allowing an automated vehicle to negotiate complex driving scenarios while interacting with other vehicles. A robust trajectory planning scheme using the ALGAMES dynamic game solver was proposed to enforce safety constraints that account for uncertainty.

In recent years, the automated driving community has not only focused on optimizing the trajectory generation for the ego-vehicle by itself, but also on cooperating with the surrounding vehicles, aiming to conceive future smart cities where connectivity is a must. The PhD work in [93] explored motion planning approaches for cooperative and autonomous vehicles. The author presents a review of the state-of-the-art in cooperative approaches, and proposes a decision-making algorithm to coordinate up to twelve autonomous or semi-autonomous vehicles using the mixed-integer programming optimization method.

The next group of approaches is learning-based approaches. As described previously, there are four types of sub-models that try to mimic human driving. For instance, authors in [47] formulated the planning problem as a constrained Markov Decision Process focusing on learning the driving constraints from human driving trajectories, instead of defining them manually in the cost function. An end-to-end interpretable neural motion planner was presented in [43] dealing with traffic lights, yields and populated intersections as urban scenarios. An end-to-mid approach was presented in [44] for planning the trajectory of the ego-vehicle and predicting the trajectories of the surrounding objects by using a probabilistic approach with a Gaussian mixture motion prediction model constrained by a polynomial formulation. There are other learning-based approaches such as [45] that focus on analyzing trajectories from real driving data in order to train an LSTM model for predicting early failures in the trajectory generation. Finally, some reviews of deep reinforcement learning approaches applied for motion planning have been published recently such as [79], [94], [95], and [80].

2) SPEED PLANNING BEFORE PATH PLANNING APPROACHES

This approach consists of first specifying a desired speed profile and then finding a feasible collision-free path. For this purpose, this strategy has been mostly used in non-structured or semi-structured environments, where the available driving space is not strongly defined by lane markings. Therefore, this strategy is mostly used in the robotics navigation problem, but not in automated driving. De Beaucorps *et al.* applied Reachable Interaction Sets (RIS) and Bézier curves in highly

dynamic environments to plan collision-free trajectories for car-like robots. First, the RIS constrains free space by considering the risk of collision among the obstacles and the ego-vehicle; and secondly, a path is computed by the interpolation of Bézier curves surrounding the RIS and allowing the robot to move up to its destination [37]

3) SIMULTANEOUS PATH AND SPEED PLANNING APPROACHES

To better account for the interaction between the ego-vehicle and surrounding objects, some works add time as a dimension in the configuration space in order to plan simultaneously the path and speed, increasing the problem complexity. Model Predictive Control (MPC) based approaches are the most common for simultaneous path and speed planning, as well as for simultaneous planning and tracking. An MPC based method was presented in [42] for obstacle avoidance scenarios, where the reference trajectory was determined considering both the lateral position and velocity of the ego vehicle and the velocity and yaw angle of the obstacle, and it was parameterized as a cubic function in time.

V. STABILITY LEVEL (CONTROL)

The stability level corresponds to the last level of the decision-making pyramid presented in Figure 1, where control strategies are applied to select and track a reference input. In automated driving, this input can be a path, speed profile, trajectories (paths with speed profile), objects (e.g. vehicles) or lanes. For each input, the control system selects the reference to be tracked, and a control law is then applied to stabilize the vehicle around the selected reference. Thus, control systems for decision-making are more reactive than the previous levels in the pyramid, operating in a few tens of milliseconds to command the vehicle actuators. This command is often calculated in two control steps: high-level control, which computes the motion commands to follow the reference input; and low-level control, which computes the actuator commands from the motion commands. This separation allows high-level control to be independent of the actuators and accounts for the reusability. Additionally, in the automated driving domain there are two main types of control: decoupled control, where longitudinal and lateral references are tracked by two independent controllers; and coupled, where there is one single control law that tracks both longitudinal and lateral references.

Since the main focus of this work is on the strategic (route), tactical (maneuver) and operational (trajectory) levels, we refer to some of the latest and more relevant reviews of the state-of-the-art in control approaches: a historical review of lateral and longitudinal control focused on lane following, lane keeping and lane change maneuvers was presented in [96]; a review on control of connected vehicles was studied in [97]; a survey on longitudinal control of multiple connected vehicles was presented in [98]; and a survey on lateral control was carried out in [99]. Additionally, a deep learning-based control review was recently published in [100].

TABLE 4. Motion planning works in the SoA.

Motion Planning	References	Description	Testing Environment		Testing Platform	
			Urban	Highway	Vehicle	Simulation
Interpolating curves	[33], [89], [34], [35], [36], [37]	Interpolation of quintic Bézier curves for trajectory planning in urban environments; interpolation of consecutive quartic Bézier curves optimizing consecutive curves for generation smooth trajectories; B-spline curves for the interpolation of centerline of reference lane for candidate paths generation. Cubic polynomial splines for speed profile generation; Clothoids based path tentacles in dynamic environments for obstacle avoidance; assembling of circular arcs, line segments and clothoids for collision avoidance; RIS combined with Bézier curves for path generation in semi-constrained highly dynamic environments	[33], [34], [35], [36], [37]	[35]	[33], [34], [35], [36], [37]	[35], [36], [37]
Graph-search based	[49], [38]	State lattices based discretization combined with splines for the paths set generation for fast real-time planning in semi-structured environments; A* graph-search combined with RRT for the navigation of an AV through an unmapped road scenario	[38]	[38]	[38]	[49], [38]
Sampling-based	[35], [48], [39], [16]	Evidential occupancy grid for modeling the environment and allowing to represent the uncertainty, combined with clothoid tentacles; navigation through clothoid tentacles selection with a high-level maneuver planner for the obstacle avoidance application; occupancy grid discretization with optimization based path generation; sampling-based motion planner with tactical maneuver discovery reasoning	[39], [16]	[35]	[35], [48]	[35], [48], [39], [16]
Optimization-based	[40], [41], [50], [42]	Path and speed profile generation by iterative optimization, combining dynamic programming with quadratic splines; convex optimization for optimal speed profile generation for static and dynamic environments; speed profile generation based on optimal control; MPC-based simultaneous path and speed planning for obstacle avoidance scenarios	[40], [41], [42]	[42]	[40], [42]	[40], [41], [50]
Game-theory based	[46]	LUCIDGames game-theoretic motion planner combined with online parameter estimator for navigation in complex scenarios interacting with other vehicles		[46]		[46]
Learning-based	[47], [43], [44], [45]	Constrained Markov Decision Process focusing on learning the driving constraints from human driving trajectories; end-to-end interpretable neural motion planner dealing with traffic lights, yields and populated intersections as urban scenarios; end-to-mid probabilistic probabilistic approach for both planning and prediction; analysis of real driving trajectories for predicting early failures through a LSTM model	[43], [44], [45]	[47], [45]		[47], [43], [44], [45]

However, there are certain works in the state-of-the-art where both motion planning (operational level) and tracking (stability level) are performed simultaneously. Therefore, we want to highlight some of the works below. Model Predictive Control (MPC) based approaches are the most common for simultaneous trajectory planning and tracking. Some MPC-based solutions for obstacle avoidance scenarios were presented in [42], [101], and [102]. An MPC-based approach for motion planning in overtake scenarios was presented in [24]. The authors combined reachable sets, to iteratively generate reference targets based on the current maneuver, together with a nonlinear MPC to perform collision-free

trajectories in overtaking scenarios with capabilities for aborting the maneuver to merge back in the lane.

In addition to MPC, optimal control methods such as the Linear Quadratic Regulator (LQR) controller can be used for simultaneous planning and tracking. An Adaptive Constrained Iterative LQR based motion planning was used in [103] in obstacle avoidance scenarios, considering a two-stage uncertainty aware prediction.

VI. TRENDS AND CONCLUSION

In this state-of-the-art review, more than 100 scientific articles written in the last lustrum were studied. These studies

have shown the capacity of artificial intelligence-based algorithms to solve decision-making problems applied to automated driving. Although the Vehicle Route Planning Problem can be considered a solved problem (see the stagnation of works in recent years in Figure 8), there is still work to be done in local planning methods, that deal with dynamic environments. Indeed, to make these local decision-making and planning systems more robust, and thus increase their reliability and the level of acceptance by potential customers, some of the unsolved challenges are:

- An enhancement of the motion prediction approaches, considering the interaction between the ego-vehicle and the relevant surrounding objects and acting differently according to the type of object (vulnerable road user, motorbike, car, bus, truck, etc) and the type of scenario (urban intersection, roundabout, stop, yield, lane following, lane change, overtaking, obstacle avoidance, etc). In particular, most interaction-aware approaches focus on the interactions among vehicles. Better interaction models, particularly for interaction with Vulnerable Road Users (VRUs). For instance, [76] presented a review of pedestrian crossing uniquely applied to roadways.
- The robustness of current decision-making algorithms must be improved to cover more diverse driving scenarios. Current works have largely treated specific driving scenarios: either for urban driving (intersections, obstacle avoidance, parking) or highway driving (lane following, stop in lane, minimum risk maneuver). However, their performance when switching between different scenarios and handling new contexts has not yet been sufficiently demonstrated. For instance, these systems should adapt to different changes in the road surface, weather and other environmental conditions.
- Furthermore, robustness in decision-making need to be enhanced by considering the uncertainty and incompleteness of perception and maps. Although some probabilistic-based approaches have been studied [19], [27], [35], they are usually constrained either to simulations or very specific driving scenarios.
- The integration of more human factors in the decision-making process (such as driving profiles and driver condition) is needed to provide more human-like behavior and better predict the intentions of other road users, increasing the acceptance of automated vehicles, particularly when sharing the road with non automated road users [104].
- In recent years, the trend in research has been to use learning-based methods for decision making and planning in automated driving, achieving good results in some specific scenarios. These approaches depend directly on the training phase and require large training datasets that reflect the environment where the vehicle will be deployed. In addition, learning-based approaches have not yet been certified in terms of verifiability, safety and explainability. Currently,

no deep-learning method applied to decision making and planning has been integrated into production systems.

Automated vehicles will continue to affect passenger road transport in the short term. Their impact on urban development and relevant challenges were studied in [105]. Among these challenges we can highlight the following aspects: (i) Accessibility: Automated vehicles will have to adapt to operate as either private, shared or public means of transport. (ii) Traffic: AVs have the opportunity to free public space and serve areas of limited roadway capacity. (iii) Infrastructure: AVs will ease the development of new urban infrastructure, integrate the AV network into energy and telecommunication networks, developing smart cities.

In terms of communications, V2X systems are still under development and they have the potential to improve the decision-making process [106]. For instance, communicating the position, orientation, speed, route or maneuver intention of vehicles among them would provide precise information to complete the current prediction systems.

The Dimensions.ai website [107] was used to quantify the number of research publications from 2000 to 2021 for the three planning levels (route, maneuver, and motion) as well as in decision-making in general term, with special emphasis on the last lustrum, highlighted in gray. The search queries used for generating the Figures 7-10 are regular expressions that include all the previous terms for decision making, and for each specific topic they include the terms related to the methods indicated in each Figure. Additionally, we ensure that in the search there is either the term *automated driving* or *autonomous vehicle* or any of their combinations, to ensure the coverage of only AV applications.

Figure 7 shows the evolution of decision-making in automated driving. This figure shows the number of publications per year containing in the title or abstract the *decision-making* general term (depicted in yellow) and the specific terms (and their equivalences) for each level of decision-making, i.e. *route planning* (in blue), *maneuver planning* (in orange) and *motion planning* (in green).

As can be inferred from the figure, research on decision-making for automated driving has shown a growing trend during the last lustrum, from less than 100 publications in 2016 to over 500 publications in 2021. Although energy-efficient route planning approaches have been studied in recent years, research on *route planning* has had almost no growth in terms of *motion planning* and *decision-making* in general. It should also be noted that *maneuver planning* publications by themselves are not so numerous because we usually refer to them as decision-making systems in the state-of-the-art.

In terms of Route Planning, Figure 8 shows that exact algorithms remain the most commonly used, where Dijkstra's algorithm is still the most common choice for route planning. In addition, the impact of metaheuristic algorithms has significantly increased in the last five years, from less than 200 publications in 2016 to over 800 in 2021.

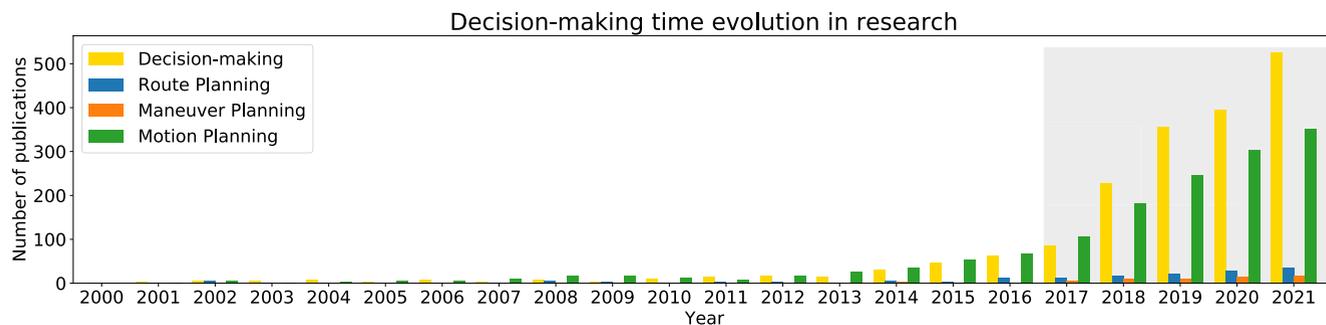


FIGURE 7. Decision-making evolution in time.

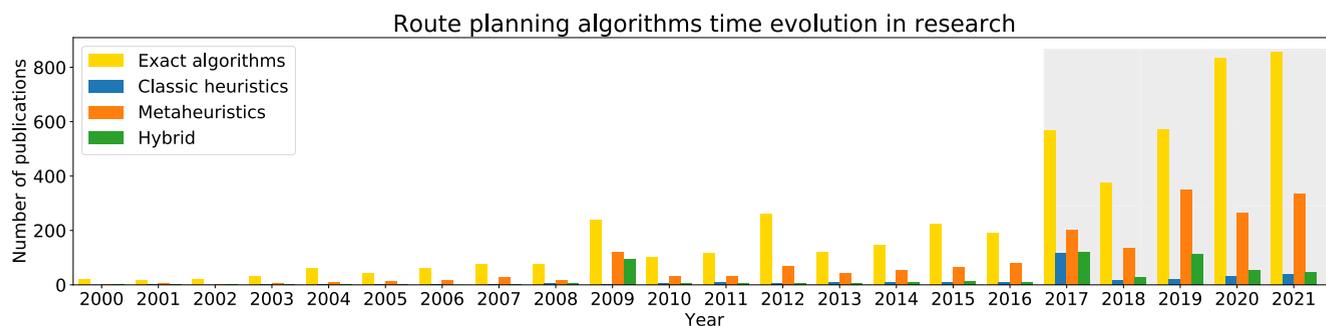


FIGURE 8. Route planning algorithms evolution in time.

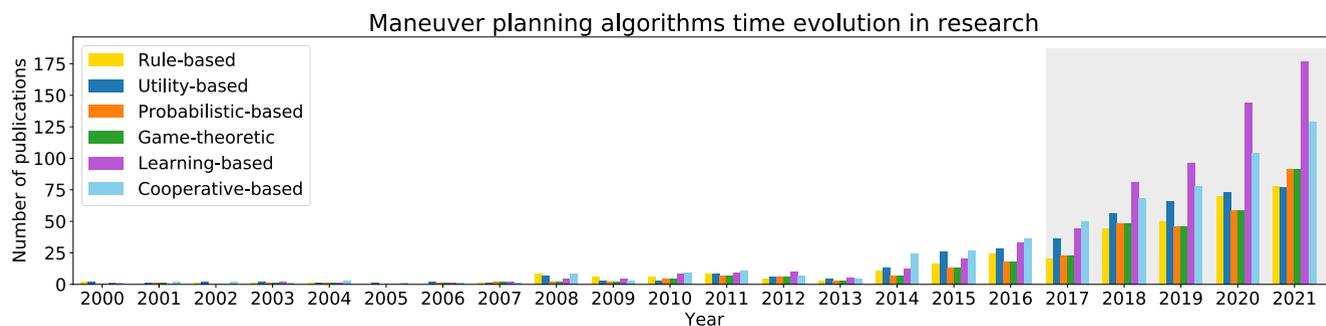


FIGURE 9. Maneuver planning algorithms evolution in time.

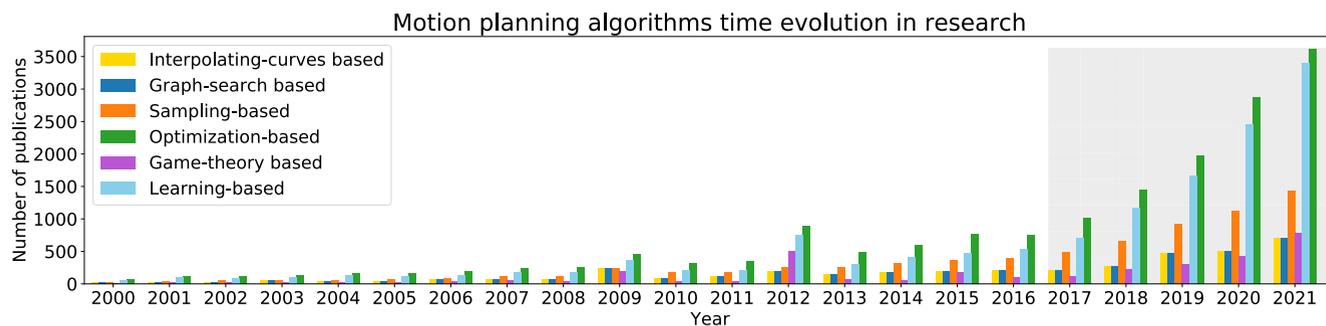


FIGURE 10. Motion planning algorithms evolution in time.

The maneuver planning algorithms data depicted in Figure 9 show a clear trend towards learning-based algorithms. Since 2014 cooperative-based approaches have become more popular, but since 2018 leaning-based approaches have surpassed all others, passing from around 30 research works in 2017 to over 175 in 2021. However, the growth of most classical algorithms (rule-based and utility-based) has appeared to stall in the last few years.

Finally, motion planning algorithms with higher growth and most used in the last lustrum are optimization-based and learning-based.

The reason why optimization-based algorithms have kept the lead since the early 2000s may be a consequence of their versatility and multi-purpose application: they are suitable not only for trajectory planning, but also for control, trajectory smoothing or even motion prediction. Learning-based algorithms have also grown at almost the same pace, from around 500 publications in 2016 to approximately 3500 in 2021, as depicted in Figure 10.

REFERENCES

- [1] R. A. Brooks, "New approaches to robotics," *Science*, vol. 253, no. 5025, pp. 1227–1232, 1991. [Online]. Available: <https://www.science.org/doi/abs/10.1126/science.253.5025.1227>
- [2] G. R. Jones and G. R. Jones, *Organizational Theory, Design, and Change*. Saddle River, NJ, USA: Pearson, 2013.
- [3] W. Schwarting, J. Alonso-Mora, and D. Rus, "Planning and decision-making for autonomous vehicles," *Annu. Rev. Control, Robot., Auto. Syst.*, vol. 1, pp. 187–210, May 2018. [Online]. Available: <https://doi.org/10.1146/annurev-control-060117-105157>
- [4] L. Yu, H. Jiang, and L. Hua, "Anti-congestion route planning scheme based on Dijkstra algorithm for automatic valet parking system," *Appl. Sci.*, vol. 9, no. 23, p. 5016, 2019. [Online]. Available: <https://www.mdpi.com/2076-3417/9/23/5016>
- [5] Z. Liu, Y. Yang, D. Li, X. Li, X. Lv, and X. Chen, "Design and implementation of the optimization algorithm in the layout of parking lot guidance," in *Proc. 16th Int. Conf. Comput. Intell. Secur. (CIS)*, 2020, pp. 144–148.
- [6] A. Kleff, F. Schulz, J. Wagenblatt, and T. Zeitz, "Efficient route planning with temporary driving bans, road closures, and rated parking areas," 2020, *arXiv:2004.09163*.
- [7] J. Sun, Z. Wang, Y. Xu, X. Li, and Z. Tang, "Design and implementation of urban parking path planning system," in *Proc. 2nd Int. Symp. Manag. Social Sci. (ISMSS)*, 2020, pp. 82–90, doi: [10.2991/assehr.k.201202.101](https://doi.org/10.2991/assehr.k.201202.101).
- [8] X. Zeng and J. Wang, "Globally energy-optimal speed planning for road vehicles on a given route," *Transp. Res. C, Emerg. Technol.*, vol. 93, pp. 148–160, Aug. 2018. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S0968090X18307484>
- [9] E. Angelelli, I. Arsik, V. Morandi, M. Savelsbergh, and M. G. Speranza, "Proactive route guidance to avoid congestion," *Transp. Res. B, Methodol.*, vol. 94, pp. 1–21, Dec. 2016. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S0191261515300357>
- [10] O. Dib, M.-A. Manier, L. Moalic, and A. Caminada, "Combining VNS with genetic algorithm to solve the one-to-one routing issue in road networks," *Comput. Oper. Res.*, vol. 78, pp. 420–430, Feb. 2017. [Online]. Available: <https://hal.archives-ouvertes.fr/hal-01761034>
- [11] C. Miao, H. Liu, G. G. Zhu, and H. Chen, "Connectivity-based optimization of vehicle route and speed for improved fuel economy," *Transp. Res. C, Emerg. Technol.*, vol. 91, pp. 353–368, Jun. 2018. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S0968090X1830500X>
- [12] F. Söderberg, "Route planning for heavy vehicles on real world maps," p. 46, Tech. Rep., 2020.
- [13] M. Rahmani, H. N. Koutsopoulos, and E. Jenelius, "Travel time estimation from sparse floating car data with consistent path inference: A fixed point approach," *Transp. Res. C, Emerg. Technol.*, vol. 85, pp. 628–643, Dec. 2017. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S0968090X17302863>
- [14] S.-B. Lee, S. M. Lee, and K.-Y. Lee, "A Gini coefficient based evaluation on the reliability of travel time forecasting," *J. King Saud Univ.-Eng. Sci.*, vol. 31, no. 4, pp. 314–319, Oct. 2019. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S1018363917303045>
- [15] B. Li, K. Wang, and Z. Shao, "Time-optimal maneuver planning in automatic parallel parking using a simultaneous dynamic optimization approach," *IEEE Trans. Intell. Transp. Syst.*, vol. 17, no. 11, pp. 3263–3274, Nov. 2016.
- [16] T. Gu, J. M. Dolan, and J.-W. Lee, "Automated tactical maneuver discovery, reasoning and trajectory planning for autonomous driving," in *Proc. IEEE/RSJ Int. Conf. Intell. Robots Syst. (IROS)*, Oct. 2016, pp. 5474–5480.
- [17] J. Nilsson, J. Silfvlin, M. Brannstrom, E. Coelingh, and J. Fredriksson, "If, when, and how to perform lane change maneuvers on highways," *IEEE Intell. Transp. Syst. Mag.*, vol. 8, no. 4, pp. 68–78, Oct. 2016.
- [18] C. Hubmann, J. Schulz, M. Becker, D. Althoff, and C. Stiller, "Automated driving in uncertain environments: Planning with interaction and uncertain maneuver prediction," *IEEE Trans. Intell. Vehicles*, vol. 3, no. 1, pp. 5–17, Mar. 2018.
- [19] J. Chandiramani, "Decision making under uncertainty for automated vehicles in urban situations master of science thesis for the degree of master of science in systems and control at Delft university of technology," M.S. thesis, 2017.
- [20] C. Hubmann, M. Becker, D. Althoff, D. Lenz, and C. Stiller, "Decision making for autonomous driving considering interaction and uncertain prediction of surrounding vehicles," in *Proc. IEEE Intell. Vehicles Symp. (IV)*, Jun. 2017, pp. 1671–1678.
- [21] P. Hang, C. Lv, Y. Xing, C. Huang, and Z. Hu, "Human-like decision making for autonomous driving: A noncooperative game theoretic approach," *IEEE Trans. Intell. Transp. Syst.*, vol. 22, no. 4, pp. 2076–2087, Apr. 2021.
- [22] N. Smirnov, Y. Liu, A. Validi, W. Morales-Alvarez, and C. Olaverri-Monreal, "A game theory-based approach for modeling autonomous vehicle behavior in congested, urban lane-changing scenarios," *Sensors*, vol. 21, no. 4, p. 1523, 2021. [Online]. Available: <https://www.mdpi.com/1424-8220/21/4/1523>
- [23] Y. Jeong, S. Kim, and K. Yi, "Surround vehicle motion prediction using LSTM-RNN for motion planning of autonomous vehicles at multi-lane turn intersections," *IEEE Open J. Intell. Transp. Syst.*, vol. 1, pp. 2–14, 2020.
- [24] J. Palatti, A. Aksjonov, G. Alcan, and V. Kyrki, "Planning for safe abortable overtaking maneuvers in autonomous driving," in *Proc. IEEE Int. Intell. Transp. Syst. Conf. (ITSC)*, 2021, pp. 508–514.
- [25] W. Qian, A. Beshah, and W. Thomas, "Predictive maneuver planning for an autonomous vehicle in public highway traffic," *IEEE Trans. Intell. Transp. Syst.*, vol. 20, no. 4, pp. 1303–1315, Apr. 2019.
- [26] Ö. c.S. Taş, N. O. Salscheider, F. Poggenhans, S. Wirges, C. Bandera, M. R. Zofka, T. Strauss, J. M. Zöllner, and C. Stiller, "Making Bertha cooperate—team AnnieWAY's entry to the 2016 grand cooperative driving challenge," *IEEE Trans. Intell. Transp. Syst.*, vol. 19, no. 4, pp. 1262–1276, Apr. 2018.
- [27] D. S. Gonzalez, "Towards human-like prediction and decision-making for automated vehicles in highway scenarios," M.S. thesis, Univ. Grenoble Alpes, Apr. 2019. [Online]. Available: <https://tel.archives-ouvertes.fr/tel-02184362>
- [28] M. Schmidt, C. Wissing, T. Nattermann, and T. Bertram, "A probabilistic model for discretionary lane change proposals in highway driving situations," *Forschung Im Ingenieurwesen*, vol. 85, no. 2, pp. 485–500, 2021.
- [29] W. Schwarting, A. Pierson, J. Alonso-Mora, S. Karaman, and D. Rus, "Social behavior for autonomous vehicles," *Proc. Nat. Acad. Sci. USA*, vol. 116, no. 50, pp. 24972–24978, 2019. [Online]. Available: <https://www.pnas.org/content/116/50/24972>
- [30] M. Garzón and A. Spalanzani, "Game theoretic decision making for autonomous vehicles merge manoeuvre in high traffic scenarios," in *Proc. IEEE Intell. Transp. Syst. Conf. (ITSC)*, Oct. 2019, pp. 3448–3453.
- [31] B. Toghi, R. Valiente, D. Sadigh, R. Pedarsani, and Y. P. Fallah, "Altruistic maneuver planning for cooperative autonomous vehicles using multi-agent advantage actor-critic," 2021, *arXiv:2107.05664*.
- [32] A. Turnwald, D. Althoff, D. Wollherr, and M. Buss, "Understanding human avoidance behavior: Interaction-aware decision making based on game theory," *Int. J. Social Robot.*, vol. 8, pp. 331–351, Apr. 2016.
- [33] A. Artuñedo, J. Villagra, and J. Godoy, "Real-time motion planning approach for automated driving in urban environments," *IEEE Access*, vol. 7, pp. 180039–180053, 2019.

- [34] X. Li, Z. Sun, D. Cao, Z. He, and Q. Zhu, "Real-time trajectory planning for autonomous urban driving: Framework, algorithms, and verifications," *IEEE/ASME Trans. Mechatronics*, vol. 21, no. 2, pp. 740–753, Apr. 2016.
- [35] H. Mouhaghir, V. Cherfaoui, R. Talj, F. Aioun, and F. Guillemard, "Using evidential occupancy grid for vehicle trajectory planning under uncertainty with tentacles," in *Proc. IEEE 20th Int. Conf. Intell. Transp. Syst. (ITSC)*, Oct. 2017, pp. 1–7. [Online]. Available: <https://hal.archives-ouvertes.fr/hal-01576974>
- [36] B. Simon, P. Riegl, and A. Gaull, "Path planning with discrete geometric shape patterns," in *Proc. IEEE Int. Conf. Veh. Electron. Saf. (ICVES)*, Sep. 2019, pp. 1–7.
- [37] P. De Beaucorps, A. Verroust-Blondet, R. Poncelet, and F. Nashashibi, "RIS: A framework for motion planning among highly dynamic obstacles," in *Proc. 15th Int. Conf. Control, Autom., Robot. Vis. (ICARCV)*, 2018, pp. 1387–1393.
- [38] G. Tanzmeister, D. Wollherr, and M. Buss, "Grid-based multi-road-course estimation using motion planning," *IEEE Trans. Veh. Technol.*, vol. 65, no. 4, pp. 1924–1935, Apr. 2016.
- [39] Y. Zhang, H. Chen, S. L. Waslander, J. Gong, G. Xiong, T. Yang, and K. Liu, "Hybrid trajectory planning for autonomous driving in highly constrained environments," *IEEE Access*, vol. 6, pp. 32800–32819, 2018.
- [40] H. Fan, F. Zhu, C. Liu, L. Zhang, L. Zhuang, D. Li, W. Zhu, J. Hu, H. Li, and Q. Kong, "Baidu Apollo EM motion planner," 2018, [arXiv:1807.08048](https://arxiv.org/abs/1807.08048).
- [41] Y. Zhang, H. Chen, S. L. Waslander, T. Yang, S. Zhang, G. Xiong, and K. Liu, "Speed planning for autonomous driving via convex optimization," in *Proc. 21st Int. Conf. Intell. Transp. Syst. (ITSC)*, 2018, pp. 1089–1094.
- [42] H. Y. Guo, C. Shen, H. Zhang, H. Chen, and R. Jia, "Simultaneous trajectory planning and tracking using an MPC method for cyber-physical systems: A case study of obstacle avoidance for an intelligent vehicle," *IEEE Trans. Ind. Informat.*, vol. 14, no. 9, pp. 4273–4283, Mar. 2018.
- [43] W. Zeng, W. Luo, S. Suo, A. Sadat, B. Yang, S. Casas, and R. Urtasun, "End-to-end interpretable neural motion planner," in *Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit. (CVPR)*, Jun. 2019, pp. 8652–8661.
- [44] T. Buhet, E. Wirbel, A. Bursuc, and X. Perrotton, "PLOP: Probabilistic polynomial objects trajectory planning for autonomous driving," 2020, [arXiv:2003.08744](https://arxiv.org/abs/2003.08744).
- [45] C. Kuhn, M. Hofbauer, G. Petrovic, and E. Steinbach, "Trajectory-based failure prediction for autonomous driving," in *Proc. IEEE Intell. Vehicles Symp. (IV)*, Jul. 2021, pp. 980–986.
- [46] S. Le Cleac'h, M. Schwager, and Z. Manchester, "LUCIDGames: Online unscented inverse dynamic games for adaptive trajectory prediction and planning," 2020, [arXiv:2011.08152](https://arxiv.org/abs/2011.08152).
- [47] K. Rezaee and P. Yadmellat, "How to not drive: Learning driving constraints from demonstration," in *Proc. IEEE Intell. Vehicles Symp. (IV)*, Jun. 2022, pp. 1297–1302.
- [48] A. Chebly, "Trajectory planning and tracking for autonomous vehicles navigation," M.S. thesis, Univ. de Technologie de Compiègne, France, Dec. 2017. [Online]. Available: <https://tel.archives-ouvertes.fr/tel-01727720>
- [49] T. Stahl, A. Wischnewski, J. Betz, and M. Lienkamp, "Multilayer graph-based trajectory planning for race vehicles in dynamic scenarios," in *Proc. IEEE Intell. Transp. Syst. Conf. (ITSC)*, Oct. 2019, pp. 3149–3154.
- [50] Y. Wang, J.-R. Chardonnet, and F. Merienne, "Speed profile optimization for enhanced passenger comfort: An optimal control approach," in *Proc. 21st Int. Conf. Intell. Transp. Syst. (ITSC)*, 2018, pp. 723–728.
- [51] V. T. N. Nha, S. Djahel, and J. Murphy, "A comparative study of vehicles routing algorithms for route planning in smart cities," in *Proc. 1st Int. Workshop Veh. Traffic Manag. Smart Cities (VTM)*, 2012, pp. 1–6.
- [52] C. Lin, K. L. Choy, G. T. S. Ho, S. H. Chung, and H. Y. Lam, "Survey of green vehicle routing problem: Past and future trends," *Exp. Syst. Appl.*, vol. 41, no. 4, pp. 1118–1138, 2014. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S095741741300609X>
- [53] Y. Liu, "Optimisation de problème de tournées de véhicules de service à domicile," M.S. thesis, Ecole Centrale de Lille, Jun. 2017. [Online]. Available: <https://tel.archives-ouvertes.fr/tel-01736280>
- [54] G. D. Konstantakopoulos, S. Gayialis, and E. Kechagias, "Vehicle routing problem and related algorithms for logistics distribution: A literature review and classification," *Oper. Res.*, vol. 22, no. 3, pp. 2033–2062, 2020.
- [55] M. R. Khouadja, B. Sarasola, E. Alba, E.-G. Talbi, and L. Jourdan, *Metaheuristics for Dynamic Vehicle Routing*. Berlin, Germany: Springer, 2013, pp. 265–289, doi: [10.1007/978-3-642-30665-5_12](https://doi.org/10.1007/978-3-642-30665-5_12).
- [56] H.-Y. Zhang, W.-M. Lin, and A.-X. Chen, "Path planning for the mobile robot: A review," *Symmetry*, vol. 10, no. 10, p. 450, 2018. [Online]. Available: <https://www.mdpi.com/2073-8994/10/10/450>
- [57] H. Bast, D. Delling, A. Goldberg, M. Müller-Hannemann, T. Pajor, P. Sanders, D. Wagner, and R. F. Werneck, "Route planning in transportation networks," 2015, [arXiv:1504.05140](https://arxiv.org/abs/1504.05140).
- [58] G. Laporte and Y. Nobert, "Exact algorithms for the vehicle routing problem the authors are grateful to the Canadian natural sciences and engineering research council (grants A4747 and A5486) and to the Quebec government (FCAC grant 80EQ04228) for their financial support," in *Surveys in Combinatorial Optimization* (North-Holland Mathematics Studies), vol. 132, S. Martello, G. Laporte, M. Minoux, and C. Ribeiro, Eds. 1987, pp. 147–184. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S0304020808732353>
- [59] F. Theurich, A. Fischer, and G. Scheithauer, "A branch-and-bound approach for a vehicle routing problem with customer costs," *EURO J. Comput. Optim.*, vol. 9, Jan. 2021, Art. no. 100003. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S192440620300034>
- [60] K. Dalmeijer and R. Spliet, "A branch-and-cut algorithm for the time window assignment vehicle routing problem," *Comput. Oper. Res.*, vol. 89, pp. 140–152, Jan. 2018. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S030505481730223X>
- [61] P. Munari and R. Morabito, "A branch-price-and-cut algorithm for the vehicle routing problem with time Windows and multiple deliverymen," *TOP*, vol. 26, no. 3, pp. 437–464, Oct. 2018.
- [62] D. Sever, L. Zhao, N. Dellaert, E. Demir, T. V. Woensel, and T. D. Kok, "The dynamic shortest path problem with time-dependent stochastic disruptions," *Transp. Res. C-Emerg. Technol.*, vol. 92, pp. 42–57, Jul. 2018.
- [63] M. Islam, S. Ghosh, and M. Rahman, "Solving capacitated vehicle routing problem by using heuristic approaches: A case study," *J. Modern Sci. Technol.*, vol. 3, pp. 135–146, Mar. 2015.
- [64] A. Signifredi, B. Luca, A. Coati, J. S. Medina, and D. Molinari, "A general purpose approach for global and local path planning combination," in *Proc. IEEE 18th Int. Conf. Intell. Transp. Syst.*, Sep. 2015, pp. 996–1001.
- [65] T. Sultana, M. A. H. Akhand, and M. M. Rahman, "A variant Fisher and Jaikumr algorithm to solve capacitated vehicle routing problem," in *Proc. 8th Int. Conf. Inf. Technol. (ICIT)*, May 2017, pp. 710–716.
- [66] R. K. Yadav, G. Kishor, and K. Kashyap, "Comparative analysis of route planning algorithms on road networks," in *Proc. 5th Int. Conf. Commun. Electron. Syst. (ICES)*, Jun. 2020, pp. 401–406.
- [67] W. Chmiel, I. Skalna, and S. Jędrusik, "Intelligent route planning system based on interval computing," *Multimedia Tools Appl.*, vol. 78, no. 4, pp. 4693–4721, Feb. 2019.
- [68] V. Buchhold, P. Sanders, and D. Wagner, "Real-time traffic assignment using fast queries in customizable contraction hierarchies," in *Proc. 17th Int. Symp. Experim. Algorithms (SEA)* (Leibniz International Proceedings in Informatics (LIPIcs)), vol. 103, G. D'Angelo, Ed. Dagstuhl, Germany: Schloss Dagstuhl–Leibniz-Zentrum fuer Informatik, 2018, pp. 27.1–27.15. [Online]. Available: <http://drops.dagstuhl.de/opus/volltexte/2018/8962>
- [69] D. Tischner, "Multi-modal route planning in road and transit networks," 2018, [arXiv:1809.05481](https://arxiv.org/abs/1809.05481).
- [70] S. Lefèvre, D. Vasquez, and C. Laugier, "A survey on motion prediction and risk assessment for intelligent vehicles," *ROBOMECH J.*, vol. 1, no. 1, pp. 1–14, Dec. 2014.
- [71] S. Paravarzar and B. Mohammad, "Motion prediction on self-driving cars: A review," 2020, [arXiv:2011.03635](https://arxiv.org/abs/2011.03635).
- [72] M. Koschi and M. Althoff, "SPOT: A tool for set-based prediction of traffic participants," in *Proc. IEEE Intell. Vehicles Symp. (IV)*, Jun. 2017, pp. 1686–1693.
- [73] R. Izquierdo, I. Parra, J. Muñoz-Bulnes, D. Fernandez-Llorca, and M. A. Sotelo, "Vehicle trajectory and lane change prediction using ANN and SVM classifiers," in *Proc. IEEE 20th Int. Conf. Intell. Transp. Syst. (ITSC)*, Oct. 2017, pp. 1–6.
- [74] A. Zyner, S. Worrall, and E. Nebot, "A recurrent neural network solution for predicting driver intention at unsignalized intersections," *IEEE Robot. Autom. Lett.*, vol. 3, no. 3, pp. 1759–1764, Jul. 2018.
- [75] A. Turnwald and D. Wollherr, "Human-like motion planning based on game theoretic decision making," *Int. J. Social Robot.*, vol. 11, no. 1, pp. 151–170, Jan. 2019.
- [76] R. E. Amini, C. Katrakazas, and C. Antoniou, "Negotiation and decision-making for a pedestrian roadway crossing: A literature review," *Sustainability*, vol. 11, no. 23, p. 6713, Nov. 2019.

- [77] K. Jo, M. Lee, J. Kim, and M. Sunwoo, "Tracking and behavior reasoning of moving vehicles based on roadway geometry constraints," *IEEE Trans. Intell. Transp. Syst.*, vol. 18, no. 2, pp. 460–476, Feb. 2017.
- [78] V. Lefkopoulos, M. Menner, A. Domahidi, and M. N. Zeilinger, "Interaction-aware motion prediction for autonomous driving: A multiple model Kalman filtering scheme," *IEEE Robot. Autom. Lett.*, vol. 6, no. 1, pp. 80–87, Jan. 2021.
- [79] B. R. Kiran, I. Sobh, V. Talpaert, P. Mannion, A. A. Al Sallab, S. Yogamani, and P. Pérez, "Deep reinforcement learning for autonomous driving: A survey," *IEEE Trans. Intell. Transp. Syst.*, vol. 23, no. 6, pp. 4909–4926, Jun. 2022.
- [80] Y. Ma, Z. Wang, H. Yang, and L. Yang, "Artificial intelligence applications in the development of autonomous vehicles: A survey," *IEEE/CAA J. Autom. Sinica*, vol. 7, no. 2, pp. 315–329, Mar. 2020.
- [81] D. Heb, R. Lattarulo, J. Perez, J. Schindler, T. Hesse, and F. Koster, "Fast maneuver planning for cooperative automated vehicles," in *Proc. 21st Int. Conf. Intell. Transp. Syst. (ITSC)*, Nov. 2018, pp. 1625–1632.
- [82] M. Düring and K. Lemmer, "Cooperative maneuver planning for cooperative driving," *IEEE Intell. Transp. Syst. Mag.*, vol. 8, no. 3, pp. 8–22, Jul. 2016.
- [83] N. Goulet and B. Ayalew, "Distributed maneuver planning with connected and automated vehicles for boosting traffic efficiency," *IEEE Trans. Intell. Transp. Syst.*, vol. 23, no. 8, pp. 10887–10901, Aug. 2022.
- [84] B. Paden, M. Cap, S. Z. Yong, D. Yershov, and E. Frazzoli, "A survey of motion planning and control techniques for self-driving urban vehicles," *IEEE Trans. Intell. Vehicles*, vol. 1, no. 1, pp. 33–55, Mar. 2016.
- [85] D. González, J. Pérez, V. Milanés, and F. Nashashibi, "A review of motion planning techniques for automated vehicles," *IEEE Trans. Intell. Transp. Syst.*, vol. 17, no. 4, pp. 1135–1145, Nov. 2016.
- [86] C. Katrakazas, M. Qudus, W.-H. Chen, and L. Deka, "Real-time motion planning methods for autonomous on-road driving: State-of-the-art and future research directions," *Transp. Res. C, Emerg. Technol.*, vol. 60, pp. 416–442, Nov. 2015. [Online]. Available: <http://www.sciencedirect.com/science/article/pii/S0968090X15003447>
- [87] S. D. Pendleton, H. Andersen, X. Du, X. Shen, M. Meghjani, Y. H. Eng, D. Rus, and M. H. Ang, "Perception, planning, control, and coordination for autonomous vehicles," *Machines*, vol. 5, no. 1, p. 6, 2017. [Online]. Available: <https://www.mdpi.com/2075-1702/5/1/6>
- [88] L. Claussmann, M. Revilloud, D. Gruyer, and S. Glaser, "A review of motion planning for highway autonomous driving," *IEEE Trans. Intell. Transp. Syst.*, vol. 21, no. 5, pp. 1826–1848, May 2019.
- [89] F. J. G. Carpio, "Two-staged local trajectory planning based on optimal pre-planned curves interpolation for human-like driving in urban areas," M.S. thesis, PSL Res. Univ., Paris, France, Dec. 2018. [Online]. Available: <https://pastel.archives-ouvertes.fr/tel-02194633>
- [90] A. Pierson, W. Schwarting, S. Karaman, and D. Rus, "Learning risk level set parameters from data sets for safer driving," in *Proc. IEEE Intell. Vehicles Symp. (IV)*, Jun. 2019, pp. 273–280.
- [91] L. Qin, R. Benmokhtar, and X. Perrotton, "Real-time model predictive safety assessment for level 3 autonomous driving," in *Proc. 9th Int. Conf. Robot Intell. Technol. Appl.*, 2021, pp. 553–565.
- [92] P. F. Orzechowski, K. Li, and M. Lauer, "Towards responsibility-sensitive safety of automated vehicles with reachable set analysis," in *Proc. IEEE Int. Conf. Connected Vehicles Expo (ICCVE)*, Nov. 2019, pp. 1–6.
- [93] F. Altche, "Decision-based motion planning for cooperative and autonomous vehicles," M.S. thesis, Univ. Paris Sciences et lettres, Paris, France, Aug. 2018. [Online]. Available: <https://pastel.archives-ouvertes.fr/tel-02073593>
- [94] S. Aradi, "Survey of deep reinforcement learning for motion planning of autonomous vehicles," *IEEE Trans. Intell. Transp. Syst.*, vol. 23, no. 2, pp. 740–759, Feb. 2022.
- [95] F. Ye, S. Zhang, P. Wang, and C.-Y. Chan, "A survey of deep reinforcement learning algorithms for motion planning and control of autonomous vehicles," in *Proc. IEEE Intell. Vehicles Symp. (IV)*, Jul. 2021, pp. 1073–1080.
- [96] A. Khodayari, A. Ghaffari, S. Ameli, and J. Flahatgar, "A historical review on lateral and longitudinal control of autonomous vehicle motions," in *Proc. Int. Conf. Mech. Electr. Technol.*, Sep. 2010, pp. 421–429.
- [97] J. Guanetti, Y. Kim, and F. Borrelli, "Control of connected and automated vehicles: State of the art and future challenges," *Annu. Rev. Control*, vol. 45, pp. 18–40, Apr. 2018. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S1367578818300336>
- [98] Z. Wang, Y. Bian, S. E. Shladover, G. Wu, S. E. Li, and M. J. Barth, "A survey on cooperative longitudinal motion control of multiple connected and automated vehicles," *IEEE Intell. Transp. Syst. Mag.*, vol. 12, no. 1, pp. 4–24, Dec. 2020.
- [99] B. Arifin, B. Y. Suprpto, S. A. D. Prasetyowati, and Z. Nawawi, "The lateral control of autonomous vehicles: A review," in *Proc. Int. Conf. Electr. Eng. Comput. Sci. (ICECOS)*, Oct. 2019, pp. 277–282.
- [100] S. Kuutti, R. Bowden, Y. C. Jin, P. Barber, and S. Fallah, "A survey of deep learning applications to autonomous vehicle control," *IEEE Trans. Intell. Transp. Syst.*, vol. 22, no. 2, pp. 712–733, Feb. 2020.
- [101] J. Ji, A. Khajepour, W. W. Melek, and Y. Huang, "Path planning and tracking for vehicle collision avoidance based on model predictive control with multiconstraints," *IEEE Trans. Ultrason. Eng.*, vol. 66, no. 2, pp. 952–964, Feb. 2017.
- [102] S. Li, Z. Li, Z. Yu, B. Zhang, and N. Zhang, "Dynamic trajectory planning and tracking for autonomous vehicle with obstacle avoidance based on model predictive control," *IEEE Access*, vol. 7, pp. 132074–132086, 2019.
- [103] Y. Pan, Q. Lin, H. Shah, and J. M. Dolan, "Safe planning for self-driving via adaptive constrained ILQR," in *Proc. IEEE/RSJ Int. Conf. Intell. Robots Syst. (IROS)*, Oct. 2020, pp. 2377–2383.
- [104] P. de Beaucorps, T. Streubel, A. Verroust-Blondet, F. Nashashibi, B. Bradai, and P. Resende, "Decision-making for automated vehicles at intersections adapting human-like behavior," in *Proc. IEEE Intell. Vehicles Symp. (IV)*, Jun. 2017, pp. 212–217.
- [105] N. Gavanas, "Autonomous road vehicles: Challenges for urban planning in European cities," *Urban Sci.*, vol. 3, no. 2, p. 61, Jun. 2019. [Online]. Available: <https://www.mdpi.com/2413-8851/3/2/61>
- [106] E. Yurtsever, J. Lambert, A. Carballo, and K. Takeda, "A survey of autonomous driving: Common practices and emerging technologies," 2019, *arXiv:1906.05113*.
- [107] D. W. Hook, S. J. Porter, and C. Herzog, "Dimensions: Building context for search and evaluation," *Frontiers Res. Metrics Anal.*, vol. 3, p. 23, Aug. 2018. [Online]. Available: <https://app.dimensions.ai/details/publication/pub.1106289502>



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