Abstraction and Decision-Making Phase in Autonomous Vehicles using Artificial Intelligence: A Review of Models, Strengths, and Limitations

(Fasa Pengambilan dan Pengambilan Keputusan dalam Kenderaan Autonomi menggunakan Kecerdasan Buatan: Kajian Model, Kekuatan, dan Batasan)

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Abstract

Autonomous vehicles (AVs) can sense their surroundings and operate without the need for human intervention. At no point is a human passenger required to assume control of the car, nor is a human passenger required to be present in the vehicle at all. A self-driving automobile can go anywhere a traditional car can go and accomplish everything a skilled human driver can do. Because of its futuristic driving experiences, the autonomous car, as an emerging and quickly rising area, has gotten a lot of attention. To operate, the AVs have their architecture consists of 4 phases: abstraction phase, decision-making phase, control phase, and chassis phase. However, some issues arise involving accidents between autonomous vehicles and others (Yuan, Gao & Li, 2016), which did not yield to the car but was predicted by the self-driving technology to delay or stop. Hereby, this paper was focused on identifying the model or methods or approaches that can be used in the abstraction phase and decision-making phase. In addition, the advantages and limitations of each model have also been reviewed in this paper. While, at the end of this paper, some conclusions on the models used in this phase have been done.

Keywords: Autonomous vehicles, artificial intelligence, abstraction phase, decision making phase.

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INTRODUCTION

Artificial intelligence (AI) is an important technology that supports daily social life and economic activities. It contributes greatly to the sustainable growth of the country's economy and solves various social problems. AI also serving as a new general-purpose "new method of invention" that have the potential to change the character of the innovation process and the organization of R&D. In recent years, AI has attracted attention as a key for growth in developed countries such as Europe and the United States and developing countries such as China and India. While Malaysia strives to be a regional leader in manufacturing, engineering, and technological development. The National Automotive Policy 2020 (NAP 2020) aims to boost Malaysia's automotive sector through new technology research and development, particularly in the fields of Next-Generation Vehicles (NxGV), Industrial Revolution 4.0 (IR 4.0), and Mobility-as-a-Service (MaaS) (Malaysian Investment Development Authority, 2020).

Besides that, this breakthrough also serves as a promising promotional tool for Malaysia, which can use the MyAV Testing Route to host technical businesses looking to test their autonomous vehicle innovations. Honda wants to mass-produce its first autonomous vehicle, the Honda Legend luxury sedan with level 3 automation, in March of next year. In September 2016, REKA, a local R&D tech business, announced the development of a self-driving Proton Perdana with level 3 automation. Celcom displayed a self-driving Proton Exora in April 2020 as part of the 5G Malaysia showcase, demonstrating the autonomous system created by MooVita and Ericsson and enhancing the momentum of autonomous car technology.

Figure 1. MyAV Testing Route

AI has the potential to directly influence products and services (and the tasks required to create these goods), there are Significant implications for output, wages, and competitiveness However, regardless of how big these effects are expected to be, artificial intelligence often can alter the invention process itself, with similarly significant implications, and may eventually outnumber the direct effect. One of the primary enablers of the development of autonomous vehicles (AVs) is advances in artificial intelligence (AI).

In fact, AI is used by autonomous vehicles to assess their surroundings, analyze their conditions, and make driving decisions. AI has evolved into an architecture discipline in which programmers are created in vast manufacturing teams of specialists from different fields. Today's AI technologies include self-driving vehicles, support robots, and smart houses. It would have a major impact on our lives. Autonomous devices embedded in cars are one of the most large-scale AI applications. A self-driving car with a sophisticated real-time perception and decision-making system is known as an autonomous vehicle (AV)(Jiang et al., 2019). It uses a variety of innovations. To aid navigation, they can be installed with Global Positioning System (GPS) sensing information. To prevent accidents, they can use sensors and other devices. They will also use virtual reality, a kind of technology in which a car shows knowledge to drivers in novel and creative ways. Some believe the mass manufacturing of autonomous vehicles would pose issues with current auto insurance and traffic regulations for human-driven vehicles. Not only in the United States but also in Europe and other areas of the world, extensive research on autonomous vehicles is ongoing. Those in the industry believe it will only be a matter of time before these advancements allow us to outsource our daily commute to a robot computer.

Simultaneously, mass transit ideas such as Elon Musk's "super loop" concept envision a futuristic world in which rapid transit networks, rather than individual car-like cars, have more driven transportation. An Autonomous Vehicle (AV) system was build according to problems that appeared in this development technology now a day. Autonomous vehicles have been a hot subject in recent years, not just in the realm of science but also in the realm of use. Several promising concepts and prototypes have been developed. However, current self-driving solutions place an excessive emphasis on "correctness" and, according to some degree, ignore human character and emotional intelligence (Sheridan, 2016).

On February 14, A Google self-driving vehicle was introduced in 2016 collided with a municipal bus, which did not yield to the car but was predicted by the self-driving technology to delay or stop. According to Google, this collision was caused by a misinterpretation and should be seen as a useful self-driving experience technology(Yuan et al., 2016). They further claim that their vehicles will be aware that bigger vehicles are not likely to yield, and that technological changes will be made to prevent any collisions. Hereby, the review concentrates on the following research objectives: (a) Identifying the models used in the abstraction and decision-making phase of AV; (b) Identifying the advantages of models used in the abstraction and decision-making phase of AV; (c) Identifying the limitations of models use in abstraction and decision-making phase of AV. Furthermore, a discussion of all findings according to the research objectives will be present below.

AUTONOMOUS VEHICLES SYSTEM OVERVIEW

In comparison to human-driven automobiles, autonomous vehicle technology may be able to offer some advantages. One potential benefit is that they could improve road safety - vehicle crashes cause many lives each year, and automated cars could potentially reduce the number of fatalities because the software used in them is likely to make fewer errors than humans. Autonomous cars may be able to reduce traffic congestion by lowering the amount of accidents, which is another possible benefit. Autonomous driving can also be accomplished by reducing human activities that generate stumbling obstacles, such as stop-and-go traffic.

Autonomous vehicles provide a number of benefits, including increased safety and reduced traffic congestion, which results in decreased fuel/energy usage(Arena & Pau, 2019; Ondrus et al., 2020). Apart from these benefits, there are certain difficulties that must be answered for AVs, such as who is legally responsible duties for AVs, what will happen if the AV controller is hacked, and so on. Table 1 summarizes the primary advantages and disadvantages of AVs. Overall, autonomous vehicles will be a significant technological advancement in the next years if the downsides are handled or minimized, because they will improve road safety and make people's lives simpler (Xie et al.,2020; (Zhao et al., 2018).

Table 1. The benefits and drawbacks of autonomous vehicles

Benefits	**Drawbacks**
Accidents: AVs have the potential to dramatically reduce the frequency of accidents.	Law: The legal definition of duties can stymie the adoption of AVs.
Fewer Expenses: Precise autonomous driving can minimise gasoline consumption while also increasing the conservation of other components.	Threat: Because of the current computer-controlled functionality, AVs may be more vulnerable to network attacks.
Productivity: By participating in things other than driving, the journey may be made more productive.	Employment: Many jobs in the transportation sector will be lost as a result of AVs.
Inside comfort: The interior of an AV can be comfortable and roomy.	Price: The price of AVs is initially high, but it will fall as more people use them.

By adding some additional components, such as sensors, a conventional car can be transformed into an autonomous vehicle that can make its own choices by perceiving the ecosystem as well as regulating the vehicle's motion (Zanchin et al., 2017; (Zong et al., 2018). Figure 2 depicts the whole AV communication process/protocol, as well as the control is provided through sensors, actuators, hardware, and software. that are necessary. The AVs architecture consists of 4 main stages or phases which are perception, decision & planning, control, and chassis. However, according to Li, Ota & Dong (2018) in their study, Autonomous Vehicles (AVs) was consisted of 3 main phases which are Perception, Abstraction, and decision-making phase (Figure 3).

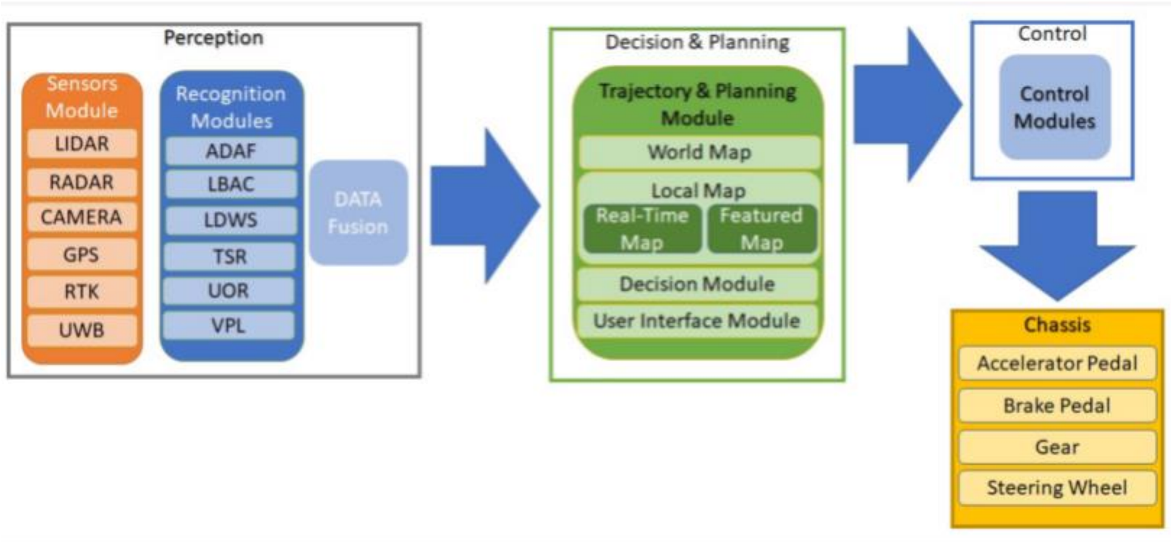

Figure 2. System Architecture for AVs (Ahangar et al., 2021)

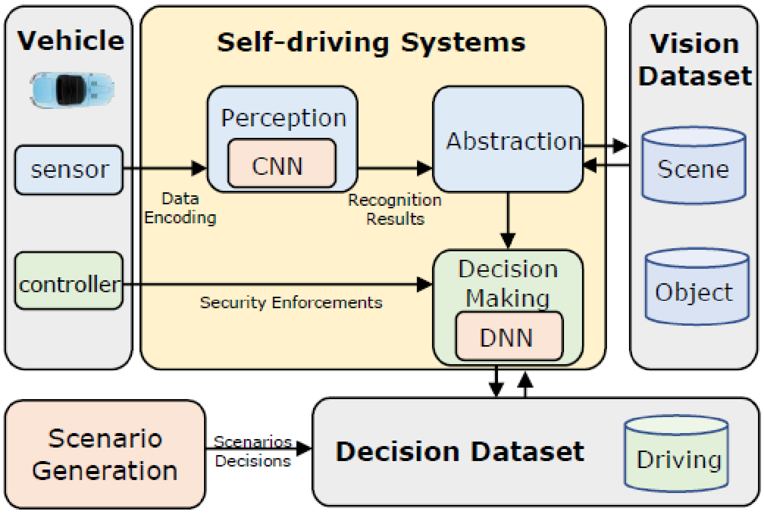

Figure 3. System Framework (Li et al., 2018).

MODELS, STRENGTHS, AND LIMITATIONS

ABSTRACTION PHASE

In general, AI was implemented in two-phase which are abstraction and decision making. In the abstraction phase, the AI system will identify, detect, and abstract information which the sensors pick up on. The abstraction of the road state is generated before driving judgments, which is a key feature of the abstraction calculation methodologies. In this approach, a reliable and efficient 3D perception method is required to acquire an accurate comprehension of the input images captured by the self-driving vehicles' sensors (Figure 3). This task is also known as scene interpretation, and it is a prominent topic in the field of computer vision. Traditional approaches, on the other hand, struggle with the perception and abstraction of road images, as indicated above, due to their reliance on unreliable RGB data (Li et al., 2018).

According to this study (Li et al., 2018), the road condition was abstracted before the systems make any driving decisions. Thus, by the Convolutional Neural Network (CNN) system, to gain a thorough grasp of the input pictures acquired by self-driving cars' sensors, a reliable and efficient three-dimensional perception system is needed. This task is also known as scenario comprehension (Figure 4).


Figure 4. The perception and abstraction of road condition

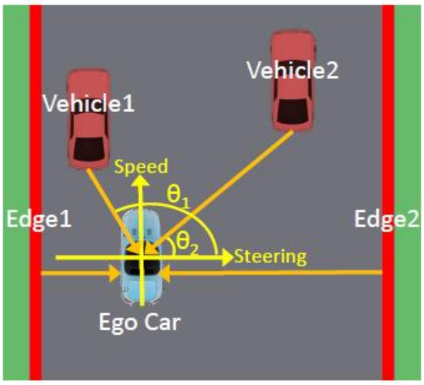

Figure 5. Input image captured by sensors.

While, there are other studies (Yang, S., Wang, Z.,&Zhang, H., 2017) they used the kinematic Model-based Real-time path planning in the abstraction phase (Figure 6). According to them, a Bezier curve-based guideline was used to develop the performance index. One of the benefits of this parametric method is that it uses the vehicle's kinematic model directly. A reduced two-dimensional kinematic model is employed to increase real-time performance.

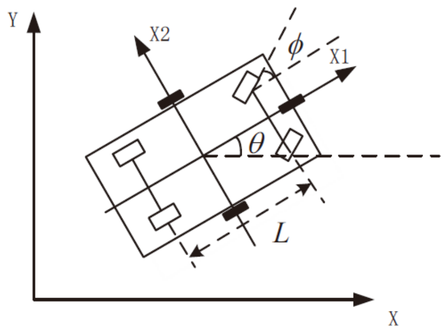

Figure 6. Vehicle's Kinematic Model

The path planning kinematic model was used in this study to complete the process of moving the vehicle from its initial state to a target one while being restricted by internal kinodynamic constraints and external obstacle constraints. A generalized two-dimensional kinematic model is used to increase real-time accuracy. Formula below shows all of the variables are members of S, and L is the vehicle's wheelbase.

$$x(t) = \mathrm{v}\cos(\theta)$$
$$y(t) = v sin(\theta)$$
$$\theta(t) = \frac{v\, tan\,(\emptyset(t))}{L}$$

However, there are a lot of models were used in this abstraction phase. According to all the studies in Table 2, Path Planning method (Yang et al., 2017)**,** Road Condition Understanding Network model (RCUN) (Li et al.,2018), LiDAR (Mekker, M.M. et al.,2018), Hardware in the loop (HiL) - local planning algorithm (Y. Chen et al., 2018); Convolutional Neural Network (CNN) with KITTI and TORCS (Li et al., 2018); AI NAAV (AI-enabled Neurocognition Aware Autonomous Vehicle) (Natarajan et al., 2020); Extended Finite State Machines (EFSM) (Zita et al., 2017); ADAS using open-source AUTOSAR design integrated with MPC574XG-324DS board (Park & Choi, 2019); Artificial Neural Network (ANN) (Salih & Olawoyin, 2020); Semantic Segmentation (Behl et al., 2020); two-level abstraction approach to scenario description language (SDL) (Zhang et al., 2020); Convolutional Network (ConvNets) (Zlateski et al., 2018) have been used in the abstraction phase. Besides, they have their own advantages and limitation.

Table 2. Models, Strengths and Limitations in Abstraction Phase

Reference	Models	Strengths	Limitations
Yang et al.(2017)	Path Planning method on Vehicle's Kinematic Model.	Real-time performance. In a dynamic environment, capable of dealing with kinodynamic restrictions and shifting impediments.	Curvature limitation.
Li et al. (2018)	Road Condition Understanding Network model (RCUN).	Understand the road scenes and use the well-known Alex model as the recognition network, and its modified version, suited to 3D input data, as the car recommendation network.	There are a plethora of alternatives for relative vehicle locations.
Mekker et al. (2018)	LiDAR (Light Detection and Ranging)-generated geometric data with connected vehicle speed data to evaluate the impact of work zone geometry on traffic operations.	Collection of geometric data can occur at highways speeds, does not require lane closures, and dramatically reduces the exposure of inspectors to traffic.	The extraction requires manual processing if markings are old and have poor retro-reflectivity characteristics. LiDAR performance significantly degrades when there is precipitation. Higher cost for the higher speed of data collection vehicles.
Y. Chen et al.(2018)	Hardware in the loop (HiL) - local planning algorithm.	uses quintic spline polynomials to simulate a few viable and smooth local paths to be selected.	The effectiveness of the technique used is not being tested in a real situation.
Li et al. (2018)	Convolutional Neural Network (CNN) model with the open racing vehicle with the well-known vision dataset for autonomous driving (KITTI). simulator (TORCS) to collect road data.	Able understand the captured road images. The Open Racing Car Simulator (TORCS) is equipped with depth suggested scene understanding technique for the planar representation may provide depth pictures to the scene understanding network in real-time, and the current road state is abstracted by the proposed scene understanding method.	Even if the RGB data is partial and unsteady, some information may be retrieved, which can be helpful. supplement to this method.

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Table 2: Continued from previous page

Reference	**Models**	**Strengths**	**Limitations**
Natarajan et al., (2020)	AI NAAV (AI-enabled Neurocognition Aware Autonomous Vehicle).	Replicating human cognitive behaviour with the help of a digital autopilot.	A safe pullover in the case of on-road driving impairment, safe drive to a real-time derived destination such as a hospital, and notification of the incident to the victim's immediate family members are still not studied.
Zita et al.(2017)	Extended Finite State Machines (EFSM) for lateral state manager of lane change module (Planner and Lateral State Manager (LSM))	Formal verification revealed that the recommended counter correction did, in fact, eliminate the erroneous behaviour.	Interactions between that module and the higher-level tactical decision module that were unexpected, Resulted in incorrect behavior of the vehicle The two primary challenges are obtaining the model from the code and locating the requirements, many of which are not clearly written down.
Park & Choi (2019)	ADAS using open-source AUTOSAR design integrated with MPC574XG-324DS board with MPC5748G MCU as the ECU and Ultrasonic sensors are used to measure the distances from obstacles in the collision warning system.	Satisfied the real-time constraints, the periodicity of the tasks constructed	undefined
Salih & Olawoyin, (2020)	Artificial Neural Network (ANN) and pattern recognition algorithm approaches.	An artificial neural network can effectively predict the steering commands Accurately given the fact that the nonlinearity and complexity of the steering system control.	undefined

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Table 2**.** Continued from previous page

Reference	Models	Strengths	Limitations
Behl et al. (2020)	Semantic Segmentation.	with only a few hundred annotated images, that can be labeled in approximately 50 hours, segmentation-based visual abstractions can lead to significant improvements over end-to-end methods, in terms of both performance and variance with respect to different training seeds.	Costly to Obtain methods are often developed independently of the final driving task.
Zhang et al.(2020)	Two-level abstraction approach to scenario description language (SDL) – SDL level 1 and SDL level 2. SDL level 1 is a textual description of the scenario at a higher abstraction level to be used by regulators or system engineers. SDL level 2 is a formal machine-readable language that is ingested by a testing platform.	An understandable and common format for describing the scenery and environment element which complies with the standards defined by standards organizations.	undefined
Zlateski et al. (2018)	Convolutional Network (ConvNets) approach of semantic image segmentation.	A larger coarsely annotated dataset can yield the same performance as a smaller finely.	The performance of ConvNets mostly depends on the time spent creating the training labels.

DECISION-MAKING PHASE

After learning the abstraction of road conditions, the system may work on the relevant driving judgments. In comparison to behavior reflex approaches that directly map input images to several pre-defined driving commands, the proposed method, which calculates reactions using abstractions rather than original images, is much more trainable and can achieve higher network precisions due to the inherent logic and structure being much simpler.

There are several methods/ models /approaches that can be used in this decision-making phase. According to all the studies summarized in the Table 3 below, we found that a lot of choices approaches can be used in this phase to decide of driving according to the data from the abstraction phase. One of the techniques used was the Six-layer decision-making network (DMN) (Li et al., 2018). The architecture of the DMN used in this study was shown in the Figure below.

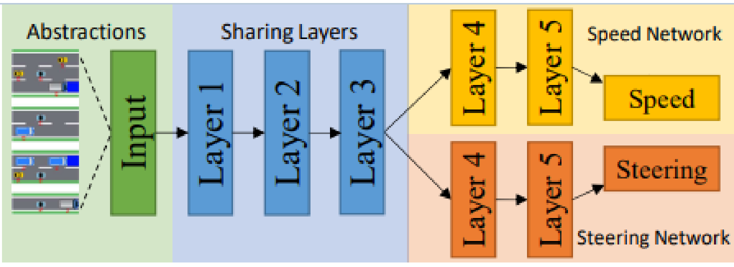

Figure 7. Decision-Making Network Architecture

While, Liu, Y., Wang, X., Li, L., Cheng, S., & Chen, Z. (2019) from their study found that the SVM model is used to solve the multiparametric and nonlinear autonomous lane change decision-making model, ensuring that the decision-making model matches the driver's behaviors. They found that this SVM has the best performance due to its strong mapping ability and its also able to improve the accuracy of prediction. The BOA optimized Gaussian kernel support vector machine model (BOA Gaussian SVM) has better accuracy Liu et al., (2019). By using this technique, the independent vehicle effectively changes its path, and the vehicle speed gradually increases to the target speed of 28 km/h.

Other than that, Xu, X., Zuo, L., Li, X., Qian, L., Ren, J., & Sun, Z. (2020) in their study found that another technique that can be used in the decision making phase was the Markov decision process (MDP) with numerous. In addition, there are more models that can be used such as a Game -hypothetical model (Tian et al., (2019), Adaptive Cruise Control (ACC) and RRT-based (Rapid-investigating Random Tree) (Y. Chen et al., 2018), vehicle following dynamic framework with Inverse support learning (IRL) calculation (Gao et al.,2018), Partially observable Markov decision process (POMDP)(Hubmann et al.,2017), Harsh Set hypothesis (X. Chen et al.,2017), Dynamic Threat Assessment Model and a Path Planner (He et al.,2019), New MDP model (You et al.,2018) and mixture mathematical/logical model (Rinaldo & Horeis,2020). All these models have their own strengths and limitations.

Table 3. Studies of Models, Strengths, and Limitations.

Reference	Models	Strengths	Limitations
Li et al. (2018)	A Six-layer decision-making network (DMN) with SGD methodology took on and consolidate with wellbeing authorization strategy, in particular the repulsive potential field (RPF).	DMN model can compute and yield the human-like choices. The framework can give out a protected and human-like driving choice.	They are yet not yet completely versatile for genuine driving circumstances, because of security reasons.
Liu et al.(2019)	Support Vector Machine (SVM) with Gaussian Kernel function and Bayesian Optimization Algorithm (BOA).	The independent vehicle effectively changes its path, and the vehicle speed gradually increases to the target speed of 28 km/h. When there is no impediment in front, the objective speed vset is set as the speed of P, and the most extreme identification scope of radar, which is 204.7 meters.	needs are further investigated because of the complexities of real-world traffic.

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Table 3**:** Continued from previous page

Reference	**Models**	**Strengths**	**Limitations**
Xu et al.(2020)	Markov decision process (MDP) with numerous objectives, multi objective rough strategy emphasis (MO-API) calculation.	Accomplish better learning effectiveness. Two-component learning procedures have been presented for MO-API.	Albeit the recreation and exploratory outcomes outline that the proposed Reinforcement Learning (RL) approach can get proper dynamic approaches in various traffic conditions, there are even more works that requirements further examinations later on.
Tian et al.(2019)	Game-hypothetical model addressing the collaborations between the conscience vehicle and an adversary vehicle and adjusts to an online assessed driver type of the adversary vehicle.	Achievement rate is 93.4%, i.e., in 934 out of 1000 recreation runs, the inner self and rival vehicles effectively come to their target paths without slamming into one another. Driving off the street or intersection the path markings that separate traffic of inverse bearings, and without causing a stop (neither one of the vehicles chooses to enter the traffic circle or the two vehicles stall out in the center of the traffic circle). Neural organization-based online execution is likewise computationally attainable.	The calculations have been a move to take care of the advancement issues from online to disconnect.
Y. Chen et al. (2018)	Equipment insider savvy (HiL) in-coordinates heuristic strategies into the control methodology of Adaptive Cruise Control (ACC) and RRT-based (Rapid-investigating Random Tree) calculation for a parking spot.	Path following module will complete both lateral and longitudinal speed control of the vehicle and at last deal exact orders for the choke, the brake, and the directing wheel regulators.	The viability of the procedure utilized is not being tested in genuine circumstances.

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Table 3**:** Continued from previous page

Reference	**Models**	**Strengths**	**Limitations**
Gao et al.(2018)	a car following decision making system for complex traffic conditions by utilizing Inverse support learning (IRL) calculation.	The reward function $R_{i,j}$ and the cumulative reward $V_{i,j}$ are calculated. The weights of each reward function $R_{i,j}$ are determined, the IRL algorithm is designed, and the reward function R is obtained. Finally, the R of the two drivers under two conditions are visualized and analyzed, which proves the validity of the proposed algorithm.	A particular car following algorithm for every individual should be planned by their own qualities.
Hubmann et al. (2017)	Partially observable Markov decision process (POMDP).	Independent driving under different climate circumstances. Upgraded for the most probable future situations coming about because of an intuitive, probabilistic movement model for different vehicles.	Restricted developing dimensionality of the conviction space. Low arranging recurrence.
X. Chen et al. (2017)	The lane-changing rules were abstracted using rough set theory for a complex urban environment	Used to deal with large amounts of data. Fast operation. Assessment models are diminished with no data misfortune. Decrease the impact of the information discretization.	There are some data loosed definitely,a superior discretization strategy is should have been further investigated. The effect of trademarks under various drivers during path changing should be further thought.
He et al.(2019)	The dynamic layer comprises a Dynamic Threat Assessment Model and a Path Planner.	The proposed arrangement. Shows more prevalent elements control execution during crisis impact evasion. The proposed arrangement can successfully oppose obscure outer aggravation.	conduct dynamic thinking about guiding and slowing down the will to stay away from impact while keeping up with the adjustment of an independent vehicle in crisis circumstances

			did not recognize yet.

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Reference	Models	Strengths	Limitations
You et al. (2018)	New MDP model (with Reward capacity and Q-learning calculation) to address the stochastic practices of the ecological vehicles in thruway traffic (investigate distinctive driving procedures during cornering).	Effectively versatile to have more vehicles and more paths in rush hour gridlock. Adaptable and can be utilized to display traffic with quite a few paths and quite a few EVs. ready to show regular driving practices like overwhelming and closely following.	Traffic model for vehicles of various sizes and types (e.g., trucks, transports) having, maybe and various speeds are haven't study.
Rinaldo & Horeis, (2020)	The mixture mathematical/logical model (Markov approach and Monte-Carlo reenactment approach).	Cost-productive, time-proficient, and practical evaluation of independent framework structures, which incorporates the thought of the interweaved conditions and impacts of wellbeing and security. The model can be applied to other mechanical regions with comparative difficulties and frameworks, like advanced mechanics, medication gear, and aeronautics.	Markov states progress outline, e.g., the chance of a state-space blast.

Another technique of AVs was used in the study of Tactical cooperative planning (Lenz et al., 2016), in this study, they used a cooperative combinatorial motion planning algorithm without the need for inter-vehicle communication based on Monte Carlo Tree Search (MCTS). TCMP-MCTS examines the interactions of several vehicles in order to create cooperative motion plans.

The Monte-Carlo Tree Search (MCTS) algorithm uses random (Monte-Carlo) samples to find the best decision. A search tree is used to direct the selection process. Before reaching a leaf node, the tree is explored using a tree policy to choose which path to follow at each branch. After that, the leaf node is expanded by doing one of the remaining acts to create a new leaf node. From this node, a simulation (also known as a rollout) is performed with default policy (i.e., the default behavior of all participating actors) beyond a defined horizon or before reaching a terminal node. Any cost function that assesses the simulation outcome modifies the value of all travelled nodes. The entire procedure is presented in Figure 8.

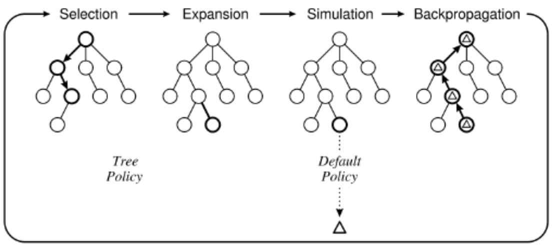

Figure 8. Process in MCTS

Two modifications to the basic MCTS algorithm have been made to make it suitable for cooperative preparation in highway scenarios. The first modification is the Filtering (we use the regular UCB1 algorithm for selection). To get the UCB value, they normalized all utilities at each decision node to be between 0 and 1. Simultaneous Actions and Data Sets was the second adjustment: they divided the preparation issue into phases. At each point, both vehicles settle on a course of action at the same time.

DISCUSSION

Prior studies have noted the models used in the abstraction and decision-making phase. Apart from that, its strength and limitation also have been studied. The Path Planning method**,** Road Condition Understanding Network model (RCUN), LiDAR, Hardware in the loop (HiL) - local planning algorithm; Convolutional Neural Network (CNN) with KITTI and TORCS, AI NAAV (AI-enabled Neurocognition Aware Autonomous Vehicle), Extended Finite State Machines (EFSM), ADAS using open-source AUTOSAR design integrated with MPC574XG-324DS board, Artificial Neural Network (ANN), Semantic Segmentation, Two-level abstraction approach to scenario description language (SDL), Convolutional Network (ConvNets) are the models used in abstraction phase of AVs.

The Path Planning method on Vehicle's Kinematic Model and ADAS using open-source AUTOSAR design has satisfied the real-time constraint. By using these models, the data collected can be analyzed in real-time to get the data at a specific time. Besides that, by adopting the Road Condition Understanding Network model (RCUN) and Convolutional Neural Network (CNN) in the abstraction phase, it can understand the road scene and as the vehicle proposal network, it has been extended to 3D input data. While by using the Two-Level abstraction approach to scenario description language (SDL), the system can understand and a common format for describing the scenery and environment element (Zhang et al.,2020).

To produce a larger coarsely annotated dataset that can yield the same performance as a smaller finely, Zlateski et al. (2018) was adapt the Convolutional Network (ConvNets) of semantic image segmentation approach in the abstraction phase of their system. While the basic Semantic Segmentation technique has been used by Behl et al. (2020) in their study. They found that the segmentation-based visual abstractions can lead to significant improvements over end-to-end methods which can produce a better performance and variance with respect to different training. However, this technique was costly to obtain, and also this method is often developed independently of the final stage of this system.

While, by using an Artificial Neural Network (ANN) in the abstraction phase, it can effectively predict the steering commands and accurately given the fact that the nonlinearity and complexity of the steering control system (Salih & Olawoyin, 2020). However, according to this study, there is no limitation was identified. This technique was different from another technique used by Natarajan et al., (2020), whereas the AI NAAV (AI-Enabled Neurocognition Aware Autonomous Vehicle) has been used. This system was able to replicate human cognitive behavior with the support of a digital autopilot.

Meanwhile, according to the literature before, found that the Technic of Markov Decision Process (MDP) was adapted with multi-objective rough strategy (MO-API) to accomplish better learning effectiveness (Xu et al.,2020). However, to get proper dynamic approaches in various traffic conditions, the researcher was suggested adapting this technique with Reinforcement Learning (RL). Another technique that has been used in the decision-making phase was the Game-hypothetical model (Tian et al.,2019). This technique was addressing the collaboration between conscience vehicle and adversary vehicle. Using this technique for the decision-making phase of AVs, making it able to be driven off the street or intersection the path markings that separate traffic of inverse bearings.

According to Y. Chen et al. (2018) in their study, the adaptive Cruise Control (ACC) and RRT-based (Rapid investigating random tree) were able to control both lateral and longitudinal speed of the vehicle also manages to handle the choke, break, and directing wheel regulators. However, this study was only done as a simulation and not being test in a real situation. Meanwhile, there are some models used for either complex traffic or complex urban condition which is the Car Following Decision-Making system has been used in a study done by Gao et al. (2018) and Rough Set Theory (X.Chen et al.,2017). However, the Car Following Decision-Making models has used Inverse Support Learning (IRL) to deal with some big data and also for many conditions of the environment. Some limitations of the Car following Decision-Making models, which is it was generalizing all vehicles with the same algorithm, which is it not very suitable as the algorithm must be planned by their (people) qualities. Meanwhile, the Rough Set Theory by X. Chen et al. (2017) have a fast operation and no data misfortune but at the same time, it also suffers from a data loss problem and needs a superior discretization.

Other than that, Hubman et al. (2017) in their study found that POMDP (Partially Observable Markov Decision Process) was given the opportunity to drive vehicles independently under different climate circumstances. This technique is also able to upgrade for the most probable future situations and probabilistic movement model for different vehicles. However, it also comes with certain limitations, developing the dimensionality of the conviction space was limited and its low arranging recurrence. Besides that, the models used by He et al. (2019) and You et al. (2018) which is the Dynamic Threat Assessment Model and also a new MDP are facing the same limitation which is they are not tested in various situations, traffics, and also speeds.

The first issue is cost. In developing the Autonomous vehicle, other vehicles' expense functions aren't transparent, and they make suboptimal decisions. Using MCTS with UCB1 array, however, the researcher discovered during the experiments that the strategy is immune to such variations. This is due to two factors. To begin, because two activities have (estimated) identical costs, they are investigated equally. As a result, the node before it in the search tree must believe that the next move will be picked at random from those two possibilities, with the mean utility accumulating.

The essence of how a strategy is discovered is the second explanation for its robustness. The effect, in the type of an MCTS tree, is an input plan that specifies what the ego vehicle can do in response to other people's actions. As a result, even if a vehicle performs an inefficient action, the MCTS-tree includes the optimum solution to that action. About the fact that this is not a shred of evidence, it does provide a clear indicator of robustness.

On the other hand, some studies of AI also facing the problem of incomplete and unstable information extracted from RGB data (Li, Ota & Dong, 2018). As a result, they'll build on our work by doing further driving tests to broaden the dataset for network preparation. While the study of the kinematic model has been done (Shuaishuai, Zhuping & Hao, 2017), they were faced some problems with algorithms. Because of the vehicle's nonholonomic constraint, the majority of algorithms cannot be applied to it. They were able to differentiate between there are two sorts of limitations as a result: internal kinodynamic constraints and external obstacle limitations. Kinodynamics constraint Assume that Vmax and Amax are the maximum velocity and acceleration, respectively. The parametric trajectory generation algorithm can deal with both static and moving obstacles in a complex environment. To do so, all of the barriers are gathered into a ro-radius circle. The system's security is not jeopardized when targeting just the moving obstacle, since a static obstacle is a single moving obstacle that does not move with a velocity of 0 m/s.

CONCLUSION

The autonomous Vehicles system was consisting of two main phases which are the abstraction phase and the decision-making phase. The data will be collected in the abstraction data, and it will be processed and analyzed. The data gathered in the abstraction phase will be used in the decision-making phase to choose how the system will make the decision in any circumstance. In this paper, we review the current related works and summarize autonomous vehicle's models used in the abstraction and decision-making phase. Besides that, the strength and limitations of each model have been reviewed. We found that there are various technics used in the abstraction phase also in the decision-making phase. Each technic also has its own strength and limitations. Future work will focus on the dominant models used in the abstraction phase and decision-making phase specifically in the automotive industry.

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