An application of artificial intelligence in trajectory planning

Zixiang Nie
Shanghai Experimental foreign language School，Shanghai，200000，China；

Abstract. Autonomous vehicle Development has accelerated recently, yet trajectory planning remains one of its most technically demanding components. A proper trajectory planning algorithm is essential for achieving safety, comfort, and immediate response capabilities in autonomous transportation systems operating in complex or changing environmental situations. The Research evaluates three typical trajectory planning methods: sampling-based, search-based algorithms, and optimization models against AI-driven planning systems. Traditional methods encounter three main drawbacks: insufficient mesh density control, the inability to efficiently adapt, and the failure to process real-time operations. By contrast, AI models — particularly those employing deep reinforcement learning — demonstrate significant robustness, generalizability, and dynamic adaptability advantages. System training through rewards allows artificial intelligence systems to produce navigational movements that respond well to multiple system elements, including dynamic obstacles, meteorological conditions, and multi-dimensional spatial restrictions. These Research findings demonstrate that AI trajectory planning methods bring revolutionary changes to autonomous driving improvement. Traditional methods have significant shortcomings, but the new approach solves these problems and provides vehicles with better efficiency and safety in unknown environments. Research into AI algorithm refinement should focus on enhancing transparency features, making systems more efficient and suitable for real-world applications.

Keywords: Autonomous vehicle; Trajectory planning; AI-driven planning systems; Deep reinforcement learning.

1. Introduction

Artificial intelligence (AI) has emerged as a dominant industry topic in recent times and leads to intelligent systems that now modify our daily existence and mobility patterns. Artificial intelligence shows its most impactful effect by integrating into driverless vehicles. Autonomous vehicles function without human intervention to provide better access to people with disabilities and the aging population while decreasing accidents and lowering production expenses for manufacturers. Implementing small automated vehicles demonstrates tangible effects in lowering death rates while simplifying manufacturing operations.

The modern intelligent driving system continues to face multiple technological hurdles. The interpretation of sensor data by self-driving systems becomes less accurate in intense snowfall conditions or at night. Delayed or inaccurate information transfer from the perception module to subsequent modules through decision-making and control causes a higher risk for critical errors that can lead to collisions. The trajectory planning stage is the most essential component within the three functional modules of perception planning and control. This module produces safety-oriented paths that deliver comfort alongside efficient motion capabilities. Insufficient performance from a vehicle's trajectory planning module leads to delayed reactions and performance of impossible paths that present safety hazards to passengers. The paper identifies low "hash rate" as a primary cause of delayed environmental analysis, leading to hazardous situations when traffic conditions rapidly change.

The Research community has created various trajectory-planning methods to handle these problems. The traditional trajectory planning approaches consist of sampling, searching, and optimization-based methods. The three planning methods have distinct advantages and disadvantages in their applications. Rapidly exploring Random Trees (RRT) succeed in high-dimensional spaces through their random approach of building branching tree structures to link start and goal states. The enhanced performance of RRT* comes from its capability to execute iterative improvement that leads to smoother results. The A* algorithm uses heuristic and cost functions to find optimal movement directions through grid-like maps during search-based planning operations. Model Predictive Control and Linear Quadratic Regulators are optimization methods that use vehicle models with high precision to solve constrained mathematical planning problems. Complex mathematical calculations and restricted responsiveness to environmental variations accompany these methods, providing mathematically proven solutions.

The standard methodology shows technical limitations whenever operational scenarios need reliable solutions and quick system adjustments. During application, these systems heavily depend on predefined models and environmental maps while facing difficulties when dealing with moving obstacles, imperfect sensing, and unexpected road conditions. The performance of sampling and searching methods decreases when mesh density becomes insufficient to handle complex or rapidly changing environments. The time-consuming Nature of equation-solving during optimization-based planning prevents its use in fast millisecond-level decision-making. The technology requires improvement to make autonomous vehicles effective in uncertain surroundings with precise navigation while maintaining quick speeds.

Artificial intelligence has emerged as a powerful solution to address existing problems in trajectory planning technology. TAI systems, especially those based on neural networks and deep learning, possess robust nonlinear pattern recognition, real-time learning, and adaptive decision-making capabilities. The systems replicate human intelligence by undergoing multiple training sessions. The reinforcement learning algorithm enables AI agents to navigate an environment by conducting experiments, while their behavior adaptation depends on a reward function that measures achievement rates. Through continuous operation, the AI system develops an improved internal model, which helps it prevent previous errors and achieve maximum operational efficiency. AI obtains expanded abilities for handling dynamic driving conditions because improvements in computing power and algorithm advancements take place. Through learned experience, this AI system develops, supplying answers to unpredictable situations and updating its operational strategies without human intervention. The learning-based adaptability mechanism solves multiple critical problems in traditional planning algorithms.

The Research evaluates standard trajectory planning technologies and then shows how deep reinforcement learning handles their restrictions as an AI-based solution. The Research is divided into four main sections. The paper begins by explaining the three traditional trajectory planning methods, sampling, searching, and optimization, while examining their strengths and weaknesses. The fundamentals of AI and its historical progression are discussed, along with neural networks and learning techniques applicable to control system applications. The paper examines trajectory planning with AI by explaining reinforcement learning methods alongside descriptions of training models and network architectures needed for implementation. The paper discusses current Research developments while explaining how AI technologies can advance autonomous vehicle autonomy from Level 4 to Level 5. This research presents an assessment approach demonstrating how artificial intelligence continues to expand into the future design of autonomous vehicles.

2. The means of traditional trajectory planning and the principal analysis

Generating navigational paths through autonomous vehicles requires planning them to meet operational restrictions while maintaining safe performance. Researchers and engineers used three distinct method categories before applying artificial intelligence: sampling-based approaches, search-based algorithms, and optimization-based techniques. The trajectory generation problem receives different solutions through these three distinct approaches. Sampling methods select points at random to explore the space. In contrast, search methods evaluate points based on cost and heuristic rules, and optimization methods transform planning problems into mathematically constrained systems to be solved. The classical toolkit for autonomous navigation consists of these methods, which require understanding both their core mechanisms and limitations to determine how AI may add improvements. This discussion examines these methods, with RRT, A*, and MPC as illustrative examples of their structural properties and benefits, and encountered difficulties.

2.1 Sampling method

First, the sampling method arranges a wide range of possible paths. The working theory is related to the map. A connecting path will be established from the starting point to the destination. Then, there is a map with various routes connecting the origin and destination. The system automatically eliminates this path if an obstacle hinders the vehicles from moving normally and safely. The system must exclude the time-consuming and strange ways that lead to the wrong accomplishment of the primary purpose. This algorithm will select some points and connect them into an entire tree. The system will move in a searching state and find a possible path starting from the initial and goal states. More specifically, a tree T involves the starting point S, and a new point is produced near the randomly selected point. Then, the system will detect the obstacle's existence and make the following judgment. If there is no obstacle in the connecting line between the randomly selected point and the adjacent point, this new point will be added to tree T, and the whole tree will be enlarged. However, this new point will be rejected, and the latest points will be selected again if an obstacle is located in the connecting line.

2.2 Searching Method

The search mean has a theory similar to that of the sampling mean, and they are all based on the planning map. The grids will be connected to a trajectory path. The particular trait of this method is that it can detect the definite steps before self-driving vehicles have a moving incentive. For instance, the system provides a specific judgment; the direction of the first step points north if the destination is located in the northern part of the map. There is another situation in which an obstacle is in front of the vehicle. The system will determine the next step and ensure the accomplishment of the main aim.

On top of that, the quality of trajectory planning is directly proportional to the mesh density, which has the same benefits as the sampling mean. Moreover, an A-star algorithm is applied in this method. Using an evaluation function, $f(x)=g(n)+h(n)$, can evaluate every point. Then, the meaning of $g(n)$ manifests the realistic cost when vehicles move from one node to another. And $h(x)$ manifests the estimated cost when vehicles move from node to the destination. Then, this algorithm will classify the speed into three levels: low-speed, medium-speed, and high-speed. And the system needs to consider the time side. During the motions of the self-driving vehicles, the system needs to detect the motion state to determine if collisions will occur. However, the limitation of this method is the difficulty in solving the problem of high-dimensional spaces. Then, the constantly changing obstacles are a significant challenge to the system, and it cannot produce an accurate trajectory planning path very rapidly.

2.3 Optimization Method

The mean of the optimization is vastly different from that of others. This system produces a function designed for trajectory planning. Suppose the trajectory planning needs to satisfy the demand for safety. In that case, the variable factors, such as acceleration and angular speed, must be considered. Moreover, soft constraints and exact penalty functions in model predictive control [1] are always included in the equation, such as $y=a\times w2\times t$. And the gradient of the function needs to be smaller so that the safety of passengers and the efficiency of moving can be ensured. Also, there is a hybrid parameter-varying model predictive control for autonomous vehicle steering [2]. If this function has a solution, it indicates that this value underlies optimum manipulation, leading to the production of the best path satisfying the primary purpose. However, the non-existence of the solution shows that there is no best path.

In addition, the computational optimal control is the algorithm used in the optimization method. Firstly, its basic mode is a mathematical function, and the input of this function includes variable factors, such as angular speed and motion state, which are linked to the primary purpose. Then, these factors will be involved in a differential equation. The aim is to satisfy the minimum time and energy related to the oil-consuming volume and the path smoothness. Moreover, the characteristic difficulties of this algorithm limit its effectiveness in autonomous driving lane changing. More specifically, the trajectory planning path needs to satisfy the conditions of vehicle dynamics and its judgment in measuring safe distance. Also, the system needs to optimize the steering wheel angle and acceleration. In general, the optimization method converts motion manipulation of dynamic problems into optimization problems that can be solved. At the same time, there are limitations in tackling robustness and timelessness. The ability to calculate cannot react to issues very well, indicating a higher possibility of safety accidents. Plus, it cannot adapt to environmental conditions very well, such as motion planning in urban environments [3].

2.4 Summary

These trajectory planning frameworks, which include sampling-based, search-based, and optimization-based, have fundamental weaknesses that decrease their capabilities in dynamic, uncertain scenes. RRT sampling and its derived methods succeed well in high-dimensional complex environments but create problems through random Nature, reduced smoothness, and dependent behavior on mesh densities. The A* search-based algorithm generates definite routes while using heuristics. However, its operations slow down when working with satisfactory grid resolution and when needs arise to re-plan trajectories following obstacle modifications. The mathematical framework of LQR and MPC creates precise solutions for path planning. Still, it needs exact system models while processing paths efficiently, which can make them burdensome for real-time operations.

Each method shows weak robustness and timeliness in responding to rapid changes in input and unpredictable environmental changes. The framework's operational performance highly depends on predefined maps and fixed assumptions, hindering its ability to learn from previous occurrences automatically. The AI-based approach constructs its foundation using distinct strategies that do not require re-computing routes every time, but enable systems to learn and achieve optimization after training. The resulting ability allows them to operate efficiently in scenarios that present noisy inputs and complex decision-making spaces with high dimensions. AI systems become essential because traditional planning methods present problems that AI can resolve effectively [4].

3. The introduction of the principles and basic classifications of AI

The following content will introduce the evolving history of AI and the different generations of AI. Then, the inventions of neural networks and deep learning networks. Also, some significant events will be referred to. In addition, the leading working theory and the different classifications of AI

3.1 Primary working process and theory

3.1.1 Neural Network Architecture and Data Flow

The trajectory planning systems that use artificial intelligence operate through artificial neural networks (ANNs) that function similarly to the human brain. The network architecture includes three distinct layers: an input layer, followed by one or more hidden layers, and finishing with an output layer [5]. The processing system accepts numerical inputs from each neuron, applying an activation function before transmitting the output to the following layer. The network accepts spatial features derived from LIDAR, radar, and vision sensors, which include road curvature information, obstacle positions, and relative vehicle speed measurements. The raw sensor data is transformed into numerical vector structures that enter the input layer. The network extracts progressively abstracted and useful representations from data as it passes through the hidden layers, which enable the identification of driving lanes, detection of nearby vehicles, and estimation of risk zones [6]. The output layer produces control parameters, including steering angle, acceleration, and braking force.

The neural network trajectory planning system creates an end-to-end process that goes from sensor inputs to output controls, a key advantage. Neural networks teach perception and control elements as a single integrated model because they differ from standard decision-making approaches that require distinct feature extraction and decision-making phases [7]. The approach enables them to learn precise decision standards that work best for complicated environments with many dimensions.

3.1.2 Training Process: Loss Function, Backpropagation, and Optimization

The performance of a successfully trained neural network depends simultaneously on its structural layout and learning process. Neural networks learn their inner weights and biases through training procedures that aim for correct output responses to specified input data. A feedback system based on loss functions determines the network output distance from target values [8]. During trajectory planning tasks, the loss function calculates path differences between predictions and the optimal route to account for deviations that could cause accidents or pain. The network applies backpropagation to determine which parameters in the network caused the error after loss calculation [9]. The optimization algorithm and SGD or Adam update the parameters to minimize total loss because it receives updated information about the error between predictions and results [10]. The network develops better performance through multiple training sessions that use thousands or millions of examples. The system enables matching specific input patterns with their most suitable output results. The process leads to a function that accurately interprets complex sensor inputs to execute precise control actions. The learning process becomes exceptionally strong because the network derives knowledge from actual data instead of pre-programmed instructions. The system maintains its ability to improve and adapt to new scenarios through high-quality training data obtained from simulations, driving logs, or synthetic environments. The system allows knowledge transfer between different environments, thus supporting driving operations under unpredictable real-world conditions [11].

3.1.3 From Manual Feature Engineering to End-to-End Learning

The significant achievement of deep learning is eliminating the need for manual feature engineering. The planning methods used traditionally, including Model Predictive Control (MPC) and rule-based systems, demand domain experts to carefully perform variable input, parameter specification, and cost definition. The workload for this technique grows steeply when complex or unpredictable environmental conditions prevail [12]. The neural network under end-to-end learning receives raw sensory data, which it transforms into control signals. The autonomous driving system allows a deep neural network to process raw camera images from front views to generate predictive steering data by navigating without lane detection or curvature estimation implementations [13]. The training exposes the model to numerous driving situations, enabling it to identify critical visual patterns needed for driving decisions.

This shift from rule-based pipelines to fully data-driven architectures greatly enhances flexibility and scalability. Through this approach, the AI system can detect hidden data relationships that human engineers might miss. Generalization to new environments is essential because it fulfills the critical need for trajectory planning in real-world driving, where each road and traffic condition remains unique. The network can adjust to new road layouts, weather conditions, and sensor Measurement variations through its learned internal environmental representation. The self-developed capability to be robust is the key factor that permits deep AI systems to excel above traditional approaches during situations needing real-time adjustments [14].

3.1.4 Encoding Spatial and Temporal Patterns for Planning

The problem of trajectory planning demands the investigation of both spatial and temporal elements. The vehicle must understand its spatial position and predict the evolution of environmental conditions and other agents. The efficient treatment of spatial and temporal dependencies relies on purpose-built neural network architecture in contemporary AI systems. The processing of spatial data through images of roads, traffic signs, and occupancy grids is performed by Convolutional Neural Networks (CNNs). The network extracts spatial features at different levels, which enable vehicles to understand lane markings, detect obstacles, and identify safe driving areas [15]. RTNNs and LSTM networks analyze sequences to forecast upcoming motions of surrounding vehicles and traffic light updates [16]. The Transformer-based architecture from natural language processing has been modified to work in driving applications. These models demonstrate excellence in tracking long-distance relationships between scene components and monitoring numerous agents in real-time, thus improving overall decision quality in complex traffic conditions [17]. AI models that use spatial and temporal methods create awareness-based trajectory predictions for the future. The systems envision future conditions while making plans, which constitute a fundamental need for the safe operation of autonomous vehicles. AI-based planning outmatches traditional reactive methods through its predictive power, thus creating conditions for better human-imitating driving performances.

3.2 The classifications of AI and basic models

The classifications of AI are divided into three types. The first type is generative artificial intelligence, also known as generative AI. This sort of AI has a technological skill in its creativity, which means that AI can self-learn and produce similar but brand-new content, such as paintings or songs, via adaptive sub-gradient methods for online learning and stochastic optimization [18]. So, its core ability is creativity compared to traditional AI. And generative AI uses deep learning structures to study on its own. A "Transformer" module is involved in the network system. Then, this module always focuses on the core word in a sentence and a deep neural network architecture for real - time semantic segmentation [19]. For example, the system provides a sentence, "I want to eat a cheeseburger," to the generative AI, and the keywords "eat" and "burger" will be captured. This module performed well in anglicizing long sentences. Also, it can produce a real-time iteration scheme for nonlinear optimization in optimal feedback control [20]. Then, the Large Language Model (LLM) module also plays a significant role in dealing with language, and this module can understand complex sentences or information, forming coherent sentences, such as ChatGPT.

In addition, generative AI has been promoted in diverse situations, like content creation. More specifically, it can produce a scientific dissertation or generate a couple of scientific data points on its own. It can combine information from different dimensions to create something. Plus, this AI can make custom-built content according to consumers' requirements. Furthermore, the other two types are "Supervised Learning" and "Unsupervised learning". Firstly, Supervised Learning could select information from a data list with labels, and the system continuously analyzes the relationship between input and output and makes a further prediction about the input information next time. This kind of AI can predict the future house price via its function, which is formed according to the past house prices. However, this AI over-depends on data of high quality and quantity.

On top of that, "Unsupervised Learning" can select information from the data list with no tags. And this AI can identify and understand the potential relationship inside the information or some rules. So, it can arrange the information involving similar content and group them without labels. Another core function of this AI is to filter out irrelevant data and capture critical information. Based on these two types of functions, it provides new information and identifies data outliers. These kinds of AI can generally arrange the information without labels, but the given explanations are not precise enough.

3.3 The main applications of AI

Nowadays, the three main applications are divided into three types. Firstly, the "Large Language Model", which is called "LLM", has high performance in language understanding and production ability. This technology underlying the "Transformer" structure can capture the keywords and accurately understand the main idea of the information. In addition, its core traits are high solving ability and generalizability. More specifically, this model has high productivity because it can analyze a large volume of data simultaneously, leading to high efficiency. The generalizability means that the system can adapt to different tasks simultaneously, and it can demonstrate a solid understanding in diverse academic regions. Then the present representative example is ChatGPT. It can engage in dialogue with humans, demonstrating its understanding and proficiency in sentence structuring during this process. AI can generate code and autonomy in developing a program based on the generated code for private individuals to discuss its generalizability. Moreover, its successful completion of the bar examination demonstrates its robust learning capabilities and strong knowledge repository. Furthermore, AI has already been able to diagnose patients 'conditions in hospitals. Beyond clinical applications, AI's transformation power extends to industrial empowerment across multiple sectors. For the healthcare sector, the AI system analyzes medical images, such as X-rays, with relative accuracy comparable to human experts. And it can enhance the success rate of surgeries. For instance, it can automatically assess an organ's capacity and provide precise diagnoses on the next steps. In the financial industry, it can judge stock price trends and conduct risk assessments. For the education industry, AI can reduce teacher troubles. To exemplify that, it can automatically prepare lessons in advance. For students, AI is like a teacher, providing strict and correct answers and explanations for many questions while also presenting its thinking process. Moreover, the second type of AI application is in the robotics industry. In a vehicle production workshop, mechanical arms can accurately select objects of different sizes because AI can utilize its perception module to adapt to the surrounding environment. It is efficient for the arms to avoid collisions by planning the route and using image-based localization with LSTMs for structured feature correlation [21]. And the "reinforcement learning" algorithm can enhance the working efficiency. Then, the "da Vinci surgical robot" dedicated to the medical industry uses visual navigation technology, improving the precision of minimally invasive surgeries to the level of millimeters. Also, the warehouse robot "Kiva," invented by Amazon, utilizes its trajectory planning technology and intelligent selection ability to improve working efficiency. The last part is linked to driverless vehicle technology. Trajectory planning technology is applied to the manipulation of vehicles. Deep learning on point sets for 3D classification and segmentation [22] can be shown in map planning and dynamic occupancy grid prediction for urban autonomous driving: Deep learning approach with fully automatic labeling.[23] Furthermore, the AI has high robustness and timelessness, enabling driverless vehicles to move efficiently and safely. So, the AI is adaptable to the self-driving cars.

4. The trajectory planning by using AI and the general means-oriented Research

This passage will discuss the working theory of trajectory planning underlying AI and how neural networks and deep learning work to form the final function of AI. Then, the advantages of AI in different conditions will be referred to, and this is why trajectory planning relies on AI but not others, showing the prominent benefits of AI and the low degree of participation by humans. The final topics discuss the two Research outcomes linked to efficiency and understanding ability.

4.1 The Trajectory Planning Theory Based on AI

The AI experiences a training process to study the trajectory planning paths. The reinforcement learning method is an algorithm to form a function. It will make the experimental subjects keep trying and making mistakes to get the rewards, leading to the formation of a function. More specifically, the system can set some rewards if the AI achieves some goals. The AI system aims to maximize its rewards so that it will avoid identical mistakes if such errors have already been committed. Plus, an algorithm is applied in the AI, which is "deep reinforcement Learning". This algorithm aims to accumulate the rewards to a maximum extent.

Furthermore, the "Multi-layer Neural network" plays a significant role in combining the functions. The neural network with three or more layers can approximate a function. The complexity of the action function and reward function is hard to express. Then, deep reinforcement learning can approximate the two functions together. In trajectory planning, learning deep neural network control policies for agile off-road autonomous driving[24], and it can achieve Continuous control with deep reinforcement learning[25].

4.2 The Advantages of AI

The AI has a series of benefits. Firstly, AI has a high generalizability. AI can adapt to various environments, including harsh conditions like rainy days or steep road sections. The AI can undergo training and develop a function dedicated to diverse surroundings. However, the drawbacks of AI also occur in the formation process of functions. During this process, it takes an extremely long time for AI to train, and a large amount of data is a big challenge to the hash rate of AI because the requirement for the elaboration of the function is the information volume. To exemplify these conditions, consider high-speed roads, such as those in cities. A complex situation can also be involved. The perception module empowers self-driving vehicles to be sensitive. Then, the "deep learning" algorithm can increase the number of neurons in a different position, which is proficient in processing information and enhances the accuracy and precision of the functions. Moreover, AI is brilliant because it can make decisions and cope with a range of problems by itself, leading to a lower participation rate of humans. Plus, AI can integrate the capabilities of various models and form a comprehensive function. Also, the AI can avoid obstacles efficiently due to its high timelessness, leading to a response in a very tiny second.

4.3 The Latest Research Progress

At present, two recent Research studies have been done. The first one is connected with rising efficiency. Scientific researchers are inventing a function capable of rapid convergence. This invention is called an "Expert system", meaning that AI can think from an expert perspective, as an expert has extensive experience and valuable knowledge. After the application of this invention, working efficiency experienced a dramatic proliferation because fewer mistakes were made, and they could utilize the expert's knowledge to cope with some complex problems rapidly. Moreover, another type is the "Large Language Model". It has a high understanding ability based on the "Transformer" model. The large amount of information allows AI to adapt to almost all situations. The neural network enables the system to be creative. Then, the combination of creativity and high hash rate allows the system to have high problem-solving ability and simultaneously think quickly. The application of AI in trajectory planning is also linked to it. The problem-solving ability, robustness, and timelessness enable AI to be proficient in tackling many problems, such as harsh conditions and high-speed roads. A strong understanding allows the system to know the motion trend and how to avoid obstacles rapidly.

5. Conclusion

Based on the explanations above, we can be aware of the importance of AI. AI can understand different information very specifically and precisely due to the "Transformer Model", leading to AI capturing the keywords, and its high understanding ability makes it convenient for us to discuss it. Plus, the ability to understand enables the system to analyze information very rapidly. Moreover, the neural network, which has more than three layers, can fit the function and a large amount of information, such as input data, leading to a fitting function. In the trajectory planning method, AI is robust and timeless. It can ensure passengers enjoy efficient, safe, and comfortable travel. The extra algorithm enables the system to be highly efficient in processing large amounts of data and to cope with problems.

On the other hand, AI is experiencing a proliferation, and it is headed towards the "Large Language Model". AI evolved from a nonlinear machine to a machine capable of handling linear problems. Then, the multi-layer perception was suggested. The "deep learning" algorithm plays a significant role in fitting the function. And the complex process of fitting two functions together triggers the invention of the "Large Language Model". The AI region still has spare space for scientific researchers to explore.

References

[1] E. C. Kerrigan and J. M. Maciejowski, "Soft constraints and exact penalty functions in model predictive control," in Proc. UKACC International Conference (Control 2000), (Cambridge, UK), September 2000.

[2] T. Besselmann and M. Morari, "Hybrid parameter-varying model predictive control for autonomous vehicle steering," European Journal of Control, vol. 14, no. 5, pp. 418–431, 2008.

[3] D. Ferguson, T. M. Howard, and M. Likhachev, "Motion planning in urban environments," Journal of Field Robotics, vol. 25, pp. 939–960, 2008.

[4] Y. Gao, T. Lin, F. Borrelli, E. Tseng, and D. Hrovat, "Predictive control of autonomous ground vehicles with obstacle avoidance on slippery roads," Proceedings of DSCC, 2010.

[5] A. Krizhevsky, I. Sutskever, and G. Hinton, "ImageNet classification with deep convolutional neural networks," Advances in Neural Information Processing Systems, vol. 25, 2012.

[6] Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning," Nature, vol. 521, no. 7553, pp. 436–444, 2015.

[7] Goodfellow, I., Bengio, Y., & Courville, A. (2016). Deep Learning. MIT Press.

[8] Chen, C., Seff, A., Kornhauser, A., & Xiao, J. (2015). DeepDriving: Learning affordance for direct perception in autonomous driving. Proceedings of the IEEE International Conference on Computer Vision (ICCV).

[9] Bojarski, M. et al. (2016). End-to-End Learning for Self-Driving Cars. arXiv preprint arXiv:1604.07316.

[10] Zhang, C., Bengio, S., Hardt, M., Recht, B., & Vinyals, O. (2016). Understanding deep learning requires rethinking generalization. arXiv preprint arXiv:1611.03530.

[11] Rumelhart, D. E., Hinton, G. E., & Williams, R. J. (1986). Learning representations by back-propagating errors. Nature, 323(6088), 533–536.

[12] Kingma, D. P., & Ba, J. (2014). Adam: A method for stochastic optimization. arXiv preprint arXiv:1412.6980.

[13] Pan, X., You, Y., Wang, Z., & Lu, C. (2017). Virtual to real reinforcement learning for autonomous driving. arXiv preprint arXiv:1704.03952.

[14] Kuderer, M., Gulati, S., & Burgard, W. (2015). Learning driving styles for autonomous vehicles from demonstration. Robotics: Science and Systems.

[15] Chen, Y., et al. (2021). Learning-based decision and control for autonomous driving: A survey. IEEE Transactions on Intelligent Transportation Systems, 22(11), 6693–6712.

[16] He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep residual learning for image recognition. Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR).

[17] Lee, N., Choi, W., Vernaza, P., Choy, C. B., Torr, P. H., & Chandraker, M. (2017). DESIRE: Distant future prediction in dynamic scenes with interacting agents. Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR).

[18] Casas, S., Gulino, C., Liao, R., & Urtasun, R. (2020). Implicit latent variable model for scene-consistent motion forecasting. Proceedings of the European Conference on Computer Vision (ECCV).

[19] Paszke, A., Chaurasia, A., Kim, S., & Culurciello, E. (2016). Enet: A deep neural network architecture for real-time semantic segmentation. arXiv preprint, 1606.02147.

[20] M. Diehl, H. G. Bock, and J. P. Schloder, "A real-time iteration scheme for nonlinear optimization in optimal feedback control," SIAM Journal on Control and Optimization, vol. 43, no. 5, pp. 1714–1736, 2005.

[21] Walch, F., Hazirbas, C., Leal-Taixé, L., Sattler, T., Hilsenbeck, S., & Cremers, D. (2017). Image-based localization using LSTMs for structured feature correlation. In 2017, IEEE International Conference on Computer Vision (ICCV) (pp. 627–637).

[22] Qi, C. R., Su, H., Mo, K., & Guibas, L. J. (2017). PointNet: Deep learning on point sets for 3D classification and segmentation, in IEEE Conference on Computer Vision and Pattern Recognition (CVPR).

[23] Hoermann, S., Bach, M., & Dietmayer, K. (2017). Dynamic occupancy grid prediction for urban autonomous driving: Deep learning approach with fully automatic labeling. In the IEEE International Conference on Robotics and Automation (ICRA).

[24] Pan, Y., Cheng, C.-A., Saigol, K., Lee, K., Yan, X., Theodorou, E. A., & Boots, B. (2017). [36] Learning deep neural network control policies for agile off-road autonomous driving. 31st Conference on Neural Information Processing Systems, NIPS 2017. Long Beach, CA, USA.

[25] Lillicrap, T. P., Hunt, J. J., Pritzel, A., Heess, N., Erez, T., Tassa, Y., Wierstra, D. (2016). Continuous control with deep reinforcement learning. ArXiv preprint, 1509.02971.