Progress of Dynamic Path Optimization Strategies for Racing Cars Based on Machine Learning

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Keywords: Autonomous Racing, Path Optimization, Reinforcement Learning, Multi-Sensor Fusion, Simulation.

Abstract: Motor racing has always been a globally popular sport that pursues the ultimate and the extreme. Among them, the racing route is undoubtedly a very important aspect. This article will elaborate in detail on how to use machine learning technology to improve the research progress of future racing in dynamic optimization of routes. Next, computer dynamic vision algorithms such as You Only Look Once (YOLO) and Faster R-CNN will be introduced in detail. Meanwhile, the hardware that assists in obtaining information will also be introduced one by one. And combine this with the simulators commonly used by drivers to create the possibility of updated simulator driving, and at the same time, this can also be utilized to cultivate better training plans. At the same time, the challenges that this plan may face will also be taken into account. The first one is the lack of precise and large amounts of data. At the same time, the ethical decision-making of AI and its temporary response ability on the track also need to be considered.

1 INTRODUCTION

On January 29, 1886, with the birth of the world's first car, "Benz Patent-Motorwagen", humanity's yearning for speed gave rise to a passionate and challenging sport - racing. Throughout the history of automobiles, motor racing has always been a test of automotive industry technology and human driving skills. As motor racing progresses, the competition has evolved from a simple comparison of speed to a sport that integrates aerodynamics, materials science, intelligent control, team strategy, and human physiological limits, and pursues precision. In this sport where the gap between drivers is one-thousandth of a second, drivers not only have to endure extremely strong physical acceleration but also face significant psychological pressure. However, to get closer to this limit, the "best lane" undoubtedly holds a core position. The "racing lane" is an ideal track that allows the racing car to pass through the entire track at its highest average speed. This route requires consideration of the curvature of the late arrival, the condition and temperature of the road surface, the physical limits of the vehicle, as well as the connection between entering and exiting the corner and the center of the corner in the curve. It also greatly tests the driver's understanding and control of speed and stability. At the same time, the racing line is also one of the key factors for winning the race (González et al., 2015).

However, traditional route optimization extremely tests the personal talent and track experience of drivers, which undoubtedly leads to very high costs and great difficulties. Throughout the history of motorsport, with the advancement of human technology, racing cars have been upgraded time and again at the technical level. The currently emerging artificial intelligence possesses extremely powerful data analysis and pattern recognition capabilities, which undoubtedly make it highly suitable for application in the racing field. It can reduce the operating costs of teams and, through the self-learning of machines, more efficiently find the best lane for racing car tuning.

This article systematically reviews and summarizes the research progress of AI in the optimal route design and planning of racing cars, elaborates on how to solve the problems mentioned above through the application of object detection, and specifically describes how artificial intelligence can help teams formulate better route planning and strategies.

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An, Z.
Progress of Dynamic Path Optimization Strategies for Racing Cars Based on Machine Learning.
DOI: 10.5220/0014362600004718

In *Proceedings of the 2nd International Conference on Engineering Management, Information Technology and Intelligence (EMITI 2025)*, pages 545-550
ISBN: 978-989-758-792-4

2 RACING CAR ENVIRONMENT PERCEPTION AND TARGET DETECTION

Before applying artificial intelligence to fleet planning and route planning, accurately perceiving the environment and collecting information are undoubtedly the primary prerequisites for making precise judgments. Take Formula One as an example. Usually, for the convenience of collecting information, a standard ECU system is installed to use mobile phone information and transmit it to the telemetry center. Team staff can understand vehicle performance in real time and intuitively, and check engine health, tire wear and fuel consumption. Many current research reports have mentioned that a perception system of Lupin is designed to achieve end-to-end autonomous driving and is suitable for rapid judgment and planning under extreme working conditions. As mentioned above, if artificial intelligence is to be applied to motorsports, it is necessary to meet the requirements of real-time and accurate identification of track conditions and the positions of competing vehicles on the same track, as well as the judgment and use of special terrains such as shoulders and buffer zones. Therefore, in order to obtain information, a series of commonly used sensors, such as cameras, may need to be equipped Devices such as LiDAR and millimeter-wave radar, in combination with advanced algorithms, interpret this sensor data(Williams et al., 2017).

2.1 Racing Car Target Detection Based on Computer Vision

Unlike traditional racing car sensors, in terms of object detection in computer vision, especially the object detection algorithms based on deep learning, they play a significant role in processing the captured image data. Currently, there are two mainstream algorithms They are respectively "One-Stage Detectors" and "Two-Stage Detectors" (Kapania et al., 2016; Kendall et al., 2019).

Firstly, regarding "One-Stage Detectors", the characteristic of this type of algorithm is that it has an extremely high recognition speed and is more efficient. It can form a Bounding Box at the edge of an object just by looking at a complete image, just like the human eye, and analyze the category. This fast response and processing algorithm is highly suitable for real-time scenarios that require reactions at the level of one-thousandth of a second. Moreover, in the F1TENTH Challenge, the researchers precisely utilized the advantage of You Only Look Once (YOLO) among One-Stage Detectors (Redmon et al., 2016). Ultra-high-frequency detection of track drop pain has been achieved.

Secondly, there are "Two-Stage Detectors", among which the most representative one is Faster R-CNN. The characteristics of this type of algorithm are that the analysis results are more accurate and the detection accuracy is also very high. It will first scan the image and propose Region Proposals that may contain objects. Then, conduct a detailed analysis and classification of each of these areas, one by one. Although it is more accurate compared to "one-stage Detectors", it can also greatly enhance the feasibility and safety of the strategy.

The reason why these algorithms can recognize objects on the track is through "learning". Researchers will prepare a dataset with many track maps in advance. Then, they will manually process these images to standards, such as drawing racing lines on the track, marking reference points, perfecting track details, etc. They will label each opponent's car and convert it into structured and semantic information that machines can understand (Geiger et al., 2012). This can also help the machine learning stage obtain more direct input (Ren et al., 2015).

2.2 Racing Perception Technology and Multi-Sensor Fusion

Considering the uncontrollability of track conditions, such as weather, humidity, and light intensity, it is crucial to introduce sensors based on other principles for information complementarity in order to stably ensure that the sensors receive information. First of all, there is LiDAR. It accurately predicts the distance to objects by emitting laser beams that are invisible to the human eye nearby and calculating the time it takes for the beam to reflect and return. It can instantly construct an accurate "three-dimensional point cloud map" composed of a vast number of data points. This map is like a virtual 3D model, clearly depicting the geometric outline of the track, the undulations of the road surface, and even the precise shapes and positions of the obstacles.

Another feasible option is millimeter-wave radar. Compared with LiDAR, it uses radar wave detection and can directly measure the relative speed of the target, which can largely avoid collisions.

However, when fusing these sensory sensors, Early Fusion and Late Fusion are usually adopted. Firstly, the Early Fusion strategy is typically used to blend the data at the most primitive stage. A typical example is projecting the 3D point cloud data of LiDAR onto the 2D images captured by the camera. This means that the halo of three-dimensional coordinates uses RGB color information, which implies that a virtual track environment can be better constructed, and the track situation can be analyzed more accurately through condition clues such as color and texture. However, the drawback is that the computational load is large, and the spatio-temporal synchronization requirements for each sensor are extremely high, which poses certain obstacles in real-time performance.

Late Fusion is just the opposite. Late Fusion enables the sensor system to independently complete the parts of perception and target detection, and draw preliminary conclusions, which are then passed to the central module for summarization and arbitration of these conclusions. If it is reflected on the track, the visual system should identify the distance between the car in front and the car behind, and then output the distance to the next corner center through the LiDAR system. After that, the relative speed with the car behind should be output through the radar system to help analyze the difference in corner speed and obtain a better corner exit Angle. The fusion center will aggregate these data together and conduct a comprehensive analysis, ultimately reaching a comprehensive judgment. This logic is clearer. Moreover, due to the modularity, if an accident or collision occurs in the racing car and a certain sensor malfunctions, other parts can still operate normally, thus providing stronger stability for the system (Kaufmann et al., 2018).

3 BEST PATH PLANNING FOR RACING CARS

In the control system of artificial intelligence racing cars, if the environmental perception system is the "eyes", then the programmed autonomy that regulates driving decisions is the "brain" that makes decisions. The definition of racing path planning is to find a driving path that allows the racing car to pass through the track safely and stably, while adhering to various constraints, such as the vehicle's dynamic response, the maximum adhesion use of tires, the track edge, and the best and fastest path within one lap or a section of the track. This means converting environmental information from perception "processing" (i.e., track edge position, obstacle position, etc.) into specific and actionable driving instructions (i.e., steering wheel Angle, accelerator and brake load), thereby providing a crucial bridge in the connection and integration of perception and control processes(Pfaff et al., 2021).

3.1 Racing Car Target Detection Based on Computer Vision

When familiar with the track conditions and layout and having sufficient data, traditional optimization methods are very effective in finding the optimal solution. One of the most prominent examples is Model Predictive Control (MPC).

For instance, one can think about how the MPC works with the mindset of a highly skilled F1 driver. Drivers have a very good understanding of the performance of their cars (which is equivalent to an accurate vehicle dynamics model). When driving a series of curves at a speed of 300 kilometers per hour, their gaze is not on the center of the curve they are about to pass, but looks towards the next center and predicts the best combination route for passing the next two or three curves to achieve the best total time (this is predicted within a short "time range").

The driver can quickly calculate the "optimal sequence of actions" (steering Angle, accelerator and brake), thereby passing through the corner at the highest possible speed while respecting the car and the track. But importantly, they do not immediately apply the entire optimal solution. They will take the actions necessary to accurately enter the first corner, but when they enter the corner, they will recalculate the plan again based on the real-time status of the car (such as the size of the tire grip or the change in the car's posture) in order to modify the order of jumping over the next corner.

This rolling optimization approach, which involves planning, predicting and correcting, makes the MPC's work very much like that of an experienced F1 driver, continuing to maximize the vehicle's performance within its physical limits. As a result, they create a very smooth and positive "optimal racing line"(Pavel et al., 2022).

3.2 Racing Path Planning Based on Reinforcement Learning

Although model-based optimization often works well, model-based optimization methods rely on accurate vehicle dynamics models. Reinforcement Learning (RL) offers an interesting option. The principle of RL is to learn the best strategic interactions in the environment through "trial and error", and it usually does not require a detailed physical model, which can also provide a large tolerance for errors. In the field of motorsport, SONY

AI's "Gran Turismo Sophy" has achieved significant success. This game uses deep reinforcement learning technology to defeat professional drivers with world-class driving skills in the simulator. Overall, RL is developing rapidly.

Initially, Q-learning was a method of filling the value "lookup table" with all possible states or actions, which was impossible in the complex racing environment. The next significant advancement is Deep Q-Network (DQN), as AI can use deep neural networks to estimate all these action values and learn directly from the data and information provided by complex observations, such as camera lenses.

The next-generation reinforcement learning, namely the latest policy gradient method, is more straightforward because artificial intelligence can learn a "policy network" to select the next action. Among the Policy gradients, Proximal Policy Optimization (PPO) is the most commonly used and accepted algorithm for complex autonomous control tasks, such as racing, due to its training consistency and speed, which is an evolution of the algorithm that allows AI to adopt complex racing strategies (Chen et al., 2018).

3.3 Racing Path Smoothing and Tracking Control

Whether generated through optimization theory or reinforcement learning, the "optimal path" produced by advanced planning modules is typically composed of a series of discrete road points. Although this path might be the most optimal on a macroscopic level, simply connecting these points would form a zigzag line with many sharp turns, which is impossible for a real vehicle to travel smoothly at high speeds. Therefore, before sending the path to the vehicle's actuator, two key subsequent steps must be taken, namely path smoothing and path tracking control.

The goal of achieving the path smoothing step is to convert the discrete sequence of path points into a geometrically continuous smooth curve. This curve must be physically feasible for the vehicle to follow, which means its curvature must be continuous to allow for a smooth steering input. Common techniques include the use of mathematical tools, such as Bezier curves or mathematical curves similar to B-Splines, to fit new trajectories to the original points and create a path that is both close to the optimal route and inherently smooth.

Realizing path tracking control is the final step to putting a smooth and ideal trajectory into practice. Its task is to design a controller that continuously compares the actual position of the vehicle with the ideal trajectory and calculates the necessary steering angles and accelerator/brake commands in real time to minimize tracking errors. In the field of autonomous driving, there are several classic path tracking control methods:

First of all, there is the Pure Pursuit Controller, which is a very intuitive geometry-based control method. The core idea is to select a target point on the ideal path in front of the vehicle with a fixed "Look-ahead Distance". Then, the controller calculates the curvature of a perfect arc, which starts from the current position of the vehicle and intersects with this forward-looking point. This curvature is directly converted into the required steering Angle, guiding the vehicle towards the target.

Secondly, there is the Stanley Controller. This is the famous controller used by the Stanford University team to win the DARPA Grand Challenge, and it shows greater stability at high speeds. It operates by simultaneously correcting two core errors: one is the "Cross-track Error", that is, the distance from the front axle of the vehicle to the nearest point on the path; The other one is "Heading Error", which is the Angle difference between the direction of the vehicle and the path tangent at that point. By correcting these two types of errors, the Stanley controller enables the aircraft to converge to the target trajectory quickly and smoothly.

These path tracking controllers form the lowest level of the "brain" of an AI racing driver. They are the "nerve endings" that faithfully execute advanced strategic intentions, ensuring that every maneuver precisely follows the planned "optimal racing route".

4 CONSTRUCTION AND SIMULATION TRAINING OF VIRTUAL RACING SCENES

In the sport of racing, which is highly dangerous and costly, it is unrealistic to directly apply the development, training and debugging of AI algorithms to real cars. Take the current Formula One as an example. The annual research and development budget cap is 175 million US dollars. Therefore, every test error may compress the overall budget of the team and also pose a great risk. Thus, the virtual simulation environment plays a crucial role in the training and learning of AI.

Virtual scenes can provide a safe, low-cost, repeatable and efficient testing condition, which can give AI sufficient space for trial and error. More importantly, it can simulate various extreme weather and dangerous working conditions that are difficult to encounter in the real world, and also enhance the robustness of AI algorithms.

First of all, open-source simulators, such as CARLA, are an important part of autonomous driving research (Dosovitskiy et al., 2017). As an open-source simulator, CARLA has a rich API that enables researchers to configure sensors (such as cameras, lidars, etc.), traffic flow, and various environmental conditions (such as weather, lighting, etc.). This makes CARLA a useful research simulator for testing perception and planning algorithms running in software. Microsoft's AirSim is another open-source emulator that offers excellent physics and realistic features. AirSim features SIL/HIL functionality, which means developers can test their algorithms in an environment similar to hardware deployment.

Secondly, some commercial racing games, such as "Assetto Corsa", "irracing" and "Gran Turismo Sport", based on minimal physical modeling, provide excellent realism in vehicle dynamics and also offer track data from laser scans. This level of fidelity significantly enhances the realism of driving feedback, which builds more accurate scenarios for the teaching of reinforcement learning agents that require precise physical interaction. For example, Project (Pfaff et al., 2021) of "Gran Turismo Sophy" utilized the high fidelity of the Gran Turismo commercial racing simulator to train AI systems to compete with human drivers.

These simulation platforms all provide researchers with an interface (such as a Python API), allowing control commands to be sent to the simulation platform and vehicle status and related sensor information to be read. Basically, each platform provides a complete definition of robots or agents that learn in a closed-loop "AI simulator" training paradigm.

5 CURRENT LIMITATIONS AND FUTURE PROSPECTS

Although the dynamic path optimization and planning strategies for racing cars through machine learning have great potential, when truly implemented in the padtrack, there are still many hidden dangers and limitations, which also point out the ultimate research direction of this study in the future.

5.1 Limitations of the Dataset

One major issue in this research is that it is difficult to obtain high-precision, diverse and genuine racing car data without the confidential information from the event officials and some teams. However, compared with the general autonomous driving field where there is a lot of public information, because racing car data has high commercial value and confidentiality, the leakage of racing car data will cause some teams to lose their competitiveness So this is also the main protected information for many teams, which makes it very difficult for researchers to obtain real and reliable information. Even if the simulator can produce some data, there will still be a significant difference from the real data (Sakai et al., 2022).

5.2 Ethical Challenges

Firstly, in the complex and highly dangerous environment of the track, when facing unavoidable accidents, the decisions made by AI are also very important. One is to preserve the vehicle and reduce damage, and the other is to protect other drivers on the track. Therefore, such moral and ethical decisions go beyond the technical scope and can be a hidden danger for AI.

So Wiesmüller think if AI can only be used for human-machine collaboration, race engineers or team managers might be more in line with the situation and be able to intervene at the moment of mistakes. Perhaps this is more likely to be the future application direction (Wiesmüller, 2023).

6 CONCLUSIONS

This article systematically studies and reviews how machine learning can be applied to the planning and optimization techniques of dynamic racing paths. Research shows that if AI is to be applied to racing cars, it requires the support and integration of key technologies such as perception, planning, and simulation.

Although there are current issues such as data scarcity, insufficient hardware computing power, and ethical challenges in AI, it is already clear that this sector will have a clear application direction and development blueprint in the future. AI can be deeply integrated with vehicle engineering, incorporating digital twin technology to optimize the engineering details of vehicles in real time, endowing racing cars with self-regulating and self-summarizing functions. Secondly, more efficient simulation display technologies can be studied and produced through predictive algorithms, ultimately achieving multi-agent collaboration in motorsports. This will also largely change the current strategies of motorsports competitions.

In conclusion, there is still much room for improvement in artificial intelligence in extreme sports such as car racing. However, as it develops, car racing will evolve from a mere test of drivers' skills and teams' strategies into an era that promotes data-driven, competitive, and human-machine interconnection and collaboration.

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