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Research on Traffic Safety Based on Local Path Planning for Intelligent Vehicle Avoidance

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ABSTRACT: In recent years, the automobile has gradually developed to intelligent direction. As a key part of automatic driving, the local obstacle avoidance path planning ability of intelligent vehicle has a great impact on the safe driving and traffic safety of intelligent vehicle. This paper analyzes the status quo of road traffic safety in China and determines the importance of path planning for avoiding obstacles. Then, by summarizing the principle and algorithm of obstacle avoidance path planning, the content of obstacle avoidance path planning is explained. Through analyzing the specific impact of local obstacle avoidance path planning on traffic safety, it is clear that vehicle dynamic constraints and collision free constraints play a major role in traffic safety. Therefore, according to different constraints, the research results of the existing obstacle avoidance path planning are summarized in detail. Finally, the future research directions are forecasted based on the analysis of the current research results.

Keywords: intelligent vehicle; Obstacle avoidance path planning; Traffic safety; Dynamic constraints; No collision constraint

I. INTRODUCTION

1.1 Research background

In daily life, car has become an indispensable means of transport for people to travel. With the continuous improvement of people's economic level, the required quality of life is also improving. In order to travel faster and more comfortably, more and more households have bought cars, making the car parc increase continuously in recent years. By 2020, the car parc in China has exceeded 280 million units, with an annual increase of more than 20 million units. In the future, the car parc in China may reach over 400 million units [1].

However, the car parc increases year by year, which not only brings convenience to people's travel, but also causes increasingly prominent traffic problems. The exhaust emission of fuel vehicles causes ozone layer damage and air pollution aggravation. Too many vehicles on many urban roads lead to serious traffic jam and frequent traffic accidents. The traffic safety of intelligent vehicles cannot be ignored. For the above problems, many scholars have conducted in-depth research and exploration, and believe that intelligent vehicles have excellent safety performance and environmental protection performance, which can effectively alleviate these problems.

According to the investigation and research, most traffic accidents are caused by misoperation of the driver [2]. The intelligent vehicle has a large number of environmental sensing devices, which can detect the surrounding environment, accurately locate the target position of the barrier and the distance between the vehicle and the barrier. Artificial intelligence will more respect traffic rules and calculate the next action of surrounding pedestrians, integrate information in real time, make optimal driving decisions, ensure the intelligent vehicle safely pass through the impact range of obstacles, so that the vehicle can effectively avoid mis-operation caused by fatigue driving, inattention and other reasons when driving in a complex and diverse road environment, and minimize the occurrence of traffic accidents. At the same time, the intelligent vehicle is equipped with intelligent positioning system and high-precision map, which can realize network connection, automatically synchronize surrounding road traffic conditions through wireless communication technology, and realize real-time information exchange between vehicles and between vehicles and roads through establishment of vehicle network and intelligent traffic infrastructure, so as to select a more smooth route at the first time, shorten driving time, reduce energy consumption, alleviate environmental pollution caused by automobile exhaust emissions, alleviate traffic congestion, and make travel more efficient, comfortable and convenient.

As one of the core functions of automatic driving, automatic obstacle avoidance of intelligent vehicle has a significant impact on the future development of intelligent vehicle, and has always been a key research content at home and abroad [3]. The automatic obstacle avoidance process is a process in which the vehicle plans a smooth and collision free local obstacle avoidance path according to the surrounding environment information after detecting the obstacle through the sensor, and then the vehicle travels along the path to actively avoid the obstacle. The ability of intelligent vehicle obstacle avoidance path planning has a great impact on the safe driving of intelligent vehicles. During driving, the surrounding environment of the vehicle is constantly changing and the vehicle runs fast, so it is necessary to plan the path to avoid obstacles in real time. At the same time, the planned path shall meet the requirements of vehicle mechanical constraints, road boundary constraints, etc., to ensure that when the vehicle runs on the path, no side slip, rollover, driving out of the road and other accidents will occur, and ensure traffic safety.

1.2 Research status of intelligent vehicles at home and abroad

The research on relevant technologies of intelligent vehicle in foreign countries is earlier than that in China. America Electronics Company developed the first AGV in the 1950s. In the 1970s, developed countries led by the United States began to research the path planning technology and achieved good results.

The Navlab series developed by the research team at the navigation laboratory at Carnegie Mellon University has progressed from Navlab-1 to Navlab-11. Most of the vehicles are semi-automatic vehicles and a few are automatic vehicles. The self-driving vehicle Navlab-5 was driven from Pittsburgh to Santiago, during which Pomerleau and Jochem operated only the throttle and brake. The direction of the vehicle was automatically controlled by the neural network, and the journey was called "crossing the United States without hands" [4]. It can be seen that the intelligent vehicle path planning technology has achieved initial success. The latest NavLab-11 is based on a WRANGLER Jeep, equipped with differential TrimbleAgGPS114, gyroscope and photoelectric code disk, SICK LMS 221-3206 laser scanner, SONY EVI-330 color camera and other sensors. The four-core computer on the vehicle can process the information collected by various sensors and send the information to each sub-unit. Navlab-11 pilotless vehicle is shown in Figure 1-1.

Fig. 1.1 Navlab-11 Unmanned Vehicle

At present, Google's driverless technology is at the leading level in the industry. Its driverless project was officially launched in 2009, and many technical personnel who participated in DARPA challenge were invited to carry out software, electronic map, radar sensing and other aspects of research. At present, a subsidiary of Google's parent company, has conducted a total of 9.81 million km of unmanned driving tests in the Phoenix area, with a total of 18 accidents. The data shows that Waymo one inevitable accident every 340000 km [5], which is enough to prove that the autopilot system can successfully complete most dynamic driving tasks in specific geographical areas and under specific conditions. Waymounmannedvehicle is shown in Figure 1-2.

Fig. 1.2 WaymoUnmanned Vehicle

In addition to the United States, Japan and some European countries have also carried out research on unmanned driving technology. Under the influence of traffic laws in Japan, the research on unmanned driving technology in Japan focuses on safety and accident free. Toyota, as one of the famous auto brands in Japan, is committed to research in the field of artificial intelligence, and has invested a lot of money for this purpose. The main research contents of its autonomous driving technology include: "intelligent driving" technology for precise recognition and prediction judgment; Intelligent connectivity "technology to assist safe driving with vehicle-to-vehicle and vehicle-to-road infrastructure; Human-vehicle intelligent interaction "technology to identify the state of the driver and carry out vehicle driving handover with the driver [6].

Although the domestic intelligent vehicle research started late, it also made some achievements. Since the first self-driving vehicle ATB-1 developed by National University of Defense Technology, Shenyang Institute of Automation and Harbin Institute of Technology in 1922 [7], China has made another breakthrough in the field of self-driving.

In 2011, the new generation of Hongqi HQ3 transformed from National University of Defense Technology completed an unmanned driving test of 286km, starting from Changsha and ending at Wuhan, with an average speed of 87km/h. With continuous efforts, Changan Automobile has achieved mass production of UNI-T models with L3 class automatic driving system, and L4 class automatic driving demonstration operation under electrification, networking, intelligence and sharing. The functions of automatic driving vehicles such as marking parking space and automatic auxiliary braking for reversing tend to be perfect.

Huawei, as a big domestic brand, does not carry out vehicle manufacturing business, but makes great contributions to the development of intelligent vehicle software. Huawei has set up an Internet of Vehicles business department, and launched intelligent driving, intelligent cockpit, intelligent network connection and intelligent electric solutions. Geehu Alpha S produced jointly by Huawei and BAIC has the ability to detect high-speed vehicles, and can automatically drive 1000 km in downtown areas without intervention, and the driving state is infinitely close to manual driving [8].

II. PLANNING PRINCIPLE AND ALGORITHM OF LOCAL OBSTACLE AVOIDANCE PATH OF INTELLIGENT VEHICLE

2.1 Planning process of local obstacle avoidance path

As a highly intelligent product, the intelligent vehicle itself has a complete set of safety obstacle avoidance system, which can realize safe driving on the road without human intervention and smoothly avoid obstacles. The intelligent vehicle obstacle avoidance system is mainly composed of three parts: obstacle detection, information processing and obstacle avoidance path generation. The intelligent vehicle uses a series of onboard environment sensors such as laser radar, camera, millimeter-wave radar and GPS to detect the surrounding environment information and determine the specific location, speed and attitude of the vehicle. The information processor combines all the information, and determines the existing safety hazards by analyzing the distance between the barrier and the vehicle, the speed of the barrier, the road boundary and other factors affecting the avoidance, and then adopts an appropriate avoidance strategy to plan the optimal avoidance path. Based on the reasonable path obtained from the planning, the vehicle can carry out the subsequent steering operation, follow the path to travel, and safely pass through the impact of the obstacle[9].The local obstacle avoidance path planning process is shown in the figure below.

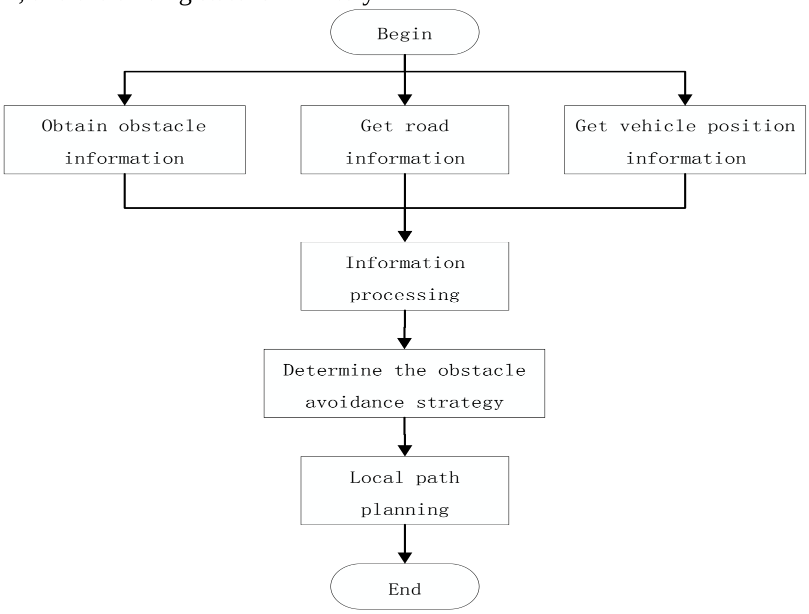

Fig.2.1 Flow chart of local obstacle avoidance path planning

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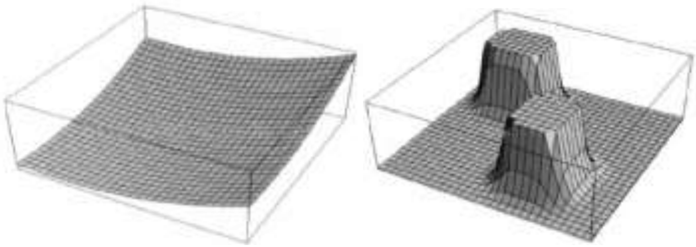
The vehicle local obstacle avoidance path planning can be divided into the local obstacle avoidance path planning under static environment and the local obstacle avoidance path planning under dynamic environment. The path planning under static environment mainly considers the vehicle speed, obstacle distance, road boundary, vehicle kinematic constraints, vehicle dynamics constraints and other factors[10]. When planning the path in dynamic environment, in addition to the above factors, the speed and direction of movement of obstacles shall be considered, so the problem is more complex. The intelligent vehicle plans a smooth and collision free local obstacle avoidance path by analyzing various factors [11]. For the vehicle running at the normal speed under the global optimal path, after detecting an obstacle in front of the driving path, the local obstacle avoidance path planning is carried out according to the obstacle and the self-driving condition, so as to avoid the obstacle reasonably and avoid the traffic accident.

2.2 Path planning algorithm

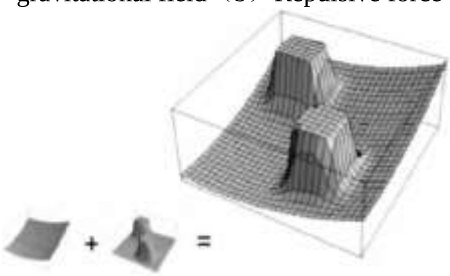
At present, many scholars have proposed good planning methods for local obstacle avoidance path planning of intelligent vehicles to ensure that intelligent vehicles can identify and detect obstacles and safely reach the target point. Typical algorithms include artificial potential field method, B-spline curve method, RRT algorithm, particle swarm optimization algorithm, grid method, etc.

2.2.1 Artificial potential field method

The artificial potential field method is a kind of feedback control strategy, which is simple and clear and convenient for real-time control of the bottom layer [12]. Artificial potential field refers to a man-made virtual force field, similar to gravitational field. The starting point is regarded as high potential energy point, while the target point is low potential energy point. The gravitational field is shown in Fig. 3.2 (a), and the barrier will generate repulsive force to the vehicle, which is shown as a peak. The repulsive force field is shown in Fig. 3.2 (b). Under the action of this potential field, the vehicle can avoid the barrier and reach the target point. The resultant force field is shown in Fig. 3.2 (c).



（a）gravitational field（b）Repulsive force field



（c）Resultant force field
Fig. 2.2 Diagram of artificial potential field

2.2.2 B-Spline Curve Algorithm

B-Spline curve belongs to the path planning algorithm based on curve fitting. The calculation principle of this algorithm is easy to understand and the calculation amount is small. The path planning will not consume a lot of time, and can meet the requirements of real-time generation of planning path. The path planned by the B-spline curve algorithm based on its own characteristics is relatively smooth, which can avoid the occurrence of dangerous accidents such as sideslip and rollover caused by large steering, and extend the service life of the vehicle.

B-spline curve is obtained by linear combination of B-spline basis functions [13]. Assuming that the B-spline curve is controlled by n+1 control vertices in total P_0, P_1, P_2,..., Pnn, the formula of k-order B-spline is:

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$$P(u) = [P_0 P_1 P_2 \ \dots \ P_n] \begin{bmatrix} B_{0,k}(u) \\ B_{1,k}(u) \\ B_{2,k}(u) \\ \vdots \\ B_{n,k}(u) \end{bmatrix} = \sum_{i=0}^{n} P_i B_{i,k}(u) \quad (2.1)$$

Where $B_{(i,k)}(u)$ represents the i-th order B-spline basis function and u is an independent variable.

B-spline basis function is defined in various ways. The most easily understood definition is the recursive expression of de Boor-Cox, which is expressed as follows:

$$B_{i,k}(u) = \begin{cases} \begin{cases} 1, u_i \le u \le u_{i+1} \\ 0, \text{other} \end{cases}, & k = 1 \\ \frac{u-u_i}{u_{i+k-1}-u_i} B_{i,k-1}(u) + \frac{u_{i+k}-u}{u_{i+k}-u_{i+1}} B_{i+1,k-1}(u), & k \ge 2 \end{cases} \quad (2.2)$$

u_is called node vector and is the continuous change value of a group of non-decreasing sequences. Generally, the first and last values are defined as 0 and 1 respectively and expressed as $[u_0, \dots, u_k, \dots, u_n, \dots, u_{n+k}]$.

2.2.3 RRT algorithm

The basic idea of RRT algorithm is to search the entire planning space by continuously expanding the leaf node until the leaf node in the random tree reaches the target area. Then, a feasible path from the starting point to the target point can be found through node backtracking. The specific expansion of the algorithm is shown in Fig. 2.3 [14].

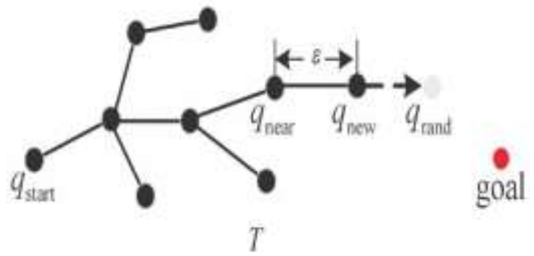

Fig.2.3 RRT algorithm expansion diagram

Where T represents an extended random tree, and there is only one node on the tree, i.e. starting point q_{start}, so q_{start} is also called root node; q_{rand} is a random sampling point, which is generated randomly by the sampling function during each node expansion process; q_{near} is the node to be extended. In the traditional RRT algorithm, the node nearest to the random sampling point q_{near} in the tree T is taken as q_{near}.

$$dist(q_{rand}, q_{near}) \le dist(q_{rand}, q_i) \quad (2.3)$$

where: i is the i-th node on the tree extending outward from the starting point; $dist$ is the calculation function of the Euclidean distance between any two points in the space; q_{new} is the generated new node, which is obtained by expanding a step ε by the node to be extended q_{near} along the connection direction of q_{new} and q_{rand}.

$$q_{new} = q_{near} + \varepsilon \frac{(q_{rand} - q_{near})}{\| q_{rand} - q_{near} \|} \quad (2.4)$$

If there is no obstacle threat between q_{near} and q_{near} connection line, add q_{near} to T; otherwise, discard the node and generate sampling point again to guide the extension direction of random tree T. This is repeated until the leaf node in the random tree is in the target area and the expansion stops to find a collision free path from the starting point to the target point.

2.2.4 Particle Swarm Optimization

Particle Swarm Optimization (PSO) was originally an evolutionary algorithm proposed by Kennedy and Eberhart in 1995 by simulating birds' foraging behavior [15], and later modified by Shi et al to form the current standard algorithm [16]. PSO algorithm imitates the foraging behavior of birds. In a known space, each individual in the group randomly forages in the region, and each individual does not know the specific location of food, but they can know their current location and the distance of food. Information is exchanged between individuals to obtain the location of the individual nearest to the food. Then, other individuals move to the nearest individual, and the speed of finding food becomes faster and faster after continuous communication. The PSO algorithm simulates the foraging behavior of birds, and its basic search unit is called particle. Each particle updates its own speed and position according to its own current position, its own optimal position, and the optimal position and current speed of group communication. Wherein the current position is obtained according to the current position of the previous iteration and the velocity calculated in the previous iteration after the previous iteration; The optimal position of an individual is the current position of a particle at the iteration closest to the final target in the process of continuous iteration; The optimal position of group communication is the position nearest to the final target among the optimal positions of all particles in the iterative process of the whole particle group; The current velocity is the particle velocity calculated in the last iteration. Each particle iteration will be compared with its optimal position according to the current position. If the current position is closer to the final target than its optimal position, the optimal position of the individual will be updated. Upon each iteration, find out the best position among all particles in this

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iteration, which is the nearest position to the final target. Compare the best position found by individuals with the best position found by the population. If the best position found by individuals is closer to the final solution than the best position found by the population, update the best position found by the population.

2.2.5 Grid method

Grid method is a commonly used environmental modeling method in UAV path planning, which was first proposed by Elfes and Moraet al. [17]. Grid method divides the real environment map into equal parts by taking the selected grid as the unit, and forms a connection diagram through these unit grids to realize environment modeling. The grid map is simple in structure, requires less information to be stored, closely corresponds to the real map, easy to create and maintain, easy to locate the unmanned vehicle, and reduces the realization difficulty of particle swarm algorithm, artificial potential field method and other unmanned vehicle path planning algorithms.

The basic idea of grid method is to divide the real environment of the whole unmanned vehicle patrol inspection into multiple grids with the same size and project them into the two-dimensional plane space. These grids are continuous but not overlapped. The state of each grid corresponds to the environmental information. Generally, the state of the grid is determined according to whether there is an obstacle in the grid. Through mathematical modeling method, the complex and continuous grid map with environment information is represented in the form of two-dimensional matrix, where "1" represents the barrier grid and "0" represents the trafficable grid. Through the grid method, after the real environment is transformed into a two-dimensional matrix, the unmanned vehicle path planning problem can be transformed into the processing of the matrix, reducing the difficulty of the path planning problem, but the accuracy of the results is greatly affected by the grid, so how to select the appropriate grid shape and size is a very important step.

Square grids are the most commonly used cell grid shapes. The number of adjacent grids of the square grid is 8, i.e. there are eight grids that can be moved forward in the next step, as shown in Figure 2.4. Corresponding to the actual map, there are eight directions: east, south, west, north, southeast, southwest, northeast and northwest. If the side length of the square is l, the distance from the center to the east-west grid is $0.5 \times l \times 2$, and the distance to the southeast, southwest, northeast and northwest is $\sqrt{2} \times l \times 2$.

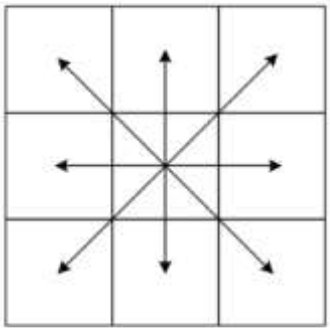
Fig.2.4 Square Grid

2.3 Impact of local obstacle avoidance path planning on traffic safety

The emergence of intelligent vehicles plays a positive and beneficial role in traffic safety, but intelligent vehicles are different from traditional vehicles, and there is no driver participating in the driving process, and all operation processes are completed by the control center. When there is an obstacle in front of the vehicle driving road, the intelligent vehicle can effectively identify the characteristics of the obstacle and drive along the planned path to avoid the obstacle, which is an important means to prevent traffic accidents. Simple based on the above obstacle avoidance path planning algorithm can not effectively meet the traffic safety, and some constraints to ensure traffic safety shall be added in the planning process. The research finds that the constraint conditions to ensure traffic safety mainly include two aspects: meeting the vehicle dynamics constraint and meeting the vehicle collision free constraint. If the obstacle avoidance path cannot meet the vehicle dynamics constraints, the vehicle is prone to roll and slide at high speed, which easily causes traffic chaos and affects traffic safety. If the avoidance path fails to meet the collision constraint of the vehicle, the collision accident will occur during the driving of the vehicle, and the avoidance path will be meaningless.

III. PLANNING CONSTRAINTS OF LOCAL OBSTACLE AVOIDANCE PATH CONSIDERING TRAFFIC SAFETY

Combined with the impact of the obstacle avoidance path on traffic safety described in the previous section, this section details the research results made by the current scholars on such problems to ensure traffic safety.

3.1 Vehicle dynamics constraints

When the vehicle runs at low speed, it can be regarded as rigid body due to small lateral force. However, when the vehicle runs at high speed, the

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lateral force of the vehicle is too large, the tire and body of the vehicle will move to a certain extent, and the vehicle cannot be completely regarded as rigid body. In order to meet the handling stability of vehicles at high speeds, vehicle dynamics issues need to be studied.

If the local obstacle avoidance path fails to meet the vehicle dynamics constraints, it is easy to cause the vehicle dynamics instability, and may also cause the vehicle unable to track the path to travel, so that the actual driving path of the vehicle is greatly different from the planned path, threatening the normal operation of the traffic, at the same time, the comfort of the vehicle is low, and the passengers cannot have a good riding experience. To avoid this, vehicle dynamics constraints are added based on safety and comfort when planning the local path.

Wang [18] et al. analyzed the limit relation between speed and front wheel corner and determined the conditions for safe operation of vehicle based on different aspects.

$$(0.22 - 0.002v)\ g \le a_y < 0.67\mu g \quad (3.1)$$

$$0.67\mu g \le a_y < 0.85\mu g \quad (3.2)$$

Xu [19] proposed angular velocity constraints, velocity constraints, maximum curvature constraints and acceleration constraints to plan a reasonable path meeting vehicle dynamics constraints.

(1) Angular velocity constraint

If the planned path is affected by the front wheel deflection angle speed, the parameters must comply with the angular speed constraints. Once the parameters exceed the actual vehicle execution capacity, the follow-up path tracking effect will be extremely poor.

$$|\omega| \le \omega_{max} \quad (3.3)$$

$$\omega_{max} = min(\frac{a_{ymax}}{v_x}, \frac{v_x \delta_{max}}{D_s(1+K_s v_x^2)}) \quad (3.4)$$

(2) Speed constraint

Based on the movement characteristics of the vehicle, when encountering a turning situation, if the speed is too fast, the overturning moment caused by the centrifugal inertia force is equal to the stable moment, it is very likely to roll over, that is, the speed during the lane change process should be less than the critical speed of roll over.

$$|v| \le |v_{max}| \quad (3.5)$$

$$|v_{max}| \le \sqrt{\frac{BgR}{2h_s}} \quad (3.6)$$

(3) Maximum curvature constraint

The designed lane change path shall meet the curvature constraint of the vehicle, and the maximum curvature shall be less than the maximum allowable value of the vehicle.

$$|\rho|_{max} \le \rho_{max} = \frac{1}{R_{min}} \quad (3.7)$$

$$R_{min} = \frac{v_x}{\omega_{max}} \quad (3.8)$$

(4) Constraint of acceleration

The acceleration index represents the comfort of the lane change path, which should not be too large. According to the comfort requirements of human body:

$$|a_{xmax}| < 2.5m/s^2 \quad (3.9)$$

$$|a_{ymax}| < 2.0m/s^2 \quad (3.10)$$

3.2 Obstacle avoidance constraint

Collision avoidance is the primary condition to complete obstacle avoidance and the premise to ensure driving safety. The path change is mainly divided into three stages: preparation stage, execution stage and post-adjustment stage. When the vehicle is driven manually, the preparation stage refers to the stage when the driver observes the movement of surrounding vehicles, turns on the direction lamp and prepares to change the lane at any time after the intention of changing the lane is generated. Execution stage refers to the process that the driver turns the steering wheel, executes the lateral displacement of the vehicle, reaches the expected target lane position and returns to the body. Post-adjustment stage refers to the process of fine-tuning the distance between the vehicle body and the lane line when the vehicle is in the target lane.

During the lane change preparation phase, in order to adjust the longitudinal position in order to perform the lane change, the driver in this phase tends to accelerate or decelerate, and therefore may collide with the front and rear vehicles in the original lane. Zhao[20] established an elliptical vehicle model to describe the hazard area around the vehicle. The specific image is as follows.

Fig.3.1 Oval Vehicle Model

The mathematical expression of the elliptical vehicle model is as follows:

$$L_{long} = \frac{L}{2} + (1 - \omega_{style})^{\frac{L}{W}} \frac{v_r}{v_f} \quad (3.11)$$

Where L_{long} is the major axis of the vehicle elliptical model; L is the length of the vehicle; ω_{style} is the driving style coefficient of the driver; W is the vehicle width; v_r is the rear vehicle speed; v_f is the front

vehicle speed.
Based on the elliptical vehicle model, the minimum safe distance between the vehicle and the vehicle in front of the lane, the vehicle in front of the target lane and the vehicle behind the target lane is specified.

(1) Minimum safe distance from the vehicle in front of the lane

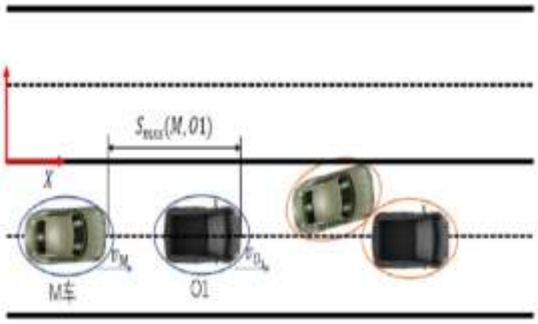

Fig.3.2 Collision time with vehicle in front of the lane

As shown in Figure 4.5. Obstruction vehicle O1 is driving right ahead of this lane. The blue outline shows the position of the two vehicles at the initial moment, and the orange outline shows the attitude of the two vehicles in collision. Assuming that the initial time is t_0, the collision time is t_1, the main vehicle speed is v_M, and the front vehicle speed is v_{O1}, then through the analysis of the collision critical position, the minimum safe distance between two vehicles is:

$$S_{mss}(M,O1) = max\left\{S_M - S_{O_1} + 2L_{long} + \frac{W}{2}sin\varphi\right\}$$
$$= max\left\{\int_0^{t_1}\int_0^{\tau}[a_M - a_{o_1}]d\tau dt + (v_M - v_{O1})t_1 + 2L_{long} + \frac{W}{2}sin\varphi\right\} \quad (3.12)$$

where $S_{mss}(M,O1)$ is the minimum safe distance between two vehicles; S_M is the distance the main vehicle travels along the reference line from the initial time to the collision time; S_{O1} is the distance of the front vehicle traveling along the reference line in this period; L_{long} is the half axle length of elliptical vehicle model; W is the vehicle width; φ is the yaw angle of the vehicle at the time of collision; a_M and a_{O1} are the accelerations of the main vehicle and the front vehicle respectively; v_M and v_{O1} speed of main vehicle and front vehicle respectively.

(2) Minimum safe distance from the vehicle in front of the target lane

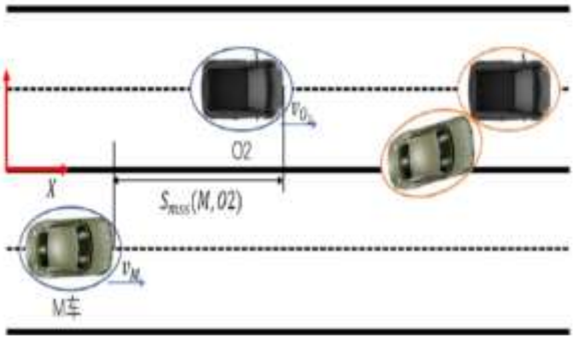

Fig.3.3 Collision time with the vehicle in front of the target lane

During lane change, if the speed of the vehicle in front of the target lane is too slow or the distance is too small, it will lead to collision and failure of lane change. The collision between the main vehicle and the front vehicle running on the target lane can be divided into three modes: side collision, corner collision and rear-end collision, but the critical collision mode is corner collision. As long as corner collision can be avoided, the other two modes can also be effectively avoided. Assuming that the angle collision time between the main vehicle and the vehicle in front of the target lane is t_2 and the vehicle speed in front of the target lane is v_{O2}, the minimum safe distance between the main vehicle and the vehicle in front of the target lane is:

$$S_{mss}(M,O2) = max\left\{S_M - S_{O_2} + 2L_{long} - \frac{W}{2}sin\varphi\right\}$$
$$= max\left\{\int_0^{t_2}\int_0^{\tau}[a_M - a_{o_2}]d\tau dt + (v_M - v_{O2})t_2 + 2L_{long} - \frac{W}{2}sin\varphi\right\} \quad (3.13)$$

where $S_{mss}(M,O2)$ is the minimum safe distance between two vehicles; S_M is the distance the main vehicle travels along the reference line from the initial time to the collision time; S_{O2} is the travel distance of the vehicle in front of the target lane in this period along the reference line; a_M and a_{O2} are the acceleration of the main vehicle and the vehicle in front of the target lane respectively; v_M and v_{O2} are the speeds of the main vehicle and the vehicle in front of the target lane respectively.

(3) Minimum safe distance from the vehicle behind the target lane

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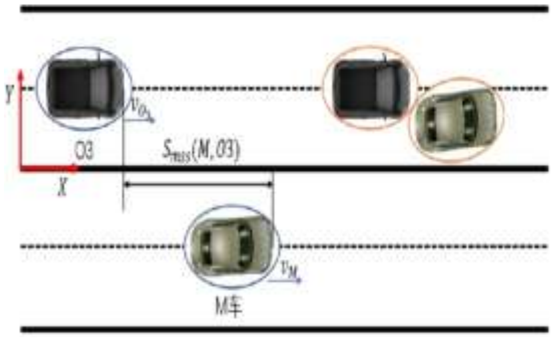

Fig.3.4 Collision time with vehicle behind the target lane

Similar to the analysis on the minimum safe distance between the main vehicle and the vehicle in front of the target lane, the collision modes of the main vehicle and the vehicle behind the target lane are also divided into corner collision, side scraping and rear-end collision. Here, the diagonal collision is analyzed. Assuming that the time of corner collision between the main vehicle and the vehicle behind the target lane is t_3 and the vehicle speed behind the target lane is v_{O3}, the minimum safe distance between the main vehicle and the vehicle behind the target lane is:

$$S_{mss}(M, O_3) = max\left\{S_{O_3} - S_M + 2L_{long}\,cos\varphi + \frac{W}{2}sin\varphi\right\}$$

$$= max\left\{\int_0^{t_3}\int_0^{\tau}[a_{o_3} - a_M]d\tau dt + (v_{O_3} - v_M)t_3 + 2Llongcos\varphi + W2sin\varphi\right\} \quad (3.14)$$

where $S_{mss}(M, O3)$ is the minimum safe distance between two vehicles; S_M is the distance the main vehicle travels along the reference line from the initial time to the collision time; S_{O3} is the distance the vehicle travels along the reference line after the target lane in this period; a_M and a_{O3} are the acceleration of the main vehicle and the vehicle behind the target lane respectively; v_M and v_{O3} are the speeds of the main vehicle and the vehicle behind the target lane respectively.

Hou [21] uses the separation axis theorem to detect collision. The basic principle is that if there is a straight line in the space with two convex polygons and the projection of the two convex polygons on the straight line does not overlap, the straight line can be considered as the separation axis of the two polygons, and there is no overlap area between the two convex polygons in the space, that is, there is no collision. The specific implementation process is to take the normal vector of each side of the convex polygon, i.e., obtain n normal vectors of one convex polygon and m normal vectors of another convex polygon respectively, and project two graphs onto each normal vector. If the line segments on each normal vector have overlapping parts, then the two convex polygons will collide. Otherwise, there is no collision.

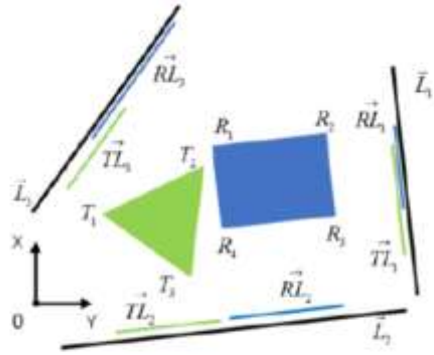

Fig. 3.5 Schematic Diagram of Splitting Shaft Theorem

Take triangle T and rectangle R for collision detection as an example, as shown in Fig. 4.8, where $\overrightarrow{L_1}$ and $\overrightarrow{L_2}$ are normal vectors of rectangle sides R_1R_2 and R_2R_3 respectively, and $\overrightarrow{L_3}$ is normal vector of triangle side T_1T_3. When two convex polygons are projected to the normal vector of the side respectively, the vectors generated by the projection to $\overrightarrow{L_1}$ and $\overrightarrow{L_3}$ have overlapping areas, and the vectors generated by the projection to $\overrightarrow{TL_2}$ and $\overrightarrow{RL_2}$ do not have overlapping areas, then the vector $\overrightarrow{L_2}$ is the separation axis of the two polygons.

To sum up, for the projection after projection of any two polygons, T_{min}, T_{max}, R_{min}, R_{max}, If present:

$$\begin{cases} T_{max} > R_{min} \\ R_{max} > T_{min} \end{cases} \quad (3.15)$$

Then it can be considered that the two polygons do not collide and the projection axis is the separation axis of the two polygons.

The separated axis theorem is only applicable to collision detection of convex polygon. Due to the complex environment of autonomous driving, the separated axis theorem sometimes cannot meet the requirements. Therefore, a more general collision detection method is required, i.e. directly determining the position relationship between a point in space and a polygon. If a point in space is located inside a polygon, the polygon to which the point belongs must collide with the previous polygon. Therefore, it is possible to use the ray method in computer graphics to determine the positional relation between an isolated point and a given polygon [22], and then expand it into a more general polygon collision detection algorithm. The basic principle of the ray method is to emit a ray from a detection point in any direction. If the ray has an even number of intersections with the polygon to be detected or does not have an intersection with the polygon, the point is located outside the polygon and does not have a collision, otherwise it is located inside the polygon.

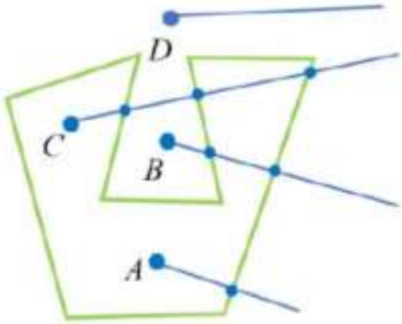

Fig. 3.6 Schematic Diagram of Radiographic Method

As shown in Fig. 4.9, point A, the number of intersection points between the emitted rays and the polygon is 0, 1, 2 and 3, respectively, with the points inside the polygon and the points outside.
In order to simplify the calculation, the ray along the X axis is generally selected. Therefore, for any point $o(x_o, y_o)$, the intersection point with polygon edge pointsp$_1(\mathrm{x}_1, \mathrm{y}_1)$ and $\mathrm{p}_2(\mathrm{x}_2, \mathrm{y}_2)$ is:

$$\left(\frac{(\mathrm{y}_0-\mathrm{y}_1)(\mathrm{x}_2-\mathrm{x}_1)}{\mathrm{y}_2-\mathrm{y}_1}+\mathrm{x}_1, \mathrm{y}_0\right) \quad (3.16)$$

IV. SUMMARY AND PROSPECT

Intelligent vehicles are very helpful in reducing traffic accidents, and as the core technology of intelligent vehicles, obstacle avoidance path planning has a great impact on traffic safety. In order to ensure that the obstacle avoidance path can maintain traffic safety, it is required to meet the dynamic constraints and non-collision constraints. The dynamic constraints of the obstacle avoidance path are mainly analyzed from the aspects of vehicle driving stability and comfort. Through the establishment of vehicle dynamic models, the stress conditions of the vehicle in the driving process are analyzed, and then the limit constraints of various dynamic parameters in the driving process of the vehicle are determined. In the process of route planning, all parameters shall be maintained under constraint conditions to avoid dynamic instability of the vehicle. Non-collision constraint is mainly based on the establishment of a vehicle geometry model, and the feasible path is screened by detecting whether the vehicle is colliding along the obstacle avoidance path, so as to determine the reasonable path meeting the requirements, avoid collision and ensure traffic safety.

The relationship between intelligent vehicle and traffic safety shall be accurately understood during the development process. As one of the main components to ensure traffic safety, the path to avoid obstacles shall be further studied in the future. The next step should be to plan a set of path clusters based on the current road environment information after an obstacle is detected. Based on various constraint conditions of the vehicle, determine the importance of each constraint condition and establish the comprehensive safety evaluation model. Finally, the safety evaluation model is used to evaluate each path in the path cluster and select the optimal path.

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