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Moving Target Tracking Method for Unmanned Vehicle Based on Laser Sensor

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In recent years, with the rapid development of electronic technology and communication technology, the manufacture of unmanned intelligent vehicles has become an increasing trend. In order to address the problem of tracking a moving, unmanned vehicle, we propose a moving target tracking method for unmanned vehicles based on laser sensor. Firstly, the kinematics model of an unmanned vehicle is linearized, and the kinematic linear tracking error model for an unmanned vehicle is obtained, which can be used to predict the future behavior of the vehicle. Then, based on this future behavior, the moving target data detected by lidar are clustered to obtain the details of the moving target by means of the nearest neighborhood method and the rule classifier algorithm. Finally, the maximum association method is used to cluster the moving target in real time and match the moving target with those stored in the list of moving targets to achieve tracking. The results show that this method can accurately and consistently control the tracking reference vehicle operation of an unmanned vehicle, and the tracking accuracy, anti-interference and collision avoidance are significantly better than other similar methods.

Keywords: Laser sensor; Unmanned vehicle; Moving target; Tracking; Clustering; Association value

1. INTRODUCTION

Nowadays, with the rapid development of science and technology, the unmanned vehicle is an integrated system which comprises environmental awareness, planning and decision-making, multi-level driving assistance and other functions. It is an important part of an intelligent transportation system [1]. It has broad application prospects in military, civil, space development and other fields. On the one hand, automobiles bring great convenience to people's lives; on the other hand, their rapidly increasing numbers have brought many problems. The excessive number of automobiles in cities creates traffic problems, environmental problems, energy problems. Safety issues are becoming increasingly prominent and attracting much attention. Although China has less than 3% of the world's vehicles, traffic accident fatality rate accounts for 16% of the world's total road fatalities. More than 100,000 people are killed under wheels every year, which leads to the conclusion that China is facing a significant traffic safety problem. The road traffic system is an important area of traffic safety research. It comprises human, vehicle and road factors. In this system, the human factor is the most important. The efforts of "people" in this system determines whether the vehicle can run as intended. A survey from the United Kingdom and the United States shows that "people", "vehicle" and "road" are three factors involved in almost every traffic accident. According to a survey report by a British agency, accidents caused by drivers alone account for 65% of the total traffic accidents (57% in the United States), but accidents involving drivers account for 95% of the total traffic accidents (94% in the United States). China's urban road traffic accident survey shows that about 90% of traffic accidents are caused entirely by drivers. In short, the fundamental problem of traffic accidents caused by drivers' inappropriate driving of vehicles, and driver negligence has been recognized worldwide as a major issue. Therefore, removing the "people" factor from this system is an effective way to solve this problem. The unmanned intelligent vehicle has emerged from

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this idea. As its name implies, the unmanned intelligent vehicle is a vehicle that can be controlled independently. The road traffic system consisting of three factors (people, vehicle and road) becomes one with two components (vehicle and road). It can completely isolate people, so that the road traffic system can become safer. It greatly reduces the possibility of traffic accidents and improves traffic safety [2]. At present, preliminary achievements have been made in the research of unmanned intelligent vehicles in China and abroad. However, in order to meet product-oriented requirements and achieve the goal of safe driving in cities and expressways, it needs to be further explored [3].

Moving-target tracking methods for unmanned vehicles have gradually become the focus of attention in related fields. A predictive control method for unmanned vehicles based on a tracking error model is proposed by [4]. This method is intended to achieve predictive control of an unmanned vehicle based on a tracking error model. The control core is an unmanned vehicle, and the tracking of a moving target near an unmanned vehicle is achieved, although the trajectory tracking accuracy is low. The robust control method for unmanned vehicle trajectory tracking based on a conditional integral algorithm is proposed in [5]. Although this makes the unmanned vehicle track a given reference trajectory, the tracking process of this method is more complex; Reference [6] proposes a trajectory tracking method for an unmanned aerial vehicle is applied to single-target and multi-target tracking problems. This method can control only the movement of the targeted UAV, and also has poor anti-interference, resulting in poor collision avoidance.

In this paper, we propose a method for tracking a moving unmanned vehicle based on a laser sensor, in order to achieve a high level of safety and precision when tracking a moving target, specifically, an unmanned vehicle [7].

2. MOVING TARGET TRACKING METHOD FOR UNMANNED VEHICLE BASED ON LASER SENSOR

2.1 Kinematics Model of Unmanned Vehicle

Firstly, the kinematics model of an unmanned vehicle is constructed and then linearized to obtain the linear tracking error model of vehicle kinematics, and to predict the future behavior of an unmanned vehicle [8].

(1) Kinematics model of unmanned vehicle

In order to simplify the design of the controller, a model of an unmanned vehicle is defined on the two-dimensional plane of Cartesian world coordinate system. In this paper, it is assumed that the unmanned wheel is in point contact with the ground, and the contact point is only pure rolling without relative sliding. This ideal constraint is essentially a non-holonomic constraint [9].

Assuming that an unmanned vehicle moves only on one plane, the non-holonomic constraint equations of front and rear wheels are:

$$\dot{x}_f \sin(\theta+\delta) - \dot{y}_f \cos(\theta+\delta) = 0 \tag{1}$$

$$\dot{x}\sin\theta - \dot{y}\cos\theta = 0 \tag{2}$$

where, x indicates the abscissa of the rear wheel center of an unmanned vehicle; y indicates the abscissa of the rear wheel center of an unmanned vehicle; x_f indicates the abscissa of the front wheel center of an unmanned vehicle; y_f indicates the longitudinal coordinate of the front wheel center of an unmanned vehicle; θ indicates the steering angle of the front wheel of an unmanned vehicle.

Many types of kinematics models for wheeled mobile robot can be transformed into unicycle models. An unmanned vehicle is a typical wheeled mobile robot [10]. The kinematics model of an unmanned vehicle can be written as:

$$\begin{bmatrix} \dot{x} \\ \dot{y} \\ \dot{\theta} \end{bmatrix} = \begin{bmatrix} \cos\theta \\ \sin\theta \\ \frac{\tan\delta}{l} \end{bmatrix} v \tag{3}$$

where, l represents the distance between the front wheel center and the rear wheel center; v represents the speed of the rear wheel center of an unmanned vehicle.

Vehicle's input variables are defined as $u = [v \quad \delta]^T$, and vehicle's current coordinates are defined as $x = [x \quad y \quad \theta]^T$.

Form (3) can also be written as:

$$\dot{x} = f(x, u) \tag{4}$$

(2) Kinematics error model of unmanned vehicle

Generally speaking, to address the problem of moving target tracking, the method of tracking reference vehicle is generally adopted. The reference trajectory is assumed to be generated by a virtual reference vehicle and the reference value is expressed by r. Therefore, the reference trajectory of an unmanned vehicle can be written as:

$$\dot{x}_r = f(x_r, u_r) \tag{5}$$

where, $x_r = [x_r \ y_r \ \theta_r]^T$, $u_r = [v_r \ \delta_r]^T$.

The right side of formula (5) is expanded by Taylor around point (x_r, u_r), and the higher order part is removed [11]. Then:

$$\dot{x} = f(x_r, u_r) + \left.\frac{\partial f(x,u)}{\partial x}\right|_{\substack{x=x_r \\ u=u_r}} \leqslant (x - x_r) + \left.\frac{\partial f(x,u)}{\partial u}\right|_{\substack{x=x_r \\ u=u_r}} \leqslant (u - u_r) \tag{6}$$

It can also be written as:

$$\dot{x} = f(x_r, u_r) + f_{x.r}(x - x_r) + f_{u,r}(u - u_r) \tag{7}$$

where, Jacobian matrix of $f_{x,r} - f$ is relative to x; Jacobian matrix of $f_{u,r} - f$ is relative to u.

Combining formula (6) with formula (7), the kinematics error model of an unmanned vehicle can be obtained.

$$\dot{\tilde{x}} = f_{x,r}\tilde{x} + f_{u,r}\tilde{u} \tag{8}$$

$$\tilde{x} = x - x_r, \tilde{u} = u - u_r \tag{9}$$

In the formula, $\tilde{x}$ represents the deviation between the current position and the reference position of the unmanned vehicle, and $\tilde{u}$ represents the deviation of the control variable.

The Euler method is applied to discretize formula (7) and the discrete linear time-varying model of the kinematics of the unmanned vehicle is obtained.

$$\tilde{x}(k+1) = A(k)\tilde{x}(k) + B(k)\tilde{u}(k) \tag{10}$$

where, $A(k) = \begin{bmatrix} 1 & 0 & -v_r(k)\sin\theta_r(k)T \\ 0 & 1 & v_r(k)\cos\theta_r(k)T \\ 0 & 0 & v_r(k)\cos\theta_r(k)T \end{bmatrix}$, $B(k) = \begin{bmatrix} \cos\theta_r(k)T & 0 \\ \sin\theta_r(k)T & 0 \\ \frac{\tan\delta_r(k)T}{l} & \frac{v_r(k)T}{l\cos^2\delta_r(k)} \end{bmatrix}$.
k represents sampling time; T represents sampling period; A and B represent discrete linear functions.

2.2 Clustering of Moving Target Data by Lidar Detection

The lidar used in this paper is a two-dimensional one produced by the SICK Company of Germany. The range data of 361 moving targets are scanned by lidar in the range of $-5°$–$+185°$, each of $0.5°$ is one data. The polar coordinate (θ_i, d_i) is used to represent the range data. The range information of lidar is transformed into rectangular coordinate information by formula (11):

$$\begin{cases} x_{mi} = (\tilde{x}(k+1))\, d_i * \cos\theta_i * \\ y_{mi} = (\tilde{x}(k+1))\, d_i * \sin\theta_{*i} \end{cases} \tag{11}$$

In the formula, x_{mi} denotes the distance between the moving target point and the horizontal direction of the unmanned vehicle; y_{mi} denotes the distance between the moving target point and the front of the unmanned vehicle.

In a Cartesian coordinate system, the spatial clustering of moving target data detected by lidar is carried out by using the nearest neighborhood and rule classification algorithm [12]. Comparing the distance difference Δx_k and Δy_k of two continuous moving target points in abscissa and ordinate at sampling time t, if the difference is less than the preset thresholds ξ_x and ξ_y in transverse and ordinate coordinates, then j is counted from 0 [13]; When the adjacent points are greater than the threshold value, the k adjacent moving targets are regarded as a class of moving targets. j starts to count from 0, then the moving target points are clustered in turn [14]. Because the distance between adjacent points increases with the increase of detection distance, the minimum domain thresholds ξ_x and ξ_y in the adjacent region are determined according to the measured distance d_i.

After clustering, it can be classified into K different sets of moving objects [15]. Let set O be the set of the same moving target points. Each clustering subset is C_k, representing a moving target chain consisting of a subset of moving object O_k in the feasible region. That is,

$$O_k(t) = \{ID_k(t), Z_k(t), L_k(\theta), V_k(t)\} \tag{12}$$

In the formula, $ID_k(t)$ denotes the state variable of moving target O_k, $Z_k(t)$ denotes the center of mass, $L_k(\theta)$ and $V_k(t)$ denote the confidence interval and velocity of the moving target respectively.

2.3 Moving Target Tracking

Firstly, a list of moving objects is created to store their clustered information, and the information is updated in real time [16]. Each moving object stored in this list contains the following information: number, time, occupancy position, velocity direction and acceleration direction when the latest clustering is obtained, velocity covariance, acceleration covariance, existence confidence and motion confidence.

When tracking the moving targets detected by laser sensors, it is necessary to match the current time clustering to obtain the moving targets stored in the list of moving targets. In this paper, a maximum association method is used to match the moving targets to achieve tracking [17]. For each moving object OB_i in the list of moving objects and each moving object OM_i obtained by clustering at the current time, there exists an association value f_{ij}. The size of the correlation value f_{ij} is related to the position, size and shape of OB_i and OM_i. For each moving object, a minimum rectangle covering it is used to parameterize it: the length L of long side, the length R of short side, and the center position $O(x, y)$ and occupancy ratio u of moving object to the rectangle.

Obviously, the central position $O(x, y)$ of OB_i and OM_i cannot be compared directly because they are clustered in different time, the central position $O_i(x_i, y_i)$ of OB_i needs to be corrected [18]. The correction methods are shown in formula (13) and formula (14):

$$t_{ij} = t_j - t_i \tag{13}$$

$$\left(x_i', y_i'\right) = (x_i, y_i) + v_i \cdot t_{ij} + \frac{1}{2} \cdot a_i t_{ij}^2 \tag{14}$$

where, t_i and t_j are the time and current moment of OB_i's latest clustering, respectively, v_i and a_i are the latest speed and acceleration of OB_i stored in the list of moving targets, and $\left(x_i', y_i'\right)$ is the corrected center position of OB_i.

Then the correlation value f_{ij} can be obtained according to formula (15):

$$\begin{aligned} f_{ij} = a \cdot & \frac{1}{\left(x_i' - x_j\right)^2 + \left(y_i' - y_j\right)^2} \\ + b \cdot & \frac{1}{\left(L_i - L_j\right)^2 + \left(R_i - R_j\right)^2} \\ + c \cdot & \frac{1}{\left(L_i R_i u_i - L_j R_j u_j\right)^2} \end{aligned} \tag{15}$$

where, a, b and c represent weights, L_i represents the length of the long edge obtained by the latest clustering, L_j represents the length of current long edge; R_i represents the length of long edge acquired by the latest clustering, R_j represents the current length of long edge; u_i and u_j represent the occupancy.

Then, set the decision matrix update threshold value f_0, and the maximum correlation value f_{mn} can be found from the decision matrix. If f_{mn} is not less than the threshold value f_0, then we can delete all the correlation values related to OB_m and OB_n from the decision matrix and get a new decision matrix. Then the maximum correlation value is found from the new decision matrix, and so on until the maximum correlation value is less than the threshold value f_0 or the decision matrix becomes empty [19].

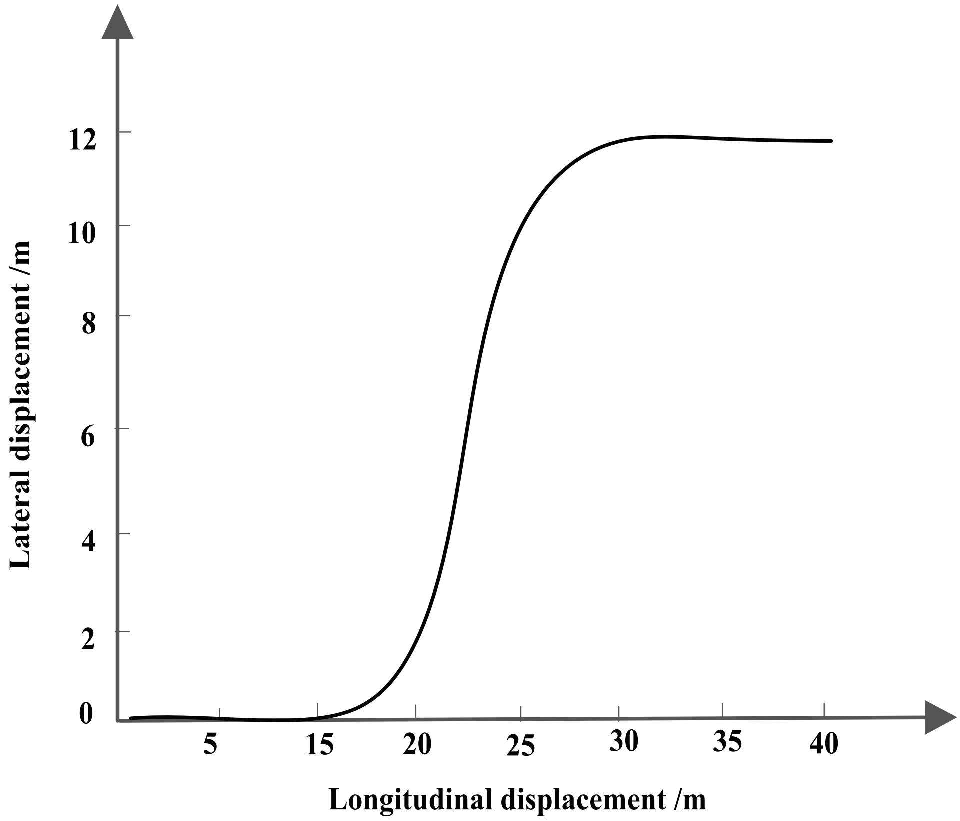


Figure 1 Test curve of vehicle lane change is set experimentally

The final matching results are processed in three steps as follows:

(1) The moving targets are stored in the list of moving objects, but without the moving objects matched by the current clustering. The existence confidence of the moving objects is reduced by 1, and the other values remain unchanged.

(2) The current clustered moving targets which are not stored in the list of moving objects are added to the list of moving objects, and the initial values of velocity, direction, acceleration and direction are all set at 0. The initial values of velocity covariance and acceleration covariance are set at 10, the initial values of confidence are 10, and the initial values of motion confidence are 0.

(3) The moving targets are stored in the list of dynamic moving targets, and with the current clustered moving targets matching them. The existence confidence of the clustered moving targets is increased by 1, and their location is updated. The velocity, acceleration, velocity covariance and acceleration covariance are obtained by updating the classical Kalman filter algorithm. Considering the inaccuracy of laser sensor, this paper considers that the moving target whose velocity value is less than a small value (such as 0.5m/s) is stationary or close to stationary, so if the updated velocity is greater than this small value, its motion confidence is increased by 1, conversely minus 1.

Of course, in practice, the upper and lower limits are set for the motion confidence and the existence confidence of the moving object in the list of moving objects. Finally, the moving targets with confidence less than a set value are deleted from the list, because this paper considers that these moving targets have disappeared from the surrounding environment of the unmanned vehicle. This also ensures that the number of moving targets in the list of moving targets will not increase indefinitely with the accumulation of time [20].

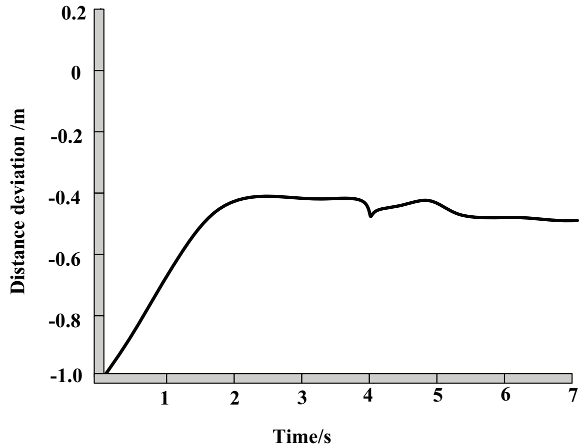
3. RESULTS

3.1 Lane-Changing Curve Test

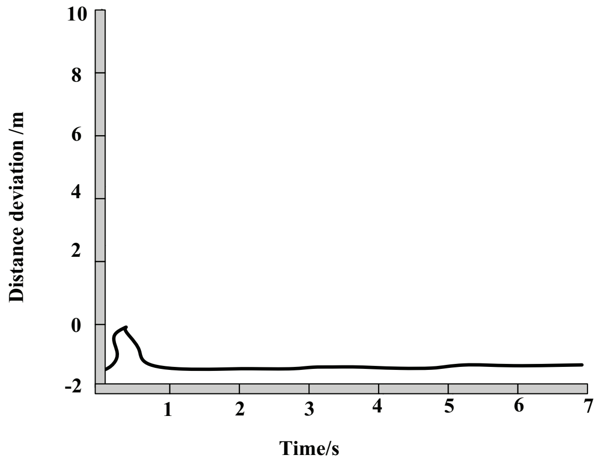
The unmanned vehicle's lane-changing curve test is usually used to test the maneuverability of an unmanned vehicle. It can test the linear tracking performance of an unmanned vehicle. A reference vehicle is set up and the unmanned vehicle is controlled to follow the reference vehicle by the method presented in this paper. The experimental curve of vehicle's lane-changing is set as shown in Figure 1.

The trajectory tracking simulation results of the unmanned vehicle in the lane-changing curve are shown in Figure 2.

As can be seen from Figure 2, the method overcomes the influence of initial deviation and has a faster convergence speed. The distance deviation of unmanned vehicle is within the range of -0.4m $\sim$ -1.0 m and the azimuth deviation is within the range of 0m $\sim$ -2 m. The errors of the curve test are all within a reasonable range, which shows that the proposed method can accurately and consistently control the tracking of the reference vehicle.



(a) Result of distance deviation



(b) Result of azimuth deviation

Figure 2 Simulation results of lane change curve

3.2 Tracking Accuracy Test

The proposed method, the predictive control method of unmanned vehicle based on tracking error model and the compound path planning method based on moving sub-targets are used 12 times to track moving targets. Three scenarios - lateral moving vehicle, frontal moving vehicle and two moving vehicles - are set up in the experimental environment. Three methods are used to track the target, and the tracking accuracy is compared, as shown in Figures 3, 4 and 5.

Figure 3, Figure 4 and Figure 5 show that the maximum tracking accuracy of the proposed method is more than 90% when tracking the turning vehicle, forward-moving vehicle and two moving vehicles near the unmanned vehicle, and is always greater than that of the predictive control method of unmanned vehicle based on the tracking error model and the compound path planning method based on moving sub-targets. By comparison, the tracking accuracy of the proposed method is the highest.

3.3 Anti-Interference

In the above experiments, the anti-interference performance of the three methods in tracking the lateral moving vehicle, the frontal moving vehicle and the two moving vehicles is analyzed. The comparison results are shown in Figure 6.

Figure 6 shows that the anti-interference ability of the proposed method is always 97%. The anti-interference ability of the predictive control method of an unmanned vehicle based on tracking error model and the compound path planning method based on moving sub-targets is lower than that of the proposed method. The anti-interference ability of the predictive control method of an unmanned vehicle based on tracking error model and the compound path planning method based on moving sub-targets shows he fluctuation trend, which indicates that the tracking performance of the two methods is inconsistent. The comparison shows that the proposed method has strong anti-interference ability and can improve the tracking performance.

3.4 Collision Avoidance

Collision avoidance can better reflect the success rate of the unmanned vehicle under the control of three methods. If the tracking performance is poor, the collision avoidance of the unmanned vehicle is poor. Three moving targets near the unmanned vehicle are set as pedestrians, bicycles and cars. The results of testing the collision avoidance of the three methods in the control of the unmanned vehicle for target tracking are shown in Table 1.

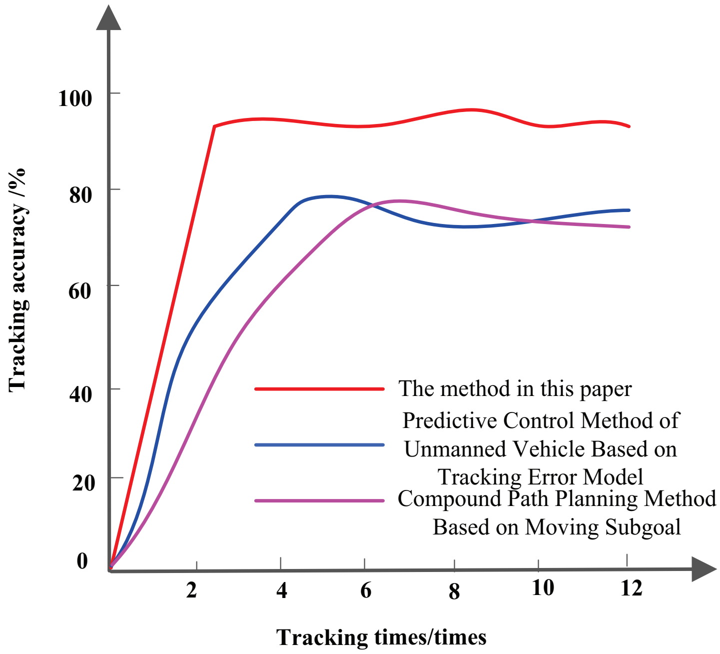


Figure 3 Tracking accuracy of three methods for lateral mobile vehicles

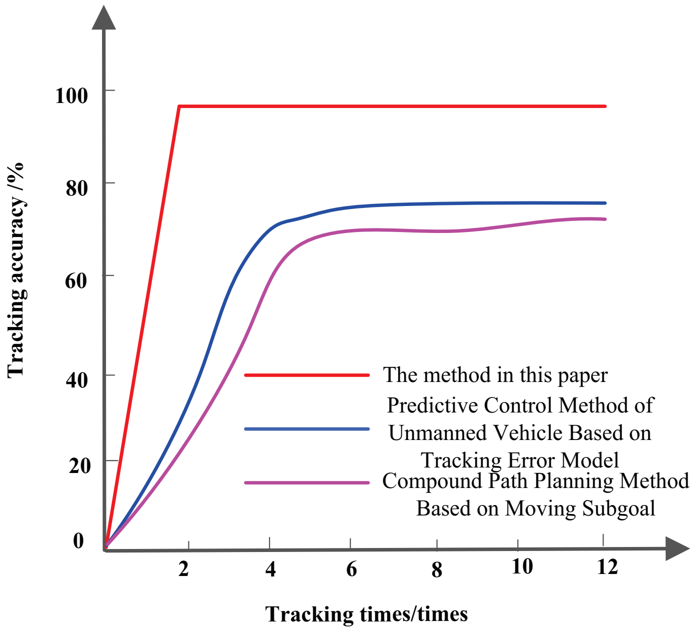


Figure 4 Comparison of three methods' tracking accuracy of frontal mobile vehicles

Analysis of Table 1 shows that the average collision avoidance of the proposed method is $(0.98+0.98+0.98)/3 = 0.98$; the average collision avoidance of the predictive control method based on tracking error model and the compound path planning method based on moving sub-target are 0.86 and 0.72, respectively. By comparison, the collision avoidance of the proposed method is the highest.

4. DISCUSSION

In this paper, the nonlinear kinematics model of unmanned vehicle is linearized, and the linear tracking error model of unmanned vehicle's kinematics is obtained. With this model as the prediction model, the linear model predictive control method is applied to the problem of the moving-target tracking of unmanned vehicles, which greatly reduces the computational complexity. Based on this research, the challenges faced by the future development of unmanned vehicles are discussed. The unmanned vehicle is a relatively new creation which combines many subjects organically. Its development is a gradual and ongoing process requiring much exploration and testing. There are many challenges in the practical application of unmanned vehicles, not only in terms of the maturity of technology, but also in regarding to social issues such as licensing, liability, insurance and so on. The first step to solving the problem is to acknowledge its existence, rather than ignore it. Some of the difficulties

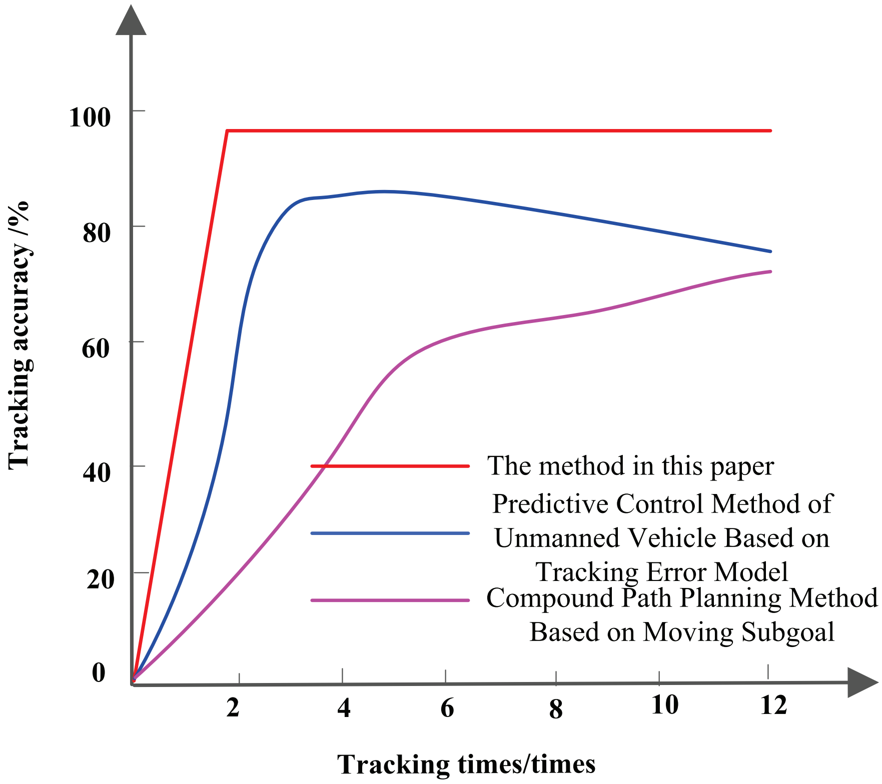


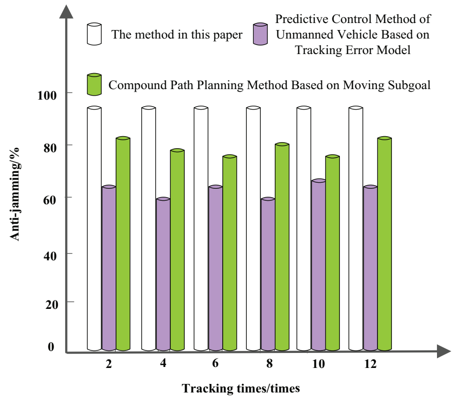
Figure 5 Comparison of three methods' tracking accuracy of two nearby mobile vehicles

Table 1 Comparisons of Collision Avoidance of Three Methods.

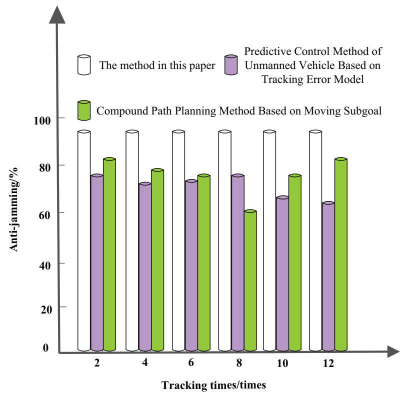
Tracking Times/Times	The Method in This Paper			Predictive Control Method of Unmanned Vehicle Based on Tracking Error Model			Compound Path Planning Method Based on Moving Subgoal		
	Pedestrian	Bicycle	Auto-mobile	Pedestrian	Bicycle	Auto-mobile	Pedestrian	Bicycle	Auto-mobile
1	0.97	0.98	0.98	0.87	0.85	0.88	0.73	0.73	0.72
2	0.98	0.98	0.98	0.86	0.84	0.88	0.73	0.74	0.72
3	0.98	0.98	0.98	0.86	0.85	0.87	0.72	0.71	0.73
4	0.97	0.98	0.99	0.87	0.84	0.87	0.71	0.74	0.72
5	0.98	0.98	0.98	0.85	0.85	0.88	0.73	0.74	0.72
6	0.98	0.98	0.98	0.87	0.84	0.88	0.73	0.71	0.72
7	0.97	0.98	0.98	0.86	0.85	0.87	0.72	0.74	0.73
8	0.98	0.98	0.99	0.86	0.84	0.87	0.71	0.74	0.72
9	0.98	0.99	0.98	0.87	0.85	0.87	0.72	0.71	0.73
10	0.99	0.98	0.98	0.85	0.84	0.87	0.71	0.71	0.72
Mean value	0.98	0.98	0.98	0.86	0.85	0.87	0.72	0.73	0.72

and challenges faced by unmanned vehicles are explained below.

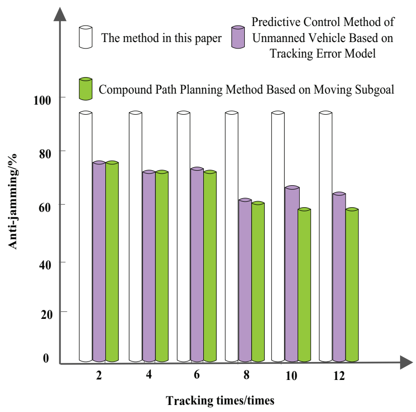
(1) Safety and reliability. Safety and reliability are always two issues that cannot be ignored when promoting unmanned vehicles. The self-safety components of an unmanned vehicle include hardware security, software security and network security. When considering the concepts of active safety and passive safety, the safety of unmanned vehicles is related more to active safety. Firstly, there is the risk of failure risk of the unmanned vehicle's environment-sensing device. The vehicle-borne, high-definition camera based on the principle of visible light reflection is vulnerable to strong light interference, which makes it impossible to obtain clear and accurate images; the ultrasonic probe which works on the principle of ultrasonic reflection is vulnerable to noise and ultrasonic adsorbent material, which makes it impossible to accurately measure the distance of obstacles; millimeter-wave radar based on the principle of electromagnetic reflection may also suffer noise and deception attack; the 64-line laser rangefinder with the highest accuracy attenuates sharply in severe weather such as heavy rain and fog, which seriously affects the accuracy of three-dimensional map generation. Secondly, algorithms for unmanned vehicles



(a) Anti-interference of three methods for tracking a vehicle moving laterally near an unmanned vehicle



(b) Anti-interference of three methods for tracking frontal moving vehicles near unmanned vehicles



(c) Anti-interference of three methods for tracking two moving vehicles near an unmanned vehicle

Figure 6 The results of anti-interference comparison of the three methods

do not take into account the security vulnerabilities, which require a great deal of test data. At present, only Google has conducted seven years of closed testing, while the testing time of other manufacturers is much shorter. It is irresponsible to promote the application of an algorithm for unmanned vehicles without long-term testing and practical verification. Finally, the accessibility of unmanned vehicles to the Internet is bound to face network security problems. Without a reliable firewall strategy, network hackers can invade the core brain of unmanned vehicles through the Internet, tamper with code to remotely control unmanned vehicles, maliciously manipulate steering or braking systems, and create targeted safety incidents.

(2) The imperfection of technical evaluation standards system. In order to evaluate the technical indicators of Intelligent Network Unified Vehicle, technical standards and measurements need to be established. The technical standards must be based on a large amount of experimental data. China clearly divides the development of Intelligent Network Unified Vehicle into five stages. The

technical requirements of the various stages are different, as are the technical parameters. At present, the technical standards system for the Intelligent Network Unified Vehicle in China is not perfect, and cannot provide evaluation measures for different stages of the Intelligent Network Unified Vehicle. In particular, there is no adequate means of defining and evaluating the maturity of high-level unmanned driving technology.

(3) The problem of having no on-road operation license. The issuing of license plates for unmanned vehicles on the road is controlled by the government. On May 8, 2012, Google obtained the first license plate for an unmanned vehicle issued by the Nevada Motor Vehicle Administration. When the futuristic car was put on the road, it also attracted people's attention. In response to applications for open test driving, Nevada requires applicants to prove that the vehicle has traveled at least 10,000 miles in automatic mode and that two drivers must be equipped to take over the unmanned vehicle at any time. Applicants must prove to the Nevada motor vehicle authority that they have a proper safety plan, a safety agreement, and their drivers have been trained to operate autopilot cars. No similar license has been issued in China, and public road testing of unmanned vehicles is not allowed under the existing laws. This seems to be a vicious cycle. Without road testing, it is impossible to determine the performance of and safety of unmanned driving technology. Without performance verification, it is impossible to conduct testing on roads.

(4) The dilemma of artificial intelligence. The final form of the Intelligent Network Unified Vehicle is a new generation of vehicles that dispense with human operation. It has the typical characteristics of artificial intelligence. It also faces all the development problems faced by the artificial intelligence domain. Artificial intelligence transcends the two major disciplines of natural sciences and social sciences. It transcends the category of pure technology and integrates human understanding and thinking related to social phenomena. The behavioral response of AI to certain phenomena is sometimes difficult to evaluate simply by right or wrong. For example, when an unmanned vehicle is driving in the middle lane, the vehicle in front suddenly brakes, and the unmanned vehicle has no time to brake, while a motorcycle and SUV are in the left lane. In this scenario, what action should the artificial intelligence of the unmanned car choose? To ensure the safety the unmanned vehicle, should it hit the motorcycle. Or, to minimize possible injury to its occupant, should the unmanned vehicle directly hit the car, thereby risking damage to itself? Or should it compromise, and hit the SUV? Perhaps different algorithms will produce different responses, although it is impossible to determine which response is correct. But one thing is certain: the programmer's algorithm will determine the result of the accident. If the said algorithm leads to more serious consequences, should the programmer who wrote the algorithm bear the responsibility? If an actual person is driving a vehicle, in 99% of cases, the driver will turn left, which is an instinctive self-protective response that might not attract much discussion and attention.

5. CONCLUSIONS

In order to achieve high accuracy and low collision rate of moving target tracking for unmanned vehicles, a method of moving target tracking for unmanned vehicle based on laser sensor is proposed and subjected to experimental testing. It is proved that this method is effective in tracking vehicles in three situations: turning vehicle, forward-moving vehicle and two moving vehicles near an unmanned vehicle. The maximum tracking accuracy is more than 90%, the anti-interference is always 97%, and the average collision avoidance is 0.98, indicating that the tracking performance is remarkable.

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