Research on Overtaking Path Planning of Autonomous Vehicles

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***Abstract*—With the advancement of technology, advanced driver assistance systems are becoming more and more mature, and autonomous driving has gradually become the future trend. In the technical field of self-driving cars, the optimal path planning for overtaking is an important key technology for self-driving cars to drive in open fields. In this study, simulation software is used to simulate the dynamics of the vehicle, assuming the distance, coordinates, steering angle, and various parameters are set to find the best path for overtaking. This research uses simulation software as a platform, establishes a radar model in the simulation software, and uses Kalman filter to achieve vehicle simulation tracking and detection. Through radar measurement, tracking the environment around the vehicle, the research results show that the actual vehicle simulation result is very close to the Kalman filter radar simulation and an appropriate overtaking path is obtained.**

Keywords—Autonomous Vehicles, Kalman filter, Overtaking path

INTRODUCTION

In recent years, the development of autonomous vehicle systems has been rapid. According to the classification of SAE International, the technology of autonomous driving is divided into five levels. Depending on the degree of computer intervention, the lowest assisted driving technology (LEVEL 1) to the highest fully automated driving technology (LEVEL 5) can be classified. Self-driving car overtaking technology is classified as highly autonomous driving technology (LEVEL 4). Relevant literature review is described below [1-3]. Kalman [1] published a famous paper on the recursive solution of discrete data linear filtering problems. The Kalman filter is a set of mathematical equations that can provide effective computational (recursive) solutions for the least squares method. Wan [2] The distribution of research states is again approximated by GRV, but now it is represented by a set of carefully selected minimum sample points. Ali [4] studied the standard Kalman's description filter and its algorithm with two main steps, the prediction step and the correction step. Weng and Kuo [5] proposed a new video moving target tracking method, and the detection result is used as the measurement feedback of the adaptive Kalman filter. Lidar and sensors are related [6-7], Li [8] proposed a cost-effective way to use linear array ultrasonic sensors to track moving objects around the vehicle. Farag [9] uses this method based on the fusion of lidar and radar measurement data, installs them on ego cars, and uses a customized lossless Kalman filter for data fusion. Related to machine learning [10-17], Khalkhali studied the use of online situation assessment (SA) in Kalman filters. Leven [12] used the unscented Kalman filter to re-examine the symmetric measurement equation method of multi-target tracking. Lade [13] has conducted extensive research on the realization of self-driving cars based on deep learning. The study of Meuter [14] assumes that the target motion can be modeled as a two-dimensional motion on a plane, and the motion and measurement models are combined by an unscented Kalman filter. Bojarski [17] trained a convolutional neural network (CNN) to directly map the raw pixels of a single front camera to steering commands. Related important research also has many contributions [18-20].

In recent years, driving safety has been a very important issue. When overtaking, the incidence of traffic accidents is one of the highest. The reason may be failure to maintain a safe distance between vehicles or failing to pay attention to the surrounding conditions of the vehicle. The resulting vehicle accidents are all caused by human factors. Therefore, it is necessary to improve similar situations in autonomous vehicles. Autonomous driving has gradually become a future trend, and in the technical field of self-driving cars, path planning for overtaking is a major key technology for self-driving cars to drive in open fields. This research department uses Kalman filter to realize overtaking path simulation. Here are some related literature studies .

RESEARCH THEORY

Usually applied to Kalman state prediction, it is necessary to introduce physical characteristics similar to those in real life into the program. And a complete physical model of the car as in figure1, in order to simulate the path and physical reaction highly similar to the actual vehicle in the program.

1. X position
2. Y position
3. X speed
4. Y speed
5. Vertical angle (θ)

6. Vertical angular velocity (ω) $\theta \doteq \omega$

The six basic parameters of the vehicle can be set in the program to set the starting position, starting speed, and steering wheel angle to set different vehicle dynamics.

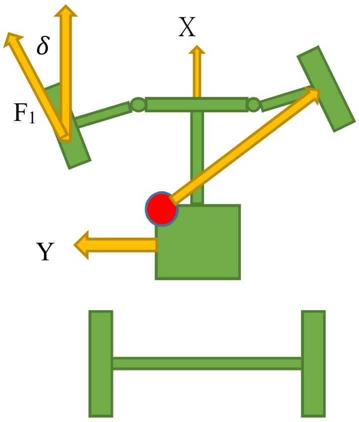

Figure 1. Physical model of the car

The six basic parameters of the vehicle can be set in the program to set the starting position, starting speed, and steering wheel angle to set different vehicle dynamics.

The state equation is as

$$\dot{x} = (x, u, t)\ . \tag{1}$$

The measurement equation is

$$\mathrm{y} = \mathrm{h}(x, u, t)\ , \tag{2}$$

Unscented kalman filter (UKF) is also called σ-point filter because it can maintain the model synchronously and the σ value (standard deviation) between the mean values. Where x is the previous state of the system determined by the state estimator or other processes, u is a structure containing all other inputs in the system that have not been estimated, η is the parameter being estimated, t is the time, and y is the measurement vector. This is a binary estimation method; this paper will not estimate x and η at the same time. In order to fully simulate the overtaking path, the paper must add two physical models of the same vehicle to the program, and the physical model of the vehicle state that the paper can observe has six variables.

These six variables determine the starting position of the two cars and the overtaking path of the following car. The dynamic equation can be written in the form of rotation:

$$\mathrm{m}(\dot{v}_x - 2\omega v_x) = \sum_{k=1}^{4} F_{k_x} - qC_{D_x}A_x u_x \tag{3}$$

$$\mathrm{m}(\dot{v}_y + 2\omega v_y) = \sum_{k=1}^{4} F_{k_y} - qC_{D_y}A_y u_y \tag{4}$$

$$\mathrm{I}\dot{\omega} = \sum_{k=1}^{4} r_k^{\times} F_k \tag{5}$$

Where the q is:

$$q = \frac{1}{2}\rho\sqrt{v_x^2 + v_y^2} \tag{6}$$

and

$$\mathrm{v} = \begin{bmatrix} v_x \\ v_y \end{bmatrix} \tag{7}$$

The unit vector is:

$$\mathrm{u} = \frac{\begin{bmatrix} v_x \\ v_y \end{bmatrix}}{\sqrt{v_x^2+v_y^2}} \tag{8}$$

The normal vector is mg, where g is the acceleration due to gravity. For tire k, the force at the point where the tire and tire touch the ground is:

$$\mathrm{F}_{\mathrm{t_k}} = \begin{bmatrix} T/(\rho - F_r\ \ ) \\ -F_c \end{bmatrix} \tag{9}$$

Among them, ρ is the diameter of the tire and F_r is the rolling friction:

$$\mathrm{F_r} = f_0 + K_1 v_{t_x}^2 \tag{10}$$

Among them, $\mathrm{v_{t_x}}$ is the speed of the wheel hub in the rolling direction. For a front-wheel drive vehicle, the torque of the rear wheel T=0, and the contact friction force is:

$$\mathrm{F_c} = \mu_c mg v_{t_y} / \, |v_t| \tag{11}$$

This force is perpendicular to the normal direction of the wheel's rolling direction, that is, entering or leaving the paper direction in the figure below. The speed term ensures that friction does not cause an infinite loop. That is, when the y speed is zero, the force is zero. μ_c is the constant of the tire. The transformation from tires to frame is:

$$\mathrm{c} = \begin{bmatrix} \cos\delta & -\sin\delta \\ \sin\delta & \cos\delta \end{bmatrix} \tag{12}$$

Here, δ is the angle of the steering wheel, so:

$$\mathrm{F_k} = cF_{t_k} \tag{13}$$

$$\mathrm{v_c} = c^T \begin{bmatrix} v_x \\ v_y \end{bmatrix} \tag{14}$$

The equation of motion related to yaw angle and yaw rate is:

$$\dot{\theta}\ = \omega \tag{15}$$

The relationship between the inertia V and the speed required by the car is:

$$\mathrm{V} = \begin{bmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{bmatrix} \mathrm{v} \tag{16}$$

First, use the Kalman filter dynamic model to create a function. The right side of the Kalman filter only considers the differential equation.

$$\begin{aligned} \dot{x} &= v_x \\ \dot{y} &= v_y \\ \dot{v_x} &= 0 \\ \dot{v_y} &= 0 \end{aligned} \tag{17}$$

The point above the symbol represents the reciprocal of time or the rate of time change. These are the vehicle state equations. This model is proportional to the position of the time change and the speed, which also means that the speed is constant. The non-linear model of the unscented Kalman filter is as follows

$$\begin{aligned} x_k &= f(x_{k-1}, k-1) + q_{k-1} \\ \mathrm{y_k} &= h(x_k, k) + r_k. \end{aligned} \tag{18}$$

The weight is defined as

$$W_m^0 = \frac{\lambda}{n+\lambda} \quad (19)$$

$$W_c^0 = \frac{\lambda}{n+\lambda} + 1 - \alpha^2 + \beta \quad (20)$$

$$W_m^i = \frac{\lambda}{2(n+\lambda)}, i = 1, \ldots, 2n \quad (21)$$

$$W_c^i = \frac{\lambda}{2(n+\lambda)}, i = 1, \ldots, 2n \quad (22)$$

The subscript m is the weight of the state mean, and c is the weight of the oblique variance. Please note that $W_m^i = W_c^i$.

$$\lambda = \alpha^2(n+k) - n$$

$$c = \lambda + n = \alpha^2(n+k) \quad (23)$$

Calculate the σ point with c (covariance, oblique variance matrix). σ= variance matrix, which is responsible for calculating the state update weight value of the Kalman filter. α、β、κ are constants. α determines the distribution range of σ points. β is the prior knowledge constant. κ is the second scale parameter. n is the order of the system. The weights can be written in matrix form:

$$w_m = [W_m^0 \ldots W_m^{2n}]^T \quad (24)$$

$$W = (I - [w_m \ldots w_m]) \begin{bmatrix} W_c^0 & \cdots & 0 \\ \cdots & \ddots & \vdots \\ 0 & \cdots & W_c^{2n} \end{bmatrix} (I - [w_m \ldots w_m])^T \quad (25)$$

The following describes the unscented Kalman for parameter estimation, using the expected value of parameter η

$$\hat{\eta}(t_0) = E\{\hat{\eta}\}. \quad (26)$$

And parameter covariance

$$P_{\eta_0} = E\{(\eta(t_0) - \hat{\eta}_0)(\eta(t_0) - \hat{\eta}_0)^T\}. \quad (27)$$

The update step starts by adding the parameter model uncertainty Q to the covariance P

$$P = P + Q \quad (28)$$

The uncertainty Q is for the parameter, not the state. Then calculate the σ points, which are obtained by adding the square root of the covariance matrix to the current estimate of the parameter.

$$\eta_\sigma = [\hat{\eta} \quad \hat{\eta} + \gamma\sqrt{P} \quad \hat{\eta} - \gamma\sqrt{P}] \quad (29)$$

Among them, γ is a factor that determines the spread of σ points. The paper use chol to calculate the square root. If there is an L parameter, the matrix P is $L \times L$, so the array will be $L \times (2L+1)$.

RESULTS AND DISCUSSION

Use the Kalman filter kinetic model to create the function, and the differential equation is $\dot{x} = v_x$, $\dot{y} = v_y$, $\dot{v_x} = 0$, $\dot{v_y} = 0$. After entering the vehicle parameters and establishing the physical model, the vehicle dynamics is established. Including the tire diameter of the vehicle, the number of tire rolling friction, the steering wheel angle, the yaw angle and the yaw rate, the dynamic simulation model of the car can be made. The parameters can be changed according to different cars to realize the overtaking simulation of different vehicles.

Figure 2 and figure 3 shows the real-time positions of the two cars. The blue line is car A, which is driving in the lane. Car B is an autonomous car that was originally behind car A and wants to accelerate to overtake car A. The two vehicles must maintain a proper safe distance to avoid collision. The X-axis is the distance, and the Y-axis is the distance between the A and B vehicles. The black, red, and green lines are the overtaking curves of car B with different θ and ω parameters. When car B is overtaking, it is cut out, after passing car A, then returning to car A. It can be seen the distance between the two cars when overtaking and the dynamics of the vehicle, and when θ = 0.03, ω = 0.03, the minimum area is 1340.4 m^2, that is, there is the least overtaking path, which represents the use of the smallest road area. Completing the overtaking action is a more efficient overtaking action.

The Kalman filter is used to simulate the car overtaking path. The research results of the Kalman filter path prediction are very close to the actual results. This technology can be introduced into current self-driving or assisted driving, which will improve the safety of the overtaking path. Figure 4 shows that the blue is the car path predicted by the Kalman filter, and the red is the actual car path simulated by the physical model. It can be seen that the simulated state is very similar to the actual one.

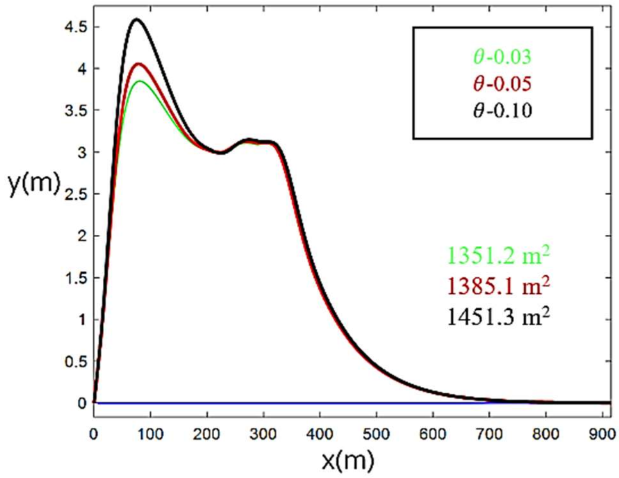

Figure 2. The position curve of two cars overtaking ω = 0.03.

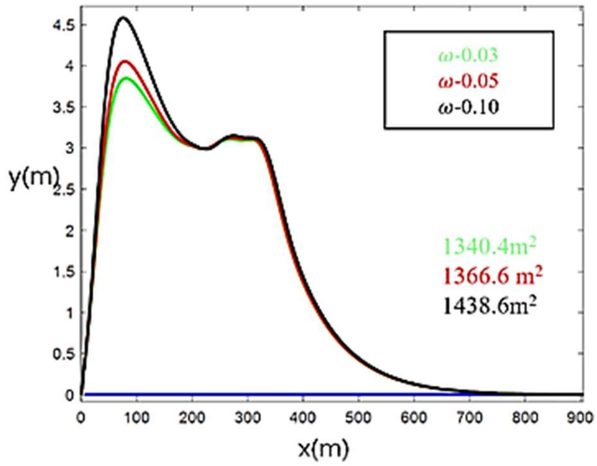

Figure 3. The position curve of two cars overtaking θ = 0.03.

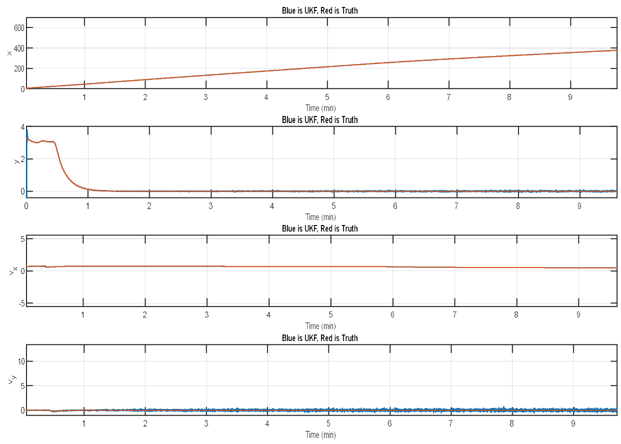

Figure 4. Kalman filter estimates the path and the difference between the real path

In future work, this theory and technology can be materialized, simulated by a remote-control car in a laboratory, or implemented in a relatively simple environment or a simple vehicle model. Prove that this theory and technology are feasible, and hope to contribute to the realization of driving.

CONCLUSIONS AND FUTURE WORK

This study simulates the overtaking path of the car to obtain a better overtaking path, and uses a Kalman filter to maintain a safe distance between the two cars. The research results show that when ω is 0.03 and θ is 0.03, there is the smallest overtaking path and the smallest road area is obtained. 1351.2 m^2 represents the least road area used for overtaking behavior, and is the most efficient overtaking path. It will be possible to improve the safety of overtaking paths. In future work, this theory and technology can be materialized and tested on the road with a real car.

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