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Accurate obstacle prediction method in unmanned vehicle driving

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Abstract

Aiming at the problems of poor prediction effect and long time in obstacle prediction method in unmanned vehicle driving, an accurate obstacle prediction method in unmanned vehicle driving is proposed. Collect obstacle data with the help of lidar in unmanned vehicle driving obstacle avoidance system; The vehicle coordinate system and lidar coordinate system are established respectively, the obstacle data is transformed into the vehicle coordinate system, and the data noise is removed by Kalman filter; By setting the clustering region to cluster the obstacle data, the obstacle points are fitted into a straight line to extract the obstacle features; Match the obstacles with the maximum similarity, determine the Kalman filter, determine the motion state of the obstacles, and complete the obstacle prediction in the operation of unmanned vehicle driving. The experimental results show that the prediction effect of the proposed method is good.

Keywords - unmanned vehicle driving, obstacle prediction, lidar, kalman filter, multi-feature fusion

1. Introduction

Unmanned vehicle driving is a wheeled mobile robot integrating cognitive science, artificial intelligence, robotics and vehicle engineering. It is one of the main directions of scientific and Technological Development [9]. Among them, it covers the improvement of many theoretical methods and the renewal of key technologies, as well as the exploration of a large number of engineering and experimental problems. With the increase of car ownership, the incidence of traffic congestion and traffic accidents is increasing. As an important means to solve this problem, the research on unmanned vehicle driving is of great significance [10]. The detection, prediction and collision avoidance of unmanned vehicle moving obstacles in outdoor complex environment has always been the focus and difficulty of research. In the complex traffic environment, unmanned vehicle driving will inevitably interact with other traffic participants [1]. The effective prediction of obstacles in driverless vehicles refers to the early perception of their driving environment and factors affecting safe driving within a certain distance, which can effectively improve the safety of driverless vehicles. In order to ensure driving safety and avoid all potential collision accidents. Therefore, unmanned vehicle driving needs to accurately predict and track obstacles.

At present, scholars in related fields have conducted research on unmanned vehicle driving and achieved some theoretical results. Dinakaran et al. [3] proposed a method for detecting targets in driverless vehicles in the field. Using deep convolution to generate countermeasure networks (dcgans) and single shot detector (SSD) to deal with field conditions. Gan is trained with low-quality images to meet the challenges brought by the harsh environment in smart city, and cascaded SSD is used as target detector to perform Gan. This method can significantly improve the detection rate of obstacles, but the long-distance prediction error of obstacles is large and has some limitations. Haris and Jin [5] proposed a methods of obstacle detection and safe navigation of autonomous vehicles in unexpected obstacles on the lane. Small and medium-sized obstacles intentionally or unintentionally left on the road are introduced, The Markov random field (MRF) model is discussed by fusing three potentials (gradient potential, curvature prior potential and depth variance potential) to segment obstacles and non obstacles in dangerous environment. DNN model is used to predict the safe driving information of autonomous vehicles in dangerous environment. This method can segment obstacles from mixed background roads and improve the navigation skills of autonomous vehicles. However, the above methods still have low prediction accuracy, long time and poor effect Problems. Grinberg and Ruf [4] proposed an unmanned vehicle path planning method based on improved RRT algorithm to predict vehicle obstacles. Firstly, this method analyzes the road conditions of driverless vehicles, sets the Ackerman angle type during the operation of driverless vehicles, sets multiple Lujiang rivers between the starting point and the end point, determines the obstacles in each path through the evaluation function, and selects the path with the least obstacles as the final path. This method can effectively improve the accuracy of obstacle prediction of driverless vehicles, but the operation process is more complex. It needs to continuously generate the path and then distinguish the obstacles in the path. It does not have universal applicability and needs further improvement.

Aiming at the above problems, an accurate obstacle prediction method in unmanned vehicle driving is proposed. Using lidar technology and multi feature fusion algorithm, the obstacle features in unmanned vehicle driving are extracted and fused. The obstacles are represented, matched and updated by establishing frame model and point model. Using the filtering mechanism and Kalman filter, the motion state of obstacles in unmanned vehicle driving is estimated and predicted, so as to realize the accurate prediction of obstacles in unmanned vehicle driving.

2. Obstacle data acquisition and preprocessing in unmanned vehicle driving

2.1. Obstacle data acquisition in unmanned vehicle driving

In unmanned vehicle driving, the extraction of obstacle data is the key to its prediction. In the research and development of unmanned vehicle, an obstacle avoidance system is designed to collect obstacles. Therefore, before the obstacle prediction, this paper first collects the obstacles in the driving of unmanned vehicles. In this paper, the obstacle data collection in the unmanned vehicle driving operation is carried out with the help of the obstacle avoidance system in the vehicle. Obstacle avoidance system is the most critical part of unmanned vehicle driving. It is a multi-disciplinary system, involving hardware environment perception, information processing, path planning, control and other research fields. Unmanned vehicle obstacle avoidance system can be divided into sensing layer, information processing layer, decision planning and control layer. The architecture of unmanned vehicle obstacle avoidance system is shown in Figure 1.

According to the system structure, the architecture of unmanned vehicle obstacle avoidance system is mainly divided into four modules:

(1) Sensing layer: The on-board sensor detects the environment around the unmanned vehicle, such as roads, traffic lights, obstacles, etc.

(2) Information processing layer: Recognize the original images detected by the on-board sensors, remove irrelevant information through related algorithms, and retain information useful to the obstacle avoidance system to provide support for subsequent operations.

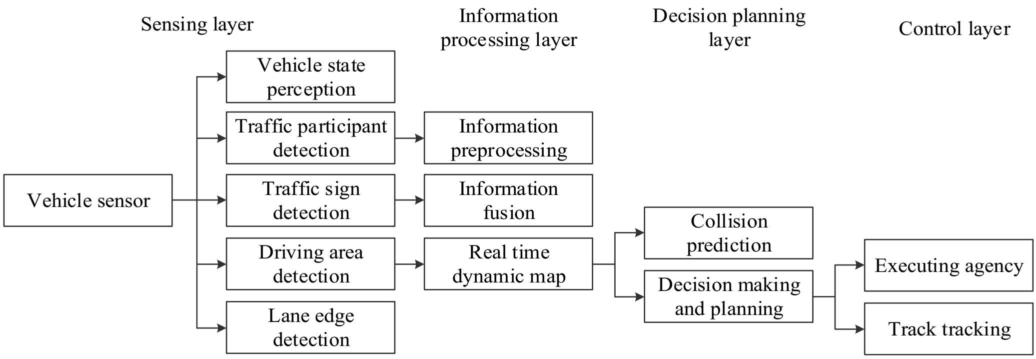

Fig. 1 - Unmanned vehicle driving obstacle avoidance system architecture

(3) Decision planning layer: It is divided into two modules. The first is to predict the trajectory of the detected dynamic obstacles and predict the collision point with unmanned vehicles. The second is the decision and planning module, which makes decisions on the next path of unmanned vehicle driving according to the collision relationship, and plans a safe obstacle avoidance trajectory.

(4) Control layer: The control execution system follows the safe trajectory output by the decision planning layer to avoid obstacles.

The obstacle avoidance system collects the obstacle data in operation, uses the laser transmitter to emit the laser beam, and then combines the modern photoelectric detection technology to measure the distance of the target [7]. Lidar carries out three-dimensional scanning and detection of objects in the environment through multiple scanning lines, constructs the three-dimensional point cloud image of the environment, obtains high-precision point cloud information, and realizes the three-dimensional scanning measurement of obstacle contour. Lidar system is mainly composed of laser transmitter, laser detector, digital signal processing and so on. Both lidar and radar use laser signals to detect objects. The laser pulse reflects the laser pulse on the object surface, and part of the reflected light wave signal will be received by the laser receiver. Therefore, the propagation speed of laser pulse is calculated by the speed of light.

Light detection and ranging (LIDAR) uses a laser transmitter to emit laser beams in the external environment, and then combines modern photoelectric detection technology to measure the distance of the target . LIDAR carries out three-dimensional scanning and detection of objects in the environment through multiple scanning lines, constructs three-dimensional point cloud images of the environment, obtains high-precision point cloud information, and realizes three-dimensional scanning and measurement of object contour. LIDAR system is mainly composed of laser transmitter, laser detector, digital signal processing and so on.

Both LIDAR and radar use laser signals to detect objects. The laser pulses reflect the laser pulses on the surface of the object, and part of the reflected light wave signals will be received by the laser receiver. Therefore, their working principle is very similar. The propagation velocity of laser pulse is calculated by the speed of light. Due to the extremely fast propagation speed, the LIDAR receiver can always receive the last laser pulse before the LIDAR transmitter transmits the next laser pulse. According to the pulse interval time calculated by the LIDAR receiver, the distance between the object and the LIDAR can be measured. This method is the time of flight (TOF) ranging method [8]. It is understood that the propagation speed Q of light in the air is a constant value. Assuming that W is the time between the emitted laser pulse and the received pulse, the distance E between the origin of the LIDAR and each point on the surface of the object is expressed as :

$$E = QW/2 \tag{1}$$

This technology can accurately obtain the three-dimensional information of obstacles in space environment, and the ranging accuracy can reach centimeter level, which can meet the prediction accuracy requirements of unmanned vehicle driving obstacles. Then collect the corresponding obstacle data with the help of the LIDAR point cloud in the system. The process is as follows:

(1) When the LIDAR is installed, there is an angular deviation, which is defined as the roll angle α, the pitch angle β, and the rotation angle γ.

(2) Use the Npos220 integrated navigation system to obtain the spatial position of the vehicle and the vehicle's roll and pitch angles in each scan period[15].

(3) Calculate the change (x', y', z') of the vehicle space position and the change (α', β') of the vehicle's roll angle and pitch angle in adjacent periods. Define R as the horizontal rotation angle of the original point $T_i = (x_i', y_i', z_i')$. The spatial position change Y_i of the original point T_i and the pose change $[\alpha_i, \beta_i, \gamma_i]$ relative to the car body coordinate system are calculated by these parameters as follows:

$$Y_i = \frac{2\pi - R}{2\pi}[x', y', z'] \tag{2}$$

$$[\alpha_i, \beta_i, \gamma_i] = \left(\frac{2\pi - R}{2\pi}\alpha' + \alpha + \frac{2\pi - R}{2\pi}\beta' + \beta\right)\gamma \tag{3}$$

(4) The calibration point T_i' of the original point $T_i = (x_i', y_i', z_i')$ in the coordinate system of the LIDAR coordinate system is as follows:

$$T_i' = T_i + Y_i \tag{4}$$

Through the original point cloud of lidar, the acquisition and research of obstacle data are completed.

2.2. Preprocessing of obstacle data in unmanned vehicle driving

Based on the obstacle data collected by the obstacle avoidance system in unmanned vehicle driving, since the obstacle data during vehicle driving is not invariable, its change affects the prediction of obstacles during vehicle driving. Therefore, it is necessary to preprocess the collected obstacle data. In order to directly apply lidar data to obstacle prediction in unmanned vehicle driving, it is necessary to establish vehicle coordinate system and lidar coordinate system respectively, and convert the original laser point cloud data to vehicle coordinate system.

(1) LIDAR coordinate system: Set the origin O of the coordinate system as the center point of the inner rotating mirror of the LIDAR. The front of the LIDAR points from the Y axis through the origin, perpendicular to the XOZ plane, the right of the LIDAR points from the X axis through the origin, perpendicular to the YOZ plane, and the top of the LIDAR points from the Z axis through the origin, perpendicular to the XOY plane. The conversion relationship between LIDAR spherical coordinate system and LIDAR Cartesian coordinate system is as follows:

$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = \begin{bmatrix} U\cos\delta\sin\varepsilon \\ U\cos\delta\cos\varepsilon \\ U\sin\delta \end{bmatrix} \tag{5}$$

where U is the distance between the laser point and the origin of the coordinate system, δ is the angle between the laser beam and the XOY plane of the coordinate system, and ε is the angle between the projection of the laser beam on the XOY plane and the Y axis.

(2) LIDAR calibration and correction: the LIDAR coordinate system is rotated in the right-handed system, and the rotation sequence is around the Z, X, Y axis in turn, and the rotation matrix I combined with Euler angles is:

$$I(\epsilon,\theta,\vartheta) = I_Z(\epsilon)\mathrm{I_Y}(\theta)\mathrm{I_X}(\vartheta) \tag{6}$$

where ϵ is the roll angle, θ is the yaw angle, and ϑ is the pitch angle. The unmanned vehicle driving system carries out laser point cloud data acquisition on a flat open space, and then carries out plane fitting on the collected point cloud data through the random sampling consistency algorithm to obtain the ground plane equation and ground plane normal vector [10]. The $\epsilon,\theta,\vartheta$ required for LIDAR calibration can be calculated as follows:

$$\begin{cases} \epsilon = \mathrm{arc}\sin(\tau - P) \\ \theta = arc\ sin(\sigma - P) \\ \vartheta = arc\ sin(\rho - P) \end{cases} \tag{7}$$

(3) LIDAR coordinate system transformation: After the LIDAR calibration is corrected, the LIDAR coordinate system needs to be translated. Assuming that the laser point coordinate of the LIDAR coordinate system is $(\mathrm{X}',\mathrm{Y}',\mathrm{Z}')$, the rotation transformation of the coordinate is realized through the rotation matrix I, and the translation of the XYZ coordinate axis is realized through the translation matrix A, and the laser point coordinate in the vehicle coordinate system is obtained as $(\mathrm{X}'',\mathrm{Y}'',\mathrm{Z}'')$. The conversion calculation process is as follows:

$$\begin{bmatrix} X'' \\ Y'' \\ Z'' \end{bmatrix} = \boldsymbol{I} \begin{bmatrix} X' \\ Y' \\ Z' \end{bmatrix} + A \begin{bmatrix} X''' \\ Y''' \\ Z''' \end{bmatrix} \tag{8}$$

where $\mathrm{X}''',\mathrm{Y}''',\mathrm{Z}'''$ represents the translation amount of the LIDAR coordinate system.

On the basis of the above obstacle coordinate system transformation, because the obstacle data is greatly disturbed by external factors and there is a certain noise, on the basis of the above analysis, the noise in the obstacle data is processed with the help of Kalman filter.

Kalman filter is a filter for linear systems [11]. When the system noise and measured noise are Gaussian white noise, it can be expressed in LIDAR space by motion model:

$$S(d) = D(\boldsymbol{d})G(d) + H(d)J(d) \tag{9}$$

where $\mathrm{D(d)}$ is the state vector, $\mathrm{G(d)}$ is the state transfer matrix of the system, $\mathrm{H(d)}$ is the process noise allocation matrix, and $\mathrm{J(d)}$ is the process noise vector. The measurement equation is as follows:

$$K(d+1) = L(d+1)G(d+1) + Z(d+1) \tag{10}$$

where $\mathrm{K(d)}$ is the measurement vector, $\mathrm{L(d)}$ is the measurement matrix, $\mathrm{Z(d)}$ is the Gaussian white noise measurement sequence, and its mean value is zero. This method uses the system model to predict the system state at time $\mathrm{d}+1$:

$$S'(d+1|d) = D(d)S'(d|d)G(d+1) + H(d)J(d) \tag{11}$$

where $\mathrm{S}'(\mathrm{d}+1|\mathrm{d})$ is the predicted result at time $\mathrm{d}+1$, and $\mathrm{S}'(\mathrm{d}|\mathrm{d})$ is the best state estimate obtained by combining measurement and prediction at time d. At the same time, the covariance predicted by the system at time $\mathrm{d}+1$ is:

$$C(d+1|d) = D(d)C(d|d)G(d+1) + V(d) \tag{12}$$

where $\mathrm{C}(\mathrm{d}+1|\mathrm{d})$ is the predicted covariance value at time $\mathrm{d}+1$, $\mathrm{C}(\mathrm{d}|\mathrm{d})$ is the covariance corresponding to $\mathrm{S}'(\mathrm{d}|\mathrm{d})$, and $\mathrm{V(d)}$ is the process noise covariance. Calculate the Kalman gain, indicating the importance of measured and predicted values to the final estimation results. When the gain is larger, the probability that the final estimation result is close to the measured value is larger, on the contrary, it is closer to the predicted value. The Kalman gain is calculated as follows:

$$B(d+1) = C(d+1|d)L(d+1)/C(d+1|d)L(d+1) + N(d+1) \tag{13}$$

where $\mathrm{N}(\mathrm{d}+1)$ is the measurement noise covariance. Finally, the optimal state estimation and covariance estimation at time $\mathrm{d}+1$ are obtained through the measured value and the prediction result:

$$M(d+1|d+1) = B(d+1) + C(d+1|d)/L(d+1) + N(d+1) \tag{14}$$

In the preprocessing of obstacle data in unmanned vehicle driving, the vehicle coordinate system and lidar coordinate system are established respectively, the obstacle data is transformed into the vehicle coordinate system, and the noise in the obstacle data is removed with the help of Kalman filter to complete the preprocessing of obstacle data.

3. Realization of obstacle prediction method in unmanned vehicle driving

This paper presents an obstacle prediction method for unmanned vehicle driving. The obstacle features in the driving process of unmanned vehicles are extracted from the three-dimensional and multi-layer LIDAR scanning data, and the obtained features are fused to establish a box model and a point model to represent the obstacles. Match obstacles, calculate the similarity between obstacle blocks, update the motion state of obstacles, filter out obstacles through the filtering mechanism, and use Kalman filter to estimate and predict the motion state of obstacles during unmanned vehicle driving, so as to achieve accurate prediction of obstacles during unmanned vehicle driving. The flow of the prediction algorithm is as Figure 2.

Based on the above preprocessed obstacle data, firstly, the geometric features of obstacles in unmanned vehicle driving are extracted. In the 3D lidar scanning data, the laser points are clustered and segmented based on the depth first growth clustering algorithm [13].

In order to extract the geometric features of obstacles during unmanned vehicle driving, the laser points are clustered and segmented based on the depth first growth clustering algorithm [6] in the 3D LIDAR scanning data.

Firstly, set the clustering area, create and store obstacle points, then carry out the clustering cycle, judge by setting conditions, cluster all laser points until the whole clustering area is traversed.

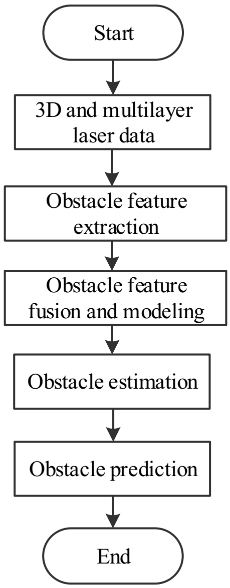

Fig. 2 - Flow chart of prediction algorithm

Finally, in the 3D LIDAR scanning data, the characteristics of obstacles during unmanned vehicle driving are as follows:

$$f_1 = (e_r, o, p, a) \tag{15}$$

where e_r is the position of the center point of the obstacle, o is the longest distance of the obstacle block, p is the number of grid points of the obstacle, and a is the average height of the obstacle.

In the multi-layer LIDAR scan data, the laser points are clustered and segmented based on distance.

First, create a list to store obstacles and the same laser point barriers, and then perform clustering loops, judge by setting conditions, and cluster all laser points until all the points are traversed. Among them, the set threshold is:

$$\aleph = q_0 + q_1 \min \mathrm{w_j} \tag{16}$$

where $\mathrm{w_j}$ represents the distance from point j to the sensor, and $\mathrm{q_0}$ and $\mathrm{q_1}$ are represented by random noise suppression parameters. Through the above algorithm, the points belonging to the same obstacle can be clustered into an obstacle block. The linear features and corner features of the obstacle boundary can better describe the contour of the obstacle. These features are extracted from the obstacle block by using the feature extraction algorithm.

For the obstacle block without corner feature points, if the obstacle points can be fitted into a straight line, they can also be used as the edge feature of the obstacle. Finally, in the multi-layer LIDAR scanning data, the characteristics of obstacles during unmanned vehicle driving are as follows:

$$f_2 = \left(e_q, e_w, e_e, r, t, u\right) \tag{17}$$

where $\mathrm{e_q}$ is the inflection point of the obstacle, $\mathrm{e_w}$ and $\mathrm{e_e}$ are the leftmost and rightmost points in the obstacle block, r is the width of the obstacle, t is the length of the obstacle, and u is the laser reflection pulse intensity of the obstacle.

Based on the above determination of obstacle data features, the obstacle features extracted from three-dimensional and multi-layer lidar scanning data are fused . The obstacle features extracted from three-dimensional and multi-layer LIDAR scanning data are fused. Taking the scanning period of the three-dimensional LIDAR as the correlation period, the data correlation is carried out once when the multi-layer LIDAR data is received, so as to obtain the obstacle features including multiple features as follows:

$$f_3 = \left(e_r, o, p, a, e_q, e_w, e_e, r, t, u\right) \tag{18}$$

In order to accurately estimate the motion state of obstacles during unmanned vehicle driving and give full play to the advantage that LIDAR can obtain the location and contour characteristics of obstacles, frame model and point model are used to represent obstacles during unmanned vehicle driving.

The motion state of the point model can be expressed as:

$$s' = (g, h, k, l, z) \tag{19}$$

where (g, h) is the coordinates of the center of the obstacle, k and l are the speed and direction of the obstacle, and z is the acceleration of the obstacle. The motion state of the frame model can be expressed as:

$$s'' = (g, h, k, l, z, x) \tag{20}$$

where x represents the yaw rate of the obstacle.

In order to improve the accuracy of obstacle feature matching in unmanned vehicle driving, the laser pulse reflection width information and obstacle height information are considered in addition to the contour features. In the matching process, a global similarity matrix is constructed to calculate the similarity between obstacle blocks, and the obstacles with the greatest similarity are matched together to complete the obstacle feature matching process in unmanned vehicle driving. Similarity calculation is as follows:

$$c = \mu \frac{1}{(g-a)^2+(h-r)^2} + \frac{1}{(g-r)^2+(h-t)^2} \quad (21)$$

where μ is the average value of the laser pulse reflection width of the obstacle. Through the above steps, the final similarity matrix [14] is:

$$\boldsymbol{v} = \begin{bmatrix} v_{11} & \cdots & v_{1c} \\ \vdots & \ddots & \vdots \\ v_{b1} & \cdots & v_{bc} \end{bmatrix} \quad (22)$$

Search the maximum value in the similarity matrix, associate the two corresponding obstacles, and delete the associated obstacles from the correlation matrix to obtain a new correlation matrix. Repeat the above process to complete the obstacle feature matching during unmanned vehicle driving . Search the maximum value in the similarity matrix, associate the two corresponding obstacles, and delete the associated obstacles from the correlation matrix to obtain a new correlation matrix. Repeat the above process to complete the obstacle feature matching during unmanned vehicle driving.

In order to more accurately estimate obstacles in unmanned vehicle driving, according to the constructed frame model and point model, Kalman filter [12] is used to estimate and predict obstacles in unmanned vehicle driving. For the point model, the location feature of the center point is used. At time d, the motion state of the obstacle in the driving operation of the n unmanned vehicle can be expressed as:

$$s'^{n}_{d} = (g^n, h^n, k^n, l^n, z^n) \quad (23)$$

For the frame model, at time d, the motion state of the obstacle in the driving operation of the n unmanned vehicle can be expressed as:

$$s''^{n}_{d} = (g^n, h^n, k^n, l^n, z^n, x^n) \quad (24)$$

The predicted motion system of obstacles in unmanned vehicle driving operation is expressed as:

$$\omega = (\psi s''^{n}_{d} + \chi)(\phi s'^{n}_{d} + \upsilon) \quad (25)$$

where ψ is the transition matrix, ϕ is the state observation matrix, χ is the noise during the system state transition, and υ is the noise introduced during the system observation.

In the obstacle prediction method of unmanned vehicle driving, firstly, the obstacle data are clustered by setting the clustering area, the obstacle points can be fitted into a straight line, and the obstacle features are extracted; The similarity between obstacle blocks is calculated through the global similarity matrix, and the obstacles with the maximum similarity are matched. On this basis, the Kalman filter is determined to determine the motion state of the obstacles, so as to complete the obstacle prediction during unmanned vehicle driving.

4. Experimental simulation and analysis

4.1. Setting the experimental environment

In order to verify the effectiveness of the accurate prediction method of obstacles in unmanned vehicle driving, a certain brand of unmanned vehicle driving was selected as the experimental platform vehicle, Linux Ubuntu 16.04 was used as the experimental simulation software environment, and the Velodyne 16-line LIDAR was used as the experimental tool. Velodyne 16-line LIDAR parameters are as Table 1.