Dangerous Behavior Recognition of Autonomous Vehicles at Intersection Based on Gaussian Mixture Model

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Abstract. Urban road intersections are a typical complex traffic scene, and they are also prone to road traffic accidents. Aimed at the safety problems of road intersections, this paper proposes a model of vehicle dangerous behavior recognition based on Gaussian mixture model method, which provides an empirical basis for autonomous vehicle behavior decision at intersections. By analyzing the characteristics and rules of driving behavior at intersections, we select parameters like PET as input parameters of the model, and then construct a simulation model based on Beijing's Weigongcun intersection, which is used to obtain the dataset in intersection scene. The obtained data was subject to Kalman filtering and normalized as data input of a Gaussian mixture model. Dangerous scenes and general scenes at the intersection scene were screened out. The screening results were analyzed and evaluated, and proved to be reliable. The model could provide an empirical basis for the decision-making design of autonomous vehicles at intersection.

1. Introduction
As an important part of the urban road system, intersections are more susceptible to the combined effects of traffic flow, pedestrian flow, and the traffic environment than other components. Among traffic accidents on urban roads, intersection accidents account for about 1/3 of total traffic accidents. Therefore, based on the needs of autonomous vehicles’ behavior decision-making, the dangerous behaviors in urban intersection scenes are identified and screened, and the driving behaviors of autonomous vehicles are evaluated. The selection of key urban road intersections is of great significance and profound significance both to the completeness of the collected data and the robustness of decision-making planning model training.

In recent years, with the rapid development of artificial intelligence, driving behavior modeling methods based on machine learning have begun to receive widespread attention. American BojarskiM¹ and others built a deep convolutional neural network (CNN) to establish an autonomous driving method from images to control parameters to imitate human driving behavior. However, due to the strong interaction between autonomous driving and other traffic objects on the road, deep-learning-based models that imitate human driving learning are still lacking. For example, CNN cannot effectively learn how human drivers interact with other traffic objects on the road. Sadigh² discussed a method combining reinforcement learning and human driving behavior, which was focused on the impact of autonomous vehicle driving behavior on other drivers. However, it only models the driving behavior of a single driver, without considering the interaction of multiple drivers, as well as the different styles of different drivers. Based on Markov model and dynamic Bayesian network theory method, Kishimoto³ and others achieved autonomous reasoning about their driving
behavior, using the driver's historical behavior data. Brechtel[4] and others used a partially observable Markov process model (POMDP) of continuous space to treat driving problems as problems in continuous space and set the belief space to infinity. Using the positions and speeds of other vehicles as model inputs, they carried out a simulation research at intersection. Aoudo[5] and others used game theory to conduct research on intersection decision making. The model was judged by the scene situation and tested at low speed. Based on the complex and changeable characteristics of actual traffic scenarios and the diversity of individual subjective preferences of drivers, Furda[6] and others proposed a multi-criteria decision-making method for driving behavior, in order to meet the requirements of various driving environments for the reasonableness of behavioral decision models. Abbee[7] and others used inverse reinforcement learning method to learn human's driving behavior, which used reward function to represent behavior motivation and individual psychological difference, and verified it in a virtual simulation environment. However, the disadvantage is that the setting of the reward function depends much on experience and cannot well adapt to obvious changes in the external environment.

Based on the Gaussian Mixture Model (GMM) method, this paper proposes a model of vehicle dangerous behavior recognition at intersections, which overcomes the shortcomings of the driving behavior model mentioned above. Firstly, based on the real intersection scene, a model of the intersection scene in the simulation environment is established, and the intersection scene data set is obtained by using the simulation test. Then, the dangerous scene is classified based on the GMM. Eventually the classification and recognition results are analyzed and evaluated.

2. Intersection scene definition
Road intersections are recognized as the most dangerous road locations, and left-turning vehicles are one of the most prone to accidents in intersection scenes. Therefore, this paper selects left-turning vehicles as the research object and considers its possible dangerous situations at intersections. In order to build a recognition model which can identify the dangerous scenes at intersections, we first need to get the test scenes of intersections with traffic lights on urban roads. Therefore, this article builds a model of the intersection scene based on the real environment, which is the intersection of Weigongcun in Beijing, as shown in figure 1. This intersection has 4 lanes in the north-south direction and 3 lanes in the east-west direction. The north-south traffic lights have a left-turn protection phase, but the east-west direction has not. Therefore, the left-turning vehicle in the east-west direction will have conflict with the oncoming straight vehicle. Therefore, in this scene, the left-turning vehicle A on the west side is selected as the research subject.

Vehicle A is a left-turn vehicle, so vehicles that have a dangerous conflict with this vehicle include oncoming vehicles and right-turning vehicles. Because the conflict between the oncoming vehicle and vehicle A is the main point of conflict in the left turn process, three direct vehicles B1, B2, and B3 are set in this scenario. In this scenario, the vehicle A turns left from the south of the intersection, and the oncoming vehicles B1, B2, and B3 start from the north side of the intersection and keep going in the same lane. Vehicle C starts from the north side of the intersection and turns right to the target lane of vehicle A.
3. Experiment and data acquisition

In this paper, we built a simulation model of the intersection scene based on the real environment scene based on the joint simulation platform of Prescan and Matlab, and conducted simulation experiments with the G27 Logitech driving simulators.

3.1. Experiment equipment

The speed and position of the intersection scene in this article can be obtained through the sensors used in Prescan modeling in the Prescan and Matlab joint simulation model. The steering wheel angle, throttle, brake and other data of this vehicle can be obtained through the G27 Logitech driving simulators. The experimental hardware equipment is shown in figure 2:

3.2. Construction of simulation scenarios

The intersection scene in this article is shown in figure 3. This scene is based on the real scene of Beijing’s Weigongcun intersection and has an intersection with traffic lights built in Prescan. In this scenario, the north-south direction is a two-way three-lane road, and the east-west direction is a two-way four-lane road. The road width is 3.5 m. Vehicle A is a left-turning vehicle entering the intersection. Enter the intersection from the first lane on the south side and enter the third lane on the west side. Vehicles B1, B2, and B3 are oncoming vehicles. They enter the intersection from the second lane on the north side, and keep the original lane straight. There is a conflict point with A. Vehicle C is a right-turning vehicle. From the right turn lane on the north side, turn right directly to the target lane of the own vehicle, forming a confluence with the own vehicle.
During driving, this vehicle is controlled by the G27 Logitech driving simulators, and is controlled by an experienced driver. All other environmental vehicles drive according to the preset scene data. During the experiment, experiments were performed by changing the speed of the surrounding vehicle, and the speed of the vehicle, and the time when different vehicles entered the intersection to obtain intersection scene simulation data in various situations. The initial values of each variable are shown in table 1:

| Vehicle | Initial velocity (km/h) | Time to enter the intersection (s) |
|---------|-------------------------|-----------------------------------|
| A       | 20, 25, 30              | 0, 5, 10                          |
| B       | 20, 25, 30              | 0, 5, 10                          |
| C       | 20, 25, 30              | 0, 5, 10                          |

By changing the above initial parameters, the experiment was repeated 200 times. In the simulation experiment, the obtained data mainly includes the steering wheel angle of the own vehicle, the throttle brake, the vehicle speed, and the relative positions and relative speeds of other surrounding vehicles and the workshop, and the initial data set is obtained:

\[ F = \{x_i, y_i, v_{iA}, a_{iA}, \text{throttle, brake}, \delta_i, x_{Ai}, y_{Ai}, v_{Ai}\} \]  

(1)

where \(i\) represents vehicles B1, B2, B3, C.

According to the initial data, the position, speed, acceleration and PET of vehicle B1, B2, B3, and C can be calculated. The definition of PET is shown in figure 4:

The resulting characterization parameters describing the interaction between environmental vehicles and vehicle A are shown in table 2:
Table 2. Characteristic Parameters in intersection scene

| Characteristic Parameters | Definition |
|---------------------------|------------|
| $v_i$                     | Velocity of vehicle $i$ |
| $v_A$                     | Velocity of vehicle $A$ |
| $v_{iv}$                  | Relative velocity, $v_i - v_A$ |
| $x_i$                     | Position of vehicle $i$ in the x direction |
| $y_i$                     | Position of vehicle $i$ in the y direction |
| $x_{iv}$                  | Relative position in the x direction, $x_i - x_A$ |
| $y_{iv}$                  | Relative position in the y direction, $y_i - y_A$ |
| $a_i$                     | Acceleration of vehicle $i$ |
| $a_A$                     | Acceleration of vehicle $A$ |
| $PET_i$                   | $PET$ of vehicle $i$ |
| $\delta$                 | Steering Wheel Angle of vehicle $A$ |
| Throttle                  | Throttle of vehicle $A$ |
| Brake                     | Brake of vehicle $A$ |

During the experiment, the vehicle $A$ is controlled by an experienced driver, and the surrounding vehicles travel according to a preset program. After each set of scenarios, the driver subjectively determines whether the scene is dangerous or not and records it.

3.3. Data pre-processing

Due to the presence of white noise in the acquisition, such as the displacement, velocity, and acceleration of the directly acquired data, the Kalman filter method is used to deal with the random errors. The system's state vector is as below:

$$X = [s, v, a]^T$$

where $s$, $v$, $a$ denote the vehicles’ displacement, velocity and acceleration. According to the principle of vehicle dynamics:

$$
\begin{bmatrix}
  s_y \\
  v_{y} \\
  a_{y}
\end{bmatrix} =
\begin{bmatrix}
  1 & T & T^2 / 2 \\
  0 & 1 & T \\
  0 & 0 & 1
\end{bmatrix}
\times
\begin{bmatrix}
  s_{y-1} \\
  v_{y-1} \\
  a_{y-1}
\end{bmatrix} + w(t)
$$

where $T$ denotes a time step, and $s_y$, $v_y$, $a_y$ are predicted values at time $t$, and $s_{y-1}$, $v_{y-1}$, $a_{y-1}$ are predicted values at time $t-1$. So we can get the position, velocity and acceleration of the vehicle at next moment.

Covariance of predicted values:

$$P_y =
\begin{bmatrix}
  1 & T & T^2 / 2 \\
  0 & 1 & T \\
  0 & 0 & 1
\end{bmatrix}
\times P_{y-1} + Q$$

Kalman gain:

$$Kg = P_y H^T / (HP_y H^T + R)$$

Optimal estimates:
\[
\begin{bmatrix}
    s_i \\
    v_i \\
    a_i
\end{bmatrix} = \begin{bmatrix}
    s_{i,p} \\
    v_{i,p} \\
    a_{i,p}
\end{bmatrix} + Kg(Z_i - H \begin{bmatrix}
    s_{i,p} \\
    v_{i,p} \\
    a_{i,p}
\end{bmatrix})
\] 

Covariance of optimal estimates:
\[P_t = (I - KgH)P_{t-1}\] 

Figure 5 shows the speed comparison results of the data before and after using Kalman filter.

In addition to Kalman filtering, the data also needs to be normalized to convert all characterization parameters into quantities ranging from 0 to 1. This makes each variable has the same effect on model.

The data normalization processing formula is as follows:
\[x = \frac{(x - x_{\text{min}})}{(x_{\text{max}} - x_{\text{min}})}\] 

4. Model establishment and result analysis

4.1. Gaussian mixture model

According to the parameters above, we can use the following vector to denote the relative state between vehicles:
\[s = [x_A, y_A, y_B, \delta, \text{throttle, brake}, \Delta x_B, \Delta y_B, v_B, \text{PET}_B, \Delta x_C, \Delta y_C, v_C, \text{PET}_C]^T\]

The goal of GMM is to identify the dangerous scenes, so a physical quantity \(d\) is set to indicate whether the intersection scene is dangerous. For instance, \(d=1\) indicates that the scene is a dangerous scene and \(d=0\) indicates a general scene, and the extended feature vector is as below:
\[z = [s^T, d]^T\]

Using a Gaussian mixture model to establish the relationship between input and output, the state feature vector should satisfy the following probability distribution:
\[p(z|\Pi) = \sum_{k=1}^{K} \pi_k N(z, \mu_k, \Sigma_k)\] 

where \(\Pi=\{\pi_k, \mu_k, \Sigma_k\}\) are relevant parameters in the GMM model. \(\Pi=\{\pi_k, \mu_k, \Sigma_k\}\) can be calculated according to the EM algorithm (Expectation-Maximization algorithm) [8]. \(K\) denotes the number of components. The model in this paper has two clusters, so two Gaussian distributions can be used to represent the feature quantity, that is, \(K = 2\). \(\mu_k, \Sigma_k\) denote the mean and variance of the \(k\)-th component, respectively.
4.2. Result analysis

The pre-processed data is used as a data sample for the above Gaussian mixture model. And the results are shown in figure 6:

![Sample distribution and prediction graphs](image)

Figure 6. Sample map

In this paper, we use the sensitivity and accuracy to evaluate the results of GMM model recognition of dangerous scenes at intersections. The definition of sensitivity and accuracy is as below:

\[
\text{Sensitivity} = \frac{TP}{TP + FN} \\
\text{Accuracy} = \frac{TP + TN}{TP + FN + TN + FP}
\]

where \( TP, FN, TN, FP \) denote the number of cases that were correctly classified as positive cases, incorrectly classified as positive cases, incorrectly classified as negative cases, and correctly classified as negative cases.

Therefore, result of the experiment is shown in table 3.

| Actual result | Predicted result | T | F | total |
|---------------|------------------|---|---|------|
| N (general scenes) | 120 | 10 | 130 |
| P (dangerous scenes) | 63 | 7 | 70 |
| total | 183 | 17 | 200 |

\[
sensitivity = 86.3\% \\
accuracy = 91.5\%
\]

After the GMM model was used to classify and verify the data in the intersection scene, the results showed that the model made correct predictions for 183 sets of data, and the accuracy rate reached 91.5%, indicating that the model has achieved good results in the identification and prediction of dangerous scenes at intersections.

5. Conclusions

This article analyzes the factors that affect the intersection scene, and selects appropriate variables (like PET) to establish an intersection danger scene prediction model based on a Gaussian mixture model. The model is trained and tested by simulation experiments. The GMM-based prediction model is feasible for predicting dangerous scenes at intersection scenes.

In future research, the identification and prediction of dangerous behaviors in more types of intersection scenes will be considered, so that the model has a wider scope of application.
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