Improved Car Following Model Based on Supervised Learning

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Abstract: Based on the existing traffic trajectory data, this paper uses a suitable neural network to construct a car following model, and then analyzes and studies the driver's car following behavior. By comparing the case with the traditional GHR car-following model, it is concluded that the improved car-following model is better.

1. Introduction
As one of the most common driving behaviors in car driving, the study of car-following behavior has been a major focus in the neighborhood of traffic engineering in recent years. Data analysis, processing, and prediction are an important part of current car-following research. In 2019, Liao Peng¹ used the FVD model to design a car-following model which related to driver attributes. The results show that the proposed model can reproduce the influence of driver attributes on each car. In 2019, Kamath G K² studied the impact of delayed feedback on the dynamics of the Classic Car Following Model (CCFM), and provided phenomenological insights into the impact of response delays on the emergence and evolution of traffic congestion. In 2020, Zhai J³ designed an experiment based on a driving simulator to learn the driver's performance in smooth driving and critical situations, and concluded that the extra workload would distract the driver. In 2020, Klawtanong M⁴ investigated dynamical properties of traffic flow using the stochastic car-following model with modified optimal velocity on circular road, the density-dependent speed limit in autonomous-free condition is obtained to achieve the optimal traffic flow. In 2021, Kuang H⁵ considered the combination of driver memory and the average expected speed field in the ITS (Intelligent Transportation System) environment, and proposed an extended car-following model to simulate traffic flow.

In order to further improve the accuracy of driving behavior data prediction, this article will rely on the method of supervised learning to analyze and study the driver's following behavior, use existing samples to calibrate the parameters, and construct the corresponding car following model to assist in following the car. Driving provides a certain theoretical reference.

2. GHR car following model
2.1. Model introduction
GHR is the most famous car following model in the late 1950s and early 1960s in the 20th century. Its expression is as follows

\[ a_n(t) = c \times v_n^{\text{ref}}(t-T) \times \frac{\Delta v(t-T)}{\Delta x'(t-T)} \]

Among them: \( a_n(t) \) is the acceleration taken by the driver of the nth car at time \( t \). \( T \) is the reaction time for the driver. \( \Delta x(t-T) \) is the space headway between the current car and the preceding car in the
previous reaction time. $\Delta v(t - T)$ is the speed difference between the current car and the preceding car in the previous reaction time. $v_a(t - T)$ is the speed of the current car in the previous reaction time. $c$, $m$ and $\ell$ are the parameters to be calibrated.

2.2. Model problems
Use the parameters $m = 0.8$, $\ell = 1$, $c = 1.1$ calibrated by Ozaki in 1993. Assuming that the position of the preceding car at the initial moment is 20 meters, the speed of the car is 8 m/s, the initial position of the following car is 0, and the speed is 12 m/s. In about 28 seconds, the speed of the car behind is equal to that of the car in front, and the space headway is finally maintained at about 15 meters.

![Fig. 1 The speed change diagram of the two cars (the initial position of the preceding car is 20m)](image1)

Keep other conditions unchanged. Assume that the position of the preceding car at the initial moment is 1000 meters. In about 700 seconds, the speed of the car behind is equal to that of the car in front, and the headway is finally maintained at about 632 meters.

![Fig. 3 The speed change diagram of the two cars (the initial position of the preceding car is 1000m)](image3)

If the distance between the front of the car in the initial state is too small, the following car will decelerate quickly, which will cause the distance between the front of the car to be too small, which does not meet the safety requirements.
If the distance between the fronts of the car in the initial state is too large, and the speed of the following car is higher than that of the preceding car this situation will cause the distance between the fronts of the car to be too large, which is not in line with the reality.

2.3. Model improvement
According to actual driving experience, the following car does not simply accelerate or decelerate according to the speed difference, but through speed adjustment, the actual space headway fluctuates around the expected space headway. In any case, the speed of the following car must be equal to the speed of the preceding car when a stable follow-up state is reached.

\[ a_n(t) = \Delta x(t - T) - f(v_n(t - T)) \]  

Among them: \( v_n(t - T) \) is the speed of the car, \( f(v_n(t - T)) \) is the expected space headway. The above formula indicates that the expected acceleration is proportional to the difference between the current space headway and the expected space headway. If the space headway is greater than the expected space headway, the car may accelerate even if the speed of the car behind is higher than the speed of the car in front.

And then, the maximum acceleration and maximum speed of the car are limited by the car and road conditions

\[-d_{\text{max}} \leq a_n(t) \leq a_{\text{max}}\]  

Among them: \( a_{\text{max}} \) and \( d_{\text{max}} \) are the maximum acceleration and deceleration, both are positive values.

Finally, the speed of the car is also limited

\[ 0 \leq v_n(t) \leq v_{\text{max}}\]  

Among them: \( v_{\text{max}} \) is the maximum speed value allowed by roads and cars, and a positive value.

Therefore, the final designed car-following model is equation (5), and the constraints of equations (3) and (4) must be satisfied.

\[ a_n(t) = \alpha \times (\Delta x(t - T) - f(v_n(t - T)))^\beta \]  

Among them, \( \alpha \) and \( \beta \) are the parameters to be calibrated.

2.4. Parameter calibration
Parameter calibration is mainly done in two parts, determining the form of the expected headway, and calibrating the parameters \( \alpha \) and \( \beta \). This section is based on the trajectory data of the US-101-Main road of NGSIM in the United States. The time interval of the data is the morning peak 7:50-8:05, a total of 15 minutes of actual traffic trajectory.

Except for a small amount of erroneous data, in general, the headway is expected to increase as the speed increases, which is approximately a linear relationship. Fit the linear function to the sample data, and the results are as follows
Since the unit used in the original data is feet, convert the unit to meters. The final car following model can be expressed as

\[ a_s(t) = 0.28 \times (\Delta x(t - T) - 1.466 \times v - 8.87) \]  

(6)

3. Supervised learning

3.1. Neural network framework

For the car following problem, the variable we need to decide is the acceleration of the following car in the following state, which is the Y value, and the dependent variable mainly selects the three factors of the preceding car speed, the speed of the own car, and the distance between the heads. Therefore, the number of nodes in the input layer of the neural network selected in this paper is three, and the number of nodes in the output layer is one. In addition, the middle layer is selected as two layers, and the number of nodes each time is 3. So the neural network constructed in this research is \([3,3,3,1]\). Relatively speaking, the scale of the neural network in this article is relatively small.

3.2. Creating sample data

This research first uses the model designed in the previous chapter to make sample data, and then calibrate the parameters. And test the car following performance in various scenarios to verify the effectiveness of the neural network model based on supervised learning. Finally, the neural network model is calibrated using real field test trajectory data, and the performance of the model is tested.

First, use the acceleration model optimized in Chapter 2 to create sample data. The sample data contains 3 independent variables: the speed of the preceding car, the speed of the following car, and the distance between the heads of the car. The value range of the speed of the preceding car and the speed of the following car is \([0,16]\), the minimum speed is 0, the maximum speed is 16, and each takes 50 points. The value interval of the space headway is \([8,60]\), the minimum interval is 8, the maximum interval is 60, and 100 points are taken. Then combine these points to create a total of 50*50*100=250,000 sample data points.

Then calculate the dependent variable which is the acceleration for these 250,000 sample points. Calculated as follows

\[ a_s(t) = \max(\min(0.28 \times (\Delta x(t - T) - 1.466 \times v - 8.87), a_{\text{max}}), a_{\text{min}}) \]  

(7)

3.3. Parameter calibration

The realization of parameter calibration is to use Google's open source Tensorflow module in the python programming environment. The hyperparameter learning rate used is 0.001.

Due to the relatively large amount of data in the calibration process, when the calibration is realized, it is divided into multi-stage calibration. Perform 1000 times in each stage, and then determine whether calibration is needed according to the error of the calibration result. If the error is large, then calibrate another stage. If the error is acceptable, stop the calibration, store the calibrated neural network, and use it Read the stored neural network at time to simulate driving behavior following the car.

This article uses a staged calibration method to calibrate the parameters, the steps are as follows:

1. The calibration in the first stage take 31.19 seconds, and the error is reduced from 15 to 2.
2. The calibration in the second stage takes 30.28 seconds, and the error is reduced from 2 to 0.06.
3. The calibration in the third stage takes 33.84 seconds, and the error is reduced from 0.06 to 0.04.
4. The calibration in the fourth stage takes 34.86 seconds, and the error is reduced from 0.04 to 0.02.
3.4. Example
Observing the linear trend through parameter calibration, we can see that the model has converged. Assuming that the position of the preceding car at the initial moment is 100 meters, the speed is 8 m/s, the initial position of the following car is 0, and the speed is 12 m/s.

Fig. 7 The speed change diagram of the two cars (the initial position of the preceding car is 100m)

Fig. 8 Change of space headway (the initial position of the preceding car is 100m)

Keep other conditions unchanged, adjust the position of the car in front at the initial moment to 500 meters.

Fig. 9 The speed change diagram of the two cars (the initial position of the preceding car is 500m)
Keep other conditions unchanged, adjust the position of the car in front at the initial moment to 10 meters. Because of the data used for calibration parameters, there is almost no such sample data. Therefore, the neural network does not know how to determine the acceleration, so it needs to give a suggested value for the missing data. When the space headway is very small, set the acceleration value to the minimum deceleration; when the space headway is very large, set the acceleration to the maximum acceleration.

4. Model comparison and analysis
The biggest problem with the GHR model is that there is a problem with the choice of stimulus information, which leads to too much emphasis on the speed difference. So there are the following problems: if the distance between the two cars is very large, the headway is beyond the range of the following car, and the speed of the two cars is exactly the same, the following car will maintain the same speed and will not accelerate to catch up with the front car.

Through comparative analysis, it can be seen that the effect of the car following model based on supervised learning is more in line with the actual situation than the GHR model. When the speed of the preceding car is the same, regardless of the initial headway distance, the following car will continuously adjust the speed. Moreover, this car following model has very good stability. No matter how the initial conditions change (The premise is that there is a solution), the following car will always develop into a stable following driving state, and will always achieve a stable following state within 3 acceleration and deceleration cycles.

5. Conclusions
This article focuses on designing a car following model based on the method of supervised learning, and verifying it in combination with existing cases. It proves that the improved car following model is more in line with the actual situation than the GHR model, and the model has good stability and applicability. However, due to the imbalance of traffic flow changes on urban roads, if a model suitable for different
traffic flows can be improved in subsequent research, the practicality and efficiency of the model can be greatly improved.

References
[1] Liao P, Tang T Q, Wang T, et al. A car-following model accounting for the driver's attribution[J]. Physica A Statistical Mechanics & Its Applications, 2019, 525:108-118.
[2] Kamath G K, Jagannathan K, Raina G. Stability, convergence and Hopf bifurcation analyses of the classical car-following model[J]. Nonlinear Dynamics, 2019.
[3] Zhai J, Lu G, F Chen. The Effects of Extra Cognitive Workload on Drivers' Driving Performance under Smooth Car-Following Drive and Critical Situations[C]// International Conference on Transportation and Development 2020. 2020.
[4] Klawtanong M, Limkumnerd S. Dissipation of traffic congestion using autonomous-based car-following model with modified optimal velocity[J]. Physica A: Statistical Mechanics and its Applications, 2020, 542.
[5] Kuang H, Lu F H, Yang F L, et al. An extended car-following model incorporating the effects of driver's memory and mean expected velocity field in ITS environment[J]. International Journal of Modern Physics C, 2021.