Vehicle-Trajectory Prediction Method for an Extra-Long Tunnel Based on Section Traffic Data

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Abstract: The driving situation is complicated in an extra-long tunnel. If a traffic collision happens, car evacuation and people rescue in the tunnel will be more challenging. The driving safety and traffic efficiency of an extra-long tunnel will be considerably enhanced if vehicle trajectory can be precisely assessed and the vehicle driving risk can be predicted in advance. However, due to the limitations of the data capture of vehicle-mounted equipment in tunnels, estimating vehicle trajectory with vehicle-side data is difficult. In this research, a vehicle-trajectory prediction model based on section traffic data in an extra-long tunnel is developed using existing roadside traffic-gathering equipment. The model re-optimizes the driver-sensitivity coefficient by calibrating the parameters of the vehicle-following model based on mining the motion laws of cars under different scenarios. The model is validated using observed velocity and position data, and the average accuracy of velocity prediction is 94.14% and 95.45% for trajectory prediction. The results show that using existing roadside collecting equipment, this model can accurately forecast vehicle trajectories in extra-long tunnels.

Keywords: extra-long tunnel; trajectory prediction; sectional traffic data; Wiedemann model; FVD model

1. Introduction

Extra-long tunnels have different grades than regular highway tunnels, and there are more portions with long and longitudinal slopes. Long-distance passage frequently results in low vehicle efficiency, which easily induces traffic accidents because of driving fatigue and inattention, and exacerbates the driving safety concerns in extra-long tunnels. When a sudden traffic collision occurs and reasonable and effective management measures are not implemented in a timely manner, the line of vehicles in the tunnel extends swiftly, and the space-time influence range of congestion becomes more severe. Due to the difficulty in accurately obtaining traffic flow parameters in extra-long tunnels and other conditions, the focus of this study is on obtaining vehicle-running data and mastering vehicle-running rules in tunnels using existing tunnel acquisition equipment to improve vehicle traffic efficiency and driving safety.

Currently, roadside equipment is used to collect tunnel traffic data. There are issues such as inadequate structured traffic data and a lack of full vehicle-trajectory data in the tunnel because of the lack of roadside equipment. Side-mounted cameras have a higher coverage rate in current tunnels than radar detection equipment and are less expensive. The section’s traffic data are easy to obtain, the information is complete, and the vehicle operating characteristics in various traffic circumstances can be studied intuitively. As a result, we fully use the existing side-mounted video monitoring equipment of the tunnel to extract traffic flow data in extra-long tunnels, and propose a manual-driving vehicle-trajectory prediction model for extra-long tunnels that can currently provide technological support for the monitoring and early warning control of traffic flow in extra-long tunnels. This study makes several contributions to the literature. Specifically:
To address issues such as insufficient traffic-data acquisition equipment, the poor condition of structured traffic data, and the lack of full vehicle-trajectory data in the long tunnel, this study fully utilizes the existing side-mounted video surveillance equipment of the tunnel to extract traffic-flow parameters.

To address the issue of the full velocity difference (FVD) model vehicle-tracking model’s constant safe trailing distance, this study uses traffic section data to demarcate the following domain of the Wiedemann model, divides vehicle running states based on time headway data, and establishes the running rules of vehicles in different running states, which can more directly reflect the track characteristics of vehicles in different running states in the tunnel.

We built a trajectory prediction model for the entire vehicle operation process in an extra-long tunnel to predict the vehicle trajectory in real time using traffic flow data from limited sections, which can support the digital twinning of traffic flow operation, traffic operation monitoring, evaluation, early warning, and control in an extra-long tunnel.

The remainder of this study is structured as follows. Section 2 outlines the existing literature review. Section 3 introduces the concept of the trajectory-prediction model and the proposed trajectory-prediction model, which includes the analysis of the traffic features of extra-long tunnels, classification of vehicle driving regimes, construction of the vehicle motion laws in different regimes, and calibration of model parameters. Section 4 validates the model and examines its outcomes. Finally, the conclusions and future perspectives are presented in Section 5.

### 2. Literature Review

Vehicle-trajectory prediction refers to the prediction of a vehicle’s trajectory in the next few seconds using information such as the vehicle’s trajectory in the previous few seconds. Researchers have proposed numerous trajectory prediction methods, which can generally be divided into three categories: physics-based trajectory prediction, behavior-based trajectory prediction, and interaction-based trajectory prediction.

Among these three methods, the first is a physics-based trajectory prediction. Such methods usually require the input of the vehicle’s motion state (such as steering, acceleration, and speed) and attributes (such as vehicle type and weight). Some models will also consider the physical and geometric conditions of the road (such as road-friction coefficient and road-line type) and use the vehicle-dynamics model to predict the motion state of the vehicle in the next few seconds. Song et al. [1] and Houenou et al. [2] presented a trajectory prediction method based on an acceleration-motion model. Sandberg et al. [3] and Raigoza et al. [4] very recently proposed a novel physics-based trajectory predictor. Chen et al. [5] proposed a driving intention-specific feature fusion mechanism in which the extracted temporal and social features can be integrated adaptively for maneuver-based multi-modal trajectory prediction. Yoon et al. [6] presented a probabilistic trajectory prediction of cut-in vehicles which exploits the information of interacting vehicles. This type of method only uses the motion state of the vehicle and lacks the use of higher level information; therefore, it can only achieve good performance in short-term vehicle-trajectory prediction.

With the improvement in hardware computing power and the continuous development of deep-learning methods, data-driven trajectory prediction methods have gradually emerged into the mainstream, mainly in the form of behavior-based trajectory prediction and interaction-based trajectory prediction. Interaction-based trajectory prediction typically uses neural networks to model the interactions between vehicles. The difficulty of this method lies in interactive detection, identification, and combination explosion. Existing interactive trajectory prediction methods mainly adopt a hidden Markov model (HMM), social pooling model, and rule-based model. With the emergence of social-LSTM [7], a structure capable of autonomous learning and interaction, the interactive modeling ability of traffic participants has further improved. Bertinetto et al. [8] extended the social pool to
the whole world to enhance the modeling of interactions between pedestrians, improve the social-LSTM, introduce generative adversarial network (GAN) networks, and establish the Social-GAN model, which is more consistent with reality. Manttari [9] used recursive and convolutional neural networks to process environmental timing information and learn hidden interactions, which predicts an uncertain trajectory. When there were no traffic lights at intersections and traffic participants did not obey traffic rules, Roy et al. [10] embedded the interaction of traffic participants into a GAN network for trajectory prediction in this scenario. Through the verification of the VisDrone dataset, the trajectory prediction method can handle complex traffic scenarios, such as vehicle merging and collision avoidance. Ju et al. [11] proposed a multilayered interactive sensing Kalman neural network (laKNN) and used the interactive layer to analyze environmental information into interactive sensing acceleration and the motion layer to further analyze the interactive sensing trajectory. Interaction-based trajectory prediction can generate the future trajectory of vehicles according to their historical information by establishing regression models and learning a large amount of trajectory data. However, when the driving intention is unclear, the output of the regression model tends to be the average of the different intention tracks, which is inconsistent with the actual scenario.

Compared to the previous two methods, behavior-based trajectory prediction can predict the trajectory in cases of long-term uncertainty because it considers the intended behavior of the driver in the future. In behavior-based approaches, two methods are commonly used to predict a vehicle’s trajectory based on its behavior. The first method is the prototype method, which can cluster vehicle trajectories in real traffic scenarios. Multiple Gaussian processes can also be used to represent the distribution of different trajectories [12], and finite trajectories or a collection of their distributions can be obtained, which is called the trajectory prototype. Common methods used to calculate similarity include point-to-point Euclidean distance [13], Hausdorff distance [14], longest common subsequence [15], and rotationally invariant longest common subsequence [16]. The second method is the intention method, which first predicts the driving intention of the vehicle (driver) and then generates the corresponding driving behavior according to the predicted driving intention for trajectory prediction. Machine-learning algorithms are typically used to classify driving intentions, including multilayer perceptions [17] and support vector machines [18]. HMM [19] can also be used to describe driving intentions as a series of events. Compared with the physics-based trajectory prediction method, the behavior-based method has higher accuracy and longer prediction time. In this study, we adopted a behavior-based trajectory prediction method.

The main difficulty of the behavior-based trajectory prediction method is that it is difficult to directly observe the behavior of the driver or vehicle, and it is difficult to express it as a single behavior owing to the uncertainty of behavior. The operating environment for the traffic in extra-long tunnels is complex. Most vehicles are in the following condition because of the lane-change restrictions. Therefore, it is necessary to study the following state of vehicles in extra-long tunnels. Since the 1950s, various models have been proposed for human-driven vehicles. After the earliest following model was established by Reuschel [20] and Pipes [21], many vehicle-following models based on the stimulus–response mechanism of front and rear vehicles have appeared successively. Newell [22,23] first proposed a simplified vehicle-following model, which is consistent with the macroscopic relationship between the three elements of traffic flow. Owing to its simplicity and flexibility, Newell’s simplified following model has been widely used, and many researchers have calibrated the model using real trajectory data. For example, Ahn et al. [24] calibrated Newell’s simplified model using real vehicle-track data at signal-controlled intersections. Taylor et al. [25] investigated drivers’ situational dependence perception and response to external stimuli using the time distortion method. At the same time, many studies have focused on calibrating various random and context-dependent following models. Consequently, the study of vehicle-trajectory prediction is based on a reasonable simulation of the car-following state in an extra-long tunnel. Existing research
on car-following models can be broadly classified into stimulus response [26,27], safe distance [28,29], optimal speed [30,31], and fuzzy control [32,33]. Most existing studies on car-following models focus on the consideration of speed difference and following distance. The classic following models mostly regard safety and workshop distance as fixed constant values; however, in reality, safety and workshop distance are variables related to driver personality, traffic environment, and vehicle running speed.

3. Materials and Methods

3.1. Overview of The Trajectory Prediction Model

Figure 1 depicts the general architecture of the complete process trajectory prediction model of extra-long tunnel vehicles based on cross-section traffic data.

![Diagram](image)

Figure 1. The overall architecture of the vehicle-trajectory prediction model for extra-long tunnels based on cross-section traffic data.

When a vehicle passes through any detection portion in the tunnel, as shown in Figure 2, it is important to re-identify the regime using the calibrated Wiedemann model and estimate the vehicle trajectory using the vehicle’s current regime.

![Diagram](image)

Figure 2. Tunnel traffic-flow detection section division.
(1) Using the side-mounted video, the detection interval and section were determined, and statistics on the velocity, headway, and average velocity of the section were recorded.

(2) According to the calibrated Wiedemann mode, the regimes are classified as “Free driving”, “Following” and “Emergency” based on the vehicle headway data.

(3) If the vehicle is in the “Free driving” mode, the vehicle-trajectory prediction equation is proposed based on the stated motion laws. The vehicle-trajectory prediction equation for the vehicle in the “Following” regime is proposed based on the calibrated FVD car-following model. A vehicle-trajectory prediction equation based on the calibrated maximum braking deceleration is provided for vehicles in the “Emergency” regime.

(4) The speed and displacement of the vehicle are calculated using the iterative idea, and the vehicle’s position coordinates are predicted every 0.1 s, which is the predicted trajectory of the vehicle, based on the vehicle-trajectory prediction equation of different regimes, with 0.1 s as the simulation step.

(5) The vehicle speed, headway time, and average speed of the segment are re-collected as the vehicle passes through the next detection section. To complete the trajectory prediction of the entire vehicle driving process, the vehicle’s regime is re-identified, and the trajectory is projected using the present regime and the accompanying trajectory prediction equation.

3.2. Traffic-Characteristics Analysis of Extra-Long Tunnel

3.2.1. Data Preparation

Fixed-coil and GPS data are typically used as data sources for extra-long tunnels, although the coverage of fixed detectors is restricted and easily broken. The GPS locating system also has the problem of weak or lack of signal in the tunnel, making data collection extremely difficult. In this study, we collected cross-sectional traffic data using the Qingdao Jiaozhou Bay extra-long tunnel side-mounted video, determined the measurement interval based on the size of the tunnel sidewall tiles, and combined the video timestamp information to collect the speed and headway of passing vehicles. Every 100 m to 150 m of the tunnel was outfitted with side-mounted video equipment. The detection section is defined by the location of the side-mounted video device, overcoming missing data in extra-long tunnels and achieving full traffic data coverage.

The detection region and measurement interval were configured in the monitoring video. The size of the ceramic tile on the side wall is 2.5 m × 2.5 m. As illustrated in Figure 3, two detection sections were established with six ceramic tiles as the interval distance to generate a 15 m speed measurement interval.

Figure 3. Vehicle speed measurement interval.

The headway detection section is shown in Figure 4. The headway of the two workshops was measured as the time delay between two adjacent cars by examining the detection section in the same lane.
3.2.2. Traffic-Flow Characteristics Analysis

This study uses the Jiaozhou Bay extra-long tunnel in Qingdao as an example to analyze the traffic operation features of the extra-long tunnel. To study the traffic-flow characteristics of the tunnel, the parameters of traffic-flow operation characteristics included traffic flow, average speed, and headway.

The entrance and exit of the Xuejiadao end of the Jiaozhou Bay extra-long tunnel in Qingdao were chosen as the traffic-flow collection locations in this study to obtain the hourly traffic flow of the tunnel on 12 April 2021 (Monday) and 14 April 2021 (Wednesday). Figures 5 and 6 illustrate the statistical results. According to statistics, the daily traffic flow reached 82,299 and 85,999, respectively, and the traffic flow peaked between the morning and evening rush hours.
According to the Qingdao Jiaozhou Bay extra-long tunnel side-mounted video, 17 video spots from v5 to v158 were chosen to count hourly traffic during the morning peak. Figure 7 shows the statistical results. The traffic flow in different lanes may be significantly different. The center lane has a somewhat higher traffic flow than the left lane, whereas the right lane has the lowest traffic flow (25.3%). The main reason for this is that the Jiaozhou Bay Tunnel requires large cars to drive to the right, while the remaining two lanes are for small cars. Second, because of the side-wall effect of the tunnel, the driver automatically tries to stay away from the wall and prefers to drive in the middle lane. Vehicles cannot change lanes or overtake other vehicles in the same lane when driving through a tunnel; therefore, the traffic flow is less chaotic.

![Figure 7. Morning-peak lane-level traffic statistics.](image)

The statistical results of collecting the speed of cars traveling through the segment under varied slopes are presented in Figure 8. Large cars impact the right lane, and the pace is substantially lower than that in the other two lanes. The speed of the vehicle is higher on the downhill section than on the uphill section. Vehicles may not change lanes or overtake cars in the same lane because of traffic laws; therefore, the short-distance segment of the traffic state is the same; with fewer dramatic fluctuations, the speed is rather consistent.

![Figure 8. Tunnel speed statistics of different slopes.](image)

Figure 9 shows the average headway statistics for various tunnel slopes. Due to the influence of large cars, the right lane has less traffic; therefore, the headway is greater than that of the left and center lanes, whereas the middle lane has the most intense traffic and the smallest headway. The headway of the downhill segment is often greater than those of
the flat and uphill sections. According to the average headway statistics, when traffic is reasonably dense and stable, the headway is primarily concentrated below 5 s, and the cars in the tunnel are stable.

Figure 9. Time headway statistical diagram of tunnel with different slopes.

Tables 1 and 2 summarize the traffic-flow parameters of different lanes and different slopes in the tunnel. Table 1 shows that the middle lane has the largest traffic flow, the fastest speed and the smallest headway. There are more large vehicles in the right lane, so the speed is the slowest and the headway is the largest. Table 2 shows the fastest speed and the largest headway is on downhill compared to flat and uphill.

Table 1. Summary of traffic-flow parameters of different lanes in the tunnel.

<table>
<thead>
<tr>
<th>Lane</th>
<th>Traffic Flow(pcu/h)</th>
<th>Velocity(m/s)</th>
<th>Time Headway(s)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>SD</td>
<td>Mean</td>
</tr>
<tr>
<td>Left</td>
<td>1287.3</td>
<td>124.4</td>
<td>18.54</td>
</tr>
<tr>
<td>Middle</td>
<td>1330.4</td>
<td>138.9</td>
<td>18.79</td>
</tr>
<tr>
<td>Right</td>
<td>886.4</td>
<td>124.8</td>
<td>15.69</td>
</tr>
</tbody>
</table>

Table 2. Summary of traffic-flow parameters of different slopes in the tunnel.

<table>
<thead>
<tr>
<th>Slope</th>
<th>Velocity(m/s)</th>
<th>Time Headway(s)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>SD</td>
</tr>
<tr>
<td>Downhill</td>
<td>18.31</td>
<td>2.31</td>
</tr>
<tr>
<td>Flat</td>
<td>17.66</td>
<td>1.22</td>
</tr>
<tr>
<td>Uphill</td>
<td>16.67</td>
<td>1.23</td>
</tr>
</tbody>
</table>

In summary, cars in the Jiaozhou Bay extra-long tunnel are subject to driving regulations and lane changes are forbidden while driving. Consequently, the overtaking action cannot be completed in the same lane. There is less traffic turbulence, the vehicle speed and headway are reasonably steady, and the vehicles in the tunnel are essentially under the “Following” regime.
3.3. Car-Following-Regime Division Based on Wiedemann Model

One of the most commonly used automobile-following models in traffic-flow simulations is the Wiedemann model. The main premise of the model is that the driver decelerates when his or her perceived threshold is reached, which is determined by the relative speed and distance to the car in front. Otherwise, the driver proceeds at the intended speed [34].

\[ AX = L_{n+1} + AX_{\text{add}} + RND1_n \cdot AX_{\text{mult}} \]  \hspace{1cm} (1)

Substituting default values for the parameters in (1), \( L_{n+1} \) is the length of the front car, which is 4.5 m by default, \( AX_{\text{add}} \) is 1.25, \( AX_{\text{mult}} \) is 2.5, and \( RND1_n \) is a random variable with a standard normal distribution, yielding \( AX \in (5.75, 8.25) \) with a mean value of 7 m.

In this paper, the congestion parking video is used to calculate the distance between vehicles when they are stationary in traffic, with a dimension of 2.5 m \( \times \) 2.5 m per tile, as shown in Figure 10.

![Figure 10. Parking-distance measurement area.](image)

The average parking distance is 2.3 m, and the vehicle length is 4.5 m, so the measured value of the expected parking distance \( AX \) is 2.3 + 4.5 = 6.8 m.

\( ABX \) is the desired minimum following distance, the value used to differentiate between the “Emergency” and “Following” regimes (see Appendix A). The formula is as follows:

\[ ABX = AX + BX \]  \hspace{1cm} (2)

\[ BX = (BX_{\text{add}} + BX_{\text{mult}} \cdot RND1_n) \cdot \sqrt{v} \]  \hspace{1cm} (3)

\[ v = \min(v_n, v_{n+1}) \]  \hspace{1cm} (4)

\( BX \) denotes the additional distance required for moving the vehicles. \( BX_{\text{add}} \) and \( BX_{\text{mult}} \) are constants; \( BX_{\text{add}} \) is 2.0, \( BX_{\text{mult}} \) is 1.0, and \( v_{n+1} \) and \( v_n \) represent the speeds of the front and rear vehicles, respectively.

In the smooth traffic condition, 718 vehicle-speed data points were collected, with an average speed of 17.37 m/s, the 85th-position vehicle speed of 19.54 m/s, and the 75th-position vehicle speed of 18.58 m/s. For the calculation, the three speed values were
substituted with \( v \). The mean value of \( ABX \) was approximately 17.5 m, and the calibration value of \( ABX \) was determined in this paper as 17.5 m.

\[
\begin{align*}
BX \in (8.34, 12.50), & \quad ABX \in (15.14, 19.30), \quad \text{if } v = 17.37 \text{ m/s} \\
BX \in (8.62, 12.93), & \quad ABX \in (15.42, 19.73), \quad \text{if } v = 19.54 \text{ m/s} \\
BX \in (8.84, 13.26), & \quad ABX \in (15.64, 20.06), \quad \text{if } v = 18.28 \text{ m/s}
\end{align*}
\]

(5)

\( SDX \) is the maximum following distance threshold, which is defined as

\[
SDX = AX + EX \cdot BX
\]

(6)

\[
EX = EX_{\text{add}} + EX_{\text{mult}} \cdot (NRND - RND_{2n})
\]

(7)

where \( EX_{\text{add}} \) and \( EX_{\text{mult}} \) are constants, \( EX_{\text{add}} \) is 1.5, \( EX_{\text{mult}} \) is 0.55, \( NRND \) and \( RND_{2n} \) are the normally distributed random parameters.

Various definitions of car following have been proposed in previous studies. The 5 s time headway threshold was used in the 1994 U.S. Road Capacity Manual to classify the “Following” regime [35]. When studying the impact of trucks on capacity, Paker also used a 5 s time headway as the boundary for the “Following” regime [36]. He Min used 5 s and 8 s headway as the dividing line between the “Following” and “Free driving” regimes [37]. Song set the “Following” regime threshold of \( SDX \) to 3.9 times \( ABX \) [38].

Given the wealth of research on domestic and international scholars’ definition standards for the car-following regime, this study no longer calibrates the \( SDX \) threshold. In this study, the criterion for judging the “Following” regime was 5 s; the \( SDX \) distance threshold was converted into the time threshold, and the value was 5 s.

An average speed of 17.37 m/s for 718 samples collected under smooth traffic in the tunnel was used to convert \( AX \) and \( ABX \) to replace the distance value (m) with the time value (s) based on the calibration results for each distance threshold in the Wiedemann model (see Appendix A).

\[
\begin{align*}
AX_t &= AX/V = 6.8/17.37 \approx 0.39 \text{ s} \\
ABX_t &= ABX/V = 17.5/17.37 \approx 1.01 \text{ s} \\
SDX_t &= 5 \text{ s}
\end{align*}
\]

(8)

In summary, Figure 11 depicts the calibrated Wiedemann model car-following regime, where the scatter points represent the headway samples collected from the side-mounted video under smooth traffic conditions, and the vehicle driving regime in the tunnel is divided based on the headway.

(1) If the headway exceeds 5 s, the vehicle is judged to be in the “Free driving” regime, and the driver is free to drive at his or her own pace without regard for the car in front.

(2) If \( 5 \text{ s} \geq \text{headway} > 1.01 \text{ s} \), the vehicle is considered to be in the “Following” regime, and the following car reacts to the leading car’s speed change.

(3) If the vehicle is determined to be in the “Emergency” regime by \( 1.01 \text{ s} \geq \text{headway} > 0.39 \text{ s} \), the following car will actively slow down to avoid colliding with the leading car.

(4) If the vehicle is judged to be in the “Crash danger” regime by \( 0.39 \text{ s} \geq \text{headway} > 0 \text{ s} \), the rear vehicle will use emergency braking measures to cease.
According to Figure 11, most vehicles in the extra-long tunnel are in the “Following” regime, with few vehicles in the “Free driving” and “Emergency” regimes. There are no vehicles in the “Crash danger” regime, which corresponds to vehicle travel regularity under normal traffic conditions.

3.4. Vehicle-Trajectory Prediction Equation in the “Free Driving” Regime

It has been discovered through various observations that when the distance between a vehicle and a vehicle in front is too large, few vehicles speed up at maximum acceleration to catch up with the preceding vehicle, but employ an almost constant speed. This study chooses the average speed of the detection section as the free-driving vehicle’s speed to better reflect the overall situation of the vehicle in the tunnel.

Figure 12a–c shows that the vehicle travels at a constant acceleration in the first 5 s after crossing Section 1, switches to \( V_1 \) at the end of the 5 s, and then travels at a constant speed, \( V_1 \). Figure 12d–e depict a constant acceleration in the first 5 s through Section 2, shifting to \( V_2 \) at the conclusion of 5 s, and then the vehicle runs at a constant speed of \( V_2 \). The vehicles in the following section were the same.

The motion equation of the vehicle in the “Free driving” regime is divided into three parts:

(1) For the first 5 s after passing through the detection section:

\[
\begin{align*}
&dV_n(t)/dt = (V_i - V_{\text{start}})/5 \\
&V_n(t + T_0) = V_n(t) + dV_n(t)T_0 / dt \\
&X_n(t + T_0) = X_n(t) + V_n(t)T_0 + dV_n(t)T_0^2 / 2dt
\end{align*}
\]

(9)

where \( v_i \) is the average speed of detection section \( i \); and \( V_{\text{start}} \) is the vehicle’s initial speed before arriving at detection section \( i \).
(2) After 5 s of examining the detection section:

\[
\begin{align*}
 & \frac{dV_i(t)}{dt} = 0 \\
 & V_i(t + T_0) = V_i \\
 & X_i(t + T_0) = X_i(t) + V_i \cdot T_0
\end{align*}
\]

(3) The first 5 s of passing the following detection section:

\[
\begin{align*}
 & \frac{dV_i(t)}{dt} = \frac{(V_{i+1} - V_i)}{5} \\
 & V_i(t + T_0) = V_i(t) + \frac{dV_i(t)}{dt} T_0 \\
 & X_i(t + T_0) = X_i(t) + V_i(t) T_0 + \frac{dV_i(t)}{2} T_0^2
\end{align*}
\]

where \(V_{i+1}\) is the average speed of the detection section \(i + 1\).

**Figure 12.** Motion law of vehicle in the free-driving regime. (a) Status 1, (b) Status 2, (c) Status 3, (d) Status 4, (e) Status 5, (f) Status 6.

### 3.5. Vehicle-Trajectory Prediction Equation in The “Following” Regime Based on FVD Model

#### 3.5.1. Motion Law of Vehicle in the Following Regime

The spacing headway in the same lane of a train fleet is not enormous, the fleet of each vehicle is running under the influence and constraints of the front vehicle, and the driver is following the speed of the vehicle in front and the space headway; thus, to control their speed, the vehicles operate in the “following” regime.

When the front vehicle A is driving freely, Figure 13a–c shows that after passing the first section, vehicle B adjusts its speed based on the speed of vehicle A and the space headway to achieve the desired following distance \(D_{\text{desired}}\). Figure 13d–f shows that as vehicle A passes the second section, the speed of vehicle B is adjusted accordingly. Finally, the two vehicles maintain their desired headway \(D'_{\text{desired}}\) while maintaining speed \(V_2\).
Figure 13. Vehicle motion law in the following regime (the preceding vehicle is free driving). (a) Status 1, (b) Status 2, (c) Status 3, (d) Status 4, (e) Status 5, (f) Status 6.

When the preceding vehicle is in the “Following” mode, as shown in Figure 14, vehicle C joins the queue by adjusting its speed and eventually reaches the desired headway.

Figure 14. Motion law of vehicle in the following regime (the preceding vehicle as follows). (a) Status 1, (b) Status 2, (c) Status 3, (d) Status 4, (e) Status 5.
3.5.2. Calibration of Velocity-Spacing Headway Relation

Jiang et al. [39] contended that the acceleration caused by the velocity difference between front and rear vehicles, whether $\Delta v > 0$ or $\Delta v < 0$, must be considered. The acceleration of the rear vehicle is affected by the space headway. They proposed a model based on the full velocity difference (FVD).

$$\frac{dv_n(t)}{dt} = a(V(\Delta x) - v_n(t)) + \lambda \Delta v$$  \hspace{1cm} (12)

where $a$ ($a > 0$) is the driver sensitivity coefficient, and the unit is $s^{-1}$; $\lambda$ ($\lambda \geq 0$) is the velocity-difference response coefficient, and the unit is $s^{-1}$; $\Delta v = v_{n+1}(t) - v_n(t)$ indicates the velocity difference between the front and rear vehicles; $x_{n+1}(t)$ and $v_{n+1}(t)$ are the displacement and velocity of the preceding vehicle at time $t$; and $x_n(t)$ and $v_n(t)$ are the displacement and velocity of the following vehicle at time $t$, respectively. The optimized velocity function $V(\Delta x)$ is expressed as follows:

$$V(\Delta x) = 0.5 \cdot V_{\text{max}} \left( \tanh(\Delta x - h_c) + \tanh(h_c) \right)$$  \hspace{1cm} (13)

where $V_{\text{max}}$ is the vehicle’s maximum limiting speed, $h_c$ is the driving safety distance, $V_{\text{max}}$ and $h_c$ are constants, and $\tanh()$ is a hyperbolic tangent function (see Appendix A).

The FVD model thoroughly considered the effect of the front- and rear-vehicle displacements and velocity differences on the rear-vehicle acceleration. However, considering the value of the driving safety distance $h_c$ to be a constant is unreasonable. As a result, this study will improve this by substituting the desired space headway for the driving safety distance.

In this study, 588 data samples of vehicle velocity and their corresponding headway under different traffic-flow conditions were used to investigate the relationship between the space headway and the velocity of the rear vehicle, as shown in Figure 15.

![Figure 15. Scatter plot of velocity-time headway.](image)

We converted the time headway to the space headway and drew a scatter plot of the velocity-space headway, as shown in Figure 16.
Figure 15. Scatter plot of velocity-time headway.

We converted the time headway to the space headway and drew a scatter plot of the velocity-space headway, as shown in Figure 16.

Figure 16. Scatter plot of velocity-space headway.

To reduce the error caused by the uneven sample size, the space headway within each velocity interval was averaged using 0.1 m/s as the width of the velocity interval to obtain the space headway that the rear vehicle is expected to maintain at different velocities, as shown in Figure 17.

Figure 17. Scatter plot of velocity-interval average headway.

A regression model with an exponential function was proposed to represent the relationship between the space headway and the velocity. With an R-squared value of 0.9313, the goodness of fit was good.

\[ y = 2.313e^{0.165v} \]  

where \( y \) is the desired space headway; and \( v \) is the velocity of the rear vehicle.

3.5.3. Calibration of Time Required for Vehicle to Reach a Stable Condition

The following vehicle adjusts its speed continuously until it is close to the preceding vehicle’s speed, reaches the desired headway, and enters a stable car-following state.
The time required for this process is also an important parameter in the car-following model, which must be calibrated. We selected five straight video points in the tunnel and established four observation sections, numbered from 1 to 20, according to the sequence of vehicles passing through. The two vehicles involved in the car chase were divided into groups, and time-headway and time-series data were collected as the vehicles passed through each section, as shown in Figure 18.

Figure 18. Division of each observation section.

One of the 50 samples collected in this study is shown in Figure 19. According to the statistical results, the time required for the vehicle to reach a stable car-following state is primarily concentrated between 15.195 s and 24.195 s. As a result, in the vehicle-trajectory prediction model developed in this study, the time required for the vehicle to reach a stable car-following state should be adjusted to be in the 15–24 s range.

Figure 19. Sample diagram of time required for vehicle to reach stable car-following state.
3.5.4. Optimization of Driver-Sensitivity Coefficient

The maximum speed limit for vehicles in the Qingdao Jiaozhou Bay extra-long tunnel is 80 km/h. However, it was discovered through observation that in a relatively smooth situation, some vehicles would exceed the speed limit to minimize the journey time or catch up with the front vehicle as soon as possible. As a result, the maximum speed limit of the tunnel for vehicles is 90 km/h, or 25 m/s.

Chen et al. [40] calibrated an FVD car-following model using expressway-traffic track data. The calibration results of the driver-sensitivity coefficient $\alpha$ and speed-difference response coefficient $\lambda$ are: $\alpha$ is 0.0633 and $\lambda$ is 0.3701.

In this study, we used $\alpha = 0.0633$, $\lambda = 0.3701$, $V_{\text{max}} = 25$ m/s, and $D_{\text{desire}} = 2.313 e^{0.165t}$ (see Appendix A) to run numerical simulation experiments on the FVD car-following model to determine whether these values are consistent with vehicle following in the extra-long tunnel scenario.

The simulation results for the experimental vehicle group 1 are shown in Figure 20. Vehicle 1 takes approximately 26 s to achieve a stable car-following state, which exceeded the optimal range of 15–24 s. The analysis of the simulation results of the three experimental vehicle groups reveals that when $\alpha = 0.0633$ and $\lambda = 0.3701$, the FVD car-following model responds less to the leading vehicle stimulation. According to the action of the leading vehicle, the following vehicle’s acceleration is slight, which prolongs the speed-change process and thus requires a long time for the vehicle to reach a stable car-following state.

![Figure 20](image)

**Figure 20.** Sample diagram of iterative simulation results of the leading vehicle and following vehicle1 (experimental vehicle group 1). (a) Velocity change relationship and (b) vehicle spacing changes.

The driver-sensitivity coefficient $\alpha$ was adjusted in this study to improve the model’s response to the front vehicle’s stimulus and shorten the time required for the vehicle to achieve a stable following state. We set $\alpha$ to different values at 0.05–0.5 and ran numerical simulation experiments for various values of $\alpha$. The simulation effect was optimal at $\alpha = 0.27$.

The simulation results of the experimental vehicle group 1 after adjustment are shown in Figure 21. We can see that the following vehicle 1 takes approximately 20 s to reach a stable car-following state, which is within the optimal range.
The driver-sensitivity coefficient $\alpha$ was adjusted in this study to improve the deceleration to avoid a collision. The safe space headway $D$ is calculated as follows:

$$D = \frac{V_{\text{max}}(\text{tanh}(\Delta x - D_{\text{desire}}) + \text{tanh}(D_{\text{desire}}))/2}{a}$$

where the maximum limited speed $V_{\text{max}}$ is 25 m/s, the desired space headway $D_{\text{desire}} = 2.313e^{0.1651v}$, the driver-sensitivity coefficient $a$ is 0.27, and the velocity-difference response coefficient $\lambda$ is 0.3701.

In summary, the vehicle-trajectory prediction equation in the “Following” regime can be constructed by combining the enhanced FVD car-following model with the trajectory equation.

$$\begin{align*}
\frac{dv_n(t)}{dt} &= a(V(\Delta x) - v_n(t)) + \lambda \Delta v \\
V(\Delta x) &= V_{\text{max}}(\text{tanh}(\Delta x - D_{\text{desire}}) + \text{tanh}(D_{\text{desire}}))/2 \\
v_n(t + T_0) &= V_n(t) + dV_n(t)T_0/dt \\
x_n(t + T_0) &= x_n(t) + V_n(t)T_0 + dV_n(t)T_0^2/2dt
\end{align*}$$

3.6. Vehicle-Trajectory Prediction Equation in the “Emergency” Regime

When the distance between the back and front vehicles is less than the safe space headway, the car enters the “Emergency” mode and the driver applies the greatest braking deceleration to avoid a collision. The safe space headway $D$ is calculated as follows:

$$D(t) = \begin{cases} 
V_n(t) \cdot t_1 + (V_n(t) - V_{n+1}(t)) \cdot t_2 / 2 \\
+ \left( V_n(t)^2 - V_{n+1}(t)^2 \right) / 2a + L + S \\
V_n(t) > V_{n+1}(t) \\
V_n(t) \cdot (t_1 + t_2) + 2V_n(t) \cdot V_{n+1}(t) - V_n(t)^2 - V_{n+1}(t)^2 / 2a \\
- V_{n+1}(t) \cdot t_2 / 2 + L + S \\
V_n(t) < V_{n+1}(t)
\end{cases}$$
where \( V_n \) is the rear vehicle speed; \( V_{n+1} \) is the front vehicle speed; \( a \) is the maximum vehicle deceleration; \( t_1 \) is the sum of the driver reaction time and brake coordination time; \( t_2 \) is the deceleration growth time; \( L \) is the vehicle length; and \( S \) is the stopping distance.

As shown in Figure 22b, when \( d' < D \), vehicle B actively brakes to avoid a collision with the preceding vehicle. Vehicle B slows down and brakes to draw away from vehicle A, as shown in Figure 22c–d. At this point, \( d'' > D \), vehicle B increases its speed to obtain the desired headway \( D_{desire} \).

Figure 23. The average speed section diagram.

Figure 22. Motion law of vehicle in the emergency regime. (a) Status 1, (b) Status 2, (c) Status 3, (d) Status 4.

When the traffic flow is smooth, most vehicles maintain a proper headway with the preceding vehicle, and few will be in the “Emergency” mode. This study considers the braking deceleration of the vehicle in the tunnel after the accident as the maximum brake deceleration and calibrates it to investigate the car’s trajectory under the “Emergency” regime. As illustrated in Figure 23, we establish a 30 m maximum brake deceleration measuring interval behind the accident car.
The average deceleration \( a \) of the vehicle over the measurement interval is calculated by determining the time interval \( T \) through which the vehicle’s front end passes \((V_1, V_3)\).

\[
a = \frac{(V_3 - V_1)}{T}
\] (18)

The braking deceleration of 15 vehicles behind the accident was collected according to six accident videos in the tunnel. The maximum braking deceleration \( a_{\text{max}} \) was calibrated to \(-4 \text{ m/s}^2\). In summary, the vehicle-trajectory prediction equation in the “Emergency” regime is as follows. The braking deceleration of 15 vehicles involved in the accident was collected using the six accident videos in the tunnel. Finally, the maximum braking deceleration \( a_{\text{max}} \) is calibrated to \(-4 \text{ m/s}^2\) (see Appendix A). In summary, the “Emergency” vehicle-trajectory prediction equation is:

\[
\begin{align*}
\frac{dV_n(t)}{dt} &= a_{\text{max}} \\
V_n(t + T_0) &= V_n(t) + a_{\text{max}} T_0 \\
X_n(t + T_0) &= X_n(t) + V_n(t) T_0 + a_{\text{max}} T_0^2/2
\end{align*}
\] (19)

4. Results and Discussion

This study chose eight video points in the Qingdao Jiaozhou Bay extra-long tunnel: V68, V69, V70, V71, V72, V73, V74, and V75, with a distance of 100 m between each video point. V68 and V72 represent the first and second sections, respectively. To predict the change in the vehicle running speed and trajectory coordinates, the traffic data collected from the sections were substituted into the trajectory prediction model. Finally, the predicted and actual values were compared for analysis.

4.1. Numerical Simulation

The experimental groups are named experimental vehicle Group 1, experimental vehicle Group 2, and experimental vehicle Group 3, with the front vehicle in the “Free driving” regime and the rear vehicle performing the following behavior. Each group contained three continuous vehicles, labeled sequentially as leading vehicle, vehicle 1 and vehicle 2, as shown in Table 3. Table 4 shows the speed and headway of each experimental vehicle group when passing through the V68 and V72 sections.

Table 3. Experimental-vehicle-group screening and corresponding time-section average speed.

<table>
<thead>
<tr>
<th>Experimental Vehicle Group</th>
<th>Time</th>
<th>Section Average Speed (m/s)</th>
<th>V68</th>
<th>V72</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>8:00–8:01</td>
<td></td>
<td>17.31</td>
<td>17.41</td>
</tr>
<tr>
<td>1</td>
<td>8:04–8:05</td>
<td></td>
<td>16.28</td>
<td>16.41</td>
</tr>
<tr>
<td>3</td>
<td>8:07–8:08</td>
<td></td>
<td>15.73</td>
<td>15.69</td>
</tr>
</tbody>
</table>

Table 4. The measured data of each experimental vehicle group.

<table>
<thead>
<tr>
<th>Experimental Vehicle Group 1/2/3</th>
<th>V68</th>
<th>V72</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Velocity (m/s)</td>
<td>Headway (s)</td>
</tr>
<tr>
<td>Leading vehicle</td>
<td>16.22/16.37/16.31</td>
<td>5.97/6.14/6.09</td>
</tr>
<tr>
<td>Following vehicle 1</td>
<td>15.38/15.74/15.91</td>
<td>3.41/3.23/2.83</td>
</tr>
</tbody>
</table>

Figures 24–26 can be summarized as follows:

Following vehicle 1 15.38/15.74/15.91 3.41/3.23/2.83 16.22/16.11/16.58 3.05/2.96/2.96

Leading vehicle 16.22/16.37/16.31 5.97/6.14/6.09 15.63/16.94/16.24/6.53/6.05/5.64

Experimental Vehicle Group 1/2/3 V68 V72

<table>
<thead>
<tr>
<th>Velocity(m/s)</th>
<th>Headway (s)</th>
<th>Velocity(m/s)</th>
<th>Headway (s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>12</td>
<td></td>
<td>13</td>
<td></td>
</tr>
<tr>
<td>14</td>
<td></td>
<td>15</td>
<td></td>
</tr>
<tr>
<td>16</td>
<td></td>
<td>17</td>
<td></td>
</tr>
<tr>
<td>18</td>
<td></td>
<td>19</td>
<td></td>
</tr>
<tr>
<td>20</td>
<td></td>
<td>21</td>
<td></td>
</tr>
</tbody>
</table>

Table 3. Experimental-vehicle-group screening and corresponding time-section average speed.

Numerical simulation results of experimental vehicle group 1. (a) Velocity change relationship and (b) Variation of shop spacing Δx.

Firstly, the regime of the vehicle is judged by the time headway of the leading vehicle. Then, the vehicle trajectory is predicted according to the vehicle operation rules established in this study. The leading vehicle takes the average speed of the current section to drive at a uniform speed, and the following vehicle 1 and 2 will adjust their own speed according to the speed taken by the leading vehicle until it is similar to the speed of the leading vehicle and then keep driving at a uniform speed. In this study, the speed change of each vehicle in the experimental vehicle group has a certain randomness. Taking the experimental vehicle group 1 as an example, the leading vehicle passes through section V68 with a speed of 16.22 m/s, and the time headway with the preceding vehicle is 5.97 s, which is greater than 5 s, and is in the “Free driving” regime. The average speed of section V68 is 17.31 m/s, the leading vehicle will accelerate to 17.31 m/s according to the established driving rules, then maintain a uniform speed, and change the speed 5 s before reaching V72 to the average speed of section V72, 17.41 m/s, then keep the uniform speed again.

Figure 24. Numerical simulation results of experimental vehicle group 1. (a) Velocity change relationship and (b) Variation of shop spacing Δx.

Figure 25. Numerical simulation results of experimental vehicle group 2. (a) Velocity change relationship and (b) Variation of shop spacing Δx.
In the first 3.4 s after the leading vehicle passed section V68, the following vehicle 1 passed section V68 with a speed of 15.38 m/s. The displacement of the leading vehicle at this moment is 56.40 m, which is the spacing between the two vehicles. It is greater than the desired headway $D_{\text{desire}}$ at the current speed of following vehicle 1. The following vehicle 1 accelerates to reduce the distance from the leading vehicle; finally, the distance headway gradually decreases and stabilizes around $D_{\text{desire}}$. The speed of the following vehicle 1 also becomes gradually closer to that of the leading vehicle and, finally, stabilizes near the speed of the leading vehicle. The time for the following vehicle 1 to reach a stable car-following state is about 20 s, which is in the optimal range.

Similarly, when the following vehicle 2 passes through section V68, the distance headway is 65.67 m, which is greater than desired headway $D_{\text{desire}}$ at the current speed of the following vehicle 2. Subsequently, the following vehicle 2 accelerates to reduce the distance from the following vehicle 1. As the speed of the following vehicle 1 is in a state of constant change, and when the following vehicle 2 passes through section V68, the speed difference between the two vehicles and the spacing is large, following vehicle 2 adjusts its own speed to reach the stable following state in a relatively long time, roughly 29 s.

4.2. Effect Teste
4.2.1. Speed Teste

The first section is V68, with a position coordinate of 0 m and the V72 point coordinate is 400 m. The speed of each vehicle in the experimental vehicle group as it passes through the 400 m coordinates is compared to the speed data obtained by the simulation iteration at the 400 m coordinates.

From the results in Tables 5–7, we can see that the accuracy of experimental vehicle group 2 is the highest, which is because, according to the vehicle operation rules constructed in this study, the speed results obtained from the simulation are close to the average speed of section V72, and the measured speed of experimental vehicle group 2 is closest to the corresponding average speed of the section; therefore, improving the accuracy of the average speed of the section is the key to improving the accuracy of trajectory prediction. The average accuracy was 94.14% when comparing the measured and simulated speeds of the three experimental groups of nine vehicles at 400 m coordinates, which is within the
acceptable range. The vehicle-trajectory prediction model was only moderately effective at predicting vehicle speed.

Table 5. Comparison of measured and simulated vehicle speeds at 400 m coordinates (experimental vehicle group 1).

<table>
<thead>
<tr>
<th>Experimental Vehicle Group 1</th>
<th>Measured Speed (m/s)</th>
<th>Simulated Speed (m/s)</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Leading vehicle</td>
<td>15.63</td>
<td>17.41</td>
<td>88.60%</td>
</tr>
<tr>
<td>Following vehicle 1</td>
<td>16.22</td>
<td>17.49</td>
<td>92.17%</td>
</tr>
<tr>
<td>Following vehicle 2</td>
<td>15.87</td>
<td>17.91</td>
<td>87.15%</td>
</tr>
</tbody>
</table>

Table 6. Comparison of measured and simulated vehicle speeds at 400 m coordinates (experimental vehicle group 2).

<table>
<thead>
<tr>
<th>Experimental Vehicle Group 2</th>
<th>Measured Speed (m/s)</th>
<th>Simulated Speed (m/s)</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Leading vehicle</td>
<td>16.94</td>
<td>16.41</td>
<td>96.87%</td>
</tr>
<tr>
<td>Following vehicle 1</td>
<td>16.11</td>
<td>16.43</td>
<td>98.01%</td>
</tr>
<tr>
<td>Following vehicle 2</td>
<td>16.26</td>
<td>16.75</td>
<td>96.99%</td>
</tr>
</tbody>
</table>

Table 7. Comparison of measured and simulated vehicle speeds at 400 m coordinates (experimental vehicle group 3).

<table>
<thead>
<tr>
<th>Experimental Vehicle Group 3</th>
<th>Measured Speed (m/s)</th>
<th>Simulated Speed (m/s)</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Leading vehicle</td>
<td>16.24</td>
<td>15.69</td>
<td>96.61%</td>
</tr>
<tr>
<td>Following vehicle 1</td>
<td>16.58</td>
<td>15.74</td>
<td>94.93%</td>
</tr>
<tr>
<td>Following vehicle 2</td>
<td>16.62</td>
<td>15.94</td>
<td>95.91%</td>
</tr>
</tbody>
</table>

4.2.2. Coordinate Trajectory Test

The experimental vehicle’s actual time passing through each point was captured using surveillance video to generate the actual trajectory, which was compared and analyzed with the predicted trajectory output from the trajectory prediction model, and the test results are shown in Figures 27–29 and Tables 8–10.

Table 8. Comparison of measured and predicted arrival times for each vehicle at the 800 m position (experimental vehicle group 1).

<table>
<thead>
<tr>
<th>Experimental Vehicle Group 1</th>
<th>Measured Time(s)</th>
<th>Predicted Time(s)</th>
<th>Accuracy</th>
<th>Average Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Leading vehicle</td>
<td>49.1</td>
<td>46.2</td>
<td>94.09%</td>
<td></td>
</tr>
<tr>
<td>Following vehicle 1</td>
<td>48.6</td>
<td>45.2</td>
<td>93.00%</td>
<td></td>
</tr>
<tr>
<td>Following vehicle 2</td>
<td>46.8</td>
<td>44.0</td>
<td>94.02%</td>
<td>93.70%</td>
</tr>
</tbody>
</table>

Table 9. Comparison of measured and predicted arrival times for each vehicle at the 800 m position (experimental vehicle group 2).

<table>
<thead>
<tr>
<th>Experimental Vehicle Group 2</th>
<th>Measured Time(s)</th>
<th>Predicted Time(s)</th>
<th>Accuracy</th>
<th>Average Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Leading vehicle</td>
<td>47.5</td>
<td>48.9</td>
<td>97.05%</td>
<td></td>
</tr>
<tr>
<td>Following vehicle 1</td>
<td>49.7</td>
<td>47.9</td>
<td>96.38%</td>
<td>96.24%</td>
</tr>
<tr>
<td>Following vehicle 2</td>
<td>48.7</td>
<td>46.4</td>
<td>95.28%</td>
<td></td>
</tr>
</tbody>
</table>
The predicted track of each vehicle in experimental group 1 and the measured track were compared, and it was discovered that the predicted track of each vehicle takes a relatively short time to reach the 800 m position, while the measured track takes a relatively long time to reach the 800 m position, but the deviation is small overall. The inaccuracy was caused by the fact that the average speed of the first and second sections was greater when experimental vehicle group 1 passed through them. The leading vehicle would modify its speed according to the average speed of the cross section and adopt the average speed of the cross section to drive at a uniform pace in the vehicle-trajectory prediction model, and the rear vehicle would adjust its speed to follow. After achieving a steady following condition, the car will also drive at a pace near to that of the leading vehicle, i.e., the section’s average speed.
The observed speeds of the second portion V72 were 15.63 m/s, 16.22 m/s, and 15.87 m/s, which are all slower than the average speed of the sections V68 and V72. As a result, the actual running speed of each vehicle in experimental group 1 is slower than that predicted by the model. As a result, the measured track takes longer than the projected track to reach 800 m.

By comparing and analyzing the anticipated and measured tracks of each vehicle in experimental group 2, it is discovered that the expected track of the first vehicle takes longer to reach the 800 m point; however, the measured track of the first car takes less time. The anticipated trajectory of Rear Car 1 and Rear Car 2 takes a comparatively short time to reach the 800 m position, whereas the observed trajectory takes a relatively long period, but the divergence is minimal overall.

Figure 28. Predicted trajectory and actual trajectory of each experimental vehicle (experimental vehicle group 2). (a) Leading car, (b) following car 1, (c) following car 2.

The average speed of the first part V68 and the second segment V72 when experimental vehicle group 1 passed them was 17.31 m/s and 17.41 m/s, respectively. The measured initial speeds of the leading vehicle, trailing vehicle 1, and trailing vehicle 2 as they travel through the first segment V68 were 16.22 m/s, 15.38 m/s, and 15.23 m/s, respectively. The observed speeds of the second portion V72 were 15.63 m/s, 16.22 m/s, and 15.87 m/s, which are all slower than the average speed of the sections V68 and V72. As a result, the actual running speed of each vehicle in experimental group 1 is slower than that predicted by the model. As a result, the measured track takes longer than the projected track to reach 800 m.

By comparing and analyzing the anticipated and measured tracks of each vehicle in experimental group 2, it is discovered that the expected track of the first vehicle takes longer to reach the 800 m point; however, the measured track of the first car takes less time. The anticipated trajectory of Rear Car 1 and Rear Car 2 takes a comparatively short time to reach the 800 m position, whereas the observed trajectory takes a relatively long period, but the divergence is minimal overall.
The average speed of the first part V68 and the second segment V72 when experimental vehicle group 2 passed them was 16.28 m/s and 16.41 m/s, respectively. The starting speeds of the front vehicle, rear vehicle 1 and rear vehicle 2 passing through section V68 in experimental group 1 were 16.37 m/s, 15.74 m/s, and 16.48 m/s, respectively, while the speeds through section V72 were 16.94 m/s, 16.11 m/s, and 16.26 m/s, respectively. As the actual running speed of the head vehicle is always greater than the average speed of the section through which it passes, the measured track of the head vehicle takes less time to reach the 800 m point and the anticipated track takes more time. Similarly, the measured speed of rear vehicle 2 is always lower than the section average speed, resulting in a longer time for the measured track to reach the 800 m location and a shorter time for the predicted track to reach the 800 m position. The observed speed of rear car 3 indicates that there is a deceleration behavior in the rear vehicle 3's actual functioning. The speed drops from 16.48 m/s when going through section V68 to 16.26 m/s while passing through section V72, which is likewise less than the segment's average speed. As a result, reaching the 800 m spot on the measured track takes a long time. To reach the 800 m spot, the estimated trajectory takes less time. The difference in time between the measured and expected arrival times of the vehicles at 800 m was utilized as the characterization parameter to test the

![Predicted trajectory and actual trajectory of each experimental vehicle (experimental vehicle group 3). (a) Leading car, (b) following car 1, (c) following car 2.](image-url)
deviation. In experimental group 2, the average accuracy of each vehicle’s anticipated time of arrival at 800 m was 96.24%.

The predicted track and measured track of each vehicle in experimental group 3 were compared, and it is discovered that the predicted track of each vehicle takes a relatively long time to reach 800 m position, whereas the measured track takes a relatively short time to reach 800 m position. The average speed of the V68 and V72 portions when experimental vehicle group 3 passed through them was 15.73 m/s and 15.69 m/s, respectively. The recorded initial speeds of the leading vehicle, trailing vehicle 1 and trailing vehicle 2 going through the first sector V68, respectively, were 16.31 m/s, 15.91 m/s, and 16.43 m/s. The observed speeds of the second portion V72 were 16.24 m/s, 16.58 m/s, and 16.62 m/s, which are all faster than the average speed of sections V68 and V72. As a result, the actual running speed of each vehicle in experimental group 3 is lower than that predicted by the model. As a result, the measured track takes a short time to reach the 800 m spot, whereas the anticipated course takes a considerable period of time. To test the deviation, the difference between the measured and expected times at 800 m was employed as the characterization parameter. In experimental group 3, the average accuracy of each vehicle’s anticipated time at 800 m was 96.40%.

The average accuracy was 95.45% based on a comparison of the measured and predicted coordinate trajectories of nine vehicles in the 800 m range. The predicted vehicle trajectory of the model agrees well with the measured trajectory, showing that the model can accurately predict the vehicle trajectory in an extra-long tunnel.

5. Conclusions

To address the critical need for dynamic monitoring and control of traffic flow in extra-long tunnels, this study extracted cross-sectional traffic data, such as speed and time headway, from video surveillance of the Qingdao Jiaozhou Bay extra-long tunnel, calibrated the vehicle-driving-regime differentiation threshold, optimized the FVD model through simulation experiments, and proposed a vehicle-trajectory prediction model. The primary conclusions are as follows:

1. The threshold of each regime in the Wiedemann model was calibrated using cross-section traffic data, yielding the following results: \( AX \approx 0.39 \text{ s} \), \( ABX_t \approx 1.01 \text{ s} \), \( SDX_t = 5 \text{ s} \). The regime was split according to the headway data, and the motion rules of vehicles in distinct regimes were established.

2. We investigated the relationship between speed and space headway and obtained the desired space-headway expression to replace the safe space headway of the FVD car-following model. The time required for the vehicle to achieve a stable car-following state was calibrated, and the driver-sensitivity coefficient was set to 0.27.

3. The accuracy of the proposed trajectory prediction model was validated using numerical simulation experiments in this study, and the results show that the trajectory prediction model proposed in this paper is more accurate for the speed and trajectory prediction of vehicles in extra-long tunnels, and can be effectively applied to real life to provide technical support for tunnel traffic-flow monitoring.

In future research, we will further investigate the influence of the velocity difference, perform a more comprehensive and detailed calibration of the Wiedemann model, and optimize the velocity-difference response coefficient \( \lambda \). In addition, the calibration of the maximum braking deceleration of the vehicle in the “Emergency” regime will be carried out by collecting the braking deceleration of the vehicle behind the accident vehicle, which can be supplemented and improved in the future.

Author Contributions: Methodology, R.X. and X.C.; validation, B.P.; data curation, T.Y.; writing—original draft preparation, Y.Z. and J.L.; writing—review and editing, Y.Z. All authors have read and agreed to the published version of the manuscript.
Funding: This work was supported in part by the Science and Technology Research Program of Chongqing Municipal Education Commission under Grant KJQN201900725 and the Young Scientists Fund of the National Natural Science Foundation of China under Grant 52002045.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The numerical data used to support the findings of this study are included within the article.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. Variables and acronyms in the text.

<table>
<thead>
<tr>
<th>Variables and Acronyms</th>
<th>Definitions</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wiedemann model</td>
<td>The Wiedemann car-following model</td>
<td>-</td>
</tr>
<tr>
<td>GPS</td>
<td>Global positioning system</td>
<td>-</td>
</tr>
<tr>
<td>AX</td>
<td>The recommended distance between stationary vehicles</td>
<td>6.8 m</td>
</tr>
<tr>
<td>Ln+1</td>
<td>The length of the front vehicle</td>
<td>4.5 m</td>
</tr>
<tr>
<td>AX_add</td>
<td>Constant</td>
<td>1.25</td>
</tr>
<tr>
<td>AX_mult</td>
<td>Constant</td>
<td>2.5</td>
</tr>
<tr>
<td>RND1n</td>
<td>A normally distributed parameter</td>
<td>7 m</td>
</tr>
<tr>
<td>ABX</td>
<td>The desired minimum following distance</td>
<td>17.5 m</td>
</tr>
<tr>
<td>BX</td>
<td>The additional distance required for moving the vehicles</td>
<td>10.7 m</td>
</tr>
<tr>
<td>BX_add</td>
<td>Constant</td>
<td>2.0</td>
</tr>
<tr>
<td>BX_mult</td>
<td>Constant</td>
<td>1.0</td>
</tr>
<tr>
<td>SDX</td>
<td>The maximum following-distance threshold</td>
<td>-</td>
</tr>
<tr>
<td>AXt</td>
<td>The time value of AX</td>
<td>0.39 s</td>
</tr>
<tr>
<td>ABXt</td>
<td>The time value of BX</td>
<td>1.01 s</td>
</tr>
<tr>
<td>SDXt</td>
<td>The time value of SDX</td>
<td>5 s</td>
</tr>
<tr>
<td>D_desire</td>
<td>Desired distance headway</td>
<td>$D_{desire} = 2.313e^{0.1651v}$</td>
</tr>
<tr>
<td>FVD</td>
<td>Full velocity difference model</td>
<td>-</td>
</tr>
<tr>
<td>α</td>
<td>The driver-sensitivity coefficient</td>
<td>0.27 m$^{-1}$</td>
</tr>
<tr>
<td>λ</td>
<td>The velocity-difference response coefficient</td>
<td>0.3701 m$^{-1}$</td>
</tr>
<tr>
<td>hc</td>
<td>The driving safety distance</td>
<td>-</td>
</tr>
<tr>
<td>tanh()</td>
<td>A hyperbolic tangent function</td>
<td>-</td>
</tr>
<tr>
<td>a_max</td>
<td>The maximum braking deceleration</td>
<td>$-4 \text{ m/s}^2$</td>
</tr>
</tbody>
</table>

References


33. Song, C.-J. Experimental Study on Car-following Model Based on Fuzzy Controller. Master’s Thesis, School of Control Science and Engineering, Shandong University, Jinan, China, 2020.


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