A Car-Following Model Considering Preceding Vehicle’s Lane-Changing Process

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ABSTRACT Car following and lane changing are two common driving behaviors in the traffic flow. Preceding vehicle’s lane changing is affected by the surroundings and will have a greater influence on the followers’ driving decision. The existing car-following theory does not fully take it into consideration that the followers’ driving behavior may change during a lane-changing process. In order to reflect the driving decision in a complex traffic flow more precisely, the influence on the following vehicle during the preceding vehicle’s lane-changing process is studied. First, the different types of stimulus during the preceding vehicle’s lane-merging (LM) process and the space gain effect produced by the preceding vehicle’s lane-passing (LP) behavior are analyzed. Then, the LM-FVDM and LP-FVDM are proposed based on the classical car-following model—FVD model. Finally, the linear stability theory, numerical simulation, and NGSIM data sets are used to analyze and validate the performance of the LM-FVDM and LP-FVDM. The numerical simulation results show that the model can reasonably reflect the driving decision of the following vehicle in various scenarios, and verification based on NGSIM shows that the $R^2$ of vehicles’ speed and distance is significantly better than the FVD model, which can more effectively reflect the speed adjustment process of the following vehicle during the preceding vehicle’s lane-changing process in the real traffic flow.

INDEX TERMS Car-following model, lane-changing behavior, multi-lane traffic, lateral separations, NGSIM.

I. INTRODUCTION

The car following model is the basis of microscopic traffic flow theory, which is mainly used to describe the following vehicle’s driving response caused by the change of preceding vehicle’s driving state in a single lane, where the overtaking behavior is limited. The car-following behavior can explain the mechanism of the evolution of traffic flow phenomena and provide guidance for traffic management and control.

According to the applicability of car-following behavior, car-following models can be divided into single-lane car-following models (SLM) and multi-lane car-following models (MLM). The research on SLM is well known to us, which can be divided into 4 types: stimulus-response model, safety distance model, psycho-physical model, and artificial intelligence-based model. Broadly speaking, these four types can be seen as a special form of the stimulus-response equation [1]. The study on SLM started earlier from 1950s [2] and the classical stimulus-response models including Bando’s optimal velocity model (OVM) [3], Helbing’s general force model [4], R Jiang’s full velocity difference model (FVD) [5] and the extended model considering multiple vehicle or more information based on the FVD [6]–[8]. So far, researchers have got a lot of great achievements in the research of car-following model [9]–[13].

The study on MLM is developed from SLM, and the influence of lane-changing behavior on the car following behavior is mainly considered. Tang et al. [14] believed that in two-lane traffic flow. The driver was always worried about the lane change from the adjacent lane, thus the car following model on two lanes was established. TQ Tang further extended the two-lane car-following model to consider the real occurrence of lane-changing behavior [15], but the model had strict assumptions: the lane-changing behavior was instantaneous and the lane-changing vehicle’s latitudinal position remains the same before and after the lane change. Furthermore, TQ Tang believed that whether or not the lane change would happen, the lane changing probability exists,
and a car-following model considering the potential lane change was proposed [16]. B Gunay thought that not every vehicle drives in the middle of the road in some developing countries such as India or China [17]. And S Jin believed that the lateral separations caused by the vehicle’s departure from lane center had an impact on the following vehicles, and established the non-lane-based FVD model (NLBCF) [18]. AK Gupta extended NLBCF by taking the heterogeneous traffic into account [19]. ZC He introduced a lateral separation parameter, overtaking expectation, and virtual preceding vehicle to reflect driver’s overtaking initiative, and a new car-following model considering lateral separation and overtaking expectation based on OVM was proposed [20]. Wei Yuguang used linear car following model simplified by Newell’st method to characterize interactions and collision avoidance between vehicles. And a control variable of time-dependent platoon-level reaction time was introduced to reflect various degrees of vehicle-to-vehicle or connectivity of vehicle-to-infrastructure communication [21]. On the other hand, the emergence of connected and automated vehicles technology inspire researchers to consider the car’s heterogeneous in a car following model [22]–[25].

The researches on MLM can be improved in two aspects: (1) the existing MLMs assume that the lane-changing behavior is instantaneous, while the lane-change process in the actual traffic lasts for a period of time, and the car-following behavior of the following vehicle may change at any time during this period; (2) when the preceding vehicle on adjacent lane merges into current lane, the following vehicle on current lane may slow down immediately to avoid collision; While the preceding vehicle on the current lane passes away, the following vehicle may accelerate to follow up. The existing MLM doesn’t consider that the response of the following vehicle is different under the different lane-changing situation. Therefore, we take the change of drivers’ behavior caused by the preceding vehicle’s lane-changing process into consideration and the change are modeled to reflect the car-following behavior in complex traffic flow more realistically.

The remainder of the paper is organized as follows: Section II introduces the different model scenarios, new car following model considered the preceding vehicle’s lane-changing process and dynamics of the model. Section III analyzes the linear stability of the car following model, followed by the model rationality analysis in Section IV. Section V verifies the validity of the proposed car following model by using NGSIM. We summaries the study in Section VI.

II. MODEL

A. DESCRIPTION OF DIFFERENT MODEL SCENARIOS

In real traffic flow, lane-changing behavior occurs as a result of obtaining better driving space from other lanes or the restraint of destination of driving [26]: the preceding vehicle on adjacent lane may merge into a current lane, or the preceding vehicle may pass away from the current lane. The former lane-changing behavior is shorted as “LM”, and the latter is named as “LP” in this paper.

(1) Car-following surroundings under LM

The surroundings under LM is illustrated in Fig. 1. When lane-changing behavior occurs on the adjacent lane, the car-following target of the following vehicle $C_{n_l}$ on the current lane will probably change to ensure safety.

The LM behavior of $C_{(n+1)_{l+1}}$ will has a great influence on the safety of $C_{n_l}$. Accidents such as rear-end collision and vehicle scraping accident are most likely to happen between $C_{n_l}$ and $C_{(n+1)_{l+1}}$ because of $C_{n_l}$’s neglect of LM behavior or untimely deceleration, which are shown in Fig. 2.

Therefore, in order to ensure the driving safety, $C_{n_l}$ needs to pay close attention to the driving state of $C_{(n+1)_{l+1}}$ when $C_{n_l}$ is following the original target $C_{(n+1)_{l}}$, and reacts in real time to avoid a collision.

(2) Car-following surroundings under LP

The surroundings under LP are illustrated in Fig. 3. The LP vehicle $C_{(n+1)_{l}}$ may accelerate to arrive at the target lane or decelerate to wait for next chance to lane change, which makes the following vehicle $C_{n_l}$ pay close attention to the state of $C_{(n+1)_{l}}$ to avoid the accident illustrated in Fig. 4.
is too conservative to accelerate when on lane the target lane. As it is shown in Fig. 5, the preceding vehicle lane change. These 3 types of LM process can be regarded ing to the headway between the LM vehicle and the following
vehicle needs to be adjusted. As shown in Fig. 6, when the headway is enough, and vehicle has no influence on the following vehicle

![Figure 3. Vehicles’ relative position in the current lane.](image)

![Figure 4. LP’s traffic accident.](image)

![Figure 5. Space preemption of the preceding vehicle from another lane.](image)

On the other hand, space ahead of \( C_n \) is likely to be occupied by the preceding vehicle from another lane if \( C_n \) is too conservative to accelerate when \( C_{(n+1)l} \) has arrived at the target lane. As it is shown in Fig. 5, the preceding vehicle on lane \( l - 1 \) changes to the front of \( C_n \) when there is a big driving space caused by \( C_{(n+1)l} \’s \) LP behavior.

Thus, in the case of LP behavior, the following vehicle should consider the safety and the benefits induced by LP at the same time to determine its driving state.

### B. Modeling Method

1. Different types of stimulus under LM

   Depending on the driving characteristics, different drivers displayed different driving styles during lane change [27], [28], which can be classified into 3 types according to the headway between the LM vehicle and the following vehicle at the moment of the beginning of the LM [29]: free lane change, forced lane change and competitive/cooperative lane change. These 3 types of LM process can be regarded as a different stimulus under different gap condition for the following vehicle:

   ① When the preceding vehicle \( C_{(n+1)l+1} \) on the adjacent lane is free changing lane, the LM behavior of the preceding vehicle has no influence on the following vehicle \( C_n \) because the headway is enough, and \( C_n \) can keep its original driving state. At the same time, because the lane change behavior will not have an impact on the rear car, the rear car will still follow the original front car. We define as follows:

   \[
   \text{Type}_{\text{sti}} = LM - 1 \\
   \text{if} : \Delta x_{n_i,(n+1)l+1}(t_0) > g_s \text{ and } \Delta \tilde{x}_{n_i,(n+1)l+1}(t_0 + t_{lc})|_{t=t_0} > g_s
   \]

   where: \( \text{Type}_{\text{sti}} \) is the stimulus type; \( t_0 \) is the beginning time of lane change; \( t_{lc} \) is the duration of the lane change, and \( \Delta \tilde{x}_{n_i,(n+1)l+1}(t_0 + t_{lc}) \) are the headway between \( C_n \) and \( C_{(n+1)l} \) at the moment of \( t_0 \) and \( t_0 + t_{lc} \) respectively. \( t_0 \) and \( t_0 + t_{lc} \) are beginning and ending moment of lane changing respectively. \( g_s \) is an acceptable safe distance for the driver. And \( \Delta \tilde{x}_{n_i,(n+1)l+1}(t_0 + t_{lc}) = \Delta x_{n_i,(n+1)l+1}(t_0) + sLC(n+1)l+1 - sLC_n \), where \( sLC_n \) and \( sLC_{(n+1)l+1} \) are the latitudinal driving distance during lane change of \( C_n \) and \( C_{(n+1)l+1} \), where \( sLC_n = v_n(t_0) \cdot t_{lc} \) and \( sLC_{(n+1)l+1} = v_{(n+1)l+1}(t_0) \cdot t_{lc} + 0.5 \cdot a_{\max} \cdot t_{lc}^2 \); \( v(t_0) \) is the speed at the moment \( t_0 \); \( a_{\max} \) is the maximum acceleration.

   ② When \( C_{(n+1)l+1} \) is competitive/cooperative changing lane, \( C_n \) makes the decision to accelerate or decelerate depending on the lane-changing state of \( C_{(n+1)l+1} \), and the following condition should be met:

   \[
   \text{Type}_{\text{sti}} = LM - 2 \\
   \text{if} : \Delta x_{n_i,(n+1)l+1}(t_0) > g_s \\
   \text{and} \Delta \tilde{x}_{n_i,(n+1)l+1}(t_0 + t_{lc})|_{t=t_0} < g_s
   \]

   ③ When \( C_{(n+1)l+1} \) is forced changing lane, \( C_n \) decelerates immediately to avoid collisions because \( C_{(n+1)l+1} \) bursts into the front of \( C_n \), and the stimulus is defined as:

   \[
   \text{Type}_{\text{sti}} = LM - 3 \\
   \text{if} : \Delta x_{n_i,(n+1)l+1}(t_0) < g_s
   \]

2. Space gain the effect of LP

   The FVD model explains the car-following behavior as the response of the following vehicle under the stimulation of the distance and the speed difference: the larger the distance and the speed difference, the greater the speed of the following vehicle needs to be adjusted. As shown in Fig. 6, when the preceding vehicle is passing the current lane, the \( \Delta W_{n,n+1} \) is also a stimulus to the driving decision of the following vehicle. Where \( \Delta W_{n,n+1} \) is the lateral deviation distance between the lane-changing vehicle and the following vehicle during lane-changing process. And \( \Delta W_{\max} \) is the maximum offset distance of the lane-changing vehicle in the current lane.

   The stimulus \( f_{\text{sti}}(\Delta W_{n,n+1}) \) should have the following attributes:

   ① When \( \Delta W_{n,n+1} = 0 \) which means the LP behavior has not happened yet, \( f_{\text{sti}}(\Delta W_{n,n+1}) = 0 \);
When \( \Delta W_{n,n+1} = \Delta W_{\text{max}} \) which means the LP vehicle has crossed the lane edge to reach the target lane, 
\[ f_{\text{st}}(\Delta W_{n,n+1}) = 1; \]

3. When \( 0 < \Delta W_{n,n+1} < \Delta W_{\text{max}} \) the following vehicle is becoming increasingly sensitive to the headway enlarged by the LP vehicle to avoid the occupancy from the vehicle on other lanes. The space gain effect parameter \( G(\Delta W_{n,n+1}) \) is defined to measure the magnification of the space caused by LP behavior, so 
\[ f_{\text{st}}(\Delta W_{n,n+1}) = f_{\text{st}}(G(\Delta W_{n,n+1})), \]
and \( G(\Delta W_{n,n+1}) \) can be defined as:
\[ G(\Delta W_{n,n+1}) = \frac{\Delta W_{n,n+1}}{\Delta W_{\text{max}}} \]  
(4)
where: \( 0 \leq \rho \leq 1 \) refers to the driver’s sensitivity coefficient to lateral distance. When \( \rho = 0 \) the driver of the following vehicle is not sensitive to space ahead and when \( \rho = 1 \) the lateral distance has a great influence on the following vehicle and the following vehicle’s driving style is highly dangerous.

In order to study the influence of LM and LP behavior on the rear car respectively, we assume that when LM or LP behavior appears in the adjacent car, the driving state of the front car is unchanged. We only consider the influence of lane change of adjacent cars on the rear car, and not considering the situation that the preceding car also changes lanes when adjacent car changes lanes

\textbf{C. DESCRIPTION OF MODEL DYNAMICS}

(1) Model dynamics considering different types of stimulus under LM

The dynamic equation of FVD model is as follows:
\[ \frac{dv(t)}{dt} = f_{\text{st}}(\Delta x_{i,i+1}(t), \Delta v_{i,i+1}, v_i(t)) \]
= \( \alpha(V(\Delta x_{i,i+1}) - v_i(t)) + \kappa \Delta v_{i,i+1}(t) \)  
(5)
where: \( \alpha \) and \( \kappa \) are the driver’s sensitivity coefficient to distance and speed difference respectively; \( V(\cdot) \) is the optimal velocity function correspond to the distance.

When LM behavior occurs, \( C_n \) needs to keep the car-following state with \( C_{n+1} \), and recognizes which type of stimulus caused by LM behavior by the headway with \( C_{n+1} \), and makes the corresponding driving decision under different LM’s stimulus. Combining (1)-(3) and (5):
\[ \frac{dv(t)}{dt} = \begin{cases} 
  f_{\text{st}}(\Delta x_{n_i,(n+1)_i}, \Delta v_{n_i,(n+1)_i}, v_{n_i}) & \text{Type}_{st} = LM - 1 \\
  f_{\text{st}}(\Delta x_{n_i,(n+1)_i}, \Delta x_{n_i,(n+1)_{i+1}}, \Delta v_{n_i,(n+1)_{i+1}}, v_{n_i}, \Delta h_{i+1,i}) & \text{Type}_{st} = LM - 2 \\
  f_{\text{st}}(\Delta x_{n_i,(n+1)_{i+1}}, \Delta v_{n_i,(n+1)_{i+1}}, v_{n_i}) & \text{Type}_{st} = LM - 3 
\end{cases} \]  
(6)
where: \( \Delta h_{i+1,i} \) is the lateral distance of \( C_{n+1} \) to the edge of the lane \( l \). \( \Delta h_{i+1,i} < 0 \) means \( C_{n+1} \) has not passed the lane edge, otherwise \( C_{n+1} \) has reached to the target lane.

When \( \text{Type}_{st} = LM - 1 \), the distance between the vehicle \( C_n \) and the front vehicle is large enough, and the vehicle is not affected by lane change vehicle \( C_{n+1} \) to maintain the original driving state.

When \( \text{Type}_{st} = LM - 2 \), \( C_n \) interacts with \( C_{n+1} \) to determine whether \( C_{n+1} \) can successfully change lanes. At this time, \( C_n \) may accelerate to compete with \( C_{n+1} \) for the front space, or cooperate with \( C_{n+1} \) to complete the implementation of its lane-changing behavior. Therefore, its state is determined by the driving characteristics of its driver, and the driving state of front-car \( C_{n+1} \) and lane-changing vehicle \( C_{n+1} \) at the same time.

When \( \text{Type}_{st} = LM - 3 \), \( C_{n+1} \) forces \( L \) lane change. Due to the small spacing, \( C_n \) pays close attention to containing the driving state of \( C_{n+1} \) to avoid a collision. At this time, its state is completely affected by \( C_{n+1} \).

Based on the information factors to be considered under the above different LM’s stimulus, based on the (5), the stimulus equation \( f_{\text{st}} \) is obtained:
\[ \begin{align*}
  f_{\text{st}}(\Delta x_{n_i,(n+1)_i}, \Delta v_{n_i,(n+1)_i}, v_{n_i}) & = \alpha(V(\Delta x_{n_i,(n+1)_i}) - v_{n_i}(t)) \\
  & + \kappa \Delta v_{n_i,(n+1)_i} \text{ Type}_{st} = LM - 1 \\
  f_{\text{st}}(\Delta x_{n_i,(n+1)_i}, \Delta x_{n_i,(n+1)_{i+1}}, \Delta v_{n_i,(n+1)_{i+1}}, v_{n_i}, \Delta h_{i+1,i}) & = \alpha(V(\Delta x_{n_i,(n+1)_{i+1}}) - v_{n_i}(t)) + \kappa \Delta v_{n_i,(n+1)_{i+1}}(t) \text{ Type}_{st} = LM - 2 \\
  f_{\text{st}}(\Delta x_{n_i,(n+1)_{i+1}}, \Delta v_{n_i,(n+1)_{i+1}}, v_{n_i}) & = \alpha(V(\Delta x_{n_i,(n+1)_{i+1}}) - v_{n_i}(t)) + \kappa \Delta v_{n_i,(n+1)_{i+1}}(t) \text{ Type}_{st} = LM - 3 
\end{align*} \]  
(7)
where:
\[ \begin{align*}
  V_L(\Delta x_{n_i,(n+1)_i}, \Delta x_{n_i,(n+1)_{i+1}}) & = V(R(\Delta h_{i+1,i})\Delta x_{n_i,(n+1)_i} + (1 - R(\Delta h_{i+1,i})) \Delta x_{n_i,(n+1)_{i+1}}) \\
  G_L(\Delta x_{n_i,(n+1)_i}, \Delta v_{n_i,(n+1)_i}) & = R(\Delta h_{i+1,i})\Delta v_{n_i,(n+1)_i} + (1 - R(\Delta h_{i+1,i}))\Delta v_{n_i,(n+1)_{i+1}} 
\end{align*} \]  
(8)
\( R(\cdot) \) is the competitive level function of \( C_n \) to the LM process when \( C_{n+1} \) is changing lane, which is represented as:
\[ R(\Delta h_{i+1,i}) = r \cdot H(-\Delta h_{i+1,i}) \cdot \frac{\Delta h_{i+1,i}}{\Delta h_{\text{max}}} \]  
(9)
where: \( r \) is the competitive parameter of \( C_n \) and the larger the \( r \) stronger the desire of the driver to use the driving space. \( H(\cdot) \) is the Heaviside function. When \( \Delta h > 0 \), \( R(\cdot) = 0 \), which means that \( C_n \) drives with no competitive consciousness as \( C_{n+1} \) has reached the target lane.
Combining (6-9), we can get the model considering different types of stimulus under LM (LM-FVDM):

\[
\frac{dv_n(t)}{dt} = \begin{cases} 
\alpha(V(\Delta x_{n,(n+1)t}) - v_n(t)) + \kappa \Delta x_{n,(n+1)t} & \text{Type}_{st} = LM - 1 \\
\alpha(V_{LM}(\Delta x_{n,(n+1)t}, \Delta x_{n,(n+1),+}) - v_n(t)) + \kappa G_{LM}(\Delta x_{n,(n+1)t}, \Delta x_{n,(n+1),+}) & \text{Type}_{st} = LM - 2 \\
\alpha(V(\Delta x_{n,(n+1),+}) - v_n(t)) + \kappa \Delta x_{n,(n+1),+} & \text{Type}_{st} = LM - 3 
\end{cases}
\]

(10)

II. LINEAR STABILITY CONDITION

The linear stability analysis is an important method to study the performance of the model under small perturbation. By analyzing the linear stability, we can know under what conditions the new model is stable. And the following research based on the new model is carried out under this condition. When Type\textsubscript{st} = LM - 1 and Type\textsubscript{st} = LM - 3, the model mechanism is completely consistent with FVD, although the source of the stimulus is different, and the linear stability condition is given [6]:

\[
\tau < 1 + 2\lambda / (2V(b)) \tag{14}
\]

where: \( b \) is the distance between the preceding vehicle and the following vehicle in the initial stable traffic.

This section focuses on the linear stability conditions of the LM-FVDM when Type\textsubscript{st} = LM - 2. Suppose the vehicle on both lanes (lane \( l \) and \( l + 1 \)) is evenly distributed, and the relative velocity \( \Delta x_{n,(n+1)t} \) and \( \Delta x_{n,(n+1),+} \) is 0, then the initial vehicles’ state is:

\[
x^0_{n}(t) = b_l \cdot n + V(b_l, b_{l+1}) \cdot t \tag{15}
\]

Let \( y_n(t) \) be a small perturbation applied to the steady state \( x^0_{n}(t) \) of the vehicle \( C_{n_l} \) in the lane \( l \):

\[
x_n(t) = x^0_{n}(t) + y_n(t) \tag{16}
\]

Take the first and second derivatives of (16):

\[
\begin{align*}
\dot{x}_n(t) &= \dot{x}^0_{n}(t) + \dot{y}_n(t) \\
\ddot{x}_n(t) &= \ddot{y}_n(t)
\end{align*}
\]

(17)

where: \( \dot{x}_n(t) = V(b_l, b_{l+1}) \); the gap’s and velocity’s difference are:

\[
\begin{align*}
\Delta x_{n,(n+1)t} &= b_l + y_{n+1}(t) - y_n(t) = b_l + \Delta y_{n,(n+1)}(t) \\
\Delta x_{n,(n+1),+} &= \ddot{y}_{n+1}(t) - \ddot{y}_n(t)
\end{align*}
\]

(18)

Equation (16) is substituted into the model (10):

\[
\ddot{y}_{n}(t) = \alpha \left( V(R(\bullet) \cdot (b_l + \Delta y_{n,(n+1),+}))(1 - R(\bullet)) \cdot (b_l + \Delta y_{n,(n+1),+}))(1 - R(\bullet)) \cdot (\Delta y_{n,(n+1),+}) - V(b_l, b_{l+1})\right)
\]

\[
-\ddot{y}_n(t) + \kappa \left( R(\bullet) \cdot (\dot{y}_{n+1}(t) - \dot{y}_n(t)) + (1 - R(\bullet)) \cdot (\ddot{y}_{n+1}(t) - \ddot{y}_n(t)) \right)
\]

(19)

where: \( R(\bullet) \equiv R(\Delta h_{l+1,t}) \). Using Taylor expansion to get:

\[
\begin{align*}
V(b_l + \Delta y_{n,(n+1),+}, b_l + \Delta y_{n,(n+1),+}) & = V(b_l, b_{l+1}) + V(b_l + \Delta y_{n,(n+1),+}), b_l + \Delta y_{n,(n+1),+}) \\
& = V(b_l, b_{l+1}) + \dot{V}(b_l, b_{l+1}) \cdot (\Delta y_{n,(n+1),+}) + \frac{1}{2} \ddot{V}(b_l, b_{l+1}) \cdot (\Delta y_{n,(n+1),+})^2 (20)
\end{align*}
\]
Fig. 8 shows the critical stable curves with and without considering the stimulus of lateral offset distance. The critical stability condition of the model shows that the vertex of the curve is shifted to the upper left, that is, the critical headway $h_c$ decreases and the critical sensitivity coefficient $\alpha_c$ increases. This indicates that the uniform traffic flow can exhibit high speed and stable operation under small head spacing, but the response coefficient of the driver is higher, especially in the vicinity of the critical stability curve.

IV. MODEL RATIONALITY ANALYSIS

A. MODEL PERFORMANCE UNDER LM-1 STIMULUS

In a two-lane traffic flow system, the vehicle can travel at an optimal speed of $v_0 = 14.6m/s$. The distance between the vehicles is large enough and the driver’s acceptable safe headway is $g_s = 15m$. Equation (1) shows that when $\Delta x_{n,(n+1)}(t_0) > 46.25m (t_c = 5s, a_{max} = 2.5m/s^2)$, the stimulus type of LM-1 is satisfied, and the speed variation of the vehicle under the control of FVDM and LM-FVDM is shown in Fig. 9.

The lane-changing behavior takes place from 3 to 8 seconds. As can be seen from Fig. 9, the LM-FVDM maintains a steady speed under the stimulation of the LM-1, and the speed of the FVDM controlled vehicle fluctuates slightly, and the speed of the lane changing is slightly lower than the steady speed. Since the spacing is large enough, even if the vehicle is accelerated at the maximum acceleration when the vehicle is changing lanes, the spacing will be greater than the threshold $g_s$. Thus, the LM-FVDM controls the collision-free risk of the following vehicle and can also maintain a higher expected speed relative to the FVDM.

B. MODEL PERFORMANCE UNDER LM-2 STIMULUS

Adjust the initial space $\Delta x_{n,(n+1)}(t_0) > 15m$ and $\Delta x_{n,(n+1)}(t_0) < 46.25m$, other conditions are the same as an experiment (1), in which the initial spacing and the competitive coefficient of the following vehicle are set as shown in TABLE 1.The reaction of the following vehicle under the control of different parameters of FVDM and LM-FVDM

Fig. 10 is the speed changes of the following vehicle with $\Delta x = 30m$, and $r = 1, 0.8, 0.6, 0.4, 0.2$ respectively. The lane-changing behavior takes place from 3 to 8 seconds, and the vehicle passed through the road edge to reach the target lane at 5.5s. Fig. 10 shows that the speed of the FVDM controlled vehicle decreases at $t = 5.5s$, while the speed of
TABLE 1. Setting of the parameters under LM-2’s stimulus.

<table>
<thead>
<tr>
<th>$\Delta x$</th>
<th>1</th>
<th>0.8</th>
<th>0.6</th>
<th>0.4</th>
<th>0.2</th>
</tr>
</thead>
<tbody>
<tr>
<td>40m</td>
<td>√</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>35m</td>
<td></td>
<td>√</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>30m</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td></td>
<td></td>
</tr>
<tr>
<td>25m</td>
<td></td>
<td></td>
<td></td>
<td>√</td>
<td></td>
</tr>
<tr>
<td>20m</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>√</td>
</tr>
</tbody>
</table>

FIGURE 10. The velocity of the following vehicle under LM-2’s stimulus with different $r$.

FIGURE 11. Acceleration of the following vehicle under LM-2’s stimulus with different $r$.

The LM-FVDM controlled vehicle begins to change at $t = 3s$, and varies with the competitive coefficient $r$.

Under the LM-2 stimulation, with the implementation of lane-changing process, the distance between the preceding lane-changing vehicle and the following vehicle is likely to be close, or even smaller than the acceptable minimum space $g_s$, which will affect the safe driving of the following vehicle.

The LM-FVDM controlled following vehicle starts to adjust the speed at $t = 3s$, that is, when the preceding vehicle on the adjacent lane is expected to change lanes to current lane, the following vehicle starts to adjust, and the adjustment amplitude is related to the competitive coefficient $r$. The higher the $r$, the lower the intention to cooperate with the lane-changing process, and the stronger the desire to maintain the original desired speed. Therefore, it can be found that the higher the $r$ smaller the speed adjustment and vice versa. The speed adjustment of the following vehicle is the lowest at $r = 0.2$ and the maximum at $r = 0.4$ in the selected five values of $r$.

In $t \geq 5.5$ seconds, the lane-changing vehicle arrives at the front of the following vehicle on the target lane, and the vehicle controlled by FVDM or LM-FVDM is further adjusted to avoid collisions due to the presence of the vehicle ahead.

The acceleration changes of the following vehicle are shown in Fig. 11. Due to different $r$ values, the cooperative degree to the lane-changing process is different, and the deceleration of the following vehicle is also different. The vehicle controlled by the FVDM model does not slow down at the beginning of the lane change, resulting in a sudden deceleration when the lane-changing vehicle crosses the lane; in addition, the bigger the $r$ value, the more competitive of the following vehicle, and the deceleration is more obvious at the moment of the lane-changing vehicle crossing the lane.

Fig. 12 shows the changes in the speed at $r = 0.2$ and $\Delta x = 40, 35, 30, 25$ respectively. When $r = 0.2$, it is indicated that the willingness of the following vehicle to cooperate with the lane-changing process is more intense, and the speed adjustment range of the following vehicles is closely related to the initial spacing $\Delta x$. The smaller the $\Delta x$ more sensitive to the lane-changing process, and the larger the adjustment of the speed. The difference in the speed adjustment from $\Delta x = 20$ to $\Delta x = 40$ shown in Fig. 12 reflected this phenomenon.

C. MODEL PERFORMANCE UNDER LM-3 STIMULUS

Adjust the initial space $\Delta x_{n(t)}(n+1)_{t=1}(t_0) < 12.5m$, other conditions are the same as an experiment (2), and observe the different reaction of the following vehicle controlled by FVDM and LM-FVDM.

Under the LM-3 stimulation, since the distance $\Delta x$ between the following vehicle and the lane-changing vehicle at the start of the lane change is less than $g_s$, the collision is most likely to take place if the following vehicle does not adjust its current speed immediately. Fig. 13 shows that the LM-FVDM controlled vehicle decelerates at $t = 3s$, while the FVDM controlled vehicle decelerates suddenly at $t = 5.5s$. From Fig.14, which is the headway between the following and lane-changing vehicle, we can find that the LM-FVDM controlled vehicle maintains a safe distance, and the FVDM controlled vehicle collided with the lane-changing vehicle at $t = 5.8s$, as the distance $\Delta x$ is less than the length $l_e$ of the vehicle.

D. MODEL PERFORMANCE UNDER LP BEHAVIOR

In order to clearly analyze and verify the performance of the proposed new model, we only considered 3 vehicles in this part. The experiments are conducted on a two-lane traffic:
V. MODEL VALIDITY VERIFICATION BASED ON NGSIM

Using GA genetic algorithm to correct the basic FVDM model parameters, the membership function [30] to identify drivers’ competitive coefficient, the NGSIM data set as the input of LM-FVDM and LP-FVDM, and the longitudinal speed of the following vehicle is output. Compared to the output with the real data from NGSIM data, to illustrate whether the model can effectively simulate the driving decision during the lane-changing process. In this paper, the optimized velocity function of Helbing was selected, and the parameter identification results of Helbing were taken as the reference. The parameters were re-calibrated with the NGSIM vehicle trajectory data, so as to conform to the vehicle driving characteristics of the NGSIM data acquisition road, where $V(\Delta x) = V_1 + V_2 \tanh[C_1(\Delta x - l_c) - C_2]$. The main iteration parameters of GA are set as follows: the population size is 20, the crossover probability is 0.9, the mutation probability is 0.1, and the iteration number is 1000. Using the GA algorithm, we get the parameters of the basic FVDM model shown in TABLE 3.

A. EFFECT OF LM-FVDM

Compare the real speed with the FVDM’s output speed and the LP-FVDM’s output speed under different LM stimulus types, and the results are shown in Fig. 16:

Table: Setting of the parameters under uniform LP behavior.

<table>
<thead>
<tr>
<th>$t_{lc}$</th>
<th>$\rho$</th>
<th>0(FVDM)</th>
<th>0.3</th>
<th>0.6</th>
<th>0.9</th>
</tr>
</thead>
<tbody>
<tr>
<td>5s</td>
<td></td>
<td></td>
<td>$\checkmark$</td>
<td></td>
<td></td>
</tr>
<tr>
<td>10s</td>
<td>$\checkmark$</td>
<td>$\checkmark$</td>
<td>$\checkmark$</td>
<td>$\checkmark$</td>
<td></td>
</tr>
<tr>
<td>15s</td>
<td>$\checkmark$</td>
<td>$\checkmark$</td>
<td>$\checkmark$</td>
<td>$\checkmark$</td>
<td></td>
</tr>
</tbody>
</table>

3 vehicles drive at a stable speed with $v_0 = 8 m/s$ and distance $\Delta x = 16.2 m$ on the first lane, and at $t = 3s$ the second vehicle began to change to the second lane, and the longitudinal speed of this lane-changing vehicle remains $v_0$, and the setting of the parameters under LP behavior is shown in TABLE 2. The results are shown in Fig. 15.

Where: $t_{lc}$ is the duration of the lane-changing process; $\rho$ is the sensitivity coefficient of the following vehicle to the lateral separation $\Delta W_{n,n+1}$.

The more sensitive the following vehicle to the $\Delta W_{n,n+1}$ higher the competitive level to the lateral position of the preceding vehicle. From Fig. 15(a), we can find that when $\rho$ increases, the time for the following vehicle to adjust the speed is advanced, and the adjustment range is bigger. Once the preceding vehicle passes through the lane edge, the following vehicle will accelerate from its current speed. When $\rho = 0$ the following vehicle does not respond to $\Delta W_{n,n+1}$ until the preceding vehicle crosses the lane edge. Fig. 15(b) shows the speed of the following vehicle when $\rho = 0.6$ and $t_{lc}$ is different. From Fig. 15(b), we can find that the longer the $t_{lc}$ slower the rate of change, as the stimulus duration is longer.

In real traffic, the reaction degree to the preceding vehicle’s lane-changing process is different: some drivers are more conservative to ensure the safety, while others are more competitive to strive for driving space ahead when the LP vehicle is changing lane. Thus, the sensitivity coefficients in our model can reflect the different competitive levels of different drivers in the actual traffic flow, and at the model $\rho$ can make a correct response to the lateral separation $\Delta W_{n,n+1}$ of the preceding vehicle.
TABLE 3. Range of the paraments in basic FVDM model.

<table>
<thead>
<tr>
<th>parameters</th>
<th>reference values</th>
<th>correction range</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \alpha )</td>
<td>0.85</td>
<td>[0,1]</td>
</tr>
<tr>
<td>( \lambda )</td>
<td>0.2</td>
<td>[0,1]</td>
</tr>
<tr>
<td>( V_1' )</td>
<td>6.75</td>
<td>[0,10]</td>
</tr>
<tr>
<td>( V_2' )</td>
<td>7.91</td>
<td>[0,10]</td>
</tr>
<tr>
<td>( C_1 )</td>
<td>0.13</td>
<td>[0,1]</td>
</tr>
<tr>
<td>( C_2 )</td>
<td>1.57</td>
<td>[0,5]</td>
</tr>
<tr>
<td>( l )</td>
<td>5</td>
<td>[4,6]</td>
</tr>
</tbody>
</table>

![FIGURE 16. Comparison of the model effect under different LM’s stimulus.](image)

During the lane-changing process, the LM-FVDM’s output speed is more stable and more accurate compared with the FVDM’s output speed.

![Fig. 16(b) is the speed change of the following vehicle on target lane under the LM-2 stimulus.](image)

The driving behavior of the following vehicle on target lane is related to the driver’s driving style, and the following vehicle decelerates and then accelerates in Fig. 16(b). From the speed distribution, we can find that the LM-FVDM’s output speed is more close to the real speed; from the speed fluctuation, we can find that the LM-FVDM can reflect the speed change correctly.

![Fig. 16(c) is the speed change of the following vehicle on target lane under the LM-3 stimulus.](image)

LM-FVDM’s speed decreases earlier than FVDM’s output, which means LM-FVDM can make the result more accurate. In Fig. 16, the negative time value indicates that the vehicle did not change lanes. However, at time 0, the lane-changing vehicle begins to change lanes. Thus, LM-FVDM’s outputs under different types of stimulus are more close to the actual value, while the FVDM’s output has greater errors, which means that the consideration of LM stimulus type can effectively reflect the driving state of the following vehicle when the preceding vehicle merges into target lane.

B. EFFECT OF LP-FVDM

When the preceding vehicle passes the current lane, the real speed, the FVDM’s output speed of FVDM and the LP-FVDM’s output speed of the following vehicle are shown in Fig. 17. It’s clear that the output speed of LP-FVDM is more close to the real speed compared with the output speed of FVDM, which means that the consideration of the distance gain effect can reflect the driving behavior of the real traffic more effectively.

![FIGURE 17. Comparison of the model effect under different LP’s scene.](image)

C. OVERALL EVALUATION OF MODELS’ EFFECT

The output speed, position (longitudinal) of the LP-FVDM model, the output speed and position of the FVDM model are compared with the true value of the velocity and the position. The R-Squared is used for the statistical analysis, which is shown in TABLE 4:

<table>
<thead>
<tr>
<th>parameter</th>
<th>LM-FVDM</th>
<th>LP-FVDM</th>
</tr>
</thead>
<tbody>
<tr>
<td>speed error</td>
<td>0.364</td>
<td>0.048</td>
</tr>
<tr>
<td>position error</td>
<td>0.391</td>
<td>0.025</td>
</tr>
</tbody>
</table>

It can be seen from TABLE 3: LM-FVDM and LP-FVDM model, compared with the FVDM model, the vehicle’s speed error and position error are reduced to a certain extent during the preceding vehicle’s lane-changing process. In terms of speed, the relative difference between our model and FVDM in LM and LP is 0.364 and 0.048, respectively. In position, the difference between our model and FV in LM and LP is 0.391 and 0.025, respectively. Thus, the fitting degree of our model to the original data is obviously better than FVDM.
In summary, the LM-FVDM and LP-FVDM models effectively reduce the vehicle’s speed error and position error: the speed and position of the model output are closer to the actual value compared with FVDM during the preceding vehicle’s lane-changing process. It can be seen that the proposed car-following model can improve the simulation precision of the car-following behavior and can more effectively reflect the driving decision in the actual traffic.

VI. CONCLUSION

According to different model scenarios, different types of stimulus during the LM process and the space gain effect produced by LP behavior are analyzed, and the LM-FVDM and LP-FVDM are proposed based on FVDM model. Linear stability theory, numerical simulation, and NGSIM data sets are used to analyze and validate the performance of the LM-FVDM and LP-FVDM. Numerical simulation results show that models can reasonably reflect the driving decision of the following vehicle in various scenarios, and verification based on NGSIM shows that the R-Squared of vehicles’ speed and distance are significantly better than FVDM model, which can more effectively reflect the speed adjustment process of the following vehicle during preceding vehicle’s lane-changing process in the real traffic flow. The research results of this paper can provide a theoretical basis for the simulation analysis of traffic behavior and the development of the automatic driving strategy.

In the future research work, we will study the influence of simultaneous lane change of the front vehicle and the adjacent vehicle on the state of the rear vehicle in the case of a large number of vehicles.

REFERENCES


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