Research Article

Distributed Model Predictive Control over Multiple Groups of Vehicles in Highway Intelligent Space for Large Scale System

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The paper presents the three time warning distances for solving the large scale system of multiple groups of vehicles safety driving characteristics towards highway tunnel environment based on distributed model prediction control approach. Generally speaking, the system includes two parts. First, multiple vehicles are divided into multiple groups. Meanwhile, the distributed model predictive control approach is proposed to calculate the information framework of each group. Each group of optimization performance considers the local optimization and the neighboring subgroup of optimization characteristics, which could ensure the global optimization performance. Second, the three time warning distances are studied based on the basic principles used for highway intelligent space (HIS) and the information framework concept is proposed according to the multiple groups of vehicles. The math model is built to avoid the chain avoidance of vehicles. The results demonstrate that the proposed highway intelligent space method could effectively ensure driving safety of multiple groups of vehicles under the environment of fog, rain, or snow.

1. Introduction

A new research concept about highway intelligent space (HIS) is proposed in the literature [1]. The main objective of the HIS system is to create an intelligent driving space where sensors are arranged in some necessary places such as highway tunnel, road sections that are prone to accidents or poor visibility under adverse weather conditions. Meanwhile, advanced vehicle-to-vehicle (V2V) and vehicle-to-server (V2S) are adopted to inform drivers of road section situation ahead to avoid collision under the environment of space communication mode. The HIS system is introduced to provide vehicles with useful driving state to ensure that vehicles could have better access to road information ahead, especially multiple groups of vehicles of driving environment. Hence, studying vehicle driving state is important for the HIS system to build an intelligent space according to the above mentioned situations. This paper mainly focuses on multi-vehicle of driving state when passing through the highway tunnel.

The highway tunnel has its own complex driving features, for example, the channel tunnel fire resulting in multiple fatalities and injuries [2], several traffic accidents appearing in some tunnels [3], and vehicle crash caused by visual dysfunction of drivers [4]. When accidents happened in some highway tunnel, the effective vehicle state should be transmitted to vehicles towards highway tunnel in real time by the communication between vehicles and HIS system, especially multivehicle driving towards highway tunnel. Multivehicle has different driving modes such as single vehicle form, groups of vehicle forms, and vehicle organizing forms, among which groups of vehicle driving forms are the common. While HIS server could store large amounts of data information for vehicles, multivehicle can be decomposed to different groups of vehicles driving towards highway tunnels and different groups of vehicles need different driving states according to the specific driving environment. Each group of vehicles driving states is defined as information framework. Information framework mainly shows that the effective driving state obtained from HIS server can ensure different

groups of vehicles of safety characteristics. Therefore, studying multiple groups of vehicles driving characteristics as well as accurate evaluations of the risk rear-end collisions is the key technologies under the environment of highway tunnel.

For the large scale of multi-intelligent vehicle systems, there are three MPC schemes for designing such large scale systems, namely, distributed MPC, centralized MPC, and decentralized MPC. The distributed MPC strategy is arguably the most promising one because it beats the centralized MPC one in terms of computational load and outperforms the decentralized MPC one in control performance [5]. In a DMPC design, different model predictive controllers communicate through a communication network to cooperate their actions in order to achieve optimal performance [6], for example, collision avoidance constraints [7]. The distributed framework of MPC is also gradually developing for the control of large scale system. There are two methods of distributed MPCs that appeared in the literature for the large scale system. One method is that each local controller exchanges estimation states with its neighbors and therefore improves the performance of closed-loop subsystem. However the performance of other subsystems is not considered in this optimization. The second method could achieve a good performance close to the centralized MPC. However, this strategy requires much more communication resources and the structure of controller is relatively complex [8]. In this paper, the neighbor optimization method is used for the large scale system in which each subsystem interacts in sequence by state.

Based on the above state, a new vehicle safety distance among groups based on the HIS system is proposed to develop a warning system. Three time warning distances will be studied considering the complex tunnel space. In nature, human beings suffer from perception limitations with a typical reactive time of 0.75 seconds to 1.5 seconds on emergency events. Therefore, it is highly important that vehicles should work in the three warning distances to guarantee its immediate and effective stopping to avoid collisions. The first warning distance is calculated by the time, the driver reaction time, and the message propagation delay. As to the second warning distance, the compensated safety distance is proposed as the buffer distance to reduce its acceleration to the range of the vehicle near the tunnel. The third warning distance is the tracking safety distance. The proposed HIS system is adapted for each group and can effectively achieve vehicle's safety. Figure 1 shows the work principle among the groups. Distributed model prediction control approach is used to solve groups of vehicles collision avoidance. Meanwhile, the method based on neighbor optimization is used to solve the large scale system. Therefore, by predicting the states based on the prediction model over the finite horizon, the third warning distance which is collision-free at discrete time steps is planned. In other words, since the collision avoidance is considered only at the discrete prediction time steps, a collision may occur in the intervals between the prediction time steps. In particular, since it is difficult to keep the sampling steps small enough to ensure the convergence of the trajectory, the collisions between prediction

FIGURE 1: The work principle among groups.

time steps become quite significant [9]. Therefore, as to the multiple groups of vehicles collision avoidance problem, adopting the above mentioned could solve vehicle environment perception.

The organization of the paper is as follows. System description and objective are presented in Section 2. In Section 3, distributed model predictive control approach is studied. In Section 4, the stability of vehicles in each group is studied. In Section 5, simulation and analysis are presented. Finally, conclusions are given.

2. System Description and Objective

In this section, we define the system dynamics and pose an integrated cost function for every group to ensure system stabilization and vehicles safety driving. Meanwhile, the three time warning distances are studied addressing the system dynamics.

2.1. System Description. Figure 2 shows the basic work principle of overall system. The set $j \in \rho := \{1, \dots, N_{v1}; 1, \dots, N_{v2}; \dots, 1, \dots, N_{vm}\}$ is used to denote the multivehicle driving towards highway tunnel. Autonomous vehicles organize different groups according to the specific driving environment or driving state. Therefore, the symbol $i \in \Gamma := \{1, \dots, n\}$ is used to denote group-1, group-2, ..., group- n . For each group- i , the leading vehicle $k \in \Omega := \{V_{11}, V_{21}, \dots, V_{n1}\}$ should track the three time warning distances. The last vehicle $\delta \in \Theta := \{1N_{v1}, 2N_{v2}, \dots, nN_{vn}\}$ acts on the intervehicle dynamics model between it and the next group. For each following vehicle in each group, the reference trajectory should track the leading vehicles. Therefore, distributed model predictive control approaches used for the leading vehicles of each group can achieve the vehicles safety driving characteristics. This study is divided into several groups. This class of serially connected subgroup is composed of many similar subgroups placed after one another, in such a way that each subgroup is connected with dynamic state between its neighbors. Some algorithms and assumptions are made as follows.

Assumption 1. The vehicles in each group are self-organization form; the following vehicles in each group can favorably track the leading vehicle. The time delay communication of the vehicle driving state transmission between vehicles is not considered.

FIGURE 2: Overall system work principle.

Assumption 2. Based on highway tunnel characteristics, the overtaking situation is not considered in the research range and the velocity change of vehicles is small.

Algorithm 3. Distributed model predictive controller for the leading vehicle $k \in \Omega$: initialization: the driving state of the vehicle V_0 is sent to the first group by HIS server, starting at time $t_0 = 0$. In addition, other groups will adjust to the driving states by the communication between the HIS system and the groups.

2.2. Analysis of the Three Time Warning Distances. The safety of the driving behavior for each group is typically related to vehicle driving environment. Hence, regarding each group of safety aspect, the information framework includes intervehicle distance, relative velocity, and acceleration. The basic principle of the three time warning distances can be seen from Figure 2. When an accident has happened in a highway tunnel, the vehicle V_0 near the tunnel has obtained the message and lowers its velocity subconsciously. The leading vehicle V_{11} received the road information ahead by the HIS server and passed through the three time warning distances. The latter groups will adjust to the driving states based on the vehicle V_0 and the former groups. The overall groups of distance could be shown as

$$s = \underbrace{v_0 \cdot t_1 + \frac{1}{2} a \cdot t_1^2}_{s_1} + \underbrace{\left\{ \min_2(s_2(t_2), x_2(t_2)), \max_2(s_2(t_2), x_2(t_2)) \right\}}_{s_2} + \underbrace{(\xi_e(t_3) + d_{des}(t_3))}_{s_3} \quad (1)$$

The first time warning distance for each leading vehicle of safety distance is calculated before arriving at its second warning and mainly includes two parts of time, the reaction time of the driver t_1 and message propagation delay t_2 . Message propagation delay is composed of two parts, t_{21} and t_{22} . t_{21} is the time when the message about an accident in tunnel is sent to the HIS server and t_{22} is the time when a message is sent to related leading vehicles of the group. With this notation, we can define the first warning distance:

$$s_1(t) = v_0 t + \frac{1}{2} a t^2, \quad (t \leq t_2). \quad (2)$$

Furthermore, we can solve the first time warning distance for each group denoted by

$$s_i = s_1(t), \quad (t \leq t_2, i = 1, \dots, n). \quad (3)$$

The second time warning distance is calculated before arriving at its third time warning distance. The goal for the second time warning distance is to lower the leading vehicle $k \in \Omega$ of velocity; after arriving at the third time warning distance, the leading vehicle of driving states could satisfy the tracking mode.

Definition 4. Compensated safety distance in our work is defined as the buffer distance among groups to avoid collisions.

Based on the above assumptions and definition, the model for compensated safety distance for each group $i \in \Gamma$ is denoted as follows:

$$\begin{aligned} \dot{x} &= Gx + Hu, & x &= \begin{bmatrix} s_{2i}(t) \\ v_1(t) \end{bmatrix}, & G &= \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix}, \\ H &= \begin{bmatrix} 0 \\ 1 \end{bmatrix}, & u &= a_{des}(t), \end{aligned} \quad (4)$$

where $s_{2i}(t)$ is the compensated safety distance and u is the desired deceleration for the leading vehicle.

Definition 5. The vehicle is in the safety driving when the desired acceleration is defined in the range $|a_i| \leq a_{11}$. a_{11} is a special state that denotes the leading vehicles entering the tracking mode after arriving at the third warning distance.

The second time warning distance is a buffer range, so we introduce the virtual vehicle concept to calculate the distance. Additional advantage of the virtual vehicle scheme is that the motion of the vehicle can be smoothly controlled when a new leading vehicle cuts in or the current vehicle cuts out [10].

Definition 6. The virtual vehicle distance $x_2(t)$ is defined as a constant safety distance. For every group $i \in \{1, 2, \dots, n\}$, the compensated safety distance should be set in the range as follows:

$$\min_i \{s_{2i}(t), x_2(t)\} < s_{2i}(t) \leq \max_i \{s_{2i}(t), x_2(t)\}. \quad (5)$$

The constant safety distance of virtual vehicle distance can be shown:

$$x_2(t) = h \cdot v + D_{\min}. \quad (6)$$

The second time warning distance is built to reduce vehicle's acceleration during some adverse weather or road sections that are prone to accidents.

The third warning time is the tracking mode before arriving at its permitted minimum distance. The vehicle V_0 is uncontrollable, so the leading vehicle $k \in \{V_{11}, V_{21}, \dots, V_{n1}\}$ in each group should be controlled to ensure a suitable relative distance. As can be seen from Figure 2, the intervehicle dynamics model is designed among groups as follows:

$$\begin{aligned} \dot{v}_{fi} &= a_{fi}, \\ \dot{\xi}_{di} &= l_{li} - l_{fi}, \\ \Delta v_i &= v_{li} - v_{fi}, \\ \dot{\xi}_{ei} &= \dot{\xi}_{di} - d_{desi}. \end{aligned} \quad (7)$$

The longitudinal dynamics of the leading vehicle $k \in \{V_{11}, V_{21}, \dots, V_{n1}\}$ are nonlinear. According to the vehicle dynamics in [11], the longitudinal dynamics is transferred as follows:

$$\begin{aligned} \dot{a}_{fi} &= g_{fi}(v_{fi}, a_{fi}) + h_{fi}(v_{fi})\delta_{fi}, \\ g_{fi}(v_{fi}, a_{fi}) &= -\frac{2K_{ad}}{m} - \frac{1}{\tau_f} \left[a_{fi} + \frac{K_{ad}}{m_{fi}} v_{fi}^2 + \frac{K_{md}}{m_{fi}} \right], \\ h_{fi}(v_{fi}) &= \frac{1}{m_{fi}} \tau_{fi}. \end{aligned} \quad (8)$$

If the parameters in (7) are exactly known, the following feedback linearizing control law could be adopted:

$$\delta_{fi} = m_{fi} \mu_{fci} + K_{ad} v_{fi}^2 + K_{md} + 2\tau_{fi} K_{ad} v_{fi} a_{fi}, \quad (9)$$

where ξ_{di} is intervehicle distance, Δv_i is the error among groups, and ξ_{ei} is the error between actual intervehicle distance and desired vehicle safety distance. v_{li}, v_{fi} are vehicle's speed and vehicle's speed. μ_{fci} is the input signal that makes the closed-loop system satisfy certain performance criteria. In controller (8), we achieve the following objectives: (1) the feedback linearization results in a linear system as discussed above: however uncertainties in parameters can potentially make the linearization process inexact; the study of such a case would be an interesting topic to be considered in future research; (2) the simplification of the system model by excluding some characteristic parameters (e.g., the mechanical drag, mass and air resistance) from the vehicle dynamics. Manipulating (6) through (8), the equation becomes

$$\dot{\alpha}_{fi} = \frac{1}{\tau_{fi}} (\mu_{fci} - \alpha_{fi}), \quad (10)$$

where τ_{fi} is the engine time constant and its value is 0.25, a single parameter that describes the dynamics of the propulsion system and internal disturbances. μ_{fci} can be viewed as the throttle/brake input causing acceleration/deceleration in the controlled vehicle. The system thus takes the form which can be described by the following standard equations:

$$\begin{aligned} \begin{bmatrix} \dot{v}_{fi} \\ \dot{\xi}_{ei} \\ \Delta v_i \\ \dot{\alpha}_{fi} \end{bmatrix} &= \begin{bmatrix} 0 & 0 & 0 & 1 \\ 0 & 0 & 1 & -h_i \\ 0 & 0 & 0 & -1 \\ 0 & 0 & 0 & \frac{1}{\tau_{fi}} \end{bmatrix} \cdot \begin{bmatrix} v_{fi} \\ \xi_{ei} \\ \Delta v_i \\ \alpha_{fi} \end{bmatrix} \\ &+ \begin{bmatrix} 0 \\ 0 \\ 0 \\ \frac{1}{\tau_{fi}} \end{bmatrix} \cdot [u(t)] + \begin{bmatrix} 0 \\ 0 \\ 1 \\ 0 \end{bmatrix} \cdot [\alpha_{li}], \\ y(t)_i &= \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \cdot \begin{bmatrix} v_{fi} \\ \xi_{ei} \\ \Delta v_i \\ \alpha_{fi} \end{bmatrix}. \end{aligned} \quad (11)$$

Writing the above equation as standard state-space equations, we have

$$\begin{aligned} \dot{x}(t)_i &= Ax(t)_i + Bu(t)_i + Cw(t)_i, \\ y(t)_i &= Dx(t)_i, \end{aligned}$$

$$\begin{aligned} A &= \begin{bmatrix} 0 & 0 & 0 & 1 \\ 0 & 0 & 1 & -h_i \\ 0 & 0 & 0 & -1 \\ 0 & 0 & 0 & \frac{1}{\tau_{fi}} \end{bmatrix}, \quad B = \begin{bmatrix} 0 \\ 0 \\ 0 \\ \frac{1}{\tau_{fi}} \end{bmatrix}, \\ C &= \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}, \quad D = \begin{bmatrix} 0 \\ 0 \\ 1 \\ 0 \end{bmatrix}, \end{aligned} \quad (12)$$

where state variables are $x(t)_i = [v_{fi} \ \xi_{ei} \ \Delta v_i \ \alpha_{fi}]^T$ and $w(t)_i$ is the acceleration of the last vehicle δ .

By (12), the overall system of vehicle dynamics can be expressed as

$$\begin{aligned} \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_{n+1} \end{pmatrix} &= \begin{pmatrix} A_1 & 0_{4 \times 4} & \cdots & 0_{4 \times 4} \\ 0_{4 \times 4} & A_2 & \cdots & 0_{4 \times 4} \\ 0_{4 \times 4} & 0_{4 \times 4} & \cdots & 0_{4 \times 4} \\ 0_{4 \times 4} & 0_{4 \times 4} & \cdots & A_n \end{pmatrix} \cdot \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{pmatrix} \\ &+ \begin{pmatrix} B_1 & 0_{4 \times 1} & \cdots & 0_{4 \times 1} \\ 0_{4 \times 1} & B_2 & \cdots & 0_{4 \times 1} \\ 0_{4 \times 1} & 0_{4 \times 1} & \cdots & 0_{4 \times 1} \\ 0_{4 \times 1} & 0_{4 \times 1} & \cdots & B_n \end{pmatrix} \cdot \begin{pmatrix} u_1 \\ u_2 \\ \vdots \\ u_n \end{pmatrix} \\ &+ \begin{pmatrix} k_1 & 0 & \cdots & 0 \\ 0 & k_2 & \cdots & 0 \\ 0 & 0 & \cdots & 0 \\ 0 & 0 & \cdots & k_n \end{pmatrix} \cdot \begin{pmatrix} w_1 \\ w_2 \\ \vdots \\ w_n \end{pmatrix}. \end{aligned} \quad (13)$$

Simplifying the above equation,

$$X_{n+1} = A \cdot X_n + B \cdot U_n + K \cdot W_n, \quad (14)$$

where $X_{n+1} = (x_1 \ x_2 \ \cdots \ x_{n+1})^T$, $X_n = (x_1 \ x_2 \ \cdots \ x_n)^T$, $U_n = (u_1 \ u_2 \ \cdots \ u_n)^T$, and $w_n = (w_1 \ w_2 \ \cdots \ w_n)^T$.

Criterion 1. The dynamics model (12) is stable, controllable, and observability.

The stability system is analyzed by eigenvalue criteria. The controllability is verified by using rank (A, B) and the observability is studied by using rank (C, A) .

As we have defined it, the three time warning distances are designed to imply that, combined with HIS space, vehicles safety driving could be guaranteed under the environment of some uncertain weather conditions, such as fog, rain, or snow.

3. Distributed Model Predictive Control Approach

3.1. Induction Process. In this section, we introduce notation and define the optimal control problem and the distributed model predictive control approach (DMPC) for the leading vehicles in each group. Combined with the above schematics derivation, the DMPC only is developed in the leading vehicle $k \in \Omega$; the following vehicles in each group can maintain the safety driving distance in the form of the platoon. The DMPC algorithm captures an important class of practical problems, including, for example, maneuvering a group of vehicles from one point to another while maintaining relative formation and/or avoiding collisions [12]. Figure 3 shows the principle of the optimal control application for each leading vehicle.

As stated above, each group exchanges information with the HIS server system. Each group sequentially achieves performance development in distributed MPC algorithms under the environment of the highway tunnel.

Because the latter groups irregularly drive on the highway tunnel, the interconnections between different subsystems are assumed to be weak and are considered as disturbances

FIGURE 3: The principle for the optimal control application.

which can send the relative driving information to the latter group via HIS server system. In addition, the driving states of the last vehicle in each group are uncontrollable but can be measured by sensors, so the acceleration $w(t)_i$ of the last vehicle $\delta \in \Theta$ can be regarded as the measured disturbance signal when calculating the latter groups. The overall of longitudinal dynamics system that is composed of m interconnected subsystems can be described by (14). The global optimization problem can be decomposed into a number of local optimization subproblems and the whole control performance can be efficiently improved [13]. The cooperation between subsystems is achieved by exchanging information between each subsystem and its neighbors in a distributed structure via network between HIS server and vehicles.

By (12), according to the vehicle driving characteristics in highway intelligent space, subsystem S_i interacts with S_j , and the output state acceleration of subsystem S_i is affected by subgroup S_j . In this case, S_j is called input neighboring subgroup of S_i . S_i is called the output neighboring subsystem. In (12), the state acceleration of the S_i is regarded as disturbance.

In every group of distributed optimal control strategy, we assume that the same constant prediction horizon $N_p \in (0, \infty)$ and constant update period $\gamma \in (0, N_p]$ are used. In practice, the update period $\gamma \in (0, N_p]$ is the sample interval. The common update times are denoted by $t_k = t_0 + \phi k$, where $t_0 = 0$ and $k \in N = \{0, 1, 2, \dots\}$. The leading vehicle in each group sequentially solves an optimal control problem at the update period $\delta \in (0, N_p]$ and applies the optimal control trajectory until its next update time. We have that $z_i(t)$ and $u_i(t)$ are the actual error state and control input, respectively. For each leading vehicle $k \in \Omega$ at any time $t \geq t_0$, over any prediction interval $[t_k, t_k + T]$, $k \in N$, associated with updated time t_k , we denote two trajectories:

$u_i^*(\tau; t_k)$: the optimal control trajectory,

$\hat{z}_i(\tau; t_k)$: the predicted state trajectory,

where $\tau \in [t_k, t_k + T]$.

The predicted value $\hat{z}_i(\tau; t_k)$ is transmitted to all other followers as soon as the optimal control problem at $t = k\delta$ is solved to take account of collision avoidance. The overall system running process is as follows.

Step 1. At the time $t = k\delta$, the leading vehicle V_{11} building the model predictive controller is defined.

Input State. $\hat{u}_i(\tau; t_k) = u_i^*(\tau; t_k)$;

Disturbance Variance $w(t)$: $w(t) = \alpha_{li}$. Because of the uncontrollable vehicle V_0 , the $v(t)$ can be regarded as a disturbance variance.

Step 2. The DMPC used for the leading vehicle $k \in \Omega$ obeys the following implementation strategy.

- (1) At the time t , all the controllers receive the full state measurement $x(t)$ from the sensors.
- (2) Each controller evaluates its own future input trajectory based on $x(t)$ and $w(t)$. Based on the input trajectories, each controller calculates the current decided set of inputs trajectories.
- (3) Each controller updates its entire future input trajectory and sends the future state to the following vehicles in each group.
- (4) When a new measurement is received, go to Step 1 ($t \leftarrow t + 1$).

At each iteration, for $p = 0, \dots, N - 1$, each controller solves the following optimization problem:

$$\begin{aligned} & \min_{u_i(t), \dots, u_i(t+N-1)} J(t), \\ & u_i(t+p) \in U_i, \quad p \geq 0, \\ & u_{l'}(t+p) = u_{l'}(t+p)^{c-1}, \quad \forall l' \neq i, \\ & x(t+p) \in X, \quad j > 0, \\ & x(t+N) \in X_f \end{aligned} \quad (15)$$

with

$$J(t) = \sum_l J_l(t),$$

$$J_i(t) = \sum_{p=0}^{N-1} [\|x_i(t+p)\|_{Q_i}^2 + \|u_i(t+p)\|_{R_i}^2] + \|x(t+N)\|_{P_i}^2, \quad (16)$$

where Q and P are the weighting matrices that tune the relative importance of the output vector's elements as well as the magnitude of the control effort. QP formulation is used to solve the model predictive control problem.

3.2. Control Objectives and Constraints. Typically, the primary control objective of the HIS server system is to keep vehicles at a safety distance. So there exit some constraints on the information framework for each group and the information unit for each vehicle.

Step 1. The first parameter is the intervehicle distance. The intervehicle distance includes two parts. One part is the intervehicle distance in each group, and the other is the intervehicle distance between the last vehicle $\delta \in \Theta$ and the leading vehicle $k \in \Omega$. About the first part of the intervehicle distance, the so-called safety distance can be defined as (6). As to constraints of relative distance error, when the vehicle V_0 runs uniformly, larger or smaller intervehicle distance may occur in real time. The inequality for subobjective is as follows:

$$\xi_{ei}^{\min} \leq \xi_{ei} \leq \xi_{ei}^{\max}, \quad (17)$$

where $\xi_{ei}^{\min} = -5$ m is the lower boundary, which is again obtained from the driver experimental data, and $\xi_{ei}^{\max} \leq 6$ m is the higher boundary in the literature [14].

The intervehicle distance between the last vehicle $\delta \in \Theta$ and the leading vehicle $k \in \Omega$ can be studied on the three time warning distances. The second time warning distance constraint can be shown in Definition 5.

The third time warning distance is the tracking mode and the constraint is the same as the first part of intervehicle distance.

Step 2. The second parameter is the intervehicle velocity. The intervehicle velocity also includes two parts. One is the intervehicle velocity in each group, and the other is the intervehicle distance between the last vehicle $\delta \in \Theta$ and the leading vehicle $k \in \Omega$. About the first part of the intervehicle velocity, we define the initial vehicle velocity as $0 \leq v_f \leq 80$ km/s. The relative velocity in each group should be minimized in the range $-1 \leq \Delta v \leq 0.9$ m/s. The second intervehicle velocity is researched based on the third time warning distance, because, during the first and the second time warning distances, the vehicle is in acceleration or deceleration without any rule. The constraint is in the range $-1 \leq \Delta v \leq 1.2$ m/s.

Step 3. The third parameter is the acceleration of the leading vehicle $k \in \Omega$ in each group. First the vehicle V_{11} of acceleration a_{11} constraint is defined in the range $a_{f_{\min}} = -3.0$ ms⁻², $a_{h_{\max}} \in [2.0, 3.0]$ ms⁻². The absolute value of $\alpha_{f_{\min}}$ being bigger than that of $\alpha_{f_{\max}}$ can accommodate larger braking degree to prevent rear-end collisions [15].

Step 4. The fourth parameter is the weight Q_e and the control input. The weight Q_e which is the weight of the error ξ_e between the desired and the actual distance has to be considered. The larger Q_e is, the smaller the time reaches a steady-state situation. Although the focus is on safety, it has to be remarked that, for increasing Q_e , the acceleration will increase as well. The control input constraint includes throttle input or brake input. So, we could define the control formulation as $u(k) \in [-1, 1]$.

4. The Dynamics Model in Each Group

We consider n groups of vehicles that travel in a straight line towards a highway tunnel. In this section, we focus on

FIGURE 4: The first group: the intervehicle distance, the intervelocity, and the acceleration.

the stability analysis for vehicles in each group $i \in \{1, \dots, n\}$. Meanwhile, we suppose the intervehicle distance following a constant time headway policy to be (6). In this way, the actual distance between vehicle ij and vehicle $ij-1$ should be defined as follows:

$$\varepsilon_{ij}(t) = x_{ij-1}(t) - x_{ij}(t) - L_{ij-1}, \quad (18)$$

where L_{ij-1} is vehicle $ij-1$ length and $x_{ij-1}(t)$, $x_{ij}(t)$ stand for the position for vehicle ij and vehicle $ij-1$. So, respectively,

the continuous vehicle of vehicle distance error is calculated by the actual distance and desired distance as follows:

$$\delta_{ij}(t) = \varepsilon_{ij}(t) - x_2(t). \quad (19)$$

From the view of vehicle platoon stability, the objective for the vehicle-to-HIS framework is that vehicle interdistance should tend to 0 which holds the desired interdistance between the leading vehicle and the following vehicle. Equation (19) can be defined as follows:

$$S_{ij} \equiv \delta_{ij}(t). \quad (20)$$

FIGURE 5: The second group: the intervehicle distance, the intervelocity, and the acceleration.

According to slid mode control method principle, when the variable $\delta_i(t)$ satisfies the following expression:

$$\dot{S}_{ij} = -\lambda_{ij} \cdot S_{ij}. \quad (21)$$

If the equation $S_{ij} \rightarrow 0$ is established, $\delta_{ij}(t) \rightarrow 0$ means that the ij th vehicle is said to provide individual vehicle stability. The spacing error derivation process for vehicle platoon is shown in [16], which is used in the paper as follows:

$$H(s) = \frac{\delta_{ij}(s)}{\delta_{ij-1}(s)} = \frac{s + \lambda}{t_g \cdot \tau \cdot s^3 + t_g \cdot s^2 + (1 + \lambda t_g)s + \lambda}, \quad (22)$$

where $t_g = 2$ s and $\tau = 0.5$ s. By using the above transfer function, string stability of vehicle platoon can be analyzed. It is shown that condition $\|H(s)\|_{\infty} \leq 1$ ensures system stability.

5. Simulation and Analysis

In this section, we mainly research the simulation process of the groups. The three time warning distances have been used to ensure multivehicle safety. The first and the second time warning distances mainly lower the deceleration of the leading vehicle in each group. The third time warning distance mainly provides the safety driving distance with groups, for example, deceleration state of safety distance

FIGURE 6: The third group: the intervehicle distance, the intervelocity, and the acceleration.

or track mode of safety distance. When the leading vehicle in each group is in the deceleration state during the third warning distance, other vehicles in each group are in a normal safety driving. Therefore, we mainly study the tracking mode for each group during the third warning distance using DMPC. It is assumed that groups $\Gamma = 4$, $N_{v1} = 5$, $N_{v2} = 3$, $N_{v3} = 4$, and $N_{v4} = 5$. The prediction horizon and control horizon for the DPMC are 300 sampling times. At time t_0 , the vehicle V_0 acceleration is defined:

$$a_0 = \begin{cases} 0, & t < 4, \\ -0.4, & t \geq 4. \end{cases} \quad (23)$$

Meanwhile, we assume that, after the first and the second time warning distance, vehicle V_{11} of velocity is 10.5 m/s. When the leading vehicle in each group lowers its acceleration $|a_i| \leq a_{i1}$ in the third time warning distance, the relative distances between the following vehicles in each group and the distance between the last vehicle and the leading vehicle are 3 m,

FIGURE 7: The fourth group: the intervehicle distance, the intervelocity, and the acceleration.

5 m, 10 m, and 15 m. The following vehicles in each group are tracking the reference trajectories. Hence, the driving state of the leading vehicles can represent each group of information framework. The leading vehicles can only be studied. Four groups of simulation results are shown as shown in Figures 4, 5, 6, and 7.

From Figure 4, it can be seen that the intervehicle5-1 distance between the leading vehicle V_{11} and the vehicle V_0 can maintain stability until the time 15 s. When the vehicle V_0 decelerated irregularly, the leading vehicle V_{11} adjusts to its velocity subsequently. Meanwhile, the following vehicles

have received the road information ahead from the HIS server system; they still retain the constant safety distance. As to the acceleration curve, the reference acceleration $a_{11} = -0.4 \text{ m/s}^2$; by using Definition 5, we can know that only if $|a_i| \leq a_{11}$, the system is controllable. Figure 5 shows the intervehicle distance between vehicles can retain stability until the time 10 s. The change range of the intervelocity is larger than the former group. Generally speaking, the first group and the second group are stability. The third and the fourth group signify that the intervehicle distance between vehicles can retain stability until the time 10 s to 15 s.

FIGURE 8: The intervehicle distance among groups.

These groups show that the intervelocity between vehicles changes in real time. The acceleration also adapts to the environment tracking characteristics. The simulated information framework demonstrated that by the first and the second time warning distances to groups of vehicles deceleration system can realize effectively vehicle safety characteristics. Figure 8 shows the intervehicle distances among groups. Through comparative analysis of the intervehicle5-1 distance in the first group, the intervehicle3-1 distance in the second group, the intervehicle4-1 distance in the third group, and the intervehicle5-1 distance in the fourth group, we can conclude that the distributed optimization based DMPC controller and the three time warning distances are carried out to verify the performance of the vehicles passing the highway tunnel environment.

6. Conclusion

The paper presents the distributed model predictive control approach for groups of vehicles of information framework analysis on the highway tunnel environment. The three time warning distances are proposed to ensure vehicles of safety driving. The framework can be adapted for a highway tunnel and some adverse weather such as fog, rain, and snow when drivers cannot distinguish the road ahead because of weather and road reasons. The system is different from traditional vehicle system of active electric functions; its goal is to provide a warning system based on the HIS system for drivers to obtain the road situation in advance, especially multiple groups of vehicles towards some road section prone to accidents or some adverse places. First, the three time warning distances are introduced to guide the mechanism. Second, the distributed model predictive control approach is studied to develop the optimal control sequence. Last, in

order to verify the feasibility for the system, four different groups are simulated. The simulation results demonstrate that the proposed three time warning distances could achieve vehicles of safety and stability. Furthermore, it is shown that the local optimization of distributed model predictive control approach could ensure that the whole control performance is effective.

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

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