Automobile Optimal Driving Control Using Surrounding Information Based on Model Predictive Control

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Abstract: In this paper, an optimal driving control system based on model predictive control (MPC) is developed for the purpose of processing more surrounding information which is essential for improving the current intelligent driving assistance and further dealing with traffic issues caused by automobiles. The proposed system provides a method of calculating a desirable driving path based on surrounding traffic environments. The performance of this system is evaluated through simulations which are carried out with introduction of surrounding information such as traffic jams, traffic signal changes, and fuel consumption. Simulation results reveal that the proposed system as a driving assist system has a potential of finding optimal driving paths for drivers.

Key Words: optimal driving path, MPC, surrounding traffic information.

1. Introduction

With the popularity of automobiles, traffic accidents have become a major social problem in every country. Heavy traffic congestions in and around cities cause significant time and economic losses. Besides, the fuel problem is also a serious issue [1]. These backgrounds have not only boosted the progress of advanced engine technologies, but also promoted developments of intelligent driving assist systems which are used to assist drivers in manipulating automobiles more efficiently.

Intelligent driving assist technologies have been developed in various aspects since the advent of an intelligent vehicle concept in 1939 [1]. A driver assistance system was designed to reduce the driver’s workload [2]. Some collision avoidance systems were developed to ensure safe driving. Sensing devices and algorithms were applied to detect other vehicles, obstacles and pedestrians [1]. An adaptive cruise control was designed for comfort and traffic efficiencies by tuning the vehicle velocity and position according to the information of predecessors in a vehicle string [3]. Besides, intelligent driving assist systems were also applied to overcome the weak points of a human driver.

In this paper, an automobile optimal driving control system based on model predictive control (MPC) is proposed. This system can calculate a desirable driving path based on information and prediction of surrounding traffic environments. As a prior research, Kawabe and Nishira [4] described an optimal path generator using the receding horizon control, and made simulations of overtaking and cutting-in. On the basis of their research, more information related to traffic jams, traffic signals, and fuel consumption is considered in this paper. Moreover, situations with consideration of such information are simulated. The results indicate that this system as a driving assist system can convert surrounding information into an optimal driving path. As a more intuitive instruction, and guide drivers to operate vehicles in a safe, smooth and economic way.

This paper is organized as follows. Section 2 shows an overview of the optimal driving control system. Section 3 explains the MPC scheme and the generalized minimal residual (GMRES) method which is applied to the calculation of optimal driving control inputs. Section 4 firstly describes modeling of a host vehicle and surrounding vehicles, and then defines criteria for evaluating driving performances. Evaluation functions of different situations are also formulated in the end of Section 4. In Section 5, surrounding information of traffic jams, traffic signals and fuel consumption is formulated and taken into account. Several situations are simulated and analyzed in Section 6. Finally, conclusion and directions of future researches are presented in Section 7.

2. Overview of Optimal Driving Control System

The proposed optimal driving control system is composed of vehicle models and MPC control block, which is depicted in Fig. 1. Vehicle models describe dynamics of the host vehicle and the surrounding vehicles. The MPC controller calculates a group of control inputs over the whole horizon, based on an overall evaluation of vehicle motion, and only the control inputs in the first sampling time are treated as optimal control inputs and fed to the block of vehicle models to predict the optimal driving state in the near future. This process is repeated when control vector is updated.

MPC is an optimization based control law, and it is applied to predict behavior from the current time, over a future prediction horizon. The control process is similar to the behavior of skillful drivers. They plan how to run their vehicles in a short future, by watching surrounding vehicles and information.

3. Model Predictive Control

In the MPC, dynamic models are usually described as [5]
4. Modeling of Vehicle Motion and Evaluation Function

4.1 Modeling of Vehicle Motion

The dynamic models are formed as equation (1). Modeling of automobile driving involves two parts of vehicles, the host vehicle and the surrounding vehicles. Motion of the host vehicle is formulated in longitudinal and lateral directions.

Equations (13)-(14) explain velocity and acceleration of the host vehicle, in longitudinal direction. Equation (15) shows vehicle dynamic in lateral position.

\[ x_0 = v_0 \]  
\[ \dot{v}_0 = u_s \]  
\[ \ddot{y}_0 = -\omega y_0 + \omega u_i \]

where, \( x_0 \) is the longitudinal position of the host vehicle, \( v_0 \) is the velocity of the host vehicle, \( \omega \) is a parameter, and \( y_0 \) is the lateral position, normalized within \(-1 \leq y_0 \leq 1\). If the host vehicle is located in the center of left lane, \( y_0 = 1 \), and when it is in the center of right lane, \( y_0 = -1 \).

The motions of surrounding vehicles are explained as velocity and acceleration in longitudinal direction [8]. For simplification, it is supposed that surrounding vehicles do not change lane.

\[ \dot{x}_i = v_i \]  
\[ \dot{v}_i = k_i' e'_i + k_2' e'_r + k_2'' e'_r \]
\[ e'_r = x_p - x_i - h_i v_i \]  
\[ e'_r = v_p - v_i \]
\[ e'_v = v_r^d - v_i \]

where, \( h_i \) is the desired time headway, \( v_i \) and \( v_i^d \) are actual and desired velocity of vehicle \( i \), respectively, and \( x_p \) is its position. \( x_p \) is the position of vehicle \( P \) in front of vehicle \( i \), and \( v_r^d \) is the corresponding velocity [4].

4.2 Evaluation Function

4.2.1 Evaluation criteria and basic evaluation function

The vehicle performance is evaluated from the viewpoint of safe and smooth driving, by the following criteria:

(1) Vehicle acceleration should be as small as possible, which is evaluated with an equation of longitudinal acceleration,

\[ L_a = \frac{1}{2} a_i^2 \]  
\[ L_v = \frac{(u_v - y_0)^2}{2} \]  
\[ L_e = \frac{(y_0 - v_0^d)^2}{2} \]
where, $v_f$ is the desired velocity.

(4) For the host vehicle, the time to collision and the time headway are long enough. That is, the host vehicle should keep a safe distance away from surrounding vehicles.

\[ L_x = c(y_0)(l_f + l_b) + c(-y_0)(l_R + l_b) \]  

(24)

where, subscript $L_f$ means vehicle that locates in left-front of the host vehicle, $L_b$ means left-behind, $R_b$ represents right-behind, and $R_f$ denotes right-front. $c(y_0)$ is defined as

\[ c(y_0) = \frac{1 + y_0}{2} \]  

(25)

$l_f$ and $l_b$ are determined by

\[ l_f(x_0, x_f) = \alpha \frac{y_0}{x_f - x_0} + \frac{1 - \alpha}{1 + e^{-\lambda(v_0 - v_f)}} \frac{v_0 - v_f}{x_f - x_0} \]  

(26)

\[ l_b(x_0, x_b) = \alpha \frac{y_0}{x_b - x_0} + \frac{1 - \alpha}{1 + e^{-\lambda(v_0 - v_b)}} \frac{v_0 - v_b}{x_b - x_0} \]  

(27)

$\alpha$ is a constant coefficient, $\lambda$ is a parameter, $v_f$ is the velocity of vehicle in front of the host vehicle, and $v_b$ is the velocity of vehicle behind the host vehicle.

The basic form of function $L$ in equation (2) is defined as

\[ L = \omega_x L_x + \omega_y L_y + \omega_{L_x} L_x + \omega_{L_y} L_y \]  

(28)

where, $L_x$, $L_y$, $L_x$, and $L_y$ are evaluation indexes, $\omega_x$, $\omega_y$, $\omega_{L_x}$, and $\omega_{L_y}$ are their weightings.

4.2.2 Evaluation functions with surrounding information

The criteria (1), (2), and (4) are the same as that mentioned in Section 4.2.1. However, criterion (3) is modified as follows:

Velocity is changed according to travelling motions of vehicle B and vehicle C. Surrounding vehicles adjust their driving state accordingly.

5.2 Traffic Jam and Traffic Signal

Traffic jam is formulated as velocity change of vehicles P

\[ T_r = v_p0 - \alpha_r \frac{1}{1 + \exp(-\lambda_r(t - T_1))} \]  

(32)

where, $v_p0$ is the velocities of vehicles P before traffic jam. $\alpha_r$ and $\lambda_r$ are tuning parameters which determine how fast velocity changes. $T_1$ is the time point when traffic jam appears. The severity of traffic jam is determined by tuning parameters. When traffic jam occurs, velocities of vehicles P ($P_a$, $P_c$ in Fig. 2) followed by the surrounding vehicles change firstly, and the host vehicle and the surrounding vehicles adjust their driving state accordingly.

Figure 3 shows an example of simulator for traffic jam. In this case, traffic jam occurs at 20 s. Vehicles P gradually decelerate to a slower velocity after traffic jam start. In this process, actual velocities of vehicles P always involve fluctuations, and do not change smoothly as Fig. 3. However, velocity variation trend in a traffic jam can be appropriated with this simplified simulator. In practical application, this simulator would be substituted with actual velocity from sensors.

\[ T_r = 16 - 10 \frac{1}{1 + \exp(-0.5(t - 20))} \]  

(33)

Traffic signal simulator is also explained with velocity change of vehicles P

\[ S_l = v_p0 \frac{1}{1 + \exp(\lambda_p(T_2^2 - (T_3 - t)^2))} \]  

(34)

where, $v_p0$ is original velocities of vehicles P before signal change, and $\lambda_p$ is a control parameter. Before $T_3 - T_2$ when signal is green, vehicles P keep original velocities, since $T_3 - T_2$, traffic signal turns to red and vehicles P stop, and then traffic signal changes to green after $T_3 + T_2$, therefore vehicles P accelerate to original velocities. In [9], Akcelik and Besley pointed out that the drive cycle during a stop at traffic signal consists.
of cruise, deceleration, stop, acceleration, and cruise processes. The applied simulator is an ideal model of actual situation without regard to deceleration and acceleration processes.

Figure 4 shows a simulator of traffic signal. Initial state of traffic signal is green. It changes to red at 20 s, and keeps the state until 40 s. During this period, vehicles P immediately slow to a stop. The host vehicle and the surrounding vehicles following vehicles P make a corresponding reaction. And then signal turns to green again, vehicles P return to the original velocities.

![Fig. 4 An example simulator of traffic signal.](image)

5.3 Fuel Consumption

Relationship between fuel consumption and automobile velocity [10] is shown as Fig. 5. Fuel consumption ratio reaches its optimum when automobile runs at 40-60 km/h, because engine mechanical loss increases at a low velocity, and air resistance grows rapidly at a high velocity.

![Fig. 5 Fuel consumption characteristic.](image)

Fuel consumption in Fig. 5 is formulated as

\[ S_f = \frac{16}{1 + \exp(0.5(10^2 - (30 - t)^2))} \]  \hspace{1cm} (35)

\[ F_{ratio} = -0.00325v^2 + 0.0907v + 0.0392 \]  \hspace{1cm} (36)

\[ L_{em} = 1 - F_{ratio} \]  \hspace{1cm} (37)

where \( v \) is vehicle velocity [m/s].

6. Simulation Results

Several simulations were performed to test the effectiveness of the proposed driving control system, and to validate whether it can calculate a reasonable optimal driving mode according to different situations. A simulation involving with a basic situation was carried out firstly, which only considered surrounding vehicles. The applied evaluation function was a basic form. Derived from this case, other complicated situations concerning traffic jam in one and two lanes, traffic signal, and fuel consumption were computed with modified evaluation functions, respectively. Simulation results are also analyzed.

6.1 Simulation Result of Basic Situation

The basic situation is shown in Fig. 6. The host vehicle A is running at 17 m/s in the left lane, vehicle B is moving at 15 m/s, slower than the host vehicle, and vehicle C is travelling at 20 m/s in the right lane. The horizon length was set to 8 s. Vehicles updated their state every 0.1 s. Weightings \([\omega_x, \omega_y, \omega_v, \omega_s] = [0.2, 0.2, 0.5, 0.1]\).

![Fig. 6 Initial simulation conditions.](image)

Simulation results within [0, 40] s are shown in Fig. 7. Figure 7(a) illustrates longitudinal positions of vehicles, and Fig. 7(b) shows their velocities, normalized lateral position and acceleration of the host vehicle, respectively. It is assumed that the host vehicle accurately follows the simulated optimal driving path. According to the computed results, the host vehicle A firstly decelerated because vehicle B was slower than the host vehicle A, and then it accelerated and changed to right lane.

![Fig. 7 Simulation results.](image)
6.2 Simulation Results with Traffic Jam

(1) It was assumed that there was a traffic jam in both lanes after 20 s. The traffic jam was defined as

\[ T_r = 15 - 10 \frac{1}{1 + \exp(-0.5(t - 20))}. \]

Vehicles updated their driving control inputs every 0.1 s, the horizon length was set to 8 s, simulation time was 50 s, and weightings \([\omega_x, \omega_y, \omega_v, \omega_s]\) = [0.85, 0.05, 0.05, 0.05]. Initial travelling state is shown in Fig. 8. Velocity of the host vehicle A is 15 m/s, velocity of vehicle B is 18 m/s, faster than the host vehicle A, and velocity of vehicle C is 17 m/s.

Figure 9 shows simulation results. Vehicle A, vehicle B, and vehicle C dramatically decelerated after 20 s since traffic jam appeared. Figure 9(a) illustrates positions of vehicles A, B, and C at different time. During simulation, the formation of the host vehicle and the surrounding vehicles did not change.

(2) It was supposed that traffic jam only occurred in the left lane, which was explained as

\[ T_r = 26 - 10 \frac{1}{1 + \exp(-0.5(t - 20))}. \]

Simulation time was set to 50 s, and weightings \([\omega_x, \omega_y, \omega_v, \omega_s]\) = [0.85, 0.05, 0.05, 0.05]. Initial travelling state is shown in Fig. 10.

Optimal driving state was obtained as Fig. 11. Vehicle B was initially faster than vehicle P in front of it. In order to keep a safe interval, vehicle B slightly slowed down, and then kept a constant velocity until 20 s when traffic jam occurred in the left lane. Vehicle A also decelerated firstly, and accelerated to go ahead of vehicle B. After that it kept the desired velocity of driver.

Figure 12 illustrates the formation of vehicles A, B, and C at different time. It is shown that the host vehicle A changed lane between [19, 25] s.

6.3 Simulation Result with Traffic Signal

In this case, traffic signal change was defined as

\[ S_I = 15 \frac{1}{1 + \exp(0.5(10^2 - (30 - t)^2))}. \]

Initial simulation conditions were set as Fig. 13. Weightings for evaluation indexes were set to \([\omega_x, \omega_y, \omega_v, \omega_s]\) = [0.85, 0.05, 0.05, 0.05].
Simulation results are shown in Fig. 14. Vehicles A, B, and C quickly decelerated after 20 s when signal changed to red, and accelerated after 40 s when signal become green again.

6.4 Simulation Result with Fuel Consumption

Simulation conditions are shown in Fig. 15. The host vehicle A runs at a velocity of 17 m/s in the left lane, vehicle B travels with a velocity of 14 m/s and it is located 50 m in front of the host vehicle, and vehicle C moves at 20 m/s in the right lane. The horizon length was also 8 s, and simulation time was set to 40 s.

Optimal driving state was obtained as Fig. 16. Vehicle A decelerated slightly, and changed to the right lane (Fig. 17). After that vehicle A kept a velocity around 14 m/s. Velocity of the host vehicle after simulation was 14.016 m/s (50.45 km/h) at which fuel consumption could make a good performance (Fig. 5), and fuel consumption ratio calculated by equation (36) was 0.6720.

7. Conclusion

In this paper, an optimal driving control system for calculating an optimal driving mode based on MPC was presented.
Surrounding information of traffic jams, traffic signals, and fuel consumption was formulated and transformed to a more intuitive and acceptable form as an optimal driving path for drivers. Computer simulations with consideration of such surrounding information were performed. Results revealed that this system can provide an optimal path for driving assistance. This predicted optimal path would assist drivers to maneuver their vehicles in a smooth, safe, and economical way, which is helpful especially for unskilled drivers.

In future researches, weightings such as $\omega_1$, $\omega_2$, $\omega_r$, $\omega_s$, and $\omega_{fr}$ would be optimized. A combination of all surrounding information including the road infrastructure should be considered. The simulator of fuel consumption would be improved for more precise prediction. Besides, with adoption of advanced sensor technologies and wireless communication systems, the estimated motions of surrounding vehicles would be replaced with actual sensor data. Traffic jams and traffic signal changes also could be determined by measured travelling states of the vehicles ahead. The optimal driving control system is expected to be applied in automatic driving systems in the future.

References


