Simulation analysis of adaptive cruise prediction control

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Abstract. Predictive control is suitable for multi-variable and multi-constraint system control. In order to discuss the effect of predictive control on the vehicle longitudinal motion, this paper establishes the expected spacing model by combining variable pitch spacing and the of safety distance strategy. The model predictive control theory and the optimization method based on secondary planning are designed to obtain and track the best expected acceleration trajectory quickly. Simulation models are established including predictive and adaptive fuzzy control. Simulation results show that predictive control can realize the basic function of the system while ensuring the safety. The application of predictive and fuzzy adaptive algorithm in cruise condition indicates that the predictive control effect is better.

1. Introduction
With the development of science and technology, security strategy is escalating and the vehicle safety gradually changes from the initial passive to active transformation. ACC (Adaptive Cruise Control) system as an active safety assistance system can reduce the driver workload and improve driving comfort. Especially in the busy traffic, ACC can help avoid rear-end and increase traffic flow [1, 2].

The MPC (Model Predictive Control) method for the ACC system can be used to realize stop-go, cooperative, nonlinear and random controls [3-6]. NMPC (Nonlinear Model Predictive Control) with extending the original linear time introduces a model corresponding to follow the vehicle speed [7-9].

Predictive control system consists of prediction model, reference trajectory, rolling optimization and online correction [10-12]. In this paper, the state model is used to represent the prediction model, and the optimal trajectory of the control variable is obtained by solving the quadratic programming problem. The adaptive fuzzy control is realized by the two-dimensional fuzzy controller and the traditional PID controller. Comparison of the two control methods can reflect the advantages of predictive control better.

2. Expected traffic spacing model
Reasonable spacing strategy is the key to ensure the driving safety and improve the traffic flow. The VT (variable distance) has the advantages of strong adaptability, high safety and reasonable distance. The safety distance is decided by the host vehicle and target speed, and can be expressed as:

\[
\begin{align*}
\text{th} &= b_1 + b_2 v_m + b_3 v_f \\
v_m &= \max \{v_n, v_f\}
\end{align*}
\]

Where \(v_f\) is relative speed, \(\text{th}\) is headway distance, \(b_1, b_2\) and \(b_3\) are constants, \(v_m\) is maximum speed.

If the host and the target vehicle are traveling on the same lane, the safety distance can be determined by the speed, deceleration, the reaction time of the driver and the minimum travel distance.
in emergency braking, and can be described by:

$$ d_s = d_{\min} + \xi v_h + \frac{v_h^2}{2g_h} - \frac{v_r^2}{2g_r} $$

(2)

Where $d_s$ is safe distance, $d_{\min}$ is minimum distance, $\xi$ is reaction time of the driver, $v_h$ is host speed, $v_r$ is target speed, $g_h$ and $g_r$ is the braking deceleration for the host and target vehicle respectively.

The actual distance is fuzzy. The expected distance of the vehicle is required not only large enough to ensure the safety, but also to improve the using efficiency of the road as far as possible. Combined with variable pitch spacing and theoretical safety distance strategy, the expected driving spacing can be calculated by:

$$d_{s_{\min}} < d_e = c_0 + c_1v_m + c_2v_r + c_3v_r^2 < d_{s_{\max}}$$

(3)

Where $d_{s_{\min}}$ is minimum safe distance, $c_0$, $c_1$, $c_2$ and $c_3$ are constants greater than zero, $d_{s_{\max}}$ is maximum safe distance.

3. Simulation model

3.1. Predictive control design

In order to establish a real time linear system, the acceleration of the host vehicle is chosen as the control variable, the relative speed, relative distance and host speed are used as the input state variables, and the expression is:

$$ u_k = a_h(k) $$

$$ x_k = (d_r(k), v_r(k), v_h(k))^T $$

(4)

Where $u_k$ is the control variable, $a_h(k)$ is host acceleration, $x_k$ is input state variable, $d_r(k)$ is real relative distance, $v_r(k)$ is real relative speed, $v_h(k)$ is real host speed.

In order to simplify the predictive model, it is assumed that the acceleration of the target vehicle is zero, and the actual change is taken as the disturbance variable. Select the change rate of acceleration as the system input to improve the stability, the acceleration rate and incremental state equation can be expressed as follows:

$$ \Delta u(k) = u(k) - u(k-1) \quad k = 0,1,2,\ldots,n $$

(5)

$$ S : \begin{cases}
    \dot{x}(k+1) = Ax(k) + Bu(k) \\
    \dot{y}(k) = Cx(k)
\end{cases} $$

(6)

Where $\Delta u(k)$ is acceleration change rate, $S$ is incremental state equation, $A$, $B$ and $C$ are coefficient, $x(k)$ is input state variable, $u(k)$ is control variable, $y(k)$ is output state variable.

The system inputs, outputs and intermediate variables are constrained, and optimization can be based on quadratic performance indicators of the secondary planning type solution for the state equation online. Relaxation factor is introduced, and soft constrained method is used to avoid the mutation. The reference trajectory and the amount of deviation can be expressed by:

$$ x_r(k) = [d_s(k) 0 v_r(k)]^T $$

$$ X(k) = x(k) - x_r(k) $$

(7)

Where $x_r(k)$ is reference, $X(k)$ is error of the true and reference value.

The specific optimization expression is described by:
\[
\min_{u(k)} J(k) = \sum_{1}^{N} [X^T(k+1|k)Q(k)X(k+1|k)] + \sum_{0}^{N} [u^T(k+1|k)R(k)u(k+1|k)] \\
\text{s.t.} \quad S : \begin{cases} 
\dot{x}(k+1) = A\dot{x}(k) + Bu(k) \\
y(k) = C\dot{x}(k) \\
u_{\min}(k) \leq u(k) \leq u_{\max}(k) \\
y_{\min}(k) \leq y(k) \leq y_{\max}(k) 
\end{cases}
\]

(8)

Where \( J(k) \) is optimization expression, \( Q(k) \) and \( R(k) \) are weighting factors.

In this paper, the predictive control model takes the acceleration as the output control signal. The feedback measurement signals are the host vehicle speed and the actual driving distance. The actual driving distance and the expected driving distance are calculated to obtain the driving error as the independent variable. The specific parameters are set according to the simulation conditions. The simulation model is shown in Figure 1.

3.2. Adaptive fuzzy control design

The actual vehicle speed is taken as the output variable and the feedback signal. The error and change rate between the input and output values are taken as the input variable of the controller, and adjust by fuzzy adaptive PID controller. The error value is controlled within a reasonable range.

This paper use the Gaussian function as the membership function, \( E, EC, KP, KI \) and \( KD \) mean linguistic variables, and the membership function curve of the variable is shown in Figure 2.

![Figure 1. Predictive control simulation model.](image1)

![Figure 2. Membership function curves of system variables.](image2)

(a) \( E \) and \( EC \) membership function curve (b) \( KP, KI \) and \( KD \) membership function curve

The control rules are incorporated into the rule editor in fuzzy toolbox, which is shown in Figure 3.
4. Simulation analysis

4.1. Cruise condition

The driver can set the target speed at any time. The simulation time is 15s, and the target vehicle speed is 40km/h. Simulate through predictive control and adaptive fuzzy control algorithm respectively to achieve cruise. The simulation result is shown in Figure 4.

![Figure 4. Simulation response curve on cruise condition.](image)

(a) Speed response curve  (b) Acceleration response curve

For the predictive control, the beginning acceleration is 2m/s$^2$, close to target speed at 6s. The acceleration is reduced to a negative value about -0.6m/s$^2$ when the target speed is reached. The acceleration is slowly increased until the vehicle speed reaches the target speed again, then the acceleration is zero, that is, after 8s, the host vehicle ups to 40km/h stable speed.

For adaptive fuzzy control, start acceleration is gradually increasing, and maximum acceleration is more than 2m/s$^2$. The acceleration suddenly reduces to about 1m/s$^2$ and continues to increase 2m/s$^2$, and reaches to the target speed at less than 6s. The acceleration quickly reduces to a negative value of about -0.2m/s$^2$, then speed is more than the target speed, acceleration gradually increases and the speed decreases. When closes to 15s, the host reaches a stable driving state.

Both control can make the host vehicle reach to the target speed and keep a stable speed. Relative to the adaptive control, vehicle speed response curve with the predictive control rise time from the beginning to the first arrival of the steady state value is longer, overshoot is smaller, and adjustment time is shorter. Acceleration response curve is always controlled within the limited range, the adjustment time is shorter, and the stability is better.

4.2. Follow condition

Assuming that the initial vehicle speed is 20km/h, the initial distance is 20m, and the acceleration of the target vehicle is the sine function with the amplitude of 0.2 and the period of 10. The simulation time is 80s, and simulation result is shown in Figure 5.
Figure 5. Simulation response curve on frequent change follow condition.

About 2s the host reaches the steady state, the both initial vehicle speed is the same, and the spacing error is negative. The host ups to the minimum acceleration -1.55m/s$^2$. When spacing distance reaches the desired distance at the first time, and the host speed is less than the target speed. Then the host accelerates at the maximum acceleration 0.75m /s$^2$, and spacing error is positive. About 1s the host reaches to the target speed. Then the speed continues to increase, about 1.5s, again to achieve the desired distance, that the host completes the distance adjustment. After that the host speed and acceleration follow the target vehicle speed and acceleration with a lag time of about 2s. Predictive control can quickly adjust the vehicle distance and keep the vehicle distance at the expected value and follow the target vehicle.

Assuming the host and the target initial speed is 40km/h, the initial spacing distance is 45m, the host speed is 50km/h, and there is no feedback signal at 10s. The simulation time is 20s, and simulation result is shown in Figure 6.
As the actual initial spacing distance is larger than the desired headway, the expected acceleration is 2m/s². The actual acceleration is gradually increasing, and spacing error decreases. About 0.6s when the vehicle speed reaches to the maximum, and exceeds the target vehicle speed, the host vehicle enters into a deceleration phase. When the spacing error is zero, the acceleration change is stable. About 8s the host reaches the target vehicle speed and enters into a cruise state. When the time is 10s, the target vehicle suddenly disappears, radar does not have speed, acceleration, and distance feedback signals, so the host begins to adjust speed to reach the driver setting speed and then continues to drive at the constant speed. After the target is left, there is no information feedback, so the system default spacing distance has reached absolute safety. Because there is a set speed as a new target, the host adjusts speed as soon as possible, and get into a new steady state.

5. Conclusion
The simulation results show that the predictive control can respond quickly and accurately under the cruise and follow-up conditions. Taking the driving distance as the primary optimization target, it can meet speed, acceleration and driving distance requirements at the same time, and suit for multi-variable and multi-target system control. In addition to the selected conditions in this paper, there are other conditions, such as vehicle insertion and parking conditions. Conditions are different, but the control objectives and methods are the same, so the initial conditions can be changed to achieve simulation.

References
[1] Zhang T P, Ge S S 2008 Adaptive Dynamic Surface Control of Nonlinear Systems with Unknown Dead Zone in Pure Feedback Form J. Automatica. 44 1895
[2] Behrang A, Ardalan V 2011 Predictive Cruise Control: Utilizing Upcoming Traffic Signal Information for Improving Fuel Economy and Reducing Trip Time J. IEEE Trans. Control System Technology. 19 707
[3] V Milanês, S E Shladover, J Spring, C Nowakowski, H Kawazoe, and M Nakamura 2014 Cooperative Adaptive Cruise Control in Real Traffic Situations J. IEEE Trans. Intelligent Transportation Systems. 15 296
[4] Martinez JJ, Canudas de WitC 2007 A Safe Longitudinal Control for Adaptive Cruise Control and Stop-and-go Scenarios J. IEEE Trans. Intelligent Transportation Systems. 15 246
[5] Yang C G, Ge S S, Lee T 2009 Output Feedback Adaptive Control of a Class of Nonlinear Discrete-time Systems with Unknown Control Directions J. Automatica. 45 270
[6] M Bichi, G Ripaccioli, SD Cairano, and D Bernardini 2010 Stochastic Model Predictive Control with Driver Behavior Learning for Improved Powertrain Control J. IEEE Conference. Decision and Control. 49 6077
[7] Behnam, G Abbas, Z Sui, Y K, and Mojtaba S 2014 Adaptive Cruise Control of a HEV Using Sliding Mode Control J. Expert Systems with Applications. 41 607
[8] M Vajedi, N L Azad 2016 Ecological Adaptive Cruise Controller for Plug-Inhybrid Electric Vehicles Using Nonlinear Model Predictive Control J. IEEE Trans. Intelligent Transportation Systems. 17 113
[9] Lee S H, Lee Y O, Kim B A, CC Chung 2012 Proximate Model Predictive Control Strategy for Autonomous Vehicle Lateral Control J. IEEE. American Control Conference. 3065
[10] Yang W, Boyd S 2010 Fast Model Predictive Control Using Online Optimization J. IEEE Trans. Control Systems Technology. 18 267
[11] Kim M G, Tomizuka M, Cheng K H 2012 Smooth Motion Control of the Adaptive Cruise Control System by a Virtual Lead Vehicle J. International Journal of Automotive Technology. 13 77