Robust control of vehicle multi-target adaptive cruise based on model prediction

Zibao Zhou¹, Juping Zhu², Yuansheng Li³

¹Automotive Engineering College, Wuhu Vocational and Technical College, Wuhu 241000, People’s Republic of China
²Department of Automation, University of Science and Technology, Hefei, People’s Republic of China
³College of Information and Communication, National University of Defense Technology, Xi’an 710106, People’s Republic of China

E-mail: luguo_qf@163.com

Abstract: On the issue of low utilisation and acceptance of current adaptive cruise control (ACC), a multi-objective adaptive cruise control (MO-ACC) algorithm is developed in this study. Based on model predictive control theory, comprehensively considering the coordination among various conflicting objectives, the decision of desired longitudinal acceleration is transformed into online quadratic programming (QP) problem. In order to compensate for prediction error caused by modelling mismatch, the robustness of control system is improved by introducing an error feedback correction mechanism. Meanwhile, vector management method is adopted to deal with the non-feasible solution owing to hard constraints during the process of optimisation. Further, under different working conditions, the focusing performance index along with constraint space varies, and therefore different ACC modes are established to meet the demand of skilled driving groups by means of slightly adjusting performance index, constraint space as well as slack relaxation. The simulations show that under the combined work conditions of the preceding vehicle, the following vehicle can realise seamless switching among various working modes, and also is able to achieve the good expectation during vehicle following, which will help to enhance the adaptability of the ACC system to the complex road traffic environment.

1 Introduction

As an advanced driving assistance system (ADAS), adaptive cruise control (ACC) aims at alleviating driving fatigue and improving driving comfort and safety. In recent years, the research on ACC has been diversified, such as full speed ACC [1], cooperative ACC for improving traffic flow [2–4], ACC and lane change assistance (LCA) [5], simulated driver following behaviour characteristic ACC [6, 7], ACC for driving comfort [8], ACC for fuel economy [9–12], ACC of trade-off with multi-performance indicators [13], and so on. In order to further improve the user utilisation of ACC and the acceptance of drivers, the research on humanised ACC has attracted wide attention [6, 7, 14, 15, 16].

In this paper, a multi-objective adaptive cruise control (MO-ACC) algorithm is developed. By using advanced modern control theory, the humanised design problem of ACC is transformed into the design problem of the control algorithm and control strategy. Based on model predictive control (MPC) theory, there are four control objectives that conflict with each other: dynamic traceability, fuel economy, driving comfort, and vehicle-following safety; feedback correction mechanism is introduced to improve the robustness of the control algorithm, and the relaxation vector method is used to extend solving the feasible region to avoid the quadratic programming (QP) infeasible solution problem caused by hard constraints. Furthermore, steady-state following condition, transient accelerating condition, transient accelerating condition, and combined following conditions are designed. By adjusting the weights of micro-calibration performance indicators and the constraints and relaxations of rolling optimisation to solve the feasible region, ACC is divided into three working modes to enhance the adaptability of the closed-loop control system to complex road traffic environment, thereby improving the acceptance of mass-produced ACC by drivers.

The main contributions of this paper are summarised as follows: (i) a MO-ACC algorithm is developed, where the quadratic performance index and linear inequality constraints are used to transform the decision-making problem of longitudinal expected acceleration into the online QP problem with constraints. (ii) The error correction term is introduced, and a closed-loop feedback correction mechanism is established. Therefore, the robustness of the MPC algorithm is improved. (iii) Three ACC modes are designed to guarantee that the habit of the skilled driving group is satisfied.

This paper is organised as follows. Section 2 describes ACC longitudinal kinematics modelling. Section 3 designs MO-ACC robust control algorithm based on MPC. Section 4 illustrates adaptation strategy of following working condition. In Section 5, experiment and results analysis are presented, Section 6 concludes this paper.

2 ACC longitudinal kinematics modelling

ACC system design mainly adopts layering design [13], and the decision-making level determines the longitudinal expected acceleration of the self-driving vehicle according to the parameters of the self-driving state, the front-driving state, and the environment, by controlling throttle opening, braking depth, and gear switching, the actual acceleration of the vehicle converges to the expected acceleration of the output of the decision-making layer, and its ideal first-order system transfer function satisfies the following formula:

\[ G(s) = \frac{K_L}{T_L \cdot s + T_L} \]  

(1)

where \( K_L \) is the ideal first-order system gain and \( T_L \) is the time constant of the lower controller.

This paper focuses on how to design and implement the upper control strategy. As shown in Fig. 1, the kinematics characteristics of ACC longitudinal vehicle following are defined as
The discrete state-space equation is obtained as

\[
\begin{align*}
\Delta d &= d - d_{des} \\
\Delta v &= v_p - v_f \\
\Delta v &= a_p - a_f \\
\text{jerk} &= a_{f,des} \\
a_f(k+1) &= a_f(k) + a_f(k)T_s = [1 - T_s/T_L]a_f(k) + K_fT_f/T_la_{f,des}(k)
\end{align*}
\]

where \(\Delta d\) is the expected distance error, \(d\) is the actual distance, \(d_{des}\) is the expected distance, \(\Delta v\) is the relative speed, \(v_p\) is the front speed, \(v_f\) is the self-driving speed, jerk is the impact of the self-driving, \(a_f\) is the actual acceleration of the self-driving, and \(a_{f,des}\) is the expected acceleration of the self-driving.

The fixed-time-distance strategy will be adopted for the expected distance in the paper [17], as follows:

\[
d_{des} = (a_f\Delta v + d_{\text{des}})
\]

where \(a_f\) is a fixed time interval and \(d_{\text{des}}\) is the limit safe distance.

Make \(x_f(k) = [\Delta d(k) \; \Delta v(k) \; a_f(k)]^T\), taking \(x_f(k)\) as the state variable, \(u(k)\) as the control variable, \(a_f(k)\) as the disturbance of the system, \(y(k)\) as the output of the system and sampling period as \(T_s\), and the discrete state-space equation is obtained as

\[
\begin{aligned}
x_f(k+1) &= A x_f(k) + B u(k) + G p(k) \\
y(k) &= C x_f(k)
\end{aligned}
\]

where \(u(k) = a_{f,des}(k)\), \(p(k) = a_f(k)\), and each coefficient matrix satisfies as follows:

\[
A = \begin{bmatrix}
1 & T_s & -a_f T_s \\
0 & 1 & -T_s \\
0 & 0 & 1 - T_s/T_L \\
0 & 1 & -T_f/T_L
\end{bmatrix},
B = \begin{bmatrix}
0 \\
0 \\
0 - T_s/K_f/\Delta a
\end{bmatrix},
C = \begin{bmatrix}
1 & 0 & 0 \\
0 & 1 & 0 \\
0 & 0 & 1
\end{bmatrix},
G = \begin{bmatrix}
0 \\
T_s \\
0
\end{bmatrix}
\]

Further, assuming that the current time is \(k\), and the predicted time domain is \([k, k+p-1]\), the following can be obtained by iterating step by step from (4)

\[
\begin{pmatrix}
x_f(k+1) \\
x_f(k+2) \\
\vdots \\
x_f(k+p)
\end{pmatrix} = A^p
\begin{pmatrix}
x_f(k) \\
\vdots \\
x_f(k)
\end{pmatrix} +
\begin{pmatrix}
B & 0 & \cdots & 0 \\
AB & B & \cdots & 0 \\
\vdots & \vdots & \ddots & \vdots \\
A^{p-1}B & A^{p-2}B & \cdots & B
\end{pmatrix}
\begin{pmatrix}
A_{f,des}(k) \\
\vdots \\
A_{f,des}(k+p-1)
\end{pmatrix} +
\begin{pmatrix}
G & 0 & \cdots & 0 \\
AG & G & \cdots & 0 \\
\vdots & \vdots & \ddots & \vdots \\
A^{p-1}G & A^{p-2}G & \cdots & G
\end{pmatrix}
\begin{pmatrix}
p(k) \\
p(k+1) \\
\vdots \\
p(k+p-1)
\end{pmatrix}
\]

The matrix representation of the above iteration equations is (see (5)) . Shorthand for

\[
\begin{aligned}
X_f &= A_p x_f(k) + B_p U + G_p p \\
Y &= C_p X_f
\end{aligned}
\]

In the formula

\[
X_f = \begin{bmatrix}
x_f(k+1) \\
x_f(k+2) \\
\vdots \\
x_f(k+p)
\end{bmatrix},
U = \begin{bmatrix}
a_{f,des}(k) \\
a_{f,des}(k+1) \\
\vdots \\
a_{f,des}(k+p-1)
\end{bmatrix}
\]

is the state sequence in the prediction time domain

\[
A_p = \begin{bmatrix}
A \\
A^2 \\
\vdots \\
A^p
\end{bmatrix},
B_p = \begin{bmatrix}
B & 0 & \cdots & 0 \\
AB & B & \cdots & 0 \\
\vdots & \vdots & \ddots & \vdots \\
A^{p-1}B & A^{p-2}B & \cdots & B
\end{bmatrix},
G_p = \begin{bmatrix}
G & 0 & \cdots & 0 \\
AG & G & \cdots & 0 \\
\vdots & \vdots & \ddots & \vdots \\
A^{p-1}G & A^{p-2}G & \cdots & G
\end{bmatrix}
\]

is a control sequence in the predictive time domain, \(x_f(k)\) is the current observation state

\[
C_p = \text{diag}(C, C, \ldots, C)
\]

is the corresponding coefficient matrix, \(Y\) is the output sequence of the system.

Cogn. Comput. Syst., 2020, Vol. 2 Iss. 4, pp. 254-261

This is an open access article published by the IET in partnership with Shenzhen University under the Creative Commons Attribution License (http://creativecommons.org/licenses/by/3.0/)
3 MO-ACC robust control algorithm based on MPC

3.1 ACC control target analysis

On the premise of ensuring driving safety, quadratic performance index and linear inequality constraints are adopted to synthetically coordinate the control objectives of ACC dynamic tracking performance, fuel economy performance, and ride comfort performance, and the decision-making problem of the expected longitudinal acceleration is transformed into the QP problem of online QP with the following constraints [13].

(i) Dynamic tracking performance indicators

Longitudinal vehicle-following dynamic tracking performance evaluation objectives are [18, 19]: expected distance error and relative speed convergence. The quadratic form of dynamic tracking performance is expressed as

$$J_T = a_{\Delta d} \Delta d^2 + a_{\Delta v} \Delta v^2$$  \hspace{1cm} (7)

where the expected distance error

$$\Delta d = d - d_{des} = (s_p + d_i - s_j) - (s_p + d_i)$$

is the initial distance, \(s_p\) is the front displacement, \(a_{\Delta d}\) and \(a_{\Delta v}\) are weight coefficients of expected distance error and relative speed, respectively.

The constraints of linear inequalities are as follows:

$$\begin{align*}
\Delta d_{\min} &\leq \Delta d \leq \Delta d_{\max} \\
\Delta v_{\min} &\leq \Delta v \leq \Delta v_{\max}
\end{align*}$$  \hspace{1cm} (8)

(ii) Fuel economic performance index

Fuel economic performance evaluation objectives are [20, 21]: expected acceleration convergence and impact convergence. The quadratic form of fuel economy performance is expressed as

$$J_F = a_{\Delta a} \Delta a^2 + a_{\text{Jerk}} \text{Jerk}^2$$  \hspace{1cm} (9)

where \(a_{\Delta a}\) and \(a_{\text{Jerk}}\) are weight coefficients of expected acceleration and impact, respectively.

Linear inequality constraints are as follows:

$$\begin{align*}
a_{\text{f,des}} &\leq a_{\text{f,des}} \leq a_{\text{f,des}} \\
\text{Jerk}_{\min} &\leq \text{Jerk} \leq \text{Jerk}_{\max}
\end{align*}$$  \hspace{1cm} (10)

(iii) Driving comfort performance index

Good driving experience evaluation objectives are [13]: expected distance error convergence, expected acceleration and impact convergence, and active driver intervention (such as throttle control or brake pedal) to converge tracking error. Furthermore, the quadratic form of ride comfort performance represents the following formula:

$$J_C = a_{\Delta d} \Delta d^2 + (a_{\Delta a} \Delta a_{\text{des}}^2 + a_{\text{Jerk}} \text{Jerk}^2) + a_{\text{f,ref}} (a_{\text{f,ref}} - a_{\text{f,des}})^2.$$.  \hspace{1cm} (11)

Since the first and second terms in the formulas above are already reflected in formulas (7) and (9), the quadratic expression of formula (11) is approximated to the following formula:

$$J_C \approx a_{\text{f,ref}} (a_{\text{f,ref}} - a_{\text{f,des}})^2$$  \hspace{1cm} (12)

where \(a_{\text{f,ref}}\) is the corresponding weight coefficient and \(a_{\text{f,ref}} = k_d \Delta v + k_a \Delta d\) is the driver's reference acceleration [22].

Linear inequality constraints are

$$\begin{align*}
a_{\text{f,des}} &\leq a_{\text{f,des}} \leq a_{\text{f,des}} \\
\text{Jerk}_{\min} &\leq \text{Jerk} \leq \text{Jerk}_{\max}
\end{align*}$$  \hspace{1cm} (13)

(iv) Hard constraint conditions for vehicle-following safety

$$d \geq d_{safe} = \max \{t_{TTC} \Delta v, d_i\}$$  \hspace{1cm} (14)

where the collision time \(t_{TTC}\) is used to indicate the safety of the braking process [23], \(d\) is the actual distance, \(d_{safe}\) is the safe following distance, and \(d_i\) is the limit safe distance.

To sum up, the matrix MO-ACC cost function with a prediction time domain of \([K, K + P - 1]\) is established as follows:

$$J = \sum_{i=1}^{p} \left( w_{\Delta d} \Delta d^2 + w_{\Delta v} \Delta v^2 \right) + \sum_{i=0}^{p-1} \left[ w_{\text{f,des}} (k+i) + w_{\text{a}} (a_{\text{f,des}} (k+i) \right]$$

$$- a_{\text{f,des}} (k+i) \right]^2 \left/ t_i^2 \right] + \sum_{i=0}^{p} \left[ w_{\text{des}} (k_i d + k_i \Delta v - a_j)^2 \right]$$

$$= X^T W X_f + U^T R U.$$

In the formula, \( W = W_j + W_c \); \( W_j = \text{diag}(\omega_1, \omega_2, ..., \omega_n) \);

$$W_c = \text{diag}(\omega_{a1}, \omega_{a2}, ..., \omega_{ao})$$

where \(\omega_{ao}\) are weight coefficients of expected distance error and relative speed, respectively.

The constraints of linear inequalities are as follows:

$$\begin{align*}
\Delta d_{\min} &\leq \Delta d \leq \Delta d_{\max} \\
\Delta v_{\min} &\leq \Delta v \leq \Delta v_{\max}
\end{align*}$$  \hspace{1cm} (8)

$$\begin{align*}
\omega \leq \alpha_{\Delta d} \omega_0, \omega_0 \leq \omega_{\Delta v} \omega_0, \omega_k \leq \omega_{\text{f,des}} \omega_k
\end{align*}$$

$$U = [a_{\text{f,des}} (k) \ a_{\text{f,des}} (k + i) \ ... \ a_{\text{f,des}} (k + P - 1)]^T.$$

$$R = \begin{bmatrix}
w_d & -w_j & \ldots & 0 & 0 \\
-w_j & w_d & \ldots & 0 & 0 \\
\vdots & \vdots & \ddots & \vdots & \vdots \\
0 & 0 & \ldots & w_d & -w_j \\
0 & 0 & \ldots & -w_j & w_d
\end{bmatrix}_{P \times P}$$

Substitute Formula (6) into Formula (15), and get

$$J = X^T W X_f + U^T R U.$$

$$= U^T (B_f W B_f + R) U + 2(\lambda^T (k) A_p)^T + \Phi^T (G_f W B_f U).$$

The system I/O constraints established by Formula (8), Formula (10), and Formula (13) are as follows:

$$u_{\Delta d} \leq u(k + 1) \leq u_{\Delta d}$$

$$\text{Jerk}_{\min} \leq \text{Jerk} (k + i) \leq \text{Jerk}_{\max}, \text{ } \in [0, p-1]$$

$$y_{\min} \leq y(k + i) \leq y_{\max}.$$  \hspace{1cm} (17)

In the formula, \(k + i\) represents the prediction of \(k + i\) time based on the information of the current time \(k\), \(u_{\Delta d} = a_{\Delta d,\max}\); \(\text{Jerk}_{\min} = a_{\text{Jerk},\min}\); \(\text{Jerk}_{\max} = a_{\text{Jerk},\max}\) is the upper bound of the control quantity, \(y_{\max} = \|A_{\text{f,des}} \|_{\max}\); \(\text{Jerk}_{\min} = \|A_{\text{Jerk}}\|_{\max}\); \(y_{\min} = [\Delta d_{\min}, \Delta v_{\min}] \) is the lower bound of control quantity, \(\text{Jerk}_{\min} = [\Delta d_{\min}, \Delta v_{\min}] \) is the lower bound of system output, \(\text{Jerk}_{\max} = [\Delta d_{\max}, \Delta v_{\max}] \) is the upper bound of system output.

The following formula is used to establish the following safety constraints from (14):

$$-qy(k + i + 1) \leq d_{safe} (k + i) - d_{safe} (k + i), \text{ } \in [0, p-1]$$  \hspace{1cm} (18)

In the formula, \(q = [1 \ 0 \ 0] \).
3.2 Design of robust vehicle-following prediction model

In order to improve the robustness of MPC algorithm, error correction term is introduced and a closed-loop feedback correction mechanism is established to compensate the prediction error caused by model mismatch, thus improving prediction accuracy and anti-jamming ability of vehicle-following prediction model [8]. Here, the error between the actual state and the predicted state of the system at k-time is defined as

\[ e(k) = x(k) - x(k|k-1) \]  

(19)

where \( x(k) \) is the actual state of the k-time system, and \( x(k|k-1) \) is the prediction of k-time state at \( k-1 \) time.

Then the discrete state-space equation (4) evolves into

\[
\begin{bmatrix}
    x_f(k+1) \\
    y(k)
\end{bmatrix} = \begin{bmatrix}
    A \lambda \Phi y(k) + Bu(k) + Gq(k) + \lambda e(k) \\
    C_{y} y(k)
\end{bmatrix} 
\]

(20)

where \( \lambda = \text{diag}(\lambda_1, \lambda_2, \lambda_3) \) is a correction matrix.

Similarly, the matrix formula of the discrete state-space equation with the predicted time domain \( k, k+p-1 \) is obtained by iteration

\[
\begin{bmatrix}
    X_f \\
    Y
\end{bmatrix} = A_p X_f(k) + B_p U + G_p \Phi + M_p e(k)
\]

(21)

In the formula

\[
M_p = \begin{bmatrix}
    \lambda & A \lambda & \vdots & A^{p-1} \lambda \\
    \end{bmatrix}_{p \times 3}
\]

3.3 Extended solution of feasible region by relaxation vector method

In MPC predictive optimisation process, hard constraints are easily used to solve the feasible region constrained and infeasible solutions. For this reason, relaxation vector method is introduced to solve infeasible solutions [8, 12, 24, 25]. The relaxation vector factor is used to relax the hard constraint condition to expand the feasible region of the solution, and then ensure the existence of the feasible solution.

In order to ensure the vehicle-following safety and avoid the rear end phenomenon, \((18)\) is the hard constraint condition of the vehicle-following safety; just relax the constraint conditions of \((17)\) and get

\[
\begin{align*}
    u_{\text{min}} + \epsilon_{\text{max}} u_{\text{max}} & \leq u(k+i|k) \leq u_{\text{max}} + \epsilon_{\text{max}} u_{\text{max}} \\
    \text{jerk}_{\text{max}} + \epsilon_{\text{max}} \nu_{\text{max}} & \leq \text{jerk}(k+i|k) \leq \text{jerk}_{\text{max}} + \epsilon_{\text{max}} \nu_{\text{max}}, \quad i \in \{0, p-1\} \\
    y_{\text{min}} + \epsilon_{\text{max}} y_{\text{max}} & \leq y(k+i|k) \leq y_{\text{max}} + \epsilon_{\text{max}} y_{\text{max}}.
\end{align*}
\]

(22)

In the formula, the relaxation factors \( \epsilon_i \geq 0, \epsilon_j \geq 0, \epsilon_k \geq 0, \nu_{\text{min}}, \nu_{\text{max}}, \nu_{\text{max}}^{\text{r}}, \nu_{\text{max}}^{\text{r}}, \nu_{\text{max}}^{\text{r}} \), respectively, are the relaxation coefficients of the lower and upper bounds of the hard constraints and satisfy the \( \nu_{\text{min}} \leq 0, \nu_{\text{min}} \leq 0, \nu_{\text{max}} \geq 0, \nu_{\text{max}} \geq 0 \).

3.4 Final evolution of MO-ACC control algorithm

In order to avoid the infinite increase of relaxation factor which leads to the limitation of enforcement inequality on I/O of the system, a quadratic penalty term \( \epsilon^T p e \) is added to the cost function to punish the relaxation factor to expand the relaxation degree of the constraint boundary, and then a balance is sought between the feasibility of solving the hard constraint problem and the relaxation degree of the constraint boundary.

Furthermore, by combining (15) and (21), the matrix MO-ACC cost function with prediction time domain of \([K, K + P - 1]\) is derived as

\[
J(y, u, \text{jerk}, \epsilon) = J + \epsilon^T p e
\]

\[
= X_f^T W X_f + U^T R U + \epsilon^T p e
\]

\[
= \begin{bmatrix} U \\ \epsilon \end{bmatrix}^T \begin{bmatrix}
    B_p W B_p + R & 0 \\
    0 & \rho
\end{bmatrix} \begin{bmatrix} U \\ \epsilon \end{bmatrix} + 2 \{ (x_f^T(k) A_p^T + \epsilon^T(k) M_p^T + \Phi^T G_p^T W B_p) U \}_e
\]

\[
= \tilde{U}^T \tilde{H} \tilde{U} + 2 \tilde{J} \tilde{U}.
\]

(23)

Compared with (16), (23) introduces relaxation vector and error correction term to ensure that the model predictive optimisation problem can be solved within the constraints and improve the robustness of the algorithm.

Thus, the design problem of MO-ACC algorithm is finally transformed into an online QP problem with constraints, that is

\[
\begin{aligned}
\min \{ \tilde{U}^T \tilde{H} \tilde{U} + 2 \tilde{J} \tilde{U} \} \\
\text{s. t.} \quad \Omega \tilde{U} \leq T.
\end{aligned}
\]

(24)

In the formula

\[
H = \begin{bmatrix}
    B_p^T W B_p + R & 0 \\
    0 & \rho
\end{bmatrix}_{(p+3)(p+3)}
\]

\[
f = \begin{bmatrix} (x_f^T(k) A_p^T + \epsilon^T(k) M_p^T + \Phi^T G_p^T W B_p) U \end{bmatrix}_e
\]

\[
\tilde{U} = \begin{bmatrix} U \\ \epsilon \end{bmatrix}_{(p+3)(1)}, \quad \epsilon = \begin{bmatrix} \epsilon_1, \epsilon_2, \epsilon_3 \end{bmatrix}^T, \quad \rho = \text{diag}(\rho_1, \rho_2, \rho_3).
\]

\[
\Omega = \begin{bmatrix}
    E & -\nu_{\text{max}} & 0 & 0 \\
    -E & \nu_{\text{max}} & 0 & 0 \\
    \nu_{\text{max}} & 0 & -\nu_{\text{max}} & 0 \\
    \nu_{\text{min}} & 0 & \nu_{\text{min}} & 0 \\
    C_p B_p & 0 & 0 & -V_{\text{max}} \\
    -C_p B_p & 0 & 0 & V_{\text{max}} \\
    -Q_p C_p B_p & 0 & 0 & 0
\end{bmatrix}_{(p+3)(p+3)}
\]
In the process of online QP secondary planning, when \( u, \text{jerk}, y \) do not exceed the hard constraint boundary, the relaxation factor is 0, while when \( u, \text{jerk}, y \) exceed the hard constraint boundary, the rolling optimisation solution will automatically increase the relaxation factor in a positive direction, so as to expand the feasible region of the solution and ensure the existence of the optimal solution \( u(k + i) \).

Specifically, at each sampling time, ACC system uses (24) to obtain the optimal control input and relaxation factor sequence \( \tilde{U} = [u(k), u(k + 1), \ldots u(k + p - 1), \nu_i, \nu_j, \nu_i] \) according to the status information of the current vehicle and the front vehicle, then the first component \( u(k) \) in \( \tilde{U} \) is selected as the optimal input of ACC control layer. In the next sampling time, the above process is repeated to realise the rolling online control of MO-ACC.

### 4 Adaptation strategy of following working condition

Under the premise of ensuring driving safety, ACC itself is a comfort system, so in the decision-making algorithm design, it is necessary to consider the comfort index to improve the utilisation rate of drivers and passengers [6]. Specifically, frequent acceleration and deceleration will lead to mechanical wear of auto-parts, shorten the service life of parts, and reduce driving comfort and fuel economy. The excessive and rapid convergence of expected distance error \( \Delta d \) will result in large overshoot, especially at low speed, which may lead to rear-end collision. A reasonable restriction on the absolute value of \( \Delta d \) can not only ensure the safety of vehicle following, but also avoid the frequent entry of adjacent vehicles [6]. Further, with the increase of working condition urgency, the constraints on expected control \( a_r, d_r(k) \) and jerk become wider, that is, the requirements on comfort and economy are reduced, while the expected constraints on distance error \( \Delta d \) and relative speed \( \Delta v \) are narrowed, that is, the requirements on safety are improved [7].

In the paper of the Sultan of the University of Southampton, the evaluation method of steady-state condition is given [26]: vehicle acceleration \( a \in [-0.6, 0.6] \text{m/s}^2 \). Based on this, this paper designs steady-state follow-up conditions, transient quick acceleration condition, transient quick deceleration condition, and combined follow-up condition. See Table 1 for the division rules and corresponding working modes of the first three types of working conditions.

As shown in Fig. 2, 0 is normal driving restraint space, 1 is steady-state following constraint space, 2 is constraint space of transient acceleration, 3 is constraint space of transient rapid deceleration. The linear inequality group in (24) defines the constraint space \( R \) when driving normally. The strengthened performance index and constraint space are different under different working conditions, according to the weight of micro-calibration performance index and the constraint bound and relaxation of rolling optimisation to solve the feasible region, ACC can be divided into three working modes to meet the following habits of skilled driving groups, and then improve the use rate and acceptance of mass production ACC.

### 5 Experiment and results analysis

This paper uses Matlab/Simulink to build MO-ACC vehicle distance control model, inverse longitudinal dynamics model, and vehicle dynamics model. Some simulation parameters are shown in Table 2.

The ACC with only steady-state following mode is called single-mode ACC, and in order to verify the adaptability of the algorithm and control strategy to complex working conditions, the performance of the algorithm is compared with the performance of single-mode ACC.

#### 5.1 Steady-state following condition

The front vehicle maintains a slow cycle condition with an acceleration of \( \pm 0.3 \text{m/s}^2 \). The initial speed of both the self-vehicle and the front vehicle is 20 m/s. The constraint boundary and relaxation degree of ACC operation under the steady-state following condition are shown in Table 3, and the simulation results are shown in Fig. 3.
Table 3 Constraint bound and relaxation degree of ACC in the steady-state following mode

| Constraint bound | Relaxation degree |
|------------------|-------------------|
| $\Delta d_{\text{min}}$ | 5 $\delta d_{\text{min}}$ | 3 $\gamma d_{\text{min}}$ |
| $\Delta d_{\text{max}}$ | -5 $\delta d_{\text{max}}$ | -3 $\gamma d_{\text{max}}$ |
| $\Delta v_{\text{min}}$ | 0.9 $\delta v_{\text{min}}$ | 1 $\gamma v_{\text{min}}$ |
| $\Delta v_{\text{max}}$ | -1 $\delta v_{\text{max}}$ | -1 $\gamma v_{\text{max}}$ |
| $u_{\text{max}}$ | 0.75 $\delta u_{\text{max}}$ | 0.1 $\gamma u_{\text{max}}$ |
| $u_{\text{min}}$ | -0.1 $\delta u_{\text{min}}$ | -0.1 $\gamma u_{\text{min}}$ |
| $v_{\text{max}}$ | 0.05 $\delta v_{\text{max}}$ | -0.05 $\gamma v_{\text{max}}$ |

Table 4 Constraint bound and relaxation degree of ACC in transient quick acceleration mode

| Constraint bound | Relaxation degree |
|------------------|-------------------|
| $\Delta d_{\text{min}}$ | 5 $\delta d_{\text{min}}$ | 3 $\gamma d_{\text{min}}$ |
| $\Delta d_{\text{max}}$ | -5 $\delta d_{\text{max}}$ | -3 $\gamma d_{\text{max}}$ |
| $\Delta v_{\text{min}}$ | 0.9 $\delta v_{\text{min}}$ | 1 $\gamma v_{\text{min}}$ |
| $\Delta v_{\text{max}}$ | -1 $\delta v_{\text{max}}$ | -1 $\gamma v_{\text{max}}$ |
| $u_{\text{max}}$ | 0.75 $\delta u_{\text{max}}$ | 0.1 $\gamma u_{\text{max}}$ |
| $u_{\text{min}}$ | -0.1 $\delta u_{\text{min}}$ | -0.1 $\gamma u_{\text{min}}$ |
| $v_{\text{max}}$ | 0.05 $\delta v_{\text{max}}$ | -0.05 $\gamma v_{\text{max}}$ |

Table 5 Constraint bound and relaxation degree of ACC in transient quick deceleration mode

| Constraint bound | Relaxation degree |
|------------------|-------------------|
| $\Delta d_{\text{min}}$ | 5 $\delta d_{\text{min}}$ | 3 $\gamma d_{\text{min}}$ |
| $\Delta d_{\text{max}}$ | -3 $\delta d_{\text{max}}$ | -1 $\gamma d_{\text{max}}$ |
| $\Delta v_{\text{min}}$ | 0.9 $\delta v_{\text{min}}$ | 1 $\gamma v_{\text{min}}$ |
| $\Delta v_{\text{max}}$ | -1 $\delta v_{\text{max}}$ | -1 $\gamma v_{\text{max}}$ |
| $u_{\text{max}}$ | 0.1 $\delta u_{\text{max}}$ | 0.01 $\gamma u_{\text{max}}$ |
| $u_{\text{min}}$ | -3.0 $\delta u_{\text{min}}$ | -0.1 $\gamma u_{\text{min}}$ |
| $v_{\text{max}}$ | 0.01 $\delta v_{\text{max}}$ | -0.05 $\gamma v_{\text{max}}$ |

Under the steady-state condition of the front vehicle, ACC works in the steady-state following mode. As shown in Fig. 3, in this mode, the expected distance error $\Delta d$, relative speed, and self-acceleration all converge in the neighbourhood of the balance point, so as to achieve stable vehicle following and comfortable driving.

5.2 Transient quick acceleration condition

The front vehicle accelerates rapidly to 20 m/s at an acceleration of 1 m/s$^2$ at 10 s, and the initial speed of both the self-vehicle and the front vehicle is 10 m/s. See Table 4 for the constraint boundary and relaxation degree of ACC operation under transient rapid acceleration, and the simulation results are shown in Fig. 4.

ACC operates in the transient quick acceleration mode under the condition of the fast acceleration of the front vehicle. As shown in Fig. 4a, the expected distance error $\Delta d$ slightly exceeds the upper bound of the constraint during the period of rapid acceleration of the front vehicle. Due to the automatic adjustment of the relaxation factor in the cost function, the constraint boundary is extended, so that the rolling optimisation has a feasible solution. In consideration of the comfort and fuel economy of driving and occupying, the acceleration of the front vehicle is accelerated at a relatively suitable impact speed. During the acceleration process, the $\Delta d$ will exceed the upper bound of the constraint for a short time and then quickly converge to the neighbourhood of the equilibrium point.

5.3 Transient quick deceleration condition

The front vehicle decelerates rapidly to 10 m/s at a deceleration degree of $-2$ m/s$^2$ at 10 s. The initial speed of the self-vehicle and the front vehicle is 20 m/s. The constraint boundary and relaxation degree of ACC operation under the transient deceleration condition are shown in Table 5, and the simulation results are shown in Fig. 5.

Under the condition of the front vehicle's rapid deceleration, ACC operates in the mode of transient rapid deceleration. Different from the condition of rapid acceleration, when the front vehicle decelerates rapidly, the self-propelled vehicle shall be able to respond quickly to ensure the safe distance between vehicles. At the same time, the constraint on the expected vehicle...
distance error $\Delta d$ is relatively narrow, especially for the negative boundary of $\Delta d$, so as to prevent the rear end phenomenon caused by the vehicle following too close. As shown in Fig. 5a, this mode has a smaller fluctuation of the expected vehicle distance error $\Delta d$ and can achieve safe and stable vehicle following, and under this working condition, single-mode ACC is obviously insufficient in braking and prone to rear-end collision.

Safety is the first priority in the case of rapid deceleration. In this case, self-vehicle decelerates at a large deceleration, which will bring pressure on the vehicle-following scenario and can achieve safe and stable vehicle following, and under this condition, single-mode ACC is obviously insufficient in braking and prone to rear-end collision.

Safety is the first priority in the case of rapid deceleration. In this case, self-vehicle decelerates at a large deceleration, which will produce a large impact in an instant.

5.4 Combined following condition

The driving conditions of the front vehicle are: uniform speed condition $\rightarrow$ rapid acceleration condition $\rightarrow$ slow cycle condition $\rightarrow$ rapid deceleration condition $\rightarrow$ uniform speed condition. The initial speed of the self-vehicle and the front vehicle are both 10 m/s, and the simulation results are shown in Fig. 6.

As shown in Fig. 6, under the combination condition of the front vehicle, the self-vehicle ACC system can realise seamless switching between various working modes and achieve good expectations and obtain good results.

6 Conclusions

In view of the problems of the user utilisation rate of ACC and the acceptance of drivers and passengers in the current market, the MO-ACC simulation platform is designed and built to analyse and verify the working performance of ACC under various working conditions. The main conclusions are as follows:

- In order to coordinate the four conflicting control objectives of ACC dynamic tracking, fuel economy, driving comfort, and vehicle-following safety, the quadratic performance index and linear inequality constraints are used to transform the decision-making problem of longitudinal expected acceleration into the online QP problem with constraints.

- In order to improve the robustness of the MPC algorithm, the error correction term is introduced, and a closed-loop feedback correction mechanism is established to compensate the prediction error caused by model mismatch, and then improve the prediction accuracy and anti-interference ability of the following prediction model. At the same time, the relaxation vector method is introduced to soften the hard constraints to expand the feasible region, so that there are feasible solutions within the linear constraints of QP problem.

- The performance indexes under different working conditions are different from the constraint space. Through the weight of the micro-school performance index and the adjustment of the constraint bounds and relaxation degree of the feasible area, three ACC modes are designed to avoid the phenomenon of single-mode acceleration or lack of braking, and then satisfy the habit of the skilled driving group.

- The simulation results show that the algorithm and condition adaptation strategy in this paper can achieve the desired purpose of vehicle following, and provide a research idea and method for improving the utilisation and acceptance of mass production ACC.

7 Acknowledgments

This work was supported by 2017 Anhui University Natural Science Key Research Project KJ2017A558 and Key Project of 2018 Excellent Young Talents Support Program in Colleges and Universities gxyqZD2018102.

8 References

[1] Gruyer, D., Pechberti, S., Glaser, S.: ‘Development of full speed range ACC with SWIC, a virtual platform for ADAS prototyping, test and evaluation’, IEEE Intelligent Vehicles Symp., Gold Coast City, Australia, 2013, pp. 100–105.

[2] Graf, P.M., Bernardini, D., Ensen, H., et al.: ‘Multi-automated vehicle coordination using decoupled prioritized path planning for multi-lane one-and bi-directional traffic flow control’, IEEE Conf. on Decision and Control, ARIA Resort & Casino, Las Vegas, NV, USA., 2016, pp. 1582–1588.

[3] Luo, L.: ‘Vehicle adaptive cruise control and the corresponding macroscopic traffic flow model’. Ph.D. dissertation, Zhejiang University, 2011.

[4] Van Arem, B., Van Driel, C.J.G., Visser, R.: ‘The impact of cooperative adaptive cruise control on traffic-flow characteristics’, IEEE Trans. Intell. Transp. Syst., 2006, 7, (4), pp. 429–436.

[5] Ding, R., Wang, J., Li, S.E., et al.: ‘Coordinated adaptive cruise control system with lane-change assistance’, IEEE Trans. Intell. Transp. Syst., 2015, 16, (5), pp. 2373–2383.

[6] Gao, Z., Yan, W., Li, H.: ‘A vehicle adaptive cruise control algorithm based on simulating driver’s multi-objective decision making’, Automobile Eng., 2015, 2015, (6), pp. 667–673.

[7] Yan, W.: ‘Study on adaptive cruise control algorithms imitating vehicle-following behaviors of drivers’. Ph.D. dissertation, Jilin University, 2016.

[8] Wu, G., Gao, X., Zhang, L.: ‘Multi-objective robust adaptive cruise control algorithm design of vehicle following mode’, J. Harbin Instit. Technol., 2016, 48, (1), pp. 80–86.

[9] Li, S.E., Peng, H., Li, K., et al.: ‘Minimum fuel control strategy in automated vehicle-following scenarios’, IEEE Trans. Veh. Technol., 2012, 61, (3), pp. 998–1007.
[10] Li, S.E.: ‘Economy-oriented vehicle adaptive cruise control with coordinating multiple objectives function’, Veh. Syst. Dyn., 2013, 51, (1), pp. 1–17

[11] Gao, H., Zhu, J., Zhang, T., et al.: ‘Situational assessment for zhihong intelligent vehicles based on stochastic model and gaussian distributions in typical traffic scenarios’, IEEE Trans. SIST MAN CY-S, 2020, DOI: 10.1109/TSMC.2020.3019512

[12] Li, S.E., Jia, Z., Li, K., et al.: ‘Fast online computation of a model predictive controller and its application to fuel economy oriented adaptive cruise control’, IEEE Trans. Intel. Transp. Syst., 2015, 16, (3), pp. 1199–1209

[13] Li, S., Li, K., Rajamani, R., et al.: ‘Model predictive multi-objective vehicular adaptive cruise control’, IEEE Trans. Control Syst. Technol., 2011, 19, (3), pp. 556–566

[14] Luo, L.: ‘Adaptive cruise control design with consideration of humans’ driving psychology’. IEEE Intelligent Control and Automation, Shenyang, China, 2014, pp. 2973–2978

[15] De Gelder, E., Care, I., Uittenbogaard, J., et al.: ‘Towards personalised automated driving: prediction of preferred ACC behaviour based on manual driving’, IEEE Intelligent Vehicles Symp., Gothenburg, Sweden, 2016, pp. 1211–1216

[16] Yi, K., Kwon, Y.D.: ‘Vehicle-to-vehicle distance and speed control using an electronic-vacuum booster’, J. SAE, 2001, 22, (4), pp. 403–412

[17] Bageshwar, V.L., Gurrard, W.L., Rajamani, R.: ‘Model predictive control of transitional maneuvers for adaptive cruise control vehicles’, IEEE Trans. Veh. Technol., 2004, 53, (5), pp. 1573–1585

[18] Zhang, J., Ioannou, P.A.: ‘Longitudinal control of heavy trucks in mixed traffic: environmental and fuel economy considerations’, IEEE Trans. Intell. Transp. Syst., 2006, 7, (1), pp. 92–104

[19] Gao, H., Li, Z., Kang, Y., et al.: ‘Adaptive fuzzy region-based control of euler-lagrange systems with kinematically singular configurations’, IEEE Trans. on Fuzzy Systems, 2020, DOI: 10.1109/TFUZZ.2020.2994991

[20] Zhang, J., Ioannou, P.A.: ‘Longitudinal control of heavy trucks in mixed traffic: environmental and fuel economy considerations’, IEEE Trans. Intell. Transp. Syst., 2006, 7, (1), pp. 92–104

[21] Boer, E., Nicholas, W., Michael, M., et al.: ‘Driver-model based assessment of behavioral adaptation’. JSAE Spring, Yokohama, Japan, 2005

[22] Zhang, L.: ‘Driver longitudinal behavior based forward collision warning system’. M.S. thesis, Dept. Automot. Eng., Tsinghua Univ., Tsinghua, China, 2006

[23] Zeilinger, M.N., Morari, M., Jones, C.N.: ‘Soft constrained model predictive control with robust stability guarantees’, IEEE Trans. Autom. Control, 2014, 59, (5), pp. 1190–1202

[24] Gao, H., Wang, J., Li, K.: ‘Trajectory prediction of cyclist based on dynamic bayesian network and long short-term memory model at unsignalized intersections’, SCIENCE CHINA: Information Sciences, 2020, DOI: 10.1007/s11432-020-3071-8

[25] Sultan, B.: ‘The study of motorway operation using a microscopic simulation model’. Ph.D. dissertation, University of Southampton, 2000