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Special Focus on Learning and Real-time Optimization of Automotive Powertrain Systems

Predictive safety control for road vehicles after a tire blowout

Fei WANG[1], Hong CHEN[1,2*], Lulu GUO[2] & Yunfeng HU[2]

[1]*State Key Laboratory of Automotive Simulation and Control, Jilin University, Changchun* 130025*, China;*
[2]*Department of Control Science and Engineering, Jilin University, Changchun* 130025*, China*

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Since driver error is considered a major cause in over 90% of all road crashes [1], driving assistance systems are widely used to improve driving safety, and are an important research direction in the intelligent vehicle field. With the rapid development of sensing, identification and communication technologies, the vehicle can obtain an increasing amount of information in real time, ranging from the vehicle status information to road information and traffic information. Therefore, the function of the driving assistance systems is gradually expanding. The application of the model predictive control theory in automobile control has received wide attention [2–5]. One of the main reasons is that it can predict the future state of the system. For an automobile's active safety control under extreme operating conditions, the safety control input can be obtained through the coordination of safety, comfort, and other indexes. Depending on the degree of risk, the weights of the indexes will be different. By comparing the safety control input with the driver input, the correctness of the human driver's action can be evaluated. Based on the evaluation results, the driving assistant system will decide whether to intervene in the movement of the vehicle. Since the safety control input is calculated by predicting the future state of the system, we call this control method the predictive safety control; a general block diagram that reflects the control idea is shown in Figure 1(a). It is an effective control method proposed for the driving assistance system under certain extreme operating conditions, for example, a tire blowout accident. In the following, we will combine the specific extreme operating condition of the tire blowout to explain how this control method can be used to design the driving assistance system. It is noteworthy that the example used in this article is only reflective of one case, and some modules have been simplified. For other cases of active safety problem, the predictive safety control diagram can be used flexibly.

Problem description. The driver has suffered a sudden tire burst while driving. The sudden change in the mechanical properties of the flat tire results in an additional yaw moment. This will pull the vehicle to the side of the flat tire. To correct the trajectory of the vehicle, the driver will take action, but some drivers often operate wrongly because of the lack of experience, leading to serious traffic accidents. Therefore, this study will design a driving assistant system with predictive safety control method to help drivers improve vehicle safety. To simplify the problem, it is assumed that (a) the road's lateral gradient and longitudinal slope are not considered; (b) the dynamics related to the vertical motion and suspensions are neglected; (c) the effects of crosswind and aerodynamics are ignored; (d) the road curvature is small; (e) a tire pressure monitoring system that

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* Corresponding author (email: chenh@jlu.edu.cn; chenh98cn@hotmail.com)

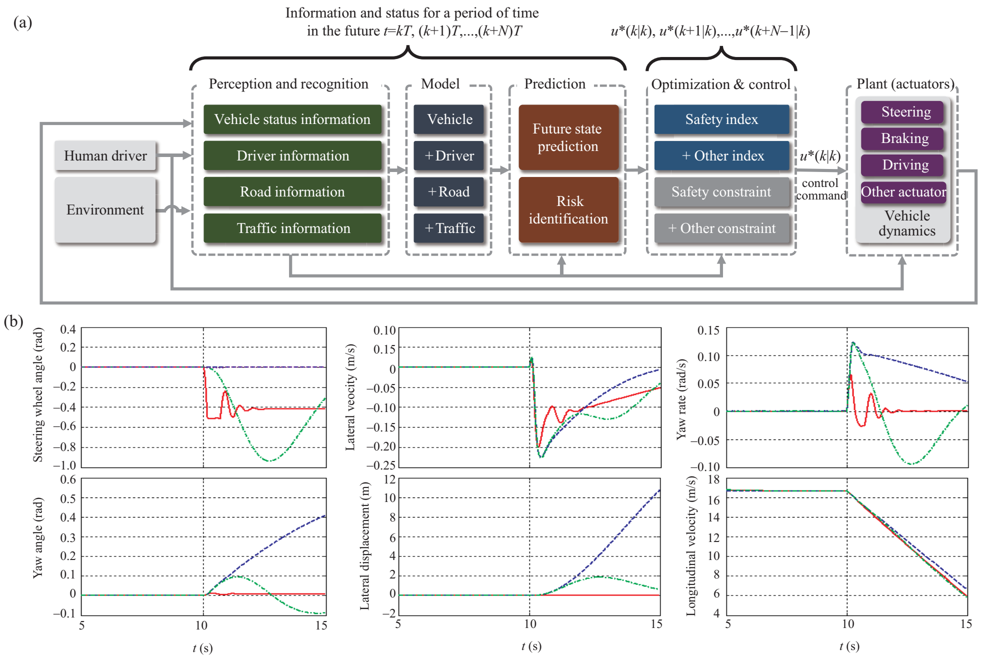

Figure 1 (a) Predictive safety control block diagram; (b) simulation results. (The blue dotted line: without control; the green dotted line: with only human driver control; the red solid line: the predictive safety control; the purple dotted line: the human driver input.)

can inform the controller that the risk has occurred is used.

Proposed method. According to Newton's second law, the lateral dynamics model of a vehicle with a flat tire is

$$\begin{aligned}\dot{v}_y &= -v_x r + \frac{K_{\rm yf}}{m}\left(\delta_f - \frac{v_y + ar}{v_x}\right)\\ &\quad + \frac{K_{\rm yr}\cdot(br - v_y)}{mv_x},\\ \dot{r} &= \frac{aK_{\rm yf}}{I_z}\left(\delta_f - \frac{v_y + ar}{v_x}\right)\\ &\quad - \frac{bK_{\rm yr}(br - v_y)}{I_z v_x} + \frac{M_t}{I_z},\\ \dot{\psi} &= r, \quad \dot{Y} = v_x \sin\psi + v_y \cos\psi,\end{aligned} \tag{1}$$

where v_y, v_x are the lateral and longitudinal velocity of the vehicle, r is the yaw rate, ψ the yaw angle, Y is the lateral displacement, δ_f is the steering angel of front wheel, a, b are the distances of CoG (center of gravity) to the front and rear wheel axels, I_z is the vehicle moment of inertia about the yaw axis, m is the vehicle mass, M_t is the additional yaw moment caused by the tire burst, and $K_{\rm yf}$, $K_{\rm yr}$ are the tire cornering stiffness of the front and rear wheels after a tire blowout. By defining the system state as $x = [v_y, r, \psi, Y]$, the system input as $u = \delta_f$, the system time-varying parameter as $p = v_x$, the dynamic equation (1) can be rewritten as $\dot{x}(t) = f(x(t), u(t), p(t))$. By using the Euler method $x(k+1) = x(k) + T \cdot f(x(k), u(k), p(k))$ and by defining $f^d(x(k), u(k), p(k)) = x(k) + T \cdot f(x(k), u(k), p(k))$, the discretized form is $x(k+1) = f^d(x(k), u(k), p(k))$. The discretization time is T. By defining the predicted time domain as NT, and by assuming that the parameter p remains unchanged during the predicted time domain, the system state can be predicted as

$$\begin{aligned}&x(k+1) = f^d(x(k), u(k), p(k)),\\ &x(k+2) = f^d(x(k+1), u(k+1), p(k)),\\ &\qquad\vdots\\ &x(k+N) = f^d(x(k+N-1), u(k+N-1), p(k))\end{aligned} \tag{2}$$

with the steering control sequence $u(k), u(k+1), \ldots, u(k+N-1)$. To correct the driving trajectory of the vehicle and to maintain the directional stability, the future system state is expected to reach the desired value $x_r(k+N)$ and the future steering control should be as small as possible, such that the objective function can be given as

$$\min \sum_{i=1}^{N} \|x_e(k+i)\|_Q^2 + \|u(k+i-1)\|_R^2, \tag{3}$$

where Q, R are weighting matrices that are used to coordinate internal conflicts of the objective function, $x_e = x - x_r$. The future control sequence needs to be constrained because the excessive steering operation can easily trigger a rollover accident

$$u_{\min} \leqslant u(k+i) \leqslant u_{\max} \ (i=0,1,2,\ldots,N-1). \quad (4)$$

In addition, the predicted lateral displacement also needs to be constrained to avoid a collision accident

$$Y_{\min} \leqslant Y(k+i) \leqslant Y_{\max} \quad (i=1,2,\ldots,N), \quad (5)$$

which is determined by the traffic environment. Theoretically, for the finite horizon open-loop optimal control problem above, a terminal state equality constraint $x(k+N) = x_r(k+N)$ should be added, which requires the system state to be the desired value at the end of the finite prediction horizon [6]. However, this will make it difficult to solve the optimization problem. Therefore, a quasi-infinite horizon nonlinear model predictive control (NMPC) scheme [7] is used to design the control system in this regard. The NMPC problem is formulated as

$$\begin{aligned}
\min_{u^*(\cdot)} & \sum_{i=1}^{N-1} \|x_e(k+i|\,k)\|_Q^2 + \sum_{i=0}^{N-1} \|u(k+i|\,k)\|_R^2 \\
& + \|x_e(k+N|\,k)\|_P^2 \\
\text{s.t. } & (2),\ (4),\ (5),\ x_e(k+N|\,k) \in \Omega, \\
& u_0(k+i|\,k) = u^*(k+i|\,k-1), \\
& \text{for } i = 0,1,\ldots,N-2, \\
& u_0(k+N-1|\,k) = -C_1 x(k-1+N|\,k-1) \\
& -\frac{(K_{\rm yf}+K_{\rm yr})\tan(C_2 x(k-1+N|\,k-1))}{K_{\rm yf}},
\end{aligned}$$

where $C_1 = [0,0,0,1]$, $C_2 = [0,0,1,0]$, $\Omega = \{x \in R^4 | x^{\rm T} P x \leqslant 0.0011\}$, $P = [0.0037,\ 0.0005,\ 0.105,\ 0.0126;\ 0.0005,\ 0.0013,\ 0.0148,\ -0.0006;\ 0.105,\ 0.0148,\ 3.085,\ 0.4086;\ 0.0126,\ -0.0006,\ 0.409,\ 0.219]$ is the terminal region, of which calculation method can referred from [7]. By considering the prediction accuracy, the first solution of the control sequence is selected as the safety control input $\delta_s(k) = u^*(k|k)$. The driving assistance system calculates the correction value δ_c based on the input of the driver δ_d and the safety control input, i.e., $\delta_c = \delta_s - \frac{\delta_d}{K_{\rm sd}}$, where $K_{\rm sd}$ is the steer ratio. This ensures that the front wheel angle is the safe steering value.

Results and discussion. To verify the effectiveness of the proposed method, it was used to control the high precision vehicle dynamics model in veDYNA®. In the simulation test environment, the influence of aerodynamics is considered in order to simulate the real environment. The test road is straight and flat, the road adhesion coefficient is 0.8, and the road boundaries are ±1.7 m. The tire burst event occurred in the tenth second. The longitudinal speed is 60 km/h. The predictive step $N = 10$. After a tire blowout, both the throttle and brake inputs are zero, and the vehicle will slow down. The human driver in this study is a simple PID (proportional-integral-derivative) controller. With the parameter setting, the driver is not experienced, but also not radical. The simulation results are shown in Figure 1(b). Because the driver has no experience, he will perform a slow and large steering operation when the vehicle is moving sideways. This will cause too large a lateral deviation of the vehicle. From the simulation results, we observed that the vehicle has exceeded the lane boundary. The red solid line in the first subgraph is the correction value $K_{\rm sd}\delta_c$, where $K_{\rm sd}$ is 20.4956, the constrained boundary of the future control sequence are ±0.0254 rad. With the intervention of the predictive safety controller, the vehicle did not experience any lateral movement. Therefore, the human driver will not perform the steering operation. This is consistent with normal driving habits.

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