Energy-efficient Longitudinal Driving Strategy for Intelligent Vehicles on Urban Roads

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Outline

Introduction

- Energy and environmental problems brought by automobiles are becoming more and more prominent
  - The number of vehicles registered in China reached an all-time high of over 300 million, according to the traffic bureau of the Ministry of Public Security.
  - In 2017, transport sector of China consumed 380 million tons of standard coal, accounting for 8.64% of the country's total energy consumption.
- Combining longitudinal driving with intelligent transportation information can significantly improve energy efficiency.

Rich information + **advanced algorithm** → **New function & system**

V2X, V2V; Radar, LIDAR, camera;
Intelligent transportation system

Optimal control;
Model predictive control;
Artificial intelligence

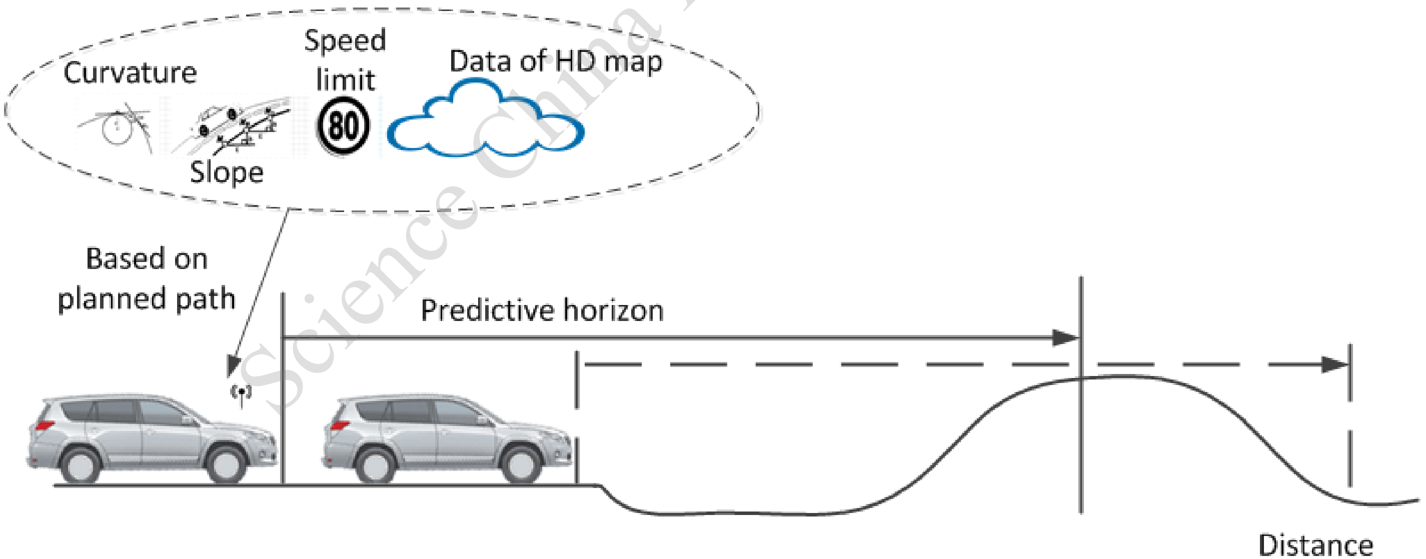
More energy efficient

Control system

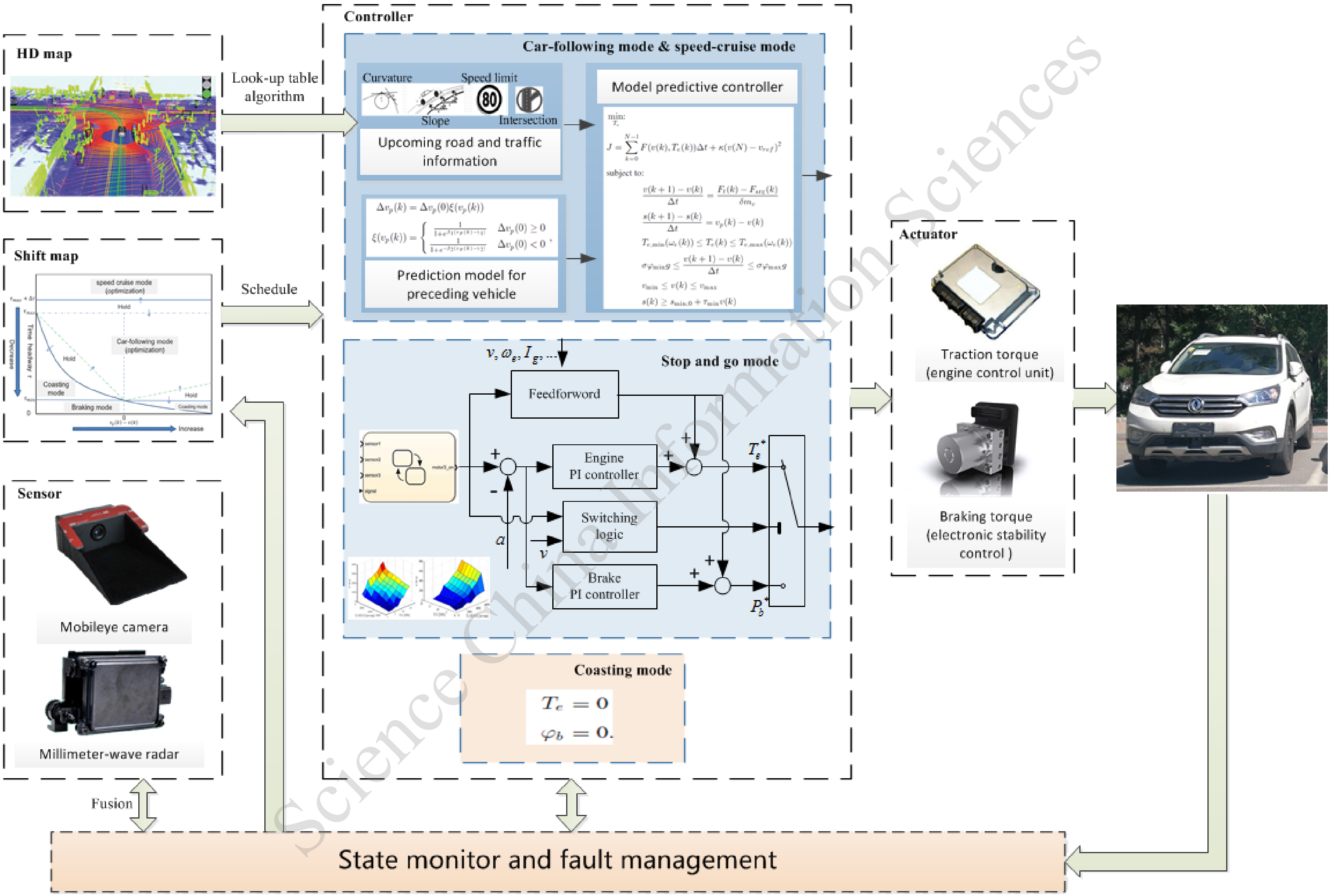
Goal: by making full use of upcoming road/traffic information, develop an energy-efficient longitudinal driving strategy with the stop-and-go function to achieve full-speed range driving

Method:

- under the framework of model predictive control (MPC), design a predictive cruise controller for car-following/speed-cruise scenarios
- by using a feedforward-feedback approach, design a hierarchical controller for stop-and-go scenarios



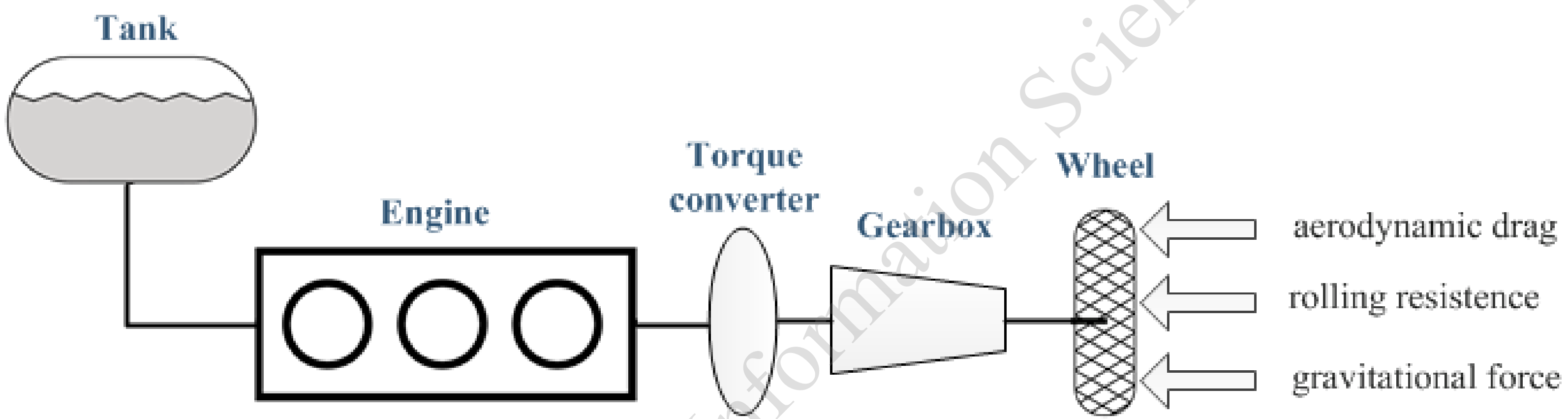
Control system



Control architecture of the proposed longitudinal driving strategy

Controller design --- system model

- Simplified schematic representation of the driveline



- System model

longitudinal dynamics for host vehicle

$$\frac{v(k+1)-v(k)}{\Delta t}=\frac{F_t(k)-F_{arg}(k)}{\delta m_v}, \quad F_{arg}(k)=\frac{1}{2}C_D A\rho v^2(k)+m_v g(f\cos(\alpha(k))+\sin(\alpha(k))),$$

$$\frac{s(k+1)-s(k)}{\Delta t}=v_p(k)-v(k) \quad , \quad \Delta v_p(k)=\Delta v_p(0)\xi(v_p(k))$$

inter-vehicle distance

prediction model of upcoming speed for the preceding vehicle

Controller design --- predictive cruise controller

- Optimization problem formulation for the predictive cruise controller

fuel consumption rate; speed tracking; ride comfort; terminal constraint

cost function

$$\min_{T_e} J = \sum_{K=1}^{N} [Q_f(k) + \kappa_1 (v(k) - v_{ref})^2 + \kappa_2 (T_e(k+1) - T_e(k))^2] \Delta t + \kappa (v(N) - v_{ref})^2$$

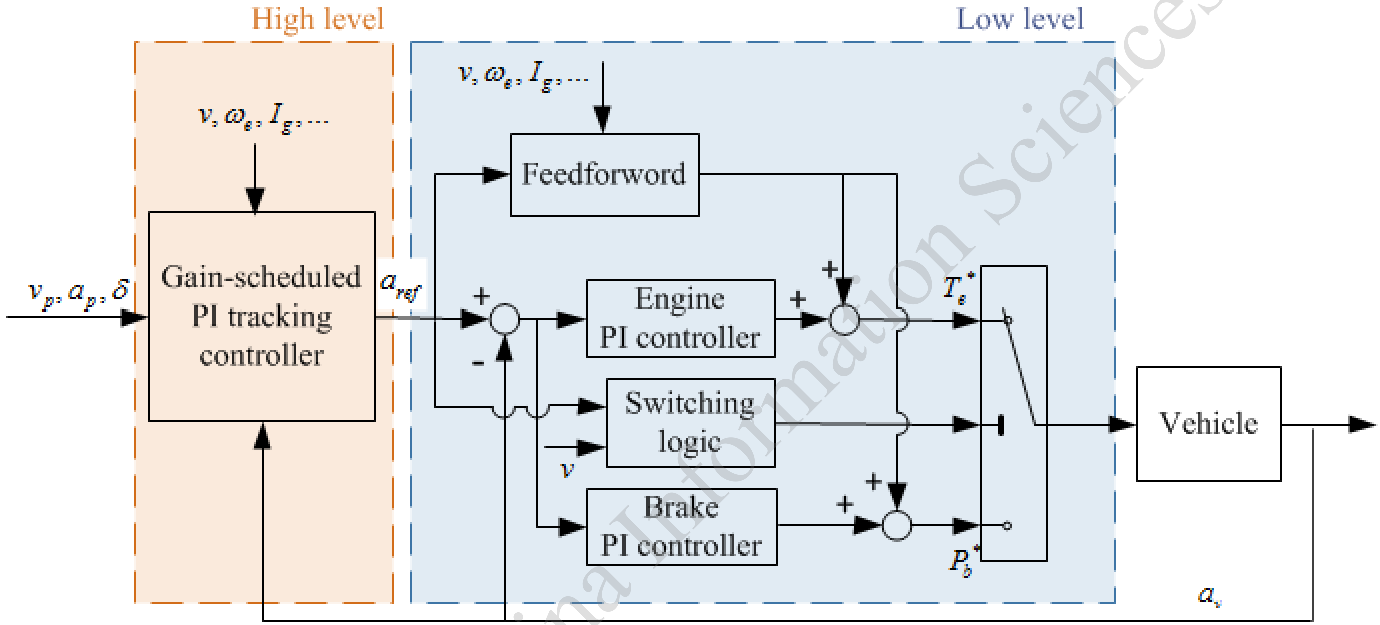
constraints

$$s.t. \begin{cases} \dfrac{v(k+1) - v(k)}{\Delta t} = \dfrac{F_t(k) - F_{arg}(k)}{\delta m_v} & \text{longitudinal dynamics} \\ \dfrac{s(k+1) - s(k)}{\Delta t} = v_p(k) - v(k) & \text{inter-vehicle distance} \\ T_{e,min}(\omega_e(k)) \le T_e(k) \le T_{e,max}(\omega_e(k)) & \text{capacity constraint} \\ \sigma \varphi_{min} g \le \dfrac{v(k+1) - v(k)}{\Delta t} \le \sigma \varphi_{max} g & \text{constraint of the longitudinal acceleration} \\ v_{min} \le v(k) \le v_{max} & \text{speed limit} \\ s(k) \ge s_{min,0} + \tau_{min} v(k) & \text{minimum inter-vehicle distance} \end{cases}$$

Require knowledge of preceding road-slope and traffic information

Controller design --- stop-and-go controller

- Hierarchical controller for stop-and-go scenarios



- Acceleration-tracking control

traction control

$$T_e^* = F_{req} \frac{r_w}{\eta_t I_0 I_g} + k_{p0}(e)e + k_{i0}(e)\int edt$$

$$P_b^* = 0,$$

scheduled gains

brake control

$$T_e^* = 0$$

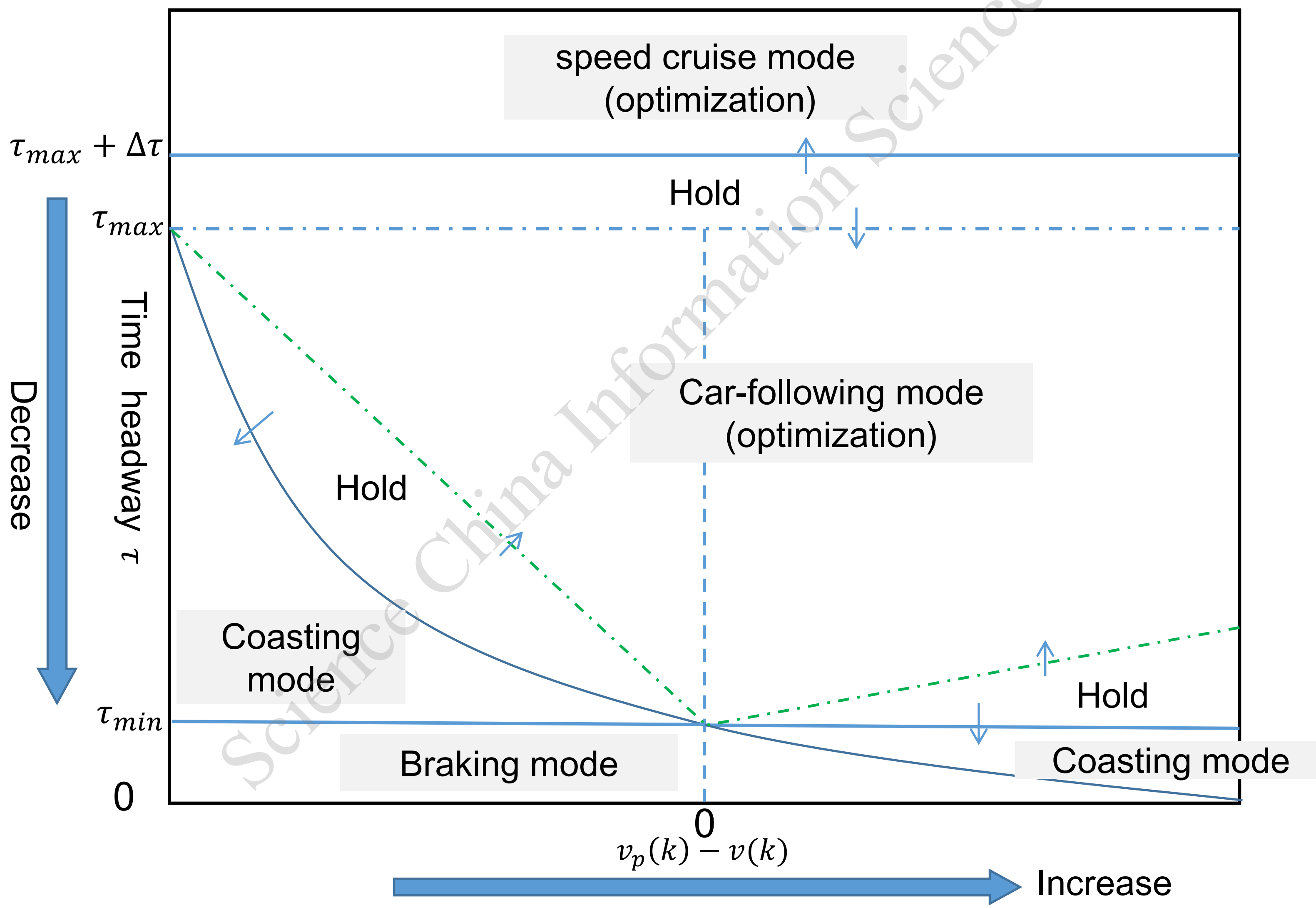
$$P_b^* = -F_{req} \frac{r_w}{K_b} + k_{p1}(e)e + k_{i1}(e)\int edt,$$

scheduled gains

where $F_{req} = \delta m_v a_{ref} + \frac{1}{2} C_D A \rho v^2 + m_v g(f\cos(\alpha) + \sin(\alpha)), e = a_{ref} - a_v$

Implementation issues

➢ Shift map for different operating modes



Implementation issues

- fast solver

$$H(v(k),\lambda(k+1),T_e(k)) = F(v(k),T_e(k)) + \lambda(k+1)\left(\frac{F_t(k)-F_{arg}(k)}{\delta m_v}\right)\Delta t,$$

→ establish the Hamiltonian

$$\boxed{\begin{aligned} &H(v^*(k),\lambda^*(k+1),T_e^*(k)) \le H(v^*(k),\lambda^*(k+1),T_e(k)), \\ &\qquad k \in [0,1,\cdots,N-1] \\ &\lambda(k+1) = -\frac{\partial H(v(k),\lambda(k+1),T_e(k))}{\partial v(k)} + \lambda(k) \end{aligned}}$$

→ necessary conditions optimal control law

$$\lambda(N) = 2\kappa(v(N) - v_{ref})$$

→ terminal necessary condition

- give a initial value of a costate $\lambda(0)$, along the necessary conditions and optimal control law, the corresponding terminal value of a costate $\lambda(N)$ can be obtained. transfer the optimal problem into solving equation problem by finding the optimal initial costate $\lambda(0)$ that satisfying the terminal necessary condition.

mapping from the initial costates $\lambda(1)$ to the terminal necessary condition

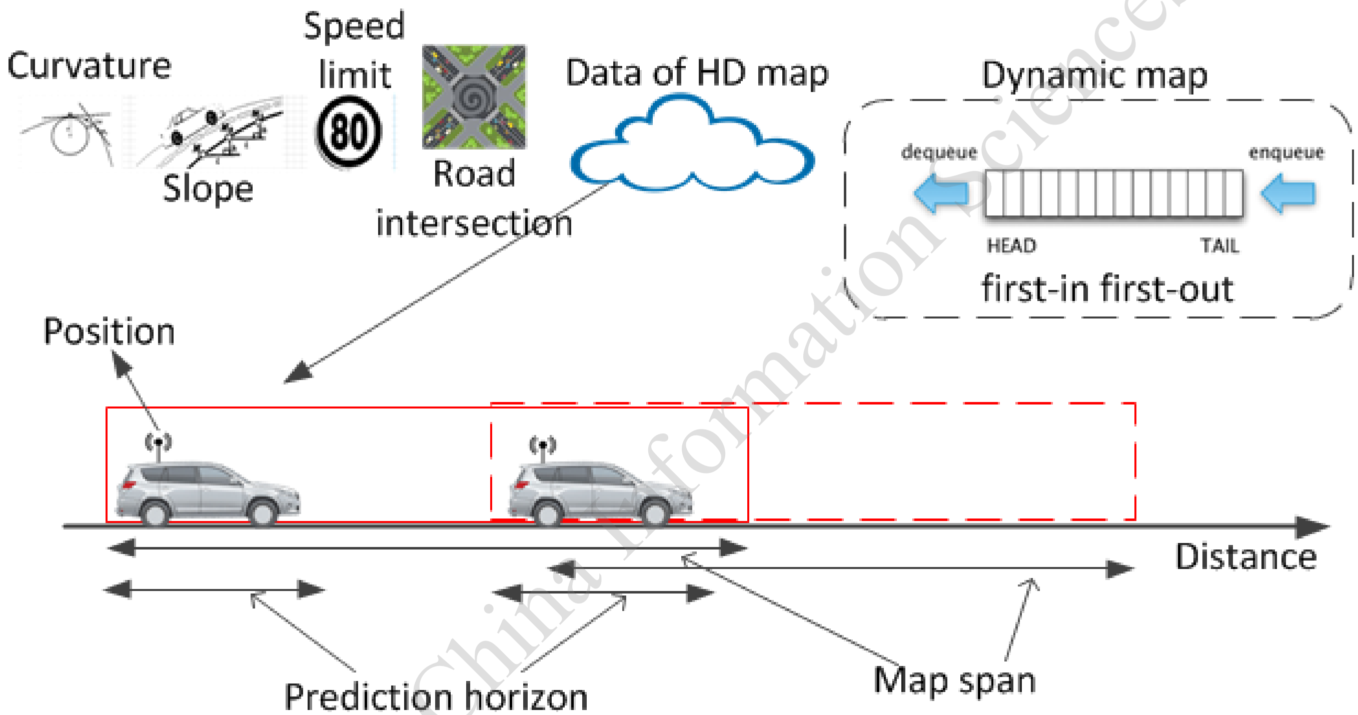
$$\{\lambda(0),x(0)\} \Rightarrow u(0) \Rightarrow \{\lambda(1),x(1)\} \Rightarrow u(1) \Rightarrow \cdots \Rightarrow \boxed{\{\lambda(k),x(k)\} \Rightarrow u(k)} \Rightarrow \cdots \boxed{\Rightarrow \{\lambda(N),x(N)\}}$$

at time step k, reformulate the Hamiltonian to find the analytical solution during iteration

solve the equation to find the optimal $\lambda(0)$ by using bisection method

Implementation issues

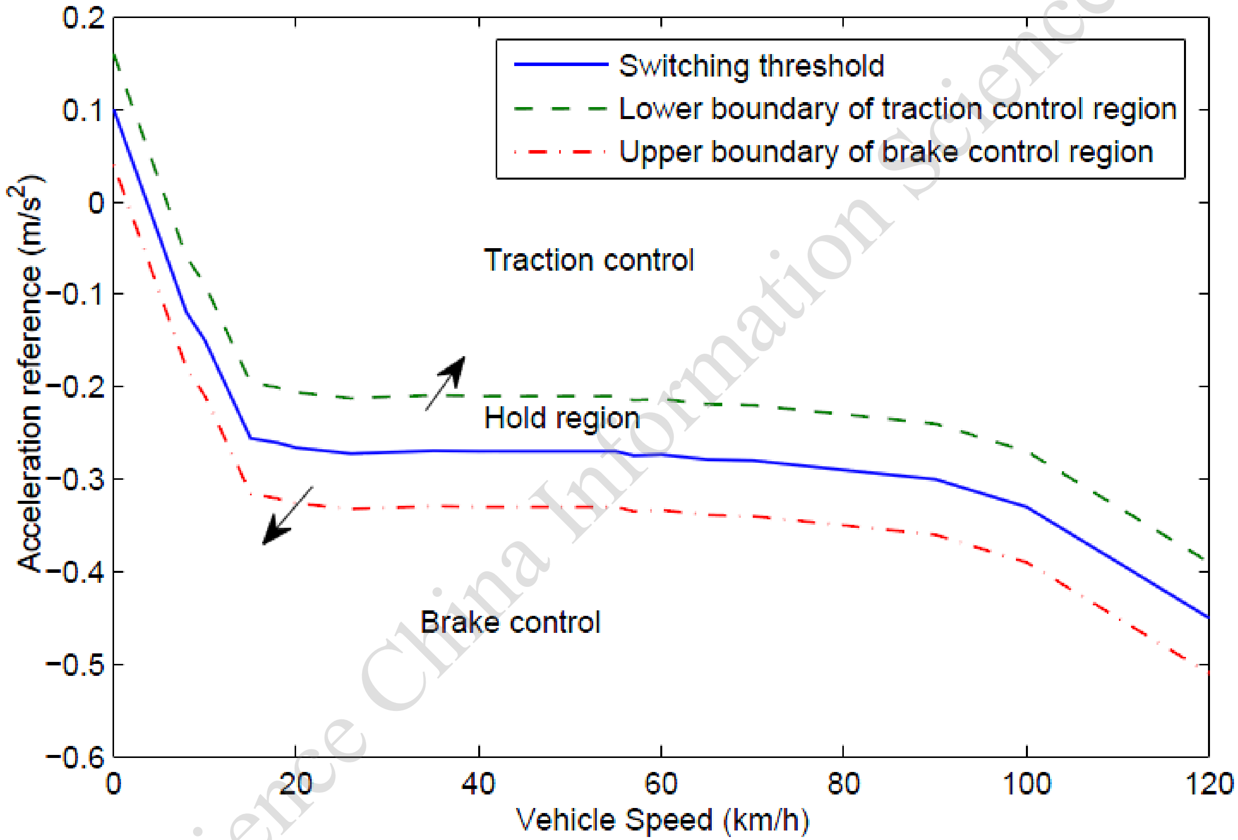
- Use of the high-definition (HD) map



- The data of HD map is location depended and stored in the incar user interface media system
- Hardware system only stores a piece of map data by using the dynamic map
- As the vehicle moves forward, the old data of the dynamic map are replaced by the new data
- Communication between hardware systems is via controller area network

Implementation issues

- Switching logic between traction control and brake control



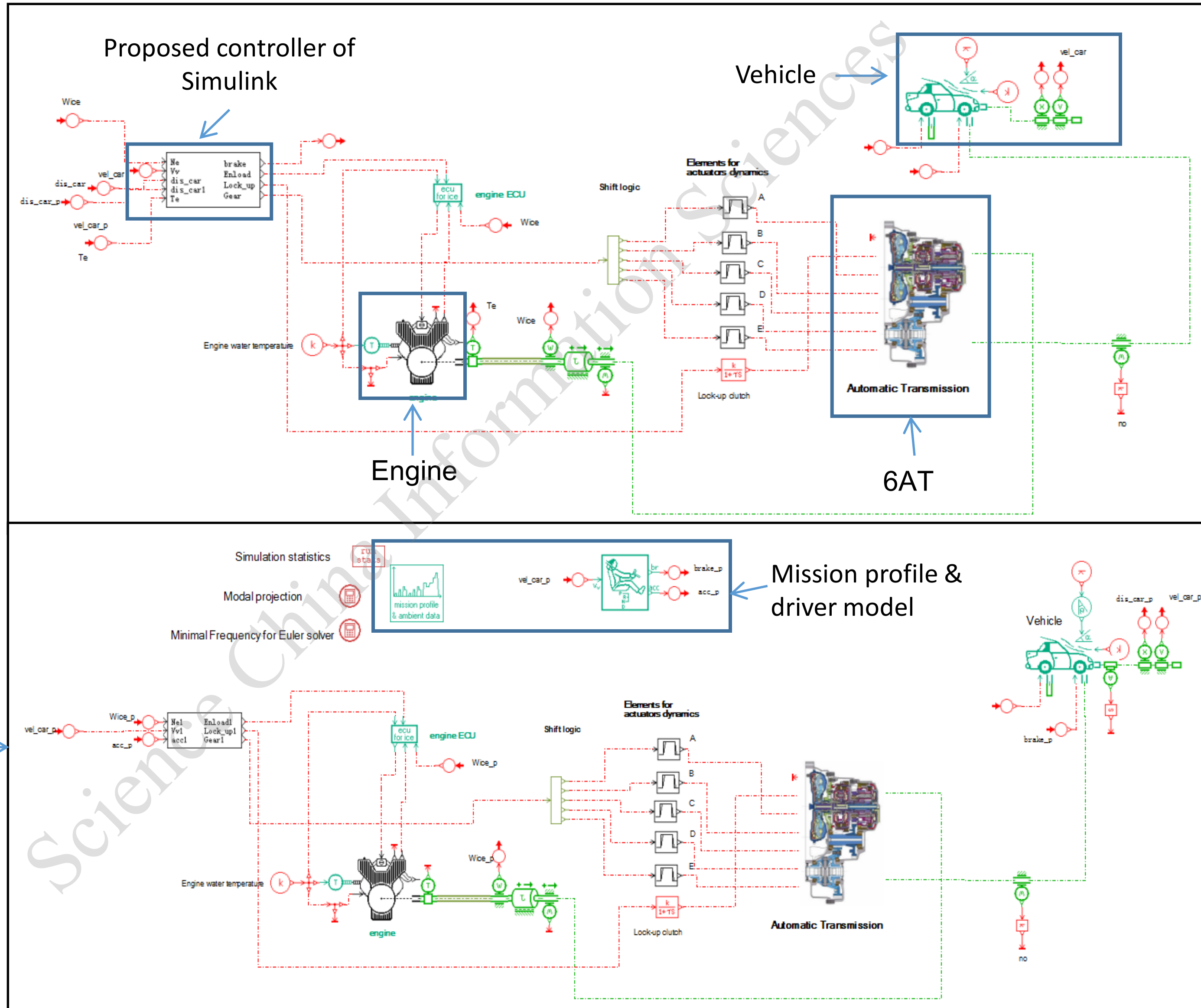
- By performing coasting experiments under different speeds, the mapping from the vehicle speed to the drag acceleration is obtained as a shifting line
- A hold region is introduced to avoid frequent mode switching

Simulation results

AMESim&Simulink

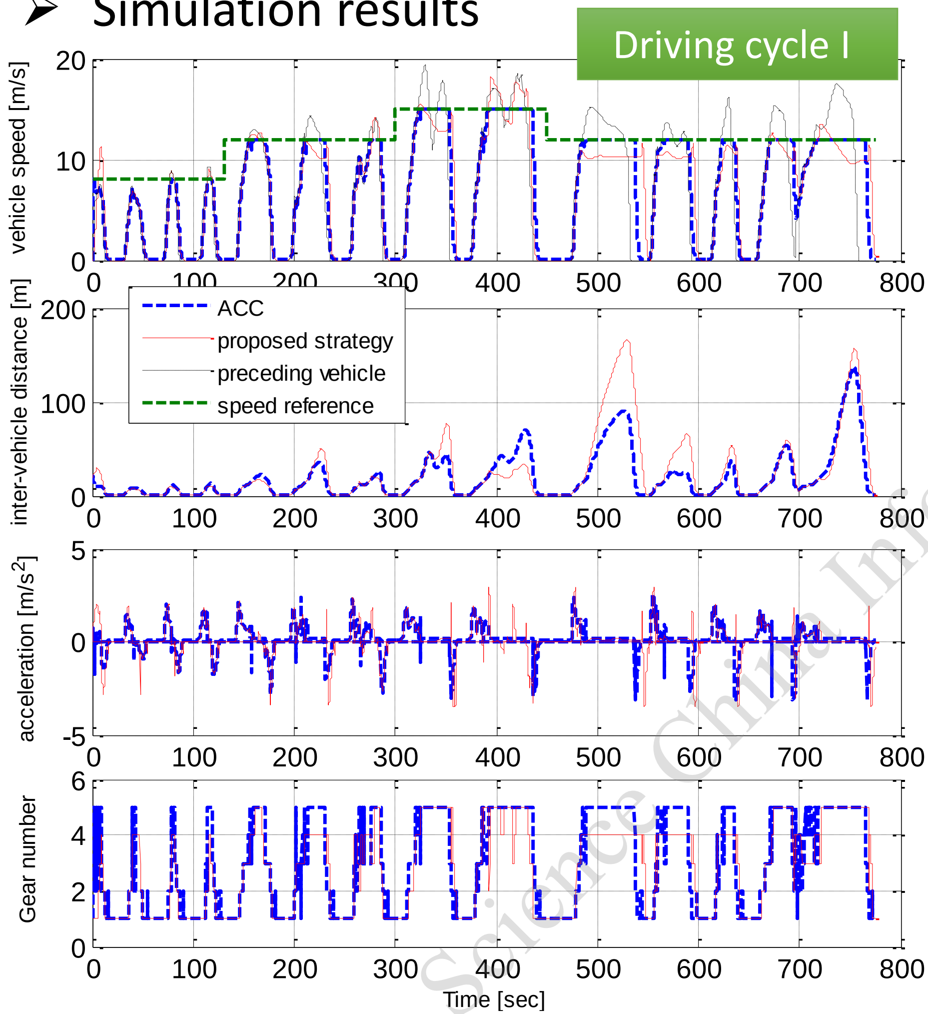
Host vehicle
(controlled by the proposed driving strategy)

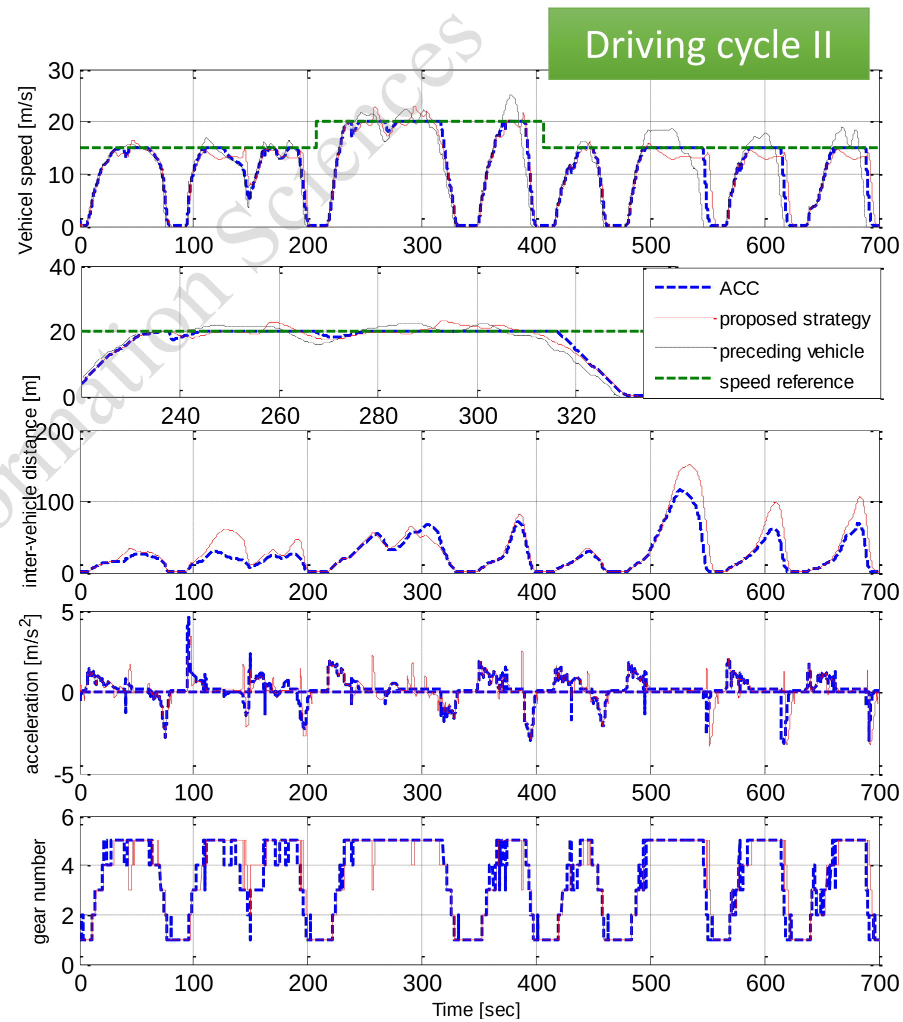
Preceding vehicle
(controlled by a driver model)



Simulation results

- Simulation results



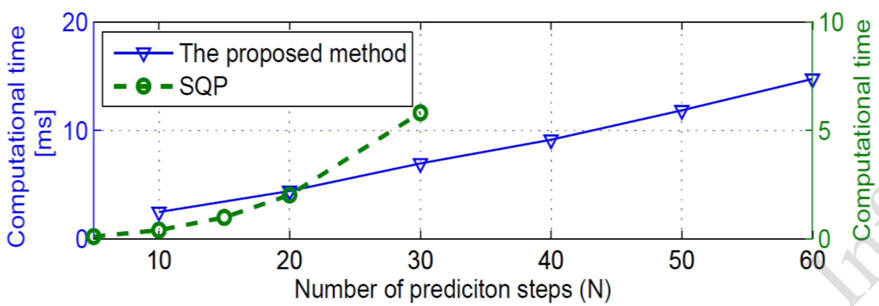


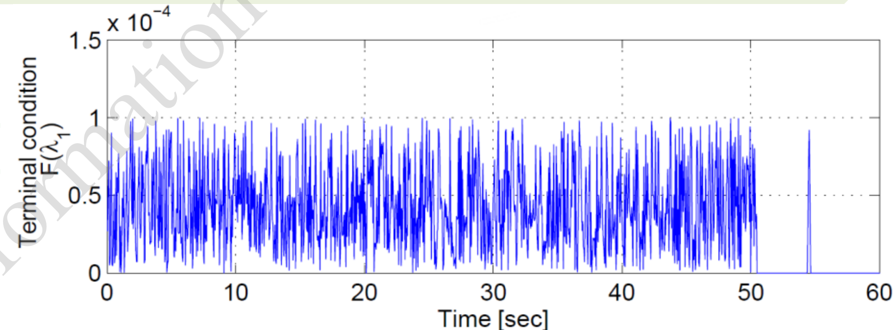
Compared with that of the traditional ACC, the fuel economy of the vehicle with the proposed strategy has increased by more than 8%

Simulation results

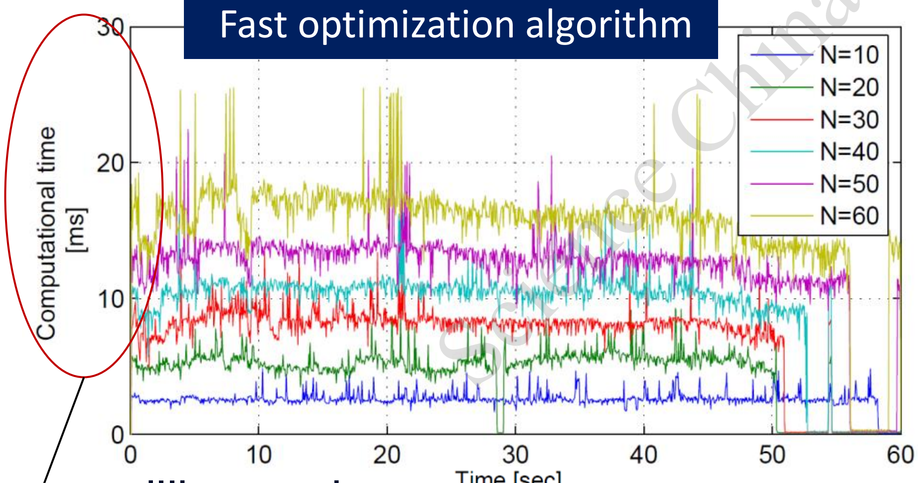
➢ Evaluation of the fast solver

- computational time increases linearly with the prediction horizon while in traditional numerical iteration algorithm SQP (sequential quadratic programming), computational time increases exponentially;
- computational efficiency is much better than SQP



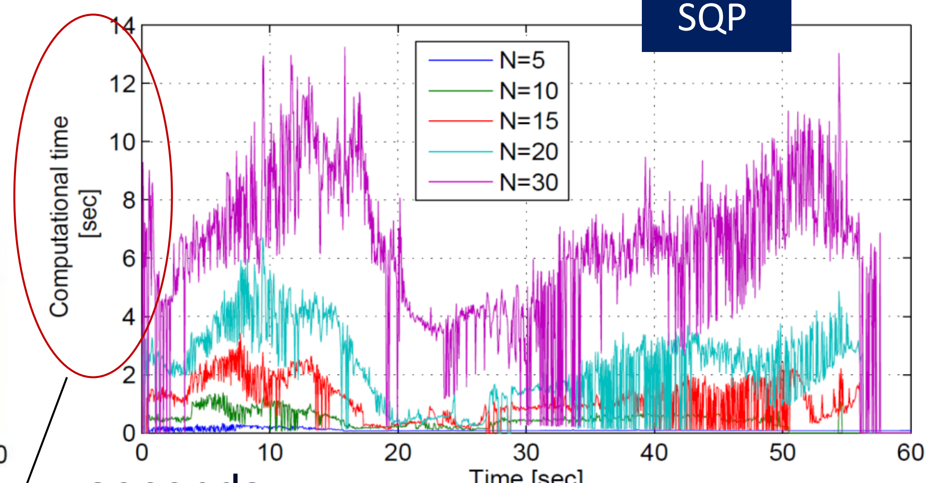


Fast optimization algorithm



milliseconds

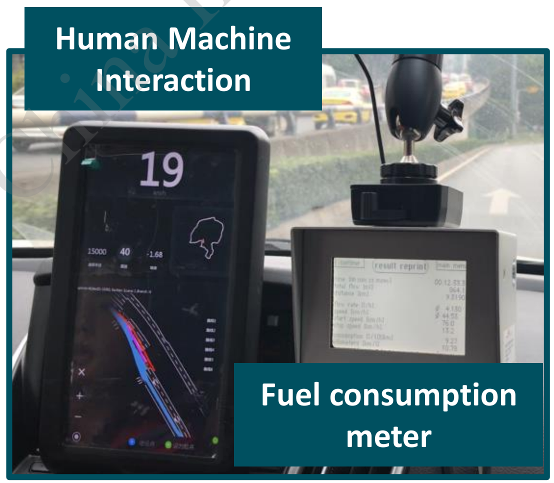
SQP

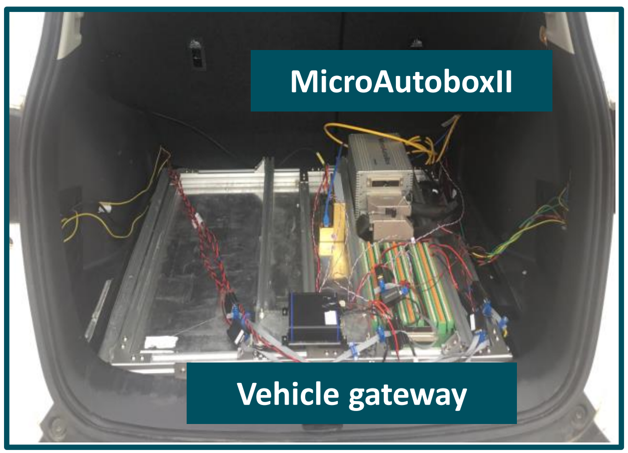


seconds

Experimental results

Experimental route



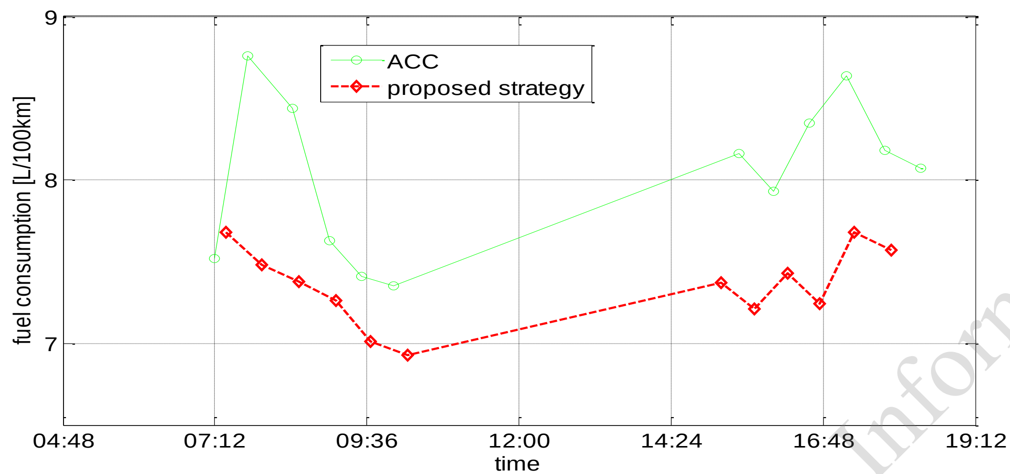


Experimental platform

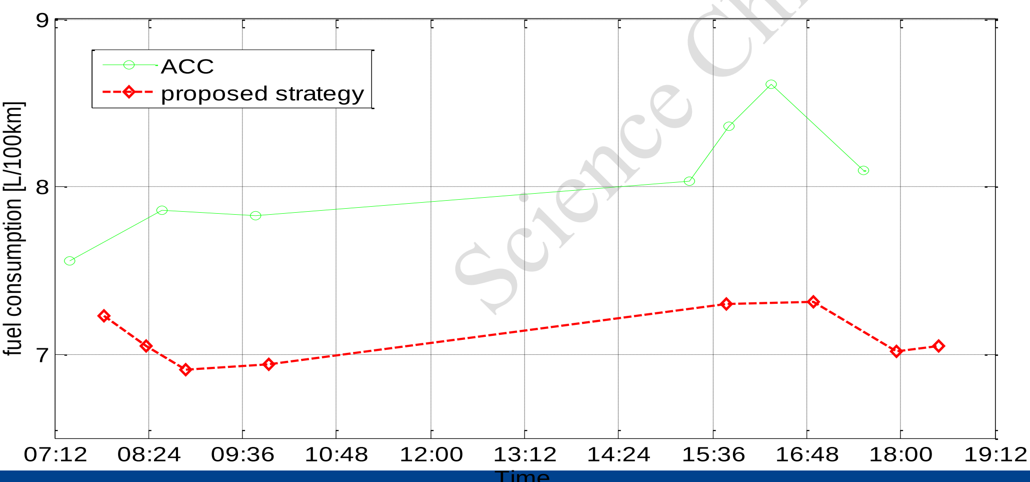
Experimental results

➢ Test results in Wuhan

Comparison of fuel consumption in different time periods of weekday



Comparison of fuel consumption in different time periods of weekend



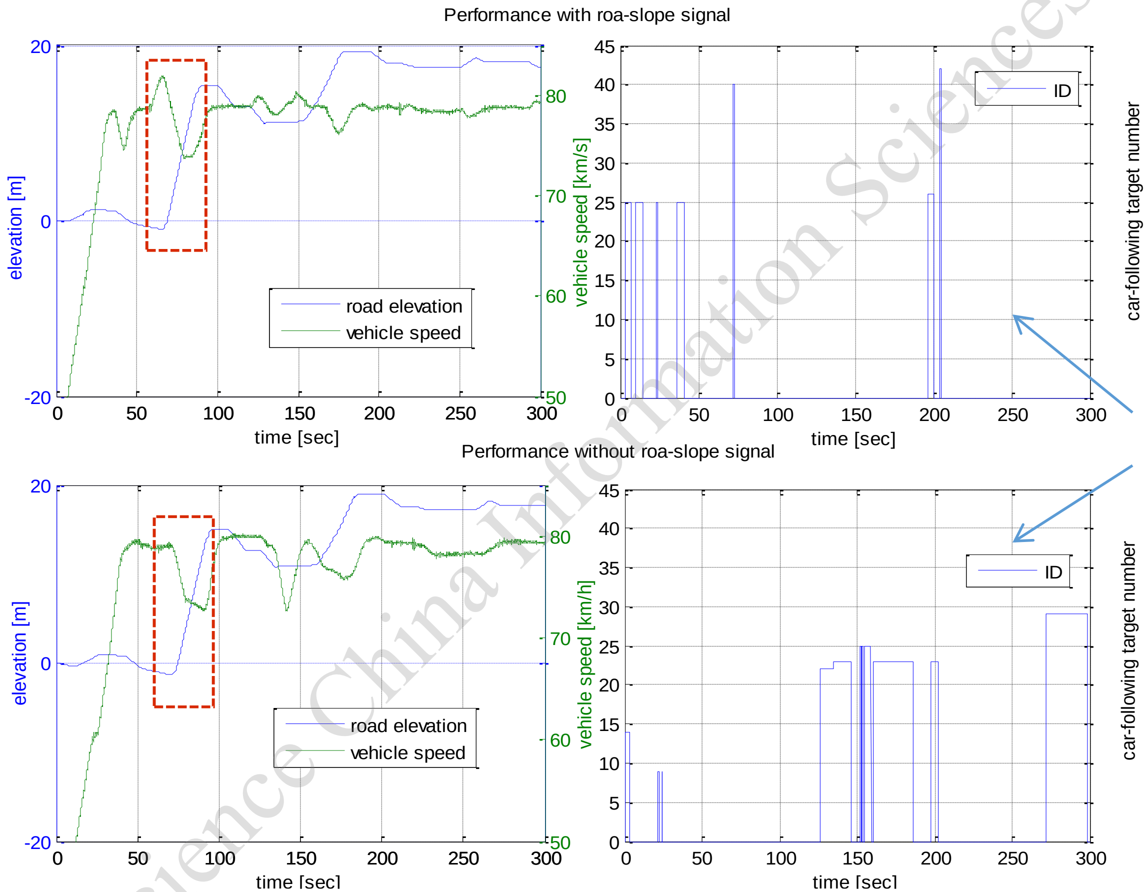
- The system sampling interval is 0.01s
- The prediction horizon is 7s
- The benchmark controller is a factory-installed ACC system

Compared with a factory-installed ACC, road tests show

- the average fuel economy is 9.28% in weekday
- the average fuel economy is 13.38% in weekend

Experimental results

- Evaluation of the influence from road-slope signal



When no preceding vehicle is ahead (no car-following target), ID equals 0

- Red boxes indicate that the vehicle using the proposed strategy will accelerate before the hill is reached
- On the selected road section of Wuhan, the contribution of slope to fuel economy is 2.69%

Experimental results

System	Distance	Fuel saving
Proposed strategy	805km	9.1%
ACC	766km	

- compared with a factory-installed ACC: road test over 1500km shows 8~9% fuel saving

Human drivers	Fuel consumption in their daily driving style	Fuel consumption in their eco-driving style
Professional driver 1	10.08L/100km	7.81L/100km
Professional driver 2	9.27L/100km	7.72L/100km

- compared with human divers:
  - *their daily driving style:* proposed strategy can reduce fuel by 15%
  - *their eco-driving style:* proposed strategy can reduce fuel by 2%

conclusion

- Acceleration and braking of the proposed driving strategy are more smoothly than that of a factory-installed ACC

- Compared with the factory-installed ACC, road tests over 1500km show that the average fuel economy of the proposed strategy is 8-9%

- On the selected road section of Wuhan, the contribution of slope to fuel economy is 2.69%

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