Comfort and energy-saving control of electric vehicle based on nonlinear model predictive algorithm

Manli Dou[1, 2*], Chun Shi[1, 2], Gang Wu[1, 2], Xiaoguang Liu[1, 2]

[1] *School of Information Science and Technology, University of Science and Technology of China, China*

[2] *National Electric Vehicle System Integration Engineering Research Center, China*

Received 1 February 2014, www.tsi.lv

Abstract

This paper develops a control-oriented drivability model for an electric vehicle and a nonlinear model predictive optimization algorithm for an electric vehicle. A cost function is developed that considers the tracking error of setting value and the variation of control volume. Longitudinal ride comfort and energy-saving is also considered. Simulations show that the developed control system provides significant benefits in terms of fuel economy, vehicle safety and tracking capability while at the same time also satisfying driver desired car following characteristics.

Keywords: Nonlinear Model Predictive, Comfort, Energy-saving, Electric Vehicle

1 Introduction

The legislation on reduction of fuel consumption and CO2 emissions has created a large interest in electric vehicle (EV) technologies. Electric vehicles have developed by world's major car manufacturers in recent years. The EVs have several advantages over vehicles with internal combustion engines, such as energy efficiency and environmental friendliness, and is seen to the right way to solve the energy and environment problems [1].

During development and calibration phases of an EV control system, it is of crucial importance to assess and optimize vehicle drivability.

Ride comfort is classified to three categories: vertical, horizontal, and longitudinal vibration. The variation in longitudinal acceleration has great influence on ride comfort [2]. Therefore, longitudinal ride comfort is one of the most crucial features to most advanced vehicle control systems.

The energy of battery carried by electric cars is limited. In the motion the process vehicles, charge and discharge processes always happen. The value of battery discharge current will directly affect the actual capacity of the battery; smaller discharge current makes the battery emit more energy [3]. Therefore, control the value of the charge current can save energy.

An important advantage of model predictive control (MPC) is its ability to cope with constraints on controls and states in an explicit and optimal way, and has experienced a growing success for slow complex plants. In the last decades, several developments have allowed using these methods also for fast system such as automotive application [4].

This paper will focus on development and implementation of a nonlinear model predictive optimization algorithm for an electric vehicle. It is organized as follows. In section 2, a nonlinear model for electric vehicle is introduced. In section 3, a model predictive optimization problem with constraints is constructed considering riding comfort, fuel economy and driver desired response. In section 4, the infeasibility issue is processed and the control law is numerically solved. In section 5, its success is demonstrated by simulations.

2 Nonlinear model for electric vehicle

A typical driving system of pure electric bus is mainly constituted by a traction electric machine (motor), a propeller shaft, a universal joint, a final drive and drive shafts [4]. Figure 1 shows the driving system configuration.

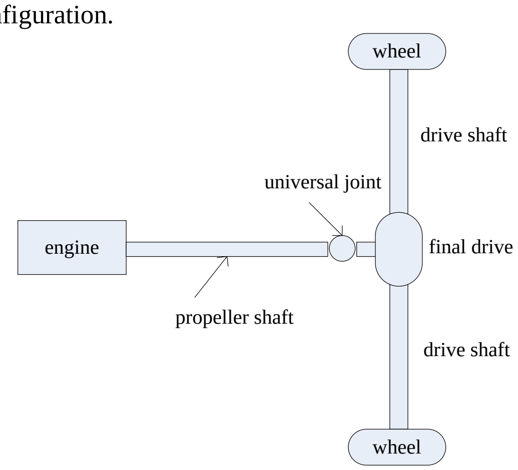


FIGURE 1 Driving system configuration

* ***Corresponding author*** e-mail: liuxg88@mail.ustc.edu.cn

From the mechanism model of the longitudinal dynamics of the vehicle, an input-output model can be deduced.

As the torque applied to the shaft T_{shaft} is generated by the torque on the motor shaft T_{em}, taking into account the main reduction gear ratio ς_{rd} and the transmission efficiency η, the relationship between T_{shaft} and T_{em} can be express as:

$$T_{shaft} = T_{em}\varsigma_{rd}\eta \,, \tag{1}$$

Ignoring the slip ratio of the tire and assume $v_{veh} = w_{wheel} r_{wheel}$, the driving force F_x can be express as:

$$F_x = \frac{T_{em}\varsigma_{rd}\eta - T_{br}}{r_{wheel}} - \frac{J_{wheel}\dot{v}_{veh}}{r^2{}_{wheel}} - F_{roll,fr} \,, \tag{2}$$

where r_{wheel} is the radius of the wheel, w_{wheel} is the wheel's angular velocity, v_{veh} is the vehicle's longitudinal velocity.

Using Newton's second law on the longitudinal direction, the following equation is obtained

$$\dot{v}_{veh} = \frac{1}{M_{veh}}(2F_{x,f} + 2F_{x,r} - \frac{1}{2}\rho_{air}C_d A v_{veh}^2 - M_{veh} g \sin(\gamma)) \,, \tag{3}$$

where ρ_{air} is the air density, C_d is the vehicle's drag coefficient, A is the vehicle's frontal area, γ is the climbing angle.

Take (2) into (3), ignore the difference of the vertical forces acting on the front and rear wheels, the longitudinal dynamics of the vehicle can be expressed as [5]:

$$M_{veh}\delta\dot{v}_{veh} = \frac{T_{em}\varsigma_{rd}\eta - T_{br}}{r_{wheel}} - F_{roll,fr} - \frac{1}{2}\rho_{air}C_d A v_{veh}^2 - M_{veh} g \sin(\gamma) \,, \tag{4}$$

where the $\delta = 1 + \frac{\sum J_{wheel}}{r^2{}_{wheel}}$ is rotating mass conversion factor.

The vehicle is assumed to driven on straight roadway, so the road inclination γ is zero, and the rolling friction $F_{roll,fr}$ is assumed to be constant, the relationship between T_{em} and v_{veh} can be express as an input-output system:

$$a_0 + a_1 v_{veh}^2 + a_2 \dot{v}_{veh} = b_1 T_{em} \,. \tag{5}$$

The input variable of the system is T_{em}, and the output variable is v_{veh}, and b_1, a_0, a_1, a_2 are parameters.

According to (5), the longitudinal dynamics of the vehicle is nonlinear, i.e. the relationship between the motor torque T_{em} of pure electric vehicle and the vehicle speed v_{veh} is nonlinear.

The discrete model can be obtained by discretization of (5) using forward difference scheme:

$$y(k+1) = -\theta_1 y^2(k) - \theta_2 y(k) + \theta_3 u(k) + \theta_4 \,, \tag{6}$$

where y is v_{veh}, u is T_{em}, $\theta = [\theta_1, \theta_2, \theta_3, \theta_4]$ is the parameter vector.

The (6) shows the non-linear model is a Non-linear Auto Regressive with eXogenous inputs (NARX)model [6], and as the model depends on its parameters in linear way, it can be treated as a linear-in-the-parameters model.

The linear-in-the-parameters model takes the form:

$$y(k+1) = \theta x(k) + \varepsilon(k+1) \,, \tag{7}$$

where $x(k) = [-y^2(k), -y(k), u(k), 1(k)]'$.

Suppose N data samples $\{x(k), y(k)\}_{k=1}^N$ are used for model identification, equation (8) can be formulated as:

$$Y = \theta X + \Xi \,, \tag{8}$$

where $Y = [y(1),...,y(k)]'$, $X = [x(1),...,x(k)]'$, $\Xi = [\theta_1,...,\theta_2]$. Then use least-squares (LS) method to determine the parameters.

3 Construction of nonlinear predictive optimization problem

Model predictive control (MPC), also referred to as moving horizon control or receding horizon control, is a control strategy in which the applied input is determined on-line at the recalculation instant by solving an open-loop optimal control problem over a fixed prediction horizon into the future [7].

The basic overall structure of a NMPC control loop is shown in Figure 2. Based on the applied input u_t and the measured outputs y_t, estimate model predictions outputs y_t is obtained. This estimate is fed into the NMPC controller, which computes a new input applied to the system. Often an additional set-point calculation model is added to the overall loop to produce setting sequence w_t.

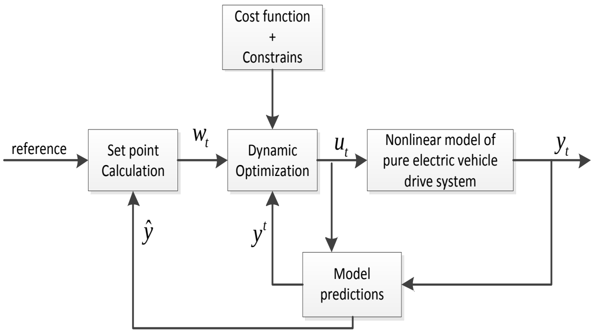


FIGURE 2 NMPC control loop

The set-point target calculation model is used to explain the driver's driving intentions. In the conventional vehicle driving behaviour, when driver depresses the accelerator pedal, the power output of the engine increases, and vehicle speed increases. In order to maintain driving habits unchanged, the pedal opening degree should correspond to the acceleration demand. So pedal opening degree α is mapped to acceleration value a as:

$$a = f(\alpha), \tag{9}$$

and the speed set point curve of vehicle is obtained as:

$$w_t(k) = v_0 + a * k , \tag{10}$$

where v_0 is current vehicle speed, and k is sampling time point.

When vehicle is driven on the road, acceleration and deceleration occurs frequently according to the driver's instructions start and stoplights, and this result in vibration, which has a great impact on the ride comfort. Therefore, improving the comfort of the vehicle during acceleration and deceleration, and can greatly improve the overall comfort of the vehicle.

Therefore, the maximum value of the vehicle acceleration and deceleration should be limit as:

$$\Delta y_{n\_\max} \le \Delta y_{t+i} \le \Delta y_{p\_\max} , \tag{11}$$

where y is the vehicle speed, and Δy stands for vehicle acceleration when $\Delta y \ge 0$ and deceleration when $\Delta y < 0$, $\Delta y_{n\_\max}$ and $\Delta y_{p\_\max}$ are the maximum value of the vehicle acceleration and deceleration.

As the energy carried by the pure electric vehicle is limited energy, efficient use of battery power on the extension of a pure electric vehicle driving range is very important. Driving range is one of the economic indicators of electric vehicle.

The actual capacity of the battery is discharged under certain conditions of the actual release of the battery power, typically less than the theoretical capacity and the rated capacity. The actual capacity of the battery is affected by the value of discharging current, the ambient temperature, the aging of battery and so on [8].

Taking into account the effect of the battery capacity ratio, low current discharge rate can reduce the loss energy and so that the battery can be more energy.

In pure electric vehicle, when the motor is in electric state, battery release energy, and the current flows to the motor from the battery; when the motor is in generation state, battery is charged, and the current flows to the battery from the motor. The current is proportional to motor torque, so the motor torque should be limited as:

$$u_{n\_\max} \le u_{t+i} \le u_{p\_\max} , \tag{12}$$

where u is the motor torque, $u_{n\_\max}$ and $u_{p\_\max}$ is the minimum value and maximum value of the motor torque.

The cost function design in predictive optimization problem should make the tracking error of actually speed and speed set point curve, and considering the control value should not change too intense, the cost function can be expressed as [9]:

$$J = E\{\sum_{t=0}^{p-1}[y_{t+i} - w_{t+i}]^2 + \lambda[u_{t+i} - u_{t-1}]^2\} , \tag{13}$$

where λ is the weighting factor.

Therefore, we have a predictive optimization problem modified by constraint expressed as

$$\min J = E\{\sum_{t=0}^{p-1}[y_{t+i} - w_{t+i}]^2 + \lambda[u_{t+i} - u_{t-1}]^2\},$$
$$s.t \begin{cases} Y = \theta X + \Xi \\ u_{n\_\max} \le u_{t+i} \le u_{p\_\max} \\ \Delta y_{n\_\max} \le \Delta y_{t+i} \le \Delta y_{p\_\max} . \end{cases} . \tag{14}$$

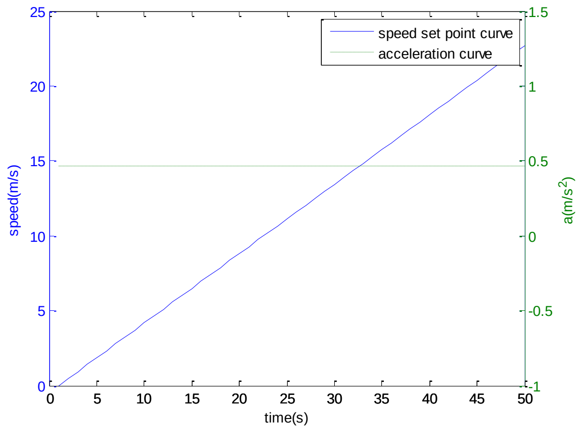
Model predictive control is formulated as a repeated solution of a horizon open loop optimal control problem subject to system dynamics and input and state constraints. Based on measurements obtained at time t, the controller predicts the dynamic behaviour of the system over a prediction horizon t_p in the future according to (9), and determines the input such that a predetermined the cost function is minimized. In the designed algorithm control horizon t_c and prediction horizon t_p is the same [10].

4 Simulation and analysis

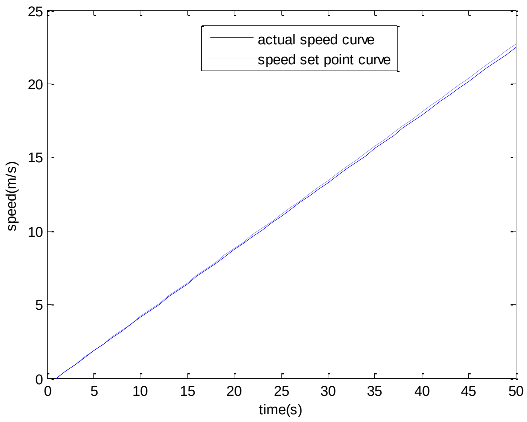
The simulation and verification of the designed algorithm is implemented in the MATLAB/Simulink environment using a variable-step solver that is suited for stiff dynamic systems.

Battery capacity is represented by SOC values and calculated by the MATLAB / Simulink battery model. The weighting factor λ is set to 0.2. All the input, output, controlled variables are normalized to [-1,1].

Time for electric bus accelerate s from start to 50km/h is about 30 seconds, so the acceleration of $0.463 m/s^2$. When the accelerator pedal value α is set to maximum, acceleration value a is $0.463 m/s^2$, assume the current vehicle speed v_0 is zero, the speed set point curve is shown in Figure 3(a). Actual speed and the set speed is shown in Figure 3 (b).



(a)

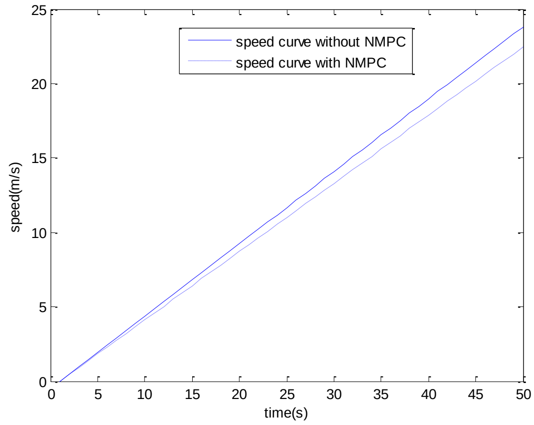


(b)

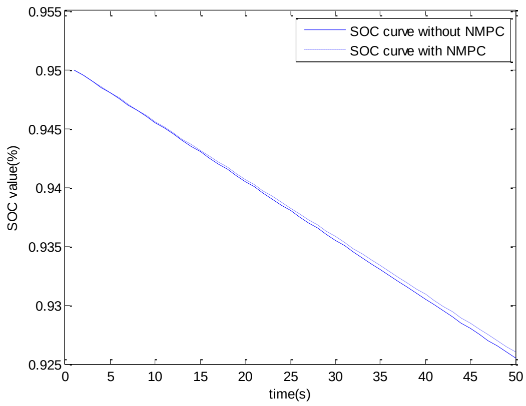
FIGURE 3 The simulation results :a) speed set point curve .b) actual speed curve and the set speed curve

In Figure 3(b), the simulation actual speed curve and the set speed curve is shown as solid line and dot-dash line, and it can be seen that the actual speed following the set point well.

Figure 4(a) shows when no control algorithm is implemented; the speed is a little higher than the speed when control algorithm is implemented. Figure 4(b) shows the SOC of the battery in the two conditions, the initial SOC value is set to 95% from figure 4(b) it can be seen that the designed algorithm reducing the change of SOC value.



(a)



(b)

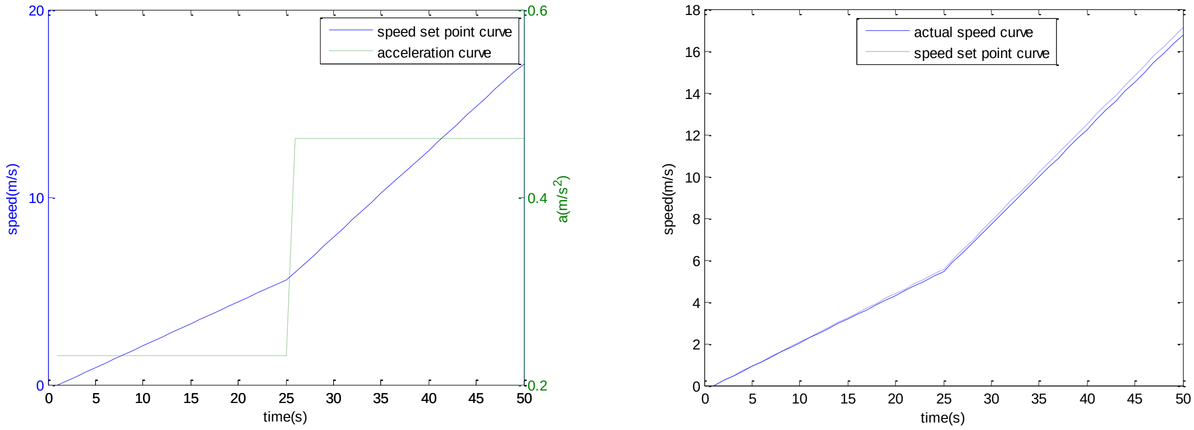
FIGURE 4 The simulation results :a) speed curve comparison .b) SOC curve comparison

When the accelerator pedal value α is set to half of the maximum for several time before change to the maximum, the initial vehicle speed is zero, the speed set point curve is shown in Figure 5(a). Actual speed and the set speed is shown in Figure 5(b), the simulation actual speed curve and the set speed curve is shown as solid line and dot-dash line.

In Figure 5(b), when accelerator pedal changes, the actual speed still following the set point well.

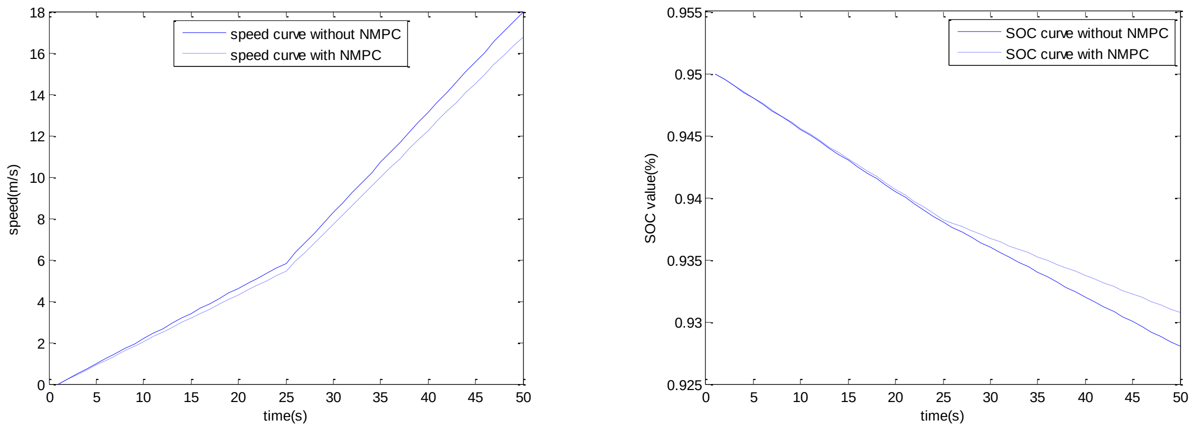
Figure 6(a) shows when no control algorithm is implemented; the speed is a little higher than the speed when control algorithm is implemented. Figure 4(b) shows the SOC of the battery in the two conditions, the initial SOC value is set to 95% from Figure 4(b) it can be seen that the designed algorithm reducing the change of SOC value.

Figure 6(a) shows when no control algorithm is implemented; the speed is changed rapidly than the speed when control algorithm is implemented. Figure 4(b) shows the SOC of the battery in the two conditions, the initial SOC value is set to 95% from figure 4(b) it can be seen that the designed algorithm reducing the change of SOC value significantly.



(a) (b)

FIGURE 5 The simulation results :a) speed set point curve .b) actual speed curve and the set speed curve



(a) (b)

FIGURE 6 The simulation results: a) speed curve comparison .b) SOC curve comparison

5 Conclusions

This paper develops a control-oriented drivability model for an electric vehicle and a nonlinear model predictive optimization algorithm for an electric vehicle.

According to the structure of the mechanism model, an input - output model is developed. As the input - output model is nonlinear; it can be described as Non-linear Auto Regressive with eXogenous inputs (NARX) model.

Then a nonlinear model predictive optimization algorithm is implemented with a cost function which is developed that considers the tracking error of setting value and the variation of control volume, and longitudinal ride comfort and energy-saving is also considered.

Simulations show that the developed optimization algorithm is energy-saving and improves the ride comfort.

Since the algorithm only considers the situation when the vehicle is driven on a straight flat road, therefore only in the direction of the longitudinal movement has been optimized. Future work will focus on the effect of lateral movement and the safety factor on the developed optimization algorithm.

Acknowledgments

The authors would like to thank Anhui Ankai Automobile Co., Ltd and National Electric Vehicle System Integration Engineering Research Centre.

References

[1] Chengqun Li, Xing Sun, Xiaolei Dong 2010 *Advanced Materials Research* **139-141** 2243-6

[2] Wang Guo-Quan, Yang Wen-Tong, Xu Xian-Feng, Yu Qun 2003 *Journal of Shanghai Jiaotong University* **37**(11) 1772-5 *(in Chinese)*

[3] Li S G, Sharkh S M, Walsh F C, Zhang C N 2011 *IEEE Transactions on Vehicular Technology* **60**(8) 3571-85

[4] Kraus T, Ferreau H J, Kayacan E, Ramon H, De Baerdemaeker J, Diehl M, Saeys W 2013 *Computers and Electronics in Agriculture* **98** 25-33

[5] Koprubasi K 2008 *Modelling and control of a hybrid-electric vehicle for drivability and fuel economy improvements* PhD Thesis The Ohio State University

[6] Parra O J S, Martinez N O D, Puente F J 2010 *NISS2010 4th International Conference on New Trends in Information Science and Service Science* 754-9

[7] He Lin, Li Liang, Yu Liangyao, Mao Enrong, Song Jian 2012 *Proceedings of the Institution of Mechanical Engineers Part D: Journal of Automobile Engineering* **226**(8) 1016-25

[8] Chen Bo-Chiuan, Wu Yuh-Yih, Tsai Hsien-Chi 2014 *Applied Energy* **113** 1764-74

[9] Li Kang, Peng Jian-Xun, Irwin G W 2005 *IEEE transactions on automatic control* **50**(8) 1211-6

[10] Zhang Ridong, Xue Anke, Wang Shu-Qing 2011 *Industrial and Engineering Chemistry Research* **50**(13) 8110-21

Authors

Dou Manli, born in 1988,Anhui, China

Current position, grades: Ph.D.student
University studies: University of Science and Technology of China
Scientific interest: automotive electronics, advanced control and optimization
Publications: 5 papers published in international journals and conferences
Experience: Engaged in automotive electronics and advanced control and optimization of theoretical and applied research. Participated in several research and development projects. Several papers published in international journals and conferences

Shi Chun, born in 1980, Jiangsu, China

Current position, grades: lecturer, doctor
University studies: University of Science and Technology of China
Scientific interest: automotive electronics, advanced control and optimization
Publications : more than 10 papers published in international journals and conferences
Experience: Engaged in automotive electronics and advanced control and optimization of theoretical and applied research, participated in more than ten research and development projects. Several papers published in international journals and conferences

Wu Gang, born in 1964, Jiangsu, China

Current position, grades: Professor, Ph.D. supervisor
University studies: University of Science and Technology of China
Scientific interest: process control, advanced control and optimization
Publications : more than 100 papers published in international journals and conferences
Experience: Engaged in industrial process control and advanced control and optimization of theoretical and applied research, including predictive control, adaptive control, system identification, constraint control, intelligent control, on-line operation optimization, Participated in more than ten research and development projects, won four ministerial-level prize and the first global Chinese community Intelligent Control and Intelligent Automation Conference Best Paper Award, Papers published in international journals and conference papers nearly one hundred.

Liu Xiaoguang, born in 1988, Anhui, China

Current position, grades: engineer, master
University studies: University of Science and Technology of China
Scientific interest: automotive electronics, advanced control, precision optics
Publications : 5 papers published in international journals and conferences
Experience: Engaged in automotive electronics and advanced control and optimization of theoretical and applied research, participated in several research and development projects. Several papers published in international journals and conferences.