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Study on super-wheelbase preview controller/algorithm for internet of vehicles suspension system used in a heavy vehicle fleet

Ce Yuan, Jiang Liu*, Xilong Zhang, Bilong Liu and Yushun Wang

Department of Shandong,
Qingdao University of Technology,
Qingdao, Shandong, 266520, China
Email: yc951204@126.com
Email: liujiang@qut.edu.cn
Email: beibitpap@hotmail.com
Email: Liubilong@qut.edu.cn
Email: Wang_yushun@163.com
*Corresponding author

Abstract: Most truck fleet transportation shows typical repetitive features in vehicle models, routes and cargos. So the internet of vehicles (IoV) theory could be easily introduced into the active control for truck suspensions. We establish a communication network structure in which paired vehicles are basic elements, and the geographic information systems are treated as a detection auxiliary. The new design reduces the overall communication demand for suspension control data. Based on this simplified IoV system, a new super-wheelbase preview control method is proposed. The optimal vehicle distance between paired trucks is calculated by the particle swarm optimisation (PSO). The traditional wheelbase preview algorithm is improved by using two equivalent parameters. The rear truck shows better comprehensive suspension performances than the front one. Finally, we perform a simple objective optimisation in the truck pairs sequence. The convergence results show that with the help of the IoV suspension system, the 6th and after trucks can get the minimised body acceleration in the fleet's first loop.

Keywords: suspension; IoV; internet of vehicles; super-wheelbase preview; PSO; particle swarm optimisation.

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Biographical notes: Ce Yuan is a Master student of Qingdao University of Technology. He graduated from Jinan University in 2014 with a Bachelor's degree. He is mainly engaged in automotive active suspension and vehicle network research.

Jiang Liu is an Associate Professor of Qingdao University of Technology. His research interests include active suspension, energy harvesting, and NVH in heavy-duty trucks. In recent years, he has published more than 40 papers and two monographs.

Xilong Zhang is an Associate Professor of Qingdao University of Technology. His research interests include flow noise, efficient use of automotive energy, heat transfer in magnetic nanocrystals, and thermal conduction in semiconductors.

Bilong Liu is a Professor of Qingdao University of Technology. His research interests include acoustic materials and structures, fluid and structure coupling vibration noise, high performance acoustic devices, active and passive noise control methods, and opportunities for the industrialisation of acoustic technology.

Yushun Wang is a laboratory technician of Qingdao University of Technology. She is mainly engaged in electronic control and testing for gasoline and diesel engines. In recent years, she has published seven papers.

1 Introduction

In recent years, the research on the internet of vehicles (IoV) has attracted widespread attention from many scholars. IoV (Kumar et al., 2015; Li et al., 2017) has dominated the transportation system due to its large network scale, reliable Internet connection, compatibility with personal equipment, and high processing capabilities, etc. (Sharma and Kaushik, 2019). Heavy road vehicle freights play an important role by providing an efficient means for transporting (Papadogiannis et al., 2010). For truck operations in freight fleets, it has the advantage of using the same vehicle types and relatively fixed transportation routes. However, in the actual fleet transportation, the long routes and the large amount of trucks cause the increase of data communication, which will lead to bad interaction efficiency and high cost. Therefore, how to apply the IoV to the freight truck fleet more smartly is the one of the focus for the transportation industry.

In order to solve this problem, scholars have proposed various valuable methods.In the literature (Roebuck et al., 2005), Roebuck et al. attempted to implement a global vehicle control strategy on a long wheelbase truck. In the literature (Zhang et al., 2018), Zhang et al. designed a large IoV system aiming to process the big data uploaded by the fleet vehicles and data driving. In the literature (Yao et al., 2019), Khan proposed an efficient communication scheme. Based on the density of traffic, the base station allocates communication channels to vehicles on the road. In the literature (Chen et al., 2019), Chen et al. analysed the fleet drivers using the big data received by IoV,including the feature selection and its statistical method. So far, most of the research studied the v2v interconnection between every truck in the fleet, or between trucks and the base stations. The former would increase the hardware cost, while the latter bring tremendous communication pressure to the base station. Therefore, this article uses as simplified combining IoV structure. Firstly each two trucks get in pairs with the former v2v mode, and then the IoV system interconnects within the pairs and the base station, which could reduce the communication by almost a half.

As one of the important systems for IoV safety and comfort, the truck suspension usually uses active control to improve the overall transportation efficiency for a freight fleet.

Among various suspension control algorithms, the preview method may suit to the fleet truck transportation best. In the literature (Thommyppillai et al., 2010), Thommyppillai et al. applied as self-adaptive linearisation preview control theory to a simple nonlinear heavy-duty vehicle model. In the literature (Krtolica and Hrovat, 1990), Krtolica and Hrovat developed a new active suspension control algorithm by previewing the contour information of the road ahead to improve ride comfort. Other research also confirms that the wheelbase preview control can achieve a good control effect on a single truck (Yoshimura et al., 2001). However, for the overall operation of the fleet, the huge amount of information may delay or even congest the control data. Soit is the authors' main purpose to properly apply the preview algorithm to IoV system, not only reducing the amount of data interaction by optimising the system architecture, but also improving each truck's suspension response.

Based on the above discussion, we propose a new suspension control method for truck fleet, which expands the traditional wheelbase preview to a super-wheelbase preview between vehicles, and constructs as simplified IoV structure with paired truck unit and base station.

The organisation of this paper is as follows: In Section 2, a truck suspension IoV solution with super-wheelbase preview control is proposed. In Section 3, PSO was used calculate the safe distance between paired trucks. In Section 3, the suspension model for heavy-duty trucks is established and simulation results are analysed. Then, in Section 4, a single-objective optimisation is performed for a truck fleet. Section 5 contains the three conclusions of this paper.

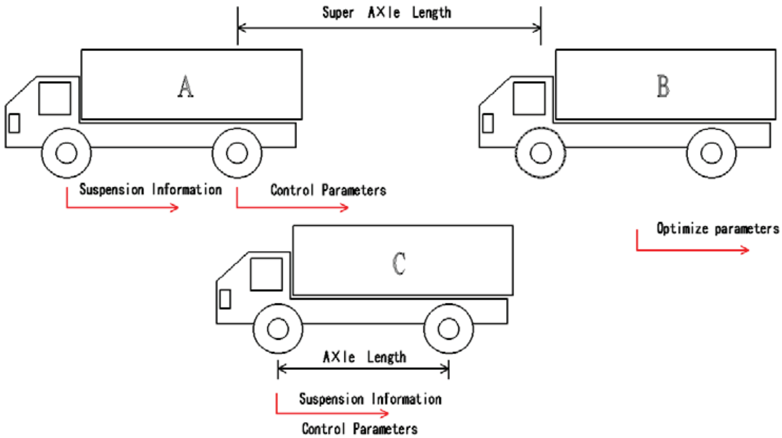
2 Super-wheelbase preview control scheme based on internet of vehicles

In order to enlarge economic benefits, the fleet truck transportation has typical repetitive characteristics, that is, we usually take the same truck model and a fixed line to complete a same transportation task. This repetitive feature is the prerequisites for the super-wheelbase preview.

In this paper, the basic principle of the algorithm is that the road input and the suspension response in the front truck are transmitted to the rear vehicle as preview inputs. The distance between the two trucks is much longer than a single vehicle's axle length, so it is named the super-wheelbase preview analogising with the traditional wheelbase preview. Subsequent vehicles are analogous to the rear axle for corresponding suspension control. Different from the conventional truck-fleet IoV forms, the fleet sequences vehicles in pairs firstly. The communication between two paired trucks may via Wi-Fi or other wireless transmission methods. The data transmission and among the pairs optimisation proceeding uses a fleet IoV system. This new net structure can reduce the data interaction amount by slightly less than a half.

In Figure 1 we show a paired unit and a single truck using wheelbase preview. The truck A and truck B of the fleet form a pair. Truck A uses a traditional wheelbase preview algorithm, as same as truck C.But the control parameters and suspension response on rear axle may be transmitted to truck B. The Super-wheelbase preview algorithms are used between the truck A and the truck B.The suspension parameters of the rear axle of the truck A are transmitted to the front axle of the truck B as the input of the improved algorithm. Since the axle length are much smaller than the distance between A and B, the rear axle in truck B could use the same control parameters as the front axle. The consequent pairs use the same control method. The IoV base station collects the rear truck's control results in each pair and performs optimisation along with pair sequence. When the suspension response calculations obtain the minimised values, the after pairs could use the optimal parameter offered by the base station. That means the two trucks in pair only need to offer their positions and speeds for the suspension control. The connection and interaction between the base station and the truck pairs are shown in Figure 2.

Figure 1 Super-wheelbase preview (see online version for colours)



In this new designed network, we uses the front trucks in each pairs as a carrier to collect, monitor and filter the road condition information, while the rear trucks communicated with the base station.

However, the Wi-Fi or Bluetooth communication mode's effective distance is limited. The data transmitted between paired vehicles may get lost. When the distance is greater than 200 m, the base station needs to switching paired data, so it is necessary to establish a fleet geographic information monitoring system via GPS.

For the operation of the monitoring system, the IoV system implemented in this article adopts GPS global satellite positioning technology and wireless communication technology to establish a GPS monitoring center, as shown in Figure 3. The monitor system can accurately locate the fleet trucks. In an e-map case, three trucks pass a certain road, and the rear vehicle obtains the geographical coordinates of the front vehicle; communication is performed through the TCP/IP protocol. When traffic conditions change, the paired vehicles communicate via synchronous/acknowledgement(SYN/ACK)request and response in one host. At this time, the TCP connection is successfully established. Then the front vehicle loads the geographic coordinates, suspension parameters, and control status into a data packet and sends it to the rear vehicle. Table 1 describes data packets transmits between the front and rear truck. And It also establishes a connection with the cloud server in the base station to update the data packets in real time. The monitoring center analyses and processes the vehicle data information through the cloud server, so as to calculate the optimal suspension parameters of the fleet trucks and send them to the following trucks in time to realise intelligent monitoring, scheduling and management for the truck fleet.

Figure 2 Data interaction system (see online version for colours)

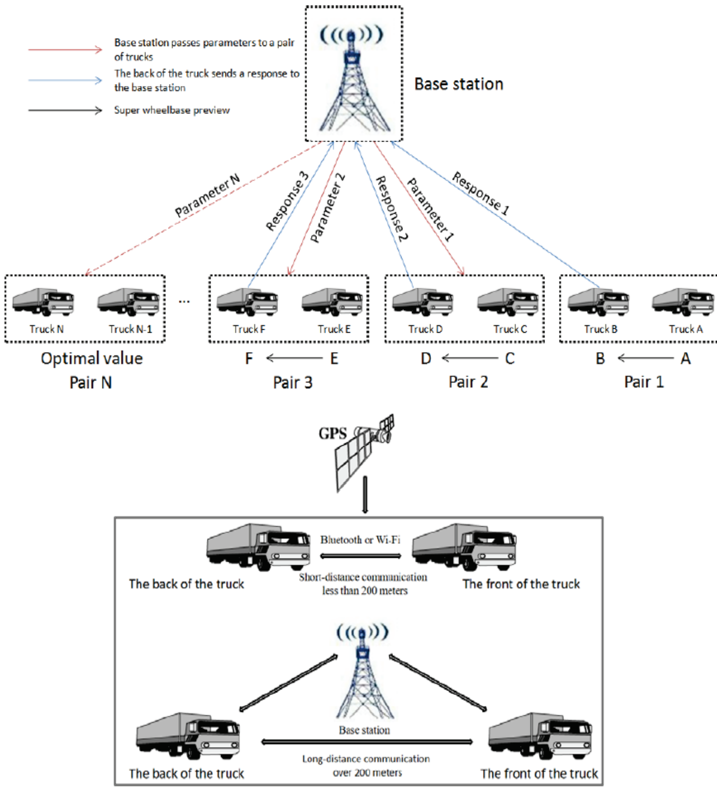


Figure 3 Geographical information of the first three trucks (see online version for colours)

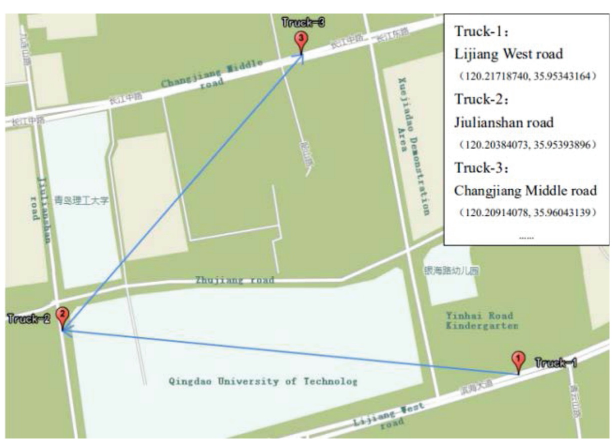
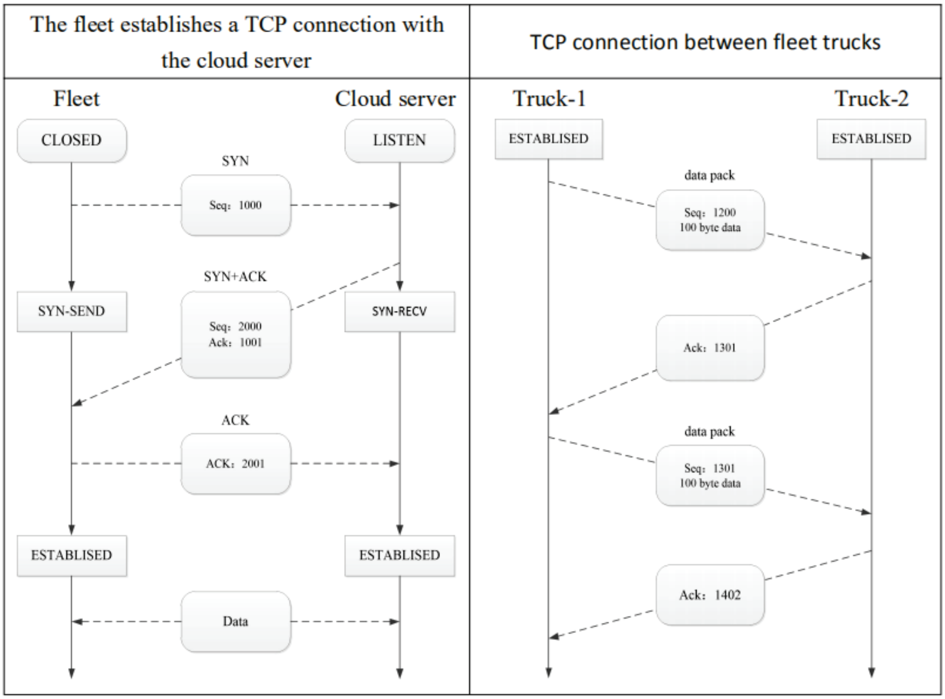


Table 1 Establishing connections between fleet trucks, fleets and the cloud



3 Optimised design for super-wheelbase preview

For traditional wheelbase preview control, the wheelbase is fixed. However, for the super-wheelbase in this paper, the distance between the paired trucks may be changing so its optimal value must be determined using PSO algorithm at first.

3.1 Particle swarm optimisation algorithm for vehicle distance

The PSO algorithm was firstly proposed by Kennedy and Eberhart. It originated from the study of bird predation (Wu, 2019). The mathematical description of the PSO algorithm is as follows. It can be assumed that the population consists of m particles in an n-dimensional search space, and the velocity and position of the ith particle are:

$$\begin{cases} V_i = (v_{i1}, v_{i2}, \ldots, v_{in}) \\ X_i = (x_{i1}, x_{i2}, \ldots, x_{in}) \end{cases}, \quad i = 1, 2, \cdots, m \tag{1}$$

Formula (1) is the mathematical description of PSO.

In an iteration procedure, the particle velocity and position update as bellow:

$$\begin{aligned} v_{ij}(k+1) =& \omega \cdot v_{ij}(k) + c_1 \cdot rand_1 \cdot (p_{ij}(k) - x_{ij}(k)) \\ & + c_2 \cdot rand_2 \cdot (p_{gj}(k) - x_{ij}(k)) \\ x_{ij}(k+1) =& x_{ij}(k) + v_{ij}(k+1) \end{aligned} \tag{2}$$

Formula (2): in an iteration procedure, the particle velocity and position are constantly updated.

In formula (2), parameter k is the current iterating number; the velocity and position particle $i = [1, m]$ and $j = [1, n]$; x_{ij} and v_{ij} respectively represent the actual position and velocity of the particles; p_{ij} is the best value when the ith particle reaches position j, while p_{ij} is the best in current searching. Parameter ω is the velocity weighting factor, while c_1 and c_2 are the learning factors. The random numbers $rand_1$ and $rand_2$ are in the interval $[0, 1]$.

The speed set of all trucks in a freight fleet at time t is defined as $V(t)$, and the acceleration set is $A(t)$. That is:

$$V(t) = \{v_1, v_2, \ldots, v_n\} \tag{3}$$

$$A(t) = \{a_1, a_2, \ldots, a_n\} \tag{4}$$

Formula (3): the speed set of a truck fleet.

Formula (4): the acceleration set of a truck fleet.

We use the safety distance as the optimal distance in this paper. It was proposed by Wipke et al. (1999) as the following formula:

$$S_{mn}(t) = S_0 + t_n \cdot v_m(t) + \frac{v_m(t) \cdot [v_m(t) - v_n(t)]}{2\sqrt{a_{\text{int},m} \cdot b_{\text{int},m}}} \tag{5}$$

In this formula (5), S_0 is the static safety distance, t_n is the headway, $v_m(t)$ and $v_n(t)$ are the speeds of the paired trucks at the time of t, $a_{\text{int},m}$ and $b_{\text{int},m}$ are the expected acceleration and deceleration of the mth vehicle. For the paired truck, there is $m = n + 1$.

Considering the differences between the trucks transportation and passenger cars driving, we could only focus on the driving adaptability, instead of three objective functions mentioned in the literature (Yu, 2019). So a single objective function is established for the paired nth and the $n + 1$th trucks. The formula is as follows:

$$\min \sum_{t=0}^{T-\Delta t} \left[\omega(t) \left(a_n(t) - a_{na}(t)\right)^2\right] \tag{6}$$

$$\min \sum_{t=0}^{T-\Delta t} \left[\omega(t) \left(a_{n+1}(t) - a_{(n+1)a}(t)\right)^2\right] \tag{7}$$

$$a_{(n+1)a}(t) = L \cdot \left[R_{n(n+1)}(t) + (v_{n+1}(t) - v_n(t))\right] \tag{8}$$

$$R_{n(n+1)}(t) = s_n(t) - s_{n+1}(t) - S_{n(n+1)}(t) \tag{9}$$

Formulas (6)$\sim$(9): A single objective function is established for the paired nth and the $n + 1$th trucks.

Among them, T is the total time driving on a certain road for each truck. Parameter Δt is its disturbance. L is the driving style coefficient. a_{na} is the expected acceleration of the nth truck at the time t, $a_{(n+1)a}$ is the expected acceleration of the $n + 1$th truck at the time

t; $R_{n(n+1)}$ is the difference between the actual and the optimal distance, $s_n(t)$ and $s_{n+1}(t)$ are the positions of the front and rear trucks respectively. $\omega(t)$ is a variable factor describing the distance changing degree, as shown in function (10). α and β are constant.

$$\omega(t) = \alpha e^{-\beta(s_{n+1}(t)-s_n(t)-S_0)} \tag{10}$$

Based on the IoV system, we establish constraint equations for a fleet of trucks in pairs:

$$\begin{aligned} & v_n(t+\Delta t) = v_n(t) + a_n(t)\Delta t \\ & v_{n+1}(t+\Delta t) = v_{n+1}(t) + a_{n+1}(t)\Delta t \\ & s_n(t+\Delta t) = s_n(t) + v_n(t)\Delta t + \frac{1}{2}a_n(t)^2 \\ & s_{n+1}(t+\Delta t) = s_{n+1}(t) + v_{n+1}(t)\Delta t + \frac{1}{2}a_{n+1}(t)^2 \\ & s_{n+1}(t) - s_n(t) \geq S_{n(n+1)}(t) \end{aligned} \tag{11}$$

Formula (11): The constraint equations for a fleet of trucks in pairs.

When the freight fleet is operating, the driving distance will change with the road condition information. According to the above algorithm, the size of the inertia factor ω plays a key role in the optimisation. A larger ω value can improve global search ability, while a smaller one is good for the convergence. After the above analysis, it can be seen that the reasonable setting of the parameter values has a positive significance for the optimisation result. So we adopt a decreasing strategy for the inertia factor, and then obtain the best distance value via the inertia factor's optimising. The decreasing strategy is:

$$\omega = \omega_{\max} - \frac{(\omega_{\max} - \omega_{\min}) \cdot k}{k_{\max}} \tag{12}$$

Formula (12): The size of the inertia factor ω plays a key role in the optimisation.

Considering the computing speed, we utilised a local optimisation method as shown in Figure 4. The factors' value is very important for the searching and convergence proceeding. For the learning factor c_1 and c_2, larger values will cause the particles converging to the local optimum prematurely. On the other hands, if c_1 and c_2 are both zero, the particle velocity will be constant, which will cause the search to fail. While for the trucks number m is small, the algorithm converges fast, but it is easy to fall into a local optimum; if the value of m is large, the algorithm has stronger optimisation ability, but the convergence speed is slow. Therefore, we set values for the parameters m, n, c_1, and c_2 as step (1). The initial position and velocity of each particle are randomly generated.

1 Initialise the population. In this paper, $m = 30, c_1 = 0.5, c_2 = 1$. Because of $T = 500$ s, take the first three pairs for optimisation, so, $n = 60$. Let the overall time $T = 500$ s, which means that the PSO algorithm would be call every 500 s. and find the value of all variables a in 5 s, and the speed of the truck can be obtained according to the kinematics relationship.

2 Calculate the fitness value of each particle as the evaluation standard. Corresponding functions need to be established for each constraint, such as the safety distance constraint:

$$D_{n,s} = \omega_s \sum_{i=1}^{2} \min\left(s_{n+1}(i\Delta t) - s_n(i\Delta t) - S_{n(n+1)}(i\Delta t), 0\right) \tag{13}$$

$$D_s = \sum_{n=1}^{6} D_{n,s} \tag{14}$$

In the formula, $D_{n,s}$ is a adaptation of safety distance of the nth vehicle, ω_s is safety distance factor. D_s is the safety distance fitness of 6 trucks.

3 Find the individual optimal value and the global optimal value.

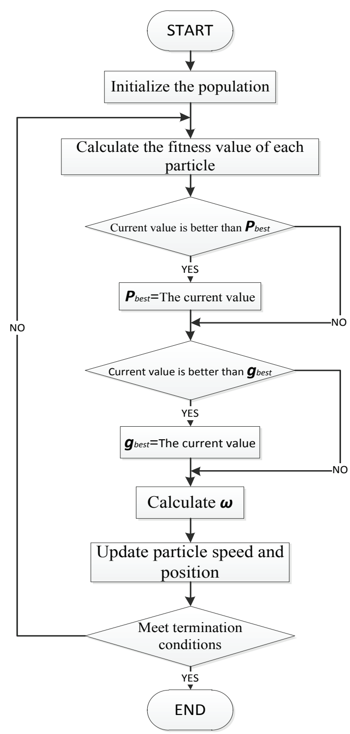
4 Calculate the value of ω according to formula (12).

5 Update the particle speed and position according to formulas (1) and (2).

6 Stop if iteration termination condition is reached, otherwise return to the second step.

This article uses Matlab to simulate the optimal distance. As shown in Figure 5, when the first two trucks of the convoy start, they will be affected by road conditions, weather, and traffic flow, and the distance between the vehicles will change accordingly. The algorithm establishes a safe distance constraint model in this article. The optimal solution is reached when S is 2.27 km.

Figure 4 Flow chart of particle swarm algorithm



3.2 *Super-wheelbase preview system model*

The Super-wheelbase Preview System Model take two paired trucks as one single truck for the preview control. The control algorithm principle is same as traditional wheelbase preview but has to substitute some equivalent parameters. The super-wheelbase suspension mode was established as shown in Figure 6.

Figure 5 The optimal distance between the two trucks before and after the departure (see online version for colours)

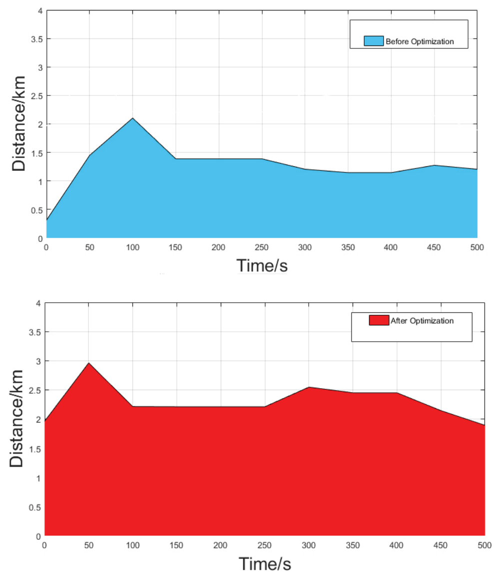
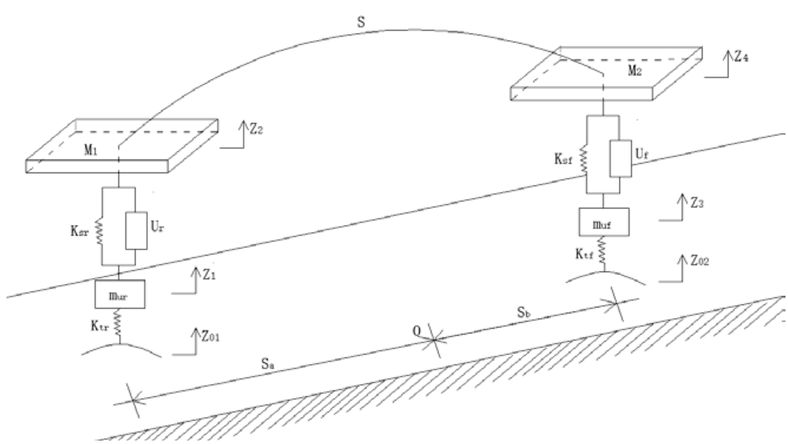


Figure 6 Super wheelbase suspension model



When a truck is fully loaded with a sprung mass M, the front axle bears a load F_f and the rear axle bears a load F_r. the center of mass point O, illustrated by S_a and S_b, can be calculated with the mechanical equations:

$$F = Mg, F = F_f + F_r, F_f \cdot S_a - F_r \cdot S_b = 0 \tag{15}$$

For the super-wheelbase preview model, the distance S between the front and rear vehicles replaces the truck's wheel base. This distance has been optimised in Figure 5, so the values of S_a and S_b in equation 15 can be obtained easily.

The dynamic equations of the mathematical model are:

$$\begin{cases} \ddot{Z}_1 \cdot m_{ur} = K_{tf}\left(Z_{01} - Z_1\right) - U_r + K_{sr}\left(Z_2 - Z_1\right) \\ \ddot{Z}_2 = \left(\frac{1}{M} + \frac{S_a^2}{I}\right) \cdot \left[U_r - K_{sr}\left(Z_2 - Z_1\right)\right] + \left(\frac{1}{M} - \frac{S_a S_b}{I}\right) \cdot \left[U_f - K_{sf}\left(Z_4 - Z_3\right)\right] \\ \ddot{Z}_3 \cdot m_{uf} = K_{tf} \cdot \left(Z_{02} - Z_3\right) - U_f + K_{sf} \cdot \left(Z_4 - Z_3\right) \\ \ddot{Z}_4 = \left(\frac{1}{M} - \frac{S_a S_b}{I}\right) \cdot \left[U_r - K_{sr}\left(Z_2 - Z_1\right)\right] + \left(\frac{1}{M} + \frac{S_b}{I}\right) \cdot \left[U_f - K_{sf}\left(Z_4 - Z_3\right)\right] \end{cases} \tag{16}$$

In the formula, K_{tr} and K_{sr} are the stiffness of the rear wheel and suspension for the front vehicle. K_{tf} and K_{sf} are the stiffness of the front wheel and suspension for the rear vehicle. U_r is the force generated by the front suspension actuator, U_f is the force generated by the front suspension actuator. M_1 and M_2 are two truck's sprung massed. m_{ur} and m_{uf} respectively represent the unsprung masses of the front and rear of the two vehicles. Z_{01}, Z_1, Z_2 are vertical displacement of the road input, the wheel and body for the front truck while Z_{02}, Z_3 and Z_4 are for the rear truck.

The dynamics equations can be written in matrix form as below:

$$\dot{X}(t) = A \cdot X(t) + B \cdot U(t) + F \cdot W(t) \tag{17}$$

In the formula, $X = \left[\dot{Z}_4, \dot{Z}_3, \dot{Z}_2, \dot{Z}_1, Z_4, Z_3, Z_2, Z_1\right]^T$ is the state variable, $U = [U_f, U_r]$ is the control variable, and $Z_0 = [Z_{01}, Z_{02}]^T$ is the road input vector.

The system matrixes A, B and F are:

$$A = \begin{pmatrix} 0\,0\,0\,0 & -\alpha_1 \cdot K_{sf} & \alpha_1 \cdot K_{sf} & -\alpha_2 \cdot K_{sr} & \alpha_2 \cdot K_{sr} \\ 0\,0\,0\,0 & \frac{K_{sf}}{m_{uf}} & -\frac{K_{sf}+K_{tf}}{m_{uf}} & 0 & 0 \\ 0\,0\,0\,0 & -\alpha_2 \cdot K_{sf} & \alpha_2 \cdot K_{sf} & -\alpha_3 \cdot K_{sr} & \alpha_3 \cdot K_{sr} \\ 0\,0\,0\,0 & 0 & 0 & \frac{K_{sr}}{m_{ur}} & -\frac{K_{sf}+K_{tf}}{m_{ur}} \\ 1\,0\,0\,0 & 0 & 0 & 0 & 0 \\ 0\,1\,0\,0 & 0 & 0 & 0 & 0 \\ 0\,0\,1\,0 & 0 & 0 & 0 & 0 \\ 0\,0\,0\,1 & 0 & 0 & 0 & 0 \end{pmatrix}; \tag{18}$$
$$B = \begin{pmatrix} \alpha_2 & 0 & \alpha_3 & -\frac{1}{m_{ur}} & 0\,0\,0\,0 \\ \alpha_1 & -\frac{1}{m_{uf}} & \alpha_2 & 0 & 0\,0\,0\,0 \end{pmatrix}^T; F = \begin{pmatrix} 0 & \frac{K_{tf}}{m_{uf}} & 0 & 0 & 0\,0\,0\,0 \\ 0 & 0 & 0 & \frac{K_{tr}}{m_{ur}} & 0\,0\,0\,0 \end{pmatrix}^T$$

Among them, there are $\alpha_1 = \frac{1}{M} + \frac{s_b^2}{I}, \alpha_2 = \frac{1}{M} - \frac{s_a s_b}{I}, \alpha_3 = \frac{1}{M} + \frac{s_b^2}{I}$.

For the super-wheelbase preview system, the information interaction occurred both vehicle-to-vehicle in pair and among the pairs. Thus, when the first truck passed a certain road, the suspension controller can get the best control force for its rear axle with common wheelbase algorithm, and communicate to the rear vehicle in time. Therefore the rear trucks, not only the paired one, can respond in advance. References the literature (Darus and Sam, 2009; Sam et al., 2000; Vaughan et al., 2003; Elmadany and Al-Majed, 2001) analysed LQR active suspension system with focus on ride quality, load varying and passenger comfort, and concluded that the LQR controller can be considered as one of the solutions for better suspension responses. The riding performance is evaluated through three indicators: body acceleration, suspension working space, and tyre dynamic displacement. Therefore, the active suspension's control index is:

$$J = \lim_{T \to \infty} \frac{1}{T} \int_0^T \Big[q_1 \cdot (Z_1 - Z_{01})^2 + q_2 \cdot (Z_2 - Z_1)^2 + \rho_1 \cdot \ddot{Z}_2^2 + q_3 \cdot (Z_3 - Z_{02})^2 + q_4 \cdot (Z_4 - Z_3)^2 + \rho_2 \cdot \ddot{Z}_4^2 \Big] dt \tag{19}$$

In the formula, $q_1, q_2, q_3, q_4, \rho_1, \rho_2$ are the weighting coefficients. The above formula is rewritten in a matrix form as following:

$$J = \lim_{T \to \infty} \frac{1}{T} \int_0^T \left(X^T Q X + U^T R U + 2X^T N U \right) dt \tag{20}$$

In the formula,

$$Q = \begin{pmatrix} 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & q_4 + K_{sf}^2 \beta_3 & -q_4 - K_{sf}^2 \beta_3 & K_{sf} K_{sr} \beta_2 & -K_{sf} K_{ss} \beta_2 \\ 0 & 0 & 0 & 0 & -q_4 - K_{sf}^2 \beta_3 & q_3 + q_4 + K_{sf}^2 \beta_3 & -K_{sf} K_{sr} \beta_2 & K_{sf} K_{sr} \beta_2 \\ 0 & 0 & 0 & 0 & K_{sf} K_{sr} \beta_2 & -K_{sf} K_{sr} \beta_2 & q_2 + K_{sr}^2 \beta_1 & -q_2 - K_{sr}^2 \beta_1 \\ 0 & 0 & 0 & 0 & -K_{sf} K_{sr} \beta_2 & K_{sf} K_{sr} \beta_2 & -q_2 - K_{sr}^2 \beta_1 & q_1 + q_2 + K_{sr}^2 \beta_1 \end{pmatrix} \tag{21}$$

$$R = \begin{pmatrix} \beta_1 & \beta_2 \\ \beta_2 & \beta_3 \end{pmatrix}, \quad \begin{pmatrix} 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ -K_{sf}\beta_2 & -K_{sf}\beta_3 \\ K_{sf}\beta_2 & K_{sf}\beta_3 \\ -K_{sr}\beta_1 & -K_{sr}\beta_2 \\ K_{sr}\beta_1 & K_{sr}\beta_2 \end{pmatrix} \tag{22}$$

Among them, $\beta_1 = \rho_1 \alpha_3^2 + \rho_2 \alpha_2^2; \beta_2 = \rho_1 \alpha_2 \alpha_3 + \rho_2 \alpha_1 \alpha_2; \beta_3 = \rho_1 \alpha_2^2 + \rho_2 \alpha_1^2$.

The optimal control feedback gain matrix K is obtained from the Ricatti equation (formula 23), and K is determined by the vehicle's parameters and the weighting coefficients as formula 24:

$$PA + A^T P - (PB + N) R^{-1} \left(B^T P + N^T \right) + Q = 0 \tag{23}$$

$$K = R^{-1} \cdot \left(B^T \cdot P + N^T \right) \tag{24}$$

According to the feedback state variable at any time, the optimal control matrix of the actuator before and after time t can be obtained:

$$U(t) = -KX(t) \tag{25}$$

Using the time domain expression of Gaussian white noise as the road surface input model, the road surface input Z_{01} is:

$$\dot{Z}_{01}(t) = -2\pi f_0 Z_{01}(t) + 2\pi\sqrt{G_0 u_c} w_1(t) \tag{26}$$

In the formula above, G_0 is the road roughness coefficient; u_c is the forward speed of the rear vehicle; $w_1(t)$ is Gaussian white noise with zero mean; f_0 is the lower cut-off frequency.

When the truck is driving in a straight line, there is a time lag τ on the road input between the front truck's rear wheels and the rear truck's front wheel. Due to this time lag, the road surface input Z_{02} can be written as:

$$\dot{Z}_{02}(t) = \dot{Z}_{01}(t)(t-\tau) \tag{27}$$

This time lag is approximately equal to the two trucks' distance divided by the forward speed of the rear truck. That is to say, in Figure 6 there is $\tau = (S_a + S_b)/u_c$.

The inputs relationship between the front and rear vehicles can be expressed by Laplace transfer function:

$$\frac{w_2(s)}{w_1(s)} = e^{-\tau s} \tag{28}$$

The second-order Pade approximation is used to transform it into the form of state space, as follows:

$$\frac{w_2(s)}{w_1(s)} = \frac{a_0 - a_1 s + a_2 s^2 - a_3 s^3 + \ldots + a_n s^n}{a_0 + a_1 s + a_2 s^2 + a_3 s^3 + \ldots + a_n s^n} \tag{29}$$

Among them, $a_0 = \left(\frac{12}{\tau^2}\right), a_1 = \left(\frac{6}{\tau}\right), a_2 = 1$.

Taking an additional state vector $\eta = \begin{bmatrix} \eta_1 \\ \eta_2 \end{bmatrix}$, the state space equations can be written:

$$\dot{\eta}(t) = A_\eta \eta(t) + B_\eta w_1(t) \tag{30}$$

Among them, $A_\eta = \begin{pmatrix} 0 & 1 \\ a_0 & -a_1 \end{pmatrix}, B_\eta = \begin{pmatrix} -2a_1 \\ 6a_0 \end{pmatrix}$.

The input equation of the system is:

$$w_2(t) = w_1(t-\tau) = C_\eta \eta(t) + w_1(t) = \eta_1(t) + w_1(t) \tag{31}$$

Among them, $C_\eta = \begin{bmatrix} 1 \, 0 \end{bmatrix}$. Then the system state equation with wheelbase preview information and additional state vector η can be obtained:

$$\begin{pmatrix} \dot{X} \\ \dot{\eta} \end{pmatrix} = \begin{pmatrix} A & FD_\eta \\ 0 & A_\eta \end{pmatrix} \begin{pmatrix} X \\ \eta \end{pmatrix} + \begin{pmatrix} B \\ 0 \end{pmatrix} U + \begin{pmatrix} FE_\eta \\ B_\eta \end{pmatrix} w_1 \tag{32}$$

Among them, $D_\eta = \begin{bmatrix} 0 \, 0 \\ 1 \, 0 \end{bmatrix}, E_\eta = \begin{bmatrix} 1 \\ 1 \end{bmatrix}$.

Therefore, the optimal parameters of the controller can be obtained by combining the state matrix and the weighting matrix of the wheelbase preview into the Riccati equation.

3.3 Simulation analysis

A half-car model is established in Matlab/Simulink environment and the software simulations are performed. The model takes heavy duty trucks Jiefang J6 as the research object, and the main parameters are listed in Table 2. The vehicle speed is set to 20 km/h, and the system sampling time T_s is 2.5 ms.The road input conditions choose Class A to D. The simulation curves of wheelbase preview and super-wheelbase preview of the active suspension are respectively shown in Figures 7–9, including the Body Acceleration, Suspension Working Space and Tyre Dynamic Displacement. Only the results in class B road are illustrated as an example.

Table 2 Main parameters of simulation

Parameter name	*Symbol*	*Unit*	*Value*
Sprung mass	M	kg	5605
Distance between two vehicles	S	km	2.27
Lead car to centroid point	S_a	km	1.28
Back to the centroid point	S_b	km	0.99
Front vehicle rear suspension stiffness	K_{sr}	$\mathrm{kg} \cdot \mathrm{m}^{-1}$	912000
Rear vehicle front suspension stiffness	K_{sf}	$\mathrm{kg} \cdot \mathrm{m}^{-1}$	241641
Front vehicle rear wheel stiffness	K_{tr}	$\mathrm{kg} \cdot \mathrm{m}^{-1}$	1660028
Rear wheel stiffness	K_{tf}	$\mathrm{kg} \cdot \mathrm{m}^{-1}$	830014
Unsprung mass in front car	m_f	kg	585
Rear unsprung mass	m_r	kg	300

Figure 7 Body acceleration simulation (see online version for colours)

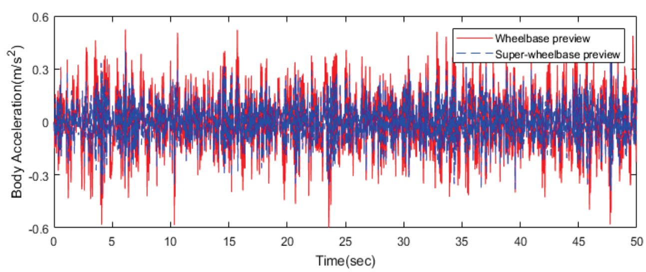


Figure 8 SWS simulation (see online version for colours)

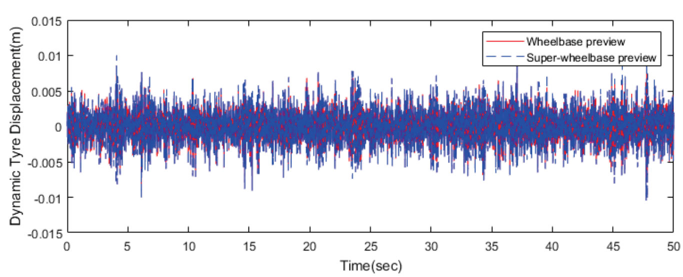
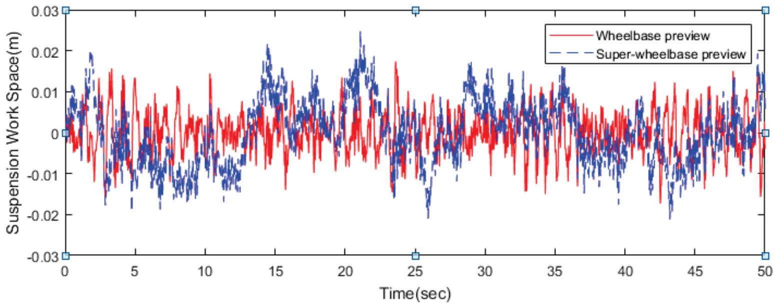


Figure 9 DTD simulation (see online version for colours)



The simulation results show that the response characteristics of the super-wheelbase preview are better than those of the classic wheelbase preview. The RMS is shown in Table 3.

4 Single-objective optimisation for body acceleration

In the super-wheelbase model, some parameters, such as the sprung mass are replaced by an equivalent value. A stable speed is also very difficult to maintain during the whole transportation.Thus,the deviations in calculation and control are almost inevitable. Besides, the first vehicle's control effect has a greater impact on the overall fleet. Therefore, we adopt a single-objective algorithm to optimise the body acceleration. Two or three objectives optimisation may get better results but a simpler algorithm is easier and faster for the potential engineering applications.

Table 3 Main parameters of simulation

Root mean square value of performance index	*Wheelbase preview*	*Super-wheelbase preview*	*Relative error*
Body Acceleration/(m/s^2)	0.381	0.288	24.4%
Suspension Working Space/mm	16.868	15.769	6.5%
Tyre dynamic displacement/mm	5.853	4.186	28.5%

4.1 Design variable

The design variables is defined as $\vec{X} = [K_{sf}, K_{sr}, C_f, C_r]$. Based on the statistics data of common truck models, the value ranges of the design variable are shown in Table 4.

Table 4 Variables and their value ranges

Variable	K_{sf}	K_{sr}	C_f	C_r
Unit	$GN \cdot m^{-1}$	$GN \cdot \mathrm{m}^{-1}$	$kN \cdot \mathrm{s} \cdot \mathrm{m}^{-1}$	$kN \cdot \mathrm{s} \cdot \mathrm{m}^{-1}$
Ranges	$0.1 \sim 0.5$	$1 \sim 4$	$0 \sim 20$	$0 \sim 30$

4.2 Constraints and objective functions

Because the suspension deflection (SWS) is limited by the bumper stops, it must be limited to a safe range to ensure the driving safety. These constrain are:

$$g_{13}(\vec{X}) = Z_1 - Z_3 \leq D_{\max} \tag{33}$$

$$g_{24}(\vec{X}) = Z_2 - Z_4 \leq D_{\max} \tag{34}$$

In the formula, $D_{\max}$ is the allowable maximum suspension deflection. In this case it takes the value as 80 mm.

The task of the fleet trucks mentioned in this article is mainly to transport glass so we take the body acceleration as the single objective. In order to improve the smoothness of the vehicle and the integrity of the cargo, the RMS value of the body acceleration is used as the optimisation index.

The RMS value of the body acceleration is:

$$a(\vec{X}) = \sqrt{\sum_{i=1}^{n} \ddot{Z}_2^2 (t_i) / n} \tag{35}$$

In this paper, the truck fleet is iteratively optimised in pairs. As shown in Figure 10, BAX_i represents the $a(X)$ value for the X_i^{th} truck pair.

When $BAX_i - BAX_{i+1} \rightarrow 0$, the body acceleration reaches a minimum, and the optimisation iteration process will stop. In this case, the fleet trucks are travelling at three different vehicle speeds of 20, 40, and 60 km/h. And the class B roads is used as the road input.

Figure 10 Iterative optimisation of body acceleration (see online version for colours)

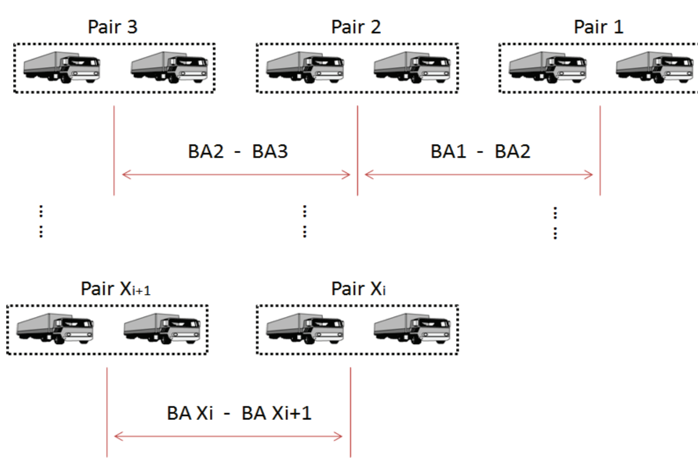


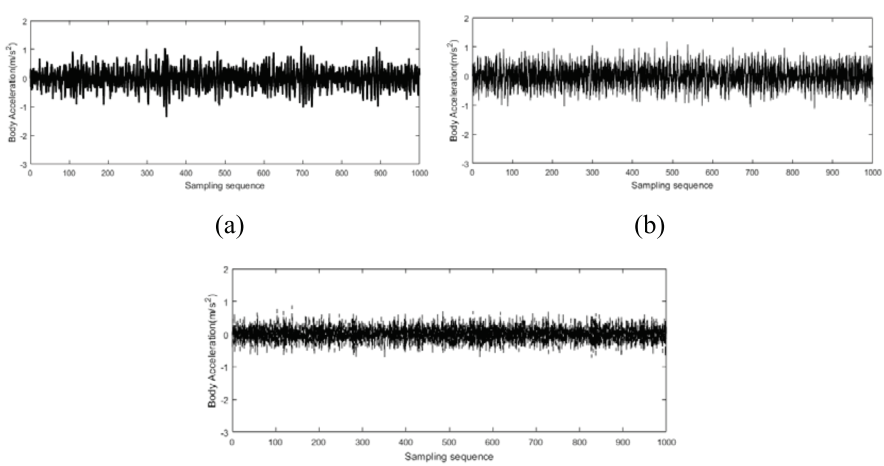
Table 5 Variables and their value ranges

Pavement level	*Speed u_c (km/h)*	*Number of iterations*	*Optimised a (m/s^2)*
B	20	1	0.381
		2	0.288
		3	0.249
	40	1	0.721
		2	0.526
		3	0.387
	60	1	0.942
		2	0.671
		3	0.422

4.3 Optimisation analysis and results

In this paper, the most classical genetic algorithm (SGA) is adopted to deal with the single-objective optimisation problem. For the repeatability characteristics of fleet transportation, the same vehicle type and fixed line, the advantage of this method is simple and practical. It also can complete iterative optimisation efficiently.The simulation is performed in Matlab/Simulink environment. Figures 11–13 show three iterations at a vehicle speed of 20 km/h, 40 km/h and 60 km/h, respectively. Data listed in Table 5 show the RMS value's change during these iterative processes. It can be seen both from figures and the table data: when the vehicle speed is 20 km/h, the body acceleration after iteration is reduced by about 24%; when the vehicle speed is 40 km/h, the body acceleration after iteration is reduced by about 46%; when the vehicle speed is at 60 km/h, the acceleration of the vehicle body after iteration drops by about 56%.

Figure 11 Iteration results at 20 km/h: (a) the first iteration; (b) the second iteration and (c) the third iteration



(a) (b)

(c)

Figure 12 Iteration results at 40 km/h: (a) the first iteration; (b) the second iteration and (c) the third iteration

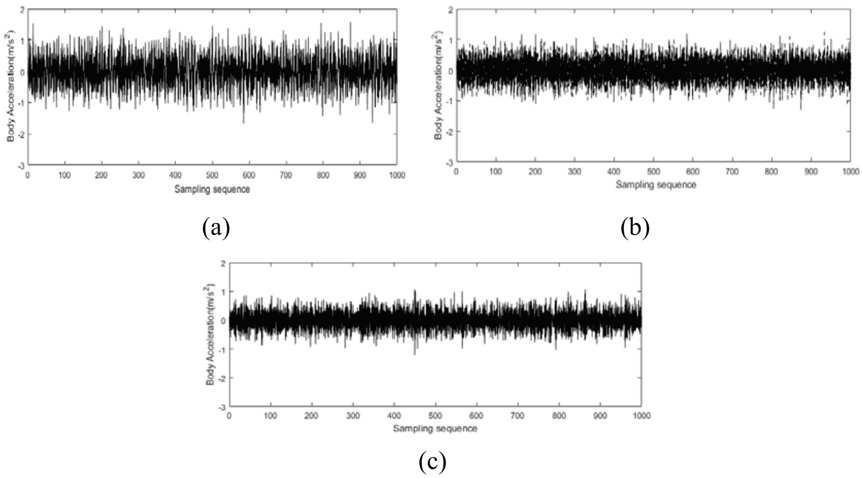
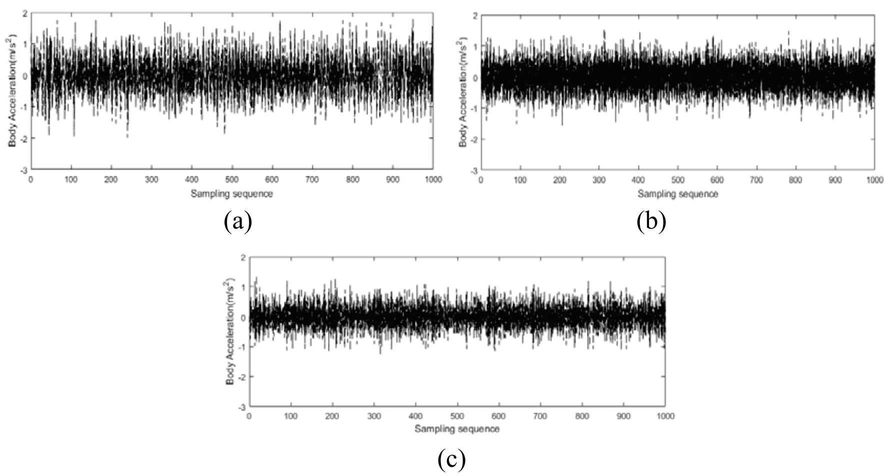


Figure 13 Iteration results at 60 km/h: (a) the first iteration; (b) the second iteration and (c) the third iteration



5 Conclusion

1. In this paper, a network framework of pair interaction supplemented by geographic information monitoring is proposed, which reduces the amount of data interaction and ensures the stability of communication in both the short distance and long distance.
2. Based on the classical wheelbase preview, the super-wheelbase preview algorithm has better control response characteristics.
3. The optimisation of the super-wheelbase preview algorithm has a more efficient iterative process.

References

Chen, M-S., Hwang, C-P., Ho, T-Y., Wang, H-F., Shih, C-M., Chen, H-Y. and Liu, W.K. (2019) 'Driving behaviors analysis based on feature selection and statistical approach: a preliminary study', *The Journal of Supercomputing*, Vol. 75, pp.2007–2026.

Darus, R. and Sam, Y.M. (2009) 'Modeling and control active suspension system for a full car model', *2009 5th International Colloquium on Signal Processing and Its Applications*, IEEE, pp.13–18.

Elmadany, M. and Al-Majed, M. (2001) 'Quadratic synthesis of active controls for a quarter-car model', *Journal of Vibration and Control*, Vol. 7, No. 8, pp.1237–1252.

Krtolica, R. and Hrovat, D. (1990) 'Optimal active suspension control based on a half-car model', *29th IEEE Conference on Decision and Control*, IEEE, pp.2238–2243.

Kumar, N., Kaur, K., Jindal, A. and Rodrigues, J.J. (2015) 'Providing healthcare services on-the-fly using multi-player cooperation game theory in internet of vehicles (IoV) environment', *Digital Communications and Networks*, Vol. 1, No. 3, pp.191–203.

Li, C-S., Franke, H., Parris, C., Abali, B., Kesavan, M. and Chang, V. (2017) 'Composable architecture for rack scale big data computing', *Future Generation Computer Systems*, Vol. 67, pp.180–193.

Papadogiannis, A., Farmakopoulos, A. and Chondros, T. (2010) 'Road tankers axles load share design', *International Journal of Heavy Vehicle Systems*, Vol. 17, Nos. 3–4, pp.256–275.

Roebuck, R., Cebon, D., Jeppesen, B. and Haque, J. (2005) 'A systems approach to controlled heavy vehicle suspensions', *International Journal of Heavy Vehicle Systems*, Vol. 12, No. 3, pp.169–192.

Sam, Y.M., Ghani, M.R.H.A. and Ahmad, N. (2000) 'Lqr controller for active car suspension', *2000 TENCON Proceedings. Intelligent Systems and Technologies for the New Millennium (Cat. No. 00CH37119)*, Vol. 1, IEEE, pp.441–444.

Sharma, S. and Kaushik, B. (2019) 'A survey on internet of vehicles: applications, security issues and solutions', *Vehicular Communications*, Vol. 20, p.100182.

Thommyppillai, M., Evangelou, S. and Sharp, R. (2010) 'Rear-heavy car control by adaptive linear optimal preview', *Vehicle System Dynamics*, Vol. 48, No. 5, pp.645–658.

Vaughan, J., Singhose, W. and Sadegh, N. (2003) 'Use of active suspension control to counter the effects of vehicle payloads', *Proceedings of 2003 IEEE Conference on Control Applications, 2003. CCA 2003*, Vol. 1, IEEE, Istanbul, Turkey, pp.285–289.

Wipke, K., Cuddy, M. and Burch, S. (1999) 'A user-friendly advanced powertrain simulation using a combined backward/forward approach', *IEEE Transactions on Vehicular Technology*, Vol. 48, No. 6.

Wu, B. (2019) *Multi-Objective Particle Swarm Optimization Algorithm and its Application*, PhD thesis, University of Electronic Science and Technology of China.

Yao, W., Yahya, A., Khan, F., Tan, Z., Rehman, A.U., Chuma, J.M., Jan, M.A. and Babar, M. (2019) 'A secured and efficient communication scheme for decentralized cognitive radio-based internet of vehicles', *IEEE Access*, Vol. 7, pp.160889–160900.

Yoshimura, T., Kume, A., Kurimoto, M. and Hino, J. (2001) 'Construction of an active suspension system of a quarter car model using the concept of sliding mode control', *Journal of Sound and Vibration*, Vol. 239, No. 2, pp.187–199.

Yu, Y. (2019) *Research on Queue Optimization of Hybrid Cars Considering Driving Style*, PhD thesis, Jiangsu University.