RBF Neural Network-based Adaptive PID Controller for Active Suspension.

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Active suspension plays a pivotal role in modern vehicles. In this paper, an adaptive PID controller of active suspension systems based on RBF neural network (RBF-NN) is developed. A quarter-car suspension system with two degrees of freedom is demonstrated. The values of proportional, integral, and derivate components are obtained by using Ziegler-Nichols(Z-N) tuning method and RBF-NN methods. The suspension system is perturbed using the sine function. Simulated in the Simulink environment is the quarter-car model. Passive suspension systems, adaptive PID controller utilizing the Z-N tuning approach, and adaptive PID based on the RBF-NN method for active suspension systems are compared. The active suspension with PID control based on the RBF-NN outperformed the active suspension with PID control utilizing the Z-N tuning approach and passive suspension, according to simulation data. The comparison demonstrates the proposed control method's superior features.

Introduction: Vehicle suspension systems play a significant role in improving the performance of passenger ride comfort and road holding [1]. There are four actuators placed between the vehicle body and wheel-axle in active suspension systems Compared with the passive and semi-active suspension systems [2], and actuators can directly generate the active force to lessen vibration by absorbing or releasing load. As a result, active suspension systems can significantly increase the ride comfort and road holding [3].

To cope with the difficult problem in improving the performance of vehicle. Many control approaches have been introduced and applied to the vehicle control [4]. Currently, PID control has been widely used in vehicle systems [5], as the PID control method is simple and efficient, high reliable and easy to implement [6]. However, the proportional, integral and derivative parts are too hard to be adjusted to get the optimal result. The most primitive method is the experimental method, but this method is time-consuming and typically challenging to identify the ideal PID control parameters [7]. Subsequently, a large traditional PID control parameter optimization methods emerged, the most common methods are Ziegler-Nichols (Z-N) method [8]. Ziegler-Nichols (Z-N) has the advantage of simplicity and easy implementation, but sometimes produce large overshoot and oscillation, which makes the control effect not ideal.

To overcome the limitation of conventional PID control, many improvements to PID control have been applied in PID control [9]. Among all the approaches to improve the PID control, Back Propagation neural network (BP-NN) is an improvement and optimization control for conventional PID control [10]. BP-NN has the ability in approximate any nonlinear function, and its structure and learning algorithm are simple and clear. For example, J Liu et.al proposed a PID controller based on the BP-NN algorithm to improve the energy-regenerative efficiency calculation for active suspension [11]. Yet, the BP-NN method has many parameters to be optimized, and the convergence speed is slow. Moreover, there are multiple extreme points in the objective function, and it is easy to fall into a local minimum value [12]. RBF-NN has strong self-learning feature for that it has a nonlinear input to output mapping while having a linear hidden layer to output space mapping, which considerably speeds up learning speed and prevents the local minimum problem [13]. As a result, adding RBF-NN to the basis of BP network adjustment parameters can also speed up the adjustment of PID parameters, and enhance its anti-interference and robustness. MG Zhang et al. applied the RBF-NN to identify the parameters of PID controller online and the weights of the adaptive PID controller are adjusted in time [14]. However, the research about adaptive PID control based on RBF-NN for active suspension systems is fewer. Hence, in this paper, the adaptive PID control based on RBF-NN method is applied to active suspension.

The structure of this paper is as follows: In section 2, the quarter car active suspension is conducted. In section 3, the PID controller using Z-N method and the PID controller based on RBF-NN method are discussed. Section 4 shows the simulation results. Conclusions are proposed in section 5.

System Model: The quarter car active suspension system model is simple and can capture the chief component parts, so the two DOF quarter car model is applied in this paper and is shown as Figure 1.
The parameters in Figure 1 are described as follows.

m_s and m_u are the equivalent mass of the vehicle body and the wheel assemble including axle and tire. k_s and k_t are the stiffness of spring and tire. u is the active effective control force.$c_s$is the damper coefficient. x_g, x_u, x_s represent the displacement of ground surface, un-sprung mass and sprung mass.

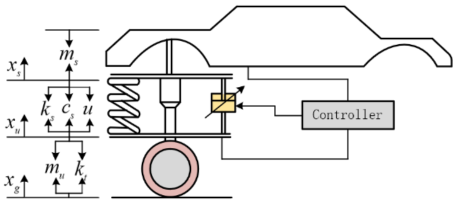


Fig. 1 *Quarter active suspension model.*

The dynamic function of quarter car suspension system is shown as.

$$\begin{cases} m_s\ddot{x}_s = u + k_s(x_u - x_s) + c_s(\dot{x}_u - \dot{x}_s) \\ m_s\ddot{x}_u = k_t(x_g - x_u) - u - k_s(x_u - x_s) - c_s(\dot{x}_u - \dot{x}_s) \end{cases} \quad (1)$$

To facilitate the control synthesis, the state variables are defined as the following. Define the state matrix and output matrix.

$$X = [x_s - x_u \quad \dot{x}_s \quad x_g - x_u \quad \dot{x}_s]^T$$
$$Y = [\ddot{x}_s \quad x_s - x_u \quad x_g - x_u \quad u]^T$$

Thus, the state space representation of the dynamics is given by the following.

$$\dot{X} = AX + BU + FW$$
$$Y = CX + DU$$

Controller Design: Two different methods used to obtain the parameters value in PID control are presented. These are the Ziegler-Nichols (Z-N) closed tuning method and RBF neural network for the PID control to reduce the vibration of the quarter car model. In addition, an adaptive PID with Z-N method is considered to compare with PID control based on RBF-NN for active suspension. The next of this section, two subsections present the PID controller with Z-N method and the adaptive PID controller based on RBF-NN are presented.

PID controller consists of proportional$P\big(e(t)\big)$, integral $P\big(e(t)\big)$ and derivative $D\big(e(t)\big)$parts [15]. Assuming each amplitude is completely decoupled and controlled independently from other amplitudes, the control input $U(t)$ is given by.

$$U(t) = k_p e(t) + k_i \int e(t)dt + k_d \frac{de(t)}{dt} \quad (2)$$

Where $e(t)$ is the control error, and can be expressed as

$$e(k) = x_d(t) - x_a(t) \quad (3)$$

Where $x_d(t)$ is the desired response and $x_a(t)$ is the actual response.

The control algorithm is shown as.

$$u(t) = u(t-1) + \Delta u(t) \quad (4)$$

Moreover, in this paper, Ziegler-Nichols closed tuning method has been used with a simple method that uses the ultimate gain value. Gain parameters of the PID controller are detailed in Table 1[16].

Table 1: Z-N method.

	K_p	T_i	T_d
PID	$1.2\,\tau/T$	2.2τ	0.5τ

RBF-NN is a neural network structure that simulates local adjustments in the human brain and covers receptive fields. Therefore, RBF neural network is a local approximation network, and has been proved that it can approximate any continuous function with arbitrary precision. The structure of the RBF neural network is shown in the Figure 3, which is a three-layer feedforward neural network. The input layer node and the output layer node are composed of linear neurons, the hidden layer node generally selects the Gaussian kernel function, which can produce a local response to the input vector, and the output node performs linear weighting on the output of the hidden layer node. Therefore, the input space can be mapped to the output space, and the aim of function approximation can be classified for the entire network. Since the mapping from input to output is nonlinear, and the mapping from hidden layer space to output space is linear, the learning rate is quickened greatly, and the local minimum problem is avoided.

$X = [x_1 \quad x_2 \quad \cdots \quad x_n]^T$, is the input vector of RBF-NN.

$H = [h_1 \quad h_2 \quad \cdots \quad h_j \quad \cdots \quad h_m]^T$, is the radial basis vector and h_j is the Gauss basis function. The h_j is given as.

$$h_j = \exp\left(-\frac{\|X - C_j\|}{2{b_j}^2}\right)$$

Where $C_j = [c_{j1} \quad c_{j2} \quad \cdots \quad c_{ji} \quad \cdots \quad c_{jn}]^T$, is the central vector of j^{th} node. b_j is the basis width value of j^{th} node, and $b_j > 0$.

The basis width vector of RBF can be expressed as:

$$B = [b_1 \quad b_2 \quad \cdots \quad b_m]^T$$

The weight vector of RBF NN is shown as

$$W = [w_1 \quad w_2 \quad \cdots \quad w_j \quad \cdots \quad w_m]^T$$

As a result, the output of RBF NN is shown as

$$y_m(t) = w_1 h_1 + w_2 h_2 + \cdots + w_m h_m$$

The rectification objective of RBF-NN is presented as

$$E(t) = \frac{1}{2} e(t)^2$$

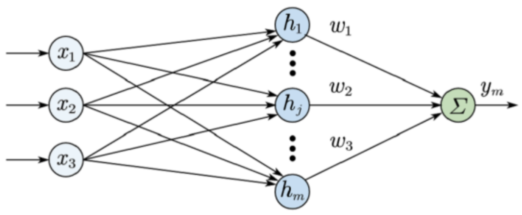


Fig. 2 *Structure of RBF-NN*

The gradient descent method is used to obtain parameters of controller.

The structure of adaptive PID controller with RBF NN is shown in the Figure 4. The controller consists of three parts.

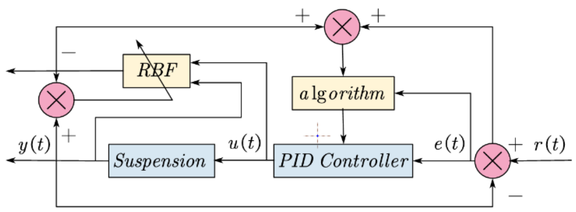


Fig. 3 *Structure of adaptive PID control based on RBF-NN*

(1) Traditional PID controller direct closed-loop control of the controlled object, in which the three parameters k_p, k_i, k_d are rectified online.

(2) RBF identification network observes the Jacobian information of the controlled object in time and provides the information to the network;

(3) The Jacobian information provided by the RBF network is used to adjust its own weight coefficients, and then the three parameters of the PID control is output, which in turn enables the PID controller to be adjusted to achieve the optimal index.

From the above, the steps of the PID parameter self-tuning algorithm based on RBF-NN method is shown as follows.

(1) First, determine the number of input nodes and the number of hidden layer nodes n of the RBF neural network by the extensive simulations. Select the learning rate, inertia coefficients, initial values of central vector, basis with parameter, and the weight coefficients of the hidden layer nodes.

(2) Then, determine the structure of RBF neural network, namely, the number of input layer nodes, implicit layer nodes,

(3) $y(t)$ and $r(t)$ are obtained by sampling. $e(t)$ is obtained by calculating, $e(t) = r(t) - y(t)$.

(4) Calculate the input and output of the neural network. The output of third layer of the neural network is the three adjustable parameters of the PID controller. And the $u(t)$ is obtained by calculating. The Jacobian information is obtained and the next output $y(t+1)$ of the control object is got.

(5) Adjust the weight coefficients, the hidden node central vector and the basis width parameters of the RBF neural network. Return to step 3 and continue.

After that, the parameters of controller with different methods can be got and are shown in Table 2.

Table 2: Parameters of controllers.

	K_p	T_i	T_d
Z-N	10.2	4.88	1.11
RBF-NN	10.01	4.35	0.99

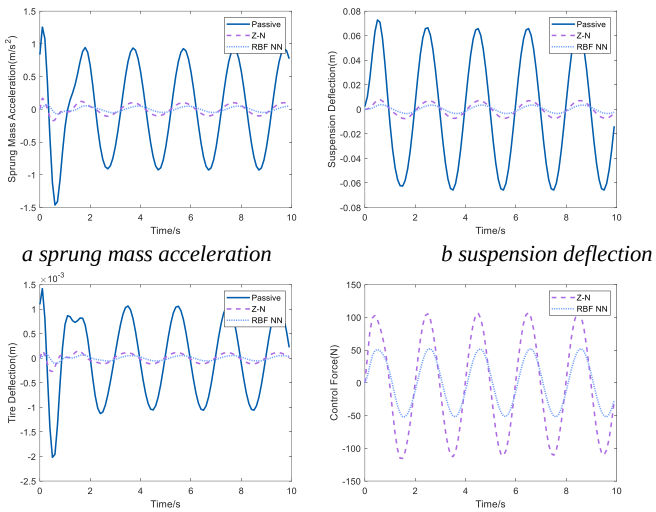
Results and Discussion： After the design of the controller for the quarter car active suspension model described in this research, the adaptive PID control utilizing Z-N technique and RBF-NN method are all taken into consideration in simulation to compare the performance of the two ways. This will help the hybrid control method become more generalizable. The quarter vehicle model is utilized in this research to verify the suggested control mechanism, and the parameters used in this research are shown in Table 3.

Table 3: Parameters of suspension.

parameters	m_s	m_u	k_s	k_t	c_s
value	$350kg$	50kg	180N/m	190kN/m	1kNs/m

To assess the primary components of the active suspension system using the suggested control strategy. As an evaluation metric, the active control force of the actuator, suspension deflection, tire deflection, and body acceleration of the vehicle are used.

Figure 4 illustrate the simulation results of sprung mass acceleration, suspension deflection, tire deflection, and active control force under different condition. Figure 5 illustrate the RMS of the evaluation indicators utilized in this work and the degree of improvement.



a sprung mass acceleration *b suspension deflection*

c tire deflection *d active force*

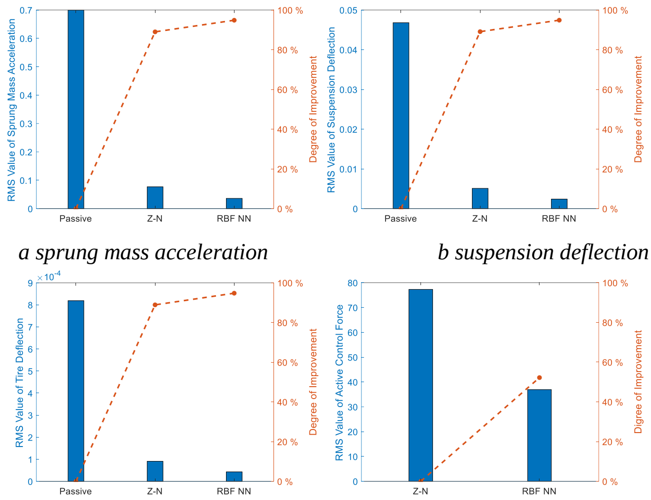
Fig. 4 *Simulation results*

It can be seen from Figure 4 that the curve of sprung mass acceleration, deflection of the vehicle suspension, tire deflection, and control force under active suspension PID control based on RBF NN is smoother than the curve for passive suspension and PID control based on Z-N method, indicating that the performance of ride comfort of the active suspension PID control based on RBF NN is better than the other two cases.

Figure 5 present the RMS values for vertical deflection and acceleration of sprung mass, tire deflection, active control force and degree of the improvement of passive suspension, adaptive PID control based on Z-N method and adaptive PID control with RBF-NN method.

The RMS value of sprung mass acceleration is observed to be reduced by 89%, the RMS value of suspension deflection is reduced by 89%, and the RMS value of tire deflection is reduced by 88% when adaptive PID control with Z-N method is used. As a result, the ride comfort and road holding are clearly improved. Meanwhile, the performance of active suspension under adaptive PID control based on RBF NN method is better than the PID control with Z-N method, since the RMS value of sprung mass acceleration is decreased by 94%, the RMS value of suspension deflection is decreased by 95%, the RMS value of tire deflection is decreased by 94.7% compared with the passive suspension. And the active control force is decreased by 52% compared with active suspension under adaptive PID control based on Z-N method.

Therefore, the proposed controller in this paper can reduce deflection and acceleration under sine input and step input to great extent, further demonstrating the viability go the proposed control method



a sprung mass acceleration *b suspension deflection*

c tire deflection *d active force*

Fig. 5 *RMS value*

Conclusion: This paper mainly discusses the RBF-NN-based adaptive PID controller for active suspension. Quarter car suspension model is considered at first. And then the adaptive PID controller with RBF neural network is conducted. After that, simulation is conducted within Simulink environment. Finally, performance of proposed controller in this paper is compared with the passive suspension, adaptive PID control using Z-N method.

From the simulation results, that adaptive PID controller with RBF-NN method high absolute the road profile tracking performance can be achieved for random road roughness. It confirms the effectiveness and robustness of the proposed control system. The effectiveness of the proposed controller algorithm is illustrated by its ability to reproduce much vibration.

Author contribution: Weipeng Zhao proposed the idea and original draft manuscript. Professor proposed the supervision and writing review.

Conflict of interest: The authors declare no conflict of interest.

Data availability statement: Data sharing is not applicable to this article as no new data were created or analysed in this study.

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