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# Adaptive Bionic Fuzzy Control for Double Mass Model of Vehicle Suspension System

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**Abstract:** Adaptive fuzzy controllers, using heuristic expert knowledge and equipped with adaption ability, are widely used in the vehicle industry in the present days as they are capable of dealing with ill-formulated nonlinear systems.Therefore, an adaptive bionic fuzzy control method is proposed for double mass model of vehicle suspension system. By regarding the niche of each species in an ecosystem as the antecedent, the fuzzy system with biological characteristics is constructed based on the niche ecostate-ecorole theory. We design a fuzzy controller using a bionic fuzzy system and provide both the adaptive law and constraint conditions of the system parameters. Finally, the simulation results demonstrate the effectiveness and superiority of the designed method compared with traditional PID control method.

**Keywords:** Vehicle suspension system; Bionic; Fuzzy control; Adaptive law

## 1 Introduction

Recently, vehicle suspension system has been an outstanding issue because of its important role in transportation vehicles [1–3]. The practical requirements,such as ride comfort and road holding, lead to the importance of suspensions [4].Therefore, many researchers are devoted to the problem and have made lots of achievements in the recent decades.

In[5], Ghosh, et al. put forward a 2-degrees of freedom PID method for controlling magnetic suspension systems. In [6], Bchle, et al. showed a novel nonlinear model predictive control strategy for magnetic suspension systems, which can achieve high control performance for stabilization and fast set-point changes. However, its very difficult to establish the precise mathematical models because of the uncertainties of the parameters and the existence of external disturbances in practical scenarios for the vehicle suspension systems [7]. There exists some uncertainties such as the uncertain sprung mass, the uncertain suspension component parameters and the unknown masses of passengers and payload. These uncertainties can even lead to the instability of control systems without taking these above uncertainties into consideration in control process.

Based on the study of [1–7], fuzzy control methods are widely used to solve the above problems. In [8], the adaptive sliding-mode with T-S fuzzy approach is used to handle the uncertainty caused by the variation of the sprung mass. According to the control principle, a fuzzy controller is established after the speed and acceleration are considered as errors and error rate. Based on the suspension mathematical model and fuzzy controller in [9]. In [10], The fuzzy controller selected the velocity and acceleration of the automotive body as the inputs to realize the control of the active suspension. In [11], the method utilized the global searching strategy of the PSO algorithm to optimize and design the parameters with the target function of chassis performance indexes. And then a simulation experiment was provided for the active vehicle chassis control. In [12], a dynamical quarter-car model of a vehicle was built, and the exact linearization of nonlinear suspension system was realized by using differential geometry method. However, the aforementioned references only considered the current state of the state variables. In the studies of [1–12], the antecedent of fuzzy rules was a fuzzy set, which only contained the current state of the state variable. Therefore, a niche concept was introduced into the antecedent of fuzzy rules in some studies, which not only considered the current state of the variables, but also took into account the development trend. In [13], a niche concept was first introduced into the Mamdani-type fuzzy system [14]. Regarding

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the optimum niche as the tracking target, a tracking feedback control method was proposed for an intelligent greenhouse system [15]. Then, integrating biological self-adaptivity into a fuzzy system using the niche-fitness degree, the type-1 T-S fuzzy system based on the niche was constructed and the universal approximation of the system was proved [16]. In [17, 18], direct and indirect adaptive type-1 fuzzy control methods were studied. In [19], an indirect adaptive type-2 bionic fuzzy control method was proposed for a class of nonlinear systems and the results demonstrated that the adaptive controller based on the niche could make the system tend to be stable quicker with a smaller amplitude, and it was also more effective regarding anti-interference than a traditional adaptive fuzzy controller.

Motivated by the previous discussions of [1–19], in this study, based on the niche ecostate-ecorole theory, biological adaptation strategies are integrated into a fuzzy system. Then, a new design method of direct adaptive bionic fuzzy controller is proposed for a vehicle suspension system. The simulation results for the a vehicle suspension system demonstrate that the proposed control system has stronger convergence, stability, and anti-interference than traditional PID control method.

# 2 Problem description

Consider a double mass model of vehicle suspension system as follows:

The dynamic equation is:

$$\begin{cases} m_2\ddot{z}_2 + c\left(\dot{z}_2 - \dot{z}_1\right) + k\left(z_2 - z_1\right) = 0, \\ m_1\ddot{z}_1 + c\left(\dot{z}_1 - \dot{z}_2\right) + k\left(z_1 - z_2\right) + k_t\left(z_1 - q\right) = 0. \end{cases} \tag{1}$$

where $m_1$ denote mass of the wheel and $m_2$ denote mass of body, $z_1$ denotes the displacement of the wheel, $z_2$ denotes the displacement of the body, $c$ denotes the damping coefficient, $k$ denotes the stiffness of suspension spring, $k_t$ denotes the stiffness of the wheel, $q$ denotes the pavement input.

Let $w_1 = z_2$, $w_2 = \dot{z}_2$, $w_3 = z_1$, $w_4 = \dot{z}_1$, then the suspension system becomes

$$\begin{cases} \dot{w}_1 = w_2, \\ \dot{w}_2 = -\frac{1}{m_2}[k(w_1 - w_3) + c(x_2 - w_4)], \\ \dot{w}_3 = w_4, \\ \dot{w}_4 = \frac{1}{m_1}[k(w_1 - w_3) + c(w_2 - w_4) + k_t(q - w_3)], \\ y = w_1. \end{cases} \tag{2}$$

Let $x_1 = w_1$, $x_2 = \dot{w}_1$, $x_3 = \ddot{w}_1$, $u = q$ then

$$\begin{cases} \dot{x}_1 = x_2, \\ \dot{x}_2 = x_3, \\ \dot{x}_3 = f + bu, \\ y = x_1. \end{cases} \tag{3}$$

where $f = \frac{c}{m_1 m_2}[c(w_2 - w_4) + k(w_1 - w_3) - k_t w_3] - \frac{c}{m_2^2}[c(w_4 - w_2) + k(w_3 - w_1)] + \frac{k}{m_2}(w_4 - w_2)$, $b = \frac{k_t c}{m_1 m_2}$.

Then

$$y^{(3)} = f + bu. \tag{4}$$

# 3 Design of adaptive bionic fuzzy controller

An adaptive fuzzy controller is designed so that the output of the vehicle suspension system can effectively track the ideal trajectory.

## 3.1 Design of adaptive bionic fuzzy system

Definition 1 [19] We consider an ecological system with $n$ biological units. The functional niche of the $k$-th biological unit is defined as

$$N_k = \frac{s_k + C_k p_k}{\sum\limits_{m=1}^{n} (s_m + C_m p_m)}, \tag{5}$$

where $N_k \in [0, 1]$; $s_m$ is the ecostate of the m-th biological unit, which indicates the state of the unit; $p_m$ is the ecorole of the $m$-th biological unit, which indicates the change rate of the unit; and $C_m$ is the dimensional conversion coefficient,$m = 1, 2, ..., n$.

Remark: The functional niche is the function and effect of the biological unit in the ecosystem. The combination of ecostate and ecorole reflects the adaptability of the biological unit to the environment. The numerator of (5) represents the absolute functional niche of the $k$-th biological unit and $N_k$ represents the relative niche. If the biological unit has a good state and development trend, its functional niche is relatively large, which indicates that the biological unit in the system plays a relatively greater role in the ecosystem. Conversely, the smaller $N_k$, the smaller the role of the biological unit in the ecosystem.

In the modeling of the unknown function$u$, a bionic fuzzy system is established. The $i$-th fuzzy rule is given as follows:

$$R_u^i : \text{if} x_1 \text{is} A_1^i \text{and} x_2 \text{is} A_2^i \text{and...and} x_n is A_n^i, \text{then} u^i = N^i, i = 1, 2, ..., N, \tag{6}$$

where $x_1, x_2, \cdots, x_n$ are the $n$ state variables of (4), which correspond to the state inputs of $n$ biological units niches in the biological system; and $A_k^i$ is fuzzy set to which the $k$-th state variable; $x_k$ is a member, which corresponds to the niche fuzzy set to which the state variable of the $k$-th biological unit is a member, $k = 1, 2, ..., n$. Based on the niche ecostate-ecorole theory, ecostate $s_k^i$ and ecorole $p_k^i$ of the $k$-th biological units niche are determined by biologists experiences; therefore, the consequent of the $i$-th fuzzy rule is determined by $N^i = \sum\limits_{k=1}^{n} s_k^i + C \sum\limits_{k=1}^{n} p_k^i$, which corresponds to the general ecostate-ecorole of the entire system with $n$ biological units.

By using the center-average defuzzifier, the product inference engine, the singleton fuzzifier and Gauss membership function, the direct adaptive bionic fuzzy controller is given as follows

$$u(X|\theta_1, \theta_2) = \frac{\sum\limits_{i=1}^{N} (\sum\limits_{k=1}^{n} s_k^i + C \sum\limits_{k=1}^{n} p_k^i) \prod\limits_{m=1}^{n} \exp[-(\frac{x_m - \bar{x}_m^i}{\delta_m^i})^2]}{\sum\limits_{i=1}^{N} \prod\limits_{m=1}^{n} \exp[-(\frac{x_m - \bar{x}_m^i}{\delta_m^i})^2]} = \theta_1^T \xi(X) + C\theta_2^T \xi(X), \tag{7}$$

where $\theta_1 = (\theta_1^1, \theta_1^2, ..., \theta_1^N)^T, \theta_1^i = \sum\limits_{k=1}^{n} s_k^i$, $\theta_2 = (\theta_2^1, \theta_f^2, ..., \theta_2^N)^T, \theta_2^i = \sum\limits_{k=1}^{n} p_k^i$,

$\xi(X) = (\xi^1(X), \xi^2(X), ..., \xi^N(X))^T, \xi^i(X) = \frac{\prod\limits_{m=1}^{n} \exp[-(\frac{x_m - \bar{x}_m^i}{\delta_m^i})^2]}{\sum\limits_{i=1}^{N} \prod\limits_{m=1}^{n} \exp[-(\frac{x_m - \bar{x}_m^i}{\delta_m^i})^2]}$, where $\theta_1$,$\theta_2$ are adaptive adjustment parameters and they represent the current state and the development trend of the state variables.

## 3.2 Design of adaptive bionic fuzzy controller

Let $\mathbf{e} = \mathbf{y}_m - \mathbf{x}$,$\mathbf{y}_m = (y_m, \dot{y}_m, \ddot{y}_m, y_m^{(3)})^T$,$\mathbf{x} = (x_1, x_2, x_3)^T = (y, \dot{y}, \ddot{y})^T$,$K = (k_3, k_2,k_1)^T \in R^3$, which make all the roots of the polynomial $s^3 + k_1 s^2 + k_2 s + k_3$ in the open left-half plane of the complex plane. Therefore, we can select the control law of (4) as

$$u^* = \frac{1}{b}[-f(X) + y_m^{(n)} + K^T \mathbf{e}]. \tag{8}$$

Substituting (8) into (4), we can obtain the closed-loop control system as follows:

$$e^{(3)} + k_1 \ddot{e} + k_2 \dot{e} + k_3 e = 0. \tag{9}$$

Replacing $u$ in (4) with $u_D$, we obtain

$$y^{(3)} = f(X) + b u_D(X). \tag{10}$$

From(9) and (10), we obtain

$$y^{(3)} = y_m^{(3)} + K^T\mathbf{e} - bu^* + bu_D(X)$$
$$= y_m^{(2)} + K^T\mathbf{e} + b[u_D(X) - u^*].$$

Then the dynamic equation of the closed-loop control system is:

$$e^{(3)} = -K^T\mathbf{e} + b[(u^* - u_D(X)]. \tag{11}$$

Let $\Lambda_c = \begin{pmatrix} 0 & 1 & 0 \\ 0 & 0 & 1 \\ -k_3 & -k_2 & -k_1 \end{pmatrix}$, $b_c = \begin{pmatrix} 0 \\ 0 \\ b \end{pmatrix}$. Then (11) becomes

$$\dot{\mathbf{e}} = \Lambda_c\mathbf{e} + b_c[u^* - u_D(X)]. \tag{12}$$

Because $|SI - \Lambda_c| = s^3 + k_1s^2 + k_2s + k_3$, there must be a unique 2-order positive definite matrix $P$ that satisfies the Lyapunov equation as

$$\Lambda_c^T P + P\Lambda_c = -Q. \tag{13}$$

where $Q$ is an arbitrary positive definite 2-order matrix.

We select the Lyapunov function $V_e = \frac{1}{2}\mathbf{e}^T P\mathbf{e}$. Then

$$\dot{V}_e = \frac{1}{2}(\dot{\mathbf{e}}^T P\mathbf{e} + \mathbf{e}^T P\dot{\mathbf{e}}) = -\frac{1}{2}\mathbf{e}^T Q\mathbf{e} + \mathbf{e}^T Pb_c[u^* - u_D(X)].$$

(1)When $V_e \le \overline{V}$, $\dot{V}_e < 0$. Therefore, $V_e$ is bounded, clearly.

(2)When $\dot{V}_e > 0$, we select supervisory controller $u_s$ to ensure $\dot{V}_e < 0$, which makes $V_e$ bounded.

The operation is as follows:

We select the supervisory controller $u_s$ such that $u = u_D + u_s$. Substituting into (4), we obtain

$$\begin{aligned}\dot{V}_e &= \frac{1}{2}(\dot{\mathbf{e}}^T P\mathbf{e} + \mathbf{e}^T P\dot{\mathbf{e}}) \\ &= -\frac{1}{2}\mathbf{e}^T Q\mathbf{e} + \mathbf{e}^T Pb_c[u^* - u_D(X) - bu_s] \\ &\le -\frac{1}{2}\mathbf{e}^T Q\mathbf{e} + \left|\mathbf{e}^T Pb_c\right|[|u^*| + |u_D(X)|] - \mathbf{e}^T Pb_c bu_s.\end{aligned} \tag{14}$$

Let $|f(X)| \le f^u(X) < \infty$, $0 < b_L < b$.

Then the supervisory controller is selected as:

$$u_s = I^*\mathrm{sgn}(\mathbf{e}^T Pb_c)\frac{1}{b_L}[|u_D(X)|\,, \tag{15}$$

where $\bar{V}$ is a given positive constant whose value can be determined by the boundary of $X$. When $V_e \le \overline{V}$, $I^* = 0$; when $V_e > \overline{V}$, $I^* = 1$; when $\mathbf{e}^T Pb_c \ge 0$, $\mathrm{sgn}(\mathbf{e}^T Pb_c) = 1$; and when $\mathbf{e}^T Pb_c < 0$, $\mathrm{sgn}(\mathbf{e}^T Pb_c) = -1$. Substituting (16) into (15), we obtain

$$\begin{aligned}\dot{V}_e &\le -\frac{1}{2}\mathbf{e}^T Q\mathbf{e} + \left|\mathbf{e}^T Pb_c\right|[|u^*| + |u_D(X)| \\ &- \frac{b}{b_L}[|u_D(X)| + \frac{1}{b_L}(f^u(x) + \left|y_m^{(n)}\right| + \left|K^T\mathbf{e}\right|) \\ &\le -\frac{1}{2}\mathbf{e}^T Q\mathbf{e} < 0.\end{aligned}$$

Therefore, $u_s$ can ensure that $V_e$ is bounded.

# 4 Design of bionic adaptive law

An adaptive law is designed to ensure the stability of the controlled system, so that the vehicle suspension system tend to be stable on the road quickly.

### 4.1 Definitions of the optimal parameters

Let

$$(\theta_1^*, \theta_2^*) = \arg \min_{\theta_1 \in \Omega, \theta_2 \in \Omega} \left[ \sup_{X \in U_C} |u(X) - u^*| \right], \tag{16}$$

where $\Omega$ is a constraint set of $\theta_1$,$\theta_2$.

The constraint set $\Omega$ satisfies the following condition: $\Omega = \{\theta_1^i, \theta_2^i | \left|\theta_1^i\right| \leq M, \left|\theta_2^i\right| \leq M\}$,$i = 1, 2, ..., M$, where $M$ is a positive constant.

### 4.2 Definition of the minimum approximation error

Let

$$\omega = u_D(X|\theta^*) - u^*. \tag{17}$$

Then (12) becomes

$$\begin{aligned}\dot{\mathbf{e}} &= \Lambda_c \mathbf{e} + b_c[u^* - u_D(X) - bu_s] \\ &= \Lambda_c \mathbf{e} + b_c[u_D(X|\theta^*) - u_D(X)] - b_c u_s - b_c \omega \\ &= \Lambda_c \mathbf{e} + b_c[(\theta_1^* - \theta_1) + C(\theta_2^* - \theta_2)]\xi - b_c u_s - b_c \omega. \end{aligned} \tag{18}$$

To minimize the tracking error $\mathbf{e}$ and parameter error $\theta_1^* - \theta_1$,$\theta_2^* - \theta_2$, we consider the following Lyapunov function:

$$V = \frac{1}{2}\mathbf{e}^T P \mathbf{e} + \frac{1}{2\gamma_1}(\theta_1^* - \theta_1)^T(\theta_1^* - \theta_1) + \frac{1}{2\gamma_2}(\theta_2^* - \theta_2)^T(\theta_2^* - \theta_2), \tag{19}$$

where $\gamma_1$,$\gamma_2$ are positive constants.

Then

$$\begin{aligned}\dot{V} = &-\frac{1}{2}\mathbf{e}^T Q \mathbf{e} - \mathbf{e}^T P b_c \omega - \mathbf{e}^T P b_c b u_s + \frac{1}{\gamma_1}(\theta_1^* - \theta_1)^T[\gamma_1 \mathbf{e}^T P b_c \xi(X) - \dot{\theta}_1] \\ &+ \frac{1}{\gamma_2}(\theta_2^* - \theta_2)^T[\gamma_2 \mathbf{e}^T P b_c C \xi(X) - \dot{\theta}_2]. \end{aligned} \tag{20}$$

We select the adaptive law as:

$$\dot{\theta}_1 = \gamma_1 \mathbf{e}^T P b_c \xi(X), \tag{21}$$

$$\dot{\theta}_2 = \gamma_2 \mathbf{e}^T P b_c C \xi(X). \tag{22}$$

Substituting (22) and (23) into (21), then (21) becomes

$$\dot{V} = -\frac{1}{2}\mathbf{e}^T Q \mathbf{e} - \mathbf{e}^T P b_c \omega - \mathbf{e}^T P b_c b u_s. \tag{23}$$

Substituting (16) into (24), we obtain $\dot{V} \leq -\frac{1}{2}\mathbf{e}^T Q \mathbf{e} - \mathbf{e}^T P b_c \omega$.

## 5 Simulation

Through the simulation, the output of the vehicle suspension system using the adaptive fuzzy control method can be more stable than the traditional PID control method [20]. Besides, the tracking error is also smaller and the controlled system has strong anti-interference.

Select the system parameters: $m = 1Kg, f = 20N, k = 100N/m$; the reference signal $y_m(t) = 1$;$K^T = (k_1, k_2, k_3) = (1, 2, 5)$,$Q = diag\,(10, 10, 10)$; dimensional transfer coefficient$C = 1$; select $\gamma_1 = 2$,$\gamma_2 = 1$.

Suppose the initial conditions $\mathbf{x}(0) = (0, 0, 0)^T$, and replace $X$ with $(1 + \delta)X$, where $\delta$ is random interference value,$\delta = 0.1$.

Fig.2 shows the outputs comparison of the system under two different methods. Fig.3 shows the tracking errors comparison under two different methods. And Fig.4 shows the effect of bionic fuzzy control under the disturbance $\delta$. It is clear that the bionic fuzzy control system can track the states of the system well. In addition, compared with the traditional PID control method, the amplitude of the output curve of the vehicle suspension system is smaller by using direct adaptive bionic fuzzy control, which shows that the direct adaptive bionic fuzzy control method has more obvious superiority than the traditional PID control method.

# 6 Conclusions

We proposed a method of direct adaptive bionic fuzzy control for double mass model of vehicle suspension system. Firstly, we design a fuzzy control system using a bionic fuzzy system. Secondly, we provide both the adaptive law and constraint conditions of the system parameters. Finally, the simulation results demonstrate the effectiveness and superiority of the designed method compared with traditional PID control method.

The niche is regarded as the antecedent of the fuzzy rules and the average niche is used as the consequent to construct the bionic fuzzy system based on the niche ecostate-ecorole theory. This method has strong advantages regarding managing unknown disturbance and training noise. Under the condition of fewer system rules, the feedback control law and the adaptive law were used to adjust the controlled system,which made the output of the controlled object able to track the reference signal effectively and improved the modeling precision for the system.

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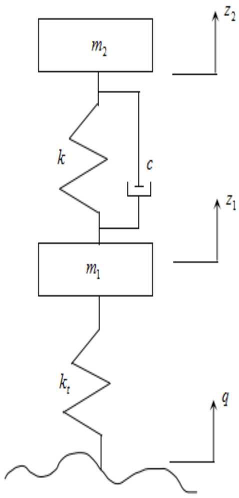


Figure 1: Double mass model of vehicle suspension system

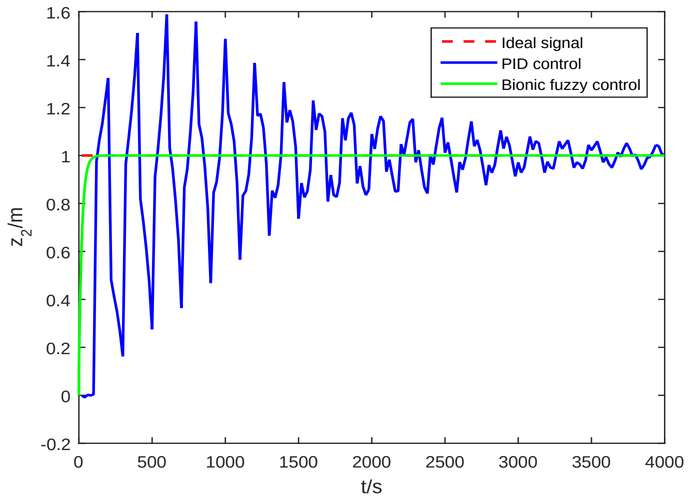


Figure 2: Outputs comparison of bionic fuzzy control and traditional PID control

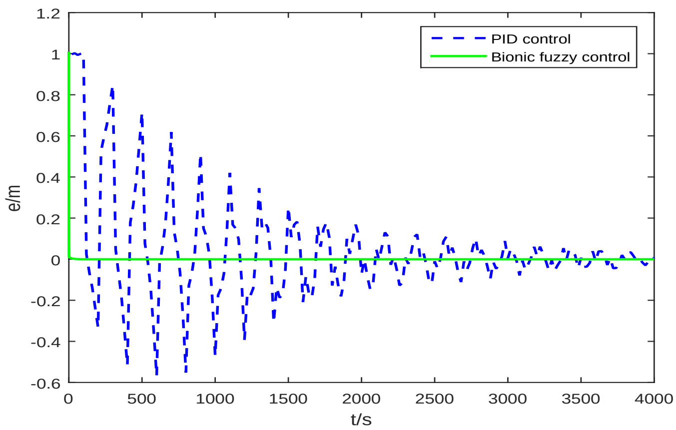


Figure 3: Tracking errors comparison of bionic fuzzy control and traditional PID control

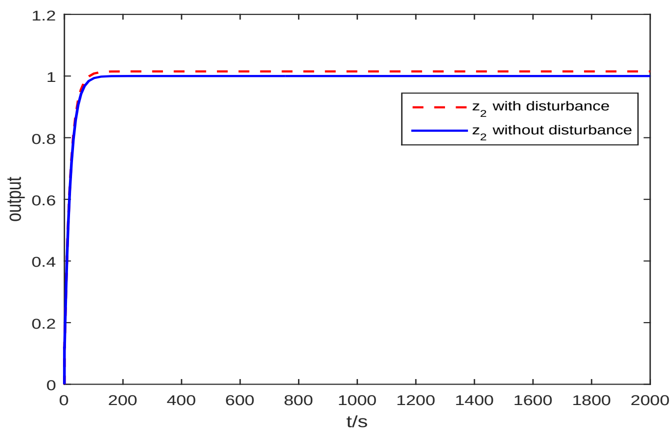


Figure 4: Output of $z_2$ with disturbance and $z_2$ without disturbance under bionic fuzzy control