Immune Evolutionary Control Strategy for Vehicle Active Safety

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Abstract – This paper prospers a new control strategy based on immune evolutionary algorithm for improving vehicle safety performance. It can put the control of active-suspension into system, and realizes the control aim. Most of the intelligent control algorithms easily converge to local extremum, and their implementations are complicated. Immune evolutionary algorithm theory can avoid these disadvantages. With simulation using MATLAB program., the results show that the proposed control strategy can effectively improve vehicle safety.

Keywords: Active safety, Active suspension, Immune evolutionary algorithm, Simulation

1 Introduction

Vehicle safety performance concludes active safety and passive safety, and active safety is one of the important vehicle performances. There are many methods to improve the vehicle active safety performance. A good vehicle should have good active safety performance. This paper aims at provide adequate suspension deflection to maintain tire-terrain contact. However, a tire-terrain contact performance and road- handling performance of a vehicle are mainly determined by the damping characteristic of the shock absorbers. Passive shock absorbers have a fixed damping characteristic determined by their design. Active or semi active suspension is desirable to adjust this characteristic to increase performance, which replace the spring damper suspension, have the potential of improving safety and comfort of vehicle under nominal conditions [1]. This helps to improve vehicle maneuverability, which is to improve vehicle safety performance.

With the development of intelligent systems research, more and more intelligent control techniques are applied to control a vehicle using an active suspension, and good performance is achived. M.V.C. Rao* and V. Prahlad (1997)[1], Qin Li, T. Yoshimura and J. Hino (1998)[3] apply fuzzy control strategies. Neural network is applied (Y. Watanabe and R.S. Sharp (1999)[4]. Genetic-based fuzzy control has been applied to active suspension systems (Sang Yong Moon and Wook Hyun Kwon, 1998)[5]. However, all of these algorithms have some disadvantages more or less.

Immune evolutionary algorithm with extend operator and mutate operator, is able to achieve the search mechanism which is from global area to local area. It can find a higher- fitness-value area in global area, meanwhile make a elaborate search in local area. This is the reason why Immune evolutionary algorithm can prevent being captured into local extremum as well as guaranteeing the precision of the optimal solution. In addition, its process is easy to understand and individuals are encoded using real number. So its program is very simple.

Hence, this paper proposes a new immune evolutionary controller in Section 3. Section 4 gives simulation study and results. Final conclusions are given in Section 5.

2 Active suspension System modle

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2.1 The equations of motion

A two-degree-of-freedom quarter-car model is shown in Fig. 1.The equations of motion are given by

$$\begin{cases} m_t \ddot{z}_1 = k_t (z_0 - z_1) + k_s (z_2 - z_1) + c_s (\dot{z}_2 - \dot{z}_1) - u \\ m_s \ddot{z}_s = k_s (z_1 - z_2) + c_s (\dot{z}_1 - \dot{z}_2) + u \end{cases}$$
(1)

In this model, the sprung and unsprung masses corresponding to the one corner of the vehicle

are denoted respectively by m_s and m_u : The suspension

system is represented by a linear spring of stiffness k_s and a

linear damper with a damping rate c_s ; while the tire is modeled by a linear spring of stiffness k_t : Since damping in the tire is typically very small, it is neglected in this study. The parameter values chosen for this study are shown in Table 1.

2.2 The equations of state-space form

And expressing Eq. (1) by a vector matrix form, then, the equations of motion in the state-space configuration take the form.

$$X = AX + BU \tag{2}$$

where the state, active control and excitation vectors are, respectively, given by

$$X = \{x_1, x_2, x_3, x_4\}^T = \{z_1, z_2, \dot{z}_1, \dot{z}_2\}^T, U = \{z_0, u\}^T$$

the state variables are defined as follows:

 x_1 : the vertical displacements of the wheels;

 x_2 : the vertical displacement of the vehicle body;

 x_3 : the sprung mass absolute velocity;

 x_4 : the unsprung mass absolute velocity.

 z_0 : the random road inputs;

u: the control force.

And A, B, C and D are, respectively, denoted as



Fig.1 The quarter-car model

$$A = \begin{bmatrix} 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \\ -\frac{k_r + k_s}{m_t} & \frac{k_s}{m_t} & -\frac{c_s}{m_t} & \frac{c_s}{m_t} \\ \frac{k_s}{m_s} & -\frac{k_s}{m_s} & \frac{c_s}{m_s} & -\frac{c_s}{m_s} \end{bmatrix} , \quad B = \begin{bmatrix} 0 & 0 & \frac{k_t}{m_t} & 0 \\ 0 & 0 & -\frac{1}{m_t} & \frac{1}{m_s} \end{bmatrix}^T$$

$$C = \begin{bmatrix} \frac{k_s}{m_s} & -\frac{k_s}{m_s} & \frac{c_s}{m_s} & -\frac{c_s}{m_s} \\ 0 & 0 & 0 & 1 \\ -1 & 1 & 0 & 0 \\ 1 & 0 & 0 & 0 \end{bmatrix} , \quad D = \begin{bmatrix} 0 & 0 & 0 & -1 \\ \frac{1}{m_s} & 0 & 0 & 0 \end{bmatrix}^T$$

The output can be expressed in terms of the state vector as

$$Y = CX + DU \tag{3}$$

where the output vector is given by

$$Y = \{ \ddot{z}_2, \dot{z}_2, z_2 - z_1, z_1 \}$$

The active control u, is generated by the actuator.

Tab. 1	The vehicle system parameters for the quarter-car model			
Parameter name	unit	Parameter value		
Sprung mass	m _s	330 kg		
Unsprung mass	m.	25 kg		
Damping coefficient	C _c	1000 Ns/m		
Suspension stiffness	k.	13,000N/m		
Tire stiffness	k.	170,000N/m		

3 Controller design based on immune evolutionary algorithm

In this paper, the semi-active suspension control system, which is based on immune evolutionary algorithm, can be illustrated as following sketch map(Figure2). Body vertical acceleration, body velocity, suspension deformation and tire dynamic load are considered as controller inputs, and control force which is generated by force actuator is the output.





3.1 Control parameters of controller

Control parameters should be determined previously according to different practical problems, when the proposed controller is implemented. Control parameters of this paper are listed in Table 2.

Parameter name	value	Parameter name	value	Parameter name	value	
Population size	30	Extend radius	1	Mutation radius	20	
Select probability $lpha$	0.3	Control force (U) range		[-700, 700]		

Tab. 2 Parameters of immune evolutionary controller

3.2 implementation of immune evolutionary algorithm

Accepting model states as inputs, the controller can find optimal control force using immune evolutionary algorithm, so the suspension has a good performance, in other words, the safety of vehicle can be improved. The flow chart of immune

evolutionary algorithm is shown in figure 3.

Following steps show the overall process of immune evolutionary algorithm:

Step 1: initialization

Randomly generate n antibodies and form initial population A_0 , make k=0;

Step 2: calculate affinity

Calculate affinity value of each antibodies in initial population A0 and arrange them in descending order. The affinity computation is carried out by following function:

$$f(x_i) = 1 / f(a_i, \Delta_i)$$
(4)

Where $f(x_i)$ is affinity value of antibody;

 a_i, Δ_i are body vertical acceleration and tire dynamic load respectively.

Step 3: selection

According to Select probability α , selection population Bk can be obtained by carrying out selection operation in population Ak.

Step 4: extend

In light of extend radius r, carrying out extend operation in selection population Bk, extended population Ck can be produced. Given vj is an antibody of selection population Bk, and its affinity value is fj, then the extend probability for each antibody of selection population Bk is:



Fig 3.Flow Chart of Immune Algorithm



Cumulate probability is:

$$q_{k} = \sum_{k=1}^{round \ (\alpha*n)} P_{j} \qquad k = 1, \ 2, \cdots, round \ (\alpha*n) \qquad (6)$$

Make $q_0 = 0$, uniformly generate random value W between 0 and 1, if $q_{k-1} \le w \le q_k$, then

 v_k extend a new one.. After producing such n random values, the number of new extend ones for each antibody in selection population Bk can be determined.

Step 5: mutation

Make some antibodies of extended population Ck, which have lower affinity values, to be mutated, then these mutated ones together with the rest ones make up of mutation population Dk;

Step 6: replacement

Have the part of mutation population Dk , which have lower affinity values, replaced by random ones, then replacement population Ek is generated.

Step 7: reservation of optimal antibody

Substitute the worst antibody of replacement population Ek to the best one of population Ak, so next generation Ak+1 appears.

Step 8: termination condition

Make k=k+1, back to step 3 if achieving the termination criterion, otherwise go to the end of the program and export the optimal antibody(optimal control force).

4 Simulation study and results

For the quarter-car suspension systems given in Section 2, the typical parameters for the suspension model are selected as Table 1. A sampling time of 0.01s is selected for both the model and plant. The pseudo-random road profile by the sum of a 0.04m amplitude, 0.97Hz sinusoid and a 0.02m amplitude, 0.54Hz sinusoid is expressed as equation(7).

$$z_0 = 0.04 \times \sin(2\pi \times 0.97t) + 0.02 \times \sin(2\pi \times 0.54t)$$
(7)



Fig. 4 Curve of the road profile

The suspension deflection and tire dynamic load for the active system are respectively shown in FIGUREe. 5 and 6.



Fig. 6 Curve of the tire dynamic load

From these figures it can be observed that the suspension deflection and tire dynamic load using immune evolutionary control are brought to a level less than that of the passive system, respectively, which decrease about 75% and 50%, therefore, the active safety of vehicle is effectively improved.

5 Conclusions

An active suspension system using immune evolutionary controller for a quarter-car model of vehicle is presented. The proposed immune evolutionary controller was found to bring down the values of suspension deflection and tire dynamic load than that of the passive suspension. This simulation results clearly show that the immune evolutionary controller can greatly improve vehicle safety. Furthermore, the proposed control algorithm can be implemented easily, having less parameter which makes debugging more convenient. Therefore, it is an ideal control algorithm.

6 Reference

- M.V.C. Rao* and V. Prahlad, A tunable fuzzy logic controller for vehicle-active suspension systems. Fuzzy Sets and Systems 85 (1997) 11-21
- 2. Christophe Lauwerys*, Jan Swevers, Paul Sas., Robust linear control of an active suspension on a quarter car test-rig., Control Engineering Practice 13 (2005) 577–58.
- 3. Qin Li, T. Yoshimura and J. Hino, Active suspension with preview of large-sized buses using fuzzy reasoning, International of Vehicle Design, Vol.19, No.2, 1998,187-198.
- 4. Y. Watanabe and R.S. Sharp, Neural network learning control of automotive active suspension systems, International of Vehicle Design, Vol.21, Nos.2/3, 1999,124-147.
- 5. Sang Yong Moon and Wook Hyun Kwon, Genetic-based fuzzy control for half-car active suspension systems, International Journal of Systems Science, Vol.29, No.7, 1998, 699-710.
- 6. Cheng Jianan. Study on Immune system model, algorithm, nerwork and application, Dissertation of in Northwest Institute University, 2000,8
- 7. Zuo Xingquan, Li Shiyong, Hunag Jinjie, A New Immune Evolutionary Algorithm and Its Performance Analysis. Journal of Systems Simulation, Vol. 15 No. 11, Nov. 2003,1607-1609.
- Jang-Sung Chun, Hyun-Kyo Jung and Song-Yop Hahn A Study on Comparison of Optimization Perfermances Between Immune Algorithm and other Heuristic Algorithms. IEEE Transactions on Magnetics, Vol.34,NO.5,1998.9
- 9. Dae Sung Joo Sliding Mode Neural Network Inference Fuzzy Logic Controller of Nonlinear Active Suspension System. University Of Detroit Mercy, 1999