Application Research on Developed Chaos-Wasp Colony Algorithm Used in Suspension-Parameter Optimization

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Abstract: Aimed at parameters matching of automobile suspension system, this paper was presented an approach to optimize suspension system parameters based on developed chaos-wasp colony algorithm . Firstly, chaos factors were initialized through cube map; Balance of local and global searching of artificial wasp colony algorithm was realized on the basis of inertia weight of exponential decline; Early maturing was judged by fitness variance values. Secondly, dynamic models of quarter suspension were established and Matlab/Simulink software was employed to conduct the simulation experiments by taking integral white noise as road surface input. Results of simulation experiments indicated that developed chaos-wasp colony algorithm was better than tradition algorithms and normal artificial wasp colony algorithm.

1 INTRODUCTION

To a great extent, the comfort level of a rid and riding performance of a car depends on the suspension system. Therefore, research on suspension system was critical to improve them. Nowadays, it was focused on the control strategy of active suspension system. However, the vehicle suspensions were mainly based on the passive suspensions. Thus how to determine the stiffness value of the spring and the damping value of the absorber were greatly important. Pan (2005) optimized the automobile suspension system parameter by the optimal control theory and the least square method; Xu (2012) realized the optimization of the main parameters of hydro -pneumatic suspension based on the genetic algorithm; Li(2015) applied the genetic optimization algorithm and the decision-making control theory to optimize the automobile suspension system parameter; Pang(2014) explored the optimization of the parameters of the vehicle air suspension system, using the general genetic algorithm and the improved multi-objective adaptive optimization algorithm; Ma(2013) investigated the optimization of parameters of vehicle suspension system, employing the two methods of ideal modification parameter selection and optimal modification parameter selection.

This paper will contribute to the artificial bee colony algorithm based on the improved chaos strategy to avoid premature convergence and local optimum. Taking optimization parameter design and simulation with 4 degree of freedom 1/2 suspension system for example, this paper will verify the improved chaos artificial bee colony algorithm compared with the traditional one has some advantages.

2 IMPROVED CHAOTIC BEE COLONY OPTIMIZATION ALGORITHM

2.1 Artificial Bee Swarm Optimization Algorithm

Artificial bee colony algorithm (ABC) (Kuang, 215) was a kind of optimization algorithm with global searching ability and fast convergence rate, which

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was simulated by bee swarm intelligence. In ABC, Bee colony was composed of leading bee, following bee and reconnaissance bee. To search for honey containing more food sources ,leading bee will constantly update their food sources .After all the leading bee search , they will dance to share with following bee the information of food source position and quantity of honey containing .Then following bee choose the food source based on the yield of the food source, and the more honey you have in the source, the more likely you were to be selected. Then they will proceed to the next round of search in the same way. So the algorithm was as follows:

Step1: initialize the population and obtain initial solution by formula (1).

$$x_i^j = x_{\min}^j + rand(0,1)(x_{\min}^j - x_{\max}^j) \quad (1)$$

Step2: leading bee search for new solutions Newfit(i) in feasible scope according to formula(2), and calculate new fitness value of Newfit (i). If Newfit (i) > Fit (i), update new solution v_i , otherwise the number of failed Lost (i) plus 1.

$$v_i^j = x_i^j + rand(0,1)(x_i^j - x_k^j) \quad (2)$$

Calculate the selection probability of each individual according to formula(3)

$$P_i = \frac{Fit(i)}{\sum_{i=1}^{N} Fit(i)} \quad (3)$$

Step3: following bee search new solution according to the selection probability P_i and formula (2) within the scope of the feasible solution.If Newfit (i) > Fit (i), update new solution v_i , otherwise the number of failed Lost (i) plus 1.

Step4: if Lost (i)>limit, abandon the solution, and leading bee was into reconnaissance bee finding new solutions according to equation (1).

Step5: if the fitness of the solution satisfies the preset accuracy or reaches the maximum number of iterations, the loop ends and the optimal solution was output.

2.2 Improvedare Algorithm

(1)Chaotic Operator

There many ways to generate chaotic variables, which logistic mapping and cubic mapping to generate it were most commonly used. The cubic mapping helps to maintain the uniformity of chaotic variables , so this paper adopts the method of cubic mapping of chaos operator to initialize (Zhou, 2012). The cubic mapping was defined by

$$\begin{cases} y_{n+1} = 4y_n^3 - 3y_n \\ -1 < y_n < 1(n = 0,1,2,\cdots) \end{cases} \quad (4)$$

Then the initial value X_i^j of the chaos artificial bee colony algorithm was given by

$$X_i^j = x_{\min}^j + (1 + y_i^j)\frac{x_{\max}^j - x_{\min}^j}{2}(i = 0,1,2,\cdots,N) \quad (5)$$

Where N was colony size . $x_{\min}^j, x_{\max}^j$ were colony variable minimum and maximum value , respectively. y_i^j was chaotic variable value.

(2) Nonlinear Inertia Weight

The above analysis shows that the key to the artificial bee colony algorithm was the quality source position update. Then quality source position v was deduce that

$$v_{it+1}^j = \omega v_{it}^j + \theta_1 r_1 (P_{ib}^j - X_{it}^j) + \theta_2 r_2 (G_b^j - X_{it}^j) \quad (6)$$

Where t was the number of iterations, T was the total number of iterations, X_{it}^j was the initial variable, v_{it}^j was locator variable, θ_1 and θ_2 were acceleration factor of the algorithm, which value 1.8 ～2. r_1 and r_2 were random factor, which value 0～1. P_{ih}^j was position variable of the best historical position, G_b^j was position variable of the best global position. ω was nonlinear inertia weight of the algorithm.

Note that large inertia weight factor was conducive to improve the global search ability of the algorithm and small inertia weight factor was beneficial to improve the local search ability. Then the exponentially decreasing inertia weight to balance the local and global search capabilities of the artificial bee colony algorithm was defined by

$$\omega = (\omega_{\max} - \omega_{\min})e^{-40(t/T)^2} + \omega_{\min} \quad (7)$$

Where

$\omega_{\min} = 0.4, \omega_{\max} = 0.9$.

(3)Early Maturity Judgment Mechanism

The artificial bee colony algorithm trends to fall into the local optimum state and the premature phenomenon in the search process. Fitness variance reflects the degree of convergence of a colony. Fitness variance σ^2 was given by

$$\begin{cases} \sigma^2 = \sum_{i=1}^{N}\left(\frac{f_i - f_{avg}}{f}\right) \le [\sigma^2] \\ f = \max(1, \max(abs(f_i - f_{avg}))) \\ f_{avg} = \frac{1}{N}\sum_{i=1}^{N} f_i \end{cases} \quad (8)$$

Where f_i was the fitness of nectar. f_{avg} was current average fitness of bee colonies. $\lfloor\sigma^2\rfloor$ was premature judgment threshold. The bigger σ^2 was, the bee swarm was in the random search stage; on the other hand, the bee colony tends to converge, and the local optimization was easier. Then it was necessary to provide a perturbation mechanism for the algorithm to make it jump out of the local optimum position and search the global optimum position. Firstly, the chaotic operator was initialized by cubic mapping method; Secondly, a random chaotic sequence to meet colony dimensions was provided, according to formula (6) chaotic sequences in each dimension were changed into numerical position variables in bee colony algorithm; Finally， With method of variance the optimal nectar in each dimension was found , and the random chaotic sequence was iteratively updated. Consequently, the global optimum was achieved.

2.3 Improved Chaotic Bee Colony Optimization Algorithm

Based on the above analysis, improved chaotic particle swarm optimization was provided, which balances the local and global search capabilities of the artificial bee colony algorithm by the cubic mapping method adopted to initialize the chaos and the inertia weight of exponential decreasing . The specific operation process was as follows：

Step1： assume that M was population size， $\omega_{\min}$ ， $\omega_{\max}$ were respectively the minimum and maximum of inertia weight factor, T was the total number of colony iteration, $\lfloor\sigma^2\rfloor$ was premature judgment threshold and θ_1, θ_2 were the acceleration factor of the algorithm.

Step2： initialize the chaotic sequence by the formula (4) , convert it to variable value in the hive dimension by the formula (5), evaluate the fitness value of honey, set the initial historical best position nectar variables P_{ib} and find initial global best position variable G_b .

Step3：Update the inertia weight factor of the algorithm by the formula (7) and the location of the algorithm by the formula (6), calculate the updated fitness value of honey, renew the value P_{ib} , G_b , calculate bee colony fitness variance σ^2 by the formula (8) and make a premature judgement. If the algorithm has been in the state of stagnation, we execute step4. Otherwise, the step5 is executed.

Step4：Reproduce a new nectar according to the formula (4) and (5), evaluate new nectar fitness, find the optimal location of nectar , Randomly replace some nectar source, and execute step5.

Step5：If the fitness value meets the some accuracy or reaches the maximum number of iterations , the loop ends and outputs the optimal value. Otherwise, the step3 is executed.

3 APPLICATION RESEARCH ON DEVELOPED CHAOS-WASP COLONY ALGORITHM USED IN SUSPENSION-PARAMETER OPTIMIZATION

3.1 Models of Half Suspension

The suspension dynamic model of half car was displayed in Fig.1,in which motion equations of 4 degrees of freedom entire car suspension system were written in two steps.Given centroid was $X_c = [x_c \quad \phi]^T$,2 motion equations of car body could be deduced:

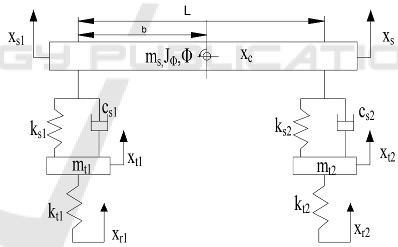

Fig .1 Half vehicle model of passive suspension

$$m_s\ddot{x}_c + c_{s1}(\dot{x}_{s1} - \dot{x}_{t1}) + c_{s2}(\dot{x}_{s2} - \dot{x}_{t2}) + k_{s1}(x_{s1} - x_{t1}) + k_{s2}(x_{s2} - x_{t2}) = 0 \quad (9)$$

$$J_\phi\ddot{\phi} - c_{s1}(\dot{x}_{s1} - \dot{x}_{t1})b + c_{s2}(\dot{x}_{s2} - \dot{x}_{t2})(L-b) - k_{s1}(x_{s1} - x_{t1})b + k_{s2}(x_{s2} - x_{t2})(L-b) = 0 \quad (10)$$

The motion equations of 2 unsprung weight systems were:

$$m_{t1}\ddot{x}_{t1} + c_{s1}(\dot{x}_{t1} - \dot{x}_{s1}) + k_{s1}(x_{t1} - x_{s1}) + k_{t1}(x_{t1} - x_{r1}) = 0 \quad (11)$$

$$m_{t2}\ddot{x}_{t2} + c_{s2}(\dot{x}_{t2} - \dot{x}_{s2}) + k_{s2}(x_{t2} - x_{s2}) + k_{t2}(x_{t2} - x_{r2}) = 0 \quad (12)$$

$$\begin{cases} x_{s1} = x_c - b\phi \\ x_{s2} = x_c + (L-b)\phi \end{cases} \quad (13)$$

where m_s was sprung weight of half car; J_ϕ was rotary inertia of car body; x_c was centroid displacement; ϕ was Longitudinal pitch angle of car body; L was the distance between the front and rear ; b was the distance from centroid to the front axle of the automobile; m_{t1}, m_{t2} were unsprung weights; c_{s1}, c_{s2} were damping coefficient; k_{s1}, k_{s2} were suspension spring parameters; x_{t1}, x_{t2} were upsprung weight displacement; x_{s1}, x_{s2} were sprung weight displacement; k_{t1}, k_{t2} were tire stiffness parameters. x_{r1}, x_{r2} were road excitation displacements.

3.2 Optimization Variables

To a great extent, the vehicle ride comfort and riding performance of a car depends on the suspension system.And suspension was mainly composed of shock absorber and spring,Therefore, the stiffness value of the spring and the damping value of the damper were taken as design variables:

$$x_i = [k_1 \quad c_1 \quad k_2 \quad c_2]^T \qquad (14)$$

3.3 Objective Function

In order to make the vehicle ride performance and riding comfort better, the objective function of the vehicle suspension system optimization algorithm was set up as follows

$$\min J = \frac{RMS[k_1(X)]}{RMS[k_{1pass}(X)]} + \frac{RMS[c_1(X)]}{RMS[c_{1pass}(X)]} + \frac{RMS[k_2(X)]}{RMS[k_{2pass}(X)]} + \frac{RMS[c_2(X)]}{RMS[c_{2pass}(X)]} \qquad (15)$$

Where $RMS[k_1(X)]$, $RMS[c_1(X)]$, $RMS[k_{1pass}(x)]$, $RMS[c_{1pass}(x)]$, $RMS[k_2(X)]$, $RMS[c_2(X)]$, $RMS[k_{2pass}(x)]$, $RMS[c_{2pass}(x)]$ were root mean square values of the passive suspension spring stiffness and damping obtained before and after the suspension of the optimized and the traditional one ,respectively.

Based on the design variables and objective functions above, the optimization model of passive suspension system was established as follows

$$\begin{cases} x_i = [k_1 \quad c_1 \quad k_2 \quad c_2]^T \\ \min J = \dfrac{RMS[k_1(X)]}{RMS[k_{1pass}(X)]} + \dfrac{RMS[c_1(X)]}{RMS[c_{1pass}(X)]} + \\ \dfrac{RMS[k_2(X)]}{RMS[k_{2pass}(X)]} + \dfrac{RMS[c_2(X)]}{RMS[c_{2pass}(X)]} \end{cases} \qquad (16)$$

4 SIMULATION

Referring to Fig. 1, the model was based on formula (9)- (13), and establishes the corresponding simulation model using the matalb/simulink module, as shown in Figure 2.

In order to check whether optimal designed in this paper could test working effect of optimization of passive suspension, simulation experiments on this system were carried the experiment took C road surface as input and $V = 40km/h$ as the vehicle's speed. The car type parameter were shown.

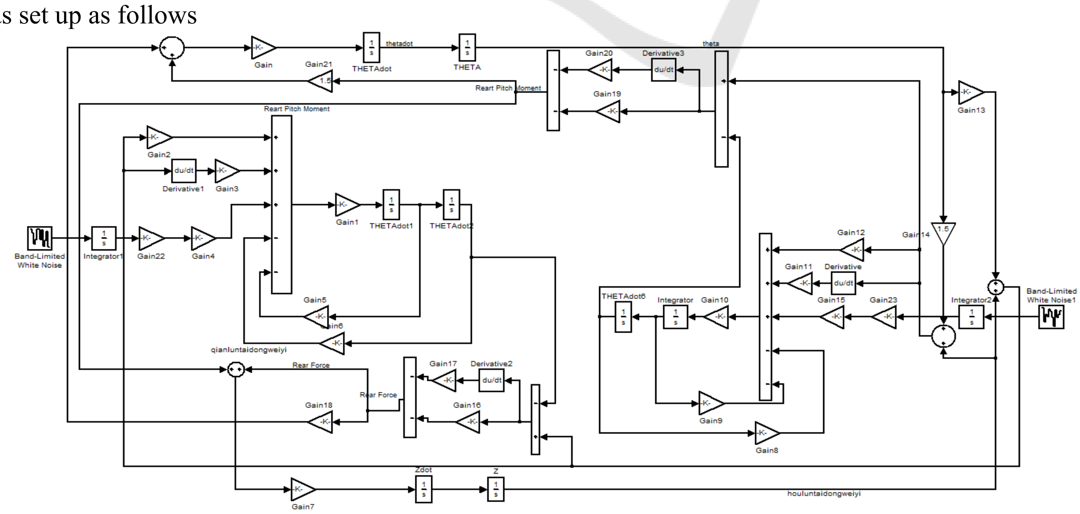

Fig.2 Simulation model

$m_s = 720kg$; $m_{t1} = 40kg$; $m_{t2} = 45kg$; $J_\varphi = 1222kg \cdot m^2$; $L = 2.8m$; $b = 1.3m$; $k_{s1} = 17000N/m$; $c_{s1} = 2500Ns/m$; $k_{t1} = 200000N/m$; $k_{s2} = 22000N/m$; $c_{s2} = 2000Ns/m$; $k_{t1} = 200000N/m$; *The search range of* k_1、c_1、k_2、c_2 were $[1 \quad 10^6]$, T=100 , $\omega_{min} = 0.4$, $\omega_{max} = 0.9$, $\theta_1 = \theta_2 = 1.8$, $[\sigma^2] = 0.01$ and the simulation results were shown in Fig. 3 to Fig. 8.

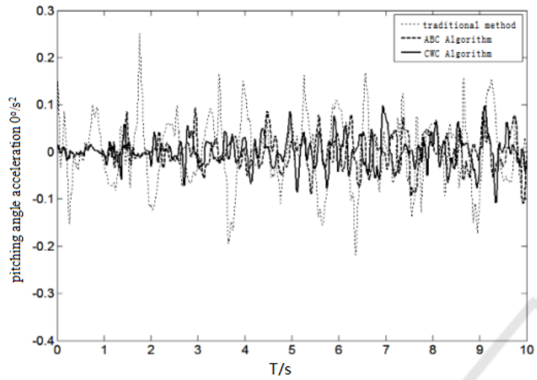

Fig.3 Simulation curve of pitching angle acceleration

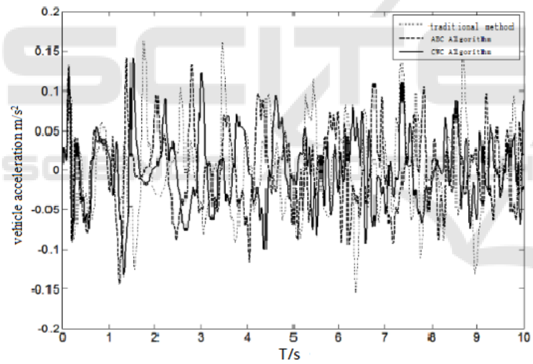

Fig.4 Simulation curve of vehicle acceleration

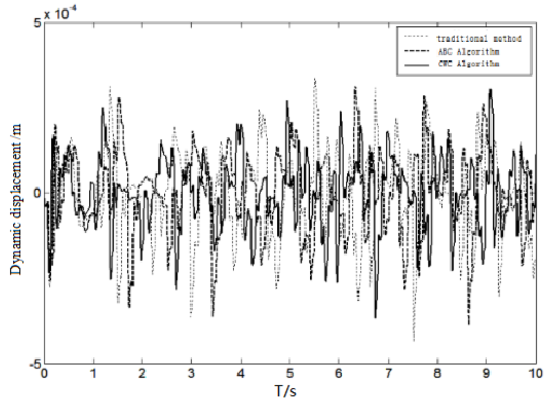

Fig.5 Dynamic displacement simulation curves of front suspension

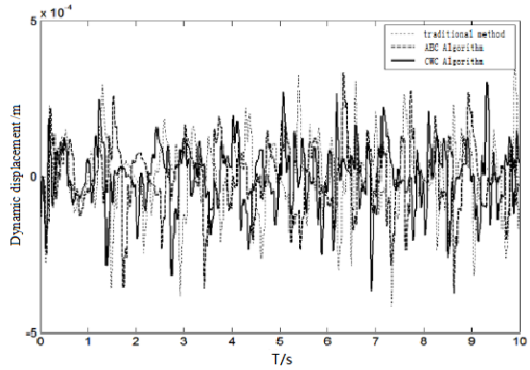

Fig.6 Dynamic displacement simulation curves of rear suspension

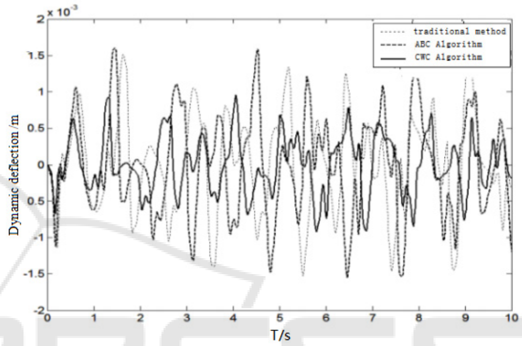

Fig.7 Dynamic deflection simulation curves of front suspension

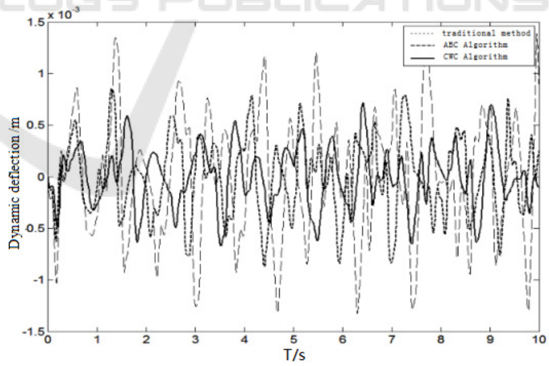

Fig.8 Dynamic deflection simulation curves of rear suspension

From Fig. 3 to Fig. 8, The vehicle suspension based on the chaotic bee colony algorithm significantly reduces the vertical acceleration of the car body, the tire moving position and the dynamic deflection of the suspension.

5 CONCLUSION

In this paper, an improved chaotic bee colony algorithm was presented , which avoids local optimization and premature convergence of the algorithm. The parameters of the passive suspension system of the 4 degree of freedom 1/2 body model were optimized, and the corresponding simulation model was established by using matlab/simulink software. The simulation shows that the performance of the suspension system parameters obtained with the improved artificial bee colony algorithm was better than the traditional and the artificial bee colony algorithm; This method can also shorten the cycle and cost of automobile suspension design; It lays a theoretical foundation for the improvement of vehicle ride comfort and handling stability and the application of chaotic bee colony algorithm.

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