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Fuzzy PID control based on genetic algorithm optimization inverted pendulum system

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Abstract: For the first-order inverted pendulum control system, a fuzzy PID control system based on the optimization of the genetic algorithm is proposed. The traditional genetic algorithm has the problem that the difference in the fuzzy subset parameter leads to a decrease in the interpretative ability of the fuzzy system. The main problem of the current genetic algorithm is the complexity of the computation and the low efficiency. Based on this problem, this paper proposes an improved genetic algorithm, i.e., it adopts the variance operator and adaptive change of the variance index and elite retention strategy, which solves the premature and local convergence problems of the standard genetic algorithm, in order to optimize the fuzzy system. The experimental results show that the optimized genetic algorithm gives full play to the advantages of fuzzy control in terms of interpretability and robustness, and at the same time guarantees the prediction accuracy, which provides a new research idea in the field of artificial intelligence control.

1. Introduction

Inverted pendulum composite control theory is one of the hot spots of the current control system. It is an experimental object studied by the engineering community when researching new control modifications, and the essential problem stripped from many engineering application systems is the stable pendulum control of the inverted pendulum. Algorithms based on the inverted pendulum control system have been widely used in intelligent robotics, aerospace, and other fields [1]. The latest research shows that the research on the control strategy of inverted pendulum systems still occupies an important role in cutting-edge science and technology [2], and the application scene is still expanding. The control research of inverted pendulum has laid the foundation for many scientific achievements.

For controlled objects that are intrinsically unstable, their motions can be stabilized in a reasonably desired state and exhibit good dynamic and static characteristics by certain means such as adding closed loops, additional controllers, and adjustable covariates. It can be said that it is the typical representativeness of the inverted pendulum stable pendulum control that makes it an ideal alternative experimental research platform to test complex control algorithms. Shahrooz et al. (2022) proposed a method to optimize the fuzzy logic controller of an inverted pendulum based on genetic algorithms [3], and achieved better results through simulation experiments, although the study did not complete the physical system algorithm verification. Wang and Mendel jointly proposed a method of obtaining fuzzy rules from sample data independent of prior knowledge [4], which can obtain a complete fuzzy rule base with good approximation performance from a complete sample set of small size and free of bad data, and achieved good results. But there are several problems with the Wang-Mendel (WM) method, as follows: First, the fuzzy rule base it produces lacks good completeness and robustness, which in turn leads to poor accuracy of the fuzzy system; Second, the efficiency of the algorithm decreases very quickly, and it can do nothing for high-dimensional big data problems; Third, the number of rules increases exponentially with the increase of the input dimensions, which makes it difficult to get rid of the spell of high dimensionality. To address this problem, many scholars have proposed improved algorithms.

Aiming at the above problems, this paper proposes a fuzzy system optimal modeling method based on the improved genetic algorithm and support degree and realizes the experimental verification by the first-order inverted pendulum. According to the simulation results, the improved genetic algorithm has better robustness in the fuzzy system and can make the inverted pendulum system enter the stable state more quickly.

2. Mathematical modeling of inverted pendulums

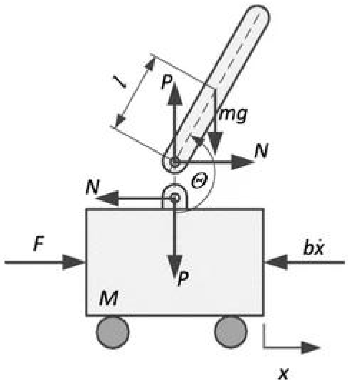

Figure 1. Structure of a first-order inverted pendulum model.

As shown in Figure 1, air resistance and friction are often neglected during model construction to facilitate the construction of the system, so that a first-order inverted pendulum in a straight line can be reduced to a system consisting of a cart and a pendulum.

The combined force on the cart in the horizontal direction is shown in Equation (1):

$$M\dot{x} = F - b\dot{x} - N \tag{1}$$

The expression of the combined force in the horizontal direction is derived from the force applied to the pendulum in the horizontal direction, as shown in Equation (2) below:

$$N = \mathrm{m}\frac{d^2}{dt^2}(x + l\sin\theta) = m\ddot{x} + ml\ddot{\theta}\cos\theta^2\sin\theta \tag{2}$$

Equation (2) is brought into Equation (1) and pushed to arrive at the first kinetic equation for the inverted pendulum system:

$$F = (M + m)\ddot{x} + b\dot{x} + ml\ddot{\theta}\cos\theta - ml\theta^2\sin\theta \tag{3}$$

After performing the force analysis in the vertical direction of the pendulum, the second dynamic equation of the system can be derived:

$$p - mg = -ml\ddot{\theta}\sin\theta - ml\dot{\theta}^2\cos\theta \tag{4}$$

After combining the given set of equations, the elimination of variables P and N is carried out to derive the second kinematic equation:

$$(I + ml^2)\ddot{\theta} + mgl\sin\theta = -ml\ddot{x}\cos\theta \tag{5}$$

By linearising the two equations of motion in Equations (3) and (5) and then performing the Laplace transform, the first equation of the system is investigated analytically with the known output angle φ of the pendulum. The system of equations is obtained as follows:

$$\frac{X(s)}{\phi(s)}=\frac{mls^2}{(I+ml^2)s^2-mgl} \tag{6}$$

We let $v=\ddot{x}$, $q=[(M+m)(I+ml^2)-(ml)^2]$ and set the state space equation of the system as:

$$\begin{cases} X = AX + Bu \\ \mathrm{Y} = \mathrm{CX} + \mathrm{Du} \end{cases} \tag{7}$$

The equation of state of the system is obtained after simplification and collation:

$$\begin{bmatrix} \dot{x} \\ \ddot{x} \\ \dot{\phi} \\ \ddot{\phi} \end{bmatrix} = \begin{bmatrix} 0 & 1 & 0 & 0 \\ 0 & \dfrac{-(I+ml^2)b}{I(M+m)+Mml^2} & \dfrac{m^2gl^2}{I(M+m)+Mml^2} & 0 \\ 0 & 0 & 0 & 1 \\ 0 & \dfrac{-mlb}{I(M+m)+Mml^2} & \dfrac{mgl(M+m)}{I(M+m)+Mml^2} & 0 \end{bmatrix} \begin{bmatrix} x \\ \dot{x} \\ \phi \\ \dot{\phi} \end{bmatrix} + \begin{bmatrix} 0 \\ \dfrac{(I+ml^2)}{I(M+m)+Mml^2} \\ 0 \\ \dfrac{ml}{I(M+m)+Mml^2} \end{bmatrix} u \tag{8}$$

The parameters of the physical model shown in Table 1 are obtained through the above derivation.

Table 1. Physical parameters of a first-order inverted pendulum.

Physical Symbol	Physical Maning	Actual values
M	Mass of trolley	$1.095kg$
m	Mass of the pendulum	$0.107kg$
b	Friction of the cart	$0.1N/m/s$
I	Moment of inertia of the pendulum	0.033
l	Length from the centre of the axis of rotation of the pendulum to the centre of mass of the pendulum	$0.25m$
x	Direction of the trolley	m
ϕ	Angle between the pendulum and the vertical upward direction	rad
F	Thrust on the trolley	N

3. Fuzzy PID control

The fuzzy PID algorithm is the application of fuzzy control in the process of PID parameter adjustment [5], the fuzzy algorithm can play the role of auxiliary optimization, the design of the fuzzy PID controller is based on the ordinary PID control, and the deviation e and the rate of change of the deviation ec are taken as the input of the fuzzy control part of the fuzzy control [6]. Through fuzzy reasoning, the outputs of defuzzification$\triangle K_p$, $\triangle K_i$, and $\triangle K_d$ are superimposed into the corresponding PID parameters to get the integrated control quantity of the controlled object and achieve the system stability control. The principle of fuzzy PID parameter setting is shown in Figure 2.

$$u(t)=K_p\left[e(t)+\frac{1}{T}\int_0^t e(t)dt+T_d\frac{de(t)}{dt}\right] \tag{9}$$

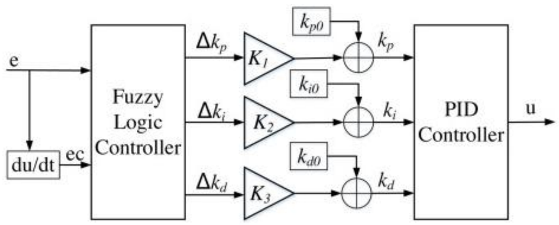

Figure 2. Principle of fuzzy PID parameter tuning.

In fact, the input variable of the fuzzy PID controller is set to 2, and the output variable is set to 3, which corresponds to the three PID regulation parameter corrections obtained after the fuzzy reasoning, so as to complete the online adjustment of the regulation parameters.

4. Fuzzy rule-making

Fuzzy control rules are usually formulated based on human experience, which is the core of fuzzy control. Its reasonable determination seriously affects the control effect, and the determination of the number of fuzzy subsets needs to be set according to the actual needs of the system control performance [7-8]. On the basis of the model analysis and continuous command tracking experience to complete the fuzzy rule formulation, the fuzzy PID parameter rule table is determined, as shown in Figure 3, and MamdanL's max-min synthesis algorithm is used for fuzzy reasoning of the parameters.

ΔK_p Fuzzy rule table

	NB	NM	NS	ZO	PS	PM	PB
NB	PB	PB	PM	PM	PS	ZO	ZO
NM	PB	PB	PM	PS	PS	ZO	NS
NS	PM	PM	PM	PS	ZO	NS	NS
ZO	PM	PM	PS	ZO	NS	NM	NM
PS	PS	PS	ZO	NS	NS	NM	NM
PM	PS	ZO	NS	NM	NM	NM	NB
PB	ZO	ZO	NM	NM	NM	NB	NB

ΔK_I Fuzzy rule table

	NB	NM	NS	ZO	PS	PM	PB
NB	NB	NB	NM	NM	NS	ZO	ZO
NM	NB	NB	NM	NS	NS	ZO	NS
NS	NB	NM	NS	NS	ZO	PS	NS
ZO	NM	NM	NS	ZO	PS	PM	PM
PS	NM	NS	ZO	PS	PS	PM	PB
PM	ZO	ZO	PS	PS	PM	PB	PB
PB	ZO	ZO	PS	PM	PM	PB	PB

ΔK_D Fuzzy rule table

	NS	NM	NS	ZO	PS	PM	PB
NB	PS	NS	NB	NB	NB	NM	PS
NM	PS	NS	NB	NM	NM	NS	ZO
NS	ZO	NS	NN	NM	NS	NS	ZO
ZO	ZO	NS	NS	NS	NS	NS	ZO
PS	ZO	ZO	ZO	ZO	ZO	ZO	ZO
PM	PB	NS	PS	PS	PS	PS	PB
PB	PB	PM	PM	PM	PS	PS	PB

Figure 3. Table of fuzzy rules.

where each symbol indicates as follows: negative big: NB; negative middle: NM; negative small: NS; zero: ZO; positive small: PS; positive middle: PM; positive big: PB.

5. Genetic algorithm optimization

In general, most of the algorithms used in the algorithm are uniform variation and boundary variation operators. However, the improved genetic algorithm used in this paper adopts the variation operator with the adaptive change of variation index [9], which adopts a larger variation index m at the early stage of the evolution in order to maintain the diversity of the population to make the range of the variation space larger, and adopts a smaller variation index at the later stage in order to increase the speed of evolution to make the space of the variation smaller in the end [10].

It is assumed that the chromosomes of an individual are $x=(x_1,x_2,\dots,x_k,x_n)$, $x_k \in [S_k, L_k]$ is a mutated element selected with mutation probability Pm, and the mutated element Pk is generated uniformly at random in the interval M:

$$M = [X_k - m(X_k - S_k), X_k + m(L_k - X_k)] \tag{10}$$

$$m = 1 - r^{[1-\frac{g}{G}]\rho} \tag{11}$$

where G is the maximum number of genetic generations; ρ is a parameter, taken to be 2 in this paper; r is a randomly generated number uniformly distributed between [0, 1].

The flow of designing the improved genetic algorithm is shown in Figure 4:

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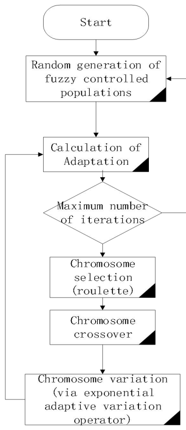


Figure 4. Flowchart of genetic algorithm.

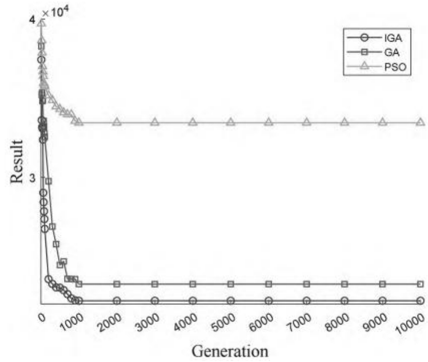


Figure 5. Iteration curve diagram.

1) The number of genetic generations $i = 0$, the initial population P_0 is randomly generated, and the population capacity is N. Then P0 is the population P at this point.

2) The objective function values are calculated, then the fitness values are ranked in order to select the optimal solution B.

3) If the iteration reaches the maximum number of hereditary generations and satisfies the robustness constraints, the optimization result is obtained; If the iteration reaches the maximum number of hereditary generations but does not satisfy the robustness constraints, it is suggested to return to Step 1; If the iteration does not reach the maximum number of hereditary generations, then it is suggested to perform Step 4.

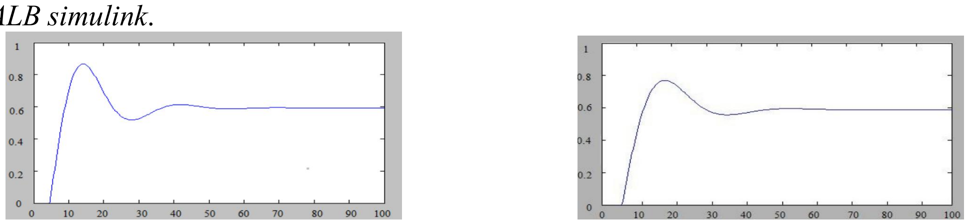
4) A new population P_i is generated. After obtaining a new population by using the roulette algorithm, it is necessary to randomly select r chromosomes on the current population N, compare the objective function values of these chromosomes, and copy the better one to P_i; ② The parent chromosomes for crossover operation are selected according to the probability; ③ Mutation operation is carried out on the population Pi according to the probability; ④ The individuals obtained from ①, ② and ③ are synthesized into a new population P_i with the number of N.

5) The newly synthesized population Pi is updated to the current population P and then it is suggested to return to Step 2.

By setting the number of iterations to 1000, the traditional genetic algorithm and the particle swarm improve the genetic algorithm and the current. The experimental improved algorithm is simulated to obtain the results shown in Figure 5. The results show that the genetic algorithm starts to converge after 10,000 iterations, while the particle swarm algorithm converges slightly earlier than the genetic algorithm. Because the particle swarm algorithm is precocious in local optimization ability and poorer in local search ability, in terms of the optimal value, the improved genetic algorithm is better than the basic genetic algorithm and the particle swarm algorithm.

6. Analysis of experimental simulation

A simulation comparison of the conventional fuzzy neural network PID controller and the fuzzy neural network PID controller optimized based on the improved genetic algorithm is carried out through *MATALB simulink*.



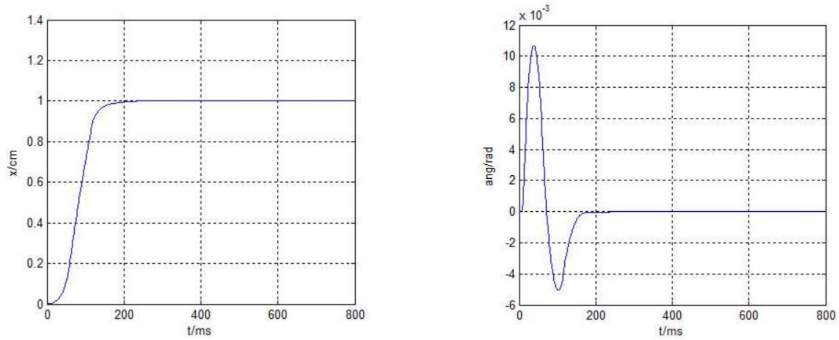
(a) Conventional fuzzy PID controller (b) Controller based on genetic algorithm optimization

Figure 6. Simulation results of two controllers.

As shown in Figure 6(a), for the traditional fuzzy neural network PID controller, although the response time curve of the final system is able to reach the steady state, it takes a long time to reach the steady state and has a large number of oscillations.

As shown in Figure 6(b), the genetic algorithm-optimized fuzzy PID control system is able to enter the steady state more quickly compared to the normal fuzzy neural network PID control system. It can be concluded that the genetic algorithm-optimized fuzzy neural network PID controller has a faster processing speed and lower oscillation amplitude.

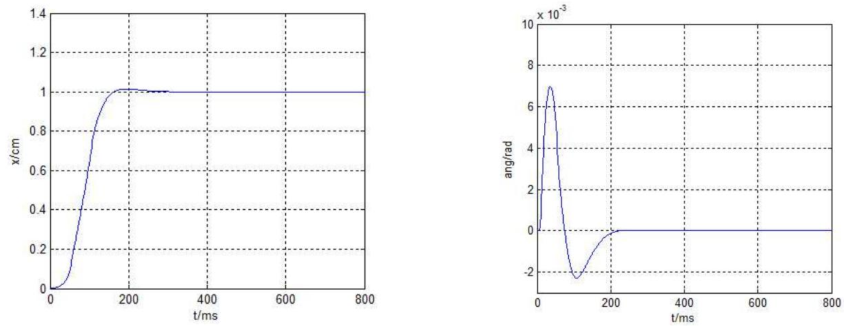
The inverted pendulum is then simulated by *MATLAB* with fuzzy PID controller simulation and genetic algorithm-optimized fuzzy PID controller respectively, and the degree of change in the pendulum is observed while changing the state of the cart. Figure 7 shows the changing state of the inverted pendulum system with conventional fuzzy PID.



(a) Trolley position change state (b) Pendulum change state

Figure 7. Conventional fuzzy PID simulation results.

The inverted pendulum is then simulated by the fuzzy PID controller optimized by the genetic algorithm of this design, as shown in Figure 8.



(a) Trolley position change state (b) Pendulum change state

Figure 8. Genetic algorithm fuzzy PID simulation results.

Comparison of the two simulation results shows that both the fuzzy PID controller and the genetic algorithm-optimized fuzzy PID controller have better control results for the inverted pendulum system, but in the case of the system of changes in the state of the trolley, the genetic algorithm-optimized fuzzy PID controller tends to be more gentle to the pendulum, and the pendulum's angle changes are a little bit smaller.

In the control motion simulation of the inverted pendulum system, based on the optimized fuzzy PID controller, excellent performance is shown in the system, which significantly improves the response speed of the system. By combining the improved genetic algorithm with the fuzzy PID control algorithm, the overall performance level of the system is effectively enhanced.

7. Conclusion

This experiment is done to optimize the fuzzy PID control of the inverted pendulum system based on an improved genetic algorithm.

Through this experiment, the fuzzy PID is set up, and the genetic algorithm is optimized to improve its adaptability, using theoretical analysis, programming implementation, and simulation experiments as the means of research.

This study shows the improvement of control motion simulation of inverted pendulum systems by adding a genetic algorithm to fuzzy control. The improved genetic algorithm used in this paper employs a variance operator with an adaptive variation of the variance index and an elite retention strategy, which solves the problems of premature maturity and local convergence of the standard genetic algorithm.

Based on the optimized fuzzy neural network PID controller, this controller shows excellent performance in the system and significantly improves the response speed of the system. The fuzzy controller with an improved genetic algorithm designed in this work has less dependency and better intelligence. It also provides a new research idea and direction in the field of artificial intelligence control.

References

[1] Wei Fen, Wang Suqing, Deng Haiqin, et al. Research on the control of a primary inverted pendulum based on fuzzy control algorithm [J]. Computer Simulation, 2023,40 (03): 320-325.
[2] Lan Xin, Wei Hongli, Chen Chaobo. Research on Fractional-order control of an improved particle swarm optimization algorithm [J]. Computer Technology and Development, 2018,28 (10): 145-149.
[3] ALIMORADPOUR S, RAFIE M, AHMADZADEH B. Providing a genetic algorithm-based method to optimize the fuzzy logic controller for the inverted pendulum [J]. Soft Computing, 2022,26(11).
[4] WANGLX, MENDELJM. Generating fuzzy rules by learning from examples [J]. EEE Transactions on Systems, Man, and Cybernetics, 1992,22(6): 1414-1427.
[5] LIU Jianbao, SHAN Shuaijie, QIN Xinxin. Method for optimizing speed control of gas turbine generator units based on improved genetic algorithm [J]. Journal of Naval Engineering University, 2022, 34 (4): 47-52.
[6] ZHANG Yiming. Application of fuzzy control theory in ship maneuvering [J]. Ship Science and Technology, 2022,44 (8): 60-63.
[7] LI Zhongxin, WANG Dalong, ZHUANG Jiacai, et al. Research on fatigue load of wind turbine yaw system based on genetic fuzzy control [J]. Journal of Power Engineering, 2022,42 (8): 745-752. (in Chinese)
[8] Ren Ziwu, Umbrella Ye. Improvement and performance study of real number genetic algorithm [J]. Electronic Journal, 2007(2):269-274
[9] GHAFOU R I M, DANESHMAND S. Design and evaluation of an optimal fuzzy PID controller for an active vehicle suspension system [J]. Transactions of Famena, 2017,41(2) : 29-44.
[10] MAJDOUB K E, GI R I F, CHAOUI F Z. Adaptive backstepping control design for semi-active suspension of half-vehicle with magnetorheological damper[J]. IEEE/CAA Journal of Automatica Sinica, 2021,8(3): 582-596