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Fractional-order Controller for USV Course-keeping based on Improved PSO Algorithm

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Abstract

Underactuated surface vessels (USV) have the characteristics of large inertia, large time lag and high nonlinearity. In order to implement the high-efficiency course-keeping of USV, a fractional-order $PI^{\lambda}D^{\mu}$ controller was proposed in this paper. However, the integral-order λ and differential-order μ increase the difficulties of $PI^{\lambda}D^{\mu}$ controller parameter tuning. So we proposed a fractional-order $PI^{\lambda}D^{\mu}$ controller based on asynchronous time-varying learning factor and self-adaptive weight particle swarm optimization (PSO) algorithm, which can control the flying speed of the particles more effectively and enhance its global convergence ability. This method can also solve the problem that the fractional-order $PI^{\lambda}D^{\mu}$ controller has many parameters and design complexity. The simulation results show that the proposed method has the advantages of short regulation time, fast convergence, small overshoot, good robust performance and strong immunity ability.

Keywords*: underactuated surface vessels, course-keeping control, particle swarm optimization algorithm, fractional-order $PI^{\lambda}D^{\mu}$ controller, asynchronous time-varying learning factor, self-adaptive weight*

1. Introduction

The underactuated system refers to the system that the spatial dimension of control input is less than spatial dimension of configuration, and it is a nonlinear system, such as underactuated surface vessels (USV), mobile robots, and spacecraft [1]. Underactuated surface vessels have the characteristics of large inertia, nonlinear and time-delay. In order to implement the high-efficiency course-keeping of USV, steering is controlled by autopilot control system, and correct the disturbance caused by yaw. But due to the complexity of ship motion and environment, it is difficult to establish a precise motion model of ship course in the autopilot design. In order to obtain satisfactory control effect, many scholars do many researches. The intelligent control algorithms of ship course mainly include generalized predictive control [2], variable structure control [3], Backstepping control [4], $H\infty$ robust control [5] et al, which have been applied to the course control, and achieved good control effect. But there are some problems, such as forecasting control, Backstepping control, $H\infty$ robust control which depend the object precise model.

Fractional calculus expands the differential-order and integral-order of integral calculus to any order, and improves the description of the integer-order calculus [6-7]. In 1999, I.Podlubny proposed the fractional-order $PI^{\lambda}D^{\mu}$ controller. Compared with traditional

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PID controller, it has two additional adjustable parameters, which can control the object more flexibly and has stronger robustness and better control effect [8-9].But it is difficult to tune the parameters of fractional-order $PI^{\lambda}D^{\mu}$ controller. Therefore, the parameters' tuning of fractional-order $PI^{\lambda}D^{\mu}$ control system has become a hot research spot.

At present, there are many optimization algorithms such as neural network, fuzzy control, genetic algorithm, particle swarm optimization, synovial control and so on. In [10], an adaptive fuzzy fractional-order controller was proposed to solve the parameter adjustment of the fractional-order $PI^{\lambda}D^{\mu}$ controller that was used for the integer-order controlled object. In [11], a modified differential evolution algorithm was proposed for tuning the parameters of fractional- order $PI^{\lambda}D^{\mu}$ controller.

In this paper, we use a fractional-order $PI^{\lambda}D^{\mu}$ controller based on improved PSO (IPSO) algorithm to control autopilot of USV and keep the ship's course. Meanwhile, the asynchronous time-varying learning factor and self-adaptive weight are proposed to optimize PSO algorithm, and the convergence speed and the global searching ability of PSO are improved. Compared with fractional-order $PI^{\lambda}D^{\mu}$ controller based on improved PSO algorithm and PID controller based on traditional PSO algorithm, the simulation results show the feasibility and effectiveness of the approach.

2. Fractional Calculus descriptions

2.1. Fractional Calculus Definition

Fractional calculus is a branch of mathematical analysis that studies the possibility of taking real number powers or complex number powers of the differentiation operator and the integration operator. The basic operator of fractional calculus is as follows

$$ {}_aD_t^{\alpha} = \begin{cases} \dfrac{d^{\alpha}}{dt^{\alpha}}, \mathrm{Re}(\alpha) > 0 \\ 1, \mathrm{Re}(\alpha) > 0 \\ \int_{\alpha}^{t} (d\tau)^{-\alpha}, \mathrm{Re}(\alpha) < 0 \end{cases} \tag{1} $$

In which, a and t are upper and lower limit of operation operator, α is calculus order which can be any complex number and assumed as real numbers.

There are three definitions of fractional calculus, Grunwald-Letnikov definition, Riemann-Liouviblle definition and Caputo definition.

The Grunwald-Letnikov definition formula is:

$$ {}_aD_t^{\alpha} f(t) = \lim_{h\to 0} \frac{1}{h^{\alpha}} \sum_{i=0}^{\left[\frac{t-a}{h}\right]} (-1)^j \binom{\alpha}{j} f(t-jh) $$

(2)

In which, $[x]$ denotes x an integer, $\binom{\alpha}{j}$ is binomial coefficient.

The Riemann-Liouviblle formula:

$$ {}_aD_t^{\alpha} f(t) = \frac{1}{\Gamma(m-\alpha)} \left(\frac{d}{dt}\right)^m \int_a^t \frac{f(\tau)}{(t-\tau)^{1-(m-\alpha)}} d\tau \tag{3} $$

In which, $\Gamma(\bullet)$ is Gamma definition function.

The Caputo definition formula:

$${}_aD_t^\alpha f(t)=\frac{1}{\Gamma(m-\alpha)}\int_a^t\frac{f^m(\tau)}{(t-\tau)^{1-(m-\alpha)}}d\tau \tag{4}$$

In which, $m-1<\alpha<m,m\in N$.

From three kinds of definitions of fractional calculus, we can see that the fractional differential and integer-order differential is different when continuous function is on a point.

2.2. Modified Oustaloup Approximation

In order to apply the research method of integer-order controller to the fractional-order controller, fractional calculus must be approximated to integer-order calculus. In this paper, a modified Oustaloup approximation method is applied. s^α is approximated as integer-order calculus, approximate fitting frequency range is (ω_b,ω_h) ,order is N. By this method, approximation integer-order transfer function is given as

$$s^\alpha=\left(\frac{d\omega_b}{b}\right)^\alpha\left(\frac{ds^2+bs\omega_h}{d(1-\alpha)s^2+bs\omega_h+d\alpha}\right)\left[\frac{1+\dfrac{s}{d\omega_b/b}}{1+\dfrac{s}{d\omega_h/b}}\right]^\alpha \tag{5}$$

In which, $0<\alpha<1$, $b>0$, $d>0$, $d=j\omega$, the fractional part of formula $K(s)$ denotes as zeros, poles form of a rational transfer function

$$K(s)=\lim_{N\to\infty}K_N(s)=\lim_{N\to\infty}\prod_{k=-N}^{N}\frac{1+s/\omega_k^{'}}{1+s/\omega_k} \tag{6}$$

The k zero, pole is

$$\omega_k^{'}=\omega_b\left(\frac{\omega_h}{\omega_b}\right)^{\frac{N+k+\frac{1}{2}(1-\alpha)}{2N+1}} \tag{7}$$

$$\omega_k=\omega_b\left(\frac{\omega_h}{\omega_b}\right)^{\frac{N+k+\frac{1}{2}(1+\alpha)}{2N+1}} \tag{8}$$

Construct the continuous rational transfer function model of fractional calculus operator:

$$G(s)=K\left(\frac{ds^2+b\omega_hs}{d(1-\alpha)s^2+b\omega_hs+d\alpha}\right)\prod_{k=-N}^{N}\frac{1+s/\omega_k^{'}}{1+s/\omega_k} \tag{9}$$

In which, $K=(\omega_b,\omega_k)^\alpha$.

3. Fractional-order $PI^\lambda D^\mu$ Controller based on IPSO

3.1. Fractional-order $PI^\lambda D^\mu$ Controller

The general form of fractional-order controller is $PI^\lambda D^\mu$ that includes an integral-order λ and differential-order μ, the differential equation is

$$u(t)=K_pe(t)+K_iD_t^{-\lambda}e(t)+K_dD_t^\mu e(t) \tag{10}$$

In which, $D_t^\alpha\equiv{}_a^CD_t^\alpha$ is the Caputo definition, $\lambda>0$ and $\mu>0$ are any real number.

The Laplace transform of Caputo definition is

$$L\left\{ {}_{a}^{C}D_{t}^{\alpha} f(t) \right\} = s^{\alpha} F(s) - \sum_{k=0}^{n-1} s^{\alpha-k-1} f^{(k)}(0) \tag{11}$$

From (10)-(11), the transfer function of fractional-order $PI^{\lambda}D^{\mu}$ controller is

$$G_c(s) = K_p + \frac{K_i}{s^{\lambda}} + K_d s^{\mu} \tag{12}$$

The fractional-order $PI^{\lambda}D^{\mu}$ controller has more than two adjustable parameters. Choosing properly integral-order λ and differential-order μ, the control performance can be improved.

3.2 The Tuning of Controller Parameters based on IPSO

From (12), the fractional-order $PI^{\lambda}D^{\mu}$ controller adds two adjustable parameters λ and μ, which make the parameters of fractional-order $PI^{\lambda}D^{\mu}$ controller are being increased to five, namely $(K_p, K_i, K_d, \lambda, \mu)$. By choosing five adjustable parameters reasonably, the performance of the controller can be further improved, but it also increases the design difficulty of the controller. Therefore, a fast and effective method is necessary to adjust controller parameters and meet the requirements of the control system.

In 1995, Kennedy and Eberhart proposed a particle swarm optimization algorithm. This algorithm has the advantages of swarm intelligence, intrinsic parallelism, simple iterative scheme, and fast convergence to the optimal solution location etc. However, with the further study of the PSO algorithm, the three major drawbacks are discovered. The first drawback is that the PSO algorithm easily traps in local optimum, which is called as premature phenomenon. Secondly, the relationship between global and local optimal values is difficult to coordinate. Finally, it is very difficult to understand the exact time of PSO algorithm at using global and local models.

According to defects that the PSO algorithm prone to fall into local optimal solution, difficult to reconcile the global and local optimal value, this paper proposes an improved particle swarm optimization (IPSO) algorithm. On the basis of the original algorithm, self-adaptive weight is introduced to PSO algorithm, which balances the ability of PSO algorithm in global search ability and local improvement. At the same time, two asynchronous time-varying learning factors are added, which can further control the flying speed of the particles and increase the local search ability of the algorithm.

Firstly, the PSO algorithm initializes group in the feasible solution space and velocity space, namely determines the initial position and speed of the particle. In the d dimensional target search space, let the position and speed of the i particle are represented as $X_i = \left[x_{i,1}, x_{i,2} \ldots x_{i,d}\right]$ and $V_i = \left[v_{i,1}, v_{i,2} \ldots v_{i,d}\right]$. During the optimization, the target functions of each particle are evaluated to determine the best position of particle $P_i = \left[p_{i,1}, p_{i,2} \ldots p_{i,d}\right]$ and the best position of whole swarm $P_g = \left[p_{g,1}, p_{g,2} \ldots p_{g,d}\right]$. According to the following formula, the positions and velocities of the particles are updated

$$v_{id}(\mathrm{t}+1) = \omega v_{id}(\mathrm{t}) + c_1 r_1 \left[p_{id} - x_{id}(\mathrm{t})\right] + c_2 r_2 \left[p_{gd} - x_{id}(\mathrm{t})\right] \tag{13}$$

$$x_{id}(t+1) = x_{id}(t) + v_{id}(t+1) \tag{14}$$

where ω is inertia factor, c_1 and c_2 are acceleration factors, r_1 and r_2 are random number between 0 and 1. To balance the global search ability and the local improved ability of PSO algorithm, the nonlinear dynamic inertia weight coefficient formula is proposed

$$\omega = \begin{cases} \omega_{\min} - \frac{(\omega_{\max} - \omega_{\min}) * (f - f_{\min})}{f_{avg} - f_{\min}}, & f \le f_{avg} \\ \omega_{\max}, & f > f_{avg} \end{cases} \tag{15}$$

In which, $\omega_{\mathbf{max}}$ and $\omega_{\mathbf{min}}$ are the maximum and minimum value of ω, f is target function value of current particle, f_{avg} and $f_{\mathbf{min}}$ are respectively the average target and the minimum target value of the current particle. Because the inertia weight is changed automatically with objective function value of the particle, so it is called as self- adaptive weight.

At the same time, because the learning factor c_1 and c_2 determine the experience information of the particles themselves, and the experience information of other particles effect on the trajectory of the particles. They reflect the information exchange between the particles. Setting the larger value of c_1 will make particles hover in the local range. However, the larger value of c_2 will lead particles prematurely converge to the local minimum. Therefore, we propose asynchronous time-varying learning factor, the asynchronous time-varying refers to the different changes of two learning factors with time during the optimization process. During the initial stage of the optimization, this makes the particles have a strong self-learning ability and weak social learning ability, and strengthens the global search ability. In the later stage, the particles have strong social learning ability and weak self-learning ability, which is advantageous to converge to the global optimization. The change formulae of learning factors are

$$c_1 = c_{1,ini} + \frac{c_{1,fin} - c_{1,ini}}{t_{\mathbf{max}}} \bullet t \tag{16}$$

and

$$c_2 = c_{2,ini} + \frac{c_{2,fin} - c_{2,ini}}{t_{\mathbf{max}}} \bullet t \tag{17}$$

Where $c_{1,ini}$ and $c_{2,ini}$ are the initial values of c_1 and c_2, $c_{1,fin}$ and $c_{2,fin}$ are the iteration final values of c_1 and c_2.

In summary, the parameters tuning process of fractional-order $PI^{\lambda}D^{\mu}$ controller based on IPSO algorithm is described as following:

a) Initialize the particle swarms, and randomly generate position and speed of each particle.

b) The position vector of each particle is successively used as the fractional-order $PI^{\lambda}D^{\mu}$ controller parameters, the current fitness value of each particle is calculated, and initialize P_i and P_g.

c) Compare the best position P_i of all particles, choose the best value and act as the best position P_g of the whole particle swarm.

d) Use formula (13)-(17) to optimize, update the speed υ_i and position x_i of each particle, $i = 1, 2, ..., n$, $d = 1, 2, ...5$ is the five parameters of fractional-order $PI^{\lambda}D^{\mu}$ controller.

e) Check to see whether the termination condition is satisfied. If it is satisfied, then exit; otherwise, go to step (b).

3.3. The Fitness Function Selection

We propose the IPSO algorithm to tune parameters $(K_p, K_i, K_d, \lambda, \mu)$ of fractional-order $PI^{\lambda}D^{\mu}$ controller, the space dimension of solution is five, and a modified Oustaloup approximation method is used. Consider the error square integral and system overshoot of the control loop, the formula of fitness function is

$$J = \omega_1 \int_0^{+\infty} e^2(t)dt + \omega_2 \sigma \tag{18}$$

In which, $e(t)$ is systematic error, σ is system overshoot, ω_1 and ω_2 are weights.

4. Underactuated Surface Vessels Mathematical Model

4.1. Maneuvering Mathematical Model

For an ocean vessel moving in 6 degree of freedom (DOF), the 6 different motion components respectively represent the position and direction. The first three coordinates (x, y, z) and their first- order differential represent the ship position and translational motion along x, y and z axes. The last three coordinates (φ, θ, ψ) and their first- order differential indicate the direction and rotation of the ship. The 6 DOF are respectively denoted as surge, sway, heave, roll, pitch, and yaw [12], see Figure1.

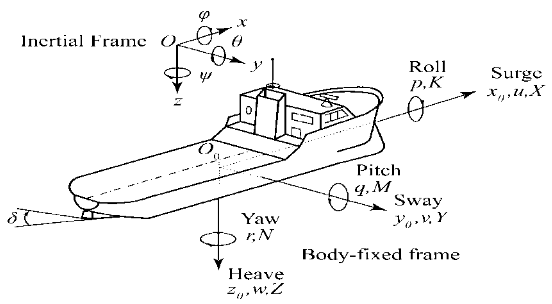

Figure 1. Reference Frames and Variables for Ship Motion Description

The ship maneuvering is usually considered in the horizontal movement of the ship, and the heave, roll, and pitch are usually neglected. So the ship motion problem is simplified to only three DOF. The maneuvering mathematical model of USV can be written

$$\begin{cases} \dot{x} = u\cos\psi - v\sin\psi \\ \dot{y} = u\sin\psi + v\cos\psi \\ \dot{\psi} = r \end{cases} \tag{19}$$

$$\begin{cases} \dot{u} = \frac{m_{22}}{m_{11}} vr - \frac{d_{11}}{m_{11}} u + \frac{1}{m_{11}} \tau_u \\ \dot{v} = -\frac{m_{11}}{m_{22}} ur - \frac{d_{22}}{m_{22}} v \\ \dot{r} = \frac{m_{11} - m_{22}}{m_{33}} uv - \frac{d_{33}}{m_{33}} r + \frac{1}{m_{33}} \tau_r \end{cases} \tag{20}$$

where x, y and ψ denote the surge, sway, and yaw angle in the earth fixed frame. u , v and r are the surge, sway and yaw velocities. m_{11}, m_{22} and m_{33} are the inherent and additional mass of ship, that are model uncertainties. d_{11} , d_{22} and d_{33} are the hydrodynamic damping of the surge displacement, sway displacement, and yaw angle, that are model uncertainties. τ_u , τ_r denote longitudinal force and torque of ship propeller.

4.2. Norrbin Nonlinear Model for USV Course Control

In the design of the USV course controller, the ship is considered as a dynamic system. The input is the rudder angle δ , and the output is the yaw angle ψ . In the case of steering is not very frequent, the Norrbin nonlinear model of USV course control deduced from the maneuvering mathematical model is obtained

$$\ddot{\psi} = -a_1\dot{\psi} - a_2\psi^3 + b\delta \tag{21}$$

where ψ and δ respectively are the yaw angle and rudder angle control. $a_1 = \alpha b$, $a_2 = \beta b$ and $b = K / T$ are model parameters, K and T are ship indexes, α and β are nonlinear coefficient. K , T , α and β are relevant to the speed and structure of ship.

5. Simulations

The simulation experiment uses the data of 5446TEU container ship in COSCO Group. Suppose the rated speed of this ship is $V = 19.80$ knots, then $K = 0.1955$, $T = 255.8837$, $\alpha = 14.3601$ and $\beta = 19.3172$. According to the design procedure of fractional-order $PI^\lambda D^\mu$ controller based on IPSO algorithm, the fitting frequency of modified Oustaloup filtering method (ω_b , ω_h) chooses [0.001, 1000], and order N = 5. The total number of the particles is 50, the particle size is five that is $[K_P, K_i, K_d, \lambda, \mu]$ of fractional-order $PI^\lambda D^\mu$ controller. The initial parameters of asynchronous time-varying learning factor are $c_{1,ini} = 2.25$, $c_{1,fin} = 0.35$, $c_{2,ini} = 2.25$ and $c_{2,fin} = 0.35$ .The minimum and maximum inertia weights are $\omega_{\min} = 0.6$ and $\omega_{\max} = 0.9$. The weights ω_1 and ω_2 of fitness function are both 10. Respectively choosing the fractional-order $PI^\lambda D^\mu$ controller based on IPSO algorithm and integer-order PID controller based on PSO algorithm, the maximum rudder angle limits at -35°~+35°, the expected course angle takes30°in 0 ~ 1000 seconds.

Choosing the fractional-order $PI^\lambda D^\mu$ controller based on IPSO algorithm, the five parameters of the controller are respectively $K_p = 14.794$, $K_i = 9.285$,

$K_d = 83.637$, $\lambda = 0.275$, $\mu = 0.823$, rise time $t_r = 104s$, adjust time $t_s = 104s$, overshoot $M = 0.20\%$, steady-state error $E_{ss} = 0.00579$ .Choosing integer-order PID controller based on PSO algorithm, the three parameters of the controller $K_p = 29.015$, $K_i = -2.485$, $K_d = 67.766$, rise time $t_r = 61s$, adjust time $t_s = 465s$, overshoot $M = 48.54\%$, steady-state error $E_{ss} = 0.02455$.

The design method of the traditional PID ship autopilot [13], the proportional, integral and differential parameters of controller are

$$K_p = \frac{T\omega_n^2}{K}, K_i = \frac{T\omega_n^3}{10K}, K_d = \frac{2T\varepsilon\omega_n - 1}{K} \tag{22}$$

where ω_n is system natural frequency, ε is system relative attenuation coefficient. Usually take $0.8 \le \varepsilon \le 1.0$, $\omega_n = 0.06$, $\varepsilon = 0.9$. From (22), we can obtain $K_p = 4.712$, $K_i = 0.028$, $K_d = 136.2426$, rise time $t_r = 69s$, adjust time $t_s = 625s$, overshoot $M = 11.32\%$, steady-state error $E_{ss} = 0.01602$. The simulation results are shown in Figure2, Figure3.

As shown in Figure2, Figure3, we can see that the control effect based on fractional-order $PI^{\lambda}D^{\mu}$ controller is obviously superior to other two PID controllers. The proposed method has the advantages of less overshoot, shorter regulation time and precise control.

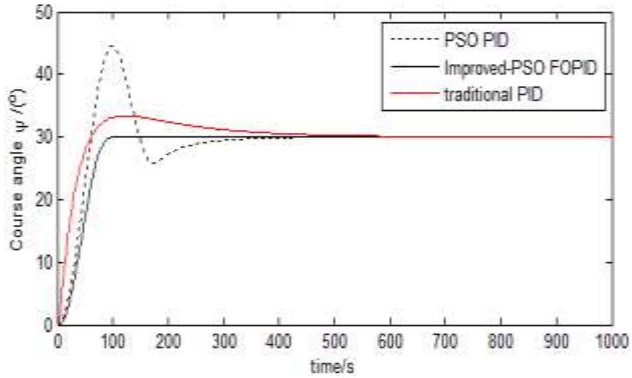

Figure 2. Ship Course Tracking Curve without Disturbance

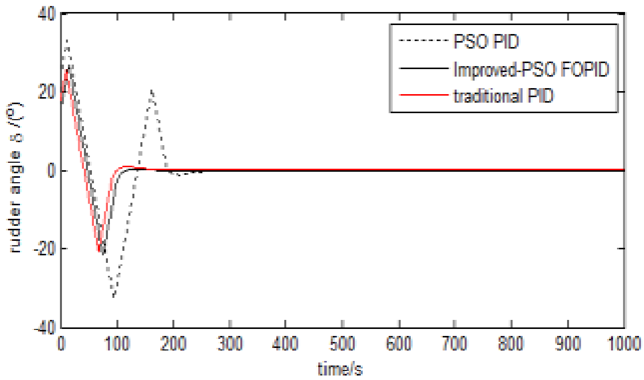

Figure 3. Ship Rudder Angle Output Curve without Disturbance

When the ship is sailing, the disturbance of wind and waves is the main cause of the ship yaw. In order to validate the robustness of fractional-order $PI^{\lambda}D^{\mu}$ control system, the wind and wave disturbance is introduced into this control system. It is used as the system disturbance that is using white noise to drive a typical two-order oscillation system [14]. The transfer function of wave model in six-level winds is

$$h(s) = \frac{0.4198s}{s^2 + 0.3638s + 0.3675} \tag{23}$$

The simulation results are shown in in Figure4, Figure5. Under wind and wave disturbance, the fractional-order $PI^{\lambda}D^{\mu}$ controller based on IPSO algorithm is obviously superior to other two PID controllers. The system can achieve stability quickly and have good control effect. It can be shown that the fractional-order $PI^{\lambda}D^{\mu}$ controller based on IPSO algorithm has stronger robustness and better regulation quality.

Similarly, the simulation experiment uses the data of 5446TEU container ship. From formula (21), we can know that the uncertain parameters K, T, α and β of ship course control model are changed with the ship speed. In 600 seconds, we can set that the ship is sailing at 16.20knots speed firstly, and accelerates to 26knots speed, and then keeps 27knots speed.

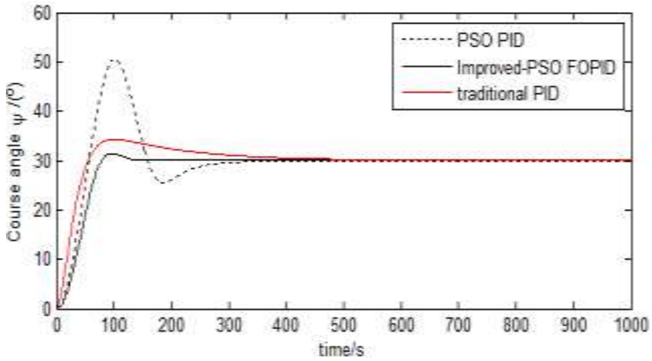

Figure 4. Ship Course Tracking Curve with Wind, Wave Disturbance

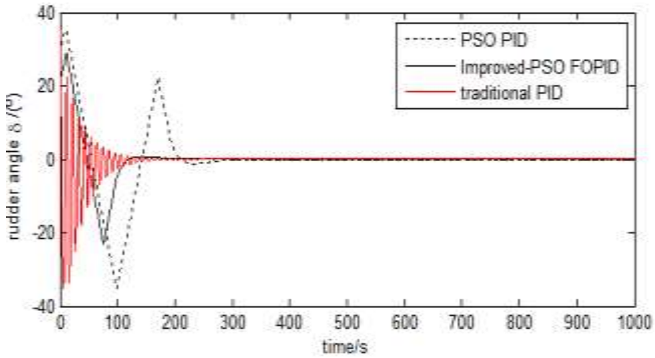

Figure 5. Ship Rudder Angle Output Curve with Wind, Wave Disturbance

Use the fractional-order $PI^{\lambda}D^{\mu}$ controller based on IPSO algorithm to control USV course. Set the change schedule of USV course angle is $\psi_r(t) = 30$ in $0 \le t \le 300$, and $\psi_r(t) = 50$ in $300 \le t \le 600$. The simulation results of the ship model with parameter perturbation are shown in Figure 6 and Figure 7. The ship can track the desired course quickly, and the autopilot responds quickly and the steady error is small.

In the case of uncertain modeling parameters of ship, when the expected course is changed, the ship can achieve the expected course quickly by fast speed adjustment, and eventually maintain the stable tracking effect. From the experimental results, it can be seen that the controller can effectively overcome the impact of the uncertain model parameters on the ship course control, and realize the tracking control of the ship course.

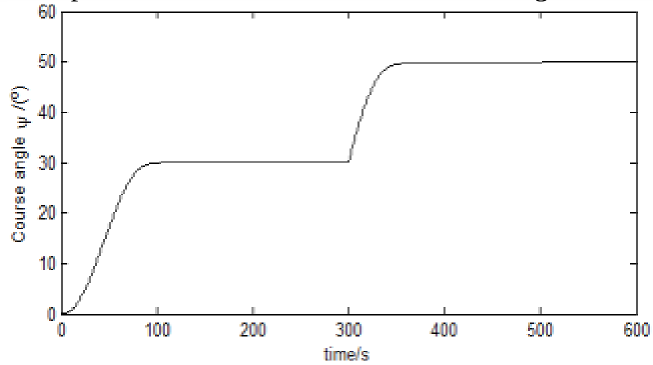

Figure 6. Course Tracking Control Curve with Uncertain Model Parameters

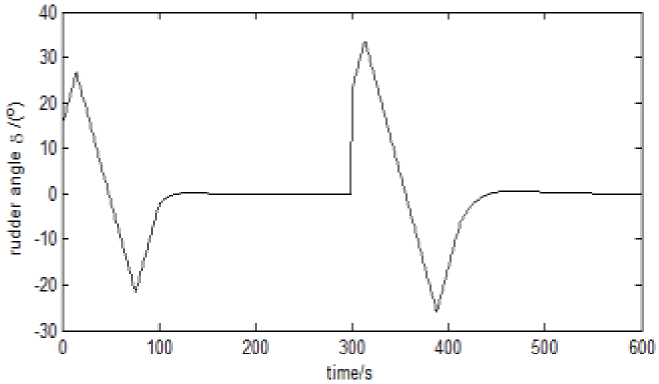

Figure 7. Rudder Angle Output Control Curve with Uncertain Model Parameters

6. Conclusions

This paper deals with the course-keeping problem of large inertia, nonlinear and time-delay ship system with uncertain model parameters. A fractional-order $PI^{\lambda}D^{\mu}$ controller based on IPSO algorithm is proposed for ship's course control with uncertain model parameters. Meanwhile, according to the shortcomings of the PSO, the asynchronous time-varying learning factor and the self-adaptive weight are introduced into the algorithm to improve the performance of the PSO. The simulation results demonstrate the effectiveness of the proposed control method. When the controller output is changed under the wind, wave disturbance or the control object is changed due to some factors, fractional-order $PI^{\lambda}D^{\mu}$ controller based on IPSO algorithm can overcome these effects. This controller has a high robustness, small overshoot and strong immunity.

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