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Enhanced PID Control in Internal Combustion Engines and Ship Motion Control

Jiajun Xu

New York University, New York, 10011, USA

Abstract. Traditional PID control methods have been widely used in various industries due to their simplicity and effectiveness in regulating system outputs. However, challenges arise when dealing with systems characterized by non-linearity, delays, or external disturbances, necessitating the development of advanced PID control strategies. This paper presents two enhanced PID control approaches tailored for specific applications: intelligent PID control for temperature regulation of internal combustion engines and radial basis function (RBF) neural network-based PID control of marine motion control. The operating principles and algorithms of both approaches are detailed, and by comparing the enhanced methods with traditional PID control algorithms, their superior performance in terms of accuracy and adaptability is demonstrated, and conclusions are drawn regarding the effectiveness and suitability of each approach for their respective applications.

Keywords: PID; Internal combustion engines; marine sports.

1. Introduction

The conventional PID (Proportional-Integral-Derivative) control method is extensively utilized across various industrial sectors. It is believed that PID control is employed in more than 90% of control cases [1] and generates ideal outputs when the system parameters are unchangeable. However, in many cases, such as rocket motors, the parameters of the system are changeable due to the application of variable-thrust solid-propellent rocket motors [2]. The current use of traditional PID control may not be an excellent one as constant control parameters cannot satisfy the requirements of variable inputs [3]. To improve accuracy and shorten responding time, an updated PID control that can adjust the parameters with system parameters change should be implemented to overcome the difficulties. Self-adjusting-parameter PID control has been applied in many fields with great performance, such as particle swarm optimizers to improve the particles' position information [4], database-driven PID(DD-PID) control schemes for machines motors [5], and internal combustion engines [6]. Regarding the internal combustion engine, the gas valve is regulated by the furnace temperature, and the temperature control system is non-linear with lag, so the accuracy of the temperature control has a significant impact on the normal function of the internal combustion engines, so it is crucial to discover a more accurate control method. Therefore, the PID control based on self-adjusting parameters is introduced in the paper, which is called intelligent PID control. Its algorithm is derived from traditional PID control but with more regulations for error and deviation. It is applied with the help of a PLC (Programmable Logic Controller) [6].

Besides the application of PID control in internal engines, PID control is also used in ship motion control to guarantee the ship navigates automatically along a predetermined course. Compared to the internal combustion engine, however, ship motion control subjected to external disturbance, such as wind or sea conditions, is more difficult to process [7]. Disturbance may trigger changes in the system's linear conditions or nominal working conditions, making the parameters considered for the controller not optimal [8] to produce satisfactory control performance. Currently, some solutions that can adjust the control parameters in response to changes occurring within the system have been applied in ship steering, such as the use of the Band-band method to improve control speed, fuzzy PID control to bolster robustness, PID control based on BP neural network and PID control based on RBF neural network [7][9]. However, Band-band and fuzzy PID methods cannot solve optimization problems of control parameters [9], while the BP network has a slow training speed [7]. This problem can be solved by RBF-based PID control (Radial Basis Function), which has the best approximation property and fast learning speeds [10], and can improve the system control performance significantly due to its ability to approximate intricate nonlinear mappings from input-output data using a straightforward topological structure [11].

In the paper, the conventional PID control method and RBF neural network algorithm will be first introduced in section 2. The algorithm and application of Intelligent PID control of the internal combustion engine will be demonstrated in section 3, and the algorithm and application of RBD-based PID control for ship steering will be in section 4. Finally, the comparison between the two new control methods will be made in the conclusion part.

2. Background and Preliminaries

2.1 Conventional PID Control Algorithm

To implement the traditional PID algorithm, we need to transfer the continuous time into sampling time to apply the PID algorithm which is based on the discretization method.

$$
\begin{aligned}
& t \approx kT, (k = 0,1,2\cdots) \\
& \int_0^t e(\tau)d\tau \approx \sum_{j=0}^{k} e(jT) = T\sum_{j=0}^{k} e(j) \\
& \frac{de(t)}{dt} \approx \frac{e(kT) - e[(k-1)T]}{T} = e(k) - e(k-1)
\end{aligned} \tag{1}
$$

The original PID controller equation could be changed into this form:

$$
\begin{aligned}
u(k) &= k_p \left\{ e(k) + \frac{T}{T_i}\sum_{j=0}^{k} e(j) + \frac{T}{T_d}[e(k) - e(k-1)] \right\} \\
&= k_p e(k) + k_i \sum_{j=0}^{k} e(j) + k_d [e(k) - e(k-1)] \\
\Delta u(k) &= k_p[e(k) - e(k-1)] + k_i e(k) + k_d[e(k) - 2e(k-1) + e(k-2)]
\end{aligned} \tag{2}
$$

where T represents the sampling time, k denotes the sampling number, and the error signals at time k and k-1 are denoted as e(k) and e(k-1). k_p, k_i and k_d stand for proportional, integral, and differential parameters. The proportional term is used to examine the magnitude of the error, but it cannot eliminate the steady-state error or offset. The integral term will remove offsets and increase the system responding speed at the cost of continued oscillation. The derivative term will reduce the system's oscillation and exert no effect on the offset, but too much of it may cause an overshoot. [12]

Here is the graph showing the traditional PID control.

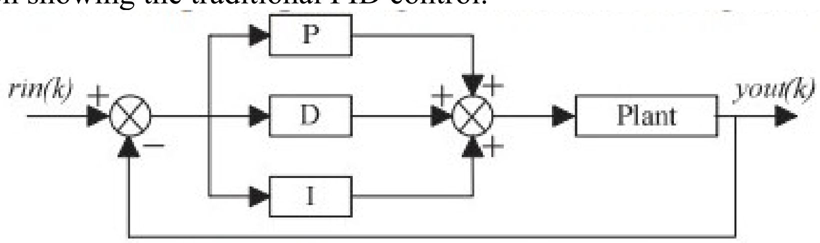

Fig.1 The traditional PID control

2.2 Radial Basis Function (RBF)

Radial Basis function (RBF) is a real-valued function that relies solely on the distance between the input and specific fixed points to determine its values. It is used to approximate the continuous function with arbitrary precision.

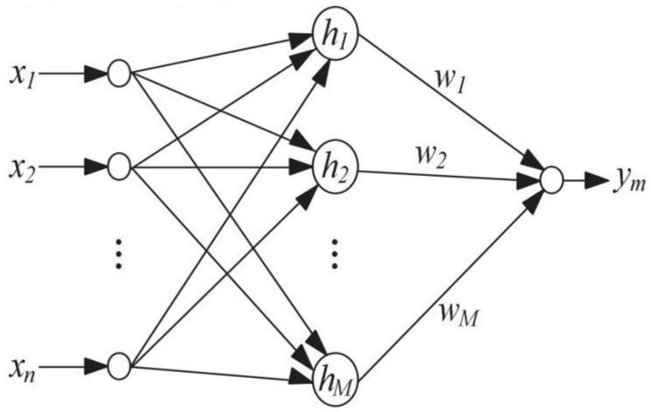

Fig.2 The configuration of the RBF network

Just as Fig.2 shows, the input x_i is put into the system to produce the Gauss basis function h_i. The sum of the product of the Gauss basis function and the weight of the network product will generate the neural network output. Gauss basis function is shown below:

$$h_j = \exp\left(-\frac{\|X - C_J\|^2}{2b_j^2}\right), (j = 1, 2, \cdots, M) \quad (3),$$

where $X = (x_1, x_2 \dots x_n)^T$ is the input vector, and $C_j = (C_{j1}, C_{j2} \dots C_{jn})^T$ is the center vector of the gauss function for the j-th hidden node, b_j is the shape parameter of the gauss function for the j-th hidden node. Then, the neural network output is obtained by the summing $h_i w_i$.

$$y_m = \sum_{j=1}^{M} w_i h_j \quad (4)$$

The output derived from equation (4) will be put into the performance index of the RBF neural network, which is

$$J_I = \frac{1}{2}\left[y(k) - y_m(k)\right]^2 \quad (5)$$

where $y(k)$ represents the output value at time k in the traditional control system, and $y_m(k)$ denotes the neural network output at time k.

Based on the method of gradient descent, the performance index function, along with $y_m(k)$ and $y(k)$, will be used to produce the weights for the output, center of the node, and shape parameter based on nodes at time k by the derivative of Performance index first:

$$\begin{cases} \dfrac{\partial J_I}{\partial w_j} = -\left[y(k) - y_m(k)\right] h_j \\ \dfrac{\partial J_I}{\partial c_{ji}} = -\left[y(k) - y_m(k)\right] w_j h_j \dfrac{x_j - c_{ji}}{b_j^2} \\ \dfrac{\partial J_I}{\partial b_j} = -\left[y(k) - y_m(k)\right] w_j h_j \dfrac{\|x_j - c_{ji}\|^2}{b_j^3} \end{cases} \quad (6)$$

According to the derivative of the performance index concerning weight, center of node, and shape parameters, the values of the three parameters at time k

$$\begin{cases} w_j(k)=w_j(k-1)-\eta\dfrac{\partial J_I}{\partial w_j}+\alpha\left[w_j(k-1)-w_j(k-2)\right] \\ c_{ji}(k)=c_{ji}(k-1)-\eta\dfrac{\partial J_I}{\partial c_{ji}}+\alpha\left[c_{ji}(k-1)-c_{ji}(k-2)\right] \\ b_j(k)=b_j(k-1)-\eta\dfrac{\partial J_I}{\partial b_j}+\alpha\left[b_j(k-1)-b_j(k-2)\right] \end{cases} \tag{7}$$

η denotes the learning rate, while α represents the momentum factor.

3. Intelligent PID Control Method of The Engine

3.1 Algorithm of Intelligent PID control.

The intelligent PID algorithm derives from the traditional one. The intelligent one is realized by several regulations involving some parameters: here are five regulations ：

When the absolute value exceeds the maximum value $|e(t)| > e_{max}$, it indicates the error is too big and the output must be maximum or minimum to cancel the error

$$\begin{aligned} &(1)\, u(t) = u_{\max}(t) \text{ when } e(t) \geq 0; \\ &(2)\, u(t) = u_{\min}(t) \text{ when } e(t) < 0. \end{aligned} \tag{8}$$

1. When the product of change of error and error at that point is non-negative $e(t) \cdot \Delta e(t) \geq 0$, it means the error's absolute value is increasing. To mitigate the error, the parameter k1 is added to the proportional term to reverse the current direction of change of error:

$$\begin{aligned} u(t) = u(t-1) + k_1\{k_p[e(t) - e(t-1)] + k_i e(t) + \\ k_d[e(t) - 2e(t-1) + e(t-2)]\}. \end{aligned} \tag{9}$$

When the absolute value of the error is reduced so that it is smaller than the mid-value, the error is small enough to use the original PID algorithm which can reverse the error in varying directions.

$$\begin{aligned} u(t) = u(t-1) + k_p[e(t) - e(t-1)] + k_i e(t) + \\ k_d[e(t) - 2e(t-1) + e(t-2)]. \end{aligned} \tag{10}$$

2. When $e(t) \cdot \Delta e(t) < 0$ and $e(t) \cdot \Delta e(t-1) > 0$, it signifies the absolute value of error is decreasing or the system is approaching equilibrium. Hence, the output should be unchangeable:

$$u(t) = u(t-1). \tag{11}$$

3. When $e(t) \cdot \Delta e(t) < 0$ and $e(t) \cdot \Delta e(t-1) < 0$ it signifies the error has reached its minimum value. If the absolute value of error is greater than or equal to its mid-value, the error is so big that the following regulator is needed:

$$u(t) = u(t-1) + k_1 k_p e(t) \tag{12}$$

Conversely, if the absolute value of error is smaller than its mid-value, the error is so small that the following regulator is needed:

$$u(t) = u(t-1) + k_2 k_p e(t). \tag{13}$$

4. When the absolute value is smaller than the minimum value $|e(t)| < e_{min}$, it means the error is so small that the algorithm needs to add integral to decrease the error.

$$u(t) = k_3 e(t) + k_d e(t-1). \tag{14}$$

Regulators 1, 3, and 5 can assure the stability and speed of the system; Regulators 2 and 4 make the system adaptable to multiple parameters.

3.2 Application to the internal combustion engine.

The configuration of the intelligent PID design for the combustion engine comprises components such as a temperature sensor (T.Sensor), flame Sensor(F.Sensor), human machines interface (HMI), programmable logic controller (PLC), electrical-gas valve(E.Value), A/D and D/A conversion modules:

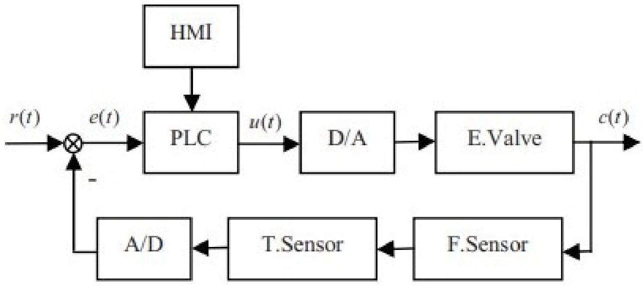

Fig.3 Structure of the control system

When the system starts operation, F.Sensor detects the presence of a flame within 10 seconds. Once detected, the flames temperature, ascertainable by the T.Sensor, is registered. Subsequently, the temperature data is converted into digital signals by an A/D conversion process. These digital signals are then fed into a programmable logic controller (PLC), where the PID process is executed. The resulting outcomes are converted back into analog data, which governs the opening degree of the engines electric gas valve. However, if no flame is detected within the initial 10-second window, an alarm is triggered, and all outputs are deactivated.

3.3 Experimental result for internal combustion engine

The Transfer function which shows how the signals in the input are transferred to output is demonstrated here:

$$G(s)=\frac{523500}{s^3+87.35s^2+10470s} \tag{15}$$

The PID control performance is shown in the table

Parameters	Intelligent PID	Traditional PID
k_p	0.60	0.60
k_i	0.03	0.03
k_d	0.01	0.01

From the table, the parameters k_p, k_i, k_d are the same for both traditional and intelligent PID control. For the intelligent one, however, has additional initial parameters $e_{max} = 0.2$, $e_{mid} = 0.05$, $e_{min} = 0.001$, $k_1 = 2$, $k_2 = 0.05$, $k_3 = 0.01$, so the intelligent PID control generates different tracking trajectories and error paths of the PID outcomes, which are shown below (The dotted lines reflect traditional PID control; the solid lines reflect the intelligent PID control)

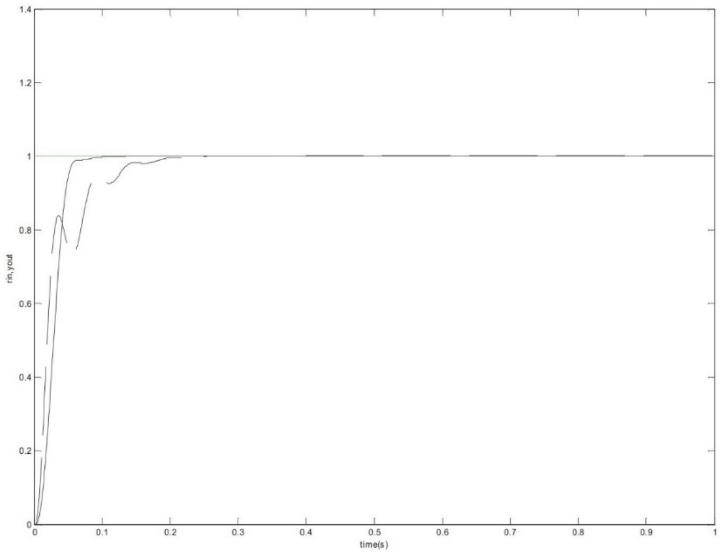

Fig.4 The tracking curves of both PID control results(dotted line: conventional PID; solid line: Intelligent PID)

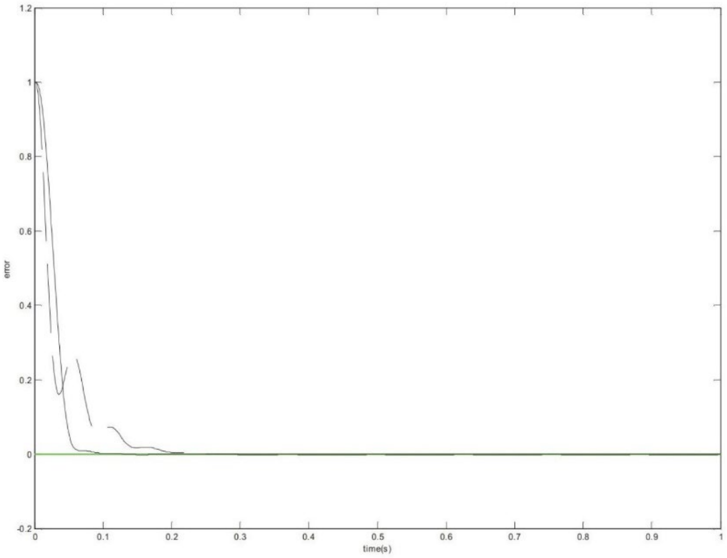

Fig.5 the error paths of both PID control results (dotted line: conventional PID; solid line: Intelligent PID)

From the graph, the benefits of intelligent PID control over traditional PID control are demonstrated. The overshooting time for intelligent PID is about 0.05s and for the traditional one is over 0.2s, so the overshooting time is reduced a lot. The number of oscillations also decreases so that the stability of the system is assured. In contrast to traditional PID control, therefore, the intelligent PID control offers increased stability and reduced responsive time.

4. RBF Neural Network PID Control For The Ship Steering

Compared to the internal combustion engine, ship motion control is more difficult to realize because it is affected by external factors, including wind, turbulence sea conditions, and so on. The intelligent method applied in the internal combustion engine can improve the accuracy and reduce reaction time, but no study shows that it can avoid the effect of disturbance. Therefore, it is necessary to use the RBF-based PID to efface the influence of disturbance.

4.1 Algorithm of RBF-based PID

Different from the traditional PID control system, the system contains an additional part, which is the RBF identifier. The RBF identifier is used to identify the approximation model of the system by processing the input and output data and producing a neural network that approximates the output of the controller, which adaptively adjusts using the RBF neural network identifier. Here is the graph showing the process:

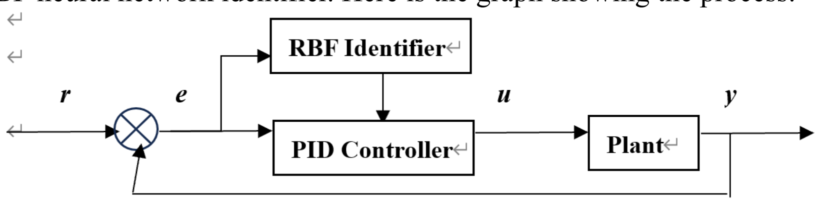

Fig. 6 The configuration of RBF-based PID

With the RBF neural network adjusting the PID control parameters, the RBF-based PID control algorithm could be implemented. From equation (2), the original PID controller equation could be changed into this form:

$$u(k)=k_p\left\{e(k)+\frac{T}{T_i}\sum_{j=0}^{k}e(j)+\frac{T}{T_d}[e(k)-e(k-1)]\right\}$$

$$=k_pe(k)+k_i\sum_{j=0}^{k}e(j)+k_d[e(k)-e(k-1)]$$

$$\Delta u(k)=k_p[e(k)-e(k-1)]+k_ie(k)+k_d[e(k)-2e(k-1)+e(k-2)] \tag{16}$$

Set the PID parameter tuning indicator as

$$J_C = \frac{1}{2}e(k)^2 \tag{17}$$

From the equation (7) RBF neural network algorithm above, c_{ji}, b_j, and w_i have been known. Plug the three values into the equation:

$$\frac{\partial y}{\partial \Delta u} \approx \frac{\partial y_m}{\partial \Delta u} = \frac{\partial y_m}{\partial x_1} = \sum_{j=1}^{M} w_i h_i \frac{c_{ji} - x_1}{b_j^2} \tag{18}$$

Knowing the $\delta y/(\delta \Delta u)$, the derivatives of PID parameter tuning indicator J concerning the adjusted k_p, k_i, k_d are obtained

$$\begin{cases} \dfrac{\partial J_C}{\partial K_p} = \dfrac{\partial J_C}{\partial y}\dfrac{\partial y}{\partial \Delta u}\dfrac{\partial \Delta u}{\partial K_p} = -e(k)\dfrac{\partial y}{\partial \Delta u}xc(1) \\ \dfrac{\partial J_C}{\partial K_i} = \dfrac{\partial J_C}{\partial y}\dfrac{\partial y}{\partial \Delta u}\dfrac{\partial \Delta u}{\partial K_i} = -e(k)\dfrac{\partial y}{\partial \Delta u}xc(2) \\ \dfrac{\partial J_C}{\partial K_d} = \dfrac{\partial J_C}{\partial y}\dfrac{\partial y}{\partial \Delta u}\dfrac{\partial \Delta u}{\partial K_d} = -e(k)\dfrac{\partial y}{\partial \Delta u}xc(3) \end{cases} \tag{19}$$

Then, the adjusted value of k_p, k_i, k_d can be obtained using the gradient descent method:

$$\begin{cases} K_p(k) = K_p(k-1) - \eta_2 \dfrac{\partial J_C}{\partial K_p} \\ K_i(k) = K_i(k-1) - \eta_2 \dfrac{\partial J_C}{\partial K_i} \\ K_d(k) = K_d(k-1) - \eta_2 \dfrac{\partial J_C}{\partial K_d} \end{cases} \tag{20}$$

where η_2 is the learning rate.

4.2 Application of RBF-based PID to the ship steering

The GPS device in the 'Course Measurement' part is used to track the ship's trajectory and location and compare the tracked data with the data of the ideal trajectory to obtain the degree of deviation of the real track from the ideal one. Then, the "Course Controller' will process the information based on some algorithms and produce the new adjusting angles, which can guide the ship in the right course with the help of the ship model. The fundamental configuration of the automated steering system is depicted in Fig.7

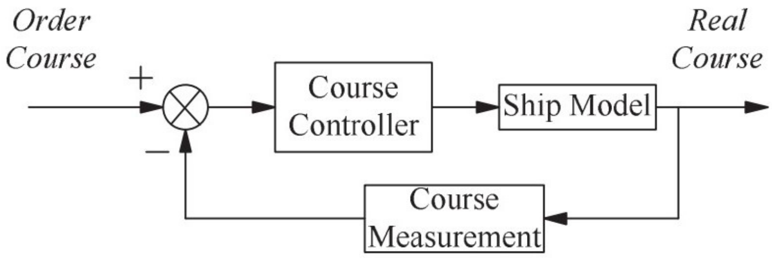

Fig.7 The basic structure of the automatic steering system

The ship motion equation is the third-order K-T equation.

$$\begin{cases} T_1 T_2 \dddot{\psi} + (T_1 + T_2)\ddot{\psi} + \dot{\psi} + \psi^3 = K\left(T_3\dot{\delta} + \delta\right) + w \\ K = \dfrac{K_0 V}{L} \\ T_i = \dfrac{T_{0i} L}{V}, (i = 1, 2, 3) \end{cases} \tag{21}$$

where V_0 represents the speed, L stands for the length, and w denotes the external disturbance

4.3 Experimental result for Ship Steering

The table shows the data on the ships motion

Length	Rudder limit	K_0	T_{10}	T_{20}	T_{30}
161	$\pm 35^{\circ}$	3.86	5.66	0.38	0.89

The table demonstrates the initial values of the three parameters

Parameters	*Initial value*
k_p	*10*
k_i	*0.02*
k_d	*200*

RBF neural network takes three inputs: *u(k-2), y(k), y(k-1)*. The adjusting curves of PID parameters without disturbance are given below: the first one is k_p, *the* second one is k_i, and the third one is k_d

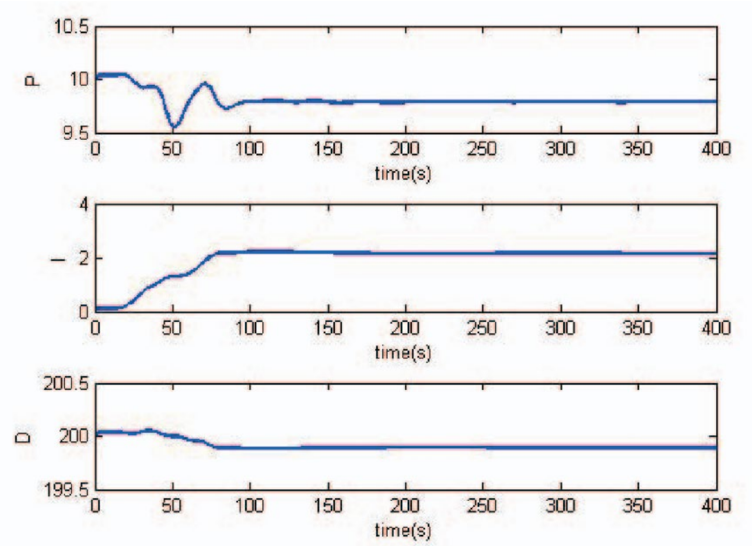

Fig.8 PID parameter adjusting curve without disturbance

Here is the graph showing the PID parameter adjusting curve in the presence of disturbance.

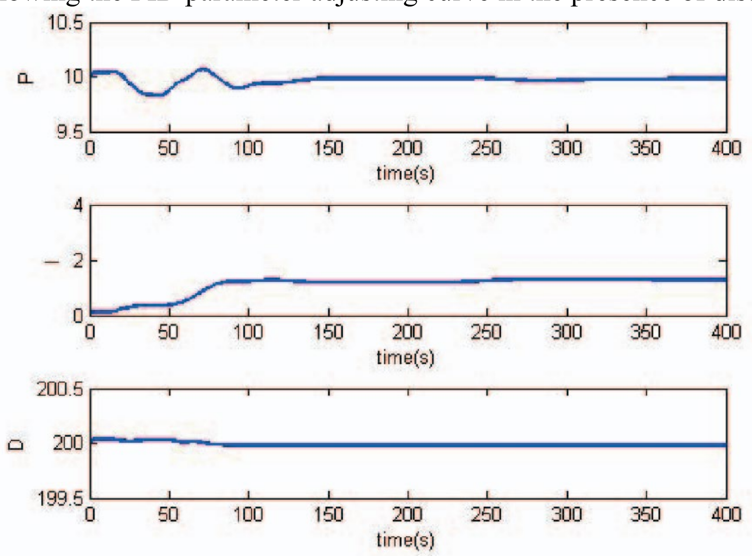

Fig.9 PID parameter adjusting curve in the presence of disturbance

All three values start from their initial values, experience some changes, and become stabilized at a certain value. RBF neural network adjusts the parameters until it finds the most suitable PID parameters so that high accuracy is achieved. The PID parameter adjusting curves with disturbance are smoother than those without disturbance, meaning the RBF network has higher adaptability for the ship steering with disturbance.

The tracking trajectories and the error paths without disturbance are demonstrated below:

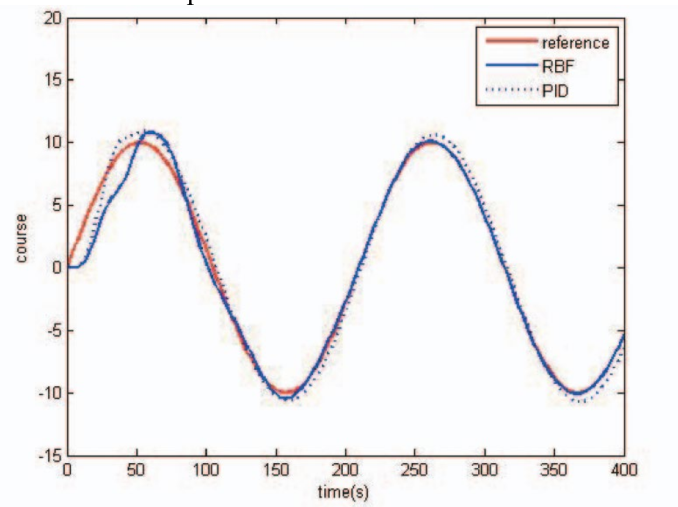

Fig.10 The tracking trajectories of PID control vs real track vs RBF-based PID control without disturbance

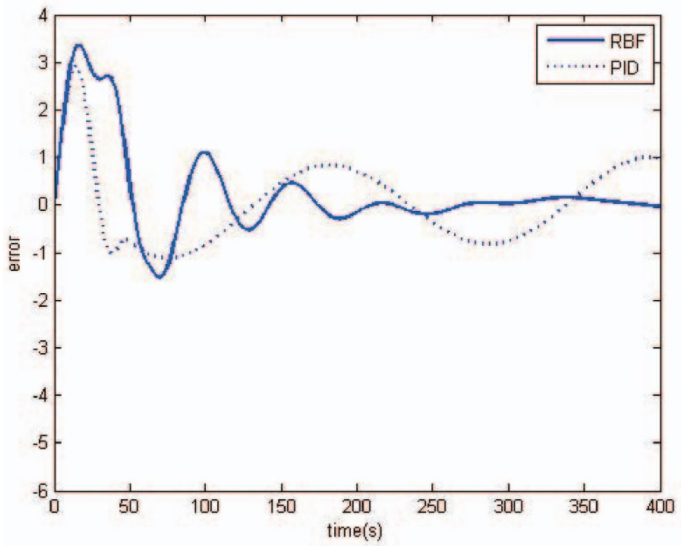

Fig.11 The error paths of PID control vs RBF-based PID control **without** disturbance

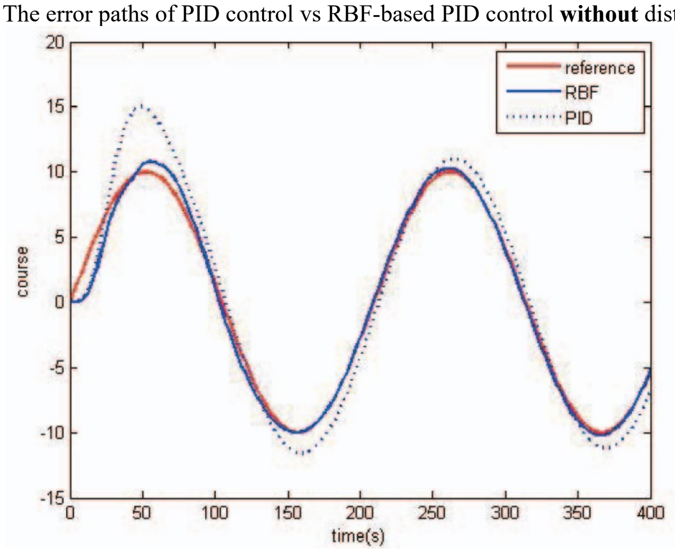

Fig.12 The tracking trajectories of PID control vs real track vs RBF-based PID control with

disturbance

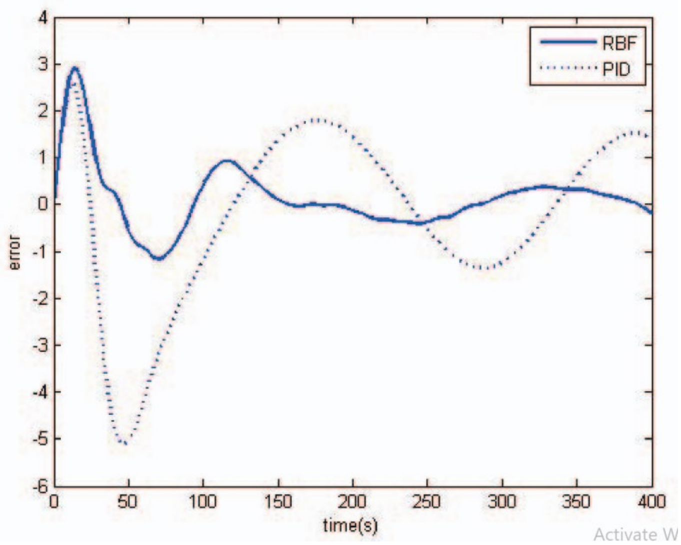

Fig.13 The error paths of PID control vs RBF-based PID control with disturbance

From Fig10, there is no significant difference between the tracking curves of the conventional PID control method and those of the RBF-based PID method. Both of the two methods can reflect the real course of the ship when there is no disturbance. However, in Fig 12, the tracking curves of the conventional PID method are more deviated from the real course than those of the RBF-based PID method, which means when the disturbance takes place, the conventional PID method is less effective and RBF-based PID method still maintains its high accuracy and stability. Also, the PID control based on RMF takes less time than the traditional PID control to minimize the error to 0 regardless of whether the disturbance occurs, whereas the conventional PID method oscillates the error profile more in perturbations, which means that the traditional PID method is less effective in disturbances.

In all, the advantages of the RBF-based PID method are more prominent, especially in disturbance, which can maintain the right track for a ship regardless of whether disturbance occurs.

5. Conclusion

In this paper, a comparison between the conventional PID control and the intelligent PID control for internal combustion engines has been made. The Intelligent one which adjusts the PID parameters with the help of PLC has less overshoot time and higher accuracy and stability.

Then, the comparison between the conventional PID control and RBF-based PID control and based on the RBF neural network for ship steering is also being made. The RBF-based PID control can change PID parameters adaptively until it generates an optimum course. The RBF PID method has less time to minimize the error than the traditional one in both disturbance and non-disturbance cases and has higher accuracy and stability than the traditional PID method within disturbance. Thus, the RBF-based PID is more suitable to be applied in disturbance.

As for internal combustion engines, intelligent PID control (Regulation control) needs self-regulation of PID parameters to correspond to the changes in engine system parameters but does not have to consider external disturbance. The RBF-based PID method (tacking control) not only can adjust the PID parameters continuously to follow the right track but also still maintain good performance within the disturbance, so the RBF-based PID method is more advantageous than the Intelligent PID control.

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