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Procedia Computer Science 111 (2017) 361–366

Procedia Computer Science

www.elsevier.com/locate/procedia

8th International Conference on Advances in Information Technology, IAIT2016, 19-22 December 2016, Macau, China

A course control system of unmanned surface vehicle (USV) using back-propagation neural network (BPNN) and artificial bee colony (ABC) algorithm

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Abstract

Course control is the basis of Unmanned Surface Vehicle (USV) control system, largely determines the performance of USV. Because of some uncontrollable factors such as wind, wave and other random disturbances, the course control of an Unmanned Surface Vehicle (USV) is always difficult. In recent years, there have been some studies of adaptive course control system for USV, but they are not precise enough for engineering practice. In this paper, we propose a novel adaptive course control method based on Back-propagation Neural Network (BPNN) and Artificial Bee Colony (ABC) algorithm. We use classic PID algorithm as the main course control algorithm, and back-propagation neural network (BPNN) is also utilized to achieve more effective self-adaptive PID control. At the same time, in order to improve the convergence speed and precision of BPNN, we bring in Artificial Bee Colony (ABC) algorithm to minimize the error of system and adjust the weight of BPNN. The system has been proven in simulation that it can accurately output the rudder angle according to the input course angle and can perform better than that without ABC algorithm optimization. The error of parameters obtained by this method is within the acceptable range, which can provide reference for engineering practice.

Peer-review under responsibility of the organizing committee of the 8th International Conference on Advances in Information Technology

Keywords: Course control system; Back-propagation Neural Network; Artificial Bee Colony algorithm; PID algorithm.

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Peer-review under responsibility of the organizing committee of the 8th International Conference on Advances in Information Technology
10.1016/j.procs.2017.06.035

1. Introduction

Because of some uncontrollable factors such as wind, wave and other random disturbances, the course control of an Unmanned Surface Vehicle (USV) is always difficult. In recent years, there have been some studies of adaptive course control system for USV, for example, literature[1, 2] adopt fuzzy adaptive control to the course system, but they are not precise enough for engineering practice.

BPNN has been playing a vital role in control optimization algorithm, it can realize the adaptive control of any nonlinear uncertain system by continuous learning, and the structure is simple. For example, Literature[3] designs an observer-based adaptive controller using BPNN. In order to achieve the precise control of the system, we need to set the appropriate weights for the transfer function of each neuron. Literature[4] uses Genetic Algorithms to adjust the weight of BPNN in the prediction of Postgraduate Entrance Examination, but using genetic algorithm to correct the weight is easy to fall into local minimum value. So we use the artificial bee colony (ABC) here, which is an optimization algorithm based on the intelligent behavior of honey bee swarm and used for optimizing numerical test functions. Literature[5, 6] shows ABC is better than or similar to those population-based algorithms including Genetic Algorithm (GA), Particle Swarm Algorithm (PSO) and Particle Swarm Inspired Evolutionary Algorithm (PS-EA), etc. Using ABC can make BPNN jump out of the local minimum, and find the global optimum, and this hybrid neural network can improve the search speed and accuracy of the network.

In order to precisely output the rudder angle according to the input course angle, in this paper, we mainly use the back-propagation neural network (BPNN) and the artificial bee colony (ABC) algorithm to eliminate the system error in the adaptive course control system. And it has been proved in simulation that the performance of the USV can be better in adaptive course control.

2. PID Self-adaptive Control Based on BPNN

PID control effect is good or bad, largely depends on whether the proportional, integral / differential control can coordinate and adjust with each other perfectly[7]. Since BPNN has the ability to approximate any nonlinear function, and the structure and learning algorithm is relatively simple, we can use it to achieve the self-adaptive PID parameters.

In this paper, a BPNN is utilized for online training, using three layers: an input layer, a hidden layer, an output layer, where j represents the input layer nodes, i represents the hidden layer nodes, l represents the output layer node. In this network, the input layer has three neurons, the hidden layer has 5 neurons and the output layer has three neurons (k_p, k_i, k_d). Figure.1 is the structure of the proposed BPNN.

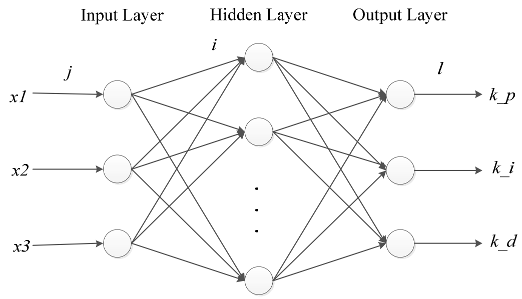

Fig. 1. The structure of the proposed BPNN

The controller algorithm is as follows:

Step 1: Determine the structure of BPNN. The number of input nodes M and the number of hidden nodes Q are determined, and the learning rate η and inertia coefficient α are given for the initial value $\omega_{ij}(0)$ and $\omega_{il}(0)$ of each layer, in this case, $k=1$.

Step 2: $y^*(k)$ and $y'(k)$ is gotten from the sampling, and then we can calculate the time error $error(k) = y^*(k) - y'(k)$.

Step 3: Calculate the inputs and outputs of each layer, and the outputs of the output layer are the three adjustable parameters k_p, k_i, k_d of PID controller.

Step 4: Calculate the output $u(k)$ of PID controller according to the classical incremental digital PID algorithm, which is $u(k)=u(k-1)+k_p\left(error(k)-error(k-1)+k_i error(k)+k_d\left(error(k)-2error(k-1)\right)+error(k-2)\right)$.

Step 5: Carry out neural network learning. Online adjust the weight coefficients $\omega_{ij}^{1}(0)$ and $\omega_{ij}^{2}(0)$ to achieve adaptive PID parameter adjustment.

Step 6: Set $k=k+1$, return to (1).

3. Adjusting the Weight of BPNN by ABC Algorithm

In practice, the standard BPNN is generally based on Gradient Descent Method to update the weights, but there are some shortcomings, such as the convergence rate is slow, easy to fall into the local minimum and so on[8-10]. In this paper, the ABC algorithm is applied to the weight adjustment of BPNN to improve the convergence speed and precision of BPNN. The specific process is as follows:

Step 1: BPNN initialization: the weights $\omega_{ij}(0)$ and $\omega_{il}(0)$ are regarded as the optimization targets of the artificial bee colony (ABC) algorithm.

Step 2: ABC algorithm initialization: Set the number of food sources N, the maximum number of iterations *maxcycle*, the maximum number of detention *limit* and so on.

Step 3: Do hired bees, following bees and detective bees operations to find the best food source.

a. Hired bees search for new food sources according to Equation (1),

$$X_{ij}^{new}=X_{ij}+rand(0,1)\times\left(X_{ij}-X_{neighbour,j}\right) \tag{1}$$

Among them, $neighbour\in\{1,2,\cdots,N\}$ and $neighbour\neq i, \mathrm{j}\in\{1,2,\cdots,m\}$ are all selected randomly. And if X_{ij}^{new} is out of the range of parameter space, deal with it as the following Equation (2) and transfer it into a boundary value.

$$X_{ij}^{new}=\begin{cases}X_{ij}^{\min}, X_{ij}^{new}<X_{ij}^{\min}\\ X_{ij}^{\max}, X_{ij}^{new}>X_{ij}^{\max}\end{cases} \tag{2}$$

b. Calculate the probability of selection p_i corresponding to the solution X_i as Equation (3)

$$p_i=\frac{fit_i}{\sum_{j=1}^{m} fit_j} \tag{3}$$

Among them, fit_i represents the fitness value ("Profitability") corresponding to the solution X_i, we can see from Equation (3) that, this allows a higher profitable solution to be more likely to be selected.

c. Following bees select the food source according to the probability proportional to the fitness value, and then choose to generate new solutions in accordance with Equation (2) , followed by calculating the fitness value of the new solution and updating the food source like step *b*.

d. If the maximum number of times a stranded continuous solution X_i reached the before maximum number of dwellings *limit*, then the food source needs to be given up. At this time, the detective bees will appear and randomly generate a new food source to replace the given-up food source.

e. Record all current optimal food sources (global optimal solution), that is, the fitness value of the solution is the highest, and determine whether the maximum cycle number *maxcycle* and the specified precision are reached. Otherwise, return step *a* to continue.

Step 4: Return the best food source to the BP neural network.

4. Design of the Adaptive Course Control System of USV

In this paper, an adaptive course control system is presented below. Adaptive control theory and Artificial Bee Colony algorithm are used together to minimize the error of system and BPNN. Among them, ABC algorithm also takes the role of weight adjustment of BPNN.

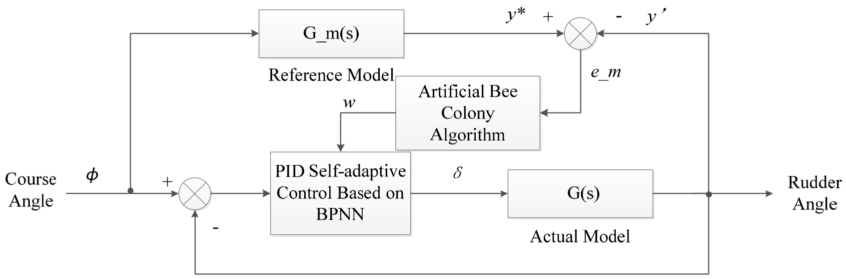

Fig. 2. Diagram of the Adaptive Course Control System of USV

Specifically, first, a course angle is given to the system, then it will be substituted into reference model and BP neural network for comparison, thus the course error is drawn. Afterwards, it will be sent to ABC algorithm for the adjustment of the net weight of BPNN. Then optimized angles are reached actual model to transfer into rudder angles, at the same time, after continuous optimization, this course will compare constantly with the reference model as a feedback, so a closed loop control system is established. This is prepared for correction of ABC algorithm. In this way, we can get rudder angle precisely and can achieve efficient and accurate adaptive course control of USV.

The error equation is given below:

$$error = \frac{1}{2} e_m^2 \tag{4}$$

where $e_m = y^* - y'$.

5. Results and Discussion

We select the reference model taken from reference[11] as:

$$G_{ref}(\mathrm{s}) = \frac{0.01}{s + 0.01} \tag{5}$$

And the actual model taken from reference[11] as:

$$G(\mathrm{s}) = \frac{1}{s(38\mathrm{s}+1)} \tag{6}$$

The number of BPNN's layers / neurons and the colony size of the ABC algorithm can directly affect the performance of the system PID control. If the number of BPNN layers and the number of neurons are too small or the colony size of the ABC algorithm is too small, then the PID parameters will not be fully trained, then the weight optimization of BPNN will not be in place; on the contrary, the computation will increase a lot, which will make the convergence speed slow, thus leading to poor system performance.

The neural network in this paper has an input layer, a hidden layer and an output layer, where the input layer has three neurons, the hidden layer has 5 neurons and the output layer has three neurons (k_p, k_i, k_d).And the total number of initial bees is 50, including 25 collecting bees.

The weights $\omega_{ij}(0)$ and $\omega_{il}(0)$ of BPNN before and after optimization of ABC algorithm are given below:
The matrix of $\omega_{ij}(0)$ from input layer to hidden layer before ABC algorithm optimization is

$$\begin{bmatrix} -0.0729 & 0.4554 & 0.2242 & 0.0809 & 0.0403 \\ -0.2921 & -0.4604 & -0.0306 & -0.3499 & 0.4913 \\ 0.4332 & 0.4716 & -0.1391 & 0.1442 & -0.4321 \end{bmatrix}^T$$

After the optimization of ABC algorithm, it turns to

$$\begin{bmatrix} -0.3424 & 0.4706 & 0.4572 & 0.0146 & 0.3003 \\ -0.4025 & -0.2215 & 0.0469 & 0.4575 & 0.4649 \\ 0.3147 & 0.4058 & -0.3730 & 0.4134 & -0.1324 \end{bmatrix}^T$$

The matrix of $\omega_{il}(0)$ from hidden layer to output layer before ABC algorithm optimization is

$$\begin{bmatrix} -0.3246 & -0.2723 & -0.3947 & 0.3055 & -0.2809 \\ 0.2673 & 0.4195 & -0.2318 & -0.3957 & 0.4227 \\ 0.4971 & 0.1420 & 0.2638 & -0.0302 & -0.1797 \end{bmatrix}$$

After ABC algorithm optimization, it turns to

$$\begin{bmatrix} 0.1557 & 0.4340 & 0.2431 & -0.3288 & -0.2231 \\ -0.4643 & 0.1787 & 0.1078 & 0.2060 & -0.4538 \\ 0.3491 & 0.2577 & 0.1555 & -0.4682 & -0.4029 \end{bmatrix}$$

And the waveform of the input course angle and the output rudder angle is given below:

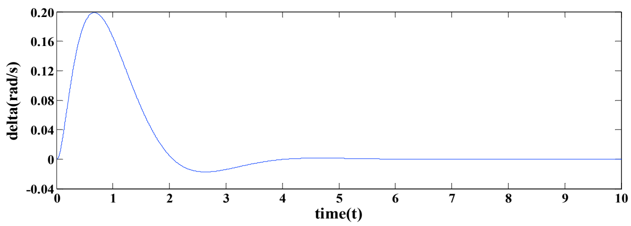

Fig. 3. Waveform of the input course angle

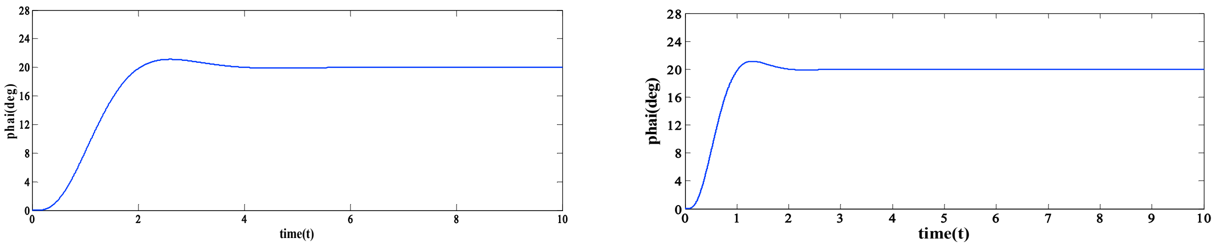

Fig. 4. Waveform of the Output Rudder Angle (left one) Before ABC algorithm optimization; (right one) After ABC algorithm optimization

It can be seen from the figure that the PID Course Control System based on BPNN can track the actual motion of the USV better, and after optimizing the BPNN weights by ABC algorithm, the performance of the USV can be better in adaptive course control. After simulation, the system regulation time is reduced by 38% when the BPNN weights are optimized by ABC algorithm. This result proves the algorithm proposed in this paper has high effectiveness and feasibility in optimizing the weight of BPNN by using bee colony algorithm for adaptive course control.

6. Summary

In summary, in this paper, we mainly use the back-propagation neural network (BPNN) and Artificial Bee Colony (ABC) algorithm to eliminate the system error in the adaptive course control system of USV. Since BPNN has the ability to approximate any nonlinear function, and the structure and learning algorithm is relatively simple, we use it to achieve more effective self-adaptive PID control. At the same time, adaptive control theory and Artificial Bee Colony algorithm are used together to minimize the error of system and BPNN. Among them, ABC algorithm also takes the role of weight adjustment of BPNN. Tus it is not easy to fall into the local minimum, and can improve the convergence speed and precision of BPNN.

And it has been proven in simulation that the system can precisely output the rudder angle according to the input course angle and can perform better than that without ABC algorithm optimization in adaptive course control of USV. The error of parameters obtained by this method is within the acceptable range, which can provide reference for engineering practice.

Acknowledgements

The authors wish to thank the National Natural Science Foundation of China (61603284) and Undergraduate Program of Independent Innovation Research Fund of Wuhan University of Technology (166811003) for supporting this research.

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