IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received December 9, 2018, accepted December 30, 2018, date of publication January 7, 2019, date of current version January 29, 2019.

Digital Object Identifier 10.1109/ACCESS.2019.2891106

Heading Control of Unmanned Marine Vehicles Based on an Improved Robust Adaptive Fuzzy Neural Network Control Algorithm

ZAOPENG DONG[1,2,3], TAO BAO[1,2], MAO ZHENG[4], XIN YANG[1,2], LIFEI SONG[1,2], AND YUNSHENG MAO[1,2]

[1]Key Laboratory of High Performance Ship Technology, Wuhan University of Technology, Ministry of Education, Wuhan 430070, China
[2]School of Transportation, Wuhan University of Technology, Wuhan 430070, China
[3]Science and Technology on Underwater Vehicle Laboratory, Harbin Engineering University, Harbin 150001, China
[4]National Engineering Research Center for Water Transport Safety, Wuhan University of Technology, Wuhan 430070, China

Corresponding author: Mao Zheng (zhmao2018@126.com)

This work was supported in part by the National Natural Science Foundation of China under Grant 51709214, Grant 51779052, Grant 51809203, and Grant 51879210, in part by the China Postdoctoral Science Foundation under Grant 2018M642941, in part by the Stable Supporting Fund of Science and Technology on Underwater Vehicle Laboratory under Grant SXJQR2018WDKT001, in part by the Open Fund of Key Laboratory of High Performance Ship Technology, Wuhan University of Technology, Ministry of Education, under Grant gxnc18041404, and in part by the Fundamental Research Funds for the Central Universities under Grant 2017IVA006 and Grant 2018IVB069.

ABSTRACT A robust adaptive fuzzy neural network control (RAFNNC) algorithm is proposed based on a generalized dynamic fuzzy neural network (GDFNN), proportion–integral–differential (PID), and improved bacterial foraging optimization (BFO) algorithm, for heading the control of the unmanned marine vehicle (UMV) in the presence of a complex environment disturbance. First, the inverse dynamic model of the motion control of UMV is established based on the GDFNN for the uncertain disturbance caused by the complex environment disturbance. Then, the adaptive rate of the fuzzy neural network is designed based on the error between the real UMV heading angle and designed reference heading angle, so as to further adjust the weight parameter of the GDFNN, and then, the output control value of the neural network is obtained. In order to further reduce the computation amount and computation time of the RAFNNC, the parameters of the PID control algorithm were optimized in advance by using the improved BFO algorithm. The fractal dimension step size and the intelligent probe operation are integrated into the BFO algorithm, in order to optimize the operation time and accuracy of the algorithm. Stability of the designed RAFNNC algorithm for the heading control of the UMV in the presence of complex marine environment disturbance is proved by the Lyapunov stability theory, and the effectiveness and accuracy of the control algorithm proposed are verified by semi-physical simulation experiment carried out in our laboratory.

INDEX TERMS Unmanned marine vehicle (UMV), heading control, robust adaptive fuzzy neural network control (RAFNNC), generalized dynamic fuzzy neural network (GDFNN), bacterial foraging optimization (BFO).

I. INTRODUCTION

Unmanned marine vehicle (UMV), usually used as a generic term to describe unmanned/autonomous underwater vehicles (UUV/AUV) and unmanned/ uninhabited surface vessels (USV), can be used to perform a multitude of different tasks, such as mineral resources sampling, offshore oil and gas operations, ocean engineering maintenance, and military reconnaissance, it is attracting more and more interesting form the scientific, commercial, and naval sectors [1]–[3]. In the community of UMV automation, heading control or course keeping plays a significant role in the entire control system, and is directly related to the operation, economy, safety and effectiveness of the UMV's control system [4]–[6]. In addition, heading control is the basic of path following control in real as the long path is often divide into several short straight paths, and the UMV heading control problem has been attracting much attention from various researchers [7]–[9]. Complex environmental disturbances, such as wind, wave and ocean current disturbance, are the most important and common disturbances when an UMV is working in the sea. Precise motion control of the UMV cannot ignore the influence of environment disturbances [10]–[12].

Proportion integral derivative (PID) algorithm and various improved PID algorithm are the most applied algorithms in UMV heading control, at present, many researchers have done relevant research and obtained rich research results [13]–[23]. Many improved algorithms, such as Kalman filter [13], H-infinity control [14], self adaptive fuzzy control [15], [16], backstepping control [17], constrained self-tuning control [18], expert control and S surface control [19], adaptive control and hybrid control [20]–[23] are integrated into PID algorithm to improve the reliability, stability and accuracy of the heading control system and the whole UMV control system. A numerical method for minimum time heading control of an fixed speed UMV is proposed by Rhoads *et al.* [24], while a Sugeno fuzzy inference system and Kalman filter are integrated into the heading control system by Toe *et al.* [25], and a self-tuning fuzzy control algorithm is proposed by Fang *et al.* [26]. Artificial neural network control [27], [28], sliding mode control [29], dynamic surface control [30], global finite time control [31], backstepping control [32]–[34], visual feedback control [35], network based hybrid control [36], sliding mode observer based control [37], linear feedback control [38], artificial fish swarm algorithm [39], are all designed by researchers for the UMV's heading control system.

By analyzing the existing research results described above, we can found that the traditional PID, due to its good robustness, fast convergence, simple application and other characteristics, it is widely used in UMV control system, especially in the field of UMV's heading control, and a lot of theoretical and experimental research show its stability and reliability. However, due to its fixe control parameters and poor adaptability to different environment disturbance, many researchers try to improve and optimize it in order to improve its adaptability. Many improved algorithms, such as self-adaptive fuzzy control, constrained self-tuning control, expert control et al are proposed. However, the various nonlinear methods described above, such as sliding mode, backstepping method; its control performance depends on the parameters of the UMV model to some extent, but these model parameters are difficult to obtain and have certain errors.

Motivated by the above considerations and analysis, a robust adaptive fuzzy neural network controller is proposed in this paper, based on generalized dynamic fuzzy neural network, proportion integral differential and improved bacterial foraging optimization algorithm, for heading control of the UMV in the presence of complex environment disturbance. Compared with the existing research results on heading controllers designed for UMVs, the main contributions of this paper are as follows: (i) a novel robust adaptive fuzzy neural network controller is firstly proposed in this paper for heading control of the UMV. (ii) an inverse dynamic model of the motion control of UMV is established based on the generalized dynamic fuzzy neural network for the uncertain disturbance caused by the complex environment disturbance. (iii) an improved bacterial foraging optimization algorithm is firstly designed in this paper to optimize the parameters of PID control algorithm, and then to further reduce the computation amount and computation time of the robust adaptive fuzzy neural network controller. (iv) fractal dimension step size and intelligent probe operation are integrated into the bacterial foraging optimization algorithm, in order to optimize the operation time and accuracy of the algorithm. (v) stability of the designed robust adaptive fuzzy neural network controller algorithm for the heading control of the UMV in the presence of complex marine environment disturbance is proved by Lyapunov stability theory.

The remainder of the paper is organized as follows. Nonlinear maneuvering model of UMV and the complex environment disturbance are modeled in Problem Formulation, and a novel robust adaptive fuzzy neural network controller is designed by combing with the improved bacterial foraging optimization algorithm in Controller Design. The stability of the controller proposed is proved in Stability Analysis, and some simulation experiments of the UMV heading control are carried out in Simulation Experiment. In Conclusion, research results obtained in this paper and some future work are shown.

II. PROBLEM FORMULATION

A. NONLINEAR MANOEUVERING MODEL OF UMV

With the continuous development of the UMV and its maneuvering control technology, the accuracy requirement of UMV heading control system is more and more important. Compared with the traditional linear Nomoto model of UMV heading maneuvering, the nonlinear Norbbin model could better reflect the heading maneuvering characteristics of the UMV, therefore, it could provide more realistic and referential heading control characteristics. In general, the UMV heading control system based on nonlinear Norbbin model could be described as follows [40]:

$$\begin{cases} T\dot{r} + r + \alpha r^3 = K(\delta + d) \\ \dot{\psi} = r \end{cases} \tag{1}$$

where ψ, r, δ respectively represent the heading angle, yaw angular velocity and the rudder angle. T, K, α respectively represent the stability constant, turning constant, and the Norbbin coefficient, while d represents the equivalent environment disturbances rudder angle.

For the convenience of system analysis, system (1) could be transformed and designed as follows:

$$\begin{cases} \dot{\psi} = r \\ \dot{r} = -\dfrac{1}{T}r - \dfrac{\alpha}{T}r^3 + \dfrac{K}{T}\delta + \dfrac{K}{T}d \end{cases} \tag{2}$$

In order to further simplify the above control system, we design the following state variables and expressions:

$$\begin{cases} z = \psi \\ \dot{z} = r \\ \boldsymbol{\Theta} = \begin{bmatrix} z & \dot{z} \end{bmatrix}^T \\ F(\boldsymbol{\Theta}) = -\dfrac{1}{T} r - \dfrac{\alpha}{T} r^3 \\ G(\boldsymbol{\Theta}) = K \\ D = Kd \\ u = \delta \end{cases} \tag{3}$$

Then the UMV heading nonlinear control system shown in (1) and (2) could be transformed into the following system:

$$\ddot{z} = F(\boldsymbol{\Theta}) + G(\boldsymbol{\Theta}) u + D \tag{4}$$

Seen from the above nonlinear dynamic system (4), u and z are input and output vectors, $\boldsymbol{\Theta}$ is the state vector, $F(\boldsymbol{\Theta})$ and $G(\boldsymbol{\Theta})$ represent the smooth nonlinearity of the dynamic system, and D is the external disturbance.

B. COMPLEX ENVIRONMENT DISTURBANCE MODEL

For the UMV heading maneuvering control process, the disturbance of the complex environment, according to [40], they can be equivalent to the interference effect on the UMV steering rudder angle, and the specific description is shown below:

$$\begin{cases} L = \lambda_1 \times wgn \times g(s) \\ N = \left(\rho_1 L + (1 - \rho_1) \dot{L}\right) \sin\theta \cos\theta \\ M = C_1 N + C_2 N^2 \\ d = \delta_l = \dfrac{M}{\kappa V^2} \end{cases} \tag{5}$$

where L, λ_1, wgn, $g(s)$, N respectively represent the wave height, coefficient of colored noise, white Gaussian noise, transfer function from colored noise to wave height and the yawing disturbance moment. θ is the angle between course and wave, and C_1, C_2, ρ_1 are model coefficients, which are determined by model test; κ is the coefficient which related to the ship size, tonnage, transshipment, etc; V represents the UMV's speed while δ_l represents equivalent interference with rudder angle, and M is environment disturbance torque.

III. CONTROLLER DESIGN

A. OVERALL DESIGN OF RAFNNC

The structure of the robust adaptive fuzzy neural network control system, which is designed in this paper for heading control of the UMV, could be described as shown in figure 1, and the main design ideas of the system shown above are as follows:

Firstly, the control system would obtain the inverse dynamics of the UMV model by **GD-FNN_A**module, which could get the mapping from $\boldsymbol{\Theta}$ to u. The GD-FNN_A module is designed by a new generalized dynamic fuzzy neural network, which would be carried out detailed design and description in next section. The generalized dynamic fuzzy neural network learning algorithm can determine the appropriate structural parameters of the fuzzy neural network system, thus obtaining the appropriate mapping relationship between $\boldsymbol{\Theta}$ and u.

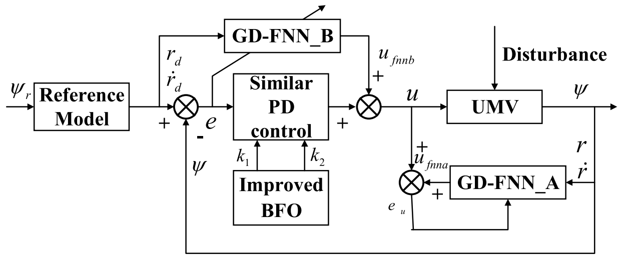

FIGURE 1. Structure of robust adaptive fuzzy neural network control system.

Secondly, considering the control precision of neural network system in the early stage of learning, and meanwhile to shorten the system control time, a similar PD control module is designed, and the control parameters would be optimized by the improved bacterial foraging optimization algorithm, which would be covered in the next section.

Thirdly, GD-FNN_B module would copy from GD-FNN_A module, but its weight vector would be further adjusted by the adaptive law designed below, and then the modeling error of generalized dynamic fuzzy neural network would be compensated. The output compensation control u_{fnnb} and the improved BFO-PD control together constitute the final control signal of the UMV heading control system.

B. DETAIL DESIGN OF GDFNN

Comparing with the traditional fuzzy neural network controller, dynamic fuzzy neural network controller has the advantages of fast learning speed, synchronous parameter adjustment and structure identification. However, it also has many disadvantages, such as the width of all Gaussian membership of input variables is the same, some membership functions are highly overlapping, and the extracted fuzzy rules are difficult to understand. To solve these problems, a novel improved generalized dynamic fuzzy neural network control algorithm is proposed in this paper for UMV heading control system based on elliptic basis function, which is functionally equivalent to Takagi-Sugeno-Kang fuzzy system. An online parameter assignment algorithm is proposed based on fuzzy ε completeness, to avoid the randomness of initial parameters selection, and meanwhile the width of input variables of each rule can be adjusted online adaptively according to its contribution to the system. The detail structure of the improved GDFNN control algorithm can be shown above in figure 2.

As shown in figure 2, r represents the number of input variable, and for or each input variable x_i $(i = 1, 2, \cdots, r)$, there are u membership functions μ_{ij} $(j = 1, 2 \cdots, u)$, and Gaussian membership function of x_i could be designed as

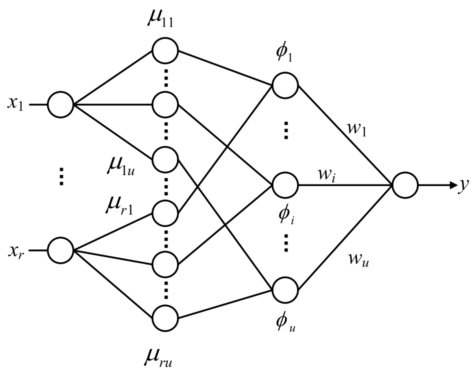

FIGURE 2. **Structure of improved generalized dynamic fuzzy neural network.**

follows:

$$\begin{cases} \mu_{ij}(x_i) = \exp\left[-\dfrac{(x_i - c_{ij})^2}{\sigma_{ij}^2}\right] \\ i = 1, 2, \cdots r \quad j = 1, 2, \cdots, u \end{cases} \tag{6}$$

where c_{ij} and σ_{ij} are respectively the center and width of the Gaussian membership function of x_i; Since the algorithm to calculate the trigger weight of each rule is multiplication, the output ϕ_j $(j = 1, 2, \cdots, u)$ can be expressed as follows:

$$\phi_j(x_1, \cdots, x_r) = \exp\left[-\sum_{i=1}^{r} \frac{(x_i - c_{ij})^2}{\sigma_{ij}^2}\right] \quad j=1, 2, \cdots, u \tag{7}$$

And then the output of the improved GDFNN could be designed as follows:

$$y(x_1, x_2, \cdots, x_r) = \sum_{j=1}^{u} w_j \cdot \phi_j \tag{8}$$

where y is the value of output variable, w_j is the weight parameter of the rule. Equation (8) can be written as a matrix, as shown below:

$$\boldsymbol{W\Phi} = \boldsymbol{Y} \tag{9}$$

where $\boldsymbol{W} \in \Re^{u(r+1)}$, $\boldsymbol{\Phi} \in \Re^{u(r+1)\times n}$, $\boldsymbol{Y} \in \Re^{n}$ respectively represent the output weight matrix, membership vector of fuzzy rules, and the output vector of the GDFNN.

C. IMPROVED BFO ALGORITHM DESIGN

The bacterial foraging optimization (BFO) algorithm is a new intelligent optimization algorithm, which is proposed based on the biological clustering algorithm created by the intelligent behavior embodied in Escherichia coli foraging.

In general, BFO algorithm has the advantages of insensitivity to initial value and parameter selection, strong robustness, simple and easy implementation, and parallel processing and global search. The algorithm mainly includes four procedures for solving the problem: tendency operation, aggregation operation, replication operation and migration operation. And among them, tendency operation is the most important step. So, in order to improve the optimization performance of the BFO algorithm, the tendency operation is adjusted by adaptive fractal dimension step size formula and an intelligent probe operation in this paper.

Firstly, adjusting the trend step size to, only carry out forward or backward random step size for each dimension, it could greatly reduce the computation amount of the algorithm and speed up the operation speed. The improved adaptive fractal dimension step size algorithm could be designed as follows, and it makes the bacteria advanced different step size in each dimension, with simple calculation and better results.

$$C_d = \frac{step_d}{j \times k \times l} \times rand \tag{10}$$

where j, k, l, C_d, $step_d$ respectively represent the chemotaxis number, replication number, secondary dispersion number, the step size of the dth dimension and the initial step size of the dth dimension. While $rand$ is a random number on $[-1, 1]$.

Secondly, an intelligent probe operation is proposed in this paper for the swimming of trending operation. The intelligent probe would calculate the location fitness value in advance for the next position that bacteria are about to enter. If the next position is better than the current position, it will move forward, while if it is worse than the current position, it will not move forward. This operation greatly speeds up the convergence speed of the algorithm, and meanwhile solves the shortcoming that the aimlessly movement of bacteria, which may lead the bacteria to move forward to a worse adaptability environment and then may swim useless and repeatedly.

Above all, when using the improved bacterial foraging optimization algorithm, the location of bacteria in searching space is used to represent the solution of the problem, and the fitness function is used to describe the quality of the solution.

The parameter optimization of robust adaptive control of UMV heading is implemented by using improved BFO algorithm. In order to accelerate the convergence of the robust adaptive controller and reduce the computational complexity of the GDFNN, parameters k_1 and k_2 are adjusted before they are connected to the UMV heading control system. Meanwhile, to adjust the parameters of the controller by the improved BFO algorithm so as to adjust the ship course quickly, this paper here designs the following fitness function for BFO:

$$\begin{cases} J = \int_0^t (\omega_1 |e(t)| + \omega_2 |\Delta y(t)|)dt + \omega_3 t_s + \omega_4 \varphi_{over} \\ \Delta y(t) = y(t) - y(t-1) \end{cases} \tag{11}$$

where $e(t)$, $y(t)$, t_s, φ_{over} respectively represent the heading error, heading angle, adjustment time and the absolute overshoot, while $\omega_i (i = 1, 2, 3, 4)$ are weight parameters.

It would accelerate the adjustment speed or reduce the overshoot by adjusting different weight parameters. For example, when ω_1 is larger than other parameters, the system would accelerate the adjustment speed, when ω_2 and ω_4 are larger, the function would lead to reduce the overshoot of the system, and when ω_3 is larger, the system would accelerate the speed of course adjustment. So, if the appropriate weight is obtained, the system could reduce overshoot while speeding up the heading adjustment time.

D. UMV HEADING CONTROLLER DESIGN

The purpose of the UMV heading controller design is to make all closed loop variables bounded and have it able to track a given desired heading angle. Since (2) is a second order system, the reference model with ideal performance could be described as follows:

$$\ddot{\psi}_d + 2\zeta\omega_n\dot{\psi}_d + \omega_n^2\psi_d = \omega_n^2\psi_r \tag{12}$$

where ψ_d, ψ_r, ω_n, ζ respectively represent the desired heading angle given by the reference model, input of the model reference system, natural frequency and relative damping coefficient of the system.

In order to track the desired heading angle ψ_d given by the reference model, the following tracking error e and tracking error vectors $\boldsymbol{E}$ could be designed:

$$\begin{cases} e = \psi_d - \psi \\ \boldsymbol{E} = \begin{bmatrix} e & \dot{e} \end{bmatrix}^T \end{cases} \tag{13}$$

The inverse dynamic model of the dynamic system plays an important role in the control system, and then designs the inverse dynamic model of the dynamic system (4), as follows:

$$\begin{aligned} u(\boldsymbol{\Omega}) &= G^{-1}(\boldsymbol{\Theta})\left[\ddot{z} - F(\boldsymbol{\Theta}) - D\right] \\ &= K^{-1}\left[r + T\dot{r} + \alpha r^3 - Kd\right] \end{aligned} \tag{14}$$

where $\boldsymbol{\Omega} = \begin{bmatrix} \boldsymbol{\Theta}^T & \ddot{z} \end{bmatrix}^T$.

Then we can design the ideal control law as follows:

$$\begin{aligned} u^* &= G^{-1}(\boldsymbol{\Theta})\left[\ddot{z}_d - F(\boldsymbol{\Theta}) - D + \boldsymbol{KE}\right] \\ &= u(\boldsymbol{\Omega_d}) + G(\boldsymbol{\Theta})^{-1}\boldsymbol{KE} \end{aligned} \tag{15}$$

where $\boldsymbol{\Omega_d} = \begin{bmatrix} \boldsymbol{\Theta}^T & \ddot{z}_d \end{bmatrix}^T$, $\boldsymbol{K} = \begin{bmatrix} k_1 & k_2 \end{bmatrix}$, k_1 and k_2 are designed parameters. Substitute (15) into (4) results to:

$$\ddot{e} + k_1\dot{e} + k_2 e = 0 \tag{16}$$

From (16), it can be seen that if k_1 and k_2 are selected appropriately, the tracking error would converge to zero. However, the external environment disturbances to the UMV are random, and it could not be accurately describe with a simple model. Therefore, in order to solve this problem, a GDFNN control law is proposed here to approximate the ideal control law. Combining with Figure 1, the ideal control law in this paper can be designed as follows:

$$u^* = \boldsymbol{W}^{*T}\boldsymbol{\Phi}(\boldsymbol{\Omega_d}) + G^{-1}(\varpi)\boldsymbol{KE} \tag{17}$$

Then the actual control law of RAFNNC could be designed as follows

$$u = \boldsymbol{W}^{\boldsymbol{T}}\boldsymbol{\Phi}(\boldsymbol{\Omega_d}) + \boldsymbol{KE} \tag{18}$$

where $\boldsymbol{W}^{\boldsymbol{T}}\boldsymbol{\Phi}$ is output of GD-FNN_B; $\boldsymbol{KE}$ is the pre-adjusted output of improved bacterial foraging optimization algorithm, which could be designed as:

$$\boldsymbol{KE} = k_1(\psi_r - \psi) - k_2\dot{\psi} \tag{19}$$

Combining (2), (17) and (18), the UMV heading control error system can be designed as follows:

$$\dot{\boldsymbol{E}} = \boldsymbol{\Lambda}E + \boldsymbol{B}\left(u^* - u\right) \tag{20}$$

where

$$\begin{cases} \boldsymbol{\Lambda} = \begin{bmatrix} 0 & 0 \\ -k_2 & -k_1 \end{bmatrix} \\ \boldsymbol{B} = \begin{bmatrix} 0 \\ G(\boldsymbol{\Theta}) \end{bmatrix} \end{cases}$$

Substituting (17) and (18) into (20), we can get:

$$\begin{aligned} \dot{\boldsymbol{E}} &= \boldsymbol{\Lambda}E + \boldsymbol{B}[(\boldsymbol{W}^* - W)^T\boldsymbol{\Phi}(\boldsymbol{\Omega_d}) + G^{-1}(\boldsymbol{\Theta})\boldsymbol{KE} - \boldsymbol{KE}] \\ &= \boldsymbol{A}E + \boldsymbol{B}[(\boldsymbol{W}^* - W)^T\boldsymbol{\Phi}(\boldsymbol{\Omega_d})] \end{aligned} \tag{21}$$

where

$$\boldsymbol{A} = \begin{bmatrix} 0 & 0 \\ -G^{-1}(\boldsymbol{\Theta})k_2 & -G^{-1}(\boldsymbol{\Theta})k_1 \end{bmatrix} \tag{22}$$

$\boldsymbol{A}$ is Hurwitz matrix, and according to (21), we can see that, in order to minimize the heading control tracking error, the weight vector $\boldsymbol{W}$ should be further adjusted, and then an adaptive control law is proposed here as follows:

$$\dot{\boldsymbol{w}}_k = \gamma\boldsymbol{\Phi}\boldsymbol{E}^{\boldsymbol{T}}\boldsymbol{P}b_k \tag{23}$$

where γ is a positive constant, b_k represents the k-th element of $\boldsymbol{B}$, $\boldsymbol{P}$ is a symmetric positive definite matrix and satisfies the following relations:

$$\boldsymbol{PA} + \boldsymbol{A}^{\boldsymbol{T}}\boldsymbol{P} = -\boldsymbol{Q} \tag{24}$$

where $\boldsymbol{Q}$ is an selected symmetric positive definite matrix. In order to ensure the stability of UMV heading control system, the adaptive control law could be detail designed as follows:

$$\dot{\omega}_i = \begin{cases} \gamma\boldsymbol{\Phi}E^{\boldsymbol{T}}\boldsymbol{P}b_k & (\|\boldsymbol{w}_k\| < \|\boldsymbol{w}_k(0)\|) \\ \quad \text{or } \left(\|\boldsymbol{w}_k\| = \|\boldsymbol{w}_k(0)\| \text{ and } \boldsymbol{w}_k^T\boldsymbol{\Phi}E^{\boldsymbol{T}}\boldsymbol{P}b_k \le 0\right) \\ -\dfrac{\boldsymbol{w}_k\boldsymbol{w}_k^T}{\|\boldsymbol{w}_k\|^2}\boldsymbol{\Phi}E^{\boldsymbol{T}}\boldsymbol{P}b_k & (\|\boldsymbol{w}_k\| = \|\boldsymbol{w}_k(0)\| \\ \quad \text{and } \boldsymbol{w}_k^T\boldsymbol{\Phi}E^{\boldsymbol{T}}\boldsymbol{P}b_k > 0) \end{cases} \tag{25}$$

IV. STABILITY ANALYSIS

In this section, it would be proved that: for a nonlinear dynamic system (2), the system could be asymptotically stable under the control law of (18) and the adaptive control law (25).

Considering the following Lyapunov function candidate:

$$V(t) = \frac{1}{2}\boldsymbol{E}^T\boldsymbol{PE} + \frac{1}{2}\gamma^{-1}tr\left[\left(\boldsymbol{W}^* - \boldsymbol{W}\right)^T\left(\boldsymbol{W}^* - \boldsymbol{W}\right)\right] \tag{26}$$

TABLE 1. Model parameters.

model parameters	value
K	2.360
T	5.489
α	0.000094
ω_n	0.500
ζ	0.900

TABLE 2. Initial control parameters.

parameters	value	parameters	value
ω_1	1.000	λ_1	3.162
ω_2	100.000	ρ_1	0.900
ω_3	2.000	θ	45°
ω_4	2.000	C_1	5600.000
k_1	23.849	C_2	90.000
k_2	15.799	κ	400.000
J	225.550	V	7.200

Differentiating both sides of (26) based on the solutions of (21) and (24) results in:

$$\begin{aligned}\dot{V}(t) &= \frac{1}{2}\dot{E}^T PE + \frac{1}{2}E^T P\dot{E} - \gamma^{-1} tr[(W^* - W)^T] \\ &= \frac{1}{2}E^T(PA + A^T P)E + E^T PB(W^* - W)^T \\ &\quad \times \Phi - \gamma^{-1} tr[(W^* - W)^T \dot{W}] \\ &= -\frac{1}{2}E^T QE + E^T PB\left(W^* - W\right)^T \Phi \\ &\quad - \gamma^{-1} tr[(W^* - W)^T \dot{W}] \end{aligned} \tag{27}$$

Firstly, considering the first condition of (25) and then (27) results to:

$$\begin{aligned}\dot{V}(t) &= -\frac{1}{2}E^T QE + E^T PB(W^* - W)^T \Phi \\ &\quad - \gamma^{-1} tr[(W^* - W)^T \dot{W}] \\ &= -\frac{1}{2}E^T QE + E^T PB(W^* - W)^T \Phi \\ &\quad - tr[E^T PB(W^* - W)^T \Phi] \\ &\leq -\frac{1}{2}E^T QE + tr[E^T PB(W^* - W)^T \Phi \\ &\quad - E^T PB(W^* - W)^T \Phi] = -\frac{1}{2}E^T QE < 0 \end{aligned} \tag{28}$$

Then considering the second condition of (25), assuming that $\omega_k^* \in \{\|w_k\| \leq \|w_k(0)\|\} k = 1, \cdots, n_o$, and (27) leads to:

$$\dot{V}(t) = -\frac{1}{2}E^T QE + E^T PB(W^* - W)^T \Phi$$

$$\begin{aligned}&- \gamma^{-1} \sum_{k=1}^{m} [(w_k^* - w_k)^T \gamma(-\frac{w_k w_k^T}{\|w_k\|^2})\Phi E^T P b_k] \\ &= -\frac{1}{2}E^T QE - \sum_{k=1}^{m} [(1 - \frac{(w_k^*)^T w_k}{\|w_k\|^2}) w_k^T \Phi E^T P b_k] \end{aligned} \tag{29}$$

Since

$$\omega_k^* \in \{\|w_k\| \leq \|w_k(0)\|\} \quad \text{and } 1 - \frac{\left(w_k^*\right)^T w_k}{\|w_k\|^2} \geq 0$$

It can be obtained that:

$$\dot{V}(t) \leq -\frac{1}{2}E^T QE \leq 0 \tag{30}$$

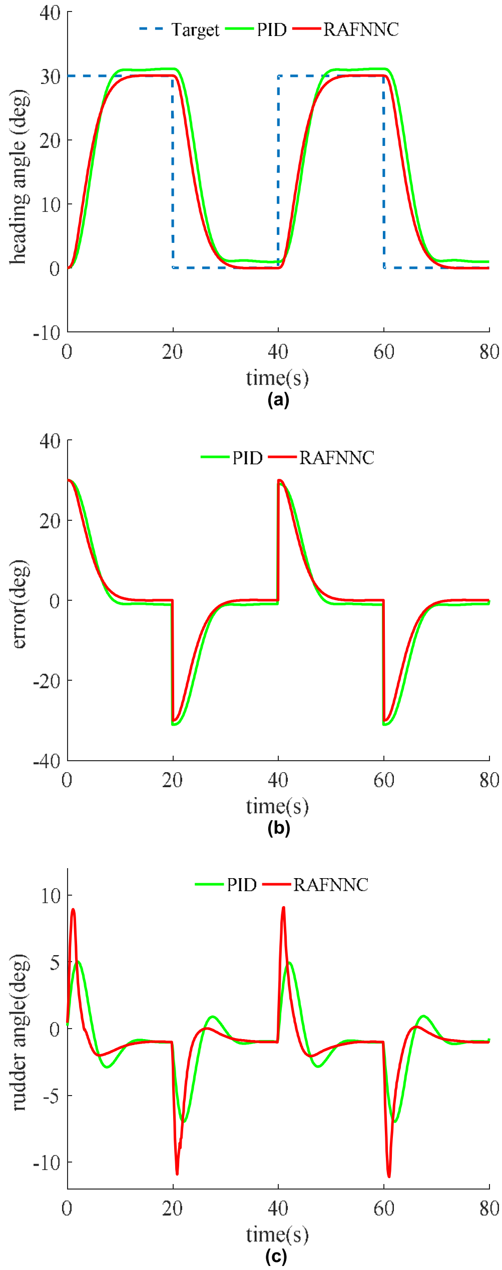

FIGURE 3. UMV heading control results of case 1. (a) Heading control results of 30-0-30-0 degree. (b) Heading control error. (c) Steering of rudder angle.

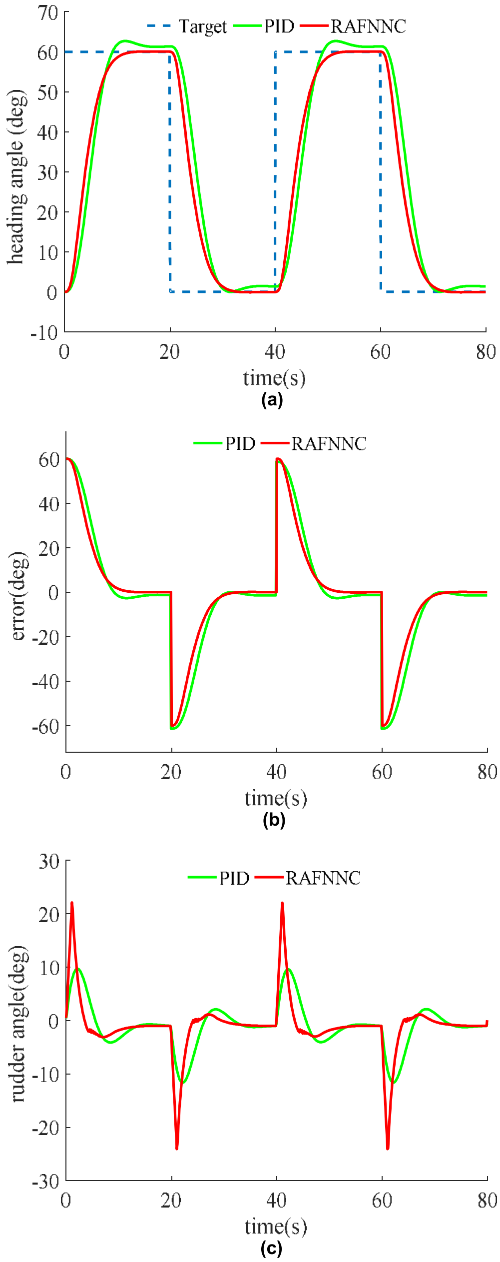

FIGURE 4. UMV heading control results of case 2. (a) Heading control results of 60-0-60-0 degree. (b) Heading control error. (c) Steering of rudder angle.

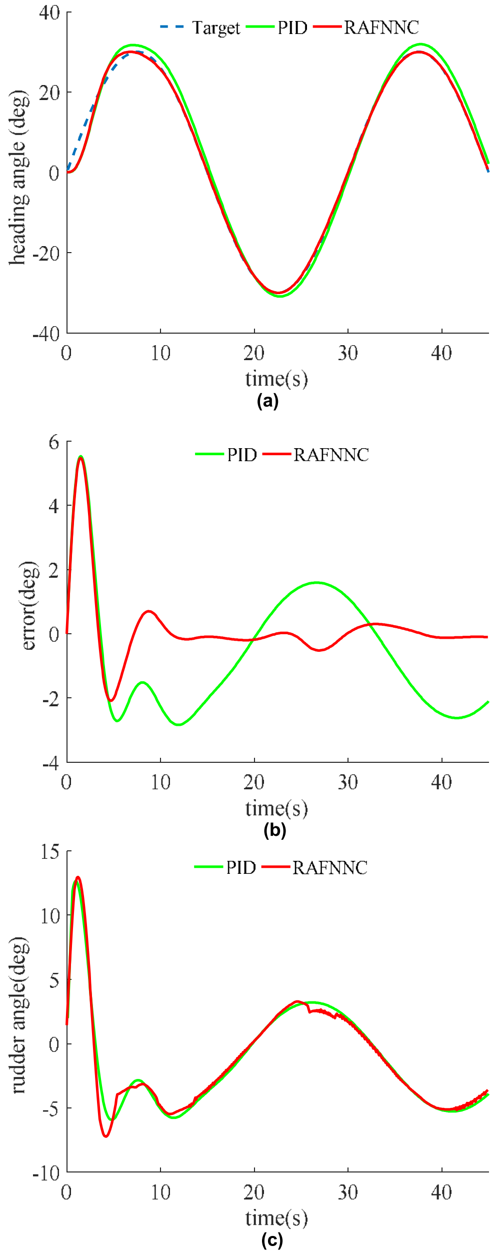

FIGURE 5. UMV heading control results of case 3. (a) Heading control results of 30 degree sine wave. (b) Heading control error. (c) Steering of rudder angle.

As $V(t) \geq 0$ and $\dot{V}(t) \leq 0$, the Lyapunov stability theorem shows that the nonlinear dynamic system (2) is globally stable, and then Barbalat lemma shows that, at that time of $t \rightarrow \infty$, we can know that $\boldsymbol{E}(t) \rightarrow 0$, thus the UMV heading control system is asymptotically stable, and the error of the system will converge to zero.

V. SIMULATION EXPERIMENTS

In order to verify and illustrate the effectiveness of the heading control algorithms proposed for the UMV, several computer simulation experiments are carried out on a UMV maneuvering motion model with model parameters in Table 1.

The angle between heading and wave is 45 degrees and the disturbance parameters of complex environment are set up while the UMV speed is 7.2m/s. Under the disturbance of complex environment such as wind, wave and ocean current, the semi-physical simulation experiments of robust adaptive fuzzy neural network control (RAFNNC) based on generalized dynamic fuzzy neural network (GDFNN) and improved bacterial foraging optimization (BFO) algorithm are carried out, and then the effectiveness are verified by comparing

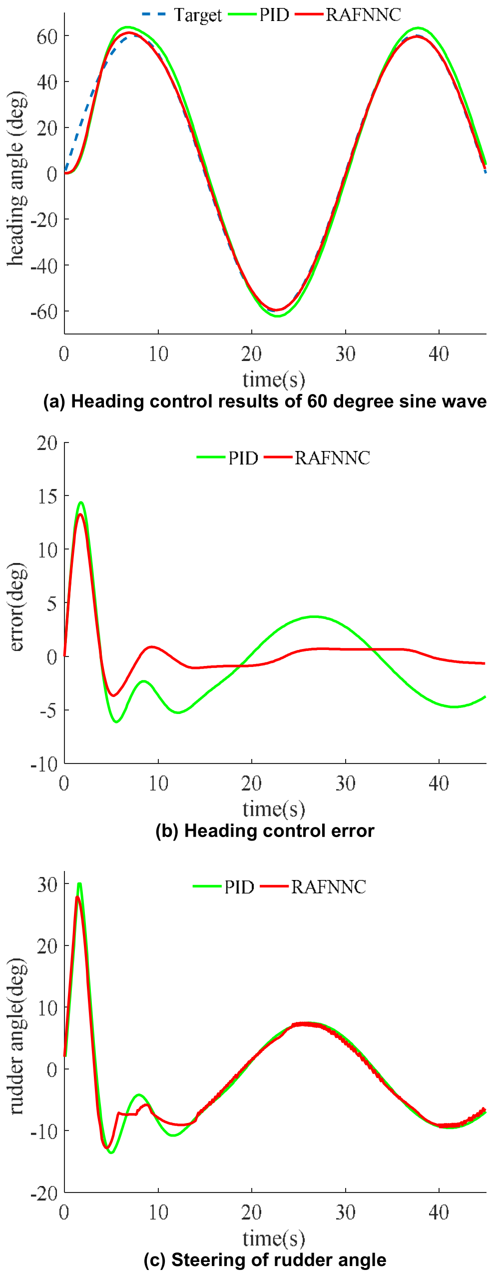

FIGURE 6. UMV heading control results of case 4. (a) Heading control results of 60 degree sine wave. (b) Heading control error. (c) Steering of rudder angle.

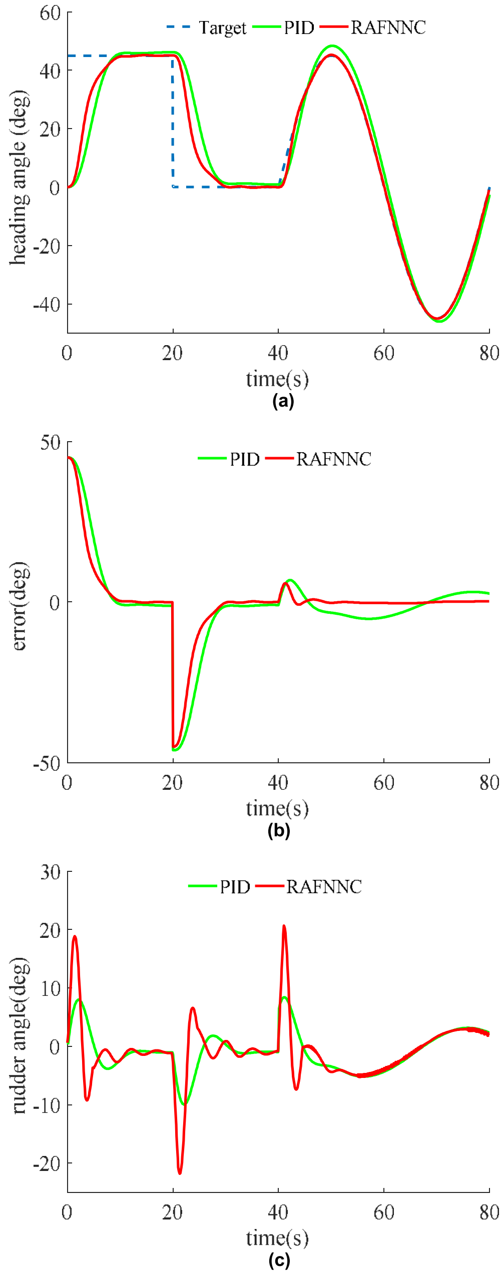

FIGURE 7. UMV heading control results of case 5. (a) Heading control results of 45 degree square wave and sine wave. (b) Heading control error. (c) Steering of rudder angle.

with PID controller. The main initial control parameters are designed in Table 2.

Five cases of different simulation experiments are carried out here to verify the effectiveness and reliability of the designed control algorithm, just as follows:

Case 1: The initial heading angle of the UMV is 0, and the desired heading angle changes in turn according to 30-0-30-0 degree, which is just like a square wave. The simulation experiment results obtained are shown in figure 3 below.

Case 2: The initial heading angle of the UMV is 0, and the desired heading angle changes in turn according to 60-0-60-0 degree, which is just like a square wave. The simulation experiment results obtained are shown in figure 4 below.

Case 3: The initial heading angle of the UMV is 0, and the desired heading angle changes like a sine curve, and the amplitude is 30 degree. The simulation experiment results obtained are shown in figure 5 below.

Case 4: The initial heading angle of the UMV is 0, and the desired heading angle changes like a sine curve, and the amplitude is 60 degree. The simulation experiment results obtained are shown in figure 6 below

Case 5: The initial heading angle of the UMV is 0, and the desired heading angle changes like a square wave first and then a sine curve and the amplitude is 45 degree. The simulation experiment results obtained are shown in figure 7 below.

Figure 3 shows that the robust adaptive neural network controller (RAFNNC), based on generalized dynamic fuzzy neural network (GDFNN) and improved bacterial foraging optimization (BFO) algorithm, has faster adjustment speed and smaller steady-state error than the PID control in the square heading control. RAFNNC generates three reasoning rules here in 30 degree square heading control, and the adjustment time is about 12 seconds. In 60 degree square heading control RAFNNC here generates four reasoning rules, and the adjustment time is about 14 seconds.

It can be seen from figure 5 and figure 6 that RAFNNC has less adjustment time, less overshoot and less steady-state error than the PID control. And RAFNNC generates seven inference rules here in the 30 degree sinusoidal heading control. After about 10 seconds, it has successfully tracked the sinusoidal course adjustment and the error is small. In 60 degree sinusoidal course control, RAFNNC here generates nine inference rules. After about 11 seconds, the sinusoidal heading adjustment is successfully tracked and the error is small. For contrast PID control, the control accuracy is much lower than that of robust adaptive controller, and the steady-state error is larger.

Figure 7 shows RAFNNC can track the target course more quickly and accurately than the PID control, and the error is smaller. Five inference rules were generated by RAFNNC here. The error and adjusting time of contrast PID control in square and sinusoidal course phases are larger than that of RAFNNC controller.

From figure 3 to 7, it can be found that RAFNNC could achieve better heading control performance in both square and sinusoidal heading control under the disturbance of complex environment, such as wind, wave and ocean current, and it also shows better convergence speed and accuracy than PID control meanwhile achieves better control effect than PID control with less time.

VI. CONCLUSION

An improved robust adaptive neural network controller (RAFNNC), based on generalized dynamic fuzzy neural network (GDFNN) and improved bacterial foraging optimization (BFO) algorithm, is proposed in this paper, for heading control of an unmanned marine vehicle (UMV) in the presence of complex environment disturbance. The inverse dynamic model of the motion control of UMV is established based on the GDFNN for uncertain disturbance caused by the complex environment disturbance, which could well restrain and compensate the influence of the complex environment disturbance, and could obviously improve the control performance of the system. An improved bacterial foraging optimization algorithm is firstly designed in this paper to optimize the parameters of control algorithm, by combining the fractal dimension step size and intelligent probe operation, which could optimize the operation time and accuracy of the algorithm, and then could further reduce the computation amount and computation time of the RAFNNC. Stability of the designed RAFNNC for the heading control of the UMV in the presence of complex marine environment disturbance is proved by Lyapunov stability theory, and many simulation experiments are carried out to verify the effectiveness too. Large amount of simulation results show that, compared with traditional PID control algorithm, the proposed RAFNNC shows better convergence speed and accuracy than PID control meanwhile achieves better control effect than PID control with less time. In the future, we will try to apply the heading control algorithm proposed in this paper to the path following control of the UMV.

REFERENCES

[1] H. Mousazadeh *et al.*, "Developing a navigation, guidance and obstacle avoidance algorithm for an Unmanned Surface Vehicle (USV) by algorithms fusion," *Ocean Eng.*, vol. 159, pp. 56–65, Jul. 2018.
[2] Z. Dong, L. Wan, T. Liu, and J. Zeng, "Horizontal-plane trajectory-tracking control of an underactuated unmanned marine vehicle in the presence of ocean currents," *Int. J. Adv. Robotic Syst.*, vol. 13, no. 3, p. 83, May2016.
[3] S. Daniela, L. Miguel, and S. Susana, "An aquatic mobile sensing USV swarm with a link quality-based delay tolerant network," *Sensors*, vol. 18, no. 10, p. 3440, Oct. 2018.
[4] N. Wang, Z. Sun, S.-F. Su, and Y. Wang, "Fuzzy uncertainty observer-based path-following control of underactuated marine vehicles with unmodeled dynamics and disturbances," *Int. J. Fuzzy Syst.*, vol. 20, no. 8, pp. 2593–2604, Dec. 2018.
[5] N. Palomeras *et al.*, "AUV homing and docking for remote operations," *Ocean Eng.*, vol. 154, pp. 106–120, Apr. 2018.
[6] H. Albitar, K. Dandan, A. Ananiev, and I. Kalaykov, "Underwater robotics: Surface cleaning technics, adhesion and locomotion systems," *Int. J. Adv. Robotic Syst.*, vol. 13, no. 1, p. 7, Jan. 2016.
[7] P. King, A. Vardy, and A. L. Forrest, "Teach-and-repeat path following for an autonomous underwater vehicle," *J. Field Robot.*, vol. 35, no. 5, pp. 748–763, Aug. 2018.
[8] S. Song, J. M. Herrmann, B. Si, K. Liu, and X. Feng, "Two-dimensional forward-looking sonar image registration by maximization of peripheral mutual information," *Int. J. Adv. Robotic Syst.*, vol. 14, no. 6, pp. 1–17, Dec. 2017.
[9] Z. Dong, L. Wan, Y. Li, T. Liu, and G. Zhang, "Trajectory tracking control of underactuated USV based on modified backstepping approach," *Int. J. Nav. Archit. Ocean Eng.*, vol. 7, no. 5, pp. 817–832, Sep. 2015.
[10] M. Zhu, A. Hahn, and Y.-Q. Wen, "Identification-based controller design using cloud model for course-keeping of ships in waves," *Eng. Appl. Artif. Intell.*, vol. 75, pp. 22–35, Oct. 2018.
[11] Z. Dong, L. Wan, Y. Li, T. Liu, J. Zhuang, and G. Zhang, "Point stabilization for an underactuated AUV in the presence of ocean currents," *Int. J. Adv. Robotic Syst.*, vol. 12, no. 7, p. 100, Jul. 2015.
[12] Đ. Nađ, N. Miškovic, and F. Mandic, "Navigation, guidance and control of an overactuated marine surface vehicle," *Annu. Rev. Control*, vol. 40, pp. 172–181, Oct. 2015.
[13] M. Caccia, M. Bibuli, R. Bono, and G. Bruzzone, "Basic navigation, guidance and control of an unmanned surface vehicle," *Auto. Robots*, vol. 25, no. 4, pp. 349–365, Nov. 2008.
[14] A. Alfi, A. Shokrzadeh, and M. Asadi, "Reliability analysis of H-infinity control for a container ship in way-point tracking," *Appl. Ocean Res.*, vol. 52, pp. 309–316, Aug. 2015.
[15] M. H. Khodayari and S. Balochian, "Modeling and control of autonomous underwater vehicle (AUV) in heading and depth attitude via self-adaptive fuzzy PID controller," *J. Mar. Sci. Technol.*, vol. 20, no. 3, pp. 559–578, Sep. 2015.
[16] Y. Li, Y.-Q. Jiang, L.-F. Wang, J. Cao, and G.-C. Zhang, "Intelligent PID guidance control for AUV path tracking," *J. Central South Univ.*, vol. 22, no. 9, pp. 3440–3449, Sep. 2015.

[17] E. I. Sarda, H. Qu, I. R. Bertaska, and K. D. von Ellenrieder, "Station-keeping control of an unmanned surface vehicle exposed to current and wind disturbances," *Ocean Eng.*, vol. 127, pp. 305–324, Nov. 2016.

[18] R. Rout and B. Subudhi, "NARMAX self-tuning controller for line-of-sight-based waypoint tracking for an autonomous underwater vehicle," *IEEE Trans. Control Syst.*, vol. 25, no. 4, pp. 1529–1536, Jul. 2017.

[19] R. Miao, Z. Dong, and L. Wan, "Heading control system design for a micro-USV based on an adaptive expert S-PID algorithm," *Polish Maritime Res.*, vol. 25, no. 2, pp. 6–13, Jun. 2018.

[20] Y. Li, L. Wang, Y. Liao, Q. Jiang, and K. Pan, "Heading MFA control for unmanned surface vehicle with angular velocity guidance," *Appl. Ocean Res.*, vol. 80, pp. 57–65, Nov. 2018.

[21] H. Sang, Y. Zhou, X. Sun, and S. Yang, "Heading tracking control with an adaptive hybrid control for under actuated underwater glider," *ISA Trans.*, vol. 80, pp. 554–563, Sep. 2018.

[22] Y. Fan, D. Mu, X. Zhang, G. Wang, and C. Guo, "Course keeping control based on integrated nonlinear feedback for a USV with pod-like propulsion," *J. Navigat.*, vol. 71, no. 4, pp. 878–898, Jul. 2018.

[23] J. Wan, B. He, Y. Shen, W. Liu, X. Ding, and S. Gao, "Heading multi-mode control based on soft-switching for autonomous underwater vehicle," *Ocean Eng.*, vol. 164, pp. 672–682, Sep. 2018.

[24] B. Rhoads, I. Mezić, and A. C. Poje, "Minimum time heading control of underpowered vehicles in time-varying ocean currents," *Ocean Eng.*, vol. 66, pp. 12–31, Jul. 2013.

[25] K. Teo, B. Goh, and O. K. Chai, "Fuzzy docking guidance using augmented navigation system on an AUV," *IEEE J. Ocean. Eng.*, vol. 40, no. 2, pp. 349–361, Apr. 2015.

[26] M.-C. Fang, S.-M. Wang, M.-C. Wu, and Y.-H. Lin, "Applying the self-tuning fuzzy control with the image detection technique on the obstacle-avoidance for autonomous underwater vehicles," *Ocean Eng.*, vol. 93, pp. 11–24, Jan. 2015.

[27] R. Furferi, R. Conti, E. Meli, and A. Ridolfi, "Optimization of potential field method parameters through networks for swarm cooperative manipulation tasks," *Int. J. Adv. Robotic Syst.*, vol. 13, no. 6, pp. 1–13, Oct. 2016.

[28] N.-K. Im and V. Nguyen, "Artificial neural network controller for automatic ship berthing using head-up coordinate system," *Int. J. Nav. Archit. Ocean Eng.*, vol. 10, no. 3, pp. 235–249, May 2018.

[29] K. Tanakitkorn, P. A. Wilson, S. R. Turnock, and A. B. Phillips, "Sliding mode heading control of an overactuated, hover-capable autonomous underwater vehicle with experimental verification," *J. Field Robot.*, vol. 35, no. 3, pp. 396–415, May 2018.

[30] J. Du, X. Hu, M. Krstić, and Y. Sun, "Robust dynamic positioning of ships with disturbances under input saturation," *Automatica*, vol. 73, pp. 207–214, Nov. 2016.

[31] N. Wang, S. Lv, and Z. Liu, "Global finite-time heading control of surface vehicles," *Neurocomputing*, vol. 175, pp. 662–666, Jan. 2016.

[32] B. Li and T.-C. Su, "Nonlinear heading control of an autonomous underwater vehicle with internal actuators," *Ocean Eng.*, vol. 125, pp. 103–112, Oct. 2016.

[33] W. B. Klinger, I. R. Bertaska, K. D. von Ellenrieder, and M. R. Dhanak, "Control of an unmanned surface vehicle with uncertain displacement and drag," *IEEE J. Ocean. Eng.*, vol. 42, no. 2, pp. 458–476, Apr. 2017.

[34] J. Jin, J. Zhang, and D. Liu, "Design and verification of heading and velocity coupled nonlinear controller for unmanned surface vehicle," *Sensors*, vol. 18, no. 10, p. E3427, Oct. 2018.

[35] A. Khan, S. S. A. Ali, F. Meriaudeau, A. S. Malik, L. S. Soon, and T. N. Seng, "Visual feedback–based heading control of autonomous underwater vehicle for pipeline corrosion inspection," *Int. J. Adv. Robot. Syst.*, vol. 14, no. 3, pp. 1–13, May 2017.

[36] Y.-L. Wang and Q.-L. Han, "Network-based heading control and rudder oscillation reduction for unmanned surface vehicles," *IEEE Trans. Control Syst. Technol.*, vol. 25, no. 5, pp. 1609–1620, Sep. 2017.

[37] J. Yuan, Z. Wu, J. Yu, and M. Tan, "Sliding mode observer-based heading control for a gliding robotic dolphin," *IEEE Trans. Ind. Electron.*, vol. 64, no. 8, pp. 6815–6824, Aug. 2017.

[38] B. Li and T.-C. Su, "Heading autopilot of autonomous underwater vehicles with internal moving mass," *J. Comput. Nonlinear Dyn.*, vol. 12, no. 2, pp. 021003-1–021003-7, Mar. 2017.

[39] L.-F. Wang, Y.-L. Liao, Y. Li, W.-X. Zhang, and K.-W. Pan, "Unmanned wave glider heading model identification and control by artificial fish swarm algorithm," *J. Central South Univ.*, vol. 25, no. 9, pp. 2131–2142, Sep. 2018.

[40] T. I. Fossen, *Guidance and Control of Ocean Vehicle*. New York, NY, USA: Wiley, 1994.

Authors' photographs and biographies not available at the time of publication.