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- · Position tracking control · Dynamic surface control
- · Neural network
- · State predictor

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Neural network adaptive position tracking control of underactuated autonomous surface vehicle

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Abstract The present study investigates the position tracking control of the underactuated autonomous surface vehicle, which is subjected to parameters uncertainties and external disturbances. In this regard, the backstepping method, neural network, dynamic surface control and the sliding mode method are employed to design an adaptive robust controller. Moreover, a Lyapunov synthesis is utilized to verify the stability of the closed-loop control system. Following innovations are highlighted in this study: (i) The derivatives of the virtual control signals are obtained through the dynamic surface control, which overcomes the computational complexities of the conventional backstepping method. (ii) The designed controller can be easily applied in practical applications with no requirement to employ the neural network and state predictors to obtain model parameters. (iii) The prediction errors are combined with position tracking errors to construct the neural network updating laws, which improves the adaptation and the tracking performance. The simulation results demonstrate the effectiveness of the proposed position tracking controller.

1. Introduction

In the last few decades, the motion control of autonoumous surface vehicles (ASVs) has attracted many scholars. Since ASVs have good flexibility, multipurpose applications and strong endurance, they can be employed to monitor the environment, explore marine sources, replenish the energy for other vehicles and so on [1-4]. However, most of the ASVs are underactuated, which indicates that the number of control inputs is less than the degrees of freedom. This can be interpreted as the existence of strong couplings between the degrees of freedom. Moreover, strong nonlinear external disturbances are a main challenge for ASVs, which are induced by ocean currents, waves and winds [5]. Therefore, the position tracking of the underactuated ASVs is a challenging problem in the marine structures.

In order to solve the motion control of the underactuated autonomous surface vehicles, different control schemes have been designed so far for the tracking problem [6-11]. Bi et al. [12] proposed a backstepping controller to solve the position tracking problem of the underactuated ASVs on the horizontal plane. Moreover, Pan et al. [13] developed an adaptive robust controller based on the backstepping method, single-layer neural network and the Lyapunov stability theory for the underactuated ASVs. However, the nonlinear external disturbances are not considered in this study. In Ref. [14], an adaptive neural network control scheme was designed to solve the position tracking problem of the underactuated ASVs. However, this scheme could not reduce the computational complexities of the conventional backstepping method. In Ref. [15], a neural-adaptive controller was proposed to track a desired trajectory for the underactuated ASVs. However, only the unknown ocean currents were considered in the designed controller, while other disturbances were neglected. Furthermore, Do et al. [16] proposed a global robust adaptive controller to track a desired path for underactuated ASVs considering the timevarying disturbances. They conducted simulation and experiments to prove the effectiveness of the proposed controller. However, they didn't consider uncertainties of parameters. Further-

© The Korean Society of Mechanical Engineers and Springer-Verlag GmbH Germany, part of Springer Nature 2020 more, a global tracking controller was presented to track a desired trajectory of underactuated nondiagonal ASVs in Ref. [17]. However, the controller was only applied to small nondiagonal ASVs, so it ignored uncertainties of the parameters. Xie et al. [18] proposed a cascaded control scheme to follow the desired trajectory of the underactuated ASVs based on the non-diagonal inertia and damping. However, the nonlinear external disturbances were not considered in the control system. Swaroop et al. [19] presented the dynamic surface control (DSC) to avoid the explosion of complexities of the conventional backstepping method so that the derivative of the virtual variables are obtained by a first-order filter. Moreover, Wang et al. [20] proposed an adaptive neural network tracking controller to realize the trajectory tracking of the underactuated AUVs. The radial basis function neural network (RBFNN) was adopted to estimate and compensate uncertainties of model parameters. However, errors between uncertain functions and the estimation model were not taken into the consideration. In Ref. [21], an adaptive sliding mode technique was designed to solve the nonlinear external disturbances. Moreover, an adaptive nonlinear robust control scheme was proposed to realize the path following for the underactuated autonomous underwater vehicles by employing backstepping method and sliding mode control in Ref. [22]. However, the damping matrix was only compensated by the adaptive law, while other uncertainties of parameters were ignored. Zheng et al. [23] designed an adaptive neural network controller to compensate uncertainties of the parameters and input saturation of the underactuated ASVs. However, the designed control scheme has unjustifiable computational complexity. Wang et al. [24] designed a nonlinear robust control scheme to follow the desired path of underactuated autonomous surface vehicles. Then, a feedback gain controller was designed to track a desired path of the underactuated ASV in the horizontal plane in Ref. [25]. However, the controller can be carried out with accurate model parameters. In Ref. [26], the command filtered backstepping method was presented to follow the desired path of the underactuated autonomous underwater vehicles. However, parameters uncertainties and the nonlinear external disturbances were not taken into consideration, which limits its real applications. Furthermore, a neural network robust controller was developed for underactuated ASVs in Ref. [27]. The control system can be effective to the dynamic uncertainties and external disturbances. In Ref. [28], an adaptive controller was designed to where x, W and $h(x)$ denote the input vector of the realize the trajectory tracking of the ASVs. However, parameters uncertainties were not considered. In Ref. [29], an adaptive output feedback control scheme was proposed to track the trajectory of the underactuated ASVs. The control system considered the underactuated ASVs model, where the mass and damping matrices were not diagonal. However, the nonlinear external disturbances were not taken into the consideration. Liu et al. Ref. [30] presented a neural network control scheme to track a desired trajectory of the underactuated ASVs. The neural network was constructed to provide an estimation of the unknown disturbances. However, parameters parameters were

Fig. 1. Structure of the three-layer RBF neural network.

ignored.

In the present study, it is intended to propose an adaptive position tracking control scheme for the underactuated ASVs in the presence of uncertainties of the parameters and nonlinear external disturbances.

The rest of this article is arranged as follows. In Sec. 2, the position tracking problem, kinematic model, dynamic model, and error equations of underactuated ASVs are introduced. Moreover, the neural network adaptive robust controller of underactuated ASVs is designed in Sec. 3. Then, the Lyapunov function is applied in Sec. 4 to prove the stability of the closed loop control system. In Sec. 5, simulation results, comparative analysis and the position tracking performance of the designed controller are presented. Finally, the conclusion of the article is presented in Sec. 6.

2. ASV modelling and problem formulation

2.1 The neural networks

The neural network has numerous intrinsic abilities in the function approximation. Therefore, it plays an important role in the robotic control. In this section, a radial basis function neural network (RBFNNs) with linear parameterization and simple mechanism [31] is introduced. Fig. 1 shows the typical threelayer RBFNN, which is applied in the present study to solve the model uncertainties provided ASVs is designed in Sec. 3. Then, the
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f(\mathbf{x}) = \mathbf{Wh}(\mathbf{x}) + \varepsilon
$$

$$
h(\mathbf{x}) = \exp\left(\frac{\left\|\mathbf{x} - \mathbf{c}_j\right\|^2}{2\mathbf{b}_j^2}\right)
$$
 (1)

RBFNN, the weight adjustment and the Gaussian basis function, respectively. Moreover, ${\bf c}_j$ and ${\bf b}_j$ represent a *j*dimensional vector denoting the center of the *j*th basis function and the standard deviation, respectively. *f* (*x*) = **xh** (*x*) + *ε* (*x*) = *x***_{***f***} (***x***) =** *x***_{***f***} (***x***) =** *c***_{***f***} (²) (²) (1) (1) (1) (2) =** *x***_{***f***} (2)** (2) (3) (4) (4) denote the input vector of the FNN, the weight adjustment and the Gaussian ba

$$
f^*(\mathbf{x}) = \mathbf{W}^* \mathbf{h}(\mathbf{x}) + \varepsilon \tag{2}
$$

where **W*** indicates the optimal weight adjustment.

$$
\hat{f}(\mathbf{x}) = \hat{\mathbf{W}} \mathbf{h}(\mathbf{x}) + \varepsilon \tag{3}
$$

where \hat{f} and \hat{W} denote the NN output and the estimation of the weight adjustment, respectively.

Assumption 1. The ideal weight matrix **W*** and the approximation error ε are bounded so that there are W_M and $\begin{array}{c|c} & & & \end{array}$

$$
\varepsilon_M, \|\mathbf{W}^*\| \leq W_M \text{ and } \varepsilon \leq \varepsilon_M \text{ [21]}.
$$

2.2 The underactuated ASV model

The kinematic and dynamic models are presented in this section. In order to simplify the derivation of the equation, the mass and the damping matrices are regarded to be diagonal. Moreover, external disturbances are taken into consideration for the underactuated ASV model. The kinematic and dynamic models are described as follows [32]: and $\hat{\mathbf{W}}$ denote the NN output and the estimation of the denotion of the denote the NN output and the estimation
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\mathbf{F}_k\n\end{bmatrix}$ and \mathbf{F}_k and the apple on error ε are bounded so that there a and $\hat{\mathbf{w}}$ denote the NN output and the estimation

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the weight adjustment, respectively.
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 \hat{w} and \hat{w} are bounded so that there are W_u an For \hat{f} and \hat{w} denote the NN output and the estimation

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mation error \hat{s} are bounded so that there are W_x , and *Mv* denote the NN output and the estimation
 $\begin{bmatrix}\n\mathbf{w} \end{bmatrix}^T = \begin{bmatrix}\n\mathbf{w} \end{bmatrix}^$

$$
\begin{cases} \dot{\eta} = J(\psi)\nu \\ M\dot{\nu} + C(\nu)\nu + D\nu = \tau + \tau_e \end{cases}
$$
 (4)

where

aximation error *c* are bounded so that there are
$$
W_M
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 and

\n7.1. $W^* \leq W_M$ and $c \leq c_M$ [21].

\n2.1. $2 \cdot \frac{W}{V}$ and $c \leq c_M$ [21].

\n2.2. $3 \cdot \frac{W}{V}$ and $C \leq C_M$ [23].

\n2.3. $2 \cdot \frac{W}{V}$ and $C \leq C_M$ [24].

\n2.4. $2 \cdot \frac{W}{V}$ and $C \leq C_M$ [25].

\n2.5. $2 \cdot \frac{W}{V}$ and $C \leq C_M$ [26].

\n2.6. $2 \cdot \frac{W}{V}$ is a real set of the equation, the quadratic and dynamic derivatives are the same into consideration to the quadratic and dynamic derivatives are the same-varying to the quadratic equation.

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M = \begin{bmatrix} m - X_{ii} & 0 & 0 \\ 0 & m - Y_{i} & 0 \\ 0 & 0 & m - N_{i} \end{bmatrix} = \begin{bmatrix} m_{11} & 0 & 0 \\ 0 & m_{22} & 0 \\ 0 & 0 & m_{33} \end{bmatrix}
$$
 (6)

$$
C(v) = \begin{bmatrix} 0 & 0 & -m_{2}v \\ 0 & 0 & m_{11}u \\ m_{22}v & -m_{11}u & 0 \end{bmatrix}
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 $\qquad (7)$ \qquad

$$
M = \begin{bmatrix} m - X_u & 0 & 0 \\ 0 & m - Y_v & 0 \\ 0 & 0 & m - N_v \end{bmatrix} = \begin{bmatrix} m_{11} & 0 & 0 \\ 0 & m_{22} & 0 \\ 0 & 0 & m_{33} \end{bmatrix}
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 (6) and {*e_x, e_y*}\n
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C(v) = \begin{bmatrix} 0 & 0 & -m_{21}v \\ 0 & 0 & m_{11}u \\ m_{22}v & -m_{11}u & 0 \end{bmatrix}
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D = \begin{bmatrix} X_u + X_{u|u} |u| & 0 & 0 \\ 0 & Y_v + Y_{v|v} |v| & 0 \\ 0 & 0 & N_r + N_{r|v|} |r| \end{bmatrix}
$$
 (8) Then, Eq. (9, 1),
\n
$$
\begin{bmatrix} e_x = x_e \cos \theta \\ e_y = -x_e \cos \theta \end{bmatrix}
$$

where x , y and ψ denote positions and orientations of underactuated ASVs in the earth fixed frame, respectively. Moreover, *u* , *v* and *r* denote the surge, sway and yaw velocities in the body fixed frame, respectively. X_u , Y_v , N_r , $X_{u|u|}$, $Y_{v|v|}$ and $x_e = x_d - x$ $y_e = y_d - y$

(8) Then, Eq. (6) can be conv
 $\begin{cases} e_x = x_e \cos \psi + y_e \sin \psi \\ e_y = -x_e \sin \psi + y_e \cos \psi \end{cases}$

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w velocities in where e_x and e_y denote
 $, X_{u|u|}, Y_{v|v}$ and body fixed frame.
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where *x*, *y* and *ψ* denote positions and or deractuated ASVs in the earth fixed frame, report, *u*, *v* and *r* denote the surge, sway and $\begin{bmatrix} 0 & 0 & 1 \end{bmatrix}$
 $\begin{bmatrix} m-x_1' & 0 & 0 \ 0 & m-x_2' & 0 \ 0 & 0 & m-x_1' \end{bmatrix} = \begin{bmatrix} m_1 & 0 & 0 \ 0 & m_2 & 0 \ 0 & 0 & m_3 \end{bmatrix}$
 $\begin{bmatrix} m_1' & 0 & 0 \ 0 & 0 & m_1 \end{bmatrix}$
 $\begin{bmatrix} m_1' & 0 & 0 \ 0 & 0 & m_1 \end{bmatrix}$
 $\begin{bmatrix} 0 & 0 & -m_2x \\ 0 & 0 & m_2x \\ 0$ note the combined inertia and added mass terms in the body fixed frame. τ_u and τ_r denote control force and control force moment, respectively. $\tau_{e\mu}$, $\tau_{e\nu}$ and $\tau_{e\mu}$ denote the ocean disturbances induced by ocean currents, waves and wind. C(v) = $\begin{bmatrix} 0 & 0 & m_1 u \\ m_2y & -m_1u & 0 \end{bmatrix}$ (7) and a detail considerable.
 $\mathbf{D} = \begin{bmatrix} X_x + X_{xy} |u| & 0 & 0 \\ 0 & Y_x + Y_{yy} |v| & 0 \\ 0 & 0 & N_y + N_{yy} |v| \end{bmatrix}$ (8) Then, Eq. (6) can be converted to the following or $\mathbf{D} = \begin{bmatrix} X$ **bounded** so that may be determined by the maximum of $\begin{cases} \n\frac{1}{2}x + Y_{\text{opt}}|y = 0 \\
0 & \frac{1}{2}x + Y_{\text{opt}}|y = 0\n\end{cases}$

where x, y and y denote positions and orientations of un-

detectuated ASVs in the earth fixed frame,

Assumption 2. The ocean disturbances are bounded *when* $|\tau_{ek}| \leq \tau_e^*$, *where* $k = u, v, r$ and τ_e^* represents an unknown positive constant [35].

Assumption 3. The yaw angle of the underactuated ASV is ity in the controller [12].

Fig. 2. The ASV frames in the position tracking problem.

tory and its derivatives are time-varying bounded [12].

 (4) stable in the epilogue [35].^{120} **Assumption 5.** The velocity of the underactuated ASV in the sway is bounded so that $\sup |v| \le v_M$ and the error of v is not supply that $\sup |v| \le v_M$

2.3 Error dynamics of the position tracking problem

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Example of the diagonal text and dynamic assumption 4. $\eta_x = [x_x, y_x, \psi_x]^T$ is a smooth desired trajectived ASV model. The kinematic and dynamic **Assumption 4.** $\eta_x = [x_x, y_x, \psi_x]^T$ Exactled described as follows [32]:

Exactled ASV model. The kinematic and dynamic **Assumption 4.** $n_x = x_x$, y_x , y_x]^T is a smooth desired

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 Assumption 4. $\eta_x = [x_x y_x w_x]^T$ is a story and its derivatives are time-varying bo
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are described as follows [32]:
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 ψ and the served as follows **Example 10 a** *m* **a example 10 a a example 10 a example 10 a example 10 a example 10 example 10 a example 10 ex** 0 0 $\begin{bmatrix}\nr_{\mathbf{v}} = [u \cdot v]^T & \text{In order to facilitate the problem for } \mathbf{v} = [\mathbf{v}, \mathbf{v}_1]^T & \text{In order to facilitate the problem for } \mathbf{v} = [\mathbf{v}_1, \mathbf{v}_2, \mathbf{v}_3] & \text{where } \mathbf{v} = [\mathbf{v}_1, \mathbf{v}_2, \mathbf{v}_3] & \text{where } \mathbf{v} = [\mathbf{v}_2, \mathbf{v}_3] & \text{where } \mathbf{v} = [\mathbf{v}_3, \mathbf{v}_4, \mathbf{v}_5, \mathbf{v}_6, \mathbf{v}_7, \math$ 2.3 *Error dynamics* of the po
 yr^{*Y*}
 *x*_{*x*}, *x*_{*x*}</sub> *I*
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 *Y*_{*x*}</sub> *V*_{*y*} and *Q₂*, *x*_{*x*}</sub> *Y*_{*x*} (*Y*_{*C*_{*x*}} *X*_{*x*} (*Y*_{*x*} *X*_{*n*} (*Y*_{*Q*} *X*_{*x*} (*Y*_C) **11.13** In order to facilitate the problem formulation, the fram signed to position the tracking of underactuated ASV

shows the designed frame. It should be indicated
 (5) $\begin{pmatrix} v_{e_1}, v_{e_2}, v_{e_3}, v_{e_4}, v_{e_5}, v_{e_6}, v_{e$ In order to facilitate the problem formulation, the frame is designed to position the tracking of underactuated ASV. Fig. 2 shows the designed frame. It should be indicated that { , , } *O X Y E E E* and { , , } *O X Y B B B* denote the earth fixed frame and **Example 12**

Fig. 2. The ASV frames in the position tracking problem.
 Assumption 4. $\mathbf{v}_d = [x_d, y_d, y_d]^T$ is a smooth desired trajectory and its derivatives are time-varying bounded [12].
 Assumption 5. The velocity Fig. 2. The ASV frames in the position tracking problem.
 Assumption 4. $\eta_a = [x_a, y_a \psi_a]^T$ is a smooth desired trajectory and its derivatives are time-varying bounded [12].
 Assumption 5. The velocity of the underactua Fig. 2. The ASV frames in the position tracking problem.
 Assumption 4. $\boldsymbol{\eta}_z = [x_x, y_x, \psi_x]^T$ is a smooth desired trajectory and its derivatives are time-varying bounded [12].
 Assumption 5. The velocity of the under **Example 10**
 Assumption 4. $\eta_d = [x_d, y_d, w_d]^T$ is a smooth desired trajectory and its derivatives are time-varying bounded [12].
 Assumption 5. The velocity of the underactuated ASV in the sway is bounded so that sup earth fixed frame and in the body fixed frame, respectively. sway is bounded so that suply $\leq v_M$ and the error of v is not
stable in the epilogue [35].⁶⁹
2.3 Error dynamics of the position tracking
problem
In order to facilitate the problem formulation, the frame is de-
signed **Example 10**

to facilitate the problem formulation, the frame is de-

to facilitate the problem formulation, the frame is de-

geological frame. It should be indicated that
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order to position the tracking of underactuated ASV. Fig. 2

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as the designed frame. It should be indicated that
 X_x, Y_x , and $\{O_a, X_y, Y_y\}$ denote the earth fi

The position tracking errors in the earth fixed frame are de-

$$
x_e = x_d - x \quad y_e = y_d - y \tag{9}
$$

0 $Y_{v} + Y_{v}$ $|v|$ 0 $|v|$ (8) Then, Eq. (6) can be converted to the following equations:

For example,
$$
x_{\rm s}
$$
, $y_{\rm s}$, $y_{\rm r}$ is the same and in the body fixed frame, respectively.

\nThe position tracking errors in the earth fixed frame are declared as follows:

\n $x_e = x_d - x$

\n $y_e = y_d - y$

\nThen, Eq. (6) can be converted to the following equations:

\n $\int e_x = x_e \cos \psi + y_e \sin \psi$

\n $\int e_y = -x_e \sin \psi + y_e \cos \psi$

\n(10)

where e_x and e_y denote the position tracking errors in the body fixed frame.

 $x_e = x_d - x$ $y_e = y_d - y$

(8) Then, Eq. (6) can be converted
 $\begin{cases} e_x = x_e \cos \psi + y_e \sin \psi \\ e_y = -x_e \sin \psi + y_e \cos \psi \end{cases}$

y. More-

ocities in where e_x and e_y denote the proximity, Y_{hyl} and body fixed frame.

2,3) de- Eq. (10) i Eq. (10) indicates that errors of the earth fixed frame and the body fixed frame are equivalent, which is described as the following: position tracking errors in the earth fixed frame are de-

as follows
 $= x_a - x$ $y_c = y_a - y$ (9)

n, Eq. (6) can be converted to the following equations:
 $= x_c \cos \psi + y_c \sin \psi$ (10)
 $= -x_c \sin \psi + y_c \cos \psi$ (10)
 e_x and e_y denote th **Example 10** as follows
 $e_x = x_d - x$ $y_e = y_d - y$ (9)
 e $y_e = x_d - x$ $y_e = y_d - y$ (9)
 e e $f(x) = x_c - x_c \cos y + y_c \sin y$ (10)
 e $e_x = x_c \cos y + y_c \sin y + y_c \cos y$ (10)
 e $e_y = -x_e \sin y + y_e \cos y$ (10)
 re e_x and e_y denote the position trackin

$$
\begin{cases} x_e(t) = 0\\ y_e(t) = 0 \end{cases} \Longleftrightarrow \begin{cases} e_x(t) = 0\\ e_y(t) = 0 \end{cases}
$$
\n(11)

is follows
 $x_a - x$ $y_c = y_a - y$ (9)

n, Eq. (6) can be converted to the following equations:
 $= x_c \cos \psi + y_c \sin \psi$ (10)
 $= -x_c \sin \psi + y_c \cos \psi$ (10)
 e_x and e_y denote the position tracking errors in the

ixed frame.

f(10) indica From Fourier steading since in the state integrations:
 $x_e = x_d - x$ $y_e = y_d - y$ (9)

Then, Eq. (6) can be converted to the following equations:
 $\begin{cases} e_x = x_e \cos \psi + y_e \sin \psi \\ e_y = -x_e \sin \psi + y_e \cos \psi \end{cases}$ (10)

ere e_e and e_p denote th *y* and $\int e^x e^{-x} dx$, $y'_x = y'_x - y'_x$ (9)
 y enn, Eq. (6) can be converted to the following equations:
 $e_x = x_x \cos \psi + y_x \sin \psi$ (10)
 $e_y = -x_x \sin \psi + y_x \cos \psi$ (10)
 $e_y = -x_x \sin \psi + y_x \cos \psi$ (10)
 $\int e_x (10)$ indicates that errors of the The control object is designing control inputs τ_u and τ_r , where the aim is approaching tracking errors e_x and e_y to zero. Differentiating Eq. (10) along with Eq. (4) yields:

cos sin ìï = - + + í ^ï = - + - ^î & & *^x m e y ^y m e x e u v ^ψ re e v v ^ψ re* (12) where 2 2

3. Controller design

11. IV
 ICONTATELLAR IDENTIFY A CONTINUE TO EXECUTE THE V_{*m***} of** *v_g* **(***x***) and** $r_{cf}(t)$ and $r_{cf}(t)$ denote the f
 $v_m = -v + v_m \sin \psi_c - re_x$
 $v_m = \sqrt{x_d^2 + y_d^2}$.
 C_{*u*} = $\sqrt{x_d^2 + y_d^2}$.
 C_{*u*} = $\sqrt{x_d^2 + y_d^2}$.
 In this section, a position tracking controller is designed based on the backstepping method, adaptive control techniques and neural network. It is indicated that the position tracking, surge velocity, auxiliary variable and yaw velocity errors are stabilized in steps 1, 2, 3, and 4, respectively. Moreover, adaptive control laws of the neural network are designed in step 5. based on the backstepping method, adaptive control
niques and neural network. It is indicated that the po
tracking, surge velocity, auxiliary variable and yaw ve
errors are stabilized in steps 1, 2, 3, and 4, respectively $e^{-u} + v_m \cos w_e + re$,
 $v_m = -v + v_m \sin w_e - re_x$
 $v_m = \sqrt{x_a^2 + y_a^2}$.

(12) $v_{\alpha'}(t)$ and $r_{\alpha'}(t)$ denote the
 $v_m = \sqrt{x_a^2 + y_a^2}$.

(12) $v_{\alpha'}(t)$ and $r_{\alpha'}(t)$ denote the
 $v_m = -v + v_m \sin w_e - re_x$
 $v_m = \sqrt{x_a^2 + y_a^2}$.

(12) $v_m(t)$ and $r_{$ $\begin{cases} \dot{e}_z = -u + v_{\infty} \cos \psi_z + r e_y \\ \dot{e}_y = -v + v_{\infty} \sin \psi_z - r e_x \end{cases}$ (12) $v_{\varphi}(t)$ and $r_{\varphi}(t)$ denote the $v_m = \sqrt{x_a^2 + y_a^2}$.

Here $v_m = \sqrt{x_a^2 + y_a^2}$.

Controller design Then, Eq. (17) can be c

from this section, a positi this section, a position tracking controller is designed

ed on the backstepping method, adaptive control tech-

ies and neural network. It is indicated that the position

is and neural network. It is indicated that the p s and neural network. It is indicated that the position

is and neural network. It is indicated that the position

are stabilized in steps 1, 2, 3, and 4, respectively. More-

adaptive control laws of the neural network a Controller design

this section, a position tracking controller is designed

d on the backstepping method, adaptive control tech-

is and near leave to the position

ang, surge velocity, auxiliary variable and yaw velocit this section, a position tracking controller is designed

of on the backstepping method, adaptive control tech-

s and neural network. It is indicated that the position

s and neural network. It is indicated that the posi d deural network. It is indicated that the position

stabilized that the position

stabilized in steps 1, 2, 3, and 4, respectively. More-

the control laws of the position can be designed

lin order to stabilize the posi **Controller design Eq.** (17) can be controller designed

this section, a position tracking controller is designed

exact on the backstepping method, adaptive control tech-

exact and neural network. It is indicated that t **Example 12 Controller design**

In this section, a position tracking controller is designed

y_i = - $\lambda_i e^2_x - \lambda_z e^2_y - e_e e_x + e_1 e_2$

yies and the backistepping method, adaptive control tech-

gues and neural network. It **b** section, a position tracking controller is designed
 $V_1 = -\lambda_1 e^2_x - \lambda_2 e^2_y - e^2_z e^2_x + e^2_z e^2_y + \zeta_3 \zeta_4$

and neural network. It is indicated that the position

and neural network the indicated that the position

1. *e* and neural network. It is indicated that the position

and neural network. It is indicated that the position
 $\text{u}_2 = V_1 + \frac{1}{2}(e_x^2 + \zeta_x^2)$

5. In order to stabilize the position racking errors, a

5. In order to s

Step 1: In order to stabilize the position tracking errors, a

$$
V_1 = \frac{1}{2} (e_x^2 + e_y^2)
$$
 (13)

Differentiating Eq. (13) along with Eq. (12) yields the equation below:

Step 1: In order to stabilize the position tracking errors, a
\nappunov function is defined as the following:
\n
$$
V_1 = \frac{1}{2}(e_x^2 + e_y^2)
$$
\n
$$
V_2 = V_1 + e_u e_u + \zeta_u \zeta_u
$$
\nDifferentiating Eq. (13) along with Eq. (12) yields the equal
\n
$$
V_1 = e_x \zeta_x + e_y \zeta_y
$$
\n
$$
= e_x(-u + v_m \cos \psi_e + re_y) + e_y(-v + v_m \sin \psi_e + re_x)
$$
\n
$$
= e_x(-u + v_m \cos \psi_e + re_y) + e_y(-v + v_m \sin \psi_e)
$$
\n
$$
= e_x(-u + v_m \cos \psi_e) + e_y(-v + v_m \sin \psi_e)
$$
\n
$$
= e_x(-u + v_m \cos \psi_e) + e_y(-v + v_m \sin \psi_e)
$$
\n
$$
= e_x(-u + v_m \cos \psi_e) + e_y(-v + v_m \sin \psi_e)
$$
\n
$$
= e_x(-u + v_m \cos \psi_e) + e_y(-v + v_m \sin \psi_e)
$$
\n
$$
= e_x(-u + v_m \cos \psi_e) + e_y(-v + v_m \sin \psi_e)
$$
\n
$$
= e_x(-u + v_m \cos \psi_e) + e_y(-v + v_m \sin \psi_e)
$$
\n
$$
= -\lambda_i e_x^2 + \lambda_i e_y^2
$$
\nIn order to facilitate the formula derivation, a new auxiliary
\n
$$
= -\lambda_i e_x^2 + \lambda_i e_y^2
$$
\n
$$
= -\lambda_i e_y^2 + \lambda_i e_y^2 + \lambda_i e_y^2
$$
\nTo ensure $V_1 \le 0$, *u* and *v* are considered as virtual vari-
\n
$$
= -\lambda_i e_x^2 + \lambda_i e_y^2 + \lambda_i e_y^2
$$

In order to facilitate the formula derivation, a new auxiliary variable is defined as follows:

$$
v = v_m \sin \psi_e \tag{15}
$$

To ensure $\dot{V}_1 \leq 0$, *u* and *v* are considered as virtual variables and their desired values are designed as:

$$
=e_x(-u+v_m\cos\psi_e)+e_y(-v+v_m\sin\psi_e)
$$
\nIn order to facilitate the formula derivation, a new auxiliary
\n $v = v_m \sin \psi_e$
\n $v = v_m \sin \psi_e$
\nTo ensure $V_1 \le 0$, *u* and *v* are considered as virtual vari-
\nbles and their desired values are designed as:
\n
$$
\begin{cases}\nu_e = \lambda_1 e_x + v_m \cos \psi_e \\
v_e = -\lambda_2 e_y + v_m \sin \psi_e\n\end{cases}
$$
\n
$$
= \begin{cases}\nu_e = \lambda_1 e_x + v_m \cos \psi_e \\
v_e = -\lambda_2 e_y + v_m \sin \psi_e\n\end{cases}
$$
\n
$$
= \begin{cases}\nu_e = \lambda_1 e_x + v_m \cos \psi_e \\
v_e = -\lambda_2 e_y + v_m \sin \psi_e\n\end{cases}
$$
\n
$$
= \begin{cases}\n\lambda_1 \sin \lambda_2 \sin \phi = 0 \\
\lambda_2 \sin \phi = 0\n\end{cases}
$$
\n
$$
= \begin{cases}\n\lambda_2 \sin \phi = 0 \\
\lambda_1 \sin \phi = 0\n\end{cases}
$$
\n
$$
= \begin{cases}\n\lambda_2 \sin \phi = 0 \\
\lambda_1 \sin \phi = 0\n\end{cases}
$$
\n
$$
= \begin{cases}\n\lambda_2 \sin \phi = 0 \\
\lambda_1 \sin \phi = 0\n\end{cases}
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\n
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= \begin{cases}\n\lambda_2 \sin \phi = 0 \\
\lambda_1 \sin \phi = 0\n\end{cases}
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= \begin{cases}\n\lambda_2 \sin \phi = 0 \\
\lambda_1 \sin \phi = 0\n\end{cases}
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= \begin{cases}\n\lambda_2 \sin \phi = 0 \\
\lambda_1 \sin \phi = 0\n\end{cases}
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\lambda_2 \sin \phi = 0\n\end{cases}
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$$
= \begin{cases}\n\lambda_2 \sin \phi = 0 \\
\lambda_1 \sin \phi = 0\n\end{cases}
$$
\n
$$
= \begin{cases}\n\lambda_2 \sin \phi = 0 \\
\lambda_2 \sin \phi = 0\n\end{cases}
$$
\n
$$
= \
$$

where $λ_1$ and $λ_2$ are positive constants.
Substituting Eq. (16) into Eq. (14) yields:

$$
\dot{V}_1 = -\lambda_1 e_x^2 - \lambda_2 e_y^2 \tag{17}
$$

In order to avoid the computational explosion, $u_c(t)$, $v_c(t)$

Find the total number of values are considered as follows:

\nto + ∑_n sin ψ,
$$
v = v_m sin ψ
$$
, and v_m are considered as it, $v_i = -\lambda_i e_i^2 - \lambda_i e_j^2 + e_k (e_n - e_n) + \zeta_n \zeta_n + \zeta_n \zeta_n$ (25) and the first term is given by the formula $v_i = -\lambda_i e_i + v_m cos \psi$, where λ_i and λ_3 are positive constants.

\nSubstituting Eq. (16) into Eq. (14) yields:

\nIn order to avoid the computational explosion, $u_i(t)$, $v_{i,1}$ to $v_{i,2}$ to $v_{i,1}$ to $v_{i,2}$ to $v_{i,1}$ to $v_{i,2}$ to <math display="</p>

where k_u , k_v and k_r are positive constants, which are selected later, and $u_{cf}(0) = u_c(0)$, $v_{cf}(0) = v_c(0)$, $r_{cf}(0) = r_c(0)$, $u_{cf}(t)$,

v_g(*t*) and $r_{g'}(t)$ denote the filtered signals.
 Step 2: The error variables are defined as:
 $e_u = u - u_{cf}$ $e_v = v - v_{cf}$ $\zeta_u = u_c - u_{cf}$ (19)

Then, Eq. (17) can be converted to the following equation: **Step 2:** The error variables are defined as: *u* **Technology 34 (2) 2020** *DOI 10.1007/s12206-020-0135-2***
** *(t)* **and** $r_g(t)$ **denote the filtered signals.

Step 2:** The error variables are defined as:
 $e_u = u - u_g$ $e_v = v - v_g$ $\zeta_u = u_c - u_g$ (19)
 Then, Eq. (17) can be co Thenhology 34 (2) 2020

DOI 10.1007/812206-020-0135-2
 $\int_{f}(t)$ and $r_g(t)$ denote the filtered signals.
 Step 2: The error variables are defined as:
 $e_u = u - u_{ef}$ $e_v = v - v_{ef}$ $\zeta_u = u_c - u_{ef}$ (19)

Then, Eq. (17) can be c

$$
e_{u} = u - u_{cf} \quad e_{v} = v - v_{cf} \quad \zeta_{u} = u_{c} - u_{cf} \tag{19}
$$

$$
\dot{V}_1 = -\lambda_1 e_x^2 - \lambda_2 e_y^2 - e_u e_x + e_v e_y + \zeta_u \dot{\zeta}_u \tag{20}
$$

Then, a new Lyapunov function can be defined as:

Technology 34 (2) 2020 DO1 10.1007/s12206-020-0135-2
\n(*t*) and
$$
r_{cf}(t)
$$
 denote the filtered signals.
\nStep 2: The error variables are defined as:
\n $e_u = u - u_{cf} \quad e_v = v - v_{cf} \quad \zeta_u = u_c - u_{cf}$ (19)
\nThen, Eq. (17) can be converted to the following equation:
\n $\dot{V}_1 = -\lambda_1 e_x^2 - \lambda_2 e_y^2 - e_u e_x + e_e e_y + \zeta_u \dot{\zeta}_u$ (20)
\nThen, a new Lyapunov function can be defined as:
\n
$$
V_2 = V_1 + \frac{1}{2} (e_u^2 + \zeta_u^2)
$$
 (21)
\nDifferentiating Eq. (21) along with Eq. (20) yields:
\n $\dot{V}_2 = \dot{V}_1 + e_u \dot{e}_u + \zeta_u \dot{\zeta}_u$ (22)

Technology 34 (2) 2020 DOI 10.1007/s12206-020-0135-2
\n
$$
f(t)
$$
 and $r_{cf}(t)$ denote the filtered signals.
\n**Step 2:** The error variables are defined as:
\n $e_u = u - u_{cf} - e_v = v - v_{cf} - \zeta_u = u_c - u_{cf}$ (19)
\nThen, Eq. (17) can be converted to the following equation:
\n $\vec{V}_1 = -\lambda_i e_x^2 - \lambda_2 e_y^2 - e_u e_x + e_i e_y + \zeta_u \dot{\zeta}_u$ (20)
\nThen, a new Lyapunov function can be defined as:
\n $V_2 = V_1 + \frac{1}{2} (e_u^2 + \zeta_u^2)$ (21)
\nDifferentiating Eq. (21) along with Eq. (20) yields:
\n $\vec{V}_2 = \vec{V}_1 + e_u \dot{e}_u + \zeta_u \dot{\zeta}_u$ (22)
\n $= -\lambda_i e_x^2 - \lambda_2 e_y^2 + e_u (\dot{e}_u - e_x) + e_v e_y + \zeta_u \dot{\zeta}_u$ (22)
\n**Step 3:** The error variables are define as:
\n $e_v = v - v_{cf} - \zeta_v = v_c - v_{cf}$ (23)
\nThen a new Lyapunov function can be defined as:
\n $V_3 = V_2 + \frac{1}{2} (e_v^2 + \zeta_v^2)$ (24)
\nDifferentiating Eq. (24) along with Eq. (22) yields:
\n $\vec{V}_3 = \vec{V}_2 + e_v \dot{e}_v + \zeta_v \dot{\zeta}_v$ (24)
\n $v_3 = \vec{V}_2 + e_v \dot{e}_v + \zeta_v \dot{\zeta}_v$

Step 3: The error variables are define as:

$$
e_{v} = v - v_{cf} \quad \zeta_{v} = v_c - v_{cf} \tag{23}
$$

Then a new Lyapunov function can be defined as:

$$
= -\lambda_1 e_x^2 - \lambda_2 e_y^2 + e_u (e_u - e_x) + e_v e_y + \zeta_u \zeta_u
$$
\n
$$
\text{Step 3: The error variables are define as:}
$$
\n
$$
e_v = v - v_{\text{cf}} \quad \zeta_v = v_c - v_{\text{cf}}
$$
\n
$$
e_v = v - v_{\text{cf}} \quad \zeta_v = v_c - v_{\text{cf}}
$$
\n
$$
e_v = v - v_{\text{cf}} \quad (23)
$$
\n
$$
\text{Then a new Lyapunov function can be defined as:}
$$
\n
$$
V_3 = V_2 + \frac{1}{2} (e_v^2 + \zeta_v^2)
$$
\n
$$
\text{Differentiating Eq. (24) along with Eq. (22) yields:}
$$

In order to avoid the computational explosion, () *^c u t* , () Differentiating Eq. (24) along with Eq. (22) yields: 3 2 2 2 1 2 () (cos () sin) = + + = - - + - + + - + + - & & & & & & & & & & *υ υ υ υ x y u u x u u ^υ ^υ ^υ m e d m e y c V V e e ^ζ ^ζ ^λ ^e ^λ e e e e ^ζ ^ζ ^ζ ^ζ e v ^ψ ^ψ r v ^ψ ^e ^υ* (25) cos + - = + + & *^m υy c c d m m e ^v ^λ e e ^υ v v ^ψ* 3 1 2 3 = - - - + + & & & *^V x y υu u ^υ ^υ ^λ ^e ^λ ^e ^λ ^e ^ζ ^ζ ^ζ ^ζ* (27) *^r* = - = - *cf r c cf e r r ^ζ r r* (28)

To ensure $\dot{V}_3 \leq 0$, the following desired signals are selected:

To ensure
$$
\vec{V}_3 \le 0
$$
, the following desired signals are selected:
\n
$$
r_c = \dot{\psi}_d + \frac{\dot{v}_m}{v_m} + \frac{\lambda_3 e_v + e_y - \dot{v}_c}{v_m \cos \psi_e}
$$
\n(26)
\nhere λ_4 is a positive constant.
\nSubstituting Eq. (26) into Eq. (25) yields:
\n
$$
\vec{V}_3 = -\lambda_1 e_x^2 - \lambda_2 e_y^2 - \lambda_3 e_v^2 + \zeta_u \dot{\zeta}_u + \zeta_v \dot{\zeta}_v
$$
\n(27)
\n**Step 4:** The error variables are defined as:
\n $e_r = r - r_{cf} \zeta_r = r_c - r_{cf}$
\nThen, a new Lyapunov function can be defined as:
\n
$$
V_4 = V_3 + \frac{1}{2} (e_r^2 + \zeta_r^2)
$$
\n(29)

where λ_4 is a positive constant.
Substituting Eq. (26) into Eq. (25) yields:

$$
\dot{V}_3 = -\lambda_1 e_x^2 - \lambda_2 e_y^2 - \lambda_3 e_v^2 + \zeta_u \dot{\zeta}_u + \zeta_v \dot{\zeta}_v
$$
 (27)

Step 4: The error variables are defined as:

$$
e_r = r - r_{cf} \quad \zeta_r = r_c - r_{cf} \tag{28}
$$

Then, a new Lyapunov function can be defined as:

$$
\dot{V}_3 = -\lambda_1 e_x^2 - \lambda_2 e_y^2 - \lambda_3 e_v^2 + \zeta_u \dot{\zeta}_u + \zeta_v \dot{\zeta}_v
$$
 (27)
\n**Step 4:** The error variables are defined as:
\n
$$
e_r = r - r_{cf} \zeta_r = r_c - r_{cf}
$$
 (28)
\nThen, a new Lyapunov function can be defined as:
\n
$$
V_4 = V_3 + \frac{1}{2} (e_r^2 + \zeta_r^2)
$$
 (29)

Fig. 3. The block diagram of the proposed method.

Differentiating Eq. (29) along with Eq. (27) yields:

$$
\dot{V}_4 = \dot{V}_3 + e_r \dot{e}_r + \zeta_r \dot{\zeta}_r
$$
\n
$$
= -\lambda_t e_x^2 - \lambda_2 e_y^2 - \lambda_3 e_v^2 + \zeta_u \dot{\zeta}_u + \zeta_v \dot{\zeta}_v + \zeta_r \dot{\zeta}_r
$$
\n
$$
+ e_u (e_u - e_x) + e_r (e_r - e_v v_m \cos \psi_e)
$$
\n
$$
\hat{\sigma}_u
$$
\n**Step 5:** The RBF neural network is used to approximate the unknown function. The unknown functions of underactuated ASVs are expressed as follows:\n
$$
\kappa_1 = m_{22}vr - X_u u - X_{u|u|} u | + m_{11} \dot{u}_{cf}
$$
\n
$$
\kappa_3 = (m_{11} - m_{22})uv - N_r r - N_{r|r|} r |r| + m_{33} \dot{r}_{cf}
$$
\n(31)

Step 5: The RBF neural network is used to approximate the unknown function. The unknown functions of underactuated

$$
\begin{aligned} \kappa_1 &= m_{22}vr - X_u u - X_{u|u|}u \, |u| + m_{11} \dot{u}_{cf} \\ \kappa_3 &= (m_{11} - m_{22})uv - N_r r - N_{r|r|}r \, |r| + m_{33} \dot{r}_{cf} \end{aligned} \tag{31}
$$

The prediction error between the system state and the serial parallel estimation model [34] is considered to improve the tracking performance of the underactuated ASV. The state **Example 20** $V_x = V_y + e, \hat{e}, + \zeta, \hat{c},$
 $V_x = \lambda_i e_i^2 - \lambda_i e_i^2 + \zeta, \hat{c}, + \zeta, \hat{c}, + \zeta, \hat{c},$
 $= -\lambda_i e_i^2 - \lambda_i e_i^2 + \zeta, \hat{c}, + \zeta, \hat{c}, + \zeta, \hat{c},$
 Step 5: The RBF neural network is used to approximate the $\hat{\sigma}_x = \rho_1 |e_x| -$

$$
\dot{z}_1 = \kappa_1 - \hat{\kappa}_1 \quad \dot{z}_3 = \kappa_3 - \hat{\kappa}_3 \tag{32}
$$

Step 5: The RBF neural network is used to approximate the unknown function. The unknown functions of underactuated
$$
\hat{\sigma}_{\tau} = \rho_s |e_{\tau} - \rho_s \theta_s (\hat{\sigma}_{\tau} - \sigma_{\sigma_0})
$$
 unknown function. The unknown functions of underactuated
\nANSYs are expressed as follows:
\n $\kappa_1 = m_{21} \nu r - X_{\mu} \nu + \nu_{\mu} \nu + m_{\mu} \nu_{\sigma}$
\n $\kappa_2 = (m_{11} - m_{22}) \mu \nu - N_{\tau} r - N_{\tau} \mu^2 |u| + m_{\tau} \mu_{\sigma}$
\n $\kappa_3 = (m_{11} - m_{22}) \mu \nu - N_{\tau} r - N_{\tau} \mu^2 |v| + m_{\tau} \nu_{\sigma}$
\n $\kappa_4 = m_{21} \nu r - \lambda_{\mu} \nu + \nu_{\tau} \mu_{\tau} \nu_{\sigma}$
\n $\kappa_5 = (m_{11} - m_{22}) \mu \nu - N_{\tau} r - N_{\tau} \mu^2 |r| + m_{\tau} \nu_{\sigma}$
\n $\kappa_6 = (33)$ into Eq. (4) yields:
\n $\kappa_7 = (m_{11} - m_{22}) \mu \nu - N_{\tau} r - N_{\tau} \mu^2 |r| + m_{\tau} \nu_{\sigma}$
\n $\kappa_8 = (34)$
\nand the setial
\nestabilistic motion and 134 is considered to improve the
\nproduced in the general
\nand the setial
\n $\sigma_{\tau} = -m_{11} (\alpha_{\tau} e_{\tau} + e_{\tau}) + \gamma_{\tau} \nu_{\tau} \nu_{\tau} \nu + \gamma_{\tau} \nu_{\tau} \nu_{\tau} \nu_{\tau} \nu + \gamma_{\tau} \nu_{\tau} \nu_{\$

where $\alpha_{\text{\tiny{l}}}$, $\mu_{\text{\tiny{l}}}$, $\gamma_{\text{\tiny{u}}}$, $\alpha_{\text{\tiny{3}}}$, $\mu_{\text{\tiny{3}}}$, $\gamma_{\text{\tiny{r}}}$ are positive constants.

The prediction errors are used to construct the learning de-

$$
\hat{\mathbf{w}}_1 = -m_{33}(a_3e_r + e_b v_m \cos \varphi_e) +
$$
\n
$$
\hat{\mathbf{w}}_3 \mathbf{h}(\mathbf{x}_r) + \mu_3 z_3 - \hat{\sigma}_r \tanh(v \hat{\sigma}_r e_r / \gamma_r)
$$
\nFig. 3

\ntrace $\alpha_1, \mu_1, \gamma_u, \alpha_3, \mu_3, \gamma_r$ are positive constants.

\nThe prediction errors are used to construct the learning de-
\n $\mathbf{g}_1 \mathbf{h}$, so the NN updating law are selected as:

\n
$$
\hat{\mathbf{w}}_1 = \beta_1 \left[(e_u + \delta_1 z_1) \mathbf{h}(\mathbf{x}_u) - \chi_1 \hat{\mathbf{w}}_1 \right]
$$
\nIn this

\n
$$
\hat{\mathbf{w}}_3 = \beta_3 \left[(e_r + \delta_3 z_3) \mathbf{h}(\mathbf{x}_r) - \chi_3 \hat{\mathbf{w}}_3 \right]
$$
\n(34)

\nProve that

\n
$$
\hat{\mathbf{w}}_3 = \beta_3 \left[(e_r + \delta_3 z_3) \mathbf{h}(\mathbf{x}_r) - \chi_3 \hat{\mathbf{w}}_3 \right]
$$

where β_1 , δ_1 , χ_1 , β_3 , δ_3 , χ_3 are positive constants.

The sliding mode control is combined with adaptive techniques to compensate the nonlinear external disturbances. The adaptive laws are selected as: $\begin{aligned}\n\frac{\partial}{\partial_1} \frac{\partial}{\partial_2} \frac{\partial}{\partial_3} \frac{\partial}{\partial_3} \frac{\partial}{\partial_3} \frac{\partial}{\partial_3} \frac{\partial}{\partial_3} x_3\n\end{aligned}$ are positive constants.

iding mode control is combined with adaptive tectom

becompensate the nonlinear external disturbances. T

la *u u u* β_1 *,* δ_1 *,* χ_1 *,* β_3 *,* δ_3 *,* χ_3 *are positive constants.

<i>ue* sliding mode control is combined with adaptive tech-
 u = *p*₁ $|e_u| - \rho_1 \theta_1 (\hat{\sigma}_u - \sigma_{u_0})$
 $\gamma = \rho_3 |e_r| - \rho_3 \theta_3 (\hat{\sigma}_r - \sigma_{r_0$ *r r <i>e f*₁, *δ*₁, *x*₁, *f*₃, *δ*₃, *x*₃ are positive constants.
 **Fhe sliding mode control is combined with adaptive tech-

r** *i n s s c c n n n <i>s i <i>s*

$$
\dot{\hat{\sigma}}_u = \rho_1 |e_u| - \rho_1 \mathcal{G}(\hat{\sigma}_u - \sigma_{u0})
$$

\n
$$
\dot{\hat{\sigma}}_r = \rho_3 |e_r| - \rho_3 \mathcal{G}_3(\hat{\sigma}_r - \sigma_{r0})
$$
\n(35)

where $\rho_{_{1}}$, $\theta_{_{1}}$, $\sigma_{_{u0}}$, $\rho_{_{3}}$, $\theta_{_{3}}$, $\sigma_{_{r0}}$ are positive constants. Substituting Eq. (33) into Eq. (4) yields:

here
$$
\beta_1
$$
, δ_1 , χ_1 , β_3 , δ_3 , χ_3 are positive constants.
\nThe sliding mode control is combined with adaptive techniques to compensate the nonlinear external disturbances. The
\nlaptive laws are selected as:
\n
$$
\dot{\hat{\sigma}}_u = \rho_1 |e_u| - \rho_1 \mathcal{A}(\hat{\sigma}_u - \sigma_{u0})
$$
\n
$$
\dot{\hat{\sigma}}_v = \rho_3 |e_v| - \rho_3 \mathcal{A}(\hat{\sigma}_v - \sigma_{v0})
$$
\n(35)
\n
$$
\dot{\hat{\sigma}}_v = \rho_1 |e_u| - \rho_1 \mathcal{A}(\hat{\sigma}_u - \sigma_{u0})
$$
\n(36)
\nhere ρ_1 , \mathcal{A}_1 , σ_{u0} , ρ_3 , \mathcal{A}_3 , σ_{v0} are positive constants.
\nSubstituting Eq. (33) into Eq. (4) yields:
\n
$$
m_{11} \dot{e}_u = -m_{11} (\alpha_i e_u + e_x) + \hat{W}_1 h(x_u) + \mu_1 z_1 - \kappa_1 + \tau_{\alpha} - \hat{\sigma}_u \tanh(\hat{\sigma}_u e_u / \gamma_u)
$$
\n
$$
m_{33} \dot{e}_v = -m_{33} (\alpha_s e_v + e_v w_m \cos \psi_v) + \hat{W}_3 h(x_v) + \mu_2 z_3 - \kappa_3 + \tau_{\alpha} - \hat{\sigma}_v \tanh(\hat{\sigma}_v e_v / \gamma_v)
$$
\n(36)
\nwhere γ_u , γ , are positive constants.
\nSubstituting Eq. (36) into Eq. (30) yields:
\n
$$
\dot{V}_4 = -\lambda_t e_x^2 - \lambda_2 e_y^2 - \lambda_3 e_v^2 - \alpha_t e_u^2 - \alpha_5 e_v^2 + \zeta_u \dot{\zeta}_u + \zeta_v \dot{\zeta}_v + \zeta_v \dot{\zeta}_v
$$
\n
$$
-e_u \vec{W}_1 h(x_u) - e_u \hat{\sigma}_u \tanh(\hat{\sigma}_u e_u / \gamma_u) - e_u (\tau_{\alpha} + \varepsilon_u)
$$
\n(37)
\n
$$
-e_u \vec{
$$

where *γ_{<i>v*}</sub>, *γ_{<i>r*} are positive constants.

$$
\dot{V}_4 = -\lambda_i e_x^2 - \lambda_2 e_y^2 - \lambda_3 e_v^2 - \alpha_i e_u^2 - \alpha_5 e_r^2 + \zeta_u \dot{\zeta}_u + \zeta_v \dot{\zeta}_v + \zeta_v \dot{\zeta}_r
$$

\n
$$
-e_u \widetilde{\mathbf{W}}_1 \mathbf{h}(\mathbf{x}_u) - e_u \hat{\sigma}_u \tanh(v \hat{\sigma}_u e_u / \gamma_u) - e_u (\tau_{eu} + \varepsilon_u)
$$
(37)
\n
$$
-e_r \widetilde{\mathbf{W}}_3 \mathbf{h}(\mathbf{x}_r) - e_r \hat{\sigma}_r \tanh(v \hat{\sigma}_r e_r / \gamma_r) - e_r (\tau_{ev} + \varepsilon_r)
$$

Fig. 3 provides the block diagram of the designed position tracking control scheme for an underactuated ASV.

4. Stability analysis of the overall control system

(34) prove the stability of the closed-loop control system. In this section, the Lyapunov stability theory is employed to

A new Lyapunov function is defined as the following:

Journal of Mechanical Science and Technology 34 (2) 2020 DOI 10.1007/s12206-
\n
$$
V_s = V_4 + \frac{1}{2m_{11}\beta_1}\tilde{\mathbf{W}}_1^T\tilde{\mathbf{W}}_1 + \frac{1}{2m_{33}\beta_3}\tilde{\mathbf{W}}_3^T\tilde{\mathbf{W}}_3 + \frac{1}{2}\delta_1z_1^2 + \frac{1}{2}\delta_3z_3^2
$$
\nThen, the following equations are obtained:
\n
$$
\frac{1}{2m_{11}\rho_1}\tilde{\sigma}_u^2 + \frac{1}{2m_{33}\rho_3}\tilde{\sigma}_y^2
$$
\nDifferentiating Eq. (38) yields:
\n
$$
\mathbf{\tilde{W}}_1^T\mathbf{W}_1^* - \tilde{\mathbf{W}}_1^T\mathbf{W}_1 = -\left\|\tilde{\mathbf{W}}_1 - \frac{\mathbf{W}_1^*}{2}\right\|^2 + \frac{1}{4}\left\|\mathbf{W}_1^*\right\|^2
$$
\n
$$
\tilde{\mathbf{W}}_3^T\mathbf{W}_3^* - \tilde{\mathbf{W}}_3^T\mathbf{W}_3 = -\left\|\tilde{\mathbf{W}}_3 - \frac{\mathbf{W}_3^*}{2}\right\|^2 + \frac{1}{4}\left\|\mathbf{W}_3^*\right\|^2
$$
\nDifferentiating Eq. (38) yields:
\n
$$
\mathbf{\tilde{V}}_5 = \mathbf{\tilde{V}}_4 - \frac{\tilde{\mathbf{W}}_1^T\dot{\mathbf{W}}_1}{\beta_1} - \frac{\tilde{\mathbf{W}}_3^T\dot{\mathbf{W}}_3}{\beta_3} - \delta_1z_1\dot{z}_1 - \delta_3z_3\dot{z}_3 - \frac{\tilde{\sigma}_u\dot{\tilde{\sigma}}_u}{\rho_1} - \frac{\tilde{\sigma}_r\dot{\tilde{\sigma}}_r}{\rho_3}
$$
\n(39) Substituting Eqs. (44) and (45) into Eq. (43) yields:
\n
$$
\mathbf{\tilde{V}}_5 = -\lambda_1e_x^2 - \lambda_2e_y^2 - \lambda_3e_u^2 - \lambda_4e_v^2 + \zeta_u\dot{\zeta}_u + \zeta_v\dot{\zeta}_v + \zeta_v
$$

Differentiating Eq. (38) yields:
\n
$$
\tilde{W}_{3}^{T} \hat{W}_{1} = \frac{\tilde{W}_{1}^{T} \hat{W}_{1}}{\beta_{1}} - \frac{\tilde{W}_{3}^{T} \hat{W}_{3}}{\beta_{3}} - \delta_{1} z_{1} \dot{z}_{1} - \delta_{3} z_{3} \dot{z}_{3} - \frac{\tilde{\sigma}_{u} \dot{\hat{\sigma}}_{u}}{\rho_{1}} - \frac{\tilde{\sigma}_{r} \dot{\hat{\sigma}}_{r}}{\rho_{3}}
$$
 (39) Substitute
\nThe state prediction errors can be expressed as:
\n
$$
\dot{V}_{3} = -\dot{z}_{1} = \kappa_{1} - \hat{\kappa}_{1} = \tilde{W}_{1} \mathbf{h}(\mathbf{x}_{u}) + \varepsilon_{u} - \delta_{1} z_{1}
$$
 (40)
\n
$$
\dot{z}_{3} = \kappa_{3} - \hat{\kappa}_{3} = \tilde{W}_{3} \mathbf{h}(\mathbf{x}_{r}) + \varepsilon_{r} - \delta_{3} z_{3}
$$
 (40)
\nThen, the correlations can be obtained as:

$$
\dot{z}_1 = \kappa_1 - \hat{\kappa}_1 = \tilde{\mathbf{W}}_1 \mathbf{h}(\mathbf{x}_u) + \varepsilon_u - \delta_1 z_1
$$

\n
$$
\dot{z}_3 = \kappa_3 - \hat{\kappa}_3 = \tilde{\mathbf{W}}_3 \mathbf{h}(\mathbf{x}_r) + \varepsilon_r - \delta_3 z_3
$$
\n(40)

Then, the correlations can be obtained as:

The state prediction errors can be expressed as:
\n
$$
\dot{z}_1 = \kappa_1 - \hat{\kappa}_1 = \tilde{W}_1 h(x_u) + \varepsilon_u - \delta_1 z_1
$$
\n
$$
\dot{z}_3 = \kappa_3 - \hat{\kappa}_3 = \tilde{W}_3 h(x_r) + \varepsilon_r - \delta_3 z_3
$$
\nThen, the correlations can be obtained as:
\n
$$
z_1 \dot{z}_1 = z_1 \tilde{W}_1 h(x_u) + z_1 \varepsilon_u - \delta_1 z_1^2
$$
\n
$$
z_3 \dot{z}_3 = z_3 \tilde{W}_3 h(x_r) + z_3 \varepsilon_r - \delta_3 z_3^2
$$
\nSubstituting Eqs. (34). (37) and (41) into Eq. (39) yields:

$$
\vec{v}_z = \vec{V}_s - \frac{\vec{W}_s^T \vec{W}_s}{\beta_1} - \frac{\vec{W}_s^T \vec{W}_s}{\beta_1} - \frac{\vec{W}_s^T \vec{W}_s}{\beta_1} - \frac{\vec{b}_s^T \vec{v}_s}{\beta_1} - \frac{\vec{b}_s^T
$$

Moreover, substituting Eq. (35) into Eq. (42) yields:

+
$$
\delta_1 z_3 \tilde{\mathbf{W}}_3 \mathbf{h}(\mathbf{x}_r) + \delta_2 z_3 c_3 - \delta_3 z_3^2
$$

\n $-\frac{\tilde{\sigma}_u \hat{\sigma}_u}{\rho_1} - \frac{\tilde{\sigma}_v \hat{\sigma}_r}{\rho_3}$
\nMoreover, substituting Eq. (35) into Eq. (42) yields:
\n $\vec{v}_s = -\lambda_t e_s^2 - \lambda_z e_v^2 - \lambda_z e_v^2 - \lambda_x e_v^2 + \varepsilon_u \dot{\varepsilon}_u + \varepsilon_v \dot{\varepsilon}_v + \varepsilon_v \dot{\varepsilon}_v$
\n $- e_u \hat{\sigma}_u \tanh(\hat{v} \hat{\sigma}_u e_u / \gamma_u) - e_u (\tau_{\alpha} + \varepsilon_u)$
\n $e_v \hat{\sigma}_r \tanh(\hat{v} \hat{\sigma}_v e_v / \gamma_v) - e_v (\tau_{\alpha} + \varepsilon_u)$
\n $- \tilde{\sigma}_v \hat{\sigma}_r \tanh(\hat{v} \hat{\sigma}_v e_v / \gamma_v) - e_v (\tau_{\alpha} + \varepsilon_v)$
\n $+ \delta_1 z_1 \varepsilon_1 - \delta_1 z_1^2 + \delta_2 z_3 \varepsilon_3 - \delta_3 z_3^2$
\n $- \tilde{\sigma}_1 |e_u| + \tilde{\sigma}_u (\hat{\sigma}_u - \sigma_{u_0}) - \tilde{\sigma}_r |e_r| + \tilde{\sigma}_r (\hat{\sigma}_r - \sigma_{r_0})$
\nBased on Eq. (43), the following correlations can be ob-
\n $\vec{\sigma}_u (\hat{\sigma}_u - \sigma_{u_0}) \le -q \eta_1 |\hat{\sigma}_x|^2 + \eta_2 |\sigma_u - \sigma_{u_0}|^2$
\n $z_i \varepsilon_u - \mu_1 z_i^2 = -\mu_1 (z_i - \frac{\varepsilon_u}{2\mu_3})^2 + \frac{1}{4\mu_1} \varepsilon_u^2$
\n $z_i \varepsilon_v - \mu_2 z_i^2 = -\mu_3 (z_3 - \frac{\varepsilon_v}{2\mu_3})^2 + \frac{1}{4\mu_1} \varepsilon_u^2$
\n(44)
\n $z_i \varepsilon_v - \mu_3 z_i^$

Based on Eq. (43), the following correlations can be obtained:

$$
e_{u}\tilde{\mathbf{W}}_{1}\mathbf{h}(\mathbf{x}_{u}) + \chi_{1}\tilde{\mathbf{W}}_{1}^{T}\hat{\mathbf{W}}_{1} + e_{r}\tilde{\mathbf{W}}_{3}\mathbf{h}(\mathbf{x}_{r}) + \chi_{3}\tilde{\mathbf{W}}_{3}^{T}\hat{\mathbf{W}}_{3}
$$
\n
$$
+ \delta_{1}z_{1}\varepsilon_{1} - \delta_{1}z_{1}^{2} + \delta_{3}z_{3}\varepsilon_{3} - \delta_{3}z_{3}^{2}
$$
\n
$$
- \tilde{\sigma}_{1}|e_{u}| + \tilde{\sigma}_{u}(\hat{\sigma}_{u} - \sigma_{u0}) - \tilde{\sigma}_{r}|e_{r}| + \tilde{\sigma}_{r}(\hat{\sigma}_{r} - \sigma_{r0})
$$
\nBased on Eq. (43), the following correlations can be obtained:

\n
$$
z_{1}\varepsilon_{u} - \mu_{1}z_{1}^{2} = -\mu_{1}\left(z_{1} - \frac{\varepsilon_{u}}{2\mu_{1}}\right)^{2} + \frac{1}{4\mu_{1}}\varepsilon_{u}^{2}
$$
\n
$$
z_{3}\varepsilon_{r} - \mu_{3}z_{r}^{2} = -\mu_{3}\left(z_{3} - \frac{\varepsilon_{r}}{2\mu_{3}}\right)^{2} + \frac{1}{4\mu_{3}}\varepsilon_{r}^{2}
$$
\n(44)

\n
$$
z_{3}\varepsilon_{r} - \mu_{3}z_{r}^{2} = -\mu_{3}\left(z_{3} - \frac{\varepsilon_{r}}{2\mu_{3}}\right)^{2} + \frac{1}{4\mu_{3}}\varepsilon_{r}^{2}
$$
\nwhere

\nSubs

 $\frac{1}{2}$, $\frac{1}{2}$, $\frac{2}{2}$ Then, the following equations are obtained:

Journal of Mechanical Science and Technology 34 (2) 2020 DOI 10.1007/s12206-020-0135-2
\n
$$
V_s = V_4 + \frac{1}{2m_{11}\beta_1} \tilde{W}_1^T \tilde{W}_1 + \frac{1}{2m_{33}\beta_3} \tilde{W}_3^T \tilde{W}_3 + \frac{1}{2} \delta_1 z_1^2 + \frac{1}{2} \delta_3 z_3^2
$$
\nThen, the following equations are obtained:
\n
$$
\frac{1}{2m_{11}\beta_1} \tilde{\sigma}_4^2 + \frac{1}{2m_{33}\beta_3} \tilde{\sigma}_3^2
$$
\nDifferentiating Eq. (38) yields:
\n
$$
\tilde{W}_1^T W_1^* - \tilde{W}_1^T W_1 = -\left\| \tilde{W}_1 - \frac{W_1^*}{2} \right\|^2 + \frac{1}{4} \left\| W_1^* \right\|^2
$$
\n
$$
\tilde{W}_3^T W_3^* - \tilde{W}_3^T W_3 = -\left\| \tilde{W}_3 - \frac{W_2^*}{2} \right\|^2 + \frac{1}{4} \left\| W_3^* \right\|^2
$$
\n(45)
\n
$$
\tilde{V}_s = \tilde{V}_4 - \frac{\tilde{W}_1^T \dot{\hat{W}}_1}{\beta_1} - \frac{\tilde{W}_3^T \dot{\hat{W}}_3}{\beta_3} - \delta_1 z_1 z_1 - \delta_3 z_3 z_3 - \frac{\tilde{\sigma}_0 \dot{\hat{\sigma}}_0}{\rho_1} - \frac{\tilde{\sigma}_1 \dot{\hat{\sigma}}_0}{\rho_2}
$$
\n(39)
\nSubstituting Eqs. (44) and (45) into Eq. (43) yields:
\n
$$
\tilde{V}_s = -\lambda_1 e_s^2 - \lambda_2 e_s^2 - \lambda_3 e_s^2 - \lambda_4 e_s^2 + \zeta_s \dot{\zeta}_s + \zeta_s \dot{\zeta}_s + \zeta_s \dot{\zeta}_s
$$
\n
$$
= e_s \tilde{\sigma}_u \tanh(\tilde{w}_0 e_u / \gamma_u) - e_s (\tau_{av} + \epsilon_u)
$$
\n
$$
\dot{z}_1 = \kappa_1 -
$$

Substituting Eqs. (44) and (45) into Eq. (43) yields:

Journal of Mechanical Science and Technology 34 (2) 2020 Do1 10.1007/812206-020.0135-2
\n
$$
V_3 = V_4 + \frac{1}{2m_1R_1}\hat{W}_1^T\hat{W}_1 + \frac{1}{2m_1R_2}\hat{W}_1^T\hat{W}_3 + \frac{1}{2}\partial z_1^2 + \frac{1}{2}\partial z_2^2
$$
\nThen, the following equations are obtained:
\n
$$
\frac{1}{2m_1R_1}\hat{d}_1^T + \frac{1}{2m_1R_2}\hat{d}_2^T
$$
\n
$$
\hat{W}_1^T\hat{W}_1 = -\hat{W}_1^T - \hat{W}_1^T\hat{W}_1 = -\left|\hat{W}_1 - \frac{W_1^T}{2}\right|^2 + \frac{1}{4}\left|W_1^T\right|^2
$$
\n(45)
\nDifferentiating Eq. (38) yields:
\n
$$
\hat{W}_1^T\hat{W}_1^T - \hat{W}_1^T\hat{W}_2 = -\frac{\hat{W}_1^T\hat{W}_1^T}{\beta_1} - \frac{\hat{W}_1^T\hat{W}_2^T}{\beta_2} - \frac{\hat{\sigma}_1\hat{\sigma}_2}{\beta_1} - \frac{\hat{\sigma}_1\hat{\sigma}_2}{\beta_1} - \frac{\hat{\sigma}_1\hat{\sigma}_2}{\beta_1} - \frac{\hat{\sigma}_1\hat{\sigma}_2}{\beta_1}
$$
\nSubstituting Eqs. (44) and (45) into Eq. (43) yields:
\n
$$
\hat{V}_1 = -\lambda e^2 - \lambda e^2 - \lambda e^2 + \zeta_1 \hat{\omega}_1 + \zeta_2 \hat{\omega}_2 + \zeta_1 \hat{\
$$

Lemma 1. The relation $h|x| \le xh \tanh(vhx / \mu_i)$ ensures that for any $\mu_i > 0$ and for any $\forall x \in R, h \in R$, v satisfies $v = e^{-(v+1)}$, **i 1.** The relation $h|x| \le xh \tanh(vhx / \mu_i)$ ensures that
any $\mu_i > 0$ and for any $\forall x \in R, h \in R$, v satisfies $v = e^{-(v+1)}$,
 $v = 0.2785$ [20].
coording to lemma 1, the following inequality can be ob-
ed:
 $\int_{u} |e_u| \le e_u \hat{\sigma}_u \t$ $-\delta_3 \left| \mu_3 \left(z_3 - \frac{\varepsilon}{2\mu_3} \right)^2 - \frac{1}{4\mu_3} \varepsilon_r^2 \right|$
 ma 1. The relation $h|x| \le xh \tanh(vhx / \mu_r)$ ensures that
 $\mu \mu_r > 0$ and for any $\forall x \in R, h \in R$, v satisfies $v = e^{-(v+1)}$,
 $= 0.2785$ [20].
 \therefore
 $\left| \frac{\varepsilon}{2\mu$ **and 1.** The relation $h|x| \le xh \tanh(vhx/\mu_r)$ ensures that
 $\mu_r > 0$ and for any $\forall x \in R, h \in R$, v satisfies $v = e^{-(v+1)}$,
 $= 0.2785$ [20].
 $= 0.2785$ [20].
 \therefore
 \therefore $\mu_r \le \frac{e_0}{e_0}$, $\tanh(v\partial_x e_n / \gamma_n) + \mu_s$
 $\therefore \mu_r \le \frac{e$

 $\mathbf{\tilde{W}}_h(\mathbf{x}_r) + \delta_1 z_1 \varepsilon_1 - \delta_2 z_1^2$ (According to lemma 1, the following inequality can be obtained:

$$
\hat{\sigma}_{u} |e_{u}| \le e_{u} \hat{\sigma}_{u} \tanh(v \hat{\sigma}_{u} e_{u} / \gamma_{u}) + \mu_{u}
$$
\n
$$
\hat{\sigma}_{r} |e_{r}| \le e_{r} \hat{\sigma}_{r} \tanh(v \hat{\sigma}_{r} e_{r} / \gamma_{r}) + \mu_{r}
$$
\n(47)

According to assumptions 1 and 2, the external disturbances and the approximation errors are bounded. It is assumed that:

$$
\hat{\sigma}_{u} |e_{u}| \leq e_{u} \hat{\sigma}_{u} \tanh(v \hat{\sigma}_{u} e_{u} / \gamma_{u}) + \mu_{u}
$$
\n
$$
\hat{\sigma}_{r} |e_{r}| \leq e_{r} \hat{\sigma}_{r} \tanh(v \hat{\sigma}_{r} e_{r} / \gamma_{r}) + \mu_{r}
$$
\nAccording to assumptions 1 and 2, the external disturbances
\nd the approximation errors are bounded. It is assumed that:
\n
$$
|\tau_{eu} + \varepsilon_{u}| \leq \sigma_{u}
$$
\n
$$
|\tau_{ev} + \varepsilon_{r}| \leq \sigma_{r}
$$
\n(48)\nAccording to Shojae's study [35], it is obtained as:

According to Shojaei's study [35], it is obtained as:

According to lemma 1, the following inequality can be ob-
\nincording to lemma 1, the following inequality can be ob-
\n
$$
\hat{\sigma}_{\mu} |e_{\mu}| \leq e_{\mu} \hat{\sigma}_{\mu} \tanh(v \hat{\sigma}_{\mu} e_{\mu} / \gamma_{\mu}) + \mu_{\mu}
$$
\n
$$
\hat{\sigma}_{\mu} |e_{\mu}| \leq e_{\mu} \hat{\sigma}_{\mu} \tanh(v \hat{\sigma}_{\mu} e_{\mu} / \gamma_{\mu}) + \mu_{\mu}
$$
\nAccording to assumptions 1 and 2, the external disturbances
\nand the approximation errors are bounded. It is assumed that:
\n
$$
|z_{\alpha\mu} + \varepsilon_{\mu}| \leq \sigma_{\mu}
$$
\n(48)
\n
$$
|z_{\alpha\mu} + \varepsilon_{\mu}| \leq \sigma_{\mu}
$$
\nAccording to Shojaei's study [35], it is obtained as:
\n
$$
\tilde{\sigma}_{\mu} (\hat{\sigma}_{\mu} - \sigma_{\mu 0}) \leq -q_1 |\tilde{\sigma}_{\mu}^2| + q_2 |\sigma_{\mu} - \sigma_{\mu 0}|^2
$$
\n
$$
\tilde{\sigma}_{\mu} (\hat{\sigma}_{\mu} - \sigma_{\mu 0}) \leq -q_1 |\tilde{\sigma}_{\mu}^2| + q_2 |\sigma_{\mu} - \sigma_{\mu 0}|^2
$$
\n(49)
\n
$$
\tilde{\sigma}_{\mu} (\hat{\sigma}_{\mu} - \sigma_{\mu 0}) \leq -q_1 |\tilde{\sigma}_{\mu}^2| + q_2 |\sigma_{\mu} - \sigma_{\mu 0}|^2
$$
\n(49)
\nwhere $q_1 = 1 - 0.5 / l^2$, $q_2 = 0.5 / l^2$ and $l > \sqrt{2} / 2$.
\nSubstituting Eqs. (47), (48) and (49) into Eq. (47) yields:
\n
$$
\tilde{\sigma}_{\mu} (\tilde{\sigma}_{\mu} - \tilde{\sigma}_{\mu} - \tilde{\sigma}_{\mu
$$

 $\frac{1}{2} \varepsilon^2$ where $q_1 = 1 - 0.5 / \ell^2$, $q_2 = 0.5 / \ell^2$ and ℓ

2 2 2 2 5 1 2 3 4 ² ² min min 1 ³ 1 3 2 2 ¹ ³ min 1 ³ 2 2 1 1 3 3 max ² max ² min 2 2 1 1 0 3 3 ⁰ 2 2 2 2 2 2 *x y u ^υ u u ^υ ^υ r r ^u ^r u r M M u u r r V λ e λ e λ e λ e ζ ζ ζ ζ ζ ζ ^ε ^ε ^δ ^μ ^z ^z ^μ ^μ χ q σ q σ δ χ ε W μ q σ σ q σ σ* * * £ - - - - + + + ^é ^ù æ ö æ ö - ^ê - + - ^ú ç ÷ ç ÷ êè ø è ø ^ú ë û é ù - - + - ^ê ^ú ^ë ^û - - + + + - + - **W W** & & & & % % J J % % ^J ^J (50) / / / / / / *u cf c u u c ^υ cf c ^υ ^υ ^c r cf c r r c ^ζ u u ^ζ k du dt ^ζ ^υ ^υ ^ζ k dυ dt ^ζ r r ^ζ k dr dt* = - = - + = - = - + = - = - + & & & & & & *^c* / , / , / £ *u c* £ £ *^υ ^c ^r du dt d* ^v ^v ^v *υdt dr dt* (52)

Differentiating Eqs. (19),(20) and (25) yields:

$$
\dot{\zeta}_u = \dot{u}_{\zeta} - \dot{u}_c = -\zeta_u / k_u + du_c / dt
$$
\n
$$
\dot{\zeta}_v = \dot{v}_{\zeta} - \dot{v}_c = -\zeta_v / k_v + dv_c / dt
$$
\n
$$
\dot{\zeta}_r = \dot{r}_{\zeta} - \dot{r}_{\zeta} = -\zeta_r / k_r + dr_c / dt
$$
\n(51)

According to Shojaei's study [35], it is obtained as

$$
\left| du_c / dt \right| \le \varpi_u, \left| dv_c / dt \right| \le \varpi_v, \left| dr_c / dt \right| \le \varpi_r \tag{52}
$$

where ϖ_{u} , ϖ_{v} , ϖ_{r} are positive constants. Substituting Eq. (52) into Eq. (51) yields:

According to Shojaei's study [35], it is obtained as	In summary, trol system are sluts. The pc neighbourhood	
$ du_c/dt \le \varpi_u, \varpi_u \le \varpi_v, \varpi_u \le \varpi_v$	(52)	
$\text{here } \varpi_u, \varpi_v, \varpi_r \text{ are positive constants.}$	(52)	
$\zeta_u \dot{\zeta}_u \le -\zeta_u^2 / k_u + \varpi_u \varpi_u \le -\zeta_u^2 / k_u + \zeta_u^2 + 0.25 \varpi_u^2$	In this section let is discourse stepping method	
$\zeta_u \dot{\zeta}_u \le -\zeta_u^2 / k_u + \varpi_u \varpi_u \le -\zeta_u^2 / k_u + \zeta_u^2 + 0.25 \varpi_u^2$	(53)	
$\zeta_v \dot{\zeta}_v \le -\zeta_v^2 / k_v + \varpi_v \varpi_v \le -\zeta_v^2 / k_v + \zeta_v^2 + 0.25 \varpi_v^2$	(53)	simulations are by the Univers mass and the terms are shown Assume that as all the less are shown Assume that ASV is as follow
$V_s \le -\lambda_t e_s^2 - \lambda_2 e_v^2 - \lambda_3 e_u^2 - \lambda_4 e_v^2 - q_1 J_1 \tilde{\sigma}_u^2 - q_3 J_3 \tilde{\sigma}_v^2 $	$x_d = 10 \sin(0$ $y_d = 10 \cos(0)$	

5 1 2 3 4 1 1 3 3 2 2 2 ² ² min min 1 ³ 1 3 2 2 ¹ ³ min 1 ³ max ² max ² min 1 1 1 2 2 0.25 2 2 *x y u ^υ ^u ^r ^u ^υ ^r ^u ^υ ^r u r M M u ^V ^λ ^e ^λ ^e ^λ ^e ^λ e q ^σ ^q ^σ ^ζ ^ζ ^ζ k k k ^ε ^ε ^δ ^μ ^z ^z ^μ ^μ χ δ χ ε W μ* * * £ - - - - - æ ö æ ö æ ö - - - - - - ç ÷ ç ÷ ç ÷ è ø è ø è ø ^é ^ù æ ö æ ö - ^ê - + - ^ú ç ÷ ç ÷ êè ø è ø ^ú ë û é ù - - + - ^ê ^ú ë û + + + **W W** % % () 2 2 2 2 2 1 1 0 3 3 ⁰ *^υ ru u r r ^q ^σ ^σ ^q ^σ ^σ*+ + + - + - J J ⁵ ⁵ *^V*& £ - + ²*ξV* ^Φ (55)

Then, the \dot{V}_s can be expressed as the following:

$$
\dot{V}_s \le -2\zeta V_s + \Phi \tag{55}
$$

where

$$
\frac{1}{2} \text{ Technology } 34 \text{ (2) } 2020 \qquad \text{DOI } 10.1007 \text{/s}12206-020-0135-2}
$$
\n
$$
\zeta = \min \{ \lambda_1, \lambda_2, \lambda_3, \lambda_4, q_1, \beta_1, q_3, \beta_3, \qquad 1 - \frac{1}{k_0}, 1 - \frac{1}{k_0}, 1 - \frac{1}{k_0}, \delta_{\min} \mu_{\min}, \chi_{\min} \}
$$
\n
$$
\Phi = \frac{\delta_{\max}}{2\mu_{\min}} \varepsilon_{M}^2 + \frac{\chi_{\max}}{2} W_{M}^2 + 0.25 \left(\varpi_{u}^2 + \varpi_{v}^2 + \varpi_{v}^2 \right) + q_1 \vartheta_1 |\sigma_{u} - \sigma_{u_0}|^2 + q_3 \vartheta_3 |\sigma_{v} - \sigma_{v_0}|^2 + \mu_{u} + \mu_{v} \text{Eq. (55) can be converted to the following equation:}
$$
\n
$$
V \le \frac{\Phi}{2\zeta} + \left[V(0) - \frac{\Phi}{2\zeta} \right] e^{-2\zeta t} \qquad (56)
$$
\nThe equality can be obtained as:
\n
$$
\lim_{t \to \infty} V = \frac{\Phi}{2\zeta} \qquad (57)
$$

Eq. (55) can be converted to the following equation:

$$
V \leq \frac{\Phi}{2\xi} + \left[V(0) - \frac{\Phi}{2\xi} \right] e^{-2\xi t}
$$
\n(56)

The equality can be obtained as:

$$
\lim_{t \to \infty} V = \frac{\Phi}{2\xi} \tag{57}
$$

In summary, all error signals for the overall closed-loop control system are uniformly bounded in the abovemetioned results. The position tracking errors converge to a small neighborhood of the zero.

5. Simulation and comparative analysis

² ² ² ² / / 0.25 or $\int_{\infty}^{\infty} -\frac{1}{2} \pi \int_{\infty}^{\infty} \int_{\infty}^{\infty} \int_{\infty}^{\infty} \int_{\alpha}^{\infty} \int_{\alpha$ org Eqs. (19),(20) and (25) yields:
 $\lim_{x \to -\zeta_n / k_n + du_r / dt}$
 $= -\zeta_n / k_n + dv_r / dt$
 $= -\zeta_n / k_n + dv_r / dt$
 $= -\zeta_n / k_n + dv_r / dt$
 $= -\zeta_n / k_n + dv_r / dt$
 $= -\zeta_n / k_n + dv_r / dt$
 $= -\zeta_n / k_n + dv_r / dt$
 $= -\zeta_n / k_n + dv_r / dt$
 $= -\zeta_n / k_n + dv_r / dt$
 $= -\zeta_n / k_n + dv_r / dt$ 2π
 $u_x = a_x$ = $\frac{1}{2}$, $k_x + a_y$ = k_z = $\frac{1}{2}$, $k_x + a_y$ = $\frac{1}{2}$ = $\frac{1}{2}$, $k_y = b_z$ = $\frac{1}{2}$, $k_z + a_z$ + a_z + a Function of the section of the set of the duality can be obtained as:
 $u_y - u_z = -\zeta_z/k_x + du_z/dt$
 $v_y - \dot{v}_z = -\zeta_z/k_z + du_z/dt$
 $v_y - \dot{v}_z = -\zeta_z/k_z + du_z/dt$

(51) $\lim_{|z| \to \infty} V = \frac{\Phi}{2\zeta}$

(51) $\lim_{|z| \to \infty} V = \frac{\Phi}{2\zeta}$

(51) \lim entiating Eqs. (19),(20) and (25) yields:
 $\vec{u}_g - \vec{u}_c = -\zeta_c / k_s + du_c / dt$
 $\vec{v}_g - \vec{v}_c = -\zeta_c / k_s + du_c / dt$
 $\vec{v}_g - \vec{v}_c = -\zeta_c / k_s + dv_c / dt$
 $\vec{v}_g - \vec{v}_c = -\zeta_c / k_s + dv_c / dt$
 $\vec{v}_g - \vec{v}_c = -\zeta_c / k_s + dv_c / dt$

In summary, all error s *γ* $\frac{d\mu}{dx}$ *c* $\frac{d}{dx}$ *c* $\frac{d}{dx}$ $\frac{d}{dx}$ *V* $\leq \frac{1}{2\xi} + [\nu(0) - \frac{1}{2\xi}]e^{-2\phi}$

Differentiating Eqs. (19),(20) and (25) yields:
 $\zeta_* = i_{\alpha} - i_{\alpha} = -\zeta_* / k_* + du_* / dt$
 $\zeta_* = i_{\alpha} - i_{\alpha} = -\zeta_* / k_* + du_* / dt$
 \z is. (19),(20) and (25) yields:
 $\int_{\gamma_{\mu}}^{x} k_{\mu} + du_{\epsilon} / dt$
 $\int_{\gamma_{\mu}}^{x} k_{\mu} + dv_{\epsilon} / dt$
 $\int_{\gamma_{\mu}}^{x} k_{\mu} + dv_{\epsilon} / dt$

(51)
 $\int_{\gamma_{\mu}}^{x} k_{\mu} + dv_{\epsilon} / dt$
 $\int_{\gamma_{\mu}}^{x} k_{\mu} + dv_{\epsilon} / dt$

(51)
 $\int_{\gamma_{\mu}}^{x} k_{\mu} + dv_{\epsilon} / dt$
 \int s. (19),(20) and (25) yields:

The equality can be obtained as:
 $\int_{x}^{x} k_x + du_x/dt$
 $\int_{x}^{x} k_x + dv_x/dt$
 $\int_{x}^{x} k_y + dv_y/dt$

(51) $\lim_{x} V = \frac{6}{2\zeta}$
 $\int_{x}^{x} k_y + dv_z/dt$

In summary, all error signals for the

in summary, all (53) simulations are performed on an underactuated ASV designed $\int_{\alpha_{\nu}}^{\infty} \int_{\alpha_{\nu}}^{\infty} = -\zeta_{\nu} \cdot k_{\nu} + dv_{\nu} / dt$
 $\int_{\alpha_{\nu}}^{\infty} = -\zeta_{\nu} \cdot k_{\nu} + dv_{\nu} / dt$
 $\int_{\alpha_{\nu}}^{\infty} = -\zeta_{\nu} / k_{\nu} + dv_{\nu} / dt$
 $\int_{\alpha_{\nu}}^{\infty} \int_{\alpha_{\nu}}^{\infty} \int_{\alpha_{\nu}}^{\infty} \int_{\alpha_{\nu}}^{\infty} \int_{\alpha_{\nu}}^{\infty} \int_{\alpha_{\nu}}^{\$ (51) $\lim_{x \to \infty} V = \frac{0}{2\xi}$

In summary, all error signals for the overall closed-location

it is obtained as

to system are uniformly bounded in the above

studs. The position tracking errors converge to a

reighborhood In this section, the efficiency of the proposed robust controller is discussed by comparing it with the conventional backstepping method using the MATLAB software environment. In order to prove the performance of the designed controller, the by the University of Western Australia. It is assumed that the mass and the damping matrices are diagonal. Model parameters are shown in Ref. [36]. mmary, all error signals for the overall closed-loop con-
tem are uniformly bounded in the abovemetioned re-
The position tracking errors converge to a small
orhood of the zero.
nulation and comparative analysis
sesecti by the mate uniformly bounded in the above
metioned re-
The position tracking errors converge to a small
borhood of the zero.
 imulation and comparative analysis

his section, the efficiency of the proposed robust contr *n* summary, all error signals for the overall closed-loop con-

system are uniformly bounded in the abovemetioned re-

ts. The position tracking errors converge to a small

diphorhood of the zero.
 Simulation and compar *y* system are uniformly bounded in the abovemetioned re-

ts. The position tracking errors converge to a small

ghborhood of the zero.
 Simulation and comparative analysis

in this section, the efficiency of the propos Her is discussed by comparing it with the conventional back-
stepping method using the MATLAB software environment. In
order to prove the performance of the designed controller, the
biginualtions are performed on an under *upping method using the MATLAB software environment. In*
ure to prove the performance of the designed controller, the
*unulations are performed on an underactuated ASV designed
the the University of Western Australia. I*

Assume that the tracking trajectory of the underactuated ASV is as follows:

$$
x_d = 10\sin(0.01t)m / s
$$

\n
$$
y_d = 10\cos(0.01t)m / s
$$
\n(58)

 $2\mu_1$ μ_2 μ_3 μ_4 μ_5 μ_6 plication in practice, the initial conditions of the underactuated ASV are selected as the following: In order to realize the position tracking and gurantee the ap-

In practical underactuated ASVs system, the control inputs are constrained so that the control input system can be protected. For the selected underactuated ASVs system, the input constraint are described as the following: iv is as follows:
 $x_a = 10 \sin(0.01t)m/s$ (58)
 $x_a = 10 \cos(0.01t)m/s$ (58)

n order to realize the position tracking and gurantee the ap-

ration in practice, the initial conditions of the underactuated

vivare selected as the f *r <i>s*
 r s
 i c *n n n n n n n n n n n n <i>n**n <i>n n**<i>n**s**n**n**n* *****n <i>s n n a n n a a n a**a**n**a**a**a**a*

$$
0 \leq |\tau_u| \leq 30N, \quad 0 \leq |\tau_r| \leq 20N \cdot m
$$

In order to represent the tracking error clearly, a new trajec-

Fig. 4. Position tracking of the underactuated ASV.

$$
L = \sqrt{x_e^2 + y_e^2} \tag{59}
$$

To verify the control performance and effectiveness of the designed control system, the nonlinear external disturbances are selected as:

$$
d(t) + P\dot{d}(t) = T\omega \tag{60}
$$

the time constant matrix, the white high frequency measurement noise and the gain parameters matrix, respectively. Considering the worst case, $P = diag\{100, 100, 100\}$, $\omega = 1$ and $\omega = 2$ $\omega = 1$ Backstepping $\omega = 1$ SMC

In this numerical simulation, the control parameters are given by $\lambda_1 = 0.5$, $\lambda_2 = 0.4$, $\lambda_3 = 0.3$, $\lambda_4 = 0.2$, $\alpha_5 = 1$, $\gamma_u = 0.1$, $\gamma_{\kappa} = 0.1, \quad \gamma_{\kappa} = 0.1, \quad \eta_{1} = 0.2, \quad \eta_{3} = 0.2, \quad \rho_{1} = 0.3, \quad \rho_{3} = 0.2,$ deractuated ASV. Moreover, the $\mathbb{J}_1 = 0.2, \quad \mathcal{G}_3 = 0.2.$

Moreover, the parameters of the RBF neural network with five hidden nodes designed in the present study are given by $\beta_1 = 30$, $\beta_3 = 30$, $\chi_1 = 0.1$, $\chi_3 = 0.1$, $\delta_1 = 0.2$, $\delta_3 = 0.2$.
The standard deviation and the centre vector are setively.

Finally, to express the control performance, the simulation time is set to 1000 s. Figs. 5-8 show the simulation results of the proposed method, the conventional backstepping method, and sliding mode control [37].

Figs. 4 and 5 illustrate that the proposed method has better tracking performance than the backstepping method and the sliding mode control method in the presence of the parameters uncertainties and nonlinear external disturbances for the un-

Fig. 5. The errors of the position tracking of the underactuated ASV.

Fig. 6. The errors of the velocity tracking of the underactuated ASV.

deractuated ASV. Moreover, the absolute value of tracking errors can be obtained every 40 s from 200 s to 1000 s. The average tracking error of the backstepping mehod, sliding mode control and the proposed method are 0.0060 m, 0.0055 m and 0.0042 m, respectively. Furthermore, Fig. 6 shows that the velocity can track the desired variables rapidly. It should be indicated that the velocity tracking errors of proposed method are significantly smaller than those of the backstepping method and sliding mode control.

Fig. 7 shows the control inputs of the underactuated ASV. The absolute value of control inputs can be obtained every 40 s from 200 s to 1000 s. The average control forces of the backstepping method, sliding mode control and the proposed method are 9.2 N, 8.5 N, and 8.1 N, respectively. Moreover, it is observed that the average control moments of the backstepping method, sliding mode control and proposed method are

Fig. 7. The control force and moment of the underactuated ASV.

Fig. 8. The estimated uncertainties with the RBF neural network.

6.3 N.m, 5.0 N.m and 4.5 N.m, respectively. It should be indicated that the chattering is obviously reduced in the control force and control moment.

All unknown model parameters can be approximated accurately by employing the RBF neural network and state predictors in Fig. 8.

6. Conclusion

In the present study, the position tracking control problem of the underactuated ASV is investigated in the presence of the model parameters uncertainties and the nonlinear external disturbances. Moreover, an adaptive neural network robust control scheme is proposed to deal with the multiple uncertainties and the nonlinear external disturbances. The derivative of virtual control variables are obtained by applying the dynamic surface control, which avoids the computational complexities of the conventional backstepping method. Furthermore, the stability of the closed-loop control system is proved by the Lyapunov stability theory. Finally, the reasonable robustness and effectiveness of the designed controller are shown in the simulation results.

Acknowledgments

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References

- [1] E. Fredriksen and K. Y. Petterson, Global k-exponential wavpoint maneuvering of ships: Theory and experiments, *Automatica*, 42 (4) (2006) 677-687.
- [2] M. Chen, S. S. Ge, B. V. E. How and Y. S. Choo, Robust adaptive position mooring control for marine vessels, *IEEE Transactions on Control Systems Technology*, 21 (2) (2013) 395-409.
- [3] J. Gao, A. A. Proctor, Y. Shi and C. Bradley, Hierarchical model predictive image-based visual servoing of underwater vehicles with adaptive neural network dynamic control, *IEEE Transactions on Cybernetics*, 46 (10) (2016) 2323-2334.
- [4] S. R. Oh and J. Sun, Path following of underactuated marine surface vessels using line-of-sight based model predictive control, *Ocean Engineering*, 37 (2) (2010) 289-295.
- [5] K. Shojaei, Observer-based neural adaptive formation control of autonomous surface vessels with limited torque, *Robotics and Autonomous Systems*, 78 (2) (2016) 83-96.
- [6] Z. Zhao, W. He and S. S. Ge, Adaptive neural network control of a fully actuated marine surface vessel with multiple output constraints, *IEEE Transactions on Control Systems Technology*, 22 (4) (2014) 1536-1543.
- [7] M. Wondergem, E. Lefeber, K. Y. Pettersen and H. Nijmeijer, Output feedback tracking of ships, *IEEE Transactions on Control Systems Technology*, 19 (2) (2011) 442-448.
- [8] A. Thakur, P. Svec and S. K. Gupta, GPU based generation of state transition models using simulations for unmanned surface vehicle trajectory planning, *Robotics and Autonomous Systems*, 60 (12) (2012) 1457-1471.
- [9] M. E. Serrano, G. J. E. Scaglia, S. A. Godoy, V. Mut and O. Ortiz, Trajectory tracking of underactuated surface vessels: A linear algebra approach, *IEEE Transactions on Control Systems Technology*, 22 (3) (2014) 1103-1111.
- [10] L. Liu, D. Wang and Z. H. Peng, Path following of marine surface vehicles with dynamical uncertainty and timevarying ocean disturbances, *Neurocomputing*, 173 (2016) 799-808.
- [11] L. Liu, D. Wang, Z. H. Peng and H. Wang, Predictor-based LOS guidance law for path following of underactuated marine surface vehicles with sideslip compensation, *Ocean Engineering*, 124 (2016) 340-348.
- [12] F. Y. Bi, Y. J. Wei, J. Z. Zhang and W. Cao, Position tracking control of underactuated autonomous underwater vehicles in the presence of unknown ocean currents, *IET Control Theory and Applications*, 4 (11) (2010) 2369-2380.
- [13] C. Z. Pan, X. Z. Lai, S. X. Yang and M. Wu, A biologically inspired approach to tracking control of underactuated surface vessels subject to unknown dynamics, *Expert Systems with Applications*, 42 (4) (2015) 2153-2161.
- [14] C. Z. Pan, S. X. Yang, X. Z. Lai and L. Zhou, An efficient neural network based tracking controller for autonomous underwater vehicles subject to unknown dynamics, *Control and Decision Conference*, *IEEE* (2014) 3300-3305.
- [15] C. Z. Pan, X. Z. Lai, S. X. Yang and M. Wu, A bioinspired neural dynamics-based approach to tracking control of autonomous surface vehicles subject to unknown ocean currents, *Neural Computing and Applications*, 26 (8) (2015) 1929-1938.
- [16] K. D. Do. Z. P. Jiang and J. Pan. Robust adaptive path following of underactuated ships, *Automatica*, 40 (6) (2004) 929-944.
- [17] K. D. Do and J. Pan, Global tracking control of underactuated ships with nonzero off-diagonal terms in their system matrices, *Automatica*, 41 (1) (2005) 87-95.
- [18] W. J. Xie, B. L. Ma, W. Huang and Y. X. Zhao, Global trajectory tracking control of underactuated surface vessels with non-diagonal inertial and damping matrices, *Nonlinear Dynamics*, 92 (2018) 1481-1492.
- [19] D. Swaroop et al., Dynamic surface control for a class of nonlinear systems, *IEEE Transactions on Automatic Control*, 45 (10) (2000) 1893-1899.
- [20] J. Q. Wang, C. Wang, Y. J. Wei and C. J. Zhang, Command filter based adaptive neural trajectory tracking control of an underactuated underwater vehicle in three-dimensional space, *Ocean Engineering*, 180 (2019) 175-186.
- [21] J. Q. Wang, C. Wang, Y. J. Wei and C. J. Zhang, Threedimensional path following of an underactuated AUV based on neuro-adaptive command filtered backstepping control, *IEEE Access*, 6 (2018) 74355-74365.
- [22] J. Q. Wang, C. Wang, Y. J. Wei and C. J. Zhang, Position tracking control of autonomous underwater vehicles in the disturbance of unknown ocean currents, *ACTA ARMAMENTARII*, 3 (40) (2019) 583-591.
- [23] Z. Zheng and L. Sun, Path following control for marine surface vessel with uncertainties and input saturation, *Neurocomputing*, 177 (2016) 158-167.
- [24] N. Wang and J. E. Meng, Direct adaptive fuzzy tracking control of marine vehicles with fully unknown parametric dynamics and uncertainties, *IEEE Transactions on Control Systems Technology*, 24 (5) (2016) 1845-1852.
- [25] X. Liang, X. J. Hua, L. F. Su, W. Li and J. D. Zhang, Path following control for underactuated AUV based on feedback gain backstepping, *Technical Gazette*, 22 (4) (2015) 829- 835.
- [26] H. J. Wang, Z. Y. Chen, H. M. Jia, J. Li and X. H. Chen, Three-dimensional path following control of underactuated autonomous underwater vehicle with command filtered backstepping, *Acta Automatica Sinica*, 41 (3) (2015) 631-645.
- [27] H. Wang, D. Wang and Z. H. Peng, Neural network based adaptive dynamic surface control for cooperative path following of marine surface vehicles via state and output feedback, *Neurocomputing*, 133 (2014) 170-178.
- [28] Z. W. Zheng, Y. T. Huang, L. H. Xie and B. Zhu, Adaptive trajectory tracking control of a fully actuated surface vessel with

asymmetrically constrained input and output, *IEEE Transactions on Control System Technology*, 26 (5) (2018) 1851-1859.

- [29] B. S. Park, J. W. Kwon and H. Kim, Neural network-based output feedback control for reference tracking of underactuated surface vessels, *Automatica*, 77 (2017) 353-359.
- [30] L. Liu, D. Wang and Z. Peng, Coordinated path following of multiple underacutated marine surface vehicles along onecurve, *ISA Transactions*, 64 (2016) 258-268.
- [31] R. Sanner and J. Slotine, Gaussian networks for direct adaptive control, *IEEE Transations on Neural Network*, 3 (1992) 837-863.
- [32] K. Shojaei, Leader follower formation control of underactuated autonomous marine surface vehicles with limited torque, *Ocean Engineering*, 105 (2015) 196-205.
- [33] D. Swaroop, J. Hedrick, P. Yip and J. Gerdes, Dynamic surface control for a class of nonlinear systems, *IEEE Transactions Automation Control*, 45 (2000) 1893-1899.
- [34] B. Xu, C. G. Yang and F. C. Sun, Composite neural dynamic surface control of a class of uncertain nonlinear systems in strict-feedback form, *IEEE Transactions on Cybernetics*, 44 (2014) 2626-2634.
- [35] K. Shojaei, Line-of-sight target tracking control of underactuated autonomous underwater vehicles, *Ocean Engineering*, 133 (2017) 244-252.
- [36] M. Reyhanoglu, Exponential stabilization of an underactuated autonomous surface vessel, *Automatica*, 33 (12) (1997) 2249- 2254.
- [37] F. Y. Bi, Y. J. Wei, J. Z. Zhang and W. Cao, Robust position tracking control design for underactuated AUVs, *Journal of Harbin Insititute of Technology*, 42 (11) (2010) 1690-1695.

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