Ocean Engineering 127 (2016) 82–89

Contents lists available at ScienceDirect

Ocean Engineering

journal homepage: www.elsevier.com/locate/oceaneng

Observer-based adaptive neural network control for a class of remotely operated vehicles

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ARTICLE INFO

Keywords:
Adaptive control
Neural network
Observer
Remotely operated vehicles

ABSTRACT

In this paper, a new adaptive neural network control approach is developed for a class of remotely operated vehicles whose velocity state and angular velocity state in the body-fixed frame are unmeasured. Unlike most previous control approaches, it doesn't need thrust model and the thruster control signal is considered as the input of control system directly. Using local recurrent neural network to approximate the unknown nonlinear functions, an adaptive observer is introduced for state estimation. Under the framework of the backstepping design, adaptive neural network control law is constructed based on the output of local recurrent neural network and state estimation. The stability analysis is given by Lyapunov theorem. The effectiveness of the proposed control scheme is illustrated by simulations.

1. Introduction

A remotely operated vehicle (ROV) works in a complex marine environment. In underwater observation, manipulator operation and other tasks, a stable and high precision control system can provide higher working efficiency (Mohan and Kim, 2015; Chen, 2008; Shim et al., 2010). Recently, many control approaches have been proposed for dynamic positioning, trajectory tracking and path following (Souza and Maruyama, 2007; Hoang and Kreuzer, 2007), such as sliding mode control (Zhang and Chu, 2012; Chu et al., 2016b), adaptive control (Miao et al., 2013), neural network control (Chatchanayuenyong and Parnichkun, 2006) and so on. In these control approaches, it is mostly assumed that all the states of ROV system are known. Obviously, this assumption can't be met by most ROVs. Because of the small ROVs are only equipped with the sensors for position and orientation measurement, but without Doppler Velocity Log (DVL), inertial navigation system and other sensors for velocity and angular velocity measurement (Li et al., 2013; Gao, et al., 2004; Zhang, et al., 2009). Some large ROVs are equipped with DVL, but they sometimes need to perform bottom-following control for some special tasks (Silvestre et al., 2008). If the altitude is very low, DVL may be unable to work. Therefore, it needs to be considered in the controller design of ROVs that the velocity state and angular velocity state in the body-fixed frame cannot be measured directly.

Since the position and orientation in the earth-fixed frame can be measured directly, ROV is an observable system. Considering the complexity and uncertainty of ROV modeling, some adaptive control methods based on high gain observer have been proposed (Boizot et al., 2010; Hankovic, 1997; Lee and Khalil, 1997; Tong and Li, 2002). One of the advantages of a high gain observer is that the information of the ROV dynamic model is not needed, and a large gain coefficient can be used to guarantee the convergence of state estimation errors, so that the velocity state and angular velocity state in the body-fixed frame can be estimated online. However, the large gain coefficient will be introduced into the control law, which will result in the system output oscillation and affect the tracking quality. Based on the above considerations, the high gain observer is not very suitable for ROV control. In these adaptive control methods, neural network are usually used for adaptively learning of unknown term of ROV dynamic model. Therefore, we consider that if the information from online identification can be used to construct the full order observer. Thus, the large gain coefficient will not be needed and the problem of that how to improve the learning accuracy and speed of neural network is only needed to be taken into account.

In addition, the actual input of ROV control system is the thruster control signal (Gan et al., 2004), so ROV is a nonaffine nonlinear system essentially. Thus, it is very difficult to design the control law to obtain the thruster control signal directly. In most previous control approaches, the outputs of controllers are usually thruster thrust, then the thruster control signal is calculated by the thrust model (Yu et al., 2008; Fischer et al., 2014; Lapierre and Jouvencel, 2008). However, the thrust model is related to not only the control signal but also the

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http://dx.doi.org/10.1016/j.oceaneng.2016.09.038
Received 1 December 2015; Received in revised form 5 September 2016; Accepted 24 September 2016

advance speed of the propeller (Alessandri et al., 1999), so that it is very difficult to establish the accurate thrust model (Kim and Chung, 2006). In practical control process, the inaccurate thrust model may influence the control performance (Zhang and Chu, 2012). Therefore, the problem that how to obtain the thruster control signal directly without thrust model needs to be considered, and then a high precision tracking control system can be obtained.

In this paper, considering the complex nonlinear relationship between thrust and control signal, an affine transformation is carried out for thrust model and a scale factor is introduced, thus the thruster control signal can be seen as the input of the tracking control system directly. Since it is difficult to accurately establish ROV's dynamics model and the velocity state and angular velocity state in the body-fixed frame cannot be measured directly, an adaptive state observer based on local recurrent neural network is proposed to estimate the velocity state and angular velocity state online. Furthermore, the scale factor of thrust model is also estimated by adaptive learning. According to the estimated values of observer and the output of local recurrent neural network, the adaptive control law is designed. The uniformly ultimately bounded of tracking error is analyzed by Lyapunov theory and is verified by simulation results.

This paper is organized as follows. ROV's tracking control problem is described in Section 2. In Section 3, the observer-based adaptive neural network tracking controller is given. In Section 4, the effectiveness of the proposed method is verified by simulation results. Finally, we make a brief conclusion of the paper in Section 5.

2. Problem formulation

The mathematical model of a ROV in 6 DOF can be described as (Biggs and Holderbaum, 2009):

$$\begin{aligned}\dot{\eta} &= J(\eta)v\\ M\dot{v} + C(v)v + D(v)v + G(\eta) + \tau_d &= \overline{B}\tau(u)\end{aligned} \tag{1}$$

where η denotes the vector of position and orientation in the earth-fixed frame, v is the vector of velocity and angular velocity expressed in the body-fixed frame. M is an inertia matrix including extra mass, the matrix $C(v)$ groups centripetal and Coriolis forces, including the centripetal force and Coriolis force produced by extra mass, $D(v)$ is the hydrodynamic damping term, the vector $G(\eta)$ is the combined gravitational and buoyancy forces in the body-fixed frame, τ_d is the external disturbances, $J(\eta)$ is the kinematic transformation matrix expressing the transformation from the body-fixed frame to earth-fixed frame, $\tau(u)$ is the thruster thrust, u is the thruster control signal and $\overline{B}$ is distribution matrix of thrusters.

In Eq. (1), $\tau(u)$ is a nonlinear function about the thruster control signal and the advance speed of the propeller, where the latter is a variable that might be difficult to measure in actual. Therefore, the accurate thrust model is very difficult to be established. In this paper, a Taylor expansion will be introduced to convert (1) into an affine nonlinear system, thus the thrust model is not needed and it will also be convenient for control law design. The Taylor expansion of $\tau(u)$ about u^* is given as:

$$\tau_i(u_i) = \gamma_i u_i + \tau_i(u_i^*) - \left.\frac{\partial \tau_i(u_i)}{\partial u_i}\right|_{u_i=u_i^*} u_i^* + O((u_i - u_i^*)^2) \tag{2}$$

where i=1,..., n, n is the number of thrusters and γ_i is a scale factor:

$$\gamma_i = \left.\frac{\partial \tau_i(u_i)}{\partial u_i}\right|_{u_i=u_i^*} \tag{3}$$

Define $x=[x_1;x_2]$, $x_1=\eta$, $x_2=J(\eta)v$. According to (1) and (2), it can be obtained:

$$\dot{x} = Ax + b(f(x) + B(x_1)\gamma u) \tag{4}$$

where $u=[u_1, \ldots, u_n]^T$ is the vector of thruster control signals. $\gamma=\text{diag}([\gamma_1, \ldots, \gamma_n])$. $f(x)$, $B(x_1)$, A and b are as shown in (5)–(8), respectively.

$$f(x) = J'(\eta)v - J(\eta)M^{-1}(C(v)v + D(v)v + G(\eta) + \tau_d) + B(x_1)\left(\tau_i(u_i^*) - \left.\frac{\partial \tau_i(u_i)}{\partial u_i}\right|_{u_i=u_i^*} u_i^* + O((u_i - u_i^*)^2)\right) \tag{5}$$

$$B(x_1) = J(\eta)M^{-1}\overline{B} \tag{6}$$

$$A = \begin{bmatrix} 0_{6\times6} & I_{6\times6} \\ 0_{6\times6} & 0_{6\times6} \end{bmatrix} \tag{7}$$

$$b = \begin{bmatrix} 0_{6\times6} \\ I_{6\times6} \end{bmatrix} \tag{8}$$

When using (4) to describe the tracking system for a particular ROV system, it has the following property:

Property 1. The state x_2 and control law u are all bounded, namely:

$$\|x_2\| \le x_{20},\ \|u\| \le u_0 \tag{9}$$

where x_{20}, u_0 are known positive constants.

As can be seen from (4), after the affine transformation, an affine nonlinear system is obtained, which will be convenient for control law design. However, since the ROV's dynamic model is difficult to be established accurately, the nonlinear function item $f(x)$ is unknown. In addition, due to the fact that the ROV is usually not equipped with the sensors to measure the velocity state and angular velocity state in the body-fixed frame, the state x_2 is unknown. Therefore, the control objective of this paper is to develop a control law u such that the tracking error is uniformly ultimately bounded under the situation that the ROV dynamic model is unknown and the state x_2 is unmeasured.

3. Controller design

In (4), since the nonlinear function item $f(x)$ is usually unknown, neural network is mostly used for online learning. In most neural network based-adaptive controllers, RBF neural network, BP neural network, and recurrent neural network are usually used. However, these neural networks have some disadvantages (Zhang and Chu, 2012). For example, in the RBF neural network-based adaptive controller, if there is a big disturbance or the desired value has an abrupt change, the weights of neural network would take a long time to converge. Although the recurrent neural network can overcome this problem, the learning efficiency of recurrent neural network is very poor. Therefore, the local recurrent neural network were proposed in (Zhang and Chu, 2012; Chu et al., 2016a). Compared with the traditional recurrent neural network and BP neural network, there are only some of the hidden layer neurons regress to recurrent layer in local recurrent neural network. As the training results given in (Chu et al., 2016a), it shows that the local recurrent neural network has the advantages of faster learning speed and good learning performance and it also very suitable for adaptive control for ROVs. In this paper, the local recurrent neural network will be introduced into observer designing, and then the adaptive control law will be constructed. The structure of the local recurrent neural network are shown in Fig. 1.

For the local recurrent neural network as shown in Fig. 1, from the nonlinear mapping ability of neural network, there are optimal network weights W, V, such that:

$$f(x) = W\varphi(VH) + \varepsilon \tag{10}$$

where $x=[x_1; x_2]$ is the input vector of input layer neurons. $H=[x; H_1]$ is the input vector of hidden layer neurons. H_1 is the output vector of recurrent layer neurons, which is equal to the output of the hidden layer neurons with recurrent structure. W is the weight matrix between hidden layer neurons and output layer neurons. V is the weight matrix between input layer neurons, recurrent layer neurons and hidden layer