Ocean Engineering 88 (2014) 426–434

Contents lists available at ScienceDirect

Ocean Engineering

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

Fault reconstruction of thruster for autonomous underwater vehicle based on terminal sliding mode observer

Zhen-zhong Chu *,[1], Ming-jun Zhang

College of Mechanical and Electrical Engineering, Harbin Engineering University, Harbin 150001, Heilongjiang, China

A R T I C L E I N F O

Article history:
Received 17 October 2013
Accepted 22 June 2014
Available online 24 July 2014

Keywords:
Autonomous underwater vehicle
Fault reconstruction
Motion modeling
Terminal sliding mode
Neural networks

A B S T R A C T

The motion modeling and thruster fault reconstruction for autonomous underwater vehicle (AUV) system are addressed in this paper. Considering the modeling uncertainty of the AUV motion model given by dynamics analysis method, we present an AUV motion modeling method based on RBF neural networks. Since there is asymptotic convergence problem in the process of using traditional sliding mode observer to estimate the state signal, which cannot be measured directly by sensor, the fault signal cannot be reconstructed timely. Therefore, a Terminal sliding mode observer is presented to ensure each estimated state signal converge in a finite time. According to the output of Terminal sliding mode observer, the equivalent output injection method is used to reconstruct thruster fault. Finally, the feasibility and effectiveness of the proposed approach is demonstrated with pool experiments of the experimental prototype.

1. Introduction

AUV works in high-pressure and poor-visibility marine environment. Once an accident happens, not only the underwater task could not be achieved, but also the AUV sometimes could not be reclaimed, which would cause economic loss. As the basic and key technology of AUV, fault diagnosis has great significance to the safe operation of AUV (Takai and Ura, 1999; Xu and Xiao, 2007).

In the research of AUV thruster fault diagnosis, the state estimation method has been widely used, which reflects the inconsistencies between the expected behavior of the system and the actual operation mode by using residual signal structured by AUV motion modeling and the observed input and output, and does fault diagnosis through the analysis of the residual signal (Venkatasubramanian et al., 2003). The existing state estimation methods include the Kalman filter (Alessangri et al., 1999a; Loebis et al., 2004), sliding mode observer (Alessandri et al., 1999b; Wang et al., 2005), etc. However, it is known that the state estimation method requires an exact mathematical analytical model (Xiao et al., 2010). Due to the complexity of the marine environment, as well as the the strong nonlinearity and intercoupling characteristics of the AUV 6-DOF motion, the AUV motion model based on dynamics analysis method has great uncertainty (Ahmad and Jalal, 2009). If fault diagnosis is done based on this model, the misdiagnosis and missed diagnosis of the fault will be caused easily due to the lack of the prior knowledge of the system uncertainty in practice. As the neural networks has arbitrary nonlinear approximation ability, many scholars have used neural networks to study AUV motion modeling and state estimation for the residual signal according to the established neural networks model. Wang et al. (2006) has monitored the AUV thruster fault based on fuzzy neural networks. Wang and Ding (2007) has established AUV motion model based on wavelet neural networks and then analyzed thruster fault diagnosis. However, the internal knowledge representation of neural networks is like a black-box, which make it difficult to explicitly reflect the relationship between input and output and bring difficulties for the thruster fault reconstruction.

Sliding mode observer is a nonlinear observer, which overcomes the uncertainty and nonlinearity of the system model by its robustness and obtains fault information through the introduction of the equivalent output injection. Thus, the fault reconstruction is achieved. Edwards et al. (2000) studied fault reconstruction problems of actuator and sensor for a class of linear systems. Based on this, the fault diagnosis problems of nonlinear uncertain systems were further explored (Tan and Edwards, 2001, 2003; Yan and Edwards, 2007; Chen and Saif, 2008). A remarkable characteristic of this method for fault reconstruction is that the sliding

* Corresponding author. Tel.: +86 45182519161; fax: +86 45182519709.
E-mail address: chuzhenzhong@hrbeu.edu.cn (Z.-z. Chu).
[1] *Postal address:* No. 145, Nantong Street, Harbin, Heilongjiang, China.

http://dx.doi.org/10.1016/j.oceaneng.2014.06.015
0029-8018/

mode motion still needs to be maintained when the fault happens to actuator. That is, the state estimation error is zero. But we find that the sliding mode motion would be damaged when fault occurs in thruster from the AUV thruster fault diagnosis study based on sliding mode observer. This requires the state estimation error converges to zero in a finite time for fault reconstruction. However, Tan et al. (2010) pointed out that the sliding mode observer given in the reference (Edwards et al., 2000; Tan and Edwards, 2001, 2003; Yan and Edwards, 2007; Chen and Saif, 2008) can only guarantee the finite-time convergence of the state which can be measured directly by sensor, but for the state which can not be measured directly, it has asymptotic convergence. Thus, thruster fault reconstruction can not be achieved timely based on the method.

A modeling method of AUV motion model described in the form of affine nonlinear system based on neural networks is given for a class of AUV systems, whose position and orientation state with respect to the earth-fixed frame can be measured by sensors while the velocity and angular velocity state can not be measured in the paper. In this model, the relationship between the input and output of the AUV system can be reflected clearly. Based on the established AUV motion model, a Terminal sliding mode observer is built to guarantee the finite-time convergence for system position, orientation, velocity and angular velocity state, and then the equivalent output injection method is used for thruster fault reconstruction online.

This paper is organized as follows. Section 2 describes the AUV thruster fault reconstruction problem studied in the paper. In Section 3, the motion modeling method based on RBF neural networks is given. And in Section 4, the thruster fault is reconstructed based on Terminal sliding mode observer. Then Section 5 verifies the established motion model and fault reconstruction approach. Finally, a brief conclusion is given in Section 6.

2. Problem formulation

The AUV mathematical model in 6 DOF can be described as

$$\begin{aligned}&\dot{\eta}=J(\eta)\nu M\dot{\nu}+C(\nu)\nu+D(\nu)\nu+g(\eta)=B\tau(\nu,u)\\&y_{out}=\eta\end{aligned}\tag{1}$$

where $\eta\in\mathbb{R}^6$ denotes the vector of position and orientation in the earth-fixed frame, $\nu\in\mathbb{R}^6$ is the vector of velocity and angular velocity expressed in the body-fixed frame. $M\in\mathbb{R}^{6\times6}$ is inertia matrix including extra mass, the matrix $C(\nu)\in\mathbb{R}^{6\times6}$ groups centripetal and Coriolis forces, including the centripetal force and Coriolis force produced by extra mass, $D(\nu)\in\mathbb{R}^{6\times6}$ is the hydrodynamic resistance and lift matrix, $g(\eta)\in\mathbb{R}^6$ is restoring force and torque vector, $\tau(\nu,u)\in\mathbb{R}^n$ is the thruster force, $u=[u_1,\ldots,u_n]^T$ is the vector of thruster control signal from the controller output and satisfies $\|u\|\le u_d$, n is the number of the thrusters, $y_{out}\in\mathbb{R}^6$ are the state variables which can be measured directly by sensors. $J(\eta)\in\mathbb{R}^{6\times6}$ is the transformation matrix. $B\in\mathbb{R}^{6\times n}$ is the thruster distribution matrix. In the paper, the situation of redundant thrusters configuration is not considered, namely matrix B has full column rank.

There exists a linear change of coordinates $w=T\nu$, such that

$$\begin{aligned}&\dot{\eta}=J(\eta)T^{-1}w\\&\quad TMT^{-1}\dot{w}+TC(T^{-1}w)T^{-1}w+TD(T^{-1}w)T^{-1}w+Tg(\eta)\\&=\underline{B}\tau(T^{-1}w,u)y_{out}=\eta\end{aligned}\tag{2}$$

where, $\underline{B}=[0_{6-n}\quad I_n]^T$.

Define

$$\begin{aligned}&\overline{\xi}_1=\eta\\&\overline{\xi}_2=J(\eta)T^{-1}w\end{aligned}\tag{3}$$

Then (2) can be expressed as strict feedback nonlinear system shown as below.

$$\begin{aligned}&\dot{\overline{\xi}}_1=\overline{\xi}_2\\&\dot{\overline{\xi}}_2=h(\overline{\xi}_1,\overline{\xi}_2)+\overline{B}\tau(J^{-1}(\overline{\xi}_1)\overline{\xi}_2,u)\\&y_{out}=\overline{\xi}_1\end{aligned}\tag{4}$$

where,

$$\begin{aligned}h(\overline{\xi}_1,\overline{\xi}_2)=&J(\overline{\xi}_1)M^{-1}\{-C(T^{-1}w)T^{-1}w-D(T^{-1}w)T^{-1}w-g(\overline{\xi}_1)\}\\&+\dot{J}(\overline{\xi}_1)T^{-1}w\\\overline{B}=&J(\overline{\xi}_1)M^{-1}T^{-1}\underline{B}\end{aligned}$$

In the research of AUV motion modeling, the thruster thrust model should be established first in most of the existing methods to determine the mapping relationship between control signal and thrust (Kim and Chung, 2006; Omerdic and Roberts, 2004). But the thrust is related to the propeller speed, the AUV state and other factors, so it is difficult to establish accurate thrust model (Kim and Chung, 2006). An inaccurate thrust model will lead to modeling error, and will affect the fault diagnosis. Since the purpose of AUV motion modeling is for thruster fault reconstruction in the paper, thus, the thruster control signal u is used as the input of AUV system directly without considering the thrust modeling.

If u is regarded as system input in (4), then the AUV is a non-affine nonlinear system. For the subsequent research for AUV thruster fault reconstruction, the affine transformation to the equation shown in (4) is applied, and the affine nonlinear system which uses u as system input is obtained.

The Taylor expansion of $\tau(J^{-1}(\overline{\xi}_1)\overline{\xi}_2,u)$ about u^* is given as

$$\begin{aligned}&\tau(J^{-1}(\overline{\xi}_1)\overline{\xi}_2,u)=\tau(J^{-1}(\overline{\xi}_1)\overline{\xi}_2,u^*)\\&\quad+\left.\frac{\partial\tau(J^{-1}(\overline{\xi}_1)\overline{\xi}_2,u)}{\partial u}\right|_{u=u^*}(u-u^*)+O((u-u^*)^2)\end{aligned}\tag{5}$$

where, $O((u-u^*)^2)$ is the higher order term of Taylor expansion.

Let

$$\begin{aligned}&\overline{F}(\overline{\xi}_1,\overline{\xi}_2)=a\overline{\xi}_2+h(\overline{\xi}_1,\overline{\xi}_2)+\tau(J^{-1}(\overline{\xi}_1)\overline{\xi}_2,u^*)\\&\quad-\left.\frac{\partial\tau(J^{-1}(\overline{\xi}_1)\overline{\xi}_2,u)}{\partial u}\right|_{u=u^*}u^*+O((u-u^*)^2)\end{aligned}$$

$$\overline{G}(\overline{\xi}_1,\overline{\xi}_2)=diag\left(\left.\frac{\partial\tau(J^{-1}(\overline{\xi}_1)\overline{\xi}_2,u)}{\partial u}\right|_{u=u^*}\right)$$

Then (4) can be rewritten in the form of affine nonlinear system which uses thruster control signal u as input, which is as follows

$$\begin{aligned}&\dot{\overline{\xi}}_1=\overline{\xi}_2\\&\dot{\overline{\xi}}_2=-a\overline{\xi}_2+\overline{F}(\overline{\xi}_1,\overline{\xi}_2)+\overline{B}\overline{G}(\overline{\xi}_1,\overline{\xi}_2)u\end{aligned}\tag{6}$$

where, a is a matrix and is chosen such that the eigenvalues of matrix $\overline{A}=[0,I_6;0,-a]$ are non-positive.

In practice, there are some different fault types on AUV thrusters, such as stuck, blade drop and blade fracture. As for the different fault types, they can be described by the following fault model:

(1) Stuck fault model: $\tau_r=\alpha$. Where α is a constant, τ_r is the practical thrust.
(2) Constant gain fault model: $\tau_r=\beta\tau_u$. Where β is factor of proportionality of constant gain change, τ_u is theoretical thrust.
(3) Constant bias fault model: $\tau_r=\tau_u+\Delta$, Δ is a constant.