

Development of Self-Diagnosis System of an Autonomous Underwater Vehicle Tuna-Sand 2

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Abstract

For autonomous underwater vehicle (AUV), high autonomy is required in order to accomplish mission such as inspection, observation, manipulation under extreme environments, deep-ocean. One of necessary function for AUV is the self-diagnosis system to detect the abnormality can be said to be an important feature. In this paper, we propose a self-diagnostic system using the dynamical model of Sampling-AUV “TUNA-SAND2”, where the fault device detection is carried out using the model, and evaluated through tank tests.

Keywords: AUV, Self-Diagnosis System .

1. Introduction

Underwater robots have attracted attention as useful tools¹⁻⁶ to observe deep-sea floor. Especially, Autonomous Underwater Vehicle (AUV) can move wide area freely not having tethered cable with support vessel. On the other hand, for AUV, high autonomy is required in order to accomplish mission such as inspection, observation, manipulation under extreme environments, deep-ocean. One of necessary function for AUV is the

self-diagnosis system to detect the abnormality can be said to be an important feature.

As a previous study, Takai⁷ et al. proposed a self-diagnosis system utilizing a dynamic model by a neural network (NN) However, NN cannot prove the stability of the model theoretically.

In this paper, we propose a self-diagnostic system using the dynamical model of Sampling-AUV “TUNA-

SAND2⁸⁾, where the fault device detection is carried out



using the model, and evaluated through tank tests.

Fig.1 Newly Developed AUV ‘‘TUNA-SAND 2’’

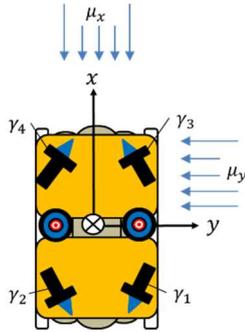


Fig. 2 Thruster Arrangement in Horizontal Plane.

2. Dynamic Model of AUV

Depending on the mission objectives, AUV has mounted different sensors and thrusters, so the mathematical model also changes. Therefore, a hovering type AUV ‘‘TUNA-SAND2’’ jointly developed by the University of Tokyo and Kyushu Institute of Technology was set as target robot. We assume two abnormalities to be detected are (1) tidal disturbance and (2) low thruster output.

TUNA-SAND 2 has six thrusters, as shown in Fig. 2, it has a redundant drive system using four thrusters for the horizontal movement of the three DOF of Surge, Sway and Yaw. In order to develop an algorithm to solve this redundancy, AUV models the horizontal plane movement in diagnosing the failure of the thruster.

Based on the above condition setting, we define the equation of motion of AUV⁹ in eq. (1) and the current consumption of AUV in eq.(2).

$$\dot{\mathbf{v}}_t = \mathbf{M}^{-1}\{-\mathbf{C}(\mathbf{v}_{t-1} - \boldsymbol{\mu})|\mathbf{v}_{t-1} - \boldsymbol{\mu}| + \mathbf{B}(\mathbf{I} - \boldsymbol{\gamma})\boldsymbol{\tau}_{t-1}\} \quad (1)$$

$$I_t = I_0 + e_\tau \sum (1 - \gamma_l)\tau_{t-1}^l \quad (2)$$

Here, $\mathbf{v}_t = [v_t^x \ v_t^y \ \omega_t^z]^T$ means the velocity vector of AUV, $\boldsymbol{\tau}_t = [\tau_t^1 \ \tau_t^2 \ \tau_t^3 \ \tau_t^4]^T$ is the thruster control signal vector, $\mathbf{M} \in \mathbb{R}^{3 \times 3}$ is the mass and inertia moment including additional mass, $\mathbf{C} \in \mathbb{R}^{3 \times 1}$ is the hydraulic coefficient, $\mathbf{B} \in \mathbb{R}^{3 \times 4}$ is the inverse kinematics transfer thruster output to the force to the center of gravity of AUV. Regarding eq. (2), I_t is the total consumption current of AUV, I_0 is the steady consumption current of CPU and others excluding thrusters, e_τ is the conversion coefficient from command thrust to thruster consumption current. Also, $\boldsymbol{\mu} = [\mu_x \ \mu_y \ 0]^T$, $\boldsymbol{\gamma} = \text{diag}\{\gamma_1, \gamma_2, \gamma_3, \gamma_4\}$ are the ambient power flow rate to be diagnosed, the power reduction rate of each thruster (0 to 100 [%]).

State vector \mathbf{x}_t , observation vector \mathbf{y}_t , manipulation vector \mathbf{u}_t , abnormal variable $\boldsymbol{\beta}$ to be diagnosed as in equations (3) - (6).

$$\mathbf{x}_t = [\dot{v}_t^x \ \dot{v}_t^y \ \dot{\omega}_t^z \ v_t^x \ v_t^y \ \omega_t^z \ I_t]^T \quad (3)$$

$$\mathbf{y}_t = [v_t^x \ v_t^y \ \omega_t^z \ I_t]^T \quad (4)$$

$$\mathbf{u}_t = [\tau_t^1 \ \tau_t^2 \ \tau_t^3 \ \tau_t^4]^T \quad (5)$$

$$\boldsymbol{\beta} = [\gamma_1 \ \gamma_2 \ \gamma_3 \ \gamma_4 \ \mu_x \ \mu_y]^T \quad (6)$$

\mathbf{y}_t , the translational speed, angular velocity, current consumption, can be observed from the velocity sensor, the inertial navigation device and the current sensor. Using eqs. (1) to (6), the state equation motion is in (7) and observation equation is in (8) .

$$\mathbf{x}_t = \mathbf{F}(\mathbf{x}_{t-1}, \mathbf{u}_{t-1}, \boldsymbol{\beta}) \quad (7)$$

$$\mathbf{y}_t = \mathbf{G}\mathbf{x}_t = [\mathbf{O}^{4 \times 3} \ \mathbf{I}] \cdot \mathbf{x}_t \quad (8)$$

3. Self-Diagnosis System

The basic concept of self-diagnosis system is shown in Fig. 2. Based on the time series data of the manipulated variable \mathbf{u}_t and observation variable \mathbf{y}_t of AUV, the observer to estimate $\boldsymbol{\beta}$ is constructed.

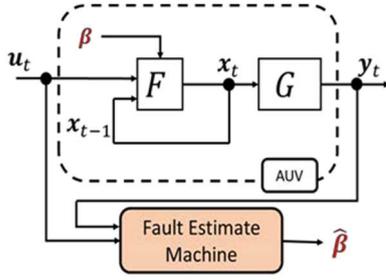


Fig. 3 The concept of self-diagnosis system

First, the diagnostic data is the time series of data in time $[t, k-t]$. The initial state in the diagnosis at time t is $x_{t,k}$ and the manipulated variable are $u_{t,k}, \dots, u_{t,1}$. By substituting these into the eqs. (7) and (8), the observations $\hat{y}_{t-k}(\beta)$ to $\hat{y}_{t-1}(\beta)$ are estimated. Here, the estimation error $RSS(\beta)$ is calculated in eq. (9).

$$RSS(\beta) = \sum_{m=1}^M \sum_{i=t-k}^{t-1} \varepsilon^m (\hat{y}_i^m(\beta) - y_i^m(\beta)) \quad (9)$$

Here, M is the dimension number of the observation vector, ε is the weighting parameter, and $RSS(\beta)$ shows the error between the proposed model and the measured value. By finding the optimal solution β that minimizes this function $RSS(\beta)$, the model estimates the current defaults. The steepest descent method was used for searching for the optimal solution β (see Fig.4).

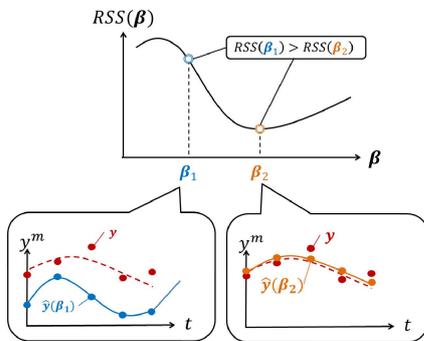


Fig.4 Parameter search by changing β .

4. Evaluation of Proposed System

4.1. Simulation

The simulations are carried out supposing that defaults and disturbances happen during the cursing at 0.2 m/s in forward direction as shown in Table 1.

Table 1 Simulation Condition for Observer Evaluation

ID	Time[s]	Condition	Parameters
-	0 - 5	Normal	-
1	10 - 25	Thruster 1 stop	$\gamma_1 = 1$
-	25 - 50	Normal	-
2	50 - 75	Thruster 1&3 50% down	$\gamma_1, \gamma_3 = 0.5$
3	75 - 100	All thruster 50% down	$\gamma_{1-4} = 0.5$
4	100-125	Current	$\mu_x=0.2$

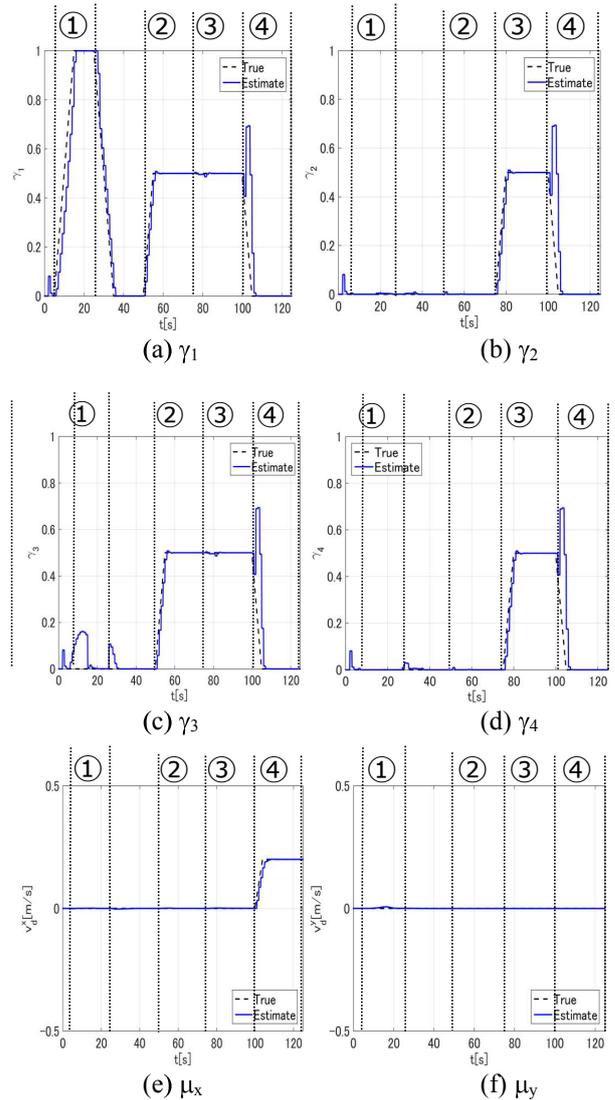


Fig.5 Performance Evaluation by Simulations.

We evaluated the diagnostic performance by simulation as shown in Fig.5, assuming the case where

four kinds of defaults occurred. The solid line means the estimated defaults and dot line true value. In the simulations, the observer can estimate the defaults and disturbances.

4.2. Experiments

We had evaluation experiments using AUV TUNA-SAND2, where the AUV is cruising at 0.2 m/s in surge direction and all thrusters outputs become half after 10 seconds passed. The evaluation results are shown in Fig.6. The estimation of reduction percentage is over-estimated than commanded values, thrusters' defaults are detected.

5. Conclusions

In this research, we proposed a model based faults detection system for diagnosis of AUV. The system is evaluated by simulations and experiments using AUV TUNA-SAND2, and the results show good performance and detect the faults.

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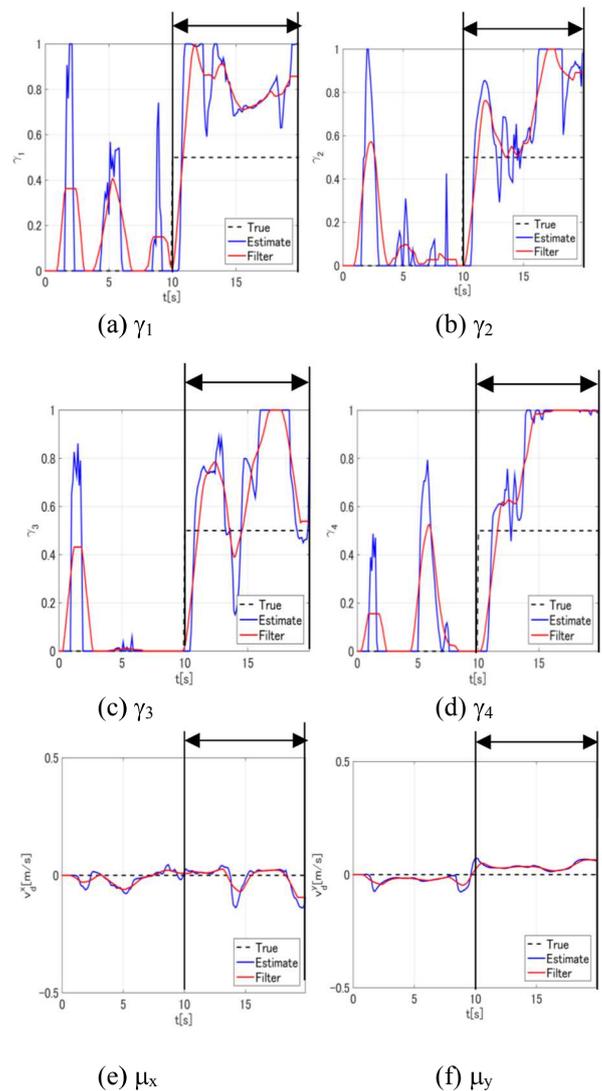


Fig. 6 Evaluation Using TUNA-SAND2.