FAULT DIAGNOSIS OF ACTUATOR FAULTS USING STF IN AUTONOMOUS UNDERWATER VEHICLE

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Abstract:

AUVs are being developed for oceanographic survey, as well as military, missions. Now that underwater navigation to sufficient precision within cost limits is possible, the remaining technical issue is to improve the reliability of the mission completion. Increasing mission reliability implies many things having something to do with automatic fault detection.

So it is necessary to build the fault supervisory system which has the ability of on-line, real time detection and diagnosis of the dynamic faults during the system operation. This paper develops a system that can automatically detect the presence of fault in the actuators of the Autonomous Underwater Vehicle (AUV).

In this paper, we study actuator failures on an autonomous underwater vehicle and design the fault diagnosis system for thruster faults. Actuator faults have been considered, relying on approximate mathematical models of the vehicles' dynamics. Fault detection and diagnosis is accomplished by evaluating any significant change on-line in the behavior of the vehicle, applying the theory of the strong tracking filter. This task is performed by a bank of estimators: a suboptimal fading extended Kalman filter (SFEKF) is implemented for each actuator fault type, including the no-fault case, and here are five SFEKFs all together. The fault diagnosis methods are based on the idea of determining changes between the measured and the estimated values of the same variable at each time instant. An assessment of these changes in these variables are given by the so-called 'residuals', which are indices of model matching. In order to improve the isolation capabilities, the residuals are filtered with low-pass filters against the effects of noise. Low-pass filtering enables one to extract the steady-state value and to reduce the variance of the residual. On the basis of the residual generation, the decision scheme could be designed in various different ways, here we give simple diagnostic rules to detect fault.

The simulation results suggest that the strong tracking filter constructed here has the characteristic of strong tracking, the precision of the state estimation can satisfy with the demand of the fault diagnosis. And fault diagnosis experimental results are reported in order to demonstrate the effectiveness of the proposed approach. This paper is helpful for constructing the automated diagnosis system ensuring the AUV system robustness. Future work will be devoted to improve the reliability of fault diagnosis.

Key Words: autonomous underwater vehicle, fault diagnosis, strong track filter(STF), suboptimal fading extended Kalman filter (SFEKF)

1. Introduction

In recent years, the need and desire to explore and utilize the vast oceanic environment for extraction of resources have encouraged the development of unmanned underwater vehicles which are usually classified as autonomous underwater vehicle(AUV) and remotely operated vehicle(ROV). In this field, as we know, an autonomous underwater vehicle (AUV) acts as an important role just as a rocket in outer space for AUV can move around in a larger area, dive deeper, research under complicated surroundings. With the improvement of AUV's autonomy ability, the tasks required for AUV are more difficult, so AUVs need stronger reliabilities and can detect faults and deal with them in time.

In order to ensure that autonomous underwater vehicle can complete tasks successfully in unstructured and hazardous oceanic environment with the high pressure and low visibility, so an efficient and effective fault detect and fault-tolerant control system becomes imperative for AUVs. There are two main fault detection methods: the model-free method and the model-based method. The extended Kalman Filter(EKF) has many applications in mobile robotics ranging from perception, to position estimation, to control. Here, an Suboptimal Fading Extended Kalman Filter (SFEKF) is used to detect actuator faults of an AUV.

2. Strong track filter theory

For the discrete nonlinear model, an extended Kalman Fileter(EKF) can be used to estimeate the state vaule.

$$x(k+1) = f(k, u(k), x(k)) + \Gamma(k)v(k) \quad (1)$$

$$y(k+1) = h(k+1, x(k+1)) + e(k+1) \quad (2)$$

In the discrete model, the names and sizes of the vectors and matrices are:

$x(k)$ is the $(n \times 1)$ system **state vector**

$f(k, u(k), x(k))$ is nonlinear **transition function**

$\Gamma \in R^{n \times q}$ is the **process noise distribution matrix**

$v(k)$ is $(q \times 1)$ white **disturbance sequence** or **process noise sequence** with known
covariance structure.

$y(k)$ is a $(m \times 1)$ **measurement**

$h(k+1, x(k+1))$ is nonlinear **measurement function** or **observation function**

$e(k)$ is $(m \times 1)$ white **observation noise sequence.**

The covariance matrices for the white sequences are:

$$Ev(k) = Ee(k) = 0$$
$$E[v(k)v^T(j)] = Q(k)\delta_{k,j}$$
$$E[e(k)e^T(j)] = R(k)\delta_{k,j}$$
$$E[v(k)e^T(j)] = 0$$

where $\delta_{k,j}$ is the Kronecker delta.

When the model (1)(2) have enough precision, and the initial value chosen of $\hat{x}(0|0)$, $P(0|0)$ are proper, EKF can give accurate state estimation. But the robustness of EKF is not good, it will give poor estimated value even not convergent. In additional, EKF can not track the system's mutation when the system balances.

To get over the disadvantage of EKF, a better filter called Strong track filter(STF) will appear and with following specification :

① Good robustness about parameters change；

② Low sensitivity about noise ,iniatial value；

③ Strong track capability for break, it can keep track gradual change and break when it balances;

④ Moderate computation complicacy.

A sufficient conditoin to make a general filter (EKF) have strong track specialties is to choose the gian matrix $K(k+1)$ online which makes:

$$E[x(k+1)-\hat{x}(k+1|k+1)][x(k+1)-\hat{x}(k+1)]^T = \min \tag{3}$$

$$E[\gamma^T(k+1)\gamma(k+1+j)]=0, \quad k=0,1,2,\cdots, \; j=1,2,\cdots \tag{4}$$

the first condition minimizes covariance, and the second condition requires output residuals to keep orthogonal.

So suboptimal fading timevarying factor(λ) is introduced which can fade the historical data and adjust covariance and gain matrix real-time. Here, we obtain the suboptimal fading extended Kalman filter(SFEKF) which is a strong track filter.

The suboptimal fading extended Kalman filter equations for the system model are as follows:

$$\hat{x}(k+1|k+1) = \hat{x}(k+1|k)+K(k+1)\gamma(k+1) \tag{5}$$

$$\hat{x}(k+1|k) = f(k,u(k),\hat{x}(k|k)) \tag{6}$$

$$K(k+1)=P(k+1|k)H^T(k+1,\hat{x}(k+1|k)) \cdot [H(k+1),\hat{x}(k+1|k)) \cdot P(k+1|k)H^T(k+1,\hat{x}(k+1|k)) + R(k+1)]^{-1} \tag{7}$$

To get over the disadvantage of EKF, To get over the disadvantage of EKF,

$$P(k+1|k)=\lambda(k+1)F(k,u(k),\hat{x}(k|k)) P(k|k)F^T(k,u(k),\hat{x}(k|k)) + \Gamma(k)Q(k)\Gamma^T(k) \tag{8}$$

$$P(k+1|k+1)=[I-K(k+1) H(k+1,\hat{x}(k+1|k))]P(k+1|k) \tag{9}$$

$$\gamma(k+1)=y(k+1)-\hat{y}(k+1) = y(k+1)-h(k+1,\hat{x}(k+1|k)) \tag{10}$$

$$H(k+1,\hat{x}(k+1|k) = \frac{\partial h(k+1,x(k+1))}{\partial x}\Big|_{x(k+1)=\hat{x}(k+1|k)} \tag{11}$$

$$F(k,u(k),\hat{x}(k|k) = \frac{\partial f(k,u(k)x(k))}{\partial x}\Big|_{x(k)=\hat{x}(k|k)} \tag{12}$$

$$V_0(k+1)=E[\gamma(k+1)\gamma^T(k+1)] \approx H(k+1,\hat{x}(k+1|k))P(k+1|k) H^T(k+1,\hat{x}(k+1|k))+Q_2(k+1) \tag{13}$$

Suboptimal Fading factor $\lambda(k+1)$ can caculate as equation (14):

$$\lambda(k+1)=\begin{cases}\lambda_0, & \lambda_0 \ge 1 \\ 1, & \lambda_0 < 1\end{cases} \tag{14}$$

where

$$\lambda_0 = \frac{tr[N(k+1)]}{tr[M(k+1)]} \tag{15}$$

$$\begin{aligned} N(k+1) &= V_0(k+1) - \\ & H(k+1,\hat{x}(k+1|k)\Gamma(k)Q(k)\Gamma^T(k) \\ & H^T(k+1,\hat{x}(k+1|k)) - R(k+1) \end{aligned} \tag{16}$$

$$\begin{aligned} & M(k+1) = H(k+1,\hat{x}(k+1|k)) \\ & F(k,u(k),\hat{x}(k|k))P(k|k) \\ & \cdot F^T(k,u(k),\hat{x}(k|k))H^T(k+1,\hat{x}(k+1|k)) \end{aligned} \tag{17}$$

3. Fault diagnosis for AUV

3.1 Motion model

In this work, a problem of fault detection for a vehicle operating on the horizontal plane is considered. The underwater vehicle is "ZhiShui 3", an AUV, which was designed by HEU, Fig. 1shows"ZhiShui 3" in the operational configuration for sea trial.

A small UV can be modelled by a set of hydrodynamic equations (Fossen, 1994). In particular, the horizontal motion can be described by the following nonlinear equations:

$$\begin{aligned} & m\cdot\left[(\dot{u}-vr)-x_G r^2\right] \\ & = X_{rr}r^2 + X_{\dot{u}}\dot{u} + X_{vr}vr + X_{uu}u^2 + X_T \end{aligned} \tag{18}$$

$$\begin{aligned} & m\cdot\left[(\dot{v}+ur)+x_G\dot{r}\right] \\ & = Y_{\dot{r}}\dot{r} + Y_{\dot{v}}\dot{v} + Y_r ur + Y_{v|r|}v|r| \\ & + Y_v uv + Y_{v|v|}v|v| + Y_T \end{aligned} \tag{19}$$

$$\begin{aligned} & I_z\dot{r} + mx_G(\dot{v}+ur) \\ & = N_{\dot{r}}\dot{r} + N_{r|r|}r|r| + N_{\dot{v}}\dot{v} + N_r ur \\ & + N_{v|r|}v|r| + + N_v uv + N_{v|v|}v|v| + N_T \end{aligned} \tag{20}$$

They can be expressed as model （1）（2），

$$\begin{cases} x(k+1) = f(k,u(k),x(k)) \\ y(k+1) = Gx(k+1) + e(k+1) \end{cases} \tag{21}$$

where

$$x = \begin{bmatrix} x_1 & x_2 & x_3 \end{bmatrix}^T = \begin{bmatrix} u & v & r \end{bmatrix}^T$$

$$y = [y_1 \quad y_2 \quad y_3]^T = \begin{bmatrix} u & v & r \end{bmatrix}^T$$

$$u = \begin{bmatrix} u_1 & u_2 & u_3 \end{bmatrix}^T = \begin{bmatrix} X_T & Y_T & N_T \end{bmatrix}^T$$

$$A = m - X_{\dot{u}} \quad B = m - Y_{\dot{v}}$$

$$C = mx_G - Y_{\dot{r}} \quad D = I_z - N_{\dot{r}}$$

$$E = mx_G - N_{\dot{v}}$$

$$f(k,u(k),x(k)) = \begin{bmatrix} x_1(k) + T\dfrac{X_f(k)}{A} \\ x_2(k) + T\dfrac{Y_f(k)\cdot D - N_f(k)\cdot C}{P} \\ x_3(k) + T\dfrac{N_f(k)\cdot B - Y_f(k)\cdot E}{P} \end{bmatrix} \tag{22}$$

$$G = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \tag{23}$$

$$X_f(k) = mx_2(k)x_3(k) + mx_G x_3^2(k) + X_{uu}x_1^2(k) + X_{vr}x_2(k)x_3(k) + X_{rr}x_3^2(k) + u_1 \tag{24}$$

$$Y_f(k) = -mx_1(k)x_3(k) + Y_v x_1(k)x_2(k) + Y_r x_1(k)x_3(k) + Y_{v|v|}x_2(k)|x_2(k)| + \tag{25}$$

$$+Y_{v|r|}x_2(k)|x_3(k)| + Y_{r|r|}x_3(k)|x_3(k)| + u_2$$

$$N_f(k) = -mx_G x_1(k)x_3(k) + N_v x_1(k)x_2(k) + N_r x_1(k)x_3(k) + N_{v|v|}x_2(k)|x_2(k)| + +N_{v|r|}x_2(k)|x_3(k)| + N_{r|r|}x_3(k)|x_3(k)| + u \tag{26}$$

3.2 Actuator faults model

Denote by X_T^*, Y_T^*, N_T^* the expected surge force, the expected sway force, and the expected yaw torque, given by motion controller; T_{ML}^*, T_{MR}^*, T_{HB}^*, T_{HS}^* are the expected thrusts exerted by left main , right main , bow horizontal and stern horizontal thrusters, respectively。

Based force allocation, there are formula (27):

$$T_{ML}^* = T_{MR}^* = 0.5\, X_T^*$$

$$T_{HB}^* = \frac{Y_T^* \cdot l_{HS}}{l_{HB}+l_{HS}} + \frac{N_T^*}{l_{HB}+l_{HS}} \tag{27}$$

$$T_{HS}^* = \frac{Y_T^* \cdot l_{HB}}{l_{HB}+l_{HS}} - \frac{N_T^*}{l_{HB}+l_{HS}}$$

when there is no fault occurs

$$T_{ML} = T_{ML}^*,\quad T_{MR} = T_{MR}^*\quad,$$

$$T_{HB} = T_{HB}^*,\quad T_{HS} = T_{HS}^*$$

and then

$$X_T = X_T^*,\quad Y_T = Y_T^*,\quad N_T = N_T^* \tag{28}$$

If there is a left main thruster fault occurs, $T_{ML} = 0$, and then the results are

$$X_T = 0.5X_T^*,\quad Y_T = Y_T^*,$$

$$N_T = N_T^* - T_{MR}l_M = N_T^* - 0.5X_T^* l_M \tag{29}$$

If there is a right main thruster fault occurs, $T_{MR} = 0$, and then the results are

$$X_T = 0.5X_T^*,\quad Y_T = Y_T^*,$$

$$N_T = N_T^* + T_{ML}l_M = N_T^* + 0.5X_T^* l_M \tag{30}$$

If there is a bow horizontal thruster fault occurs, $T_{HB} = 0$, and then the results are

$$X_T = X_T^*,$$

$$Y_T = T_{HS} = \frac{Y_T^* \cdot l_{HB}}{l_{HB}+l_{HS}} - \frac{N_T^*}{l_{HB}+l_{HS}}, \tag{31}$$

$$N_T = T_{HS}l_{HS} = \left(\frac{Y_T^* \cdot l_{HB}}{l_{HB}+l_{HS}} - \frac{N_T^*}{l_{HB}+l_{HS}}\right)l_{HS}$$

If there is a stern horizontal thruster fault occurs, $T_{HS} = 0$, and then the results are

$$X_T = X_T^*,$$

$$Y_T = T_{HB} = \frac{Y_T^* \cdot l_{HS}}{l_{HB}+l_{HS}} + \frac{N_T^*}{l_{HB}+l_{HS}} \tag{32}$$

$$N_T = T_{HB}l_{HB} = \left(\frac{Y_T^* \cdot l_{HS}}{l_{HB}+l_{HS}} + \frac{N_T^*}{l_{HB}+l_{HS}}\right)l_{HB}$$

3.3 A fault-detection scheme

This task is performed by a bank of estimators: a suboptimal fading extended Kalman filter (SFEKF) is implemented for each actuator fault type, including the no-fault case, and here are five SFEKFs all together. The fault diagnosis methods are based on the idea of determining changes between the measured and the estimated values of the same variable at each time instant. An assessment of these changes in these variables are given by the so-called ‘residuals’, which are indices of model matching. On the basis of the residual generation, the decision scheme could be designed in various different ways, here we give simple diagnostic rules to detect fault.

Rules are summarized from substantive tests:

if(R_u_ml=R_u_mr<R_u_n
and R_r_ml<R_r_n<R_r_mr)
fault type=tleft main thruster fault

if(R_u_ml=R_u_mr<R_u_n
and R_r_mr<R_r_n<R_r_ml)
fault type=right main thruster fault

if(R_v_ha<R_v_hf<R_v_n
and R_r_ha<R_r_n<R_r_hf)
fault type=bow horizontal thruster fault

if(R_v_hf<R_v_ha<R_v_n
and R_r_hf<R_r_n<R_r_ha)
fault type=stern horizontal thruster fault

There, R_u_ml means the magnitude of u residual from left main thruster fault model, the other symbols use the same naming rules. If we get the same result three times continuously, we think a fault occurs here. In order to improve the isolation capabilities, the residuals are filtered with low-pass filters against the effects of noise. Low-pass filtering enables one to extract the steady-state value and to reduce the variance of the residual.

The tests presented in this section refer to cases where the vehicle is advancing ahead at a constant speed of almost 0.3 m/s. In the case of Figs. 2, at about 110 sec, the left main thruster fault occurs. Figs. 3 are filtered residuals. From these pictures, the left main thruster fault at about 110 sec is easy to be detected.

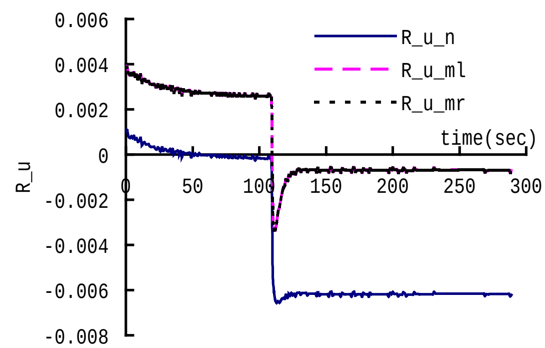

Fig.2(a) the residuals of u (left fault)

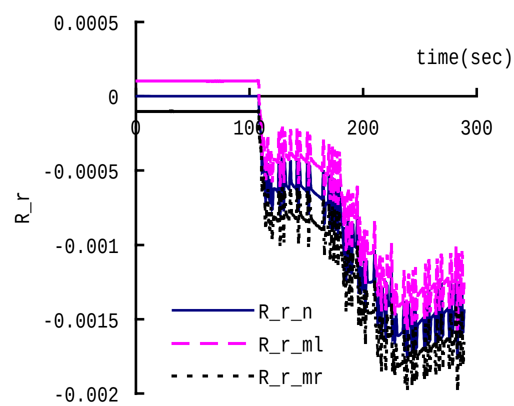

Fig.2(b) the residuals of r (left fault)

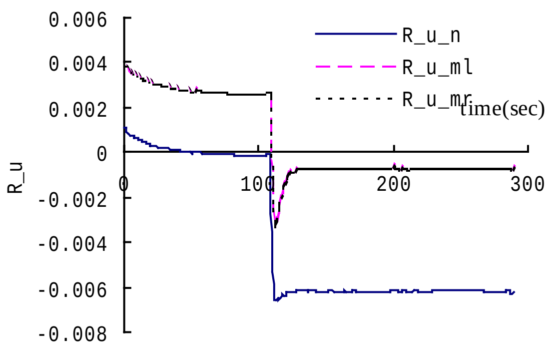

Fig.3(a) the filtered residuals of u (left fault)

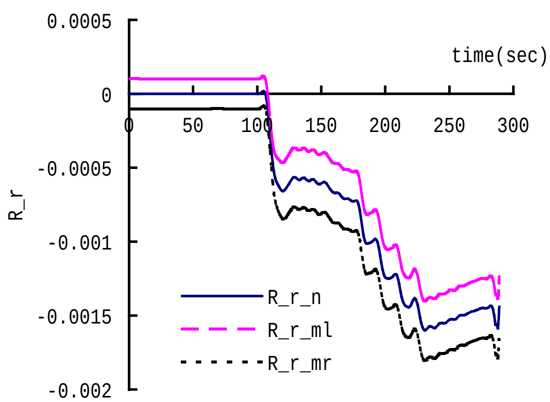

Fig.3(b) the filtered residuals of r (left fault)

4. Conclusions

The simulation results suggest that the strong tracking filter constructed here has the characteristic of strong tracking, the precision of the state estimation can satisfy with the demand of the fault diagnosis. And fault diagnosis experimental results demonstrate the effectiveness of the proposed approach. This paper is helpful for constructing the automated diagnosis system which intents to ensure the AUV system robustness.

Future work will be devoted to improve the reliability of fault diagnosis. Residuals contain abundant fault information, various different fault diagnosis ways can be designed, information fusion technology is one of good ways to improve the reliability of fault diagnosis. The active diagnosis and fault-tolerant control system can enhance autonomous capabilities which must be very useful and significant in the field of AUV. These will be investigated in future work.

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