SENSOR FAULT DETECTION FOR THE ANSAT HELICOPTER USING OBSERVERS

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Abstract

The problem of sensor fault detection using observers for helicopters operating in wind disturbances is investigated in this paper. The idea of the method for obtaining reliable information about sensor failures is via the utilization of observers with estimation of external disturbances. In this case, the disturbance estimates are also used in the controller for disturbance compensation. The capabilities of the observer to detect sensors failures were experimentally tested on a helicopter rig.

Nomenclature

θ,ϕ,ψ	pitch, roll and yaw angles (deg)	$\delta_{lon}, \delta_{lat}$	lateral and longitudinal cyclic of the swash plate caused by the atmospheric turbulence (deg)
u,v,w	longitudinal, lateral and normal velocity components (m/sec)	δ_{col}, δ_p	collective deviation of the main and tail rotor caused by the atmospheric turbulence (deg)
p,q,r	roll, pitch and yaw rates (deg/sec)	V_r	mean wind speed in turbulence model (m/sec)
R_m, R_t	main and tail rotor radii (m)	σ_w	root mean square value of vertical gust velocity (m/sec)
θ_0, θ_{0t}	main and tail rotor collective (deg)	w_n	white noise with unit covariance
θ_{1c}, θ_{1s}	longitudinal and lateral cyclics (deg)	ω_{rotor}, ω_t	main and tail rotor rotational speed, (deg/sec)
$a_{10\beta}, b_{10\beta}$	flapping coefficients of equivalent main rotor in stability axis coordinate system coordinate system	PID	the proportional-integral-derivative controller
		MR, TR	main rotor and tail rotor
$b_{1\beta}$	blade flapping coefficient in stability axis coordinate system coordinate system	SDP	semi-definite programming
$\lambda_0, \lambda_{eq}, \lambda_t$	main rotor, equivalent rotor, and tail rotor inflow	FDI	fault detection and isolation
		DOB	disturbance observer
$\bar{\upsilon}_i$, $\bar{\upsilon}_{ti}$	average relative induced velocity of main and tail rotor (m/sec)	UIO	unknown input observer

1. INTRODUCTION

In case of sensor failure during flight the helicopter must remain controllable and maintain its ability to perform mission tasks. It is therefore important to create a fault-tolerant control system that can continue operation in case of failure and recover the aircraft state vector.

To detect failure, there should be some redundancy in the system hardware (dual sensors and actuators) or analytical information, based on a priori knowledge of the relationship between the measured inputs and outputs in the system.

Over the past few decades different approaches to the problem of fault detection and isolation (FDI) have been developed, a detailed review can be found in [1]. They can be grouped as model-based and data-based.

Data-based methods include spectral analysis, pattern recognition, statistical classifiers, neural networks and fuzzy algorithms [2].

For control systems the most commonly used approach is model-based, due to the rapid response to a sudden failure and simple implementation in real-time algorithms [3]. Model-based FDI approaches include parameter estimation, state estimation, and parity space [4].

Parameter estimation methods are based on various identification algorithms (least squares, regression analysis). These compare an identified model with a reference one. A joint parameter and state estimation can also be used. This is based on adaptive filters, extended Kalman filters, or two-stage Kalman filters.

Various types of observers are used in FDI systems for state estimation. The estimates are compared with the outputs of the model. The Luenberger observer [5] was found to be not robust to external disturbances. Therefore, it may produce biased estimates in presence of unknown disturbances and, as a result, false fault detection. If disturbance is stochastic then a Kalman filter [6] can be used. However, if there are unknown disturbances and model inaccuracy, these types of observers cannot be applied. In this case disturbance observer (DOB) [7] or unknown input observer (UIO) [8, 9] can be used. In this work the observer with disturbance estimation [10] is applied.

Model-based methods include two stages of fault detection: 1) detection of deviations from the predicted behavior of the model and residual generation; 2) making a decision about fault occurrence.

The residual should be close to zero in the absence of failure and take sufficiently large values when it occurs. In addition, they must have the orthogonality property, i.e. each residual should be sensitive to only one failure.

This paper considers the problem of sensor fault detection using observers for helicopter under wind disturbances.

The idea of the method for obtaining reliable information about a sensor failure is utilization of observers with estimation of external disturbances. In this case, the resulting disturbance estimate is also used in the controller for disturbance compensation, as shown in [10].

2. HELICOPTER MODEL

To simplify the model of the helicopter [12], the equations describing the helicopter motion with main and tail equivalent rotors are used.

Aerodynamic parameters of the main and tail rotors were determined using a mathematical model, which was established on the basis of the classic Glauert and Lock theory of a rotor with hinged blades [13].

The following assumptions were made:

1. the induced velocity is uniformly distributed over the main rotor (MR) disc;
2. the lift slope of the MR blade section is linear;
3. the profile drag coefficient can be replaced by averaged value and identical for all blade sections;
4. blade tip losses are ignored;
5. a hingeless hub is considered (the MR torsion stiffness is taken into account in the model);
6. the dynamics of the hydraulic servo

actuators of the main and tail rotors is neglected.

Similar assumptions are made for the tail rotor (TR).

In view of these assumptions, the equations in the fuselage coordinate system, and generalized form are described by nonlinear differential equations, in which the aerodynamic parameters of the main and tail rotors implicitly depend on the coordinates of the state and controls:

(1) $\dot{x} = f\left(x, \mathrm{u}, \varphi(z_0, z_t), \xi\right)$,

(2) $\varphi_0\left(z_0, x, \mathrm{u}\right) = 0$,

(3) $\varphi_t\left(z_t, x, \mathrm{u}\right) = 0$,

where $x = \left(u, v, w, p, q, r, \theta, \phi, \psi\right)^T \in R^n$ is the state vector of the system, $n = 9$; $\mathrm{u} = \left(\theta_{1c}, \theta_{1s}, \theta_0, \theta_{0t}\right)^T \in R^m$ is the vector of the swash plate and tail rotor attitude, $m = 4$; $\varphi(z_0, z_t) \in R^4$ is the vector of aerodynamic forces and moments obtained from references [13,14]; $z_0 = \left(a_{10\beta}, b_{10\beta}, \lambda_0, \lambda_{eq}, b_{1\beta}, \bar{\upsilon}_i\right)^T$ are the aerodynamic parameters of the MR, $z_t = \left(\lambda_t, \bar{\upsilon}_{ti}\right)^T$ is the aerodynamic vector of the TR; $\xi \in R^4$ is the vector of atmospheric turbulence, which, according to [15], is modeled in the form of additional inputs causing change in the position of the swash plate controls.

Modeling of the helicopter dynamics using equations (1)-(3) is performed with a constant integration step. For each point in time the values z_0, z_t that satisfy equations (2), (3) are obtained from the known values x, u using Newton's method.

From equations (1)-(3) with $\dot{x} = 0$, $\xi = 0$ the trim values $x^*, \mathrm{u}^*, z_0^*, z_t^*$ are obtained with a given accuracy. Then from equation (1) the simplified equation of deviations $\Delta x = x - x^*$, $\Delta \mathrm{u} = \mathrm{u} - \mathrm{u}^*$ from trim are:

(4) $\Delta\dot{x} = A\Delta x + B\Delta \mathrm{u} + D\,\mathrm{w}\left(x, \mathrm{u}, \xi\right)$,

where $B = [\tilde{B}^T \; 0_{m\times(n-s)}]^T$, $D = \left[I_s \; 0_{s\times(n-s)}\right]^T$, $\mathrm{w}\left(x, \mathrm{u}, \xi\right) = \tilde{B}\xi + \Delta\,\mathrm{w}\left(x, \mathrm{u}, \xi\right)$, $\Delta\,\mathrm{w} \in R^s$.

It is assumed that the initial deviation of the system and external disturbances are constrained:

(5) $\Delta x(t_0)\Delta x^T(t_0) \le Q_{\Delta x}$,

(6) $\mathrm{w}\mathrm{w}^T \le Q_{\mathrm{w}}$, $\dot{\mathrm{w}}\dot{\mathrm{w}}^T \le Q_{\dot{\mathrm{w}}}$,

(7) $\mathrm{v}\mathrm{v}^T \le Q_{\mathrm{v}}$,

where $Q_{\Delta x}$, Q_{w}, Q_{v} are positive definite matrices of appropriate dimensions. Note that these restrictions are equivalent to the corresponding ellipsoid membership of the vectors (for example, $\Delta x(t_0) Q_{\Delta x}^{-1} \Delta x^T(t_0) \le 1$).

3. ATMOSPHERIC TURBULENCE MODEL

In this paper, atmospheric turbulence is modeled according to the approach, described in [15]. Turbulence effects are obtained as additional control inputs by passing white noise through appropriate transfer functions, parameterized by main rotor diameter, angular velocity of the rotor, turbulence intensity, and mean wind speed. The transfer functions obtained for one helicopter model can be scaled for other using the technique in [15]. The turbulence model for the UH-60 rotorcraft was scaled for the Ansat aircraft of the Kazan Helicopter Plant at the following conditions: the mean wind speed was $V_r = 5{,}144$ m/sec, and the turbulence intensity was $\sigma_{\mathrm{w}} = 1{,}03$ m/sec. The transfer functions for the control inputs of the UH-60 were also scaled for the Ansat helicopter:

(8) $$\frac{\delta_{lat}}{\mathrm{w}_n} = 0,837\sigma_{\mathrm{w}}^{-0,6265}\sqrt{\frac{\sigma_{\mathrm{w}}^2 V_r}{\pi R_m}} \times \times\left[\frac{1}{s+(2V_r/R_m)}\right]\frac{\omega_{rotor}|_{UH-60}}{\omega_{rotor}|_{Ansat}}H,$$

(9) $$\frac{\delta_{lon}}{\mathrm{w}_n} = 1,702\sigma_{\mathrm{w}}^{-0,6265}\sqrt{\frac{\sigma_{\mathrm{w}}^2 V_r}{\pi R_m}} \times \times\left[\frac{1}{s+(2V_r/R_m)}\right]\frac{\omega_{rotor}|_{UH-60}}{\omega_{rotor}|_{Ansat}}H,$$

(10) $$\frac{\delta_{col}}{\mathrm{w}_n} = 0,1486\sigma_{\mathrm{w}}^{-0,7069}\sqrt{\frac{3\sigma_{\mathrm{w}}^2 V_r}{\pi R_m}} \times \times\left[\frac{(s+33,91(V_r/R_m))}{\left[s+1,46(V_r/R_m)\right]\left[s+9,45(V_r/R_m)\right]}\right]\times \times\frac{R_m\omega_{rotor}|_{UH-60}}{R_m\omega_{rotor}|_{Ansat}}H,$$

(11) $$\frac{\delta_p}{\mathrm{w}_n} = 1,573\sigma_{\mathrm{w}}^{-0,6493}\sqrt{\frac{\sigma_{\mathrm{w}}^2 V_r}{\pi R_t}} \times \times\left[\frac{1}{s+(2V_r/R_t)}\right]\left[\frac{R_t\omega_t|_{UH-60}}{R_t\omega_t|_{Ansat}}\right]^2,$$

where the transfer function H is:

$$H = \frac{\left.\dfrac{(\pi V_r/8R_m)}{s+(\pi V_r/8R_m)}\right|_{Ansat}}{\left.\dfrac{(\pi V_r/8R_m)}{s+(\pi V_r/8R_m)}\right|_{UH-60}}.$$

This atmospheric turbulence model resulted in a vector of external disturbances $\xi = [\delta_{lon}\ \delta_{lat}\ \delta_{col}\ \delta_p]^T$.

4. PROBLEM STATEMENT

The most common types of sensor failures are:
1) full sensor failure - constant zero output signal;
2) stuck with a constant signal at the output;
3) drift, or additive type of failure;
4) multiplicative sensor failure - nominal value of the sensor is multiplied by a coefficient.

For example, in the case of drift sensor fault, the results of measurements can be presented in a form:

(12) $$y = C\Delta x + f_s + \mathrm{v},$$

where $y \in R^l$; $\mathrm{rank}\, C = l$; $\mathrm{v} \in R^l$ is noise vector; $f_s \in R^l$ is vector of possible sensor failures.
At the nominal mode $f_s = 0$, in a case of sensor failure the corresponding element of the vector f_s takes a non-zero value. Depending on the helicopter flight mode, the number of measured elements of the vector y changes:

$$\begin{cases} V = \sqrt{u^2+v^2+w^2} \geq 10 \text{ km/h}, \ C = I_n; \\ V < 10 \text{ km/h}, \ C = \left[0_{l\times(n-l)} \quad I_l\right], \ l = 6. \end{cases}$$

The problem is to detect the fault and isolate the faulty angular velocity sensor.

5. THE OBSERVER SYNTHESIS

For the detection of sensor failure the observer discussed earlier in [11] is used. It is able to produce state $\Delta\hat{x}$ and external disturbance $\hat{\mathrm{w}}$ estimates.

The observer equation is of the form:

(13) $$\Delta\dot{\hat{x}} = A\Delta\hat{x} + B\Delta\mathrm{u} + D\hat{\mathrm{w}} + L_1\left(y - C\Delta\hat{x}\right),$$

(14) $$\mu\dot{\hat{\mathrm{w}}} + \hat{\mathrm{w}} = D^+\left(\Delta\dot{\hat{x}} - A\Delta\hat{x} - B\Delta\mathrm{u}\right) + +L_2\left(y - C\Delta\hat{x}\right).$$

Here $D^+ = \left(D^T D\right)^{-1} D^T$; μ is a small parameter, L_1, L_2 are coefficient matrices to be determined.

Taking into account (13), equation (14) can be rewritten as

(15) $$\dot{\hat{\mathrm{w}}} = \mu^{-1}\left(D^{+}L_1 + L_2\right)\left(y - C\Delta\hat{x}\right),$$

It is obvious, that for an arbitrary disturbance and for (15) to hold it is necessary that $rank\left(D^{+}L_1 + L_2\right) = s$, $l \geq s$.

Introducing the extended vector $\hat{x}_{ext} = \left[\Delta\hat{x}^T\ \hat{\mathrm{w}}^T\right]^T$, we can then write the equation of the observer:

(16) $$\begin{aligned}\dot{\hat{x}}_{ext} &= A_{ext}\hat{x}_{ext} + B_{ext}\Delta\mathrm{u} + \\ &+ H_{ext}L_{ext}\left(y - C_{ext}\hat{x}_{ext}\right),\end{aligned}$$

where $C_{ext} = \left[C\ 0_{l\times s}\right]$,

$$A_{ext} = \begin{bmatrix} A & D \\ 0_{s\times n} & 0_{s\times s}\end{bmatrix},\ B_{ext} = \begin{bmatrix} B \\ 0_{s\times m}\end{bmatrix},$$
$$L_{ext} = \begin{bmatrix} L_1 \\ L_2\end{bmatrix},\ H_{ext} = \begin{bmatrix} I_n & 0_{n\times s} \\ \mu^{-1}D^{+} & \mu^{-1}I_s\end{bmatrix}.$$

Then the deviations $\Delta x_{ext} = x_{ext} - \hat{x}_{ext}$, where $x_{ext} = \left[\Delta x^T\ \mathrm{w}^T\right]^T$, will have the form:

(17) $$\Delta\dot{x}_{ext} = P_{ext}\Delta x_{ext} + D_{ext}\dot{\mathrm{w}} - H_{ext}L_{ext}\mathrm{v},$$

where $P_{ext} = A_{ext} - H_{ext}L_{ext}C_{ext}$, $D_{ext} = \left[0_{s\times n}\ I_s\right]^T$.

Equations (13), (17) imply that for the observer (16) to work, the matrices $A - L_1C$ and P_{ext} must be stable. At the same time taking into account the constraints (6), the solution $\Delta x_{ext}(t)$ will be limited.

To define L_{ext} in (17) we use the method described in [10] with $f_s = 0$, assuming $H_{ext} = I_{n+s}$. Then for the system (17) the following matrix inequality holds:

(18) $$\begin{aligned}&A_{ext}X + XA_{ext}^T + \alpha X - L_{ext}C_{ext}X - \\ &-XC_{ext}^TL_{ext}^T + \alpha_1^{-1}D_{ext}Q_{\dot{\mathrm{w}}}D_{ext}^T + \\ &+\alpha_2^{-1}L_{ext}Q_{\mathrm{v}}L_{ext}^T \leq 0.\end{aligned}$$

Using $\tilde{X} = X^{-1}$, $Y = X^{-1}L_{ext}$ we can rewrite (18):

$$\begin{bmatrix} -\left(A_{ext}^T\tilde{X} + \tilde{X}A_{ext} + \alpha\tilde{X} - YC_{ext} - C_{ext}^TY^T\right) & \tilde{X}D_{ext} & Y \\ D_{ext}^T\tilde{X} & \alpha_1 Q_{\dot{\mathrm{w}}}^{-1} & 0_{s\times l} \\ Y^T & 0_{l\times s} & \alpha_2 Q_{\mathrm{v}}^{-1}\end{bmatrix} \geq 0,$$

$\tilde{X} > 0$.

Here the inequality

$$C_0\Delta x_{ext}(t)\Delta x_{ext}^T(t)C_0^T \leq C_0XC_0^T$$

holds for the matrix of defined inputs C_0.

We then come to the semi-definite problem (SDP): $\mathrm{tr}\left(C_0\tilde{X}C_0^T\right) \to \max$ taking into account the inequalities. This is equivalent to $\mathrm{tr}\left(C_0XC_0^T\right) \to \min$. Given that $L_{ext} = \tilde{X}^{-1}Y$, we should check the stability of the matrix P_{ext}.

A key feature of the observer (16) is the presence of the matrix H_{ext}, which, depending on the setting of the parameter μ, affects the accuracy of the external disturbance estimation. Moreover, in contrast to references [16-19], for the observer (16) the assumption about the full measurement of the state vector is not required. Also in [17, 19] it is assumed that the disturbances are constant.

Note that for the particular case of the observer (16) with $C = I_n$, $D = I_n$, $L_1 = 2\theta I_n$, $L_2 = \mu\theta^2 I_n - D^{+}L_1$ follows the observer reported in [19] for linear system, in which the parameter θ is chosen accordingly [16]. To ensure the accuracy of estimation of disturbances and noise filtering, setting θ only may not be enough. In addition it requires a full measurement of the state vector of the system (4).

The drawback of unknown input observer [8, 9] is a lack of estimation of the disturbance vector that can be used to control the values of disturbances and compensate them by control.

6. FAULT DETECTION OF ANGULAR VELOCITY SENSORS

The use of a single observer can detect and isolate one failure. If the FDI system needs to isolate more than one failure, a bank of observers can be used. The number of observers in the unit should match the number of faults to be isolated. Each of them must be fed with all control inputs and all but one outputs. In this case, when a failure occurs, the minimal mismatch will be at the output of the observer, which is not receiving a signal from the failed sensor. Thus the sensor fault can be isolated. The residual in this case is calculated as a vector norm $\mathrm{r}^{(i)} = \left\| y^{(i)} - \hat{y}^{(i)} \right\|$, where $y^{(i)}$ is measured output that is fed to the i-th observer, $\hat{y}^{(i)}$ is the output estimate of the i-th observer.

A necessary condition for the existence of the observer is the observability of (A,C). For helicopter when designing a bank of observers this condition holds with no measurement for only one angular velocity. Therefore, the failure of angular velocity sensors can be detected and isolated. With no measurement of linear velocities or angles the system becomes unobservable, and sensor failure can be detected, but not localized.

In this work, a bank of 3 observers of the form (16) is designed for fault detection of angular velocity sensors in conditions of horizontal flight for $V = 10$ km/h and 500 m altitude.

In the case of drift we assume that

$$y^{(i)} = C^{(i)}x + f_s^{(i)} + \mathrm{v}^{(i)},\; i = \overline{1,3}, \tag{19}$$

where $y^{(i)} \in R^{l-1}$, $l = 9$, matrix $C^{(i)}$ is obtained by deleting one row of the matrix C, corresponding to an output p, q and r.

7. MODELING THE DYNAMICS OF THE HELICOPTER AND SENSOR FAULT DETECTION

In [11] we presented a method for the synthesis of control laws with compensation of disturbances for the ANSAT helicopter. Therefore, it is assumed here that the control laws are known.

Using the described observer synthesis approach, the matrix L_{ext} is obtained with $Q_{\dot{w}} = \dot{\mathrm{w}}_{\max}^2 I_s$, $\dot{\mathrm{w}}_{\max} = 0{,}1$, $Q_{\mathrm{v}} = 10^{-4} I_n$ for assumed values $C_0 = \left[I_{9\times 9} \quad 0_{9\times 6} \right]$, $\alpha_1 = 1$, $\alpha_2 = 14$ $\mu = 0{,}2$. In this case the eigenvalues of $A - L_1 C$ are:

-27.3324 -29.1653 -30.2007 -30.6920
-30.7813 -30.4625 -15.0914 -15.0936
-15.0657

The eigenvalues of P_{ext} are:

-13.6652 ± 29.5773i -14.5882 ± 32.0469i
-15.4016 ± 33.6428i -15.3335 ± 33.5450
-15.1017 ± 33.0416i -15.2312 ± 33.2831i
-15.0873 -15.0893 -15.0655

As shown in [11], for the turbulence model (8)-(11) with $V_r = 5{,}144$ m/sec, $\sigma_w = 1{,}03$ m/sec, with ANSAT helicopter parameters $R_m = 5{,}75$ m, $R_t = 1{,}05$ m, $\omega_{rotor} = 38{,}22$ rad/sec, $\omega_t = 209{,}44$ rad/sec, the observer (16) with $l = 9$ estimates the vector of external disturbances w with high accuracy.

In order to check the ability of the observer with disturbance estimation to detect failures of angular velocity sensors, the simulation results of the considered observer (a) and unknown input observer [8, 9] (b) are presented in fig. 2-10.

The helicopter dynamics modeling was conducted with a roll angle reference signal of $2\sin(0,5t)$, deg/sec.

The signals to noise ratios in decibels have the following values are given in Table 1.

Table 1 Signal to noise ratio, dB

SNR_u	SNR_v	SNR_w
7.7	15.6	17.3
SNR_p	SNR_q	SNR_r
31.3	30.3	24.9
$SNR_{\Delta\theta}$	$SNR_{\Delta\phi}$	$SNR_{\Delta\psi}$
15.5	26.9	20.7

As Figures 2-4 show, the observer with disturbance estimation detects not only the drift fault of the sensor, but also estimates its value. Fault isolation is done by selecting the minimum of the residual signal in the excess of the threshold for the other channels. UIO also detects the failure, but the magnitude of the residual is much less. Figures 5-10 show that the observer with disturbance estimation is efficient in the cases of stuck with constant bias fault and total sensor failure, while UIO was unable to detect these types of faults.

8. EXPERIMANTAL SENSOR FAULT DETECTION ON THE LABORATORY HELICOPTER RIG

Verification of observer (16) for fault detection is made by an experimental study on the Raptor helicopter rig (Figure 1).

The rig has two degrees of freedom for roll ϕ and yaw ψ angles, which are measured with accuracy of 0.5 deg. Using experimental data, the second order model ($n=2$, $m=1$) of the form (4) is identified for each control channel. Using the model (4), the discrete PID-controller is designed for each control channel with sampling period and delay $T_0 = 0.1$ sec.

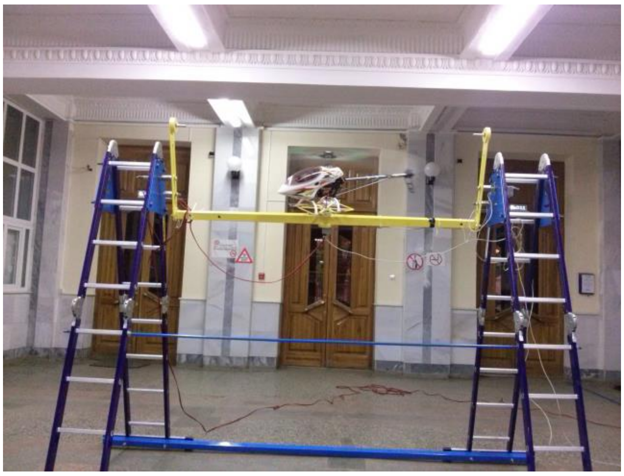

Figure 1: Raptor helicopter rig

Using the model (4) of roll channel the observer (16) is designed for the case of roll ϕ ($l=1$) and control signal measurement. The discrete model of the observer (16) is obtained with sampling period T_0. It is used for drift fault detection of a virtual angular velocity p sensor. The disturbance in the roll channel is created by the motion of the helicopter in yaw in accordance with command signal $g_\psi[kT_0] = 20\sin(0.628kT_0)$ deg; $g_\phi[kT_0] = 0$.

For the roll channel the following results are obtained: Figure 11 presents estimation of angular velocity $\dot{\hat{\phi}}$ (graph 1) and angular velocity $\dot{\tilde{\phi}}$ (graph 2), calculated by the formula

(20) $$\dot{\tilde{\phi}}[kT_0] = \left(\phi[kT_0] - \phi[(k-1)T_0]\right)/T_0,$$

Figure 12 presents the disturbance estimate (graph 1) and yaw angle ψ (graph 2). Here for sensor fault detection the residual is calculated:

(21) $r[kT_0] = |\dot{\tilde{\phi}}[kT_0] - \dot{\hat{\phi}}[kT_0]|$.

The signal $r[kT_0]$ is passed through a digital elliptic filter of 6^{th} order, the filtered signal $\hat{r}[kT_0]$ is obtained at the output.

Figure 13 presents $\hat{r}[kT_0]$ in case of drift fault of the virtual sensor (20) $\dot{\tilde{\phi}}[kT_0] + 0.08$ at $t = 20\,\mathrm{sec}$. As can be seen, the fault is detected after approximately 2 seconds.

9. CONCLUSIONS AND FUTURE WORK

In this paper, the results of modeling the dynamics of the ANSAT helicopter show that utilization of the observer with disturbance estimation improves the detection accuracy of various types of angular speed sensors faults.

The efficiency of the observer is also confirmed by experiments on the laboratory helicopter rig. To evaluate the effectiveness of the proposed algorithm of fault detection an experimental study on the Raptor helicopter rig is conducted. It is shown that in the presence of disturbances and measurement noise it can detect drift failures of angular velocity sensors.

In the future the considered observer will be used in the algorithms of sensor fault detection for the ANSAT helicopter based on flight tests.

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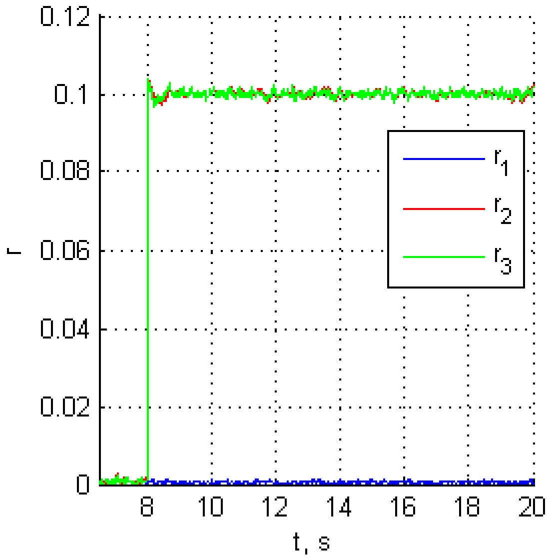
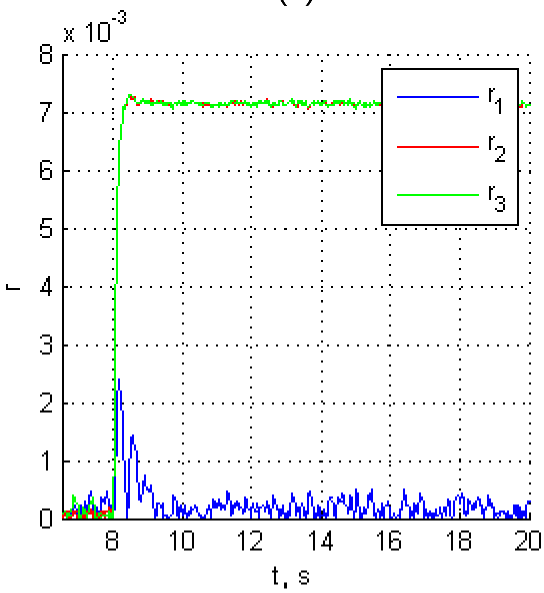
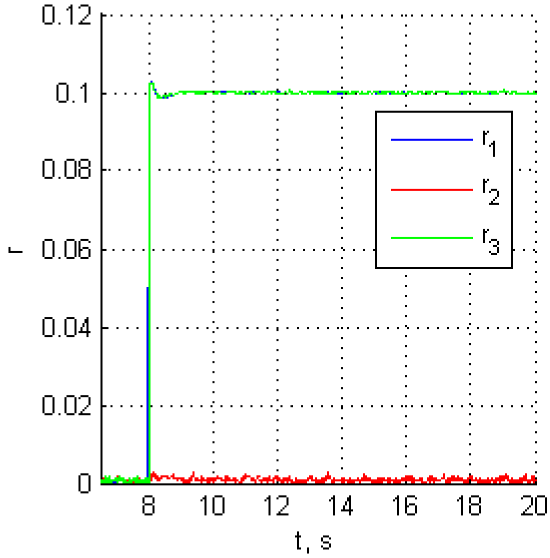


(a)



(b)

Figure 2: Drift failure detection of the angular velocity p sensor by (a) the observer with disturbance estimation, (b) the unknown input observer



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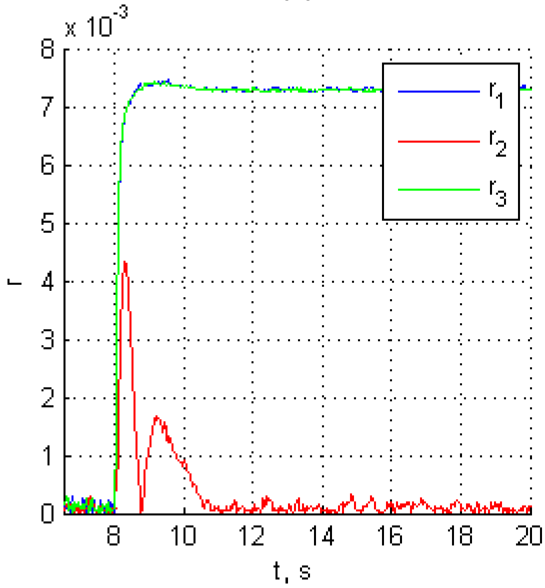
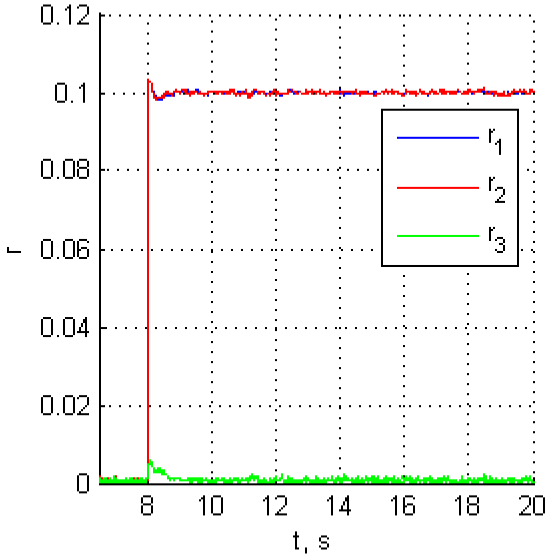


(b)

Figure 3: Drift failure detection of the angular velocity q sensor by (a) the observer with disturbance estimation, (b) the unknown input observer



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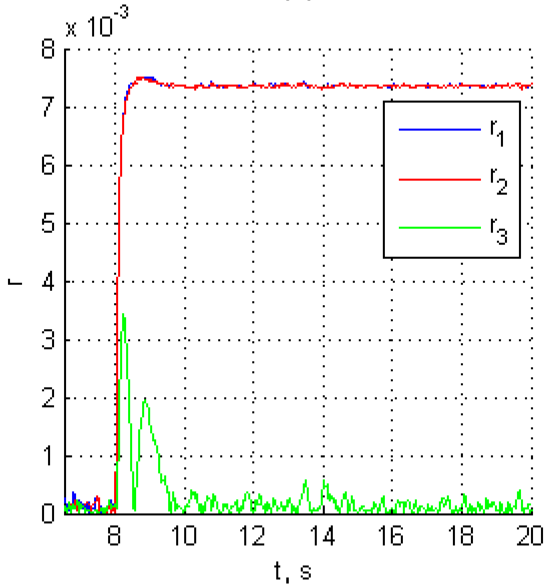
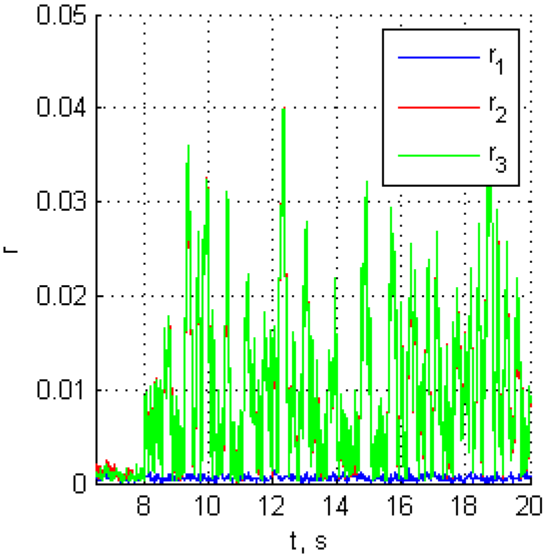


(b)

Figure 4: Drift failure detection of the angular velocity r sensor by (a) the observer with disturbance estimation, (b) the unknown input observer



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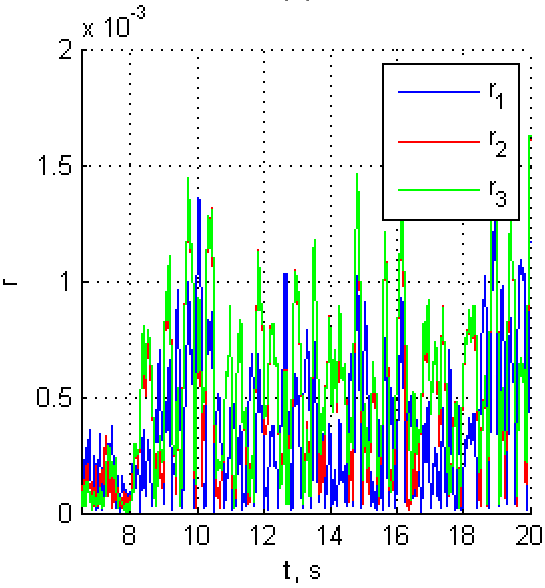
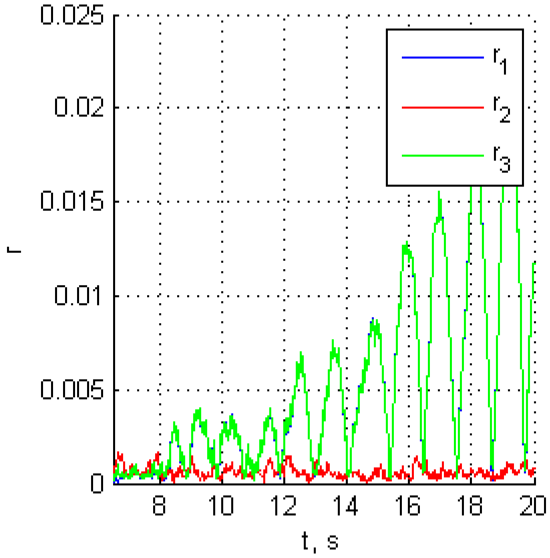
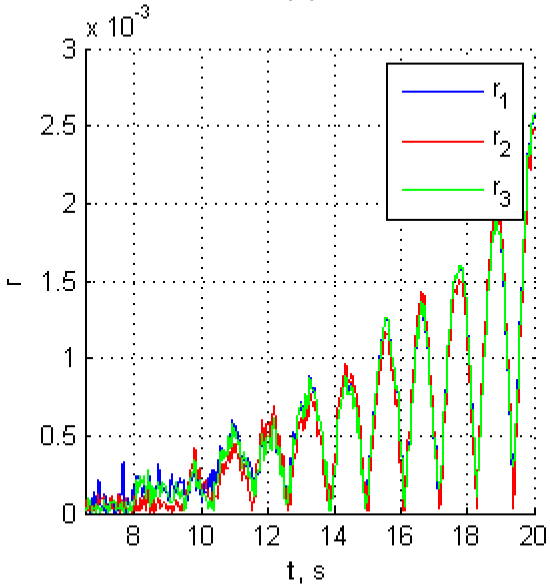


(b)

Figure 5: Detection of constant bias failure of the angular velocity p sensor by (a) the observer with disturbance estimation, (b) the unknown input observer



(a)



(b)

Figure 6: Detection of constant bias failure of the angular velocity q sensor by (a) the observer with disturbance estimation, (b) the unknown input observer

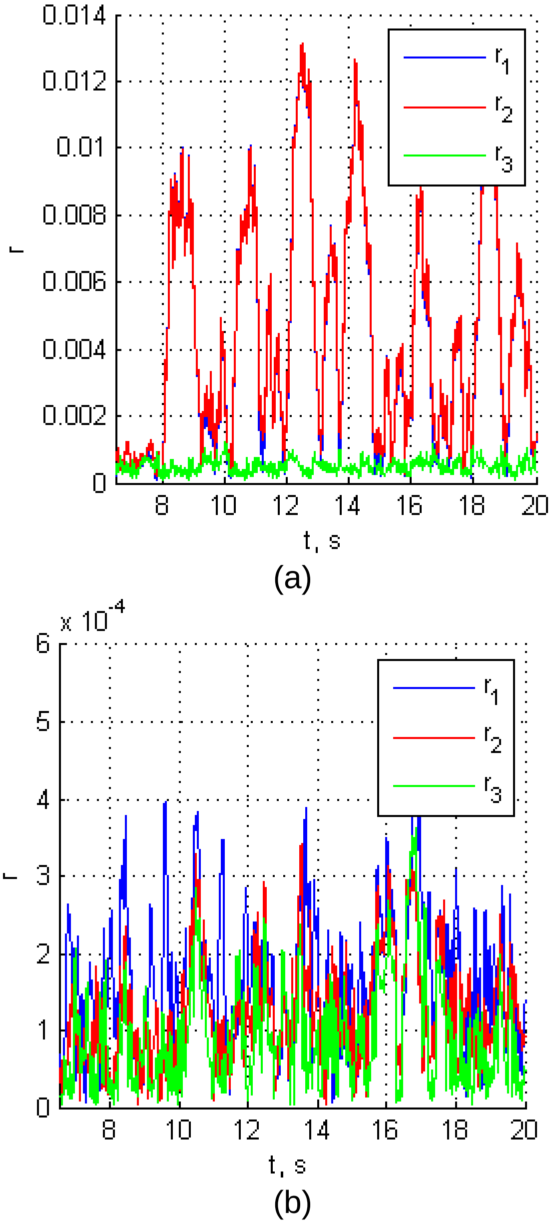


Figure 7: Detection of constant bias failure of the angular velocity r sensor by (a) the observer with disturbance estimation, (b) the unknown input observer

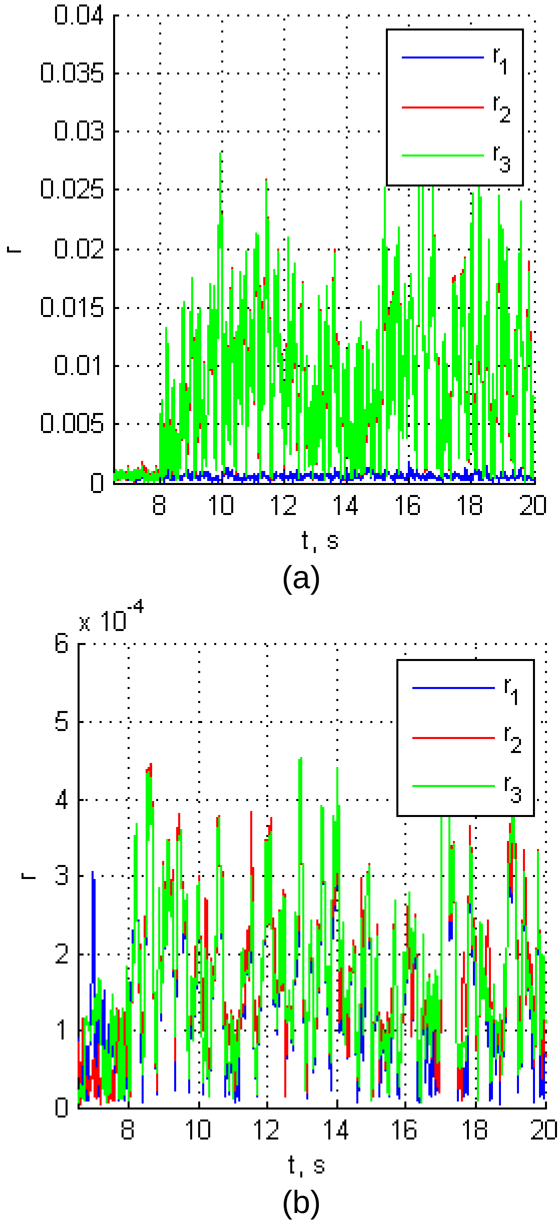
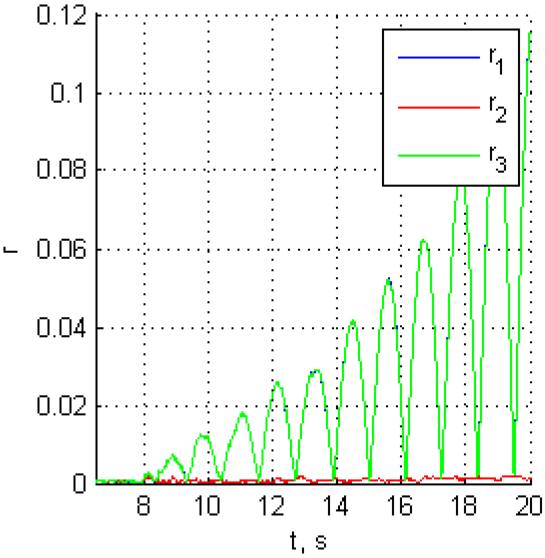
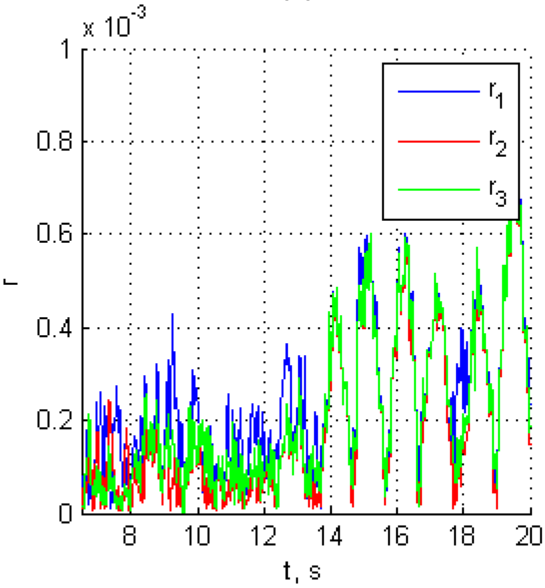


Figure 8: Detection of total failure of the angular velocity p sensor by (a) the observer with disturbance estimation, (b) the unknown input observer

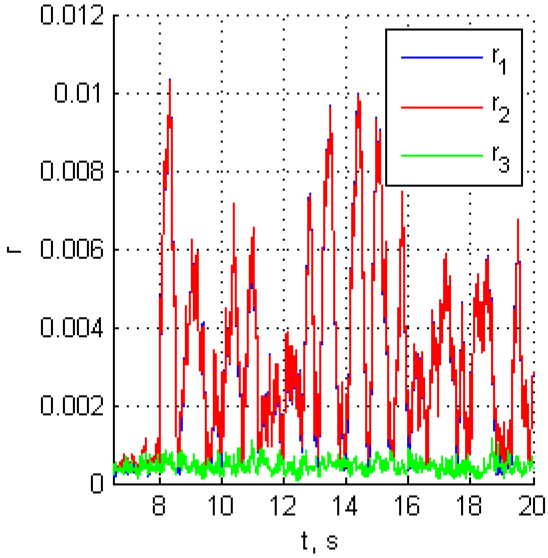


(a)

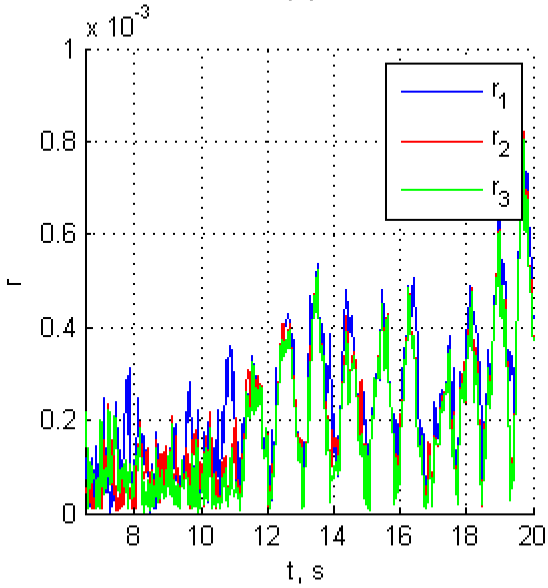


(b)

Figure 9: Detection of total failure of the angular velocity q sensor by (a) the observer with disturbance estimation, (b) the unknown input observer



(a)



(b)

Figure 10: Detection of total failure of the angular velocity r sensor by (a) the observer with disturbance estimation, (b) the unknown input observer

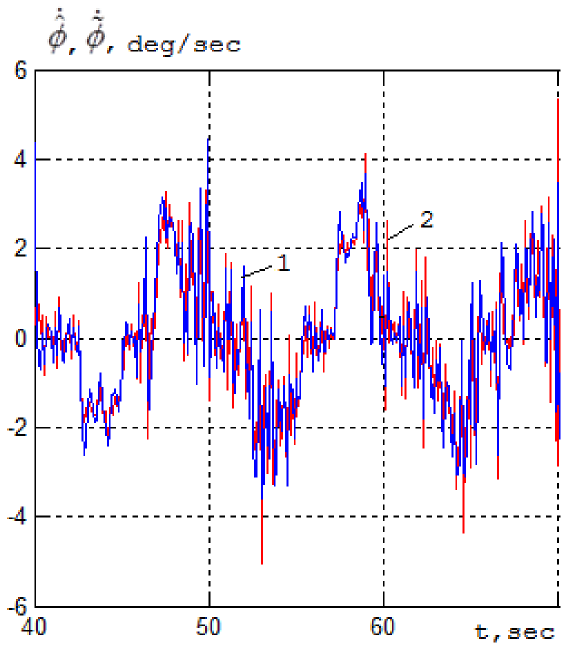


Figure 11: Estimation results of the observer (16): 1 – angular velocity estimate $\dot{\hat{\phi}}$, deg/sec; 2 – angular velocity $\dot{\tilde{\phi}}$, deg/sec.

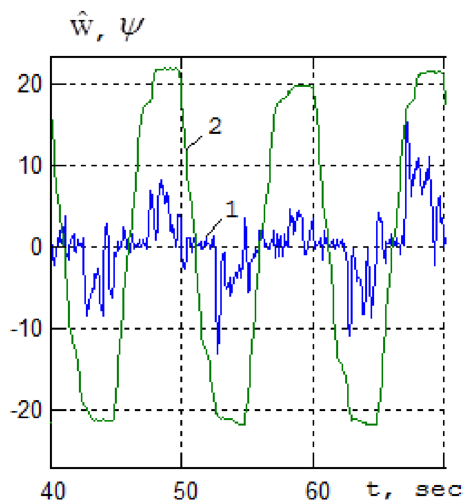


Figure 12: Estimation results of the observer (16): 1- disturbance estimate $\hat{w}$, deg/sec^2; 2- yaw angle ψ, deg.

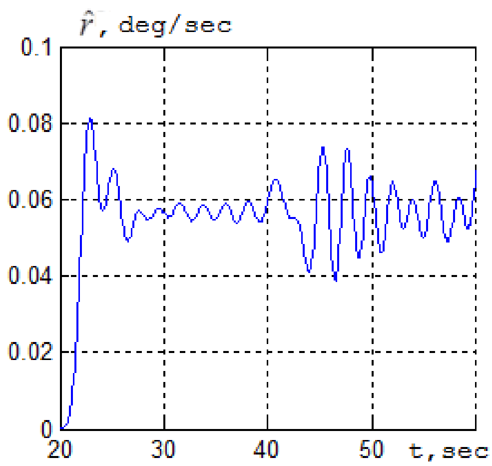


Figure 13: Residual signal $\hat{r}$, deg/sec.