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Design of a fault detection and diagnose system for intelligent unmanned aerial vehicle navigation system

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Abstract

A secure control system is of great importance for unmanned aerial vehicles, especially in the condition of fault data injection. As the source of the feedback control system, the Inertial navigation system/Global position system (INS/GPS) is the premise of flight control system security. However, unmanned aerial vehicles have the requirement of lightweight and low cost for airborne equipment, which makes redundant device object unrealistic. Therefore, the method of fault detection and diagnosis is desperately needed. In this paper, a fault detection and diagnosis method based on fuzzy system and neural network is proposed. Fuzzy system does not depend on the mathematical model of the process, which overcomes the difficulties in obtaining the accurate model of unmanned aerial vehicles. Neural network has a strong self-learning ability, which could be used to optimize the membership function of fuzzy system. This paper is structured as follows: first, a Kalman filter observer is introduced to calculate the residual sequences caused by different sensor faults. Then, the sequences are transmitted to the fault detection and diagnosis system and fault type can be obtained. The proposed fault detection and diagnosis algorithm was implemented and evaluated with real datasets, and the results demonstrate that the proposed method can detect the sensor faults successfully with high levels of accuracy and efficiency.

Keywords

Unmanned aerial vehicles, fault detection and diagnosis, fuzzy system, neural network, Kalman filter

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Introduction

The unmanned aerial vehicles (UAVs) have been increasingly used in civil and military applications in which ground vehicles cannot gain access to the desired location. The applications include the search and rescue operations, area mapping, weather monitoring, agricultural operations, etc.[1–4] Fault occurrence in UAVs can cause fatal human safety and financial loss, therefore, a secure control system should be designed to be as safe and robust as possible in order to face different types of emergencies.[5,6] So it is necessary to design a fault detection and diagnosis (FDD) strategy in control system. In airborne equipment of UAVs, size, weight, and cost are the three critical factors, which indicate that hardware redundancy is not feasible. Therefore, the method of analytical redundancy has been proposed as an alternative solution. Since the analytical redundancy approach is based on mathematical model of the system, they are called model-based techniques for FDD.

The microelectromechanical systems (MEMSs) are universally used in the navigation system of UAVs,[7,8] which have the characteristics of light weight, small mass, less expensive, and lower power consumption.[9] In order to improve the performance of MEMS navigation system, the combination of INS/GPS is used to provide an ideal navigation system with full capability of continuously outputting position, velocity, and attitude of UAVs.[10,11] The reliability of INS/GPS system is prominently important because any fault of navigation system can lead to the feedback loop error of control system. In this paper, a sensor FDD system for integrated navigation system used in UAVs is presented.

Several methods have been used for FDD. An observer/Kalman filter identification has been used to detect sensor faults applied to a helicopter mathematical method[12]; experiments with an autonomous

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helicopter had been conducted to collect input–output data in many different flight conditions and the fault diagnosis effects are significantly. In Gu et al.,[13] a bank of Kalman filters and Mahalanobis distance are used to estimate the UAV attitude. However, these methods all need to establish multiple Kalman filters for different fault conditions, which lead to a dramatic computational cost. Some nonlinear algorithms have been developed for fault detection.[14–16] A detection strategy based on neural network (NN) is used to detect faults in sensors and actuators of UAV systems.[5] The algorithm was implemented and evaluated on an aircraft model and the results show that the method can detect the sensor and actuator faults successfully.

In general, unmodeled dynamics, disturbances, and not linear parameterizable uncertainties often make the control approach much too complicated, which leads to inaccurate observation residuals obtained by fault detection system and unreliable diagnosis results. Fuzzy system is a kind of control algorithm imitating human mind, and it does not depend on the mathematical model of the process.[17,18] However, the fuzzy rules are approximately ratiocinated by prior knowledge and it lacks the ability of self-study or online adjusting, therefore, the results of algorithm relay on the human experience. NN has a strong self-learning ability, which can get the black-box learning mode from a lot of input and output data.[19,20] In this paper, first, a Kalman filter observer is introduced to calculate the residual sequences which are caused by different sensor faults. Then, an improved method based on fuzzy system in which membership functions are updated by NN is proposed to implement fault diagnosis. In this way, the complex relationship between sensor faults and observation residuals can be described by a set of learning coefficients and membership functions. The FDD algorithm was implemented and evaluated with real datasets from experimental UAVs; the results show that the proposed method can detect the sensor faults successfully with high levels of accuracy and efficiency.

The article is organized as follows: In the next section, the theoretical basis of Kalman filter observer is presented and part of the implementation results of residual estimation are discussed. In "FDD algorithm based on fuzzy system and NN" section, the faults detection method based on fuzzy system and NN is introduced and the training process is derived step by step. The numerical experiments based on real datasets are processed in "FDD system testing and experimental results" section, followed by conclusion in the final section.

Kalman filter identification method

The Kalman filter is known as a linear quadratic estimation method, which is an algorithm that uses a series of measurements to produce estimates of unknown variables that tend to be more accurate than those based on a single measurement alone.[21,22] The filter is named after Rudolph E. Kalman, one of the primary developers of this theory. The discrete linear system model with faults can be presented by the following equations

$$\begin{cases} X_k = \Phi_{k,k-1}X_{k-1} + \Gamma_{k-1}W_{k-1} \\ Z_k = H_kX_k + V_k + f_{k,\varphi}\gamma \end{cases} \tag{1}$$

where $Z_k \in R^m$ is the measure of the output, $X_k \in R^n$ represents the system state, $\Phi_{k,k-1} \in R^{n\times n}$ is one step transfer matrix of system state, and $\Gamma_{k-1} \in R^{n\times r}$ is the noise matrix. $W_k \in R^r$ and $V_k \in R^m$ are independent Gaussian white noise sequence

$$E\{W_k\} = 0,\ E\left\{W_kW_j^T\right\} = Q_k\delta_{kj} \tag{2}$$

$$E\{V_k\} = 0,\ E\left\{V_kV_j^T\right\} = R_k\delta_{kj} \tag{3}$$

where δ_{kj} is Krone Nick function, γ is a random vector which presents the size of the fault. $f_{k,\varphi}$ is a piecewise function which can be described as

$$f_{k,\varphi} = \begin{cases} 1, & k \geqslant \varphi \\ 0, & k < \varphi \end{cases} \tag{4}$$

The goal of the Kalman filter is to find an a-posteriori state estimate as the sum of an a-priori estimate and a weighted difference of the time and measurement updates.[23] In the process of INS/GPS integrated navigation system with Kalman filter, a priori estimation is effected by sensors of gyroscope and accelerometer and the measurement estimation is effected by sensor of GPS. Therefore, the residual estimation method based on two groups of Kalman filter functions can be summarized as follows

$$\begin{cases} \hat{X}_k = [I - K_kH_k]\Phi_{k,k-1}\hat{X}_{k-1} + K_kZ_k \\ P_{k/k-1} = \Phi_{k,k-1}P_{k-1}\Phi_{k,k-1}^T + \Gamma_{k-1}Q_{k-1}\Gamma_{k-1}^T \\ P_k = [I - K_kH_k]P_{k/k-1} \\ K_k = P_{k/k-1}H_k^T\left[H_kP_{k/k-1}H_k^T + R_k\right]^{-1} \end{cases} \tag{5}$$

$$\begin{cases} \hat{X}_k^S = \Phi_{k,k-1}\hat{X}_{k-1} \\ P_k = \Phi_{k,k-1}P_{k-1}\Phi_{k,k-1}^T + \Gamma_{k-1}Q_{k-1}\Gamma_{k-1}^T \end{cases} \tag{6}$$

where $\hat{X}_k$ is the state estimation with measurement vector Z_k, $\hat{X}_k^S$ is the state estimation result of priori information, which is called state recursive device or shadow filter.

Then the difference between the two states can be regarded as the residual, and the two filters can be considered as supervision to each other

$$\beta_k = \hat{X}_k^S - \hat{X}_k \tag{7}$$

In general, the precision of navigation system depends on the inertial error, system noise, and modeling errors, which can be overcome through the measuring value of Kalman filter. However, there is no measurement vector in state recursive device which leads to the state estimation error of $\hat{X}_k^S$ increasing with the state of recursive deviates, thus, the residual β_k will become inaccurate.

Here, define the step prediction estimation as the shadow filter estimation

$$\hat{X}_{k/k-1} = \Phi_{k,k-1}\hat{X}_{k-1} \tag{8}$$

Then, the residual can be rewritten as

$$r_k = Z_k - H_k\hat{X}_{k/k-1} \tag{9}$$

A set of residuals can be obtained by using the Kalman filter in detecting faults. In order to verify the feasibility of this method, some simulated sensor faults are superimposed on the actual navigation data from UAVs; the sensor faults type consists of horizontal gyroscopes, horizontal accelerometers, and velocity and position information of GPS. To reduce the amount of calculation, 13-dimensional Kalman filter is used. The state vector and measurement vector can be described by

$$X = \begin{bmatrix} \delta V_e & \delta V_n & \delta\varphi & \delta\lambda & \Delta\phi_e & \Delta\phi_n & \Delta\phi_u & \ldots \\ & \Delta\varepsilon_X & \Delta\varepsilon_Y & \Delta\varepsilon_Z & \Delta a_X & \Delta a_Y & \Delta a_Z \end{bmatrix}^T \tag{10}$$

$$Z = [\delta V_E^n \quad \delta V_N^n \quad \delta\varphi^n \quad \delta\lambda^n]^T \tag{11}$$

The experiment was processed and the navigation results of Kalman filter sensor fusion are demonstrated in Figure 1. In this contrast experiment, we add 0.5 m/s error on the original measurement of GPS east velocity as shown in Figure 2. The results show that the east velocity and position have a deviation from the normal condition after the fourth minute. As shown in Figure 3, the attitudes have minor changes at the time of four.

In order to verify the reliability, faults of multiple levels are applied to GPS east velocity. The normalized residual sequence in this situation is described in Figure 4; corresponding with the state vector, it can be seen that the residuals of east velocity and roll angle change larger than others; moreover, the trend of the residual sequence is similar, no matter what the size of the fault is.

The other residual sequences of faults condition can also be calculated in the same way. Due to space limitations, residual sequences of east position fault and X gyroscope fault are demonstrated in Figures 5 and 6.

Comparing the above multiple figures of residual sequence, it can be seen that the shape of the residual sequence changes with the fault state, but it is very similar in certain case with different fault amplitude. Therefore, a clustering algorithm is needed to be put

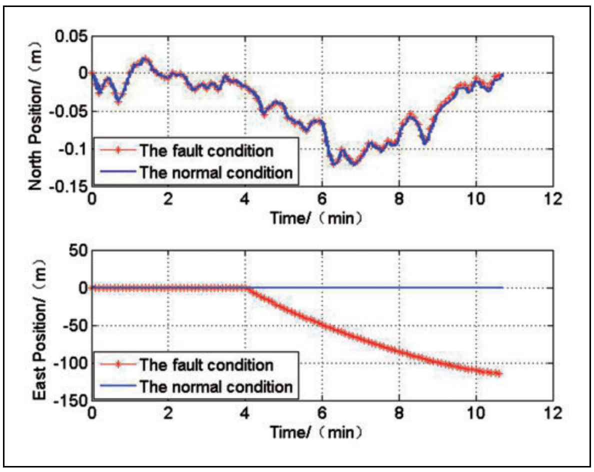

Figure 1. The position error in different conditions.

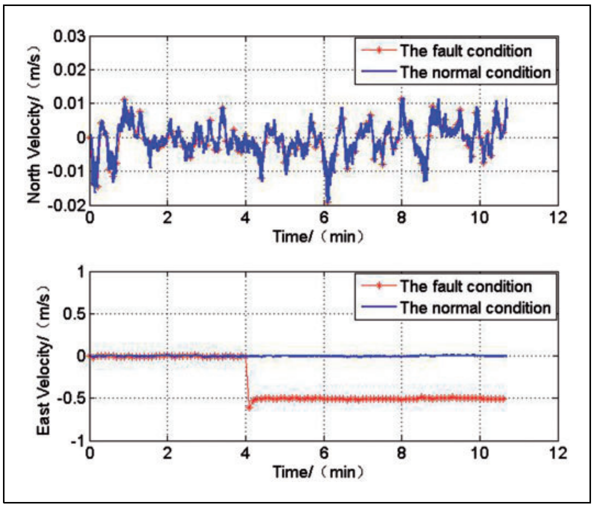

Figure 2. The velocity error in different conditions.

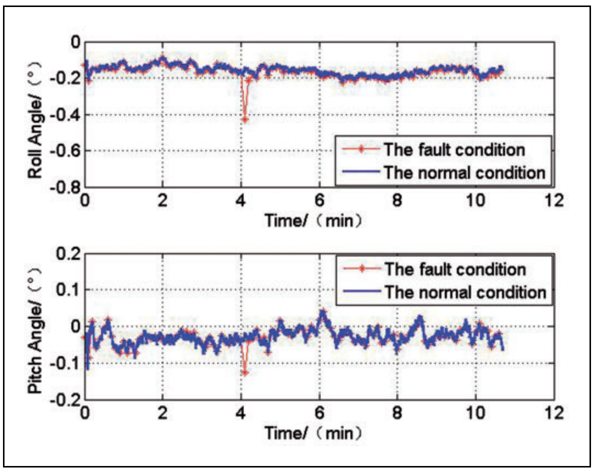

Figure 3. The attitude angle in different conditions.

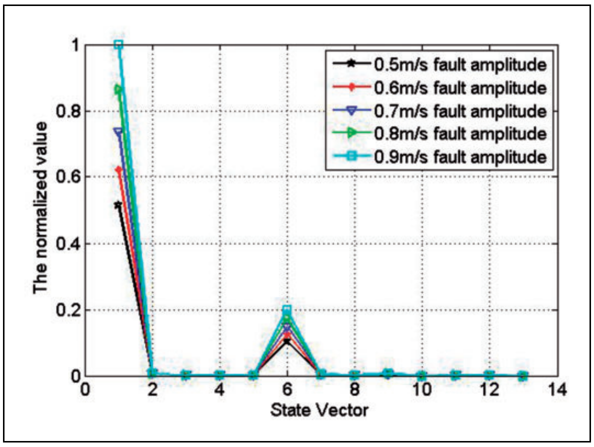

Figure 4. The residual sequence of east velocity fault.

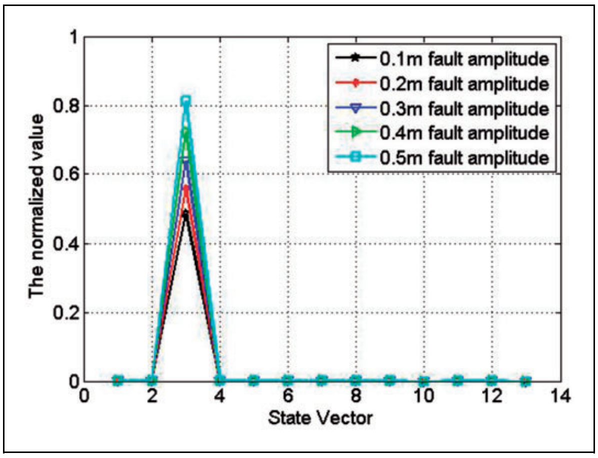

Figure 5. The residual sequence of east position fault.

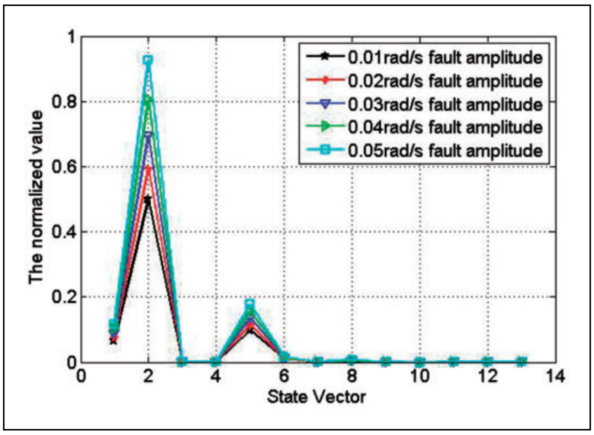

Figure 6. The residual sequence of X gyroscope fault.

forward to analyze the fault state based on the normalized values of residual sequence.

FDD algorithm based on fuzzy system and NN

Intelligent fuzzy logic system is an effective method in clustering analysis field. The membership functions of fuzzy system can be realized by summarizing a large amount of practical data or by actual operation experience, and an accurate function can improve the effect of the fault detection system. In this paper, the NN is used as an induction method for fuzzy system. The NN consists of smaller units called neurons which are trained through a learning process, while interneuron connection strengths, known as synaptic weights, are used to store knowledge. In this method, the neurons of NN are replaced by membership functions of fuzzy system. As shown in Figure 7, the system has a simple architecture of four layers (input layer, membership function layer, hidden layer, and output layer). The input layer just transfers input signal to next layer. The hidden layer performs a fixed nonlinear transformation with no adjustable parameters and maps the input space onto a new space. The membership function layer is a kind of deformation of the hidden layer, whose neurons are replaced by membership functions of fuzzy system. The output layer then implements a linear combiner.

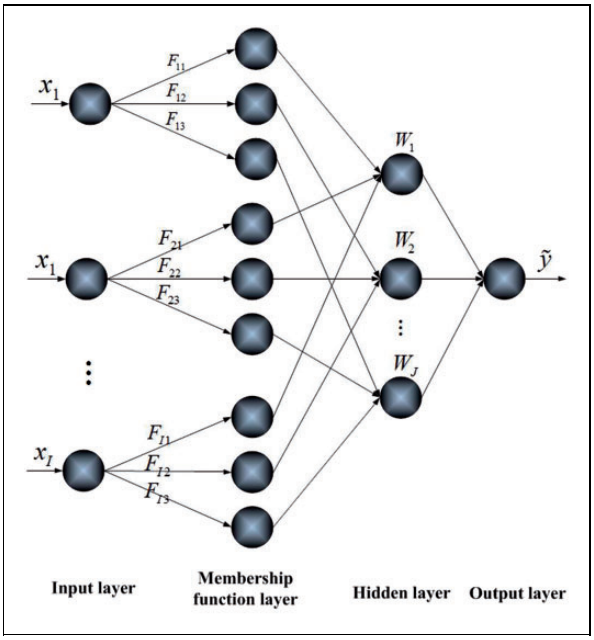

Figure 7. The model structure of NN.

As is shown in Figure 8, the input layer is a one-dimensional vector which represents the residual vector. The neurons F_{ij} are Gaussian membership functions which can be described as

$$F_{ij} = \exp\left(-\frac{[x_i - m_{ij}]^2}{\sigma_{ij}^2}\right) \tag{12}$$

where m_{ij} and σ_{ij} are mean value and variance of Gaussian membership function, respectively.

In order to simplify the system, three linguistic values are used in fuzzy, namely NH, ZE, PH. Figure 8 shows the Gaussian membership function of fuzzy system before NN training. The Takagi–Sugeno model is used as the fuzzy rules.

The training process of FDD method based on fuzzy and NN is composed of four steps: generating failure data, establishing the structure of FDD system, parameter optimization training, parameter extraction.

Generating failure data

The fault sample data are obtained by adding fault information to the several experimental data. In order to simplify the training process, fault types are numbered from 1 to 8 which represents X accelerometer, Y accelerometer, X gyroscope, Y gyroscope, east velocity, north velocity, east position, and north position, respectively.

Establishing the structure of FDD system

The structure of FDD system is established according to the introduction above.

Parameter optimization training

First, a series of residual sequence needs to be generated by calculating the fault sample data and be normalized. Then, the residual sequences and fault numbers are transported to the FDD system as the input and output.

Parameter extraction

After training, the membership functions are obtained which can be used by fault detection.

Table 1. Specification of the system.

Sensor performance	GPS	
Location accuracy	1.2 m(*RMS*)	
Velocity accuracy	0.03 m/s(*RMS*)	
Sensor performance	Gyroscope	Accelerometer
Full scale	−450 to +450 °/s	−18 to + 18 *g*
Bias stability	5.1 °/h	0.07 mg
Scale factor error	35 ppm/°C	25 ppm/°C

GPS: Global navigation system; RMS: Root Mean Square

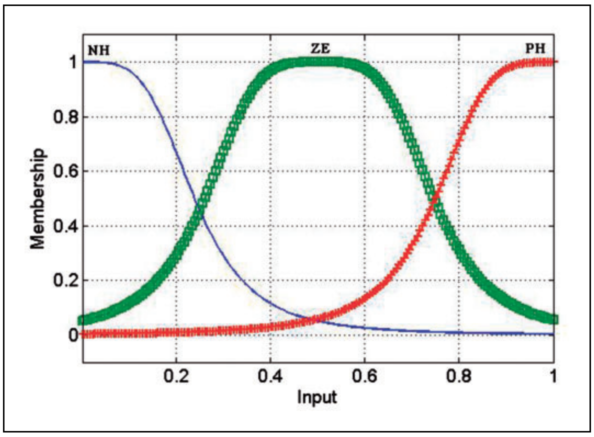

Figure 8. The membership function before NN training. NH: Negative High; PH: Positive High; ZE: Zero.

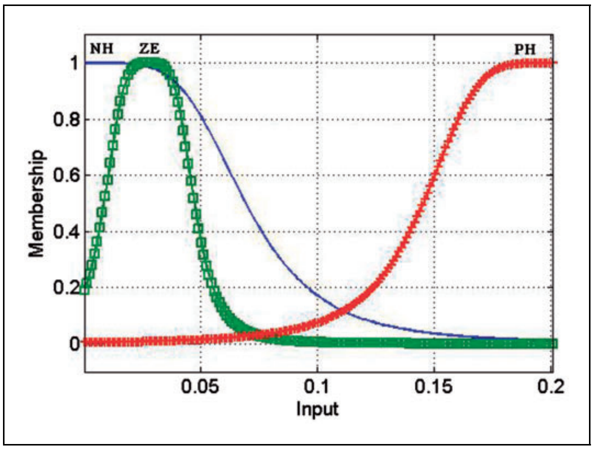

Figure 10. The membership function after NN training. NH:; PH:; ZE:[redacted].

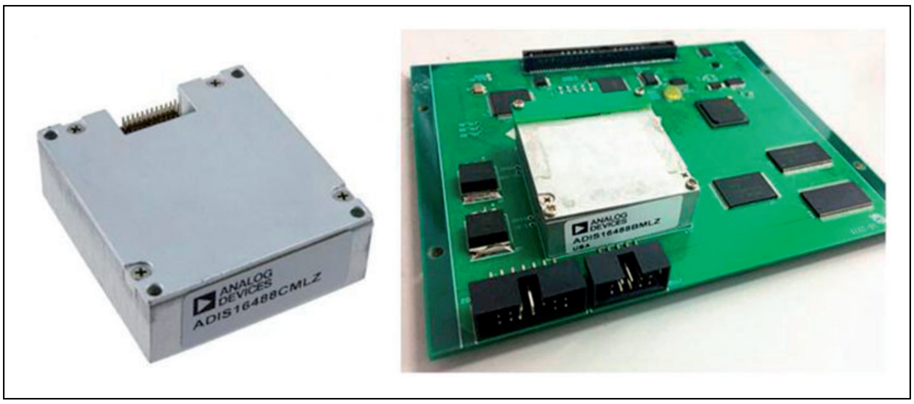

Figure 9. The MEMS system of ADIS16488.

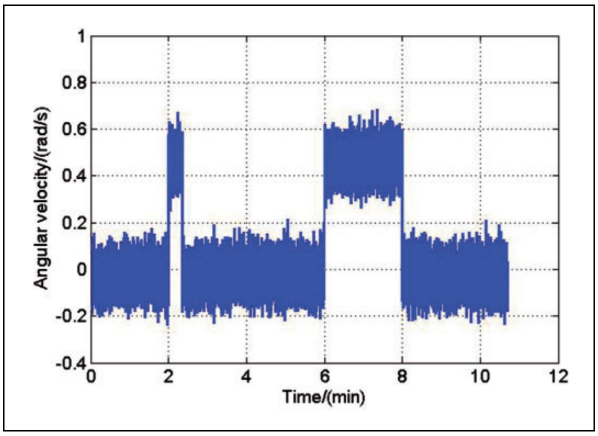

Figure 11. The signal of Y gyroscope.

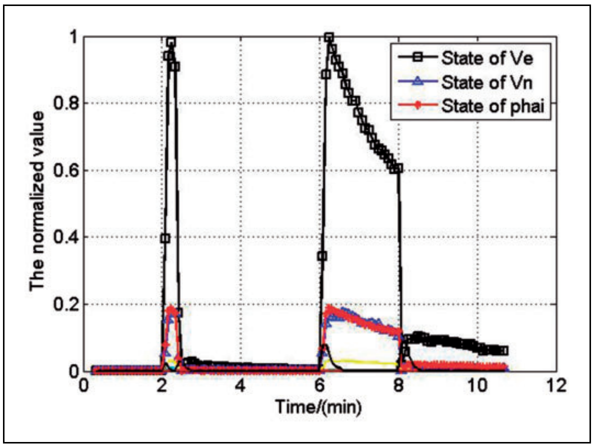

Figure 12. The residuals of all states.

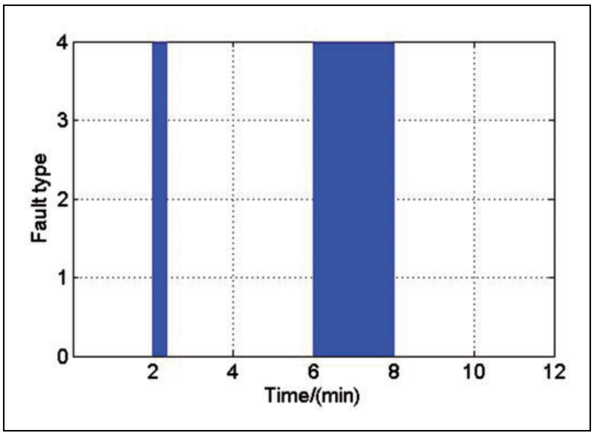

Figure 13. The result of FDD.

FDD system testing and experimental results

In this section, several off-line experimental tests have been implemented to confirm the validity of the proposed method. As shown in Figure 9, the original signal is acquired from a navigation and flight control system which is equipped with a MEMS IMU named ADIS16488 and a GPS board. The key manufacture specifications of the system are listed in Table 1.

To verify the performance of the proposed method, several experimental data with different faults are used as samples to optimize the system parameters. Figure 10 shows the trained membership function which has changed a lot compared with before.

Then, the checking experiments are performed. Since many kinds of failures were mentioned before, here only Y gyroscope fault is introduced as an example. In Figure 11, the bias of 0.5 rad/s, which is an appropriate fault size in the real gyroscope, is added to the output of Y gyroscope at 2 and 6 min with different duration time. Then, the residual sequence changes immediately. As shown in Figure 12, the residuals of V_e, V_n, and φ are larger than others when the fault occurs. Finally, depending on the residual sequence, in Figure 13, the fault type of number 4 is obtained from the FDD system, and it is response to the sensor fault.

Conclusion

The use of UAVs requires the improvement of control system to avoid potential accidents. As a core component of UAVs, INS/GPS system plays an important role in flight control system. This paper has presented a FDD system for sensor fault detection of integrated navigation system. The proposed FDD method is based on fuzzy system and NN, which has an advantage of requiring no accuracy model of UAVs. After calculating the residual sequences of sensor faults using the Kalman filter, the FDD method is put forward for fault detection and the complex relationship between sensor faults and observation residuals can be described by a set of learning coefficients and membership functions. Several experimental tests have been implemented on a control and navigation system, then, the proposed fault detection algorithm was implemented. The results show that the proposed method can detect the sensor faults successfully with high levels of accuracy and efficiency.

Declaration of Conflicting Interests

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