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Fault Detection and Identification for Quadrotor Based on Airframe Vibration Signals: A Data-Driven Method

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Abstract: This paper proposes a new method to detect and identify rotor's fault of quadrotor by using airframe vibration signals. A three-level wavelet packet decomposition method is used to analyze vibration signals. Then, the standard deviations of wavelet packet coefficients construct feature vectors that are used as input signals to design a fault diagnostor based on Artificial Neural Network (ANN). Output signals of the fault diagnostor reflect rotor health status. Finally, the effectiveness and performance of the proposed method are validated by airframe vibration data collected from a hovering experiment of a quadrotor.

Key Words: Fault Detection and Identification, Quadrotor, Vibration Signal,Wavelet Packet Decomposition, Artificial Neural Network

1 Introduction

Quadrotors are well-suited to a wide range of mission scenarios, such as search and rescue, border patrol, military surveillance and agricultural production. The structural characteristics, complicated missions and flight environment result in the increasing requirements for flight quality, security and reliability. Affected by aerodynamic forces, the quadrotor is a nonlinear and multivariable system [1]. A fault or failure in any part of the quadrotor may lead to catastrophic consequences. Therefore, the quadrotor should be equipped with Fault Detection and Identification (FDI) module so that it can automatically change the control strategy and mission planning after detecting a fault.

Existing approaches on FDI are divided into three categories: analytical/model-based approaches, knowledge-based approaches and signal processing-based approaches [2]. Model-based approaches rely on the use of mathematical descriptions of the monitored system. It mainly uses various kinds of observers and Kalman filters to estimate system states or parameters [3]. Cen *et al*. [1] developed a novel adaptive thau observer to estimate the quadrotor system states and built a set of offset residuals to indicate actuators faults. Amoozgar *et al*. [4] developed a fault detection and diagnosis algorithm for a quadrotor helicopter system. The algorithm modelled faults as losses in control effectiveness of rotors and used a two-stage Kalman filter to simultaneously estimate and isolate possible faults. Relative works on model-based approaches are comprehensively described in [5–7]. Knowledge-based approaches make full use of knowledge of experts in FDI and avoid a reliance on accurate mathematical models [2]. Details of knowledge-based approaches are presented in [8]. Signal-processing-based approaches have attracted widespread attention for applying to both linear systems and nonlinear systems without requiring accurate analytical model [3]. As vibration signals extensively exist in rotating machinery, the approaches based on vibration-signal-processing are widely used in the condition monitoring and fault diagnosis systems of rotating machinery [9].

In FDI field of aircraft, the approaches based on vibration-signal-processing are mainly used in helicopter transmission system, like gears and bearings. For FDI of quadrotor, model-based approaches are widely used due to including more system information which is the basis of fault identification and estimation. In practice, there are sufficient airframe vibration signals in the flying course of quadrotor which contain a large amount of information about aircraft conditions. Thus, this paper attempts to use airframe vibration signals collected by accelerometer to achieve rotor FDI for quadrotor.

To the best of author's knowledge, the main contribution of this paper is to apply the approaches based on vibration-signal-processing to the FDI of quadrotor for the first time. Compared to the model-based approaches, the proposed method is a data-driven method, which has a wide range of application and is easy to implement in practice.

This paper is organized as follows. In Section 2, the airframe vibration signals based FDI problem is presented and analyzed. Preliminaries are given in Section 3. The proposed FDI method based on airframe vibration signals is described in Section 4. Section 5 presents a hovering experiment of quadrotor to validate the effectiveness and performance of the proposed method and the experimental results are given and discussed. Section 6 gives the conclusion and future development of the proposed method.

2 Problem Formulation

According to [10], the lift provided by a rotor is stated as

$$T = \frac{1}{2}\rho A C_T R^2 \Omega^2 \tag{1}$$

where T is lift; ρ is air density; A is rotor disk area; C_T is lift coefficient; R is blade radius; Ω is rotor rotary speed.

According to the blade element theory [10], when the quadrotor hovers in the air, there exists direct relation between the lift coefficient C_T and setting angle θ of blade element. Fig.1 presents the schematic diagram of the setting angle θ of blade element. Fig.2 describes the rotation plane of blades and the coordinate system of blade element. The x-axis is parallel to the rotation plane and points in the direction of rotation; the y-axis is perpendicular to the rotation plane; the z-axis is perpendicular to the xoy plane.

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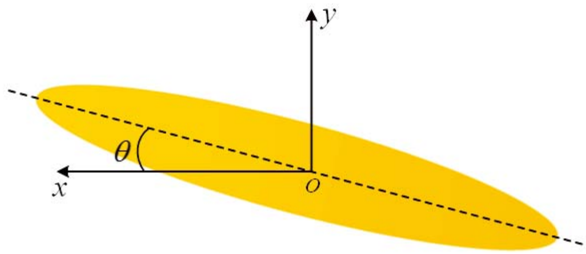

Fig. 1: The setting angle of blade element

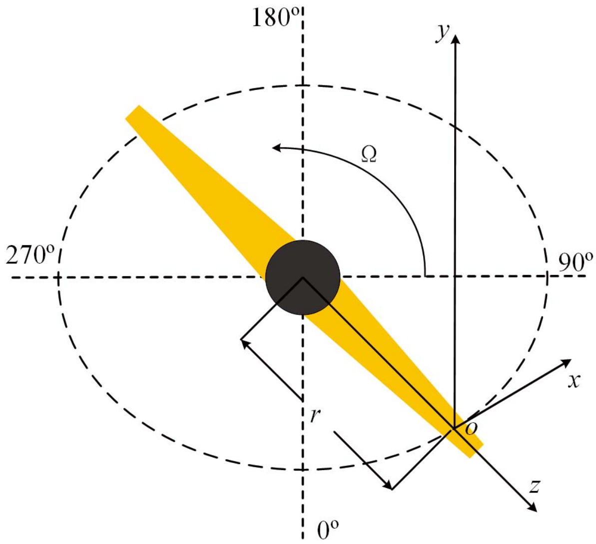

Fig. 2: The coordinate of blade element

Formula (1) and Fig.1 indicate that the value of lift is related to the geometric shape of blade. For a fractured blade, the decrease of blade radius R results in the decrease of lift; for a distorted blade, the change of the setting angle θ leads to the change of the lift.

As shown in Fig.3, when the quadrotor hovers with faultless rotor, the lift T_1 is equal to T_2, T_3 and T_4. If the blades in rotor L_1 are impaired suddenly, the lifts T_1, T_2, T_3 and T_4 have the relation as follow

$$T_1 \neq T_2 = T_3 = T_4 \tag{2}$$

In order to hover, the quadrotor will change the rotary speed of rotor L_1 , which results in

$$\Omega_1 \neq \Omega_2 = \Omega_3 = \Omega_4 \tag{3}$$

That means the rotary speed of rotors are inconsonant when quadrotor hovers with impaired blade. Thus, two assumptions are given below:

Assumption 1: The damage of blade gives rise to the feature changes of the airframe vibration signals.

Assumption 2: Different types of blade damage result in different features of airframe vibration signals.

Based on the assumptions above, an FDI method based on airframe vibration signals is developed in the following.

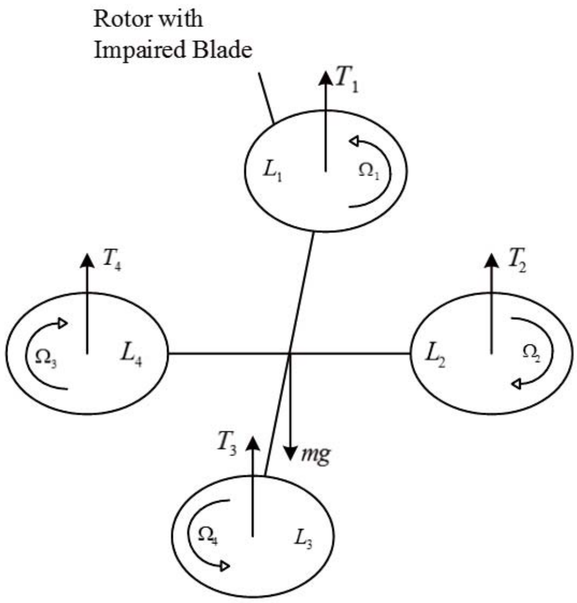

Fig. 3: The schematic diagram of quadrotor

3 Preliminaries

3.1 Wavelet Packet Decomposition

Discrete wavelet transform decomposes the signal into a hierarchical structure with wavelet details and approximations. It can't improve the frequency resolution of the wavelet detail for further decomposing wavelet approximation instead of the wavelet detail.

Wavelet Packet Decomposition (WPD) concurrently further decomposes the wavelet approximation and the wavelet detail, which means wavelet packets contain a complete set of decompositions and details at every level and hence provide a higher resolution in the high frequency region.

If the j level WPD method is applied to the original signal $f(t)$, the original signal $f(t)$ can be stated as [9]

$$f(t) = \sum_{i=1}^{2^j} f_j^i(t) \tag{4}$$

where the wavelet packet component signal $f_j^i(t)$ can be stated by a series of wavelet packet function $\psi_{j,k}^i(t)$ as

$$f_j^i(t) = \sum_{k=-\infty}^{\infty} c_{j,k}^i(t)\psi_{j,k}^i(t). \tag{5}$$

Here, the Wavelet Packet Coefficients (WPC) $c_{j,k}^i(t)$ can be stated by the original signal $f(t)$ and the wavelet packet function $\psi_{j,k}^i(t)$ in such a way:

$$c_{j,k}^i(t) = \int_{-\infty}^{\infty} f(t)\psi_{j,k}^i(t)d_t \tag{6}$$

providing that the wavelet packet functions are orthogonal:

$$\psi_{j,k}^m(t)\psi_{j,k}^n(t) = 0 \quad if\ m \neq n. \tag{7}$$

Taking the three-level WPD for example, the original signal is decomposed into 8 wavelet component signals.

Fig.4 depicts schematically the three-level WPD tree, where $f_j^i(t), j = 1, 2, 3; i = 1, 2, \cdots, 8$ denotes the ith wavelet packet component signal in the jth level.

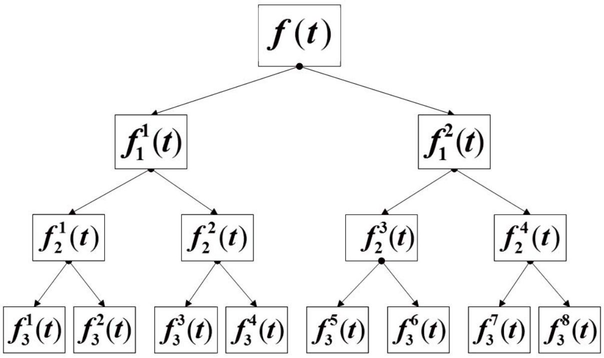

Fig. 4: Three-level WPD tree

Each wavelet component signal contains a set of WPCs. The most common-used method to extract the features of original signal is to use the energy of wavelet coefficients as the feature vector. Rafiee *et al*. [9] used the standard deviation of the wavelet coefficients as the feature vector to train the Artificial Neural Network (ANN) and proved that the network has faster convergence and better performance.

3.2 Artificial Neural Network (ANN)

The ANN is non-linear statistical data modeling tool and can be used to model complex relationships between inputs and outputs or to find patterns in data. ANN has two main architectures: feedforward network and recurrent network. The feedforward network is frequently exploited in fault diagnosis and condition monitoring systems while the recurrent networks are principally used in non-linear dynamic feedback systems [11].

Multi-layer feed-forward neural networks (MFNN) consist of i) an input layer with nodes representing input variables to the problem, ii) one or more hidden layers containing nodes to help capture the nonlinearity in the data, and iii) an output layer with nodes representing the dependent variables [12]. The learning of MFNN means using a set of observations to find a function which solves the non-linear mapping issue in some optimal sense. Trained MFNN has non-linear pattern classification properties and offers advantages for automatic detection and identification of system fault, whereas it does not require an in-depth knowledge of the behavior of the system.

4 FDI Method Using Airframe Vibration Signals

The procedure of the FDI method using airframe vibration signals is depicted in Fig.5. If n health statuses of rotor are taken into account, the FDI method firstly acquires n airframe vibration datasets. Then the n datasets are preprocessed. Next, the processed data are used to extract feature vectors. Finally, the feature vectors are used to train ANN, then the fault diagnostor for quadrotor is acquired. In the following, the explicit procedure for the proposed method is presented.

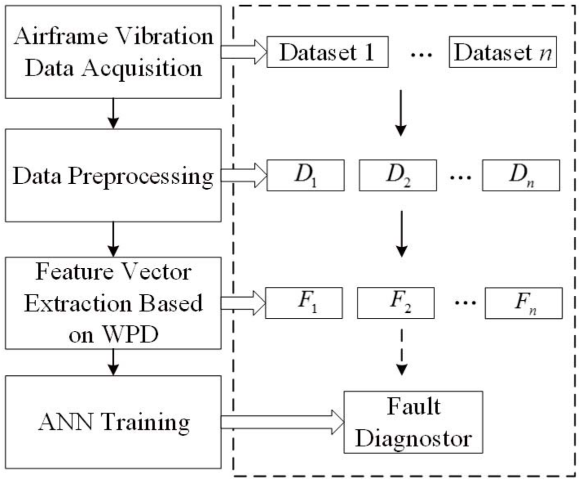

Fig. 5: Procedure for the proposed method

4.1 Airframe Vibration Data Acquisition and Preprocessing

Airframe vibration data are collected from a quadrotor in hovering. Fig. 6 gives the hovering scene of the quadrotor we used.

Fig. 6: The hovering scene of quadrotor used in this research

The process of collecting airframe vibration data is as follows: i) make the quadrotor fly with faultless rotors, meanwhile, accelerometer mounted in airframe collects the vibration dataset 1; ii) make the quadrotor fly in different rotor fault conditions, then collect the vibration dataset i $(i = 2, \cdots, n)$ by the accelerometer mounted in airframe.

After obtaining datasets, the first issue is to remove the superfluous data, including duplicate data and vibration data along certain sensitive axis. Besides, in order to obtain more training sample, it is necessary to divide the vibration dataset into a lot of subsets according to time.

4.2 Feature Vector Extraction Based on WPD

As shown in Fig.5, after data preprocessing, the dataset $(D_1, \cdots, D_n)$ are used to extract the feature vectors. In this research, the j level WPD method is applied to each subset in $D_1, \cdots, D_n$, then the standard deviations of WPCs are used to construct l-dimensional feature vectors, that is

$$v = [\sigma_1, \sigma_2, \cdots, \sigma_l] \tag{8}$$

where $l = 2^j$ and

$$\sigma_i = \sqrt{\frac{1}{n_i}\sum_{k=1}^{n_i}(c_{j,k}^i - \mu)^2 i} \qquad i = 1, \cdots, l \tag{9}$$

Here, $c_{j,k}^i$ is the kth WPC in the ith wavelet component signal, which is obtained by equation (6); n_i is the number of WPC in the ith wavelet component signal; μ is the arithmetic mean value of WPCs in the ith wavelet component signal.

If $D_r, r = 1, \cdots, n$ is divided into p_r subsets, p_r l-dimensional feature vectors are extracted to construct the $l \times p_r$ matrix V_r. As shown in Fig.5, all feature vectors (samples) are stored in matrices $V_r, r = 1, \cdots, n$.

4.3 ANN Training and Fault Diagnostor Validation

Fig.7 depicts schematically the MFNN structure used in the proposed method. The resilient back propagation training algorithm is applied to all net layers. The Tan-Sigmoid transfer function and the Log-Sigmoid transfer function are applied to hidden layer and output layer, respectively. The initial weights coefficients are obtained randomly and error function was chosen to be least mean square.

The input signals are the l-dimensional feature vectors constructed by the standard deviation of WPCs. The n output signals are corresponding to the n health statuses of rotor. If the quadrotor is in the ith health status, the ith neuron O_i will output a "1", otherwise output a "0".

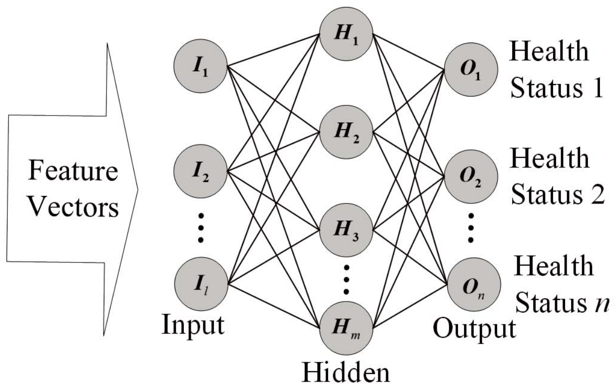

Fig. 7: Schematic diagram of MFNN

After sufficient samples training, the ANN acts as a fault diagnostor to detect and identify the fault of quadrotor. The health status of quadrotor can be obtained when feature vector representing health status is inputted to the diagnostor.

In order to validate the trained fault diagnostor, samples are split into training samples and validation samples. However, different partition methods will generate diagnostors with different performances. Thus, the ten-fold Cross-Validation (CV) method [13] is used to select the fault diagnostor with the best performance.

5 Experiment

The airframe vibration signals-based FDI method is tested in a hovering experiment of quadrotor. The experiment consists of four steps, namely airframe vibration data collection and preprocessing, feature vectors extraction, ANN training, fault diagnostor validation and evaluation.

5.1 Airframe Vibration Data Collection and Preprocessing

A cellphone (iPhone) with embedded triaxial accelerometer is fixed at the bottom of quadrotor to collect acceleration data. Fig.8 depicts the sensitive direction of the triaxial accelerometer.

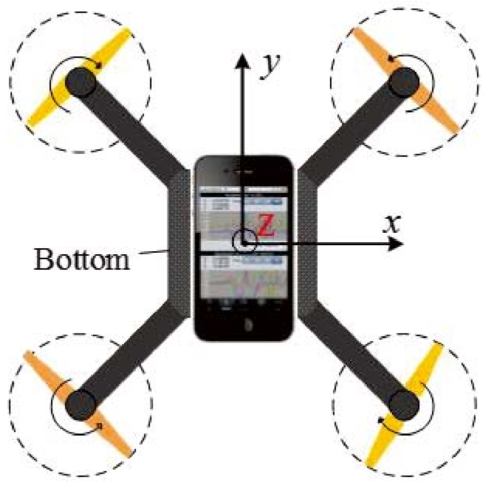

Fig. 8: The sensitive direction of the triaxial accelerometer

Three different types of health statuses ("blades are faultless", "one blade is fractured" and "one blade is distorted") are tested. Fig.9 shows the three states of blade. Dataset 1, Dataset 2 and Dataset 3 are collected in the three different health statuses, which are available online (http://rfly.buaa.edu.cn/resources/#DataSetFDI). In this experiment, only the acceleration vibration data along y-sensitive axis are used to extract feature vectors.

Data preprocessing consists of two steps. The first step is to remove superfluous data in Dataset 1, Dataset 2 and Dataset 3 caused by data acquisition software; the second step is to divide Dataset 1, Dataset 2 and Dataset 3 into 295, 145 and 156 subsets, respectively. Then, the datasets after preprocessing are rewritten as D_1, D_2 and D_3.

5.2 Feature Vectors Extraction

Three-level WPD is applied to each subset in D_1, D_2 and D_3, then each subset is decomposed into 8 wavelet component signals and generates a 8-dimensional feature vector. Finally, 295 feature vectors (samples) are extracted from D_1; 200 of those construct matrix A_1 and 95 of those construct matrix A_2. 145 feature vectors (samples) are extracted from D_2; 100 of those construct matrix B_1 and 45 of those construct matrix B_2. 156 feature vectors (samples) are extracted from D_3; 100 of those construct matrix C_1 and 56 of those

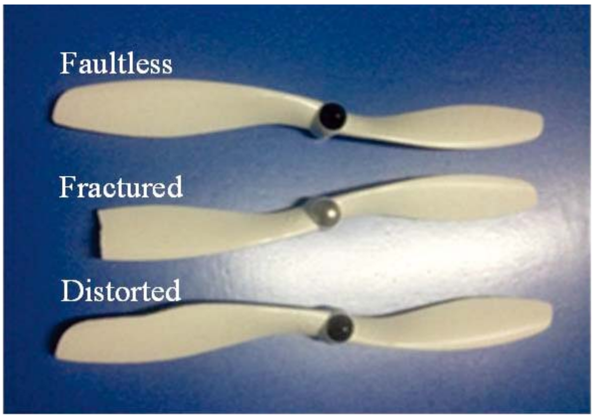

Fig. 9: Three states of blade

construct matrix C_2. As shown in formula (10) and (11), A_1, B_1 and C_1 act as training samples and A_2, B_2 and C_2 serve as validation samples.

Training Samples:

$$\left[[A_1]_{8\times200}, [B_1]_{8\times100}, [C_1]_{8\times100}\right]_{8\times400} \tag{10}$$

Validation Samples:

$$\left[[A_2]_{8\times95}, [B_2]_{8\times45}, [C_2]_{8\times56}\right]_{8\times196} \tag{11}$$

5.3 ANN Training

An ANN with an 8:20:3 structure is used to develop fault diagnostor. The input is the 8-dimensional feature vector obtained above and the output signals of neurons O_1, O_2 and O_3 have three modes. The specific corresponding relation between rotor health statuses and output modes of fault diagnostor is shown in Table 1. When the input vectors are from A_1, the output signal is "100". In the same way, when the input vectors are from A_2 and A_3, the output signals are "010" and "001", respectively.

Table 1: Specific Correspondence Table

Mode	Output Signal			Rotor Health Status
	O_1	O_2	O_3	
Mode1	1	0	0	Blades are faultless
Mode2	0	1	0	One blade is fractured
Mode3	0	0	1	One blade is distorted

According to ten-fold CV method, training samples shown in formula (10) is randomly split into 10 disjoint subsets of equal size, then ANN is trained ten times, each time one of the subsets is left out from the training samples, but used only to compute the detection and identification accuracy. Then, the trained ANN with the highest detection and identification accuracy is saved.

5.4 Fault Diagnostor Validation and Evaluation

In this experiment, ten-fold CV is repeated 10 times. The average training time is 0.3238s and average MSE is 0.0034. Then, 10 fault diagnostors with the highest accuracy are picked out and validated by the validation samples shown in formula (11).

In order to quantitatively evaluate the performance of the fault diagnostor, the following performance indices are used in this experiment: percentages of correct detection and identification (CDID), false alarm (FA), missed fault detection (MFD), incorrect fault identification (IFID) and no mode detection (NMD) [14].

A CDID is obtained if the output mode is identical to the actual mode at the given time. An FA is obtained if the output mode is fault mode (Mode2 and Mode3) while the actual mode is faultless mode (Mode1) at the given time. An MFD is obtained if the output mode is faultless mode while the actual mode is fault mode at the given time. An IFID is obtained if the output fault mode is not identical to the actual fault mode at the given time. An NMD is obtained if the output mode is not identical to any mode presented in Table 1 at the given time. It is obviously essential for an excellent fault diagnostor to have a higher CDID and lower FA, MFD, IFID and NMD.

5.5 Experiment Results

The five performance indices of the ten fault diagnostors are presented in Table 2.

Table 2: The Five Performance Indices of The Ten Fault Diagnostors

	CDID(%)	FA(%)	MFD(%)	IFID(%)	NMD(%)
1	97.5	0	0.51	1.02	1.02
2	98.0	0	0	1.02	1.02
3	98.5	0	0	0.51	1.02
4	99.0	0	0	0	1.02
5	97.5	0	0.51	0.51	1.53
6	99.0	0.51	0	0.51	0
7	98.0	0.51	0.51	0.52	0.51
8	98.5	0.51	0	1.02	0
9	97.5	1.02	0	1.53	0
10	98.5	0	0.51	0	1.02
Mean	98.2	0.26	0.20	0.67	0.71

The mean value in Table 2 shows that the fault diagnostor has a 98.2% CDID and the FA, MFD, IFID and NMD are lower than 1.0%. Beyond that, the highest CDID reaches up to 99.0% and the lowest CDID is over 97%. It demonstrates the effectiveness of the proposed method. In other words, the assumptions in Section 2 are tenable and the FDI approaches based on vibration signals are able to apply to quadrotor.

In order to make a clear view of the validation result, the validation results of the fourth fault diagnostor and the fifth fault diagnostor are given in Fig.10 and Fig.11.

Fig.10 and Fig.11 present the output signals of neurons O_1, O_2 and O_3 where the red solid lines stand for actual mode (rotor health status) and the blue dotted lines represent the output signals of neurons in fault diagnostor. If misjudgment takes place at the given time, the blue dot will deviate from the red solid lines. Both of the Fig.10 and Fig.11 consist of three sections. In the first section, the actual rotor health status is "blades are faultless"; if the diagnostor can detect fault correctly, the output signal is "100". In the second section, the actual rotor health status is "one blade is fractured"; if the diagnostor can identify fault correctly, the output signal is "010". In the third section, the actual rotor health status is "one blade is distorted"; if the diagnostor can

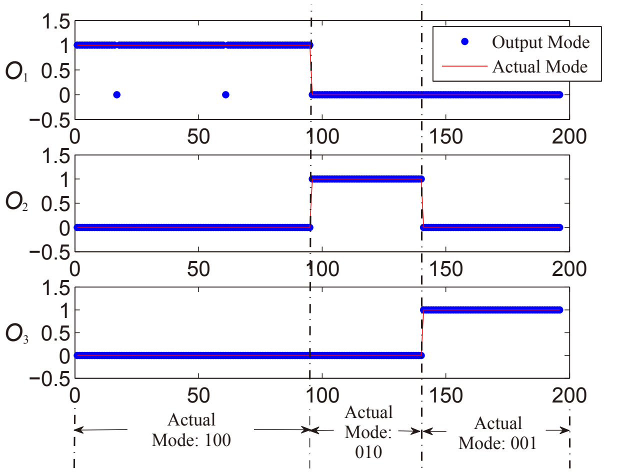

Fig. 10: The validation result of the fourth fault diagnostor

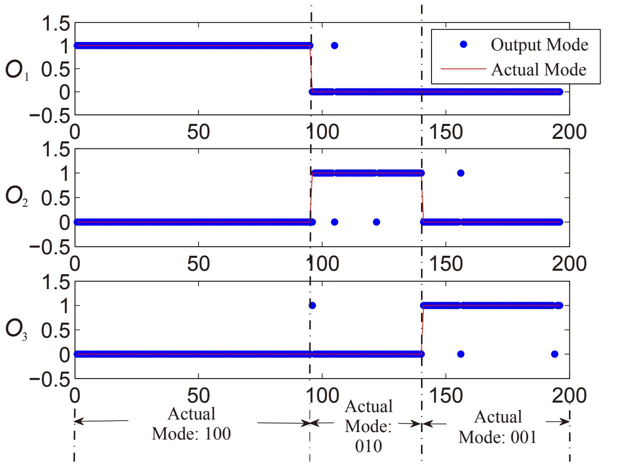

Fig. 11: the validation result of the fifth fault diagnostor

identify fault correctly, the output signal is "001".

Fig.10 shows that the fourth fault diagnostor only has 2 times no mode detection in 196 times detection and identification. Fig.11 shows the fifth fault diagnostor has 5 times misjudgments, including 1 missed fault detection, 1 incorrect fault identification and 3 times no mode detection.

The existing unsatisfied results may be caused by two respects: i) the environmental disturbance may mixed into the vibration signal generated by the quadrotor, which will change the original characteristic of the signal; ii) there exists inaccuracy in the accelerometer measurement, especially when the accelerometer is not well fixed in the quadrotor.

6 Conclusion and Discussion

In this paper, a new FDI method based on airframe vibration signals for quadrotors is proposed. This method uses a time-frequency-based WPD method to extract feature vectors from airframe vibration signals. Then, the feature vectors are used to train the ANN which acts as a fault diagnostor to detect and identify rotor fault. Experiment results demonstrate that the proposed method has an almost perfect 98.0% accuracy and good performance. Compared to the existing methods, the proposed method is a data-driven method, which is characterized by the advantages of simplicity, flexibility and easy extensibility. In future research, more fault patterns will be considered and more accurate measuring instruments will be located in the experiment.

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