Data-Driven Sensor Fault Diagnosis for Fighter under Harsh Conditions

Qi Wang¹, Fuyang Chen¹ and Li Wang²
¹College of Automation Engineering, Nanjing University of Aeronautics and Astronautics, Nanjing, China
²North Information Control Research Academy Group Co., Ltd, Nanjing, China
Email: brookwon@163.com

Abstract. This paper presents a multi-classification fault diagnosis scheme for the sensor of fighter. It is difficult to diagnose sensor faults for fighter under harsh conditions like hyper maneuver because the states change rapidly and the data of fault-free and faulty sensor are similar to each other. The rapidly changing states means that values of sensor faults may be small compared with states variation. Similar data may raise the difficulty to find the separating plane. Wavelet packet decomposition can transform the raw dataset to fault features by computing the energy values of each frequency band. And principal component analysis (PCA) can grasp the main features and reduce computational complexity by transform a group of dependent parameters into a group of independent parameters via orthogonal transformation. A support vector machine (SVM) trains fault features to achieve a multi-classifier via one-versus-rest method. The classifier can obtain fault diagnosis results by inputting features of new data. Numerical simulation results illustrate the effectiveness and accuracy of the proposed fault diagnosis scheme.

1. Introduction
Fighters often work under harsh environmental conditions and take hyper maneuver, and the flight control system is the core to ensure the stability of the flight. In the flight control system, sensors play a key role and the reliability of sensors affects the stability and accuracy of the flight control system directly. Actually, the failure of sensors accounts for a considerable part of the flight control system failure. As precision instruments, sensors have a relatively high probability to fail under harsh conditions. And when taking hyper maneuver such as rolling, pitching and even cobra maneuver, the difference between fault-free and faulty signals is small compared with the change of states so as to make their features mixed. If the false information obtained from sensors is sent to the feedback control system, it may even cause a flight crash. Many researchers have designed methods to relieve it. Ref. [1] proposed a parameter separation technique for a system with sensor faults to avoid disturbing the control loop. Ref. [2] used Kalman filters to detect the sensor and actuator fault on Boeing planes. Therefore, it is quite significant to apply fault diagnosis to the sensors of the fighter to ensure the reliability of the flight and convenience of the maintenance.

The existing fault diagnosis approaches are commonly classified into three kinds of methods that are analytical model based methods, qualitative knowledge based methods and data-driven based methods. Analytical model based methods work well if the dynamic model of the diagnosed object can be described accurately in mathematics. And then observers can be designed to obtain residuals between the real outputs and the model outputs, adopting estimation methods [3, 4]. Qualitative
knowledge based methods are often adopted while the system is hard to be modeled accurately or the system cannot have enough sensors to supply the data that fault diagnosis methods need. The representative method is expert system [5]. However, qualitative knowledge based methods sometimes can be impractical for the reason that they require quantities of professional knowledge and experience. Data-driven methods do not need accurate dynamic model nor the expert knowledge, just require online or offline data from sensors to separate the faulty one. Massive recorded data and growing computing power make data-driven methods possible. So, this paper adopts data-driven methods for sensor fault diagnosis.

Among data-driven methods, time domain signal and frequency domain signal are two common processed objects. Wavelet packet decomposition is able to maintain time domain features and frequency domain features, and at the same time it overcomes the defect of the wavelet decomposition that it has poor frequency resolution in high frequency and poor time resolution in low frequency. The features that wavelet packet decomposition gives often have several dimensions with redundant information, so it is preferred to reduce the dimensions and highlight the main features. Principal component analysis (PCA) was proposed by Pearson [6], and it is often used to dealing with dependent data to reduce dimensions. Support vector machine (SVM) was first proposed by Cortes [7]. SVM works well on linear separable problem and it can also solve nonlinear classification problem if using kernel methods [8]. When facing multi-classification problem, one-versus-rest (OVR) support vector machine can also achieve good results. Therefore, a multi-classification SVM can be adopted to train the classifier.

The remaining of this paper is organized as follows. A data generation scheme is presented in the section 2. A complete sensor fault diagnosis scheme is introduced in section 3. The numerical simulation and result analysis are presented in section 4. And at last conclusions are drawn in section 5.

2. The Modeling of the Faults
2.1. The Model of the Fighter
In order to obtain the simulation data as accurate as possible, this paper adopts a nonlinear F-16 fighter model (according to Lars Sonnevelt’s version) [9] to generate the data. This model is a complex nonlinear system with six degrees of random. The equations of motion can be written as a system of 12 scalar first order differential equations. The detailed model can be seen in Ref. [9].

2.2. The Data Generation Scheme
There are two common types of fault that may often occur on sensors, which are constant deviation fault and random value fault. The former may often result from that the sensor has some mechanical failure or electrical failure, this kind of failure may last long and even get worse. While the latter may result from a slight strike and will not last too long and then disappear.

The constant deviation fault: the error between the output values of the sensor and the real values keeps a constant value since a moment. The mathematical model is:

\[
y(t) = \begin{cases} 
y_r(t), & t \leq t_f \\
y_r(t) + C, & t > t_f 
\end{cases}
\]

\[y(t) = \begin{cases} y_r(t), & t \leq t_{low} or t > t_{high} \\
y_r(t) + \text{random}, & t_{low} < t \leq t_{high} 
\end{cases}
\]

where \(y(t)\) denotes the output, \(y_r(t)\) denotes the real value, \(C\) denotes a constant value, \(t, t_f\) denote the time and the start time of the fault.

The random value fault: the error between the output values of the sensor and the real values and the time of it are random. The mathematical model is:
where \( y(t) \) denotes the output, \( y_r(t) \) denotes the real value, random denotes a random value, \( t, t_{low}, t_{high} \) denote the time, the start time and the end time of the fault.

The data of fault-free sensor and faulty sensor can be generated as the following steps:

- Initialize the nonlinear model with the data of initial states;
- Change the control command to obtain different states of the fighter;
- Add faults and white Gaussian noise to the sensors;
- Record a duration of time signals.

### 3. The Fault Diagnosis Scheme

#### 3.1. Energy Feature Extraction

Wavelet packet decomposition optimizes wavelet decomposition. It decomposes both the low frequency subband and the high frequency subband for every level. And then it minimizes a cost function to figure out the optimal decomposition path. The 3-level wavelet packet decomposition is shown in figure 1.

![Figure 1. A 3-level wavelet packet decomposition.](image)

In figure 1, S denotes the original signal, L denotes the low frequency signal and H denotes the high frequency signal. The relationship can be expressed as follows:

\[
\begin{align*}
\mu_{2n}(t) &= \sum_k h_k \mu_n(2t-k) \\
\mu_{2n+1}(t) &= \sum_k g_k \mu_n(2t-k)
\end{align*}
\]

where \( \mu_n \) denotes the wavelet and its subscript denotes location of the wavelet, \( h_k, g_k \) denote wavelet functions. Suppose \( C_j(k), k = 1,2,\ldots,N \) is the coefficient of the ith node of the jth level. Define energy as the sum of the squares of the coefficients of this node,

\[
E_j = \sum_{k=1}^{N} |s_j(k)|^2
\]

where \( s_j(k) \) denotes the coefficient of the wavelet of this node. This paper adopts a 3-level wavelet packet decomposition to obtain 8 energy features for classification.

Principal component analysis (PCA) is a statistical method, which transforms a group of potentially dependent variables into a group of independent variables via orthogonal transformation. These independent variables are called principal components. Eight energy features are obtained by wavelet packet decomposition and they can be taken as the inputs of the model training algorithm in theory. But this may raise the time complexity and space complexity, as a result, it occupies too much memory and takes a long time to obtain the model. Figure 2 shows that not every one of the eight energy features of fault-free data and faulty data distinguishes too much, and this means there are redundant features among them and the dimensions of feature can be reduced. By PCA, several main features which can separate faulty data from fault-free data can be extracted to train the classification.
3.2. Multi-Classification SVM

Support vector machine (SVM) is a two-classification model. Its basic model is a linear classifier which has the max interval under the feature space. And it can become a nonlinear classifier when using kernel technique. Suppose \( T = \{(x_1, y_1), (x_2, y_2), \ldots, (x_m, y_m)\}, y_i \in \{+1, -1\} \) is a training set under the feature space, where \( x_i \) denotes the vector of features, \( y_i \) denotes the label of the vector. The learning aim is to find a separating hyperplane to separate different samples. But there are an infinite number of hyperplanes and SVM is to find the one with max interval. The separating hyperplane can be described as a linear equation:

\[
\theta^T x + b = 0
\]  

(5)

where \( \theta \) denotes the vector of weights, \( x \) denotes the vector of features, \( b \) denotes the intercept term. The distance between a point and the separating hyperplane is as follows:

\[
r = |\theta^T x + b| / \|\theta\|
\]  

(6)

If the separating hyperplane can separate the samples correctly, then it satisfies the inequations following:

\[
\begin{cases}
\theta^T x_i + b \geq +1, & y_i = +1 \\
\theta^T x_i + b \leq -1, & y_i = -1
\end{cases}
\]  

(7)

The sum of the distance of a positive point and a negative point which are nearest to the hyperplane is as follows:

\[
\gamma = 2 / \|\theta\|
\]  

(8)

In order to find the max margin, maximize the sum:

\[
\max_{\theta, b} (2 / \|\theta\|) \\
\text{s.t. } y_i(\theta^T x_i + b) \geq 1, \ i = 1, 2, \ldots, m
\]  

(9)

Figure 3 shows the scatter points of the features obtained from PCA. It shows clearly that the points can be separate into 3 parts. This paper adopts the one-versus-rest (OVR) strategy that it treats the training set as a two-classification problem at one time, and repeats the operation on the rest samples until every category has been classified.

3.3. Fault Diagnosis

The hypothesis obtained by multi-classification SVM can be described as:

\[
h(x) = \theta^T x + b
\]  

(10)
The fault diagnosis process is inputting the new sample, and computing the value of the hypothesis, and then classifying the sample into the corresponding category.

![Figure 3. Scatter points of tagged points.](image)

4. Simulation
In order to verify the effectiveness of the proposed sensor fault diagnosis scheme, numerical simulation is shown in this section. The data set is obtained from the F-16 nonlinear model via MATLAB/Simulink. The model training and fault diagnosis are running on PyCharm.

4.1. Data Collection
The analysed signal is pitching signal captured from pitching angle sensor. The dataset can be separated into 3 parts, fault-free data, constant value fault data and random value fault. Every group of samples is different from each other by changing the control command of attack angle ranging from 0 to 20 degrees. They have the same sampling duration and frequency to ensure the consistency. The detailed information is shown in table 1.

| Type           | No. of groups | Duration (sec) | No. of samples |
|----------------|---------------|----------------|----------------|
| Fault-free     | 100           | 10             | 100            |
| Constant value | 100           | 10             | 100            |
| Random value   | 100           | 10             | 100            |

4.2. Data Processing
The energy features are obtained by wavelet packet decomposition and shown in figure 2. The feature vector has eight dimensions, and it is shown in the figures above that 2 features may be the main features, so it is rational to reduce the dimension to two. The contribution rate is about 0.9 and 0.1. Figure 3 shows the scatter points of the 2-dimension features.

4.3. Model Training
Tag the data set by fault-free data corresponding to 1, constant value fault data corresponding to 2, random value fault data corresponding to 3. Figure 3 shows the tagged data with red representing 1, blue representing 2, green representing 3. It implies that the data set is linearly separable.

The data set is divided into training set and test set. The test results shown in table 2 illustrate that the model is effective for the classification. Two random value fault data are separated into the constant value fault category because they have similar fault values and duration. This problem does not affect much and can be solved by add sampling time to highlight their features.
Table 2. Test results of the classifier.

| Type          | No. of samples | No. of test result |
|---------------|----------------|--------------------|
| Fault-free    | 30             | 30                 |
| Constant value| 30             | 32                 |
| Random value  | 30             | 28                 |

4.4. Fault Diagnosis
Collect 500 samples of fault-free data, 500 samples of constant value fault data, 500 samples of random value fault data. The fault diagnosis results are shown in table 3. According to table 3, the accuracy is 98.47% and fault-free data and faulty data can be separated apparently. However, some random value fault data may be classified into the constant value fault category, just like the test data does. One way to solve it is to add the sampling time to get more information about the time domain signal. The results imply that the classifier for fault diagnosis works well on the new data and it has good generalization performance.

Table 3. Sensor fault diagnosis results.

| Type          | No. of samples | No. of Test Result |
|---------------|----------------|--------------------|
| Fault-free    | 500            | 500                |
| Constant value| 500            | 523                |
| Random value  | 500            | 477                |

5. Conclusion
This paper studies the problem of sensor fault diagnosis for fighter. In this paper, sensor’s signals are collected from the mathematical model of the fighter and then the energy features are extracted by wavelet packet decomposition and the dimension of the features is reduced using PCA. The classifier for fault diagnosis is trained by multi-classification SVM. Simulation results reinforce the analytic results. The future work will focus on more types of fault of sensor and the better accuracy of diagnosis.

Acknowledgments
The project was supported by the National Natural Science Foundation of China (Project Nos. 61533009), a project funded by the Priority Academic Program Development of Jiangsu Higher Education Institutions.

References
[1] Zhai D, An L and Zhang Q 2018 Adaptive fault-tolerant control for nonlinear systems with multiple sensor faults and unknown control directions IEEE Trans. Autom. Control 60 4436-46.
[2] Amirarfaei F, Baniamerian A and Khorasani K 2013 Joint Kalman filtering and recursive maximum likelihood estimation approaches to fault detection and identification of Boeing 747 sensors and actuators AIAA Aerospace Sciences Meeting Including the New Horizons Forum and Aerospace Exposition pp 111-27.
[3] Bagheri F, Khaloozadeh H and Abbaszadeh K 2007 Stator fault detection in induction machines by parameter estimation using adaptive Kalman filter Proc. of 2007 Mediterranean Conf. on Control and Automation pp 2635-46.
[4] Li L L and Zhou D H 2004 Fast and robust fault diagnosis for a class of nonlinear system: Detectability analysis Computers and Chemical Engineering 28 2635-46.
[5] Wu J D, Wang Y H and Mingsian R B 2007 Development of an expert system for fault diagnosis in scooter engine platform using fuzzy-logic inference Expert Systems with Application 33 1063-75.

[6] Pearson K 1901 Principal components analysis The London, Edinbursh, and Dublin Philosophical Magazine and Journal of Science 6 559.

[7] Cortes C and Vapnik V N 1995 Support vector networks Machine Learning 20 273-97.

[8] Cristianini N and Shawe-Taylor J 2000 An Introduction to Support Vector Machines and Other Kernel-Based Learning Methods (Cambridge: Cambridge University Press).

[9] Sonneveldt L 2006 Nonlinear F-16 Model Description (The Netherlands: Delft University of Technology).