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MAKING HEALTH MANAGEMENT MORE CONCISE AND EFFICIENT: AIRCRAFT CONDITION MONITORING BASED ON COMPRESSED SENSING

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Abstract

With the development of aircraft, the amount of monitoring data becomes larger and larger, and the transmission channel bandwidth limitation and the onboard computational capability limitation become challenges for aircraft condition monitoring system. In this study, from the view point of aircraft condition monitoring, a remote fault diagnosis scheme based on compressed sensing is proposed, the monitoring data are compressed on-board after acquisition, and the compressed data can be either used for on-board diagnosis directly, or transmitted to the ground for data reconstruction, and later used for enhanced diagnosis or preventive maintenance. From the view point of compressed sensing, a bi-step compression method is presented, considering the requirements and characteristics of aircraft condition monitoring. The effectiveness of the proposed method is demonstrated with a hydraulic plunger pump, and the results indicate that the monitoring data is well recovered from the compressed data, and the accuracy of fault diagnosis is satisfactory.

1 Introduction

Aircraft Condition Monitoring System (ACMS) provides operators with performance and trend information about aircraft systems, and its data can be used for fault detection or diagnosis on-board, and transmitted in flight to the ground for real-time monitoring, or downloaded after flight for performance assessment. However, with the development of aircraft, the aircraft systems are more complex than ever, and the amount of monitoring data becomes larger and larger. Thus, the transmission channel bandwidth limitation (especially for satellite communications) and the onboard computational capability limitation become challenges for the development of aircraft prognostics and health management (PHM).

Nowadays, many data compression techniques have been proposed for monitoring data compression. Ref. [1] compares different direct compression techniques used for Electrocardiogram data. Parameter extraction methods design a pre-processor to extract features from the original signal first and then compress the signal based on the extracted features. Ref. [2] presents a comparison between the performances of neural network and linear predictors for near-lossless compression of electro-encephalo-graph (EEG) signals. Unfortunately, neural network based methods require a large amount of computing resources, which is difficult to achieve from a remote port. Transformation compression methods include Fast Fourier Transform (FFT), wavelet transform (WT) [3], and Hilbert–Huang transform (HHT) [4]. However, with these data compression methods, the compressed data cannot be used for fault detection or diagnosis directly, and a large amount of original data still handled by on-board embedded computer.

The other way is to extract the features on-board, and then conduct fault diagnosis on-board based on these features, meanwhile, these features are transmitted to the ground. For example, Wavelet packet transform (WPT) could be employed as an effective tool for description of distribution of signal energy in time-frequency domains [5]. Empirical mode decomposition (EMD), proposed by Huang et al., is a superior approach to decompose nonlinear signals to achieve desirable feature vectors [6]. A review of advanced time-frequency analysis methods for machinery fault diagnosis is carried out by Feng [7], and some performance assessment methods for typical mechanical components such as bearings and gearboxes are proposed [8]. However, a problem is usually arises that the original monitoring data cannot recovered from these features, and it is hard to support enhanced fault diagnosis, preventive maintenance and in-depth investigations.

Fortunately, the emerging compressed sensing technique, proposed by Emmanuel Candès, Terence Tao, and David Donoho around 2004[9, 10], provides effective solutions

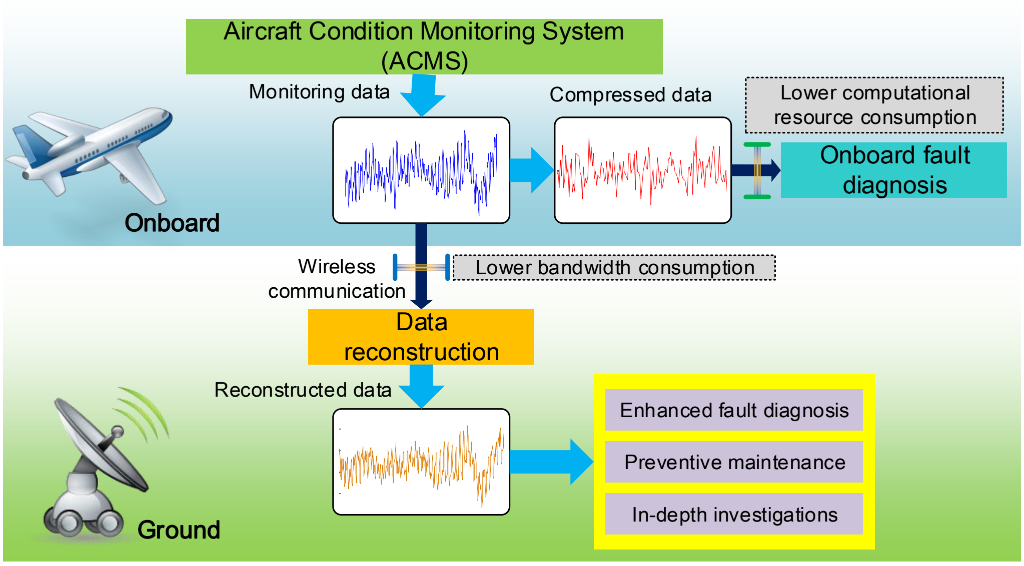

Fig. 1 Architecture of condition monitoring based on compressed sensing

to the challenges. Compressed sensing is based on the principle that, through optimization, the sparsity of a signal can be exploited to recover it from far fewer samples than required by the Shannon-Nyquist sampling theorem. With compressed sensing, on the one hand, the original monitoring data are compressed on-board, and these compressed data can be used for fault diagnosis directly, according to Calderbank Robert's research [11], on the other hand, the compressed data can be transmitted to the ground for data recovery, the recovered data are nearly same with original data, and can be used for enhanced fault diagnosis, etc.

The remainder of this paper is organized as follows. In section 2, the architecture and the methodology is described in detail. In Section 3, the effectiveness of the proposed approaches is demonstrated by using hydraulic pump monitoring data with different faults, and the results of experiment are presented and discussed. In section 4, a conclusion of this research is presented.

2 Methodology

The architecture of condition monitoring based on compressed sensing is shown in **Fig. 1**. First, the onboard monitoring data are compressed with measurement matrix, then, the compressed data are used for fault diagnosis onboard directly without data reconstruction, based on compressed learning method. Meanwhile, the compressed data are transmitted to operational ground centers or service providers for enhanced diagnosis or in-depth investigations after signal reconstruction. Since the monitoring data is compressed before fault diagnosis onboard, the computational resources and transmission bandwidth consumption are much lower.

Since the original data is compressed with measurement matrix, the time domain features, frequency domain features and time-frequency domain features of compressed data are completely changed, therefore, for fault diagnosis based on compressed data, traditional fault diagnosis algorithms, that is, feature extraction and then classification, are generally useless. Fortunately, in compressed sensing framework, machine learning in the measurement domain (with compressed data directly) is possible[11], a family of matrices widely used in compressed sensing, which satisfy near isometry property, preserve the learnability of original data set. In other words, from the machine learning view-point, compressed sensing can be regarded as an efficient universal dimensionality reduction method from data domain in $\mathbb{R}^n$ to the measurement domain $\mathbb{R}^m$ where $m \ll n$. If the compressed data is measured directly in the compressed domain, a classifier that is trained based on the compressed data performs almost as well as the classifier in the high domain.

Furthermore, a high compression ratio, is beneficial for the data reduction of machine learning algorithms. However, if the compression ratio is too high, that is, if m in $\mathbb{R}^n \xrightarrow{\text{compress}} \mathbb{R}^m$ is too little, the original data are hardly recovered from the compressed data accurately. To reduce the data size of on-board fault diagnosis and ensure the data reconstruction accuracy, a bi-step compression scheme is used in this study, as shown in Fig. 2.

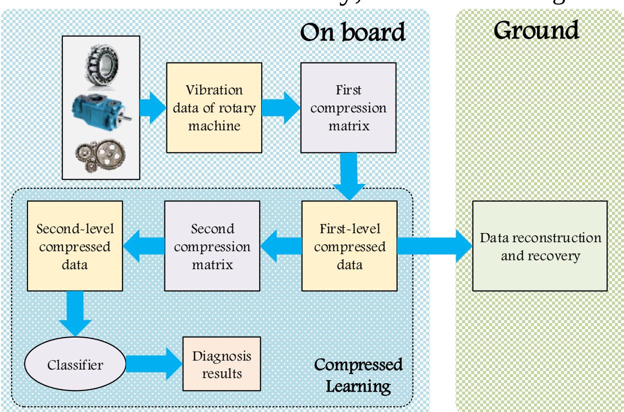

Fig. 2 Bi-step Compression Scheme for Monitoring Data

In bi-step compression scheme, two measurement matrices are used for data compression. The first-level compressed data is transmitted to the ground, and can be used for data reconstruction. To minimize the data size used for fault diagnosis, the other measurement matrix is employed to compress the first-level compressed data, and the size of second-level compressed data is suitable for common classifiers. These re-compressed data can be regarded as features, in fact, the computation of data compression is less than traditional feature extraction, hence, it is more suitable for on-board fault diagnosis.

2.1 Compressed sensing and data reconstruction

This section gives a brief introduction of compressed sensing, and it is a guidance for data reconstruction in the ground monitoring center. Compressed sensing is a signal processing technique for efficiently acquiring and reconstructing data, by finding solutions to underdetermined linear systems. This is based on the principle that, through optimization, the sparsity of a signal can be exploited to recover it from far fewer samples than required by the Shannon-Nyquist sampling theorem. There are two conditions under which recovery is possible, the first one is sparsity which requires the signal to be sparse in some domain, the second one is incoherence which is applied through the isometric property which is sufficient for sparse signals. Generally speaking, nearly all natural signals have concise representations when expressed in a convenient basis. In compressed sensing, similar to sparse representation, it is assumed that a signal can be sparse in some domain, therefore, a one-dimensional signal x in $\mathbb{R}^N$ with length N can be represented as:

$$x = \Psi \theta \tag{1}$$

Where Ψ is a $N \times N$ dictionary matrix, θ is the sparse vector of x, and the sparsity of θ is $K\left(K \ll N\right)$, meaning that there are K nonzero coefficients in θ.

The measurement process can be represented as:

$$y = \Phi x \tag{2}$$

Where Φ is a $M \times N$ measurement matrix and y is a $M \times 1$ vector, and $K < M \ll N$. In other words, y is a linear measurement or a condensed representation of x.

For data reconstruction process, y, Φ and Ψ are known, and θ is unknown. By substituting Eq.(1) to Eq.(2), the problem can be described as:

$$y = \Phi\Psi\hat{\theta} = A^{CS}\hat{\theta} \tag{3}$$

The last problem is to estimate $\hat{\theta}$ from A^{CS} and y, later, with dictionary matrix Ψ, $\hat{x}$ can be estimated. In general, the sparse vector $\hat{\theta}$ is estimated from the compression signal y using the following optimization process:

$$\hat{\theta} = \arg\min \|\theta\|_1, \text{s.t.} \, y = A^{CS}\theta \tag{4}$$

Where $\|\theta\|_1$ is the L_1 norm of the vector θ. This convex optimization problem conveniently reduces to a linear program known as basis pursuit (BP) algorithm, and another well-known reconstruction algorithm is the orthogonal matching pursuit (OMP).

2.2 Bi-step compression and fault diagnosis

For fault diagnosis, we suppose the number of patterns is p, include normal and all fault types, and these patterns are denoted as $T_1, T_2, \cdots, T_p$, and each pattern contains s data segments, the length of each data segment is N, represented as $x_i^{T_j}$, where $i = 1, 2, \cdots, s, \, j = 1, 2, \cdots, p$. The training matrix $X \in R^{N \times sp}$ is composed of monitoring data acquired from all patterns:

$$X = \begin{bmatrix} x_1^{T_1}, x_2^{T_1}, \cdots, x_s^{T_1}, x_1^{T_2}, x_2^{T_2}, \cdots, \\ x_s^{T_2}, \cdots, x_1^{T_p}, x_2^{T_p}, \cdots, x_s^{T_p} \end{bmatrix} \tag{5}$$

Before the training process of classifier, the training matrix is normalized:

$$X^N = X / \max\left(\max\left(X\right)\right) \tag{6}$$

Define the first compression matrix as $\Phi_1 \in R^{M_1 \times N} \left(M_1 \ll N\right)$, Φ_1 satisfying restricted isometry property (RIP), and $\left\|\Phi_{1i}^T\right\|_2 = 1, i = 1, 2, \cdots, M_1$. With the first compression matrix, the length of training data is compressed to M_1 from N, and the first-level compressed data X^{NC} is used for reconstruction:

$$X^{NC} = \Phi_1 \cdot X^N \tag{7}$$

To minimize the size of data used for on-board fault diagnosis, the first-level compressed data is re-compressed with the other measurement matrix $\Phi_2 \in R^{M_2 \times M_1} \left(M_2 \ll M_1\right)$, and the length of the second-level compressed data is M_2, the re-compression process is represented as:

$$X^{NCC} = \Phi_2 \cdot X^{NC} \tag{8}$$

The length of the second-level compressed data is much smaller than the original data, and can be used for on-board fault diagnosis directly.

In this study, a radial basis function (RBF) neural network is used as fault classifier, based on the training matrix, the target matrix of training process is $G \in R^{p \times sp}$,

$$G = \begin{pmatrix} G_1 & G_0 & G_0 & \cdots & G_0 \\ G_0 & G_1 & G_0 & \cdots & G_0 \\ G_0 & G_0 & G_1 & \cdots & G_0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ G_0 & G_0 & G_0 & \cdots & G_1 \end{pmatrix} \tag{9}$$

Where $G_0 = \left[\overbrace{0, 0, \cdots, 0}^{s}\right]$, and $G_1 = \left[\overbrace{1, 1, \cdots, 1}^{s}\right]$.

The RBF neural network C is trained with X^{NCC} and G. Later, the trained classifier C can be used for fault diagnosis, based on the re-compressed monitoring data.

3 Case study

In this study, a test rig of hydraulic plunger pump, shown in Fig. 3, was tested and analyzed to verify the presented method. In the test, two common fault types in plunger pump were introduced: slipper loose fault and valve plate wear fault. Under three kinds of states, including normal state, vibration signals were acquired from the end face of plunger pump, respectively. The rotational speed was 528r/min, and the sampling rate was 1000Hz.

Fig. 3 Hydraulic plunger pump test rig

3.1 Data compression and reconstruction

Data reconstruction is conducted in the monitoring center, and the original vibration data is reconstructed from the first-level compressed data. In this study, Gaussian random matrix was selected as measurement matrix, and the dictionary matrix is a Fourier matrix, and data reconstruction is based on OMP algorithm.

In this test, vibration data acquired from normal state was used for data compression and reconstruction validation. A segment of vibration data was acquired from the test rig, and the length was $N = 2048$, as shown in Fig. 7, the red curve. Then, the compression ratio of the first-level compression was 0.5, and the size of the first measurement matrix was $M \times N = 1024 \times 2048$, shown in Fig. 4, the length of the first-level compressed data was $M = 1024$, shown in Fig. 5. Since the size of dictionary matrix is determined by the length of original data, the size of dictionary matrix used in this case was $N \times N = 2048 \times 2048$, shown in Fig. 6.

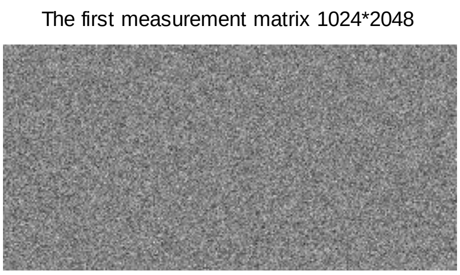

Fig. 4 The First Measurement Matrix

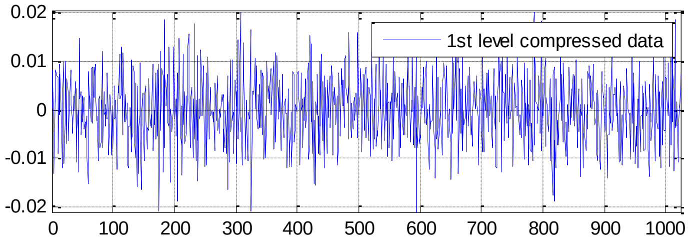

Fig. 5 The First-level Compressed Data-Normal

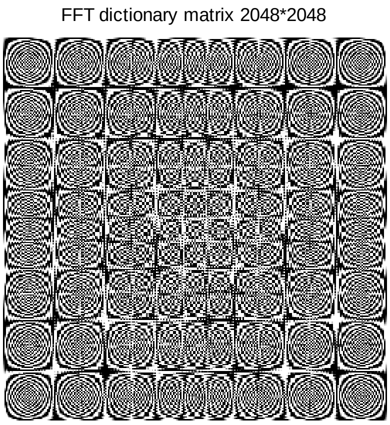

Fig. 6 The Dictionary Matrix

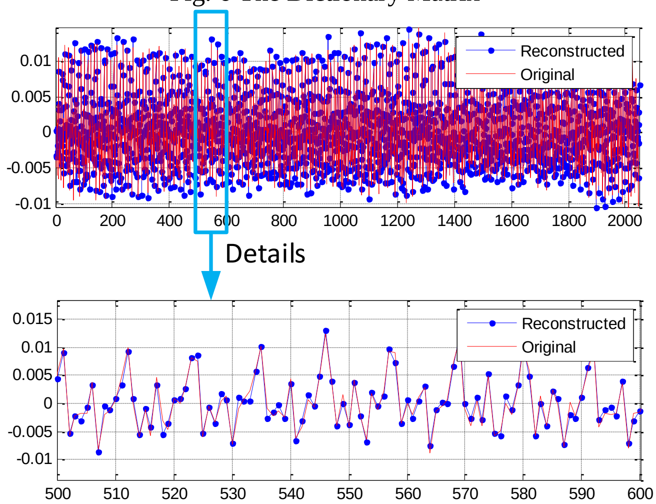

Fig. 7 The Original Data and The Reconstructed Data-Normal

The reconstructed data is shown in Fig. 7, the blue curve. The reconstruction results indicate that the reconstructed data were nearly same with the original data, and it suggests that we can use the reconstructed data to conduct enhanced fault diagnosis, preventive maintenance or in-depth investigations.

3.2 Fault diagnosis based on bi-step compression

Since the fault classifier was RBF neural network, the training matrix and test matrix should be constructed before fault diagnosis. In this case, the data were acquired based on sliding window method, and the interval of sliding window is $\Delta=4$, the length of each data segment was $N=512$, and the number of patterns was $p=3$. In training matrix, each pattern contains $s_{Tr}=192$ data segments, and in test matrix, each pattern contains $s_{Te}=64$ data segments. The arrangement of training matrix and test matrix is shown in Table 1.

Table 1 The Arrangement of Training Matrix and Test Matrix

Pattern	Normal	valve plate wear fault	slipper loose fault
Pattern Number	1	2	3
Training matrix column number	1~192	193~384	385~576
Test matrix column number	1~64	65~128	129~192

As previously mentioned, the ratio of the first-level compression was 50%, the size of the first compression matrix is $\Phi_1 \in R^{256\times 512}$, and Gaussian random matrix was selected as the compression matrix (or measurement matrix), after the first-level compression, the size of training matrix was compressed to $X^{NC} \in R^{M_1\times(s_{Tr}*p)} = R^{256\times(192*3)}$, as shown in Fig. 8.

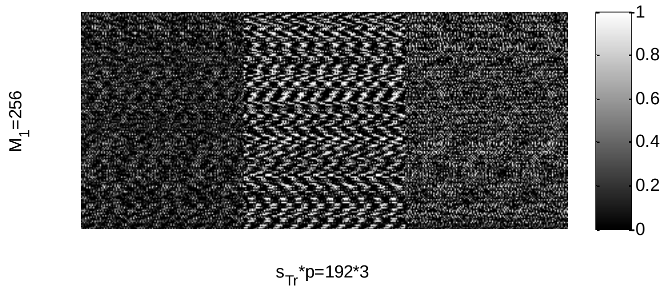

Fig. 8 The First-level Compressed Training Matrix

Later, several second-level compression matrices were designed to validate the accuracy of fault diagnosis based on bi-step compression. The sizes of these Gaussian random matrix were $\Phi_{21} \in R^{32\times 256}$, $\Phi_{22} \in R^{16\times 256}$, $\Phi_{23} \in R^{8\times 256}$, $\Phi_{24} \in R^{7\times 256}$, $\Phi_{25} \in R^{6\times 256}$, $\Phi_{26} \in R^{5\times 256}$, $\Phi_{27} \in R^{4\times 256}$, $\Phi_{28} \in R^{3\times 256}$, these second-level compressed training matrices are shown in Fig. 9 and Fig. 10. with these second-level compression matrices, the length of training matrix and test matrix were compressed to $M_2 = 32,16,8,7,6,5,4,3$, respectively. Then, these second-level compressed data were used to train and test the fault classifier.

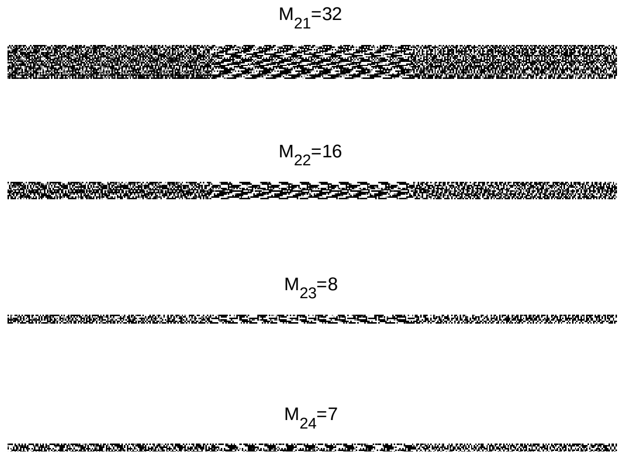

Fig. 9 Second-level Compressed Training Matrices (1)

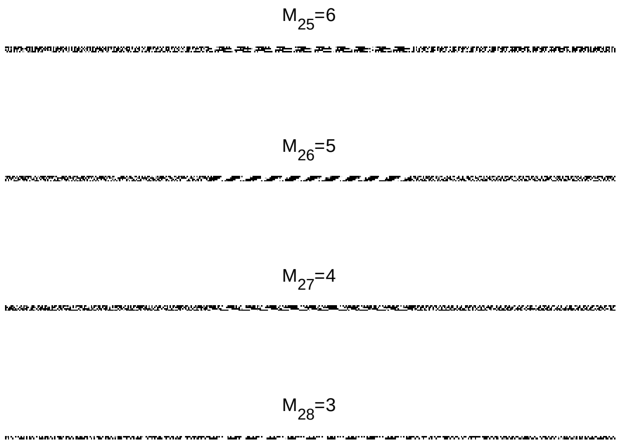

Fig. 10 Second-level Compressed Training Matrices (2)

Here, RBF neural network were selected as fault classifier, the parameters of neural network were: the mean squared error goal was 0.001, the spread of radial basis was 3, and the maximum number of neurons was 240.

Based on the test matrix arrangement and pattern number listed in Table 1, the fault diagnosis results are shown in Fig. 11 and Fig. 12.

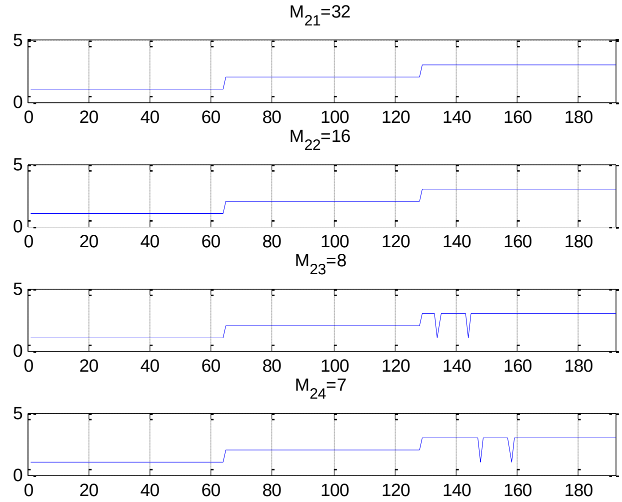

Fig. 11 Fault Diagnosis Results based on Second-level Compressed Data (1)

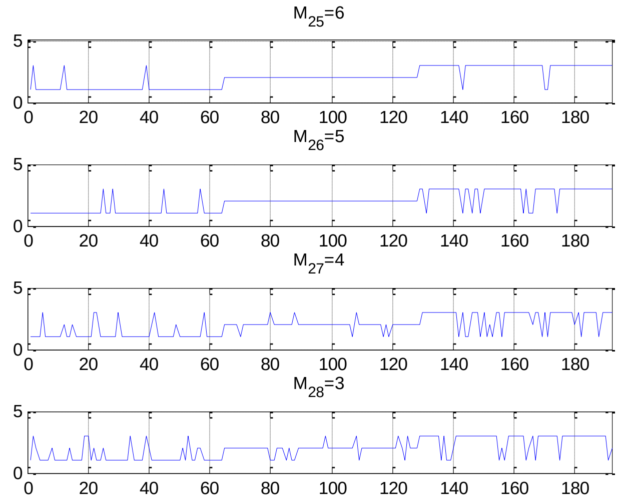

Fig. 12 Fault Diagnosis Results based on Second-level Compressed Data (2)

Fault diagnosis time consumption and accuracy were shown in Fig. 13 and Fig. 14. The number of horizontal axis (1~8) represent the different tests based on the different second-level compression matrix (from left to right, $M_2 = 32$, $M_2 = 16$, $M_2 = 8$, $M_2 = 7$, $M_2 = 6$, $M_2 = 5$, $M_2 = 4$, $M_2 = 3$). It can be seen from Fig. 13, the time consumption of fault diagnosis decreases with the increase of second-level compression ratio, and the results indicated that based on bi-step compression method, the computational resource were decreased significantly. However, with the increase of second-level compression ratio, the fault diagnosis accuracy also decreased, nevertheless, the accuracy is higher than 95%, when the length of second-level compressed data is longer than $M_2 = 6$, generally speaking, it is acceptable for on-board fault diagnosis.

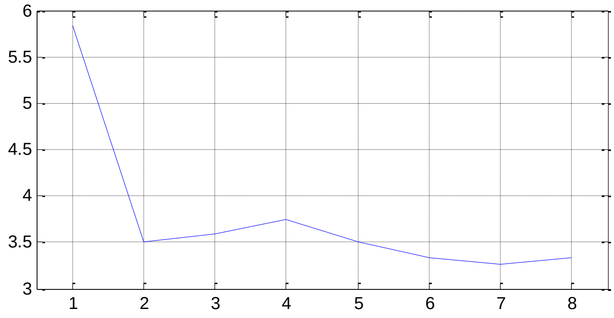

Fig. 13 Time Consumption of Neural Network Training (s)

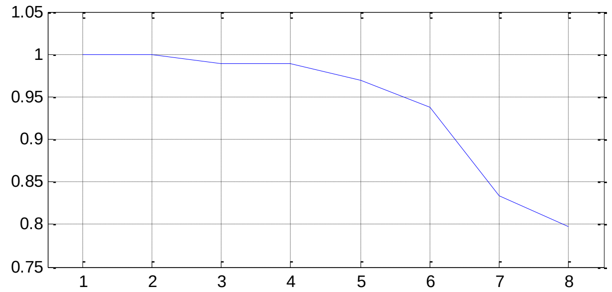

Fig. 14 Fault Diagnosis Accuracy

4 Conclusion

This study presents a compressed sensing based fault diagnosis scheme. The monitoring data are acquired and compressed on-board, and these compressed data can be used for fault diagnosis directly, or transmitted to the ground monitoring center for reconstruction. Compared with commonly used prognostics and health management scheme, the advantage of the proposed scheme is the size of data to be processed on-board or transmitted via wireless communication is relatively low, meanwhile, original data can be well reconstructed from the compressed data, these features make it very adept in aircraft condition monitoring. However, one of the requirements for data reconstruction process is the enormous computational capability, and the data reconstruction is a time-consuming process, fortunately, these requirements can be satisfied based in computing center on the ground.

Future works mainly concentrate on the fault diagnosis algorithm design based on compressed data, and the on-board compression matrix construction, considering the characteristics and requirements of aircraft condition monitoring system. Meanwhile, data from other aircraft systems will be used to validate and improve the fault diagnosis scheme/algorithms based on compressed sensing.

Acknowledgements

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