Comparison of SOM and PCA-SOM in Fault Diagnosis of Ground-testing Bed

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Abstract

In order to compare the fault diagnosis reliability and fault diagnosis efficiency (time consumption property) of PCA-SOM and SOM in liquid propellant rocket engine ground-testing bed, two types of ground-testing bed fault data are used. One is generated by the mechanism model of ground-testing bed. The other is generated according to the expert's experience and the statistical model of fault mode. The comparison results using these two types of fault data both indicate that the fault diagnosis reliability and fault diagnosis efficiency of PCA-SOM are better than SOM.

keywords: Ground-testing bed; Fault diagnosis; PCA (Principal Component Analysis); SOM (Self-organizing Map)

1. Introduction

Liquid propellant rocket engines (LRE) are the heart of space vehicles and space transporting systems [1]. After a rocket engine is produced, in order to check out whether the rocket engine fulfills the design requirements, it should be tested on the ground-testing bed. Furthermore, the ground-testing bed is used to research and test the control or other methods for rocket engine. The testing bed provides a structure strong enough to hold a rocket engine in place as it is fired, and a fuel feed system to provide fuel and oxidizer to the engine. Usually, the fuel is liquid hydrogen and the oxidizer is liquid oxygen. In the ground-testing process, it is clearly that if there are any faults occurring on the testing bed, it will provide fuel and oxidizer for the rocket engine improperly. The rocket engine will work abnormally or even will

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be destroyed. So it is very necessary and important to detect anomalies of the ground-testing bed so as to
decrease the bad effects of its faults to the rocket engine [2].

In order to detect the anomalies and diagnose the fault in ground-testing bed, researchers are
concentrated on the research of fault detecting and diagnosis method from 2000. Temple proposes a
testability analysis methodology that improves efficiency in maintainability and availability of a system.
They modeled a rocket engine testing bed and utilized the existing testing bed sensors as a baseline for the
testability analysis [3]. The researchers of NASA Ames Research Center explore a particular data driven
approach, which is based on a normally detection algorithms from the machine learning community [4].
To solve the fault diagnosis problem of liquid propellant rocket engine ground-testing bed, a fault
diagnosis approach based on self-organizing map (SOM) is proposed by Ning Zhu [5]. To implement
effective diagnosis of the deterministic faults which have been established the mechanism model or can
generate enough reliable fault data, the fault diagnosis based on principal component analysis (PCA) and
self-organizing map (SOM) is proposed by Zhigang Feng [6]. These two approaches can both implement
fault diagnosis of ground-testing bed with good visualization property. But there is no comparison of these
two approaches, such as the fault identification ratio, time consumption property .etc.

In this paper, the comparison of PCA and PCA-SOM in fault diagnosis of ground-testing bed is studied,
including fault diagnosis reliability and fault diagnosis efficiency (time consumption property). Two types
of ground-testing bed fault data are used. One type of data is generated by the mechanism model of
ground-testing bed. The other type of data is generated according to the expert’s experience and the
statistical model of fault mode.

2. Principle of fault diagnosis with SOM

The Self Organizing Map (SOM) developed by Kohonen [7] is a special kind of artificial neural
network that is based on competitive learning. The purpose of SOM training is the computation of an
optimal clustering of a collection of patterns in \( \mathbb{R}^n \). In the Self Organizing Map the neurons are typically
arranged in a two dimensional lattice: the feature map. Each neuron receives inputs from the input layer
(vectors in \( \mathbb{R}^n \)) and from the other neurons in the map. During the learning the network performs
clustering and the neurons are moved in the lattice so as to reflect cluster similarity by means of distances
in the map. To each element in the SOM map it is associated one real vector (in \( \mathbb{R}^n \)) that can be
considered as a prototype of the patterns in the cluster.

In the fault diagnosis of liquid propellant rocket engine ground-testing bed, the SOM projects the
multidimensional ground-testing bed data into a two dimensional map. Visualization of the SOM is used
to cluster the ground-testing bed data. The out map of the SOM is divided to several regions. Each region
is represented for one fault mode. The fault mode of testing data is determined according to the region of
their labels belonged to [5]. The steps of fault diagnosis using SOM show as following:

1. Select training samples for every fault mode and normalize them.
2. Determine the structure of the SOM and train it using all training samples, label the fault mode
names on their respective winning neurons. The out map will be divided to several regions. Each region
is represented for one fault mode.
3. Map the testing data on to the trained SOM and label their corresponding winning neurons.
4. The fault mode of the testing data is determined according to the region of their labels belong to.

3. Principle of fault diagnosis with PCA-SOM

Principal component analysis (PCA) is a kind of multivariable analysis method, which is also called
matrix data analysis. By using variable transform, correlated variables are changed into uncorrelated new
variables, which is useful to data analysis. So it is used in multi-dimension analysis widely. The general method of PCA is described in references 8 and 9. The principal component analysis (PCA) is now widely used for lowering redundancy and realizing reduction of data to enhance the analysis efficiency. It reduces the dimensionality of high variable space with a minimum loss of information.

In the fault diagnosis of liquid propellant rocket engine ground-testing bed with PCA-SOM, through the dimension reduction process of PCA, it not only reduces data size, but also reduces noise influence. After that the SOM is trained. The output of the map with labels which is called U-matrix is divided into several regions and each region represents one fault. Finally, the fault type is determined using Variable U-matrix and load factor. It implements visualization of fault status identification and fault variable orientation [6].

The steps of fault diagnosis using PCA-SOM show as following:
1. Normalization of fault samples. Select training samples for every fault mode and normalize them.
2. Dimension reduction and noise elimination using PCA. Apply PCA to the training samples, and select the first $m$ PCs as the new input data through calculating the contribution rate of each PC.
3. Clustering using SOM. Determine the structure of the SOM and train it using the new training samples composed by the first $m$ PCs. The labeled U-Matrix is generated by labeling the fault mode names on their respective winning neurons. The out map is divided to several regions according to the labeled U-Matrix, and each region is represented for one fault mode. Map the testing data on to the trained SOM and label their corresponding winning neurons. The fault mode of the testing data is determined according to the region of their labels belong to.
4. Fault variable deduction. The fault variable can be determined by analyzing the relationship between fault and PC using Variable U-matrix and calculating the load factor of each variable to every PC.

4. Experiment and results

In order to compare the fault diagnosis reliability and fault diagnosis efficiency of SOM and PCA-SOM, Two types of ground-testing bed fault data are used. One type of fault data is generated by the mechanism model of ground-testing bed. The other type of data is generated according to the expert’s experience and the statistical model of fault mode.

4.1. Experiment and result with fault data generated by the mechanism model

In order to compare the fault diagnosis reliability and fault diagnosis efficiency of SOM and PCA-SOM, Two types of ground-testing bed fault data are used. One type of fault data is generated by the mechanism model of ground-testing bed. The other type of data is generated according to the expert’s experience and the statistical model of fault mode.

The researchers from Beijing institute of aerospace testing technology have established the mechanism model of four fault modes for XXI ground-testing bed. 150 groups of fault data are generated by this model, in which 100 groups are used for training the SOM or PCA-SOM, the other 50 groups are used for testing. There are five parameters for every testing data. They are pressure of hydrogen reducing valve (Pejr), pressure of hydrogen tank (Pxr), pressure of hydrogen pipeline (PGr), pressure of hydrogen pump (Pohr) and flow of hydrogen pipeline (Gr).

1) Fault diagnosis with PCA-SOM

The detail training and testing procedure of PCA-SOM is described detailed in reference 6. In this paper, we just give the results. Fig. 1 is the fault area map of training samples. From Fig. 1, we can see that the output map of the SOM is divided in to five regions and each region represents one type of fault.
Table 1. Fault simulation data of liquid hydrogen system

| Class Num | Fault mode                                                  | Groups | Fault label |
|-----------|-------------------------------------------------------------|--------|-------------|
| 1         | Regulating valve opening abnormity of hydrogen providing system | 150    | F1          |
| 2         | Leakage of hydrogen emergency closing valve                 | 150    | F2          |
| 3         | Hydrogen emergency closing valve opening abnormity           | 150    | F3          |
| 4         | Leakage of coupling flange before flowmeter 1 on hydrogen providing pipe | 150    | F4          |
| 5         | Normal                                                      | 150    | Nor         |

Table 2. Fault diagnosis result of the testing samples with PCA-SOM

| Testing data  | Fault diagnosis result | Identification ratio /% |
|---------------|------------------------|-------------------------|
| F1 (50 groups)| 50 0 0 0 0             | 100%                    |
| F2 (50 groups)| 0 41 0 0 9             | 82%                     |
| F3 (50 groups)| 0 0 50 0 0             | 100%                    |
| F4 (50 groups)| 0 0 0 50 0             | 100%                    |
| Nor (50 groups)| 0 0 0 0 50            | 100%                    |

Table 3. Fault diagnosis result of the testing samples with SOM

| Testing data  | Fault diagnosis result | Identification ratio /% |
|---------------|------------------------|-------------------------|
| F1 (50 groups)| 50 0 0 0 0             | 100%                    |
| F2 (50 groups)| 0 40 0 0 10           | 80%                     |
| F3 (50 groups)| 0 0 50 0 0             | 100%                    |
| F4 (50 groups)| 0 0 0 50 0             | 100%                    |
| Nor (50 groups)| 0 8 0 0 42           | 84%                     |

Fig. 2 is the output map with labels of the testing samples. It indicates that some F2 samples are determined as Nor falsely. Table 2 shows the detail fault diagnosis result of the testing samples with PCA-SOM, which indicates that the identification ratio for all fault mode are very high.

(2) Fault diagnosis with SOM

The detail training and testing procedure of SOM is described detailed in reference 5. Here just give the results. Fig. 3 shows the fault area map of training samples. Compare Fig. 1 and 3, we can see that the fault region determined by PCA-SOM and SOM are different. Fig. 4 is the output map with labels of the testing samples. It indicates that some F2 samples are determined as Nor falsely and some Nor samples are determined as F2 falsely. Table 3 shows the detail fault diagnosis result of the testing samples with SOM, which indicates that the identification ratio is lower that PCA-SOM.
(3) Comparison result of PCA-SOM and SOM

Table 4 shows the detailed comparison result of PCA-SOM and SOM, including the identification ratio and time consumption property. The comparison results indicate that the both fault diagnosis reliability and fault diagnosis efficiency of PCA-SOM are better than SOM. Through PCA, the data dimension of input data are reduced, so the training time of PCA-SOM is less than SOM. Meanwhile, through PCA, the noise in the input data is eliminated, so the identification ratio of PCA-SOM is higher than SOM.

|          | Identification ratio (%) | Training time consumed (s) |
|----------|--------------------------|---------------------------|
| PCA-SOM  | 96.4%                    | 2.2                       |
| SOM      | 92.8%                    | 18.1                      |

4.2. Experiment and result with fault data generated by the statistical model

This part describes the comparison result of PCA-SOM and SOM using fault data generated by the statistical model. Fifteen fault modes are studied. They are A type oxygen reducing valve fault, B type oxygen reducing valve fault, C type oxygen reducing valve fault, D type oxygen reducing valve fault, A type filter jam fault above oxygen tank, B type filter jam fault above oxygen tank, A type pressure measurement pipe rupture of oxygen reducing valve, B type pressure measurement pipe rupture of oxygen reducing valve, filter jam fault on oxygen pipeline, pressure measurement pipe rupture of oxygen tank, pressure measurement pipe rupture of oxygen pipeline, pressure measurement pipe rupture of oxygen pump, leakage of oxygen pre-cooling valve, leakage of relief valve, leakage of monomial valve. They are represented by name F1 to F15, the normal state is represented by name Nor. There are five parameters for every testing data. They are pressure of oxygen reducing valve (Pejy), pressure of oxygen tank (Pxy), pressure of oxygen pipeline (PGy), pressure of oxygen pump (Pohy) and flow of oxygen pipeline (Gy). 100 groups of fault data are generated by this model, in which 20 groups are used for training the SOM or PCA-SOM, the other 80 groups are used for testing.

Fig. 5 is the output map with labels of the testing samples using PCA-SOM. It indicates that some Nor samples are determined as F12 falsely. Fig. 6 is the output map with labels of the testing samples using SOM. It is obviously that the identification ratio of SOM is lower than PCA-SOM. Table 5 shows the detail comparison result of PCA-SOM and SOM. The comparison results also indicate that the both fault diagnosis reliability and fault diagnosis efficiency of PCA-SOM are better than SOM.
5. Conclusions

The comparison results using the fault data generated by mechanism model and statistical model both indicate that the both fault diagnosis reliability and fault diagnosis efficiency of PCA-SOM are better than SOM. Through PCA, the data dimension of input data are reduced, so the training time of PCA-SOM is less that SOM. Meanwhile, through PCA, the noise in the input data is eliminated, so the identification ratio of PCA-SOM is higher that SOM.

![Fig 5. The output map with labels of the testing samples(PCA-SOM)](image1)
![Fig 6. The output map with labels of the testing samples(SOM)](image2)

Table 5. Comparison result of PCA-SOM and SOM

|                | Identification ratio (%) | Training time consumed (s) |
|----------------|--------------------------|----------------------------|
| PCA-SOM        | 97.2%                    | 8.3                        |
| SOM            | 91.4%                    | 63.3                       |

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