A Comparison of Learning Machines for Turboshaft Engine Gas Path Fault Pattern Recognition

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Abstract. Since the operating environment of a turboshaft engine is complex and harsh, gas path components are easily damaged. It is quite important of gas path fault diagnosis for turboshaft engine from the huge accumulated data. The paper presents the data-driven ways of learning machine algorithms for gas path fault diagnosis of the engine and the performance comparisons. Various Extreme Learning Machine (ELM), including basic ELM, Kernel ELM (KELM) and Multiple Layer KELM (MLKELM), are involved. Besides, the Deep Belief Network (DBN) as one of the deep learning machines is also employed to recognize fault patterns. The simulation is carried out on a turboshaft engine with typical gas path fault modes. The results show that the MLKELM and DBN provide better classification accuracy than the ELM and KELM, and the DBN consumes less training time compared to the MLKELM.

1. Introduction

Fault diagnosis for aero-engine is the core part of engine health management system, which is also an important prerequisite to reduce maintenance cost and ensure flight safety. Aero-engine gas path fault is caused by erosion, fouling and objective damage during engine operation. As using time increases, the engine component performance degradation may also cause engine gas path components to fail\cite{1}. Key rotating components in turboshaft engines have the higher probability to break down. Hence, it is significant to diagnose the fault of the gas path components for the turboshaft engine\cite{2}.

Up to now, researchers have proposed many methods for engine fault diagnosis. There are mainly three categories\cite{3}: analytical model based method, knowledge based method and data-driven based method. The engine analytical model based method uses various filtering algorithms such as Kalman filter and particle filter to achieve component fault diagnosis. The data-driven based method directly relies on the engine measurement data, and no additional prior component characteristic maps and aero-thermal principle are involved\cite{4,5}. Since learning machine algorithms owns the strong nonlinear mapping capabilities, the trained network related to learning machine algorithms might be a satisfactory candidate to represent the mathematical relationship between sensor measurement parameters and health parameters.

With the functional demands increase, more sensor measurements are utilized to gas path condition monitoring and fault diagnosis for the turboshaft engine. The available measurements enrich the fault database, and it is urgent to find the more effective way to make full use of these large-scale data to mine the valuable information for fault diagnosis.

For these purposes, several machine learning methods of ELMs and DBN are presented to the turboshaft engine. The ELM algorithm is with simple topology and fast training speed, and it is
extremely suitable to real time classification and regression. In this paper, the basic ELM and its improved algorithm are given and applied for the engine fault pattern recognition. The MLKELM, developed from the conventional ELM, has multiple hidden layers structure with stronger feature extraction capabilities. Besides, the DBN is introduced to gas path fault diagnosis due to the more accumulated fault data. The performance comparisons of the examined algorithms are carried out using the typical fault database of the turbo shaft engine.

The purpose of the paper is to find an effective way to identify gas path fault patterns. The sections are as follows: the principles of ELMs and DBN are presented for fault classification in Section 2. Section 3 gives the comparison results of the involved learning machines for gas path fault diagnosis, followed by the performance analysis with regard to classification accuracy. Finally, the conclusion is received in Section 4.

2. The Principle of learning machines and DBN

2.1 ELM, KELM and MLKELM

The Extreme Learning Machine (ELM) algorithm, developed from a single hidden layer feedforward neural network (SLFNs), was proposed by Professor Huang to overcome the shortcomings of the back propagation (BP) algorithm [6].

The ELM algorithm builds a model by randomly generating input weights $a$, thresholds $b$ and then output weights $\beta$ can be obtained by solving equation $H\beta=T$. The $T$ is training sample output sets and feature space $H(x)$ is defined as $H(x)=[g(a_1x+b_1)\cdots g(a_lx+b_l)]$ where $g(\cdot)$ is the activation function of the hidden layer. The ELM parameters do not need to be iteratively calculated and has only one hidden layer, so it has the advantages of fast training speed and simple model. However, the ELM algorithm has poor stability because of generating randomly input weights and thresholds. The kernel function instead of randomly map is used to improve the stability, where is defined as $k(x, y)=H(x)\cdot H(y)$. Therefore, the KELM’s output weight is received by calculating formula $\beta=H'(HH'^{T}+\nu/C)^{-1}T$, where $C$, an artificially setting parameter, is usually used to balance empirical and structural risk. The MLKELM, developed from KELM, has multiple hidden layers structure and owns stronger feature extraction ability and generalization ability compared to the rest ELMs.

2.2 The DBN algorithm

Geoffrey Hinton proposed the Deep Belief Network (DBN) in 2006 [7]. Restricted Boltzmann Machine, which are basic component of DBN, has two layers neurons. The RBM network structure has been presented in figure 1. One layer neurons named visible layer ($v$) have basically accepting a great numbers of data collected by engine sensors, the other layer neurons is mainly extracting features that was known as hidden layer ($h$).

![Figure 1. RBM network structure](image)

The RBM is fully connection layers, no connection within the layer. Therefore, the neuronal states of the hidden and visible layers are independent of each other. Hence, the hidden layer $h$ can be obtained by $P(h|v)$ when the input is $v$, and then the visible layer can be obtained by $P(v|h)$. The neuron state probability can be expressed as the following formula:
\[ P(h|v) = \prod_{j=1}^{N} P(h_j|v) \]
\[ P(v|h) = \prod_{i=1}^{M} P(v_i|h) \]

where \( v = [v_1, v_2, \ldots, v_M]^T \) is visible layer vector, \( h = [h_1, h_2, \ldots, h_N]^T \) is hidden layer vector and \( M, N \) represent the number of the visible and hidden layer respectively.

The goal of RBM training is to find the best weight that plays a key role in the distribution. Consequently, we need to do mathematical analysis to determine the weights between the visible layer node and hidden layer node. The energy of a joint configuration can be expressed as
\[ E(v,h;\theta) = -\sum_{ij} W_{ij} v_i h_j - \sum_i b_i v_i - \sum_j a_j h_j \]  

where \( \theta=\{W, a, b\} \) are the model parameters.

Then the probability of 1 or 0 of the \( k \)-th hidden layer can be easily obtained based on the known visible layer \( v \) by factorizing equation (3). Similarly, the probability of the visible layer can also be obtained based on the known hidden layer \( h \).
\[ P(h_k = 1|v) = \text{sigmoid}(b_k + \sum_{i=1}^{M} W_{ik} v_i) \]
\[ P(v_i = 1|h) = \text{sigmoid}(a_i + \sum_{j=1}^{N} W_{ij} h_j) \]

DBN is composed of some restricted Boltzmann machines. The hidden layers mainly gain high-order dependence of the visible layers during the training stage. First of all, the visible vector maps to the hidden layer, and then the visible layer are reconstructed by hidden layer. The new hidden layers can obtain these new visible layers and map to the hidden layers again. After pre-training, DBNs can use labeled data and BP algorithms to fine-tune the result.

3. The principle of gas path fault diagnosis for turboshaft engine based on DBN

The figure 2 illustrates the structure of gas path fault diagnosis based on DBN. The sensor data used in this paper is generated by simulating a turboshaft engine digital model under various operating conditions.

**Figure 2. Structure of gas path fault diagnosis**

The table 1 displayed turboshaft engine some parameters. The table is comprised of control variables, health parameters and measurement parameters. Control variables have contained fuel flow (\( W_f \)) and load torque (\( \text{angle} \)). Simultaneously Gaussian noise is added to the measurement parameters to simulate the actual working environment of the turboshaft engine. The maximum state correspond the relative
rotational speed of the power turbine speed $N_p=100\%$, the fuel flow $W_f=0.101\text{kg/s}$, load torque angle $\alpha=10$ at design point on the ground.

Particularly, health parameters $SE$ and $SW$ are defined as follows:

$$SE = \frac{\eta}{\eta^*}, SW = \frac{W}{W^*}$$  \hspace{1cm} (4)$$

where $\eta, \eta^*$ are actual and ideal efficiency of engine rotor component respectively; $W, W^*$ are actual and ideal flow of engine rotor component respectively.

**Table 1.** Turboshaft engine parameter comparison

| Control Variables | Health Parameters | Measurement Parameters |
|-------------------|-------------------|------------------------|
| $W_f$- Fuel flow  | $SE_1$- Compressor efficiency | $N_p$- Power turbine speed |
| $\alpha$- Load torque | $SW_1$- Compressor flow | $N_e$- Gas turbine speed |
| $SE_2$- Gas turbine efficiency | $T_3$- Compressor outlet temperature |
| $SW_2$- Gas turbine flow | $P_3$- Compressor outlet pressure |
| $SE_3$- Power turbine efficiency | $T_7$- Power turbine outlet pressure |
| $SW_3$- Power turbine flow | $P_7$- Power turbine outlet pressure |
|                      | $T_7$- Outlet temperature at the rear section of power turbine |
|                      | $P_7$- Outlet pressure at the rear section of power turbine |

The gas path faults are divided into eleven fault modes which includes a free fault mode according to bias health parameters. The relative mode patterns of changing in health parameters is shown in table 2.

**Table 2.** Turboshaft engine gas path performance fault mode

| Mode | Bias Health Parameter | Faulty Section |
|------|-----------------------|----------------|
| I    | $SE_1-1\%$           | Compressor     |
| II   | $SW_1-1\%$           |                |
| III  | $SE_1-0.7\%, SW_1-1\%$| Gas Turbine   |
| IV   | $SE_2-1\%$           |                |
| V    | $SW_2+1\%$           |                |
| VI   | $SE_2-1\%, SW_2-1\%$ | Power Turbine |
| VII  | $SE_3-1\%$           |                |
| VIII | $SW_3-1\%$           |                |
| IX   | $SE_3-0.4\%, SW_3-1\%$|              |
| X    | $SE_3-0.6\%, SW_3+1\%$|               |

The paper selected four operate points on a small rectangular envelope from engine flight envelope as a set of train data, then randomly selected a operate point in it as test data. Fault classification accuracy is calculated by ELM, KELM and MLKELM algorithms, which is expressed as the following formula:

$$Acc = \frac{N_a}{N_t}$$  \hspace{1cm} (5)$$

where $N_a$ is the number of correct classification samples, $N_t$ is the number of overall samples.

**4. Experiments and Analysis**

The train data selected four operating points including $H=600\text{m}, Ma=0.1; H=600\text{m}, Ma=0.4; H=1000\text{m}, Ma=0.1; H=1000\text{m}, Ma=0.4$ from the steady gas path flight envelope, then test data selected operating point $H=700\text{m}, Ma=0.2$ and control variables remain unchanged. A total of four operating points were selected, then 50 new samples were obtained by adding 0.003 Gaussian noise for each fault mode.
Consequently, there are 550 testing samples and 2200 training samples.

The topological parameters involved in the three algorithms are as follows: the number of hidden layer neurons in ELM is 42; the regularization parameter of KELM is 17, the kernel parameter is 6; MLKELM has 3 hidden layers structure and the regularization parameter is [1; 50; 10], the kernel parameter is [13; 20; 1]. DBN can maintain a small network model and can have good precision when dealing with big data. Therefore, we can obtain 500 new samples by adding 0.003 Gaussian noise for each fault mode. The number of each layer of DBN, set up 2-layer structure, has 50 neurons which are used to extract sensor parameter characteristics. Its learning rate is 0.1 and the number of per batch training samples are 100.

The simulation results of the steady-state gas path fault diagnosis testing time of turboshaft engine are shown in table 3. The training time of ELMs and DBN is 0.0096s, 0.3316s, 2.6201s and 0.4813s respectively. It indicates that the DBN consumes less training time compared to the MLKELM and less testing time compared to the KELM and MLKELM.

| Table 3. Gas path fault diagnosis testing time of turboshaft engine based on DBN |
|-----------------------------|----------|----------|----------|----------|----------|----------|----------|----------|----------|----------|----------|
| algorithms      | I        | II       | III      | IV       | V        | VI       | VII      | VIII      | IX       | X        | XI       | Mean     |
|-----------------------------|----------|----------|----------|----------|----------|----------|----------|----------|----------|----------|----------|----------|
| ELM                 | 0.00220  | 0.00400  | 0.00300  | 0.00300  | 0.00400  | 0.00300  | 0.00400  | 0.00400  | 0.00400  | 0.00040  | 0.00080  |
| KELM                | 0.00540  | 0.00570  | 0.00480  | 0.00520  | 0.00540  | 0.00490  | 0.00500  | 0.000580  | 0.00500  | 0.000540  | 0.00059  | 0.0447   |
| MLKELM              | 0.11780  | 0.11600  | 0.11570  | 0.11650  | 0.11520  | 0.11700  | 0.11550  | 0.11810  | 0.11620  | 0.11800  | 0.1148   | 0.2846   |
| DBN                 | 0.08030  | 0.04380  | 0.00200  | 0.00170  | 0.00210  | 0.00180  | 0.00190  | 0.00170  | 0.00200  | 0.00230  | 0.0021   | 0.0053   |

The simulation results of the steady-state gas path fault diagnosis classification accuracy of turboshaft engine are shown in table 4. As we can be seen from table 4, the four algorithms have a high fault diagnosis classification accuracy for the turboshaft engine envelope. Since the DBN and MLKELM has better feature extraction ability compare to rest ELMs, their mean testing accuracy which approximately reach 90% display higher. However, the ELM and KELM have poor results for the third and ninth fault mode.

| Table 4. Gas path fault diagnosis classification accuracy of turboshaft engine based on DBN |
|-----------------------------|----------|----------|----------|----------|----------|----------|----------|----------|----------|----------|----------|----------|
| Accuracy      | I        | II       | III      | IV       | V        | VI       | VII      | VIII      | IX       | X        | XI       | Mean     |
|-----------------------------|----------|----------|----------|----------|----------|----------|----------|----------|----------|----------|----------|----------|
| training ELM | 0.91640  | 0.91000  | 0.89550  | 0.89000  | 0.89900  | 0.91910  | 0.89280  | 0.90170   | 0.89860  | 0.90470  | 0.89260  | 0.8905   |
| training KELM| 0.94270  | 0.89500  | 0.89050  | 0.94250  | 0.94860  | 0.95320  | 0.92590  | 0.89540   | 0.89550  | 0.89590  | 0.91650  | 0.8977   |
| Accuracy MLKELM | 0.96640  | 0.97320  | 0.96550  | 0.99000  | 0.96730  | 0.99820  | 0.96590  | 0.96270   | 0.99590  | 0.96860  | 0.9700   |
| DBN           | 0.97050  | 0.76800  | 0.93750  | 0.99950  | 0.99850  | 0.99650  | 0.98450  | 0.83880   | 0.89500  | 0.89800  | 0.84650  | 0.8997   |
| training ELM | 0.88000  | 0.88000  | 0.72000  | 0.95200  | 0.91600  | 0.96000  | 0.99200  | 0.89600   | 0.80000  | 0.98000  | 0.80000  | 0.8109   |
| accuracy MLKELM | 0.96000  | 0.90000  | 0.58000  | 0.92000  | 0.90000  | 0.94000  | 0.90000  | 0.98000   | 0.54000  | 0.98000  | 0.88000  | 0.8091   |
| DBN           | 0.96200  | 0.83600  | 0.83200  | 0.98000  | 0.99600  | 0.99200  | 0.95000  | 0.98200   | 0.98200  | 0.93000  | 0.85000  | 0.9102   |

5. Conclusion
The paper introduced a method that the deep belief network is applied to the gas path fault patterns for turboshaft engine. The objective is to obtain engine steady-state fault diagnosis results through sensor data that indicates the working condition of the turboshaft engine. The engine's health parameters are offset to obtain the corresponding fault mode, then the 8 sensor parameters was selected to train the DBN network model to recognize the fault identification accuracy in the selected operating points of engine flight envelope. The simulation results show that the DBN is superior to the rest ELMs for engine gas path performance fault identification with regard to stability and correct rate.

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