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Aircraft Engine Multi-Condition Detection Method Based on Single Classification Limit Learning Machine Algorithm

Wen Hong
Shandong Transportation Vocational College,
Shan dong,261206,China
Wh160826@163.com

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***Abstract*: This paper provides a method to detect multiple working conditions of aircraft engines based on single category limit learning machine algorithm. The k-means clustering algorithm is used to realize automatic division of working conditions. By building detection models under different working conditions, the parallel monitoring of multiple models is realized. The semi supervised single category limit learning machine algorithm is used as the anomaly detection algorithm. By building the normal domain of complex data sets, The abnormal index of the equipment is calculated according to the output deviation of the sample to be tested. In addition, the method of moving average filtering and standardization is adopted to deal with noise and dimensional problems, and data preprocessing is completed. This paper is a complete multi working condition anomaly detection system for the aircraft engine system. The degradation status of the engine is obtained through the obtained anomaly indicators, and the anomaly warning is realized before the equipment failure, which ensures the safety and reliability of the aircraft operation.**

Keyword: airplane engine; Single classification limit learning; Working condition detection

I. Introduction

With the high development of science and technology, a new military revolution with electronic technology and information technology as the main driving force and information technology as the core has taken place in the military field, and military equipment has been developed by leaps and bounds. High-tech equipment must be supported by high-tech means, and the two must be coordinated. Otherwise, combat equipment will not give full play to its operational effectiveness, and the phenomenon of "long legs" of combat equipment and "short legs" of technical support equipment will occur[1]. With the increasing complexity of equipment, rapid and accurate judgment and fault isolation have become the key to eliminate faults in peacetime, implement rapid battlefield repair in wartime, and quickly restore the technical state and combat effectiveness of equipment. The research and development of multi-functional testing equipment and diagnostic instruments coordinated with the main equipment can not only shorten the time of troubleshooting, but also make the maintenance system transition from preventive maintenance to the combination of regular detection and condition based maintenance[2]. This requires military academies and scientific research institutions to strengthen the research on technical support equipment, apply modern science and technology to technical support equipment, and continuously improve the support level, support efficiency and economic benefits. The ultimate goal is to improve the practical ability of equipment technical support. This paper is based on this idea to carry out the research on the performance testing system of an aircraft engine.

Due to the continuous growth of the modern civil aircraft fleet, its engine, as the core component of the aircraft, has been working in a complex environment, and the complexity of its fault problems has also increased exponentially. Although the maintenance personnel will carry out detailed visual inspection and basic troubleshooting for the aircraft in each segment, some complex faults cannot be eliminated in time, leading to flight with faults. Because the actual aircraft engine fault detection needs to be overhauled when the aircraft is grounded. The maintenance personnel rely on specific instruments and meters in the hangar to detect the engine performance. This manual diagnosis method is related to many factors, For example, in terms of maintenance conditions, equipment and apparatus, the deeper reason is that the maintenance of aircraft by maintenance personnel is related to the actual operating experience and level of maintenance. The internal faults of the system are not easy to be found, so it is impossible to make accurate judgments. Moreover, such maintenance means will lead to wrong judgments of system faults, and will replace some components that can work normally, thus increasing maintenance time and cost, A lot of resources were wasted. Fault analysis and elimination need to rely on FIM: Fault Isolation Manual, and the fault location can be determined step by step through each detection result. For maintenance personnel, this makes it a very difficult task to quickly and accurately find out the fault location, or although the work is not difficult, it is not only a huge workload, but also requires a lot of time. This not only increases the burden of maintenance personnel, but also affects the normal flight mission of the aircraft.

As a modern ground attack aircraft that meets the operational radius of deep attack and all-weather precision strike capability, a certain type of aircraft has been equipped with large-scale troops since its inception and has become the backbone of air force ground attack aircraft. It mainly completes the ground and sea attack and annihilation escort tasks. It has the characteristics of large operational radius, large number of missiles and strong attack power[3]. It has very important strategic and tactical significance in land air defense and deterrence against the enemy, For a long time to come, it will become the main weapon and equipment of our aviation force. The power unit of this type of aircraft is a certain type of engine that has been successfully localized after long-term research and imitation of the Spey mk-202 afterburner turbofan engine imported from rollsroyce company in the late 1970s in Xi'an 430 factory. Its structure is shown in Figure 1. The performance testing system of this type of engine is a kind of testing equipment necessary for field engine inspection, parameter adjustment and correction, analysis, judgment and troubleshooting[4]. However, the army has not been equipped with this equipment. When necessary, the engine production plant Xi'an 430 uses the ut1210 detector and ut1130 detector specially developed by British rollsroyce company for this type of engine in the 1970s, It brings great inconvenience to the maintenance and support work of the army, and becomes the bottleneck of the formation of the combat effectiveness of the army. Based on this, the air force equipment department has assigned a scientific research task to develop the aircraft engine performance testing system.

II. PROBLEM PROPOSED

A. Multi condition detection method of aircraft engine based on single class limit learning machine algorithm

1) Separation of working conditions;

Firstly, the working conditions are separated from the multi working condition data set, and k-means algorithm is used to cluster the working condition operation data in the training set. Each cluster in the clustering results represents a working condition mode, and the working condition labels of the training data are obtained, so as to realize the working condition separation;

Using the condition label and sensor data in the data set, the characteristics of different working conditions are learned through the classification method of the limit learning machine, so as to obtain the classification model of the limit learning machine, so that the working conditions can be separated in the test phase;

2) Data preprocessing;

After the division of working conditions, the sub data sets under each working condition are obtained respectively. The data preprocessing includes three processes: feature scaling, feature selection and smoothing filtering;

a) Feature scaling

Z-score standardization method is adopted to calculate the mean value of original data x under each working condition μ And standard deviation σ , Substitute the results into the following Z-score conversion formula:

$$x^* = \frac{x-\mu}{\sigma} \tag{1}$$

The standardized new data x * is obtained, and the new data follows the normal distribution with the mean value of 0 and the standard deviation of 1;

b) Feature Selection

Under each working condition, the sensor shall be selected according to the trend, and the slope change of the selected sensor on all engines shall increase or decrease at the same time.

c) Smooth filtering

The filtering method adopted is moving average filtering. Each time the result is to take the average value of the data in the fixed length window as a new data point. After completing a calculation, the window will be moved for a new calculation, so as to achieve data smoothing and play a role in noise reduction; Assume that the input x (n) and output y (n) at time n are as follows:

$$y(n) = \frac{x(n)+x(n-1)+\cdots+x(n-N+1)}{N} \tag{2}$$

where N is the window length;

3) Building parallel anomaly detection model

The output function of the ELM network is:

$$\mathrm{f(x)} = \mathrm{h(x)}^{\mathrm{T}}\beta \tag{3}$$

Among them, β is the output weight, h (x) is the hidden layer output vector with respect to the input vector x;

The expected output of the target class in a single classifier should be the same, that is, meet the following equation:

$$\mathrm{y_j} = \mathrm{p}, \forall x_j \in X, \mathrm{j} = 1,2,\ldots,\mathrm{N} \tag{4}$$

Where, X represents the total input sample set, p is a real value, and the expected output of all training samples should be set as the same boundary of the p-value learning detection model; The expected output vector of the target data class is:

$$\mathrm{Y} = [\mathrm{y_1}, \mathrm{y_2}, \ldots, \mathrm{y_N}]^{\mathrm{T}} = [\mathrm{p}, \mathrm{p}, \ldots, \mathrm{p}]^{\mathrm{T}} \tag{5}$$

B. Test phase

1) Working condition identification

For the sample to be tested, first identify the working condition of the sample to be tested, and use the classification model of the extreme learning machine trained in the training phase to bring the sample to be tested into the classification model of the extreme learning machine to achieve the separation of working conditions in the testing phase;

2) Data preprocessing;

The sample to be tested was preprocessed by the preprocessing step in the training stage;

a) Feature scaling

After the classification of working conditions is achieved, the data of the samples to be tested under the corresponding working conditions are standardized;

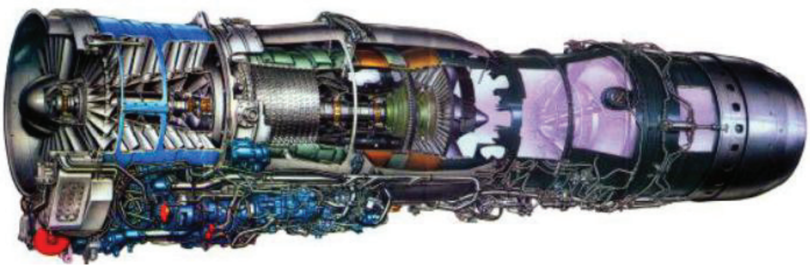

Fig. 1. Engine structure diagram

a) Feature Selection

The selection of sensors under different working conditions in the test stage is based on the selected sensors under the corresponding working conditions in the training stage;

b) Smooth filtering

Carry out moving average filtering under corresponding working conditions;

c) Implement anomaly detection

After the recognition of the working conditions of the samples to be tested and the data preprocessing are completed, the single category limit learning machine detection model trained in the training phase is used for anomaly detection under each working condition, and the distance between the expected output of the samples to be tested and the health samples is taken as the anomaly monitoring indicator. Since n parallel limit learning machine classification model models are established, n anomaly monitoring indicators of the same equipment under different working conditions are obtained respectively;

d) Reorganization of abnormal monitoring indicators under various working conditions

After obtaining the anomaly monitoring indicators under n working conditions, arrange and represent the anomaly monitoring indicators under n working conditions according to the running time sequence of the equipment, and draw the image, that is, take the engine running time as the horizontal axis and the anomaly monitoring indicators as the vertical axis. Draw the image, and observe the change of the degradation trend of the equipment during the whole running period, so as to obtain the global monitoring indicators, The global monitoring indicators reflect the change of degradation degree of equipment under different working conditions over time during the whole operation period. The anomaly monitoring indicators corresponding to each time in the global monitoring indicators are compared with the anomaly threshold value. When the anomaly monitoring indicators are greater than the anomaly threshold value, an abnormal alarm is prompted, otherwise, it is considered that there is no anomaly. Therefore, the detection of abnormal state of equipment is realized based on the global monitoring indicators and corresponding threshold settings, Finally, the anomaly detection of the sample to be tested is realized.

III. AIRCRAFT ENGINE MULTI CONDITION DETECTION BASED ON SINGLE CLASSIFICATION LIMIT LEARNING MACHINE ALGORITHM

A. Basic principle of limit learning machine

The extreme learning machine (ELM) can be regarded as a single hidden layer network as shown in Figure 2, with full connection inside, in which the number of neurons in the input layer, hidden layer and output layer are n, l and m respectively.

The performance indicators of single classification limit learning algorithm include training time traintime, testing time TestTime and classification accuracy testaccuracy.

Traintime: represents the time required to train the classification model with the training data as input. The shorter the training time, the faster the establishment of the model, which is also the core advantage of elm algorithm.

Test time testtime: represents the time required to calculate the classification results through the classification model with the test data as the input. The shorter the test time, the faster the classification results will be obtained.

Testaccuracy: it represents the accuracy of classifying a known fault into the correct category on the premise of its occurrence, that is, the accuracy of the test data after the classification results obtained through the classification model are compared with the known corresponding correct fault category[10]. The higher the classification accuracy, the better the effectiveness of the classification algorithm in classifying the data into the correct category.

In the process of model building, whether the historical database is huge or not is crucial, and whether the amount of information in the historical data is accurate or not determines the good or bad performance of the model. Feature extraction is a technical method in data analysis and identification. This method extracts the deterministic information by identifying the data, and judges whether each group of data is similar to a certain feature. The result of feature extraction is that the data in the database is divided into different groups, and these data can often be divided or combined

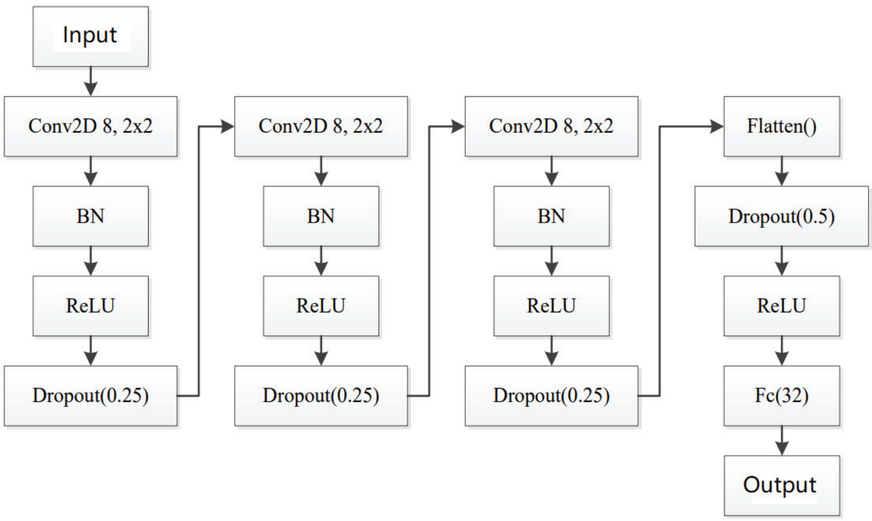

Fig. 2. Single category limit learning structure

according to their similarity. Principal component analysis is the most widely used feature extraction method.

Principal component analysis (PCA) has a long history of development. It has been successfully used in aeroengine condition monitoring, so this paper also uses principal component analysis to extract effective features to describe the engine condition. Principal component analysis is a commonly used and effective method in data mining and data analysis. Its main role is to select the most suitable parameter class from a large number of database parameter classes, and then extract the main features from the parameter columns of these databases. It is the process of feature selection from data extraction to feature extraction. Principal component analysis is mainly to convert the original large amount of data into a small number of principal components by calculating the characteristic values and characteristic variables, and these principal components can reflect the information of most of the data in the original data, so as to achieve the purpose of dimension reduction, and simplify the problem that a large number of data and variables overlap.

In general, its dimension is the same in the feature space or data space. However, there is a case where the dimension can be reduced and the main information can be extracted. This method of reducing the dimension of feature space is called dimension reduction for short.

B. *Application process of aircraft engine multi condition detection*

Automatic condition clustering is an automatic condition clustering technology based on similarity algorithm. According to the similarity of operating conditions, the operating conditions are aggregated into different categories, and the accurate number of operating conditions is intelligently given for each aggregated category. In this paper, Jose Garcia uses and compares several automatic clustering methods to solve the clustering of nonlinear discrete data.

On the basis of the research results, the maximum and minimum automatic clustering method can be selected to cluster the complex working conditions of aircraft engines. The principle of this method is briefly introduced as follows:

Normalize the data, and select the automatic working condition clustering algorithm with the maximum and minimum distance according to the data type. Its basic idea is to take the objects as far away as possible as the clustering center, and intelligently determine the number of initial clustering centers. The multi condition engine inspection process is shown in Figure 3.

In the process of model building, whether the historical database is large or not is very important, and whether the amount of information in the historical data is accurate or not determines the performance of the model. Feature extraction is a technical method in data analysis, calculation and data identification. This method extracts deterministic information from data identification to judge whether each group of data is similar to a certain feature. The result of feature extraction is that the data in the database is divided into different groups, and these data can often be divided or combined according to their similarity. Principal component analysis is the most widely used feature extraction method. Principal component analysis (PCA) has a long history of development. It has been successfully used in aeroengine condition monitoring, so this paper also uses principal

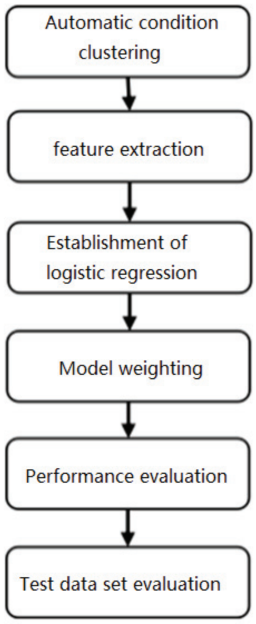

Fig. 3. Engine multi condition detection process

component analysis to extract effective features to describe the engine condition.

The troubleshooting of the engine electronic control module is as follows: the electronic monitoring warning panel in the cockpit of the aircraft displays "thrust rod fault", which is independent of "fault information: throttle rod angle sensor at J3 position of the aircraft engine electronic controller and throttle rod angle sensor at J4 position of the engine electronic controller", which most likely indicates the internal fault of the engine electronic controller. In this case, the aircraft electronic central monitoring warning is usually displayed together with other engine related aircraft electronic central monitoring warnings.

This can be checked in the previous flight report. If the test does not give the fault information "throttle lever angle sensor at J3 position of engine electronic controller and throttle lever angle sensor at J4 position of engine electronic controller", replace the engine electronic controller. If the fault is repeated and accompanied by the fault message "No flight data of engine electronic controller 1 (2)", replace the (1TV).

If the fault still exists: conduct a continuous and insulated check on the wire between J3 connector and J4 connector of the engine electronic controller. If damage is found during inspection: replace or repair the wiring as required; If no damage is found during inspection: repeat the fault isolation procedure. If the test gives the fault information "throttle lever angle sensor at J3 position of the engine electronic controller and throttle lever angle sensor at J4 position of the engine electronic controller", perform the relevant troubleshooting steps.

Perform the operation test of full power digital engine control 1A and 1B on the ground (the engine will not start). If the fault is not confirmed, no additional maintenance operation is required; If the fault continues, repeat the fault isolation procedure. The algorithm's parameters setting is shown in table 1.

TABLE I. ALGORITHM'S PARAMETERS SETTING

Parameters	Setting value
Learning rete	1*10-3
Iterative times	500
Batch size	32
Exponential decay rate of first-order moment estimation	0.9
Exponential decay rate of second-order moment estimation	0.999

IV. MODEL SIMULATION AND ANALYSIS

A. Data Set Selection

The data in this paper are taken from PW2000 engine experimental data in NASA database. However, due to the confidentiality of industry information, it is the data that is given after preprocessing. Since its column vector has no specified sensor parameter description, and such parameters may have undergone equal or equal difference changes in the range. In addition, the data itself is incomplete, lacking some project attributes (neither interpretative data), which may have some impact on modeling. Due to the variety and large quantity of data sets, they should be preprocessed before using them.

When preprocessing data, first of all, it is necessary to clearly understand the meaning of the relevant dataset parameters of its database, check the accuracy of its data sources, including the possible missing parts in the data, and then conduct necessary analysis and positioning of its dataset to understand whether its dataset contains missing items and obvious error information (such as negative data values, etc.). Due to the fuzziness of the data set, the lack of data has become an inevitable factor. Therefore, we should first analyze and clarify the meaning of the data, and then process it. Because of the particularity of the aviation industry, the data has no legal person to repair, so this paper adopts the method of directly ignoring the missing value for missing data. When the unit body of the aircraft engine fails, it can accurately and quickly find the fault of its unit body, so that relevant solutions can be quickly queried from the fault manual, and the fault can be accurately handled in time to reduce time loss. And it can locate the fault unit and establish a prediction model to simulate the possible faults and troubleshooting methods of related components in a certain period in the future. Through the analysis of the parameters in this paper, we can timely find the factors that cause aircraft engine failures and predict the health of the engine.

The premise of using logistic regression analysis is that the data are normally distributed, as shown in Figure 4. The data used in this paper is 55156 × In a matrix of order 26, the first column is the serial number, the second column is the number of cycles, and the third to fifth columns are the operating status values of PW2000 engines. This operating status can be used for new clustering, while the sixth to twenty sixth columns are the sensor measurement values. These data are composed of data with uncertain vector attributes, and there are some missing items in these data and changes in the range have been made.

All methods only show the model performance index when the super parameter is adjusted to the optimal value. Anomaly detection of LLCPF1, LLCPF2, AASWLL1 and AASWLL2 methods proposed in this paper compared with other comparison methods is shown in Table 2. The column diagram corresponding to Table 2 is shown in Figure 4, in which "Fbeta" represents F_β.

B. Experimental data processing

After standardization, there is still too much data. At this time, the three columns of data can be automatically clustered to make their images, and further trade-offs can be made according to the specific images. Specifically, cluster analysis is carried out for different working conditions. After observation, each column can be grouped into 6 categories. One of the 12 standardized columns from the 6th to the 26th column can be selected as the independent variable, and then analysis and comparison can be carried out one by one. In this paper, three columns will be selected for analysis, and finally the data will be weighted to draw a conclusion.

First, the data is preprocessed, and then a complete historical data can be obtained. It will also be expanded around this dataset. According to the automatic working condition clustering method mentioned in this paper, when the sixth clustering center is found, no eligible clustering center can be found, and the number of working conditions can be determined as.

TABLE II. COMPARISON BETWEEN DIFFERENT METHODS IN ANOMALY DETECTION PERFORMANCE

Methods	Accuracy(%)	Precision ratio (%)	Recall ratio (%)	F β (%)
SVM	91.52±1.8	98.38±2.50	53.75±10.06	65.31
ELM	92.08±1.84	94.14±5.88	60.00±10.35	69.89
DELM	91.63±1.92	96.01±4.15	55.62±9.56	66.55
BPNN	95.00±1.89	96.12±6.33	73.25±12.04	80.75
SLSTM	96.35±1.36	93.61±7.11	84.75±5.88	88.00
CNN	97.42±0.72	96.63±5.74	84.46±5.97	88.82
KNN	96.46±1.18	100.0±0.00	80.31±6.56	87.00
LLCPF1(t=0.1)	97.13±0.53	98.69±2.13	85.31±4.2	90.08
LLCPF2(t=0.6)	97.25±0.85	100.0±0.00	84.69±4.73	90.07
AASWLL1(w=1.5)	96.85±0.88	98.61±1.86	84.33±6.26	89.38
AASWLL2(w=1)	97.47±0.76	99.66±1.01	87.93±2.49	92.16

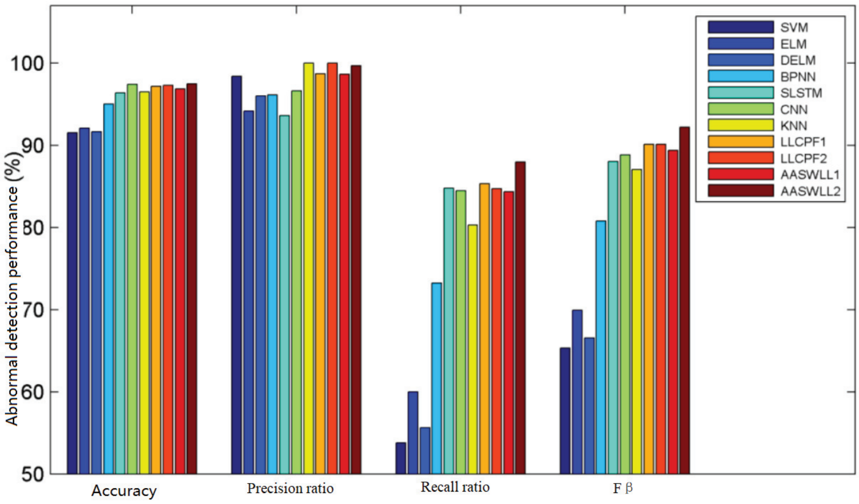

Fig. 4. Anomaly detection performance of different methods on OEM data

Before reaching a conclusion through regression analysis, it is necessary to prove the significance level of F test value in its variable attributes, which can measure the accuracy of variables. The value of F test depends on the actual situation of the regression analysis object. In general, there must be a certain number of variables in the final regression equation, so the order of magnitude of the F test value must be small enough, which is equivalent to the significance level α It needs to be big enough. In addition, the size of the F test value is also related to the degree of freedom of its variables. Through its stepwise regression process, the number of its variables is increasing. Generally, the degree of freedom of its variables is calculated according to n-k-1. N represents the number of data attributes in the database, and k represents the parameter brought into the logistic regression model. In this formula, we can use the usual case, that is, the significant level in the F test α The value is 0.05.

V. Conclusion

In this paper, an aircraft engine multi condition detection method based on single classification limit learning machine algorithm is proposed. Firstly, the data are standardized, and then the working conditions are automatically identified by clustering. Then, the sensor variables closely related to the engine performance degradation trend are selected from the huge amount of sensor variable parameter data for analysis and feature extraction, and then the model is established Logistic model is used to fit the data. Finally, the health status of aircraft engine is evaluated. This method is verified on the aircraft engine sensor data provided by NASA. It can not only evaluate its health performance status, but also predict and troubleshoot engine faults.

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