Health status prediction of airborne systems based on transfer learning

Qinhao Sun¹, Dong Song²*, Bin Lin³

¹School of Aeronautics, Northwestern Polytechnical University, Xi’an, Shan’xi, 710072, China
²School of Aeronautics, Northwestern Polytechnical University, Xi’an, Shan’xi, 710072, China
³*Corresponding author’s e-mail: songdong@nwpu.edu.cn

Abstract. In this paper, based on the prediction of the decay mode of the system health state, a health pattern recognition and prediction method based on transfer learning is proposed. In the context of big data, the system's healthy decline mode is summarized from the massive historical flight data, and then the research on the health status of the airborne system based on the recognition results is carried out. Firstly, this paper demonstrates the feasibility of transfer learning applied to the prediction of the health status of airborne systems. Then, a HMM-based parameter migration health state prediction method is proposed. Finally, the model is verified by the hydraulic system of a certain type of aircraft. The results show that the model can predict the time when the health state changes.

1. Introduction

With the increasing power of airborne function, the complexity and comprehensiveness of the system are constantly improved. The reliability, stability, early fault diagnosis and fault prediction of the system have attracted more and more attention. If we can evaluate the health status of the system in time, monitor the possible faults in advance and predict the future health status of the system, we can take timely and effective maintenance and maintenance measures according to the situation of the equipment system, improve the utilization efficiency of the equipment system and extend its service time [1].

At present, from the research status at home and abroad, the research on evaluation methods for aviation system and equipment has gradually increased, and the methods used are generally classic evaluation method, machine learning algorithm, distance measurement method, etc. [2,3]. The traditional methods are mostly aimed at mechanical systems or equipment, and the signals involved in feature extraction are mostly periodic signals such as vibration, and lack of early detection methods for faults, which restrict its development in the field of airborne equipment health state prediction. In the context of big data, as a method that can use the knowledge learned in previous similar fields to assist the current task, transfer learning is applied to the degradation pattern recognition and health state prediction of airborne system when the flight data is small [4,5].

The purpose of this paper is to predict the health decline mode of airborne system. A general steps of health state prediction method are proposed. On this basis, the health state prediction model of airborne system based on parameter migration is constructed, and the corresponding case analysis is carried out with the hydraulic system of a certain aircraft.
2. Health state prediction method of airborne system

In the process of using airborne system, its health state will go through a process from good to bad until it can not work normally. However, if the process of system health decline is simply divided into "0" (no fault) and "1" (with fault), it will ignore the fact that the health decline of complex system is not a sudden change process. But over time It is continuously accumulated and gradually reflected from the performance. The stage without fault can be divided into two stages: good system with stable performance, and health state decline with performance instability. The latter often contains information related to system decline and early fault. So it is necessary to reasonably distinguish the two stages. Therefore, the process of system health decline will be divided into "normal stage", "decline stage" and "fault stage". The data in "normal stage" and "decline stage" show similar characteristics, but some of the latter data may conform to some characteristics of subsequent failures.

2.1. Prediction of observation series based on exponential smoothing

Exponential smoothing (ES) was proposed in 1959 by Robert G. brown, an American economist. In his book, he believes that the situation of time series is stable or regular, so it can be reasonably postponed; and the recent past situation will continue to the nearest future to some extent. Compared with the traditional method, the exponential smoothing method has more advantages. It does not abandon the past data, but only gives the gradually weakened influence degree. That is, with the data far away, the weight gradually converges to zero[6].

2.2. Health state prediction based on HMM

Hidden Markov model (HMM) is a complex model based on Markov chain. Viterbi algorithm is an algorithm of hidden Markov model prediction. Its principle is to use dynamic programming to solve the state sequence with the maximum probability. According to the principle of dynamic programming, if the optimal path passes through the node \( i^* \) at time \( t \), then the partial path from node \( i^* \) to node \( i^* \) must be optimal for all possible partial paths. Therefore, from time \( t = 1 \), the maximum probability of each partial path in state \( i \) at time \( t \) is calculated recursively until the maximum probability of each path with state \( i \) at time \( t = T \) is obtained. The maximum probability \( p^* \) of time \( t = T \) is the probability of the optimal path, and the end point \( i^* \) of the optimal path is also obtained. In order to find out each node of the optimal path, start from the end point \( i^* \), and gradually find the node \( i^* \), from the back to the front to get the optimal path \( I^* = (i^*, i^*, \ldots, i^*) \). This is Viterbi algorithm[7].

2.3. Health state prediction of airborne system

In this paper, a HMM based health state prediction method based on parameter migration is proposed. The reconstructed time series are predicted by using the three exponential smoothing method. The health feature time series are extracted and segmented. The processed time series is the predicted observation sequence. On this basis, combined with the definition of health status, the health status of airborne system is predicted. The prediction method needs to be realized through the following two steps:

2.3.1. Construction and calculation of hidden Markov model.

In the previous discussion, the health state of the system is divided into "normal state", "decline state" and "fault state", which are regarded as hidden states of hidden Markov model. With the decline of system performance, the health state will transfer with a certain probability. When estimating the state transition probability, we need to consider a problem. Although the system decay process reflected by flight parameter data may have an inverse process from "poor" to "good", this situation will not occur in the system without maintenance. Once it leaves the good state, it cannot return to this state again, as shown in Figure 1. Therefore, the transition probability of this part needs to be changed to 0 when the matrix is estimated, and the Markov chain needs to be recalculated and the initial state probability...
should be changed after maintenance. The system under different health states may get the same observation value, that is, there is a one to many mapping relationship between the health state and the observation sequence, but the observation probability of the observation value under different health states is different.

The airborne system has different decay modes, and the state transition probability and observation probability are different under different decay modes. The maximum likelihood estimation can be used to calculate the state transition probability and observation probability. The maximum likelihood estimation function is asymptotically efficient, that is, the variance of the function decreases with the increase of the sample number, and reaches the minimum value when the sample number tends to be infinite. The system has accumulated a large amount of historical data in each decline mode. Therefore, the state transition matrix and the observation probability matrix can be calculated by using the historical data of each decay mode, so as to construct the hidden Markov model corresponding to each decay mode. This step is shown in Figure 2.

2.3.2. Parameter transfer and health state prediction.

The hidden Markov model constructed in the previous step contains the state transition probability and other information of the decay mode, so the state transition probability and observation probability under the decay mode can be transferred to the health state prediction task of the target in the form of parameters. The model is used to identify the current decline mode and health status of the system. If the system is in the early stage of the decline process and does not show the characteristics of any decay mode, then the observation sequence is substituted into each model trained, and the "path" with the maximum probability under each model is calculated by using the Weibull algorithm, that is, the most likely health state sequence. Compared with the results, the model corresponding to the "path" with the highest probability is selected. If the decay mode of the system can be identified directly, the hidden Markov model corresponding to the decay mode is directly matched according to the identification result. Then, combined with the matched hidden Markov model, the time series of health state, which is the most likely corresponding hidden state sequence of the predicted observation sequence, can be obtained by using Viterbi algorithm, so as to realize the prediction of health state.

3. Example verification

Considering that the system will have maintenance or no failure in the process of use, this paper takes the hydraulic system of a certain type of aircraft with complete decay process as an example to carry out the corresponding decline state prediction.
3.1. **Prediction of reconstructed time series**

The reconstruction time series of the actual flight data of main hydraulic pressure of aircraft is shown in the blue line in Figure 3(a). As a comparison, three exponential smoothing method, multi-scale support vector machine, and support vector machine (SVM) were selected to predict the prediction\cite{8}. The results are shown in the red line in Figure 3. In order to compare the three methods more intuitively, the mean absolute error (MAE), mean square error (MSE) and mean relative error (MRE) are selected as evaluation indexes. The comparison results are shown in Table 1. It can be seen from the results that the three exponential smoothing method is the best among the three prediction methods. At the same time, with the increase of the number of prediction steps, the prediction accuracy will also have a corresponding decline.

![Figure 3.Aircraft actual flight parameter data reconstruction time series prediction results.](image)

| Method               | MAE   | MSE   | MRE  |
|----------------------|-------|-------|------|
| Three exponential smoothing | 73.6155 | 6.5906 | 4.69% |
| Multi-scale SVM       | 110.747 | 9.5495 | 7.18% |
| SVM                   | 119.068 | 20.8578 | 7.60% |

3.2. **Observation sequence extraction**

The time series of health characteristic parameters are processed in the following sections

\[ X_{\text{new}} = \left\lfloor \frac{X}{100} \right\rfloor \tag{1} \]

\( X \) is the raw data, \([x]\) is the rounding function, \(X_{\text{new}}\) is the observation sequence. In this way, the change range of the time series is converted from \([-1000,1000]\) to an integer between \([-10,10]\). For example, the time series values of the range segment of \([100,200)\) are all \(1\) in the observation sequence. Results show that the original information of health characteristics can be well maintained while simplifying the observation sequence data.
3.3. Health status prediction

The health states are classified as hidden states, and combined with the observation sequence, the corresponding hidden Markov models under different decay modes are constructed. The model is used to identify the current object system, and the corresponding hidden Markov model is selected. Combined with the predicted observation sequence, the health status prediction results are as follows:

The prediction results of the decline state of aircraft are shown in Figure 4. Figure 4(a) shows the reconstructed time series of the actual flight data and its health status; Figure 4(b) shows the health status of the reconstructed time series of the actual flight data; and Figure 4(c) shows the time series and health status results predicted one step in advance. Among them, the point in decline state is identified as purplish red, and the fault state is marked as black.

It can be seen from Figure 4(b) that in the actual flight data, the health status changed from "normal state" to "decline state" in the 34th sorties, from "normal state" to "decline state" in 73 sorties, and from "decline state" to "failure state" in 76 sorties. In Figure 4(c), it can be seen that the prediction results can accurately predict changes in the state of decline in the 34th, 74th, and 76th sorties.

4. Conclusion

The research content of this paper is to predict the degradation state of airborne system based on parameter migration. The exponential smoothing method and hidden Markov model are studied respectively for time series and state prediction methods. The three exponential smoothing method is used to predict the reconstructed time series, and the observation series are extracted from the health feature time series by subsection processing. According to the decay mode of airborne system, the corresponding hidden Markov model is selected to predict. The feasibility of the model is verified on the hydraulic system of a certain aircraft.

References

[1] Reda Taha M M, Lucero J. Damage Identification for Structural Health Monitoring Using Fuzzy Pattern Recognition. Engineering Structures, 2005, 27(12): 1774∼1783.
[2] Erdogan Altunok, Mahmoud M, Reda Taha. Damage Pattern Recognition for Structural Health Monitoring Using Fuzzy Similarity Prescription. Computer-Aided Civil and Infrastructure Engineering, 2006, 549~560.

[3] Vichare N, Rodgers P, Eveloy V, et al. In situ temperature measurement of a notebook computer - a case study in health and usage monitoring of electronics[J]. IEEE Transactions on Device & Materials Reliability, 2005, 4(4):658-663.

[4] Cui Y. Fault Diagnosis for Drive Train of Wind Turbines Based on Wavelet Packet Transform and RBF Neural Network[J]. Modular Machine Tool & Automatic Manufacturing Technique, 2013, 373-375:1102-1105.

[5] Pan S J, Yang Q. A Survey on Transfer Learning[J]. IEEE Transactions on Knowledge & Data Engineering, 2010, 22(10):1345-1359.

[6] Qiong Z. Building Material Price Forecast Based on the Three Exponential Smoothing Method[J]. Railway Engineering Cost Management, 2013.

[7] Stewart W J. Introduction to the numerical solution of Markov chains[M]. Princeton: Princeton University Press, 1994.

[8] Wang J, Shi J, He Q. Research on component-level health quantitative assessment based on SVM algorithm for analog electronic circuits[C]// Prognostics and System Health Management Conference. IEEE, 2016.