Особенности приложения:

– использование параметризованных моделей инструментов и станочных приспособлений. В базовый комплект поставки входит набор готовых трехмерных моделей инструментов и приспособлений. При этом есть возможность создания пользователем собственных моделей;

– использование скриптового языка программирования Python для редактирования и разработки постпроцессоров;

– возможность включения в управляющую программу станочных циклов систем ЧПУ.

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BEARING REMAINING USEFUL LIFE PREDICTION BASED ON NAP-HSMM

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The prediction of remaining useful life (RUL) is the most challenge task in the area of reliability and safety of rolling bearing. Nuisance attribute projection (NAP) is used in this paper to eliminate the impact of operating conditions in vibration signals, as the inevitable errors in the manufacturing, installation, or operation of the bearings. Due to the limitation of hidden Markov model (HMM), an HSMM with aging factor is designed to solve problem of RUL prediction. Time-domain and other features are extracted from vibration signals and then transformed by NAP projection so can be used to train HSMM model. When the health state is determined by HSMM, state remaining duration estimation is used to help calculation of RUL. In order to test the prediction ability of the model, PHM 2012 challenge data are used, the result showed that the HSMM with NAP has made a great improvement than ones without.

Keywords: remaining useful life, nuisance attribute projection, hidden Semi-Markov Model.

Rolling bearings are one of the most important components in rotating machinery, which failure could cause dramatic damage to industrial production or military machinery. The key of rolling bearing life prediction is to extract proper state characteristics [1]. However, it is difficult to extract effective signal features because vibration signals are affected by noise and abnormal values. In this paper a method integrates NAP and HSMM is introduced.

NAP is a technology used in face recognition and image recognition [2], and it can also identify bearing state degradation in rolling bearing fault diagnosis [3].

In N-dimensional feature space, n samples can be represented as an $N \times n$ order data matrix $F = [f_1, f_2, ..., f_n]$, and the NAP transformation matrix F' is calculated as follows:

$$F' = PF; \tag{1}$$

$$P = E - \sum_{i=1}^{d} w_i w_i^T, \tag{2}$$

where P is $N \times N$ order matrix, E for $N \times N$ unit matrix, i represents thebase vector of the itheigenvector of NAP, w_i represents the itheigenvector of the NAP, and parameter d represents the number of base vectors obtained from the original eigenvector space. The parameter d can be determined by actual operating conditions and sampling points [4].

Hidden Markov model has rigorous data structure and can offer reliable computing performance. An HMM model can be noted as $\lambda = (N, M, \pi, A, B)$, the parameters arenumber of states,the number of possible observations corresponding to each state,initial probability distribution vector,state transition probability matrix,observed probability matrix, respectively [5].

In normal HMM, the probability that the equipment will stay in a certain state for a certain period of time is $P_i(d) = a_{ii}^{d-1}(1 - a_{ii})$. This probability fit geometric distribution, which is not obeyed in most practical applications. Hidden Semi-Markov Model (HSMM) which considers the explicit distribution of the state residence probability is proposed to overcome this disadvantage. The probability value $p_i(d)$ is used to describe the state dwell time [6].

Hidden states of HSMM represents different levels of health states and failure state of equipment. When model parameters are known, the average duration of each health state can be calculated based on the state duration distribution. So,the RUL of the equipment at a current moment can be evaluated based on the average duration of the state, the health status of the current equipment and the model parameters. Dong proposed a life prediction method based on HSMM. $D(h_i)$ is the duration time when the equipment is in health state i, then the whole life cycle of the equipment is:

$$Useful\ Life = \sum_{i=1}^{N} D(h_i). \tag{3}$$

But when equipment is in the process of degradation, the RUL of equipment in the current state should gradually decrease over time. To solve this problem, Peng [8] incorporates the effects of aging factors into HSMM-based life prediction. Based on that, the state transition probability decreases over time. The remaining time of the equipment in the state h_i after time I is obtained by equation:

$$D(h_i^I) = D(h_i)\left[\left[1 - \left(\left(1 - a_{ij}^I\right)\right]\right) \big/ \prod_{n=0}^{I-1} a_{ii}^n\right], \tag{4}$$

where the a_{ii}^n is the state transition probability considering the aging factor after time I at state h_i. Therefore, the RUL of the equipment after time I at state h_i is:

$$RUL^1 = D(h_i^I) + \sum_{j=i+1}^{N-1} D(h_j). \tag{5}$$

The main steps of a HSMM based life prediction method considering aging factors are as follows (fig. 1).

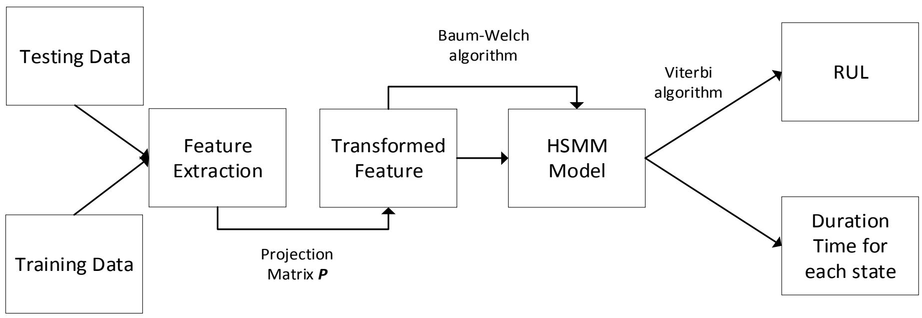

Fig. 1. RUL procedures of method based on NAP-HSMM

The run to failure dataset of bearings published by the PHM 2012 prognostic challenge is used in this paper. The data was produced by the PRONOSTIA platform, which has been designed for testing and validating bearing fault detection, diagnostic and prognostic purposes.Three different working conditions by changing the spindle speed and load values has been conducted.

Under Condition 1, a total of 7 groups of test bearing life data were collected. The types and operating conditions of the 7 groups of bearings are the same, but their life cycles vary, and their failure modes also have their own characteristics.

Only the data of condition 1 is used in this paper, 350 sets of data before and 150 sets of data after the health state turning points were intercepted to train the model. Intercepted segment mainly includes a health state and a failure state, so the number of hidden states for HSMM is set to 2.

During feature extraction, 17 dimensional features including time-domain, frequency-domain, and time-frequency domain are used. Then multiple sets of bearing features aretransformed based on NAP in order to eliminate nuisance attribute information caused by operating conditions.

First 6 sets of data in condition 1are used for training NAP-HSMM model. After projecting the features from intercepted dataof the bearing1_7, the RUL can be calculated, and failure is predicted at 2214’th sets of files, as shown in fig. 2.

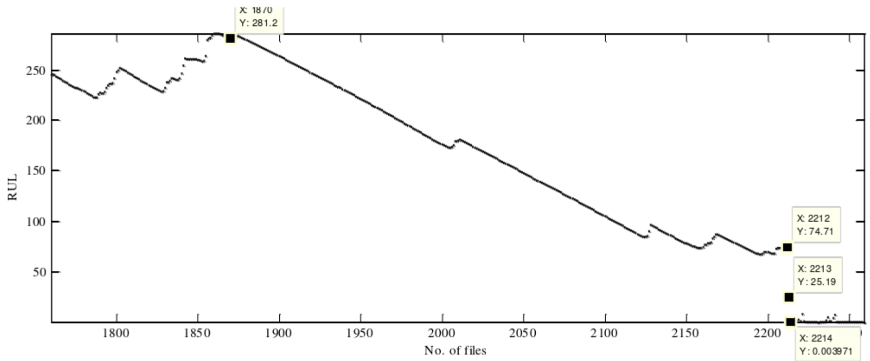

Fig. 2. Predicted RUL of Bearing1_7 with NAP

As comparison, original features of bearing 1_7 without NAP transformation have been put into the model. With everything else unchanged, the prediction of RUL of is shown in fig. 3. The difference in the prediction results during the initial period of time is not significant. However, when the bearing approaches the failure state, the prediction of RUL without using NAP has significant fluctuations over a period of time, which are significantly inconsistent with the actual situation.

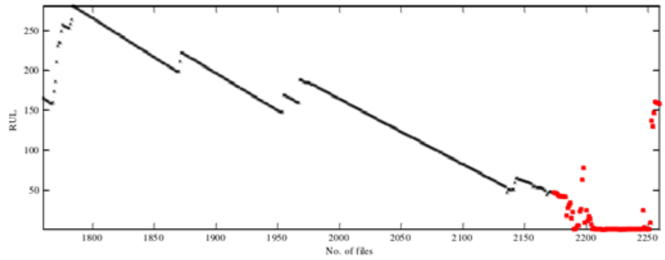

Fig. 3. Predicted RUL of Bearing1_7 without NAP

Therefore, the prediction ability of the RUL model trained by unprojected features is weaker. The results validate the importance of the algorithm based on NAP in HSMM RUL prediction methods.Since the model presented in the paper concerns at this time only on two-state HSMM, the health state will be considered to be divided into more segmentation in the future work.

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