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Article

A Novel Method for Remaining Useful Life Prediction of Bearing Based on Spectrum Image Similarity Measures

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Abstract: Accurately predicting the remaining useful life (RUL) of bearing by analyzing vibration signals is challenging and meaningful. To address this issue, a novel method based on spectrum image similarity is proposed in this paper. First, spectrum images for the whole lifecycle data of reference bearings are obtained by performing fast Fourier transformation (FFT). Second, the similarity is calculated between the current monitored data of operating bearing and run-to-failure images of reference bearings. Then, the weights of reference bearings are derived based on the similarity measures. Finally, the RUL of the operating bearing is estimated with the weighted average of the RULs of referenced bearings. The proposed method is demonstrated based on 2012 PHM Data Challenge Competition data, which shows its effectiveness and practicality.

Keywords: RUL prediction; spectrum image; similarity; weight

MSC: 94A12

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1. Introduction

Bearing is the basic component of rotating machinery, faults occurring in it may cause the performance deterioration of equipment or even fatal breakdowns and personal casualties [1]. Aiming at avoiding accidents and ensuring safety, prognostics and health management (PHM) for bearing has received extensive attention in recent years [2,3]. As a key technology for PHM, remaining useful life (RUL) prediction serves to indicate the component's lifetime before it loses function, based on which necessary maintenance actions and preventive replacement are implemented [4–6]. Therefore, bearing RUL prediction is critical for rotating machinery to reduce maintenance costs and improve reliability.

In order to conduct bearing RUL prediction, several kinds of signals could be used, e.g., vibration, acoustics, temperature, oil analysis, pressure, etc. Among them, vibration data is most commonly used due to the easy-to-measure signals and analysis [7–9], as well as the abundant information carried regarding the health condition [10,11]. The physic-based or model-based prognostics and data-driven prognostics are two main categories of prognostic methods which employ vibration data [12]. Physic-based methods utilize mathematic formulations of failure physical models to predict defect propagation [13,14]. They can provide reasonable and satisfying RUL predictions based on precise physical models. However, it is usually difficult or expensive to construct an accurate physical model of a complex system. In addition, these methods have shown obvious limitations because of the simplifications and distortions of the adopted models [6,15]. On the contrary, the data-driven methods perform RUL estimation only based on the monitored performance data related to system health. These approaches are suitable when the failure physical model is complicated but the condition monitoring data is available.

With regard to the data-driven methods, they mainly take two steps: degradation indicator selection and prediction model establishment [12,16,17]. An appropriate indicator extracted from the raw vibration data which tracks the performance degradation process is the premise of data-driven RUL prediction and the selection result is crucial to the prediction accuracy. A wide range of literature has studied this topic from time domain, frequency domain, and time–frequency domain. Mahamad et al. [18] selected RMS and kurtosis obtained from time waveform as indicators, while Wu et al. [19] used the power value on the sensitive frequency band to characterize bearing status. Ocak et al. [20] and Pan et al. [21] firstly applied wavelet packet decomposition to the vibrations and then adopted the node energies to indicate bearing degradation. Based on the selected degradation indicator, various prediction models have been utilized to perform RUL prediction, e.g., SVM [22–24], ANN [25–27], HMM [28–30], etc. Due to the training process of the above-mentioned machine learning techniques, sufficient monitoring data is required to obtain an accurate prediction model. Some researchers have investigated RUL prediction using similarity measures. Niu et al. [31] measured the similarity of indicator degradation curves between the monitored system and reference bearings and achieved a remarkable prognostic result by calculating the weighted sum of referenced RULs. Lin et al. [32] firstly mapped the original vibration data to a binary symbolic sequence with statistical linguistic analysis (SLA) and then utilized the sequence similarity to detect changes in health conditions. These methods are based on the assumption that an operating bearing has a similar RUL if it has similar recent performance with a reference bearing [15].

This paper develops a novel prognostic method based on spectrum image similarity for the RUL prediction of bearing. First, spectrum images for the current monitored data of an operating bearing and the whole lifecycle vibrations of reference bearings are obtained with FFT, where all images are of the same size in pixels. Second, the calculation unit is constructed by combining two adjacent images. Third, the similarities between the current calculation unit and referenced run-to-failure units are computed and the weights are derived. Finally, the RUL of the operating bearing is estimated through the weighted sum of the RULs of reference bearings. The remainder of this paper is organized as follows. Section 2 presents the procedures of the proposed method in detail. Section 3 describes an experimental validation for the proposed method. Finally, some conclusions are drawn in Section 4.

2. Description of the Proposed Approach

2.1. Image Creation

Instead of extracting various features from original vibrations, in this study, we utilized FFT spectra to represent the health status of the bearing. The reason is that all information contained in the spectrum images can be captured, which provides much more useful knowledge of bearings than single or fusion features [33]. The x-axis of the spectrum is the frequency in Hertz, and the y-axis is the amplitude. For a given signal, the range of the x-axis in the spectrum is determined by the sampling rate, while the y-axis is auto-scaled. However, the range of the y-axis is crucial for similarity measurement and RUL prediction due to its influence on the value of each pixel. With auto-scaled images, the health status is distorted and the deteriorated phase is confusing. Therefore, in order to indicate the degradation process correctly through the spectrum images, the boundary of the y-axis should be specified in the priority.

Supposing that there are M reference bearings, the number of monitored vibrations of the ith reference bearing in its whole lifecycle is N_i ($i = 1, 2, \cdots M$). Transforming each vibration signal into an FFT spectrum image (with $w \times h$ pixels), then the ith reference bearing can be denoted as follows:

$$A_i = \left[A_{i1}, A_{i2}, \cdots A_{ij}, \cdots A_{iN_i}\right] \quad (1)$$

A_{ij} is an $w \times h$ matrix that represents the jth spectrum image, $j = 1, 2, \cdots N_i$.

Therefore, the calculation unit is defined as:

$$\widetilde{A_{ik}} = [A_{i(k-1)} A_{ik}] \tag{2}$$

where $k = 2, \cdots N_i$. It is reasonable that two adjacent images are selected as a calculation unit. On the one hand, the spectra at current and previous inspections can not only indicate the degradation status but also introduce the change information. On the other hand, we choose the images at two inspections instead of more because it can give the algorithm better generalization capability [19].

2.2. Similarity Calculation

Given the operating bearing B:

$$B = [B_1, B_2, \cdots, B_{N_B}] \tag{3}$$

Similarity is measured as the distance between B and the ith reference bearing A_i. The expression is shown as:

$$d(q,i) = \min(d(\widetilde{B_q}, \widetilde{A_{i2}}), d(\widetilde{B_q}, \widetilde{A_{i3}}), \cdots, d(\widetilde{B_q}, \widetilde{A_{iN_i}})) = d(\widetilde{B_q}, \widetilde{A_{ih_i}}) \tag{4}$$

where q is the index of the current monitored data of bearing B, $q = 2, \cdots N_B$, and h_i is the life position of reference bearing A_i when the distance is minimal.

In this study, Euclidean distance is applied to measure the distance between two spectrum images:

$$d(\widetilde{B_q}, \widetilde{A_{ik}}) = \left\| \widetilde{B_q}, \widetilde{A_{ik}} \right\|_F = \sqrt{trace((\widetilde{B_q} - \widetilde{A_{ik}})^* (\widetilde{B_q} - \widetilde{A_{ik}}))} \tag{5}$$

where $\|\cdot\|_F$ denotes the Frobenius norm and $(\widetilde{B_q} - \widetilde{A_{ik}})^*$ denotes the conjugate transpose matrix of $(\widetilde{B_q} - \widetilde{A_{ik}})$.

2.3. Weight Distribution

A smaller distance between operating bearing B and reference bearing A_i indicates a larger similarity. As a function of similarity degree, a higher weight should be assigned to the reference bearing with a smaller distance. Thus, the weight distribution function can be defined as:

$$w^*(q,i) = \frac{1}{d(q,i)} \tag{6}$$

After normalization, Equation (6) is transformed into:

$$w(q,i) = \frac{w^*(q,i)}{\sum_{i=1}^{M} w^*(q,i)} \tag{7}$$

2.4. RUL Estimation

The RUL of the operating bearing B can be estimated through the weighted sum of the RULs of reference bearings. The RUL of A_i when B is at the current inspection q can be calculated as:

$$RUL(q,i) = N_i - h_i \tag{8}$$

where h_i is the life position of reference bearing A_i when the operating bearing B is at the current inspection q. Therefore, the RUL of bearing B at monitored time q is determined as:

$$RUL(q) = \sum_{i=1}^{M} (w(q,i) \cdot RUL(q,i)) \tag{9}$$

To summarize, the framework of the proposed method is presented in Figure 1.

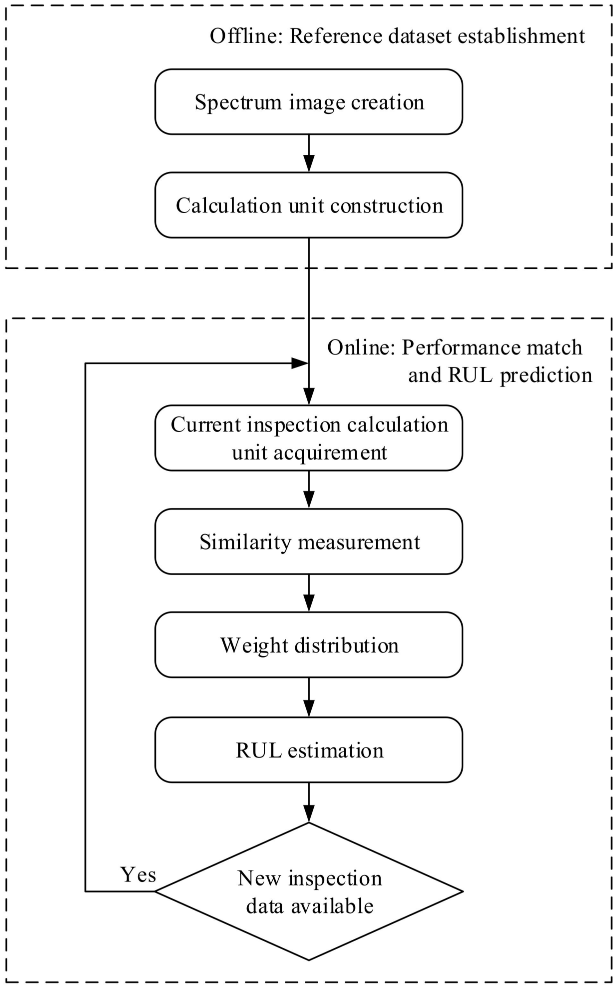

Figure 1. The flowchart of the proposed method.

3. Experiment and Analysis

The vibration signals used in this paper are provided by the IEEE PHM 2012 prognostic challenge [34] to demonstrate the effectiveness of the proposed prognostic method.

3.1. Experimental Setup

An experimental setup named PRONOSTIA is shown in Figure 2. In order to accelerate the degradation process, a radial force of 4 kN is exerted on the tested bearings. The rotation speed of the bearing is kept constant at 1800 rpm. The accelerometers are placed radially on the external race of the bearing to capture the vibrations. With the sampling rate of 25.6 kHz, a set of data consisting of 2560 points is collected for 0.1 s every 10 s. In order to avoid the propagation of damage to the whole setup (and for security reasons), tests are stopped when the amplitude of the vibration signal exceeds 20 g. More detailed information about this experiment can be found in [34].

Each tested bearing is naturally degraded without seeding defects initially. The vibration signals during the whole lifetime of four tested bearings are presented in Figure 3. Taking bearing 4 as an example, the spectrum images in three different operation stages are shown in Figure 4. In this paper, bearing 4 is selected as the target bearing whose RUL is estimated by the other three reference bearings 1–3.

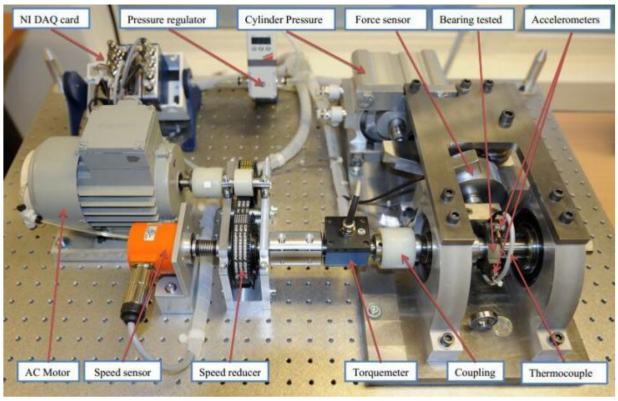

Figure 2. Overview of the experimental setup.

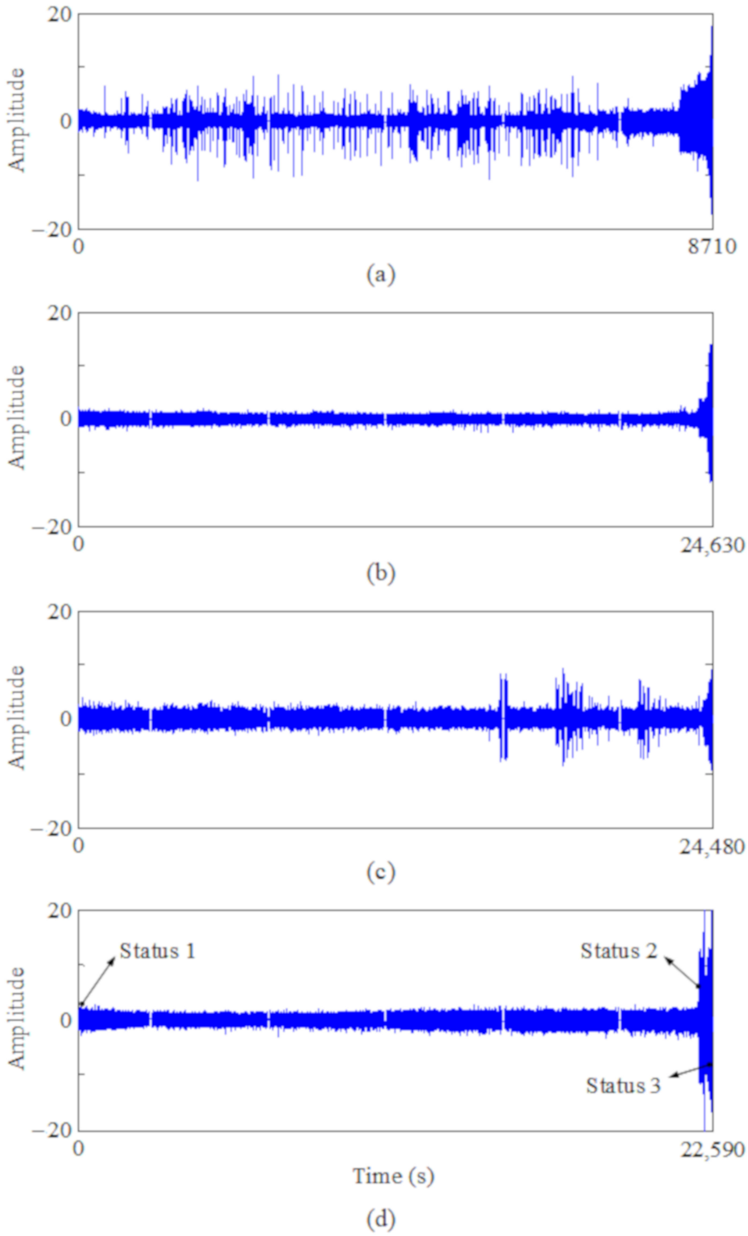

Figure 3. Vibration signals of four bearings: (**a**) bearing 1, (**b**) bearing 2, (**c**) bearing 3, and (**d**) bearing 4.

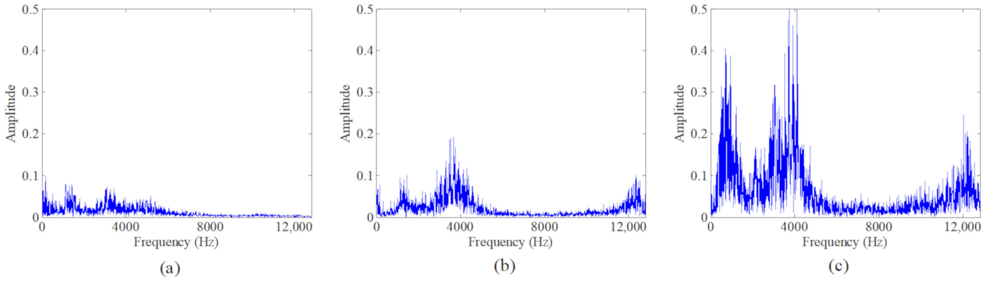

Figure 4. Spectrum images of bearing 4 in three operation stages: (**a**) Status 1, (**b**) Status 2, and (**c**) Status 3.

3.2. Experimental Analysis

In most practical applications, it is meaningless and time-consuming to predict the RUL from the beginning of the bearing's lifetime. What counts more in RUL estimation is the accurate prediction closer to the final failure. Therefore, it is necessary to pick the first predicting time (FPT) from the whole lifecycle by a certain principle. In this paper, the FPT is determined by a 3σ interval [35]. The data of bearing 4 after FPT is utilized to construct the calculation unit and measure the minimum distance from each reference bearing. As mentioned above, an appropriate range of the *y*-axis for spectra is required when the proposed method is conducted. The reason for this involves two aspects. First, the spectrum images will be ambiguous if the boundary of the *y*-axis is too large. Second, the images will lose useful information in the large-amplitude range, especially at the end of the bearing's lifecycle, if the boundary is too small. By making a general view of the spectral amplitudes of three reference bearings, the boundary is set to 0.5. Then, the spectrum is captured as an image of 420 $\times$ 560 pixels. As a result, the calculation unit is constructed by a 420 $\times$ 1120 matrix. For the sake of better understanding the process of RUL estimation for bearing 4 with the proposed method, a pictorial presentation is delivered in Figure 5.

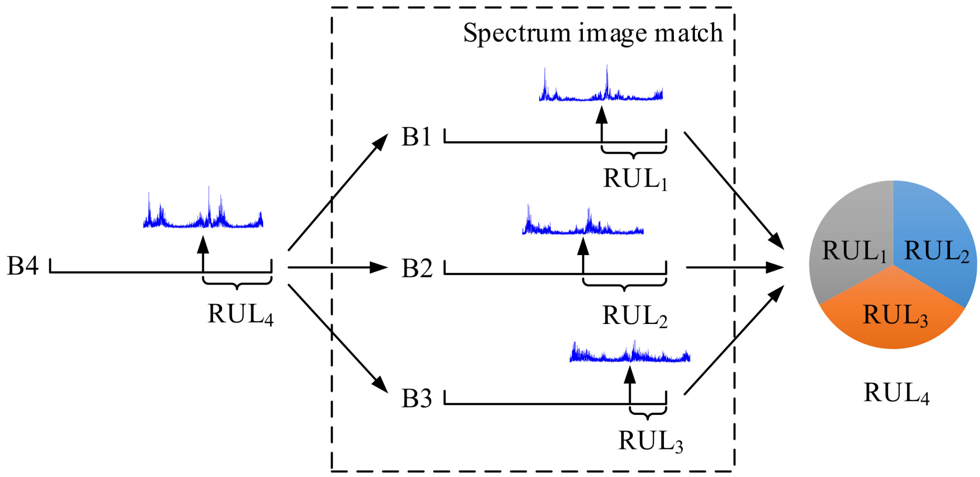

Figure 5. Schematic sketch of the RUL estimation process.

From Figure 5, we can see that the prediction method consists of three steps. First, the calculation units of the operating bearing B4 at current monitored data and three reference bearings B1, B2, and B3 in the entire life cycle are established. In the middle step, the nearest distances between the current calculation unit of B4 and each reference bearing are obtained by traversing the life cycle of B1, B2, and B3. Finally, the weights for the reference bearings are derived through the nearest distances according to the principle that a smaller distance indicates a higher similarity degree. As a result, the RUL of the operating bearing B4 at the current time is estimated as a weighted sum of the RULs of the three reference bearings.

Through measuring the similarity between the current calculation unit of bearing 4 and the run-to-failure units of three reference bearings, the RUL of bearing 4 is estimated and the results are shown in Figure 6, which indicates a satisfactory RUL prediction of the proposed method. In order to show the advantage of this method using two successive images, two other similarity-based approaches are compared, namely similarity calculated by a single spectrum image and similarity calculated by a spectral line. Thereinto, the first contrast method utilizes a single spectrum image to represent the health status of the bearing and the calculation unit is a 420×560 matrix. The second contrast method utilizes a spectral line to represent the health status of the bearing and the calculation unit is a 2049-element vector. The other procedures are the same as the proposed method.

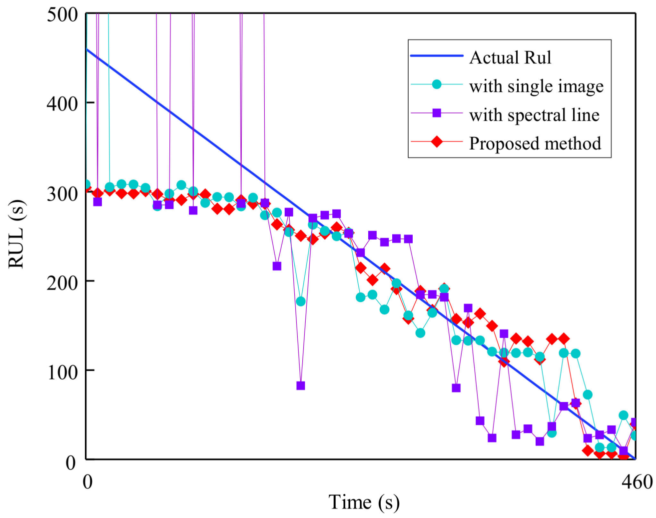

Figure 6. RUL prediction results of bearing 4.

From Figure 6, we can see that the proposed method and the method calculated with a single spectrum image outperform the approach calculated with a spectral line in terms of prediction accuracy and convergence. The proposed method generates stable and acceptable results earlier than the method calculated with a single image. This demonstrates that a spectrum image is more suitable than a spectral line for similarity-based prediction due to its abundant useful information regarding the degradation process. Two successive images instead of one can represent the health status more accurately and reduce random errors. In addition, the performance is not very desirable at the beginning of prediction because bearing 4, at that stage, experiences an early defect process, the fault signature is weak, and the degradation does not exhibit a strong tendency to certain reference bearings. To quantify the prediction performance, the root mean squared error (RMSE) [24], mean absolute percentage error (MAPE) [36], and convergence [37,38] are calculated and summarized in Table 1. RMSE and MAPE quantify how accurately a prediction method performs at a specific time index with absolute and relative prediction error, respectively. Lower values mean better accuracy. Convergence depicts how fast the accuracy improves with time to reach its perfect result. A lower value indicates a faster convergence.

Table 1. Metrics comparison of different prediction methods.

Metric	With Spectrum Image	With Spectral Line	The Proposed Method
RMSE	248.24	1093.74	62.98
MAPE	0.36%	2.43%	0.21%
Convergence	400.94	1112.38	141.03

It is noticed from Table 1 that the RMSE and MAPE of the proposed method are the smallest among these methods, which means that the proposed method has the most accurate prediction result. The convergence of the proposed method is the lowest, which implies that the proposed method approaches the actual RUL fastest. In conclusion, the proposed method performs better than the two comparative approaches in RUL prediction for bearing 4.

Moreover, due to the common ground in adopting similarity-based approaches, Reference [31] is utilized to compare with the proposed method. By predicting the RUL of the same bearing, the RMSE in comparative literature is 108.02, while the RMSE in this paper is 62.98, which indicates a better accuracy of the proposed method.

To make the conclusion more convincing, we utilize bearing 1 as the target bearing to conduct another validation following the same technical process with the other three bearings 2–4 as the reference bearings.

The prediction results are shown in Figure 7.

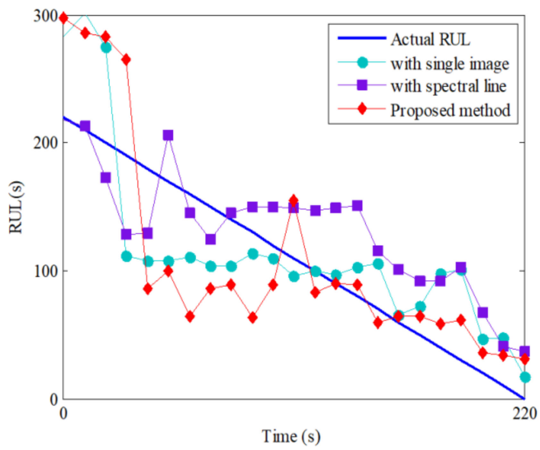

Figure 7. RUL prediction results of bearing 1.

It can be seen that the prediction performance using the proposed method outperforms the comparative approaches in terms of prediction accuracy and convergence, especially at the stage closer to the final failure.

4. Conclusions

The accurate RUL prediction of bearing is significant to perform PHM of rotating machinery for the sake of improving reliability and reducing maintenance costs. Most of the literature on RUL prediction mainly concentrates on the search for the so-called 'good' degradation indicators or the development of an excellent prediction model. In this paper, a similarity-based method is proposed to perform RUL estimation. The spectrum image is utilized to represent the bearing degradation process. In order to improve the generalization capability and reduce random error, two successive spectra are combined as a calculation unit. Then, the similarity between the target bearing at current inspection and the reference bearings throughout failure histories is computed and the weight of each reference bearing is distributed. Finally, the RUL of the target bearing is estimated through the weighted sum of the referenced RULs.

In the experimental verification, two prognostic methods were compared with the proposed method. The results showed that the proposed method provided a more accurate prediction and a faster convergence, which demonstrated the effectiveness of this method in predicting the RUL of bearings. It needs to point out that the proposed method is suitable for the situation in which similar bearings with whole lifecycle data are available. For the key rotating parts in modern industry, it is increasingly common to collect vibrations throughout the lifecycle. When the operating bearing fails, it can be viewed as another reference bearing to update the prediction results of the new bearing. There is no need to explore the operating mode of monitored bearing or the failure modes of reference bearings because the operating status of monitored bearing can be matched to the most similar life stage of reference bearings by similarity measures.

Future work will develop deeper research on similarity measurement optimization, which will provide a more accurate localization of the referenced degradation phase and contribute to a sounder weight distribution. The normal data of operating bearing is supposed to be exploited sufficiently to perform domain adaptation and space alignment with the reference bearings as the assistance in similarity measurement. In addition, the exact relationship between the boundary of the y-axis and the prediction performance should be further investigated as well.

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