

Research on Residual Life Prediction of Rolling Bearings Based on STFT-CNN

Qi Liu*, Sunqing Xu and Xiangyu Cao

Unit 92493 of PLA, Huludao, Liaoning, China

Email: 670426139@qq.com.

Abstract. Rolling bearings are one of the key components in rotating machinery equipment. It is of great significance to carry out state monitoring and residual life prediction for rolling bearings to strengthen service management of bearings and maximize the use value of bearings. In this paper, a bearing remaining life prediction model based on STFT-CNN was built. The STFT transform was performed on the original signal before the CNN model was input, and the one-dimensional time series signal was converted into the time-frequency domain. Finally, experimental verification was completed on the IEEE PHM 2012 dataset, and comparative experiments were conducted. Experimental results show that the residual life curve predicted by the STFT-CNN model is more accurate and fits the actual curve.

Keywords. Rolling bearings, convolutional neural networks, Short-time Fourier transform, residual life prediction

1. Introduction

Rolling bearing is one of the key components of rotating machinery and is widely used in many fields such as national life, industrial manufacturing, and national defense construction. However, compared with other mechanical parts, rolling bearings have great life discreteness, and their lives vary greatly under different working conditions [1]. This is very likely to occur such a situation, in the same batch of bearings produced, some bearings have good performance but in fact have exceeded the service life, and some bearings have not reached the design life has been degraded. Therefore, the maintenance cycle of bearings cannot be determined absolutely in accordance with the design life of bearings. It is of great significance to monitor the state of rolling bearings and predict their life in combination with the actual use of bearings [2].

Studies have been carried out by predecessors. For example, Shen et al. solved the problem of lack of information in small samples based on relative features and MSVM methods [3]. Qiu et al. used the optimal wavelet filter and self-organizing adaptive method to effectively detect bearing defects in the early stage [4]. Li et al. improved the state-space model of bearings, allowing the establishment of different degradation stages to predict the remaining life, and used particle filter to predict the degradation trend [5]. Jia, Lei, Ding made good progress in characterizing the degradation state of bearings and transmission by using the deep learning method and the method of establishing health indicators [6-8].

2. Rolling Bearing Fault Mechanism and Data Set

2.1. Analysis of Bearing Degradation Law

By studying the degradation law of rolling bearings, the curve of rolling bearing degradation state variation is shown in figure 1.

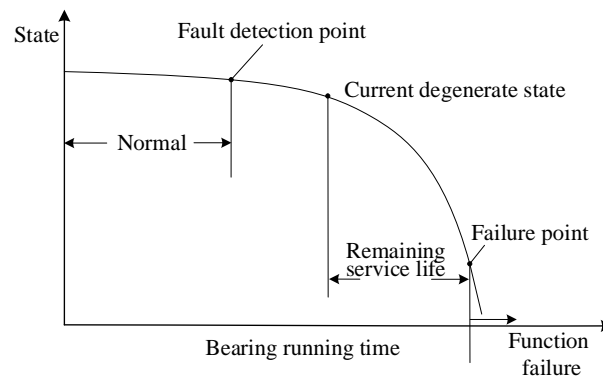


Figure 1. Rolling bearing degradation law.

As can be seen from figure 1, the time from the moment of degradation to the complete failure of the bearing is the remaining life, which is also one of the main indicators to be studied and predicted in this paper [9].

2.2. Rolling Bearing Life Data Set

Bearing life prediction data came from IEEE PHM 2012 Data Mining Competition, and the experimental platform is shown in figure 2 [10].

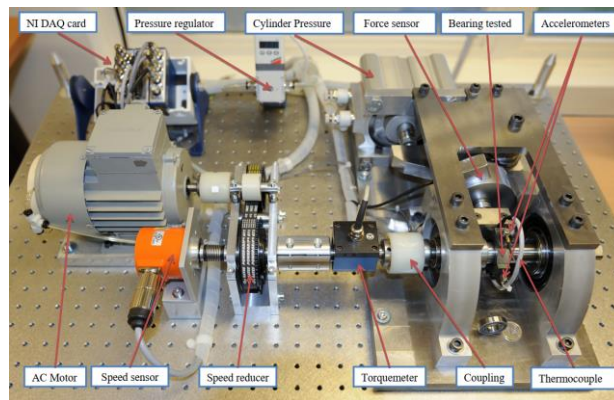


Figure 2. IEEE PHM 2012 data acquisition device.

The sampling frequency was 25600Hz, and the duration of each sample was 0.1s. So each sample included 2560 sampling points, and the recording interval was 10s. The data were collected under three working conditions respectively.

The remaining life prediction experiment in this paper selected the experimental data under working condition 1, the load is 4000N and the speed is 1800rpm. Bearing1-1, Bearing1-2, Bearing1-4, Bearing1-5, Bearing1-6, and bearing1-7 were selected as the training set, and Bearing1-3 was selected as the test set.

After the rolling bearing reaches the starting point of degradation and enters the degradation stage, the time from the degradation moment to the complete failure of the bearing is the remaining life of the bearing, and the remaining life time is normalized to (0,1) as the label of the remaining life prediction experiment. Therefore, the experimental labels before the bearing reaches the degradation point are all 1. When the bearing completely fails to work, the experimental labels are 0, and the experimental labels between them are decimal points from 0 to 1. Taking bearing 3 as an example, a total of 2375 pieces of

data were collected, and each piece of data was recorded at an interval of 10 s. Therefore, its entire service life was 23750 s, and the starting point of bearing degradation was the collection point corresponding to 16160 s of operation. When the data in article 2000 is collected, the bearing has worked for 20000 s, and the corresponding remaining life is 3750 s. Assuming that the time from the current moment to the failure moment is T_1 , and the time from the degradation point to the failure moment is T_2 , then the label is the ratio of T_1 to T_2 , that is 0.494071.

3. Convolutional Neural Network

In this paper, a two-dimensional convolutional neural network model is adopted, including four convolution-pooling layer pairs, two full connection layers, and one output layer. The network structural parameters of this model are given in table 1.

Table 1. Structural parameters of convolutional neural network.

Number	Name	Size	Convolution kernel number	Step length	The activation function
1	Convolution layer 1	3×3	4	1	ReLU
2	Pooling layer 1	2×2	-	2	-
3	Convolution layer 2	3×3	8	1	ReLU
4	Pooling layer 2	2×2	-	2	-
5	Convolution layer 3	3×3	16	1	ReLU
6	Pooling layer 3	2×2	-	2	-
7	Convolution layer 4	3×3	32	1	ReLU
8	Pooling layer 4	2×2	-	2	-

100 neurons were obtained after full-connection transformation at the first layer, 10 neurons were obtained after full-connection transformation at the second layer, and 1 neuron was obtained after full-connection transformation at the third layer. ReLU function was selected as the activation function. In addition, the small batch processing size of each training iteration was set as 100, the initial learning rate was 0.01, and the number of iterations in the training process was 40. In order to reduce overfitting and improve the training speed of the algorithm, the dropout algorithm is adopted, and the dropout ratio was 0.1. After 20 rounds of training, the learning rate is reduced by multiplying factor 0.1.

4. Residual Life Prediction of Rolling Bearings Based on STFT-CNN

4.1. Short Time Fourier Transform (STFT)

In 1946, Dennis Gaor proposed the short-time Fourier Transform (STFT) algorithm, which can Transform one-dimensional time series signals into two-dimensional matrices containing information in the time domain and frequency domain [11].

The basic idea of STFT is to select a fixed-length window function as a segmentation tool and sequentially intercept small time domain signals from the original time domain signals. Fourier transform is used for analysis, and the local spectrum in a very small time period near time is obtained.

4.2. Signal Preprocessing

Short-time Fourier Transform (STFT) was applied to the original signal, and then it was input into the CNN model. In equation (1), the time-frequency domain conversion method of one-dimensional time series signal is adopted to obtain the time-frequency information representation similar to the speech spectrum of acoustic signal, namely the fault spectrum. In this experiment, gauss window was selected as the window function, and the length of the window function was selected as 150. Taking Bearing1-3 as an example, at the moment of complete bearing degradation, the image of the signal after STFT is shown in figure 3.

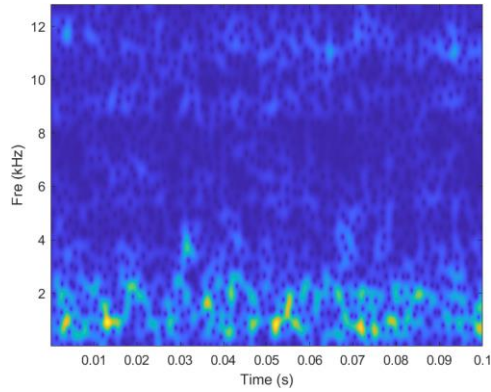


Figure 3. Time frequency diagram of STFT transform.

4.3 Bilinear Interpolation for Dimensional Reduction

One-dimensional vibration signals are mapped to two-dimensional coefficients by STFT, which can be regarded as high-dimensional features. In order to reduce the computational burden of subsequent models, it is necessary to reduce the dimension of high-dimensional features. Bilinear interpolation is adopted in this chapter, and the arrangement of pixels of this algorithm is shown in figure 4. Point P is the pixel to be obtained, and Q_{11} , Q_{12} , Q_{21} and Q_{22} are the four pixels adjacent to point P . By mining the correlation between the four pixels, the value of point P can be obtained by linear interpolation twice.

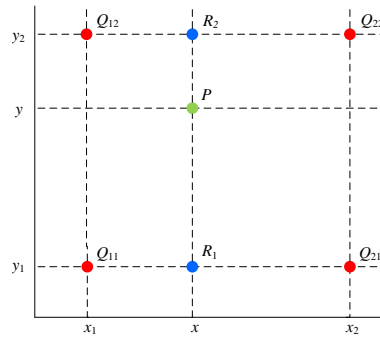


Figure 4. Bilinear interpolation algorithm for dimensionality reduction of pixels.

As shown in figure 5, the original signal features are still abundant after dimensionality reduction, which is conducive to subsequent analysis and processing.

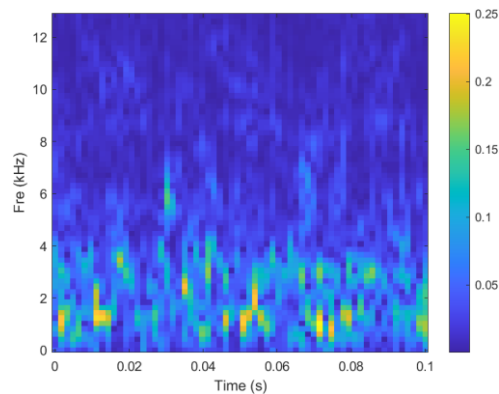


Figure 5. Time-frequency diagram of STFT transform after dimensionality reduction.

4.4 Weighted Average Noise Reduction

Because of the noise in the prediction process, the prediction curve of residual life fluctuates greatly and brings about errors. In this paper, the method of weighted average denoising is selected, and a fixed period of time is selected to carry out weighted average on the predicted value of a period of time. The principle of weighting is related to the distance between the point and the predicted point, and the arithmetic series is taken. Finally, the weighted average is used to replace the predicted value of the last moment. In this way, after noise reduction calculation, the results at one moment will immediately participate in a new round of weighted average calculation at the next moment, and keep iterating and updating.

5. The Experimental Results

The decimal from 0 to 1 represents the remaining life as labels. And the fault atlas processed by STFT was sent to CNN network for training and testing, and a single value result was finally output, namely the normalized value of the predicted residual life of the rolling bearing, as shown in figure 6.

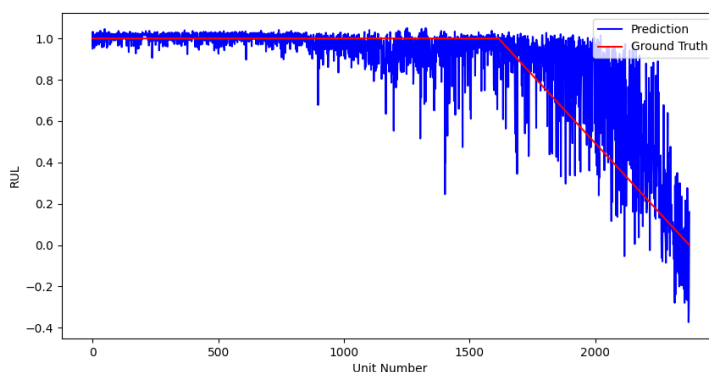


Figure 6. Prediction curve of bearing remaining life before denoising of STFT-CNN model.

As can be seen from figure 6, for some adjacent time points, especially in the middle and later parts, the prediction results differ greatly, and the prediction curve fluctuates significantly, so the noise reduction is required. After denoising according to the weighted average method before, the prediction results are shown in figure 7. The noise of the curve after processing is significantly reduced, and the deviation degree of points with large deviation degree before denoising is also reduced after denoising. Figure 7 shows that the prediction curve is consistent with the actual remaining life curve and has a high degree of fitting. The inflection points of the actual curve 1616 is the starting point of bearing degradation, and the prediction curve also accurately finds this moment, which can realize the early warning of bearing failure.

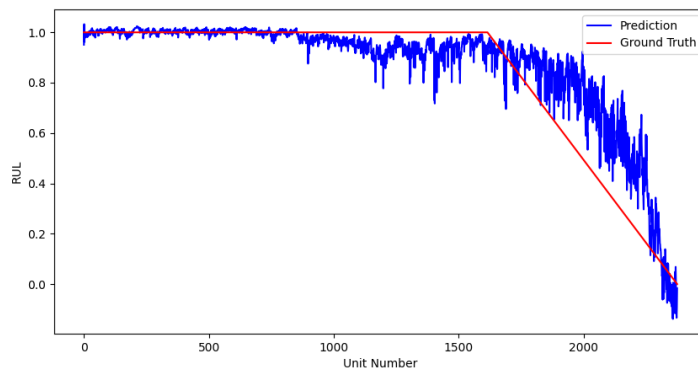


Figure 7. Prediction curve of bearing remaining life after denoising of STFT-CNN model.

In order to quantitatively express the effectiveness of the STFT-CNN model, root mean square error (RMSE) was used to characterize the fitting degree of the prediction curve while observing the prediction curve. The RMSE of STFT-CNN model before and after denoising are shown in table 2.

Table 2. RMSE of STFT-CNN model before and after denoising.

Time	RMSE
Before denoising	0.1624
After denoising	0.1229

In order to verify the prediction ability of STFT-CNN model, the prediction result was compared with that of BP neural network. The prediction results of BP neural network before and after denoising are shown in figures 8 and 9.

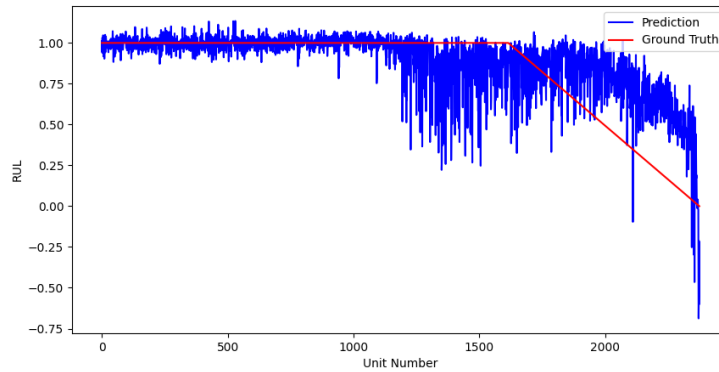


Figure 8. Prediction curve of bearing remaining life before denoising of BP model.

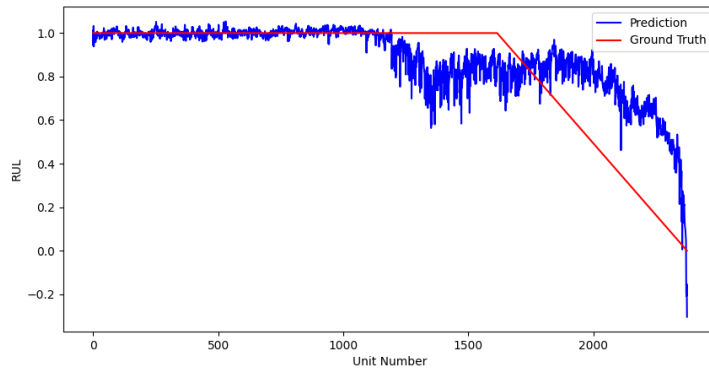


Figure 9. Prediction curve of bearing remaining life after denoising of STFT-CNN model.

The RMSE of BP neural network model before and after denoising are shown in table 3.

Table 3. RMSE of BP model before and after denoising.

Time	RMSE
Before denoising	0.2099
After denoising	0.1862

By comparing figure 8 with figure 9, the prediction curve based on STFT-CNN adopted in this paper is more consistent with the actual curve and captures the starting point of bearing degradation more

accurately. At the same time, the RMSE of the prediction model based on STFT-CNN is lower.

6. Prospect

Due to the limitation of time and experimental conditions, some contents can be further studied. Although the data set adopted in this paper is collected through experimental simulation, the working conditions are relatively single. In practical work, some rolling bearings operate under extremely complex working conditions. For example, rolling bearings working on ships need to comprehensively consider the influence of unfavorable conditions such as temperature and noise. In the follow-up, further research can be carried out.

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