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RUL Prediction for Bearings Using MSCNN and LSTM Networks

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Abstract: To address the challenges of effectively capturing spatiotemporal features from data using a single prediction model and the limitations of artificially constructed degradation indices in accurately representing the bearing's degradation state at specific time points, this study introduces a novel bearing Remaining Useful Life (RUL) prediction model. The model integrates a Multi-Scale Convolutional Neural Network (MSCNN) and Long Short-Term Memory (LSTM) networks, grounded in a monotonic degradation index. Initially, a monotonic optimality criterion is employed to identify an appropriate health index for bearing degradation. Subsequently, a comprehensive spatiotemporal feature set is developed by merging the multi-scale spatial features extracted by MSCNN with the temporal features derived from LSTM. The proposed LSTM-MSCNN model's effectiveness is validated using the XJTU-SY bearing dataset from Xi'an Jiaotong University as a case study.

Keywords: Deep learning, remaining life prediction, multi-scale convolutional neural network, long and short-term memory neural network.

1.Introduction

In recent years, during the prediction stage of Remaining Useful Life (RUL), deep learning technology has achieved significant success in the field of RUL prediction due to its powerful nonlinear mapping capabilities [1-8]. The primary deep learning methods in this field include Convolutional Neural Networks (CNN), Long Short-Term Memory networks (LSTM), Recurrent Neural Networks (RNN), Deep Neural Networks (DNN), and Generative Adversarial Networks (GAN), among others. These models have gradually become the mainstream research trend in RUL prediction due to their unique network structures and computational approaches [9-11]. Reference [12] proposed an RUL prediction method combining a Deep Convolutional Autoencoder (DCAE) with a One-Dimensional Convolutional Neural Network (1D-CNN). This approach uses DCAE to establish the Health Indicator (HI) for the bearing degradation process and takes the HI along with the original degradation data as inputs to the 1D-CNN to predict bearing RUL. Reference [13] introduced an RUL prediction method based on a hybrid model of CNN and BDLSTM, and validated the effectiveness of the designed model using the C-MAPSS dataset. Reference [14] proposed a CNN-LSTM-PSO RUL prediction method that employs CNN-LSTM to extract the spatiotemporal relationships of multivariate time series data and capture degradation features, with Particle Swarm Optimization (PSO) used to optimize the CNN-LSTM model parameters. A comparison with other models was made to verify the superiority of this method. Reference [15] presented a hybrid prediction method combining CNN, LSTM, and DNN to predict the RUL of lithium-ion batteries, with experimental validation conducted on NASA and CALCE lithium-ion battery datasets. The results demonstrated that this method effectively improves RUL prediction accuracy. Inspired by the above research, this paper focuses on rolling bearings and proposes an RUL prediction model based on a combination of Long Short-Term Memory neural networks and Multi-Scale Convolutional Neural Networks (LSTM-MSCNN). First, the time-frequency features of the original bearing data are extracted, and trend analysis and smoothing of these features are performed to determine the bearing's health status index. Second, the LSTM-MSCNN model extracts the multi-scale spatial and temporal features of the data. Finally, high-precision prediction of bearing RUL is achieved using the LSTM-MSCNN model.

2. Theoretical analysis

2.1. Convolutional Neural Network (CNN)

CNN is a typical feedforward multi-layer neural network, and its main structure consists of three parts: the convolutional layer, pooling layer, and fully connected layer. The operation formula of the convolutional layer is as follows:

$$a_i^l = f\left(u_j^l\right)$$

$$u_j^l = \sum_{i \in M_j} a_i^{l-1} * k_{ij}^l + b_j^l$$

2.2. Long Short-Term Memory Neural Network

The LSTM module contains three "gating" units: the "input gate," "forget gate," and "output gate," along with a memory cell. The calculation method for each gated unit is as follows:

$$f_t = \sigma\left(W_f \bullet \left[a_{t-1}, x_t\right] + d_f\right)$$

Among them, the forget gate transfers the previous hidden state and the current input information into the sigmoid function, where information with an output value close to 1 is retained, and information close to 0 is forgotten. W_f is the weight matrix corresponding to the forget gate, b_f is the bias, and h_{t-1} is the hidden state information from the previous unit.

$$u_t = \sigma\left(W_u \bullet [a_{t-1}, x_t] + d_u\right)$$

$$C_t = tanth\left(W_c \bullet [a_{t-1}, x_t] + d_c\right)$$

$$C_t = f_t * C_{t-1} + u_t * C_t$$

Among them, u_t represents the input gate, which is responsible for updating the cell state. W_u is the weight matrix associated with the input gate, and b_u is the corresponding bias. C_t represents the updated cell state of the current unit, C_{t-1} is the previous cell state.

$$o_t = \sigma\left(W_o \bullet \left[[a_{t-1}, x_t] + d_o\right]\right)$$

$$a_t = o_t * tanh\left(C_t\right)$$

2.3. LSTM-MSCNN prediction model

The structural diagram of the LSTM-1DMSCNN prediction model proposed in this paper is shown in Fig. 1.

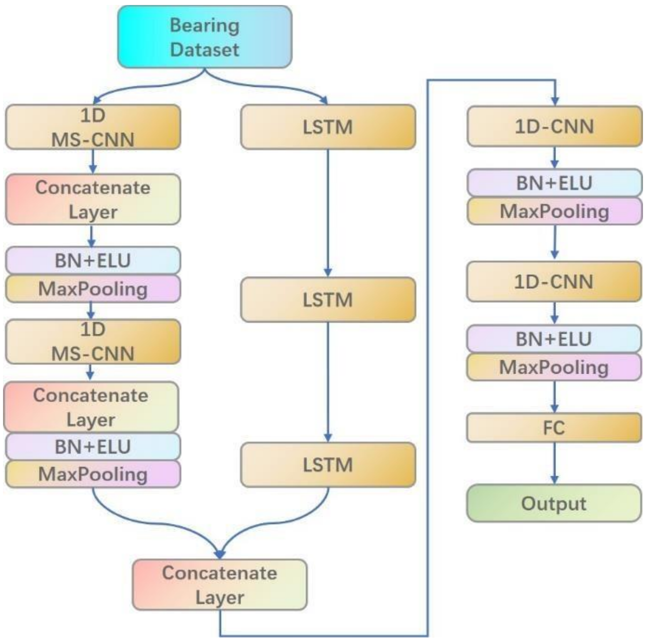

Fig. 1 LSTM-1DMSCNN prediction model structure diagram

In the 1D-MSCNN structure for extracting spatial features, three sizes of convolutional kernels are used: K1 = 3 , K2 = 5 , and K3 = 7 . The number of these convolutional kernels is N = 16 , with a stride S = 2 for each sliding operation, and "same padding" is employed. The features extracted at these three different scales are concatenated through a stitching layer to form a multi-scale feature map. A batch normalization layer is added after the stitching layer and the second convolutional layer to prevent overfitting and to accelerate convergence during training.

3. Experiment and Analysis

3.1. Data Sources

The bearing dataset XJTU-SY used in this paper is from Xi'an Jiaotong University [16]. The dataset includes the lifetime vibration signals of 15 rolling bearings under three working conditions. In the degradation experiment, the sampling frequency is 25.6 kHz, the sampling interval is 1 min, and the duration of each sampling is 1.28 s. Table 5.1 shows the vibration dataset of the experimental bearing LDK UER204 under 3 operating conditions.

Table 1: Dataset Description

Condition	Load（KN）	Speed (rpm)	Dataset
1	12	2100	Bearing 1-1 Bearing 1-5
2	11	2250	Bearing 2-1 Bearing 2-5
3	10	2400	Bearing 3-1 Bearing3-5

3.2. Construction of health indicators

In this paper, 14 time-domain features and 4 frequency-domain features are extracted, and monotonicity is used to quantify the applicability of the degradation index. One set of features is selected from the 18 time-frequency domain features to represent the degradation trend of bearing health.

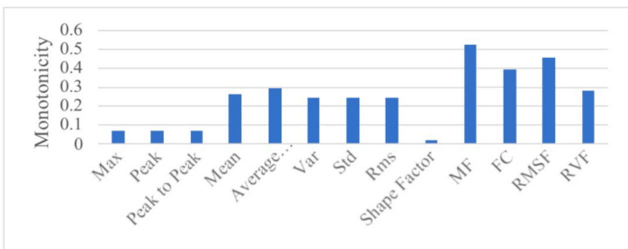

Fig. 2 Monotonicity of performance metrics

The monotonicity quantification index diagram of the time-frequency feature is shown in Fig. 2. It can be observed from the figure that, compared to other time-frequency features, the frequency domain feature MF has a higher monotonicity index, with a value of 0.524. This indicates that MF better describes the bearing degradation process.

3.3. Experimental results and analysis

The prediction results of the XJTU-SY bearing dataset are shown in Fig. 3/4.

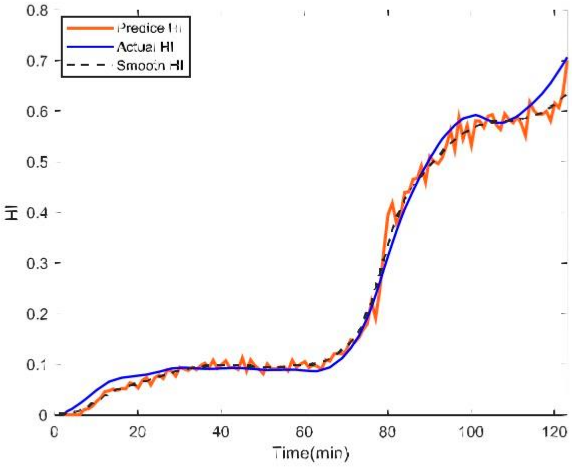

Fig. 3 Prediction results:(a)

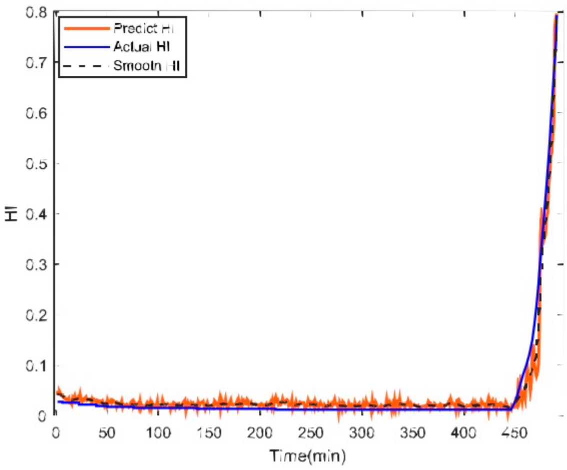

Fig. 4 (b) Bearing 2-1

Table 2: Model evaluation results

Model	Evaluation Metrics		
	RMSE	SMAPE	RA
MSCNN	0.0856	0.0434	0.9544
CNN	0.1022	0.0674	0.8144
LSTM	0.0732	0.0341	0.9752
RNN	0.1143	0.0709	0.8214
LSTM-1DMSCNN	0.0645	0.0244	0.9834

To verify the predictive advantages of the LSTM-1DMSCNN model, this paper compares it with four common deep learning prediction models: MSCNN, CNN, LSTM, and RNN. The model performance evaluation is presented in Table 2. Compared to these four methods, the LSTM-1DMSCNN model achieves the lowest RMSE and SMAPE, and the highest RA, demonstrating its superiority in the bearing RUL prediction task.

4. Conclusion

In this paper, a spatiotemporal feature fusion bearing RUL prediction model, LSTM-1DMSCNN, is proposed. The method leverages time-frequency features from the bearing data as the degradation index, providing a more accurate description of the actual bearing degradation trend. Additionally, LSTM-1DMSCNN integrates a multi-scale convolutional network with a long short-term memory neural network to learn deeper spatiotemporal features. By reducing the network's depth while extracting multi-scale feature information, the model fully captures the characteristic information in the data. Experimental results show that the LSTM-1DMSCNN model achieves high RUL prediction accuracy and offers a novel solution for RUL prediction in rotating equipment.

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