

Technical Paper

Bearing remaining useful life prediction based on deep autoencoder and deep neural networks

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ABSTRACT

Bearings play a crucial part in reliable operation of rotating machinery in manufacturing systems. There is a growing demand for smart prognostics of bearing remaining useful life (RUL). The data driven approach for bearing RUL prediction has shown promising potential to support smart prognostics. The recent advances in deep learning and industrial big data provide new solutions for data driven bearing RUL prediction yet still face significant challenges, e.g. optimal feature selection and efficient feature compression. This paper proposes a new deep learning based prediction framework for bearing RUL by using deep autoencoder and deep neural networks (DNN). A novel eigenvector based on time–frequency-wavelet joint features is proposed to effectively represent bearing degradation process. A deep autoencoder based joint features compression and computing method is presented to retain effective information without increasing the scale of DNN. The experiment results showed that the proposed method can achieve better efficiency in bearing RUL prediction.

1. Introduction

As an essential component of modern manufacturing industry, bearings play a crucial part in reliable operation of most rotating machinery in manufacturing systems [1]. The bearings health analysis has major impacts on the reliability and safety of manufacturing systems. Recently, the advances in bearing remaining useful life (RUL) prediction have provided increasingly powerful techniques enabling smart prognosis and health management of bearings. However, the complex decisive factors associated with bearing health conditions make bearing RUL still a challenging issue [2,3].

Most approaches for bearing RUL prediction apply the principle of model-based or data-driven method [4,5]. The model-based method mainly depends on precise mathematical models of degradation mechanisms of bearings, which currently is still a complex problem difficult to solve [6]. The data-driven method aims at mining the underlying relationships between the current condition data of a bearing and RUL by taking advantage of big data computing and Artificial Intelligence (AI) [7]. And recently the data-driven method has become increasingly promising approach to bearing RUL prediction [8]. Especially with the breakthrough innovations in deep learning [9], the deep learning based approach has demonstrated superiority in bearing RUL prediction [10], which makes this research area face new opportunities.

The typical deep learning framework involves four stages: data acquisition and processing, feature extraction and computing, training by deep learning model, and RUL prediction. Despite the inspiring advances mentioned above, deep learning based bearing RUL prediction still faces significant challenges. The first issue is optimal feature selection and extraction. Bearing RUL usually involves three categories of features: time domain features, frequency domain features, and time–frequency domain features. The time domain features have a good consistency with whole degradation tendency but is weak in reflecting the detailed degradation process, thus often lead to relatively big prediction errors. The frequency domain features are sensitive to both earlier and later stages of bearing degradation, but not in middle stage. The time–frequency domain features, e.g. wavelet, often lead to low accuracy caused by information loss. The second issue is efficient feature compression. The adoption of all these three types of features usually results in information redundancy as well as increase of neural network nodes which would further lead to model training difficulty and overfitting. In addition, most current prediction methods need to know the bearing failure threshold as a precondition for feature computing as well as training model configuration. But in a real situation, it is hard to know the breakdown point when the bearing is in normal operation [10]. As a whole, the bearing RUL prediction with deep learning is in its initial phase, and most existing prediction frameworks,

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e.g. self organizing maps [11] and Gaussian regression [12], are based on traditional machine learning. There still lacks efficient deep learning methods for bearing RUL prediction.

To address these issues, this paper proposes a deep learning based approach for bearing RUL prediction combined with deep autoencoder and deep neural networks (DNN). The experiment results showed that the proposed method can achieve better efficiency in bearing RUL prediction. The contributions of this paper can be summarized as follows:

- (1) We propose a novel eigenvector based on time–frequency–wavelet joint features that can effectively represent bearing degradation process comprehensively.
- (2) We present a deep autoencoder based joint features compression and computing method, which can retain effective information without increasing the scale of DNN.
- (3) We present a new deep learning based prediction framework for bearing RUL, and experiment results verified the proposed framework.

The rest paper is organized as follows. Section 2 presents the basic theory of deep autoencoder. Section 3 presents the deep learning based prediction framework for bearing RUL. The experiment and result discussion are given in Section 4. Section 5 concludes the paper.

2. Basic theory of deep autoencoder

Deep autoencoder is a kind of signal compression model based on neural network. It is a non-supervised learning network [13]. The most widely used classical dimensionality reduction method is principal component analysis (PCA) [14]. Since PCA is a linear dimensionality reduction method, it is not suitable for the nonlinear feature compression [15]. In terms of feature compression, it presents strong nonlinear characteristics. As a result, deep autoencoder is a promising approach comparatively.

The simplified network structure of deep autoencoder is shown in Fig. 1.

The network to achieve data compression is mainly encoded and decoded in two steps [16][17]: (1) In encoding stage, the input vector $x = (x_1, x_2, x_3, \dots, x_n)$ is compressed to the middle layer vector $z = (z_1, z_2, z_3, \dots, z_m)$. (2) In decoding stage, the intermediate layer vector $z = (z_1, z_2, z_3, \dots, z_m)$ is extended to the output layer vector $\hat{x} = (\hat{x}_1, \hat{x}_2, \hat{x}_3, \dots, \hat{x}_n)$, and the following formula needs to be satisfied:

$$h_{w,b}(x) = \hat{x} \quad (1)$$

Training process of deep autoencoder network including two steps [18]: (1) Data forward propagation. The input vector $x = (x_1, x_2, x_3, \dots, x_n)$ is propagated forward from the input layer to the output layer, and the network will output vector $\hat{x} = (\hat{x}_1, \hat{x}_2, \hat{x}_3, \dots, \hat{x}_n)$, which will be represented as $h_{w,b}(x)$. (2) Error back propagation. After the output is obtained, the loss function can be calculated with the following formula,

$$h_{w,b}(x) = \frac{1}{m} \sum_{i=1}^m (\hat{x} - x)^2 \quad (2)$$

By using gradient descent method, the network weights (w, b) can be updated in order to minimize the loss function value from back to front.

3. Methodology

The structure of the bearing RUL prediction model proposed is shown in Fig. 2.

The original data used for bearing RUL prediction is the bearing vibration signal. Firstly, different features are extracted from the vibration signal data, including time domain features, frequency domain features and time–frequency domain features. Secondly, the autoencoder model is used to compress the time domain features. Then, the frequency domain features, time–frequency domain features, and the autoencoder-time features are input into a deep neural network (DNN) for RUL prediction. Finally, the prediction results are smoothed.

3.1. Feature extraction

3.1.1. Time domain feature

Although time domain features do not provide adequate information for bearing RUL prediction, they can describe the bearing decay trend quite well. Bearing damage point is the time point with its vibration amplitude greater than a certain threshold [19]. Thus, according to the amplitude of vibration signal and other time domain features, we are able to determine whether the bearing damage occurs [20]. There are many time domain features for vibration signal data, different features have different characterization capabilities for the bearing health state, and even some time domain features with barely characterization capabilities. So selecting appropriate time domain features is essential [21]. Since the number of time domain features is

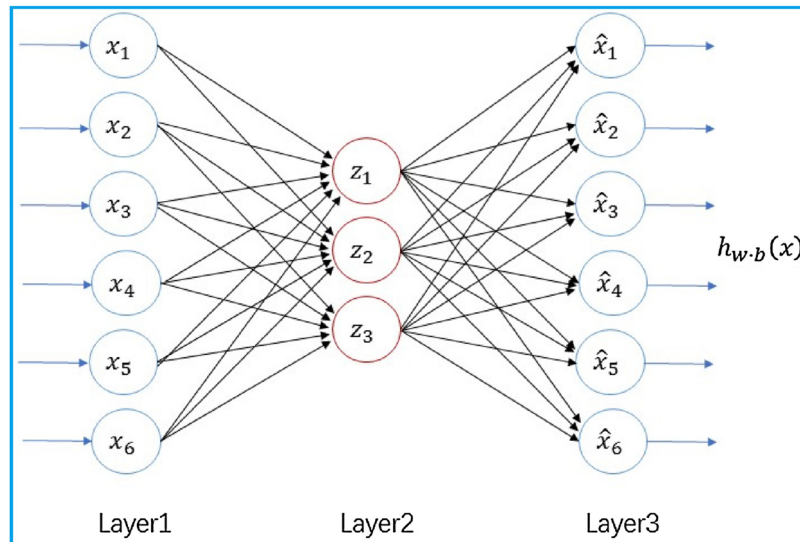


Fig. 1. Autoencoder network.

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