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Bearing remaining useful life estimation based on time–frequency representation and supervised dimensionality reduction

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ABSTRACT

The extraction of ideal age feature is a challenging task in vibration-based bearing remaining useful life (RUL) estimation. Aiming at this problem, a new approach is proposed on the basis of time–frequency representation (TFR) and supervised dimensionality reduction. Firstly, S transform and Gaussian pyramid are employed to obtain TFRs at multiple scales. Textural features of TFRs are used as the high-dimensional features. Then, a two-step supervised dimensionality reduction technique, i.e. principal component analysis (PCA) plus linear discriminant analysis, is employed to reduce the dimensionality, in which the target dimension and number of classes are taken as variable parameters. Finally, the simple multiple linear regression model is utilized to estimate the RUL. Experimental results indicate that the proposed approach outperforms the methods using traditional statistical features and/or PCA. Additionally, variable conditions of load and speed should be considered in the future to further improve the proposed approach.

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1. Introduction

Remaining useful life (RUL) estimation of bearings plays a crucial role in the condition based maintenance. Its significance can be explained in several aspects. First, bearings have always been considered to be a frequent cause of failures in rotating machinery [1]. Second, bearing RUL estimation can improve the reliability and operational safety of rotating machinery, decrease the breakdown and reduce the maintenance costs [2]. This point is extremely important especially for the critical assets which are not allowed to run to failure. Third, RUL estimation also has a crucial role in the management of bearing reuse, which means the reused bearings must have sufficient long lives left [3]. However, accurate estimation of bearing RUL is still a considerable challenge for both scientific and industrial researchers up to now.

In the literatures, the RUL estimation methods are roughly categorized into two types: model (or physics)-based approaches and data-driven models [4–6]. Model-based approaches describe the growth trend of a failure mode quantitatively using the physical laws, estimating the RUL of a component by solving one or a number of deterministic equations derived from empirical data [7]. However, it is often difficult to build accurate physical models for RUL estimation in the practical applications, especially when the mechanism of fault propagation is

Abbreviations: LBP, local binary pattern; LDA, linear discriminant analysis; MAE, mean absolute error; MAPE, mean absolute percentage error; PCA, principal component analysis; RMSE, root mean square error; RMS, root mean square; RUL, remaining useful life; STFT, short-time Fourier transform; TFR, time–frequency representation.

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complicated and/or has not been understood in depth [4]. Data-driven models, which adopted in this paper, employ collected condition data (*e.g.* lifetime data) and artificial intelligence or statistical tools to derive the model, and apply it to predict the RUL [5].

One of the key processes for robust data-driven RUL prediction is to extract representative features by the usage of appropriate signal processing techniques. Over the past decade, a number of features have been introduced for bearing RUL estimation. For instance, in the time domain, root mean square (RMS) and kurtosis are two of the widely used features for bearing fault diagnosis and prognostics [2,8,9]. Furthermore, 24 statistical features, including 11 features in time domain and 13 features in frequency domain, have been summarized in Ref. [10]. However, these features always have no obvious and stationary variation tendency until incipient fault or severe fault occurs. Moreover, previous researches have shown that many features may probably be only effective for a certain defect at a certain stage [11]. In recent years, time–frequency analysis techniques have received increasing interest due to their effectiveness in analyzing non-stationary and transient vibration signals. Wavelet packet node energy, which refers to the energy of each wavelet packet node, has been extensively used in various literatures [5,12]. Other statistical features can also be extracted similarly on the basis of wavelet packet transform or other advanced time–frequency analysis techniques, such as short-time Fourier transform (STFT), wavelet transform, Wigner–Ville distribution, empirical mode decomposition and ensemble empirical mode decomposition. Contrary to the above features, which have already been used for bearing fault diagnosis and directly further used for RUL estimation, a few novel features have been presented specially for bearing RUL prediction in recent studies. Ali et al. [2] proposed the RMS entropy estimator, to avoid the fluctuation of RMS which is undesirable for the prognostic task. Huang et al. [13] used the minimum quantization error derived from self-organizing map, which is trained by three time features and three frequency features. Loutas et al. [5] introduced Wiener entropy for the first time in the RUL prediction of rolling bearings. Zhang et al. [6] used the normalized cross correlation as a measure to evaluate the similarity of phase space trajectory. Boškoski et al. [1] employed Jensen-Rényi entropy based features to represent the condition of bearings. However, the dimensions of these features are always rather low, which mostly lower than 100 or even 10. As a result, the information contained in these features may be quite limited. There may be still a significant amount of useful information not represented by these features, which this paper refers to as the problem of information loss.

The curse of dimensionality has always been regarded as a serious problem in machine learning and statistics [14]. However, a new viewpoint has been proposed and validated in the field of face recognition that with sufficient training data and appropriate feature construction strategies, high dimensionality is able to lead to high performance [15]. One of the vital reasons is that the high-dimensional feature contains more useful information. Inspired by this viewpoint, this paper attempts to construct high-dimensional feature from vibration signals, trying to include as much as information of vibration signal in the proposed feature, so that the problem of information loss can be solved naturally.

It is important to note that the high-dimensional feature in this paper does not simply refer to the traditional high-dimensional features in the field of mechanical condition monitoring, although they can also be included. For example, Su et al. [16] extracted 72 features from the intrinsic mode functions generated by empirical mode decomposition and regarded the feature set as a high-dimensional feature. There is no fault since the high dimensionality is a relative concept. However, such a dimension is always not considered to be a high dimension in the current fields of statistical data analysis or image processing. Dimensions in thousands or more have already been widely used in real-world applications. For example, the famous scale invariant feature transform in image processing has 128 dimensions in each descriptor, and a single image can have hundreds or thousands of descriptors [17]. Furthermore, a new notion, *i.e.* Big Dimensionality, has been specially introduced recently [18]. Therefore, to distinguish from traditional understandings of dimensionality in condition monitoring, the high-dimensional feature in this paper has 25,600 dimensions, which is at least two orders of magnitude greater than most existing high-dimensional features in this field.

In this paper, textural feature of time–frequency representation (TFR) is used to construct the high-dimensional feature. Then, a two-step supervised dimensionality reduction technique, *i.e.* principal component analysis (PCA) + linear discriminant analysis (LDA) [15], is employed to reduce the dimensionality, which is expected to have a good performance in discovering common degradation laws from the training bearings. Finally, bearing RUL is estimated using the multiple linear regression (MLR) [19]. To emphasize the major innovations of this research, the proposed approach for feature extraction is abbreviated as TFR-LDA. In addition, the major work of this paper focuses on the construction and validation of the overall feature extraction scheme. The selection and optimization of concrete techniques in the steps are not studied in depth.

The remainder of this paper is organized as follows. Section 2 presents the detailed steps of the proposed feature extraction scheme. In this section, an in-depth discussion on the ideal age features of bearings is presented, and the techniques used in each step are explained in detail, which can be helpful for the further development of proposed feature extraction scheme. Section 3 presents the overall scheme of RUL estimation. Section 4 deals with the experimental verification. Discussions and suggestions for the future development are provided in Section 5. Finally, the conclusions of this paper are summarized in Section 6.

2. Feature extraction

Sudden degradation is the most existing type of bearing defects in industrial environments [20], which means the

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