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A new time–frequency method for identification and classification of ball bearing faults

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ABSTRACT

In order to fault diagnosis of ball bearing that is one of the most critical components of rotating machinery, this paper presents a time–frequency procedure incorporating a new feature extraction step that combines the classical wavelet packet decomposition energy distribution technique and a new feature extraction technique based on the selection of the most impulsive frequency bands. In the proposed procedure, firstly, as a pre-processing step, the most impulsive frequency bands are selected at different bearing conditions using a combination between Fast-Fourier-Transform FFT and Short-Frequency Energy SFE algorithms. Secondly, once the most impulsive frequency bands are selected, the measured machinery vibration signals are decomposed into different frequency sub-bands by using discrete Wavelet Packet Decomposition WPD technique to maximize the detection of their frequency contents and subsequently the most useful sub-bands are represented in the time-frequency domain by using Short Time Fourier transform STFT algorithm for knowing exactly what the frequency components presented in those frequency sub-bands are. Once the proposed feature vector is obtained, three feature dimensionality reduction techniques are employed using Linear Discriminant Analysis LDA, a feedback wrapper method and Locality Sensitive Discriminant Analysis LSDA. Lastly, the Adaptive Neuro-Fuzzy Inference System ANFIS algorithm is used for instantaneous identification and classification of bearing faults. In order to evaluate the performances of the proposed method, different testing data set to the trained ANFIS model by using different conditions of healthy and faulty bearings under various load levels, fault severities and rotating speed. The conclusion resulting from this paper is highlighted by experimental results which prove that the proposed method can serve as an intelligent bearing fault diagnosis system.

1. Introduction

In industrial milieu, the rotating machines have a special importance due to their large utilization in almost all applications. Hence, the maintenance of all their pieces is required to assure not only the successful operation of the rotating machine itself but also a successful continuation of the plant operation. Among the frequently encountered components in the vast majority of rotating machinery, bearings are one of the most crucial elements [1,2] that can cause about 40–50% of all failures of rotating machine [3–5]. Therefore, an improved quality of bearing fault diagnosis is needed in preventive

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maintenance scheduling or other actions in the production line in order to keep machinery operating at its best, avoid catastrophic damages, improve the reliability and availability of the machinery, and decrease downtime. However, the inspection of the bearing components is very difficult due to the disassembly problem and other possible hazards that are responsible for 27% of all bearing failures [2,6].

The nondestructive vibration analysis of the rotating systems is one of the most commonly used techniques that offer a real and best solution to bearings fault diagnosis. In fact, the vibration signal, such as displacement, acceleration and velocity, includes a very specific and predictable signature depending on the bearings condition [5,7,8] and thus, the analysis of these signals allows knowing the state of health of the bearings without dismantling. But, in order to automatically identify and classify the real state of the bearing element, an intelligent classification system is needed. For this aim, many of the modern machine learning tools such as the artificial neural network (ANN) [9], support vector machines (SVM) [10], adaptive neural-fuzzy inference system [11], etc., are currently used. However, these tools are limited by the problem of parameter estimation. In fact, if the number of parameters increases, the amount of data required to train the machine learning tool must increase to achieve satisfactory performance [12]. Thus, the use of the original measured signals that are defined as attributes or patterns as features to machine learning tool may be expensive, ineffective or even impossible because of their large dimensionality, high correlations and poor performance [12]. Hence, the modern diagnostic techniques passe generally through two steps which are feature calculation and selection or dimensionality reduction, and classification stage.

The first is the most important step in diagnostic approaches while consisting of extracting the features that are related to the faults evolution in order to give a reduced representation of the input vibration data before performing fault identification and classification. In the literature, intensive research on feature extraction for vibration monitoring was focused on the use of time domain, frequency domain and time-frequency domain techniques.

The time domain feature extraction techniques include statistical methods such as Peak value (PV), Root mean square (RMS); Crest factor (Crf), Kurtosis (Kv), Skewness (Sw), Entropy (E) [13,14] and Lempel-Ziv Complexity (LZC) [15,16]. However, due to nonlinear behaviors and unknown noises in machinery, these temporal indicators do not easily identify the real defect responsible of the degradation, and when the analyzed signals are not Gaussian, the extracted features are varying from sample to sample, which can generate the false alarms [17]. But, the intelligent classification systems based on significant statistical-time features that maximize the discrimination between the considered faults can give better results as in [14,18]. Moreover, the signal decomposing methods include empirical mode decomposition EMD, local characteristic-scale decomposition LCD, wavelet transform, filters and local mean decomposition LMD techniques associated with different statistical methods in time domain have also been applied to assist in bearing fault diagnosis [19–28]. Only if a good signal decomposing method is used, the general performance of the bearing fault diagnosis technique can be expected to improve.

The simplest frequency-domain analysis method used for bearing fault detection is the FFT technique that provides a frequency spectrum for vibration signal, performing the derivation of the characteristic frequencies of bearing faults [29,30]. Although that the frequency-domain analysis can provide more detailed information compared to time-domain analysis, the effectiveness of frequency analysis is strongly sensitive to nonstationary conditions. However, using a good choice of the statistical-frequency features, many works have used the intelligent classification systems with different signal decomposing methods to improve the performance of the fault diagnosis procedure in nonstationary conditions [26,31].

Also, when the frequency information of bearing fault changes over time, the time-frequency domain feature extraction techniques prove an advanced method for bearing fault diagnosis. However, these methods can cause a high-dimensional feature vector that can be a primary reason for classification accuracy degradation [32]. Thus, feature selection or dimensionality reduction is needed to find the most useful fault features that keep the intrinsic information about the defects. In the recent years, various intelligent classification systems based on many time–frequency techniques such as short-time Fourier transform [33–35], Wigner-Ville distribution [34,35], resonance demodulation technique [36], and continuous wavelet transform (CWT) [12,34,35,37] have been widely developed for monitoring the condition of bearing element in rotating machines with varying degrees of success. However, the main disadvantage of these approaches is the very high computational complexity.

The modern diagnosis techniques passe generally by a dimensionality reduction stage that has some very important benefits like, it reduces computational complexity of learning algorithms, saves time and improve performance by reducing the dimensionality of the input features to machine learning tool before performing fault identification and classification. In the literature, intensive research on feature dimensionality reduction for signal monitoring was categorized mainly into feature reduction and feature selection. Feature selection procedures that can be categorized into filter models and wrapper models aims to select a small subset from original features, whose goals includes facilitating data, reducing the measurement and storage requirements, reducing training times, minimizing redundancy and maximizing relevance to the target such as the class labels in classification. The filter model, as Relief [38], Fisher score [39] and Information Gain based methods [40], do not consider underlying classifier. Based on measurements of the general characteristics of the training data such as distance, consistency, dependency, information, and correlation, these methods which are computationally less expensive and also more generic than wrappers methods filter out insignificant features that have little opportunity to be useful in analysis of data. The wrapper model that is usually applied as a pre-processing step in machine learning tasks includes the predetermined classifier learning in the feature selection process, where the results of the prediction are used in order to determine the quality of selected features. The wrapper model is often computationally more expensive than the filter model, and its selected features are biased toward the classifier used. In fact, for a large number of features, the wrapper model is prohibitively expensive to run and can break down [41]. On the other hand, the feature extraction approach such as Principal Component Analysis PCA, LDA, Locally Linear Embedding LLE and Locality Preserving Projections