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Gearbox fault diagnosis based on deep random forest fusion of acoustic and vibratory signals

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ABSTRACT

Fault diagnosis is an effective tool to guarantee safe operations in gearboxes. Acoustic and vibratory measurements in such mechanical devices are all sensitive to the existence of faults. This work addresses the use of a deep random forest fusion (DRFF) technique to improve fault diagnosis performance for gearboxes by using measurements of an acoustic emission (AE) sensor and an accelerometer that are used for monitoring the gearbox condition simultaneously. The statistical parameters of the wavelet packet transform (WPT) are first produced from the AE signal and the vibratory signal, respectively. Two deep Boltzmann machines (DBMs) are then developed for deep representations of the WPT statistical parameters. A random forest is finally suggested to fuse the outputs of the two DBMs as the integrated DRFF model. The proposed DRFF technique is evaluated using gearbox fault diagnosis experiments under different operational conditions, and achieves 97.68% of the classification rate for 11 different condition patterns. Compared to other peer algorithms, the addressed method exhibits the best performance. The results indicate that the deep learning fusion of acoustic and vibratory signals may improve fault diagnosis capabilities for gearboxes.

1. Introduction

Gearboxes have been widely used as key machine components for delivering torque and providing speed conversions from some rotating power sources to other devices. Any failures in gearboxes may introduce unwanted downtime, expensive repair procedures and even human casualties. As an effective component for condition-based maintenance [1], the fault diagnosis has gained much attention in order to guarantee safe operations of gearboxes.

Gearbox conditions can be reflected by measurements of vibratory [2], acoustic [3], thermal [4], electrical [5], and oil-based signals [6]. In vibration-based gearbox fault diagnostics, Cheng et al. [7] proposed an order tracking technique using local mean decomposition of the vibration signal for gear fault diagnosis. Wang et al. [8] used wavelet decomposition for robust health evaluation of gearbox subject to tooth failure. Lei et al. [9] analyzed vibration characteristics in both time and frequency domains for the diagnostics of the planetary gearboxes. In addition to vibratory signals, acoustic ones are also

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sensitive to the existence of gearbox faults. Li et al. [10] applied adaptive morphological gradient lifting wavelet to detect gear fault. Chacon et al. [11] used acoustic emission (AE) to detect shafts angular misalignments. Hamel et al. [12] researched the influence of the oil film thickness on helical gearboxes fault detection via the AE signal. Abad et al. [13] applied acoustic signals for gearboxes fault detection using the discrete wavelet transform and artificial neural networks.

To explore different symptoms for gearboxes fault diagnosis, Rafael et al. [14] combined acoustic emissions and vibration measurements to detect gearbox failures. Li et al. [15] used fault features from vibration and acoustic emission signals for gearboxes fault detection using the K-nearest neighbor (KNN) algorithm. The combined vibratory and AE signature was suggested by Soua et al. [16] as a pre-requisite for condition monitoring of a wind turbine gearbox. Khazaee et al. [17] developed a fault classifier using data fusion of the vibration and the acoustic signals for planetary gearboxes using the Dempster–Shafer evidence theory.

Usually, gearboxes are operated within harsh environments with heavy noises and interferences. For better diagnosis performance, therefore, the fault-sensitive features should be extracted from raw signals. An optimal mathematical morphology demodulation technique was reported by Li and Liang [18] to extract the impulsive feature for bearing defect diagnosis. Raad et al. [19] employed the cyclostationarity as an indicator to the diagnostics of the gears. A criterion fusion approach was reported by Li et al. [20] to optimal demodulation of vibration signals. Chen et al. [21] proposed an intelligent diagnosis model including wavelet support vector machines and immune genetic algorithms for gearboxes. A generalized synchrosqueezing transform was developed to diagnose gearbox faults and bearing defects [22,23]. To reduce the dimensionality of data, Hinton and Salakhutdinov [24] developed a deep leaning framework, and further applied to feature extraction [25], classification [26], regression [27] for images, signals, and time series. Under deep learning framework, deep belief networks were introduced to diagnose reciprocating compressor valves [28] and gearboxes [29]. A deep belief learning based health state classification was applied for different dataset such as iris dataset and wine dataset [30]. The researches indicate that deep learning is capable of better extracting features compared to traditional learning approaches.

The existing reports directly applied deep learning for the fault diagnosis using one signal. In this work we propose the fusion of acoustic and vibratory signals as a fault diagnostics tool for gearboxes using a deep random forest fusion (DRFF) technique. The fault-sensitive features of such signals are extracted using the statistical parameters of the wavelet packet transform (WPT) and deep learning with deep Boltzmann machines (DBMs). Instead of a traditional combination of the two signals, we suggest random forest (RF) as a data fusion tool for the integration of the deep feature representations. With deep learning feature representations and data fusion strategies, this work improves the performance of gearbox fault diagnosis, which is validated by experiments and comparisons with peer techniques.

The structure of the paper is presented as follows. Deep representations of the AE and the vibratory features using WPT and DBM are introduced in Section 2. In Section 3, the RF is proposed to fuse deep representations of the AE and the vibratory features in an integrated fashion; the application of the proposed DRFF method to the gearbox fault diagnosis is also detailed in this section. In Section 4, the gearbox fault diagnosis experiments are carried out to evaluate the present approach. Finally, conclusions are given in Section 5.

2. Deep learning for the condition feature representations

2.1. WPT statistical parameters of the gearbox condition measurements

The operating condition of a gearbox can be determined using measurements from different sensors. In this research, both the AE sensor and the accelerometer are defined as the gearbox measurements $x(t)$ as

$$x(t) = \{x^{(1)}(t), x^{(2)}(t)\}, \tag{1}$$

where $x^{(1)}(t)$ and $x^{(2)}(t)$ denote the acoustic and the vibratory signals, respectively. The gearbox condition measurements can be decomposed into different depths using the WPT as [31]

$$Wx_n(j,k) = \langle x(t), \mu_n(t,j,k) \rangle = \int_{-\infty}^{+\infty} x(t)\mu_n(t,j,k)\mathrm{d}t. \tag{2}$$

where $\langle *,* \rangle$ denotes the inner product operator, μ_n the n-th wavelet packet function (n=0,1,2,…2^j), j the level and k the wavelet coefficient. The gearbox condition can be reflected by the information included in different wavelet packet nodes. Usually, statistical parameters are good indicators for extracting the condition information. In this research, the following statistical parameters for each node are used [32]

$$S_1(j,n) = \frac{\max|Wx_n(j,k)|}{\sqrt{\frac{1}{K}\sum_{k=1}^{K}(Wx_n(j,k))^2}}, S_2(j,n) = \frac{\sqrt{\frac{1}{K}\sum_{k=1}^{K}(Wx_n(j,k))^2}}{\frac{1}{K}\sum_{k=1}^{K}|Wx_n(j,k)|}, S_3(j,n) = \frac{1}{K}\sum_{k=1}^{K}|Wx_n(j,k)|,$$

$$S_4(j,n) = \left(\frac{1}{K}\sum_{k=1}^{K}\sqrt{|Wx_n(j,k)|}\right)^2, S_5(j,n) = \frac{1}{K}\sum_{k=1}^{K}(Wx_n(j,k))^4, S_6(j,n) = \frac{1}{K}(Wx_n(j,k))^2,$$

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