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Multimodal deep support vector classification with homologous features and its application to gearbox fault diagnosis

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A B S T R A C T

Gearboxes are crucial transmission components in mechanical systems. Fault diagnosis is an important tool to maintain gearboxes in healthy conditions. It is challenging to recognize fault existences and, if any, failure patterns in such transmission elements due to their complicated configurations. This paper addresses a multimodal deep support vector classification (MDSVC) approach, which employs separation–fusion based deep learning in order to perform fault diagnosis tasks for gearboxes. Considering that different modalities can be made to describe same object, multimodal homologous features of the gearbox vibration measurements are first separated in time, frequency and wavelet modalities, respectively. A Gaussian-Bernoulli deep Boltzmann machine (GDBM) without final output is subsequently suggested to learn pattern representations for features in each modality. A support vector classifier is finally applied to fuse GDBMs in different modalities towards the construction of the MDSVC model. With the present model, "deep" representations from "wide" modalities improve fault diagnosis capabilities. Fault diagnosis experiments were carried out to evaluate the proposed method on both spur and helical gearboxes. The proposed model achieves the best fault classification rate in experiments when compared to representative deep and shallow learning methods. Results indicate that the proposed separation–fusion based deep learning strategy is effective for the gearbox fault diagnosis.

1. Introduction

Gearboxes are key components in mechanical transmission systems. A gearbox fault may result in unwanted fatal breakdowns, production losses and even human casualties [1]. Hence any gearbox's defective components such as gears, bearings, and shafts should be diagnosed as early as possible [2]. Due to complicated configuration of the gearbox, it is challenging to recognize fault existences and, if any, the failure patterns.

Three basic steps are commonly used to diagnose gearbox fault patterns. The first one is to choose condition symptoms for the gearbox to be diagnosed. Such condition symptoms as vibration, acoustic, oil debris, electrical current, and heat measurements have been used for the gearbox fault diagnosis [3–5]. Within these symptoms, vibration analysis is the most commonly-used technique for condition monitoring and performance monitoring [6,7]. Although the vibration signal can be combined with other signals for failure recognition [8], in most cases only vibration measurements are used due to their cheap expense and simple implementation.

As condition symptoms are often confused by noises and interferences, raw signal of vibration measurements are usually insensitive to component defects, especially to incipient faults which are present at the early stage [9]. There, a second step to determine failure-sensitive features is usually needed and applied. In vibration based fault diagnosis, the most commonly-used features have been generated from temporal, spectral, wavelet [10–12], and other signal representations. Such different representations can be regarded as different observations of the vibration signal, and from a specific point of view each observation is a modality of the vibration signal [13]. Although they come from the same source, i.e., the vibration signal, different modalities may lead to different sensitivities for failure patterns [14]. In the time modality, Raad et al. [15] employed cyclostationarity as an indicator for gear diagnosis. In the frequency modality, Li and Liang [16] suggested an optimal mathematical morphology demodulation technique to extract impulsive feature for bearing defect diagnosis. In the wavelet modality, different statistical parameters have been introduced to classify fault patterns [17]. Features with different modalities have been reported effective for the fault

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diagnosis, but none of the modality can outperform others in all cases. Hence, some researchers suggested to observe the fault information in wider fashion, i.e., with multiple modalities. For instance, two diagnostic parameters from both time and frequency modalities have been reported for planetary gearbox diagnosis based on the examination of vibration characteristics [18].

With the extraction of defect-sensitive features by using one or more modalities, it is still not easy to specify a condition pattern due to the similarity between different fault patterns. For real applications, engineers may employ the diagnosed fault pattern information to prepare special measures for gearbox maintenances. Hence, building an effective classifier is always the third required step used by the fault diagnosis community. Tayarani-Bathaie et al. [19] developed a dynamic neural network as a classifier for gas turbine fault diagnosis. Guo et al. [20] suggested using a support vector machine in collaboration with envelope spectrum analysis to classify three health conditions of planetary gearboxes. For the gearbox fault diagnosis, Chen et al. [21] proposed an intelligent diagnosis model based on wavelet support vector machine and immune genetic algorithm. Among all the typical classifiers, the support vector classification (SVC) family (i.e., the standard SVC and its variants) attracted much attention due to its extraordinary classification performance. Recently, different data-driven approaches have been used for industrial processes [22,23]. The most popular and traditional classifiers are belong to "shallow" learning category [24]. Comparing with conventional methods, deep learning received great success in the classification due to its "deeper" representations for faulty features. Up to now, different deep learning networks such as deep belief network [25], deep Boltzmann machines (DBMs) [26], deep autoencoders [27], and convolutional neural networks [28] have been reported; however, few have been used for fault diagnosis cases. Tran et al. [29] introduced the application of the deep belief networks to diagnose reciprocating compressor valves. Tamilselvan and Wang [30] employed the deep belief learning based health state classification for iris dataset, wine dataset, Wisconsin breast cancer diagnosis dataset, and Escherichia coli dataset. Limited reports show deep learning structures for the fault diagnosis using one-modality features.

The deep learning represents an object in a "deep" style, while multiple modalities can observe the object in a "wide" fashion. This philosophy inspires the authors to propose here a multimodal deep support vector classification (MDSVC) with homologous features for the gearbox fault diagnosis. From the real world point of view, the fault diagnosis has been applied for different industrial cases. For the gearboxes, it is helpful for detecting the early defects and monitoring the healthy conditions [31,32]. The proposed method is capable of improving diagnosis accuracy from limited vibration signal sources. Although with greater computational burden during model training by the deep learning, application procedure using the trained model is time-saving. The proposed method employs a separation–fusion based deep learning strategy. Due to limited availability of vibration signals, one vibration measurement of a gearbox can be represented in time, frequency and wavelet modalities, separately. In each modality, a Gaussian-Bernoulli deep Boltzmann machine (GDBM), without final output, is suggested to learn the pattern information from homologous features. To integrate "wide" modalities with "deep" learning, a SVC is applied to fuse the GDBMs in different modalities as the MDSVC model. The proposed model is evaluated in gearbox fault diagnosis experiments and is compared with other state-of-the-art shallow and deep learning methods.

The rest of this paper is organized as follows. The MDSVC approach and its elements are introduced in Section 2. Section 3 presents in detail the application of the present MDSVC model to the gearbox diagnosis. In Section 4, fault diagnosis experiments based on two gearbox set-ups are carried out to evaluate the proposed method. Finally, some conclusions are addressed in Section 5.

2. Multimodal deep learning with support vector classification

In this section, deep learning with the GDBM is first introduced. For better accommodating multiple modalities of homologous features, a multimodal structure is subsequently proposed. To combine outputs of a multimodal structure, a data fusion technique based on the SVR is suggested for developing the MDSVC model.

2.1. Deep learning with GDBM classifier

The deep learning with different networks have claimed state-of-the-art performances in different tasks. The deep learning tries to hierarchically learn deep features from input data with very deep networks. The deep network is usually layer-wise initialized with unsupervised training, followed by supervised fine-tuning for the whole model. In this way, more abstract and complex features can be extracted at higher layers. Appropriate features can be therefore formulated for the classification at the top of the model.

Recent researches indicate that deep learning models are capable of producing better approximation for nonlinear functions comparing to "shallow" models. The DBM is a prominent type of the deep learning model. For a DBM, each layer represents complicated correlations between hidden features in the layer below. Hence the DBM has the potential of learning internal representations that become increasingly complex, highly desirable for solving different classification tasks. In this paper, therefore, the DBM is chosen as the basic network for our MDSVC model.

The standard DBM is a network of symmetrically couple stochastic binary neurons. As shown in Fig. 1, a single visible layer $\mathbf{v}$ and L hidden layers $\mathbf{h}^{(1)},\ldots, \mathbf{h}^{(l)}, \ldots$, and $\mathbf{h}^{(L)}$ contribute a DBM network, where the connections are only allowed between the visible neurons and the first hidden ones, as well as between hidden neurons in adjacent hidden layers. The energy E of the state $\{\mathbf{v}, \mathbf{h}^{(1)}, \ldots, \mathbf{h}^{(L)}\}$ is defined as [33]

$$E(\mathbf{v}, \mathbf{h}^{(1)}, \ldots, \mathbf{h}^{(L)} \mid \theta) = -\sum_{i=1}^{N_v}\sum_{j=1}^{N_1} W_{ij} v_i h_j^{(1)} - \sum_{i=1}^{N_v} b_i v_i - \sum_{i=1}^{N_v}\sum_{j=1}^{N_l} b_j^{(l)} h_j^{(l)} - \sum_{i=1}^{L-1}\sum_{j=1}^{N_l}\sum_{k=1}^{N_l+1} w_{jk}^{(l)} h_j^{(l)} h_k^{(l+1)}, \quad (1)$$

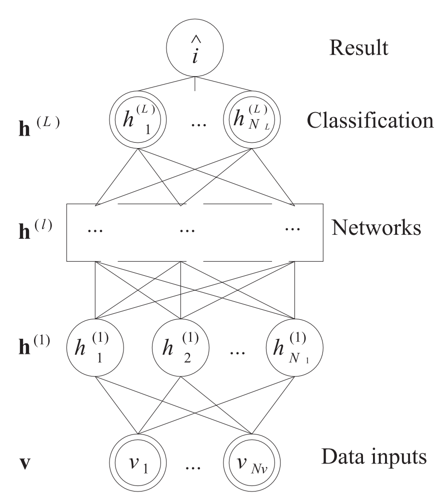

Fig. 1. Structure of the GDBM classifier.