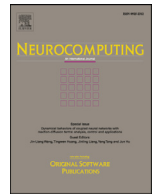




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A robust intelligent fault diagnosis method for rolling element bearings based on deep distance metric learning

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ABSTRACT

Intelligent data-driven fault diagnosis methods for rolling element bearings have been widely developed in the recent years. In real industries, the collected machinery signals are usually exposed to environmental noises, and the bearing operating condition changes in different working scenarios. That leads to distribution discrepancy between the labeled training data and the unlabeled testing data, and consequently the diagnosis performance deteriorates. This paper proposes a novel deep distance metric learning method for rolling bearing fault diagnosis based on deep learning. A deep convolutional neural network is used as the main architecture. Based on the learned representations through multiple hidden layers, a representation clustering algorithm is proposed to minimize the distance of intra-class variations and maximize the distance of inter-class variations simultaneously. A domain adaptation method is adopted to minimize the maximum mean discrepancy between training and testing data. In this way, the robustness of the fault diagnosis method can be significantly improved against noise and variation of working condition. Extensive experiments on a popular rolling bearing dataset are carried out to validate the effectiveness of the proposed method, and the diagnosis performance is widely evaluated in different scenarios. Comparisons with other approaches and the related works on the same dataset demonstrate the superiority of the proposed method. The experimental results of this study suggest the proposed deep distance metric learning method offers a new and promising tool for intelligent fault diagnosis of rolling bearings.

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1. Introduction

Rolling element bearings are one of the most critical components in rotating machines. Since the unexpected failures of rolling bearings usually result in serious loss of safety, production delays and large costs of maintenance in modern industries [1], accurate and timely fault diagnosis of them has always been highly demanded, and received increasing research attention in the past decades [2–8]. While the traditional signal processing methods such as wavelet analysis [2,3], stochastic resonance techniques [4,9,10] etc. have achieved satisfactory diagnosis results based on machinery vibration data [5–8], intelligent fault diagnosis methods are becoming more and more popular nowadays since they do not require prior expertise and can efficiently provide reliable diagnosis results [11–16].

In the past years, a large number of intelligent fault diagnosis methods have been proposed based on machine learning and statistical inference techniques, such as artificial neural networks (ANN) [11,12,17], support vector machines (SVM) [15,16], random forest (RF) [18], fuzzy inference and other improved algorithms [13,14]. Generally, neural networks are one of the most popular data-driven methods to identify faulty and healthy machine conditions, where fault diagnosis is treated as a classification problem through feature extraction. Especially, deep learning has recently emerged as a highly effective network architecture for pattern recognition, that holds the potential to overcome the obstacles in the current intelligent fault diagnosis. Deep learning is characterized by the deep network structure where multiple layers are stacked in the network to fully explore the collected signal information [19]. High level abstract data representations can be efficiently learned through multiple linear and non-linear transformations for machine health condition classification. In general, better diagnosis results have been obtained comparing with shallow architectures [20–26].

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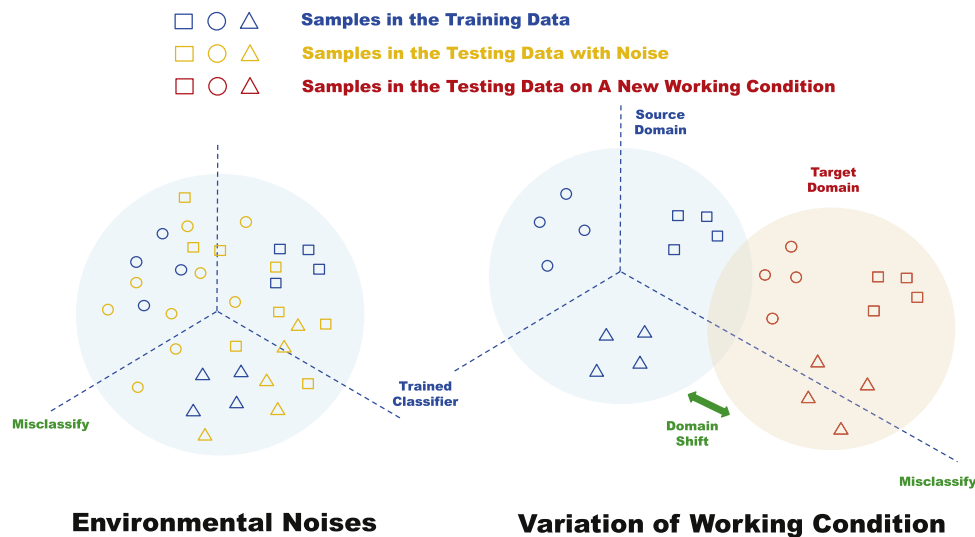


Fig. 1. Illustration for bearing fault diagnosis problem with environmental noises and variation of working condition.

Most data-driven methods for fault diagnosis are currently implemented under the assumption that training and testing data are subject to the same distribution. However, in real industries, environmental noise and variation of machine operating condition inevitably make the distributions of training and testing data different from each other and consequently, it is difficult for the well-trained neural network to generalize the learned pattern knowledge from the labeled training data, denoted as *source domain*, to the new unlabeled testing data, denoted as *target domain*. This challenge of pattern learning validity is known as the domain shift problem [27] and therefore, one of the main challenges for intelligent fault diagnosis is the robustness of the algorithm [28] against domain shift.

Fig. 1 presents an illustration of the domain shift problem. In general, the deep architecture can be effectively trained and performs excellent machine health condition classifications on the source domain. However, due to interference of noise and variation of working situation, domain shift phenomenon may significantly deteriorate the network classification performance on the target domain. In real-world industries, such problem is very common since rotating machines are subject to random environmental noises all the time during operations [28]. Moreover, the labeled vibration data for model training are usually collected under one working load of rolling bearings, but testing data are possibly from different working loads and thus subject to new distributions. The distribution discrepancy poses an obstacle in adapting the well-trained models across domains. The signal characteristics may change remarkably for different working scenarios even with the same bearing fault.

Generally, applying the learned fault patterns on new data distributions requires specific customization to accommodate the new domain information. One straight-forward solution is by the means of collecting a certain number of labeled data in the target domain for training. However, that is very expensive and almost impossible in many cases. As an alternative way, the available labeled source domain data and unlabeled target domain data can be further explored to calibrate the established model, that is relatively easy to be carried out in real-world applications.

In order to address the aforementioned domain shift problem and enhance the algorithm robustness, this paper proposes a novel deep distance metric learning method. Recent machine learning-based studies show that learning a distance metric from the available data has large potential to achieve promising results,

compared with the use of hand-crafted distance metrics [29,30]. In the past years, a number of metric learning methods have been successfully developed and applied in many research tasks such as person re-identification [31], human activity recognition [32], image classification [29,30] and so forth.

In this study, as Fig. 1 shows, higher diagnosis accuracies are expected to be obtained if the distribution discrepancy between training and testing data is minimized and data samples belonging to the same fault type cluster better. Therefore, two techniques of distance metric learning are proposed in this paper to improve the model generalization ability, i.e. representation clustering [33–35] with respect to different fault types and domain adaptation, which is a particular case of transfer learning that leverages labeled data in the source domain to learn a classifier for unlabeled data in the target domain [27]. In the recent years, advanced representation clustering methods have been successfully developed [36–38], and domain adaptation has also attracted much research attention [39,40]. The scheme of the two techniques are illustrated in Fig. 2.

While promising results have been achieved by deep distance metric learning, limited researches can be found with respect to its application on machinery fault diagnosis. An adaptive batch normalization method was proposed by Zhang and colleagues [39] to improve the cross-domain fault diagnosis performance of neural network. Lu et al. [40] proposed a deep neural network-based domain adaptation method for diagnosis, where the feature maximum mean discrepancy (MMD) is minimized, and a weight regularization term is used to strengthen the representative features. Xie et al. [41] addressed the cross-domain feature extraction and fusion from time and frequency-domain with spectrum envelop pre-processing and time domain synchronization average principle using transfer component analysis (TCA).

This paper proposes a novel data-driven fault diagnosis method for rolling bearings based on deep convolutional neural network. Industrial domain shift problem due to environmental noise and variation of working condition is addressed using deep distance metric learning algorithm. Labeled source domain data for training and unlabeled target domain data for testing are assumed to be available. Different from existing researches, an integrated optimization objective function is used to enhance the generalization ability of the proposed method to new data distribution, which consists of classification error, domain discrepancy, and inter-class and intra-class representation distance optimization. Experiments

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