Mechanical Systems and Signal Processing 100 (2018) 439–453

Contents lists available at ScienceDirect

Mechanical Systems and Signal Processing

journal homepage: www.elsevier.com/locate/ymssp

A deep convolutional neural network with new training methods for bearing fault diagnosis under noisy environment and different working load

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ARTICLE INFO

Article history:
Received 25 January 2017
Received in revised form 16 June 2017
Accepted 19 June 2017

Keywords:
Intelligent fault diagnosis
Convolutional neural networks
Load domain adaptation
Anti-noise
End-to-end

ABSTRACT

In recent years, intelligent fault diagnosis algorithms using machine learning technique have achieved much success. However, due to the fact that in real world industrial applications, the working load is changing all the time and noise from the working environment is inevitable, degradation of the performance of intelligent fault diagnosis methods is very serious. In this paper, a new model based on deep learning is proposed to address the problem. Our contributions of include: First, we proposed an end-to-end method that takes raw temporal signals as inputs and thus doesn't need any time consuming denoising preprocessing. The model can achieve pretty high accuracy under noisy environment. Second, the model does not rely on any domain adaptation algorithm or require information of the target domain. It can achieve high accuracy when working load is changed. To understand the proposed model, we will visualize the learned features, and try to analyze the reasons behind the high performance of the model.

1. Introduction

Machine health monitoring is of great importance in modern industry. Failure of these machines could cause great economical loss, and sometimes poses threats to the people who work with the machines. Therefore, in order to keep the industrial machines working properly and reliably, demand for better and more intelligent machine health monitoring technique has never ceased [1–3]. Rolling element bearings are the core components in rotating mechanism, whose health conditions, for example, the fault diameters in different places under different loads could have enormous impact on the performance, stability and life span of the mechanism. The most common way to prevent possible damage is to implement a real-time monitoring of vibration when the rotating mechanism is in operation [4,5].

In recent years, Deep Learning techniques have achieved huge success in Computer Vision [6,7] and Speech Recognition [8,9]. Some deep learning techniques have already found their way into machine health monitoring systems. Lu et al. presented a detailed empirical study of stacked denoising autoencoders with three hidden layers for fault diagnosis of rotary machinery components [10]. In their work, they evaluated the effects of receptive input size, deep structure, sparsity constraint and denoising operation on the performance. Some researchers focused on AE models using frequency domain features as inputs instead of AE models directly fed with raw signals. Jia et al. fed the frequency spectra of time-series data

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http://dx.doi.org/10.1016/j.ymssp.2017.06.022
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into SAE for rotating machinery diagnosis [11], because frequency spectra may better discriminate the health conditions of rotating machinery. Zhu et al. proposed a SAE based DNN for hydraulic pump fault diagnosis that uses frequency features generated by Fourier transform [12]. Liu et al. uses normalized spectrum generated by STFT of sound signal as inputs of a 2-layer SAE based DNN. Some researchers [13,14] feed multi-domain statistical features including time domain features, frequency domain features and time-frequency domain features into SAE as a way of feature fusion.

Convolutional neural networks or CNNs are first proposed by LeCun [15], which aims at processing data with known grid-like shape, such as 2D image data, or 1D time-series data. In recent years, CNNs have been successfully applied to image recognition. Many CNNs architectures such as VGG-net [16], Res-net [17] and inception v4 [18] are proposed. However, these CNNs are not compatible with 1-D vibration signals. For example, all those models use two successive $3 * 3$ convolutional layers, which can gain a receptive region of the same size with that of a $5 * 5$ convolutional kernel while using only $2 * 3 * 3$ weights. However, for 1-D signal, two $3 * 1$ convolutional layers have a $5 * 1$ receptive region at the price of $2 * 3$ weights. Besides, for inception v4, successive $1 * 7$ and $7 * 1$ convolutional layers are used, but for 1-D vibration signal, $7 * 1$ convolutional operation can't be performed. The comparisons above show that classical 2-D CNN model may lose its advantages on 1-D signals. Therefore, a new CNN model is necessary for 1-D vibration signal. Since 2015, CNN has been used for fault diagnosis. Janssens et al. used a shallow structure with one convolutional layer ($2 * 64 * 32$) and one fully-connected layer (200 neurons) to diagnose bearing health conditions [19], whose input is the DFT of normalized vibration signal collected by two accelerators placed perpendicular to one another, and the outputs are four classification categories representing Healthy bearing (HB), Mildly inadequately lubricated bearing (MILB), Extremely inadequately lubricated bearing (EILB), and Outer raceway fault (ORF), respectively. Abdeljaber et al. proposed a method to detect and localize structural damage using 1D CNN [20]. The experiment was conducted using QU grandstand simulator, with 30 accelerometers installed on the main girders at the 30 joints. In this paper, an adaptive 1D CNN architecture is devised in order to fuse feature extraction and learning (damage detection) phases of the raw accelerometer data. In [21], we proposed a 5-layer WDCNN model with large first-layer kernels and small following kernels to diagnose the fault of bearings with huge number of training data, which can achieve high accuracy even in noisy environment.

However, currently in the field of fault diagnosis, the study of Deep Learning technique usually focused on how to use less training samples to learn more information, so that it can achieve higher performance than traditional Machine Learning algorithms [11,22,23]. However, this is not consistent with real world situation where in industry, it's easy to acquire large amount of data, and also with the help of data augmentation technique [24], we can further increase the size of training samples. Since the amount of data is no longer a problem, no matter we use traditional algorithms or deep learning algorithm, almost all of them can reach nearly 100% accuracy. Therefore, more attention should be paid on the adaptation ability of the algorithm in real world industrial environment. In the field of fault diagnosis, algorithm's adaptability can be evaluated in two aspects: First, when the working load of a machine is changed, can the model trained under one working load still achieve high accuracy if it is tested on samples from another working load [25,26]? Second, since noise is an evitable problem, then can the model trained with samples that has no noise achieve high accuracy when testing on noisy samples [27,28]? In the experiments in following sections, it is shown that even the state-of-the-art DNN [11] fails to diagnose properly in noisy environment, and the performance of our former model WDCNN decreases rapidly without the help of AdaBN algorithm which requires statistical knowledge of the whole test data. Therefore, we can see that currently, Deep Learning models have not solved this problem yet.

In order to address the problems above, in this paper, we proposed a method named Convolution Neural Networks with Training Interference (TICNN). The contributions of this paper are summarized below.

(1) We proposed a novel and simple learning framework with tricks that are easy to implement, and this model works directly on raw temporal signals.
(2) This algorithm performs pretty well under the noisy environment, and works directly on raw noisy signals without any pre-denoisng methods.
(3) This proposed algorithm has strong domain adaptation capacity, and therefore can achieve high accuracy under different working load.
(4) We try to explore the inner mechanism of proposed TICNN model in mechanical feature learning and classification by visualizing the feature maps learned by TICNN.

The remainder of this paper is organized as follows. A brief introduction of CNN is provided in Section 2. The intelligent diagnosis method based on TICNN is introduced in Section 3. Some experiments are conducted to evaluate our method against some other methods. After this, visualization about the proposed model is presented in Section 4. We draw the conclusions and the future work in Section 5.

2. Convolutional neural network with batch normalization

Convolutional neural network is a multi-stage neural network which consists of some filter stages and one classification stage [26]. The filter stage is used to extract features from the inputs, which contains four kinds of layers, the convolutional