Mechanical Systems and Signal Processing 110 (2018) 349–367

Contents lists available at ScienceDirect

Mechanical Systems and Signal Processing

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

Deep normalized convolutional neural network for imbalanced fault classification of machinery and its understanding via visualization

Feng Jia, Yaguo Lei *, Na Lu, Saibo Xing

State Key Laboratory for Manufacturing Systems Engineering, Xi'an Jiaotong University, Xi'an, Shaanxi 710049, China

ARTICLE INFO

Article history:
Received 28 July 2017
Received in revised form 9 March 2018
Accepted 12 March 2018

Keywords:
Deep learning
Convolutional neural network
Imbalanced classification
Visualization
Intelligent fault diagnosis

ABSTRACT

Deep learning has attracted attentions in intelligent fault diagnosis of machinery because it allows a deep network to accomplish the tasks of feature learning and fault classification automatically. Among deep learning models, convolutional neural networks (CNNs) are able to learn features from mechanical vibration signals and thus several studies have applied CNNs in intelligent fault diagnosis of machinery. However, these studies suffer from the following weaknesses. (1) The imbalanced distribution of machinery health conditions is not considered. (2) What CNNs have learned is not clear. Therefore, in this paper, a framework called deep normalized convolutional neural network (DNCNN) is proposed for imbalanced fault classification of machinery to overcome the first weakness. Meanwhile, neuron activation maximization (NAM) algorithm is developed to handle the second weakness. To verify the proposed methods, three bearing datasets containing single faults and compound faults are constructed with different imbalanced degrees. The classification accuracies of the three datasets demonstrate that DNCNN is able to deal with the imbalanced classification problem more effectively than the commonly used CNNs. By analyzing the kernels of the convolutional layers of DNCNN via NAM algorithm, we find that these kernels act as filters and they become complex when the layers go deeper. This result may help us understand what DNCNN has learned in intelligent fault diagnosis of machinery.

1. Introduction

In modern industries, machinery becomes more automatic and sophisticated than ever before. Incipient faults in any location of the machinery could produce chain reaction and lead to its damage [1–3]. Aiming to inspect the health conditions of the machinery comprehensively, massive signals are acquired by the mounted sensors after the long-time collection [4]. Since intelligent fault diagnosis methods are able to process these massive signals and recognize the health conditions of the machinery automatically, lots of efforts have been made to study these methods. Asr et al. [5] designed a feature extraction method using empirical mode decomposition and fed the extracted features into non-naive Bayesian classifier for intelligent fault diagnosis of rotating machinery. A symbolic aggregate approximation framework was proposed by Georgoulas et al. [6] to extract features from bearing signals and the nearest neighbor classifier was employed to classify the faults. Xiong et al.

* Corresponding author.
E-mail address: yaguolei@mail.xjtu.edu.cn (Y. Lei).

https://doi.org/10.1016/j.ymssp.2018.03.025
0888-3270/

[7] considered that the vibration signals of bearings present multifractal properties, and thus they applied multifractal detrended fluctuation analysis to extract multifractal features for intelligent fault diagnosis of bearings. Based on the dynamic characteristics of gearbox signals, Li et al. [8] applied symbolic dynamic entropy features to extract features of the gearbox signals and applied support vector machine to recognize the health conditions. Considering that the amplitudes of the carrier rotating frequency and the difference spectrum would change when a fault occurs in gearboxes, Lei et al. [9] designed two features for the gearboxes specifically and fed these features into relevance vector machine to recognize the health conditions of the gearboxes.

Through literature review, it can be found that the prior studies of intelligent fault diagnosis have two main steps: feature extraction and fault classification. In the step of feature extraction, the researchers should first analyze the signals collected from machinery and understand the properties of the signals, and then design the suitable features according to the specific diagnosis issue. Such feature designing processes make full use of human knowledge in signal processing techniques and diagnostic expertise, but consume much human labor. In order to change this situation, it would be desirable to use advanced artificial intelligence techniques to accomplish the tasks of feature learning and fault classification automatically. Therefore, deep learning is introduced into the intelligent fault diagnosis of machinery [10–12].

Among the deep learning models [13,14], convolutional neural networks (CNNs) are suitable to learn features from mechanical vibration signals because of their ability in handling the periodic signals. Therefore, the researchers have applied CNNs in intelligent fault diagnosis of machinery. For instance, Janssens [15] applied a CNN to learn features from the spectra of bearings and classify their health conditions. Based on multi-source data, Lee et al. [16] used CNNs to diagnose the faults in semiconductor manufacturing processes. Guo et al. [17] proposed a CNN based method for intelligent fault diagnosis of bearings and showed its advantages compared with the diagnosis methods using manual features. Wang et al. [18] presented an adaptive deep convolutional neural network for feature learning and fault classification of bearings. Ding et al. [19] first transformed the vibration signals into wavelet packet image and then used a CNN to recognize the health conditions of bearings. Through the analysis of these studies, it can be found that the intelligent fault diagnosis methods based on CNNs have two weaknesses as follows.

(1) The imbalanced distribution of machinery health conditions is not considered. In real cases, the machinery works under normal condition in most of its operating phases, and the faults seldom happen during the operation [20–22]. Consequently, the data samples of the machinery faults are more difficult to collect than the data samples of the normal condition. Thus, the data samples of different machinery health conditions follow a long tail distribution, i.e. the data samples of the normal condition are abundant while the data samples of the faults are relatively scarce. The imbalanced distribution of the data samples forces CNNs to be biased towards the majority health conditions [23]. As a result, the characteristics of the minority health conditions are learned inadequately, leading to their misclassification.
(2) What CNNs have learned is not clear. The reason why deep learning models are applied in intelligent fault diagnosis is that they can accomplish the feature learning and fault classification of machinery simultaneously, which releases us from the tough work of manually designing feature extraction algorithms. However, deep learning models are always treated as a "black box" in the field of intelligent fault diagnosis and few papers attempt to discover and analyze the patterns in these models. CNNs also suffer from the same dilemma. Although intelligent fault diagnosis methods based on CNNs have achieved good results, it is not easy to understand how CNNs learn features automatically. Intuitively, one way to understand the feature learning process is to analyze the weight matrices of a neural network quantitatively. The reported results may afford us some inspirations. In our previous work [24], we tried to explore the interpretation of a shallow neural network in mechanical feature learning, and the results indicated that the weight matrix of the network is viewed as Gabor-like filters. Following this work, we can directly visualize the kernels (The weight matrix of a convolutional layer in CNNs is called kernels) of the first layer of a CNN since the kernels are connected to the input signals. But it is hard to visualize the kernels in a deeper layer because of the indirect effect on the inputs. Thus, how to solve this problem needs to be further studied.

To overcome the first weaknesses, this paper proposes a framework called deep normalized convolutional neural network (DNCNN) for imbalanced fault classification of machinery. In DNCNN, firstly, normalized layers based on Rectified linear units (ReLU) [25] and weight normalization strategy [26] are used for the effective training of DNCNN. Secondly, weighted softmax loss is developed to deal with the balanced and imbalanced fault classification of machinery adaptively. The proposed DNCNN is validated by three bearing datasets with different imbalanced degrees. By comparing with the commonly used CNNs, the superiority of DNCNN is verified in imbalanced fault classification of machinery.

To overcome the second weakness, this paper proposes a neuron activation maximization (NAM) algorithm. By using the NAM algorithm, we can visualize the kernels of the convolutional layers of DNCNN to understand its feature learning process. The visualization results show that the kernels in the first convolutional layer are the filters with single peak characteristics and the kernels in the second convolutional layer are the filters with more complex properties. Therefore, DNCNN attempts to learn filters in the convolutional layers automatically. With the help of these filters, DNCNN is able to retain the important components of the signals and suppress the useless aspects for classification. This result may help us understand how DNCNN learns the features from vibration signals.