A Fault Diagnosis Method of CNC Machine Tool Spindle Based on Deep Transfer Learning

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Abstract. Data-driven fault diagnosis methods such as deep learning is a remarkable new way to find the problem. In this paper, considering the small volume of labeled samples in fault diagnosis of CNC machine tool spindle, we propose a fault diagnosis method based on deep transfer learning to achieve our goals more quickly and efficiently. First, the original vibration signals acquired by multiple 3-axis acceleration sensor mounted on spindle were collected and a transformation method converting signals to image is developed to get inputs. Second, several pre-trained networks are compared and the best one is used to extract lower level features. Third, the output layer with target classes is replaced and the higher levels of the neural network are fine-tuned. Finally, the learning method is employed to learn the features of the network and has been tested on the datasets. The experimental results in this paper have proved that our method was correct identify machine tool spindle conditions and showed considerable potential for fault detection in manufacturing.

Introduction

CNC machine fault diagnosis has been studied by many researchers in recent years. With the rapid development of smart manufacturing, data generated by machines and devices is boosting and can be collected well[1][2]. The failure may incur higher operating costs, lower productivity, more disqualified part waste, and even unexpected downtime . In modern smart manufacturing, more than half of the downtime of a CNC machine tool is caused by its mechanical failures. In order to implement smart manufacturing, it is crucial for a smart factory to monitor machinery conditions, identify the incipient defects, diagnose the root cause of failures, and then incorporate the information into manufacturing production and control. Data-driven fault diagnosis can establish the fault modes using historic data without any prior explicit models or signal symptoms, which is very suitable for the complex systems. Deep learning architectures can automatically extract multiple complex features from the input data without human engineers: layers of features are extracted from raw data by a general purpose learning procedure. With that ability, deep learning architectures possess the ability to deal with the difficulty of conventional ML.[3][4] In actual machining processes, the working conditions are affected by many factors, such as different cutting tools, different work pieces, different cutting parameters, etc.. However, it is common signals such as vibration in spindle when CNC machine fault occur for real applications. Research [5]–[8] use various signals such as vibration, current signature, acoustic emission etc., to address the issue. However, most of the existing method, which are based on one signal(i.e., Acceleration sensor with 1 [9]or 3 [10]channel).

To fill this research gap, by using deep transfer learning, this paper proposes a method for fault diagnosis method of CNC machine tool spindle based on multiple accelerate sensors. As we know, transferred deep learning is meaningful and promising for smart manufacturing to enable knowledge updating and intelligence upgrading.[11] In addition, considering the small volume of labeled samples in fault diagnosis of CNC machine tool spindle, the fault diagnosis method based on deep transfer learning to achieve our goals more quickly and efficiently. This method is performed in three steps.

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Fault Diagnosis Method by Deep Transfer Learning

Deep Learning Methods. Different from traditional methods, deep learning is a new proposed machine learning, which has the great capacity to automatically learn the valuable features from the raw data. The deep learning models for fault diagnosis can be divided into three main types: CNN, DBN, and AE[5]:

DBNs. Deep belief network (DBN) can be constructed by stacking multiple RBMs (restricted Boltzmann machine), [3]where the output of the hidden units is used as the input of the visible units. DBN can be trained in a greedy layer-wise unsupervised way. After pre-training, the parameters of this deep architecture can be further fine-tuned with respect to a proxy for the DBN log-likelihood, or with respect to labels of training data by adding a softmax layer as the top layer.

AEs. Auto Encoder has been investigated for unsupervised feature learning, and the learned features are then fed into a traditional machine learning model for model training and classification.

CNNs. CNNs are widely used in images processing tasks, which can learn hierarchical features automatically from input images. With aggregated data from smart sensory and automation sys-tems, more and more deep learning techniques have been widely investigated for machinery fault diagnosis and classification. Convolutional Neural Network integrates feature learning and defect diagnosis in one model, and has been used in many aspects, such as bearing, gearbox, wind generator, and rotor, etc. CNN networks always contain three kind of layers: convolution layers, pooling layers, and fully connected layers.

Imaging Methods. Since CNN was originally developed for image analysis, different approaches are investigated to construct two dimensional input from time series data. The frequency spectrum of multi-channel vibration data is also investigated to fit the model requirement. Time frequency spectrum of vibration signal by wavelet transform is used as image input of a CNN model. Time frequency imaging can be obtained by short-time Fourier transform (STFT), continuous wavelet transform (CWT), Wigner-Ville distribution, etc. We can find these imaging methods in [3],[4],[10]. These methods can be regard as a mathematical tool to transform time series to another form.

Wavelet Transform. The wavelet transform is widely used in feature extraction in fault diagnosis tasks and is an effective way to represent signals in multiple resolutions.

Multi-channel Frequency Spectrum. The wavelet transform results can convert to 2-D RGB images which have three channels corresponding to three-axis vibration signals using the method mentioned above.

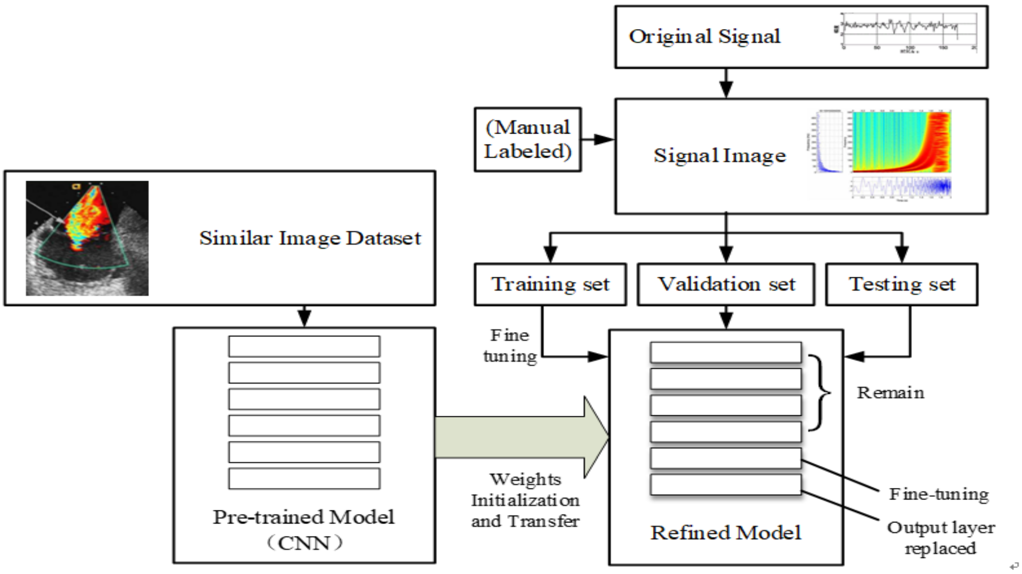

Fig.1 –Flowchart of the fault diagnosis method

Transfer Learning Strategy. For a new problem setup, deep learning may need to rebuild the model from scratch and the existing knowledge may be difficult to utilize. Compare with training from scratch, the pre-trained model always has better convergence speed and classification accuracy. It is necessary to enable deep learning with incremental learning capabilities.

Multi-Input Strategy. In order to increase the volume of manufacturing information obtained by machine sensor system, it is crucial to develop and implement an intelligent MIMO (Multi-Input and Multi-Output) strategy that allows manufacturers to determine the systems condition and the fault types.

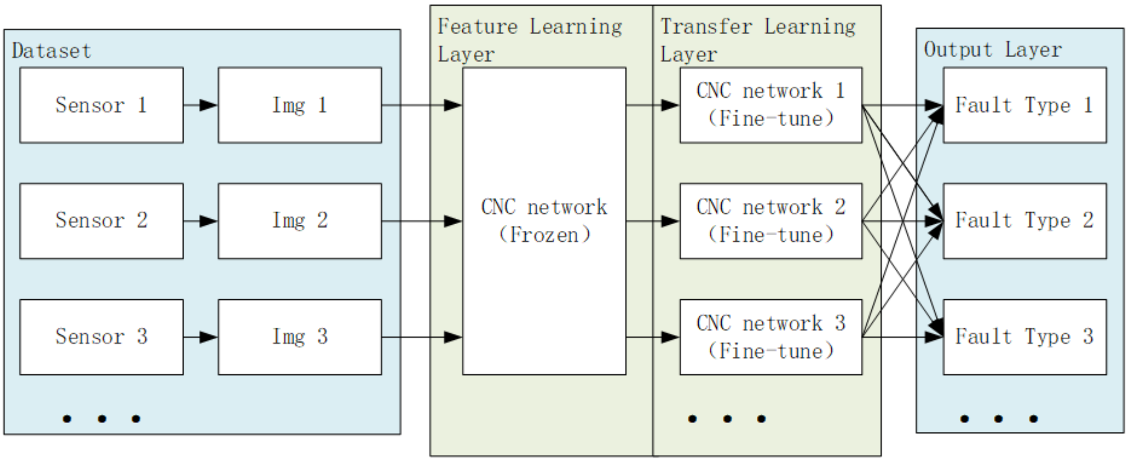

Fig.2 –Flowchart of multi-sensor dataset processing

In this paper, a method for Multi-Input strategy is proposed. The framework of this method is shown in fig.1 and fig.2 and the general procedures are summarized as follows:

Step1: Collect large volumes of the vibration signal of the CNC machine tools by sensors installed on CNC machine tool spindle in long-term running.

Step2: Take samples of a vibration signal and convert it to 2-D RGB images.

Step3: The processed images are divided into smaller samples with fix volume.

Step4: As shown in fig.1, the training dataset is used to train the pre-trained model and fine-tune its weights of the transfer learning layer while the basic feature learning layer is frozen.

Step5: Using the same steps (1~4) to train vibration signal of another sensor, with the new pre-trained CNN network obtained in Step4.

Step6: Using training dataset and the multiple model result to retrain the whole system shown in Fig.2.

Step7: Using testing dataset to validate the precision of the designed model on the CNC machine tool spindle fault diagnosis task.

Experimental Setup

Pretrained Model. the pre-trained model used in this paper was VGG-16 trained with tensorflow, the detailed information can be found in *https://cs231n.github.io/convolutional-networks/#case*.

Dataset. The dataset used in this experiment is obtained by CNC machine tools (as shown in fig.3) with different conditions, show in table.1. Vibration signals are acquired by three acceleration sensors mounted on these four CNC machine tools.

Table.1 Fault type description

	Condition	Condition Description
Health	Normal spindle	CNC MT1 /healthy one
Fault type 1	Unbalanced rotor	CNC MT2 /added washers on the rotor
Fault type 2	Gearbox crack	CNC MT3 /using cracked gearbox
Fault type 3	Bearing crack	CNC MT4 / using cracked Bearing

Sensors. Machine tools have been equipped with a variety of sensors. Vibration signals are acquired by three acceleration sensors when the CNC machine tools operates under four different conditions, which are mounted on the spindle surface near the bearing under circumferential uniform distribution.

Fig.3 –Experimental facility-a CNC machine tool

Data Acquisition System. To digitize the continuous vibration signals, a data acquisition system is used in the experiment. Detailed specifications of data acquisition system are presented in table.2.

Table.2 Specifications of the data acquisition system

Data acquisition device	Specifications
Acceleration sensor (Kistler:8688A0-P)	1) Sensitivity: 10 mV/g sensitivity 2) Range F.S. For±5 Volts Output:±500 g 3) Frequency response: 0.3–10 000 Hz 4) Resonant frequency: >40 kHz 5) Temperature range: –60 to +250 F
Data acquisition system (cRIO-9118, NI 9263)	1) 16bit 250kHz/5kHz conversion 2) Gain accuracy:±0.05% of reading 3)4 channels

Results

The results show that the proposed pre-trained model is able to achieve an acceptable result in processing multi-sensor data. Firstly, it takes much less time to train Sensor 2 and Sensor 3 than the first training, which means that little workload has been added. Secondly, Multi-sensor accuracy is little increase by contrast with single-sensor situation.

Summary

In conclusion, this research presents a new Transfer CNN framework for fault diagnosis and type classification. The experiment result shows that proposed method shows higher performance and achieves better results on these datasets than single-sensor system. As a result, it is possible to apply more sensor signals in fault diagnosis system, and to show great reliability by overcoming the limitations of number of the same kind sensors.

Some limitations of proposed method are as follows: Firstly, there are few fault conditions and types. The faults which have not been learned would be misclassified to be the known ones. Secondly, it may be difficult to transfer this model to another machine even in the same kind. Even though, this method can be expected to play a useful role in fault detection and classification across different mechanical systems.

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