A New Data-Driven Intelligent Fault Diagnosis by Using Convolutional Neural Network

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Abstract - **Along with the boosting of big data in manufacturing, applying the data-driven analysis method to support the intelligent fault diagnosis becomes a new trend. Recently, deep learning emerged as a potential artificial intelligence technique. It can obtain the features of raw data automatically, which provides a new way to reduce the expert's bias as more as possible and to mine the inherent relationships hidden in data. Convolutional neural network (CNN) is a promoting kind of deep learning. A new intelligent fault diagnosis method based on CNN is proposed in this paper. Firstly, a transformation from signals to images is investigated to deal with the raw signal data in a simple way. Then these images are trained by CNN. The proposed method is tested on the motor bearing dataset from Case Western Reserve University. The results show that the proposed method achieves as high as 99.51% of the prediction accuracy. The good performance of proposed method is also proved by comparing it with other deep learning methods and traditional methods.**

Keywords – **Fault diagnosis, Convolutional Neural Network, Data-Driven method**

I. INTRODUCTION

System fault diagnosis is a key process to avoid the dangerous situation of the manufacturing system. with the develop of smart manufacturing, the intelligent fault diagnosis becomes a new trend. At the moment, the data in the enterprise is boosting and it can be collected much faster and more widely than ever [1], which causes a new demand on the data analytical method to find out the inherent association hided in the massive mechanical data to support intelligent fault diagnosis.

According to the data type and the data process [2], the fault detection and diagnosis can be classified into model-based online data-driven methods, signal-based methods, and knowledge-based history data-driven methods. The knowledge-based method is also referred as data-driven method, and it has been receiving a considerable increasing attention in recent years [3]. The first famous artificial intelligent approach which has had been applied to the fault diagnosis is published in 1980s [4]. The data-intensive machine learning method has been adopted in the decision-making process across in manufacturing field [5].

However, most machine learning method can't cope with the raw signal, the feature extraction on signals become an important process, and it has a heavy effect on the final prediction of machine learning method. But this disadvantage has been remedied when deep learning emerged as a new potential approach in the artificial intelligent field. Deep learning has the abilities of feature representation of the raw data automatically [6]. The key aspect of deep learning is that these represented feature are not bias by the engineers, and can reflect deeper characteristic features of the raw data.

Convolutional neural network (CNN) is a classical deep learning method and has been successfully applied to many science, engineering and business filed. In 2012, Alex Krizhevsky et al proposed a typical type of CNN called AlexNet [7], which remarks a breakthrough on the large scale image classification task. The special of CNN is the convolution layer and the weight shared architecture and can obtain the translation invariance feature of images.

In this research, a new data-driven intelligent fault diagnosis method based on CNN is proposed. For most data-intensive method, they need a predefined complex data preprocessing before putting the data to the learning system. Even though in traditional deep learning, to transform from the time-domain signals to frequency-domain is a common technique. The main contribution of the new method is to investigate a time-domain learning system with a new simple data preprocessing method. This method maps time-domain signals to images and then a deep CNN is proposed to classify the images. The result shows that this method achieves a good result.

The rest of this paper is organized as follows: the new CNN based intelligent fault diagnosis is introduced in Section II. In section III, an experiment has been conducted and the results are explained. The conclusion makes up section IV.

II. PROPOSED INTELLIGENT FAULT DIAGNOSIS BASED ON CNN

This section describes the concept of CNN network, the transformation method from signals to images and the padding method of the CNN.

A. The Convolutional Neural Network

CNN is a special instance of artificial neural network (ANN). Different from the fully connected ANN, each neuron of the feature map in each layer is only sparsely connected to a small set of neurons in previous layer. This

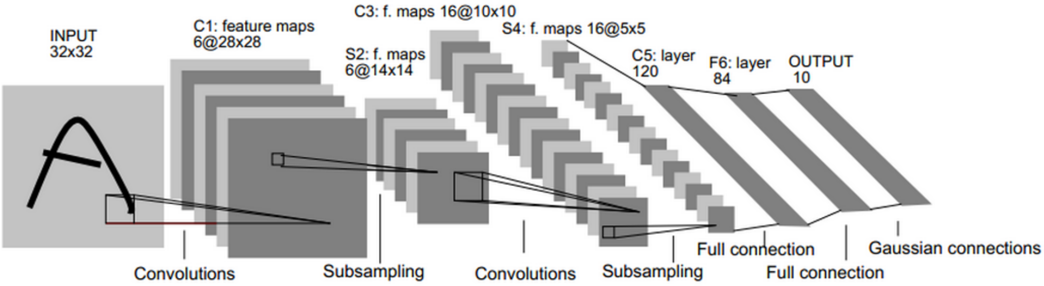

Fig.1. The typical structure of LeNet-5 CNN model

is inspired by the concept of simple and complex cell in visual cortex in brain [8], and the visual cortex contains some cells that only sensitive to a local receptive field [9].

There are three major layers in CNN: 1) Convolutional layer; 2) Pooling layer; 3) Fully connected layer. The input data of CNN is the raw images. For most cases, it is a 2-dimension datatype. The convolutional layer applies a set number of filters to obtain the feature maps of input images. The pooling layer is the down-sampling layer to reduce the size of images. Finally, a fully connected layer is followed, and a softmax regression is applied to classify the final output.

LeNet-5 CNN is a classical release of CNN [10], and it has been applied to recognize the handwritten digit characters and computer printed characters. Fig. 1 shows the typical structure of the LeNet-5 CNN model. Its input is a 32×32 images. There are two convolutions layers and pooling layers in the model, and a two-layer fully connected ANN. In this research, a modified LeNet-5 CNN is designed to solve the classification task on the fault diagnosis.

The designed CNN structure is shown in Figure. 2. It is similar to LeNet-5 CNN model. The detail definitions would be discussed in next section, and the CNN is developed based on tensorflow.

B. Transformation from Signals to Images

Traditional data-driven fault diagnosis method uses statistical analysis, fuzzy logic expert system or neural network to mine the signal patterns from large volume of historic data. In this paper, we promote a new data preprocessing method to transform the signals to images to explore the $2D$ feature of the signals [11].

The transformation is shown in Figure. 3. Since the signals are sampling in time-domain, so each time, fetch a M^2 length signals to obtain an image which has $M \times M$ size. Each image has been normalized from 0 to 255 separately. $L(i), i = 1...M^2$ denotes the value of the signals, and $P(j,k)$ denotes the pixel strength of the images. there are relations:

$$P(j,k) = \frac{L(j \times M + k) - Min(L)}{Max(L) - Min(L)} \times 255 \quad (1)$$

C. The Padding Methods

Padding methods is critical for CNN. It adds zero value to the image in order to change the size of image too large. In this research, the padding method is zero-padding, and it is the 'SAME' type in Tensorflow. This padding method is shown in Figure 4. The filter width is 3, stride is 2, and M = 7.

The zero padding at the beginning is essential. In no-padding model, the last rest element would be dropped. in zero padding, zeros would be added to the end automatically to fill the convolution process. The output size is:

$$OutSize = ceil(\frac{float(InSize)}{float(strides)}) \quad (2)$$

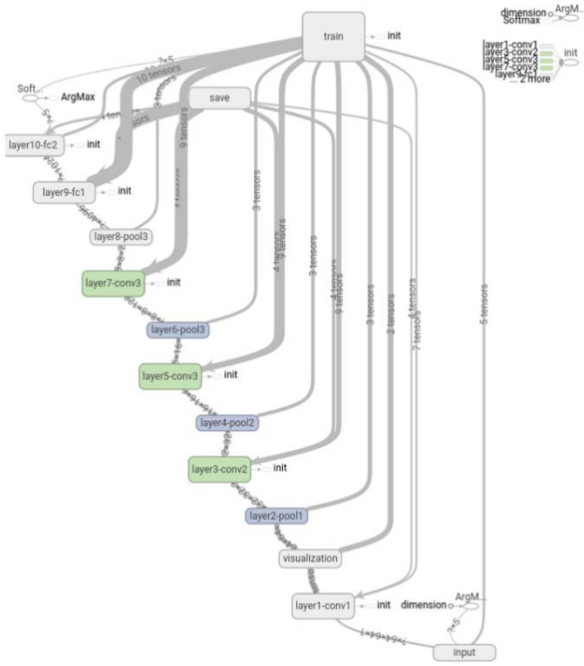

Fig.2. The designed structure of the proposed CNN model

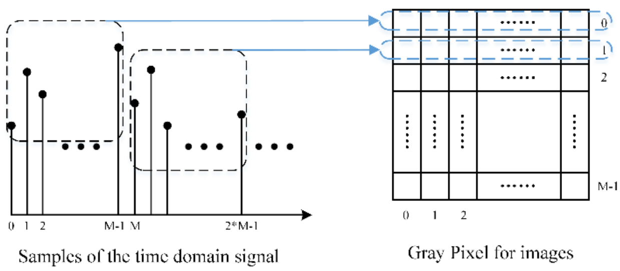

Fig. 3. The transformation method from signals to images

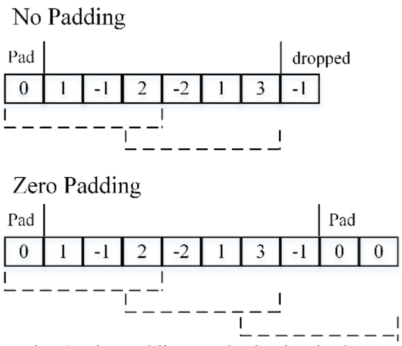

Fig. 4. The padding method using in CNN

III. CASE STUDY AND RESULT ANALYSIS

In this section, a case study is conducted. Firstly, the setup and the data is presented. Then, the signals transformation result and the testing result are given. Following is the discussion about this case study.

A. Data Description

In this research, the famous motor bearing data provided by the Case Western Reserve University (CWRU) [12] is selected to validate the performance of this new method. There are three fault types: outer race fault (OF), inner race fault (IF) and roller fault (RF). Each fault type has three patterns, and the damage sizes are 0.18mm, 0.36mm and 0.54mm respectively. So there are 10 different operation types in addictive on the normal condition.

These data will be directly input to the proposed method after being processed with our new data preprocessing method. It just obtains many M^2 segments to form the dataset. Each fault type has 6400 sample in the training dataset and 1600 in the testing dataset. The testing results are shown below.

B. Signals Transform to Images

The size of images is set to 64×64. In Figure. 5, the transformation on the normal condition is presented. All the images are gray images, and there are 4096 pixels in each image. Figure. 6 presents the rest 9 kinds of image samples.

C. Result of Proposed CNN

There are five types of CNN designed for this testing. Their structures are present in Table. 1. CNN-1 has three Conv-Maxpool layers, CNN2~4 has four Conv-Maxpool layers with different full connected layers, and CNN-5 has five Conv-Maxpool layers. The stride of Conv and maxpool operator is 1, and these five CNNs are written in tensorflow 1.0 and run on Ubuntu 16.04 with a GTX 1080. In all CNNs, the batch size in the training process is set to 200. The final prediction result on the testing dataset is also presented on Table. 1.

The loss of the proposed CNNs is presented on Figure. 7. The convergence speed of CNN-3 is the fastest, and that of CNN-4 is the worst. The prediction on the testing dataset of CNNs are shown on Figure. 8, and the result shows that CNN-5 is inferior than others, and CNN-1~CNN-4 are close to each other. From Figure.9, it can be seen that CNN-2 achieves the best result, CNN-1 and CNN-3 is slightly inferior then CNN-2. The prediction of CNN-5 is the worst.

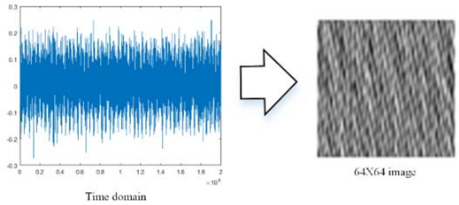

Fig. 5. Transformation from signals to images of normal condition

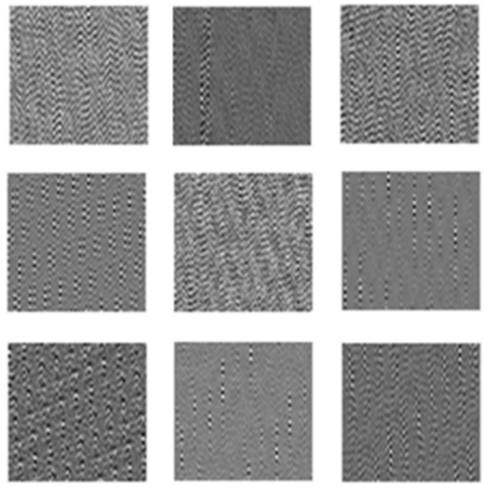

Fig. 6. Transformation from signals to images on fault condition

TABLE I
THE LAYER CONFIGURATION OF CNNS

	CNN-1	CNN-2	CNN-3	CNN-4	CNN-5
L1	Conv(5*5*32)				
L2	Maxpool(2*2)				
L3	Conv(3*3*64)				
L4	Maxpool(2*2)				
L5	Conv(3*3*128)				
L6	Maxpool(2*2)				
L7	-	Conv(3*3*256)			
L8	-	Maxpool(2*2)			
L9	-	-	-	-	Conv(3*3 *512)
L10	-	-	-	-	Maxpool(2*2)
FC1	1024	1024	1024	1024	128
FC2	-	-	256	512	-
Acc	99.37%	99.51%	99.40%	99.12%	98.74%

D. Result Analysis

In order to show the good performance of the proposed CNNs, other traditional statistical method and deep learning method are selected to compare the prediction result on this case study.

From the result of TABLE II, it can be clearly seen that the proposed CNN-2 achieves a good result compared with these methods. The prediction accuracy is as high as 99.51%, and it is better than all other method. The prediction results of DBN, DBN Based HDN, SVM are 87.45%, 99.03%, 87.45. The Prediction result of traditional ANN is 67.7%, and this result is obviously inferior to these five proposed CNNs.

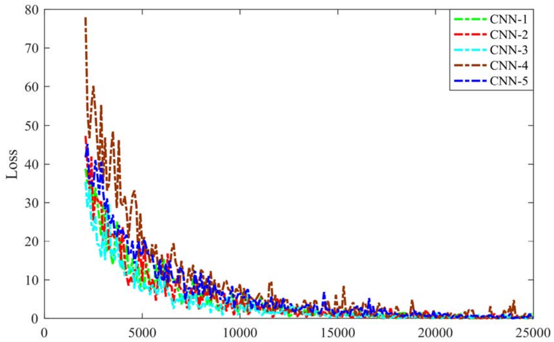

Fig. 7. The loss curve of the proposed CNNs

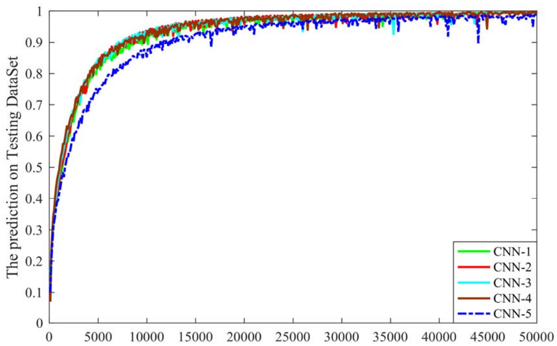

Fig. 8. The prediction on testing dataset of the proposed CNNs

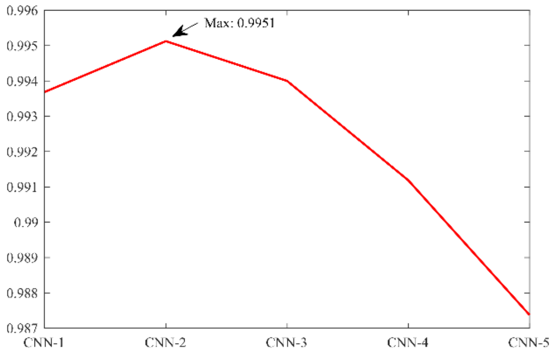

Fig. 9. Prediction result on testing dataset among CNNs

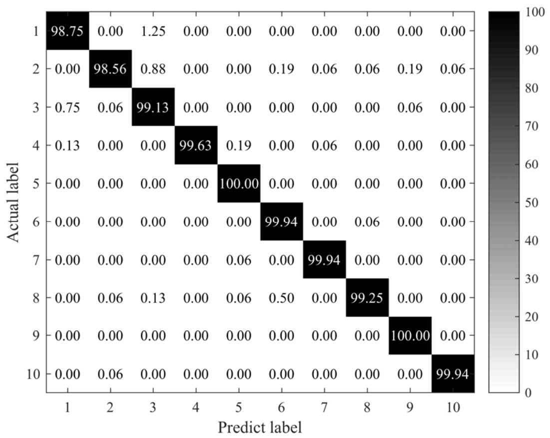

Fig. 10. The confusion matric of the prediction result on CNN-2

TABLE II
THE COMPARISON RESULT OF CNN AND OTHER METHODS (%)

Methods	Accuracy
CNN-2	**99.51**
DBN [14]	87.45
DBN Based HDN [13]	99.03
SVM [14]	87.45
ANN [14]	67.70

Figure. 10 shows the confusion matric of CNN-2. The rows stand for the actual label, and the columns stand for the predicted label for each class. From the result, it shows that class 5, 9 are 100%, followed by class 6, 7, and 10, which has the accuracy of 99.94%. Class 1 and class 2 are the worst, which only have the accuracy of 98.75% and 98.56%.

E. Discussion

In this case study, the potential of the proposed CNN is validated. It used a transformation process to convert signals to images and then to explore its 2 dimension features. It obtains 99.51% accuracy, which is much higher than the traditional ANN and SVM, and the results also outperform other deep learning method, showing that the performance of this method. What's more, with the new promoted data preprocessing method in this paper, we can reduce the expert's bias as more as possible, and enhance the ease of usability of the proposed method.

IV. CONCLUSION

This research presents a new intelligent fault diagnosis method. The main contributions of this study are applying the transformation from signals to images and then designing a new CNN network. The proposed method achieves a good result on the famous motor bearing dataset from Case Western Reserve University. The result shows that the proposed CNN has achieved a wonderful result with the new proposed data preprocessing method. So this method can reduce the expert's bias as most as possible. The prediction of the proposed method is as high as 99.51%, indicating the potential of this method on the intelligent diagnosis field.

The future studies can be extended in the following ways. Firstly, developing a more powerful CNN has no end. Secondly, more famous testing should be done. Thirdly, this method can be extended to other related fields, such as on-line fault diagnosis.

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