Fault Dianosis Method Using Convolutional Recurrent Neural Network for Rotating Machine

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***Abstract*— Rotating machines are important constituents of mechanical parts. Many faults in rotating machines are caused by component defects such as those related to bearings, axis alignment, or belts. Therefore, failures of the components of the machinery in operation must be diagnosed. In this study, we propose a convolutional recurrent neural network (CRNN) for fault diagnosis related to rotating machines. The proposed CRNN is constructed using convolutional neural networks (CNN) followed by a recurrent neural network (RNN). First, the constant-Q transform (CQT) features are extracted from a vibration signal acquired from a rotating machine. Next, the proposed CRNN model is constructed to diagnose the faults in the rotating machines using the CQT features. The "Machine Facility Failure Prediction Sensor" dataset is used to validate the proposed method. The fault-classification accuracy of the proposed method is found to be higher than those of other CNN-based methods.**

Keywords*— *Convolutional recurrent neural network, machine learning, fault diagnosis, rotating machine

I. Introduction

Early and accurate detection of emerging faults is crucial for ensuring the reliability and safety of machinery. Especially, the failure of rotating machines can potentially lead to the collapse of multiple machinery systems, thereby causing substantial economic losses and compromising the safety of personnel [1]. Therefore, research on fault diagnosis is essential.

Rotating machines often operate under diverse load conditions such as varied electrical specifications and amidst environmental noises [1]. These intervening factors complicate fault diagnosis. Traditional fault-diagnosis techniques apply signal processing methods. In general, fault diagnosis techniques commonly use a vibration signal, which is a time-varying signal. Some effective techniques, such as fast Fourier transform (FFT) and adaptive signal decomposition methods that behave as filter banks [2, 3] are applied to construct the characteristic features of vibration signals. The extracted features are input into machine learning algorithms, such as K-Nearest Neighbor(k-NN) algorithms [4], support vector machines(SVM)[5], artificial neural network [6], and recurrent neural networks (RNNs) [7], to monitor fault diagnosis.

In this study, we propose a fault diagnosis method using a convolutional recurrent neural network (CRNN) that is applicable to rotating machines. More specifically, constant-Q transform (CQT) features are extracted from a vibration signal obtained from a rotating machine. The CQT, in which the frequency axis is logarithmically spaced, is a possible solution to show resolution of pitch harmonics [8] in vibration signals. Therefore, we used CQT features extracted from a vibration signal for fault diagnosis. A CRNN-based classifier is proposed to utilize the extracted CQT features. The proposed CRNN model is composed of a convolutional neural network (CNN) followed RNN with gated recurrent units. The "Machine Facility Failure Prediction Sensor" dataset provided by Korea AIHub [9] is applied to the proposed method. Finally, the performance of the proposed model is compared with those of conventional CNN-based methods.

II. Proposed Method

A. Dataset

The "Machine Facility Failure Prediction Sensor" dataset consists of the normal states of machinery and labeling of four abnormal states that are related to shaft misalignment, unbalanced rotating bodies, loose belts, and bearing defects. In this study, we used vibration data containing 1,080,000 normal states and 1,030,000 abnormal states, and the data are evenly distributed according to each abnormal state [9]. Each vibration data is stored as a single channel signal that is sampled at 4,000 Hz, yielding 12,000 data samples.

B. Fault diagnosis model

CRNNs have successfully been applied to classification problems based on time-varying signals [10]. The proposed CRNN-based classifier consists of three different neural networks that are constructed using an input layer, a CNN, an RNN, and a fully connected (FC) layer. First, the extracted CQT features are grouped as a (57×188) input matrix at the input layer. Subsequently, CNN-backbone networks in the form of residual neural networks (ResNets), which contain multiple residual blocks, are applied. The extracted features are applied to an RNN after feedforwarding all the residual blocks. The RNN consists of two bidirectional gated recurrent units (BiGRUs), in which a rectified linear unit (ReLU) is used as the activation function for each gated recurrent unit. Finally,

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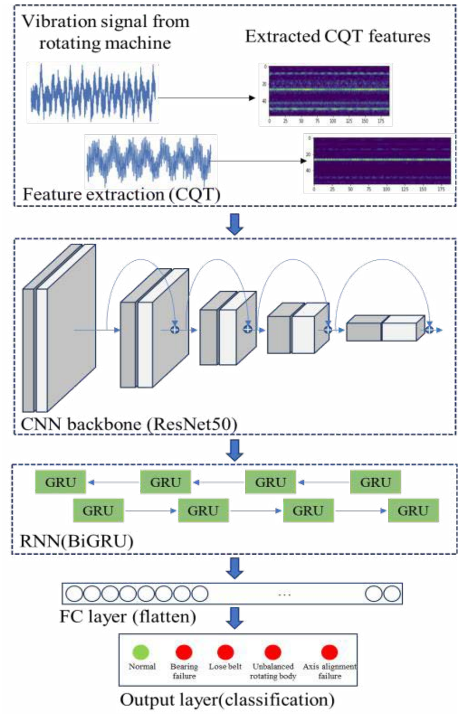

Fig. 1. Proposed rotating-machine fault diagnosis method

the RNN output is aggregated by the FC layer, which is used as the output layer to classify the four abnormal fault states.

More specifically, the extracted CQT features are grouped as a (57 × 188) matrix for inputting into the CNN. The ResNets are composed of one stem conventional block and four residual blocks with a (3× 3) convolutional kernel and a stride size of (2 × 2). By following the aforementioned procedure, CNN outputs with dimensions of (512×1×4) are obtained. Subsequently, these outputs are converted into (512 × 4) matrices. The (256 × 4) outputs of the BiGRUs are flattened by the FC layer and subsequently by a sigmoid function, Finally, the FC layer is connected to a (1×5) output layer, where 4 denotes the number of abnormal fault classes and a normal state class to be classified.

III. Experimental Results

A. Model training

The neural network weights of the CRNN model were initialized by using Xavier initialization, and all the biases were initialized to zero. Next, the mini-batchwise adaptive moment estimation optimization algorithm was applied with a dropout rate of 0.5. In addition, the learning rate was set according to a cosine decay schedule of 20 epochs, such that the maximum learning rate reached 0.001.

B. Performance evaluation

For the given dataset, we first employed frame segmentation to yield consecutive frames of 2048 samples with a hop length of 256 samples. Then, a 2048-point FFT was applied to each separated signal, and a 128-dimensional CQT analysis was performed for each frame. As every 12,000 vibration-sample data are represented by 188 frames, the dimension of the input feature of the model is 57 × 188.

Table 1: Comparison of the accuracies obtained using the validation test dataset.

Model	Accuracy (%)
CNN (ResNet18)	97.0
CNN (ResNet50)	97.5
CNN (ResNet18 + BiGRU)	98.2
CNN (ResNet50 + BiGRU)	99.0

Finally, the extracted CQT features were normalized using the global mean and the standard deviation over all the training vibration data. Notably, the validation test dataset was composed of 126,713 vibration signals.

To demonstrate the effectiveness of the proposed method, we compared the accuracies of the CNN- and CRNN-based fault diagnosis methods. As listed in Table 1, the accuracy of the proposed method is higher than that of the CNN-based methods. In particular, the accuracy of the proposed method is 1.2% and 1.5% higher than those of the ResNet18- and ResNet50-based models, respectively.

IV. Conclusion

This study proposed a method for diagnosing faults in rotating machines using a CRNN model and CQT features, which are well-adapted to signals with strong harmonics. The CNN part uses ResNets to extract hidden features from CQT features. Temporal information is learned via the BiGRUs. Performance evaluations revealed that the accuracy of the proposed method is higher than those of the fault diagnosis methods employing other CNN-backbone networks.

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