

Bearing fault diagnosis on various operation condition of rotating machinery based on LSTM – RNN algorithm

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1. Introduction

Bearing part is the most important component in rotating machinery to support the mechanical rotating body and reduce the movement friction. Generally, it has a failure mode resulting from the relative motion between mating surfaces would cause a damage. Several studies have shown that the bearing fault is the major source in rotating machinery faults[1]. An effective fault diagnosis method could obtain the healthy condition of bearings and probe the fault condition, which are also the most important directions in research and practice. Conventional fault diagnosis methods generally extract features from the raw process data. Then certain classifiers are adopted to make the diagnosis system. However, the typical methods require expert knowledge of feature extraction, classifier design, and adaptive processing of dynamic information in raw data, such as frequency domain analysis or statistical analysis[2,3,4]. This paper proposes fault diagnosis and condition monitoring method based on Recurrent Neural Network (RNN) and Long Short-Term Memory (LSTM) algorithm. The suggested method can directly classify the raw process data without specific feature extraction and classifier design. It is also able to adaptively learn the dynamic information in raw data.

2. Sensor signals

In order to construct the diagnosis system, the rotating equipment which causes frequent failure in the bearing part was selected as shown in Fig. 1. The vibration sensors were installed to the bearing part and the sensor signals were measured for a certain period. Fig. 2 shows the x and y-axis vibration signal histories measured on the bearing axis of the rotating equipment. The history of each vibration signal clearly shows the characteristics of the condition of the rotating equipment in operation, stop, and loading or unloading conditions.

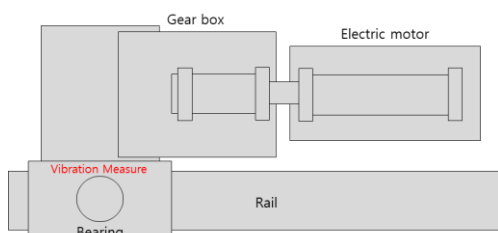


Fig. 1 Schematic view of rotating machine

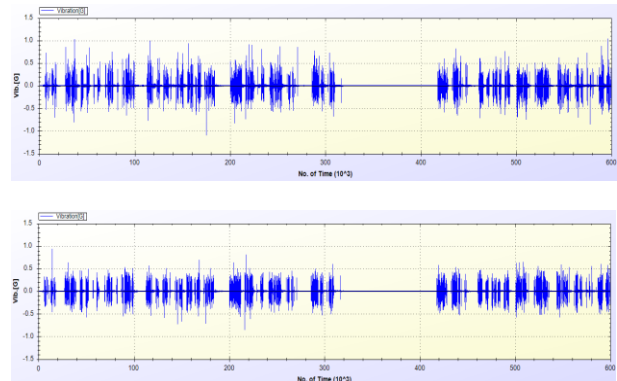


Fig. 2 Histories of vibration signals of bearing part (x, y direction)

3. Fault diagnosis algorithm

The fault diagnosis method focuses on distinguishing signals under different operating conditions and detecting faults in real time. Therefore, each operation states are classified and learned based on the measured sensor signal history, and the diagnosis system is configured by applying a test signal capable of detecting each state and detecting a fault. Fig. 2 shows the procedure for classifying states by learning each state using the RNN-LSTM method. The RNN is a class of artificial neural networks (ANN) where connections between nodes form a directed graph along a temporal sequence. This allows it to exhibit temporal dynamic behavior. LSTM is a type of RNN, which is a deep learning method that can classify and regress timeseries data such as natural languages and voices in consideration of feature changes at each time step. LSTM is an improvement of RNN in order to capture long-term dependencies[5].

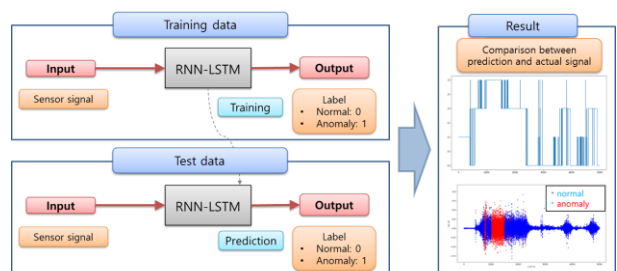


Fig. 3 Overall process of proposed fault diagnosis method

4. Results

Applying test data to the RNN-LSTM learning model predicts the state of the signal in real time. As a result, Fig. 3, the loss value converged up to 0.0014 during Epoch 200 of the learning model. The accuracy of the learning model was also very high at 99.97 percent. The operation states according to the test scenarios are shown in Fig. As shown in Fig. According to the scenario of the applied signal, the data flow was observed at the beginning of the signal in the state that the rotating equipment was turned on, the loading state, the abnormal state, the loading state, and the power off state.

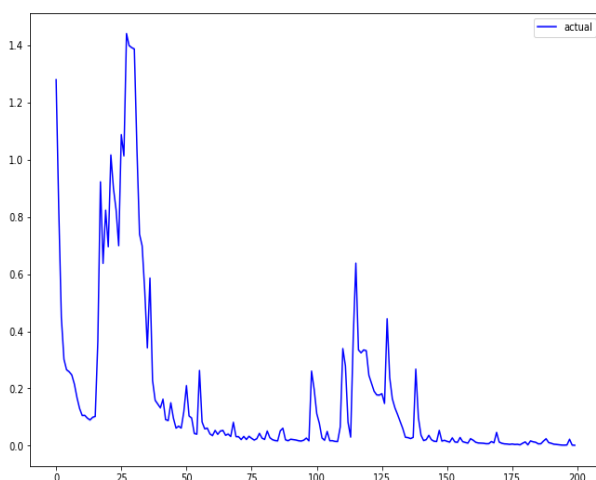


Fig. 4 Test results of the RNN-LSTM model

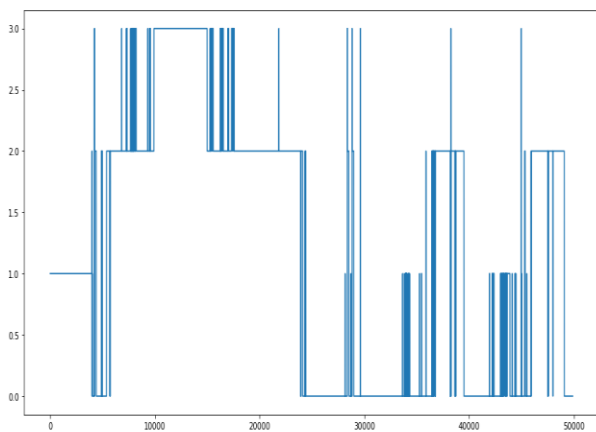


Fig. 5 Classification of operation condition according to test data scenario

5. Conclusions

In this study, the RNN-LSTM diagnostic models have been suggested. The applied models are designed to detect the bearing fault of rotating machine. The signal classification process is adopted to detect the several operation condition from the vibration signal histories. The training

method is proposed that using data of normal operation condition and virtual failure condition. The RNN-LSTM models gained these advantages more stable than other statistical methods. From the obtained vibration signal, various operating conditions can be classified, such as stop state, loading state, moving state, and so on. The suggested models could detect bearing fault and identify the operation condition using the proposed training method. In future studies, the noise of the acquired results should be removed to verify the results with higher accuracy. It is also necessary to verify how the accuracy changes as the training progresses by applying various data.

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