A Novel Fault Detection Method of Industrial Robots Using Motor Current Signals via Convolutional Neural Network (CNN)

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1. Introduction

Industrial robots are becoming indispensable parts of production lines due to the high efficiency and flexibility for the tasks of the production lines. However, faults on the industrial robots can lead to a drastic decline in terms of manufacturing quality, so a fault detection of the industrial robots has been paid attention. The previous studies of fault detection have been investigated based on vibration signals, and model-based simulation [1-3]. However, vibration-based fault detection methods should require additional sensors to measure vibration signals on the joints of the industrial robots. Also, fault detection using model-based simulation are not robust under various operating conditions such as velocity, temperature, and so on. In recent years, convolutional neural networks(CNN) has been applied to detect the faults adaptively with various operating conditions of mechanical systems such as gearboxes, and bearings [4], but few attempts were tried to detect the faults of the industrial robots using CNN. In this study, we propose a novel fault detection method using motor current signals based on CNN. In order to apply CNN, the pre-processing for extracting the features related to the faults is necessary. So, firstly, high-pass filtering is executed to eliminate the motion effects of the motor current signals. Second, a sliding window (SW) based data augmentation is performed to overcome a small amount of the data. Third, the CNN model is trained with the augmented dataset. Fourth, the classification performance for the test samples is visualized with t-stochastic neighbor embedding (t-SNE) of the last hidden fully-connected layer representation. This research contributes, 1) data-driven approach using motor current signals via CNN, and 2) robust fault detection method under various operating conditions without feature engineering.

2. Proposed fault detection method via CNN

One of the main causes of robots' fault is reducer fault [5]. A reducer is the main component of robots assembled with a motor. As shown in Fig.1, normal and fault signals are distinguishable in the high-frequency region while robot joint is rotating. It is because fault signals are different from normal signals during gravity compensation control caused by the fault on the reducer. Therefore, we perform pre-processing with Butterworth high-pass filtering to highlight the fault-related features and remove the influence of low-frequency motion components from 0 to 20Hz that is not related to the faults of the robot. After pre-processing, training, validation, and test sections are divided to segment the data. Also, to augment input data of CNN, we use sliding window-based data augmentation [4]. Through the data augmentation, the number of training samples increases and the generalization performance of the training model is enhanced. Finally, CNN is trained for stacked data with under variants of operating conditions (i.e. the direction of rotation, rotating velocity, unit-axis rotation, multi-axis rotation, and temperatures). The summary of the proposed method is shown in Fig.2.

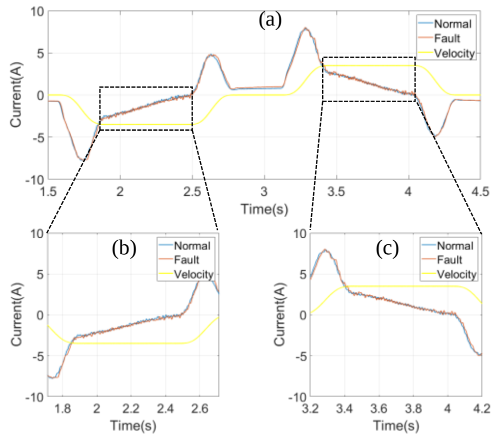

Fig.1 (a) Motor current signal of Normal/Fault cases; (b) constant clockwise rotation; (c) constant counter-clockwise rotation

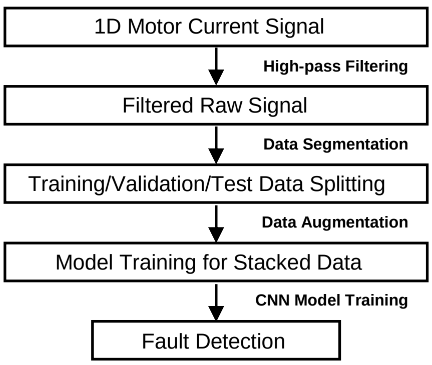

Fig.2 The overall framework of proposed fault detection method

3. Experimental Validation

To validate our proposed method, industrial robot testbed was used to acquire data as shown in Fig. 3. Among the reducers, we used the 4th joint reducer, which plays an important role as the wrist of the robot. The motor current signals were acquired from the controller without any additional sensors (sampling rate, 1000 Hz). Also, to train the CNN model, normal and fault data were equally collected under various operating conditions as explained in section 2. Detailed parameters of the proposed CNN architecture and data descriptions are described in Table 1.

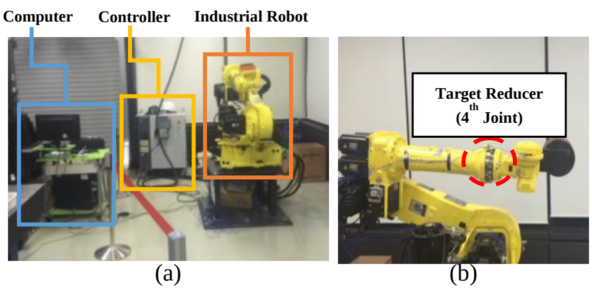

Fig.3 A tested configuration of the industrial robot: (a) a schematic view; (b) reducer in 4th joint

Table 1 Parameter descriptions

# of Parameters	8,441	Training Data	18,625
Window Length	1.5s	Validation Data	3,499
Window Shifting	0.05s	Test Data	4,754

4. Performance evaluation based on CNN

Fig.4 shows the performance of classification using t-SNE. As shown in Fig.4, raw data are hard to distinguish the normal and faults, however, through a trained model, pre-processed signals with CNN were classified with 97% accuracy. As a result, the proposed CNN model detected better the faults of reducers.

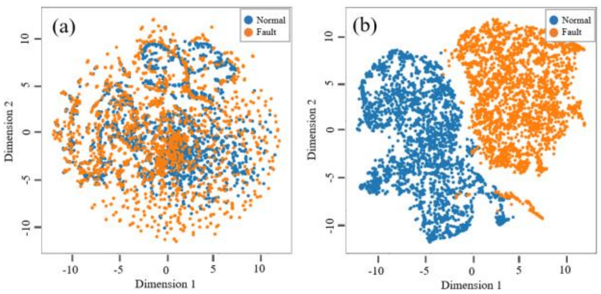

Fig.4 (a) t-SNE with raw data, (b) t-SNE with a pre-trained model

5. Conclusion and Future works

In this paper, we proposed a novel fault detection method of the industrial robot via CNN. Compared with the existing methods, 1) our model does not require any hand-crafted feature extraction procedures, and 2) as the pre-trained model includes variants of operating conditions, even if the operating condition changes, normal and fault classification is possible. For future works, we will develop a generalized fault detection method that motion operated in the actual lines such as welding, spot welding, and assembly.

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