
Data-driven fault diagnosis of industrial robots with a cloud computing framework

Soonyoung Han, Van Huan Pham, KiHoon Lee, SeungYon Cho and Hae-Jin Choi*

School of Mechanical Engineering, Chung-Ang University, Seoul, Korea

hsy4190@cau.ac.kr

Abstract

In modern manufacturing industry, industrial robots have been widely used. Health status of the robots should be always monitored to prevent a sudden shutdown of manufacturing lines. Supervising the signals measured from the industrial robot and diagnosing the status of machines in real time are essential tasks for us to manage the manufacturing lines.

In this work, we developed a system for data-driven fault diagnosis of industrial robots, which includes a data acquisition and mining process, a machine learning process, and a cloud computing framework. The signals gathered from attached sensors on the robot are stored in a database within the framework. Structured data are extracted from the stored raw signals. The most important features are selected from the structured data for preventing the overfitting problems in the machine learning process. The fault diagnosis models are trained based on several machine learning algorithms and selected features. Finally, the fault diagnosis results are monitored by operators using mobile devices in real time. All monitoring and diagnosing processes including signal processing, feature extraction, feature selection, and diagnosis operate in the server of our cloud computing framework.

Keywords: Artificial Intelligence, Cloud Computing, Diagnostics, Manufacturing, Robot

1. Introduction

In modern manufacturing industry, monitoring the health status of industrial robots has become important. Faults of industrial robots may decrease the quality of manufactured products and cause shut down of manufacturing lines. Fault diagnosis of machineries have been widely studied [1]. However, model-based or signal-based fault diagnosis, which rely on prior knowledge, are difficult to apply to industrial robots because of their complicated structure and movement. In this work, we developed a data-driven fault diagnosis, which does not require prior knowledge, for industrial robots. A cloud computing framework is also developed to minimize the resource of humans.

Our data-driven fault diagnosis system with a cloud computing framework includes a data acquisition module, data processing module, fault diagnosis module, process monitoring module and alarming module. The data acquisition module is located in the physical space where the industrial robot is installed. Data processing and fault diagnosis module run in a server of our cloud computing framework. Monitoring and alarming modules are developed with web application program interface. With the combination of the two powerful modules, we provide a complete solution to monitor the health status of industrial robots in real time.

2. Research flow

The cloud computing framework for fault diagnosis is shown in Fig. 1. The analog signals measured by sensors were transformed into digital signals by the data acquisition (DAQ) module and transferred to a local gateway. The local gateway transmitted the gathered signals to the cloud to analyze data

using signal processing techniques and machine learning algorithms.

2.1. Data acquisition module

In this work, we attached accelerometers and acoustic emission sensor on the industrial robot. The status of an input gear in the joint of the industrial robot is diagnosed. The sensors are attached near the target input gear and measure the signals while the industrial robot is in the programmed motion. The measured signals are converted into digital signal via DAQ and transmitted to server using the local gateway.

2.2. Data analysis and diagnosis module in server

The developed server includes programs of signal processing, feature extraction/selection, machine learning and database. The transmitted digital signals are decomposed using signal processing techniques like wavelet packet decomposition, and seven numbers of structured data are extracted as follows: max, min, mean, absolute mean, root mean square, variance, and kurtosis.

The number of structured data is large because of multiple sensors and 12 decomposition levels while processing the signal. 252 numbers of features are extracted in one experiment using three sensors. The massive numbers of features may cause overfitting problems and reduce the accuracy of the diagnosis models. We employed feature selection process including filter and wrapper method [2]. The most important features are selected from the structured data before the machine learning process.

We employed support vector machine, artificial neural network, convolutional neural network [3], and critical information map [4] as the machine learning algorithms. The fault diagnosis models are trained based on the mentioned machine learning algorithms and selected features. All data

including raw signals, diagnosis results, and fault diagnosis models (diagnosis AIs) are saved in mongoDB repository [5].

The fault diagnosis results are transmitted through the Web API and monitored using mobile devices in real time.

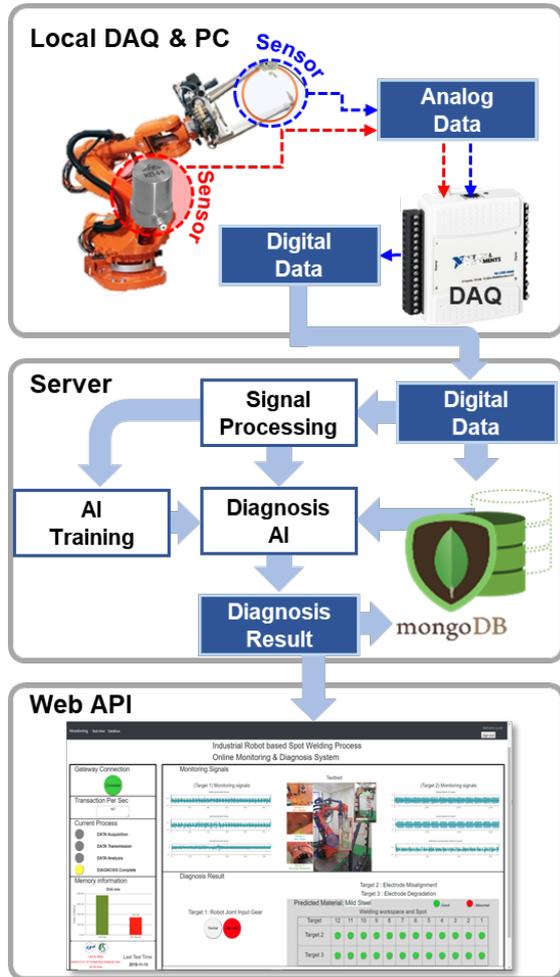


Figure 1. A schematic diagram of the cloud computing framework

3. Results

We validate the fault diagnosis model using data which is not used during the model training process. Table 1 and 2 show the diagnosis results of the unused data using the trained models with feature selection process and without the process respectively. The fault diagnosis model with feature selection classify normal and abnormal conditions with 98% accuracy, which are 9% higher than the model without the process. This result shows that the extracted features cause overfitting problems during machine learning process and feature selection process can effectively prevent the problem.

Table 1 Validation result of the input gear fault diagnosis with feature selection process

| | | Predicted status | |
|-------------|----------|------------------|----------|
| | | Normal | Abnormal |
| True status | Normal | 30 | 0 |
| | Abnormal | 1 | 29 |

Table 2 Validation result of the input gear fault diagnosis without feature selection process

| | | Predicted status | |
|-------------|----------|------------------|----------|
| | | Normal | Abnormal |
| True status | Normal | 26 | 4 |
| | Abnormal | 2 | 28 |

4. Conclusions

In this work, we developed a data-driven fault diagnosis system with a cloud computing framework for industrial robots. The fault diagnosis model classified normal and abnormal status of the input gear with very high accuracy.

All process except the data acquisition operates automatically in the cloud computing system. Therefore, our cloud computing framework may provide an efficient diagnosis operation by giving prompt and accurate monitoring results regardless of location. In addition, our framework may facilitate quality control in a manufacturing process which has become critical in autonomous factory.

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