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A Study on Fault Classification of Machining Center using Acceleration Data Based on 1D CNN Algorithm

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1D CNN 알고리즘 기반의 가속도 데이터를 이용한 머시닝 센터의 고장 분류 기법 연구

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ABSTRACT

The structure of the machinery industry due to the 4th industrial revolution is changing from precision and durability to intelligent and smart machinery through sensing and interconnection(IoT). There is a growing need for research on prognostics and health management(PHM) that can prevent abnormalities in processing machines and accurately predict and diagnose conditions. PHM is a technology that monitors the condition of a mechanical system, diagnoses signs of failure, and predicts the remaining life of the object. In this study, the vibration generated during machining is measured and a classification algorithm for normal and fault signals is developed. Arbitrary fault signal is collected by changing the conditions of un stable supply cutting oil and fixing jig. The signal processing is performed to apply the measured signal to the learning model. The sampling rate is changed for high speed operation and performed machine learning using raw signal without FFT. The fault classification algorithm for 1D convolution neural network composed of 2 convolution layers is developed.

Key Words : Machining Center(머시닝센터), Machine Learning(머신러닝), Fault Signal Classification(고장신호 분류), CNN(합성곱 신경망)

1. Introduction

The structure of the machinery industry following the Fourth industrial revolution is changing from the H/W center of the machine, such as precision and durability, to the intelligence and smartization of mechanical equipment through sensing and interconnection (IoT). The smart technology of the machinery industry includes the learning-based processability diagnosis and control technology of machine tools, which monitors, predicts, and controls

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autonomously to maintain machine precision and prevent abnormal conditions. In addition, it enables continuous optimization of process conditions to respond to customized production needs of various types. However, cutting of machine tools is highly influenced by equipment, materials, tools and process characteristics, and it is difficult to analyze by machining variables[1-3].

There is a growing need for research on prognostics and health management (PHM) to prevent system abnormalities and to accurately diagnose and predict conditions. Failure of the machine can lead to functional degradation and physical and time damage. Maintenance is carried out regularly to prevent the failure or damage of most mechanical systems. However, it is costly to replace normal parts and it is difficult to cope with sudden failure. PHM is a technology that monitors the condition of mechanical systems, diagnoses signs of failure, and predicts the remaining life of a subject. Many studies have been conducted to develop or verify a diagnostic technique by constructing a test bed and to verify data collected using simulation[3-6].

The purpose of this study is to classify normal and fault signals by using the acceleration data generated during actual machining on the field instead of the test bed. The translational acceleration in three directions of normal and fault signal including external noise signal is measured. A machine tool fault diagnosis algorithm based on 1D convolution neural network deep learning using raw signal without frequency conversion(FFT) is developed.

2. Normal and fault data acquisition

In order to develop a fault diagnosis classification algorithm, the acceleration signals of the machine tools in the actual work site is collected. Signals is collected by attaching an acceleration sensor to Doosan's Mynx6500 machining center[7]. Workpiece material is aluminium, and working time is about 40 minutes and working conditions are shown in Table 1.

Table 1 Machining condition

Tool	Cutter	End mill	Ball end mill
RPM	7000	2000	5000

Table 2 Acquisition condition

Parameters	Sampling rate	Bandwidth	Resolution	Window
Value	3.9e-5 s	4096 Hz	0.5 Hz	Hanning

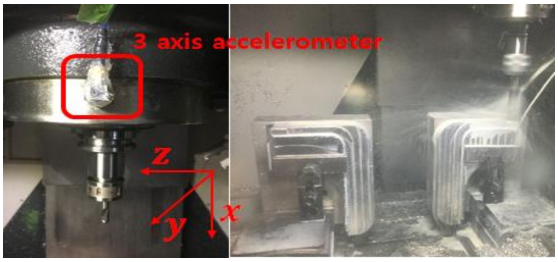
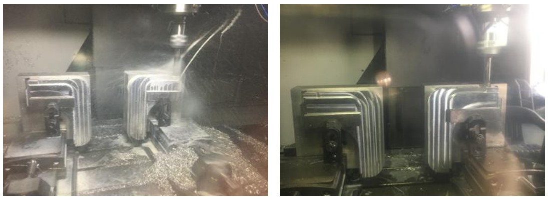


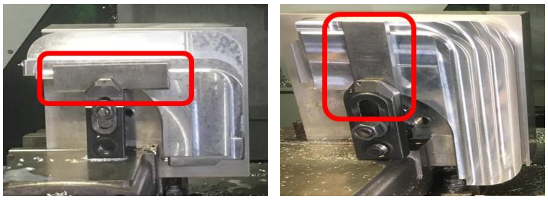
Fig. 1 Data acquisition

Acceleration generated during machining, is measured using Siemens vibration measuring module and TestLab[8]. The acceleration measurement condition is shown in Table 2.

A 3-axis acceleration sensor is attached to the head of the machine tool and it is shown in Fig 1. Normal and fault signal is measured for all processes of the workpiece[9-11]. In this study, fault is defined as the vibration generated during machining affects the quality of the workpiece. An arbitrary fault condition is created for fault classification. The first fault condition is performed under condition where the cutting oil supply is significantly reduced. In the second fault condition, the bite direction of the jig to fix the workpiece is set differently and it is shown is Fig. 2. The measured acceleration is shown in Fig. 3, in case of normal signal, amplitude is constant and periodicity. Noise signal at the actual machining site is measured. In the first fault condition, large amplitude occur and it is aperiodic. The second fault signal is measured a lot of noise and larger amplitude than the normal signal.

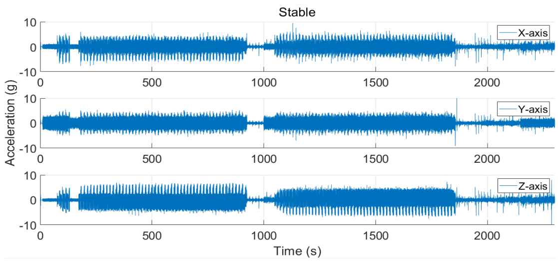


(a) condition (1) : Unstable cutting oil supply

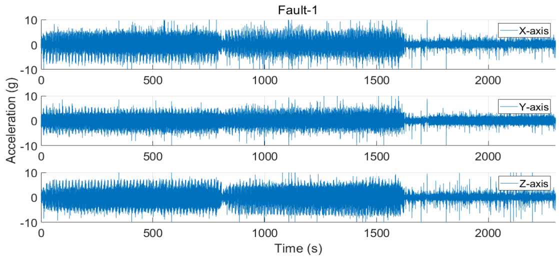


(b) condition (2) : Zig direction

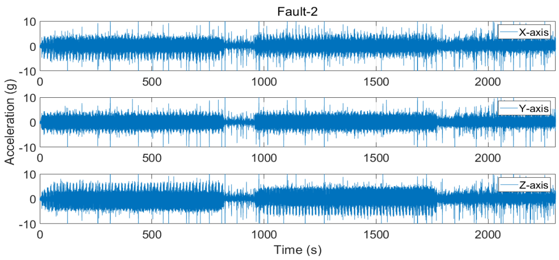
Fig. 2 Fault condition



(a) Normal signal



(b) Fault signal 1



(c) Fault signal 2

Fig. 3 Measurement data

3. Fault classification algorithm

3.1 Data preprocessing

The acceleration data is preprocessed for the learning model. The y-axis and z-axis signals are extracted based on the x-axis signal to adjust the length of the data. The raw signal is used without performing FFT for high speed computation[12]. The sampling frequency is changed from 25kHz to 512Hz by extracting only the 50th signal to operate at low sampling rates. The training data is generated by sliding 300 pieces. Also each data overlaps 50% and it is shown is Fig. 4. In order to make the data the same scale, a normalization is performed as shown in Equation (1). The training data for the normal and fault signals on the y-axis after preprocessing are shown in Fig. 5.

$$z = \frac{x - \bar{x}}{\sigma} \qquad (1)$$

Where, x is the input value, $\bar{x}$ is the mean, and is the σ standard deviation.

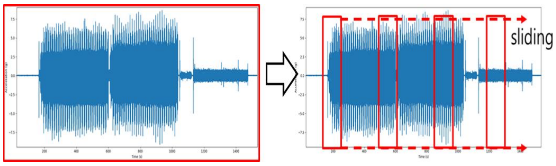


Fig. 4 Creating data through sliding

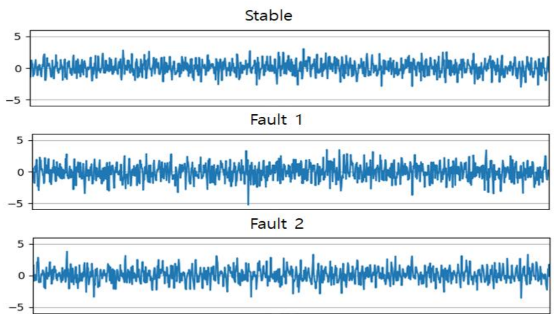


Fig. 5 Learning data for the y-axis

3.2 CNN Model

Convolution Neural Network (CNN) is an operation mainly used in the field of image processing or signal processing. The complexity of the model can be reduced and good features can be extracted. The desired characteristics are obtained by multiplying the input signal by a specific form and multiplying each of the areas covered by the filter and adding the result. Time series data, such as acceleration data, is highly correlated between measurements. Measurement data is classified by using CNN that can utilize data correlation[13-14].

The basic structure of feature extraction using acceleration measured in this study is shown in Fig. 6. Takes input data and performs convolution to extract the feature. The convolution of the lth layer is shown in Equation (2). The pooling layer contributes to the performance improvement by removing noise and extracting summary statistics from the feature map. In addition, feature map is made smaller, which contributes to speed improvement and memory efficiency. In this study, max pooling is used to extract the maximum value, which is shown in Equation (3)[14-16].

$$c_i^{l,j} = \sigma\left(b_j^l + \sum_{m=1}^{M} \mathrm{w}_{\mathrm{m}}^{\mathrm{l,j}} x_{i+m-1}^{l-1,j}\right) \tag{2}$$

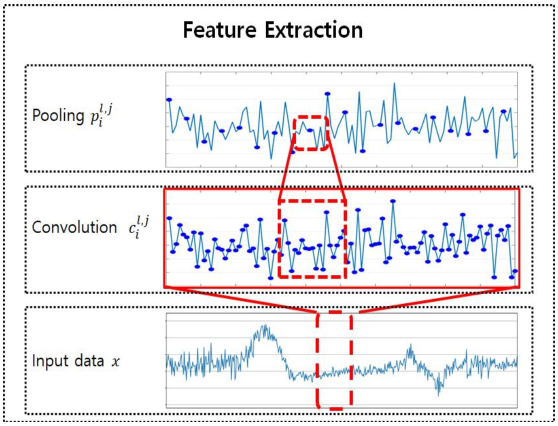


Fig. 6 Feature Extraction

Where, l is the index of the layer, σ is the active function, b_j is the bias of the jth feature map, M is the kernel size, $\mathrm{w}_{\mathrm{m}}^{\mathrm{j}}$ is the weight of the jth feature map, and m is the index of the filter.

$$p_i^{l,j} = \max(c_{i\times T+r}^{l,j}) \tag{3}$$

Where, R is the pooling size, T is pooling stride. Multiple convolution and pooling layers can be stacked to form a deep neural network. After the convolution, the output is delivered to the pooling layer through the ReLU activation function. The ReLU activation function is a derived from the active sample of a neuron and it is shown in equation (4).

$$\begin{aligned} z &= \mathrm{w}^{\mathrm{T}}\tilde{\mathrm{x}} + b \\ y &= ReLU(z) = \max(0, z) \end{aligned} \tag{4}$$

Where, w is a weight, x is input data, b is bias. The ReLU activation function outputs zero if the input value is less than zero and outputs the input value if it is greater than zero. The extracted data can be classified normal and fault signal through a fully connected layer and Softmax activation function. The structure of classification is shown in Fig. 7. The Softmax activation function is shown in Equation (5) and it is converted to a value between 0 and 1, and the output is treated as a probability distribution.

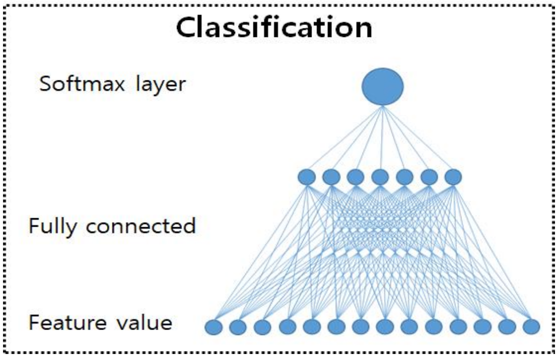


Fig. 7 Classification

$$o_j = \frac{e^{s_j}}{\sum_{i=1}^{c} e^{s_i}} \tag{5}$$

Where s is the output from the previous layer. Equations (1) through (5) represent forward propagation and return error values of the network. Weight is updated through training and error value is minimized. This is called backward propagation. The fault diagnosis algorithm repeats the forward and backward propagation until a stop condition or number of epochs is reached.

In this study, the algorithm is constructed using two convolutional layers and the drop out regulation is applied to prevent overfitting and it is shown in Fig. 8. The cost function is used cross entropy and Adam optimizer is used to optimize the error[12,17,18]. The hyper parameters used for the fault classification algorithm are shown in Table 3.

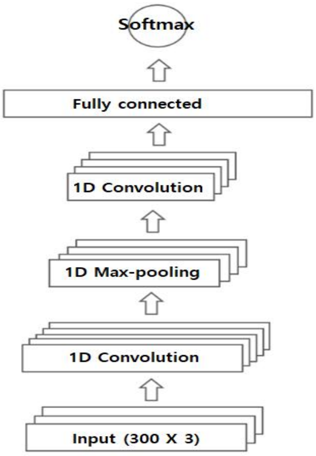


Fig. 8 1D CNN classification architecture

Table 3 Experimental setup

Parameter	Value
Input size	300×3
Filter size	2
Pooling size	2
Learning rate	0.001
Batch size	10
Maximum epochs	40

4. Result of Fault Classification

The input data is 300×3 acceleration amplitude. Training and validation data are consisted of a ratio of 8:2. The first fault signal, the unstable cutting oil supply condition, is trained for 11609 training data and 2903 validation data. The second fault signal, the position change of the fixed jig, is trained by 12189 training data and 3048 validation data. The accuracy and loss according to the epoch for the fault signals are shown in Fig. 9, Fig. 10, respectively.

Training data show that as the epoch passes, the accuracy converges to about 99% and the loss decreases. The accuracy of the validation data is similar according to the epoch. When 40 epochs are performed, the accuracy of the first fault condition is about 75.9% accurate and the second fault condition is about 81.1% . As epochs increases, the accuracy of the training data increases, the validation data shows similar accuracy.

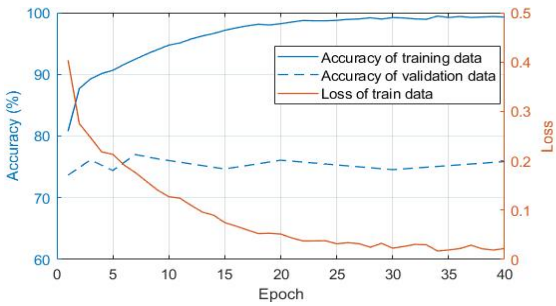


Fig. 9 Accuracy and loss for fault signal 1

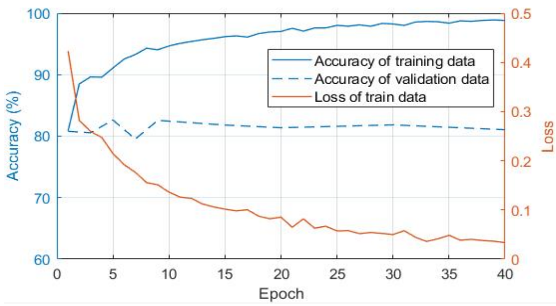


Fig. 10 Accuracy and loss for fault signal 2

5. Conclusion

In this paper, a fault signal classification algorithm for machine tool diagnosis and control technology development is proposed. A three-axis accelerometer is used to measure normal and two fault signals generated by the machine tool. Machine learning is performed using the raw signal to enable high-speed computation of the measured data and to apply it directly to the field. CNN consisting of two convolutions and a pooling layer are applied the fault classification algorithm. The following conclusions can be drawn :

1. Fault signal classification is performed using one-dimensional amplitude data, and the accuracy for the two fault conditions are about 76% and 81%, respectively.
2. The acceleration data is measured in the workplace with high external noise signal is used, not the test bed or the lab test.
3. 300 pieces of input data can be used to determine a fault in a very short time of about 1 second during 40 minutes of the working time. It is expected to be applicable to the actual industry.
4. The process of selectively acquiring and learning the data during the cutting process is difficult, and it is desirable to learn the data of the entire process in order to apply it to the actual workplace. The actual time for the acquisition data is about 2500 seconds, and cutting process is about 2100 seconds. The process of cutting is 84% of the whole process. The accuracy of the whole process is over 76%. If the learning is performed only for the cutting process, the accuracy is further increased.

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