Deep learning application of vibration data for predictive maintenance of gravity acceleration equipment

SeonWoo Lee\textsuperscript{a,1}, Yu-Hyeon Tak\textsuperscript{b,2}, Ho-Jun Yang\textsuperscript{a}, Jae-Heung Yang\textsuperscript{c}, Gang-Min Lim\textsuperscript{c}, Kyu-Sung Kim\textsuperscript{a}, Byeong-Keun Choi\textsuperscript{b,*} and JangWoo-Kwon\textsuperscript{a}

\textsuperscript{a}Department Electric Computer Engineering, Inha University, 100, Inha-ro, Michuhol-gu, Incheon, Republic of Korea
\textsuperscript{b}Department Mechanical Engineering, Gyeong-Sang National University, 38, Cheondaegukchi-gil, Tongyeong-si, Gyeong sangnam-do, Republic of Korea, 530-64
\textsuperscript{c}R&D Center, ATG, #1104, KINS Tower, 331-8, Seongnam-daero, Bundang-gu, Seongnam-si, Gyeonggi-do, Korea
\textsuperscript{d}Department of Otolaryngology-Head and Neck Surgery, Inha University College of Medicine, Incheon, 3-Ga Shinheungdong, Jung-Gu, Incheon 400-711, Korea

Abstract. Hypergravity accelerators are used for gravity training or medical research. They are a kind of large machinery, and a failure of large equipment can be a serious problem in terms of safety or costs. In this paper, we propose a predictive maintenance model that can proactively prevent failures that may occur in a hypergravity accelerator. The method proposed in this paper is to convert vibration signals into spectograms and perform classification training using a deep learning model. We conducted an experiment to evaluate the performance of the method proposed in this paper. We attached a 4-channel accelerometer to the bearing housing which is a rotor, and obtained time-amplitude data from measured values by sampling. Then, the data was converted into a two-dimensional spectrogram, and classification training was performed using a deep learning model for four conditions of the equipment: Unbalance, Misalignment, Shaft Rubbing, and Normal. Experimental results showed that the proposed method has an accuracy of 99.5\%, an increase of up to 23\% compared to existing feature-based learning models.

Keywords: Artificial Intelligence, Deep Learning, Preventive maintenance, Hyper-gravity Machine, Vibration Monitoring

1. Introduction

All objects on Earth are affected by the Earth's gravity. There are many practical difficulties in conducting research on microgravity on the ground, not in outer space. On the other hand, research on
hypergravity can be carried out relatively easily using centrifugal force by spinning simulation. However, hypergravity research requires a gravity simulator which can control gravity by a constant rotation angular speed. Thus, to conduct hypergravity research, we developed a gravity simulator which that enables the creation and maintenance of an environment of hypergravity up to 15 times the Earth's gravity (15 G) for an experimental object, as shown in Fig 1.

![Gravity Simulator for the research of hypergravity](image)

Gravitational accelerators are generally used for hypergravity training of astronauts, and can also be used for animal testing in basic research for medical purposes. In addition, they can be used to conduct ground experimental tests on sudden changes in gravity, such as hypergravity and hypogravity, and changes in pressure that the human body undergoes in the space environment in order to assess and investigate the biological responses to these harmful stimuli to the human body. These changes in gravity can result in fluid shift and redistribution in the human body, fluid loss, red blood cell loss, muscle damage, bone damage, hyperalcemia, immune system changes, or spatial disorientation and vertigo [1].

As studies on such changes in the human and animal body due to changes in gravity have been actively carried out, the necessity of monitoring the safety and reliability of large gravity acceleration equipment has emerged as an important issue. One of the major issues regarding gravity acceleration equipment is the occurrence of abnormal vibrations when machinery failures occur due to high-speed rotation. If small vibrations generated in the rotating part of gravity acceleration equipment are amplified, it may result in the damage of the shafts rotating at high speeds, so equipment failures may lead to serious accidents. Therefore, in this study, we aim to detect abnormal vibrations of gravity acceleration equipment.
So far, many studies on vibration-related failures and predictive failure diagnosis have been conducted.[2, 3, 4, 5, 6] The major methods used in these studies [6] are largely characterized by application of algorithms such as Support Vector Machine (SVM) [7] after calculation and enumeration of features such as mean, standard deviation, fast Fourier transform (fft), and kurtosis and selection of features which appropriately express patterns or properties for classification tasks based on the genetic algorithm or principal component analysis. In recent years, Artificial Neural Network (ANN) has become one of the most widely used methods due to advances in hardware technology and a large number of data which express relevant features well. [8]. In the case of Convolution Neural Network (CNN), one of the ANN methods, training is carried out as follows: multiple inputs are received, computation is performed using a model form that the user wants, and one output is produced. The method of applying a 1-D CNN model using time-amplitude data with a constant period has been presented as a failure diagnosis method [9, 10]. Another CNN model is 2-D CNN in which computation produces images of 3-D shapes with a width and length like input data as the output [11, 12, 13]. Since 2-D CNN has been shown to have high performance, many attempts have been made to apply it to speech recognition and failure diagnosis [14, 15, 16, 17].

This paper proposes a preventive maintenance model that enables monitoring of vibrations that can occur in machinery to proactively prevent mechanical failures described above. The method proposed in this study is largely divided into two major methods. The first method is to convert vibration data into two-dimensional data by converting time-amplitude data with a constant period, such as existing signals, into spectrograms which display time, frequency (Hz), and amplitude, which are mainly used in speech recognition [14, 16, 17]. The second method is to apply the preprocessed data to a deep neural network model and compare the results with those obtained by existing machine learning models.

The rest of this paper is organized as follows. Section 2 provides a brief review of previous studies on predictive maintenance using machine learning. In Section 3, the methods proposed in this study are explained. In Section 4, experimental results are presented, and in Section 5, conclusions of this study are drawn and the direction of future research is briefly described.

2. The Proposed Method

2.1. Design and fabrication of experimental rotating equipment

To conduct an experiment, simulation equipment was manufactured as described below. Pulse 3560C and 4 accelerometers (B&K 4371) were used for rotation and vibration data acquisition, and the data acquisition time for each condition was 30 seconds. Table 1 shows the detailed specifications of the data acquisition system.

| Type                | Properties                                      |
|---------------------|-------------------------------------------------|
| Pulse 3560C (B&K)   | 4/2-ch Input/output Module                      |
|                     | Operating Freq. rang : 0–25.6kHz                |
|                     | Direct/CCLD/MIC, preamp 1 Tacho Conditioning    |
| Accelerometer       | Operating Freq. rang : 1–25.6kHz                |
| (B&K 4371)          | Operating Temp. -50C–121C                       |
|                     | Sensitivity : 9.84 pC/g                         |
Fig. 1 shows the RK4 (Rotor-kit) of the lab-scale rotating simulation equipment, which is the experimental model, and locations of sensors used in the experiment. This experiment system is composed of a motor to operate rotating equipment, a flexible coupling connecting the rotor and motor, and two copper sleeve bearings supporting the rotor, and a 800g disk was installed between the bearings to simulate the unbalance fault. Sensors were installed on the drive-end side of the motor and the rotor, and measurements were taken at locations in the vertical and axial directions of the motor and rotor. As for the operating speed of the experimental equipment, it was operated at 2000 RPM, avoiding 2400 RPM, which is the first critical speed. 

In this experiment, fault simulations were carried out by simulating four representative conditions of rotating equipment: Normal, Unbalance, Misalignment, and Shaft rubbing conditions. Fig. 2 shows the methods of application of Normal condition and each type of fault. A normal condition was obtained after performing shaft balancing using the RK4, and residual unbalance was measured to be 0.02g/117.4° after balancing. Unbalance was induced by attaching an object with a mass of 3.2 g in a direction towards the location of residual unbalance (117.4°). Misalignment was given by installing a 4mm shim plate at the foot of the drive-end side of the motor, and shaft rubbing was applied in a horizontal direction using a magnetic base. Also, a contact device made of Teflon was used to minimize the damage of the axis that may occur due to rubbing.
Unbalance is the most fundamental and basic fault that causes vibrations in rotating equipment. Unbalance occurs when the mass distribution of the rotor is asymmetric with respect to the axis centerline, and all the causes of unbalance exist to some degree in rotors. Excessive unbalance increases the vibrations and noise of rotating equipment, and as a result, fatigue destruction may occur due to the deterioration of bearings and consumable parts.

Misalignment is one of the most common faults of rotating equipment along with unbalance [18]. It refers to the condition where the centers of the two axes do not coincide, or the condition where the centers coincide but are not parallel. A large degree of misalignment may cause overheating of the coupling, an increase in shaft cracks and fatigue, and damage to bearings and consumable parts.

The rubbing fault is a secondary transient phenomenon caused by excessive Unbalance and Misalignment in rotating machinery [19]. Rubbing may be caused by the occurrence of friction between the stator and rotor due to excessive vibrations, or a narrow gap due to thermal expansion during equipment operation. If rubbing occurs continuously during the operation of rotating machinery, it may cause separation of parts or axis bending, and severe rubbing may lead to the destruction of the rotating equipment.

The sampling rate of obtained signals was 65536 Hz. Signals measured for 30 seconds were divided into 0.48 second units in consideration of the measurement environment of the actual equipment, and each of 0.48 second units was assumed to be one data. Machine learning was performed by dividing 1 data into 14 samples. Sampling is performed because a vibration is a periodic signal in the time domain [20], and most fault signals also have periodicity. Therefore, sampling is used to examine the consistency and continuity for each condition by using features calculated from the signals.

The signal segmentation for sampling was based on the rotational frequency of the rotor. Generally, in rotating equipment, the rotational frequency is the most dominant component, and the majority of fault components appear in a harmonic form of the rotational frequency. Therefore, the length of the sample of experimental data was set to 0.06 seconds, which is twice 0.03 seconds, which is the period of vibrations at 2000 RPM, and the number of samples was increased by overlapping half the signal.

The total number of training and test data was 1056, and the dataset was divided into training and testing datasets by allocating 80% to the training dataset and 20% to the testing dataset. At this time, the training dataset consisted of 229 Normal data, 199 Rubbing data, 205 Unbalance data, and 211 Misalignment data, while the testing dataset included 43 Normal data, 61 Rubbing data, 55 Unbalance data, and 53 Misalignment data.
2.2. The method of data visualization

The data conversion method proposed in this paper is shown in Figure 4. After receiving data from the experimental equipment at intervals of 0.06 seconds as described in Section 1.1, the data are converted into STFT(Short Time Fourier Transform) signals or MFCC(Mel Frequency Cepstral Coefficient) signals, and they are again converted into spectrograms. Through this process of data visualization, vibration data are converted into spectrograms.

Fig. 4 An example of conversion of vibration signals into images

Fig. 5 Original signals of each target class: Normal, Misalignment, Rubbing, and Unbalance (Left); Examples of SFTF conversion of Normal, Misalignment, Rubbing, and Unbalance signals (Right)

Fig. 5 shows an example of representation of signals for Normal condition and each type of Fault
described in Section 1.1 as two-dimensional amplitude-time graphs and an example of converting the graphs using STFT. In general, the amplitude of a Fault signal tends to be larger than that of a Normal signal.

2.3.1 STFT (Short-Time Fourier Transform)

With respect to the method for converting time-amplitude data into 2D images, we used spectrograms after performing Short-Time Fourier Transform (STFT). STFT is the method of partitioning continuous signals over a long time period into shorter segments at short time intervals and applying a Fourier transform to each signal segment, and this technique allows us to see how vibrations of signals change with time. These changes in vibrations can be expressed as Eq (1) [24].

$$X[k, n] = \sum_{m=0}^{L-1} \omega[m] x[n + m] e^{-j(2\pi k/N)m}$$  (1)

It is assumed that \(\omega[m]\) is a non-zero window signal in the interval \(m = 0, 1, \cdots, L - 1\) and \(L\) is a smaller signal than the signal \(x[m]\). \(\omega[m] x[n + m]\) is a non-zero signal in \(m = 0, 1, \cdots, L - 1\). The signal \(x[m]\) is a form that undergoes \(N\) point DFT (Discrete Fourier Transform) according to the size of \(n\). Therefore, FFT is computed according to the size of \(m\). Since a signal generated through this process constitutes a different spectrum with time, it cannot be represented as a spectrum. Thus, it was represented as shown in Fig.6 by taking \(|X[k, n]|\) and applying a color map.

Fig. 6 Examples of changes in STFT spectrograms
2.3.2 MFCCs (Mel Frequency Cepstral Coefficients)

MFCC is a conversion algorithm mainly used in speech recognition. It is one of the methods for extracting features from sound signals and the procedure for feature extraction consists of the following six steps [16, 17]:
- Frame the signal into short frames.
- For each frame, calculate the periodogram estimate of the power spectrum.
- Apply the mel filterbank to the power spectra, and sum the energy in each filter.
- Take the logarithm of all filterbank energies.
- Take the DCT of the log filterbank energies.
- Keep DCT coefficients 2-13, and discard the rest.

![Image of signal changes in the spectrograms of MFCC signals](image)

Fig. 7 Example of signal changes in the spectrograms of MFCC signals

2.3. Deep learning network

The deep learning neural network architecture proposed in this study is based on VGG19 [11]. VGG19 is a model that is widely used as a basic deep learning method because it is relatively easy to implement and modify since it uses only \(3 \times 3\) convolutional layers. In this study, the number of parameters was reduced by using 'average pooling' to eliminate the last 'fully connected layer', which is one of the parts of VGGNet that take up a lot of computation, and to match with the output layer, and the deep learning architecture was built as shown in Fig. 4.
The proposed network architecture. The amount of computation was reduced by replacing the last Fully Connected Layer with Global Average Pooling.

The image size of the spectrogram in Fig. 8 used as a training data was changed by converting a rectangular shape with a width greater than the length (432, 288) into a square shape (298, 298) before using it in the experiment. For convergence of learning errors, we tried to find the Global Minimum Error by using the Learning Rate Decay Strategy, which reduces the learning rate by 0.04% at 60, 120, and 160 epochs, and other hyperparameters were set as shown in Table 2.

2.4. Deep learning environment

In this study, the deep learning environment for training and testing a deep learning model was built with a PC with a configuration of 32GB RAM, i5-8500 3.0GHz CPU, and RTX 2080 Ti GPU. The experimental software environment was developed in a Python 3.7.6 environment, and the main packages used to set up the environment were Pytorch 1.5 [20], librosa 0.6.3 [21], and sklearn 0.22 [22].

3. Performance evaluation

In the experiments of this study, accuracy, precision, recall, and F1-Score were measured using True
Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN), and accuracy, precision, and recall, F1 Score can be expressed by Eqs. (2) – (5), respectively.

\[
\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN}
\]

\[
\text{Precision} = \frac{TP}{TP+FP}
\]

\[
\text{Recall} = \frac{TP}{TP+FN}
\]

\[
\text{F1 Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}
\]

At this time, to demonstrate the superiority of the methods used in this experiment, these methods were compared with one of the most commonly used existing methods, the method of applying SVM (Support Vector Machine) after feature selection based on the genetic algorithm after extracting features from a raw signal and [6]. The proposed methods were also compared with the MLP (Multi Layer Perceptron) method [8] to demonstrate that it shows better performance in training after data visualization. The experimental results are shown in Table 3. In all four conditions of Normal, Rubbing, Unbalance, and Misalignment, the proposed methods showed better performance than the existing methods [6, 7, 8].

| Class      | Model  | Accuracy | Precision | Recall | F1    |
|------------|--------|----------|-----------|--------|-------|
| Normal     | SS-VGG19 | 1.0      | 0.98      | 0.99   | 0.99  |
|            | MS-VGG19 | 1.0      | 1.0       | 0.98   | 0.99  |
|            | MLP     | 0.93     | 0.95      | 0.95   | 0.95  |
|            | GA-SVM  | 0.76     | 0.90      | 0.94   | 0.92  |
| Rubbing    | SS-VGG19 | 1.0      | 1.0       | 1.0    | 1.0   |
|            | MS-VGG19 | 1.0      | 1.0       | 1.0    | 1.0   |
|            | MLP     | 0.93     | 0.90      | 0.89   | 0.90  |
|            | GA-SVM  | 0.76     | 0.72      | 0.66   | 0.69  |
| Unbalance  | SS-VGG19 | 1.0      | 1.0       | 0.99   | 0.99  |
|            | MS-VGG19 | 1.0      | 0.98      | 1.0    | 0.99  |
|            | MLP     | 0.93     | 0.96      | 0.95   | 0.96  |
|            | GA-SVM  | 0.76     | 0.78      | 0.77   | 0.78  |
| Misalignment | SS-VGG19 | 1.0      | 1.0       | 1.0    | 1.0   |
|            | MS-VGG19 | 1.0      | 1.0       | 1.0    | 1.0   |
|            | MLP     | 0.93     | 0.89      | 0.91   | 0.90  |
|            | GA-SVM  | 0.76     | 0.65      | 0.68   | 0.66  |
Table 2 shows that the deep learning methods proposed have better performance than a method based on MLP or SVM. This can be attributed to the fact that a lot of information that cannot be expressed as features get lost when selecting features of input data in the preprocessing stage. Even though all 30 data were selected and learned using the MLP algorithm, it was not possible to achieve a performance equal to or better than that of deep learning. In addition, the results were not different even when MFCC or STFT was selected during preprocessing. It was found that almost all the information of the label which needed to be obtained in this experiment could be acquired from the form of the input image.

As shown in Fig. 9, the performance of the deep learning model is shown by training errors and accuracy curves obtained as experimental results. A unique aspect of this experiment is that the errors and test accuracy of the data training models to which data preprocessed by MFCC and STFP conversions were applied converge when the completion rate is about 75%. In both the two models, the loss value was small in the initial stage of training and then it converged as the vibration amplitude became larger.
Fig. 10 shows the Confusion Matrix of the models used in the experiments, and the results of both the models were the same. As for the training errors of the models, there was a classification error of 2% for Normal and Unbalance.

4. Conclusion and Future Work

In this study, in order to prevent accidents that may occur in large equipment such as a gravitational accelerator, we measured vibration signals with accelerometers, used the measured data to train and test a deep learning model by using spectrogram visualization based on MFCC and STFT, and attempted to evaluate the proposed method.

The major methods used in this experiment were to convert vibration signals into images and apply a modified VGGNetwork to a fault model. The proposed deep learning architecture enables the diagnosis of a total of 4 conditions, such as Normal, Rubbing, Misalignment and Unbalance, and both MFCC and STFT models showed the average accuracy rate of 99.5%. In addition, the proposed models were compared with feature-based machine learning models using existing traditional methods. Experimental results showed that the proposed models have better performance in all evaluation parameters of accuracy, recall, precision, and F1-Score, compared to existing feature-based learning models. These results indicate that the proposed method can be successfully used as a fault diagnosis and assessment model if a monitoring environment is constructed by attaching sensors in the
assessment of the stability of gravity acceleration equipment in the future.

In addition, it was shown that existing vibration data can also be converted into image data such as spectrograms, one of the methods used in speech recognition, and they can be applied to an image-based deep learning model. The method proposed in this study has the following limitations. First, the patterns of fault data should be prepared in advance. These shortcomings should be addressed through further studies such as research on outlier detection. Second, training takes considerable time and requires additional hardware such as GPUs. Taking into account these limitations, a method of reducing computation amounts should be performed so that the proposed method can be used for small edge devices required for commercialization.

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