Deep Learning Based Diagnostics of Orbit Patterns in Rotating Machinery

Haedong Jeong, Sunhee Woo, Suhyun Kim, Seungtae Park, Heechang Kim, and Seungchul Lee

Ulsan National Institute of Science and Technology, Ulsan, Korea

hdhd13@unist.ac.kr
wsh0319@unist.ac.kr
kimsh12191@unist.ac.kr
swash21@unist.ac.kr
chang1094@unist.ac.kr
seunglee@unist.ac.kr

ABSTRACT

Vibration-based orbit analysis has been employed as a powerful tool in diagnosing the operating state for rotating machinery in power plants. However, due to the difficulties of extracting mathematical features for data-driven approaches in the orbit analysis, it heavily depends on the expert knowledge or experience. In this paper, the deep learning algorithm in machine learning is used to develop autonomous orbit pattern recognition. In details, the convolutional neural network is implemented to build up weights between convolution kernels and pixels, and to construct the entire structure of the neural networks. Finally, the trained network enables us to classify the shapes of the orbit via orbit shape images and its result can estimate fault modes of the rotating machinery. The proposed framework is demonstrated with a rotating testbed.

1. INTRODUCTION

In most power plants, faults from the rotating machinery may cause its performance degradation and entire system breakdowns. It is directly related to plant operation/maintenance costs. The condition-based maintenance (CBM) helps to avoid and prevent system failures through monitoring vibration signals collected by accelerometer or proximity sensors in various locations. The vibration signals need to transform to useful information via signal processing. Generally, time-domain analysis, frequency-domain analysis and time-frequency analysis are known as traditional, but main methods (Jardine et al. 2006).

Frequency-domain analysis handles the data related to frequency domain. The spectrum analysis based on fast Fourier transform (FFT) is widely used. Conventionally, the principal harmonic frequency amplitudes (1X, 2X, 3X, etc.) are extracted and used to diagnose the state of rotating machinery.

Time-domain analysis directly handles a time waveform itself as applying filters or extracting characteristic features such as simple statistics (mean, standard deviation, etc.) or high-order statistics (root mean square, skewness etc.). In time domain, there are many techniques to remove the effect of other source and noise such as time synchronous average (TSA) and autoregressive moving average (ARMA) model.

Time-frequency analysis is combined concepts of time and frequency domains. Short-time Fourier transforms (STFT) and Wigner-Vile distributions are the popular methods. These methods are used to handle non-stationary waveform signals or inspect trend information over time.

It is well known that the harmonic frequency elements (1X, 2X, 3X, etc.) are often selected as principal features especially for the rotating machinery health monitoring. The orbit constructed by two non-contacting proximity sensors (x and y axes) provides important and relevant information on rapidly changing machinery conditions. Generally, perturbations or malfunctions can usually be detected by shaft rotation (orbit) in rotating machinery. Furthermore, the malfunction of machine will adversely cause change of shaft rotation and generate the special orbit pattern. Therefore, an understanding of orbit shapes helps to identify how the dynamics of machinery malfunctions takes place, and how they can be more accurately detected before failure (Eisenmann, 1997).

Although the orbit shape from orbit analysis contains the most important information of the rotating machinery health condition, it is not well utilized in power plants because it is not easy to extract numerical features that represent the specific orbit shape. As a result, orbit shapes are manually monitored by human operators in most case.

Therefore, in this paper, the deep learning based approach is proposed for the autonomous orbit pattern recognition. Especially, Convolutional Neural Networks (CNN) for image pattern recognition has been applied to orbit images to diagnose the fault mode.

2. THEORETICAL BACKGROUND

The following section outlines general (non-formatting) guidelines to follow. These guidelines are applicable to all authors and include information on the policies and practices relevant to the publication of your manuscript.

2.1. Previous Machine Learning Methods for Diagnostics

There are a variety of machine learning algorithms used to diagnose a fault in the rotating machinery. Basically, machine learning is to make a category (or class) of the pattern from raw data and build auto-cognitive systems for some tasks (Duda, 2012).

An expert system method is based on the causes of fault and symptoms from an empirical knowledge, which came from direct experience of engineers. Generally, causes-systems are expressed in the form of IF (symptom) and THEN (cause). Because observed symptoms are able to be known information or cases, Bayesian algorithm that calculates the probability of an accident occurring based on condition probability is adopted in the expert system (Yang, 2005).

Support Vector Machine (SVM) is a supervised learning model. In SVM, a feature-based input vector is used to build a feature space. Frequency elements and statistical elements are selected as features to diagnose rotating machinery. Then, SVM will provide a decision boundary by considering relationship between input feature vector pattern1s and fault types.

Artificial Neural Network (ANN) is a mathematical or computational model for information processing. ANN structure generates appropriate classification boundaries based on information that flows through the network during iterative training (Zurada, 1992). After training is completed, the trained model can classify state of machine (Kankar, 2011).

ANN is chosen as a classifier in “Automatic Recognition of Orbit Shape for Fault Diagnosis in Steam Turbine Generator Sets” (C. Yan 2010). In this paper invariant moments are used as features of the ANN classifier by experts who have domain knowledge. Hence the paper does not automatize feature extraction process for orbit images.

On the other hand, our paper directly deals with image recognition problem. That is, we provide an image itself as an input without computing any features based on either training dataset or domain knowledge. Furthermore, CNN is known for outperformance on selecting image features automatically using convolution layers.

2.2. Deep Learning

In conventional machine-learning techniques, it is necessary to extract appropriate feature vector with careful engineering and considerable domain expertise to detect or classify patterns.

Representation learning methods are a set of methods that allow a machine to automatically discover the representation needed for detection or classification. Deep learning methods are representation learning methods with multiple levels of representation, obtained by composing simple but non-linear modules that each transforms the representation at one level (starting with the raw input) into a representation at a higher, slightly more abstract level. The key advantage of deep learning is that very complex functions can be learned and good feature can be automatically extracted using general-purpose learning procedure. As a result, deep learning is a computational model, which is composed of multiple processing layers that perform non-linear input-output mappings to learn representations of data with multiple levels of abstraction. Then, deep learning can find complicated hidden patterns in large data sets by using the backpropagation algorithm to calculate its internal parameters that are used to compute the representation in each layer from the representation in the previous layer (LeCun, 2015).

2.3. Image Pattern Recognition and Convolutional Neural Networks

Image pattern recognition is a method to generate and match descriptions to classify images. (Azriel et al. 1988). Descriptions are similar to features used to represent the waveform data in signal processing. Characteristic element of pattern in image can be express by good descriptions. Some points and edges can be descriptions such as Harris corner (Harris et al. 1988) and canny edge (CANNY. 1986). A matching operator between trained descriptions and input descriptions are interrupted by the variance of image patterns such as rotation and scale change. Extracting features or developing matching algorithm are used to solve image pattern recognition problem.

CNN is used as a key algorithm for the orbit image pattern recognition in this paper. CNN models are known as one of biologically inspired models and have been widely used for image pattern recognition problems such as hand-written digit recognition and face recognition (Matsugu et al. 2003). In image recognition, CNN consists of multi-layers of small parameters and collect the information to obtain better representation of the original image (Korekado et al. 2003). Figure 1 illustrates the CNN architecture. It includes pairs of convolution, sub-sampling layers (Lecun et al. 1998). The last sub-sampling layers are fully connected and the output vector classifies the input using max-pooling between overall values of activation function. This hierarchical organization helps to extract proper features in image classification tasks (Abdel-Hamid O. 2012).

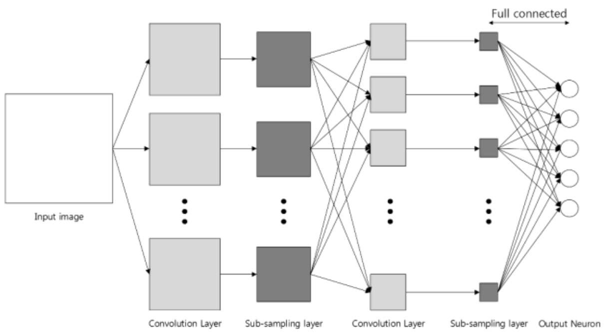
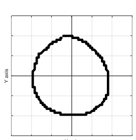
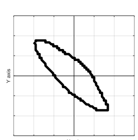
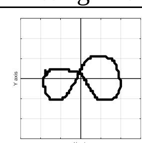
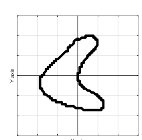
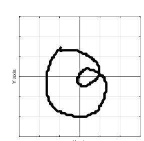


Figure 1. Structure of Convolutional Neural Networks

2.4. Orbit Shape and its Fault Type

The malfunction of rotating machinery causes a variety of faults such as unbalance, shaft misalignment and oil whirl in a rotor shaft. It has been well studied that the fault types in a rotor dynamics have a corresponding orbit shapes. The representative corresponding orbit shapes are summarized in Table 1 (Patel *et al*. 2009, Shia *et al*. 2005).

Table 1. Different Orbit Shapes according to Fault Types

Fault	Normal	Unbalance	Shaft misalignment
Orbit Shape			  

2.5. Full Spectrum: Complex Representation of Orbit

An orbit shape is mathematically related to the full spectrum which was introduced by Bently Nevada Corporation in 1993. Full spectrum analysis considers the orbit in the complex space in that the orbit signal constructed by two sensors attached 90 degree apart can be expressed by a linear combination of complex unit circles.

The full spectrum analysis is defined in Equation (1) where $x(n)$ and $y(n)$ are the vibration signal, and $Z(k)$ is a complex coefficient which contains an amplitude and a phase of each unit complex circle (Goldman *et al*. 1999).

$$z(n) = x(n) + y(n)\cdot j$$
$$Z(k) = \sum_{n=0}^{N-1} z(n) e^{-j\frac{2\pi}{N}nk} \qquad k = 0,\cdots,M-1 \tag{1}$$

As a result of the full spectrum analysis, the orbit expressed in a complex form can be approximated with the finite number *N* of harmonic frequencies (1X, -1X, 2X, -2X, etc.). Equation (2) is the approximation of $z(n)$, where ω is an angular velocity, m is a positive integer, $R_{m\cdot\omega+}$ and $R_{m\cdot\omega-}$ are complex values.

$$\hat{z}(n) = \sum_{m=1}^{N} (R_{m\cdot\omega+} e^{jm\omega n} + R_{m\cdot\omega-} e^{-jm\omega n}) \tag{2}$$

3. PRE-PROCESSING OF ORBIT IMAGES

The pre-processing step is necessary to orbit images before we train a classification model for image pattern recognition. In the pre-processing step, as the orbit image pattern is independent of a rotated angle of pattern, size of image, and an orbit image location, normalizing an orbit image with respect to rotation, size, and location is conducted.

For example, the orbit image of shape 8 and counter-clock wise rotated image as shown in Figure 3 can be recognized by a human operator. However, it is not easy to recognize the same pattern of rotated image in machine learning algorithm or it requires large computational time. To reduce the time for the image pattern machine learning process, it is necessary to conduct pre-processing steps such as re-orienting, offset shifting, and size normalization. Figure 2, 3, and 4 show these pre-processing steps.

3.1. Orbit Image Offset Shifting

A translation of the center point of the orbit image to the origin in an image canvas is performed to guarantee the invariance of the center position. Orbit signals which take place from the rotating machinery usually have the center point at origin point because sensors are attached based on the shaft midpoint. However, problem of the sensor calibration or the specific state of machine (hard rubbing, etc.) may cause offset of the center point.

The matrix A consists the column vector of each axis vibration data. The new orbit matrix $\bar{A}$ is obtained by subtracting the mean values from matrix *A*.

$$A = [x\ y]$$
$$\bar{A} = A - m \tag{3}$$

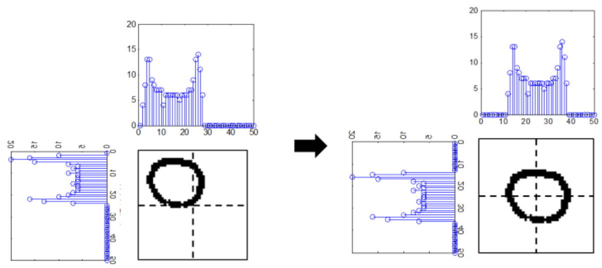


Figure 2. Image Offset Shifting

3.2. Orbit Image Re-orienting

Although phases are different, the shape of orbit is same with tilted orbit in a geometry viewpoint. A human operator can easily identify the same orbit pattern even if two images are tilted. However, machine learning algorithm is most likely to fail to recognize them as the same pattern. Consequently, before applying any pattern recognition algorithm, it is necessary to re-orient all the orbit pattern images to the same direction.

Covariance matrix, C is obtained by matrix $\bar{A}$. Subsequently, eigenvector matrix V can be obtained by eigen-analysis. V is a set of basis where matrix Λ is a diagonal eigenvalue matrix. The coordinate of an orbit is changed to matrix $\bar{A}_R$ by applying a rotation transformation.

$$
\begin{aligned}
C &= \bar{A}^T \bar{A} = V \Lambda V^T \\
\bar{A}_R &= \bar{A} V
\end{aligned} \tag{4}
$$

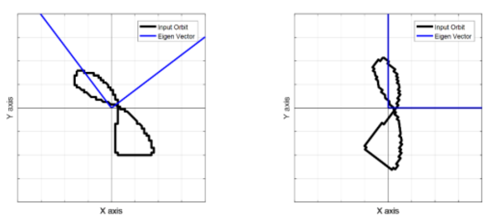


Figure 3. Image Re-orienting

3.3. Orbit Image Re-scaling

Although the degree of machine fault determines the size of an orbit shape, the fault type classification is not related to the size of image. Therefore, the scale of orbit pattern images can be normalized based on an input image size.

The size of orbit shape is resized with maintaining a ratio between a vertical length and a horizontal length. To resize the original image to the training image size, the re-scaling is conducted based on the longer length between a horizontal and a vertical length.

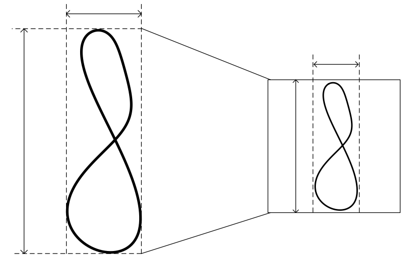


Figure 4. Scale Normalization

3.4. Orbit Shape De-noising

Moreover, an orbit pattern de-noising step is important to enhance an accuracy of orbit pattern recognition. In most cases, the orbit shape contains a sensor noise. Because of these noises, the shape of orbit will be disguised. Optimization method discussed in section 2.3 can be remove the effect of noise and improve the quality of orbit pattern.

Using the least square method, we make a projection of the given noisy orbit image onto a full spectrum model with the finite harmonic frequencies of 1X, -1X, 2X, -2X, 3X, -3X. Then, the approximated orbit trajectory is converted to the binary image for the image pattern recognition process.

$$
\begin{aligned}
&\min_z \left\| \Phi z - b \right\|_2 \\
&\Phi = \left[e^{j\omega n} \;\; e^{-j\omega n} \;\; e^{j2\omega n} \;\; e^{-j2\omega n} \;\; e^{j3\omega n} \;\; e^{-j3\omega n} \right] \\
&b = x + j\,y \\
&z \in \mathbb{C}
\end{aligned} \tag{5}
$$

$$
\hat{z} = \left(\Phi^T \Phi \right)^{-1} \Phi^T b \tag{6}
$$

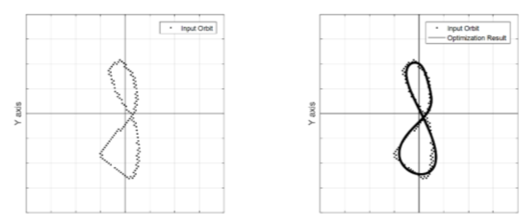


Figure 5. Optimization Result

4. EXPERIMENTS AND RESULTS

4.1. Model Training for Image Pattern Recognition

The testbed consists of a rotor, shaft, disc, bearing, and coupling. The shaft with a length of 470 *mm* is coupled with a flexible coupling to reduce the effect of the high frequency vibration, two discs, and three bearing housings. To construct the patterns of the orbits, two sensors to measure accelerations are attached on x and y-axis at the bearing housing. 1700rpm is set for this experiment.

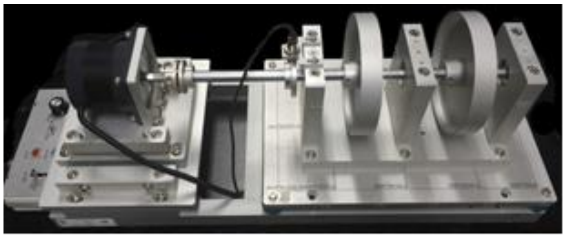
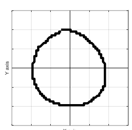
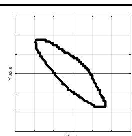
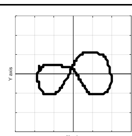
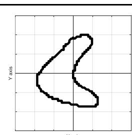
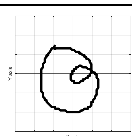


Figure 6. Testbed

The orbit image pattern recognition algorithm is applied to the orbit images collected from the rotor kit, shown in Figure 6. There are five classes of orbits: circle (C), ellipse (E), eight (8), heart (H), and tornado (T). The orbit shapes depend on the rotor status such as normal, unbalance, misalignment, etc. Table 2 shows the relationship between the rotor status and orbit classes.

Table 2. Five Classes of Orbit Shapes

Status	Classes	Orbit Shape
Normal	Circle (C)	
Unbalance	Ellipse (E)	
Shaft misalignment	Eight (8)	
	Heart (H)	
	Tornado (T)	

4.2. Training Tool

The training set of 300 images are acquired by each class (circle, ellipse, eight, heart and tornado in Table 2). The orbit images are normalized to maximize the effect of training although deep learning (CNN) is able to capture invariances of images with respect to location, rotation, size, and deformation. These data sets are used to train weight parameters for CNN. In our experiment, CNN architecture is formed by a stack of two convolution layers, two max fooling (sub-sampling) layers, followed by fully connected layers. Table 3 and Figure 7 show the detailed training constraints and information. TensorFlow (open source software library for machine intelligence developed by Google) is used for training the orbit pattern recognition.

Table 3. Detailed training constraints

Constraints	Value
Training set	$300 \times 5 = 1500$
Number of patterns	5
Activation Function	ReLU
Epoch	~ 50
Batch size	50

Figure 7. Training Graph

A structure of CNN is shown in Figure 8. The first convolution layer has 32 filters of size $7 \times 7 \times 1$. The second convolution layer has 64 filters of size $7 \times 7 \times 32$. Max pooling layers reduce both the size of images and the number of parameters. The first max pooling layer reduce the image size by selecting max value in a filter size of 2×2. The second max pooling layer with a filter size of 4×4 are applied. Then, 1024 neurons in a final layer are fully connected to all the outputs from the previous layers. The ReLU function is used as an activation function.

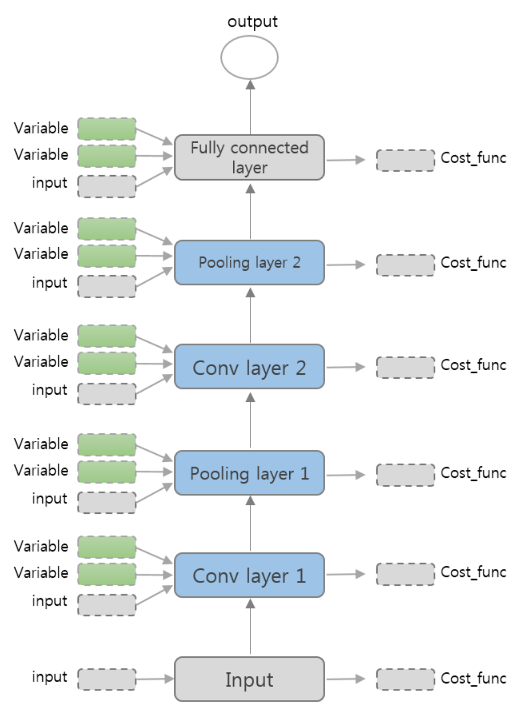


Figure 8. TensorFlow Structure of CNN

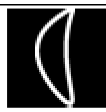
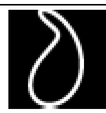
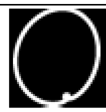
4.3. Orbit Image Classification and Results

The result of a test set of 500 orbit images is listed in Table 4 as a confusion matrix form. The total misclassification for the given test set is overall 1.8 %. The confusions occur between heart and ellipse, heart and eight, tornado and circle.

Table 4. Confusion Matrix of CNN

True shape	Classified				
	C	E	H	8	T
C	100	0	0	0	0
E	0	100	0	0	0
H	0	2	94	4	0
8	0	0	1	99	0
T	2	0	0	0	98

Table 5. Error Image Type

True class	Heart	Heart	Tornado
Result of classification	Ellipse	Eight	Circle
Orbit Image			

To illustrate the effectiveness of a CNN classifier, the performance with a different classifier, Gaussian discriminant analysis (GDA) is benchmarked. As Table 6 shows, the GDA classifier demonstrates poor classification performance especially when evaluating '8' shape. This comparison shows that the GDA classifier is not expressive enough to accommodate all the orbit shapes than the used CNN classifier.

Table 6. Confusion Matrix of GDA

True shape	Classified				
	C	E	H	8	T
C	98	2	0	0	0
E	7	91	2	0	0
H	0	0	97	3	0
8	0	0	18	82	0
T	0	0	0	0	100

4.4. Classification Performance

This images set in Table 7 is artificially created by hands, but it is similar to those of the real orbit shape acquired by rotor test kit. These images are used to measure classification performance.

To compute the error rate of the CNN classifier, we use the nested 10 folds cross validation method. We choose the area under curve (AUC) as the evaluation metric since prediction is in a form of probability. Validation estimates CNN's general error is about 1.3% with standard deviation 0.3%. Figure 9 shows errors calculated with one fold.

Table 7. Classified Orbit Images

Various Orbit Images	Classified
	C
	E
	H
	8
	T

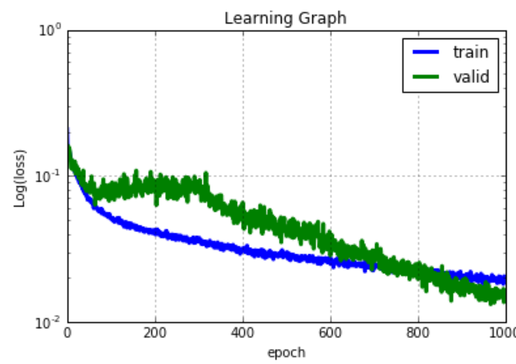


Figure 9. Learning Graph of CNN

A deep learning autonomously extracts abstract features, so deep learning algorithm can provide robust classification results even with a subtle difference of shape, orientation and position as shown in Table 7.

5. CONCLUSION

Using the deep learning algorithm, we develop autonomous the orbit pattern recognition systems for the rotating machinery diagnostics since the orbit shapes are typical characteristics to classify rotating machinery dynamics and status. To demonstrate the feasibility of this method, an image pattern recognition using convolution neural networks is applied to orbit shapes generated by a rotor testbed.

Even though the orbit shape is well classified by the proposed algorithm with a trained model, the current version of the deep learning classification model cannot take probabilistic perspectives into account. Therefore, the classification model will need further to be developed to provide not only the estimate of orbit pattern information, but also decision accuracy with higher confidence through the probability model.

ACKNOWLEDGEMENT

This work was partially supported by the Research Fund (Project Number: 1.13005301) of UNIST (Ulsan National Institute of Science and Technology), BK21 Plus project (Project Number: 2.160035.01) of the National Research Foundation of Korea Grant, and Ministry of Science, ICT and Future Planning (Project Number: 2.160198.01).

REFERENCES

Jardine, A. K., Lin, D., & Banjevic, D. (2006). A review on machinery diagnostics and prognostics implementing condition-based maintenance. *Mechanical Systems and Signal Processing*, vol. 20, pp. 1483-1510.

Robert, C. E. (1998). *Machinery malfunction diagnosis and correction: Vibration analysis and troubleshooting for the process industries*. Prentice Hall.

Morgan, E. (2014). *Steam turbine seal rub: Vibration data helps to identify a steam turbine seal rub*. Orbit Magazine.

Duda, R. O., Peter, E. H., & David, G. S. (2012). *Pattern classification*. John Wiley & Sons.

Yang, B. S., Lim, D. S., & Tan, A. C. C. (2005). VIBEX: an expert system for vibration fault diagnosis of rotating machinery using decision tree and decision table. *Expert Systems with Applications*, vol. 28 (4), pp. 735-742.

Widodo, A., & Yang, B. S. (2007). Support vector machine in machine condition monitoring and fault diagnosis. *Mechanical Systems and Signal Processing*, vol. 21 (6), pp. 2560-2574.

Jacek, M. Z. (1992). *Introduction to artificial neural systems*. St. Paul: West publishing company.

Kankar, P. K., Sharma, S. C., & Harsha, S. P. (2011). Fault diagnosis of ball bearings using machine learning methods. *Expert Systems with Applications*, vol. 38 (3), pp. 1876-1886.

Yan, C., Zhang, H., & Wu, L. (2010). Automatic recognition of orbit shape for fault diagnosis in steam turbine generator sets. Journal of Computational Information Systems, 6(6), 1995-2008.

LeCun, Y., Begio, Y., & Hinton, G. (2015). Deep learning. *Nature,* vol. 521, pp. 436-444.

Rosenfeld, A. (1981). Image pattern recognition. *Proceedings of the IEEE*, vol. 69 (5), pp. 596-605.

BIOGRAPHIES

Haedong Jeong is received his B.S. in Ulsan National Institute of Science and Technology, Ulsan, Korea, in 2014. He is a Ph.D. student in Ulsan National Institute of Science and Technology. His research interests include condition based monitoring, deep learning for prognostics, and image pattern recognition.

Sunhee Woo is received her B.S. in Ulsan National Institute of Science and Technology, Ulsan, Korea, in 2015. She is a M.S. student in Ulsan National Institute of Science and Technology. Her research interests include real-time monitoring system for diagnostics, algorithm visualization, and data visualization.

Suhyun Kim is received his B.S. in Konkuk University, Seoul, Korea, in 2016. He is a M.S. student in Ulsan National Institute of Science and Technology, Ulsan, Korea. His research interests include condition based monitoring, machine learning for prognostics, and data science.

Seungtae Park is a B.S. student in Ulsan National Institute of Science and Technology, Ulsan, Korea. His research interests include deep learning, machine learning for prognostics, and data science.

Heechang Kim is received his B.S. in Ulsan National Institute of Science and Technology, Ulsan, Korea, in 2015. He is a M.S. student in Ulsan National Institute of Science and Technology. His research interests include 3D printing, system control and dynamics.

Seungchul Lee is an assistant professor of Ulsan National Institute of Science and Technology, Ulsan, Korea. He is received the B.S. in Mechanical and Aerospace Engineering from Seoul National University, Seoul, Korea, in 2001, the M.S. in Mechanical Engineering from University of Michigan at Ann Arbor, USA, in 2007, the Ph.D. in Mechanical Engineering from University of Michigan, in 2010. He was a Postdoctoral Research Fellow from University of Michigan at Ann Arbor from 2010 to 2013. His current research interests include application to electro-mechanic systems and healthcare, and automotive systems.