Procedia Manufacturing
Volume 5, 2016, Pages 1107–1118
44th Proceedings of the North American Manufacturing Research Institution of SME http://www.sme.org/namrc

Rotating Machinery Diagnostics using Deep Learning on Orbit Plot Images

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Abstract
Although the orbit analysis (orbit shape and size) is commonly used to diagnose rotating machinery, the diagnosis heavily depends on the expert knowledge or experience due to the difficulties of extracting mathematical features for data-driven approaches. Therefore, in this paper, we propose an autonomous orbit pattern recognition algorithm using the deep learning method on shaft orbit shape images. In details, the convolutional neural network is implemented to construct weights between neurons and to generate the entire structure of the neural network. Then, the created network enables us to classify fault modes of rotating machinery via orbit images. Furthermore, we demonstrate the proposed framework through a rotating testbed.

Keywords: Deep Learning, Convolutional Neural Networks, Rotating Machinery, Orbit Analysis, Image Pattern Recognition, Machine Learning

1 Introduction

In most power plants, rotating parts are key components to generate electric power. Faults from the rotating machinery may cause its performance degradation and entire system break downs. These problems are directly related to plant operation/maintenance costs and even the level of safety. To avoid and prevent system failures, the condition-based maintenance (CBM) is being implemented through monitoring vibration signals collected by accelerometer or proximity sensors in various locations.

There have been many pieces of research work on condition monitoring and PHM (prognostics and health management) to predict machine status as early as possible so that catastrophic failure can be prevented. Monitored signals from the rotating machinery need to be transformed 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).

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

Selection and peer-review under responsibility of the Scientific Programme Committee of NAMRI/SME

doi:10.1016/j.promfg.2016.08.083

(root mean square, skewness etc.). In time domain, many techniques are performed to remove the effect of other source and noise such as time synchronous average (TSA) and autoregressive moving average (ARMA) model.

Frequency-domain analysis is used when the data is related to frequency domain. The widely used traditional analysis is the spectrum analysis based on fast Fourier transform (FFT). In frequency domain, information which is hardly seen in time domain might be extracted to monitor easily. Conventionally, the principal harmonic frequency amplitudes (1X, 2X, 3X, etc.) are extracted and used to diagnose the state of rotating machinery.

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. In addition, wavelet transform has shown powerful performance in faults of bearings, gears and other mechanical systems.

Since 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) shown in Figure 1 is used to provide 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 shapes contain the most significant information of turbine machine health condition, it is not well utilized in typical plant applications because of its significantly complicated shape pattern from various causes. Moreover, it is not easy to define numerical features to represent specific orbit patterns when considering subtle difference of size or shape, although human experts can easily discriminate between orbits and define its patterns robustly. As a result, it is still true that orbit shapes are continuously, but manually monitored by naked eyes of human operators in many manufacturing factory floors.

Therefore, in this paper, we propose a machine learning method to autonomously identify different orbit shapes generated by rotating machinery so that more robust and automatic monitoring system can be established. Convolutional Neural Networks (CNN) for image pattern recognition has been applied to orbit images to pinpoint the type of malfunctions. The proposed method is also demonstrated and validated with a rotor kit testbed.

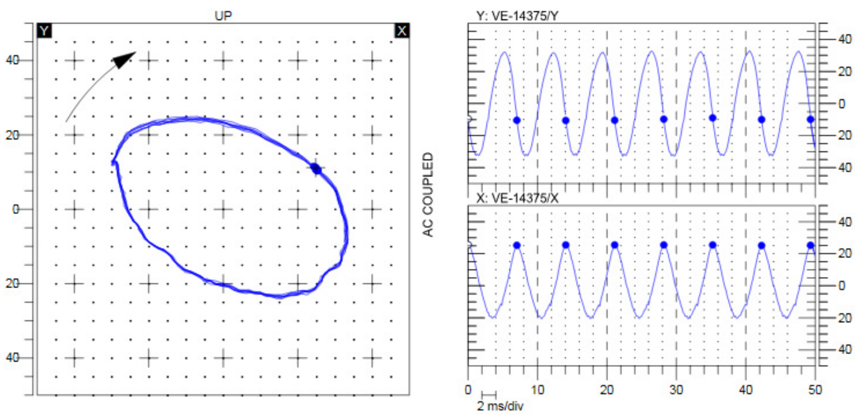


Figure 1. Orbit Analysis (Morgan, 2014)

2 Theoretical Background

2.1 Previous Machine Learning Methods for Diagnostics

A variety of machine learning algorithms have been used to diagnose fault in the rotating machinery. Basically the machine learning method is related to making 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, as causality between symptoms and causes, causes-symptoms are expressed in the form of IF (symptom) and THEN (cause). Because observed symptoms are able to be known information or cases, Bayesian algorithm which 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 which can classify data into discrete categories. In SVM, a feature-based input vector is usually used to build a feature space. To conduct diagnostics in rotating machinery, frequency elements and statistical elements are often selected as features. Then, SVM will optimally provide a decision boundary by considering relationship between input feature vector patterns and fault types (Widodo, 2007).

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

2.2 Deep Learning

Conventional machine-learning techniques were limited in their ability to process natural data in their raw form. To detect or classify patterns in the input, appropriate feature vector should be extracted with careful engineering and considerable domain expertise.

Representation learning is a set of methods that allow a machine to be fed with raw data and 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. With the composition of enough such transformations, very complex functions can be learned and good feature can be automatically extracted using general-purpose learning procedure. This is key advantage of deep learning. 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 descriptions and match descriptions to classify images (Azriel *et al*. 1988). Descriptions are similar as features which used to represent the waveform data in signal processing. Good descriptions can express characteristic element of pattern in image and be shown high performance in matching problem. Some points and edges can be descriptions such as Harris corner (Harris *et al*. 1988) and canny edge (CANNY. 1986). However the variance of image pattern which include rotation and scale change interrupts matching operator between trained descriptions and input descriptions. Many techniques are performed to solve image pattern recognition problem as extracting features or developing matching algorithm.

We will briefly describe how CNN works since it 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). CNN architecture as illustrated in Figure 2 includes pairs of convolution and sub-sampling layers (Lecun *et al*. 1998). The last sub-sampling layers fully connect output layer such as artificial neural networks, and the output vector classifies the input using max-pooling between overall values of activation function. This hierarchical organization is able to extract proper features in image classification tasks (Abdel-Hamid O. 2012).

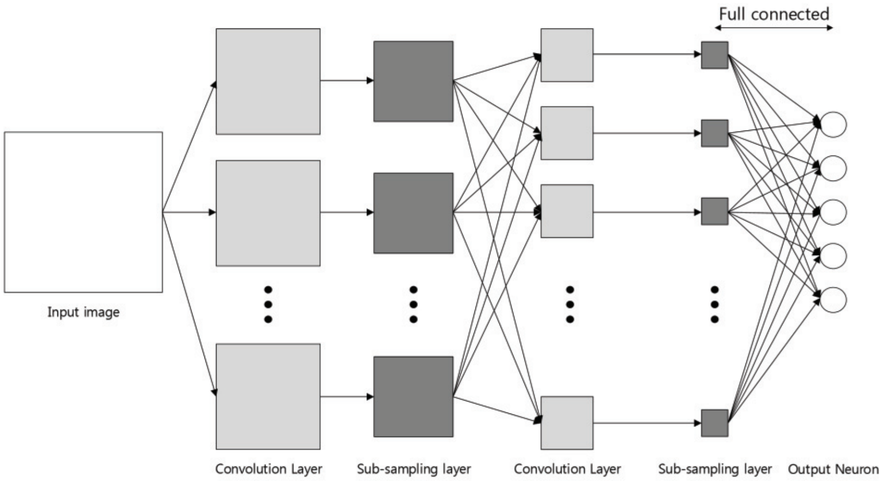
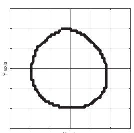
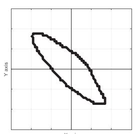
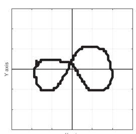
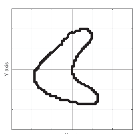
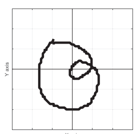


Figure 2. Structure of Convolutional Neural Networks

2.4 Orbit Shape and its Fault Type

Different types of faults such as unbalance, shaft misalignment and oil whirl in a rotor shaft are caused by malfunction of rotating machinery. It has been well studied on the corresponding orbit shapes due to fault types in a rotor dynamics. The representative faults and the 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 which attached 90 degree apart can be expressed by a linear combination of complex unit circles.

The full spectrum analysis method 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).

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

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.

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

3 Pre-processing

Before we feed orbit images to CNN to train a classification model for image pattern recognition, it is necessary to conduct a pre-processing step. Since the orbit image pattern is independent of an image location, a rotated angle, and its size, we will normalize an orbit image with respect to location, rotation, and size in the pre-processing step.

For example, a human operator can recognize the same pattern of shape 8 even if two images are rotated as shown in Figure 4. However, machine learning algorithm is most likely to fail such a task or requires expensive computational time. To speed up the image machine learning process, pre-processing steps such as offset shifting, re-orienting, and size normalizing are necessary. These pre-processing steps are pictorially illustrated in Figures 3, 4, and 5.

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.

$$
\begin{aligned}
A &= \begin{bmatrix} x & y \end{bmatrix} \\
\bar{A} &= A - m
\end{aligned} \tag{3}
$$

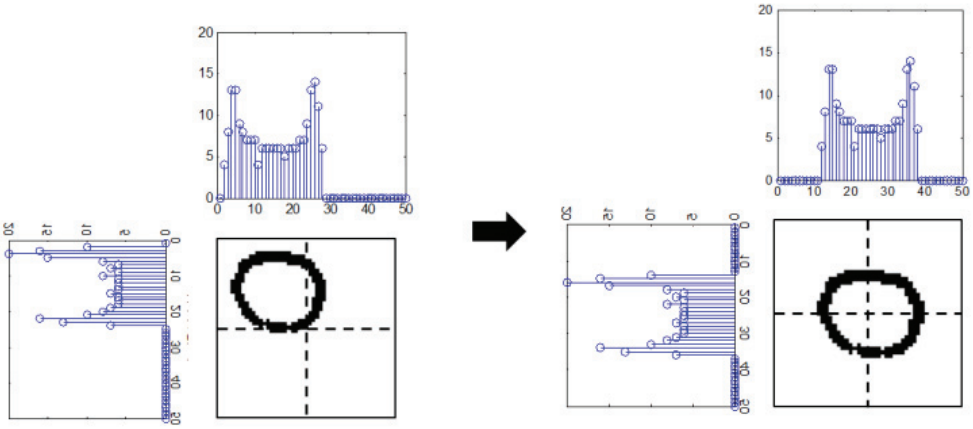


Figure 3. Image Offset Shifting

3.2 Orbit Image Re-orienting

The shape of orbit would be the same as tilted orbit in a geometry viewpoint although phases are different from a numerical viewpoint. A human operator can easily recognize the same pattern of orbit shape even if two images are rotated. However, it is not easy for machine learning algorithm to identify them as the same shape. Therefore, aligning all the orbit images to the same direction is necessary before applying any pattern recognition algorithm.

The matrix C is a covariance matrix obtained by orbit matrix $\bar{A}$. Then, eigen-analysis provides eigenvector matrix V for a set of basis where matrix Λ is a diagonal eigenvalue matrix. After a rotation transformation, the coordinate of an orbit shape is changed to become matrix $\bar{A}_R$.

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

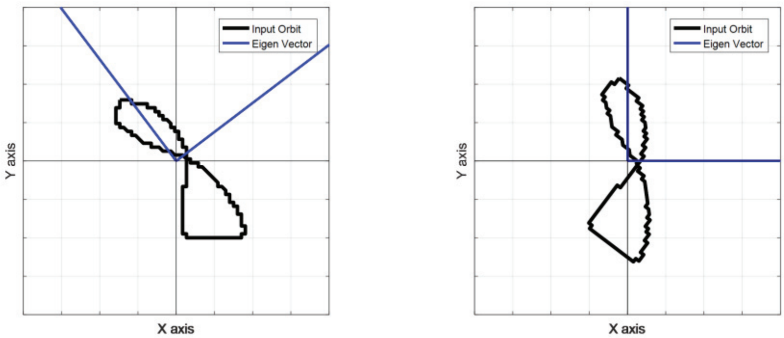


Figure 4. Image Re-orienting

3.3 Orbit Image Re-scaling

Although the size of an orbit shape is determined by the degree of machine malfunction, the fault type classification is not related to the size of image. Since the scale of an orbit shape is not a key component to identify a pattern, the size of orbit can be normalized based on an input image size.

The scale of orbit is normalized with maintaining a ratio between a vertical length and a horizontal length. The resampling is conducted based on the longer length between a horizontal and a vertical length to resize the original image to the training image size.

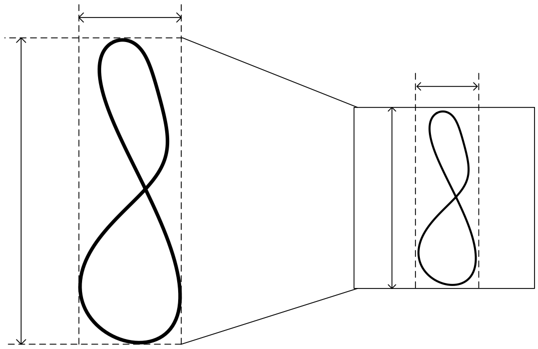


Figure 5. Scale Normalization

3.4 Orbit Shape De-noising

In addition to offset shifting, re-orienting, and size normalizing, an orbit shape de-noising step will enhance an accuracy of correct pattern identification rate. Generally the orbit signal contains a sensor noise. These noises may disguise the shape of orbit so that it cannot be explained by the rotor dynamics. Optimization method based on the mathematical orbit model discussed in section 2.3 will be able to remove the influence of noise and improve the quality of signal.

We use the linear least square method to 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.

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

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

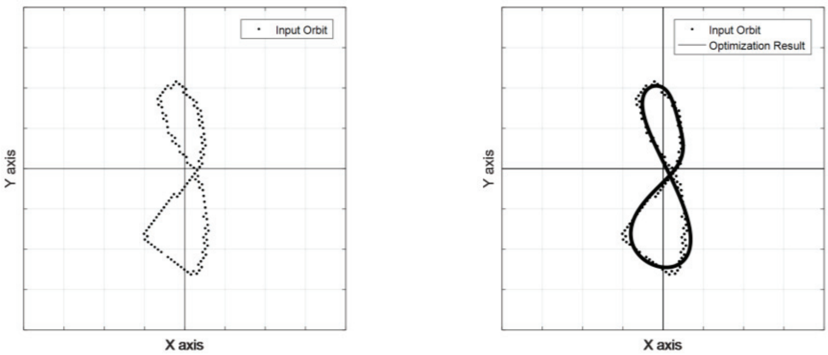


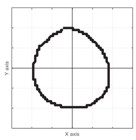
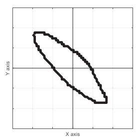
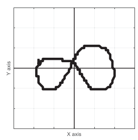
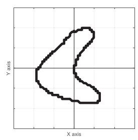
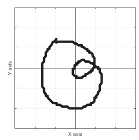
Figure 6. Optimization Result

4 Experiments and Results

4.1 Model Training for Image Pattern Recognition

We apply the proposed orbit image pattern recognition algorithm to the orbit images collected from the rotor kit, shown in Figure 7. There are pre-defined five classes of orbits: circle (C), ellipse (E), eight (8), heart (H), and tornado (T) shapes according to the rotor status. Different orbit shapes are produced, depending on the rotor status such as normal, unbalance, misalignment, rubbing, etc.

Table 2. Five Classes of Orbit Shapes

Fault	Circle (C)	Ellipse (E)	Eight (8)	Heart (H)	Tornado (T)
Orbit Shape					

The testbed consists of a shaft with length of 470 *mm* coupled with a flexible coupling to reduce the effect of the high frequency vibration, two discs and three bearing housings. Two accelerometers are mounted at bearing housing along *x* and *y* directions. All the experiments are conducted at 1700 rpm.

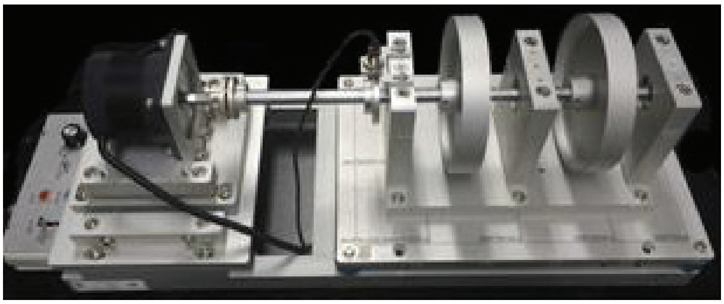


Figure 7. Testbed

The training set of 150 orbit images are acquired by each pattern (normal, unbalance, misalignment in Table1). The orbit images are changed *x* and y axial symmetry images to maximize the effect of training. These data sets are used to train weight parameters for CNN. Total 3 layers structure (convolution and sub-sampling layer, and fully connected to 5 output neurons) is used for CNN in our experiment. Table 3 and Figure 8 show the detailed training constraints and information.

Table 3. Detailed training constraints

Training set	Number of patterns	Activation Function	Epoch	Batch size
$150 \times 5 = 750$	5	Sigmoid	~ 250	50

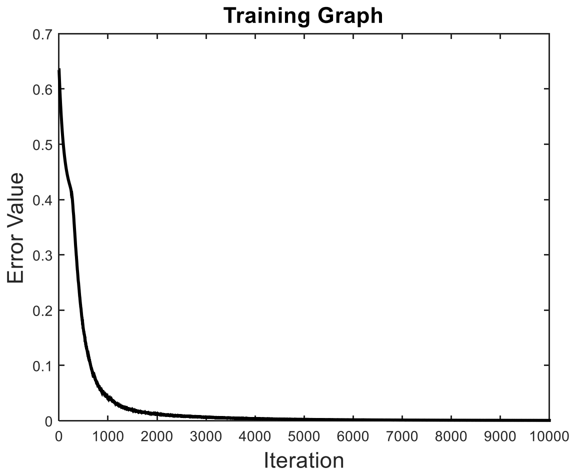


Figure 8. Training Graph

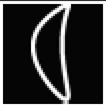
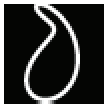
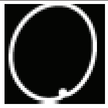
4.2 Orbit Image Classification and Results

The classification result of a new test set of 350 orbit images is listed in Table 4 as a confusion matrix form. The total misclassification for the given test set is overall 1.1 %. As you can see, the confusions occur between heart and ellipse, heart and eight, tornado and circle, which we believe that those orbit shapes are pretty similar and most likely to be misclassified even by humans.

Table 4. Confusion Matrix

True shape	Classified				
	C	E	H	8	T
C	70	0	0	0	1
E	0	70	1	0	0
H	0	0	67	0	0
8	0	0	2	70	0
T	0	0	0	0	69

Table 5. Error Image Type

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

4.3 Classification Performance

Artificially generated-orbit image set is used to measure classification performance. This image set is artificially created by hands, but their orbit shapes and orientations are similar to those of the real rotor test kit.

Because deep learning can autonomously extract abstract features which, in general, cannot be seen in a training data set, the deep learning algorithm with CNN can provide robust classification results even with subtle difference of shape, orientation and position, as shown in Table 6.

Table 6. Classified Orbit Images

Various Orbit Images	Classified
	C
	E
	H
	8
	T

5 Conclusion

Since the orbit patterns are well known characteristics to identify rotating machinery dynamics and status, we develop autonomous orbit shape recognition systems for the rotor diagnostic purpose using the deep learning algorithm. Image pattern recognition technique based on convolution neural networks is applied to orbit shapes generated by a rotor kit to demonstrate the feasibility of the proposed algorithm.

Although the orbit shape will be classified by the proposed method with a trained classification model, the current version of a deep learning model do not consider probabilistic approaches. In future work, through combining the probability model, the trained model can provide not only orbit shape information, but also decision confidence with higher accuracy.

This work will help to continuously monitor turbine health in many power plants with higher accuracy, but otherwise it is manually conducted by human operators.

Acknowledgement

This work was supported by the Research Fund (Project Number: 1.13005301) of UNIST (Ulsan National Institute of Science and Technology)

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