Since January 2020 Elsevier has created a COVID-19 resource centre with free information in English and Mandarin on the novel coronavirus COVID-19. The COVID-19 resource centre is hosted on Elsevier Connect, the company's public news and information website.

Elsevier hereby grants permission to make all its COVID-19-related research that is available on the COVID-19 resource centre - including this research content - immediately available in PubMed Central and other publicly funded repositories, such as the WHO COVID database with rights for unrestricted research re-use and analyses in any form or by any means with acknowledgement of the original source. These permissions are granted for free by Elsevier for as long as the COVID-19 resource centre remains active.
Fault Diagnosis of Ball Screw in Industrial Robots Using Non-Stationary Motor Current Signals

Qibo Yang\textsuperscript{a}, Xiang Li\textsuperscript{a,}\textsuperscript{*}, Yinglu Wang\textsuperscript{a}, Abhijeet Ainapure\textsuperscript{a}, Jay Lee\textsuperscript{a}

\textsuperscript{a}NSF I/UCR Center for Intelligent Maintenance Systems, Department of Mechanical and Materials Engineering, University of Cincinnati, PO Box 210072, Cincinnati, Ohio 45221-0072, USA

* Corresponding author. Tel.: +1-513-394-9787. E-mail address: li5xi@ucmail.uc.edu

Abstract

With the advancement of intelligent manufacturing, different kinds of industrial robots have been applied in modern factories. The liquid crystal display transfer robot (LCDTR) has been widely used in LCD production lines to transport panels. Effective fault diagnosis and prognosis of the industrial robots are of great importance, since unplanned downtime caused by faulty robots significantly reduces the production capacity. Specifically, the ball screw is the critical component in the LCDTR. The failure of the ball screw can cause long downtime. Conventionally, the fault diagnosis of the ball screw is usually based on the vibration signals. However, it is extremely difficult to install the vibration sensors in the industrial robots. Therefore, in order to address this issue in condition monitoring, this paper proposes a data-driven fault diagnosis methodology using the motor current signals of the ball screw. Two time-frequency domain analysis methods are investigated, including short-time Fourier transform (STFT) and wavelet packet decomposition (WPD). The statistical features are extracted, and Fisher score is used to select features. Furthermore, the logistic regression and k-nearest neighbors are applied for the final fault diagnosis. Experiments on a real-world industrial robot dataset are carried out for validation. 100% diagnosis accuracy can be basically achieved by the proposed method, which indicates the non-stationary current signal can be effectively used to identify the health states of the ball screw in the LCDTR.

Keywords: Ball screw; fault diagnosis; motor current signals; data-driven; intelligent manufacturing.

1. Introduction

With the development of intelligent manufacturing, the industrial robots have been popularly used in a number of manufacturing applications. In the production line, if an industrial robot fails, it will affect the operation of the entire production line. Therefore, it is very important and meaningful to identify and predict failure of industrial robots. In the recent decades, many researches have been carried out in this direction. Olsson et al. \cite{1} studied fault diagnosis of industrial equipment using sensor readings and case-based reasoning. It shows that time-based features and frequency-based features can be extracted from sensor readings and then feed into a case-based classifier to do fault diagnosis. Anand et al. \cite{2} presented a fault detection and isolation method for robotic manipulator using neural networks and residual analysis. Golombek \cite{3} discussed model-based and data driven fault detection for component based robotic systems. Qiao et al. \cite{4} developed a quick health assessment approach to identify the positional health (position and orientation accuracy) changes of industrial robots. However, most studies discussed the performance of industrial robots in the laboratory, and a few papers studied the behavior of industrial robots in factories.

This paper investigates the fault diagnosis problem for a liquid crystal display transfer robot (LCDTR) in the real factory. The industrial robot \cite{5} is shown in Fig. 1. This robot has been widely used for a long time, but there is very limited research on this kind of robot. That is mostly because the robot is too large and difficult to investigate in the laboratory. See et al. \cite{5} presented dynamic load analysis and design approach for the robot. However, no study in the current literature can be found on fault diagnosis problem of this robot.
Practically, in the LCD manufacturing factories, large glass is handled by this robot. If a robot fails, the entire production line needs to be stopped for maintenance, which causes great losses in productivity. Therefore, the fault diagnosis of this industrial robot is of great importance. The ball screw is one of the key components of this robot. Its role is to move the glass up and down, and it locates in the Z1-Frame and the Z2-Frame. The failure of the ball screw generally has more significant influence than the other components. Therefore, it is important to monitor the health status of this ball screw, and optimally schedule maintenance to avoid unplanned downtime.

In the recent years, many studies have been carried out on fault diagnosis and prediction problem of the ball screw. Jin et al. [6] presented a methodology for ball screw component health assessment and failure using vibration and temperature signals. Lee et al. [7] developed failure diagnosis system for ball screw by using vibration signals. Wen et al. [8] proposed a method to identify different degradation level of ball screw using multiple classifiers based on vibration signals. Li et al. [9] proposed a systematic methodology for prognosability of the ball screw degradation, where the built-in controller signals and vibration signals of add-on sensors are used. Huang et al. [10] presented a diagnosis method of hollow ball screw preload classification, and they used current signals to classify if the ball screw of computer numerical control (CNC) machines is with or without oil-cooling circulation.

In the literature, most of the reviewed papers on fault diagnosis and prediction of the ball screw use vibration signals for analysis. However, it is very difficult to directly install accelerometers or other sensors on the ball screw of the industrial robot in this study, because the space inside the robot is small. High-frequency controller signal could be an alternative for analysis, but it cannot be collected in this scenario, neither. Therefore, it is straightforward to use the current sensor for condition monitoring and fault diagnosis.

Using current signals to detect faults for induction motors has been studied for a long time. Corne [11] comprehensively studied the method by using Fourier transform to process signals, and identifying fault-related harmonics for diagnosis. However, the LCDTR in this research does not move at a constant speed, and the current signal is non-stationary, so there is no visible harmonics that can be used by Corne's method. Widodo et al. [12] proposed a method based on discrete wavelet transform (DWT) for induction motor fault diagnosis using transient current signals. Mehrjou et al. [13] reviewed the papers of wavelet-based approach of motor current signature analysis (MCSA), and in its case, a method of wavelet packet decomposition using statistical features is presented. Kim et al. [14] proposed an approach using wavelet decomposition and template matching for fault detection for AC servo motor. However, most papers use current signals to do fault diagnosis for rotors, stators, and bearings, but not ball screws. In addition, most of the articles are about induction motors, and very few is about AC servo motors, which is in the LCDTR.

This paper proposes a methodology of data-driven fault diagnosis using motor current signals for the ball screw on the LCDTR. The contribution of this article is as follows:

1) This paper presents a systematic fault diagnosis methodology for ball screws in industrial robots based on motor current signals, which includes the working flow from data collection to data analysis. This method is suitable for the industrial scenario in which it is difficult to install add-on sensors directly.

2) The fault diagnosis problem of a large LCDTR is investigated. Although the robot is very important in the industries, very limited study can be found in this direction.

3) The non-stationary current signal is investigated in this study.

This paper is organized as follows: Section 2 proposes the methodology including data acquisition and data analytics. Section 3 describes the experiments, presents the results and discusses the results. Section 4 summaries the conclusions of this study.

2. Proposed Methodology

This paper presents a fault diagnosis methodology for the ball screws using motor current signals. The overview of proposed method is shown in Fig. 2.
In the literature, Lee et al. [15] presented four main enabling technologies of industrial artificial intelligence including data technology, analytic technology, and platform technology and operations technology. Data technology in this paper enables the successful data acquisition. In the application scenario, as the Z1-Frame and the Z2-Frame move up and down, and the space inside the robot is small. Therefore, it is very difficult to install a vibration sensor on the ball screw directly. However, the motor currents of Z1-Frame and Z2-Frame can be readily collected near the ground. The idea of this paper is to install a current probe on a certain wire of the motor, and then read the sensory data to the computer through a data acquisition system.

Analytic technology transfers the current data from the ball screw into valuable information for fault diagnosis. From the current probe, high-frequency continuous time-series data of current signals can be obtained. The first step of the analysis is data preprocessing, which is to divide the signal into small segments generated by the up-and-down motion, so that the part of the static signal generated by the stable status of the robot is removed. Considering the signal is non-stationary, this paper first converts the data to the time-frequency domain for analysis. This paper compares the results of two methods for transform: short-time Fourier transform [16] and wavelet packet decomposition [17]. In time-frequency domain, some statistical features such as energy, root mean square (RMS) and kurtosis as summarized by Mehrjou et al. [13], can be extracted. The features are normalized to a normal distribution with zero mean and unit variance before further analysis. Fisher score [18] is used to select useful features that distinguish different classes. Data suitability [19] for diagnosis needs to be assessed, so principle component analysis (PCA) [20] is then used to observe the distribution of data. Afterwards, the features can be fed into the classical machine learning models for fault diagnosis, such as logistic regression (LR) [21] and k-nearest neighbors (KNN) [22]. In addition, deep learning as an end-to-end analysis method, also has strong automatic feature extraction capabilities. Therefore, this paper compares the results of the statistical features with deep learning for better evaluation of the proposed method.

Finally, the results of the model are evaluated from several perspectives: accuracy, computation time, and sensitivity to features. The accuracy is the number of samples that are correctly predicted divided by the total number of samples. The computation time is the total time of training the model and predicting the test samples. The sensitivity to features represents the impact of redundant features on the model. It is defined by Eq. (1).

\[
\text{Sensitivity} = \frac{|\text{Acc}_{\text{all}} - \text{Acc}_{\text{sel}}|}{\text{Acc}_{\text{sel}}} \tag{1}
\]

where \(\text{Acc}_{\text{all}}\) is the accuracy while using all features to train the model, and \(\text{Acc}_{\text{sel}}\) is the accuracy while using the features selected by Fisher score to train the model. The higher the sensitivity, the more susceptible the model is to the redundant features.

2.1. Short-Time Fourier Transform

Short-time Fourier transform (STFT) [16] is used to describe quasi-stationary signal that changes slowly over time. The idea is to segment a signal into multiple short segments and apply Fourier transform on each segment. Eq. (2) is the mathematical definition of STFT [23].

\[
X_m(n) = \sum_{n=-\infty}^{\infty} x(n) e^{-j2\pi mR} \tag{2}
\]

where \(x(n)\) is the input signal at the time \(n\), \(e^{-j2\pi mR}\) is length \(m\) window function and \(R\) is the hop size in samples between successive windows, \(w(n)\) is the discrete Fourier transform of data in a window centered at time \(m\).

2.2. Wavelet Packet Decomposition

Wavelet packet decomposition (WPD) [17] is a form of wavelet transform that discrete-time signal is passed through many filters, such as the example with level 3 shown in Fig. 3. The idea is to start from a scale-oriented decomposition, and to analyze the signals in frequency sub-bands. As wavelets are also localized in time and frequency, it is an alternative approach for the STFT to do time-frequency analysis.

Fig. 3. An example of wavelet packet decomposition at Level 3 [24].

2.3. Fisher Score

Fisher score [18] is a feature selection method that prefers the features whose feature values within a class are small and across classes are large. For fth feature, the feature score \(s_f\) is shown in Eq. (3) [25]. Larger score means the feature is more important.

\[
s_f = \frac{\sum_{j=1}^{c} n_j(\mu_{ij} - \mu_i)^2}{\sum_{j=1}^{c} \sigma_{ij}^2} \tag{3}
\]

where \(n_j\) is the number of samples in class \(j\), \(c\) is the number of classes, \(\mu_i\) is the mean value of fth feature, \(\mu_{ij}\) is the mean value of fth feature of the samples in class \(j\), and \(\sigma_{ij}^2\) is the variance value of fth feature of the samples in class \(j\).

2.4. Deep Learning

Convolutional neural network (CNN) is a classical model of deep learning. It was first proposed by LeCun [26] for image processing, and it has two characteristics, i.e. spatially shared weights and spatial pooling. CNN has achieved significant success in computer vision [27], natural language processing, and speech recognition [28]. It has also been popularly used in the field of prognostics and health management (PHM). Wang et al. used CNN [29] for motor fault diagnosis. Li et al. [30] developed a method using CNN for remaining useful life estimation of aircraft engine. Deep learning-based transfer
learning [31, 32] is also very popular to solve the issue of machine-to-machine variations for fault diagnosis.

3. Experiments

All the experimental data was collected on an industrial robot made, and alternating current (AC) server motors are used in this robot. The engineers replaced three different ball screws at the Z1-Frame of the robot, so that all the other units are identical. The first is almost new and labeled as healthy, and the second and the third have run in the factory for some time. Therefore, they are faulty and labeled as “faulty 1” and “faulty 2” respectively. Each ball screw moved up and down and the condition monitoring are collected correspondingly. The data description is shown in Table 1. The sampling rate is 1250 Hz, each movement takes approximate 4 seconds, and no load is added.

50% samples are used for training and the remaining samples are used for testing. All the experiments are carried out on a PC with Intel Core i7 CPU, 24-GB RAM and NVIDIA GeForce GTX 1050 Ti.

Table 1. Data description

| No | # of Samples | Label     |
|----|--------------|-----------|
| 1  | 20           | Healthy   |
| 2  | 20           | Faulty 1  |
| 3  | 20           | Faulty 2  |

4. Results & Discussion

The data is continuously collected during the acquisition process, and it needs to be segmented for each movement. As shown in Fig. 4, since Z1-Frame is responsible for up-and-down movement, two different forms of signals can be observed. When the robot moves up, more force is need, and the magnitude of the current signal is larger. Fig. 4 also compares the time-domain current signals of a healthy ball screw and a faulty one, and their shapes are quite similar. Hence, advanced signal processing techniques are required to extract effective features.

STFT and WPD are used to transform data into time-frequency domain for analysis. The time-frequency domain data of the upward movement of the robot is shown in Fig. 5.

For STFT, this article uses the Hamming window recommended by MATLAB [33], and chooses window length \( m = 256 \) and hop size \( R = 128 \) through try-and-error to ensure that the change of the frequency can be seen clearly. For WPD,
the mother wavelet is “db4” and the decomposition level is 4. It can be seen that the current frequency significantly increases during the upward movement of the robot, and it becomes stable while the robot moves at a constant speed. Afterwards, it decreases. Therefore, the STFT can clearly present the dynamic status of the signal.

For each frequency band obtained by STFT, the following statistical features are calculated: energy, RMS and kurtosis. For each node from WPD, the same statistical characteristics are also calculated. All the samples are randomly divided into training and testing data, and the ratio of training and testing data is 0.5. The feature matrix of the training data is reduced by PCA for visualization to assess the data suitability, and the first 2 principle components (PCs) are shown in Fig. 6. In the figures, both the STFT and WPD feature sets show that the features of the upward and the downward movements are well clustered. Therefore, it can be considered as two different working regimes. Likewise, different classes of data are clearly distinguishable.

Fisher score is applied on the obtained STFT and WPD features respectively. A high score indicates that the feature can better distinguish different classes. Fig. 7 shows the top 10 features with the highest scores for both groups of features. While it is observed in Fig. 5 (a) that the time-frequency signal from STFT shows most of the energy is within 200 Hz, Fig. 7 (a) indicates that most important features to distinguish different classes are larger than 200 Hz. For example, “Freq. 380.86 Hz RMS”, “Freq. 371.09 Hz RMS”, “Freq. 380.86 Hz Energy”, etc. “Freq. 380.86 Hz RMS” represents the RMS value of a small frequency band starting with 380.86 Hz. Therefore, the data beyond 200 Hz is also required to be collected. Similarly, for the WPD features, the same conclusion can be drawn. The data that has small energy can be still used to distinguish different classes. However, compared with the STFT features, the WPD features have relatively low Fisher scores.

The Fisher scores of the features can be used as a reference for feature selection. In this paper, the features with scores greater than 1 are selected, and PCA is applied afterwards to visualize the selected features. Fig. 8 shows the results of the first two PCs. In Figure 8, the data of the same class cluster together, although they are from different working regimes. Therefore, feature selection is able to pick useful features that are more sensitive to class discrepancy rather than regime discrepancy. In addition, although both the conditions “faulty 1” and “faulty 2” are defined as “faulty”, their fault levels are also distinguishable and can be observed in the figure.

The features obtained by STFT and WPD, including both the original feature sets and the selected feature sets, are fed into LR and KNN for training and testing respectively. KNN takes 3 neighbors for computing. Similarly, the 2D images from STFT and WPD are inputted to the CNN algorithm for modeling. The CNN has the following structure: the first layer is a convolutional layer with 64 neurons and the kernel size is 3 * 3; the second layer is a convolutional layer with 48 neurons and the kernel size is 3 * 3; the third layer is a pooling layer with the pool size of 2 * 2; the fourth layer is a convolutional layer with 48 neurons and the kernel size is 3 * 3; the fifth layer is a flatten layer, the sixth layer is a dropout layer of 0.5, and the seventh layer is a fully-connected layer. Finally, the softmax function is adopted for classification. The rectified linear unit activation function (ReLU) is generally used in each layer, and the Adam optimizer is adopted. The learning rate is 0.001, the mini-batch size is 12 and the epoch is 50.

The results of the fault diagnosis are shown in Table 2. It is noted that the methods “STFT + Statistic features + LR”, “WPD + Statistic features + LR” and “STFT + Selected statistic features + LR” can achieve the accuracy = 1, which means that the statistical features extracted manually lead to promising diagnostic performance.
The computation time of CNN is more than 3 seconds, but the computation time of LR and KNN is within 0.2 seconds. Therefore, CNN is too time-consuming compared with LR and KNN.

The minimum sensitivity to features of LR is 0, but the minimum sensitivity of KNN is 0.072, indicating that LR is more robust to redundant features. Overall, the influence of redundant features is not obvious, and the reason is because the features with low scores do not have obvious negative impacts on classification.

In summary, “STFT + Selected statistic features + LR” is recommended because it can reach maximum accuracy with minimum computation time, and LR is not sensitive to redundant features in this case. Therefore, the effectiveness and superiority of the proposed method have been numerically demonstrated in this section.

Table 2. Fault diagnosis results.

| No | Method                        | Accuracy | Computation Time/s | Sensitivity to Features |
|----|-------------------------------|----------|--------------------|-------------------------|
| 1  | STFT + Statistic features + LR| 1.000    | 0.014              | N/A                     |
| 2  | STFT + Statistic features + KNN| 0.900    | 0.109              | N/A                     |
| 3  | WPD + Statistic features + LR | 1.000    | 0.001              | N/A                     |
| 4  | WPD + Statistic features + KNN| 0.800    | 0.107              | N/A                     |
| 5  | STFT + Selected statistic features + LR| 1.000    | 0.001              | 0.000                   |
| 6  | STFT + Selected statistic features + KNN| 0.967    | 0.108              | 0.069                   |
| 7  | WPD + Selected statistic features + LR| 0.933    | 0.002              | 0.072                   |
| 8  | WPD + Selected statistic features + KNN| 0.967    | 0.111              | 0.173                   |
| 9  | STFT + CNN                    | 0.900    | 3.693              | N/A                     |
| 10 | WPD + CNN                    | 0.933    | 3.486              | N/A                     |

* N/A: Not applicable.

5. Conclusions

This paper proposes a novel methodology that uses the motor current signal to diagnose the health status of the ball screw. While vibration data have been popularly used in related studies, it is extremely difficult to install the vibration sensor in the real industrial scenarios with respect to the robots. The non-stationary data are investigated for diagnosis, which has been seldomly studied in the literature. Different time-frequency transform methods are evaluated in this paper, as well as different machine learning models. The experiments on the real-world industrial robot ball screw dataset are carried out for validation. The proposed method achieves 100% testing accuracy in this challenging fault diagnosis problem. This study offers an effective and promising approach on industrial diagnostics with motor current non-stationary signal.

Admittedly, different weights of LCDs could affect the signal, and heavier LCDs could make it easier to detect faults, but the differences of LCD weights could produce different signals while the robot is in the same healthy condition, which makes the modeling more complex. Therefore, in this paper, at first, the experiments were carried out with no load, and different health conditions can already be classified, so no further experiments on LCDs with different weights were performed.

However, it should be pointed out that despite the promising results, the mechanism of the effectiveness with current signal is supposed to be further investigated, as well as other related tasks such as remaining useful life prediction with such signal. Meanwhile, this research only considers the results of a movement and the performance of the algorithms could be different if the robot went faster or slower. More experiments will be done in later studies about different speeds to verify the approach.

Acknowledgement

The authors would like to thank the support by the National Science Foundation (NSF) Industry/University Cooperative Research (I/UCR) Center for Intelligent Maintenance Systems and AU Optronics. Especially, the authors thank the support by Chun Hung Yang, Zong Li Li, and Ming Yi Lin in AU Optronics.

References

[1] Olsson E, Funk P, Xiong N. Fault diagnosis in industry using sensor readings and case-based reasoning. J Intell Fuzzy Syst 2004;15(1):41-46.
[2] Anand DM, Selvaraj T, Kumanan S. Fault Detection and Isolation In Robotic Manipulator Via Hybrid Neural Networks. JSIMM 2008;7(1).
[3] Golombek R. Data-driven fault detection for component based robotic systems. 2014.
[4] Qiao G, Schlenoff C, Weiss BA. Quick positional health assessment for industrial robot prognostics and health management (PHM). ICRA 2017; p. 1815-1820.
[5] Seo JH, Yim HJ, Hwang JC, Choi YW, Kim DJ. Dynamic load analysis and design methodology of LCD transfer robot. J Mech Sci Technol 2008;22(4):722-30.
[6] Jin W, Lee Y. Lee J. Methodology for ball screw component health assessment and failure analysis. NAMRC 2013.
[7] Lee WG, Lee JW, Hong MS, Nam SH, Jeon Y, Lee MG. Failure diagnosis system for a ball-screw by using vibration signals. Shock. Vib 2015.
[8] Wen J, Gao H, Liu Q, Hong X, Sun Y. A new method for identifying the ball screw degradation level based on the multiple classifier system. Measurement 2018;130:118-27.
[9] Li P, Jia X, Feng J, Davari H, Qiao G, Hwang Y, Lee J. Prognosability study of ball screw degradation using systematic methodology. Mech Syst Signal Process 2018;109:45-57.
[10] Huang YC, Kao CH, Chen SJ. Diagnosis of the hollow ball screw preload classification using machine learning. Appl Sci 2018;8(7):1072.
[11] Corne B. Condition monitoring with motor current signature analysis. 2017.
[12] Widodo A, Yang BS, Gu DS, Choi BK. Intelligent fault diagnosis system of induction motor based on transient current signal. Mechatronics 2009; 19(5):680-9.
[13] Mehrjou MR, Marian N, Karanam M, Noor SBM, Zolfaghari S, Misron N, ... & Marhaban MH. Wavelet-Based Analysis of MCSA for Fault Detection in Electrical Machine.In: Wavelet Transform and Some of Its Real-World Applications; 2015. p. 79.
[14] Kim Y, Bae H, Kim S, Vachtsevanos G. Fault diagnosis of AC servo motor with current signals based on wavelet decomposition and template matching methods. IFAC 2008;41(2):7239-44.

[15] Lee J, Davari H, Singh J, Pandhare V. Industrial Artificial Intelligence for industry 4.0-based manufacturing systems. Manuf Lett 2018;18:20-3.

[16] Allen JB, Rabiner LR. A unified approach to short-time Fourier analysis and synthesis. Proc IEEE Inst Electr Electron Eng 1977;65(11):1558-64.

[17] Coifman RR, Meyer Y, Quake S, Wickerhauser MV. Signal processing and compression with wavelet packets. In: Wavelets and their applications. Dordrecht: Springer; 1994. p. 363-379.

[18] Duda RO, Hart PE, Stork DG. Pattern classification. In: John Wiley & Sons; 2012.

[19] Jia X, Zhao M, Di Y, Yang Q, Lee J. Assessment of data suitability for machine prognosis using maximum mean discrepancy. IEEE Trans Ind Electron 2017;65(7):5872-81.

[20] Wold S, Esbensen K, Geladi P. Principal component analysis. Chemometr Intell Lab Syst 1987;2(1-3):37-52.

[21] Cox DR. The regression analysis of binary sequences. J R Stat Soc Series B Stat Methodol 1958;20(2):215-32.

[22] Cover T, Hart P. Nearest neighbor pattern classification. IEEE Trans Inf Theory 1967;13(1):21-7.

[23] Smith JO. Spectral Audio Signal Processing. W3K Publishing; 2011

[24] MATLAB. Wavelet Packets. 2019.

[25] Li J, Cheng K, Wang S, Morstatter F, Trevino RP, Tang J, Liu H. Feature selection: A data perspective. ACM Comput Surv 2018;50(6):94.

[26] LeCun Y, Bengio Y. Convolutional networks for images, speech, and time series. In: The handbook of brain theory and neural networks. 1995; 3361(10).

[27] Krizhevsky A, Sutskever I, Hinton GE. Imagenet classification with deep convolutional neural networks. NeurIPS 2012; p. 1097-105.

[28] Abdel-Hamid O, Mohamed AR, Jiang H, Penn G. Applying convolutional neural networks concepts to hybrid NN-HMM model for speech recognition. ICASSP 2012; p. 4277-80.

[29] Wang LH, Zhao XP, Wu JX, Xie YY, Zhang YH. Motor fault diagnosis based on short-time Fourier transform and convolutional neural network. CJME 2017;30(6):1357-68.

[30] Li X, Ding Q, Sun JQ. Remaining useful life estimation in prognostics using deep convolution neural networks. Reliab Eng Syst Saf 2018;172:1-11.

[31] Li X, Zhang W, Xu NX, Ding Q. Deep Learning-Based Machinery Fault Diagnostics with Domain Adaptation Across Sensors At Different Places. IEEE Trans Ind Electron 2019.

[32] Li X, Zhang W, Ding Q, Li X. Diagnosing Rotating Machines with Weakly Supervised Data Using Deep Transfer Learning. IEEE Trans Industr Inform 2019.

[33] MATLAB. Spectrogram. 2019.