Overview of Automatic Machine Fault Diagnosis using Generative Adversarial Network

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Abstract— Fault detection problem for sampled-data system has attracted a lot of attention in industrial factories. A design method of the machine fault detection model for enrich the dataset is presented using the generative adversarial network. The generated fault data has high similarity with the original data and it significantly improves the model performance.

Keywords— fault diagnosis; generative adversarial network

I. Introduction

In the industrial context, machine maintenance is one of the most significant sectors. Predictive maintenance is extremely cost-effective, thus, 79% of businesses see this method as the main application of industrial data analytics [1]. In the modern industrial environment, predictive maintenance focuses on the IoT and artificial intelligence (AI) platforms. In Figure 1, the maintenance includes data collection and signal processing to conducts early fault detection and diagnosis. Various predictive maintenance schemes and AI models, which mostly use supervised learning, have been proposed lately.

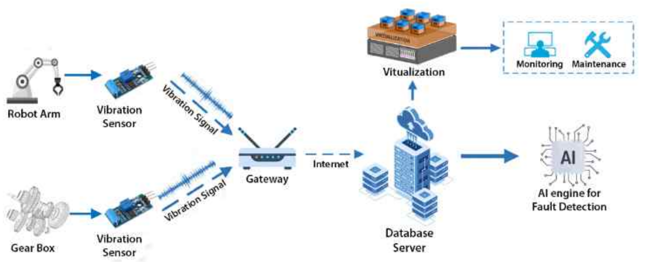

Figure 1: An example of Internet of Things (IoT) and artificial intelligence (AI) in fault detection application.

However, the training process for fault classification applications is difficult to conduct because of the imbalance of the input data. Therefore, data augmentation is necessary to increase the performance of the model training process when dealing with small fault datasets. The general generative models produce outputs similar to the samples in the training dataset [2] by mimic the probability distribution function of the original data. The most popular generative method in data augmentation is the generative adversarial network (GAN).

In this paper, vibration data from Spectra Quest's Gearbox Prognostics Simulator (GPS) is tested using various fault detection approaches for both limited and unlimited input data. We also introduce GAN algorithms to generate a broken machine signal and compare it with the original data.

II. Fault Detection Data

The vibration signal used in this study is collected from the GPS and then uploaded to OpenEI data storage [3]. The GPS simulates a real gearbox device and has configurations with different options and working behaviors. Based on these configurations, the GPS can simulate gearbox working behavior, condition monitoring, and vibration data for further study.

The basic GPS includes replaceable parts that are combined for gearbox operation simulation. With various characteristics, the GPS can be customized to handle and examine heavy loads. GPS is also designed with a large reserve space so that the users can place, set up, and install new monitoring devices.

III. Data Generation in Machine Fault Detection

In general, data augmentation is mostly used in image processing [4] because it is easy to evaluate whether the generated data is similar to the original data based on the judgement of human. In contrast, it is difficult to evaluate the data augmentation in data analysis because it depends on a different characteristic of the data. Therefore, to evaluate the generation data, we require a comprehensive test with various conditions. The training and testing process using both generated data by GAN and real data is shown in Figure 2.

To improve the accuracy of the predictive model, we introduce data augmentation using GAN to generate broken data similar to the original data. With different approaches and AI models, we can guarantee the evaluation process with high accuracy and similarity with the original data, which can help to improve the predictive model.

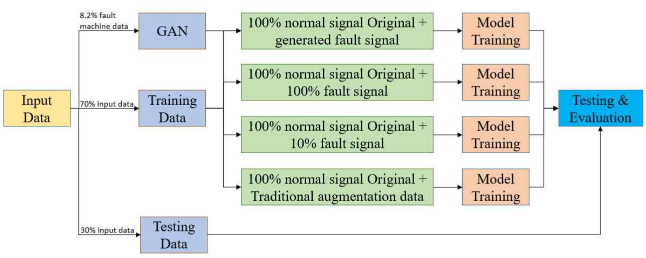

Figure 2: Training process using both real data and generated data by generative adversarial network (GAN).

A. *Full Analysis and PCA Transform*

In this approach, the FFT of the signal is fed directly into the AI model to determine whether or not the machine has errors. The AI models analyzed in this study are artificial neural network (ANN) [5], K-mean clustering [6], and support vector machines (SVM) [7]. These models have proved to be robust for classification applications. Moreover, ANN, K-mean clustering, and SVM are very flexible when dual with different data types and structures. However, K-mean clustering and SVM-based models are not effective when applied with high-dimension input data [8]. Therefore, we also consider the PCA to reduce the dimensions of the input data.

B. *GAN*

GAN is a technique designed by Ian Goodfellow to generate new data from a fixed training data set. In this technique, the discriminative and the generative neural networks compete in a zero-sum game to improve themselves. Using a limited training set, the GAN techniques learn by themselves to generate data using the specific structure. The most well-known GAN applications are those in computer vision, in which a photograph set is trained to generate new output with realistic characteristics for human observers.

The adversarial procedure is illustrated in Figure 3. Most existing GANs perform a similar adversarial procedure in different adversarial objective functions. In this paper, the GAN algorithm is used to generate the broken machine data signal; therefore, only broken training data is fed into the generator. The generator generates the broken data using random noise, which ranges from 0 to 1 with normal distribution to guarantee the difference in the output data.

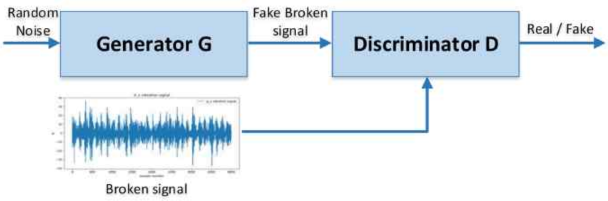

Figure 3: GAN model for vibration data augmentation.

C. *Data Generating*

The preprocessing procedure for the generated signal is the same as that for the original signal, and, based on that, we can evaluate its quality using previous fault detection methods. Note that we generate the signal only for the broken machine because the broken signal is assumed to be less than the signal obtained for the original data.

D. *Fault Diagnosis Using Generated Signal*

Based on both the original and generated data, we evaluated the final results using ANN, K-mean clustering, and SVM. Keeping the same testing data, we simulated the actual situation of the AI model in real life. In contrast, the training data is a mix of the real data and the generated data. The ratio of the real data over generated data is 100%, 80%, 60%, 40%, 20%, and 0%. With this testing condition, different signal processing approaches, and AI model, the generated data will be evaluated comprehensively if it can satisfy the data augmentation requirement in a fault machine detection application.

To verify the similarity between original data and generated data, we conducted the Kolmogorov-Smirnov test using Python version 3.7.4 [9].

Data augmentation is useful in the training process when the number of fault samples is so small that the model cannot be trained effectively. This characteristic is very suitable in machine fault detection because of the lack of fault machines at the start of the implementation phase. With the improvement of GAN, we can generate fault data for applying the machine fault diagnosis with high similarity to the original data. Using various experiments and evaluations, we can conclude that the generated data has a high similarity with the original data in both the time domain and frequency domain. The generation data significantly improved the application of training performance with a large machine fault sample. Although we could generate high-quality input data, the original fault data are also necessary for testing and partial training.

IV. CONCLUSIONS

This study proposed a novel method to generate the fault machine vibration signal data, thus enhancing the model performance in the case of a limited fault dataset for training. After testing, we conclude that the generated data has high similarity to the original data and significantly improves the accuracy of the model with limited real fault machine data in the training dataset.

However, the data augmentation method using GAN still has a limitation, since the high variety can reduce the output signal and unstable during the training process. Therefore, the architectures of both the generator and discriminator should be considered carefully, and the output of GAN has to be carefully evaluated.

With the disadvantages of GAN, we consider to provide other generative AI models for the data augmentation and compare with the current scheme.

REFERENCES

[1] Zhang, W.; Yang, D.; Wang, H. Data-driven methods for predictive maintenance of industrial equipment: A survey. IEEE Syst. J. **2019**, 13, 2213–2227.

[2] Xu, J.; Li, H.; Zhou, S. An overview of deep generative models. IETE Tech. Rev. **2015**, 32, 131–139. [CrossRef]

[3] Openei. Gearbox Fault Diagnosis Data. 2018. Available online: https://openei.org/datasets/dataset/gearbox-fault-diagnosisdata (accessed on 15 January 2021).

[4] Shorten, C.; Khoshgoftaar, T.M. A survey on image data augmentation for deep learning. J. Big Data **2019**, 6, 60. [CrossRef]

[5] Goodfellow, I.; Bengio, J.; Courville, A. Deep Learning; MIT Press: Cambridge, MA, USA, 2016.

[6] Smola, A.; Vishwanathan, S.V.N. Introduction to Machine Learning; Cambridge University Press: Cambridge, UK, 2008.

[7] Mohri, M.; Rostamizadeh, A.; Talwalkar, A. Foundations of Machine Learning, 2nd ed.; Cambridge University Press: Cambridge, UK, 2018

[8] Christopher, M.B. Pattern Recognition and Machine Learning; Springer: Berkeley, CA, USA, 2006.

[9] Vrbik, J. Small-sample corrections to kolmogorov–smirnov test statistic. Pioneer J. Theor. Appl. Stat. 2018, 15, 15–23.