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Machinery fault diagnosis with imbalanced data using deep generative adversarial networks

Wei Zhang [a,b], Xiang Li [b,c,d,*], Xiao-Dong Jia [d], Hui Ma [b,e], Zhong Luo [b,e], Xu Li [f]

[a] School of Aerospace Engineering, Shenyang Aerospace University, Shenyang 110136, China
[b] Key Laboratory of Vibration and Control of Aero-Propulsion System Ministry of Education, Northeastern University, Shenyang 110819, China
[c] College of Sciences, Northeastern University, Shenyang 110819, China
[d] NSF I/UCR Center for Intelligent Maintenance Systems, Department of Mechanical Engineering, University of Cincinnati, Cincinnati 45221, USA
[e] School of Mechanical Engineering and Automation, Northeastern University, Shenyang 110819, China
[f] State Key Laboratory of Rolling and Automation, Northeastern University, Shenyang 110819, China

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ABSTRACT

Despite the recent advances of intelligent data-driven fault diagnosis methods on rotating machines, balanced training data for different machine health conditions are assumed in most studies. However, the signals in machine faulty states are usually difficult and expensive to collect, resulting in imbalanced training dataset in most cases. That significantly deteriorates the effectiveness of the existing data-driven approaches. This paper proposes a deep learning-based fault diagnosis method to address the imbalanced data problem by explicitly creating additional training data. Generative adversarial networks are firstly used to learn the mapping between the distributions of noise and real machinery temporal vibration data, and additional realistic fake samples can be generated to balance and further expand the available dataset afterwards. Through experiments on two rotating machinery datasets, it is validated that the data-driven methods can significantly benefit from the data augmentation, and the proposed method offers a promising tool on fault diagnosis with imbalanced training data.

1. Introduction

In the recent years, with the development of the advanced rotating machines in modern industries such as intelligent manufacturing, aerospace industry *etc*., the conventional physical model-based methods are becoming less capable of providing reliable fault diagnostic results, and the intelligent data-driven approaches are emerging to offer promising tools for accurate machine condition assessment [1–6]. Generally, data-driven fault diagnosis models are established through exploration of the statistics of the supervised training data, which are assumed to cover a wide variety of machine health conditions. Therefore, the effectiveness of the fault diagnosis method is highly dependent on the quality and quantity of the training data.

In the current literature, the data-driven fault diagnosis studies are mostly carried out under the assumption that balanced training data can be obtained, indicating similar amount of labeled samples in different machine conditions can be used for training. However, this assumption usually does not hold in real industries, since it is generally difficult and expensive to collect data in machine faulty conditions, despite the easy data collection in machine healthy state. Consequently, the imbalanced training data are available in most cases, which poses negative effect on the data-driven fault diagnosis model.

Fig. 1 illustrates the influence of the imbalanced training data on the model performance. Using balanced training data, effective discriminative features of different classes can be learned by the data-driven methods, which generalize well on the testing samples. However, when the training data are imbalanced, the model is inclined to be over-trained by the majority classes, and the decision boundaries of the minority classes tend to shrink, resulting in degraded generalization on the testing samples. Therefore, the data-driven models are generally less confident of identifying machine faults in such scenarios.

In order to address the imbalanced data issue, different sampling methods have been proposed, which basically fall into two categories, i.e. under-sampling the majority classes and over-sampling the minority classes. While the under-sampling methods generally lead to information losses, the over-sampling approaches have been much preferred in the latest studies [7–9]. Especially,

* Corresponding author at: College of Sciences, Northeastern University, Shenyang 110819, China.
E-mail address: xiangli@mail.neu.edu.cn (X. Li).

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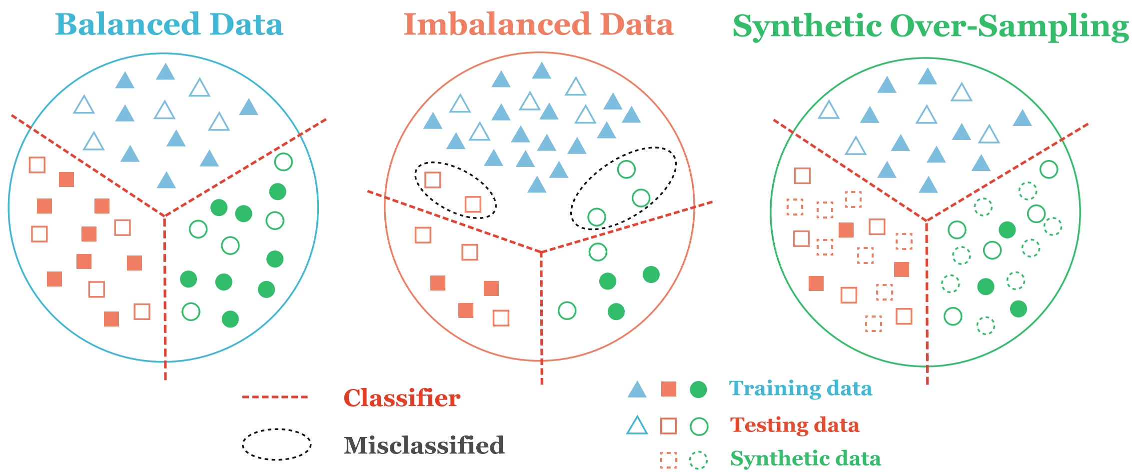

Fig. 1. Data-driven fault diagnosis performances with balanced and imbalanced data, and the effect of synthetic over-sampling methods.

the synthetic over-sampling methods have been promising on the imbalanced data problems, which create additional training samples based on the available data as shown in Fig. 1. For instance, the popular synthetic minority oversampling technique (SMOTE) [10] aims to interpolate a new data sample between a certain real sample and one of its nearest neighbors. In this way, additional samples can be generated to expand and balance the imbalanced training dataset, leading to improvements in the model performance. While a number of synthetic over-sampling methods have been proposed in the past years, most studies are based on data interpolation, and less effective in creating data variants subject to the underlying distribution of the real data. Therefore, the existing methods still suffer from overfitting the limited minority data.

Recently, deep learning is emerging as a highly efficient data-driven technique, which is characterized by the deep neural network architecture with multiple linear and nonlinear data transformation operations. A number of tasks including intelligent fault diagnosis have largely benefited from the development of deep learning in the past years [11–14]. Besides the successful application in establishing the relationship between measured signal and machine health conditions, deep learning has also shown promising effects in data generation. For instance, in image processing tasks, realistic images have been artificially generated using generative adversarial neural networks [15]. Therefore, deep generative adversarial neural networks hold the potential to effectively address the imbalanced data problem by creating additional reliable data samples for training.

In this paper, a deep learning-based synthetic over-sampling method is proposed for machinery fault diagnosis with imbalanced data. Two stages are included in the proposed method. In the first stage, generative adversarial networks are adopted to learn the distributions of the real data samples, which can be used to balance and further expand the training dataset by creating additional realistic fake samples. In the second stage, a deep convolutional neural network is employed afterwards for fault diagnosis, which is trained using the enlarged dataset. Experiments on two rotating machinery datasets are carried out to validate the proposed method, and promising results are obtained in different tasks with imbalanced data.

The remainder of this paper starts with the related works and preliminaries in Section 2. The proposed fault diagnosis method is presented in Section 3, and experimentally validated and investigated in Section 4. We close the paper with conclusions in Section 5.

2. Related works and preliminaries

2.1. Synthetic over-sampling approaches

Generally, synthetic over-sampling approaches aim at generating new data samples of minority classes to alleviate the imbalanced data problem. The synthetic minority oversampling technique (SMOTE) is one of the most widely used methods, which generates new samples through interpolation of the real data [10]. Some variants of SMOTE were also proposed to improve the data generation effect, including MSMOTE [7] which is modified to eliminate noise samples by adaptive mediation, borderline-SMOTE [16] where only the minority examples near the borderline are over-sampled *etc*. The adaptive synthetic sampling approach (ADASYN) was proposed by He et al. [17] where a weighted distribution is used for different minority class examples based on their level of difficulty in learning, and more synthetic data are generated for the minority class examples that are harder to learn. Bunkhumpornpat et al. proposed the Safe-Level-SMOTE method [18], where each minority class instance is assigned a safe level, and SMOTE is implemented to generate new data only in the safe region.

While a wide variety of over-sampling methods have been developed, data interpolation is mostly used which fails to learn the underlying distribution of the real data, and incorrect samples may possibly be generated in this way. Recently, deep neural networks have shown promising ability on data generation [15], and have been successfully applied to address the data imbalance problem. The conditional generative adversarial network (CGAN) was proposed by Mirza et al. [9], where the network can be trained to generate data conditioned on class labels. Additional samples of the minority classes can be explicitly created for data augmentation. The balancing generative adversarial network (BAGAN) was proposed by Mariani et al. as a data augmentation tool to restore balance in imbalanced image datasets [8]. The generative neural network learns useful features from the majority classes, which facilitate data generation of the minority classes. High-quality images can be created with BAGAN using imbalanced data.

2.2. Data-driven fault diagnosis methods

In the past years, machinery fault diagnosis has been popularly investigated in the literature [19,20]. A combined polynomial chirplet transform and synchroextracting technique was proposed by

Yu et al. [21] for analyzing non-stationary signals of rotating machinery, which is helpful for fault diagnosis. Jiang et al. [22] proposed a coarse-to-fine decomposing strategy for weak fault detection of rotating machines, where the variational mode decomposition (VMD) is adopted to analyze different kinds of signals [23]. Especially, deep learning has been widely used in machinery fault diagnosis tasks due to the great merits of reliable condition assessment, easy model establishment, low requirement of special expertise *etc.* Promising fault diagnosis results have been obtained in a number of studies using different kinds of deep neural networks [24–28] such as convolutional neural network (CNN) [29–31], recurrent neural network (RNN) [32] *etc.* Lei et al. [33] proposed a two-stage learning method for intelligent fault diagnosis, where sparse filtering and a two-layer neural network are used for feature extraction, and softmax regression is adopted for machine health condition classification. Lu et al. [29] utilized a stacked denoising auto-encoder for machinery fault identifications with signals containing ambient noise and operating condition fluctuations. Sparse auto-encoders were proposed by Sun et al. [34] in unsupervised deep neural network for induction motor fault diagnosis. Partial corruption of the auto-encoder input is added to enhance the robustness of the learned feature representation.

While most fault diagnosis studies are carried out with balanced data, the imbalanced data problem has also attracted much attention [35]. An online sequential prediction method was proposed by Mao et al. [36] for imbalanced fault diagnosis problem, where extreme learning machine is used, and the principal curve and granulation division are introduced to simulate the machine faulty data distributions. Martin-Diaz et al. [37] proposed a supervised classification approach for fault diagnosis based on the adaptive boosting algorithm with an optimized sampling technique dealing with the imbalanced dataset. In [38], a new synthetic over-sampling approach called weighted minority over-sampling (WMO) was devised to balance the data distribution with imbalanced dataset. A deep auto-encoder was used afterwards for feature extraction, and a decision tree was adopted for fault classification. To enlarge the training dataset, Li et al. [39] proposed an data augmentation method using different signal processing techniques. The results show the deep learning-based fault diagnosis methods can largely benefit from the expanded dataset with more valid instances.

In the latest studies, generative neural networks have been applied to generate machinery data samples. Khan et al. [40] utilized generative adversarial networks (GAN) for modeling the bearing degradation behavior. The future trajectory of the bearing health indicator can be generated for prognostics. GAN was also adopted in the planetary gearbox fault pattern recognition task with imbalanced data by Wang et al. [41]. The fault diagnosis module is integrated in the adversarial training scheme, which can be optimized using both the real and fake data. In this paper, a GAN-based method is proposed to address the fault diagnosis task with imbalanced data. Different from most existing studies which implicitly explore the fake data. Additional realistic samples are generated first to explicitly expand the training dataset, which are further used to improve the performance of data-driven fault diagnosis methods.

2.3. Generative adversarial networks

Generative adversarial networks (GAN) have been successfully developed in the recent years with the promising performance on realistic data generation. Generally, two modules are adopted, i.e. generator G and discriminator D, which are both parameterized as deep neural networks. GAN aims to learn the distribution of the generator p_g over the target data $\mathbf{x}$, using noise variables $\mathbf{z}$ as inputs. The prior on the input noise distribution is denoted as $p_z(\mathbf{z})$, and the generated data are thus $G(\mathbf{z};\boldsymbol{\theta}_G)$ where $\boldsymbol{\theta}_G$ denotes the parameters in G. The discriminator D with parameters θ_D takes the real data and the generated fake data $G(\mathbf{z};\boldsymbol{\theta}_G)$ as inputs, and the output $D(\mathbf{x};\theta_D)$ denotes the probability that the input comes from the real data rather than the generated data. Adversarial training is implemented that the discriminator is updated to accurately classify the real and fake data, while the generator is optimized to generate realistic samples which can not be distinguished by the discriminator. In summary, the network optimization can be formulated as [15],

$$\min_G \max_D V(G,D) = \mathbb{E}_{\mathbf{x}\sim p_{data}(\mathbf{x})}[\log D(\mathbf{x})] + \mathbb{E}_{\mathbf{z}\sim p_z(\mathbf{z})}[\log(1-D(G(\mathbf{z})))], \tag{1}$$

where p_{data} denotes the distribution of the real data. Through adversarial training between G and D, the noise distribution p_z can be projected to be similar with p_{data} by the generator, and additional realistic fake data can be thus generated.

In the current literature, some initial studies [42–44] have been carried out on using generative neural networks to address the data imbalance problem. However, most of the existing methods generally focus on feature-based data generation. Despite the promising performance, expertise on signal processing and fault diagnosis is basically required. In this study, the raw machinery vibration data are focused on, and realistic vibration acceleration data are generated to enhance the training dataset. In this way, little prior knowledge is required, which largely facilitates the application in the real industries.

3. Proposed method

3.1. Overview

Fig. 2 shows the overview of the proposed method on fault diagnosis with imbalanced data, including 2 stages i.e. data generation and fault classification. First, deep neural networks are used to learn the underlying distributions of the machinery vibration data in different health conditions using the available imbalanced dataset. The projection from noise to real data distribution is established, suggesting additional realistic fake samples can be generated from noise. In this way, the original imbalanced dataset can be balanced and further expanded with the generated samples, which can be used for developing an effective data-driven fault diagnosis method afterwards.

3.2. Stage 1: data generation

The generative adversarial networks are used to learn the distributions of the machinery vibration data, and generate fake realistic samples to expand the training dataset. In this study, fault diagnosis of multiple machine health conditions is investigated, and multiple networks are adopted for distribution learning. Fig. 3 shows the scheme of this stage and the network architecture.

N_{im} generation modules are employed and each one aims to learn the data distribution of each machine health condition, respectively. N_{im} denotes the number of the classes that need to be enhanced. In each generation module, a generative adversarial network is adopted, including a generator and a discriminator as introduced in Section 2.3. The prior distribution of the input noise $\mathbf{z} \in \mathbb{R}^{\mathbb{N}}_z$ is assumed to be standard Gaussian distribution, and N_z is the dimensionality of $\mathbf{z}$.

In the generator, one fully-connected layer with N_{input} neurons are first used, and three convolutional layers are then adopted whose filter numbers are 128, 64 and 32, respectively. After the flatten layer, two fully-connected layers are further used with

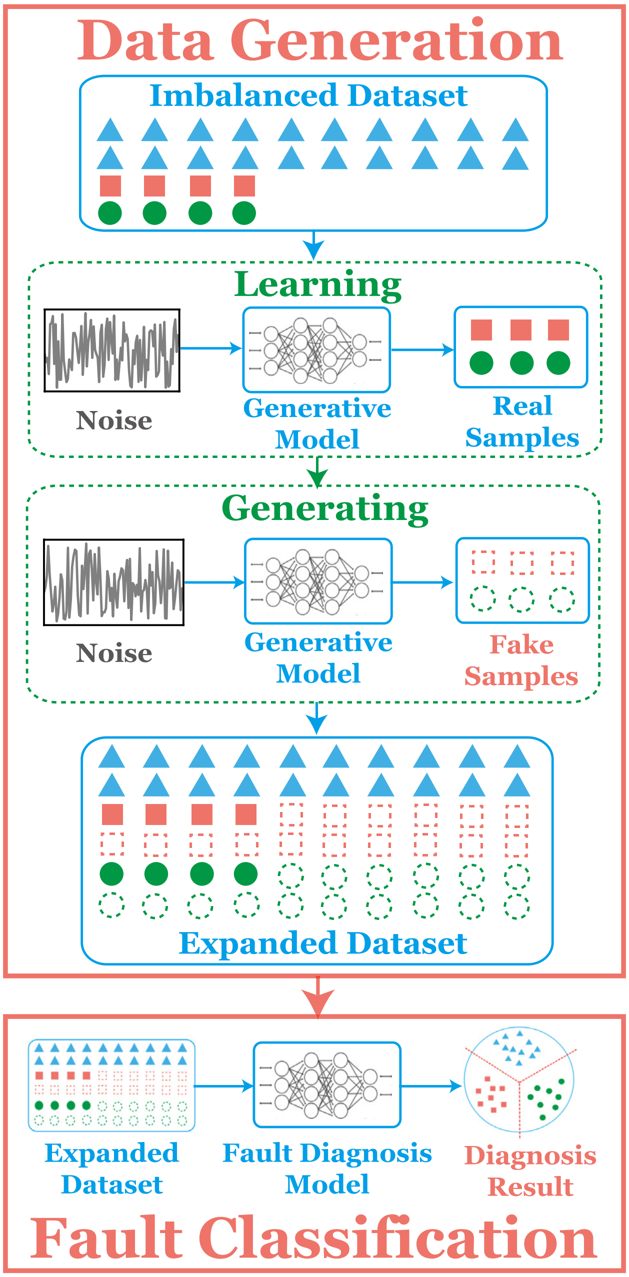

Fig. 2. Overview of the proposed method.

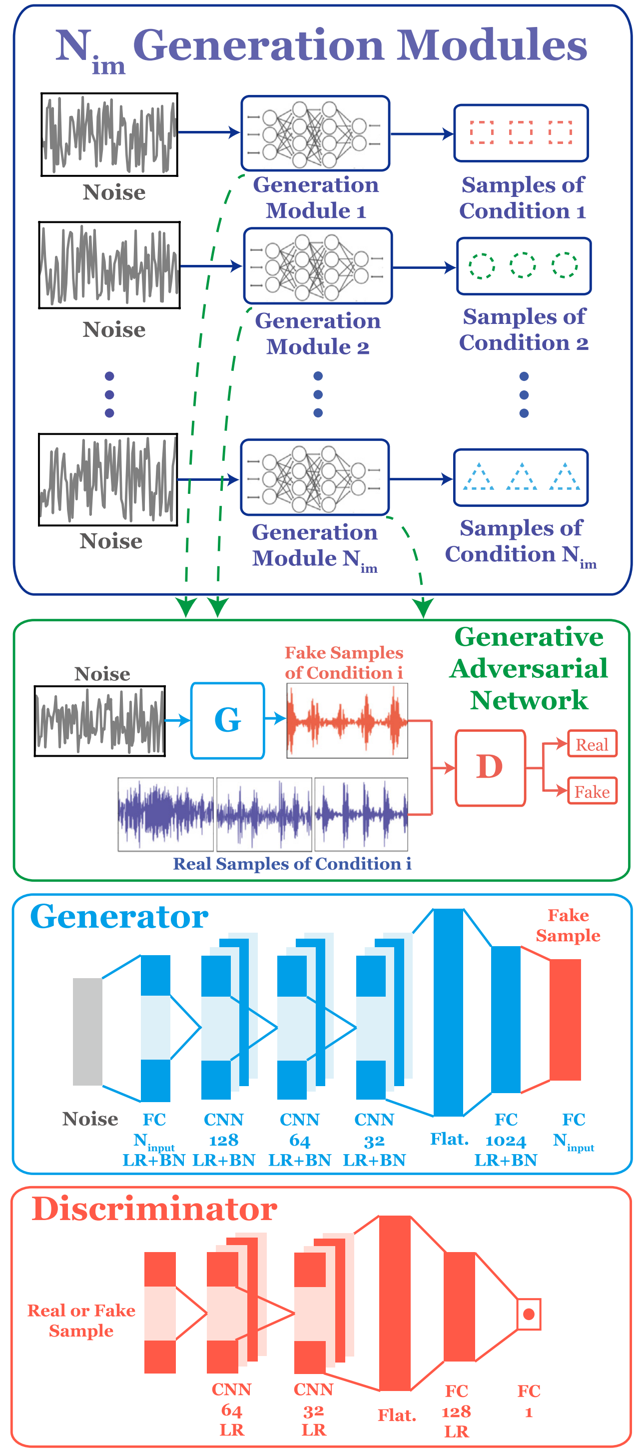

Fig. 3. Data generation scheme. LR: Leaky ReLU activation function. BN: Batch normalization.

1024 and N_{input} neurons, and the output is thus the generated sample from the noise input. In the discriminator, two convolutional layers are adopted with filter numbers of 64 and 32, respectively. After the flatten layer, two fully-connected layers with 128 and 1 neurons are used. Throughout the network, the leaky rectified linear unit (leaky ReLU) activation functions are generally adopted [45], batch normalization is applied in the generator to accelerate model training [46], and the filter size of 10 is used for the convolutional layers.

In network optimization, adversarial training is implemented, where the discriminator is trained to distinguish the real and fake data, while the generator is trained to generate realistic samples which can not be identified by the discriminator. For the i-th generation module, the network parameters are optimized to achieve,

$$\begin{aligned}\hat{\theta}_G &= \arg\max_{\theta_G} D(G(\mathbf{z};\theta_G);\hat{\theta}_D),\\ \hat{\theta}_D &= \arg\left\{\min_{\theta_D} D(G(\mathbf{z};\hat{\theta}_G);\theta_D), \max_{\theta_D} D(\mathbf{x};\theta_D)\right\},\\ &\quad \mathbf{z}\sim N(\mathbf{0},\mathbf{I}), \mathbf{x}\in S^i_{train},\end{aligned} \tag{2}$$

where $\hat{\theta}_G$ and $\hat{\theta}_D$ denote the optimal values of θ_G and θ_D, respectively. S^i_{train} is the set of the available samples in the i-th concerned machine condition.

The popular stochastic gradient descent (SGD) algorithm can be readily used to solve Eq. (2). Specifically, a 2-step optimization is applied in each training epoch. First, the parameters $\boldsymbol{\theta}_D$ in the discriminator are fixed, and the parameters $\boldsymbol{\theta}_G$ in the generator are optimized as,

$$\boldsymbol{\theta}_G \leftarrow \boldsymbol{\theta}_G + \delta \frac{\partial L_g}{\partial \boldsymbol{\theta}_G}, \qquad L_g = \frac{1}{n_{batch}} \sum_{i=1}^{n_{batch}} D(G(\mathbf{z}_i; \boldsymbol{\theta}_G); \boldsymbol{\theta}_D), \tag{3}$$

where L_g denotes the objective for the generated data, evaluated by n_{batch} randomly sampled instances of noise from Gaussian distribution, n_{batch} is the size of the mini-batch, and δ represents the learning rate. Next, $\boldsymbol{\theta}_D$ is updated while θ_G remains constant as,

$$\boldsymbol{\theta}_D \leftarrow \boldsymbol{\theta}_D - \delta \left(\frac{\partial L_g}{\partial \boldsymbol{\theta}_D} - \frac{\partial L_d}{\partial \boldsymbol{\theta}_D} \right), \qquad L_d = \frac{1}{n_{batch}} \sum_{i=1}^{n_{batch}} D(\mathbf{x}_i; \boldsymbol{\theta}_D), \tag{4}$$

where L_d denotes the objective for the real data, evaluated by n_{batch} randomly selected real samples from the dataset. Through iterations of the 2-step optimization in Eqs. (3) and (4), the generated fake samples become more and more realistic, building parameterized relationship between the noise and real data distributions.

3.3. Stage 2: fault classification

Fig. 4 shows the network architecture in the fault classification stage. Generally, the proposed network follows the typical supervised learning scheme. Three convolutional and max-pooling layers are first adopted with filter numbers of 64, 32 and 16 respectively, followed by a flatten layer. Two fully-connected layers are used next, with 1024 and N_c neurons respectively, where N_c denotes the number of the machine health conditions. The softmax function is adopted for classification, and the cross-entropy loss L_s is minimized to reduce the empirical classification error, which is defined as,

$$L_s = -\frac{1}{n_{aug}} \sum_{i=1}^{n_{aug}} \sum_{j=1}^{N_c} 1\{y_i = j\} \log \frac{e^{x_{c,i,j}}}{\sum_{k=1}^{N_c} e^{x_{c,i,k}}}, \tag{5}$$

where $x_{c,i,j}$ denotes the j-th element of the output vector, taking the i-th sample as input, and y_i represents the corresponding machine condition label. n_{aug} is the number of the samples in the expanded training dataset, including both the real and generated fake data.

4. Experimental study

4.1. Dataset descriptions

4.1.1. CWRU dsataset

The CWRU rolling bearing dataset is provided by the Bearing Data Center of Case Western Reserve University [47]. The dataset is publicly available and has been widely used on fault diagnosis. The vibration data used in this study were collected from the drive end of the motor under the rotating speed of 1797 rpm, and on four health conditions: 1) healthy (H), 2) outer race fault (OF), 3) inner race fault (IF) and 4) ball fault (BF). Different fault severities are considered with fault diameters of 7, 14 and 21 mils, respectively. Therefore, 10 bearing conditions are diagnosed.

4.1.2. Bogie dataset

The Bogie dataset is collected from an experimental setup of high-speed multi-unit train bogie bearing system shown in Fig. 5. The accelerometer is placed on the load module for vibration data collection with sampling frequency of 5 kHz. The rotating speed of 1950 rpm is implemented, corresponding with the train speed of 320 km/h. Three kinds of faulty bearings are generated, i.e. outer race fault (OF), roller fault (RF) and inner race fault (IF). Three levels of fault severities are also considered, i.e. incipient, medium and severe faults, resulting in 10 bearing conditions including the healthy state (H). The detailed information of the two datasets is presented in Table 1.

4.2. Compared approaches

In this study, different methods for the imbalanced data problem are implemented for comparisons [48]. As the baseline, the Imbalanced approach is carried out where only the imbalanced training dataset is used with no data augmentation technique. The UnderSampling method performs random under-sampling for the majority classes, and the ADASYN method uses the adaptive synthetic sampling approach [17]. The popular SMOTE method [10], i.e. the synthetic minority oversampling technique, is also implemented.

In the proposed framework of data augmentation, the Pro-Balanced method denotes the scenario where additional samples of the minority classes are added to balance the dataset. Furthermore, since the data-driven fault diagnosis methods generally benefit from larger training dataset, the proposed method is used to generate additional data for all the machine conditions, resulting in a significantly expanded dataset, that is denoted as the Pro-Expand method. In order to evaluate the generation effect, the

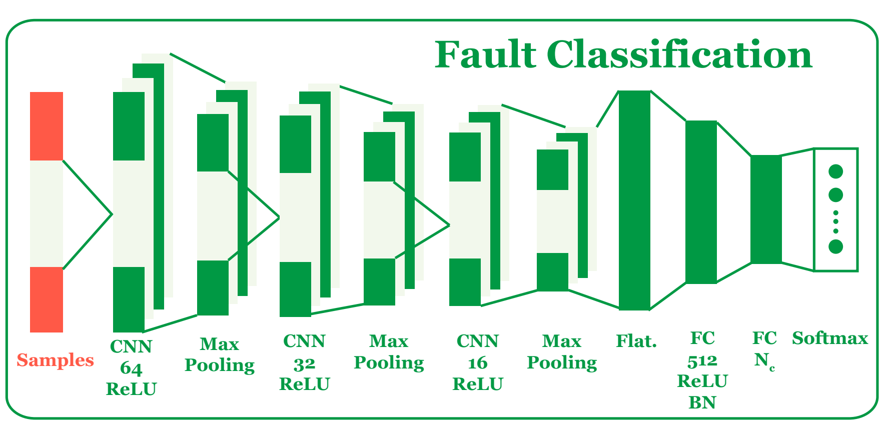

Fig. 4. Fault classification network architecture.

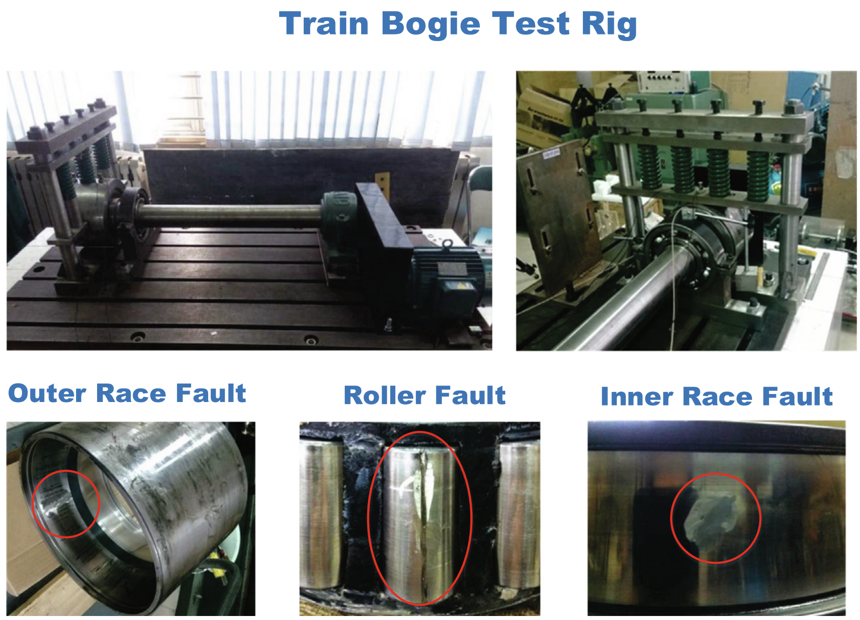

Fig. 5. Test rig and bearing faults in the Bogie dataset.

AllFake method is carried out where only the generated fake data are used. In addition, the RealBalanced method is used as a reference for evaluations of different methods, where the balanced dataset containing only the real samples in different classes is considered.

All the methods are carried out to prepare the training datasets, which are used to develop the data-driven fault diagnosis approaches afterwards. For simplicity, the fault classification model in the proposed method as presented in Section 3.3 is shared by all the compared methods.

4.3. Experimental results and performance analysis

In this section, the proposed method is experimentally validated using the two bearing datasets. Multiple tasks with different imbalance ratios are investigated, as presented in Table 2.

Specifically, six tasks are evaluated on each dataset. With respect to the CWRU dataset, three tasks are implemented with different imbalance ratio, i.e. C1, C2 and C3. In order to examine the robustness of the proposed method against environmental noise, additional Gaussian noise is added to the testing data for evaluation, and the noisy data are generated based on different signal-to-noise ratio (SNR), which is defined as,

$$\mathrm{SNR(dB)} = 10\log_{10}(P_{signal}/P_{noise}), \tag{6}$$

where P_{signal} and P_{noise} denote the powers of the original signal and the additional Gaussian noise, respectively. In this way, each task is also evaluated using noisy data, that makes C1-Noise, C2-Noise and C3-Noise tasks for the CWRU dataset respectively. Similarly, B1, B2 and B3 tasks are implemented on the Bogie dataset, and

Table 1
Information of the two datasets. Inc., Med. and Sev. denote incipient, medium and severe, respectively.

Dataset	Class Label	1	2	3	4	5	6	7	8	9	10
CWRU	Fault Location	N/A (H)	IF	IF	IF	BF	BF	BF	OF	OF	OF
	Fault Size (mil)	0	7	14	21	7	14	21	7	14	21
Bogie	Fault Location	N/A (H)	IF	IF	IF	RF	RF	RF	OF	OF	OF
	Fault Severity	N/A	Inc.	Med.	Sev.	Inc.	Med.	Sev.	Inc.	Med.	Sev.

Table 2
Descriptions of the fault diagnosis tasks.

Dataset	Task	Imbalance Ratio (Class Label)										Noise
		1	2	3	4	5	6	7	8	9	10	(SNR)
CWRU	C1	1	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	$+\infty$
	C1-Noise	1	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	2
	C2	1	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	$+\infty$
	C2-Noise	1	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	2
	C3	1	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	$+\infty$
	C3-Noise	1	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	2
Bogie	B1	1	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	$+\infty$
	B1-Noise	1	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	2
	B2	1	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	$+\infty$
	B2-Noise	1	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	2
	B3	1	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	$+\infty$
	B3-Noise	1	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	2

the B1-Noise, B2-Noise and B3-Noise tasks are under noisy environments respectively.

In this study, different methods are evaluated for comparisons. For both the two datasets, it is assumed that the sample dimension is 512. By default, 200 labeled samples in the machine healthy condition are available in the training dataset, and the number of the samples in the other conditions is determined by the imbalance ratio in different tasks. The testing data include 2000 samples, with each class containing 200 samples respectively. The Pro-Expand method indicates the training dataset is expanded to contain 1000 samples of each class including the real data, and the AllFake method includes 1000 generated fake samples of each class.

In network training, the back-propagation (BP) algorithm is applied for the updates of all the network parameters, and the Adam optimization method [49] is used. The reported experimental results are generally averaged by 10 trials to reduce the effect of randomness. The model parameters are presented in Table 3. They are mostly determined from the validation results in the task C1, which is a relatively easy task containing less imbalanced training data and environmental noise is not applied.

4.3.1. Diagnostic results

The fault diagnostic results in different tasks using different methods are presented in Table 4. It can be observed that the performance of the data-driven fault diagnosis methods is significantly influenced by the imbalanced training data. Lower testing accuracies are generally obtained by the same method with smaller imbalance ratio. The proposed methods outperform the compared approaches in most cases, showing the effectiveness and superiority of the proposed data augmentation method.

Specifically, the Pro-Balanced method achieves higher testing accuracies than the other existing approaches in different tasks, and its performance improvements are more significant in the scenarios with smaller imbalance ratio and additional noise. Furthermore, better performance can be mostly achieved by the Pro-Expand method with expanded dataset, and its testing accuracy is even higher than that of the RealBalanced method in the noisy environments. That shows the proposed method significantly enhances the data robustness of the fault diagnosis methods against additional noise. It is also noted that the AllFake method where the diagnostic model is trained only using the generated fake data, still obtains promising diagnostic results. That suggests high similarity between the generated fake samples and the real data, thus showing the effectiveness of the proposed data generation scheme.

It should be pointed out that different amount of data in the minority classes are explored by the proposed method for data generation in different tasks. Since the performance of the generative adversarial network generally depends on the size of the training data, lower testing accuracies are mostly obtained with smaller imbalance ratio for each bearing dataset. However, the proposed method still achieves promising results using limited available data in tasks C3 and B3, further showing its effectiveness in data augmentation.

Table 3
Parameters used in this paper.

Parameter	Value	Parameter	Value
Epochs (Stage 1)	2e5	δ	1e−5
Epochs (Stage 2)	5e3	N_{input}	512
N_z	256		

Table 4
Average testing accuracies in different tasks using different methods (%).

Method	C1	C1-Noise	C2	C2-Noise	C3	C3-Noise	B1	B1-Noise	B2	B2-Noise	B3	B3-Noise
Imbalanced	90.3	72.7	51.7	37.8	22.6	18.2	65.4	44.5	28.7	23.7	15.7	12.6
UnderSampling	91.5	71.7	52.5	38.3	33.6	29.8	66.3	51.3	42.7	30.6	24.4	20.1
SMOTE	92.7	74.4	63.4	48.3	40.4	32.9	80.1	62.6	45.2	38.3	26.3	24.7
ADASYN	94.1	72.3	65.2	55.7	35.0	30.4	82.0	63.7	50.0	39.5	25.8	22.6
RealBalanced	99.9	74.2	99.9	73.8	99.9	74.0	99.9	86.4	99.9	86.2	99.9	85.7
AllFake	76.5	51.6	73.4	48.6	52.0	44.6	83.6	58.3	56.5	43.7	48.7	36.4
Pro-Balanced	90.5	74.6	81.6	72.2	61.3	52.8	88.6	68.2	60.4	45.3	47.6	38.5
Pro-Expand	90.3	79.2	82.5	78.7	61.2	58.4	95.5	72.6	70.1	48.5	50.2	42.7

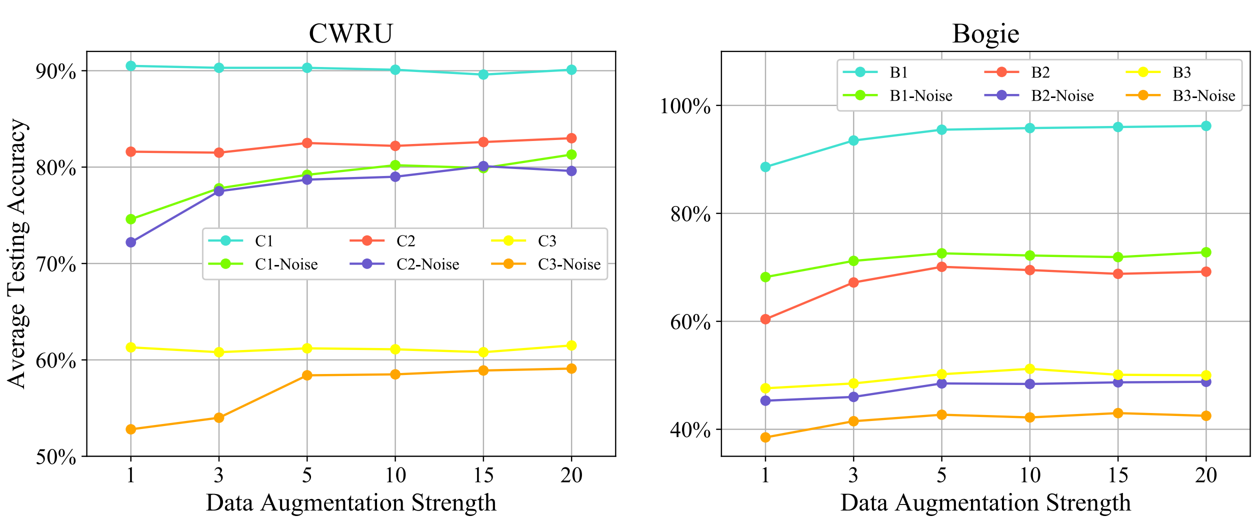

Fig. 6. Effects of the data augmentation strength on the model testing performance in different tasks.

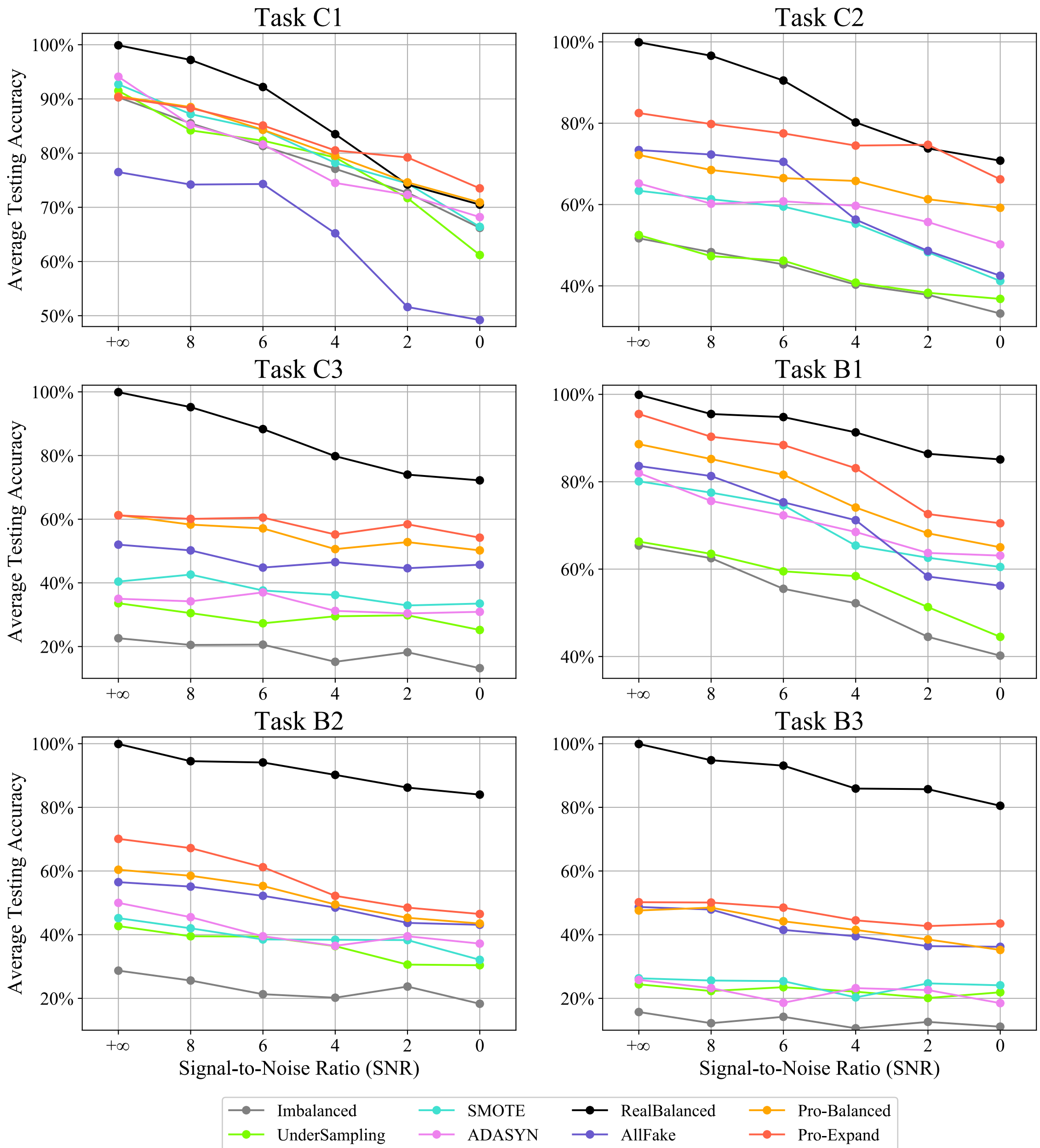

Fig. 7. Performances of different methods under different signal-to-noise ratio of the testing data.

4.3.2. Performance analysis

In this section, the performance of the proposed method is investigated in different scenarios with imbalanced data. Fig. 6 shows the effects of the data augmentation strength on the model testing performance. Concretely, the augmentation strength denotes the size of the expanded dataset. For instance, strength 1 is the same with the Pro-Balanced method, and strength 5 means the dataset is enlarged to be 5 times of that with strength 1.

It can be observed that generally, larger augmentation strength leads to higher testing accuracy in different tasks. The improvements are more significant in the tasks with additional noise, and close to 10% increase can be mostly obtained. The results indicate the proposed method is able to learn the underlying distribution of the real data, and the noisy data distribution can be effectively covered through data augmentation.

Next, the robustness of the proposed method against additional noise is further investigated, where the testing data are contaminated with Gaussian noise of different signal-to-noise ratio, and the results are presented in Fig. 7. It clearly shows that the additional noise remarkably deteriorates the model performance in the imbalanced data problems, and smaller signal-to-noise ratio results in lower testing accuracy. The proposed methods generally obtain better results than the other compared approaches in different scenarios. The Pro-Expand method further achieves higher testing accuracies than the Pro-Balanced method, especially in the cases with strong noise. Therefore, the relationship between the noise and real data distributions is effectively captured by the data generation scheme, and the proposed method is further validated.

4.3.3. Data visualizations

The proposed method aims to explicitly generate realistic fake samples for data augmentation. Fig. 8 shows examples of the generated instances in different machine health conditions in the task

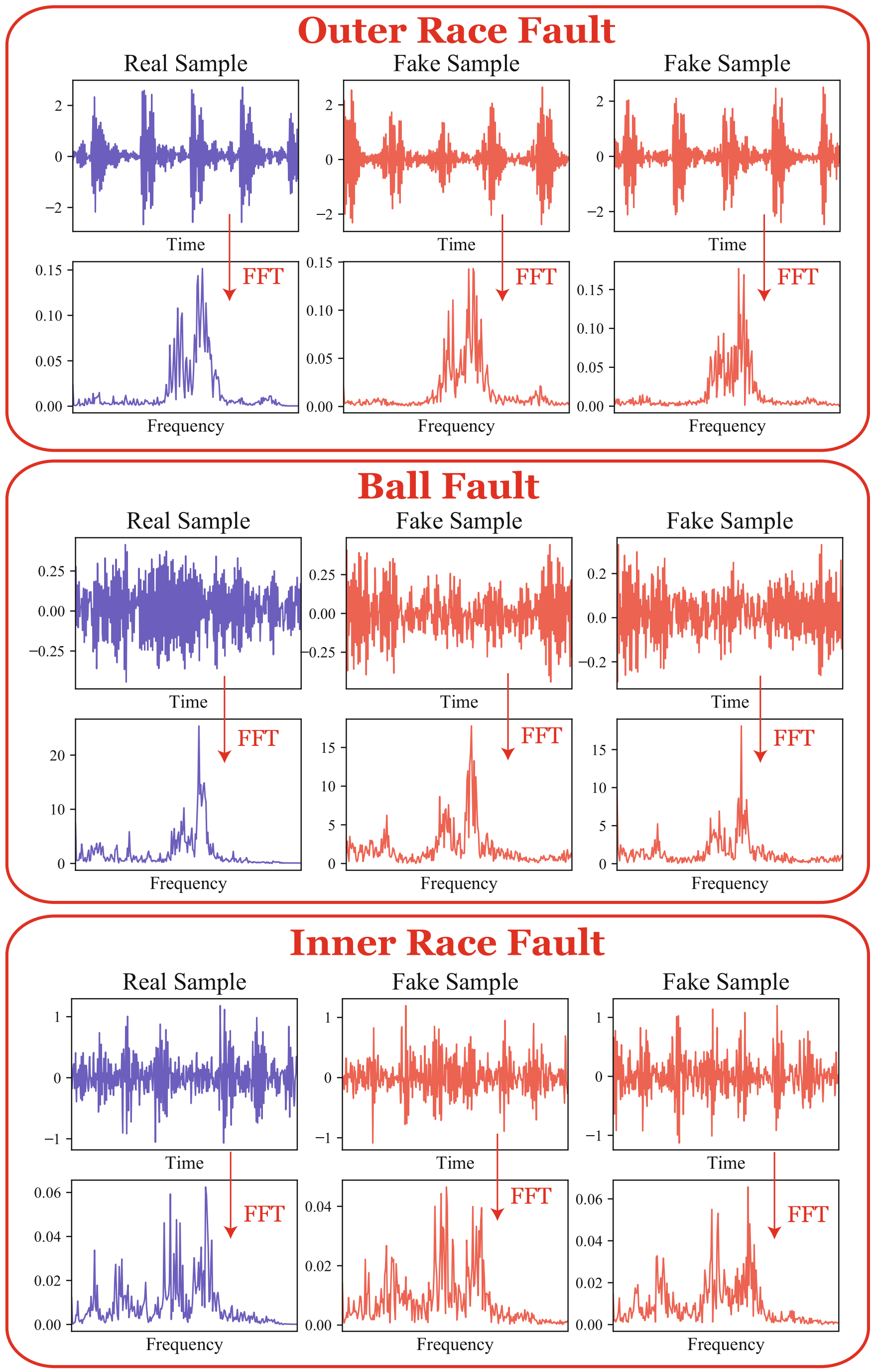

Fig. 8. Examples of the real and generated fake data samples in different bearing health conditions in the task C1, as well as the corresponding frequency spectra.

C1, and the corresponding real data samples are also presented. It can be observed that the temporal vibration patterns of the real and fake data are similar with each other. Furthermore, the fast Fourier transformation is applied on the samples, and the frequency spectra of the real and fake data also have high similarity.

Moreover, in order to further show the consistence of the generated data and the real data, more fake samples are presented in Figs. 9–11, which correspond with the inner race fault, ball fault and outer race fault conditions respectively. It can be observed that the generated data are generally pretty similar with the real vibration signals. The results show the proposed method is able to effectively learn the underlying distributions of the real data, and realistic fake samples can be generated for data augmentation.

5. Conclusion

In this paper, a deep learning-based fault diagnosis method is proposed to address the imbalanced data problem using generative adversarial networks. Multiple generation modules are adopted for data augmentation of the minority classes. Through adversarial training between the generator and discriminator, the mapping between the distributions of noise and real data can be established, which can be used to generate additional fake samples to balance and further expand the training dataset. Based on the experimental validations on two rotating machinery datasets, the data-driven fault diagnostic model can significantly benefit from the generated fake samples, that suggests the proposed data augmentation

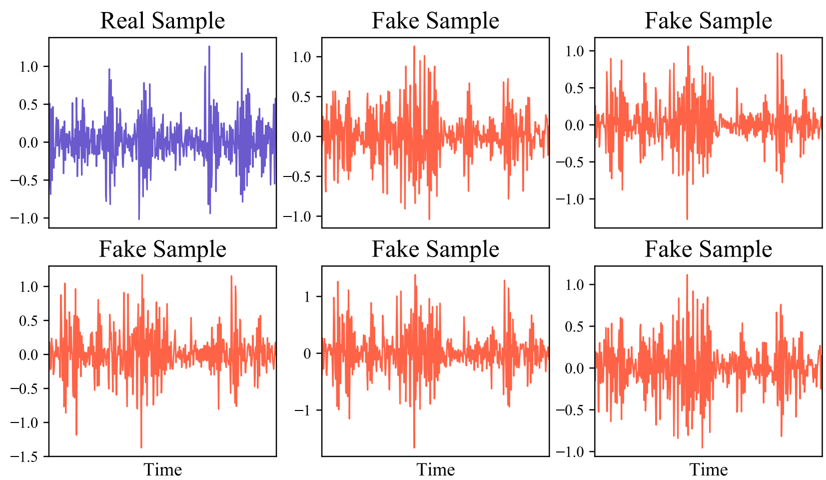

Fig. 9. Examples of the real and multiple generated fake data samples in the inner race fault condition.

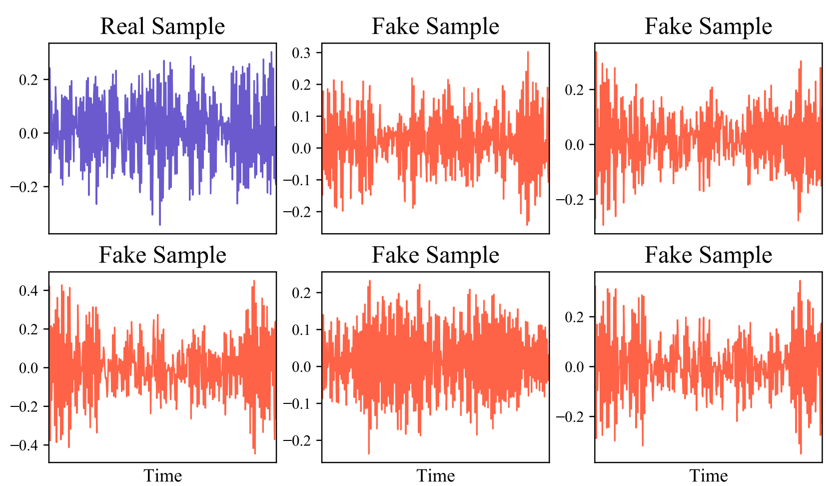

Fig. 10. Examples of the real and multiple generated fake data samples in the ball fault condition.

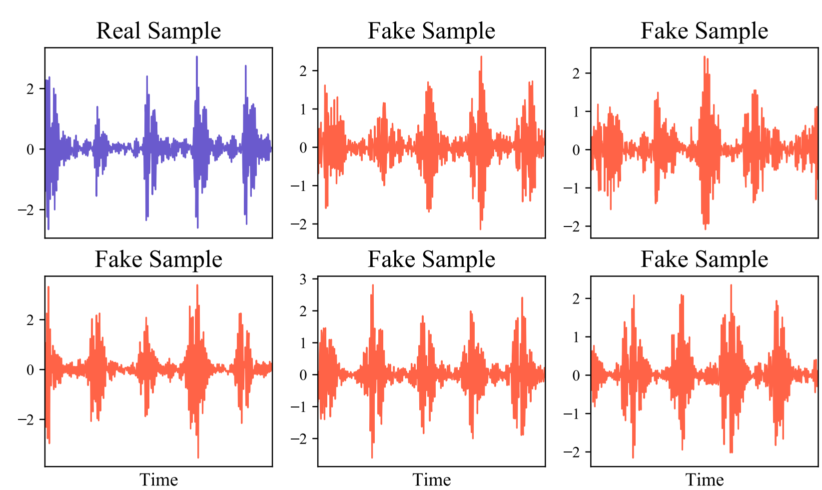

Fig. 11. Examples of the real and multiple generated fake data samples in the outer race fault condition.

method is promising for fault diagnostic tasks with imbalanced data.

It should be pointed out that while some model such as the conditional GAN is able to generate data of different kinds at the same time, it is not suggested in this study based on the experiments. Instead, multiple generators are preferred in the fault diagnosis task on the vibration data, with each generator focusing on one machine health condition respectively. Furthermore, the same operating condition of the rotating machines is considered in this study. In practice, the rotating speeds usually change in different cases, that results in cross-domain fault diagnosis problems. While it is beyond the scope of this study on the data imbalance problem, it is straight-forward and promising to integrate the well developed transfer learning techniques in the proposed framework to address the data imbalance and cross-domain fault diagnosis issues simultaneously.

Despite the improvements in the testing performances, the main drawback of the proposed method lies in the relatively large model, consisting of multiple GANs for the minority classes. Further research works will be carried out on the optimization of the network structure.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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