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An Active Learning Method Based on Uncertainty and Complexity for Gearbox Fault Diagnosis

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ABSTRACT It is crucial to implement an effective and accurate fault diagnosis of a gearbox for mechanical systems. However, being composed of many mechanical parts, a gearbox has a variety of failure modes resulting in the difficulty of accurate fault diagnosis. Moreover, it is easy to obtain raw vibration signals from real gearbox applications, but it requires significant costs to label them, especially for multi-fault modes. These issues challenge the traditional supervised learning methods of fault diagnosis. To solve these problems, we develop an active learning strategy based on uncertainty and complexity. Therefore, a new diagnostic method for a gearbox is proposed based on the present active learning, empirical mode decomposition-singular value decomposition (EMD-SVD) and random forests (RF). First, the EMD-SVD is used to obtain feature vectors from raw signals. Second, the proposed active learning scheme selects the most valuable unlabeled samples, which are then labeled and added to the training data set. Finally, the RF, trained by the new training data, is employed to recognize the fault modes of a gearbox. Two cases are studied based on experimental gearbox fault diagnostic data, and a supervised learning method, as well as other active learning methods, are compared. The results show that the proposed method outperforms the two common types of methods, thus validating its effectiveness and superiority.

INDEX TERMS Active learning, gearbox fault diagnosis, uncertainty and complexity, supervised learning.

I. INTRODUCTION

Harsh working environments make the gearbox prone to a variety of failures, such as tooth spalling, scratches, corrosion, crack damage and bumps. These unexpected failures would cause the breakdown of the complicated mechanical systems and even result in serious loss of safety, property, and customer satisfaction. To possibly eliminate such problems, condition monitoring and fault diagnosis of the gearbox has gained wide attention for its significance in preventing catastrophic accidents and guaranteeing sufficient maintenance [1]. Continuous condition monitoring and real-time fault diagnosis play an indispensable role that not only results in detection and diagnosis of fault information in advance of damage but also enables fault prognosis to provide support for crucial decision-making regarding maintenance [2].

Currently, the development of effective and accurate fault diagnostic methods for gearboxes has become a research hot topic. With the increasing attraction in prognostic and health management (PHM), fault diagnostic methods based on machine learning are becoming the focus in this field [3], [4]. A large number of studies have reported on fault diagnostic methods [5]–[8]. Most of these methods are based on supervised learning [9]–[11], which refers to using a set of known labeled data as training data to diagnose fault modes of test data composed of a set of unlabeled data. Supervised learning methods have been widespread in the field of fault diagnosis [12]. This is because the research objects are usually basic components, such as bearings, gears, etc., leading to (1) a small number of fault modes and easy classification, (2) small amount of data and easy data processing, and (3) relatively small cost to label the data. However, it is more difficult to complement an accurate and effective fault diagnosis of a gearbox. Its difficulty mainly lies in the following three aspects:

(1) Different from the simple failure mechanism of a single component, a gearbox is composed of a series of mechanical units, which leads to the cause and mechanism of its faults to be full of complexity and uncertainty.

(2) Simultaneous, since a variety of mechanical units exist in a gearbox, typically including bearings and gears,

it results in various failure modes. These multimodal fault types increase the difficult of diagnostic work, especially when only using single vibration signal processing.

(3) Moreover, in real applications, unlabeled data are often abundant whereas labeled data are scarce. Labelling the raw unlabeled data, which is then used to train the classification model, is usually expensive due to the involvement of human experts.

Therefore, due to higher rotary machinery system complexity and sensory data heterogeneity, the effective diagnosis of multiple fault modes classification based on sensory data with strong ambient noise and working condition fluctuations is still a problem and a major challenge for the application of the proposed methodologies in complex engineering systems because of possible information loss and external influences [13]. As a consequence, the key task is to effectively use as few labeled data as possible to complete an accurate multi-fault diagnosis of the gearbox.

Active learning is a kind of machine learning strategy that reduces the labeling cost by actively selecting the most valuable data to query their labels [14]. To improve the generalization performance of supervised learning algorithms, they require a large number of labeled samples to train the classifier iteratively. Previous researches have reported that the accurate labeling of training samples, which is the prerequisite for supervising learning, not only requires the participation of plenty of experts, but also takes more than 10 times as long as the acquisition time of the labeled samples [15]. However, compared to current supervised learning algorithms, active learning-based methods simulate the learning process of human, and actively select part of samples to be labeled and added to the training set to improve the performance of the classifier. Therefore, active learning has emerged gradually as another isolated group of research specialized for pattern recognition. In recent years, the active learning methods have been applied widely in the field of information retrieval, image and speech recognition, text classification and natural language processing. Literatures have shown that 90.7% of researchers think the active learning methods are effective in their projects [16] and big companies, such as Google, CiteSeer, IBM, Microsoft and Siemens, use active learning algorithms in their projects to improve effectiveness [14].

Generally, active learning consists of three important parts: (1) the method to construct the initial training sample set and its improvement; (2) the sample selection strategy and its improvement; (3) the termination condition and its improvement. The key and challenged step is the second part, which is to design a selection criterion such that the queried labels can optimize the improvement of the classification model [17]. Over the past few years, many active selection criteria have been proposed. For example, informativeness measures the ability of a sample to reduce the uncertainty of a statistical model; representativeness measures whether a sample well represents the overall input patterns of the unlabeled data [14]; diversity measures how different an instance is from the labeled data [18]; density measures the representativeness of a sample to the entire data set [19]; and uncertainty measures the confidence of the current model to classify a sample [20]. However, most active learning algorithms deploy only one criterion for query selection, which could significantly limit their performance [21]. Several researchers have reported attempts to consider different criteria simultaneously and obtain better results [17], [21], [22]. Although active learning has advantages over supervised learning in many aspects, it is rarely used in the field of fault diagnosis.

In this paper, we develop an active learning method based on uncertainty and complexity that guarantees diagnosis accuracy and improves fault pattern classification robustness with respect to fewer labeled data and complex mechanical signals, where the active learning method is used to achieve better feature selection. The active learning algorithm is constructed based on uncertainty and complexity, where uncertainty is defined to describe the confusion degree of the samples, and complexity is defined to express the ambiguity of samples and measure differences between local and global in samples. In this way, the most valuable samples are obtained and are used as the input for the subsequent fault classifier, such as random forests (RF). Therefore, a diagnostic method for gearboxes based on the proposed active learning strategy is proposed. Due to the application of the proposed sample selection strategy, the most complex and uncertain samples are chosen to train the classifier. This not only greatly increases the stability of the results but also significantly improves the accuracy and efficiency of the diagnostic method.

The structure of the paper is presented as follows. In Section 2, the basic theories of active learning and RF are reviewed. The proposed diagnostic method is presented in Section 3. In Section 4, experimental validation is conducted based on the data collected from the 2009 PHM data challenge to evaluate the present approach. Finally, conclusions are given in Section 5.

II. RELATED WORKS

A. ACTIVE LEARNING

Different from supervised learning methods, active learning, first proposed by Angluin [23], uses unlabeled samples to aid the training process of the classifier. To illustrate clearly the effectiveness of the active learning and its effect on improvement to the classifier, a two-classification problem in 2D space is studied as a case as shown in [14, Figs. 1–3].

Fig. 1 shows a dataset consisted of 400 points evenly sampled from two class Gaussians. Supervised learning and active learning methods are applied to implement classification with 30 labeled points. As shown in Fig. 1, points nearby the $x = 0$ interference are the most helpful for the training process of a classifier. For supervised learning methods shown in Fig. 2, 30 points are selected randomly and far away from the interface $x = 0$. It leads to difficulty for a classifier to find the right interface and low

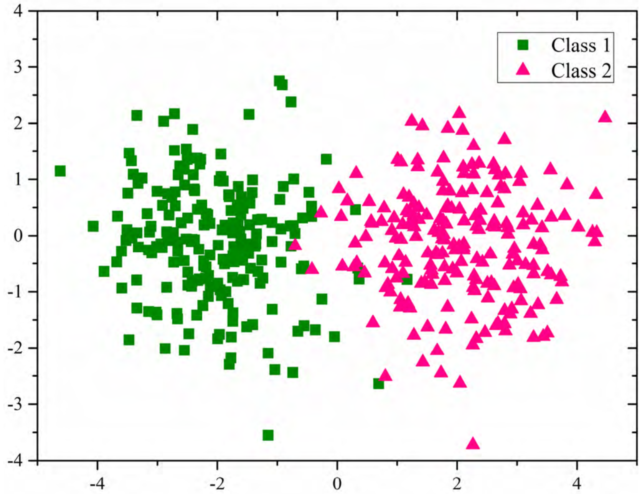

FIGURE 1. A dataset consisted of 400 points evenly sampled from two class Gaussians.

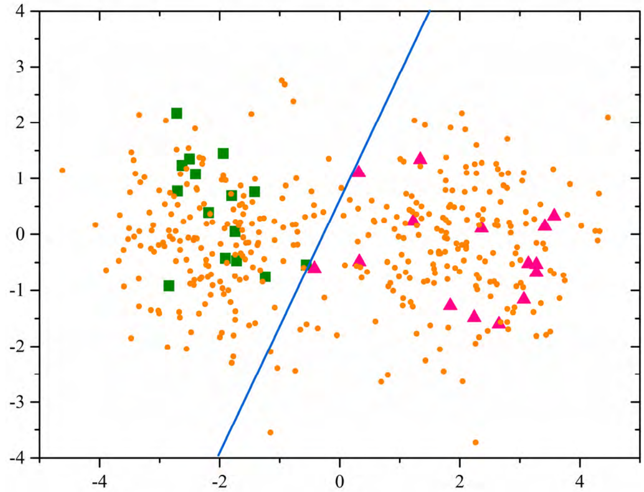

FIGURE 2. Classification results obtained by supervised learning methods.

TABLE 1. Pseudo code of the framework for active learning.

```
Algorithm 1 Framework of active learning
Input: Labeled Data Set L, Unlabeled Data Set U, LE, SE;
Output: LE
Begin For i from 1 to N
      Train(LE,L);                  Step (1)
      T=Test(LE,U);                 Step (2)
      S=Select(SE,U|T);             Step (3)
      Label(S);
      L=L+S;                        Step (4)
      U=U-S;                        Step (5)
END For                             Step (6)
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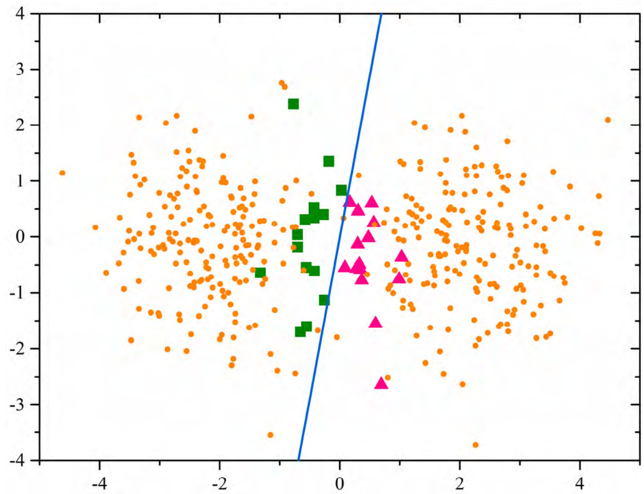

FIGURE 3. Classification results obtained by active learning methods.

recognition accuracy, which is almost 70%. In contrast, active learning methods select 30 points, which are mostly close to the interface x = 0, through effective selection strategy. As the results shown in Fig. 3, the classification accuracy is improved to approximately 90%. Therefore, compared to supervised learning, active learning can provide more useful samples and improve the accuracy of a classifier at the same labeling cost.

The working mechanism of active learning is an iterative process of training the classifier, and its construction consists primarily of two parts: the learning engine (LE) and sampling engine (SE) [24].

The framework of active learning is shown in Table 1 and as follows:

(1) Train a classifier using labeled data.

(2) Predict the probability and labels of unlabeled data.

(3) Select the unlabeled examples using the SE and label them.

(4) Add the new samples to the training set for the next training.

(5) Renew the unlabeled data set.

(6) End the algorithm when a condition is satisfied.

B. RF

Leo Breiman developed a kind of ensemble learning algorithm, namely, the RF [25]. An RF is a combined classifier consisting of a collection of tree-structured classifiers $\{C(X, \theta_k), k = 1, \ldots\}$, where θ_k is defined as an independent identically distributed random vector and each decision tree casts a unit vote for the most popular class at input X [26], [27].

A general RF framework is shown in Fig. 4 and is described as follows [28]:

(1) By employing bootstrap sampling, k samples are selected from the training set and the sample size of each selected sample is the same as the training sets.

(2) Then, k decision tree models are built for k samples and k classification results are obtained from these decision tree models.

(3) Based on the k classification results, the final classification result is decided by voting on each record. The RF increases the differences among classification models by building different training sets. Therefore, the extrapolation forecasting ability of the ensemble classification model is

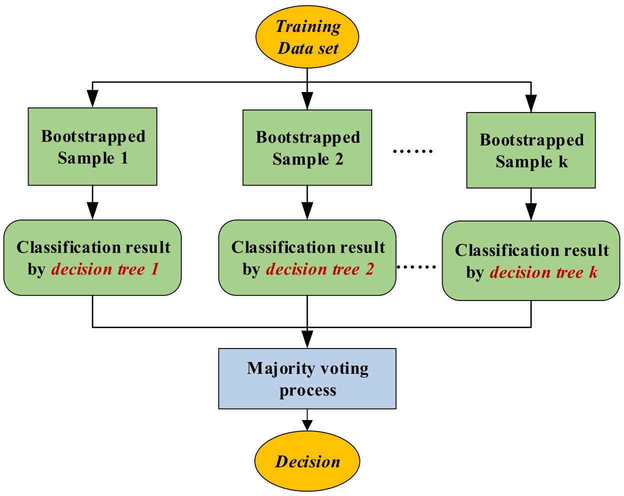

FIGURE 4. Framework of a RF.

enhanced. After k training incidents, a classification model series $\{h_1(X), h_2(X), \cdots, h_k(X)\}$ is obtained, which is utilized to structure a multi-classification model system. The final classification result of the system is simple majority voting and the final classification decision is as (1):

$$H(x) = \arg\max \sum_{i=1}^{k} I(h_i(x) = Y) \tag{1}$$

where $H(x)$ is the ensemble classification model, h_i is a single decision tree classification model, Y is the objective output, and I is an indicative function. Equation (1) explains the final classification that is decided by majority voting.

III. METHODOLOGY

We first propose the algorithms to calculate the uncertainty and complexity of samples in subsection A and then introduce our active learning strategy in subsection B to select the most useful samples. Finally, a new fault diagnostic method for a gearbox is described in subsection C.

A. CALCULATIONS FOR UNCERTAINTY AND COMPLEXITY

We denote $\{(x_1, p_1), (x_2, p_2), \ldots, (x_u, p_u)\}$ as the unlabeled data with u samples, where each x_i is a d-dimensional feature vector. Assuming there is a total of k possible labels, the probability vector for each label of x_i is denoted as:

$$p_i = [p_{i1}, p_{i2}, \ldots, p_{ik}] \tag{2}$$

where p_i is predicted using a classification model, with RF being used as the model here. In addition, p_i obeys:

$$\sum_{j=1}^{k} p_{ij} = 1 \tag{3}$$

Generally, a sample with a small probability has more information, and a sample with a large probability tends to contain little information. Since uncertainty can express data ambiguity, it is believed to be an effective and the most widely used criterion for active learning [20], [29], [30]. To measure the uncertainty of a sample, the concept of entropy is introduced. In this paper, the marginal entropy over all labels is taken to measure the uncertainty of a sample. The formula can be formally defined as:

$$UN(x_i) = -\sum_{j=1}^{k} p_{ij} \ln p_{ij} \tag{4}$$

In addition, for multi-label classification, the right label tends to concentrate on the top two categories based on the probability ranking. This concentration is what causes complexity and makes it difficult to detect. Therefore, complexity is introduced and defined as the distance from the sample with the largest probability to the sample with the second largest probability. The formula can be formally defined as:

$$CO(x_i) = |p_{i1st} - p_{i2nd}| \tag{5}$$

where p_{i1st} and $\mathrm{p_{i2nd}}$ denote the labels with the largest and second largest probability, respectively.

TABLE 2. Pseudo code of the proposed active learning strategy.

Algorithm 2 The proposed active learning strategy

Input:
  data set D
Initialize:
  divide D to D_l and D_u
  train the RF model f on D_l
Repeat:
  obtain predictions and labels for samples in D_u with f
  compute $UN(x)$ for all $x \in D_u$ with (4)
  select the first m samples with (6) and compose D_m
  compute $CO(x)$ for all $x \in D_m$ as (5)
  select the sample x^* with minimum CO value with (7)
  manually add the labels y^* and x^*
  move x^* from D_u to D_l
  update the RF model f with (x^*, y^*)
Until the number of selected samples n reached

B. ACTIVE LEARNING STRATEGY BASED ON UNCERTAINTY AND COMPLEXITY

In this subsection, we present the strategy of active learning based on the previously introduced uncertainty and complexity. Inspired by [31], the pseudo code of this algorithm is presented in Table 2. First, the data set is denoted by D and divided into two parts: the labeled data D_l and the unlabeled data D_u with N_u samples. In the initialization part, the labeled data D_l is used to train the RF model f. In the loop part, predictive probabilities and labels of samples can be obtained through the trained f. According to (4), the UN values of all the samples belonging to D_u can be computed and the m most uncertain samples can be selected according to:

$$D_m = \arg\max_m (UN(x_i)), \quad x_i \in D_u \tag{6}$$

where D_m denotes the dataset that contains the first m samples with the largest UN values.

Then, the CO values for all the samples belonging to D_m are computed and the sample x^* can be selected using:

$$x^* = \arg\min(CO(x_i)), \quad x_i \in D_m \tag{7}$$

The label y^* for x^* are manually added and are moved into D_l from D_u to update the RF model f. This loop is repeated until the number of selected samples n is reached.

C. PROPOSED GEARBOX FAULT DIAGNOSTIC METHOD BASED ON ACTIVE LEARNING

In this paper, we propose a gearbox fault diagnostic method based on active learning. The flowchart of the proposed approach is shown in Fig. 5 and the procedure to implement is as follows.

Step 1: Collect the original vibration signals of a gearbox and decompose the signals into intrinsic mode functions (IMFs) using empirical mode decomposition (EMD). EMD is one of the most powerful signal processing techniques and has been extensively studied and widely applied in fault diagnosis of rotating machinery [32]. Through EMD, any complicated data set can be decomposed into a finite number of components, which form a complete and nearly orthogonal basis for the original signal and are namely IMFs. Then, through singular value decomposition (SVD), singular values of each IMF are obtained to construct the feature vectors. SVD is a promising technique in signal processing area and has been widely used in many modern industries, such as image processing, electrocardiogram, sensor anomaly detection and fault feature extraction [33].

Step 2: The dataset D consists of feature vectors and is divided into the labeled dataset D_l and unlabeled data set D_u. Using the active learning algorithm described in subsection B, the sample with the most uncertainty and complexity can be selected and manually added to the labeled dataset. With the increment of the selected samples, a new labeled data set will be built until the condition, the number of selected samples, is satisfied. Here, the condition should be set according to the size of the samples. Because the training set is consisted of the initial samples and the selected samples, the condition is important to avoid the overfitting phenomenon.

Step 3: An RF classifier is trained with the training data from the new labeled dataset and is then used to recognize the fault modes with the test data. Finally, the fault diagnostic results can be obtained.

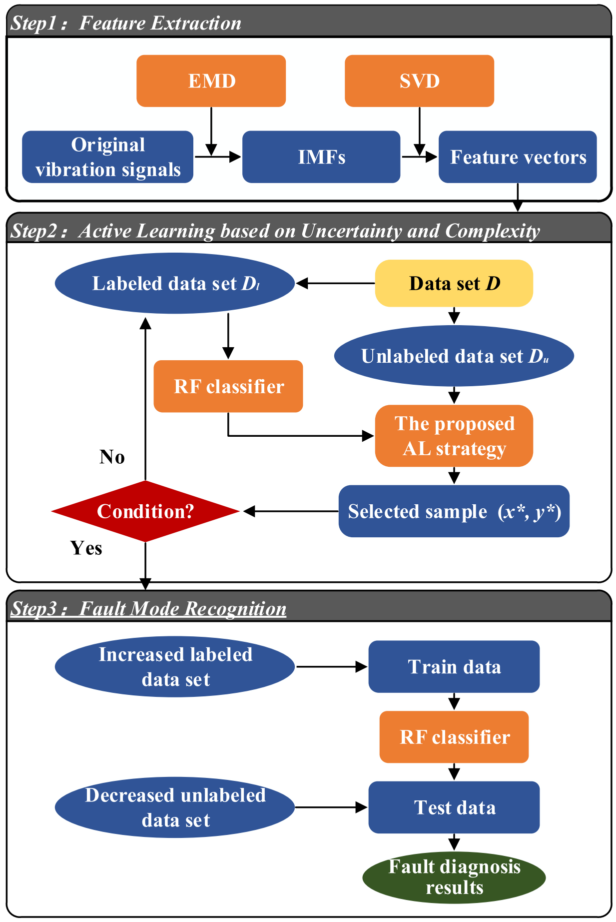

FIGURE 5. Framework of the proposed fault diagnostic method.

TABLE 3. Fault patterns of the gearbox.

Fault pattern	Gear	Bearing	Shaft
A	Good	Good	Good
B	32T Chipped;	Good	Good
C	48T Eccentric	Good	Good
D	48T Eccentric	IS:IS Ball	Good
E	48T Eccentric;	IS:IS Inner ID:IS Ball OS:IS Outer	Good
F	80T Broken	IS:IS Inner ID:IS Ball OS:IS Outer	Input Imbalance
G	32T Chipped;	IS:IS Inner	Output Keyway Sheared
H	48T Eccentric;	ID:IS Ball OS:IS Outer	Input Imbalance

IS-Input Shaft, ID-Idler Shaft, OS-Output Shaft, IS-Input Side

IV. CASE STUDY

The experimental data were collected from a two-class standard cylinder spur gear reducer in the 2009 PHM data challenge competition. The reducer contains an input shaft, an idler shaft and an output shaft. The first and second stage reduction gear ratio are 1.5 and 1.667 respectively. There are 32 teeth in the input shaft and 80 teeth in the output shaft. The two gears on the idler shaft have 96 teeth and 48 teeth. Fig. 6 shows the physical picture and schematic diagram of two-stage reducer.

The data were acquired using input shaft speeds of 30 Hz with a high load. The sampling frequency is 66.7 kHz, and the sampling time is set to 4 s. The fault was detected as shown in Table 3. To validate the effectiveness and superiority of the proposed method, two cases were conducted and considered for gearbox fault diagnosis. In both cases, the number of points in one sample was set as 1000, and 500 samples were collected for each pattern.

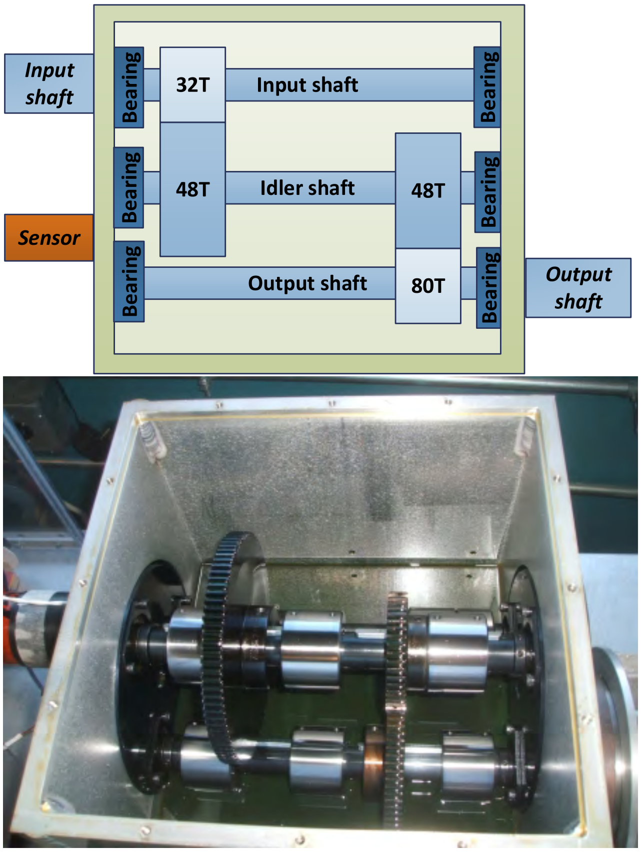

FIGURE 6. Physical picture and schematic diagram of the two-stage reducer.

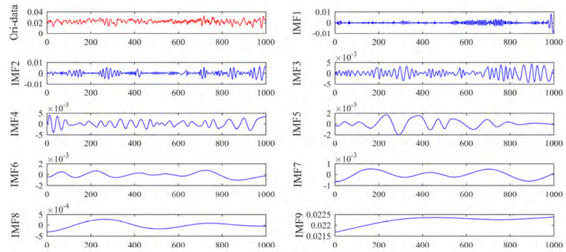

FIGURE 7. An original signal sample of fault pattern A and its IMFs decomposed by EMD.

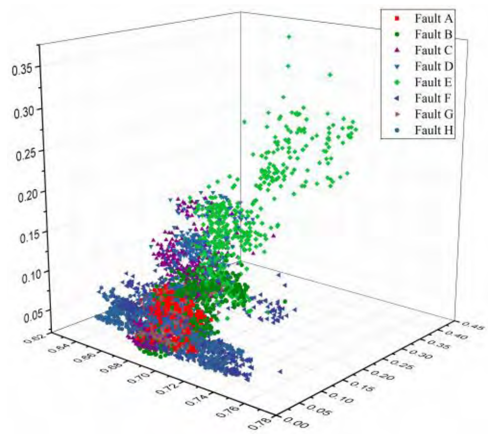

FIGURE 8. Features distribution of eight fault patterns in the 3-dimensional space.

A. CASE STUDY 1: FAULT DIAGNOSIS BASED ON THE PROPOSED METHOD

To illustrate the proposed diagnostic method clearly and effectively, a corresponding supervised learning method, integrated by EMD-SVD and RF, is applied for comparison. The fault diagnostic process of the gearbox is described as follows:

1) SIGNALS DECOMPOSITION BY EMD AND FEATURE EXTRACTION BY SVD

The first step of obtaining the feature vectors is to apply EMD to decompose the vibration signals into a series of IMFs. As shown in Fig.7, an original signal sample of fault pattern A, the red signal in the Fig. 7, is decomposed into 9 IMFs. With the increasement of the IMF component, the intensity of the signal becomes weak, which indicates the major characteristics of the original data concentrate on the first several IMF components. After decomposition, feature vectors are obtained by computing SVD of each IMF. As an example, one feature vector of each fault pattern is calculated and shown in Table 4. Due to main information of fault feature focusing on the first several components, we map these features into 3-dimensional space using their the first 3 SVDs for better understanding of the relationships among eight fault patterns. Thus, the distribution of features can be seen in Fig.8, and eight different colors and shapes represent eight fault features. From the figure, it is noted that they are mixed up to some degree and is difficult to classify them intuitively.

2) FEATURE SELECTION BASED ON THE PROPOSED ACTIVE LEARNING STRATEGY

Before input the feature vectors to the classifier, the proposed method uses the active learning strategy based on uncertainty and complexity to select most informative features rather than random selection in the supervised learning methods. To validate the effectiveness of the proposed active learning strategy, an example of features distribution of two kinds of fault patterns chosen respectively by the proposed method and the supervised method is given and shown as Fig.9-11. Features distribution in the 3-dimensional space using the first three SVDs of fault A and fault B are shown in Fig.9. From the figure, it is obvious that two types of feature distributions have a certain coincidence, which indicates similarity exists in these features and the importance is to find the representative features for classification.

Fig. 10 and Fig. 11 show the feature distributions selected respectively by the proposed method and supervised method, and these features are then applied to the classifier for the fault patterns recognition. Initialized with 400 random features, the proposed method uses the proposed active learning strategy

TABLE 4. Fault patterns of the gearbox.

Fault pattern	SVD 1	SVD 2	SVD 3	SVD 4	SVD 5	SVD 6	SVD 7	SVD 8	SVD 9
A	0.7026	0.0587	0.0496	0.0468	0.0376	0.0233	0.0159	0.0073	0.0039
B	0.6956	0.0339	0.0278	0.0243	0.0233	0.0188	0.0178	0.0161	0
C	0.6697	0.1204	0.0836	0.0679	0.0614	0.0555	0.0532	0.0273	0
D	0.6736	0.0584	0.0508	0.0488	0.0398	0.0353	0.0257	0.0046	0
E	0.6843	0.3232	0.1613	0.1537	0.1200	0.0819	0.0473	0.0000	0
F	0.7126	0.0400	0.0381	0.0342	0.0304	0.0274	0.0265	0.0178	0
G	0.6773	0.0644	0.0559	0.0410	0.0387	0.0277	0.0256	0.0058	0
H	0.7135	0.0678	0.0591	0.0582	0.0437	0.0289	0.0280	0.0141	0

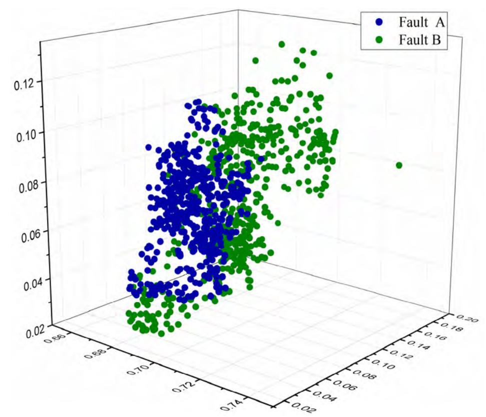

FIGURE 9. Features distribution of fault A and fault B in the 3-dimensional space.

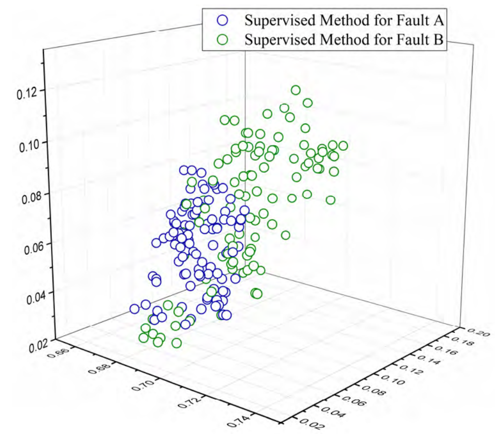

FIGURE 11. Features distributions selected by the supervised method for training.

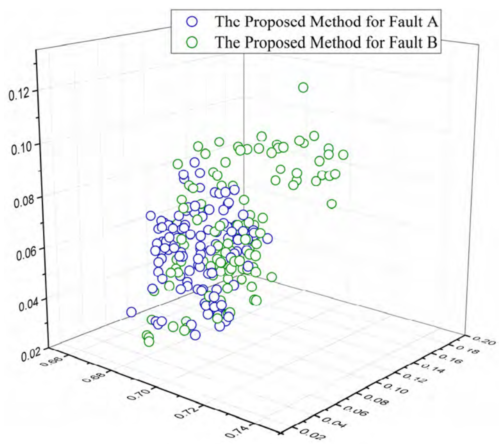

FIGURE 10. Features distributions selected by the proposed method for training.

based on uncertainty and complexity to select 400 features as shown in Fig. 10, meanwhile the supervised method choses 800 features for classification randomly as shown in Fig. 11. Compared the Fig. 10 and Fig. 11, we notice that the features obtained by the proposed method are more gathered and concentrated on the edges of the intersection of the two types of fault modes than the features chosen by the supervised method. It demonstrates the ability of the proposed active learning strategy to select most informative and effective features.

3) FAULT RECOGNITION BASED ON RF CLASSIFIER

The last step of the proposed method is to implement the fault recognition based on the RF classifier. In this section, 400 features are selected randomly to initialize the algorithm and 400 features are selected by the proposed active learning strategy. Next, these 800 features are input as the training set to the classifier to complete the fault diagnosis with the testing set of 4000 samples. For the supervised method, 800 samples are selected randomly to form the training set. To achieve stable results and avoid contingency, 20 iterations have been conducted. The classification results obtained by the proposed method and the supervised method are shown in the Fig. 12 and table 5. In the table 5, N_{test} denotes the number of samples in testing set. In this paper, N_{train} and N_{test} represent respectively the number of samples in training set and testing set.

From the Fig.12, we can notice that the accuracies of each fault mode obtained by the proposed method are larger than that obtained by the supervised method, and the proposed method achieves undoubtedly better total accuracy. Table 5 shows the detail data of the results and the proposed method realizes that diagnostic accuracy of each fault mode is over 80%. Moreover, the best accuracy obtained by the proposed method is over 91% and the total accuracy is 84.48%, while the total accuracy of the supervised method is only 78.53%. These results validate the effectiveness of the

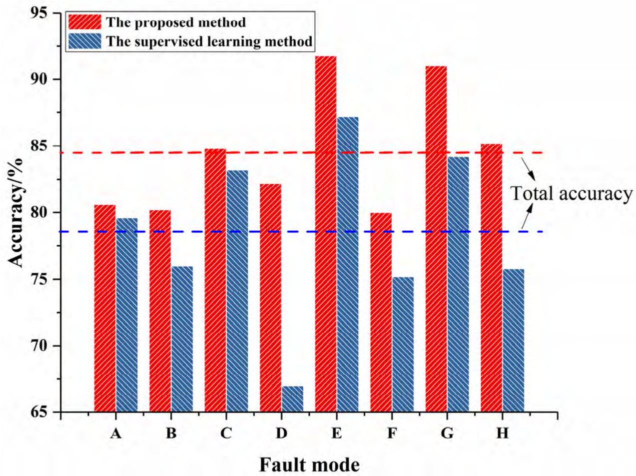

FIGURE 12. Fault diagnostic results obtained by two methods with 800 training samples.

TABLE 5. Fault diagnostic results comparison with 400 initial features.

Results / Fault mode	N_{test}	The proposed method: Error samples	The proposed method: Accuracy	The supervised learning method: Error samples	The supervised learning method: Accuracy
A	500	97	80.60%	102	79.60%
B	500	99	80.20%	120	76.00%
C	500	76	84.80%	84	83.20%
D	500	89	82.20%	165	67.00%
E	500	41	91.80%	64	87.20%
F	500	100	80.00%	124	75.20%
G	500	45	91.00%	79	84.20%
H	500	74	85.20%	121	75.80%
Total accuracy	4000	84.48%		78.53%	

proposed method in the multiple fault modes diagnosis with 400 initial samples.

B. CASE STUDY 2: COMPARISONS WITH THE SUPERVISED LEARNING METHOD AND THE SINGLE-STRATEGY ACTIVE LEARNING METHOD

To validate the superiority and effectiveness of the proposed method, two experiments are conducted by comparing the proposed method with the supervised learning method and the single-strategy active learning method.

1) FAULT DIAGNOSTIC RESULTS COMPARED WITH THE SUPERVISED LEARNING METHOD

In this experiment, the traditional supervised learning method is employed to be compared with the proposed method considering the different initial samples for the proposed method. Similarly, a total of 800 samples were randomly selected for the supervised learning method training, and the total 4000 samples composed the test dataset. For the proposed method, 800-n samples were randomly selected to initialize the RF and n samples were selected by the active learning strategy, where the values of n were 100, 200, 300, 400, 500, 600, and 700. Additionally, the test dataset consists of the total 4000 samples as well.

TABLE 6. Fault diagnostic results compared with the supervised learning method.

Results / n	N_{train}	N_{test}	The proposed method	The supervised learning method
100	800	4000	81.30%	79.22%
200	800	4000	82.07%	77.08%
300	800	4000	84.05%	78.55%
400	800	4000	84.48%	79.30%
500	800	4000	87.50%	78.20%
600	800	4000	88.75%	78.20%
700	800	4000	90.02%	79.63%

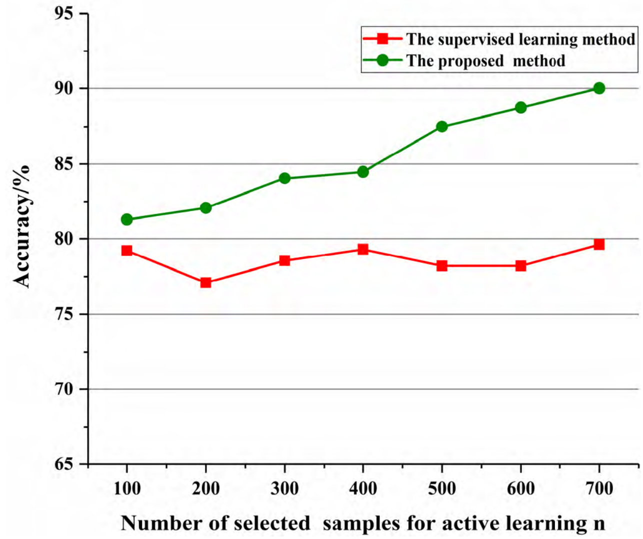

FIGURE 13. Comparison results with the supervised learning method.

The average results after 20 iterations are shown in Fig. 13 and table 6. As shown in Fig. 13, with the increment of the samples selected by the proposed active learning strategy, the diagnostic accuracy gets larger, which indicates the proposed active learning has the ability to effectively select the most distinguish samples for the diagnosis of the gearbox faults. Moreover, by comparison with the supervised learning method, the proposed method outperforms it even though only 100 samples are selected by the proposed active learning strategy. From detail data in table 6, it is difficult for the supervised learning method to achieve a diagnostic accuracy over 80%. Conversely, all diagnostic results obtained by the proposed method are over 80% and the best result is over 90%, which means it can precisely recognize the multiple fault modes in the gearbox.

2) FAULT DIAGNOSTIC RESULTS COMPARED WITH TWO SINGLE-STRATEGY ACTIVE LEARNING METHODS

In the second experiment, two single-level active learning strategies are used as a comparison case, that is, the uncertainty-based strategy and complexity-based strategy individually. Similar to experiment 1, 800-n samples are

TABLE 7. Fault diagnostic results compared with two single-strategy active learning methods.

Results / n	N_{train}	N_{test}	Proposed method	Uncertainty-based strategy	Complexity-based strategy
100	800	4000	81.30%	81.05%	76.85%
200	800	4000	82.07%	80.00%	75.35%
300	800	4000	84.05%	82.50%	73.26%
400	800	4000	84.48%	83.35%	74.48%
500	800	4000	87.50%	81.48%	74.50%
600	800	4000	88.75%	81.25%	71.39%
700	800	4000	90.02%	80.80%	66.38%

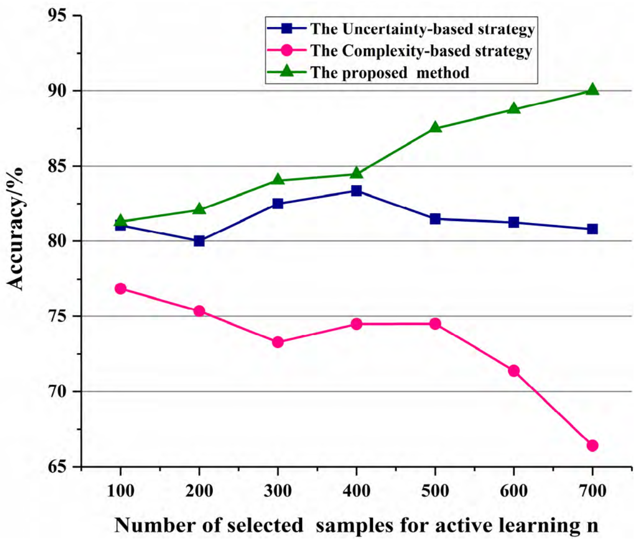

FIGURE 14. Comparison results with two single-strategy active strategies.

randomly selected to initialize the RF and n samples are selected with the active learning strategy, where the values of n are 100, 200, 300, 400, 500, 600, and 700. A total of 4000 samples compose the test dataset.

The results are shown in Fig. 14 and table 7. The diagnostic accuracy obtained from the complexity-based method decreases with the increment of the queried number n and drops to the lowest at 66.38% when 700 samples selected, which is the lowest among these three methods, and explains that the samples selected by the complexity-based strategy cannot represent the characteristics of each fault pattern. Therefore, the single complexity-based method is validated to be not appropriate for the multiple faults diagnostic problem. For the uncertainty-based method, the diagnostic accuracy reaches its highest value at 83.35% when the queried number n equals 400. Furthermore, all diagnostic accuracies obtained by the single uncertainty-based method are over 80%. These evidences show that the uncertainty-based method is effective to diagnose the gearbox fault, however the results are sensitive to the number of samples selected by the active learning process. Among these three methods, the proposed method achieves the best performance, and the diagnostic accuracy improves with larger n. In conclusion, the proposed method is validated to outperform the other two methods in the fault diagnosis of a gearbox.

V. CONCLUSION

In this paper, we propose a gearbox fault diagnostic method based on active learning with uncertainty and complexity strategies. The main contributions of this paper are as follows: (1) an active learning strategy based on uncertainty and complexity is developed to select the most useful samples for classification, which alleviates the difficulty in labeling and improves the diagnostic efficiency; (2) a new fault diagnostic method based on this active learning is proposed and outperforms the traditional supervised learning method; and (3) the proposed method can make full use of a small amount of labeled data to complete the high efficient and accurate fault diagnosis.

Two cases of gearbox fault diagnosis were conducted. The results of the first case show that present method can effectively complete the gearbox fault diagnosis with a high diagnostic accuracy. The second case verifies comprehensively that the proposed active learning approach can obtain the best results compared with the supervised learning method, EMD-SVD-RF, as well as the single-strategy active learning methods, the uncertainty-based method and complexity-based method. Therefore, the effectiveness and superiority of the present method are validated, and the results show the present method realizes high diagnostic accuracy using a small number of labeled samples.

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