Hindawi
Shock and Vibration
Volume 2021, Article ID 9936080, 11 pages
https://doi.org/10.1155/2021/9936080

*Research Article*

# Intelligent Fault Diagnosis of Machines Based on Adaptive Transfer Density Peaks Search Clustering

**Meng Li**,[1] **Yanxue Wang**,[1,2] **and Chuyuan Wei**[1]

[1]*School of Mechanical-Electronic and Vehicle Engineering, Beijing University of Civil Engineering and Architecture, Beijing 100044, China*
[2]*Beijing Key Laboratory of Performance Guarantee on Urban Rail Transit Vehicles, Beijing University of Civil Engineering and Architecture, Beijing 100044, China*

Correspondence should be addressed to Yanxue Wang; yan.xue.wang@gmail.com

Received 8 March 2021; Revised 15 March 2021; Accepted 26 March 2021; Published 7 April 2021

Academic Editor: Yi Qin



Intelligent fault diagnosis technology of the rotating machinery is an important way to guarantee the safety of industrial production. To enhance the accuracy of autonomous diagnosis using unlabelled mechanical faults data, a novel intelligent diagnosis algorithm has been developed for rotating machinery based on adaptive transfer density peak search clustering. Combined with the wavelet packet energy feature extraction algorithm, the proposed algorithm can enhance the computational accuracy and reduce the computational time consumption. The proposed adaptive transfer density peak search clustering algorithm can adaptively adjust the classification parameters and mark the categories of unlabelled experimental data. Results of bearing experimental analysis demonstrated that the proposed technique is suitable for machinery fault diagnosis using unlabelled data, compared with other traditional algorithms.

## 1. Introduction

Modern machinery is developing in the direction of high speed, precision, and efficiency. Intelligent fault diagnosis technology can ensure the safe operation of machines by automatically extracting the fault information implied in the monitoring data and intelligently identifying the health condition [1]. In the research of fault diagnosis of rotating machinery, vibration signal analysis is the most widely used method, which has less influence on the operation status and is easy to be collected. However, the complexity of vibration signal makes the research more difficult. Intelligent fault diagnosis technology is a comprehensive discipline developed in recent years and consists of three main components [2]: (a) signal acquisition, (b) feature extraction, and (c) fault identification. In recent years, some methods have been developed by vibration signals in the field of fault diagnosis. A deep transfer diagnosis method is proposed in [3] to identify the faults in a practical machine by using the diagnosis knowledge derived from the machine in a laboratory. In order to obtain better generalization capability, Wang et al. [4] combined integrated learning with differential probabilistic neural networks and further proposed a new method based on selective integrated learning with particle swarm optimization. In order to solve this issue of the separation of multiple faults, Hu et al. [1] developed a novel multifault detecting technique based on tensor factorization. Liu et al. [5] proposed a novel approach based on the classification to integrate all three aspects (impulsiveness, cyclostationarity, and health reference) for frequency band selection. The above-mentioned methods, however, suffer from low classification accuracy or cannot determine the target domain fault types for unlabelled data.

In the study of diagnosing for a small amount of unlabelled mixed data, transfer learning recently has been applied in the fields of mechanical fault diagnosis by researchers [6]. For example, transfer learning was utilized to detect machine tool chatter based on the detected features of a vibration signal via wavelet packet transform (WPT) and ensemble empirical modal decomposition (EEMD) [7]. Shao

et al. proposed a method based on deep transfer autoencoder for intelligent diagnosis of bearing faults among different mechanical equipment [8].

In the research of source domain sample classification, this paper uses an improved algorithm based on the fast density peak search clustering algorithm. The density peak search clustering (DPS) [9] algorithm is a novel centroid clustering algorithm developed by Alex and Alessandro. Some scholars have also proposed the improved versions based on the idea of DPS and achieved good results. For example, to overcome the issue of high computational complexity, Xu and Jia [10] proposed a fast sparse search density peaks clustering (FSDPC) algorithm. In [11], a clustering approach based on DPS and a modified gravitational search algorithm (GSA) has been developed. D'Errico and Rodriguez [12] introduced an approach based on the optimized cluster center set selected by DPS to achieve the best clustering distribution. Cheng et al. [13] propose a dense member of local core-based density peaks clustering algorithm DLORE-DP, which is more effective, efficient, and robust than other algorithms.

For the purpose of fault diagnosis on small sample data sets, the adaptive transfer density peak search clustering (ATDPS) algorithm was proposed in this paper. The transfer learning was applied to the DPS algorithm to improve the classification accuracy and reduce the computational time consumption. The results of the source domain are transferred to the classification of data in the target domain with only a small amount of data according to the data distribution and the best classification pattern. The main contributions of the intelligent mechanical fault diagnosis algorithm in this paper are summarized as follows:

(1) A feature weight analysis algorithm is proposed to improve the classification accuracy of the DPS algorithm combined with wavelet packet transform energy feature analysis.

(2) An adaptive transfer density peak search clustering algorithm (ATDPS) is developed to adjust the parameters for the classification of sample data adaptively. The algorithm can select the optimal clustering classification results and transfer to the clustering analysis in the target domain.

(3) An intelligent fault diagnosis model has been designed based on the proposed ATDPS and feature extraction algorithm.

(4) The proposed intelligent fault diagnosis algorithm using transfer learning can not only classify but also accurately determine the fault status.

This work is organized as follows. DPS and the proposed ATDPS are both introduced in Section 2. Section 3 describes the WPT energy features extraction technique and intelligent fault diagnosis method. In Section 4, two benchmark case studies are carried out for the evaluation of the proposed method using experimental data sets, compared with affinity propagation clustering [14] and K-means [15]. Conclusions are drawn in Section 5.

## 2. Adaptive Transfer Density Peaks Clustering

*2.1. The DPS Algorithm.* The principle of the DPS algorithm is to obtain the best classification results and clustering centers based on the distribution of data points, relying only on the distance and density between the data points. The innovation of the algorithm lies in the analysis of the clustering centers: (a) Clustering centers are often surrounded by neighbors with lower local densities. (b) They are at a relatively large distance from any point with higher local density [16]. The calculation process of the algorithm is proposed as follows.

*2.1.1. Calculating Local Density.* Define the source domain data set with enough labeled samples: $D_s = \{(x_s^i, y_s^i)\}_{i=1}^{N_s}$, where $x_s^i$ is the set of samples $i$ in the source domain, $y_s^i$ is the sample $x_s^i$'s label, the number of labels is $K_s$, and the number of samples is $N_s$. The density $\rho_i$ of point $x_i$ is calculated as

$$\rho_i = \sum_j \chi\left(d_{ij} - d_c\right), \tag{1}$$

where $d_{ij}$ is the distance between point $x_i$ and $x_j$ and $d_c$ is the cutoff distance. $\chi(d)$ is a function written by

$$\chi(d) = \begin{cases} 1, & d < 0, \\ 0, & d \geq 0, \end{cases} \tag{2}$$

where $\rho_i$ is the local density of point $x_i$ and the value of $\rho_i$ is equal to the number of points that are closer than $d_c$ to point $x_i$.

*2.1.2. Calculate the Minimum Distance.* According to the definition of clustering center, it is necessary to calculate a minimum distance $\delta_i$, which is measured by the minimum distance between the data point $x_i$ and any other point whose local density is higher than that of point $x_i$:

$$\delta_i = \min_{j:\rho_j > \rho_i}\left(d_{ij}\right). \tag{3}$$

If point $x_i$ has the highest density $\rho_i$ among all data points, $\delta_i$ is defined as

$$\delta_i = \max_{j:\rho_j \leq \rho_i}\left(d_{ij}\right). \tag{4}$$

*2.1.3. Determine the Clustering Centers.* It is difficult to determine the clustering centers only by density $\rho_i$ and distance $\delta_i$. Besides, a solution is provided by the value of $\gamma_i$ sorted in decreasing order. Each $\gamma_i$ is given by

$$\gamma_i = \rho_i * \delta_i. \tag{5}$$

This algorithm still requires a manual setting of parameters to find the number of clustering centers. To build an intelligent fault diagnosis model for autonomous classification, a novel adaptive transfer density peaks search (ATDPS) algorithm is proposed in this paper.

*2.2. The Feature Weight Analysis.* The features obtained by extraction need to be reduced in dimensionality before they can be fed into the clustering algorithm. We proposed a feature self-weighting algorithm that is suitable for calculating the correlated weights for a large amount of data. The proposed algorithm only relies on the features themselves and achieves the weights. The steps of the proposed algorithm are as follows.

(i) Set up a data set, assuming that the input contains $M$ kinds of fault categories, each category contains $C$ samples, the number of features is $K$, set $J = M \times C$, and the feature set of the original data can be expressed as $\{v_{j,k}\}_{j=1,\ldots,J;k=1,\ldots,K}$. A feature set of $200 \times 8$ containing 4 states of data is shown in Figure 1.

(ii) Similarization. To process data from different testbeds to improve portability, the feature set is similarized so that the numerical size and distribution of different data can be as close as possible.

$$v'_{j,k} = \sqrt[4]{|v_{j,k}|}. \tag{6}$$

(iii) Calculate the self-similarity coefficient:

$$\mathrm{SS}_{nj,k} = \left\| v'_{n,k} - v'^{2}_{j,k} \right\|, \quad n, j = 1, 2, \ldots, J; k = 1, 2, \ldots, K. \tag{7}$$

The self-similarity coefficient represents a measure of variability between the same features for different samples. The self-similarity matrix for each feature is obtained as

$$W_j = \begin{bmatrix} \mathrm{SS}_{12,k} & \mathrm{SS}_{23,k} & \mathrm{SS}_{34,k} & \cdots & \cdots & \mathrm{SS}_{(J-1)J,k} \\ \mathrm{SS}_{13,k} & \mathrm{SS}_{24,k} & \mathrm{SS}_{35,k} & \vdots & \iddots & \\ \mathrm{SS}_{14,k} & \mathrm{SS}_{25,k} & \vdots & \iddots & & \\ \vdots & \vdots & \mathrm{SS}_{3J,k} & & & \\ \vdots & \mathrm{SS}_{2J,k} & & & & \\ \mathrm{SS}_{1J,k} & & & & & \end{bmatrix}_{(J-1)\times(J-1)}. \tag{8}$$

Thus, the self-similarity weight coefficient of each feature is

$$\mathrm{SW}_j = \frac{2}{J(J-1)} \sum_{i=1}^{J-1} \sum_{j=1}^{J-1} W_j(i, j). \tag{9}$$

The weight size of each feature in the data set is obtained according to the self-weighting algorithm, as shown in Figure 2 for the feature data set given in Figure 1. The sensitive features with high weights are selected as classification transfer features, and these classification features form the similarity matrix of the sample set $S$ as the initial input for clustering.

*2.3. The Proposed ATDPS Algorithm.* The ATDPS algorithm is a major improvement on the DPS algorithm. It can adaptively adjust the value of $d_c$ in the iteration until the optimal clustering centers are found. The proposed ATDPS algorithm is described in detail below.

Determine $d_{ij}$ with squared Euclidean distance:

$$d_{ij} = \left\| x_i - x_{j2}^2 \right\|, \quad j = i+1, i+2, \ldots, N. \tag{10}$$

The calculation of parameters $\rho_i$ and $d_c$ is changed in ATDPS. Initialize $t = 1$ and $d_c^{(t)} = \Xi_{\max}^N(\{d_{ij}\})([N\%])$, where $\Xi_{\max}^N(\cdot)$ is used to select top $N$ maximum entities and $[\cdot]$ denotes round operator.

$$\rho_i = \sum_j e^{-\left(d_{ij}/d_c^{(t)}\right)^2}. \tag{11}$$

Calculate $\gamma_i$ using (5), and $\gamma_i$ is normalized with

$$\beta_i = \frac{\gamma_{i-\min(\gamma_i)}}{\max(\gamma_i) - \min(\gamma_i)}, \quad i = 1, 2, \ldots, N. \tag{12}$$

If $\beta_i - \beta_{i+1} \geq \theta$, the subscript $i$ should be selected as a centroid. Then, the remaining data points are divided into the nearest clustering centers to get the classification results. Here $\theta$ is a key parameter in the ATDPS algorithm. We will discuss the selection of $\theta$ in the following case studies.

In the experimental validation, it was found that the clustering effect of the algorithm can be difficult to determine as the number of iterations increases. A plot of the number of clusters with iterations for sample data with 4 classes is shown in Figure 3, where the clustering effect is shown in Figure 4.

In order to get the best and correct clustering results, a clustering effect evaluation index is established based on the clustering results:

$$\mathrm{SL}_i = \frac{b(i) - a(i)}{\max\{a(i), b(i)\}}, \quad i = 1, 2, \ldots, N, \tag{13}$$

where $a(i)$ is the average distance of the data point $x_i$ to other points in the same cluster as $i$ and $b(i)$ is the minimum average distance from the data point $x_i$ to points in a different cluster of which $x_i$ is not a member. Update $t$ and $d_c^{(t)}$, and calculate the average value of $\mathrm{SL}_i$:

$$\mathrm{SL}a^{(t)} = \frac{\sum_{i=1}^N \mathrm{SL}_i}{N}. \tag{14}$$

Finally, the best clustering result can be obtained based on the value of the maximum $\mathrm{SL}a^{(t)}$.

Transfer learning is used to solve the problem of classifying unlabelled target domain data and determining the categories in this paper. After the clustering analysis of the target domain, the coordinates and density of its clustering center and the source domain clustering centers are jointly analyzed to get the clustering result.

Suppose that the clustering center set of the source domain is $C_s = (C_{s1}, C_{s1}, \ldots, C_{sK})$, and the local density of clustering centers is $D_{sK}$. The clustering center set of the target domain is $C_t = (C_{t1}, C_{t1}, \ldots, C_{tJ})$, and the local density of clustering centers is $D_{tJ}$. Set up the distance

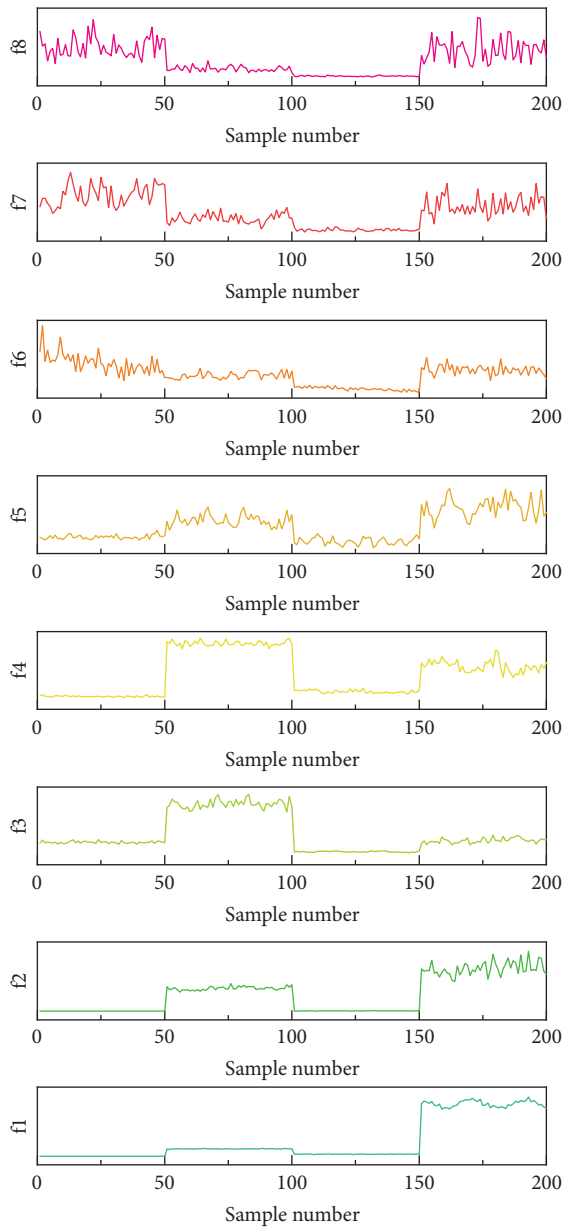


Figure 1: Data feature sets.

parameter $\Phi_d$, density parameter $\Omega_d$, and comprehensive parameter $\Upsilon_c$; they are calculated as follows:

$$\Phi_d = \sum_{\substack{k=1,2,\ldots,K \\ j=1,2,\ldots,J}} \left\| C_{sk} - C_{tj2}^2 \right\|,$$
$$\Omega_d = \sum_{\substack{k=1,2,\ldots,K \\ j=1,2,\ldots,J}} \left( D_{sk-} D_{tj} \right)^2, \tag{15}$$

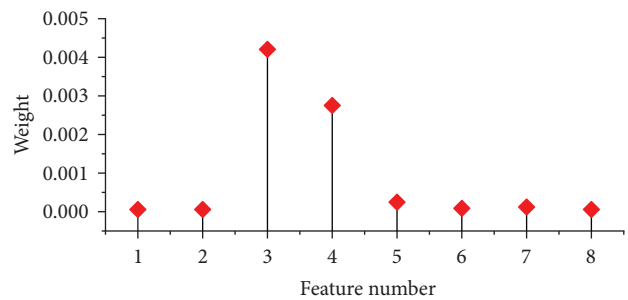


Figure 2: Data feature set weights.

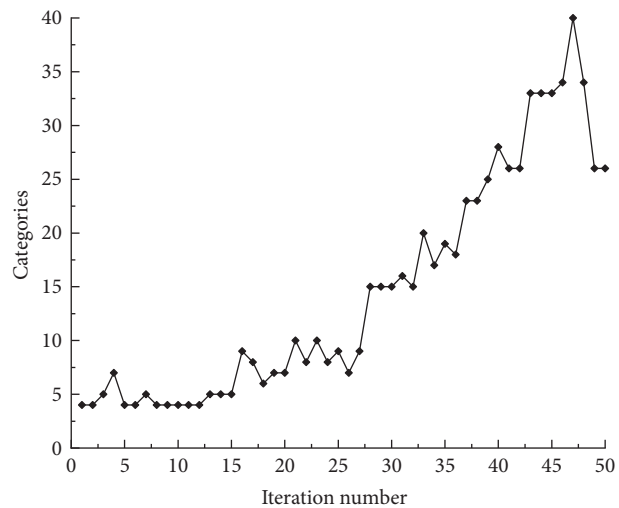


Figure 3: The plot of clustering centers with iterations.

where $\Phi_d$ and $\Omega_d$ are normalized with

$$\overline{\Phi_d} = \frac{\Phi_d - \min(\Phi_d)}{\max(\Phi_d) - \min(\Phi_d)},$$
$$\overline{\Omega_d} = \frac{\Omega_d - \min(\Omega_d)}{\max(\Omega_d) - \min(\Omega_d)}. \tag{16}$$

The comprehensive parameter $\Upsilon_c$ is obtained as

$$\Upsilon_c = \min\left(\overline{\Phi_d} + t\overline{\Omega_d}\right). \tag{17}$$

The best clustering result of the target domain data can be obtained as long as the minimum $\Upsilon_c$ is found. It is worth noting that, in the ATDPS algorithm, the target domain is clustered again as a new sample along with the source domain samples after the learning of the source domain data. Therefore, the target domain samples are classified into existing classes or form a new class. When the variety and number of source domain samples are sufficient, the categories of the small amount of unlabelled target domain data can be accurately classified.

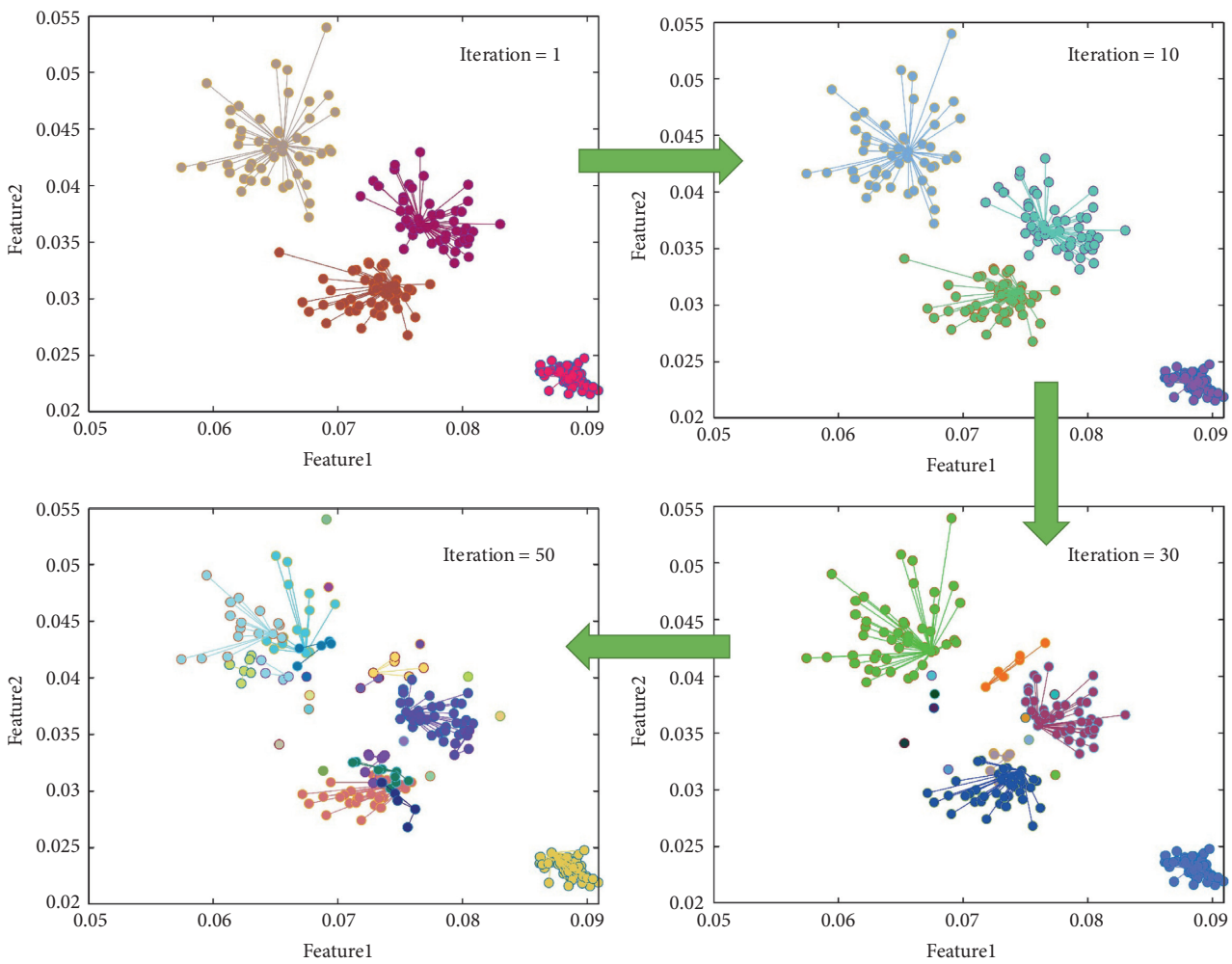


Figure 4: The clustering results with iterations.

## 3. The Intelligent Fault Diagnosis Algorithm of Machine

*3.1. Wavelet Packet Transform.* The wavelet packet transform (WPT) is a further extension and deepening of the wavelet transform with rigorous mathematical reasoning. The WPT inherits the characteristics of wavelet time-frequency localization while decomposing the high-frequency and low-frequency parts of the signal. The WPT divides the signal into multiple levels in the full-frequency band, maps the signal into these bands so that weak features are revealed, and provides a way to describe the signal more finely. For a vibration signal $x(t)$, its wavelet packet transform process and the corresponding decomposition bands are shown in Figure 5.

WPT has the two following functions: (1) WPT can accurately extract the fault signal characteristics. (2) WPT can remove the noise influence. The original signal $x(t)$ and the signal after WPT satisfy the energy equivalence relationship as follows:

$$\int_{-\infty}^{+\infty} |x(t)|^2 \mathrm{d}t = \sum |C(j,k)|^2, \tag{18}$$

where $C(j,k)$ is the amplitude of node $k$ in layer $j$ after WPT. Therefore, the wavelet packet energy spectrum can be chosen as the sum of squares of signals in different frequency bands after its transform. The signal energy $E_{j,k}$ in different frequency band intervals is shown in the following equation:

$$E_{j,k} = \sum_{k=1}^{N} |C(j,k)|^2, \quad k = 0, 1, \ldots, 2^j - 1, \tag{19}$$

where $N$ is the length of the original signal.

*3.2. The Proposed Intelligent Fault Diagnosis Approach.* The proposed intelligent machine fault diagnosis approach practically involves four main stages, which are shown in Figure 6. First, the original signal is decomposed by WPT to extract all energy features. In the second stage, the self-

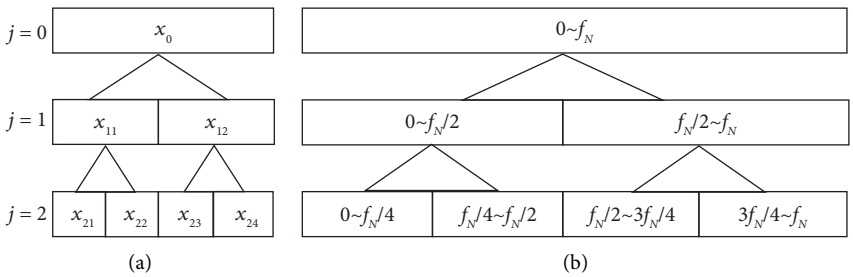


Figure 5: Principle of WPT. (a) WPT of signal. (b) Frequency band of WPT.

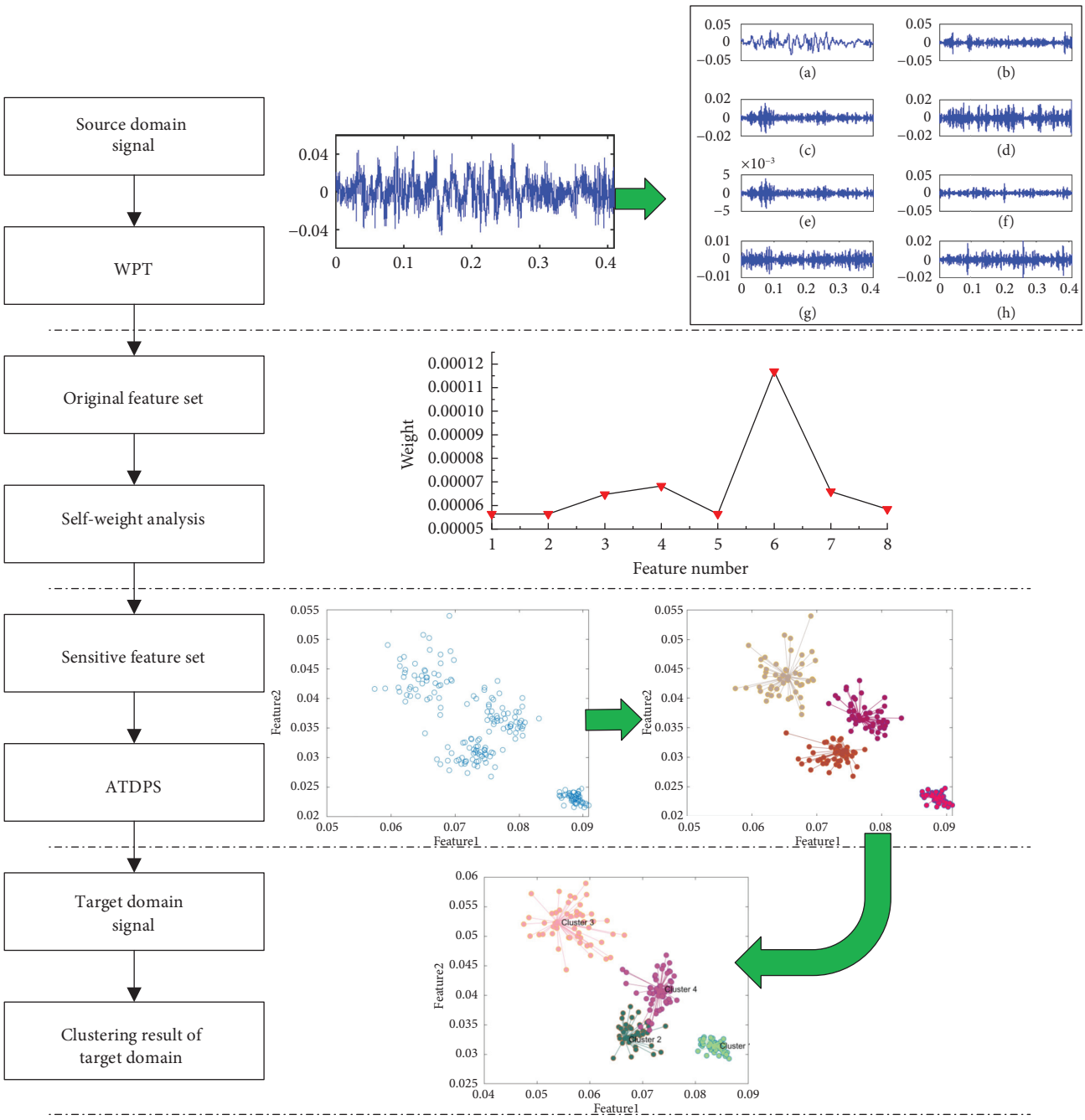


Figure 6: The flowchart and illustration of the proposed intelligent diagnosis method.

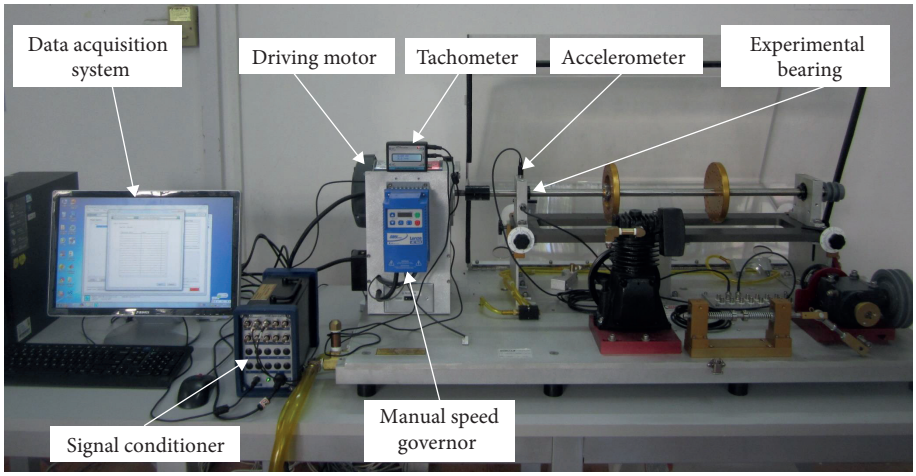


Figure 7: The MFS-MG test rig.

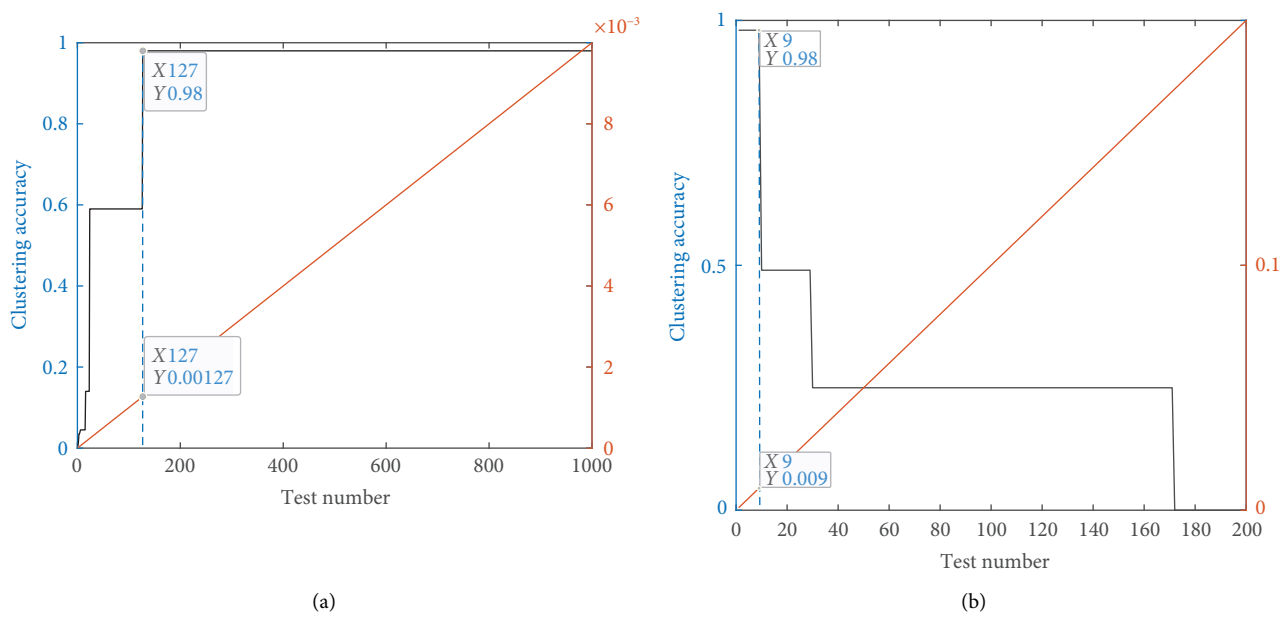


Figure 8: Clustering accuracy with different value of $\theta$. (a) $\theta \in [10^{-5}, 0.01]$; (b) $\theta \in [0.01, 0.2]$.

weight analysis algorithm is used to downscale the energy features to obtain the sensitive feature set. In the third stage, the sensitive feature set is input into the clustering algorithm for unsupervised cluster analysis to establish the adaptive fault diagnosis model. Finally, the unsupervised fault diagnosis is performed on the target domain data to obtain the diagnosis results.

## 4. Experimental Verification

*4.1. Bear Fault Diagnosis on MFS-MG Test Rig.* To verify the advantages of the proposed potential energy features, this section uses the three groups' experiments to evaluate the ATDPS algorithm. In this case, vibration signals were acquired on the MFS-MG test rig shown in Figure 7. The sample set contains normal, outer ring fault, inner ring fault, and rolling element fault, and there are 50 sets of samples for each set.

The threshold value $\theta$ is the most important parameter mentioned in the ATDPS algorithm, and it should be primarily investigated. If the value of $\theta$ is too large, it will lower the discrimination of categories, and all data points would be classified as one cluster. However, too small value of $\theta$ will classify each data point as a cluster due to the fine distinction. In order to select an appropriate parameter $\theta$, there are two investigations of different spans as illustrated in Figures 8(a) and 8(b). The range of $\theta$ is between $10^{-5}$ and 0.009 with step size of $10^{-5}$ in the first evaluation, and in the second evaluation the value of $\theta$ varies from 0.01 to 0.2 with step size of 0.001. A higher accuracy rate is achieved when the value of $\theta$ is in the range of $[1.27 \times 10^{-3}, 0.009]$. Therefore, the value of $\theta$ is set to 0.0015 in our study.

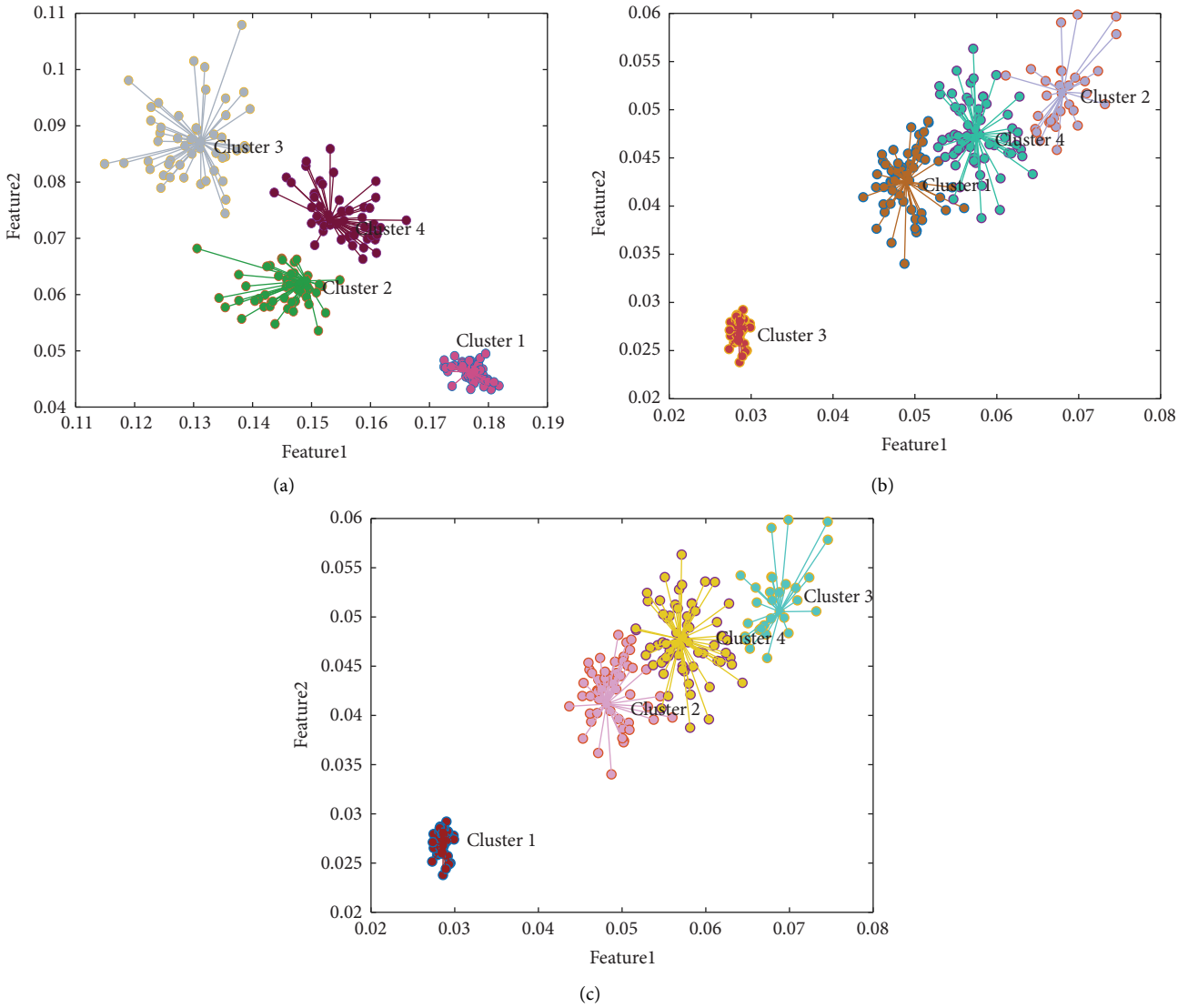


Figure 9: Cluster result of the MFS-MG data sets. (a) ATDPS; (b) K-means; (c) AP.

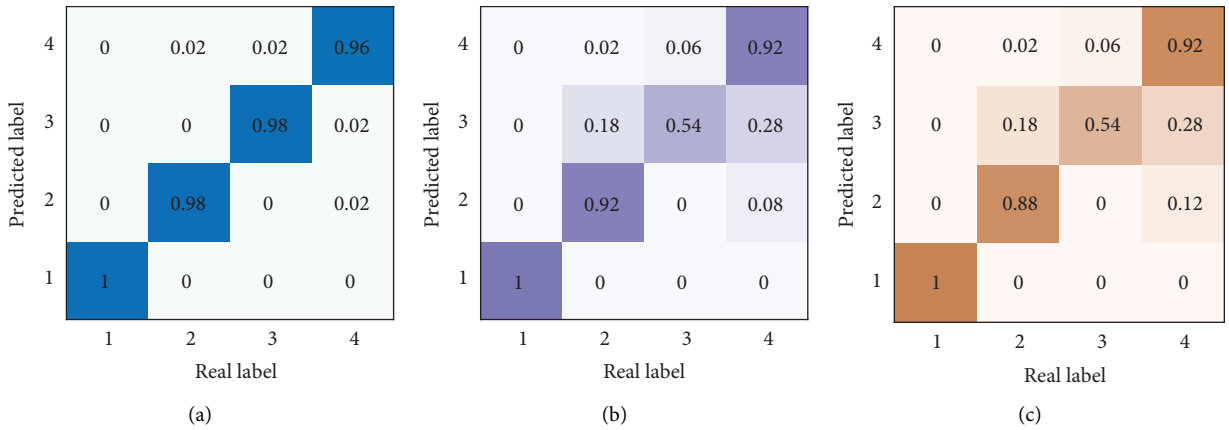


Figure 10: Clustering accuracy of MFS-MG data sets. (a) ATDPS; (b) K-means; (c) AP.

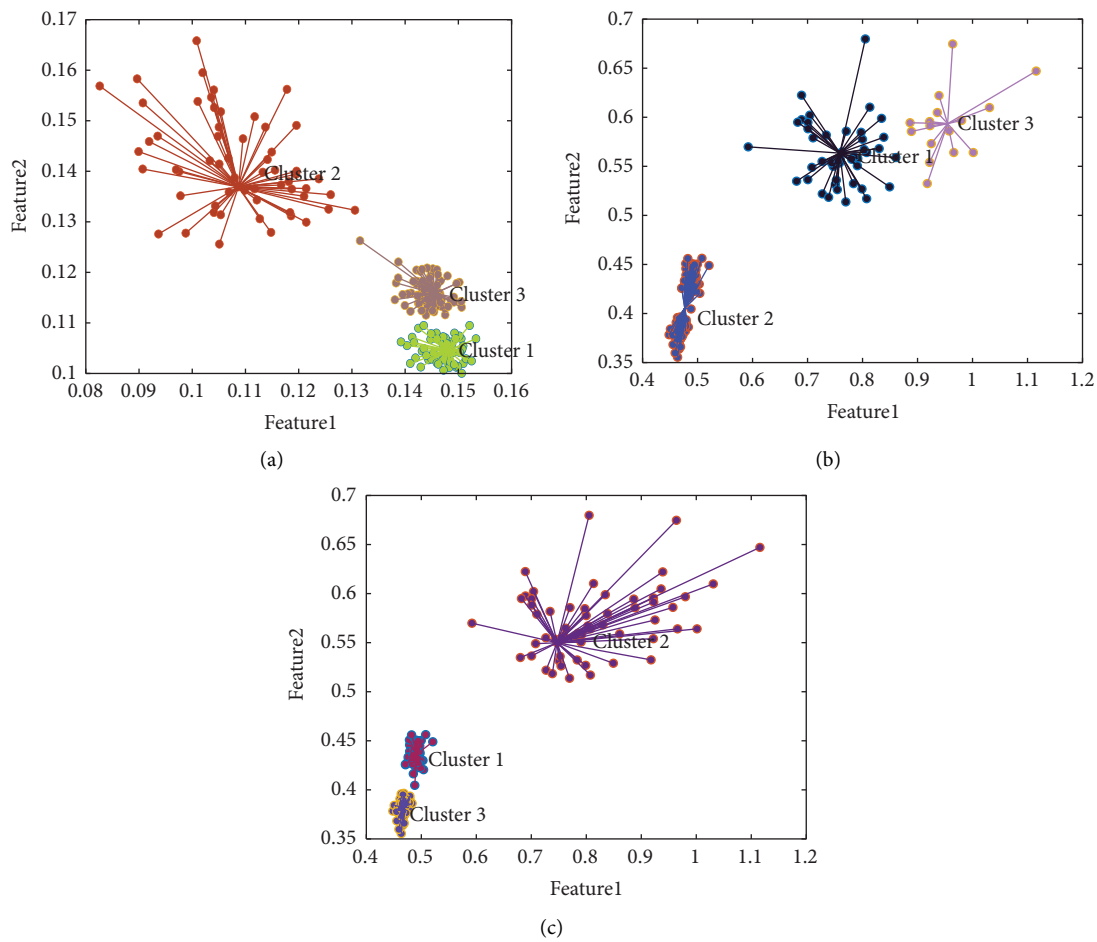


Figure 11: Cluster result of the CWRU data sets. (a) ATDPS; (b) K-means; (c) AP.

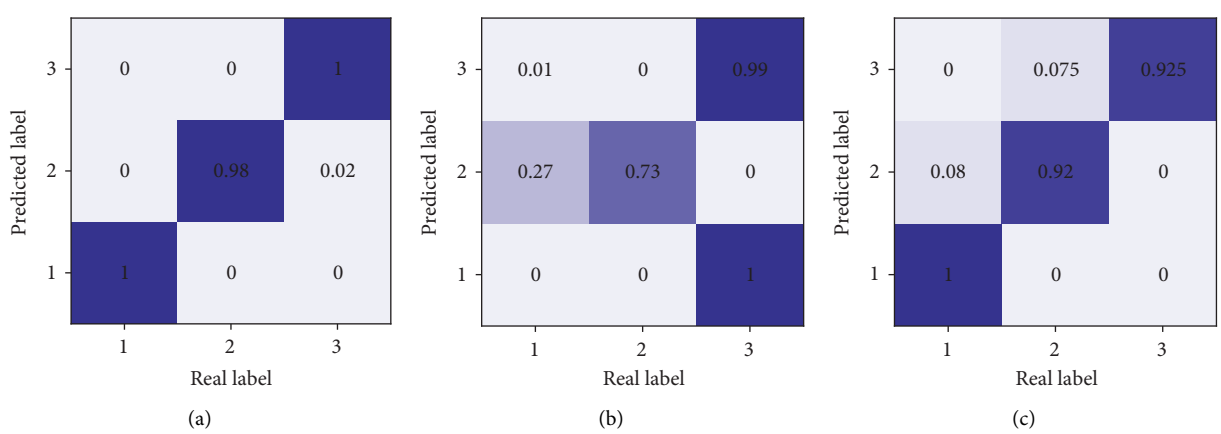


Figure 12: Clustering accuracy of CWRU data sets. (a) ATDPS; (b) K-means; (c) AP.

In this experiment, 3 sets of experimental comparison experiments are used to verify the effectiveness of the algorithm. The classification methods are K-means clustering, AP clustering, and the proposed ATDPS. Firstly, the original feature set obtained by WPT feature extraction methods is analyzed for feature self-weighting. Then the sensitive feature set form after the self-weight analysis is put in the different clustering. The result of clustering is shown in Figure 9. The classification accuracy of the different algorithms is shown in Figure 10.

*4.2. Bearing Fault Diagnosis Using CWRU Data Set.* An intelligent fault diagnosis experiment is conducted on the data set from the Bearing Data Center of Case Western Reserve University (CWRU) [17]. The CWRU bearing

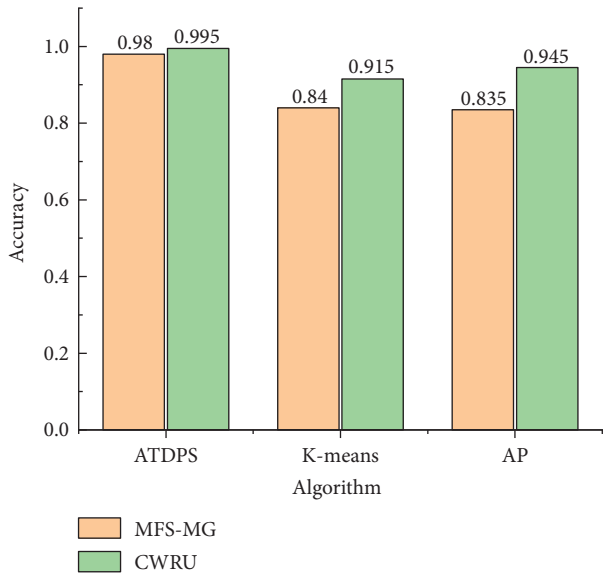


Figure 13: Accuracy of different algorithms.

vibration signals under three fault conditions were collected, that is, normal, outer ring fault, and inner ring fault. The original vibration signal is divided into 200 segments with 2048 samples.

In this section, K-means clustering, AP clustering, and the proposed ATDPS are used to classify the three-fault data. The accuracy of the clustering will illustrate the performance of the algorithms. After feature extraction, self-weight analysis, and (transfer) cluster analysis, the classification results of the three methods are shown in Figure 11. The classification accuracy of each class of faults is shown in Figure 12.

*4.3. Discussion.* The performance of the ATDPS algorithm in the two-bearing-fault data set is verified in different methods. The comparison of the fault classification of ATDPS, AP clustering, and K-means clustering is shown in Figure 13. From the comparison, it can be seen that ATDPS can achieve an accuracy of 98% in the unlabelled mixed MFS-MG bearings data differentiation and label the categories, which is higher than the other two algorithms. The algorithm also achieves 99.5% accuracy in the classification of unlabelled CWRU bearing fault data. In addition, compared with the other two algorithms, the ATDPS algorithm using transfer learning can not only classify but also accurately determine the fault status, while AP clustering and K-means clustering cannot achieve labeling the samples. The superior performance of ATDPS can make the algorithm play a greater role in practical mechanical fault diagnosis.

## 5. Conclusion

For the problem of fault diagnosis of unlabelled data in practical applications, this paper proposed an intelligent fault diagnosis algorithm for rotating machinery based on ATDPS. Transfer learning provided a new idea for the diagnosis of small sample unlabelled data. The accurate and intelligent determination of mechanical faults using nondeep learning algorithm is conducted in combination with the high-performance adaptive clustering algorithm. In this work, WPT is used to extract energy features, and an unsupervised intelligent fault diagnosis model is built autonomously from the source domain data through transfer learning and self-weighting analysis. The model can be used for classification of the unlabelled data in the target domain. Experimental results on different bearing test rigs demonstrated that the proposed algorithm can autonomously identify faults compared with K-means clustering and AP clustering. In particular, the capability of ATDPS in the diagnosis of unlabelled fault data is well suitable for practical industrial applications without prior knowledge.

## Data Availability

The data used to support the findings of this study are included within the article.

## Conflicts of Interest

The authors declare that they have no conflicts of interest regarding the publication of this paper.

## Acknowledgments

The financial sponsorship from the projects of the National Natural Science Foundation of China (51875032) and Architecture under Grant X20159 is gratefully acknowledged.

## References

[1] C. Hu, Y. Wang, and T. Bai, "A tensor-based approach for identification of multi-channel bearing compound faults," *IEEE Access*, vol. 7, pp. 38213–38223, 2019.

[2] Y. Lei, F. Jia, D. Kong, J. Lin, and S. Xing, "Opportunities and challenges of machinery intelligent fault diagnosis in big data era," *Journal of Mechanical Engineering*, vol. 54, no. 5, pp. 94–104, 2018.

[3] Y. Lei, B. Yang, Z. Du, and L. Ü Na, "Deep transfer diagnosis method for machinery in big data era," *Journal of Mechanical Engineering*, vol. 55, no. 7, pp. 1–8, 2019.

[4] Z. Y. Wang, C. Lu, and B. Zhou, "Fault diagnosis for rotary machinery with selective ensemble neural networks," *Mechanical Systems and Signal Processing*, vol. 113, pp. 112–130, 2016.

[5] Z. Liu and D. Peng, "ACCUGRAM: a novel approach based on classification to frequency band selection for rotating machinery fault diagnosis," *ISA Transactions*, vol. 95, 2019.

[6] H. Zheng, R. Wang, J. Yin, Y. Li, H. Lu, and M. Xu, "A new intelligent fault identification method based on transfer locality preserving projection for actual diagnosis scenario of rotating machinery," *Mechanical Systems and Signal Processing*, vol. 135, 2020.

[7] M. C. Yesilli and A. Otto, "On transfer learning for chatter detection in turning using wavelet packet transform and ensemble empirical mode decomposition," *CIRP Journal of*

*Manufacturing Science and Technology*, vol. 28, pp. 118–135, 2020.

[8] S. Haidong, Z. Xiaoyang, C. Junsheng, and Y. Yu, "intelligent fault diagnosis of bearing using enhanced deep transfer auto-encoder," *Journal of Mechanical Engineering*, vol. 56, no. 9, p. 84, 2020.

[9] A. Rodriguez and A. Laio, "Clustering by fast search and find of density peaks," *Science*, vol. 344, no. 6191, p. 1492, 2014.

[10] X. Xu and W. Jia, "A fast density peaks clustering algorithm with sparse search," *Information Sciences*, vol. 554, p. 3, 2020.

[11] L. Sun, T. Tao, X. Zheng, S. Bao, and Y. Luo, "Combining density peaks clustering and gravitational search method to enhance data clustering," *Engineering Applications of Artificial Intelligence*, vol. 85, pp. 865–873, 2019.

[12] M. D'Errico and A. Rodriguez, "Automatic topography of high-dimensional data sets by non-parametric density peak clustering," *Information Sciences*, vol. 560, pp. 467–492, 2018.

[13] D. Cheng, S. Zhang, and J. Huang, "Dense members of local cores-based density peaks clustering algorithm," *Knowledge-Based Systems*, vol. 193, p. 105454, 2020.

[14] A. Khatami, S. Mirghasemi, A. Khosravi, C. P. Lim, and S. Nahavandi, "A new PSO-based approach to fire flame detection using K-Medoids clustering," *Expert Systems with Applications*, vol. 68, pp. 69–80, 2017.

[15] Z. Li, G. Wang, and G. He, "Milling tool wear state recognition based on partitioning around medoids (PAM) clustering," *International Journal of Advanced Manufacturing Technology*, vol. 88, pp. 1203–1213, 2016.

[16] Y. Wang, Z. Wei, and J. Yang, "Feature trend extraction and adaptive density peaks search for intelligent fault diagnosis of machines," *IEEE Transactions on Industrial Informatics*, vol. 15, no. 1, pp. 105–115, 2019.

[17] https://mfpt.org/fault-data-sets/.