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EARLY BEARING FAULT DETECTION AND RECOGNITION METHOD BASED ON INSTANCE TRANSFER

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Abstract: Under the condition of data category imbalance, this paper proposes a TrAdaBoost-Least Squares Support Vector Machine (TrAdaBoost-LSSVM) algorithm based on instance transfer to solve the problem of low diagnostic accuracy of traditional machine learning methods. Firstly, use the K-means algorithm to screen the source domain data in order to eliminate those data with low similarity to the target domain, and then increase the inter-domain similarity; then, optimize the evaluation index of the base classifier to improve the model generalization ability. The simulation test results show that the method proposed in this paper exhibits the advantage of high fault recognition accuracy compared with the traditional machine learning method.
Keywords: Data category imbalance; Instance transfer; Machine learning; Least squares support vector machine

1 INTRODUCTION

With the rapid development of sensing technology and machine learning technology, data-driven intelligent fault detection and identification methods have received widespread attention [1-2]. Data-driven intelligent diagnostic algorithms are based on the assumption that the amount of sample data in each category is basically balanced, and the classification of unbalanced data in practical applications is widely used in product and equipment fault diagnosis [3-4]. Since the normal operation time of mechanical equipment is much larger than the time of equipment fault state, the fault state data of mechanical equipment is difficult to obtain, and the number of fault samples is usually much smaller than the number of samples under normal conditions [5-7]. For the sample distribution situation of category imbalance, the performance of traditional intelligent diagnosis may be seriously reduced, and even lose the actual diagnostic significance [8-9]. Therefore, there is an urgent need to improve the generalization of rolling bearing fault identification based on the category imbalance fault state recognition technique.

At present, the research on classifying category-imbalanced data mainly focuses on the data level and the algorithm level. At the data level, over-sampling and under-sampling are mainly used [10-11], but the shortcomings are that the over-sampling method introduces noise and the under-sampling method loses important information. At the algorithmic level, integration learning methods are mainly used to train different base classifiers for the same training set, and then integrate the base classifiers to form a stronger final classifier. Among them, the TrAdaBoost algorithm proposed by Wang et al. and the Bagging algorithm proposed by Freund et al. are more classic [12-13], and the TrAdaBoost algorithm is a kind of iterative algorithm, and the modified weights of the classifiers can be used as the basis for the final classifier. TrAdaBoost algorithm is an iterative algorithm, in which a new dataset with modified weights is fed into the next base classifiers for training, and then the base classifiers are integrated as the final decision classifiers. TrAdaBoost algorithm is advantageous in that it is able to complement the strengths of a number of base classifiers, which can improve the accuracy of the classifiers significantly. TrAdaBoost also has a problem of mismatch of the weights. Xia et al. show that assigning more initial weights to the target samples can alleviate this problem [14]; Wilson et al. show that increasing the proportion of classifiers for the more difficult samples reduces the proportion of classifiers for the majority of the samples [15]; and Hao et al. propose to resample the data in each iteration [16].

In view of the shortcomings of data-driven intelligent diagnostic algorithms in the classification method when dealing with category-imbalanced data, this paper proposes an improved TrAdaBoost method based on instance transfer. The method first uses a clustering algorithm to filter the source domain data to improve the similarity of data distribution between domains. Then the evaluation index of the base classifier is optimized to improve the generalization ability of the model. Finally, the feasibility of the proposed method is verified by the experimental data of accelerated life of rolling bearings from Xi'an Jiaotong University.

2 DYNAMIC MODELING OF ROLLING BEARING HEALTH STATE

The harsh working conditions cause rolling bearing vibration signals to be often interfered by noise, which seriously affects the extraction of weak fault characteristics. The Local Mean Decomposition (LMD) method can separate the effective information from the noise for multi-scale analysis [17-19] . Meanwhile, the TrAdaBoost method based on instance transfer improves the important role of diagnostic accuracy under unbalanced dataset conditions.

2.1 Local Mean Decomposition

Noting that the vibration signal acquired by monitoring is, the $x(t), t=1,2,\cdots,L$, t is the sampling time, the L is the total

sampling time. The LMD method is implemented as follows.
(1) Apply the sliding average method of smoothing to obtain the local mean function, the $m_{11}(t)$ and the envelope estimator $\chi_{11}(t)$ 。
(2) By placing the local mean function, the $m_{11}(t)$ Separate it out and get a pure FM signal $s_{11}(t)$ 。

$$h_{11}(t) = x(t) - m_{11}(t) \tag{1}$$

$$s_{11}(t) = h_{11}(t) / \chi_{11}(t) \tag{2}$$

Repeat until,is satisfied that $\lim_{n\to\infty} \chi_{1n}(t) = 1$ conditions.
(3) Multiply the envelope function to obtain the envelope signal, the

$$\chi_1(t) = \chi_{11}(t) \cdot \chi_{12}(t) \cdots \chi_{1n}(t) \tag{3}$$

(4) FM signals $s_{1n}(t)$ with the envelope signal $\chi_1(t)$ The Product Functions (PF) component is obtained by multiplying the Product Functions (PF).

$$PF_1(t) = s_{1n}(t) \cdot \chi_1(t) \tag{4}$$

(5) Will $PF_1(t)$ from $x(t)$ The new signal is obtained by separating it from the $\mu_1(t)$ Repeat q Times, until, uh $\mu_q(t)$ stops iterating when it is a monotonic function.

$$\begin{cases} \mu_1(t) = x(t) - PF_1(t) \\ \mu_2(t) = \mu_1(t) - PF_2(t) \\ \quad\vdots \\ \mu_q(t) = \mu_{q-1}(t) - PF_q(t) \end{cases} \tag{5}$$

(6) The vibration signal is finally decomposed into a series of PF components and a residual component, the $\mu_q(t)$ 。

$$x(t) = \sum_{i=1}^{q} PF_i(t) + \mu_q(t) \tag{6}$$

2.2 Extraction of Fault Features

In this paper, the LMD decomposition obtained by q The PF components were extracted in the following steps.
(1) Constructing a signaling matrix that $M(t) = \left[f_1(t), f_2(t), \cdots, f_q(t) \right]$;
(2) Calculate the covariance matrix, the H :

$$H = \frac{MM^T}{trace\left(MM^T\right)} \tag{7}$$

Where. $trace(\cdot)$ for the trace operation on the matrix inside the parentheses.
(3) For the matrix H Perform eigenvalue decomposition: the

$$H = U\Sigma U \tag{8}$$

Where. U for H matrix composed of eigenvectors; Σ is the diagonal matrix composed of the corresponding eigenvalues.
(4) Use it to whiten the covariance matrix to obtain the matrix, the S :

$$\begin{cases} p = \sqrt{\Sigma^{-1}} U^T \\ S = pHp^T \end{cases} \tag{9}$$

(5) Perform the eigenvalue decomposition and construct the space that $\tilde{X}$

$$\begin{cases} S = U_1 \Sigma_1 U_1^T \\ \tilde{X} = U_1^T p \end{cases} \tag{10}$$

Where. U_1 is the matrix consisting of S eigenvectors; the Σ_1 is the diagonal matrix formed by the corresponding eigenvalues.
(6) Perform the projection to obtain the principal element space and the residual space: the

$$\bar{X} = \tilde{X} + e \tag{11}$$

T^2 Control charts are a quality control tool based on the chi-square distribution for statistical process control. This control chart is mainly used to monitor the variability of categorical data, and to determine whether anomalies occur in the collected sample data by comparing the statistics with the control limits. The basis for anomaly detection is mainly the comparison of T^2 and Squared Prediction Error (SPE) statistics and control limits.
T^2 The statistic is used to measure the distance of the sample from the origin of the principal element space, the statistic expression is.

$$T^2 = U^T p \Lambda^{-1} p^T U \tag{12}$$

T^2 The expression for the control limit of

$$UCL = \frac{a\left(n^2 - 1\right)}{n\left(n - a\right)} F_{a(a,n-a)} \tag{13}$$

The SPE statistic is used to characterize the variance of the data and is obtained from the residual space with the expression.

$$SPE = \left\| \left(I - pp^T\right) U \right\|^2 \tag{14}$$

The control limit UCL of the SPE can be obtained from the probability density function, expressed as follows.

$$UCI = \theta_1 [\frac{h_0 C_a \sqrt{2\theta_2}}{\theta_1} + \frac{\theta_2 h_0 \left(h_0 - 1\right)}{\theta_1} + 1]^{\frac{1}{h_0}} \tag{15}$$

$$\theta_j = \sum_{i=t+1}^{T} \lambda_i^j, j = 1,2,3 \tag{16}$$

$$h_0 = 1 - \frac{2\theta_1 \theta_3}{3\theta_2} \tag{17}$$

In the formula, the C_α is normally distributed α Loci.

3 IMPROVED TRADABOOST ALGORITHM BASED ON INSTANCE TRANSFER

Sample data in different domains are similar, so the useful information in the source domain can be utilized to build classifiers in the target domain.TrAdaBoost has an advantage over Bagging algorithm in dealing with the problem of imbalance in the classification of datasets in that it is able to improve the accuracy of the classifier by adjusting the weights in real time to make a number of weak classifiers into a strong classifier [20-22] .

3.1 Screening for Redundant Data

The process of filtering redundant data is as follows.

Input: source domain dataset is $T_a = \{(x_a^i, y_a^i)\}_{i=1}^m$, target domain dataset $T_b = \{(x_b^j, y_b^j)\}_{j=1}^n$, the number of data blocks is n 。

Output: Filtered source domain dataset $T_a^{'}$ and target domain datasets $T_b^{'}$ 。

(1) Construct the training dataset that $T = T_a \cup T_b$ 。

(2) The dataset T is partitioned into n block of data.

(3) The K-means algorithm is used on the data block to filter out the data with little similarity to the target domain and remove them. The

(4) According to the source domain feature distribution after screening, select the features that are closest to the target domain feature distribution.

3.2 Steps to Improve the Implementation of the TrAdaBoost Algorithm Based on Instance Transfer

TrAdaBoost algorithm and Bagging have obvious shortcomings: in the iterative process of the error samples are given a larger weight, and the correct samples are given a smaller weight, which can easily lead to an infinite increase in the weight of the error samples, and the correct samples are neglected, which affects the training effect of the samples [23-25]. Based on this deficiency, the TrAdaBoost algorithm is improved, and the improved algorithm process is as follows.

Input: source domain training set $D_{a_1}, D_{a_2}, ..., D_{a_N} = \{(x_{a_1}, y_{a_1}), (x_{a_2}, y_{a_2}), ..., (x_{a_N}, y_{a_N})\}$, the target domain training set $D_b = \{(x_b, y_b)\}$, the maximum number of transfers is N 。

Output: target classifier function that

$$F(x_i) = sign\{\prod_{h=1}^{\frac{N}{2}} [\beta_h^{-f_h(x_i)}] - \prod_{h=1}^{\frac{N}{2}} [(\beta_h)^{-1/2}] \tag{18}$$

(1) Preprocess the training dataset, call the K-means algorithm to output the filtered source domain dataset $T_a^{'}$ and target domain datasets $T_b^{'}$, the number of datasets are, respectively r and q 。

(2) The weight vector is initialized as $W^1 = (\omega_1^1, ..., \omega_{r+q}^1)$, where

$$\omega_i^1 = \begin{cases} \frac{1}{r} & i = 1,2,...,r \\ \frac{1}{q} & i = r+1,...,r+q \end{cases} \tag{19}$$

(3) Setting the source domain weight update factor, the

$$\beta = \frac{1}{1 + \sqrt{\frac{2 \ln r}{N}}} \tag{20}$$

(4) Normalize the weights by

$$P^h = \frac{W^h}{\sum_{i=1}^{r+q} \omega_i^h} \tag{21}$$

Among them. $h = 1,...,N$

(5) For a weight distribution of P^h of the dataset $T^{'}$ training, input to LSSVM weak classifier, to get strong classifier f_b^h 。

(6) Calculation f_b^h exist $T_b^{'}$ The error rate on the

$$\pi_i^h = \frac{\sum_{i=r+1}^{r+q} \omega_i^h \left| y_b^j - f_b^h x_b^j \right|}{\sum_{i=r+1}^{r+q} \omega_i^h} \tag{22}$$

Among them. x_i for data set no i Data.

(7) Setting the target domain weight update factor, the

$$\beta_i^h = \pi_i^h / (1 - \pi_i^h) \tag{23}$$

(8) Updating the weight vector, the

$$\omega_i^{h+1} = \begin{cases} \omega_i^h \beta^{\left| y_b^j - f_b^h x_b^j \right|}, & 当 i = 1,2,...,r \\ \omega_i^h \beta_i^{-\left| y_b^j - f_b^h x_b^j \right|}, & 当 i = r+1,...r+q \end{cases} \tag{24}$$

if $\pi_i^h = 0$, then $\left| y_b^j - f_b^h x_b^j \right|$ is denoted as a sample x_b^j . The probability of belonging to category 0 but being misclassified as category 1. Similarly, if the $\pi_i^h = 1$, then $\left| y_b^j - f_b^h x_b^j \right|$ is denoted as a sample x_b^j . Probability of belonging to category 1 but being misclassified as category 0.

4 ROLLING BEARING FAULT DETECTION AND ABNORMAL OPERATION STATE IDENTIFICATION METHOD FLOW

4.1 Based on LMD-PCA Rolling Bearing Fault Detection

Rolling bearings are often interfered by noise due to complex and severe working conditions, which is not favorable to the extraction of weak fault characteristics [26-29]. In this paper, the LMD method is used to separate the effective information from the noise, and on the basis of which the PCA method is applied to extract the fault features. Based on the LMD-PCA rolling bearing fault detection framework, which contains the following three main steps.

(1) Dynamic modeling of vibration signals. The vibration signal is decomposed using the LMD method, and is obtained by n A matrix composed of the IMF components of the X ;

(2) For the matrix, the X Standardization;

(3) The PCA method is used to decompose the eigenvalues of the matrix to obtain the principal element space and the residual space. Then the main element space and residual space are decomposed several times to obtain the subspace, and the statistics and control limits of each subspace are calculated and compared to determine whether there is a fault.

(4) Abnormal operation state identification.

4.2 Improved TrAdaBoost Anomalous Run State Identification Method Based on Instance Transfer

The schematic diagram of the improved TrAdaBoost multi-classification algorithm.The steps are as follows.

(1) Segmentation of source and target domain samples; and

(2) Setting up the training and test sets;

(3) initialize the weights $W_{n+m} = (1/n,...,1/n,1/m,...,1/m)$, samples are drawn from the joint training set to obtain the subsample set;

(4) Update the weights using the error on the multiple classifiers to obtain a new set of subsamples;

(5) Repeat (3) to (4) N times, to obtain the abnormal operation state recognition model $F_N(x_i)$;

(6) Repeat (5) Z times, to obtain Z abnormal operation state identification models $F_{Nj}(x_i)$, $j = 1,2,...,Z$;

(7) Category-consistent voting on the Z results.

5 EXAMPLE ANALYSIS

The fault detection model should have good accuracy and real-time performance. Firstly, the LMD-PCA method is used to extract the features, and the statistics are calculated sequence by sequence according to the sliding window, and compared with the control limit to determine whether the bearings are abnormal or not. Secondly, when the abnormal state of the bearing is detected, the TrAdaBoost algorithm is used to recognize the abnormal operation state based on the instance transfer improvement.

5.1 Experimental Data Collection and Parameterization

The data set selected for this experiment is the XJTU-S data set [30] . The experimental platform for collecting this dataset is shown in Fig. 3, which is capable of conducting accelerated degradation experiments on bearings, providing the actual degradation data of five rolling bearings modeled as LDKUER204 throughout their service life, as shown in Table 1 Two PCB352C33 accelerometers were placed on the vertical and horizontal axes to test the vibration signals. The data types and labels of XJTU-S dataset are shown in Table 1, the sampling frequency is set to 25600Hz, the loads of two working conditions are 11kN and 12kN, and the driving speeds of the control motor are 2100r/min and 2400r/min, respectively.The types of faults include rolling body faults, inner ring faults, outer ring faults and cage faults, and there are four types of samples.In order to validate the effectiveness of the proposed In order to verify the validity of the proposed method to recognize the fault state of rolling bearings, 1000 sampling points are taken as a sample.

Table 1 Data Types and Labels of the XJTU-SY Dataset

data sets	Sample length	the type of fault	data sets	Sample length	the type of fault
Bearing 1_1	1000	inner ring failure	Bearing 2_1	1000	Rolling body failure
Bearing 1_2	1000	outer ring failure	Bearing 2_2	1000	Cage failure
Bearing 1_3	1000	Cage failure	Bearing 2_3	1000	inner ring failure
Bearing 1_4	1000	outer ring failure	Bearing 2_4	1000	inner ring failure
Bearing 1_5	1000	Rolling body failure	Bearing 2_5	1000	outer ring failure

5.2 Rolling Bearing Fault Detection

In order to verify the effectiveness of the LMD-PCA method proposed in this paper for the fault detection of the outer ring of rolling bearings, the vibration signals of the bearing 2_4 inner ring fault are taken as an example, firstly, the LMD decomposition is carried out and then reconstructed, and then the features of the bearing are extracted using the principal component analysis (PCA) method, and by comparing it with the traditionalempirical modal decompositionThe Empirical Mode Decomposition (EMD)-PCA method is compared to verify the detection capability of the method for the early faults of rolling bearings. Figure 1 depicts the fault detection results of the inner ring of rolling bearing based on the traditional EMD-PCA method, where the red dotted lines indicate the control limits and the black solid lines indicate the statistics, and Figure 2 depicts the fault detection results of the outer ring of rolling bearing based on the LMD-PCA method. The red dotted line indicates the control limit, and the black solid line indicates the statistics. From the Figure 2, it can be concluded that the LMD-PCA method can detect the abnormal state earlier than the traditional EMD-PCA method.

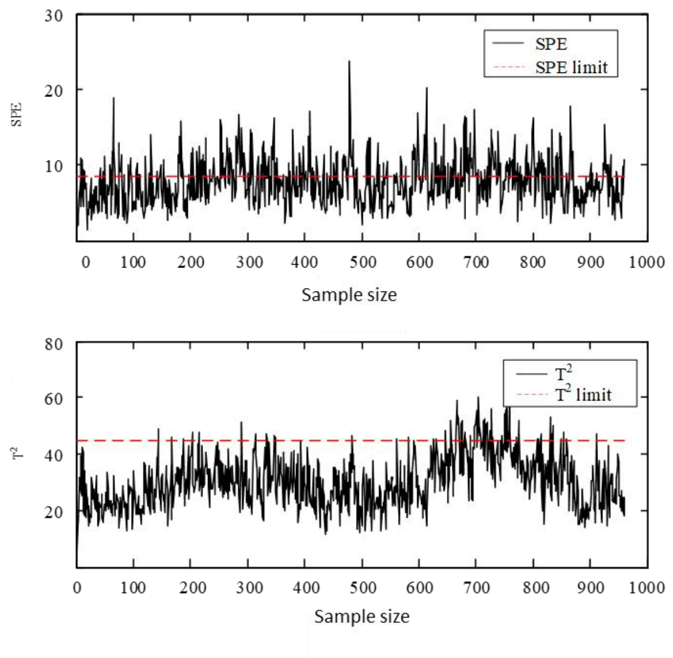

Figure 1 Detection Results of the EMD-PCA Method

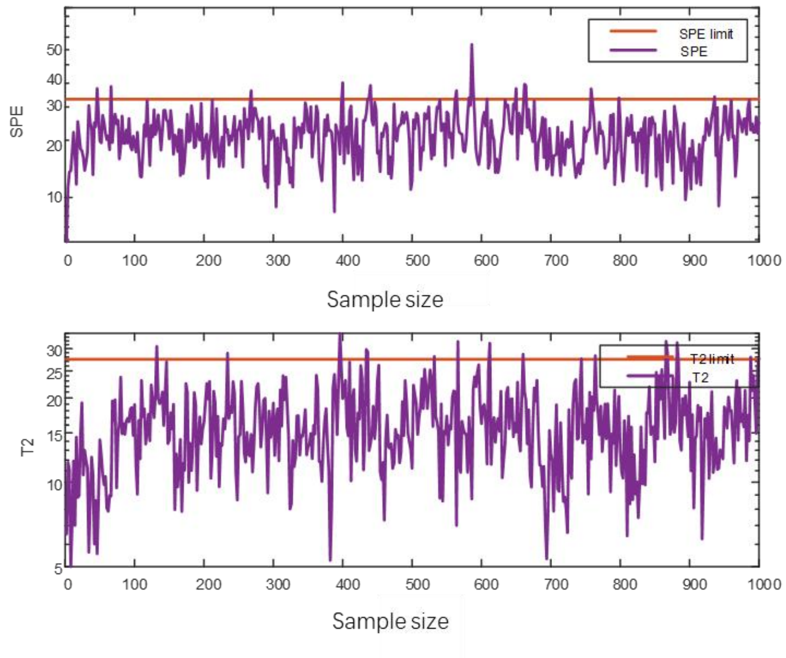

Figure 2 Detection Results of the LMD-PCA Method

5.3 Rolling Bearing Abnormal State Identification

In order to verify the validity of the method in this paper, the following experiments are designed with 11kN load and 2100r/minr motor drive speed as the auxiliary samples in the source domain, and 12kN load and 2400r/min motor drive speed as the samples in the target domain: 1. Training set: 400 normal state training samples in the source domain, and 40, 80, 120, 160 (10, 20, 30, 40 for each of the four fault states) training samples in the target domain; 2. Test set: 240 unlabeled samples (10, 20, 30, 40 for each of the four fault states) in the target domain; and 3. 160 samples (10,20,30,40 samples for each of the 4 fault states); 2. Test set: 240 unlabeled samples in the target domain (60 samples for each of the 4 fault states), and 100 normal state samples in the source domain to form a class-imbalanced distribution.

LSSVM was used as the base classifier of the algorithm and optimization was carried out using the Genetic Algorithm Toolbox of the University of Sheffield, UK.The average recognition rate of faulty operating states was used as the fitness function to obtain the parameter combinations of the LSSVM as. $\iota = 0.71, \gamma = 5.56, g = 7.75$. Finally, the recognition rate of faulty operation state is obtained by calculating and comparing the performance of two algorithms: (1) SVM method, and (2) LSSVM classifier with optimized parameters is used as a weak classifier of AdaBoost. The results of the experiment are shown in Table 2.

Table 2 Faulty Operating State Recognition Rate (%)

Source domain samples	Target domain training samples	SVM	AdaBoost-LSSVM	TrAdaBoost-LSSVM
400	40	65.6	65.3	69.5
	80	73.4	77.6	79.8
	120	81.2	89.6	92.5
	160	89.6	94.8	95.7

5.4 Discussion of N-values vs. Z-values

Consider whether different ratios of the number of data samples in the target domain of the test set to the number of data samples in the source domain would have an impact on the accuracy of the algorithm,setting $N = 10, Z = 1000$,The percentage of randomly selected target domain data was set to 5%, 10%, 15%, 20%, 25%, and 30% in turn. The experimental results are shown in Table 3.

Table 3 Accuracy of the Algorithm for Different Proportions of Target Domain Data

Methods	5%	10%	15%	20%	25%	30%
TrAdaBoost-LS-SVM	0.66	0.69	0.72	0.79	0.87	0.92
SVM	0.53	0.65	0.67	0.73	0.75	0.81
AdaBoost-LSSVM	0.56	0.66	0.69	0.76	0.78	0.89

As can be seen from Table 3, the classification accuracy of the TrAdaBoost-LSSVM algorithm based on instance transfer is significantly higher than that of the other algorithms, indicating that after the increase of training data in the target domain, the inter-domain similarity is getting higher and higher, and the classification performance of the classifier is better.

For the values of N and Z, first set Z to a larger value ($Z=1000$) Mr. José Antonio González, Minister Counsellor, Permanent Mission $N \in [1,20]$ corresponding to the recognition rate at the time.

As shown in Fig. 6,when, the $N \in [1,12]$ .When ,the recognition rate of each group of samples varies with N value increases; when, the N When it exceeds 15, the recognition rate increases N The increasing of the decreases instead. Take the $N \in [12,14]$ is reasonable.

Although $Z=1000$ Ensure the stability of diagnostic results, but the algorithm is more time-consuming. when the Z value is 500 and above, the variance of the recognition rate is already smaller and begins to stabilize. Therefore, the $Z=500$ It can already meet the requirements for use.

6 CONCLUSION

In the case of complex working conditions and lack of training sample data, the stability of online detection is very important, and the reduction of false alarm rate is an important goal to improve the effectiveness of online detection. Therefore, in this paper, we extract the fault characteristics by LMD method, calculate the statistics of bearing data in different working conditions and determine the control limit as the threshold standard to detect whether the abnormal state occurs or not. Secondly, the TrAdaBoost-LSSVM algorithm based on instance transfer is used to recognize the abnormal state of the bearing. The method firstly uses the K-means algorithm to filter the source domain data, eliminate those data with low similarity to the target domain, and then increase the inter-domain similarity. Then the evaluation index of the base classifier is optimized to improve the generalization ability of the model. The experimental results prove the feasibility and effectiveness of the proposed method, and enhance the ability of recognizing the fault features of weak samples.

COMPETING INTERESTS

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REFERENCES

[1] WANG Taiyong, GONG Liming, WANG Peng, et al. Fault diagnosis model of rotating machinery based on KD -DenseNet. Vibration and Shock, 2020, 39(16): 39-45.

[2] Xingxing Zhang, Shaobo Li, Longxuan Tsu, et al. Research on rolling bearing fault diagnosis based on machine learning algorithm. Combined machine tools and automated machining technology, 2020, 10(7): 36 -39.

[3] CHEN Renxiang, HUANG Xin, YANG Lixia, et al. Rolling bearing fault diagnosis based on convolutional neural network and discrete wavelet transform. Journal of Vibration Engineering, 2018, 31(5): 883-891.

[4] Mao WT, Tian SY, Dou Z, et al. A deep transfer learning-based online detection method for early faults in rolling bearings. Journal of Automation, 2022, 48(1): 302-314.

[5] Liu JC, Quan H, Yu X, et al. Rolling bearing fault diagnosis based on parameter optimization VMD and sample entropy. Journal of Automation, 2022, 48(3): 808-819.

[6] Shakya P, Kulkarni M S, Darpe A K. A novel methodology for online detection of bearing health status for naturally progressing defect. Journal of Sound & Vibration, 2014, 333(21): 5614-5629.

[7] Taylor M E, Stone P H. Transfer learning for reinforcement learning domains: a survey. The Journal of Machine Learning Research, 2009, 10(10):1633-1685.

[8] Yang S, Liu Z, Lu G. Early change detection in dynamical bearing degradation process based on hierarchical graph model and adaptive inputs weighting fusion. IEEE Transactions on Industrial Informatics, 2021, 17(5): 3186-3196.

[9] XU Le, YU Ruxin, XING Bangsheng, et al. Rolling bearing fault feature extraction based on LMD arrangement entropy. Mechanical Transmission, 2019, 43(1): 136-139.

[10] Chawla N V, Bowyer K W, Hall L O, et al. SMOTE: Synthetic minority over-sampling technique . Journal of Artificial Intelligence Research, 2011, 16(1): 321-357.

[11] Yen S J, Lee Y S. Cluster-based Under-sampling Approaches for Imbalanced Data Distributions. Expert Systems with Applications, 2006, 36(3): 5718-5727.

[12] Wang W, Wang C, Wang Z, et al. Abnormal detection technology of industrial control system based on transfer learning. Applied Mathematics and Computation, 2022, 412(1): 126-139.

[13] Freund Y. A decision-theoretic generalization of on-line learning and an application to boosting // Proceedings of the Second European Conference on Computational Learning Theory. Springer-Verlag, 1995.

[14] Qian Z, Hai G L, Yong Z, et al. Instance transfer learning with multisource dynamic trAdaBoost. The Scientific World Journal, 2014, 20(14): 1-8.

[15] Wang C, Yang A, Yuan A, et al. Diagnosis of wind turbine faults with transfer learning algorithms. Renewable Energy, 2021, 16(3): 2053-2067.

[16] Xia R, Zong C, Hu X, et al. Feature ensemble plus sample selection: domain adaptation for Sentiment Classification . IEEE Intelligent Systems, 2013, 28(3): 10-18.

[17] Wilson C, Check J H, Amui J, et al. Effect of multiple sources vs. single source of donor embryos on pregnancy and Implantation Rates per Transfer . Clinical and experimental obstetrics & gynecology, 2011, 38(4):324-325.

[18] Hao S. Kernel methods for transfer learning to avoid negative transfer . International Journal of Computing Science and Mathematics, 2016, 7(2):175-190.

[19] Wang T, Liu Z, Lu G, et al. Temporal-spatio graph based spectrum analysis for bearing fault detection and diagnosis. IEEE Transactions on Industrial Electronics, 2021, 68(3): 2598 -2607.

[20] Li Y, Xu M, Wang R, et al. A fault diagnosis scheme for rolling bearing based on local mean decomposition and improved multiscale fuzzy entropy.Journal of Sound and Vibration, 2016, 3(6): 277-299.

[21] Lei Y, He Z, Zi Y. EEMD method and WNN for fault diagnosis of locomotive roller bearings. Expert Systems with Applications, 2011, 38(6): 7334-7341.

[22] Fu C, Wu Z, Xue M, et al. Cross-domain decision making based on TrAdaBoost for diagnosis of breast lesions. Artificial Intelligence Review, 2023, 56(5): 3987-4017.

[23] Zheng L, Liu G, Yan C, et al. Improved TrAdaBoost and its application to transaction fraud detection. IEEE Transactions on Computational Social Systems, 2020, 7(5): 1304-1316.

[24] He H, Khoshelham K, Fraser C. A multiclass TrAdaBoost transfer learning algorithm for the classification of mobile lidar data. ISPRS Journal of Photogrammetry and Remote Sensing, 2020, 16(6): 118-127.

[25] Yong Z, Chengbin W. An indoor positioning system using Channel State Information based on TrAdaBoost Tranfer Learning //2021 4th International Conference on Advanced Electronic Materials, Computers and Software Engineering (AEMCSE). IEEE, 2021: 1286-1293.

[26] Wang W, Wang C, Wang Z, et al. Abnormal detection technology of industrial control system based on transfer learning. Applied Mathematics and Computation, 2022, 4(12): 126-139.

[27] GUO Xiaoping, LIU Shiyang, LI Yuan. Research on multi-operating condition process fault detection method based on sparse residual distance. Journal of Automation, 2019, 45(3): 618-625.

[28] ZHAO Zhihong, YANG Shaopu. A sample entropy-based bearing fault diagnosis method. Vibration and Impact, 2012, 31(6): 136-140.

[29] Su W-S, Wang F-T, Zhang Z-X, et al. Application of EM noise reduction and spectral cliff method in early fault diagnosis of rolling bearings. Vibration and Shock, 2010, 29(3): 18-21.

[30] Lei Yaguo, Han Tianyu, Wang Biao, et al. Interpretation of XJTU-SY rolling bearing accelerated life test dataset. Journal of Mechanical Engineering, 2019, 55(16): 1-6.