An intelligent unsupervised fault diagnosis method based on subspace distribution alignment

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Abstract: Recently, marvelous success has been obtained for machine learning approaches in solving the mechanical defect detection problems. However, the traditional machine learning algorithms usually fail to generalize to new input distributions, which may cause the classification accuracy drops dramatically. To overcome this deficiency, domain adaptation techniques can be employed for transferring and adapting source domain to target domain. In this paper, an effective unsupervised domain adaptation approach called subspace distribution alignment (SDA) is applied to the defect diagnosis of gearbox. Firstly, the Fast Fourier Transform (FFT) is adopted for preprocessing the raw vibration signals into the frequency domain. Then, SDA algorithm is employed for mapping the source and target domain into the same subspace. In addition, the z-score normalization is applied to the source and target subspace. At last, the different fault types of gearbox are classified by the softmax regression classifier. The detection results show that our approach outperforms the other intelligent fault detection approaches listed in this paper.

Keywords: intelligent fault detection; domain adaptation; subspace distribution alignment; z-score; softmax regression

I. INTRODUCTION

With the continuous development of the technology, agricultural mechanization has become an important feature for modern agriculture. Agricultural machineries usually work in tough environment which may results in higher fault rate compared with the automobiles. Engine is widely used as the key component to provide power for the agricultural machinery. Any defects in engine may cause unwanted fatal breakdowns, expensive maintenance costs and even human casualties. Thus, any engine's defective components such as gears should be identified as early as possible. As a result, the fault diagnosis of gears has drawn extensive attention to guarantee the normal operation of the engine [1, 2].

Recently, machine learning algorithms have been widely used in many mechanical defect diagnosis, such as RBM (restricted boltzmann machine) [3], auto-encoders [4], ANN (artificial neural networks) [5], CNN (convolutional neural networks) [6] etc. Jia et al. [7] utilized the DNNs algorithm with a five layers SAE and applied the spectral for rolling motor bearing defect detection. Li et al. [8] employed a random deep forest to fuse the outputs of the two layers DBMs (deep Boltzmann machines) for gearbox fault diagnosis. The machine learning techniques perform well only based on an assumption: the labeled training data and the unlabeled testing data obey the same distribution. Nevertheless, the fault detection accuracies of these methods may reduce dramatically when the distributions are distinct. Unfortunately, in many practical applications, particularly in mechanical fault detections, this kind of phenomenon is difficult to avoid, which seriously reduces the effectiveness of machine learning in practical defect detection. This is called the cross-domain learning issue. The source domain denotes the training data applied to establish the algorithm. In addition, the test data applied to validate the model is called as the target domain.

To overcome the deficiency of the machine learning approaches owing to the domain shift, many domain adaptation (DA) algorithms [9-13] have been researched which attempt to obtain the transferable features or subspaces. The unlabeled target domain which belongs to the unsupervised category is selected in this paper. Most of the domain adaptation approaches have achieved adaptation via respectively mapping the distributions of the source and target domain to a lower dimension subspace, and researching the optimum transform to make the subspaces of the two domains closer. Geodesic learning approaches [14, 15] adopt the geodesic distance for measuring the length of a path along the subspace manifold, and either mapping the source domain and the target domain data to the points along that path [15], or a

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closed linear mapping is discovered to project the source domain points to target domain [14]. Furthermore, this domain adaptation approach named Subspace Alignment (SA) [16], the subspaces can be aligned via calculating the linear mapping, which may minimize the Frobenius norm of the discrepancy among them. Intuitively, the redundant dimensions can be removed by mapping the data into a lower dimension subspace, which may make it easier to discover the projection. Nevertheless, this method not considers the overall discrepancies of the distribution in the subspaces, even if the subspace base is aligned. Since the variance difference of every dimension, the distribution of these two domains in the aligned subspace may still be distinct. The main contributions of the proposed approach are summarized as below.

(1) An intelligent unsupervised domain adaptation approach named Subspace Distribution Alignment (SDA) is employed to detect the mechanical faults in this paper.

(2) FFT is adopted for preprocessing the raw vibration data into the frequency-domain, and the z-score normalization is adopted for normalizing the subspaces.

(3) Different fault types of gearbox are classified by the softmax regression classifier [17].

The remainder of this work is described as below: The subspace distribution alignment algorithm is briefly introduced in Section 2. The details of the proposed approach are shown in Section 3. The validity for my approach is verified via fault diagnosis of a gear dataset. Finally, conclusion is drawn in Section 5.

II. SUBSPACE DISTRIBUTION ALIGNMENT

The original data are firstly mapped to lower dimension subspaces, and then a mapping between these subspaces is researched [18]. Assume the labeled source domain contains samples $D_s = [x_{s,1}, \cdots]$, $x_{s,i} \in \mathbb{R}^N$, with labels $L_s = [y_1, \cdots]$, and the unlabeled target domain only includes the points $D_t = [x_{t,1}, \cdots]$. Furthermore, S_s and S_t can be calculated by PCA or other dimension reduction methods, which denote the d dimension of source and target subspaces, separately. The purpose is to mapping source domain into target domain. Assume T represents the matrix which applied to the transformation between these two domains, and then S_t^T maps the transformed source domain subspace back to the target one. Therefore, the mapping is obtained as follows.

$$M_s = S_s T S_t^T \tag{1}$$

As a result, the classifier learned on $D_s M_s$ can be utilized for the target domain directly. Generally, $\boldsymbol{T}$ is obtained by projecting the source domain subspace as close as possible to the target one.

However, the above transformation might not fully align the data distributions in the subspaces. Thus, the statistics approach, mean and the variance are employed to represent a distribution in this paper.

As we can see from the Fig.1, even though the zero mean and unit variance are gained by Normalizing he raw data, the subspace mapping alters the variance of the subspace. Consequently, the variance of the source subspace may be distinct from that of the target subspace. In addition, distribution alignment is not addressed for the subspace alignment.

In order to make sure the source and target domain distribution in the subspaces to be aligned as well, the Subspace Distribution Alignment (SDA) is proposed. For SDA, the distributions and the subspace bases of distinct domains dataset are both aligned at the same time. SDA

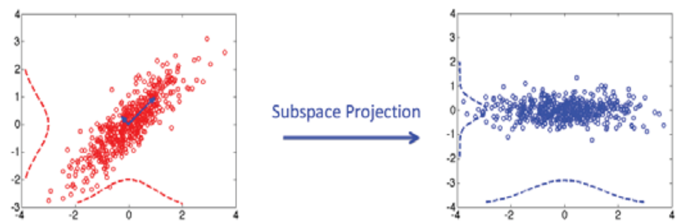

Figure 1: An illustration of standard feature normalization and align distributions in subspace [12].

establishes the projection between source and target samples as below:

$$M_s = S_s T A S_t^T \tag{2}$$

Where $\boldsymbol{A}$ represents a matrix applied to align the distributions in the subspace. Because covariance is the general case of variance in multi-dimensional space, so A could be obtained from covariance matrices of different subspaces. Besides, matrix $\boldsymbol{A}$ transferred the statistics of source subspace distribution to the target ones.

III. THE PROPOSED FRAMEWORK

First of all, notations which are frequently applied in this paper are displayed in Table Ⅰ.

FFT is adopted for preprocessing the raw vibration signals of the source domain and target domain dataset into frequency-domain. Then, the frequency-domain data are employed for SDA to obtain the final mapping matrix Ms. For SDA, the principle component analysis (PCA) algorithm is applied to draw the two domains principle components as source subspace S_s and the target subspace S_t, separately. The matrix T_{TS} can be obtained by projecting S_s to be as close to S_t as possible in the sense of minimizing the Frobenius matrix norm. Because the matrix T_{TS} only aligns the bases for source and target domain subspaces, so the distribution alignment matrix $\boldsymbol{A}$ also acquired for S_s and S_t. E_s and E_t are denoted as the eigenvalues corresponding to S_s and S_t. In the next step, the $W_s = E_s^{1/2}$ and $W_t = E_t^{1/2}$ are applied to E_s and E_t to obtain the W_s and W_t. The final projection of SDA for source and target subspace is showed as follows:

$$M_s = S_s T_{TS} A_{TS} S_t^T = S_s (S_s^T S_t)(E_s^{\frac{-1}{2}} E_t^{\frac{1}{2}}) S_t^T \tag{3}$$

Next, the z-score normalization is employed on the source and target subspace to obtain the input and test data for the classifier. Finally, the softmax regression is adopted as the classifier to distinguish the distinct defect types for the gearbox. The algorithm of our approach is introduced as follows:

Algorithm 1 SDA

Input: Source domain dataset D_s, Target domain dataset D_t, Source domain labels L_s, Dimension of the subspace d

Output: Target labels L_t

$D_{sf} \leftarrow$FFT (D_s), $D_{tf} \leftarrow$FFT (D_t)

S_s, $E_s \leftarrow$SVDS (D_{sf}, d), S_t, $E_t \leftarrow$SVDS (D_{tf}, d)

$T_{TS}= S_sS_t$

$W_s = E_s^{1/2}$, $W_t = E_t^{1/2}$

$A_{TS} = W_s^{-1} W_t$

$M_s \leftarrow S_s T_{TS} A_{TS} S_t^T$

train=z-score (M_s D_{sf}), test=z-score (M_t D_{tf}),

$L_t \leftarrow$ softmax regression classifier (train, test, L_s)

TABLE Ⅰ NOTATIONS AND DESCRIPTIONS

Notation	Description	Notation	Description
D_s, D_t	Source/Target domain	L_s, L_t	Source/Target labels
$\boldsymbol{T}$	Transformation matrix	$\boldsymbol{A}$	Alignment matrix
E_s, E_t	Source/Target eigenvalue	d	Subspace dimension
S_s, S_t	Source/target subspace	$\boldsymbol{M_s}$	Projection matrix

IV. EXPERIMENT

A. Data description

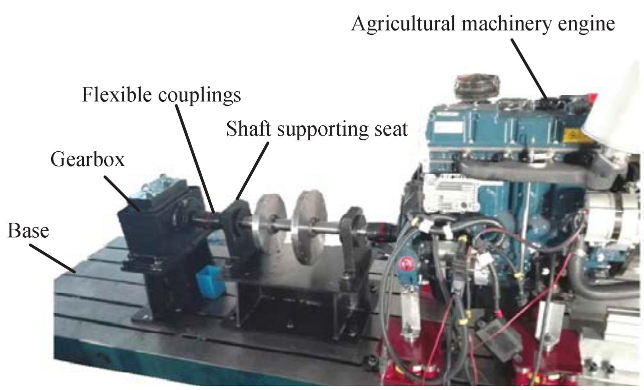

Figure 2 The experiment bench of gearbox.

Table Ⅱ THE DETAILS OF GEARS

Name	Teeth number	Modulus (mm)	Pressure angle (°)	Material
Pinion	55	2	20	S45C
Wheel	75	2	20	S45C

Making sure the accuracy of defect diagnosis is vital to the safe operation of many mechanical systems [19]. The gearbox experiment was selected for testifying the effectiveness of our approach and raw vibration signal was collected from the gearbox bench depicted in Fig. 2. The gearbox platform mainly contained a gearbox, agricultural machinery engine, the base, a coupling and bearing seats, et al. The agricultural machinery engine was employed for controlling the rotating speeds of the gearbox. In addition, the details of the two gears contained in the gearbox were described in Table Ⅱ.

There were totally four types of gear faults included for the gearbox: complex fault contains wheel pitting corrosion and pinion wear, a single pitting corrosion of wheel, complex fault contains broken teeth of wheel and pinion wear, and a single pinion wear, which were represented by Type-2 to Type-5 in this paper, separately. Besides, the normal gear was denoted as Type-1. Every defect category was obtained under three distinct rotating speeds, which represented three cases. The raw vibration signals were obtained by the accelerometer installed on the bearing seats of gearbox at a sampling frequency of 5120Hz.

B. Experimental performaances

For the sake of verifying the validity of the proposed method, three intelligent domain adaptation approaches which have shown good performance in fault diagnosis are adopted: (1) the time-domain SDA, (2) subspace alignment (SA) and (3) transfer component analysis (TCA).

For clarity, three cases of gearbox were represented by C1, C2 and C3, respectively. Furthermore, each case contained five fault types, and each fault consisted of 100samples. Considering the sampling frequency, 512 data points were contained for each sample. In order to make a fair comparison, FFT was conducted for SDA, SA and TCA. After the FFT processing, a 256×100 matrix could be obtained for each fault type. For SA, the optimum subspace dimension was fixed as 90. For TCA, the optimal value of the parameter μ is set to 0.1, and the Laplace kernel is chosen. For SDA, subspace dimension d is fixed as 100. The classification accuracies of these domain adaptation approaches are illustrated in Fig. 3. It should be pointed that 15 trials were conducted in total for the sake of reducing the randomness of the defect detection experiments.

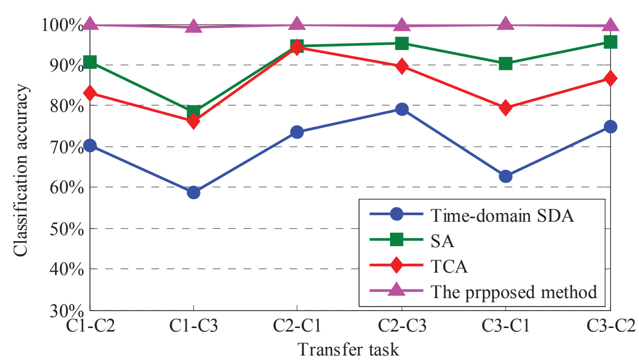

Figure 3 Diagnosis accuracies of gear for different transfer task.

As we can observe from Fig. 3, the averaged detection accuracy of the proposed approach reaches 99.67%, which outperforms the other comparison methods. For the time-domain SDA, the average classification accuracy is the lowest which not reaches 70%. For TCA method, the accuracy is 84.9%, which is 14.77% lower than our method. The average classification accuracy of SA achieved 90.8%, which is the highest one among the comparison methods, but still has

8.87% disparity comparing with the proposed method. All in all, the diagnosis accuracy of the proposed approach is relatively high and stable, which validate its effectiveness and robustness comparing with the other method listed in this paper.

True labels \ Predicted labels	Type - 1	2	3	4	5
Type - 1	99	0	0	0	0
2	0	100	0	0	0
3	1	0	100	0	0
4	0	0	0	100	0
5	0	0	0	0	100

Figure 4 Confusion matrix of the gear dataset.

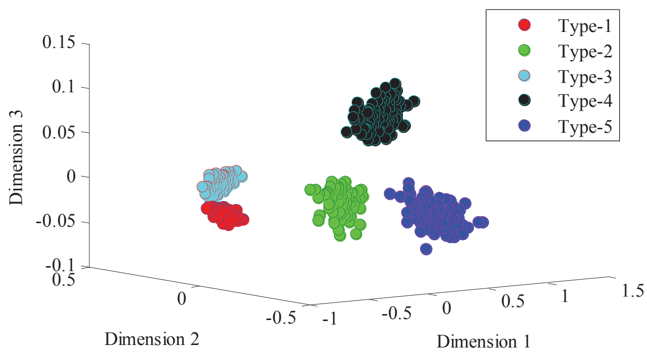

Figure 5 Visualization maps of the features learned by our approach.

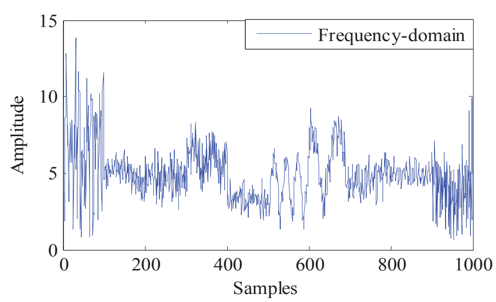

Figure 6 The features distribution obtained by SA.

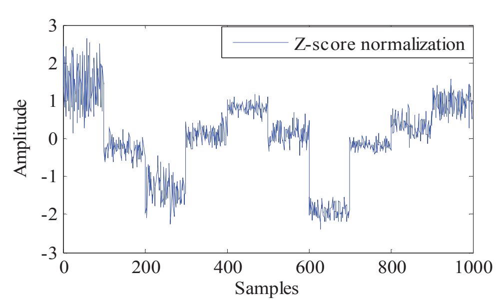

Figure 7 The features distribution obtained by SDA.

In order to explain the diagnosis details more clearly, the confusion matrix of the proposed approach is displayed in Fig. 4. The task C1-C2 is taken as the sample. It can be seen from the confusion matrix, there are 100 samples for each fault type, and only one sample extracted from Type-1 is misclassified to the Type-3. To validate fault diagnosis ability of our approach, t-SNE [22] is adopted for transforming the 256-dimension vector into a three-dimensional map. The results of task C1-C2 are depicted in Fig. 5. The results in Fig. 5 indicate that most of the features extracted from the same defect type are assembled in the relevant cluster and each cluster is separated from each other.

As can be observed from Fig.6 and Fig.7, the source and target subspace are aligned better for SDA than SA. As a result, different fault types can be easier to classify and higher classification accuracy can be obtained.

V. Conclusion

In this paper, an intelligent defect detection approach used the time-frequency transform is presented. In addition, the fault diagnosis experiments under different speeds are carried out. Firstly, the sparse filtering algorithm is employed for extracting the features adaptively. Then the softmax regression classifier is applied to identify the learned defect features. A gearbox dataset is utilized for testifying the validity of the proposed approach. Finally, we summarize the conclusions as below:

(1) The proposed approach can effectively align the distributions and the subspace bases of the source domain and the target domain data.

(2) Via comparing with the other intelligent domain adaptation method, the results verify the validity and robustness of our method.

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