Bearing failure as the most common failure mode in many rotating parts frequently leads to heavy economic losses or even casualties. Benefiting from data mining technology, massive data sampled from sensors are applied for monitoring bearing healthy condition. Unfortunately, variable motor speeds and different loads in rotary machine result in huge distribution differences between training data and test data, which readily causes failure diagnosis. Thus, one of the serious challenges in bearing fault diagnosis is improving the diagnostic performance under different working conditions. In this paper, a novel transfer learning-based strategy (TLS) for bearing fault diagnosis under different working conditions is proposed. The dataset of normal bearing and faulty bearings is acquired via the fast Fourier transformation (FFT) of raw vibration signals under various motor speeds and load conditions. Then distributional difference across domains based on maximum mean discrepancy (MMD) by reweighting instances in shared feature space is reduced, and simultaneously domain invariant cluster is considered in the embedding feature representation for separating different faults. Finally a robust feature representation for training and test domains is obtained after several iterations, and with the help of the Support Vector Machine (SVM) classifier, bearing fault categories are identified accurately. Extensive experimental results under different working conditions demonstrate the effectiveness of TLS and show that it outperforms obviously competitive methods.

Keywords: Fault diagnosis; Vibration signal; Transfer learning; Domain invariant cluster

1. Introduction

Bearings are a vital part of rotating machinery, whose health conditions have effect on reliability and residual life of the equipment or even can lead to heavy casualties [1-3]. However, the working environment of bearings is variable, these conditions cause robust fault feature information extraction becomes more difficult. Therefore, the study of bearing fault diagnosis under different working conditions is important.

Many fault diagnosis methods can be divided into model driven methods and data driven methods [4]. The former methods have to be confronted with the difficulty of setting up its physical structure model. However, data driven methods can directly resort vibration signal collected by sensors to recognize faults [5,6], and based on these cases, many data driven fault diagnosis methods have already acquired tremendous success. In [7], manifold learning and wavelet networks are used for feature extraction and diagnosis. Lei et al [8] proposed a bearing fault diagnosis method based on DNNs and it can adaptively mine available fault features from original data.

To be true, most of data driven fault diagnosis methods work well only under a general assumption: the training and test data must be in the same working condition and draw from the same distribution. However, in the real world, different working conditions often make the distribution of sensor signals inconsistent. Taking a rolling element bearing fault diagnosis problem as an example,
classifier was trained under a very concrete type of data sampled under a certain motor speed and load, however, the actual application in fault diagnosis is to recognize test data collected under another motor speed and load. Although the fault diameter and categories are not changed, the distribution differences between training data (training domain) and test data (test domain) changes with working condition varies. As a direct result, the classifier can achieve high accuracy on training domain while performing poorly on test domain [9]. This is caused by distribution differences between two domains, since features extracted from one domain can not represent for another domain. Of course we can spend lots of time and efforts to recollect data to build a new classifier for effective fault diagnosis on test domain. However, we can not always to replace classifier by repetitively recollecting data. Worse, it is so expensive or even impossible to rebuild the fault diagnosis model from scratch using newly recollected training data for the actual task. Therefore, there is still plenty of room for improvement.

In order to avoid such repetitive work, it is expected that a fault diagnosis model trained in one condition (training domain) can be applied for a new working condition(test domain). This leads to the research of transfer learning [10], which aims to leverage the knowledge learnt from a training domain to use in a different but related test domain by reducing distribution differences. Maximum mean discrepancy (MMD) [11] in the field of transfer learning can be applied to evaluate distribution divergences.

In this paper, considering actual fault diagnosis application, a novel transfer learning-based strategy (TLS) for bearing fault diagnosis under different working conditions is proposed. Dataset of normal bearing and faulty bearings are acquired via the fast Fourier transformation (FFT) of raw vibration signals under different motor speeds and load conditions. Distributional difference across domains based on maximum mean discrepancy (MMD) by reweighting instances in a shared Reproducing Kernel Hilbert Space (RKHS) is reduced, and simultaneously domain invariant cluster is considered in the embedding feature representation, so that robust feature representation for training and test domains could be learnt. Finally, SVM classifier is built with extracted robust features and bearing faults are identified accurately.

The rest of this paper is organized as follows. Section 2 sketches out previous works and preliminaries, including transfer learning and maximum mean discrepancy. Section 3 introduces fault diagnosis using transfer learning-based strategy, including feature space generation and transferable feature extraction and diagnosis. Section 4 presents the experimental evaluations. The conclusion are given in Section 5.

2. Previous works and preliminaries

2.1 Transfer learning

Transfer learning, a new machine learning method, allows distribution P(X) and feature space \( \mathcal{X} \) used in training domain being different from those in test domain, where \( X = \{x_1, \ldots, x_n\} \subseteq \mathcal{X} \) is a series of learning samples [10]. In real world application, it should be noted that distributional difference of two domains exist and likely to be large when training domain and test domain are different, that is \( X_S \neq X_T \) and \( P(X_S) \neq P(X_T) \) [10,12].

In this paper, the target of transfer learning-based strategy is to extract transferable features between two domains for realizing successfully bearing fault diagnosis under different working conditions. The labeled training domain is defined as follows: \( X_{tr}=\{(x_{tri1},y_{tri1}),\ldots,(x_{trim1},y_{trim1})\} \), where \( x_{tri} \in \mathcal{X} \) is the input and \( y_{tri} \in \mathcal{Y} \) is the corresponding class label. Similarly, let the unlabeled test domain be \( X_{te}=\{x_{te1},\ldots,x_{ten2}\} \), where the input \( x_{tei} \in \mathcal{X} \). In terms of distribution, let \( P(X_{tr}) \) and \( P(X_{te}) \) be the marginal distributions of \( X_{tr}=\{x_{tri}\} \) and \( X_{te}=\{x_{tei}\} \), respectively. Similarly let \( Q(Y_{tri}|X_{tri}) \) and \( Q(Y_{tei}|X_{te}) \) be the conditional distributions of \( X_{tri}=\{x_{tri}\} \), respectively [12].

In this literature, the following settings are worthy of attention: 1)one training domain and one test domain share the same faults and feature space. 2)training domain \( X_{tr} \) are of labels while test
domain $X_{te}$ are fully unlabeled. 3) the marginal distribution $P(X_{tr}) \neq P(X_{te})$ and the conditional distribution $Q(Y_{tr} | X_{tr}) \neq Q(Y_{te} | X_{te})$. Above settings tally with real-world different working conditions fault diagnosis.

2.2 Maximum mean discrepancy

The core idea of transfer learning is to reduce distributional difference between two domains. A nonparametric distance metric, known as MMD, is adopted for estimating the discrepancy between distributions. In this paper, MMD measures the discrepancy in a RKHS. Taking training domain $X_S$ and test domain $X_T$ for example, the MMD measures the difference across domains in the $k$-dimensional embedding \cite{11,12}.

$$D(X_S, X_T) = \left\| \frac{1}{n_t} \sum_{i=1}^{n_t} A^T \phi(x_i) - \frac{1}{n_t} \sum_{j=1}^{n_t} A^T \phi(x_j) \right\|_{H}$$ (1)

where $D$ is the distributional difference across domains, $A$ is the adaptation matrix, $H$ is a universal RKHS, $\phi: X_S, X_T \rightarrow H$ and $n_t$ and $n_t$ denote the number of training instances and test instances, respectively.

3. Fault diagnosis using transfer learning-based strategy

In this section, a novel bearing fault diagnosis method under different working conditions is presented. The framework of the proposed method is illustrated in Fig. 1. Details of each part are elaborated in the following subsections.

![Figure 1: The framework of TLS for different working conditions fault diagnosis.](attachment:figure1.png)

3.1 Feature space generation

Raw time series vibration signal is readily available and abound in bearing information. Owing to the rotating nature of raw vibration signals from a defective bearing, the periodic impulse would appear in obtained signals once a fault occurs. Thus, these fault impacts can be detected generally in frequency domain. In this paper, FFT amplitudes with the same dimension are directly caught from the raw time series vibration signal under different motor speeds and load conditions as samples,
which are divided into two parts: training data $X_{tr} \in \mathbb{R}^{n_{tr} \times d}$ with label $Y_{tr} \in \mathbb{R}^{n_{tr} \times 1}$ and unlabeled test data $X_{te} \in \mathbb{R}^{n_{te} \times d}$. According to Kernel principal component analysis (PCA) [15], the feature space can be generated as follows:

$$\max_{V^T, V_1} \text{tr}(V^T K H K^T V)$$  \hspace{1cm} (2)

where $K = \phi(X)^T \phi(X) \in \mathbb{R}^{n \times n}$, $X=[X_{tr}, X_{te}]$, $H = I - 1/(n_{tr}+n_{te})11^T$ and $V$ is adaptation matrix. Then feature space $Z = V^T K$.

### 3.2 Transferable feature extraction and diagnosis

According to Eq. (1), distributional difference can be measured as follows:

$$|| \frac{1}{n_{tr}} \sum_{j=1}^{n_{tr}} V^T k_j - \frac{1}{n_{te}} \sum_{j=n_{tr}+1}^{n_{tr}+n_{te}} V^T k_j || = \text{tr}(V^T K M K^T V)$$  \hspace{1cm} (3)

where $M = \begin{bmatrix} M_{tr, tr} & M_{tr, te} \\ M_{te, tr} & M_{te, te} \end{bmatrix}$ is the MMD matrix and is computed by [13,14]:

$$M = \begin{cases} \frac{1}{n_{tr}}, & x_i, x_j \in X_{tr} \\ \frac{1}{n_{te}}, & x_i, x_j \in X_{te} \\ -1, & \text{otherwise} \end{cases}$$  \hspace{1cm} (4)

The distributional difference across domains can be closer under the new representation $Z = V^T K$ by minimizing Eq. (3).

In order to avoid interference caused by some training instances that are not relevant to the test instances, $l_{2,1}$ norm structured sparsity regularizer is be introduced to reducing difference. Formally, instance reweighting is defined by [15]

$$|| V_s ||_{2,1} + || V_t ||_F^2$$  \hspace{1cm} (5)

where $V_s := V_{tr}$ is the adaptation matrix $V$ corresponding to training instances, and $V_t := V_{te}$ is the adaptation matrix $V$ corresponding to test instances. $|| \cdot ||_F$ is the Frobenius norm that guarantees the optimization problem to be well defined. By minimizing Eq. (5) such that weight of training instances which are of weak irrelevance to the test instances in feature space can be reduced.

Inspired by LDA [16], we adopt domain invariant cluster to maximum separability of features extracted via minimizing the within-class scatter matrix $S_w$.

$$S_w = \sum_{c=0}^{C} \sum_{i=1}^{N_c} (k_{tr}^{(i)} - \mu_c)(k_{tr}^{(i)} - \mu_c)^T$$  \hspace{1cm} (6)

where $k_{tr}^{(i)}$ denotes the $i$th sample of class $c$ in training domain, $\mu_c$ is the mean of class $c$ and $N_c$ is the number of samples belong to class $c$.

Thus, the problem of fault diagnosis under different working conditions comes down to an optimization problem Eq. (7) comprised from Eq. (3), Eq. (5) and Eq. (6) in this paper.

$$\min_{V^T, K, H, V_1} (1-\lambda)\text{tr}(V^T (K M K^T + S_w) V) + \lambda (|| V_s ||_{2,1} + || V_t ||_F^2)$$  \hspace{1cm} (7)

where $\lambda \in (0,1)$ is the regularization parameter that trades off the impact of regularization term on the adaptation matrix $V$. According to the constrained optimization theory, above optimization problem can be solved by lagrange multiplier method [17]. The Lagrange function for Eq. (7) can be constructed as follows:

$$L = (1-\lambda)\text{tr}(V^T (K M K^T + S_w) V) + \lambda (|| V_s ||_{2,1} + || V_t ||_F^2) + \text{tr}(I-V^T V K H K^T V)$$  \hspace{1cm} (8)
where $\Phi = \text{diag}(\phi_1, \cdots, \phi_n)$ is the Lagrange multiplier. According to $dL/dV=0$, the optimal solution of Eq. (8) can be acquired through the generalized eigen decomposition.

\[
((1 - \lambda)(\mathbf{K}\mathbf{M}^T + S_n) + \lambda \mathbf{G})\mathbf{V} = \mathbf{K}\mathbf{H}^T\mathbf{V}\Phi
\]

where $\mathbf{G}$ is a diagonal sub-gradient matrix [15] with $i$th element equal to

\[
G_{ii} = \frac{1}{2 \|v_i\|}, x_i \in X_{\nu}, v \neq 0
\]

\[
G_{ii} = 0, \quad x_i \in X_{\nu}, v = 0
\]

\[
G_{ii} = 0, \quad x_i \in X_{\nu}
\]

The adaptation matrix $\mathbf{V}$ is obtained from solving Eq. (9) for $k$ smallest eigenvectors via updating the sub-gradient matrix $\mathbf{G}$ for several times, and then robust features are extracted by $\mathbf{Z} = \mathbf{V}^T\mathbf{K}$.

With the help of SVM classifier, bearing faults are identified accurately.

4. Experimental evaluations

In order to demonstrate the effectiveness of the proposed fault diagnosis method, the vast bearing vibration signals collected from a bearing test rig are used. TLS is compared with the baseline approaches.

a. Baseline1: NN classifier with no projection and no transfer learning is created. That is, original input is directly used for diagnosis.

b. Baseline2: NN classifier with no transfer learning is created. Specifically, we use a new representation extracted from original input by PCA without domain adaptation.

4.1 Experimental setup and dataset preparation

The experiment is carried from the machinery fault simulator illustrated in Fig. 2 at a sampling frequency of 20 kHz, which contains a variable speed motor, a variable speed motor controller, a flexible coupling and a shaft [18]. A well-balanced mass rotor is installed in the middle of a steel shaft between two bearing housings and supported by two rolling element bearings. This simulator is driven by a 3-hp ac motor and several ICP accelerometers are mounted on the bearing housings. Finally the dataset is collected by these sensors located on the top of the right bearing housing.

Figure 2: Bearing test rig of Machinery fault simulator experimental setup.

In order to explore the proposed fault diagnosis method in depth, four fault types of bearings with fault size being 3/4" rotor bearing are considered, i.e., normal (NO), inner race fault (IF), out race fault (OF) and ball fault (BF). Each working condition of Load0 (L0) = 3 hp/720 rpm, Load1 (L1) = 3 hp/840 rpm and Load2 (L2) = 3 hp/960 rpm contains four fault types. Each fault from Load0-Load2 contains 200 samples and each sample has 2049 FFT amplitudes. In this experiment, linear kernel is used for kernelization, and it is impossible to find the optimal $k$ and $\lambda$ via cross validation, since labeled training data and unlabeled test data are sampled from different working con-
ditions. Thus, empirically searching the parameter space is used to find the optimal parameter settings. Finally, \( \lambda = 0.1 \) and \( k = 100 \) dimensional feature representation is extracted for diagnosis.

In order to validate the effectiveness of TLS, baseline methods are also carried out simultaneously. The scenario settings of this experiment are trained on labeled data under one load (training domain) to diagnose the unlabeled data under another load (test domain). Totally, 9 different transferring tests shown in Table 1 are conducted.

Table 1: Description of the experimental setup

<table>
<thead>
<tr>
<th>Task</th>
<th>Diagnose unlabeled data under different working conditions</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Labeled data</td>
</tr>
<tr>
<td>1</td>
<td>L0,L1,L2</td>
</tr>
<tr>
<td>2</td>
<td>L0,L1,L2</td>
</tr>
<tr>
<td>3</td>
<td>L0,L1,L2</td>
</tr>
</tbody>
</table>

4.2 Experimental results analysis

The diagnostic results are shown in Fig. 3, which is composed of three subfigures and test domains in every subfigure are ordered from the left to right: L0, L1 and L2.

![Figure 3: The results with fault size being 3/4" rotor bearing.](image)

The left of the symbol "->" in every subfigures represents the training domain and the right represents the test domain. For each set of bars in Fig. 3, the performances indicate transferring from training domain to test domain, which simulates fault diagnosis under different working conditions. The load and speed between different domains have large discrepancies. For example, in figure 3(a), the test domain is L0 (3 hp/720 rpm), the training domain are L0 (3 hp/720 rpm), L1 (3 hp/840 rpm) and L2 (3 hp/960 rpm).

From the performances of bearing fault diagnosis in Fig. 3, the highest accuracy rates can always be achieved when the distribution of two domains are identical, that is, training data and test data are collected under the same working condition, and this phenomenon is reasonable theoretically. It is obviously found that Baseline2 is slightly better than Baseline1. Although the results of baseline methods can reach 90% when transferring between L1 and L2, others in this experiment are unsatisfying in Fig. 3. For example, the accuracy rates are 72.75% corresponding to Baseline1 and 74.12% corresponding to Baseline2 when we transfer L1 to L0 in Fig. 3 (a). These results indicate that baseline methods can not be applied to bearing fault diagnosis under different working conditions. What is exciting that the proposed method is evidently superior to baseline methods in all cases, whatever the training domain and test domain are. and note that all accuracy rates are 100%. Through above result analysis, we can conclude that the proposed method is very potential for solving bearing fault diagnosis problems under different working conditions.

In order to deeply understand the impact of distributional difference across domains and explain why TLS works, t-SNE technique [19] is introduced into visualizing high dimensional representation of mentioned methods in a two-dimensional map. In all the test in table 1, taking the test that transferring L1 to L0 as an example in Fig. 4.
From Fig. 4, it is obvious that TLS makes distributions between L1 and L2 more similar and extracted features are of better separability compared with baseline methods. These results verify that TLS can figure out a robust feature representation for training domain and test domain, and extracted features in this shared space are of satisfactory clustering results.

5. Conclusion

In this paper, a new way for diagnosing bearing faults under different working conditions is proposed. It can extract robust features for training and test data via bridging the cross-domain discrepancy and simultaneously strengthen the recognizable information contained in the raw vibration signal. The experimental results confirm that TLS is of superiority on improving the performance of bearing fault diagnosis under different working conditions.

6. Acknowledgment

This work is supported by National Key R&D Program of China (2016YFC0802900), National Natural Science Foundation of China (Nos. 51475455, 51605478), the Natural Science Foundation of Jiangsu Province (No. BK20160251), and the China Postdoctoral Science Foundation (No. 2016M590513).

REFERENCES


10 S. J. Pan, Q. Yang, A survey on transfer learning, *IEEE Transactions on Knowledge and Data Engineering*, **22** (10), 1345-1359, (2010).


17 S. Li, Y. Fu, Learning robust and discriminative subspace with low-rank constraints, *IEEE Transactions on Neural Networks and Learning Systems*, **27** (11), 2160-2173, (2016).
