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FAULT DIAGNOSIS OF ROLLING BEAR USING GENERALIZED ORTHOGONAL MATCHING PURSUIT

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Abstract： Sparse representation classification has been used in fault diagnosis of rolling bears, aim at the problem of low processing speed in this method, a fault diagnosis method of rolling bears based on gOMP-KSVD, which integrates the strengths of generalized orthogonal matching pursuit with the benefits of KSVD dictionary learning algorithm, is proposed in this paper. Sub-dictionaries are learned from each type of vibration signals using gOMP-KSVD; An over-complete dictionary is built by combining all the sub-dictionaries into a single one; The vibration signal is linearly decomposed into a set of best matching waveform by solving the sparse representation problem on the redundant dictionary. Then the gOMP-KSVD method is applied to the classification of the experimental vibration signal of rolling bears, compared with the traditional KSVD algorithm. Results show that the time cost of classification using our method reduced by 40% while achieving almost the same accuracy as KSVD does.

Keyword: vibration signal; sparse representation; dictionary learning; fault diagnosis

1. Instruction

In the condition monitoring and fault diagnosis of mechanical equipment, how to accurately extract the feature signals of complex the vibration signals is one of the core issues in the field[1-3].In the acquisition process of vibration signals, a variety of symbiotic factors such as noise and signal modulation caused the redundant information. Therefore, the feature components of mechanical fault are often sparse in the whole vibration signal (or in certain transform domain). In other words, the feature extraction of vibration signal in equipment condition monitoring and fault diagnosis essentially is a redundancy compression process of information. Based on this, the sparse decomposition algorithms, which can accurately characterized and extracted different components and details of the signal, have become a new research hotspot in the feature extraction of vibration signal [4-6]. Sparse representation is to find the most concise representation of a signal in terms of linear combination of atoms in an over-complete dictionary. Signal can be accurately represented with few atoms if the atoms share the similar inner structure with the signal, or decomposed into a large number of atoms if inappropriate dictionary was selected which will lead to information dilution [7]. Therefore, the search for an appropriate dictionary becomes one of the focuses of sparse representation theory [8]. A predefined dictionary (such as fourier or wavelet transforms) is often used due to its computational efficiency [9, 10], but it is usually based on a prior knowledge of the target signal and cannot adapt to new kind of signals which were interested [11].

In order to break through these limitations, researchers propose a new approach, learning a dictionary from training samples. In 1996, Olshausen et al [12] published the famous Sparsenet dictionary learning algorithm in Nature, which established the foundation of dictionary learning theory. Engan et al.[13] proposed the method of optimal directions (MOD) algorithm, it alternates between getting the sparse coding and updating the dictionary and proved to be a very efficient method for low-dimensional data requiring just a few iterations to converge. However, due to the high complexity of the matrix-inversion operation, computing the pseudoinverse in high-dimensional is intractable in many cases. This shortcoming has inspired the development of other dictionary learning methods. Aharon et al. [14] present a new method called the KSVD algorithm, it performs SVD at its core to update the atoms of the dictionary one by one different to MOD. This algorithm is considered to be standard for dictionary learning and used in a variety of applications. Liu et al.[15] introduced the SISC algorithm into the field of fault diagnosis, trained a redundant dictionary from a large number of existing signals using the SISC algorithm for bearing fault classification. Zhang et al.[16] used matching pursuit and K-SVD dictionary learning for state identification of rolling bear, and proposed A bearing fault diagnosis method based on sparse decomposition theory; Chen[17] proposed an impulse extraction method based on adaptive dictionary learning, and applied it to detect gearbox fault.

However, dictionary learning method can acquire a better dictionary by searching the latent structure of various complex signals, but this is at the cost of higher computational costs. In order to speed up the training process, we combined the generalized orthogonal matching pursuit (gOMP) algorithm[18] with KSVD dictionary learning method, and proposed the gOMP-KSVD method. Then applied it to fault diagnosis of rolling bears.

2. Materials and methods

If there are K class of training signals from different kind of working state. Built specific dictionary $D_i = (\mathrm{d}_{i,1}, \mathrm{d}_{i,2}, ..., \mathrm{d}_{i,n_i}) (i = 1, 2, ...K)$ for each class. Then giving a signal y from class i, it can be represented as a linear combination of basic functions from D_i :

$$y = D_i x_i = d_{i,1} x_{i,1} + d_{i,2} x_{i,2} + ... + d_{i,n_i} x_{i,n_i} \tag{1}$$

In practice, the type i of the input signal is usually unknown, in order to represent it, merging all the K dictionaries into a redundant dictionary $D = [D_1, D_2, ..., D_K] = [\mathrm{d}_{1,1}, \mathrm{d}_{1,2}, ..., \mathrm{d}_{K,n_k}]$. then the signal can be decomposed as follow:

$$y = Dx \tag{2}$$

Where, $x = [0, ..., 0, x_{i,1}, x_{i,2}, ..., x_{i,n_i}, 0, ..., 0]$ is the sparse coefficient vector, ideally its entries are zero except those associated with i-th class. This means the entries of the coefficient vector encode the identity of the input signal, so we can find the class of y by solving the linear system of equations $y = Dx$.

Two issues need to be addressed in order to solve the above equations, one is to solve the sparse coefficient, and the other is the design of dictionary.

2.1 Sparse representation

Consider the linear system of Eq. (2), where $y \in R^n$ is the input signal, $D \in R^{n \times m}$ is an underdetermined matrix (n<<m) , called the dictionary, which is giving. The column vectors of the matrix D are called atoms. The Eq. (2) is undetermined which have an infinite number of solutions, the objective of sparse representation is to find the sparsest solutions, as the decomposition result would be closer to the inner structure of the signal if the signal can be represent more sparsely. Then the problem can be written as:

$$\min_x \| x \|_0 \quad s.t. \quad y = Dx \tag{3}$$

Where $\| x \|_0$ is the l_0 norm and stands for the number of non-zero entries in the vector x. But finding the solution of Eq. (3) is NP hard[19]. Generally suboptimal solution such as orthogonal matching pursuit (OMP) has been wildly used to solve this problem due to its simplicity and efficiency. In each iteration of OMP algorithm, only one atom from dictionary D that most correlated to the signal is chosen, while the gOMP algorithm picks multiple correct atoms per iteration, and owing to this, the gOMP is finished with much smaller number of iterations while having excellent recovery performance.[20]

2.2 Dictionary learning

The other problem is the design of the dictionary D, we chose the learning method, training a dictionary from training samples. As this method can acquire the latent structure of the input signals automatically and adaptively. The dictionary elements can be found by minimizing the average representation error with l_0 regularization on the coefficient to enable sparsity :

$$\underset{D,X}{Min} \sum_{i=1}^{M} \| Dx_i - Y_i \|_2^2 \quad s.t. \forall i = 1, 2..., M \quad \| x_i \|_0 \le k \tag{4}$$

Where $\{\mathrm{Y_i}\}_{\mathrm{i=1}}^{\mathrm{M}}$ are the M training samples with the length of n.

KSVD is an effective dictionary learning algorithm used to create a dictionary, via the singular value decomposition approach, it works by iteratively alternating between sparse coding the training signals, and updating the atoms in the dictionary to better fit the data.

In the sparse coding step, the dictionary is first fixed and the best coefficient matrix is found by applying the matching pursuit method, here we use gOMP to speed up the process:

$$\min_{x_i} \| Dx_i - Y_i \|_2^2 + \lambda \| x_i \|_0 \tag{5}$$

Then, the next step is to search for a better dictionary:

$$\min_D \| DX - Y \|_F^2 \tag{6}$$

Where $\| \cdot \|_F$ is the Frobenius norm. process is to update only one column of the dictionary each time, while fixing X. The update of the k-th column is done by rewriting the Eq. (6) as follow:

$$\begin{aligned} \min_D \| Y - DX \|_F^2 &= \min_{d_i} \| Y - \sum_{j=1}^{M} d_j x^j \|_F^2 \\ &= \min_{d_i} \| (Y - \sum_{j \ne k} d_j x^j) - d_i x^i \|_F^2 \\ &= \min_{d_i} \| E_i - d_i x^i \|_F^2 \end{aligned} \tag{7}$$

After updating the whole dictionary, then turns to iteratively solve X, then iteratively solve D, until meets the requirements

2.3 Fault diagnosis method

Given a new signal y from one of the classes in the training set, compute its sparse representation, Ideally, the nonzero entries in the coefficient vector will all be associated with the columns of D from a single object class i, and we can easily assign the signal y to that class. However, noise and modeling error may lead to small nonzero entries associated with multiple object classes. So a classifier was designed to deal with this recognition task, after get the coefficient vector:

$$\hat{x} = [x_{1,1}, ..., x_{1,n_1}, ..., x_{i,1}, x_{i,2}, ..., x_{i,n_i}, ..., x_{K,1}, ..., x_{K,n_K}] \tag{8}$$

Let $\delta_i(\hat{x}) = [0, ..., 0, x_{i,1}, x_{i,2}, ..., x_{i,n_i}, 0, ..., 0]$, approximate the given test signal y on the i-th sub-dictionary as:

$$\hat{y}_i = D\delta_i(\hat{x}) \tag{9}$$

Then compute the reconstruct residual:

$$\min_i r_i(y) = \| y - D\delta_i(\hat{x}) \|_2 \tag{10}$$

Now we can classify y to the object class which minimizes the residual.

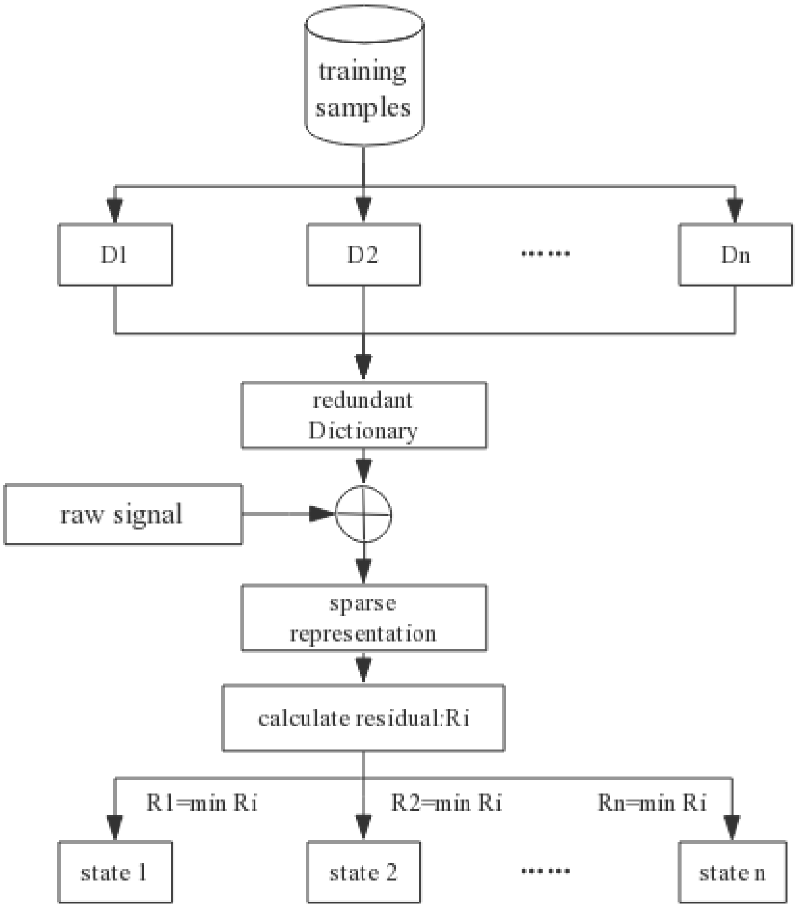

Figure 1.Flow chart of the proposed method

3. Engineering verification and discussion

The vibration data of rolling element bearings from Bearing Data Center of Case Western Reserve University was used to test the effectiveness of the proposed method. The test stand of rolling bear is shown in Fig. 2, it consists of a 2 hp motor (left), a torque transducer (center), a dynamometer (right), and control electronics. The test bearings support the motor shaft. Single point faults were introduced to the test bearings using electro-discharge machining. The data was collected at 12,000 samples per second.

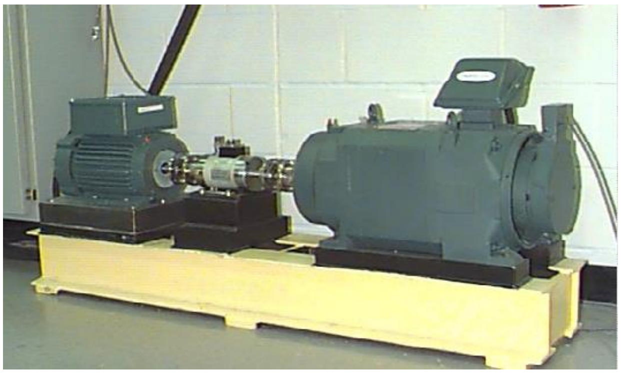

Figure 2.The bearing test stand

Table 1. data of bearing faults

Fault Diameter	Motor Load (HP)	Approx. Motor Speed (rpm)	Inner Race	Ball	Outer Race Position		
					Centered @6:00	Orthogonal @3:00	Opposite @12:00
0.007"	0	1797	IR007_0	B007_0	OR007@6_0	OR007@3_0	OR007@12_0

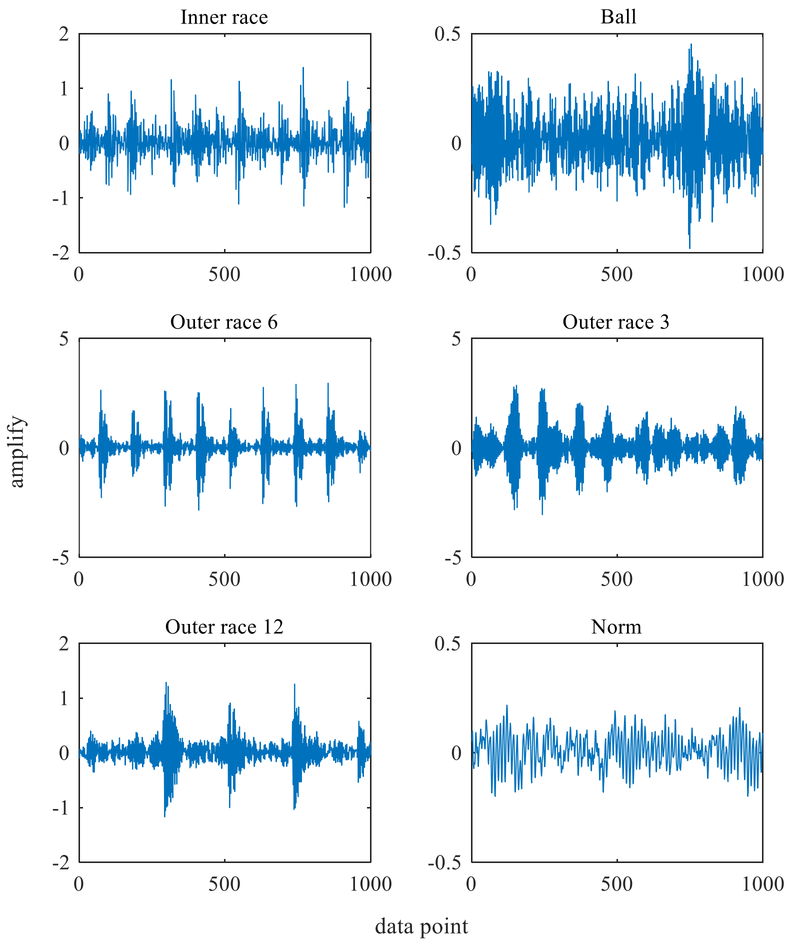

Figure 3 .The vibration signals under different states

In our experiment, use the vibration data of rolling bearing under both normal and faults conditions, the fault locations were on inner race, ball, and outer race at three different orientations (6:00, 3:00 and 12:00 directions), as shown in table 1. There are six types of signals, part of the data points is plotted in Fig. 3.

Each class of data set was truncated into time-series with a 512-point block, and overlaps with 256 data points, now 550 samples for each class are generated, then divide them into two set, training samples and test samples, the former was used to training the dictionary (including 450 samples per class), the second was used to evaluate the accuracy of the classification. In the learning process, the number of atoms selected in every iteration in gOMP algorithm is 3,and the size of the each sub-dictionary is set to 512×200, then the redundant dictionary is 512×1200.

After the dictionary learning process, one segment of each class of signal is taken from the test sample, then calculate the sparse representation respectively. Intuitively, the coefficient of each signal is mainly concentrate on the columns of D from the true class of the signal. More accurately, classify the signal by computing the reconstruct residuals, and the result is shown in Fig. 4, Class 1-6 denote for ball, inner race, norm and outer race (3:00, 6:00 and 12:00 directions) fault type. For example, the reconstruct residual of the inner raceway fault signal reaches its minimum at the second class sub-dictionary, that mean it belong to class 2.

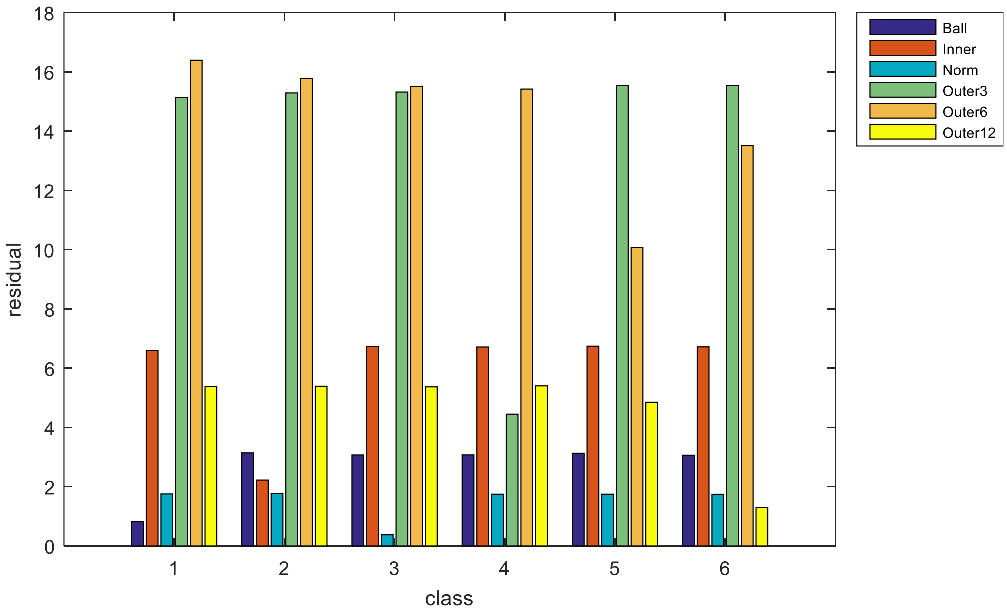

Figure 4. reconstruct residual

In order to verify the reliability of this method, and compared to the dictionary learning method which use OMP in sparse coding step, training two dictionary using the two methods with the same training samples in the computer with dual-core 2.5Ghz and 8G memory, our method cost 687 seconds while the other method cost 1160s. Then we compared the performance of the two dictionary by the classification task. One hundred test samples for each class of signals, and the accuracy of recognition is shown in Fig. 5. The 6×6 matrix at the upper-left corner of the figure is the confusion matrix, and digit in the $i-th$ row and $j-th$ column represents for the number of signals which are class j but classified to class i. The row under the confusion matrix is the recognition rates, and the total recognition rate of our method reaches to 95%, almost the same with the other method while having a reduction in time consumption (40%).

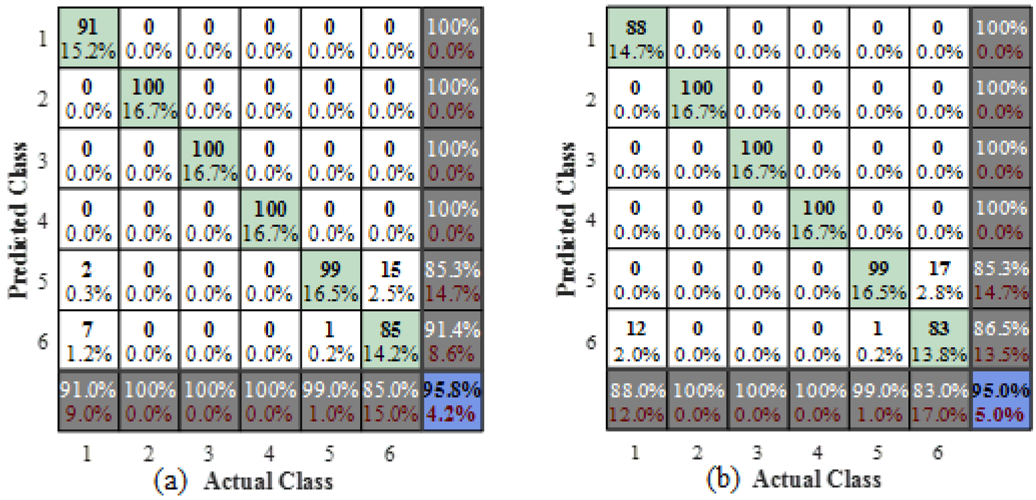

Figure 5. (a) confusion matrix of OMP-KSVD ;(b) confusion matrix of gOMP-KSVD

4. Conclusion

In this paper, we studied the sparse representation of vibration signals based on dictionary learning, proposed an improved dictionary learning method by introducing the gOMP into the KSVD dictionary learning algorithm, and applied to fault diagnosis of rolling bearing. Experiment results show this method can train a dictionary more efficiently, and has a high accuracy in the condition monitoring of mechanical equipment.

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