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Study on motor fault feature extraction based on MED- KSVD dictionary learning method.

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Abstract

Motor bearings, widely used in rotating mechanical equipment such as motors, gearboxes, wind turbines, generators and engines, are important basic components in modern industry, and any failure of which may lead to serious failure of the rotating machine. In order to ensure the efficient, accurate and safe operation of this important component, the fault characterization of motor bearings is of very far-reaching significance. On the basis of studying the basic structure and vibration principle of motor bearings, this thesis utilizes the constructed motor bearing signals for the traditional KSVD algorithm which is easily affected by noise, and conducts a research based on the MED- KSVD dictionary learning method by using the sparse representation method, which extracts the obvious shock signals and proves the ability of the MED-KSVD algorithm to extract the fault shocks.

Keywords

Motor bearing; Feature extraction; Sparse representation; Dictionary Learning.

1. Introduction

Electric motors are one of the common rotating mechanical devices, which are widely used in aviation, automotive and other related fields. However, since motors usually work in harsh environments, they are prone to failures that can lead to downtime, posing a serious threat to production safety. However, the failure of bearings in electric motors is one of the most important reasons why the motors cannot operate normally [1]. In order to ensure safe production and reduce economic losses due to faulty repairs, it is important to quickly and accurately diagnose faults in motor bearings [2-4]. When the bearing fails, due to the collision of other coupling elements, so that the repeated transients in mechanical vibration, and in the complex working environment, usually, the measured vibration signal is high noise, non-Gaussian non-smooth, which leads to the characteristics of the fault is obscured, so then solve the problem of obtaining a more comprehensive and accurate research and analysis of vibration signals under the noise interference is critical.

In recent years, Sparse Representations (SR) has been widely used in the direction of fault diagnosis, and its core idea is to obtain a small number of basis vectors from an overcomplete dictionary through the corresponding sparse decomposition algorithm, which can characterize the main features of the signal and reduce the data dimensions, so as to overcome the problems of traditional time-frequency analysis methods, such as the low time-frequency resolution, poor adaptability of basis functions, and so on. poor adaptivity and other problems, and has been applied in the direction of target recognition [5], image noise reduction [6], machinery fault diagnosis and so on.SR is usually divided into two steps: constructing a dictionary and learning sparse coefficients. For the computation of sparse coefficients, i.e., sparse decomposition algorithms, they are generally divided into two types: greedy algorithms and relaxation optimization algorithms. Greedy methods are mainly categorized into Matching

Pursuit (MP) [7] and Orthogonal Matching Pursuit (OMP) [8], of which the latter converges faster. Relaxation optimization algorithms mainly include Basis Pursuit (BP), Matrix Factorization (MF) and FOCUSS algorithms. Among the above algorithms, OMP and BP solve sparse coefficients better, so they are widely used.

For the construction of overcomplete dictionaries, they can be roughly categorized into two kinds: analysis dictionaries and learning dictionaries. The predefined analysis dictionaries mainly include Gabor atomic dictionary [9], discrete cosine transform dictionary[10], wavelet dictionary [11], etc. Meanwhile, several of these analysis dictionaries can be combined into a cascade dictionary. However, the construction of predefined analysis dictionaries requires a priori knowledge of the signals and a large number of sample signals for training, and requires the user to artificially select dictionaries based on the different characteristics of different signals. Commonly used dictionary learning algorithms include Maximum Likelihood Estimation (MLE)[12], Method of Optimal Direction (MOD)[13]and Decomposition (K-Singular Value Decomposition, KSVD) [14], and so on. The KSVD adaptive dictionary learning algorithm has received much attention due to its effective application in sparse representations, which was proposed by Aharon et al. in 2006.The KSVD algorithm is not only adaptive, but also very fast, and it has been firstly widely used in the fields of image compression, noise reduction, enhancement, and speech noise reduction, enhancement, and blind separation. In 2014, Chen et al. proposed a cardinality feature extraction method based on the KSVD algorithm to extract the impulse components of vibration signals in a strong noise background, i.e., impulse sparse extraction by adaptive dictionary, and applied it to gearbox fault detection[15].ZHOU H et al. and Wang H et al. proposed shift-invariant dictionary (SID) and shift-invariant-to-K-means VD (KSVD) respectively to to extract the periodic shock characteristics of vibration signals[16,17].A new dictionary learning method [18] called Joint Sparse Model-based Discriminative K Singular Value Decomposition (JSM-DKSVD) has been proposed, which utilizes all the spectra on the local neighborhoods of the labeled training pixels for discriminative dictionary learning, and can generate redundant dictionaries and spatial information with rich spectra.

Based on sparse representation and dictionary learning method, this paper studies the feature extraction and fault diagnosis method of rolling bearings with rolling bearings as the research object. The paper optimizes the existing dictionary learning fault diagnosis methods, and applies the KSVD dictionary learning method, which is optimized by Minimum entropy deconvolution (MED) and clustering, to rolling bearing fault feature extraction.

2. Fundamental principle

2.1. Sparse representation

Sparse representation makes use of the idea of “replacing more with less” to represent the signal. Based on the base atoms of the over-complete dictionary, the sparse representation coefficients that characterize the main features of the signal can be obtained by solving the corresponding sparse target equations through the sparse decomposition algorithm, which achieves the effect of lowering the dimensionality of the data, that is to say:

$$Y = Da + \varepsilon \tag{1}$$

Where Y - vibration signal ($Y \in R$), D - dictionary set ($D \in R^{nxm}$), a - sparsity coefficient ($a \in R^m$), ε - noise ($\varepsilon \in R^n$).

The n distinct atoms in the overcomplete dictionary D are denoted by d_k. The above equation (1) can be expressed as:

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$$Y = \sum_{i=1}^{n} d_k a_k + r \tag{2}$$

The choice of atoms in the overcomplete dictionary is uncertain, so the sparse representation of the original signal possesses more than one result. When the coefficient matrix a has the least number of nonzero entries, the cleanest signal representation in the mathematical model of sparse representation can be obtained. Therefore, the problem of sparse representation is essentially a l_0 paradigm coefficient solving problem as shown in Eq. (3):

$$\min \|a\|_0 \text{ subject to } Y = DA + r \tag{3}$$

2.2. Minimum entropy deconvolution

In 1977, Wiggins proposed the Minimum entropy deconvolution (MED), which is a method that can be used to achieve effective feature extraction in the case of multi-source signal interference. MED is able to optimize the back-convolution of the input signal impulses, and use the design of filters to minimize the entropy of the output signal, thus achieving the improvement of the contrast between the impact and the signal. The contrast between the impact and the signal is improved, so it is highly suitable for dealing with the fault characteristics of certain mechanical parts similar to rolling bearings. Assuming that the input signal x(n) of the system is a sparse sharp pulse sequence with small entropy value, this signal first passes through the system h(n) of linear links, and then is interfered by the additive Gaussian white noise w(n), and the final output z(n) of the system can be expressed as follows:

$$z(n) = x(n) * h(n) + w(n) \tag{4}$$

Because of the dual and combined effects of the linear system h(n) and the additive white noise w(n), the entropy magnitude of the output signal z(n) will be much larger than the entropy magnitude of the input signal x(n). The goal of the algorithm is to find a suitable L-order inverse filter g(l) so that y(n) after the inverse filter is restored to the input x(n),as follows:

$$y(n) = z(n) * g(l) \approx \beta x(n) \tag{5}$$

Where the inverse filter g(l) plays a role in the design process is to recover the original input signal, so that the signal becomes a sparse and well-defined sequence function again, so as to achieve the entropy reduction. In the MED algorithm, the kth order accumulation is usually used as the optimization objective function:

$$O_k(g(l)) = \sum_{i=1}^{N} y^k(i) \Big/ \left[\sum_{i=1}^{N} y^2(i)\right]^{\frac{k}{2}} \tag{6}$$

Usually k = 4 is chosen. For $O_4(y(n))$ to be minimized, its first order inverse $O_k(y(n))'$ is 0, is satisfied:

$$\partial(O_4(g(l)))/\partial(g(l)) = 0 \tag{7}$$

$\partial(y(k))/\partial(g(l)) = z(k-1)$ substitute this into equation (7):

$$\underbrace{\left[\sum_{k=1}^{N} y^2(k) \Big/ \left[\sum_{k=1}^{N} y^4(k)\right]\right] \sum_{k=1}^{N} y^3(k) z(k-1)}_{b} = \underbrace{\sum_{p=1}^{L} g(p)}_{g} \underbrace{\sum_{k=1}^{N} z(k-i) z(k-p)}_{A} \tag{8}$$

Where A is the autocorrelation matrix of the input signal and g is the inverse filter parameter. The specific algorithm flow of this paper using the MED algorithm is as follows:

Step 1: The inverse filter g^0 is initialized and the matrix A is solved at the same time.

Step 2: Solve the output signal $y^{(k)}$ using a non-recursive type filter.

Step 3: Calculate the left term $b^{(k+1)}$ in Eq. (8) and update the parameters $g^{(k+1)} = A^{-1} b^{(k+1)}$.

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Step 4: Calculate the error E(err).

$$E(err) = \left\| g^{(k+1)} - g^{k} \right\|_2^2 \tag{9}$$

When E(err) is greater than the given threshold, return to step two; otherwise, the iteration ends.

In the process of experimental data acquisition, the bearing signal cannot be acquired directly from the bearing seat, but through a cumbersome transfer process, so the acquired signal has a certain degree of error. Here, assuming that the bearing signal acquired by the sensor is z(t), it can be considered to be generated by the convolution of the bearing letter x(t), noise n(t), periodic signal p(t), etc., with the transmission path h(m), denoted as:

$$z(t) = (x(t) + n(t) + p(t)) * h(m) \tag{10}$$

In the processing of the original signal, first of all, through the minimum entropy deconvolution method on the collected signal to reduce the influence of the transmission path on the rolling bearing signal, so as to realize the effective extraction of signal fault characteristics and pattern recognition.

2.3. KSVD Dictionary Learning

By way of description in Section 2.1, assume that the signal to be analyzed is denoted Y , the overcomplete dictionary is denoted D , and the sparse coefficient matrix is denoted A . The problem of sparse representation is essentially to solve the following objective function:

$$\min_a \|a\|_0 \ \text{s.t.}\, Y = DA \tag{11}$$

Eq, $A = [a_1, a_2, \ldots, a_k]^T$. However, directly acquired signals usually contain a noise component, and Eq. (11) cannot directly represent a signal containing noise interference. If the magnitude of the Gaussian white noise error contained in the signal is set to be T and the mean value is 0, then the objective function when the signal contains a noise component is:

$$\min_a \|Da - y\|_2^2 + \mu \|a\|_0 \tag{12}$$

Where μ is the penalty factor. It can be noted that if μ tends to zero, then the error also tends to zero; if μ is larger, then the error becomes larger.

Typically, a set of training data is used for dictionary learning. Assume that the dataset of training samples is Y. There are a total of M training samples in the dataset, which all originate from a common sparse model. In summary, in order to solve the overcomplete dictionary D trained from this set of data, while balancing the signal sparsity and signal representation error, the objective function needs to be solved:

$$\min_{D,a} \sum_{j=1}^{M} \left[\mu_j \|a_j\| + \|Da_j - y_j\|_2^2 \right] \tag{13}$$

Where a_j is the sparsity coefficient of sample y_j by dictionary D, and μ_j represents the relationship between sparsity and error.

3. Fault feature extraction based on MED-KSVD

3.1. Minimum entropy deconvolution parameter selection

The key parameters of MED: higher order statistics order k, optimization algorithm iteration allowable error E and filter order L. Generally, k is taken as 4. During the optimization process, the number of iterations of its algorithm affects the efficiency and accuracy, and the filter order affects the effect of the deconvolution, so we first discuss the optimization selection of the filter

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order L. The MED algorithm is set as follows: k=4, E=0.01, and L=10, 20, 30, 40 respectively for the processing of the simulated signals.

After determining the filter order L, it is necessary to discuss the selection of the iterative allowable error E of the optimization algorithm, set in the MED algorithm: k=4, and take E=0.001, 0.01, 0.1, 1 for the simulated signals, respectively.

3.2. Fault Feature Extraction Process

According to the above section, the flow of the motor bearing feature extraction method based on MED-KSVD dictionary learning is shown in Fig.1:

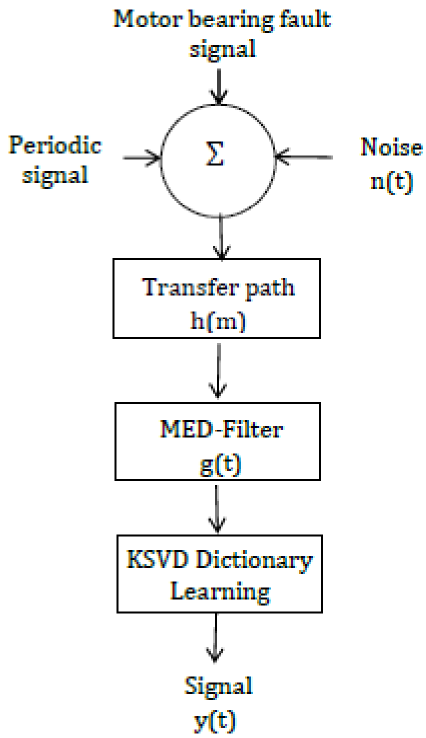


Fig. 1 Flow chart of fault feature extraction based on MED-KSVD dictionary learning

4. Experimental validation

Based on the gearbox vibration data set from Southeast University, the experimental platform is shown in Fig.2, which is mainly composed of six parts, namely, motor controller, motor, planetary gearbox, reduction gearbox, load and load controller. A total of seven vibration sensors, model 608A11, were installed to collect vibration data in the x, y, and z axes of the planetary gearbox and reduction gearbox as well as in the direction of the motor's z-axis, with a sampling frequency of 5,120 Hz. On this experimental platform, vibration data were simulated and collected for different operating states of the motor bearings under different working conditions.

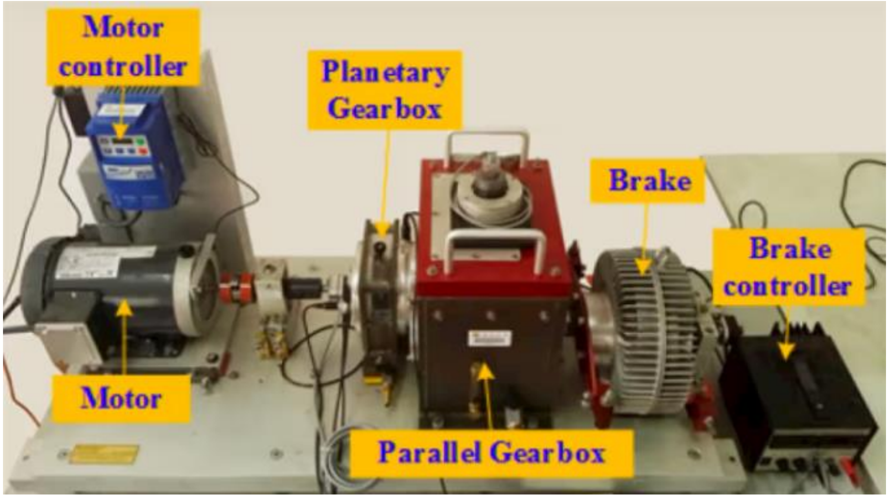
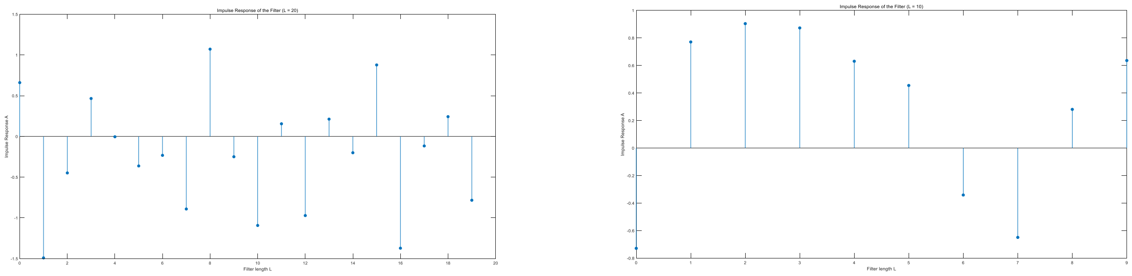
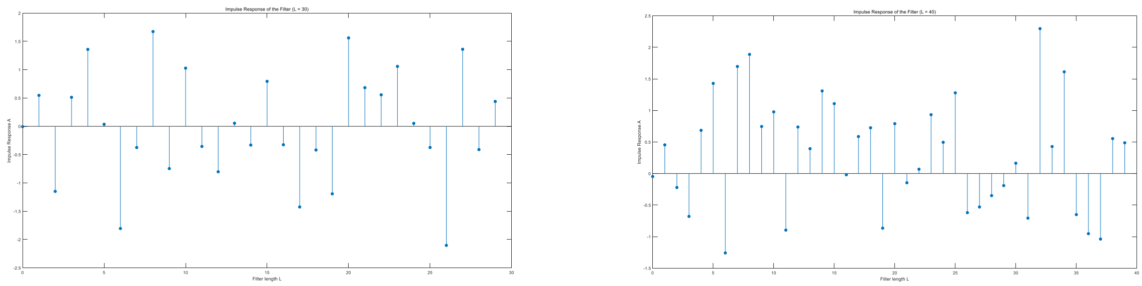


Fig. 2 Experimental platform

Firstly, the optimal selection of filter order L is discussed, and the MED algorithm is set in: k=4, E=0.01, and the simulated signals are processed by taking L=10,20,30,40, respectively. In order to visualize the effect of filter length L on MED, simulated signals are used for simulation analysis.



(a)L=10 (b) L=20



(c) L=30 (d) L=40

Fig. 3 Response of deconvolution signal under different filter length L

From Fig. 3, it can be found that when the filter order L increases, the impulse response of the deconvolution signal of the bearing fault first increases significantly and then decreases gradually. It can be concluded that when the filter order L is within the optimal range, increasing the order L has little effect on the deconvolution of the signal.

Next, the selection of iterative allowable error E of the optimization algorithm is discussed, and the MED algorithm is set: k = 4, L = 30, and E = 0.0001, 0.001, 0.01, 0.1,10 are taken to process the simulated signals, respectively. In order to intuitively observe the relationship between the iterative allowable error and the cliff, the experimental signals are still used for simulation and analysis, and the relationship between the cliff values of the deconvolution signals with different iterative allowable errors E is shown in Table 1.

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Table 1. Kurtosis value of deconvolution signal under different iteration allowable error

The iterative allowable error E	Kurtosis
10	14.6645
1	24.7455
0.1	25.0544
0.01	25.0621
0.001	25.0954
0.0001	25.0954

According to Table 1, it can be seen that when the iterative allowable error precision is higher, the kurtosis value of the deconvolution signal is larger and the extracted signal features are more obvious.When E<0.01, the kurtosis value increases faster; when E>0.01, the kurtosis value increases gently and tends to a stable value.

In addition, it should be noted that when the filter order L is longer or the iterative allowable error E is smaller, the time to be consumed will be longer, which will lead to slow computation time. Therefore, considering the effects of these aspects, this paper takes k = 4 , L = 30 , E = 0.01. The subsequent related values are the same as here.

The experimental signals are first MED filtered, and then dictionary learning is performed using the KSVD algorithm to obtain the dictionary D .

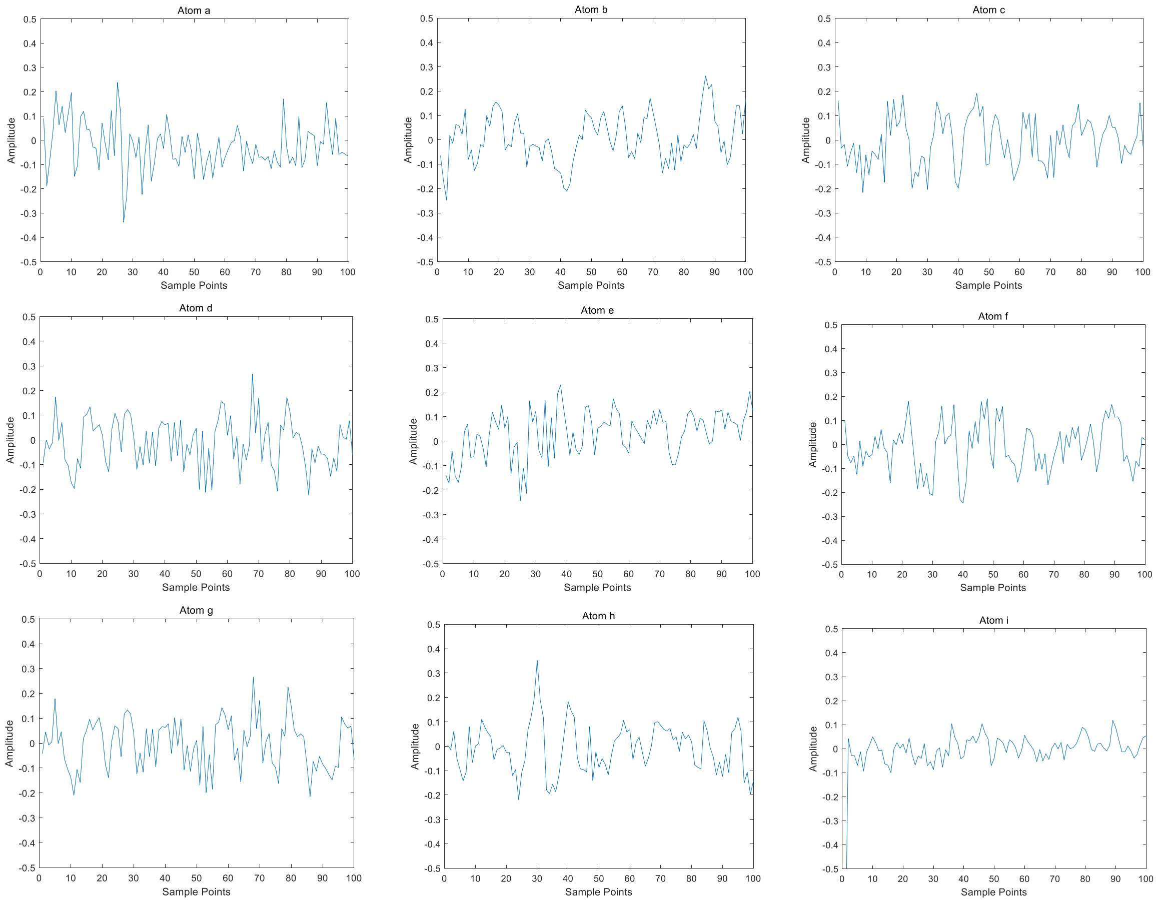

Fig. 4 Schematic diagram of random 9 atoms (MED-KSVD)

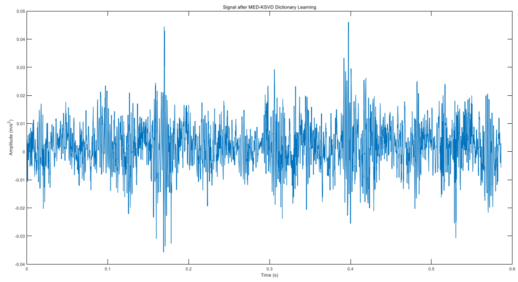

Fig. 5 MED-KSVD noise reduction signal

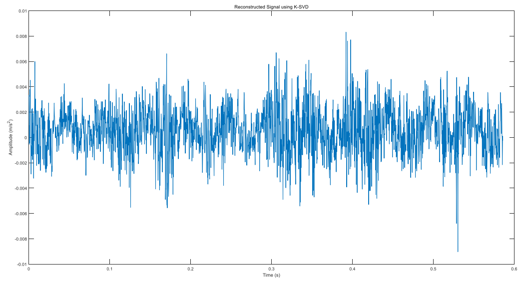

Fig. 6 Initial KSVD noise reduction signal

Fig.4 shows 9 atoms arbitrarily selected from the dictionary D, from which it can be seen that all the atoms contain significant shock features. Therefore, the MED-KSVD dictionary learning method can be more effective in enabling the dictionary to obtain shock components from the original signal than the dictionary obtained by traditional KSVD dictionary learning. The sparsity of the OMP algorithm is set to 1, and the reconstructed signal is obtained by using the dictionary D, as shown in Fig.5. It can be seen that the signal y(t) is processed by the MED-KSVD method to obtain all the transient shock components, and the shock interval can be seen to be 0.0065 s. The OMP algorithm is used to obtain the shock components from the original signal. As can be seen in Fig.6, although the traditional KSVD algorithm and OMP are able to capture some of the shock components, the harmonics and noise interference are more obvious, making some of the shock characteristics masked by the presence of interference.

5. Summary

In this paper, the feature extraction method based on MED- KSVD dictionary learning is mainly investigated.

Firstly, the dictionary learning mathematical model of the signal and the fault model of the motor bearing are introduced and established, and the constructed motor bearing signal is used to adopt an improved dictionary learning method based on MED-KSVD to address the problem that the traditional KSVD method is very susceptible to the influence of noise.

This method utilizes the minimum entropy deconvolution algorithm to reduce the influence of the transmission path on the noise, and then extracts the shock signal features in the signal adaptively by the KSVD dictionary learning method.

Finally, the feasibility of the MED-KSVD method is examined by experimental signals, and by comparing it with the traditional KSVD method, it is proved that the method has an obvious and effective extraction effect in reducing noise.

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