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A Novel Feature Enhancement Method Based on Improved Constraint Model of Online Dictionary Learning

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ABSTRACT Online dictionary learning (ODL) is an emerging and efficient dictionary learning algorithm, which can extract fault features information of fault signals in most occasions. However, the typical ODL algorithm fails to consider the interference of noise and the structural features of the fault signals, which leads to the fault features of weak fault signals that are difficult to extract. For that, a novel feature enhancement method based on an improved constraint model of an ODL (ICM-ODL) algorithm has been proposed in this paper. For the stage of dictionary learning, the elastic-net constraint is used to promote the anti-noise performance of the dictionary atoms. For the stage of signals sparse coding, the $l_{2,1}$ norm constraint is added to learn the structural features of fault signals. In addition, a variational mode decomposition algorithm is used to reduce the impact of noise on the signal initially. Taking the weak fault signals of bearing as examples for analysis, the results show that the feature enhancement of the weak fault signals is fulfilled by using the ICM-ODL algorithm. Compared with the typical ODL method, the ICM-ODL algorithm can not only improves the anti-noise performance of the dictionary atoms, but also removes the noise compositions of the reconstructed signal significantly.

INDEX TERMS Online dictionary learning, sparse representation, elastic-net, $l_{2,1}$ norm, feature enhancement.

I. INTRODUCTION

The health of the rotating machinery directly affects the operation of the industrial production system [1], [2]. Once the rotating machinery fail, they will cause serious economic losses and even casualties [3], [4]. Bearings have an important influence on the performance and efficiency of rotating machinery, about 40% of rotating machinery fault events are caused by bearing faults [5]. Therefore, there is necessity in both social and economic value for condition monitoring and early fault diagnosis of bearings [6], [7]. A notable feature of bearings early fault features is that the impact component is weak and concealed in interference components such as noise, which leads to fault features are difficult to be extracted [8], [9]. In the past few decades, weak fault diagnosis methods have attracted widespread attention in the academic community and researchers have proposed many ways to extract weak fault features. Li [10] *et al.* proposed an adaptive stochastic resonance method based on coupled bistable system, which has good band pass filtering features. Therefore, it is possible to enhance the target signal while suppressing low frequency and high frequency interference information, which making some excellent work for rolling element bearings weak fault diagnosis. Zhang *et al.* [11] proposed a weak feature enhancement method based on empirical wavelet transform (EWT) and an improved adaptive bistable stochastic resonance (IABSR). First, EWT is used to decompose the signal and achieve low-band fault feature enhancement. Then, the component containing the main fault information is processed by IABSR to remove residual noise. Finally, fault features are identified in the Fast Fourier Transform (FFT) spectrum. Chen *et al.* [12] used a convolution

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restricted Boltzmann machine model combined with the shift-invariant features of vibration information to propose a signal reconstruction method for adaptive and unsupervised feature learning, which can effectively suppresses random noise in early faults stage. The above methods succeeded in weak fault features enhancement, but there are still some issues that need to be solved. For example, prior knowledge is difficult to get and the algorithm is computationally intensive. In recent years, as one of the effective methods for extracting weak fault features under strong background noise, sparse representation has been widely used in fault diagnosis of bearings [13], [14], which is almost independent of prior knowledge. Simultaneously, the significance of signal sparse representation lies in that a small number of non-zero values can be used to preserve the impact features in the original signal, simplifying the solution process of signal fault features enhancement [15]. Therefore, the sparse representation method has the potential ability to reduce useless components in the original signal and achieve weak fault diagnosis.

Ren *et al.* [1] proposed a sparse representation method based on Majorzation-Minimization algorithm and completed the feature enhancement of bearing and gear fault signals under the premise of using the unit matrix as a dictionary. Cui *et al.* [13] established a new dictionary model based on the features and mechanism of rolling bearing faults, and combined with matching pursuit algorithm to achieve the features enhancement. In recent years, dictionary learning algorithms have also become a major research direction in the field of sparse representation. In the stage of dictionary learning, the dictionary atoms are updated by learning the feature information of target signal adaptively, combined with the corresponding sparse coding algorithm, the features of the target signal can be extracted, which has higher value of engineering application [16], [17]. The method of directions (MOD) is one of the classical dictionary learning algorithms, which continuously updates the dictionary during the training stage to reduce the residual of the sparse representation and satisfy the convergence conditions. However, the algorithm updates the entire dictionary in every iteration, which will reduce the efficiency of dictionary learning stage [18]–[20]. Subsequently, the K-singular value decomposition (K-SVD) algorithm was proposed to solve this problem, however, although the K-SVD algorithm can update only one column of atoms in once update, the signal SVD process is quite time consuming. It is also inefficient to process signal with a large amount of data [21]–[23]. In recent years, an emerging online dictionary learning algorithm has received extensive attention from scholars, which, currently, is mainly used in the field of image processing [24]–[26]. The algorithm can not only update one column of atoms in once update, but also use a simple operation of a numerical value or matrix to update the dictionary [27]. Therefore, this algorithm can updates the dictionary with higher efficiency and has the potential ability to acquire fault features of bearing.

The VMD algorithm is used to reduce the impact of noise on the signal initially [28], it can be used as a good foundation for the ODL method to extract fault features. However, when the typical ODL algorithm is combined with the VMD algorithm for fault feature enhancement, the dictionary atoms are susceptible to the interference by noise during dictionary learning stage, resulting in false atoms without impact components is produced. Simultaneously, the sparse coding stage lacks the ability to learn signal structure information, so that a large amount of noise composition is still retained in signal after sparse coding stage. All of these caused the typical ODL algorithm cannot effectively fulfill weak fault feature enhancement of bearings. In view of the above problems, this paper adds elastic-net constraints in the dictionary learning stage of the typical ODL algorithm, and block coordinate descent method optimized by pathwise coordinate is used to update the dictionary. Therefore, the improved dictionary learning stage can reduce the interference degree of noise on the dictionary atoms, meanwhile, ensuring the dictionary update efficiency. In the sparse coding stage, it is observed that the $l_{2,1}$ norm has the ability to sparse signals between groups, which matches the block sparse structure of the bearings fault signals [29]. Therefore, this paper proposed ICM-ODL algorithm, and combined with VMD algorithm to complete the feature extraction of bearing weak faults.

The main work of this paper is organized as follows, the theoretical background of typical ODL algorithm is introduced and a new ICM-ODL algorithm is proposed in Section II. In Section III, the weak fault enhancement model based on ICM-ODL algorithm is introduced. Simulation and experiment verification are carried out in Section IV, and the performance of typical ODL algorithm and ICM-ODL algorithm is discussed. The final conclusion is reflected in the Section V.

II. THEORETICAL BACKGROUND

A. BASIC IDEA OF THE TYPICAL ODL

1) DICTIONARY LEARNING STAGE

The constraint model of the typical ODL algorithm in dictionary learning step can be expressed by:

$$\begin{aligned} D_t &= \arg\min \frac{1}{t}\sum_{n=1}^{t}\frac{1}{2}\|Y_n - D\alpha_n\|_2^2 + \lambda\|\alpha_n\|_1 \\ &= \arg\min \frac{1}{t}(\frac{1}{2}Tr(D^T DA_t) - Tr(D^T B_t)) \end{aligned} \tag{1}$$

where:

$$\begin{aligned} A_t &\leftarrow A_{t-1} + \alpha_t\alpha_t^T \\ B_t &\leftarrow B_{t-1} + x_t\alpha_t^T \end{aligned} \tag{2}$$

and then update the j-th column to optimize for (1)

$$\begin{aligned} u_j &\leftarrow \frac{1}{A_{jj}}(b_j - Da_j) + d_j \\ d_j &\leftarrow \frac{1}{\max(\|u_j\|_2, 1)}u_j \end{aligned} \tag{3}$$

where Tr is represents the transpose of the matrix, subscript t represents the number of iteration, $\lambda\|\alpha_n\|_1$ is the constraint used in the sparse encoding stage, refer to equation (1) results, $\lambda \|\alpha_n\|_1$ is no practical significance in the dictionary update stage, A_{jj} is the diagonal element of the matrix A, a_j, b_j and d_j is the j column of matrix A, B and dictionary D_t, respectively. Since no effective constraint is added in the dictionary learning stage, When the fault is weak, the learned dictionary atoms are easily affected by noise, and false atoms without impact components is generated, which is not conducive to learn the impact components of the signal.

2) SPARSE CODING STAGE

The constraint model of the typical ODL algorithm in sparse representation step can be expressed by:

$$\alpha_t = \underset{\alpha \in R^M}{\arg\min} \frac{1}{2} \|Y_t - D_{t-1}\alpha\|_2^2 + \lambda \|\alpha\|_1 \tag{4}$$

where the first term in the formula is the fitting item, the second term is the penalty item. Y_t is the resulting residual signal after t iterations, $D_{t-1} \in R^{N \times K}$ is learning dictionary after $t-1$ iterations, α_t is sparse representation coefficient after t iterations, $\|A\|_2 = \sqrt{tr(A^H A)}$ is the frobenius norm of the matrix, $\lambda \in [0, 1]$ is a parameter that adjusts the degree of sparsity, the larger value of λ, the more value of zero in the sparse representation coefficient and the fewer selected original signal features.

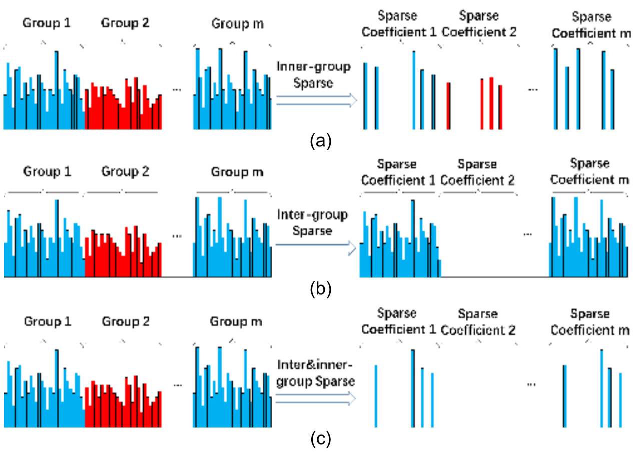

FIGURE 1. Schematic diagram of three signal sparse modes. (a) Inner-group sparse; (b) Inter-group sparse; (c) Inter & inner-group sparse.

Define three nouns in this chapter: The "intra-group sparsity" means the number of non-zero coefficients generated by feature selection within each groups. The "inter-group sparsity" means the number of non-zero groups generated by feature selection between groups. The "Inter-group and intra-group sparsity" means the number of non-zero coefficients generated by feature selection within each non-zero group which generated by feature selection between groups. These three cases are shown in (a), (b) and (c) of Fig 1. The dictionary update and sparse coding stage of the ODL algorithm are alternated. That is fixed dictionary D_t to solves the sparse coefficient α_{t+1}, and then updates the dictionary D_{t+1} with the sparse coefficient α_{i+1}. In this process, if the constraint model of the typical ODL algorithm is used to solve the problem, in each column of the signals will all contain non-zero sparse coefficient, that is, the information in each column of signals is retained [30], only have "intra-group sparsity" characteristics.

B. PROPOSED ALGORITHM OF ICM-ODL

1) DICTIONARY LEARNING STAGE AFTER ADDING ELASTIC-NET CONSTRAINT

Since the typical ODL method does not have a constraint on the dictionary learning stage, when applied it to the extraction of weak fault signal from bearings, the dictionary atoms obtained by learning usually contain noise components, which is not conducive to extract the signal features. Hence, this section introduces elastic-net constraints in the dictionary learning stage to reduce the interference of noise components on dictionary atoms.

The dictionary learning stage of ODL algorithm with elastic-net constraints is as follows:

$$\begin{aligned} u_j &\leftarrow \frac{1}{A_{jj}}(b_j - Da_j) + d_j \\ d_j &\leftarrow \arg\min \|u_j - d\|_2^2 \quad s.t.\ \|d\|_2^2 + \frac{\gamma}{2}\|d\|_1 \leq \varepsilon \end{aligned} \tag{5}$$

and then update the j-th column d_j using the following equations:

$$d_j \leftarrow \begin{cases} u_j & \|u_j\|_1 + \frac{\gamma}{2}\|u_j\|_2^2 \leq \varepsilon \\ \dfrac{sign(u_j)(u_j - \eta)^+}{1 + \eta\gamma} & \|u_j\|_1 + \frac{\gamma}{2}\|u_j\|_2^2 > \varepsilon \end{cases} \tag{6}$$

where parameter η is defined as follows: First define a set $E \leftarrow \{1, \ldots, K\}$, K is the number of columns of dictionary D. Then pick $k \in E$ at random, and divide E into two parts $U = \{j \in E\ s.t.\ |u_j| \geq |u_k|\}$ and $G = \{j \in E\ s.t.\ |u_j| < |u_k|\}$, define $\mu \leftarrow 0; \rho \leftarrow 0; \Delta\rho \leftarrow |U|; \Delta\mu \leftarrow \sum_{j \in U} |u_j| + \frac{\gamma}{2}|u_j|^2$. Update μ, ρ with the following equation (7) until E become an empty set.

$$\begin{cases} if\ \mu + \Delta\mu - (\rho + \Delta\rho)\left(1 + \frac{\gamma}{2}|u_k|\right)|u_k| \\ \quad < \varepsilon\,(1+\gamma\,|u_k|)^2 \quad \mu \leftarrow \mu + \Delta\mu;\ \rho \leftarrow \Delta\rho;\ E \leftarrow G \\ if\ \mu + \Delta\mu - (\rho + \Delta\rho)\left(1 + \frac{\gamma}{2}|u_k|\right)|u_k| \\ \quad \geq \varepsilon\,(1 + \gamma\,|u_k|)^2 \quad E \leftarrow U \backslash \{k\} \end{cases} \tag{7}$$

Finally, $\eta \leftarrow \frac{-b+\sqrt{b^2-4ac}}{2a}$, where, $a \leftarrow \gamma^2\varepsilon + \frac{\gamma}{2}\rho$, $b \leftarrow 2\gamma\varepsilon + \rho$, $c \leftarrow \varepsilon - \mu$.

2) SPARSE CODING STAGE AFTER ADDING $l_{2,1}$ NORM CONSTRAINT

The bearing fault signal has a block structure features. When the bearing fails, the fault signal is divided into equally length blocks, and only a few blocks contain the fault impact features component, and the other blocks are noise or other useless components. So based on the block structure features of the bearing fault signal, this paper proposes new constraints for the sparse coding and the dictionary update step of ODL algorithm. The new sparse coding model constraint is as follows:

$$\alpha_t = \arg\min_{\alpha \in R^M} \frac{1}{2} \|Y_t - D_{t-1}\alpha\|_2^2 + \lambda_1 \|\alpha\|_1 + \lambda_2 \left\|\alpha^T\right\|_{2,1} \tag{8}$$

where, $\left\|\alpha^T\right\|_{2,1} = \sum_{j=1}^{M} \sqrt{\sum_{i=1}^{K} \alpha_{i,j}^2} = \sum_{j=1}^{M} \left\|\alpha_j\right\|_2$ is the $l_{2,1}$ norm of the sparse coefficient (i is the row of matrix α, j is the column of matrix α), which role is to promote the sparsity between columns and columns. Let $\lambda = \lambda_1 + \lambda_2$ is the regularization parameter, $\beta = \lambda_1/(\lambda_1 + \lambda_2)$ is group sparse effect parameter, equation (8) can be written as follows:

$$\alpha_t = \arg\min_{\alpha \in R^M} \frac{1}{2} \|Y_t - D_{t-1}\alpha\|_2^2 + \lambda \left[\beta \|\alpha\|_1 + (1-\beta) \sum_{j=1}^{M} \left\|\alpha_j\right\|_2 \right] \tag{9}$$

where, $\beta \in (0, 1)$, Since the equation (9) is strictly convex, so when solving α_j it can be represented by a subgradients equation:

$$D_{t-1}^T(Y_t - D_{t-1}\alpha_j) = (1-\beta)\lambda u + \beta\lambda v^i \tag{10}$$

where u and v are the subgradients of $\left\|\alpha_j\right\|_2$ and $\left\|\alpha_j\right\|_1$, use α_j^i to represent the i-th variable in the j-th group, then:

$$u = \begin{cases} \alpha_j / \left\|\alpha_j\right\|_2 & \alpha_j \neq 0 \\ \in \{u : \|u\|_2 \leq 1\} & \alpha_j = 0 \end{cases} \tag{11}$$

$$v^i = \begin{cases} sign\left(\alpha_j^i\right) & \alpha_j^i \neq 0 \\ \in \left\{v^i : \left\|v^i\right\|_1 \leq 1\right\} & \alpha_j^i = 0 \end{cases} \tag{12}$$

Solving by simple algebra with equation (10), (11) and (12), then $\alpha_j = 0$ if

$$\left\| sign(D_{t-1}^T r_j)(|D_{t-1}^T r_j| - \beta\lambda)_+ \right\|_2 \leq (1-\beta)\lambda \tag{13}$$

equation (13) is a criterion for determining whether the sparse coefficient of signal is all zero, where r_j is a part of residual of Y_t, $sign(D_{t-1}^T r_j)(|D_{t-1}^T r_j| - \beta\lambda)_+$ is coordinate-wise soft threshold operator.

$$r_j = Y_t - \sum_{l=1, l\neq j}^{M} D_{t-1}\alpha_l \tag{14}$$

when solving α_j^i equation (9) can be represented by a subgradients equation:

$$D_{t-1}^{iT}(Y_t - D_{t-1}\alpha_j) = (1-\beta)\lambda \frac{\alpha_j^i}{\|\alpha_j\|_2} + \beta\lambda v^i \tag{15}$$

then $\alpha_j^i = 0$ if

$$|D_{t-1}^{iT} r_j^i| \leq \beta\lambda \tag{16}$$

where $r_j^i = r_j - \sum_{k=1, k\neq i}^{K} D_{t-1}^k \alpha_j$, D_{t-1}^k is the k-th column of D_{t-1}, α_l^k is the l-th column and k-th row of α, equation (16) is a criterion for determining whether the sparse coefficient of signal is zero.

Therefore, the sparse coefficients solved by the improved sparse model are not only have intra-group sparsity, but also have inter-group sparsity. In other words, it can produce a more sparse solution and filter out redundant components such as noise, so that the features of weak faults are got better enhancement.

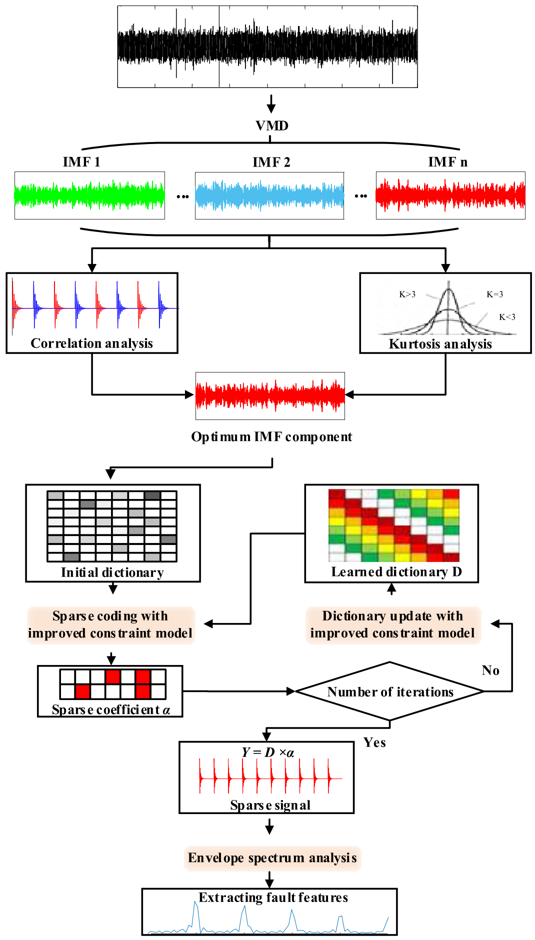

FIGURE 2. Fault feature enhancement strategy.

III. FAULT FEATURE ENHANCEMENT STRATEGY USING ICM-ODL ALGORITHM

As previously explained, it is reasonable to remove redundant components from the data and enhance the weak features by sparse representation, in view of the problem that it is difficult to extract the weak fault features effectively. Therefore, this paper investigates the bearing fault enhancement strategy based on ICM-ODL algorithm. The flow chart is shown in Fig 2. The process is as follows: the VMD algorithm is selected as the preprocessing of the signal. Considering that the correlation coefficient can reflect the extent of the original signal information contained in the IMF components, and the kurtosis can reflect the strength of the impact component energy in the IMF components. So that selecting correlation coefficient and kurtosis as parameters to select the optimal component.

The correlation coefficient and kurtosis formula is as follows:

$$r\langle u_k, Y\rangle = \frac{Cov(u_k, Y)}{\sqrt{Var(u_k)Var(Y)}} \tag{17}$$

where u_k is IMF components, Y is original signal, $Cov(A, B)$ is the covariance of A and B, $Var(B)$ is variance of B.

$$Kur = \frac{1}{Q}\sum_{\mathrm{i}=1}^{N}\left(\frac{u_k - \bar{u}}{\sigma_t}\right)^4 \tag{18}$$

where $\bar{u}$ is the averaged value of IMF components, Q is the length of IMF components, σ_t is standard deviation.

Inspired by structural sparse and constrained dictionary, the convex optimization objective function of sparse coding and dictionary update stage are designed respectively. In the dictionary update stage, the interference of the noise component to the dictionary atom can be reduced. In the sparse coding stage, the obtained reconstructed signal can have both intra-group and inter-group sparsity, further reducing data redundancy and improve the identifiability of fault impact components. Finally, envelope analysis is used to extract fault features. In this study, the outer-race and inter-race faults of rolling bearings are conducted to verify the effectiveness of the proposed method. The comparison experiments show that the performance of the ICM-ODL algorithm is better than the typical ODL algorithm.

The specific implementation steps of the fault feature enhancement model as seen below:

(1) Using the rotating machinery fault test bench to collect the fault signal, the VMD method is used to transform the fault signal to obtain several IMF components.

(2) Selecting the optimal component by correlation analysis and kurtosis criterion, when two parameters of one component simultaneously obtain the largest, this component is the optimal component.

(3) Learning the feature information of the optimal component based on the ICM-ODL algorithm. First, fix the initial dictionary and use LARS algorithm to achieve sparse coding. Then use the sparse coefficient obtained by sparse coding stage as the input of the dictionary update stage, use equation (6) and (7) to update a column of the dictionary and replace the initial dictionary with the updated dictionary, repeat the above process until the number of iterations is reached. Finally, a dictionary that can accurately matches the fault impact features is obtained.

(4) Reconstructing the signal use the learned dictionary and sparse coefficients.

(5) Envelope spectrum analysis of the reconstructed signal, extract the fault features frequency, and judge the types of fault signals.

IV. APPLICATION CASES

A. SIMULATION ANALYSIS AND DISCUSSION

In order to verify the enhancement effect of the proposed method on the impact features, The simulation experiments are carried out in this section. A simulation signal consisting of periodic transient impact and random noise components is constructed. The simulation signal expression is as follows:

$$\begin{aligned} y\left(t_n\right) &= A\left(t_n\right) e^{-2\pi f_n \xi\left(t_n - k\tau\right)} \\ &\quad \times \sin\left[2\pi f_n \times \left(t_n - k\tau\right) + \Phi_0\right] + v\left(t\right) \end{aligned} \tag{19}$$

where n, k are integers, $A\left(t_n\right) = 1$ is the amplitude of n-th impact in the signal, $f_n = 3000Hz$ is the natural frequency, $\xi = 0.1$ is attenuation damping coefficient, $\Phi_0 = 5rad$ is the initial phase angle. In order to get enough fault information, the sampling time is set to 0.4 seconds. $\tau = 0.05s$ is the impact time interval, therefore, the fault features frequency of the constructed simulation signal is 20 Hz, the sampling frequency is 20000Hz. $v\left(t\right)$ is the white noise signal which mainly used to simulate background noise, which parameter value depends on SNR, and the SNR is defined as follows:

$$SNR = 10 \times \log\left(P_s/P_n\right) \tag{20}$$

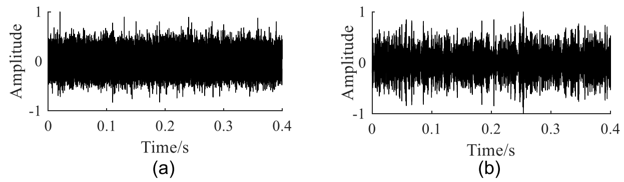

FIGURE 3. Time domain waveform. (a) Simulation signal; (b) optimal IMF component.

TABLE 1. Kurtosis values and correlation coefficients of the IMF components.

Components	u_1	u_2	u_3	u_4	u_5	u_6	u_7
Kurtosis value	3.173	2.973	2.760	3.179	3.732	3.192	2.969
Correlation coefficients	0.007	0.021	0.027	0.071	0.273	0.074	0.023

u_8	u_9	u_{10}	u_{11}	u_{12}	u_{13}	u_{14}
2.905	2.974	2.961	3.242	2.905	3.015	2.896
0.008	0.005	0.003	0.001	0.003	0.001	0.001

Fig. 3(a) shows the time domain waveform of simulation signal after adding −5dB noise and normalization. Decomposing the time domain signal using VMD to get 14 IMF components u_i and calculate the kurtosis value and correlation coefficient of each u_i are shown in Table 1. The kurtosis value and the correlation coefficient of the optimal component are the largest, so u_5 is selected as the optimal IMF component, its time domain waveform is shown in Fig. 3(b).

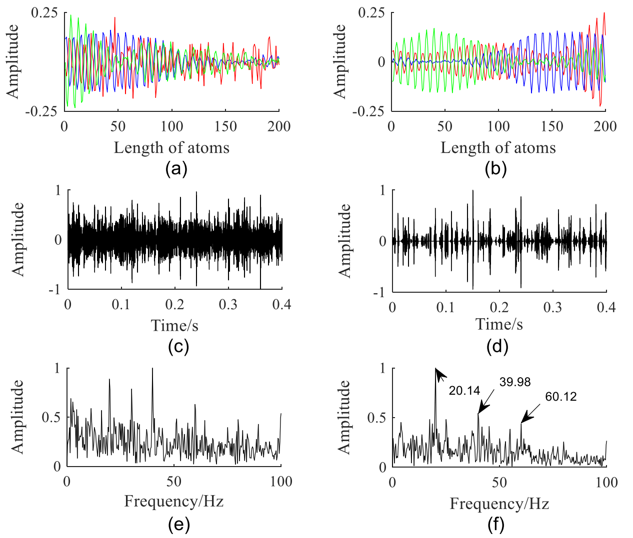

FIGURE 4. Feature enhancement results by typical ODL algorithm (left) and ICM-ODL algorithm (right). (a),(b) waveforms of dictionary atoms; (c),(d) time domain waveform of reconstructed signal; (e),(f) envelope spectrum of reconstructed signal.

Using the typical ODL algorithm to learn the feature information of the optimal component. The random dictionary is selected as the initial dictionary, the number of iterations is set to 400, and in order to make the reconstructed signal as sparse as possible, setting parameters $\lambda = 1$. Set the dictionary atom length to 200, the dictionary atom length should be larger than the length of one impact in the signal. At the same time, the reduction of the dictionary dimension is beneficial to improve the efficiency of dictionary learning. The learned dictionary atoms are shown in Fig. 4(a), obviously the dictionary atoms not only contains the periodic sinusoidal component, but also contains the noise component. Sparse coding and reconstruction of optimal components using LARS algorithm, a reconstructed signal as shown in Fig. 4(c) is obtained, it is easy to see that there is lots of noise components remain in the time domain waveform of the reconstructed signal. The result of the envelope spectrum analysis of the reconstructed signal is shown in Fig. 4(e), the fault feature frequency and its higher harmonics can't be accurately extracted.

Using the ICM-ODL dictionary learning algorithm to learn the feature information of the optimal component. The initial dictionary also uses random dictionary, and the number of iterations is set to 400, in order to make the reconstructed signal as sparse as possible, setting parameters $\lambda = 1$, $\beta = 0.5$, $\gamma = 1$, $\varepsilon = 0.5$. The learned dictionary atoms are shown in Fig. 4(b), obviously the waveforms of dictionary atoms are consistent with the periodic sinusoidal component of the simulated signal and contains impact features. The reconstructed signal is shown in Fig. 4(d), the fault impact component is already evident in the time domain waveform of the reconstructed signal. The result of the envelope spectrum analysis of the reconstructed signal is shown in Fig. 4(f). The fault features frequency and its higher harmonics can be accurately extracted.

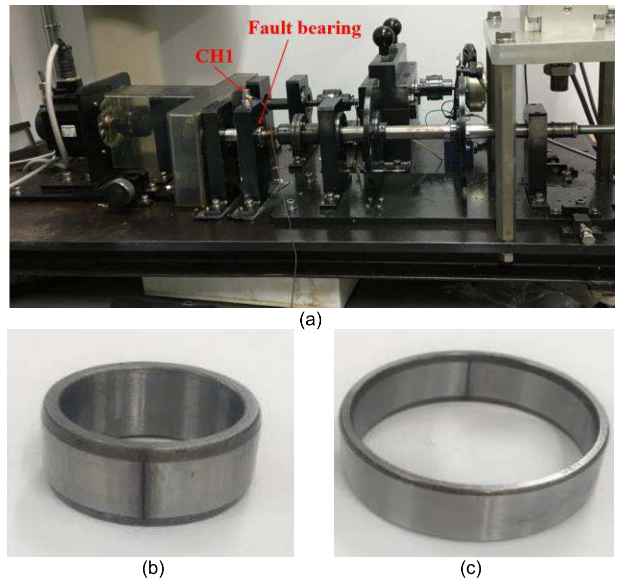

FIGURE 5. Experiment system. (a) Experimental table; (b) inner-race fault of bearing; (c) outer-race fault of bearing.

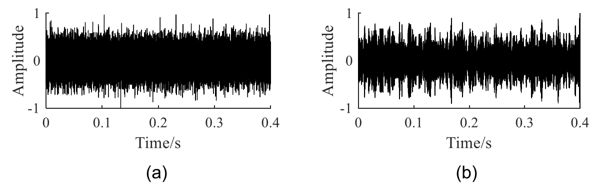

FIGURE 6. Time domain waveform. (a) Bearing outer-race fault signal; (b) optimal IMF component.

B. EXPERIMENTAL VERIFICATION AND DISCUSSION

1) EXPERIMENTAL PLATFORM

In order to verify the ability of the proposed method to deal with the actual weak faults, in this section, the roller bearing is taken as the research object, and the rolling mechanical fault simulation experimental platform shown in Fig. 5(a) was built. The test bench consists of a motor, a cylindrical roller bearing and acceleration sensor composition. An acceleration sensor was installed at the bearing housing CH1 to collect the vibration signal. The fault bearing adopts NTN-N204 cylindrical roller bearing, and an indentation with the width of 0.5mm and the depth of 0.15mm are cut by the wire cutting method in the inner-race and outer-race of the bearing. During this experiment, the operate speed was 1300r/min and the sampling frequency was 100KHz. The fault features frequencies of the outer-race and inner-race of the bearing are calculated to be 86.32Hz and 145.84Hz respectively.

2) DETECTION OF THE BEARING FAULT IN THE OUTER-RACE

Fig. 6(a) is a time-domain waveform of the bearing outer-race fault signal after normalization. Because the fault size is small, the vibration energy is weak, so the impact components in the signal are submerged by other interference components such as noise. Then use the VMD and typical ODL algorithm to process the outer ring fault signal. Parameters selection are

TABLE 2. Kurtosis values and correlation coefficients of the IMF components.

Components	u_1	u_2	u_3	u_4	u_5	u_6	u_7
Kurtosis value	3.053	3.078	2.982	3.007	2.735	3.109	3.038
Correlation coefficients	0.043	0.001	0.001	0.015	0.009	0.002	0.019

u_8	u_9	u_{10}	u_{11}	u_{12}	u_{13}	u_{14}
3.397	3.114	2.805	3.201	3.036	3.105	2.759
0.293	0.054	0.002	0.001	0.022	0.001	0.001

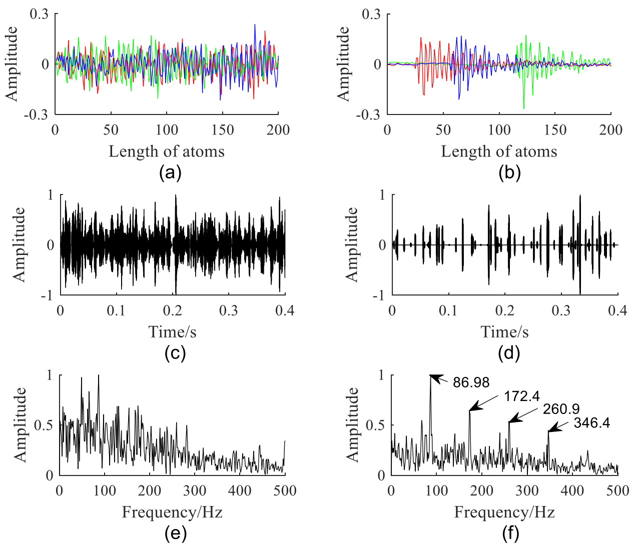

FIGURE 7. Feature enhancement results by typical ODL algorithm (left) and ICM-ODL algorithm (right). (a),(b) waveforms of dictionary atoms; (c),(d) time domain waveform of reconstructed signal; (e),(f) envelope spectrum of reconstructed signal.

as same as simulation analysis. The optimal IMF component selection results are shown in Table. 2 and Fig. 6(b). The waveforms of dictionary atoms can be seen from Fig. 7(a) that the dictionary atoms are greatly affected by noise and the impact features are not obvious. The reconstructed signal is shown in Fig. 7(c), it can be seen that there is also lots of noise components in the reconstructed signal. The result of the envelope spectrum analysis of the reconstructed signal is shown in Fig. 7(e), the fault features frequency and its higher harmonics can't be accurately extracted.

When using the ICM-ODL algorithm to learn the feature information of the optimal component u_8, and parameters selection are as same as simulation analysis. The waveforms of dictionary atoms can be seen from Fig. 7(b) that the impact features in the dictionary atoms are obvious. The fault impact components are already evident in the time domain waveform of the reconstructed signal that shown in Fig. 7(d). The result of the envelope spectrum analysis of the reconstructed signal is shown in Fig. 7(f), the fault features frequency and its higher harmonics can be accurately extracted.

TABLE 3. Kurtosis values and correlation coefficients of the IMF components.

Components	u_1	u_2	u_3	u_4	u_5	u_6	u_7
Kurtosis value	2.917	2.988	3.018	3.091	2.949	3.145	3.151
Correlation coefficients	0.001	0.001	0.001	0.001	0.001	0.002	0.026

u_8	u_9	u_{10}	u_{11}	u_{12}	u_{13}	u_{14}
6.014	4.299	3.079	2.861	2.894	2.873	3.178
0.522	0.083	0.002	0.001	0.003	0.001	0.001

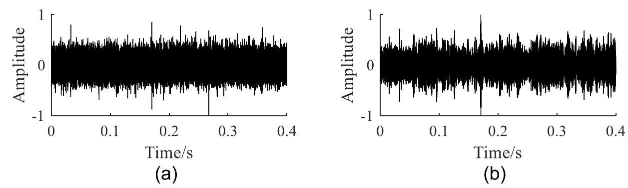

FIGURE 8. Time domain waveform. (a) Bearing inner-race fault signal; (b) optimal IMF component.

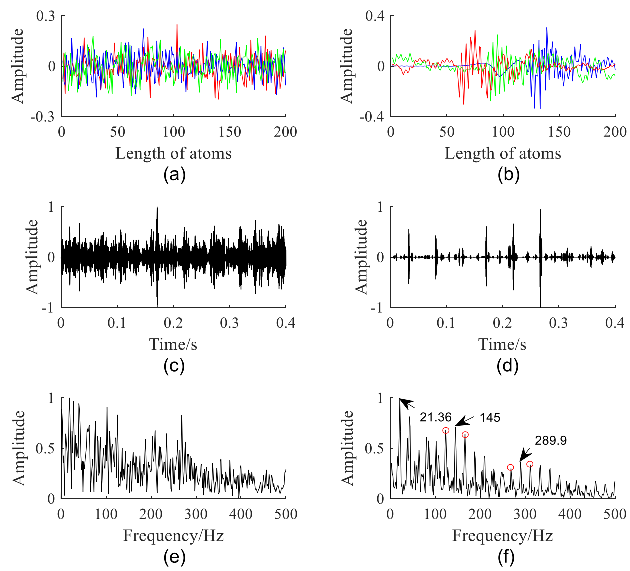

FIGURE 9. Feature enhancement results by typical ODL algorithm (left) and ICM-ODL algorithm (right). (a),(b) waveforms of dictionary atoms; (c),(d) time domain waveform of reconstructed signal; (e),(f) envelope spectrum of reconstructed signal.

3) DETECTION OF THE BEARING FAULT IN THE INNER-RACE

In order to prove the commonality of this method, the experimental verification of the bearing inner-race fault signal is added, and parameters selection are as same as simulation analysis. It can be seen from Fig. 9(a),(c),(e) that when the bearing inner-race fault signal is processed by the typical ODL method, the fault feature frequency is not effectively extracted.

It can be seen from Fig. 9(b), (d), (f) that when the bearing inner-race fault signal is processed by the ICM- ODL method. The fault feature frequency is extracted effectively,

TABLE 4. Time-consuming of MOD, K-SVD, ODL and ICM-ODL algorithms (100 tsets and averaged).

Algorithm	The average of time-consuming
MOD	13.732s
K-SVD	4.376s
ODL	1.680s
ICM-ODL	1.938s

where 21.36Hz is the rotational frequency of the faulty bearing and the part marked with a red circle are side-band frequencies, the reason is that the fault frequency is modulated by the rotational frequency.

4) EFFICIENCY COMPARISON

In this section, the data processing efficiency of MOD, K-SVD, ODL and ICM-ODL algorithms are compared. These four kinds of algorithms are used to process the outer-race fault signal with 40,000 data points, and the number of iterations are all set to 400. the time-consuming averaged of 100 tests is shown in Table 4, it can be seen that the ICM-ODL and the ODL algorithm have higher data processing efficiency than the MOD and K-SVD algorithms.

V. CONCLUSION

In this study, a fault features enhancement method based on ICM-ODL algorithm is proposed. This method adds the $l_{2,1}$ norm constraint in the sparse coding stage, so that the structural information of the bearing fault signal can be learned. For the stage of dictionary learning, the elastic network constraint is added to enhance the anti-noise performance of the dictionary atoms. Compared with the typical ODL method, the ICM-ODL method proposed in this paper has the following advantages: The structural information of the bearing fault signal is incorporated into the sparse coding stage, so that the inter-group sparsity of impact components is promoted. At the same time, the increase of the anti-noise performance of the dictionary atoms makes the impact feature easier to extract. Therefore the ICM-ODL method can remove the redundant information of the data and enhance the fault features effectively. To verify the validity of the ICM-ODL method, simulated and experimental signal based on bearings fault are analyzed. It can be seen from the results that the typical ODL algorithm has limited ability when it is applied to the enhancement of bearing weak fault features. As an improvement, the ICM-ODL algorithm retains the advantages of data processing efficiency of typical ODL algorithm. Simultaneously the ICM-ODL algorithm can capture and enhance the transient impact features of weak signal, and the fault characteristic frequency can be directly extracted from the feature-enhanced signal by using an envelope spectrum analysis method.

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