High-Resolution Signal Reconstruction Method Based on Sparse Structure Preservation

CONG WANG©, CHANG LIU©, AND MENG LIANG LIAO©
Faculty of Mechanical and Electrical Engineering, Kunming University of Science and Technology, Kunming 650093, China
Corresponding author: Chang Liu (liuchang3385@gmail.com)

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ABSTRACT Given the problem that the low sampling period of the servo controller cannot provide high-frequency information for high-precision servo control system state recognition, this paper proposes a high-resolution signal reconstruction method based on sparse structure preservation. The servo system status data is reconstructed to obtain high sampling rate data equivalent to direct measurement, which provides support for extracting system features and status recognition. The main research content of this paper includes verifying the sparseness of the servo control signal, analyzing the consistency of the sparse structure of different sampling rates signals; extracting characteristics based on the combination of empirical mode decomposition (EMD) and principal component analysis (PCA) method. An adaptive sparse dictionary for servo control signals is trained by K-SVD. An objective function is constructed for high-resolution signal reconstruction based on the sparse structure retention properties. It is proved by simulations and experiments that the high-resolution reconstructed signal can be obtained, which is consistent with the high-resolution signal obtained by direct measurement. The method can be used as a reference for the analysis of low-sampling signals of servo control systems of industrial robots and similar equipment and has certain engineering application value.

INDEX TERMS Low sampling servo control signal, sparse structure preservation, feature extraction, high-resolution reconstruction.

I. INTRODUCTION

With the increase in labor costs and the development of manufacturing, industrial robots play an increasingly important role and are widely used in repetitive and continuous work [1], [2]. As the types and use time of industrial robots continue to increase, unplanned downtime and frequent failures of robots result in serious economic losses to enterprises. Therefore, the fault diagnosis of industrial robots is very important to detect the early faults of robots.

Vibration signals and acoustic emission signals are widely used in fault diagnosis of industrial robot systems [3]–[5]. However, due to the complex joint signals of the robot and the complex structure of the reducer, the current fault diagnosis of the robot based on the vibration signal and the acoustic emission signal is not ideal. The reasons include the problems of the vibration and the acoustic emission signal itself, such as the complexity of sensor location installation, high accuracy of acquisition hardware, a large amount of data and prone to faults, etc. [6]. There is also a problem that the vibration signal is greatly interfered by environmental noise, so it is difficult to extract effective features to realize the accurate diagnosis of the robot [7].

Compared with the vibration signal and acoustic emission signal, the servo control signal can be directly obtained from the servo control system, and the signal collection is not limited by the external environment and the collection hardware. However, due to the limitations of the hardware resources of the servo control system, the refresh rate of data acquisition on the servo control system cannot be very high. As a result, the servo control signal obtained is a “lacking signal” with a low sampling rate and part of high-frequency signal components lost. The diagnosis and analysis of equipment based on these “lacking signals” will affect the accuracy of the results.
If the resolution of the collected low-sampling signal can be improved by a certain method, that is, the high-frequency detail components lost in the signal are reconstructed, which will provide better signal characteristics for subsequent fault diagnosis and improve the accuracy of the analysis.

The sparse representation method exhibits powerful problem-solving capabilities in signal processing, image processing, and machine learning [8]–[10]. Sparse representation of different signals can be achieved using a well-designed dictionary [11]. There are many pieces of research on image super-resolution reconstruction based on the sparseness of signals. Yang et al. used the idea of sparse representation to accurately reconstruct the original high-resolution image through joint dictionary learning of high and low resolution, and based on the similarity of sparse representation between high and low-resolution image blocks [12]. Elad et al. optimized the method proposed by Yang et al., using a sparse representation model and K-SVD dictionary training method to achieve super-resolution reconstruction of images [13]. Gao et al. proposed a sparse signal reconstruction method for highly coherent dictionaries. By dividing the dictionary in the preprocessing step, a new matching tracking algorithm was used to solve the reconstruction of hierarchical sparse signals [14]. Zhao et al. proposed a signal reconstruction algorithm for sequential equivalent time sampling. The sparseness of the signal was exploited, and the compressed sensing theory was used to reconstruct the signal from sub-Nyquist samples captured by the sequential equivalent time sampling system [15].

II. BACKGROUND

A. SPARSE STRUCTURE RETAINS PROPERTIES

Assuming that the signal $x_h$ is high resolution, the low-resolution signal $y_l$ is obtained by down-sampling the high-resolution signal $x_h$, and the signal downsampling process can be expressed as

$$y_l = Sx_h$$  \hspace{1cm} (1)

where $S$ is the downsampling factor.

Within a certain constraint, the low-resolution signal $y_l$ and the high-resolution signal $x_h$ have approximately uniform sparse structures in the sparse space. This property is called the sparse structure retention property. The goal of this paper is to hope that the signal $\hat{x}_h$ can be obtained by reconstructing $y_l$, as close as possible to the original high-resolution signal $x_h$.

Assume that the high-resolution signal $x_h$ can be sparsely represented on the dictionary $D_h \in R^{m \times m}$, that is

$$x_h = D_hq$$  \hspace{1cm} (2)

where $q \in R^m$ is a sparse coefficient with only $k(k \ll m)$ non-zero coefficients and $q$ is the sparse representation coefficient of $x_h$ on $D \in R^{n \times m}$. Then the low-resolution signal $y_l$ corresponding to $x_h$ can be expressed as

$$y_l = Sx_h + v = SD_hq + v$$  \hspace{1cm} (3)

$$\|y_l - SD_hq\|_2 \leq \epsilon$$  \hspace{1cm} (4)

where $v$ is the noise signal, $\epsilon$ is small enough and is related to the power of the noise signal.

It can be seen from the above formula that according to the sparse structure-preserving property of the signal, within the error range $\epsilon$, the sparse representation of the low-resolution signal $y_l$ in the dictionary $D_l$ is approximately the same as the sparse representation of the high-resolution signal $x_h$ in the dictionary $D_h$, as shown in Fig. 1. As long as the dictionary...
pair \( \{D_h, D_l\} \) can be obtained, for the low-resolution signal \( y_l \) that needs to be reconstructed, the first choice is to get the sparse representation \( q \) under the dictionary \( D_l \), and then multiplied it with the dictionary \( D_h \) to obtain the high-resolution signal \( \hat{x}_h \). The obtained high-resolution signal \( \hat{x}_h \) is used to approximate the original high-resolution signal \( x_h \).

The key to the high-resolution reconstruction method of low-sampling signals is to build an overcomplete dictionary pair containing rich structure and information and to design an accurate over-complete sparse representation algorithm.

**B. SPARSENESS OF SERVO CONTROL SIGNALS**

Given a finite-length signal \( x \in \mathbb{R}^{n \times 1} \), if there are at most \( k \) non-zero atoms in the signal, that is

\[
\|x\|_0 = \sum_{i=1}^{n} |x_i|^0 \leq k \tag{5}
\]

Then the signal \( x \) is called a sparse signal. We stress that this \( l_0 \) norm is not a norm as it does not satisfy the positive homogeneity and subadditivity of the norm. It merely is the number of nonzero entries in \( x \). This concept is very intuitive. More precisely, signal \( x \) is sparse if there is a basis \( D \) that can sparsely represent \( x: x = D\theta \), where \( \theta \) is a \( k \)-sparse vector that retains the largest \( k \) term of \( \theta \). The premise of the sparse structure retention property is that the signal has sparseness. The servo control signal of the research object in this paper is not sparse itself, but if the signal can be sparsely transformed under a certain basis, the low-sampling servo control signal can be reconstructed using the sparse structure retention property.

The servo control current signal was collected through experiments. The sampling frequency is 256 Hz and the number of sampling points is 2048. The signal is sparsely represented using the DWT transform basis, as shown in Fig. 2. It can be seen from Fig. 2 that compared with the original current signal, the current signal on the DWT basis has better sparsity.

**III. SIGNAL HIGH-RESOLUTION RECONSTRUCTION**

The high-resolution signal reconstruction method based on sparse structure preservation is mainly divided into two steps: dictionary learning and signal reconstruction.

1. Dictionary learning steps: First, the high- and low-resolution signal pairs of the signal are given and preprocessed. To reduce the influence of the distorted signal on dictionary learning, the feature extraction method of the low-sampling signal which has a greater influence on the reconstruction effect is very important. To extract local features corresponding to high-resolution signals as much as possible, feature extraction is performed on low-resolution signals, and feature signals of different time scales representing low-sample signals are combined into a data set. Then, the high- and low-resolution signals are formed into training sample data set pairs, and the dimensionality reduction processing is performed on the low-resolution signals to reduce the calculation amount of the subsequent dictionary learning and
reconstruction process. Finally, the dictionary learning process is completed by using the dictionary learning algorithm, and the sparse representation vector and the low-resolution dictionary are obtained. According to the consistent property of the sparse representation vector of the two signals, the high-resolution dictionary is obtained by solving the least-squares optimization problem, and the high-resolution dictionary pair is finally obtained.

Compared with the traditional complete dictionary (DCT, Gabor dictionary), the K-SVD dictionary can adaptively extract features according to the training set, so its sparse representation ability is relatively strong. Therefore, this article quotes the K-SVD dictionary learning algorithm proposed by Aharon et al. [18] and uses the alternate iteration method to solve the problem, which can realize the simultaneous update of the dictionary and the sparse coefficient. Sparse representation vector \( q \) and low-resolution dictionary \( D_l \) can be obtained by using the k-SVD algorithm to complete the dictionary learning. The OMP method is used for sparse coding of each sample to obtain the sparse representation vector of low-resolution signal, which is then multiplied by a high-resolution signal data set to obtain a high- and low-resolution dictionary pair.

Suppose the training sample set \( T = \{P_l, P_h\} \), where \( \{P_l, P_h\} \) is the low-resolution signal sample set, \( \{P_h, P_{h2}, \ldots, P_{h4}\} \) is the sample set of the high-resolution signal corresponding to \( P_l \). Then the specific steps of the K-SVD algorithm are

Step 1 Dictionary initialization, using \( m \) randomly selected samples to construct \( D_h \in \mathbb{R}^{n \times m} \).

Step 2 Sparse coding, using the OMP algorithm to calculate the sparse coefficient, namely

\[
\text{min}_{q_l} \| P_l - D_l q_l \|_2^2 \quad \text{s.t.} \quad \| q_l \|_0 \leq m, \quad i = 1, 2, \ldots, n \tag{6}
\]

Step 3 Dictionary update, need to update the \( j \)th column \( d_j \) of the dictionary and the \( j \)th row \( q_j \) of the sparse matrix \( q \), then the dictionary update formula is

\[
\| P_l - D_l q \|_F^2 = \left( P_l - \sum_{j=1}^{m} d_j q_j^T \right) \|_F^2
\]

\[
= \left( P_l - \sum_{j \neq j_0} d_j q_j^T \right) \|_F^2 - \sum_{j=1}^{m} d_j q_j^T \|_F^2
\]

\[
= E_j - \sum_{j=1}^{m} d_j q_j^T \|_F^2 \tag{7}
\]

where \( E_j \) is the decomposition error after removing the atom \( d_j \). Assume that \( w_j \) is a non-zero index of \( q_j \), namely

\[
w_j = \left\{ i \mid 1 \leq i \leq m, \quad q_j^T (i) \neq 0 \right\} \tag{8}
\]

The matrix \( \Omega_j \in \mathbb{R}^{n \times |w_j|} \) is 1 at \( (w_j (i), i) \), and 0 in the rest. Only select the column corresponding to \( \Omega_j \) to restrict \( E_j \), and get the matrix \( E_j^R = U \Delta V^T \) by SVD, thereby updating the dictionary atom \( d_j = u_1 \) and the sparse representation \( q_j = \Delta [1, 1] \cdot v_1 \).

Step 4 The stop condition limits the number of iterations. The empirical value of the number of iterations obtained in the experiment is 40.

According to the obtained sparse representation \( q_k \), the matrix \( Q \) is formed by columns, and the high-resolution dictionary formula is

\[
D_h = \arg \min_{D_h} \sum_k \| P_h^k - D_h q_k \|_2^2
\]

\[
= \arg \min_{D_h} \sum_k \| P_h - D_h Q \|_F^2 \tag{9}
\]

The above formula can be simplified as

\[
D_h = P_h Q^T = P_h Q^T \left( Q Q^T \right)^{-1} \tag{10}
\]

2. Signal reconstruction steps: First, feature extraction is performed on the input low-resolution signal. In this paper, the EMD method and PCA method are combined to extract the feature of the signal. The input low-resolution signal is distorted due to the low sampling frequency. The main information carried in the signal is hidden in the noise. At this time, it is necessary to filter out the specific band frequency or interference information in the signal to suppress the influence of noise and irrelevant signals on the reconstruction process. The EMD method adaptively decomposes the low-resolution
FIGURE 3. High-resolution reconstruction algorithm flow chart of the low-sampling signal.

signal into a series of stable time-domain signals from high frequency to low frequency. The IMF components representing the characteristic signals of different time scales of the low-sample signal are formed into a data set, and the residual signal containing the lowest frequency component is removed to obtain the characteristic information related to the high-frequency signal; considering the impact of the increase in the amount of data on the reconstruction process, the PCA method is used to perform a data set composed of data segments dimensionality reduction processing. Then, the low-resolution dictionary obtained in the dictionary learning step and the orthogonal matching pursuit OMP method is used to obtain the sparse representation vector of the low-resolution signal, and the reconstructed high-resolution signal data segment is solved according to formula (2). The flow chart of the high-resolution reconstruction algorithm of the low-sampling signal is shown in Fig. 3.

Given a low-resolution signal $y_l$ that will be used for testing. It is assumed that it is obtained by down-sampling the high-resolution signal $x_h$. Considering that the data length of the signal is long, the signal is segmented in actual processing. The following are the steps of the high-resolution reconstruction test algorithm for low-sampling signals:

Step 1 Input the low-resolution signal $y_l$ to be tested.

Step 2 The $y_l$ is preprocessed and decomposed by the EMD method, and extract F IMF components that are highly correlated with the original signal to reduce the impact of uncorrelated or low-correlation signals on the subsequent reconstruction process.

Step 3 The data segment is extracted at the position of $k$ in $F$ signals, and the length of each data segment is $n$. Ensure that there is a certain overlap between data segments to avoid loss of low-resolution signal feature information, and these overlapped parts can improve the quality of the reconstructed signal. $F$ data segments at the same position are connected to form a data segment vector $\hat{p}_k$, and a vector set $\{\hat{p}_k\}_F$ is obtained.

Step 4 The PCA algorithm is used to reduce the dimension of the vector set $\{\hat{p}_k\}_F$ to obtain the vector set $\{p_k\}_F$.

Step 5 Orthogonal matching pursuit (OMP) algorithm is used to sparsely encode the vector set $\{p_k\}_F$ to obtain the sparse representation vector $\{q_k\}_F$.

Step 6 The high-resolution dictionary is multiplied by the sparse representation vector to get the high-resolution data segment $\{\tilde{p}_k\}_F = (D_0 q_k)_F$.

Step 7 The final high-resolution data is reconstructed by placing $\tilde{p}_k$ in the correct position, averaging the overlaps, and adding $y_l$.

IV. ANALOG SERVO CONTROL SIGNAL VERIFICATION
A. DICTIONARY TRAINING

Construct a current signal to simulate the controller signal, the signal frequency is 50Hz, the stator current of the motor is modulated, and there is a side frequency near the fundamental frequency. Simulate the motor structure and power supply harmonic interference in the signal, and the motor stator current has a multiple of the power supply frequency. The inner ring, outer ring, rolling element, and cage of the motor bearing are faulty. There are four kinds of fault characteristic frequencies in the current signal. The specific parameters are shown in Table 1. The function expression of the analog current signal is

$$x_h = \sum_{i=1}^{7} a_i \sin(2\pi f_i t) + \sum_{i=8}^{10} a_i \sin(2\pi f_i t) * a_1 \sin(2\pi f_1 t)$$

(11)
where $a_i$ is the signal amplitude; $f_i$ is the different frequency of the signal.

The time-domain waveform of the analog current signal $x_h$ is shown in Fig. 4(a), and its Fourier transform is used for spectrum analysis as shown in Fig. 4(b). It can be seen that there are obvious peaks at the fundamental frequency and the fault frequency, and the side frequency and the double frequency appear at the frequencies $f_1 \pm 0.12f_1$, $nf_1 (n = 2, 3, 4)$.

According to the algorithm proposed in this paper, first, the low-resolution dictionary is trained for the analog signals. In the dictionary learning process, the signal is segmented according to the algorithm requirements. The data size of each segment is 256. Under the conditions of ensuring that the signal is as distorted as possible and the algorithm reconstruction indicators in this paper are good, the lower sampling factor $S = 32$ is set through a large number of data verification and experience summary. The analog signal is down-sampled with this down-sampling factor to obtain the low-sampling signal. The EMD decomposition of the low-sampling signal yields 6 layers of IMF components and extracts the first 5 layers of IMF components with a large correlation coefficient with the original signal. In the case of ensuring signal energy retention of 99.9%, the PCA method is used for dimensionality reduction to reduce the signal size from $256 \times 256$ to...
FIGURE 7. Curves of reconstruction index of different feature extraction algorithms. (a) MSE comparison chart. (b) SNR comparison chart.

FIGURE 8. Comparison of reconstructed signal and the original high-resolution signal. (a) High-resolution signal waveform. (b) The waveform comparison chart of the reconstructed signal and the original high-resolution signal. (c) Low-resolution signal waveform. (d) The spectrum comparison of the reconstructed signal and the original high-resolution signal.

According to experience, the atomic number of the training dictionary is 40, and the iteration number of the K-SVD algorithm is 90. The high/low-resolution dictionary obtained through learning is shown in Fig. 5, and the first 10 atoms in each dictionary are compared.

By comparing and analyzing the atoms of the trained high/low-resolution dictionary, it can be seen from Fig. 5 that the amount of information containing the original signals in the two dictionary atoms is different. The high-resolution dictionary atoms contain more feature information and are closer to the original high-resolution signal.

B. SIGNAL TEST
To test the reconstruction effect of the high- and low-resolution dictionary obtained by training, an analog signal composed of 3 signal frequencies is constructed as a high-resolution signal in the test process. The functional
The expression of the signal is

$$y_h = \sum_{i=1}^{3} a_i \sin (2\pi f_i t) + a_6 \sin (2\pi f_6 t)$$  \hspace{1cm} (12)

The signal $y_h$ is down-sampled to obtain the test signal $y_l$, and its time-domain waveform and frequency spectrum are shown in Fig. 6. It can be seen that there are three kinds of frequency components in the test signal, the fundamental frequency, the side frequency, and the fault frequency.

To evaluate the reconstruction accuracy of the signal, the mean square error (MSE) and signal-to-noise ratio (SNR) are selected as evaluation indicators in this paper. MSE reflects the difference between the original signal and the reconstructed signal, and the smaller the value, the closer the reconstructed signal is to the original high-resolution signal; SNR reflects the energy-to-noise ratio of the signal to noise. The larger the value, the closer the reconstructed signal is to the original high-resolution signal.

As shown in Fig. 7, it can be seen that under the condition of ensuring the loss of high-frequency components in the low-resolution signal, the reconstruction indexes of different algorithms under different down-sampling rates are very different. Overall, the MSE in Fig. 7(a) increases with the downsampling rate. This is because the information of the original signal obtained under the high and low sampling rate is less, which leads to a worse reconstruction effect. Compared with the wavelet packet decomposition (WPD) algorithm and the singular value decomposition (SVD) algorithm, the signal MSE of the EMD algorithm after reconstruction is lower. In Fig. 7(b), the SNR decreases with the increase of the downsampling rate. The SNR of the signal after reconstruction by the EMD algorithm is better. Although the WPD algorithm has the best SNR at a downsampling rate of $S = 28$, the SNR of the reconstructed signal is poor at other downsampling rates. The comprehensive analysis shows that the EMD algorithm is superior to the other two algorithms.

The method presented in this paper is used to reconstruct the low-resolution signal and the comparison between the reconstructed signal and the original high-resolution signal is shown in Fig. 8. The original signal frequency of 177Hz in Fig. 6(b) cannot be identified by Fourier transform, and only the aliased frequency of 79Hz can be obtained. It can be seen in Fig. 8(d) that the original signal frequency has been reconstructed successfully. The above analysis shows that the signal quality reconstructed by the algorithm in this paper is better and the comprehensive reconstruction efficiency is higher.

The traditional reconstruction method for low-resolution signals with the reduced size is to use scale amplification to restore the original signal, as shown in Fig. 9 is the time-domain waveform comparison and spectrogram of the

**TABLE 1. Current signal parameter table.**

| Parameter | Sampling frequency $f_s$/Hz | Sampling points/N | Fundamental frequency $f_1$/Hz | Side frequency $f_{5,3}$/Hz | Failure frequency/Hz | Frequency doubling/Hz |
|-----------|----------------|------------------|-----------------|----------------|------------------|------------------|
| Value     | 8192          | 8192             | 50              | $f_1 \pm 0.12f_1$ | 177              | 100              |
|           |               |                  |                 |                 | 134              | 150              |
|           |               |                  |                 |                 | 235              | 200              |
|           |               |                  |                 |                 | 89               |                  |
|           |               |                  |                 |                 |                  |                  |

**FIGURE 9.** Time-domain waveform comparison and spectrogram of cubic interpolation amplification. (a) Comparison of the original signal with the cubic interpolated amplified waveform. (b) The cubic interpolated signal spectrum diagram.

**FIGURE 10.** Test bench for simulating the single-joint motion of industrial robots.
signal after cubic interpolation and amplification. The signal reconstruction MSE based on the cubic interpolation amplification method and the method in this paper are 0.75 and 0.27, and the SNR is 1.23 and 5.74, respectively. From the evaluation index, this method has better reconstruction quality. Comparing Fig. 9(b) and Fig. 8(d), it can be seen that the frequency information of the original signal in the spectrum of the cubic interpolated signal cannot be reconstructed. Therefore, compared with the traditional low-resolution signal reconstruction method, the method in this paper has better reconstruction effects.

V. EXPERIMENTAL SIGNAL VERIFICATION

In this paper, the method is further verified through experiments, and the experimental data collected on a test bench for simulating a single-joint motion of industrial robots. The test bench is composed of servo drives, AC servo motors, gearboxes, encoders, articulated arms, and bases, as shown in Fig. 10.

In the test, a current sensor is used to collect the three-phase current signal when the main joint servo motor is working. The speed of the AC servo motor is 500rpm, the reduction ratio of the reducer is 10, the sampling frequency is 256Hz, the number of sampling points is 2040 points, and the ZHTK25 open-close current transformer is used to collect the three-phase current signal of the servo motor. The collected three-phase current signal data is used as the training set, first, dictionary training is carried out to obtain a sparse dictionary with high- and low-resolution transforms. Then a set of data is randomly selected as test data to verify the validity of the method in this paper. The original sampling frequency of the test data is 256Hz. To simulate the process of obtaining a low sampling signal by servo controller, and to make the original signal as distorted as possible and the reconstruction effect is the best. Through experimental verification and experience summaries, the low-resolution signal with a sampling frequency of 12.8 Hz and a sampling point of 102 points is obtained by setting the signal down-sampling rate to $S = 20$.

The method presented in this paper is used to reconstruct the low-sampling current signal, and the algorithm SNR and MSE are 1.5 and 0.26 respectively. It can be seen
from Fig. 11(b) and (d) that the time-domain waveform of the current signal is better reconstructed within the error range.

The algorithm in this paper reconstructs the signal based on the sparse structure-preserving property. To obtain the down-sampling boundary conditions that meet the needs of signal reconstruction, the corresponding signal MSE curves of different lower sampling rates are compared, as shown in Fig. 12. It can be seen that as the down-sampling rate increases, the amount of data in the signal decreases, and the degree of signal distortion increases, MSE also increased accordingly.

Here, 15% is regarded as an ideal reconstructed signal, and 30% or more is regarded as an almost unusable reconstructed signal. When the down-sampling rate is within 16 and the E-MS of the algorithm in this paper is within the ideal range, the down-sampling rate $S$ corresponding to the signal can be accurately reconstructed ranges from 1 to 16. At the same time, the sampling frequency range of the low-sampling signal that does not satisfy the Nyquist sampling theorem is $0 \sim 2f_m$ ($f_m$ is the maximum frequency of the high-resolution signal). Therefore, the sampling frequency range of the low sampling signal used for reconstruction is $f_s/16 \sim 2f_m$ ($f_s$ is the sampling frequency of the high-resolution signal), which means that the lowest signal sampling frequency that can be reconstructed in this paper is the sampling frequency of the high-resolution signal /maximum down-sampling rate ($S = 16$).

Experimental results show that as the sampling frequency of the signal decreases, the MSE of the signal gradually increases. Since the given low-sampling signal has different degrees of distortion, the application range of this algorithm can be obtained by analyzing the MSE curve of the signal at different downsampling rates. When the sampling frequency is $f_s/16 \sim 2f_m$, this algorithm can effectively reconstruct the motor current signal and obtain the corresponding frequency information in the time domain waveform, which has a more reliable application value.

VI. CONCLUSION

In this paper, the sparse structure-preserving property is introduced into the reconstruction process of low-sampling signals, and a high-resolution signal reconstruction method based on sparse structure preservation is proposed. This method accurately reconstructs the original low-resolution signal by using feature extraction and dictionary learning algorithms. Experimental and simulation results show that the high-resolution signal reconstruction method based on sparse structure preservation can be used for accurate reconstruction of low-sampling current signals. Under the current background of big data and the high efficiency of industrial robots, the method proposed in this paper is easy and fast to implement, which alleviates the difficulties of data collection limited by software and hardware conditions and large transmission volume. However, the high-resolution reconstruction of other different types of servo control signals needs further research, so that the method in this paper is universal f-or the reconstruction of such servo control signals.

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CONG WANG was born in Shaanxi, China, in 1992. She received the bachelor’s degree in mechanical engineering from the Xi’an University of Architecture and Technology in 2015. She is currently pursuing the master’s degree with the Faculty of Mechanical and Electrical Engineering, Kunming University of Science and Technology. Her research interests include compressed sensing and fault diagnosis.

CHANG LIU received the Ph.D. degree in engineering from the Faculty of Mechanical and Electrical Engineering, Kunming University of Science and Technology, in 2017. He is a member of the Fault Diagnosis Professional Committee, Chinese Society of Vibration Engineering. In the past five years, he has hosted or participated in several scientific research projects and published more than ten articles. His current research interests include signal processing theory and methods, compressed sensing and sparse representation, and machinery fault diagnosis.

MENGLIANG LIAO was born in Hunan, China, in 1996. He received the bachelor’s degree in mechanical engineering from the Kunming University of Science and Technology in 2018, where he is currently pursuing the master’s degree with the Faculty of Mechanical and Electrical Engineering. His research interests include deep learning and fault diagnosis.