Based on K-SVDDictionary learning algorithm of sparse said vibration signal compression measurement Reconstruction Methods

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Abstract: For the current mechanical vibration signal band more and more wide basis traditional Shannon-In quest sampling theorem data collection of an arcane will get big vibration data the storage, transmission and processing bring difficult of problem put forward. Based on K-SVDDictionary learning algorithm of sparse said vibration signal compression measurement reconstruction methods. First analysis the vibration signal in based on K-Singular Value Decomposition (K-Singular Value decomposition K-SVD) Dictionary learning algorithm get of over-complete dictionary on the approximate sparse of CAN compression; then use Gaussian random matrix of vibration signal the compression measurement; finally based on compression measurements the orthogonal Matching Pursuit algorithm the original vibration signal the reconstruction. Simulation Test results show that when vibration signal compression ratio in 60%~90% When based on K-SVDDictionary learning algorithm structure of over-complete dictionary than based on discrete cosine over-complete Dictionary Compression sensing reconstruction relative error small. The methods not only can get is high signal compression ratio and has accurate of Signal Reconstruction performance in don't lost vibration information of situation under greatly reduce the original vibration data.

Keywords: Vibration signal; over-complete dictionary; sparse representation; compression perception; Accurate

Intersection dictionary has a strong non-correlation. 2011Year, Candes[16] It is pointed out that it is still possible to recover the compressed measurement signal with the measurement matrix formed by independent and identically distributed Gaussian random variables and any supper complete dictionary. Wang Yi It satisfies the perceptual matrix formed by sparse representation system when it is a Gaussian random matrix. Rip And has a smaller constraint isometric constant Wang Yi. In this paper, the classical Gaussian random matrix is used as the Compressed Sensing Measurement Matrix. The data transmission part mainly contains all kinds of wired and wireless data transmission network. Y Transfer to the remote monitoring center. The data processing part is based on the over complete dictionary. DR econstruction of vibration signals. Based on the factors such as low computational complexity, short running time, high reconstruction accuracy and easy implementation, orthogonal Matching Pursuit Algorithm (Orthogonal Matching Pursuit, OMP)[17] As compressed Sensing reconstruction algorithm. Measured value over the data transmission network Y After transmission to the remote monitoring center, K-SVDA lgorithm[18] Yes, already.

Dynamic signal training get over complete dictionary DAs a sparse way of vibration signals, while using OMP Reconstruction Algorithm finally gets the reconstructed Vibration Moving Signal F For analysis and diagnosis by remote monitoring center staff.

Vibration Signal F The sparsity or compressibility of the signal is an important prerequisite and theoretical basis for compressive measurement. In recent years, the common sparse dictionary is mainly orthogonal basis dictionary. Because the dictionary Sparse Mode can not be flexible enough to represent the complexity of vibration signal, the vibration signal can not be sparse enough in this Sparse Mode, which affects the reconstruction accuracy of Vibration

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Signal Compression measurement. At present, the construction of non-orthogonal over-complete Dictionary Based on optimized learning algorithm is widely concerned. The over-complete dictionary can accurately sparse represent signals and improve the reconstruction accuracy of compressed measurement. Commonly used dictionary learning algorithms have the optimal direction method\(^\text{19}\) (Method of Optimal direction, MoD) And KMean Singular Value Decomposition (K-SVD). Many experimental results show that, K-SVDThe algorithm has better effect on all kinds of signal processing. However, different signals correspond K-SVDThe training algorithm also has different parameter values, resulting in the training of the complete dictionary is also different. At present, few researches are focused on the corresponding vibration signals. K-SVD Training parameter values, K-SVDThe selection of parameters in the algorithm is very important to the over-complete Dictionary of the vibration signal, which directly affects the sparsity of the vibration signal and the number of compressed measurements and the compression reconstruction accuracy. K-SVDIn the process of dictionary learning algorithm getting over complete dictionary, the influence of parameter value on the sparsity of vibration signal, number of compressed measurements and reconstruction accuracy of compressed measurements is studied.

2. Reconstruction Method of Vibration Signal Compression Measurement Based on over complete dictionary

2.1 Over-complete dictionary design and sparsity Analysis

K-SVDSaidKSingular Value Decomposition, the algorithm and KMean poly

Algorithm has a deep connection, is K Generalization of the mean clustering algorithm. When K-SVDArithmetic in requirements of each signal only a atomic to approximate an arcane K-SVDDegenerate KMean clustering algorithm. That Matrix

\[ \mathbf{R}^N \] k Said training get of over-complete dictionary Vector S \[ \mathbf{R}^N \times \mathbf{R}^N \] Respectively said training sample signal and its corresponding

Sparse representation coefficient vector S \{S\}_i \in \mathbf{R}^N \_i For NA training sample of signal collection Matrix X \{X\}_i \in \mathbf{R}^N \_i For NA coefficient vector of collection

Dictionary learning process available optimization problem said

\(-\text{In}_{\mathbf{R}}\quad \text{Sparse representation coefficient in non-zero component number of objective upper limit.} \)

K-SVDArithmetic main points three step implementation the first step for dictionary initialization. Initial Dictionary of select can in the following two kind of way in optional one: a kind of is given a dictionary (Such as over-complete DCTDictionary) The initialization; the other a is in data sample concentration random select KA. This paper select the second kind of style. The second step for Sparse Coding according to known dictionary D Use common optimal atomic Search Algorithm OMP Algorithm get signal S In dictionary D On the best Sparse Coefficient Matrix X; The third step for Dictionary Update fixed Sparse Coefficient Matrix X According to iterative number or error requirements update dictionary Until find optimal dictionary D So far. The specific algorithm steps are as follows.

Steps 1 Select has been vibration signal.

Steps 2 Determine the initial Dictionary of atomic length? N And quantity K Stay decomposition signal sparse said when most "with the linear combination atomic number LK-SVDArithmetic iterative number J And Sample Signal Collection SOF atomic number N."

Steps 3 Based on initial dictionary atomic Length NSegmentation selected vibration signal random select which KA atomic constitute the initial dictionary D And make its each atomic has2-Norm. Select NA atoms vibration signal sample collection S.

Steps 4 Use OMP Algorithm vibration signal initial dictionary under the Sparse Coefficient Matrix X.

Steps 5 Fixed Sparse Coefficient Matrix X Use Singular Value Decomposition one by one update each atomic make Approximation Error minimum.

Steps 6 Repeat steps 4, 5 Straight to stop to book iterative number end.
Steps 7/Find optimal Sparse Coefficient Matrix X And optimal over-complete dictionary D.

According to rolling bearing vibration signal itself of characteristics by the above K-SVD Algorithm adaptive to structure the suitable for a given vibration signal of over-complete dictionary it can the vibration signal more targeted of processing. Random select American West storage University bearing data in a length

400 Data the vibration signal sparse of analysis vibration signal of Time-Domain Waveform as shown in Figure 2a Showed in from the can see the signal not only contains have Cosine Signal composition and have impact attenuation signal. Will vibration signal respectively in DCT over-complete dictionary and K-SVD Training. Complete

Dictionary on the orthogonal Matching Pursuit algorithm the Sparse Decomposition, K-SVD Training Algorithm in different parameters L The get of over-complete dictionary sparse said vibration signal decomposition coefficient curve as shown in Figure 2b Different parameters

The get of over-complete dictionary sparse said vibration signal decomposition coefficient curve as shown in Figure 2c Showed in. From the can see K-SVD Training Algorithm in parameters different the get of over-complete dictionary performance also different caused by vibration signal sparse of also different. In addition vibration signal in K-SVD Training over-complete dictionary on the sparse decomposition coefficient attenuation speed than in DCTOver-complete dictionary sparse said vibration signal decomposition coefficient curve as shown in Figure 2c Showed in. From the can see K-SVD Training Algorithm in parameters different the get of over-complete dictionary performance also different caused by vibration signal sparse of also different. In addition vibration signal in K-SVD Training over-complete dictionary on the sparse decomposition coefficient attenuation speed than in DCT.

K-SVD Training Algorithm in parameters value is structure over-complete dictionary in core problem one as long as select appropriate of parameters to assurance said coefficient has enough of sparse of and decay, to in reduce compression measurement of at the same time assurance signal of reconstruction accuracy.

2.2 Vibration Signal Compression measurement reconstruction methods of implementation

Based on K-SVD Dictionary learning algorithm sparse said vibration signal compression measurement reconstruction methods of implementation steps are as follows.

Steps 1 From American West storage University bearing database in extraction vibration data which part for get vibration signal over-complete dictionary D Rest for compression perception was measurement of data F.

Steps 2 Random select vibration data training sample set collection K A atomic as an initial dictionary D Reasonable select K-SVD Learning Algorithm in parameters from sample set collection training get best sparse said vibration signal of over-complete dictionary D.

Steps 3 In over-complete dictionary D On the has been Vibration Signal F The sparse Transform F D Get prior knowledge.

Steps 4 Selection Gaussian random matrix as an Measurement Matrix Use Y F On N Dimension Vibration Signal F The projection get M Dimension measurement Y.

Steps 5 By data transmission network will measurements Y Transmission Vibration Signal Processing Center OMP Algorithm and use measurement Value Y Measurement Matrix And over-complete dictionary D Reconstruction Sparse Coefficient .

Steps 6 Use reconstruction Coefficient By F D Get Vibration Dynamic signal F.

Steps 7 Adjustment K-SVD Learning Algorithm in the related parameters and Measurement Matrix In M Of value Repeat steps 2–6.

Based on K-SVD Dictionary learning algorithm of sparse said vibration signal compression measurement Reconstruction Methods Flow chart as shown in Figure 3 Shown in.

3. Test and Analysis

Test in the of is American West storage University bearing database bearing data and category relationship [20] Such
as table 1 Shown in select 10 Class so

Barrier data including normal data and bearing outer ring, inner ring, ball fault of data the of sampling frequency 12 kHz. The test in bearing outer ring, inner ring, rolling elements are distributed on the single point of failure fault

Depth Size respectively 0.007 " , 0.014 " , 0.021 " ( 1 " = 2.54 ) Each fault state load 0 HP, 1 HP ( 1 HP = 746 W ) This paper in select each type fault load 0 HP State under data as an-like

This signal Normal Said NORMAL STATE, IR, B And OR Respectively said inner ring, ball and outer ring fault its after of digital representative the fault

Degree, @ Behind said point of failure which orientation. Such, OR 014 @ 3 Said bearing there are outer fault Depth Size 0.014 " Point of failure is located in 3 At orientation.

This paper the relative error To measure vibration signal of reconstruction performance the compression ratio CRT To measure vibration signal of compression of its definition are as follows.

Structure Vibration Signal. Relative error the small ( Reconstruction vibration signal and the original vibration signal of difference the small reconstruction vibration signal the more approximation or instead of original vibration signal.

3.1 K-SVD Learning Algorithm of parameters change the reconstruction error of Influence Analysis

The K-SVD Algorithm structure mechanical vibration signal over-complete dictionary when main involves five A parameters they respectively is: initial dictionary a single atomic of Length N Atomic number K Sample Collection ST he atomic number NS Stay decomposition signal sparse said when most " with the linear combination atomic number L K-SVD Training for an arcane of iterative number J, Parameters of value different directly influence the vibration signal sparse of and of reconstruction error. The following validation single factors analysis methods is to change its

1A parameters fixed other 4A parameters. Select the bearing outer ring fault Depth Size 0.007 " Point of failure is located in 6 At orientation ( OR 007 @ 6 ) Of signal data the test the data respectively is motor drive end and fan end 12 At the location of acceleration sensor collection of income. In order to training Dictionary of need to because the signal is weeks

Of signal so will signal from 0 ~ 121991 Sampling points extended 0 ~ 609955 Sampling points. Drive end and fan end data of over-complete dictionary generation training 0 ~ 563200 Sampling Points compression perception test signal 563201 ~ 609955 Sampling points.

Initial dictionary atomic of Length N Of value from 100 Change 500 When its reconstruction relative error change as shown in Figure 4 Shown in other four parameters value respectively is set: K = 600 N = 1100, L = 14, J = 10.

Compressed Sensing test signal 563 201 Starting N Sampling points. Compression rate Cr For 60%, Use OMP Algorithm for reconstruction. In figure 3. The vibration signal of the driving end is based on DCT Orthogonal basis, DCT Over complete dictionaries and K-SVD Reconstruction of relative error curves in three sparse ways over complete dictionaries. Figure 5. In 3. The vibration signal of the fan end in the corresponding three sparse ways.

Reconstruct the relative error curve. It can be seen from the two diagrams that in the same N Value, signal based K-SVD Over complete dictionary sparse way than based on DCT Orthogonal basis sparse approach and based on DCT Sparse over complete dictionary

The Reconstruction Error of sparse Compressed Sensing is low. N = 400 The relative reconstruction error of mechanical vibration signals in three sparse ways is relatively small. N For this value, it can effectively cover all the characteristics of the vibration signal in a period, which is in line with the characteristics of the vibration signal itself. N Select 400. In select N = 400 The influence of the other four parameters on the reconstruction error is analyzed.

Number of initial dictionary Atoms K The change of relative reconstruction error is shown in Fig.6. As shown, the test signal is 563201 ~ 563600 Between
400 Sample Points, other parameter settings and Graphs. Same. To ensure the completeness of the dictionary, K-Value range selection is 500–800. Because N Fixed value, observation matrix Wang Yitu unchanged, DCT Orthogonal basis Sparse Mode

The relative reconstruction error of the curve under 6. Only given in K-Value-affected DCT Over complete dictionaries and K-SVDOver-complete dictionary sparse style. A Article curve. From the can see, K = 750 When vibration signal in two kind of sparse style. of Reconstruction Error Relative is Small so test in K Take 750. Figure 7/For sample collection S The atomic number N The relative reconstruction error curve. K = 750 Other parameters is set and figure 6 Same for assurance over-complete dictionary training of adequacy; N Parameters L The relative reconstruction error curve as shown in Figure 8 Shown in, N = 000 Other parameters is set and figure 7 Same. Parameters L Value Test Range 2–Natural 20 From the can found, L = 10 After curve change smooth due L Increase will cause over-complete dictionary training time of extended so test in L Value Choice 10. Figure 9 For Parameters J The relative reconstruction error curve, L = 10 Other parameters is set and figure 8 Same.

Parameters J Value Test Range 2–Natural 20 From the can see, J = 10 Signal to come close to in original vibration signal. From table 2 In can see, An arcane reconstruction error is small so test in J Take 10 More appropriate. In K-SVDOver-complete dictionary sparse style. Drive end and fan end

After the above test verification after in compression ratio 60% Situation under, K-SVDOver-complete dictionary learning of main parameters best choices are as follows: initial dictionary atomic of Length N = 400 Atomic number K = 750 Sample Collection S The atomic number N = 1 000 Stay decomposition signal sparse said when most "with the linear combination atomic number L = 10 K-SVD Training for an arcane iterative number J = 10."

### 3.2 Fixed compression ratio under relative reconstruction error compare

#### 3.2.1 A single mechanical vibration signal data test analysis

The test using or above of the same vibration signal (OR007 @ 6) K-SVDOver-complete dictionary learning of parameters is set by top of conclusion in 1 000 A training sample atomic in random.

750 A As an initial dictionary atomic. Observation matrix 160 × 400 Gaussian random matrix. Because the observation matrix size is 160x400, Based on the compression rate formula (3) Computing available Cr = 60%. Figure 10 Tutu 11 They are respectively Or007 @ 6 Vibration signals collected by acceleration sensors at the driving and fan ends are DCT Orthogonal basis, DCT Over complete dictionaries and K-SVDAfter a complete dictionary, the reconstructed signal waveform in three sparse ways is obtained. K-SVDSparse Mode reconstruction effect is good, reconstruction Vibration

Because the signals of the same measurement point have different sparsity, the relative reconstruction error of the vibration signal based on Compressed Sensing will also be changed. To further validate this article

The effectiveness of the algorithm is 563 712 After the sample point 6. 1400 Signal segment of each sampling point. Table 3 Is in compression rate 60% The relative Reconstruction Error Test Results of different signal segments in different sparse ways. As can be seen from the table, for Vibration Signals in K-SVDSparse way over complete dictionary, the relative reconstruction error is small. This result verifies the validity of the proposed method from different test signal segments. K-SVDOver-complete dictionary obtained by learning algorithm in the application of Compressed Sensing theory.

#### 3.2.2 Experimental Analysis of mechanical vibration signal data sets

Experimental results of mechanical vibration signal data of single test point are insufficient.

To fully illustrate the effectiveness of the proposed method, in order to further verify the effectiveness and applicable scope of the proposed method 10 Vibration Signals of different test points were reconstructed. Following Western Reserve from USA

Random selection in university bearing Database 10 The data of each category was tested. Parameters and
conditions in the test with a singleOr007 @ 6Vibration Signals are the same, the test results are as shown in table4. The data in the table shows that whether the drive signal or the fan signal, the vibration signal is K-SVDT. The relative reconstruction error ratio in the sparse way of over complete dictionary. Vibration Signal have is high reconstruction of so no matter is a single

4. Conclusion

To solve the problem of storage, transmission and processing of massive vibration data K-SVDSparse representation based on dictionary learning algorithm for Vibration Signal Compression measurement reconstruction. Reasonable Selection of Vibration Signals K-SVDBecause the dictionary can make full use of the characteristics of the mechanical vibration signal itself and get a better sparsity of the vibration signal through the experiment, therefore, it is conducive to improving the reconstruction accuracy of vibration signals. Gaussian random matrix is selected from the observation matrix. RipNature. Vibration Signal Reconstruction SelectionOMPReconstruction algorithm has the advantages of high reconstruction accuracy and short running time. Experiments using the bearing database of the Western Reserve University show that 60%-90% Time-based K-SVD. The relative error of over complete dictionary is smaller than that of Compressed Sensing Reconstruction Based on the discrete cosine orthogonal basis and the discrete cosine over complete dictionary. The algorithm greatly reduces the original vibration data without losing the vibration signal information.

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