Pisco Med Publishing

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

Mingzhi Zhang

Xinjiang University, Shijiazhuang 050000, Hebei, China

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 onK-SVDDictionary learning algorithm of sparse said vibration signal compression measurement reconstruction methods. First analysis the vibration signal in based onK-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 in60%~90%When based onK-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 YiIt satisfies the perceptual matrix formed by sparse representation system when it is a Gaussian random matrix.RipAnd has a smaller constraint isometric constantWang Yi$_K$. 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.YTransfer to the remote monitoring center. The data processing part is based on the over complete dictionary.DReconstruction 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 networkYAfter transmission to the remote monitoring center,K-SVDAlgorithm[18]Yes, already.

Dynamic signal training get over complete dictionaryDAs a sparse way of vibration signals, while usingOMPReconstruction Algorithm finally gets the reconstructed Vibration

Moving SignalFFor analysis and diagnosis by remote monitoring center staff.

Vibration SignalFThe 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 vibra-tion signal can not be sparse enough in this Sparse Mode, which affects the reconstruction accuracy of Vibration

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[19](Method of Optimal direction, MoD)AndKMean 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 correspondK-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-SVDTraining 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 andKMean poly

Algorithm has a deep connection, isKGeneralization of the mean clustering algorithm. WhenK-SVDAlgorithm in requirements of each signal only a atomic to approximate an arcane,K-SVDDegenerateKMean clustering algorithm. That Matrix

$R^{N \quad K}$Said training get of over-complete dictionary VectorS R^NX R^KRespectively said training sample signal and its corresponding

Sparse representation coefficient vector,S $\{S_I\}_I^N$ $_1$ForNA training sample of signal collection MatrixX $\{X_I\}_I^N$ $_1$ForNA coefficient vector of collection

Dictionary learning process available optimization problem said

-InT_0-Sparse representation coefficient in non-zero component number of objective upper limit.

K-SVDAlgorithm 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-completeDCTDictionary)The initialization; the other a is in data sample concentration random selectKA. This paper select the second kind of style. The second step for Sparse Coding according to known dictionaryDUse common optimal atomic Search AlgorithmOMPAlgorithm get signalSIn dictionaryDOn the best Sparse Coefficient MatrixX; The third step for Dictionary Update fixed Sparse Coefficient MatrixXAccording to iterative number or error requirements update dictionaryDUntil find optimal dictionaryDSo far. The specific algorithm steps are as follows.

Steps1Select has been vibration signal.

Steps2Determine the initial Dictionary of atomic length?NAnd quantityKStay decomposition signal sparse said when most "with the linear combination atomic numberLK-SVDAlgorithm iterative numberJAnd Sample Signal CollectionSOf atomic numberN.

Steps3Based on initial dictionary atomic LengthNSegmentation selected vibration signal random select whichKA atomic constitute the initial dictionaryDAnd make its each atomic has2-Norm. SelectNA atoms vibration signal sample collectionS.

Steps4UseOMPAlgorithm vibration signal initial dictionary under the Sparse Coefficient MatrixX.

Steps5Fixed Sparse Coefficient MatrixXUse Singular Value Decomposition one by one update each atomic make Approximation Error minimum.

Steps6Repeat steps4,5Straight stop to book iterative number end.

Steps7/Find optimal Sparse Coefficient MatrixXAnd optimal over-complete dictionaryD.

According to rolling bearing vibration signal itself of characteristics by the aboveK-SVDAlgorithm 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

400Data the vibration signal sparse of analysis vibration signal of Time-Domain Waveform as shown in Figure2aShown in from the can see the signal not only contains have Cosine Signal composition and have impact attenuation signal. Will vibration signal respectively inDCTOver-complete dictionary andK-SVDTraining. Complete

Dictionary on the orthogonal Matching Pursuit algorithm the Sparse Decomposition,K-SVDTraining Algorithm in different parametersLThe get of over-complete dictionary sparse said vibration signal decomposition coefficient curve as shown in Figure2bDifferent parameters

The get of over-complete dictionary sparse said vibration signal decomposition coefficient curve as shown in Figure2cShown in. From the can seeK-SVDTraining 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 inK-SVDTraining over-complete dictionary on the sparse decomposition coefficient attenuation speed than in

DCTOver-complete dictionary fast that is signal inK-SVDTraining over-complete dictionary on the sparse of is good. From figure2In can see after more times iterative after vibration signal inK-SVDTraining dictionary on the sparse decomposition coefficient in iterative120Times when coefficient gradually attenuation and tends to zero so sparse degreeKEstimation120.

K-SVDTraining 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 onK-SVDDictionary learning algorithm sparse said vibration signal compression measurement reconstruction methods of implementation steps are as follows.

Steps1From American West storage University bearing database in extraction vibration data which part for get vibration signal over-complete dictionaryDRest of for compression perception was measurement of dataF.

Steps2Random select vibration data training sample set collectionKA atomic as an initial dictionaryDReasonable selectK-SVDLearning Algorithm in parameters from sample set collection training get best sparse said vibration signal of over-complete dictionaryD.

Steps3In over-complete dictionaryDOn the has been Vibration SignalFThe sparse TransformF D Get prior knowledge.

Steps4Selection Gaussian random matrix as an Measurement Matrix UseY FOnNDimension Vibration SignalFThe projection getMDimension measurementY.

Steps5By data transmission network will measurementsYTransmission

Vibration Signal Processing CenterOMPAlgorithm and use measurement Value

Y, Measurement Matrix And over-complete dictionaryDReconstruction Sparse Coefficient .

Steps6Use reconstruction Coefficient ByF D Get Vibration

Dynamic signalF.

Steps7/AdjustmentK-SVDLearning Algorithm in the related parameters and Measurement Matrix InMOf value Repeat steps2~6.

Based onK-SVDDictionary learning algorithm of sparse said vibration signal compression measurement Reconstruction Methods Flow chart as shown in Figure3Shown in.

3. Test and Analysis

Test in the of is American West storage University bearing database bearing data and category relationship[20]Such as table1Shown in select10Class so

Barrier data including normal data and bearing outer ring, inner ring, ball fault of data the of sampling frequency12 kHz. The test in bearing outer ring, inner ring, rolling elements are distributed on the single point of failure fault

Depth Size respectively0.007 ″,0.014 ″,0.021 ″ (1 ″ = 2.54)Each fault state load0 HP,1 HP (1 HP = 746 W)This paper in select each type fault load0 HPState under data as an-like

This signal.NormalSaid NORMAL STATE,IR,BAndORRespectively said inner ring, ball and outer ring fault its after of digital representative the fault

Degree,@Behind said point of failure which orientation. Such,OR014 @ 3Said bearing there are outer fault Depth Size0.014 ″Point of failure is located in3At orientation.

This paper the relative error To measure vibration signal of reconstruction performance the compression ratioCRTo 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-SVDLearning Algorithm of parameters change the reconstruction error of Influence Analysis

TheK-SVDAlgorithm structure mechanical vibration signal over-complete dictionary when main involves five A parameters they respectively is: initial dictionary a single atomic of LengthNAtomic numberKSample CollectionSThe atomic numberNStay decomposition signal sparse said when most "with the linear combination atomic numberLK-SVDTraining for an arcane of iterative numberJ. 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 other4A parameters. Select the bearing outer ring fault Depth Size0.007 ″Point of failure is located in6At orientation(OR007 @ 6)Of signal data the test the data respectively is motor drive end and fan end12At 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 from0~121 991Sampling points extended0~609 955Sampling points. Drive end and fan end data of over-complete dictionary generation training0~563 200Sampling Points compression perception test signal563 201~609 955Sampling points.

Initial dictionary atomic of LengthNOf value from100Change500When its reconstruction relative error change as shown in Figure4Shown in other four parameters value respectively is set:K= 600N= 1 100,L= 14,J= 10.

Compressed Sensing test signal563 201StartingNSampling points. Compression rateCrFor60%, UseOMPAlgorithm for reconstruction. In figure3.The vibration signal of the driving end is based onDCTOrthogonal basis,DCTOver complete dictionaries andK-SVDReconstruction of relative error curves in three sparse ways over complete dictionaries. Figure5.In3.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 sameNValue, signal basedK-SVDOver complete dictionary sparse way than based on

DCTOrthogonal basis sparse approach and based onDCTSparse over complete dictionary

The Reconstruction Error of sparse Compressed Sensing is low.N= 400The relative reconstruction error of mechanical vibration signals in three sparse ways is relatively small.NFor 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.NSelect400. In selectN= 400The influence of the other four parameters on the reconstruction error is analyzed.

Number of initial dictionary AtomsKThe change of relative reconstruction error is shown in Fig.6.As shown, the test signal is563 201~563 600Between

400Sample Points, other parameter settings and Graphs5.Same. To ensure the completeness of the dictionary,KValue range selection is500~800, BecauseNFixed value, observation matrixWang YiUnchanged,DCTOrthogonal basis Sparse Mode

The relative reconstruction error of the curve under6.Only given in

KValue-affectedDCTOver complete dictionaries andK-SVDOver-complete dictionary sparse style.4Article curve. From the can see,K= 750When vibration signal in two kind of sparse style. of Reconstruction Error Relative is

Small so test inKTake750. Figure7/For sample collectionSThe atomic numberNThe relative reconstruction error curve.K =750Other parameters is set and figure6Same for assurance over-complete dictionary training of adequacy,N

ParametersLThe relative reconstruction error curve as shown in Figure8Shown in,N=

000Other parameters is set and figure7/Same. ParametersLValue Test Range2~Natural 20From the can found,L =10After curve change smooth dueLIncrease will cause over-complete dictionary training time of extended so test inLValue Choice10. Figure9For ParametersJThe relative reconstruction error curve,L= 10Other parameters is set and figure8Same.

ParametersJValue Test Range2~Natural 20From the can see,J= 10Signal to come close to in original vibration signal. From table2In can see,

An arcane reconstruction error is small so test inJTake10More appropriate.InK-SVDOver-complete dictionary sparse style. Drive end and fan end

After the above test verification after in compression ratio60%Situation under,K-SVDOver-complete dictionary learning of main parameters best choices are as follows: initial dictionary atomic of LengthN =400Atomic numberK= 750Sample CollectionSThe atomic numberN= 1 000Stay decomposition signal sparse said when most "with the linear combination atomic numberL= 10K-SVDTraining for an arcane iterative numberJ= 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 in1 000A training sample atomic in random.

750A As an initial dictionary atomic. Observation matrix160 × 400Gaussian random matrix. Because the observation matrix size is160x400, Based on the compression rate formula(3)Computing availableCr = 60%. Figure10Tutu11They are respectivelyOr007 @ 6Vibration signals collected by acceleration sensors at the driving and fan ends areDCTOrthogonal basis,DCTOver complete dictionaries andK-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 is563 712After the sample point6.I400Signal segment of each sampling point. Table3.Is in compression rate60%The relative Reconstruction Error Test Results of different signal segments in different sparse ways. As can be seen from the table, for Vibration Signals inK-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-SVDThe effectiveness of the over-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 method10Vibration Signals of different test points were reconstructed. Following Western Reserve from USA

Random selection in university bearing Database10The 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 isK-SVDThe relative reconstruction error ratio in the sparse way of over complete dictionaryVibration 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 dataK-SVDSparse representation based on dictionary learning algorithm for Vibration Signal Compression measurement reconstruction. Reasonable Selection of Vibration SignalsK-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 that60%~90%Time-basedK-SVDThe 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.

References

1. Cai Weiwei, Tang Baoping, Huang qingqing.Design of wireless sensor network node for Mechanical Vibration Signal Acquisition[J].Vibration and impact,2013,32 (1):73-78.
2. Donoho D. Compressed Sensing [J]. IEEE transaction on Information Theory,2006,52 (4):1289-1306.
3. Candes E,Romberg J,Tao t. Robust uncertainty principles:Exact Signal reconstruction from highly
4. CANDES EWakin m. An introduction. compressive sampling [J]. IEEE Signal Processing Magazine2008 25 (2):21-30.
5. Shi brilliant Liu Dan high Dahua and.Compression Perception Theory and Its Research Progress[J].Electronic Journal,200937 (5):1070-1081.
6. Rauhut HSchnass KVandergheynst P.Compressed Sensing, redundant dictionaries [J]. IEEE Trans Inform Theory200854 (5):2210-2219.
7. Wang light bed Perlin Wu Dinghai and.Based on lifting wavelet of mechanical vibration signal adaptive compression perception[J].Central South University Journal,201647 (3):771-776.
8. Guo jun feng of jian xu Ray Chun-Li and.A rolling bearing vibration signal of Data Compression collection of methods[J].Vibration and impact,201534 (23):8-13.
9. Lee S JLUAN JChou p h. ECG Signal reconstruction from undersampled measurement using a trained overcomplete dictionary [J]. Contemporary Engineering Science20147/(29):1625-1632.
10. Doneva MBornert PEGGERS HEt A1. Compressed Sensing reconstruction. magnetic resonance parameter mapping [J]. Magnetic Resonance. Medicine201064 (4):1114-1120.
11. Sun she Yang Zhen season so and.Based on over-complete linear prediction Dictionary of compression perception voice reconstruction[J].Instrument instrument Journal,201233 (4):743-749.
12. Peng East Zhang Hua Liu ji zhong.Based on over-complete Dictionary of body area network compression perception ECG Reconstruction[J].Automation Journal,201440 (7):1421-1432. PENG XiangdongZHANG HuaLIU jizhong. ECG
13. WU Jian Ning Xu Haidong was Frank Wang Jue.Based on over-complete dictionary sparse representation of multi-channel EEG Signal Compression perception combined with reconstruction[J].Electronic and information Journal,201638 (7):1666-1673.
14. Wang Qiang bed Perlin Wang light and.Based on Sparse Decomposition of vibration signal Data Compression Algorithm[J].Instrument instrument Journal,201637 (11):2497-2505.
15. Yu fajun, Zhou fengxing, Yan Baokang.Sparse Feature Extraction for early fault of Bearings Based on dictionary Learning[J].Vibration and impact,2016,35 (6):186-181. Yu fajun,Zhou fengxing,Yan Baokang. Bearing initial Fault Feature Extraction via sparse representation based on dictionary learning [J]. Journal of vibration and shock,2016,35 (6):181-186.
16. Candes E,Eldarb Y C,Needella d,Et al. Compressed Sensing with heritage and redundant dictionaries [J]. Applied and computational Harmony Analysis,2011,31 (1):59-73.
17. Tropp J,Gilbert a C. signal recovery from random Measurements via orthogonal Matching Pursuit [J]. IEEE Trans

inform Theory,2007,53 (12),4655-4666.
18. Aharon m,Elad m,Bruckstein A. K-SVD:An Algorithm for designing overcomplete dictionaries Sparse representation [J]. IEEE Transactions on Signal Processing,2006,54 (11):4311-4322.
19. Engan K,Aase s o,Husoy j h. Method of Optimal Directions for Frame Design [c]/Procedures of the 1999 IEEE International Conference on Acoustics,Speech,And signal processing. Phoenix:AZ,1999:2443-2446.
20. Wang Pengfei, Wang Xinqing, Cao Lei, *et al*.Bearing Based on discriminative Sparse Coding Fault Diagnosis Method[J].Instrumentation Technology and sensors,2016 (8):77-80. Wang Pengfei,Wang Xinqing,Cao Lei,[J]. Instrument Technology and sensor,2016 (8):77-80.