

Retraction

Retracted: The Analysis about Compressed Sensing Reconstruction Algorithm Based on Machine Learning Applied in Interference Multispectral Images

Advances in Multimedia

Received 15 August 2023; Accepted 15 August 2023; Published 16 August 2023

Copyright © 2023 Advances in Multimedia. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

- (1) Discrepancies in scope
- (2) Discrepancies in the description of the research reported
- (3) Discrepancies between the availability of data and the research described
- (4) Inappropriate citations
- (5) Incoherent, meaningless and/or irrelevant content included in the article
- (6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

 C. Han, "The Analysis about Compressed Sensing Reconstruction Algorithm Based on Machine Learning Applied in Interference Multispectral Images," *Advances in Multimedia*, vol. 2021, Article ID 8020473, 6 pages, 2021.



Research Article

The Analysis about Compressed Sensing Reconstruction Algorithm Based on Machine Learning Applied in Interference Multispectral Images

Chang Han 🝺

Laboratory of Control and Application Technology of Robotic, Wuhan Business University, Wuhan, Hubei 430056, China

Correspondence should be addressed to Chang Han; 2015225010129@stu.scu.edu.cn

Received 19 August 2021; Accepted 21 October 2021; Published 26 November 2021

Academic Editor: Zhendong Mu

Copyright © 2021 Chang Han. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

Interferometric multispectral images contain rich information, so they are widely used in aviation, military, and environmental monitoring. However, the abundant information also leads to the disadvantages that longer time and more physical resources are needed in signal compression and reconstruction. In order to make up for the shortcomings of traditional compression and reconstruction algorithms, the stacked convolution denoising autoencoder (SCDA) reconstruction algorithm for interference multispectral images is proposed in this paper. And, the experimental code based on the TensorFlow system is built to reconstruct these images. The results show that, compared with D-AMP and ReconNet algorithms, the SCDA algorithm has the advantages of higher reconstruction accuracy and lower time complexity and space complexity. Therefore, the SCDA algorithm proposed in this paper can be applied to interference multispectral images.

1. Introduction

Interference spectroscopy technology began in the 1980s, which integrates spectroscopy, precision mechanics, electronics, and other disciplines [1, 2]. Interferometric multispectral images are usually composed of several to hundreds of frequency bands in which both spatial two-dimensional information and one-dimensional spectral information are contained. Because of the abundant information, interferometric multispectral image technology is widely used in aerospace, military reconnaissance, and environmental monitoring [3]. However, the abundant information also hinders the further application of interferometric multispectral images, because compression processing is required in storage and transmission in which the amount of data collected is very large. In order to remove the redundant information such as spatial correlation and spectral correlation of interference multispectral images, many scholars have carried out a lot of research and tried different algorithms, such as discrete cosine transform, three-dimensional

wavelet transform, and wavelet-domain matching algorithm [4, 5]. However, these methods cannot fully adapt to interferometric multispectral images that have the characteristics of unstable interference curve data as a whole and segments, thus leading to the bad compression effect. In 2006, Donoho, Candes, and Tao creatively put forward the compressed sensing theory, which holds that sparse or compressible signals can be accurately reconstructed through collecting a small amount of signals [6]. This theory overcomes the problems including huge amount of sampling data and serious waste of physical resources for data storage and transmission.

Taking the interferometric multispectral images as the research object, at first, this paper studies the theory and research results of reconstruction algorithm related to compressed sensing. And then, this paper attempts to combine the theory of machine learning with the compressed sensing reconstruction algorithm to reduce the calculation time of the algorithm and improve the image reconstruction accuracy at the same time.

2. Building the Theoretical Model Combining Machine Learning and Compressed Sensing Reconstruction Algorithm

Donoho, Candes, and Tao first proposed compressed sensing theory. They hold that the sparse signal or compressible signal can be reconstructed with high probability by applying an observation matrix independent of the transformation basis to project the high-dimensional signal transformed onto a low-dimensional space and then solving an optimization problem. This method breaks through Nyquist sampling theorem; that is, only when the sampling frequency is more than twice the highest frequency in the signal, the sampled digital signal can completely retain the information in the original signal [7]. Therefore, the sampling data can be greatly reduced, the sampling time can be reduced, and the physical resources of data storage and transmission can be saved [8, 9]. Figure 1 clarifies the comparison results.

The signal acquisition and coding process based on compressed sensing theory is shown as follows [10, 11]:

$$Y = \phi X,\tag{1}$$

where Φ is the observation matrix, *X* is a sparse signal with length *N*, and *Y* is the observed value.

When X is not a sparse signal, a transform basis ψ is needed to make signal X sparse and the transformation process is shown as follows [12]:

$$S = \psi^T X, \tag{2}$$

where ψ is the transform basis which can be wavelet basis, Fourier basis, or orthogonal basis. *S* is the equivalent sparse representation of *X*.

After transformation, the observed value of sparse signal *S* is solved, as shown in the following [13, 14]:

$$\phi S = \phi \psi^T X. \tag{3}$$

The restricted isometry property (RIP) theory holds that for the sake of higher accuracy, any *M*-order square matrix from observation matrix Φ is a nonsingular square matrix. Therefore, for the sparse signal *S*, the premise that the observation matrix satisfies RIP theory equivalent to Inequality 4 in [14] holds.

$$(1 - \varepsilon) \|S\|_2 \le \|\phi S\|_2 \le (1 + \varepsilon) \|S\|_2, \tag{4}$$

where $0 < \varepsilon < 1$.

The general equivalent condition of RIP theory is that Φ and ψ are irrelevant. Therefore, the correlation coefficient is used to determine the uncorrelation of Φ and ψ . The smaller the measured correlation coefficient, the greater the uncorrelation [14].

For the reconstructed signal X, M << N results in that the signal reconstruction process faces the problem of solving the underdetermined equations. When the signal X is compressible, the problem of solving the underdetermined equation can be transformed into the problem of solving the minimum 0 norm, as shown in the following [13, 14]:

$$\min \left\| \psi^T X \right\|_0 \text{s.t. } A^{CS} X = \phi \psi X = Y.$$
(5)

However, the solution of equation (5) is a NP-hard problem, which can just be solved by approximation. At present, compressed sensing reconstruction algorithms mainly include four categories: (1) greedy algorithm, (2) convex optimization algorithm, (3) nonconvex optimization algorithm, and (4) model-based optimization algorithm. Among them, the first three kinds of algorithms are suitable for sparse signals. For the images whose original signals do not meet the sparsity, they cannot be reconstructed accurately within a certain error range. The model-based optimization algorithm can improve the reconstruction accuracy, but the computational cost is high [13].

With the deep integration of machine learning and artificial intelligence, more and more scholars begin to try to reduce the time complexity of traditional compressed sensing reconstruction algorithms through in-depth learning. In 2015, Mousavi proposed signal reconstruction through stacked denoising autocoding (SDA) technology. Due to ignoring the local correlation of image pixels, the time complexity of this algorithm is high and excessive redundant connection leads to overfitting problem. Based algorithm, Kulkarni on SDA proposed the ReconNet algorithm. The algorithm only adopts one full connection layer, so the network complexity is reduced, thus reducing the time complexity of signal reconstruction significantly [10-12].

Considering the spatial correlation and interspectral correlation of interference multispectral images and for the sake of lower time complexity and higher accuracy, a convolution stack denoising autocoding (SCDA) algorithm is proposed and its model diagram is shown in Figure 2.

2.1. The Strategy of SCDA Algorithm. After building the model of SCDA algorithm, it is necessary to design some corresponding strategies. The structure diagram of strategies is shown in Figure 3.

Here, the network of SCDA algorithm has nine layers. In the stage of CDA, it is necessary to add noise to the signal to improve the robustness of the network and Gaussian random noise is selected in this paper. The specific process of CAE structure is shown as follows [13]:

1 1

,

$$h^{k} = s\left(X * W^{k} + b^{k}\right),$$

$$y = s\left(\sum_{k \in H} h^{k*} W^{k} + c\right),$$
 (6)

where h^k represents the characteristic mapping result of the *k*-th neuron, *X* is the input value, *b* is the offset value, and *s* is the activation function. And, * represents 2-dimensional convolution, *H* is the number of neurons in each layer, and W^k is the transpose of the weight matrix.

Considering SCDA, the core process of compressed sensing reconstruction algorithm includes single-layer pretraining algorithm and global optimization algorithm. Firstly, the objective loss function of the single-layer



FIGURE 1: The comparison results of encoding and decoding process. (a) Based on Nyquist sampling theorem. (b) Based on compressed sensing theory.



FIGURE 2: The model diagram of SCDA algorithm.

pretraining algorithm is constructed, which is shown as follows [14]:

$$L(O,R) = \frac{1}{S} \sum_{k=1}^{S} \sum_{i=1}^{n} \left(\frac{1}{2} \left\| R_i^{(k)} - O_i^{(k)} \right\|^2 \right) + \frac{\lambda}{2} \sum_{l=1}^{h_l-1} \sum_{i=1}^{m_l} \sum_{j=1}^{m_l+1} \left(w_{ij}^{(l)} \right)^2, \quad (7)$$

where l and h_l represent the number of layers and CDA layers, respectively, m_l represents the number of l-th layer neurons, and $w_{ii}^{(l)}$ represents the weight.

After repeated iterative training of BP algorithm, L(O, R) tends to be stable, which indicates the end of the first CDA training process.

During the process of global optimization, the weights of the first layer are randomly initialized and the pretraining results are used as the initial values of the next 8 layers. The global loss function constructed in this paper is shown as follows [10]:

$$C = \frac{1}{\text{batch}} \sum_{k=1}^{\text{batch}} \frac{1}{L \times W} \sum_{i=1}^{L-1} \sum_{j=1}^{W-1} \left(\left\| R_{i,j}^{(k)} - O_{i,j}^{(k)} \right\|^2 \right) + \frac{\lambda}{2} \sum_{l=1}^{h_l-1} \sum_{i=1}^{m_l} \sum_{j=1}^{m_l+1} \left(w_{i,j}^{(l)} \right)^2,$$
(8)

where L and W represent the size of interference multispectral images.

3. Experiment and Analysis

Before the experiment, 110 images are selected as research samples, including 100 training samples and 10 test samples. And then, the experimental code is built based on the TensorFlow system. Finally, the image is compressed and reconstructed according to the model diagram shown in Figure 2.

To detect the feasibility of the algorithm proposed in this paper, the reconstruction results of D-AMP and ReconNet algorithm are selected for comparison. The evaluation index in this paper includes three aspects: reconstruction accuracy, time complexity, and network space complexity.

The measurement rates as set to 0.20, 0.10, 0.05, and 0.01. The reconstruction accuracy comparison results of 10 interference multispectral images corresponding to D-AMP, ReconNet, and SCDA algorithms are shown in Tables 1–4 and Figure 4, respectively.

Furthermore, the reconstruction accuracy can be expressed by PSNR, which is shown as follows:

$$PSNR = 10 \times \log_{10} \left(\frac{Max_0^2}{Mse} \right)$$
$$= 20 \times \log_{10} (Max_0) - 10 \times \log_{10} (Mse), \qquad (9)$$

Mse =
$$\frac{1}{L \times W} \sum_{i=0}^{L-1} \sum_{j=0}^{W-1} [O(i, j) - R(i, j)]^2$$
,



FIGURE 3: The structure diagram of strategies.

where Max_0 represents the maximum possible pixel value of the image and Mse represents mean square error between the original image and reconstructed image.

From Tables 1 to 4 and Figure 4, we can find the following:

- (1) With the decrease in measurement rate, the PSNR values corresponding to D-AMP, ReconNet, and SCDA algorithms decrease. Taking the PSNR value with the measurement rate of 0.20 as the reference point, when the measurement rate is reduced from 0.20 to 0.10, the PSNR values corresponding to D-AMP, ReconNet, and SCDA algorithms are reduced by 37.49%, 13.02%, and 19.48%, respectively. When the measurement rate is reduced from 0.20 to 0.05, the PSNR values corresponding to D-AMP, ReconNet, and SCDA algorithms are reduced by 63.19%, 21.79%, and 31.28%, respectively. When the measurement rate is reduced from 0.20 to 0.01, the PSNR values corresponding to D-AMP, ReconNet, and SCDA algorithms are reduced by 83.68%, 32.45%, and 41.72%, respectively.
- (2) When the measurement rate is 0.20, the reconstruction accuracy of D-AMP algorithm is the highest and ReconNet algorithm is the worst. When the measurement rates are 0.10, 0.05, and 0.01, respectively, the PSNR values of ReconNet algorithm are 1.03, 1.57, and 3.07 times those of D-AMP algorithm and the PSNR values of SCDA algorithm are 0.87, 1.12, and 3.10 times those of D-AMP algorithm, respectively. It shows that when the measurement rate is ≤0.10, the reconstruction accuracy of SCDA algorithm is the highest and that of D-AMP is the worst.

For the three reconstruction algorithms, the comparison results of the average time required for the reconstruction process of 10 interference multispectral images are shown in Tables 5 to 8 and Figure 5.

We can find the following from Tables 5 to 8:

- (1) Under the four measurement rates, the time required for ReconNet algorithm and SCDA algorithm to reconstruct the image is three orders of magnitude lower than that of D-AMP algorithm, which indicates that for the interference multispectral image, the time complexity of D-AMP algorithm to reconstruct the image is high.
- (2) ReconNet algorithm and SCDA algorithm have the similar time complexity, but when the number of images increases significantly, the SCDA algorithm has more obvious advantage in time complexity. Taking 10000 similar images as an example, the time

TABLE 1: Reconstruction accuracy comparison results of D-AMP, ReconNet, and SCDA algorithms (the measurement rate is 0.20).

Algorithm	D-AMP	ReconNet	SCDA
PSNR (dB)	28.01	20.74	24.33

TABLE 2: Reconstruction accuracy comparison results of D-AMP, ReconNet, and SCDA algorithms (the measurement rate is 0.10).

Algorithm	D-AMP	ReconNet	SCDA
PSNR (dB)	17.51	18.04	19.59

TABLE 3: Reconstruction accuracy comparison results of D-AMP, ReconNet, and SCDA algorithms (the measurement rate is 0.05).

PSNR (dB) 10.31 16.22 16.72	Algorithm	D-AMP	ReconNet	SCDA
	PSNR (dB)	10.31	16.22	16.72

TABLE 4: Reconstruction accuracy comparison results of D-AMP, ReconNet, and SCDA algorithms (the measurement rate is 0.01).

Algorithm	D-AMP	ReconNet	SCDA
PSNR(dB)	4.57	14.01	14.18



FIGURE 4: Reconstruction accuracy comparison results of D-AMP, ReconNet, and SCDA algorithms.

TABLE 5: The average time required for the reconstruction process (the measurement rate is 0.20).

Algorithm	D-AMP	ReconNet	SCDA
Time (s)	34.01	0.05	0.04

Advances in Multimedia

TABLE 6: The average time required for the reconstruction process (the measurement rate is 0.10).

Algorithm	D-AMP	ReconNet	SCDA
Time (s)	41.28	0.05	0.04

TABLE 7: The average time required for the reconstruction process (the measurement rate is 0.05).

Algorithm	D-AMP	ReconNet	SCDA
Time (s)	36.01	0.05	0.04

TABLE 8: The average time required for the reconstruction process (the measurement rate is 0.01).

Algorithm	D-AMP	ReconNet	SCDA
Time (s)	35.22	0.05	0.04



FIGURE 5: The number of network parameters for 10 images.

required for image reconstruction by ReconNet algorithm is 500 s, while by SCDA algorithm, it is 400 s. That is to say, the more the images, the more obvious the advantage of SCDA algorithm in time complexity.

It has been found that when the measurement rate is ≤ 0.10 , the reconstruction accuracy of D-AMP is the worst compared with ReconNet algorithm and SCDA algorithm. So, for the research of network space complexity, we just count the number of network parameters for ReconNet algorithm and SCDA algorithm. For the 10 images, the number of network parameters is shown in Tables 9 to 12 and Figure 5.

We can find the following:

- (1) When the measurement rate is in the range of 0.01–0.20, the number of network parameters based on ReconNet algorithm and SCDA algorithm is positively correlated with the measurement rate
- (2) When the measurement rates are 0.2, 0.10, 0.05, and 0.01, the network parameter quantity ratio of

TABLE 9: The number of network parameters for 10 images (the measurement rate is 0.20).

Algorithm	ReconNet	SCDA
The number of network parameters (K)	2900	806

TABLE 10: The number of network parameters for 10 images (the measurement rate is 0.10).

Algorithm	ReconNet	SCDA
The number of network parameters (K)	1150	357

TABLE 11: The number of network parameters for 10 images (the measurement rate is 0.05).

Algorithm				ReconNet	SCDA
The number of	of netw	ork paramet	ers (K)	511	104

TABLE 12: The number of network parameters for 10 images (the measurement rate is 0.01).

Algorithm	ReconNet	SCDA
The number of network parameters (K)	163	72

ReconNet algorithm and SCDA algorithm is 3.60, 3.22, 4.91, and 2.26, respectively, which indicates that the space occupation of SCDA algorithm is less than of ReconNet algorithm, so the space complexity of SCDA algorithm is smaller

4. Conclusion

Interference multispectral images have the characteristics of spatial correlation and spectral correlation. Therefore, we first consider removing redundant information and then compress, transmit, and reconstruct the signal. Aiming at the shortcomings of low reconstruction accuracy and high time complexity and space complexity of traditional compression and reconstruction algorithms, this paper attempts to combine the theory of machine learning with the compressed sensing reconstruction algorithm. The algorithm transforms the denoising autocoding in SDA algorithm into convolution denoising autocoding which can be applied to interferometric multispectral images. Meanwhile, the corresponding neural network training method is proposed. The results show that when the measurement rates are 0.25, 0.10, 0.04, and 0.01, the SCDA algorithm proposed in this paper has high reconstruction accuracy and low time complexity and space complexity.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The author declares no conflicts of interest.

Acknowledgments

This research study was sponsored by the Foundation of Hubei Educational Committee, "The Studies on the Multiangle Image Registration Based on Cosparse Analysis Model," under project number B2018280 and the Applied Basic Research Programs of Science and Technology Commission Foundation of Wuhan, "Research on Guidance and Positioning System for Dynamic Assembly Line Based on Robot Vision," under project number 2019010701011390.

References

- N. Y. Chen, L. Yun, and Z. J. Zhang, "A forecasting system of micro-blog public opinion based on artificial neural network," *Journal of Internet Technology*, vol. 16, no. 6, pp. 999–1004, 2014.
- [2] F. López and J. D. Frutos, "Multispectral interference filters and their application to the design of compact non-dispersive infrared gas analysers for pollution control," *Sensors and Actuators A Physical*, vol. 37, no. 38, pp. 502–506, 1993.
- [3] J. A. Jerri and, "The Shannon sampling theorem—its various extensions and applications: a tutorial review," *Proceedings of the IEEE*, vol. 65, no. 11, pp. 1565–1596, 2005.
- [4] A. P. Bradley, "The use of the area under the ROC curve in the evaluation of machine learning algorithms," *Pattern Recognition*, vol. 30, no. 7, pp. 1145–1159, 1997.
- [5] F. Pereira, T. Mitchell, and M. Botvinick, "Machine learning classifiers and fMRI: a tutorial overview," *NeuroImage*, vol. 45, no. 1, pp. S199–S209, 2009.
- [6] E. J. Hermans, H. J. F. Van Marle, L. Ossewaarde et al., "Stressrelated noradrenergic activity prompts large-scale neural network reconfiguration," *Science*, vol. 334, no. 6059, pp. 1151–1153, 2011.
- [7] K. S. Narendra and K. Parthasarathy, "Identification and control of dynamical systems using neural networks," *IEEE Transactions on Neural Networks*, vol. 1, no. 1, pp. 4–27, 1990.
- [8] G. Hinton, L. Deng, D. Yu et al., "Deep neural networks for acoustic modeling in speech recognition: the shared views of four research groups," *IEEE Signal Processing Magazine*, vol. 29, no. 6, pp. 82–97, 2012.
- [9] S. Geman, E. Bienenstock, and R. Doursat, "Neural networks and the bias/variance dilemma," *Neural Computation*, vol. 4, no. 1, pp. 1–58, 2014.
- [10] G. Litjens, T. Kooi, B. E. Bejnordi et al., "A survey on deep learning in medical image analysis," *Medical Image Analysis*, vol. 42, no. 9, pp. 60–88, 2017.
- [11] Y. Chen, "Deep learning-based classification of hyperspectral data," *IEEE Journal of Selected Topics in Applied Earth Ob*servations and Remote Sensing, vol. 7, no. 6, pp. 2094–2107, 2017.
- [12] Y. Lv, "Traffic flow prediction with big data: a deep learning approach," *IEEE Transactions on Intelligent Transportation Systems*, vol. 16, no. 2, pp. 865–873, 2015.
- [13] K. Kulkarni, "ReconNet: non-iterative reconstruction of images from compressively sensed measurements," in *Proceedings of the Conference on Computer Vision and Pattern Recognition*, pp. 449–458, Las Vegas, NV, USA, June 2016.
- [14] C. A. Metzler, A. Maleki, and R. G. Baraniuk, "From denoising to compressed sensing," *IEEE Transactions on Information Theory*, vol. 62, no. 9, pp. 5117–5144, 2016.