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Research Article

The Compression Sensing Reconstruction for the 1-d Signal Based on Non-local Full Connection Layer

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Abstract

The compression sensing reconstruction for the 1-d signal can contribute to the communication of autonomous driving, intelligent robots, and fire exploration robots. To address the issue that fully connected layers in the LISTA method lack the ability to extract non-local features, this paper primarily designs a non-local fully connection layer and proposes a novel compressed sensing reconstruction method for audio signals. This paper designs a compression sensing reconstruction method for the 1-d signal. To reconstruct 1-d signal, the deep learning method LISTA is used. Then, the linear full connection layer in LISTA is improved by combining the output of three full connection layer to capture the non-local information. The computing regions of improved non-local full connection layer contain: 1) the full connection before; 2) the current full connection; and 3) the full connection after. Experimental results show the reconstruction results of LISTA and LISTA_nf are both close to the real signal. The MSE of LISTA_nf is reduced by 0.1 than the MSE of ISTA under the same experimental settings. The non-local full connection layer in the LISTA_nf consumes longer computing time. The LISTA_nf increase the computing time by 0.07s than the computing time of the ISTA. Experimental results show the effectiveness of the proposed method.

Keywords

Compression Sensing Reconstruction, 1-d Signal, LISTA, Non-local Full Connection

1. Introduction

Compression sensing reconstruction for the 1-d signal can contribute to the communication of autonomous driving, intelligent robots, and fire exploration robots.

The traditional compression sensing reconstruction methods include OMP [1], SAMP [2], ROMP [3], StOMP [4], CoSaMP [5]. With the developments of machine learning, the

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finite state machine (FSM) and conditional random field (CRF) are introduced to traditional compression sensing reconstruction methods. Then, with the developments of deep learning, the deep neural networks are also introduced to the compression sensing reconstruction. However, the methods based on deep learning need larger training datasets compared with traditional methods.

This paper designs a compression sensing reconstruction method for the 1-d signal. To reconstruct 1-d signal, the deep learning method LISTA is used. Then, the linear full connection layer in LISTA is improved by non-local full connection layer. The computing regions of improved non-local full connection layer contain: 1) the full connection before; 2) the current full connection; and 3) the full connection after. Experimental results show the reconstruction results of LISTA and LISTA_nf are both close to the real signal. The MSE of LISTA_nf is better than the MSE of ISTA and LISTA. The non-local full connection layer in the LISTA_nf consumes longer computing time.

2. Related Works

(1) The Compression Sensing Reconstruction of 1-d Signal

1) Traditional Methods

Defraene et al. [7] applied compressive sensing for clipping processing of one-dimensional signals. M. Kasem and EI-Sabrouty [8] proposed a comparative study on audio compression based on compressive sensing and sparse fast Fourier transform (SFFT): performance and challenges. Lin et al. [9] developed a multi-frame prediction M-LVC method for video compression. Grrggin et al. [10] proposed using compressive sensing for encoding the sinusoidal model of audio signals. A. Verburg and Fernandez-Grande [11] suggested using compressive sensing to reconstruct sound fields inside buildings. Griffin et al. [12] presented compressive sensing-based single-channel and multi-channel sinusoidal sound encoding. Valenzise et al. [13] proposed using distributed source coding and compressive sensing techniques to identify sparse audio tampering. Zahedi et al. [14] proposed audio coding for wireless acoustic sensor networks. Griffin and Tsakalides [15] presented compressive sensing reconstruction of audio signals using multiple sensors. Moreno-Alvarado [16] designed research on simultaneous audio encryption and compression using compressive sensing technology. Katzberg [17] developed a compressive sensing framework for dynamic sound field measurement. Yin et al. [18] designed a compressive sensing method based on sampling and reconstruction, applied to wireless sensor matrix networks. Mads Græsbøl [19] discussed compressive sensing methods and their applications in speech and audio signal processing. Wahab Abood [20] designed provably secure and efficient audio compression based on compressive sensing. Albiges [21] used compressive sensing data for audio signal reconstruction to achieve intelligent classification of chronic respiratory diseases. Upadhyaya [22] designed quality parameter estimation for sparse audio signal reconstruction based on compressive sensing.

2) Machine Learning Methods and Deep Learning Methods

Russell and Wang [23] proposed the application of physics-informed deep learning in big data signal compression and reconstruction for industrial condition monitoring. Palangi designed a deep learning-based distributed compressed sensing method. Bao [24] developed a machine learning approach for compressive sensing data reconstruction in structural health monitoring. L. Machidon and Pejović [25] designed applications of deep learning in compressive sensing from a ubiquitous systems perspective. Lu and Bo [26] proposed WDLReconNet: deep learning compressive sensing reconstruction for wireless fading channels. Bright [27] developed a compressive sensing-based machine learning strategy for characterizing flow around a cylinder with limited pressure measurements. Wang [28] designed time-domain signal reconstruction of vehicle interior noise based on deep learning and compressed sensing techniques. L. Machidon and Pejović [29] presented applications of deep learning in compressive sensing from a ubiquitous systems perspective. Du [30] proposed a deep learning-based fast reconstruction method for EEG signal compressive sensing. Wu [31] developed a deep compressive sensing approach.

(2) The Methods for Deformable Convolution

Dai et al. [32] proposed deformable convolutional networks. Liu et al. [33] designed attention-injective deformable convolutional network for crowd understanding. Thomas et al. [34] improved the flexible and deformable convolution for point clouds. Shi et al. [35] proposed the video frame interpolation method via generalized deformable convolution. Wang et al. [36] designed a video restoration method with enhanced deformable convolutional networks. Wang et al. [37] explored large-scale vision foundation Models with deformable convolutions. Zhu et al. [38] designed deformable convNets v2: more deformable, better results method. Chen et al. [39] designed temporal deformable convolutional encoder-decoder networks for video captioning. Deng et al. [40] improved the spatio-temporal deformable convolution for compressed video quality enhancement. Park et al. [41] designed deformable graph convolutional networks.

3. Methods

In LISTA [6] method, the convolution adopts the full connection layer. However, the full connection layer adopted in LISTA can only capture the local region features, and the non-local region features can not be captured. Therefore, the non-local full connection layer is proposed. The full connection layer in LISTA is improved by non-local full connection layer. The computing regions of improved non-local full connection contain: 1) the full connection before; 2) the current full connection; and 3) the full connection after.

Non-local Full Connection

The normal convolution computing is

$$s(i) = \sum_{c=1}^{c_0} \sum_{k=0}^{k\_s-1} I(i+k)K_1(k) \tag{1}$$

The computing regions of improved non-local full connection layer contain: 1) the full connection before; 2) the current full connection; and 3) the full connection after.

In the before the full connection before, the computing is

$$s_1(i) = \sum_{c=1}^{c_0} \sum_{k=0}^{k\_s-1} I(i-k)K_2(k) \tag{2}$$

where $s_1(i)$ is the output feature, the channel of the input feature is c_0, the kernel size is k_s, the input feature or data is I, and the convolution kernel is K_2.

In the current full connection, the computing is

$$s_2(i) = \sum_{c=1}^{c_0} \sum_{k=0}^{k\_s-1} I(i+k)K_3(k) \tag{3}$$

where $s_2(i)$ is the output feature, the channel of the input feature is c_0, the kernel size is k_s, the input feature or data is I, and the convolution kernel is K_3.

In the full connection after, the computing is

$$s_3(i) = \sum_{c=1}^{c_0} \sum_{k=0}^{k\_s-1} I(i+k\_s+k)K_4(k) \tag{4}$$

where $s_3(i)$ is the output feature, the channel of the input feature is c_0, the kernel size is k_s, the input feature or data is I, and the convolution kernel is also K_4.

The output feature is

$$s(i) = (s_1(i)+s_2(i)+s_3(i))/3.0 \tag{5}$$

and the $s(i)$ is the output feature for the convolution i-point. The different weights are set across the "before," "current," and "after" full connections layer to capture more non-local information.

4. Experimental Results

(1) The Experiments Setting

The dimensions of the sparse signal and measurement are 128, 64, respectively. The training and testing signal are no-sparsity signal. The training signals are simulated by random signal. The eps threshold is 0.00001, the maximum iteration time is 1000, and the threshold for the shrinkage computing is 0.05. The training parameters of LISTA and LISTA_nf are: the batch size is 128, the training epoch is 100, the training loss functions are the MSE loss function combined with the L1 loss function, the maximum iteration time is 32, the optimizer is SGD. The ISTA, LISTA, and LISTA_nf are tuned using identical hyperparameters for a fair comparison.

(2) The Ablation and Comparison Experiments

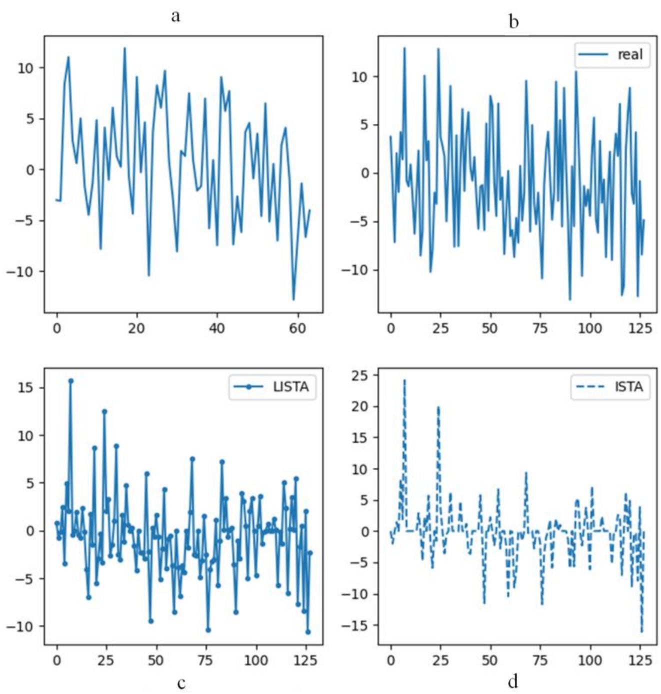

Figure 1. *The comparison results of the left above subfigure a) the sparse coefficient, the right above subfigure b) the real signal, the left down subfigure c) the reconstruction result of LISTA for the real signal, and the right down subfigure d) the reconstruction result of ISTA for the real signal.*

The comparison results of the comparison results of the left above subfigure a) the sparse coefficient, the right above subfigure b) the real signal, the left down subfigure c) the reconstruction result of LISTA for the real signal, and the right down subfigure d) the reconstruction result of ISTA for the real signal are as shown in Figure 1. From Figure 1, the reconstruction results of ISTA and LISTA are both close to the real signal.

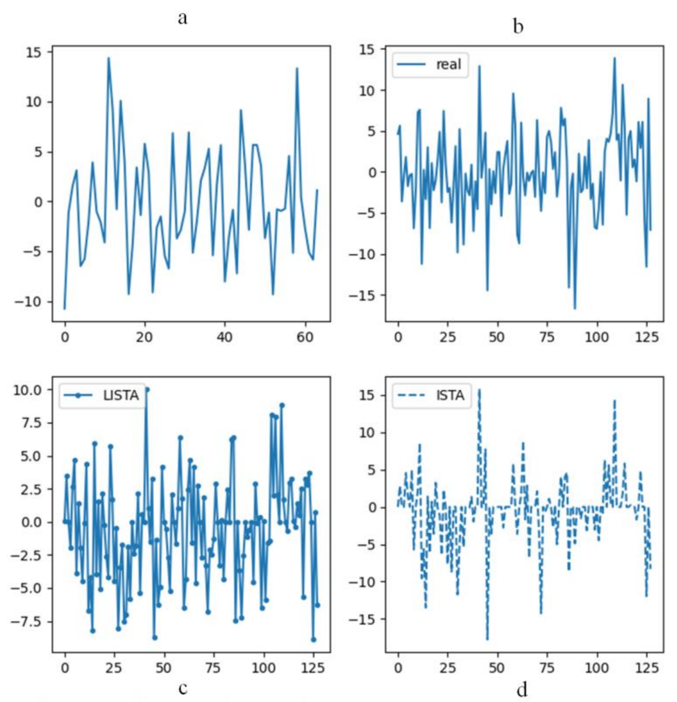

Figure 2. *The comparison results of the left above subfigure a) the sparse coefficient, the right above subfigure b) the real signal, the left down subfigure c) the reconstruction result of LISTA for the real signal, and the right down subfigure d) the reconstruction result of ISTA for the real signal.*

The comparison results of the comparison results of the left above subfigure a) the sparse coefficient, the right above subfigure b) the real signal, the left down subfigure c) the reconstruction result of LISTA for the real signal, and the right down subfigure d) the reconstruction result of ISTA for the real signal are as shown in Figure 2. From Figure 2, the reconstruction results of ISTA and LISTA are both close to the real signal.

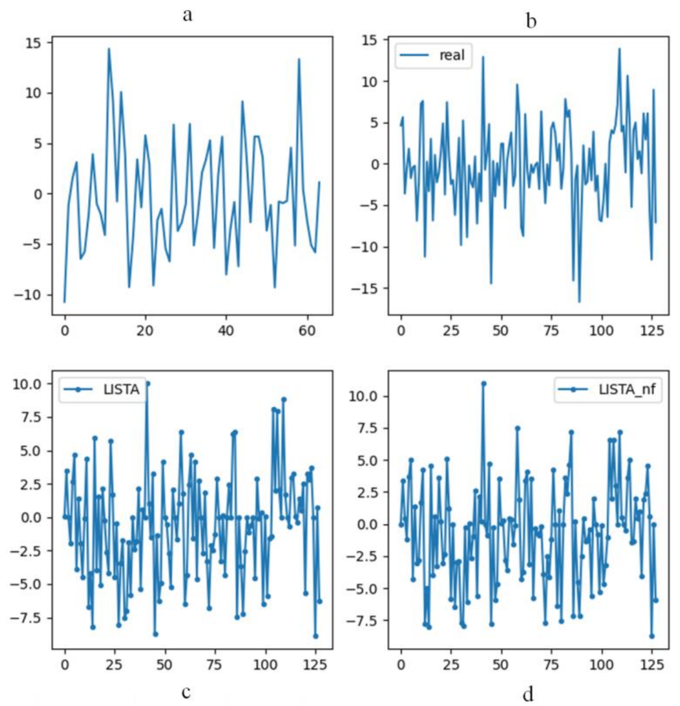

Figure 3. *The comparison results of the left above subfigure a) the sparse coefficient, the right above subfigure b) the real signal, the left down subfigure c) the reconstruction result of LISTA for the real signal, and the right down subfigure d) the reconstruction result of LISTA_nf for the real signal.*

The comparison results of the comparison results of the left above subfigure a) the sparse coefficient, the right above subfigure b) the real signal, the left down subfigure c) the reconstruction result of LISTA for the real signal, and the right down subfigure d) the reconstruction result of LISTA-nf for the real signal are as shown in Figure 3. From Figure 3, the reconstruction results of LISTA and LISTA_nf are both close to the real signal.

Table 1. *The Reconstruction MSE.*

Different Methods	MSE
ISTA	0.35
LISTA	0.33
LISTA_nf	0.25

The reconstruction mean-square error (MSE) is shown as Table 1. From Table 1, the MSE of ISTA, LISTA, and LISTA_nf are 0.35, 0.33, and 0.25, respectively. The MSE of LISTA_nf is better than the MSE of ISTA and LISTA.

(3) The Reconstruction Time

Table 2. *The Reconstruction Time.*

Different Methods	Time (s)
ISTA	0.1
LISTA	0.12
LISTA_nf	0.17

The reconstruction time of ISTA, LISTA, and LISTA_nf are 0.1, 0.12, and 0.17, respectively, which is shown in Table 2. The reconstruction time of LISTA_nf is longer than the reconstruction time of ISTA and LISTA. The non-local full connection layer in the LISTA_nf consumes longer computing time.

5. Conclusions

This paper designs a compression sensing reconstruction method for the 1-d signal. To reconstruct 1-d signal, the deep learning method LISTA is used. Then, the linear full connection layer in LISTA is improved by non-local full connection layer. The computing regions of improved non-local full connection layer contain: 1) the full connection before; 2) the current full connection; and 3) the full connection after. Experimental results show the reconstruction results of LISTA and LISTA_nf are both close to the real signal. The MSE of LISTA_nf is better than the MSE of ISTA and LISTA. The non-local full connection layer in the LISTA_nf consumes longer computing time.

Abbreviations

ISTA	Iterative Shrinkage-Thresholding Algorithm
LISTA	Learned Iterative Shrinkage and Thresholding Algorithm
LISTA-nf	Learned Iterative Shrinkage and Thresholding Algorithm-Non-local Full Connection
OMP	Orthogonal Matching Pursuit
SAMP	Sparsity Adaptive Matching Pursuit
ROMP	Regularized Orthogonal Matching Pursuit
StOMP	Stagewise Orthogonal Matching Pursuit
CoSaMP	Compressive Sampling Matching Pursuit

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Data Availability Statement

The code, data for this paper, and datasets are opened in https://download.csdn.net/download/accdgh/91668667

Conflicts of Interest

The authors declare no conflicts of interest.

References

[1] Donoho D L. Compressed sensing [J]. IEEE Transactions on Information Theory, 2006, 52(4): 1289-1306. https://doi.org/10.1109/TIT.2006.871582

[2] Do T T, Gan L, Nguyen N, et al. Sparsity adaptive matching pursuit algorithm for practical compressed sensing [C] // 42nd IEEE International Conference on Signals, Systems and Computers (ASILOMAR 2008). Pacific Grove, CA, USA: IEEE, 2008: 581-587. https://doi.org/10.1109/ACSSC.2008.5074472

[3] Needell D, Vershynin R. Signal recovery from incomplete and inaccurate measurements via regularized orthogonal matching pursuit [J]. IEEE Journal of Selected Topics in Signal Processing, 2010, 4(2): 310-316. https://doi.org/10.1109/JSTSP.2010.2042412

[4] Donoho D L, Tsaig Y, Drori I, et al. Sparse solution of underdetermined systems of linear equations by stagewise orthogonal matching pursuit [J]. IEEE Transactions on Information Theory, 2012, 58(2): 1094-1121. https://doi.org/10.1109/TIT.2011.2173159

[5] Needell D, Tropp J A. CoSaMP: Iterative signal recovery from incomplete and inaccurate samples [J]. Applied and Computational Harmonic Analysis, 2009, 26(3): 301-321. https://doi.org/10.1016/j.acha.2008.07.002

[6] Gregor K, LeCun Y. Learning fast approximations of sparse coding [C] // Proceedings of the 27th International Conference on Machine Learning (ICML-10). Haifa, Israel: ICML, 2010: 399-406. https://doi.org/10.1145/1835804.1835862

[7] Safavi S H, Torkamani-Azar F. Perceptual compressive sensing based on contrast sensitivity function: Can we avoid non-visible redundancies acquisition?[C] // Iranian Conference on Electrical Engineering. Tehran, Iran: IEEE, 2017. https://doi.org/10.1109/IranianCEE.2017.7985256

[8] Kasem Hossam M, El-Sabrouty Maha. A comparative study of audio compression based on compressed sensing and Sparse Fast Fourier transform (SFFT): Performance and challenges [C] // 2013 IEEE International Symposium on Signal Processing and Information Technology (ISSPIT). Athens, Greece: IEEE, 2013: 1-6. https://doi.org/10.1109/ISSPIT.2013.6707749

[9] Lin J P, Liu D, Li H Q, et al. M-LVC: Multiple frames prediction for learned video compression [C] // Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR). Seattle, WA, USA: IEEE, 2020. https://doi.org/10.1109/CVPR42600.2020.00359

[10] Griffin A, Hirvonen T, Mouchtaris A, et al. Encoding the sinusoidal model of an audio signal using compressed sensing [C] // 2009 IEEE International Conference on Multimedia and Expo. New York, NY, USA: IEEE, 2009: 153-156. https://doi.org/10.1109/ICME.2009.5202400

[11] Verburg S A, Fernandez-Grande E. Reconstruction of the sound field in a room using compressive sensing [J]. The Journal of the Acoustical Society of America, 2018, 143(6): 3770-3779. https://doi.org/10.1121/1.5039481

[12] Griffin A, Hirvonen T, Tzagkarakis C, et al. Single-channel and multi-channel sinusoidal audio coding using compressed sensing [J]. IEEE Transactions on Audio, Speech, and Language Processing, 2010, 19(5): 1382-1395. https://doi.org/10.1109/TASL.2010.2089350

[13] Valenzise G, Prandi G, Tagliasacchi M, et al. Identification of sparse audio tampering using distributed source coding and compressive sensing techniques [J]. EURASIP Journal on Image and Video Processing, 2009, 2009(1): 158982. https://doi.org/10.1155/2009/158982

[14] Zahedi A, Østergaard J, Jensen S H, et al. Audio coding in wireless acoustic sensor networks [J]. Signal Processing, 2015, 107: 141-152. https://doi.org/10.1016/j.sigpro.2014.08.014

[15] Griffin A, Tsakalides P. Compressed sensing of audio signals using multiple sensors [C] // 2008 16th European Signal Processing Conference. Lausanne, Switzerland: IEEE, 2008: 1-5. https://doi.org/10.1109/EUSIPCO.2008.4697622

[16] Moreno-Alvarado R, Rivera-Jaramillo E, Nakano M, et al. Simultaneous audio encryption and compression using compressive sensing techniques [J]. Electronics, 2019, 9(5): 863. https://doi.org/10.3390/electronics9050863

[17] Katzberg F, Mazur R, Maass M, et al. A compressed sensing framework for dynamic sound-field measurements [J]. IEEE/ACM Transactions on Audio, Speech, and Language Processing, 2018, 26(11): 1962-1975. https://doi.org/10.1109/TASLP.2018.2859430

[18] Yin M, Yu K, Wang Z. Compressive sensing based sampling and reconstruction for wireless sensor array network [J]. Mathematical Problems in Engineering, 2016, 2016: 9641608. https://doi.org/10.1155/2016/9641608

[19] Christensen M G, Østergaard J, Jensen S H. On compressed sensing and its application to speech and audio signals [C] // 2009 Conference Record of the Forty-Third Asilomar Conference on Signals, Systems and Computers. Pacific Grove, CA, USA: IEEE, 2009: 356-360. https://doi.org/10.1109/ACSSC.2009.5469955

[20] Abood E W, Hussien Z A, Kawi H A, et al. Provably secure and efficient audio compression based on compressive sensing [J]. International Journal of Electrical and Computer Engineering, 2023, 13(1): 335-346. https://doi.org/10.11591/ijece.v13i1.pp335-346

[21] Albiges T, Sabeur Z, Arbab-Zavar B. Compressed Sensing Data with Performing Audio Signal Reconstruction for the Intelligent Classification of Chronic Respiratory Diseases [J]. Electronics, 2024, 13(17): 3243. https://doi.org/10.3390/electronics13173243

[22] Upadhyaya V, Sharma G, Kumar A, et al. Quality parameter index estimation for compressive sensing based sparse audio signal reconstruction [C] // IOP Conference Series: Materials Science and Engineering. Bristol, UK: IOP Publishing, 2021, 1119(1): 012005. https://doi.org/10.1088/1757-899X/1119/1/012005

[23] Russell M, Wang P. Physics-informed deep learning for signal compression and reconstruction of big data in industrial condition monitoring [J]. Mechanical Systems and Signal Processing, 2022, 168: 108709. https://doi.org/10.1016/j.ymssp.2021.108709

[24] Bao Y, Tang Z, Li H. Compressive-sensing data reconstruction for structural health monitoring: a machine-learning approach [J]. Structural Health Monitoring, 2020, 19(1): 293-304. https://doi.org/10.1177/1475921718821864

[25] Machidon A L, Pejovic V. Deep Learning Techniques for Compressive Sensing-Based Reconstruction and Inference--A ubiquitous Systems Perspective [J]. arXiv preprint arXiv: 2105.13191, 2021. https://doi.org/10.48550/arXiv.2105.13191

[26] Lu H, Bo L. WDLReconNet: Compressive sensing reconstruction with deep learning over wireless fading channels [J]. IEEE Access, 2019, 7: 24440-24451. https://doi.org/10.1109/ACCESS.2019.2904040

[27] Bright I, Lin G, Kutz J N. Compressive sensing based machine learning strategy for characterizing the flow around a cylinder with limited pressure measurements [J]. Physics of Fluids, 2013, 25(12): 127102. https://doi.org/10.1063/1.4837214

[28] Wang X L, Yang D P, Wang Y S, et al. Time-domain signal reconstruction of vehicle interior noise based on deep learning and compressed sensing techniques [J]. Mechanical Systems and Signal Processing, 2020, 139: 106635. https://doi.org/10.1016/j.ymssp.2019.106635

[29] Machidon A L, Pejović V. Deep learning for compressive sensing: a ubiquitous systems perspective [J]. Artificial Intelligence Review, 2023, 56(4): 3619-3658. https://doi.org/10.1007/s10462-022-10273-6

[30] Du X L, Liang K Y, Lv Y N, et al. Fast reconstruction of EEG signal compression sensing based on deep learning [J]. Scientific Reports, 2024, 14(1): 5087. https://doi.org/10.1038/s41598-024-55731-2

[31] Wu Y, Rosca M, Lillicrap T. Deep compressed sensing [C] // International Conference on Machine Learning. Long Beach, CA, USA: PMLR, 2019: 6850-6860. https://doi.org/10.48550/arXiv.1811.08083

[32] Dai J, Qi H, Xiong Y, et al. Deformable convolutional networks [C] // Proceedings of the IEEE International Conference on Computer Vision. Venice, Italy: IEEE, 2017: 764-773. https://doi.org/10.1109/ICCV.2017.89

[33] Liu N, Long Y, Zou C, et al. Adcrowdnet: An attention-injective deformable convolutional network for crowd understanding [C] // Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. Long Beach, CA, USA: IEEE, 2019: 3225-3234. https://doi.org/10.1109/CVPR.2019.00336

[34] Thomas H, Qi C R, Deschaud J E, et al. Kpconv: Flexible and deformable convolution for point clouds [C] // Proceedings of the IEEE/CVF International Conference on Computer Vision. Seoul, South Korea: IEEE, 2019: 6411-6420. https://doi.org/10.1109/ICCV.2019.00652

[35] Shi Z, Liu X, Shi K, et al. Video frame interpolation via generalized deformable convolution [J]. IEEE Transactions on Multimedia, 2021, 24: 426-439. https://doi.org/10.1109/TMM.2021.3061416

[36] Wang X, Chan K C K, Yu K, et al. Edvr: Video restoration with enhanced deformable convolutional networks [C] // Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops. Long Beach, CA, USA: IEEE, 2019. https://doi.org/10.1109/CVPRW.2019.00085

[37] Wang W, Dai J, Chen Z, et al. Internimage: Exploring large-scale vision foundation models with deformable convolutions [C] // Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. Vancouver, BC, Canada: IEEE, 2023: 14408-14419. https://doi.org/10.1109/CVPR52729.2023.01394

[38] Zhu X, Hu H, Lin S, et al. Deformable convnets v2: More deformable, better results [C] // Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. Long Beach, CA, USA: IEEE, 2019: 9308-9316. https://doi.org/10.1109/CVPR.2019.00950

[39] Chen J, Pan Y, Li Y, et al. Temporal deformable convolutional encoder-decoder networks for video captioning [C] // Proceedings of the AAAI Conference on Artificial Intelligence. Honolulu, HI, USA: AAAI Press, 2019, 33(1): 8167-8174. https://doi.org/10.1609/aaai.v33i01.33018167

[40] Deng J, Wang L, Pu S, et al. Spatio-temporal deformable convolution for compressed video quality enhancement [C] // Proceedings of the AAAI Conference on Artificial Intelligence. New York, NY, USA: AAAI Press, 2020, 34(7): 10696-10703. https://doi.org/10.1609/aaai.v34i07.6811

[41] Park J, Yoo S, Park J, et al. Deformable graph convolutional networks [C] // Proceedings of the AAAI Conference on Artificial Intelligence. Vancouver, BC, Canada: AAAI Press, 2022, 36(7): 7949-7956. https://doi.org/10.1609/aaai.v36i7.20729