

The Compression Sensing Reconstruction for the 1-d Signal Based on Non-local 1-d Convolution Applied to LISTA

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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. 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 convolution layer in LISTA is improved by non-local 1-d convolution. The convolution regions of improved non-local 1-d convolution contain: 1) the convolution before; 2) the current convolution; and 3) the convolution after. Experimental results show the reconstructed results of LISTA is better than those of ISTA and the reconstructed results of LISTA-n1d is better than those of LISTA and the reconstruction time of ISTA, LISTA, and LISTA-n1d are 0.1s, 0.12s, and 0.17s, respectively.

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 Donoho DL (2006), SAMP Do TT et al. (2008), ROMP Needell D et al. (2010), StOMP Donoho DL et al. (2012), CoSaMP Needell D et al. (2009). With the developments of machine learning, the 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 Gregor K et al. is used.

Then, the linear convolution layer in LISTA is improved by non-local 1-d convolution. The convolution regions of improved non-local 1-d convolution contain: 1) the convolution region; 2) the current convolution; and 3) the convolution after. Experimental results show the reconstructed results of LISTA is better than those of ISTA and the reconstructed results of LISTA-n1d is better than those of LISTA and the reconstruction time of ISTA, LISTA, and LISTA-n1d are 0.1s, 0.12s, and 0.17s, respectively.

RELATED WORKS

The Compression Sensing Reconstruction Of 1-D Signal

Traditional Methods

Defraene et al. Safavi SH et al. (2017) applied compressive sensing for clipping processing of one-dimensional signals. M.Kasem and EI-Sabrouty Kasem Hossam M et al. (2013) proposed a comparative study on audio compression based on compressive sensing and

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Key words: Compression sensing reconstruction; 1-d signal; LISTA; non-local 1-d convolution.

sparse fast Fourier transform (SFFT): performance and challenges. Jianping Lin et al. (2020) developed a multi-frame prediction M-LVC method for video compression. Grrggin et al. Griffin A et al. (2009) proposed using compressive sensing for encoding the sinusoidal model of audio signals. A. Verburg and Fernandez-Grande Verburg SA et al. (2018) suggested using compressive sensing to reconstruct sound fields inside buildings. Griffin A et al. (2010) presented compressive sensing-based single-channel and multi-channel sinusoidal sound encoding. Valenzise G et al. (2009) proposed using distributed source coding and compressive sensing techniques to identify sparse audio tampering. Zahedi A et al. (2015) proposed audio coding for wireless acoustic sensor networks. Griffin A et al. (2008) presented compressive sensing reconstruction of audio signals using multiple sensors. Moreno-Alvarado Griffin A et al. (2008) designed research on simultaneous audio encryption and compression using compressive sensing technology. Katzberg F et al. (2018) developed a compressive sensing framework for dynamic sound field measurement. Yin M et al. (2016) designed a compressive sensing method based on sampling and reconstruction, applied to wireless sensor matrix networks. Christensen MG et al. (2009) discussed compressive sensing methods and their applications in speech and audio signal processing. Abood EW et al. (2023) designed provably secure and efficient audio compression based on compressive sensing. Albiges Abood EW et al. (2023) used compressive sensing data for audio signal reconstruction to achieve intelligent classification of chronic respiratory diseases. Upadhyaya V et al. (2021) designed quality parameter estimation for sparse audio signal reconstruction based on compressive sensing.

Machine Learning Methods and Deep Learning Methods

Russell M et al. (2022) 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 Y et al. (2020) developed a machine learning approach for compressive sensing data reconstruction in structural health monitoring. L. Machidon AL et al. (2021) designed applications of deep learning in compressive sensing from a ubiquitous system perspective. Lu H et al. (2019) proposed WDLReconNet: deep learning compressive sensing reconstruction for wireless fading channels. Bright I et al. (2013) developed a compressive sensing-based machine learning strategy for characterizing flow around a cylinder with 80limited pressure measurements. Wang XL et al. (2020) designed time-domain signal reconstruction of vehicle interior noise based on deep learning and compressed sensing techniques. L.

Machidon AL et al. (2023) presented applications of deep learning in compressive sensing from a ubiquitous systems perspective. Du XL et al. (2024) proposed a deep learning-based fast reconstruction method for EEG signal compressive sensing. Wu Y et al. developed a deep compressive sensing approach.

The Methods for Deformable Convolution

Dai J et al. proposed deformable convolutional networks. Liu N et al. designed an attention-injective deformable convolutional network for crowd understanding. Thomas H et al. improved the flexible and deformable convolution for point clouds. Shi Z et al. (2021) proposed the video frame interpolation method via generalized deformable convolution. Wang X et al. designed a video restoration method with enhanced deformable convolutional networks. Wang W et al. explored large-scale vision foundation Models with deformable convolutions. Zhu X et al. designed deformable conv Nets v2: more deformable, better results method. Chen J et al. (2019) designed temporal deformable convolutional encoder-decoder networks for video captioning. Deng J et al. (2020) improved the spatio-temporal deformable convolution for compressed video quality enhancement. Park J et al. (2022) designed deformable graph convolutional networks.

METHODS

In LISTA Gregor K et al. 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 cannot be captured. Therefore, the non-local 1-d convolution is proposed. The linear convolution layer in LISTA is improved by non-local 1-d convolution. The convolution regions of improved non-local 1-d convolution contain: 1) the convolution before; 2) the current convolution; and 3) the convolution after.

Non-local 1-d Convolution

The normal 1-d convolution computing is

$$(\cdot, 0) = \sum_{i=1}^1 \sum_{j=-1}^{-1} (1, \cdot) (1, 0) \quad (1)$$

The non-local 1-d convolution contain: 1) the convolution before; 2) the current convolution; and 3) the convolution after.

In the convolution before, the convolution computing is

$$1(\cdot, 0) = \sum_{i=1}^1 \sum_{j=-1}^{-1} (1, \cdot) (1, 0) \quad (2)$$

where $1(\cdot, 0)$ is the output feature for point and 0-channel, the channel of the input feature is 1, the size of input data is $\_$, the input feature or data is, and the convolution

kernel is.

In the current convolution, the convolution computing is

$$2(\cdot, 0) = \sum_{i=1}^1 \sum_{j=-1}^1 (1, i) (1, j) \quad (3)$$

where $2(\cdot, 0)$ is the output feature for point and 0-channel, the channel of the input feature is 1, the size of input data is $\_$, the input feature or data is, and the convolution kernel is.

In the convolution after, the convolution computing is

$$3(\cdot, 0) = \sum_{i=1}^1 \sum_{j=-1}^1 (1, i) (1, j) \quad (4)$$

where $3(\cdot, 0)$ is the output feature for point and 0-channel, the channel of the input feature is 1, the size of input data is $\_$, the input feature or data is, and the convolution kernel is.

The output feature is

$$(\cdot, 0) = (1(\cdot, 0) + 2(\cdot, 0) - 3(\cdot, 0)) \quad (5)$$

and the $(\cdot, 0)$ is the output feature for the convolution point and 0-channel.

EXPERIMENTAL RESULTS

The Ablation Experiments and The Comparison Experiments

The reconstruction results are as shown in Fig. 1- Fig. 6. In one figure, the above part is one part of the reconstructing signal, the down parts of Fig. 1, Fig. 3, and Fig. 5 are the real signal, the reconstructed results of the real signal for LISTA method, and the reconstructed

Figure 1: The Reconstruction Result 1

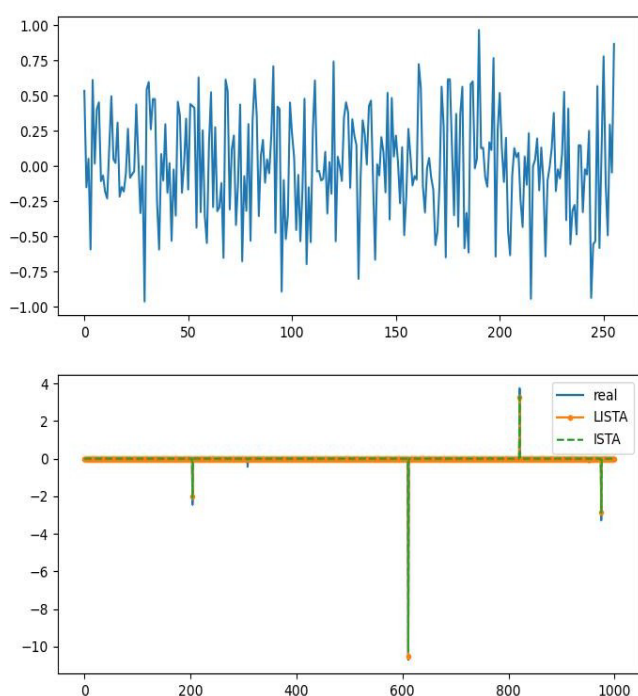


Figure 2: The Reconstruction Result 2

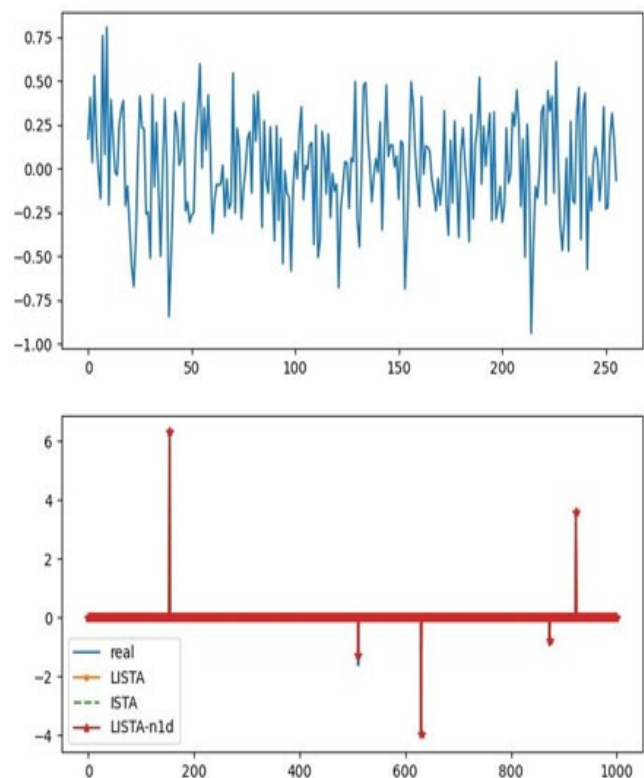
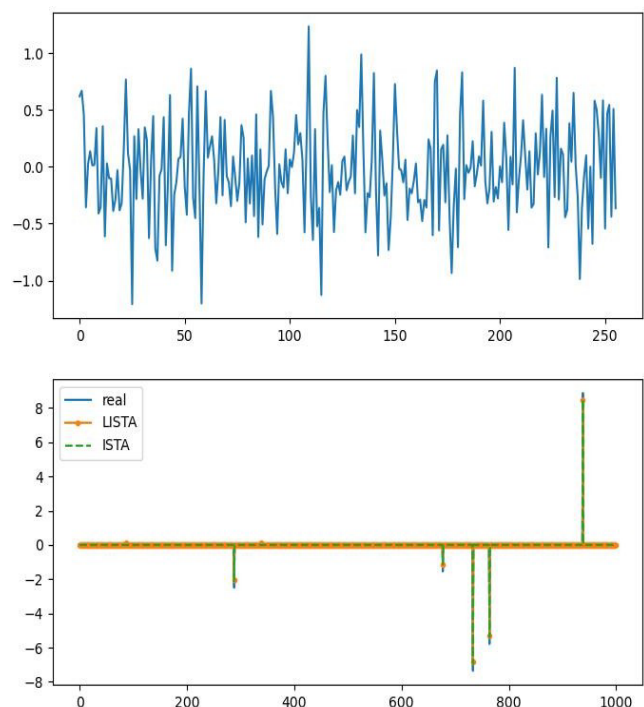


Figure 3: The Reconstruction Result 3



results of the real signal for ISTA method, and the down parts of Fig. 2, Fig. 4, and Fig. 6 are the real signal, the reconstructed results of the real signal for LISTA method, the reconstructed results of the real signal for ISTA method, and the reconstructed results of the real signal for LISTA-n1d method.

Figure 4: The Reconstruction Result 4

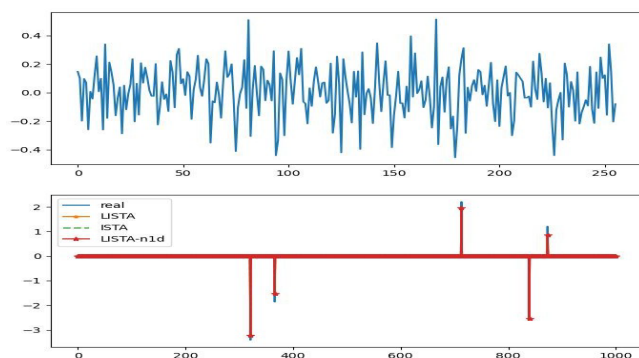
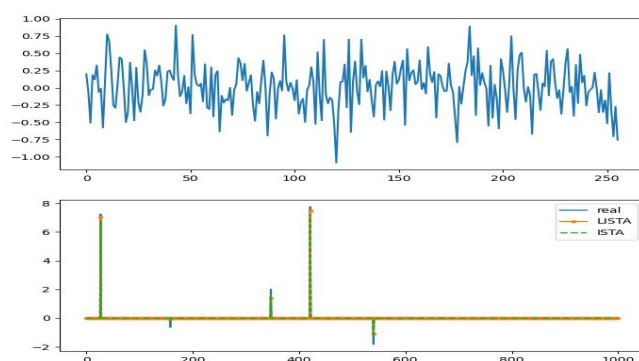


Figure 5: The Reconstruction Result 5



From Fig. 1-Fig. 6, we can find the reconstructed results of LISTA is better than those of ISTA and the reconstructed results of LISTA-n1d is better than those of LISTA.

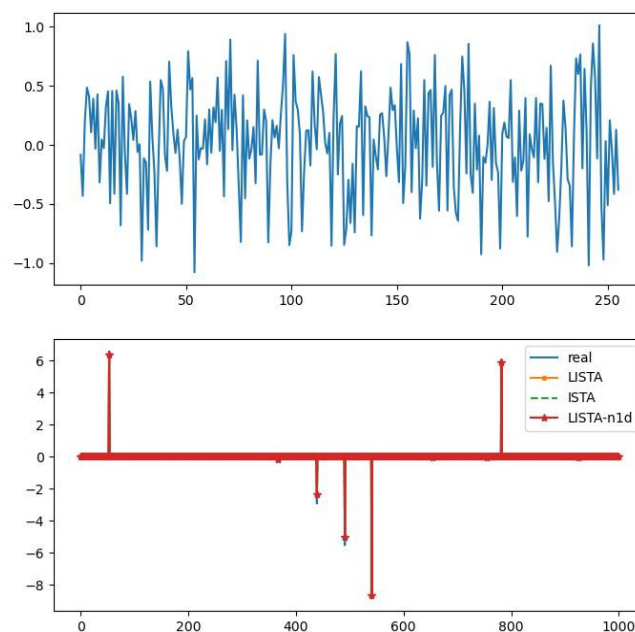
Table 1: The Reconstruction Time

	Time (s)
ISTA	0.1
LISTA	0.12
LISTA-n1d	0.17

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 convolution layer in LISTA is improved by non-local 1-d convolution. The convolution regions of improved non-local 1-d convolution contain: 1) the convolution region; 2) the current convolution; and 3) the convolution after. Experimental results show the reconstructed results of LISTA is better than those of ISTA and the reconstructed results of LISTA-n1d is better than those of LISTA and the reconstruction time of ISTA, LISTA, and LISTA

Figure 6: The Reconstruction Result 6



The Computation Time

The computation time is as shown in Table I. The Results is obtained by experimenting 1000 time, and we obtain the results by computing the mean value. From Table I, we can find the reconstruction time of ISTA, LISTA, and LISTA-n1d are 0.1s, 0.12s, and 0.17s, respectively.

-n1d are 0.1s, 0.12s, and 0.17s, respectively.

Abbreviations

The following abbreviations are used in this manuscript:

ISTA Iterative Shrinkage-Thresholding Algorithm

LISTA Learned Iterative Shrinkage and Thresholding Algorithm

LISTA-n1d Learned Iterative Shrinkage and Thresholding Algorithm-Non-local 1-d convolution

OMP Orthogonal Matching Pursuit

SAMP Sparsity Adaptive Matching Pursuit

ROMP Regularized Orthogonal Matching Pursuit

StOMP Stagewise Orthogonal Matching Pursuit

CoSaMP Compressive Sampling Matching Pursuit

DECLARATIONS

Data Availability Statement

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

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Conflicts Of Interest

The authors declare no conflicts of interest.

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