ICRICS: iterative compensation recovery for image compressive sensing

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Abstract
Closed-loop architecture is widely utilized in automatic control systems and attains distinguished dynamic and static performance. However, classical compressive sensing systems employ an open-loop architecture with separated sampling and reconstruction units. Therefore, a method of iterative compensation recovery for image compressive sensing is proposed by introducing a closed-loop framework into traditional compressive sensing systems. The proposed method depends on any existing approaches and upgrades their reconstruction performance by adding a negative feedback structure. Theoretical analysis of the negative feedback of compressive sensing systems is performed. An approximate mathematical proof of the effectiveness of the proposed method is also provided. Simulation experiments on more than 3 image datasets show that the proposed method is superior to 10 competing approaches in reconstruction performance. The maximum increment of the average peak signal-to-noise ratio is 4.36 dB, and the maximum increment of the average structural similarity is 0.034 based on one dataset. The proposed method based on a negative feedback mechanism can efficiently correct the recovery error in the existing image compressive sensing systems.

Keywords Image compressive sensing · Iterative compensation recovery · Closed-loop · Negative feedback

1 Introduction
IMAGE compressive sensing simultaneously samples and compresses source signals, utilizes a very low sub-Nyquist sampling frequency, depends on some known image prior knowledge and efficiently recovers the original image. Image compressive sensing offers a series of prominent advantages, such as a low sampling rate, low power consumption, low system cost, low radiation damage and high reconstruction performance, and it achieves extensive applications in medical imaging, biological imaging, civil imaging and military imaging [1].

On a macrolevel, with the continuous development of human society and the rapid progress of science and technology, people impose increasingly higher requirements on the performance of image compressive sensing systems, and an increasing number of disadvantages of image compressive sensing systems are exposed. The theories and applications of image compressive sensing obtain increasingly larger development space; therefore, an urgent need has emerged for scholars and engineers to research the principles and methods of high-performance image compressive sensing [2].

On a microlevel, a very low sampling rate results in the loss of vast useful information and causes image compressive sensing to become an undetermined and ill-posed problem [3–5]. At present, this problem can only be approximately
resolved, and its perfect solution will offer very important value for theories and applications.

Currently, to the best of our knowledge, image compressive sensing adopts an open-loop architecture with separated measurement and recovery units. Closed-loop architecture is broadly applied in automatic control systems to gain better dynamic and static performance, such as response time and steady-state error [6]. This paper attempts to enhance the recovery quality of the existing image compressive sensing approaches by building a closed-loop system. We refer to this as iterative compensation recovery for image compressive sensing (ICRICS). Compensation means compensating for the reconstruction error in image compressive sensing systems by an error term in closed-loop systems.

The main contributions of this paper are listed as follows: (1) A closed-loop negative feedback architecture is introduced into image compressive sensing to improve the reconstruction performance; (2) a theoretical analysis of the proposed negative feedback system is conducted in detail; (3) an approximate mathematical proof of the effectiveness of the proposed method is subtly designed; and (4) the proposed method is applicable for any existing approaches of image compressive sensing and can strengthen their reestablishment capability.

It should be mentioned that the proposed method including the negative feedback loop is not for the sampling phase (imaging phase) of an image compressive sensing system, but for the recovery phase. It is unnecessary to be implemented by a real electronic circuit. The sampling matrix of an actual image compressive sensing system can always be obtained. If the sampling matrix is given, the proposed method can be implemented by pure software.

The rest of this paper is organized as follows. Section 2 summarizes the related work of image compressive sensing, Sect. 3 describes the theoretical foundation of the proposed method, Sect. 4 designs the simulation experiments, and Sect. 5 draws some conclusions.

2 Related work

Because there is almost no previous research on image compressive sensing which is similar to the proposed method, the related work section is arranged as a mini literal review of the classical approaches including algorithms, applications, challenges and prospects [7–65]. The competing approaches compared in later experimental section are also summarized in this section.

First, the theories and methods of image compressive sensing are developing to maturity and are still in the process of continuous improvement, and their application domains include magnetic resonance imaging, radar imaging, terahertz imaging, optical imaging, optoacoustic imaging, ghost imaging, ultrasound imaging, spectrometry imaging, hyperspectral imaging, microscopy imaging, underwater imaging, single-pixel imaging, single-photon imaging and Marchenko imaging [7–27]. Li et al. summarized the sensing models, reconstruction algorithms and practical applications of compressive sensing [7]. Monika et al. summarized the challenges, innovations and applications of adaptive block compressive sensing [8]. Chen et al. surveyed the technologies, applications and future prospects of compressive sensing for magnetic resonance imaging [9]. Bustin et al. reviewed the means of magnetic resonance imaging, including low-rank reconstruction, sparse dictionary learning and deep learning [10]. Chul et al. overview magnetic resonance imaging from the viewpoint of signal processing [11]. Yang et al. summarized the foundations, challenges and developments of compressive sensing for radar imaging [12]. Cao et al. probed the development history of terahertz imaging technologies [13]. Ke et al. summarized the principles, advances, difficulties and opportunities of compressive sensing in optical imaging [14]. Hirsch et al. compared time domain compressed sensing techniques for optoacoustic imaging [15]. Wang et al. studied mathematical problems in ghost imaging [16]. Yousufi et al. surveyed the applications of sparse representation-based compressive sensing in ultrasound imaging [17]. Xie et al. strengthened the throughput of mass spectrometry imaging using joint compressed sensing and subspace modeling [18]. Oiknine et al. investigated hyperspectral imaging technologies [19]. Calisesi et al. researched microscopy imaging technology based on compressive sensing [20]. Monika et al. presented an efficient adaptive compressive sensing method for underwater imaging [21]. Edgar et al. discussed the principles and prospects of single-pixel imaging [22]. Xiao et al. reviewed single-pixel imaging and its probability and statistical analysis [23]. Gibson et al. overviewed the recent developments, hardware configurations, mask designs, reconstruction algorithms and realistic applications of single-pixel imaging [24]. Zanotto et al. surveyed the theories and technologies of single-pixel terahertz imaging [25]. Liu et al. explored the technologies of single-photon imaging based on compressive sensing [26]. Zhang proposed compressive sensing acquisition for Marchenko imaging [27].

Second, image compressive sensing generally takes advantage of various prior knowledge to recover the original image, and the classical methods comprise total variation, wavelet transform, sparse representation, low-rank representation, machine learning, deep learning, etc. [28–58]. Some deep learning-based methods are utilized as competing methods in the later experimental section [49–53, 55–58]. S. Ravishankar et al. summarized the reconstruction methods of image compressive sensing from sparsity to the data adaptation method and machine learning [28]. Xie et al. reviewed the deep learning methods and applications of compressed
sensing image reconstruction [29]. Saideni et al. overviewed the deep learning techniques for video compressive sensing [30]. Khosravy et al. surveyed random acquisition methods in compressive sensing [31]. Mishra et al. reviewed soft computing-based compressive sensing techniques in signal processing [32]. Chen et al. systematically overviewed and analyzed a rapid method of magnetic resonance imaging based on artificial intelligence [33]. Zhang et al. utilized reweighted total variation and sparse regression for magnetic resonance imaging relying on compressive sensing [34]. Zhang et al. adopted 3D-total generalized variation and tensor decomposition for compressed sensing-based magnetic resonance imaging [35]. Yin et al. proposed multilevel wavelet-based hierarchical networks for image compressed sensing [36]. Yin et al. also proposed a wavelet transform-based deep network for compressed image sensing [37]. Lv et al. employed low-rank representation for radar imaging [38]. Sun et al. researched the theory of magnetic resonance imaging based on blind compressive sensing and nonlocal low-rank constraints [39]. Li applied sparse representation and compressive-domain saliency-based adaptive measurement to video compressive sensing [40]. Suantai et al. studied the applications of the forward–backward algorithm in compressive sensing [41]. Shi et al. proposed a convolutional neural network-based image compressive sensing method including a sampling network and reconstruction network, where the former employs convolutional operations and the latter contains two parts: initial linear reconstruction and deep nonlinear reconstruction [2]. Yang et al. fused traditional model-based compressive sensing methods and data-driven deep learning methods [1]. Mardani et al. presented a compressive sensing method of magnetic resonance imaging based on deep generative adversarial networks [42]. Li et al. proposed a multiscale generative adversarial network for image compressed sensing [43]. Zeng et al. reviewed reconstruction technologies of magnetic resonance imaging based on nonfull-sampling k-space deep learning [44]. Han et al. developed acceleration technologies for magnetic resonance imaging based on low-rank k-space deep learning [45]. Kravets et al. proposed progressive compressive sensing for large images based on deep learning [46]. Wang et al. utilized a multiscale deep network for compressive sensing image reconstruction [47]. Gan et al. employed data-driven acquisition and noniterative reconstruction for image compressive sensing [48]. Zhang et al. presented a range of deep learning-based image compressive sensing methods, including a controllable arbitrary-sampling network (COAST), memory-augmented deep unfolding network (MADUN), iterative shrinkage thresholding algorithm (ISTA), ISTA++, optimization-inspired network (OPINE) and high-throughput deep unfolding network (HiTDUN), for image compressive sensing [49–54]. Zhang et al. proposed an approximate message passing network (AMP-NET) for image compressive sensing [55]. The advanced transformer structure in deep learning has also been considered for image compressive sensing [56–58].

Third, some methods, such as dictionary learning, super-resolution, denoising, optimization and regularization, are utilized to upgrade the rebuilding capacity of image compressive sensing [59–63]. Harada et al. employ K-SVD dictionary learning to improve image quality for capsule endoscopy based on compressed sensing [59]. Ueki et al. adopted generative adversarial network-based image super-resolution for accelerating brain magnetic resonance imaging [60]. Fang et al. utilized the alternating direction method of multipliers for image denoising of compressed sensing [61]. El et al. utilized regularization constraints for image denoising of compressive sensing [62]. Pham developed an enhancement method for compressive sensing images using multiple reconstructed signals [63]. Zhang et al. proposed a denoising method for compressed sensing-based magnetic resonance imaging [64].

In addition, the iterative thresholding algorithms (ITAs) are similar to the proposed method to some extent [51, 52, 65]. However, ITAs are based on the error in implicit and indirect compressive domain and the proposed method is based on the error in obvious and direct image domain; ITAs depend on sparsity regularization and the proposed method depends on Taylor-series linearization. Simulation results will show the proposed method outperforms ITAs in recovery performance.

Finally, image compressive sensing seeks an optimal balance between a low sampling rate and high reestablishment capability, and its performance still has a large improvement space. The sampling rate is expected to be further decreased, and the image recovery quality is expected to be further promoted. This paper attempts to incorporate a closed-loop negative feedback structure into image compressive sensing systems to further improve the reconstruction performance.

3 Theories

3.1 Classical open-loop architecture

The top of Fig. 1 is the block diagram of the classical open-loop image compressive sensing system, which includes detached measurement (MS) units and recovery (RC) units. MS samples the original image signal, and RC recovers it. The architecture can be described by the following mathematical equations.

$$z_0 = MS(x_0)$$

$$y_0 = RC(z_0)$$

$$r = \frac{d}{D}$$
by the following mathematical expressions.

\begin{equation}
\begin{aligned}
x_n &= \begin{cases} 
y_0, & n = 1 
y_n-1 + c, & n = 2, 3, \ldots 
\end{cases} 
c &= \lambda e \\
&= \lambda (y_0 - y_{n-1}) \\
&= \lambda (y_0 - RC(z_{n-1})) \\
&= \lambda (y_0 - RC(MS(x_{n-1}))),
\end{aligned}
\end{equation}

where \( x_1 \) is equal to \( y_0 \); it can also be zero or a random value; \( x_n \) is expected to progressively approach \( x_0 \); \( c \) is the control variable; \( e \) is the error variable; \( n \) is the number of iterations; \( \lambda \) is a constant multiplier.

### 3.3 Mathematical proof of effectiveness

The effectiveness of the proposed ICRICS in Eq. 4 can be approximately proven by the following mathematical expressions. The correctness will be successfully verified in the experimental section below in an attempt to establish an approximate mathematical proof.

\begin{equation}
\begin{aligned}
x_0 - x_n \\
&= x_0 - (x_{n-1} + c) \\
&= x_0 - (x_{n-1} + \lambda e) \\
&= x_0 - (x_{n-1} + \lambda (y_0 - y_{n-1})) \\
&= x_0 - x_{n-1} - \lambda (y_0 - y_{n-1}) \\
&= x_0 - x_{n-1} - \lambda (RC(z_0) - RC(z_{n-1})) \\
&= x_0 - x_{n-1} - \lambda (RC(MS(x_0)) - RC(MS(x_{n-1}))) \\
&\approx x_0 - x_{n-1} - \lambda \mu (x_0 - x_{n-1}) \\
&= (1 - \lambda \mu) x_0 - x_{n-1}
\end{aligned}
\end{equation}

\begin{equation}
\begin{aligned}
\mu &\approx \frac{1}{D} \sum_{i=1}^{D} \frac{\partial RC(MS(x_{n-1}))(i)}{\partial x_{n-1}(i)} \\
&\approx \frac{1}{D} \sum_{i=1}^{D} \frac{RC(MS(x_{n-1}))(i) - RC(MS(x_{n-2}))(i)}{x_{n-1}(i) - x_{n-2}(i)} \\
&= \frac{1}{D} \sum_{i=1}^{D} \frac{RC(MS(x_{n-1}))(i) - RC(MS(x_{n-2}))(i)}{\sum_{i=1}^{D} (x_{n-1}(i) - x_{n-2}(i))},
\end{aligned}
\end{equation}

where \( RC(MS(x_{n-1})) \) is regarded as a nonlinear function with multiple inputs and outputs, is expanded in a Taylor series at \( x_0 \) and is approximately linearized; it is a rough generalization of the linearization by a Taylor series of nonlinear functions with single inputs and single outputs; \( \mu \) is the approximate coefficient of the Taylor series; the partial derivation can be approximately computed by difference operation.

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**Fig. 1** The classical and proposed architectures of image compressive sensing

\[ \text{Fig. 1} \] The classical and proposed architectures of image compressive sensing.
According to the triangle inequality, the following inequality can be deduced from Eq. 5.

\[ \|x_0 - x_n\|_2 \leq |1 - \lambda \mu| \|x_0 - x_{n-1}\|_2. \]  

(6)

For a given \( \mu \), the following inequations can always be satisfied by choosing a suitable \( \lambda \).

\[ |1 - \lambda \mu| < 1 \]
\[ \Leftrightarrow -1 < 1 - \lambda \mu < +1 \]
\[ \Leftrightarrow 0 < \lambda \mu < 2 \]
\[ \Rightarrow \begin{cases} 0 < \lambda < \frac{2}{\mu}, & \mu > 0 \\ \mu < \lambda < 0, & \mu < 0, \end{cases} \]

(7)

According to Eqs. 6 and 7, the mathematical proof of the proposed method can be completed as follows.

\[ \|x_0 - x_n\|_2 \leq 1 - \|x_0 - x_{n-1}\|_2 = \|x_0 - x_{n-1}\|_2 \]
\[ \Rightarrow \|x_0 - x_n\|_2 \leq \|x_0 - x_{n-1}\|_2 \]
\[ \Rightarrow \|x_0 - x_n\|_2 \leq \cdots < \|x_0 - x_1\|_2 \]
\[ \Rightarrow \|x_0 - x_n\|_2 \xrightarrow{n \to n_{\text{max}}} 0 \]
\[ \Rightarrow x_n \xrightarrow{n \to n_{\text{max}}} x_0, \]

(8)

where \( n_{\text{max}} \) is the maximum number of iterations.

By comparing Eqs. 3, 4 and 5, it can be found that both ITAs and the proposed method take advantage of iteration approaches. Nevertheless, ITAs make use of compressive-domain bias and sparsity constraints. The proposed method makes use of image-domain bias and Taylor-series approximation.

### 3.4 Theoretical explanation of negative feedback

The bottom of Fig. 1 is a closed-loop system of global negative feedback. The system input is \( y_0 \), and the system output is \( x_n \), not \( y_n \). MS and RC constitute the controlled object. The top-left adder is the comparator that compares the difference between \( y_{n-1} \) and \( y_0 \). The bottom-left adder accumulates the difference. If \( y_n \) increases first, \( e \) decreases, \( x_n \) decreases, and \( y_n \) ultimately decreases, and vice versa. After several cycles of comparison and adjustment, the system tends to stabilize. In accordance with the theory of negative feedback, \( y_n \) is close to \( y_0 \) after the system is stable. Hence, \( x_n \) should also be close to \( x_0 \) after the system is stable to ensure that \( y_n \) is close to \( y_0 \). It should be mentioned that the bottom-left delay unit and adder formulate a local positive feedback. This can be expressed by the following mathematical formulas.

\[ y_n \to y_0 \]

Table 1 Parameters of the proposed method

| Name        | Value | Meaning                      |
|-------------|-------|------------------------------|
| \( \lambda \) | \( 1/\mu \) | Constant multiplicator      |
| \( n_{\text{max}} \) | 5     | Total number of iterations  |

\[ y_0 = \text{RC}(\text{MS}(x_0)) \]
\[ y_n = \text{RC}(\text{MS}(x_n)) \]
\[ \Rightarrow x_n \to x_0, \]

(9)

If the proposed system can be approximately viewed as a linear system similar to the aforementioned linear approximation in a Taylor series, the related transfer functions can be depicted by the following mathematical expressions.

\[ \text{MS}(s) = \frac{Z(s)}{X_n(s)} \]
\[ \text{RC}(s) = \frac{Y_n(s)}{X_n(s)} \]
\[ \text{DL}(s) = \frac{X_{n-1}(s)}{Y_n(s)} = \frac{Y_{n-1}(s)}{Y_n(s)} \]
\[ \text{H}_1(s) = \frac{X_n(s)}{C(s)} = \frac{1}{1 - \text{DL}(s)} \]
\[ \text{H}_g(s) = \frac{\lambda \text{H}_1(s) \text{MS}(s) \text{RC}(s)}{\text{Y}_0(s)} = \frac{\lambda \text{H}_1(s) \text{MS}(s) \text{RC}(s)}{\text{I} + \lambda \text{H}_1(s) \text{MS}(s) \text{RC}(s)} \]
\[ \text{H}_e(s) = \frac{\text{E}(s)}{\text{Y}_0(s)} = \frac{1}{\text{I} + \lambda \text{H}_1(s) \text{MS}(s) \text{RC}(s)} \]

\[ \text{e}_s = \lim_{s \to 0} s \text{H}_e(s), \]

(10)

where \( s \) is the variable of the complex frequency domain; \( X_n, X_{n-1}, Y_n, Y_0 \) and \( E \) are the vectors of the Laplace transform of \( x_n, x_{n-1}, y_n, y_0 \) and \( e \), respectively; \( \text{DL}, \text{MS} \) and \( \text{RC} \) are the matrices of the transfer functions of DL, MS and RC, respectively; \( \text{H}_1 \) is the matrix of the transfer function of local positive feedback; \( \text{H}_g \) is the matrix of the transfer function of global negative feedback; \( \text{H}_e \) is the matrix of the error transfer function; \( \text{I} \) is the identity matrix; \( \text{e}_s \) is the vector of steady-state error.

### 4 Experiments

#### 4.1 Experimental conditions

The goal of the experimental section is to compare the image reconstruction performance between the proposed method and the competing approaches. The experimental software platform is the PyTorch framework of deep learning implemented on the 64-bit operating system.
hardware platform is a laptop computer with a 2.6-GHz dual-core processor and 8-GB main memory. The key parameters of the proposed method are collected in Table 1.

### 4.2 Competing methods

The 10 state-of-the-art competing methods and related datasets utilized in the experiments are listed in Table 2. The number at the end of each dataset name is the total number of images in the dataset. The proposed method depends on the open-source codes of the competing approaches. The parameters of deep neural networks in the proposed method are the same as those of the competing approaches.

### 4.3 Experimental results

The experimental results are shown in Tables 3, 4, 5, 6, 7, 8, 9, 10, 11 and 12 where \( r \) is the sampling rate. In each table, the average peak signal-to-noise ratio (PSNR) and average structural similarity (SSIM) of the proposed method and competing approaches on datasets Set5, Set11 and Set14 with different sampling rates are exhibited. It should be noted that SSIM and PSNR belong to object image quality assessment method and completely depend upon the quality of the reference image. If the quality of the reference image is not up to the mark, we cannot conclude about the quality of the testing image and subject image quality assessment method can be employed [66].

First, it can be found that the proposed method outperforms the existing approaches in reconstruction performance with respect to almost all datasets and sampling rates. Only in Tables 3, 4, 5, 6 and 11, at several very low sampling

| Table 2 Competing methods |
|----------------------------|
| Abbreviations | Datasets | References |
|-----------------|----------|------------|
| COAST          | Set5, Set11, Set14, BSD68 | [49] |
| MADUN          | Set5, Set11, Set14 | [50] |
| ISTA           | Set5, Set11, Set14 | [51] |
| ISTA+          | Set5, Set11, Set14, Brain50 | [51] |
| ISTA++         | Set5, Set11, Set14 | [52] |
| OPINE          | Set5, Set11, Set14 | [53] |
| AMP-NET        | Set5, Set11, Set14 | [55] |
| MTC-CSNET      | Set5, Set11, Set14 | [56] |
| TCS-NET        | Set5, Set11, Set14, McM18 | [57] |
| TransCS        | Set5, Set11, Set14 | [58] |

| Table 3 Comparison with COAST [49] |
|----------------------------------|
| Dataset | \( r \) | Average PSNR | | | Average SSIM | | |
|        |        | Original | Proposed | | | Original | Proposed | |
| Set5   |        |          |          | | |          |          | |
|        | 0.10   | 30.50    | 30.56    | | | 0.8794    | 0.8794   | |
|        | 0.20   | 34.18    | 34.25    | | | 0.9298    | 0.9302   | |
|        | 0.30   | 36.38    | 36.59    | | | 0.9515    | 0.9523   | |
|        | 0.40   | 38.33    | 38.48    | | | 0.9645    | 0.9654   | |
|        | 0.50   | 40.21    | 40.42    | | | 0.9744    | 0.9754   | |
| Set11  |        |          |          | | |          |          | |
|        | 0.10   | 28.69    | 28.74    | | | 0.8618    | 0.8621   | |
|        | 0.20   | 32.54    | 32.59    | | | 0.9251    | 0.9257   | |
|        | 0.30   | 35.04    | 35.10    | | | 0.9501    | 0.9506   | |
|        | 0.40   | 37.13    | 37.23    | | | 0.9648    | 0.9654   | |
|        | 0.50   | 38.94    | 39.08    | | | 0.9744    | 0.9752   | |
| Set14  |        |          |          | | |          |          | |
|        | 0.10   | 27.41    | 27.41    | | | 0.7799    | 0.7799   | |
|        | 0.20   | 30.71    | 30.74    | | | 0.8672    | 0.8672   | |
|        | 0.30   | 33.10    | 33.20    | | | 0.9106    | 0.9110   | |
|        | 0.40   | 35.12    | 35.26    | | | 0.9369    | 0.9376   | |
|        | 0.50   | 36.94    | 37.13    | | | 0.9549    | 0.9557   | |
| BSD68  |        |          |          | | |          |          | |
|        | 0.10   | 26.28    | 26.30    | | | 0.7422    | 0.7422   | |
|        | 0.20   | 29.00    | 29.03    | | | 0.8413    | 0.8415   | |
|        | 0.30   | 31.06    | 31.10    | | | 0.8934    | 0.8938   | |
|        | 0.40   | 32.93    | 32.98    | | | 0.9267    | 0.9275   | |
|        | 0.50   | 34.74    | 34.82    | | | 0.9497    | 0.9505   | |

The significance of bold in the table means that the performance index, PSNR or SSIM, of the proposed method is greater than that of the competing methods.
Table 4 Comparison with MADUN [50]

| Dataset | r   | Average PSNR | Average SSIM |
|---------|-----|--------------|--------------|
|         |     | Original     | Proposed     | Original     | Proposed     |
| Set5    | 0.10| 26.13        | 26.13        | 0.7677       | 0.7677       |
|         | 0.25| 36.07        | **36.15**    | 0.9478       | **0.9485**   |
|         | 0.30| 37.34        | **37.41**    | 0.9568       | **0.9573**   |
|         | 0.40| 39.11        | **39.25**    | 0.9680       | **0.9687**   |
|         | 0.50| 40.64        | **40.95**    | 0.9758       | **0.9769**   |
| Set11   | 0.10| 22.47        | **22.51**    | 0.6968       | **0.6981**   |
|         | 0.25| 34.80        | **34.87**    | 0.9490       | **0.9495**   |
|         | 0.30| 36.07        | **36.14**    | 0.9582       | **0.9586**   |
|         | 0.40| 37.85        | **37.96**    | 0.9689       | **0.9693**   |
|         | 0.50| 39.37        | **39.60**    | 0.9763       | **0.9769**   |
| Set14   | 0.10| 23.27        | 23.27        | 0.6606       | 0.6606       |
|         | 0.25| 32.83        | **32.90**    | 0.9028       | **0.9033**   |
|         | 0.30| 34.11        | **34.18**    | 0.9203       | **0.9207**   |
|         | 0.40| 35.73        | **35.84**    | 0.9411       | **0.9414**   |
|         | 0.50| 37.17        | **37.38**    | 0.9556       | **0.9562**   |

The significance of bold in the table means that the performance index, PSNR or SSIM, of the proposed method is greater than that of the competing methods.

Table 5 Comparison with ISTA [51]

| Dataset | r   | Average PSNR | Average SSIM |
|---------|-----|--------------|--------------|
|         |     | Original     | Proposed     | Original     | Proposed     |
| Set5    | 0.10| 29.00        | 29.00        | 0.8351       | 0.8351       |
|         | 0.25| 34.00        | **34.32**    | 0.9180       | **0.9259**   |
|         | 0.30| 35.24        | **35.63**    | 0.9368       | **0.9420**   |
|         | 0.40| 37.34        | **37.60**    | 0.9571       | **0.9573**   |
|         | 0.50| 39.48        | **39.75**    | 0.9703       | **0.9719**   |
| Set11   | 0.10| 26.26        | **26.36**    | 0.7961       | **0.7991**   |
|         | 0.25| 31.85        | **32.07**    | 0.9161       | **0.9185**   |
|         | 0.30| 33.09        | **33.35**    | 0.9316       | **0.9345**   |
|         | 0.40| 35.38        | **35.59**    | 0.9533       | **0.9550**   |
|         | 0.50| 37.42        | **37.73**    | 0.9675       | **0.9692**   |
| Set14   | 0.10| 25.99        | 25.99        | 0.7270       | 0.7270       |
|         | 0.25| 30.29        | **30.38**    | 0.8647       | **0.8668**   |
|         | 0.30| 31.46        | **31.66**    | 0.8900       | **0.8918**   |
|         | 0.40| 33.60        | **33.80**    | 0.9251       | **0.9259**   |
|         | 0.50| 35.71        | **35.92**    | 0.9480       | **0.9492**   |

The significance of bold in the table means that the performance index, PSNR or SSIM, of the proposed method is greater than that of the competing methods.

Rates, such as 0.10, did the proposed method not improve the recovery quality.

Second, it can be discovered that the reconstruction performance increases in accordance with increasing sampling rate. The reason for this is that the initial value of $x_0$, i.e., $y_0$, with a high sampling rate, is closer to $x_0$ than that with a low sampling rate.

Third, it can be found that the reconstruction performance decreases when the size of the image dataset increases from dataset Set5 to Set14. This is because a larger image dataset has a larger dynamic range of image pixels, which are more difficult to rebuild.
Table 6 Comparison with ISTA+ [51]

| Dataset | $r$ | Average PSNR | Average SSIM |
|---------|-----|--------------|--------------|
|         |     | Original     | Proposed     | Original     | Proposed     |
| Set5    | 0.10| 29.07        | 29.07        | 0.8388       | 0.8388       |
|         | 0.25| 34.53        | 34.66        | 0.9306       | 0.9316       |
|         | 0.30| 35.79        | 35.96        | 0.9435       | 0.9450       |
|         | 0.40| 37.88        | 38.06        | 0.9607       | 0.9621       |
|         | 0.50| 39.83        | 40.09        | 0.9722       | 0.9737       |
| Set11   | 0.10| 26.49        | 26.49        | 0.8036       | 0.8036       |
|         | 0.25| 32.44        | 32.50        | 0.9237       | 0.9247       |
|         | 0.30| 33.70        | 33.78        | 0.9382       | 0.9392       |
|         | 0.40| 36.02        | 36.14        | 0.9579       | 0.9589       |
|         | 0.50| 38.07        | 38.23        | 0.9706       | 0.9715       |
| Set14   | 0.10| 26.13        | 26.13        | 0.7340       | 0.7340       |
|         | 0.25| 30.69        | 30.70        | 0.8737       | 0.8742       |
|         | 0.30| 31.82        | 31.86        | 0.8976       | 0.8981       |
|         | 0.40| 33.93        | 33.99        | 0.9293       | 0.9303       |
|         | 0.50| 35.98        | 36.13        | 0.9510       | 0.9521       |
| Brain50 | 0.10| 34.63        | 34.71        | 0.9035       | 0.9035       |
|         | 0.20| 38.70        | 38.73        | 0.9484       | 0.9492       |
|         | 0.30| 40.97        | 41.00        | 0.9639       | 0.9641       |
|         | 0.40| 42.64        | 42.69        | 0.9729       | 0.9732       |
|         | 0.50| 44.12        | 44.18        | 0.9792       | 0.9797       |

The significance of bold in the table means that the performance index, PSNR or SSIM, of the proposed method is greater than that of the competing methods.

Table 7 Comparison with ISTA++

| Dataset | $r$ | Average PSNR | Average SSIM |
|---------|-----|--------------|--------------|
|         |     | Original     | Proposed     | Original     | Proposed     |
| Set5    | 0.10| 30.02        | 30.28        | 0.8702       | 0.8716       |
|         | 0.20| 33.94        | 34.01        | 0.9250       | 0.9259       |
|         | 0.30| 36.27        | 36.41        | 0.9485       | 0.9498       |
|         | 0.40| 38.13        | 38.37        | 0.9621       | 0.9637       |
|         | 0.50| 39.95        | 40.34        | 0.9725       | 0.9744       |
| Set11   | 0.10| 28.34        | 28.37        | 0.8530       | 0.8541       |
|         | 0.20| 32.33        | 32.36        | 0.9216       | 0.9222       |
|         | 0.30| 34.85        | 34.92        | 0.9477       | 0.9483       |
|         | 0.40| 36.94        | 37.03        | 0.9627       | 0.9634       |
|         | 0.50| 38.73        | 38.88        | 0.9727       | 0.9739       |
| Set14   | 0.10| 27.32        | 27.33        | 0.7714       | 0.7724       |
|         | 0.20| 30.72        | 30.75        | 0.8628       | 0.8635       |
|         | 0.30| 33.07        | 33.16        | 0.9074       | 0.9080       |
|         | 0.40| 34.98        | 35.13        | 0.9341       | 0.9350       |
|         | 0.50| 36.78        | 36.96        | 0.9525       | 0.9536       |

The significance of bold in the table means that the performance index, PSNR or SSIM, of the proposed method is greater than that of the competing methods.
Table 8 Comparison with OPINE [53]

| Dataset | r   | Average PSNR | Average SSIM |
|---------|-----|--------------|--------------|
|         |     | Original     | Proposed     | Original     | Proposed     |
| Set5    | 0.01| 22.44        | 22.82        | 0.6145       | 0.6154       |
|         | 0.04| 28.48        | 28.72        | 0.8396       | 0.8404       |
|         | 0.10| 32.95        | 33.07        | 0.9202       | 0.9206       |
|         | 0.25| 37.11        | 37.25        | 0.9589       | 0.9597       |
|         | 0.50| 41.95        | 42.16        | 0.9818       | 0.9825       |
| Set11   | 0.01| 20.02        | 20.47        | 0.5362       | 0.5399       |
|         | 0.04| 25.52        | 25.74        | 0.7879       | 0.7904       |
|         | 0.10| 29.81        | 29.93        | 0.8904       | 0.8922       |
|         | 0.25| 34.81        | 34.97        | 0.9514       | 0.9527       |
|         | 0.50| 40.19        | 40.46        | 0.9800       | 0.9811       |
| Set14   | 0.01| 21.55        | 21.70        | 0.5397       | 0.5406       |
|         | 0.04| 25.69        | 25.82        | 0.7217       | 0.7237       |
|         | 0.10| 28.85        | 28.93        | 0.8347       | 0.8359       |
|         | 0.25| 33.13        | 33.26        | 0.9228       | 0.9239       |
|         | 0.50| 38.10        | 38.37        | 0.9678       | 0.9688       |

The significance of bold in the table means that the performance index, PSNR or SSIM, of the proposed method is greater than that of the competing methods.

Table 9 Comparison with AMP-NET [55]

| Dataset | r   | Average PSNR | Average SSIM |
|---------|-----|--------------|--------------|
|         |     | Original     | Proposed     | Original     | Proposed     |
| Set5    | 0.10| 32.44        | 32.54        | 0.9081       | 0.9090       |
|         | 0.25| 37.09        | 37.22        | 0.9557       | 0.9564       |
|         | 0.30| 38.18        | 38.35        | 0.9629       | 0.9639       |
|         | 0.40| 40.03        | 40.18        | 0.9733       | 0.9739       |
|         | 0.50| 41.87        | 42.02        | 0.9803       | 0.9810       |
| Set11   | 0.10| 29.40        | 29.51        | 0.8779       | 0.8785       |
|         | 0.25| 34.63        | 34.76        | 0.9480       | 0.9487       |
|         | 0.30| 36.02        | 36.15        | 0.9586       | 0.9594       |
|         | 0.40| 38.27        | 38.41        | 0.9715       | 0.9721       |
|         | 0.50| 40.33        | 40.50        | 0.9804       | 0.9809       |
| Set14   | 0.10| 28.89        | 28.98        | 0.8247       | 0.8258       |
|         | 0.25| 33.23        | 33.37        | 0.9181       | 0.9188       |
|         | 0.30| 34.39        | 34.54        | 0.9333       | 0.9342       |
|         | 0.40| 36.35        | 36.48        | 0.9535       | 0.9541       |
|         | 0.50| 38.29        | 38.44        | 0.9666       | 0.9672       |

The significance of bold in the table means that the performance index, PSNR or SSIM, of the proposed method is greater than that of the competing methods.

Fourth, Table 10 indicates that the maximum average PSNR increment is 4.36 (= 32.14–27.78) dB and the maximum average SSIM increment is 0.034 (= 0.9180–0.8840) at a sampling rate of 0.25 on dataset Set14. That is, the proposed method based on the MTC-CSNET approach exhibits the largest increment of PSNR and SSIM.

Finally, Table 12 shows that the maximum average PSNR is 43.52 dB and the maximum average SSIM is 0.9853 with a sampling rate of 0.50 on dataset Set11. In other words, the proposed method based on the TransCS approach achieves the best reconstruction performance.
Table 10 Comparison with MTC-CSNET [56]

| Dataset | $r$ | Average PSNR | Average SSIM |
|---------|-----|--------------|--------------|
|         |     | Original     | Proposed     | Original     | Proposed     |
| Set5    | 0.01| 22.07        | 22.44        | 0.5903       | 0.5964       |
|         | 0.04| 26.33        | 27.11        | 0.7943       | 0.8030       |
|         | 0.10| 30.60        | 31.37        | 0.8983       | 0.9022       |
|         | 0.25| 33.95        | 35.76        | 0.9472       | 0.9504       |
| Set11   | 0.01| 21.85        | 22.00        | 0.5718       | 0.5831       |
|         | 0.04| 25.57        | 26.01        | 0.7828       | 0.7936       |
|         | 0.10| 29.45        | 29.97        | 0.8932       | 0.8980       |
|         | 0.25| 33.73        | 34.69        | 0.9515       | 0.9543       |
| Set14   | 0.01| 20.84        | 21.56        | 0.4927       | 0.5220       |
|         | 0.04| 22.93        | 25.01        | 0.6542       | 0.6948       |
|         | 0.10| 25.53        | 28.09        | 0.7893       | 0.8183       |
|         | 0.25| 27.78        | 32.14        | 0.8840       | 0.9180       |

The significance of bold in the table means that the performance index, PSNR or SSIM, of the proposed method is greater than that of the competing methods.

Table 11 Comparison with TCS-NET [57]

| Dataset | $r$ | Average PSNR | Average SSIM |
|---------|-----|--------------|--------------|
|         |     | Original     | Proposed     | Original     | Proposed     |
| Set5    | 0.01| 22.75        | 22.75        | 0.6001       | 0.6001       |
|         | 0.04| 27.55        | 27.63        | 0.8169       | 0.8197       |
|         | 0.10| 31.48        | 31.55        | 0.9064       | 0.9079       |
|         | 0.25| 35.85        | 35.90        | 0.9557       | 0.9563       |
| Set11   | 0.01| 21.09        | 21.09        | 0.5505       | 0.5505       |
|         | 0.04| 25.46        | 25.50        | 0.7863       | 0.7881       |
|         | 0.10| 29.94        | 29.08        | 0.8834       | 0.8847       |
|         | 0.25| 33.94        | 33.99        | 0.9508       | 0.9514       |
| Set14   | 0.01| 21.65        | 21.67        | 0.5219       | 0.5222       |
|         | 0.04| 25.26        | 25.33        | 0.7074       | 0.7095       |
|         | 0.10| 28.19        | 28.25        | 0.8283       | 0.8302       |
|         | 0.25| 32.24        | 32.31        | 0.9204       | 0.9213       |
| McM18   | 0.01| 23.63        | 23.66        | 0.6144       | 0.6149       |
|         | 0.04| 27.54        | 27.60        | 0.7907       | 0.7926       |
|         | 0.10| 30.97        | 31.04        | 0.8913       | 0.8927       |
|         | 0.25| 35.89        | 35.96        | 0.9579       | 0.9584       |

The significance of bold in the table means that the performance index, PSNR or SSIM, of the proposed method is greater than that of the competing methods.

It is worth mentioning that the sampling rates in Table 3, 4, 5, 6, 7, 8, 9, 10, 11 and 12 are not uniform. It is owing to the fact that the proposed method is on the strength of the competing approaches. For the convenience of implementing the proposed method, the pretraining models of the competing approaches are utilized. The pretraining models of competing approaches adopt inconsistent sampling rates. To clearly show the differences between the proposed method and the competing approaches, the average PSNR and average SSIM on datasets Set5, Set11 and Set14 with different sampling rates are displayed in Figs. 2, 3, 4, 5, 6 and 7. The horizontal coordinate is the sampling rate, and the vertical coordinate is the average PSNR or SSIM. Because PSNR and SSIM increase as sampling rate increases, a linear approximation of PSNR or SSIM between two discrete


Table 12 Comparison with TransCS [58]

| Dataset | $r$  | Average PSNR  | Average SSIM  |
|---------|------|--------------|---------------|
|         |      | Original     | Proposed      | Original     | Proposed      |
| Set5    | 0.10 | 33.56        | 33.63         | 0.9244       | 0.9251        |
|         | 0.25 | 38.26        | 38.28         | 0.9652       | 0.9654        |
|         | 0.30 | 39.01        | 39.08         | 0.9693       | 0.9698        |
|         | 0.40 | 41.40        | 41.47         | 0.9791       | 0.9794        |
|         | 0.50 | 43.42        | 43.52         | 0.9850       | 0.9853        |
| Set11   | 0.10 | 29.54        | 29.62         | 0.8877       | 0.8880        |
|         | 0.25 | 35.06        | 35.07         | 0.9548       | 0.9550        |
|         | 0.30 | 35.62        | 35.68         | 0.9588       | 0.9595        |
|         | 0.40 | 38.46        | 38.49         | 0.9737       | 0.9739        |
|         | 0.50 | 40.49        | 40.52         | 0.9815       | 0.9816        |
| Set14   | 0.10 | 28.81        | 28.85         | 0.8343       | 0.8362        |
|         | 0.25 | 33.38        | 33.48         | 0.9244       | 0.9250        |
|         | 0.30 | 34.03        | 34.20         | 0.9349       | 0.9361        |
|         | 0.40 | 36.69        | 36.84         | 0.9572       | 0.9577        |
|         | 0.50 | 38.66        | 38.81         | 0.9693       | 0.9697        |

The significance of bold in the table means that the performance index, PSNR or SSIM, of the proposed method is greater than that of the competing methods.

Fig. 2 Comparison of PSNR on dataset Set5

Fig. 3 Comparison of PSNR on dataset Set11

The significance of bold in the table means that the performance index, PSNR or SSIM, of the proposed method is greater than that of the competing methods.

The proposed method is based on the 10 competing approaches. It can be found that the proposed method has the best reestablishment capability.

To demonstrate the recovery quality of the proposed method based on the MTC-CSNET approach, which has the largest increment of PSNR and SSIM, the reconstruction images based on datasets Set5, Set11 and Set14 at a sampling rate of 0.25 are shown in Figs. 8, 9 and 10, respectively. In each figure, the left image is the original image, the middle image is the reconstruction image of the MTC-CSNET approach, and the right image is the reconstruction image of the proposed method. Image subareas with significant differences are marked with red boxes. Only images with subareas of obvious change in the datasets are shown. The proposed method based on a negative feedback mechanism can efficiently correct the recovery errors of the competing approaches.

For the sake of comparing the reconstruction performance between the proposed method and the 10 competing approaches, the reconstruction images of the original images, parrots and monarchs, based on dataset Set11 with a sampling rate of 0.10, are displayed in Figs. 10 and 11, respectively. The image areas with large differences are also marked with
Fig. 4 Comparison of PSNR on dataset Set14

Fig. 5 Comparison of SSIM on dataset Set5

Fig. 6 Comparison of SSIM on dataset Set11

Fig. 7 Comparison of SSIM on dataset Set14

Fig. 8 Comparison with MTC-CSNET on dataset Set5 at a sampling rate of 0.25 [56]
red boxes. The proposed method in Fig. 10 is based on the TransCS approach, and the proposed method in Fig. 11 is based on the OPINE approach. The numbers in the brackets are PSNR and SSIM values. It is revealed that the proposed method has the optimal reestablishment capability (Fig. 12).

For the purpose of revealing the relationship between parameter $\mu$ and the number of iteration, the corresponding curve is shown in Fig. 13. The simulation experiment is built on MTC-CSNET approach and dataset Set5. Parameter $\mu$ is supposed to be 1 for iteration number 0. Parameter $\mu$ increases at first and then decreases when iteration number increases. Evidently, parameter $\mu$ is close to a small constant after several iterations.

In order to compare the proposed method with the conventional ITAs, the related curves between average PSNR and sampling rate are displayed in Fig. 14. Both methods are established on MTC-CSNET approach and dataset Set5.
Fig. 11 Comparison with competing approaches on dataset Set11 (Parrots) with a sampling rate of 0.10

Obviously, the proposed method is superior to ITAs in reconstruction capability.

5 Conclusion

This paper improves the reconstruction performance of conventional image compressive sensing algorithms by incorporating a closed-loop negative feedback mechanism. The closed-loop structure consists of a measurement unit, recovery unit, summator, multiplier and delay. The theoretical analysis of the negative feedback system is carried out. An approximate mathematical proof of the effectiveness of the proposed method is offered. The simulation experiments are conducted on more than 3 image datasets with 10 competing approaches. The experimental results show that the proposed method is superior to the competing approaches in recovery quality and can efficiently overcome the recovery errors brought about by the competing approaches.

In our future work, currently unavailable lossless image compressive sensing will be explored.

Fig. 12 Comparison with competing approaches on dataset Set11 (Monarch) with a sampling rate of 0.10

Fig. 13 Curve between $\mu$ and iteration number

Curve between $\mu$ and iteration number
Fig. 14 Comparison between ITAs and the proposed method

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