Journal of Engineering Science and Technology Review 11 (2) (2018) 19 - 25

Research Article

JOURNAL OF
Engineering Science and Technology Review

www.jestr.org

Sparsity Adaptive-based Stagewise Orthogonal Matching Pursuit Algorithm for Image Reconstruction

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Received 2 December 2017, Accepted 31 March 2018

Abstract

The stage wise orthogonal matching pursuit (StOMP) algorithm based on compressive sensing can effectively solve the problems of digital image storage and transmission, including the large amount of sampled data and long sampling time. However, the algorithm is only suitable for signal sparsity with known prior information. The sparsity of images is unknown in practice. In this study, a sparsity adaptive-based stagewise orthogonal matching pursuit (Sa-St-OMP) algorithm was proposed to make the StOMP algorithm suitable for images with unknown sparsity and improve the accuracy and speed of image reconstruction. First, the input image was filtered and matched by setting a threshold according to the initial residual, and a candidate set was established on the basis of the obtained atom. Second, the step size was updated on the basis of residual attenuation, and the adaptively updated step size was employed to build the support set. Third, the atom most relevant to the input signal was selected according to the observation matrix and step size, and the image reconstruction was realized on the basis of the new support set. Finally, Lena, Couple, and Cameraman images were reconstructed through the proposed Sa-St-OMP algorithm, and the reconstruction results were compared with those of the orthogonal matching pursuit, StOMP, and basis pursuit algorithms. Results demonstrate the following: (1) The average reconstruction time of the Sa-St-OMP algorithm is 63.43% shorter than that of the StOMP algorithm, and the reconstruction effect improves by 0.12 db. The reconstruction accuracy and speed of the Sa-St-OMP algorithm are superior to those of the StOMP algorithm. (2) The reconstruction time of the Sa-St-OMP algorithm is shortened by 63.43% to 98.91% compared with those of the other algorithms, and the reconstruction speed exhibits obvious advantages. (3) The Sa-St-OMP algorithm has good adaptability to sparsity, and it accurately reconstructs original signals at a low sampling rate. The study provides a technical reference for reconstructing images with unknown sparsity.

Keywords: compressive sensing, sparsity adaptability, stagewise orthogonal matching pursuit algorithm

1. Introduction

The rapid development of multimedia and Internet technologies has led to the surge of digital image data. Efficiently compressing and accurately reconstructing massive image data have become important problems to be solved in the field of image application to achieve the objectives of improving the efficiency of image sampling and reducing resource waste in storage and transmission. The sampling frequency of compressive sensing is lower than Nyquist sampling frequency, and it reduces sampling data and saves storage space. Meanwhile, adequate information can accurately reconstruct images through appropriate reconstruction algorithms [1]. Therefore, scholars have paid close attention to accurate reconstruction algorithms based on compressive sensing and proposed various algorithms such as greedy, combination, and convex relaxation algorithms [2]. Greedy algorithms update support sets via greedy iteration and gradually approximate original solutions. They have been widely used because of their simple principle and easy implementation [3].

The number of iterations of greedy algorithms can be controlled by taking unpredictable sparsity as priori information [4], hence, these algorithms have limited application. For example, wavelet multi-scale analysis is used to analyze the local features of images and to ultimately guarantee the integrity of local features. However, the algorithms take time efficiency as cost and depend on image sparsity, thereby resulting in low solution efficiency [5]. Liu Jicheng et al. [6] defined the edge similarity of reconstructed images by predefining the filtering of observation results and selecting the signal hard threshold to improve solution efficiency. Nevertheless, the sparsity of the images could not be predicted accurately, and such deficiency influenced the reconstruction effect to some extent. Searching for an image reconstruction algorithm with good reconstruction quality and efficiency suitable for prior information without sparse degree has become a crucial topic in the field of image processing, and it is also the objective of this study. In the current work, the sparsity adaptability of the stagewise orthogonal matching pursuit (StOMP) algorithm is improved to enhance the quality of reconstructed images and shorten the time of image reconstruction.

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ISSN: 1791-2377 © 2018 Eastern Macedonia and Thrace Institute of Technology. All rights reserved.
doi:10.25103/jestr.112.04

2. State of the art

Existing image reconstruction algorithms mainly focus on the greedy matching pursuit (MP) algorithm based on compressive sensing. TekeO et al. [8] proposed a new perturbed orthogonal matching pursuit (OMP) algorithm to eliminate the mismatch problem. The perturbation of the selected support vector was controlled in iteration, and the reconstruction error was small. However, additional sampling dimensions were needed to reduce calculation complexity. Zakharov Y.V. et al. [9] adopted dichotomous coordinate descent correction iteration to obtain an improved OMP algorithm with lower performance complexity than MP. Only one margin was added in the iteration process, thereby leading to a high time cost. Tawfic I.S. et al. [10] proposed a least support denoising OMP algorithm for cases involving few noise measurement times. Although sparse signal was reconstructed, it led to large computation and memory requirements. Yaghoobi M. et al. [11] found that the nonnegative OMP algorithm updated on the basis of QR decomposition and iterative coefficient could optimize calculation cost. However, the reconstruction accuracy was not substantially improved. Du Q et al. [12] proposed a method for improving the performances of segmentation image systems based on a priori, which could enhance the classification effects of hyperspectral images. However, the accuracy of prior information exerted a certain effect on the operation results. Goklani H.S. et al. [13] applied OMP to image reconstruction and evaluated its performance at different sparsity levels. The algorithm maintained good stability in the presence of noise. The shortcoming of the algorithm was that the iterative step gradually approached image sparsity, thereby reducing the quality and efficiency of image reconstruction. Kanjalkar P.M. et al. [14] designed an orthogonal wavelet filter by using the factorization of generalized semi-band polynomials and applied it to the compressive reconstruction of OMP; they achieved good results. However, the decoding end had a large computation amount. Aravkin A. et al. [15] considered a new formula and the method of sparse quantile regression and proved that the generalized OMP algorithm based on variable selection exhibited a good performance through simulation and empirical studies on genome data sets. Nevertheless, the robustness of outliers needed to be further enhanced in gene selection. Zhang Han et al. [16] diagnosed the faults of aeroengine bearings on the basis of the stepwise matching morphological analysis of sparse decomposition and realized noise reduction and signal separation. However, the iteration times and running time of the algorithm were not significantly improved. Zhou Weidong et al. [17] proposed a new speech enhancement algorithm based on compressive sensing according to the approximate sparsity of speech signals in the discrete cosine transform domain. The algorithm with good robustness not only improved the output signal-to-noise ratio (SNR) but also reduced the reconstruction time. Shi Haosu et al. [18] obtained estimated values through a conjugate gradient algorithm, which shortened the time of image reconstruction and enhanced the quality of image reconstruction. Nonetheless, the basic properties of conjugate direction indicated that the algorithm entailed a large calculation amount. Huang Huiying et al. [19] took Daubechies as sparse base and improved image reconstruction quality by approximately 2% by using an orthogonal matching tracking algorithm based on the Dice matching criterion. This algorithm was only suitable with known sparsity, and its convergence was substantially affected by sparsity. Wang Haoran et al. [20] developed a backtracking strategy and an atomic optimization strategy, both of which achieved good image reconstruction effects. However, the algorithm was likely to fall into local optimal solutions.

The aforementioned studies realized image reconstruction with known sparsity. However, the reconstruction effects were closely related to the estimation of image sparsity K. Images can never be reconstructed accurately when K values are inaccurate. K values are generally unknown or unpredictable in practical applications. Although the unknown K problem has been solved by updating support sets and gradually increasing sparsity to approximate original signals, the comprehensive performance of image processing and the time consumption are unsatisfactory.

In view of unknown K values, the sparsity of images in the current work was represented through a wavelet base, and a Gaussian random observation matrix was designed. Combined with the threshold assumption in the StOMP algorithm, the improved strategy of adaptive sparsity updating was used to reconstruct original images. The outcome provided the basis for optimizing the reconstruction effect and efficiency of images with unknown sparsity.

The remainder of this study is organized as follows. Section 3 describes the image sparse representation, image observation matrix design, image reconstruction algorithm of sparsity adaptive-based stagewise orthogonal matching pursuit (Sa-St-OMP), and reconstruction quality evaluation standard. Section 4 discusses the performance analysis of the proposed algorithm. Section 5 concludes the study.

3. Methodology

Edge sampling and compression of sparse or compressible image signals were realized through the image reconstruction method based on compressive sensing. This method reduces the number of samples and hardware costs. The following aspects are included. First, for image signal $x \in R^N$, finding a suitable sparse base Ψ is necessary so that the image signal could realize sparse representation on Ψ. Second, a stable observation matrix independent of the sparse base is designed. Third, a suitable reconstruction algorithm is designed to restore the original image.

3.1 Sparse representation of images

The sparse representation of images can highlight the characteristics of images to facilitate the subsequent studies of image processing and reduce the costs of storage and processing hardware. If the transformation coefficient vector $X_i \leftarrow X_i \Theta V_i$ of image signal $\Theta = \Psi^T X$ under sparse base Ψ satisfies $\|\Theta\|_P \equiv \left(\sum_i |\theta_i|^P\right)^{1/P} \le R$, where $0 < p < 2$ and $R > 0$, then the coefficient vector is sparse in some sense. Therefore, the representation of image signal through an appropriate base is important to ensure the sparsity and restoration accuracy of images. Discrete wavelet transform (DWT) and fast Fourier transform are generally used to realize the sparsification of images. A series of sub-images with different resolutions can be obtained after original images are subjected to DWT. The high frequency part of the image is removed, and the low frequency part that can represent the image is retained.

3.2 Observation matrix of image signal

After the sparse coefficient vector $\Theta = \Psi^T X$ of the image signal is obtained, a stationary $M \times N$ observation matrix Φ irrelevant to orthogonal base Ψ is designed. The sparse coefficient vector is projected through vector $\{\varphi_j\}_{j=1}^{M}$ in the M lines of the $M \times N$ observation matrix Φ . The inner product of Θ and each observation vector $\{\varphi_j\}_{j=1}^{M}$ are calculated to obtain M observation values $y_j = <\Theta, \varphi_j>$ *(j=1,2, ... ,M)*, denoted as $Y = (y_1, y_2, ..., y_M)$, namely, $Y = \Phi\Theta = \Phi\Psi^T X = A^{CS} X$. When the sparse vector is reduced from N dimensions to M dimensions, important information is preserved.

Only the observation matrix that satisfies the restricted isometry property (RIP) can be taken as the measurement condition for image signal reconstruction. Observation vector Y is a linear combination of K column vectors that correspond to nonzero coefficient θ_i . Proper positions of K nonzero coefficients θ_i in Θ can be determined through the $M \times K$ linear equation. δ_k is the restricted isometry constant . If $1 - \delta_k \le \frac{\|\Theta f\|_2^2}{\|f\|_2^2} \le 1 + \delta_k$, then Φ satisfies the RIP. Based on the RIP, the random observation matrix is a criterion for filtering most zero data. Existing common observation matrices include Gaussian random, Bernoulli, Fourier random, and Hadamard matrices. The Gaussian random matrix means that each element obeys a Gaussian distribution independently and satisfies the RIP condition with a large probability. Most zero data are simplified on the basis of the Gaussian random matrix. Therefore, this matrix is widely used in theory and practice

3.3 Sa-St-OMP algorithm

The reconstruction algorithm is necessary in reconstructing original images. Signals are recovered from the linear observation $Y = A^{CS} X$ in the reconstruction process. The $p-$ norm of vector $X = \{x_1, x_2, ..., x_n\}$ is $\|X\|_P = \left(\sum_{i=1}^{N} |x_i|^p\right)^{1/p}$. When $p = 0$, $0-$ norm, which represents the number of nonzero items in X, is obtained. On the premise that signal X is sparse or compressible; the problem of solving the underdetermined equation set $Y = A^{CS} X$ is transformed into a minimum $0-$norm problem $\min \|\Psi^T X\|_0$ s.t. $A^{CS} X = \Phi\Psi^T X = Y$. Image reconstruction algorithms are mainly classified into greedy reconstruction, combination, and statistical optimization algorithms. Greedy algorithms have been widely used because of their fast iterative process.

The StOMP greedy algorithm needs image sparsity as prior information, and the reconstruction accuracy is relatively low. Therefore, the sparsity adaptive idea is introduced into the StOMP algorithm. The proposed Sa-St-OMP algorithm realizes sparsity estimation and image reconstruction. The steps are as follows:

Step-1: Initialize the parameters. The input image is y, and the initial residual is $r_0 = y$. D is a complete dictionary, and the support set is $F = \varphi$.

Step-2: Set the threshold value according to the residual. The atom that is most related to the residual is obtained through Formula (1):

$$J_k = \{j : |\Phi^T \bullet r_{k-1}| > t_k \sigma_k\} \tag{1}$$

where $\sigma_k = \|r_{k-1}\| / \sqrt{n}$ and $2 \le t_k \le 3$. Φ^T is the transposition of the observation matrix. r_{k-1} is the reconstruction residual. $t_k \sigma_k$ is the threshold. k is the kth iteration. $\sqrt{n}$ is the root extracted from the dimension of the input signal. t_k is the threshold parameter. σ_k is the standard noise level.

Step-3: Select the atomic set and D_{J_k} with matching degrees that are higher than the threshold. According to the matching atom, a candidate set is established through Formula (2):

$$C_k = F_{k-1} \cup D_{J_k} \tag{2}$$

The candidate set consists of the support set of the previous iteration and the atoms selected by the current iteration-matched filter, where C_k is the candidate set. F_{k-1} is the supporting set established in the last iteration. D_{J_k} is the atomic set obtained by matched filtering.

Step-4: Determine the attenuation of the residual after obtaining the candidate set.

Step-5: If the residual in Step 4 attenuates, then take the number of candidate sets obtained in Step-3 as the step size to establish the support set through Formula (3):

$$F_k = Max(|D_{C_k}^T \bullet y|, S_k) \tag{3}$$

where S_k is the number of atoms in the candidate set. Support set F_k represents a set of atoms matched with y from a dictionary composed of atoms in a candidate set by taking S_k as the step size.

Step-6: If the residual in Step-4 does not attenuate, then update the step size of the support set to the number of atoms in the candidate set in Step-3 and the matched filter in Step-2. Through the adaptive updating of the step size, the purpose of sparsity approximation is achieved.

Step-7: Establish a support set by using the step size obtained in Step-6.

Step-8: After the support set is obtained, perform orthogonalization on the atoms in the support set through Formula (4). The least square fitting method is used to approximate the image signal to realize image reconstruction. The reconstruction residual is obtained by using Formula (5):

$$x_k = D_{F_k}^{+} y \tag{4}$$

$$r_k = y - \Phi_{F_k}^T x_k \tag{5}$$

Step-9: Return to Step-2. The reconstruction residual obtained in Step-8 is used as the residual to iterate the iteration. The termination condition of the iteration is evaluated until the two residuals are smaller than a given value, namely, $\|r\| < \varepsilon$, where ε is a given value. Finally, the optimal reconstruction image is obtained.

3.4 Quality evaluation of image reconstruction

Peak SNR (PSNR) and running time are used as the objective criteria for evaluating image reconstruction quality. PSNR, as an objective criterion for measuring image distortion or noise level, is in direct proportion to fidelity. The definition is as formula (6):

$$PSNR = 10\log(L^2 / MSE) \quad (6)$$

where L is the quantization series of the image gray value and MSE is the mean square deviation. The calculation formula (7) of MSE is:

$$MSE = \sum\sum[\Psi(x,y) - \Psi'(x,y)]^2 / M \times N \quad (7)$$

where $M \times N$ is the image size. $\Psi(x,y)$ and $\Psi'(x,y)$ are the gray values of the original image and the reconstructed image at point*(x,y)*, respectively. RMSE reflects the approximation degree between the denoised and original images. A small RMSE indicates that it is relatively close to the ideal denoising effect.

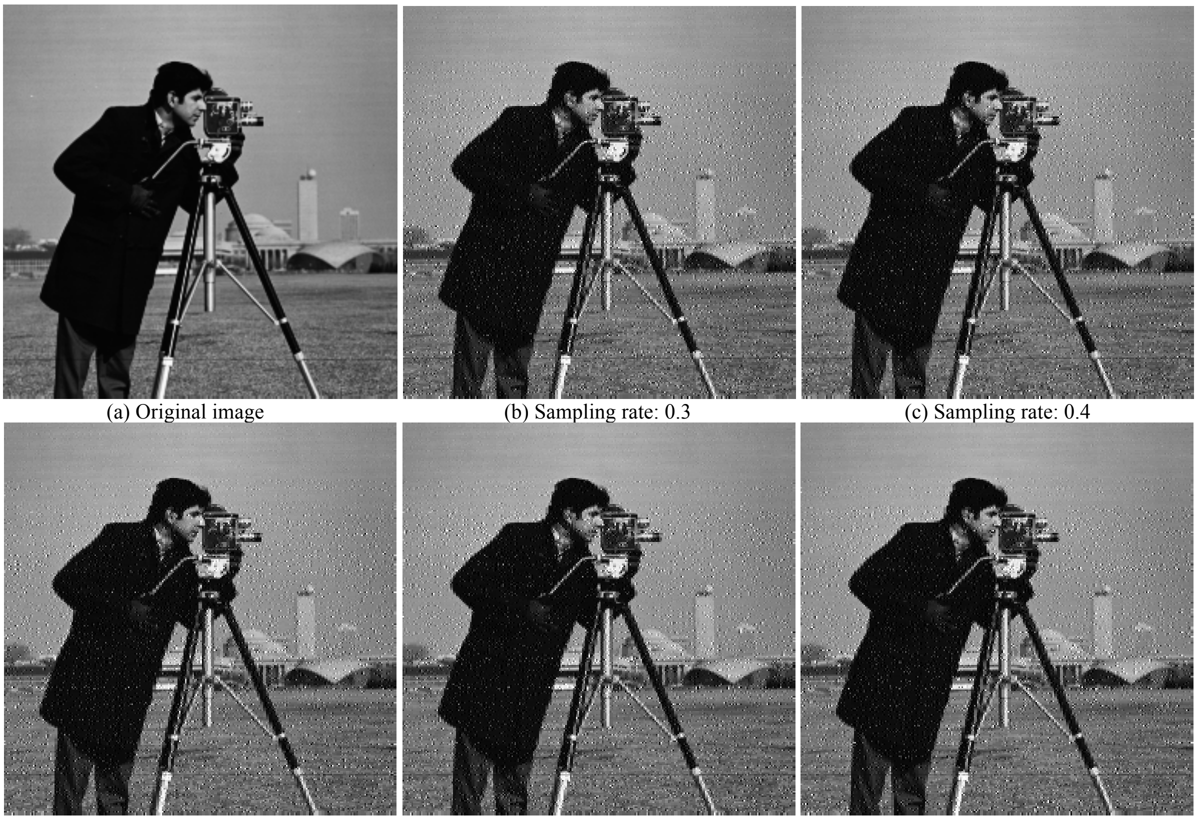
Reconstruction effects are usually measured by subjective vision. However, when the PSNR value is greater than 30 dB, finding the difference between reconstructed and original images by subjective vision is difficult. Although MSE and PSNR reflect the difference between original and reconstructed images as a whole, they cannot reflect the local difference. Under the same SNR condition, the visual effect is significant in the case of uniform errors. Otherwise, the visual effect is not ideal. Therefore, image quality is objectively evaluated through the PSNR value. Sometimes, the results may not be consistent with the subjective evaluation.

4 Result analysis and discussion

On the basis of the discrete wavelet base Ψ in Section 3.1 and the Gaussian random matrix in Section 3.2, two sets of experiments on three international standard test images with a pixel size of 256×256, namely, Cameraman, Couple, and Lena, were conducted by using the Sa-St-OMP algorithm proposed in Section 3.3 under different sampling rates. The first group was the experiment of reconstructing Cameraman and Couple through the Sa-St-OMP algorithm. The second group compared the reconstruction effects of Lena by the Sa-St-OMP algorithm and the other algorithms.

4.1 Experiment on image reconstruction with Sa-St-OMP

Cameraman and Couple were reconstructed at the sampling rates of 0.3, 0.4, 0.5, 0.6, and 0.7 to compare the reconstruction effects of the Sa-St-OMP algorithm with different sampling rates. The reconstructed images are shown in Fig. 1 and 2. The PSNR ratio and reconstruction time at different sampling rates are listed in Table 1.



(a) Original image (b) Sampling rate: 0.3 (c) Sampling rate: 0.4

(d) Sampling rate: 0.5 (e) Sampling rate: 0.6 (f) Sampling rate: 0.7

Fig. 1. Reconstruction effects of Cameraman with the Sa-St-OMP algorithm


(a) Original image

(b) Sampling rate: 0.3

(c) Sampling rate: 0.4

(d) Sampling rate: 0.5

(e) Sampling rate: 0.6

(f) Sampling rate: 0.7

Fig. 2. Reconstruction effects of Couple with the Sa-St-OMP algorithm

Table. 1. PSNR and time consumption of the Sa-St-OMP algorithm for image reconstruction at different sampling rates

Sampling rate	**0.3**		**0.4**		**0.5**		**0.6**		**0.7**	
Image	**PSNR**	**time**	**PSNR**	**time**	**PSNR**	**time**	**PSNR**	**time**	**PSNR**	**time**
Couple	25.9483	0.35328	25.9765	0.84419	26.0323	0.9642	26.3654	0.88339	26.1626	1.0141
Cameraman	23.7104	0.7782	23.8935	0.91864	23.9931	0.84498	24.0352	0.78942	24.2331	1.4694

Fig. 1 and 2 demonstrate the reconstruction effects of the improved algorithm for Couple and Cameraman at different sampling rates. The subjective vision indicates that the Sa-St-OMP algorithm showed good image reconstruction effects even at low sampling rates. As shown in Table 1, the PSNR value and reconstruction time t of the two images at the same sampling rate varied with image complexity.

4.2 Performance analysis of the Sa-St-OMP algorithm

The reconstruction effect of Lena with the Sa-St-OMP algorithm was compared with those with OMP, StOMP, and basis pursuit (BP) algorithms to further analyze the performance of the Sa-St-OMP algorithm. The reconstructed images at the sampling rate of 0.5 are shown in Fig. 3. Table 2 presents the PSNR values and reconstruction times of each algorithm at different sampling rates.


(a) Original image

(b) BP

(c) Sa-St-OMP

(d) OMP (e) StOMP

Fig. 3. Reconstruction effects of BP, Sa-St-OMP, StOMP, and OMP at the sampling rate of 0.5

Table. 2. PSNR and time consumption in image reconstruction of Sa-St-OMP, BP, OMP, and StOMP at different sampling rates

Sampling rates	**0.3**		**0.4**		**0.5**		**0.6**		**0.7**	
Algorithms	PSNR	time	PSNR	time	PSNR	time	PSNR	time	PSNR	time
BP	32.2981	27.1719	32.3994	27.9012	32.5155	26.9045	32.5053	17.7738	32.5025	27.4424
Sa-St-OMP	24.5004	0.26705	24.4962	0.24912	24.5184	0.35405	24.4567	0.25005	24.5044	0.26319
OMP	29.1798	1.5058	29.2057	1.3105	29.2359	1.3326	29.3288	1.3484	29.2955	1.4661
StOMP	24.3904	0.76354	24.4462	0.86038	24.2584	0.82191	24.3567	0.61986	24.4244	0.71831

From the subjective vision, the BP algorithm presented the best reconstruction effect at the same sampling rate, followed by OMP. The difference between Sa-St-OMP and StOMP was relatively small. The reconstructed PSNR in Table 2 implied that the BP algorithm also had the highest PSNR value and the optimal reconstruction quality. The PSNR values of Sa-St-OMP and StOMP were relatively close. The average PSNR value of the Sa-St-OMP algorithm was 0.12 db higher than that of the StOMP algorithm. This value mainly resulted from the optimal matching of atoms through the Sa-St-OMP algorithm. The reconstruction time shown in Table 2 indicated that the reconstruction time of the proposed Sa-St-OMP algorithm was much shorter than those of the other algorithms under the same sampling rate. The time consumption of the BP algorithm was the longest, and the average time was up to 47 times that of other algorithms. The time consumption of Sa-St-OMP was the shortest, that is, it was shortened by 98.91%, 80.13%, and 63.43% relative to BP, OMP, and StOMP, respectively. This result was due to the fact that the Sa-St-OMP algorithm improved the efficiency by adaptive step size. Although OMP, SP, and StOMP algorithms exerted good reconstruction effects, they need the sparsity of images, which limits their applications. The proposed Sa-St-OMP algorithm could maintain the low complexity of the original StOMP algorithm and improve the accuracy and efficiency of image reconstruction under the condition of unknown sparsity.

5. Conclusions

An improved strategy for dynamic step size approximation to original images was proposed according to the atom selection criterion of the StOMP algorithm to find a StOMP algorithm that integrates reconstruction quality and reconstruction efficiency under unknown sparsity. The proposed strategy realized fast and accurate image reconstruction. The reconstruction effects of the Sa-St-OMP algorithm were analyzed on the basis of the PSNR value and reconstruction time. The following conclusions could be drawn.

(1) The atom candidate set of the Sa-St-OMP algorithm is from the union set of the atoms most related to the residuals after matched filtering and the support set of the previous iteration. The accuracy of image reconstruction is improved to a certain extent.

(2) The step size of the support set of the Sa-St-OMP algorithm can be dynamically updated according to the number of atoms in the candidate set and the matched filtering. This feature greatly improves the reconstruction efficiency. Therefore, this algorithm is suitable for fast image reconstruction.

(3) The Sa-St-OMP algorithm has good adaptability to signal sparsity and stable reconstruction quality while maintaining low refactoring complexity. Therefore, the improvement of the StOMP algorithm achieves good results. The proposed Sa-St-OMP algorithm could realize accurate image reconstruction at low sampling rates through the introduction of the idea of sparsity adaptability to the iteration process, and it exhibited an advantage in terms of reconstruction time. With the consideration of reconstruction efficiency and reconstruction quality, this study found that the Sa-St-OMP algorithm is practical for fast and accurate image reconstruction. This algorithm has some reference values for image reconstruction without prior sparsity information, and it offers practical significance in the field of image processing. However, methods with high accuracy for selecting iterative thresholds have not been developed and will thus be studied further.

Acknowledgements

This work was supported by the Sichuan Province Social Science Key Research Base (Grant Nos. WHCY2016b10, SDJJ1627 and DSWL16-5).

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