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Correlation label image denoising based on dither factor of particle swarm optimization algorithm

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Abstract. At present, texture lose and generation mechanism for de-noising scheme is popular, which uses dictionary training mode to conduct sparse expression of noise bias so as to conduct texture feature extraction within noise bias obtained in the image; in addition, de-noising scheme for noise bias which uses sparse image expression is designed. Firstly, the scheme is based on filtering guidance to obtain noise bias of image de-noising; then, based on noise bias and in combination of training for improved K-SVD version, the dictionary is trained so as to obtain redundant dictionary; in combination of extraction of obtained dictionary to texture feature of noise bias; image completion and image de-noising are realized by taking advantages of extraction results of filtering guidance for image de-noising and feature texture. Peak signal to noise ratio of the scheme is higher than previous scheme, because noise bias texture feature is used. Meanwhile, the scheme can effectively preserve image texture features and details, which contributes to improving visual effect. Simulation data show that mentioned algorithm performance is better than selected contrast algorithm and has better visual restoration effect.

Key words. Tag image, Noise bias, Image de-noising, Filtering guidance, Particle swarm optimization.

1. Introduction

At present digital image technology is widely used and is important. However, digital image will be influenced by various noise factors in the stage of collection and data transmission, leading to low quality of transmitted image. Meanwhile, it usually has higher requirements for image resolution and equality in lots of specific application. Therefore, Research on how to realize high quality de-noising restoration is a significant topic, which is badly needed in image application industry. Traditional de-noising scheme in literatures mainly include: frequency filtering, median filter-

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ing, local filtering, ad etc. However, part of image or part of feature texture data in the above-mentioned scheme will be lost in the process of image de-noising, which influences image restoration quality.

Recently, image de-noising scheme [1–4] by using dictionary training and image de-nosing scheme by using self-similar and non-local features draw much attention and are widely researched. Research progress of image de-noising scheme by using dictionary training mainly is accompanied by research development [9–11] of sparse theory. In fact, the theory is based on local sparse image expression de-noising scheme, such as fairly mature K-SVD scheme [1, 2] and improved version [3, 4]. Image noise can be divided into image blocks in the process of using K-SVD to conduct image de-noising so as to obtain small mutual overlapping blocks. K-SVD can be used to conduct training for dictionary so as to adaptively obtain redundant dictionary of image; in combination of redundant dictionary, image block is conducted sparse expression so as to realize image de-noising effect. Image de-noising scheme which is conducted by using local self-similar non-local features is materially image de-noising based on self-similar and non-local features shown in interval image blocks within image, such as NLM scheme [5, 6] and BM3D scheme [7, 8]. Based on Euler's formula, distance scale is use to represent similarity of pixel in NLM scheme. Based on the measurement value, required weight for reconstruction of pixel is calculated so as to realize automatic evaluation of pixel value. Based on matching algorithm for image block, image block with similar structure is assembled in BM3D scheme so as to obtain its three-dimensional model; the three-dimensional model shall be subject to implementation of filtering operation; then, overlapped block shall be subject to image restoration and reconstruction by using weight. Meanwhile, sparse expression and self-similar non-local feature in literature [12, 13] are blended; based on the two algorithms, image de-noising problems are solved. Above-mentioned de-noising scheme has great effect; However, this kind of schemes will synchronously lead to loss of image texture feature at the time of realizing image de-noising effect, which causes that there are part of image texture features in noise bias. Above-mentioned condition will lead to reduction of visual sensory quality. Therefore, research on how to realize texture features and equilibrium preserving algorithm for image details has great significance.

2. Sparse dictionary expression

2.1. Filtering guidance

In case P is the image to be handled and I is guidance image, then obtained output result through filtering guidance operation is q; in addition, conditions [15] are met:

$$b_k = \bar{p}_i - a_k u_k b_k = \bar{p}_i - a_k u_k b_k = \bar{p}_i - a_k u_k b_k = \bar{p}_i - a_k u_k \,.$$

In the equation, ω_k central image position corresponding to two-dimensional coordinate of pixel k; q_i indicates No. i of pixel value for output $\mathbf{q}$; p_i indicates

No. i of pixel value for input $\mathbf{p}$; I_i indicates No. i of guidance $\mathbf{I}$; u_k is average guidance image value under the window of ω_k; σ_k^2 is guidance image variance under the window of ω_k; $\bar{p}_i$ is average input image value under the image of ω_k, which is

$$\bar{p}_i = \frac{1}{|\omega|} \sum_{i \in \omega_k} I_i p_i \,.$$

2.2. Dictionary training

In terms of given sample image $\boldsymbol{\beta} = (\boldsymbol{\beta}_1, \cdots, \boldsymbol{\beta}_K) \in R^{n \times K}$, purpose of dictionary training is to look for redundant dictionary $\mathbf{D} \in R^{n \times m}$ so as to obtain sparse expression form of sample image $\mathbf{\Gamma} = (\mathbf{\Gamma}_1, \mathbf{\Gamma}_2, \cdots, \mathbf{\Gamma}_K) \in R^{m \times K}$; the problem is:

$$\begin{cases} \min\limits_{\mathbf{D},\mathbf{\Gamma}} & \|\boldsymbol{\beta} - \boldsymbol{D}\mathbf{\Gamma}\|_F^2 \,, \\ s.t. & \|\mathbf{\Gamma}_k\|_0 \le T_0 \quad \forall k \,. \end{cases} \tag{1}$$

In terms of above-mentioned dictionary training, methods of MOD and K-SVF can be used for solving [12].

3. Sparse de-noising of noise bias

Above-mentioned methods can be divided into three procedures: 1. image de-noising shall be conducted based on filtering guidance so as to obtain noise bias; 2. redundant dictionary shall be trained based on noise bias and in combination of K-SVD improvement form; 3. image feature texture shall be extracted based on obtained noise bias; filtering guidance and image de-noising shall be used to conduct image restoration for obtained texture features.

3.1. Image noise bias

If additional noise of image to be handled is additive characteristic noise, its observed feature shall be expressed in the form of column vector:

$$\mathbf{Y} = \mathbf{X} + \mathbf{v} \,. \tag{2}$$

In the equation, parameter $\mathbf{v}$ is white noise with average value of 0 and variance of σ^2; $\mathbf{Y}$ is image to be handled which is polluted by additional noise; $\mathbf{X}$ is image to be handled. Image de-noising shall be conducted based on filtering guidance so as to obtain image $\hat{\mathbf{X}}$ and its relevant noise bias $\mathbf{\Delta}$ with the form of

$$\mathbf{Y} = \hat{\mathbf{X}} + \mathbf{\Delta} \,. \tag{3}$$

Noise bias $\mathbf{\Delta}$ obtained in filtering guidance have texture feature H of image, which will lead to loss of image feature texture in the process of image de-noising for filtering guidance.

3.2. Redundant dictionary training

Redundant dictionary $\mathbf{D} \in R^{n\times m}$ shall be obtained through learning based on obtained image noise bias $\mathbf{\Delta}$. Then, noise bias $\mathbf{\Delta}$ shall be divided into K image blocks; image block may be overlapped with the size of $\sqrt{n} \times \sqrt{n}$; image block k shall be expressed in the form of column vector: $\mathbf{\Delta}_k \in R^n$. L groups of image block shall be selected in random way to conduct D redundant dictionary training, which shows $P = \{p_1, p_2 \cdots, p_L\}$. Above-mentioned problems can be expressed into:

$$\begin{cases} \min\limits_{D.Q} & \|\mathbf{P} - \mathbf{DQ}\|_F^2 \\ s.t. & \|\mathbf{q}_l\|_0 \le T_0 \quad \forall l \end{cases} \tag{4}$$

In the equation (4), $\mathbf{Q} = \{\mathbf{q}_1, \mathbf{q}_2 \cdots \mathbf{q}_L\} \in R^{m\times L}$ is sparse matrix. The optima solving process of problem (4) is as follows:

Step 1: Coding in the sparse form

In terms of dictionary $\mathbf{D}$, its sparse matrix $\mathbf{Q}$ shall be updated. The optimal solving of equation (4) can be expressed in the form of sparse sequence coding:

$$\forall l \quad \begin{cases} \min\limits_{\mathbf{q}_l} & \|\mathbf{p}_l - \mathbf{Dq}_l\|_2^2 \\ s.t. & \|\mathbf{q}_l\|_0 \le T_0 \end{cases} \tag{5}$$

Equation (5) is traditional sparse coding form; K-SVD method is used for solving based on OMP scheme. According to literature [16, 17], norm L_0 has better effect for sparse image expression. Therefore, the minimal solving shall be conducted to equation (5) based on norm L_0.

Parameter u shall be properly selected; equation (6) can be changed to be:

$$\min_{\mathbf{q}_l} \left\{-\mu \|\mathbf{q}_l\|_0 + \|\mathbf{Dq}_l - \mathbf{p}_l\|_2^2\right\}. \tag{6}$$

Based on Gauss norm L_0, equation (6) shall be

$$n - \lim_{\delta\to 0} \sum_{i=1}^{n} \exp(-\beta_i^2/2\delta^2) = \|\mathbf{x}_k\|_0 . \tag{7}$$

Equation β_i is element i of vector quantity $\mathbf{q}_l$, then

$$F_\delta(\mathbf{q}_l) = -\sum_{i=1}^{n} \exp(-\beta_i^2/2\delta^2).$$

Under the condition of $\delta \to 0$, problem of equation (6) shall be equal to be:

$$\min_{\mathbf{q}_l} \; L_{\delta,u}(\mathbf{q}_l) = -uF_\delta(\mathbf{q}_l) + \|\mathbf{Dq}_l - \mathbf{p}_l\|_2^2 . \tag{8}$$

Equation u is relevant sparse parameter. Based on the fastest drop method, its iteration form can be:

$$\mathbf{q}_l = \mathbf{q}_l - t\ \nabla L_{\delta,\,u}(\mathbf{q}_l)\,. \tag{9}$$

t in equation (9) indicates step length and is gradient at image $\mathbf{q}_l$:

$$\nabla L_{\delta,\,u}(\mathbf{q}_l) = \frac{u}{\delta^2}\mathbf{\Lambda}\mathbf{q}_l + 2\mathbf{D}^{\mathrm{T}}(\mathbf{D}\mathbf{q}_l - \mathbf{p}_l)\,. \tag{10}$$

In the equation, diagonal matrix shall be:

$$\mathbf{\Lambda} = diag\left\{\exp(-\beta_1^2/2\delta^2),\ \exp(-\beta_2^2/2\delta^2),\ \cdots,\ \exp(-\beta_n^2/2\delta^2)\right\}\,.$$

In terms of selection of step length t, it shall conform to:

$$L_{\delta,\,u}\left(\mathbf{q}_l - t\,\nabla L_{\delta,\,u}(\mathbf{q}_l)\right) < L_{\delta,\,u}(\mathbf{q}_l)\,. \tag{11}$$

Step 2: update of dictionary training

Sparse matrix shall be fixed; dictionary $\mathbf{D}$ shall be updated. Dictionary update process form shall be:

$$\min_{\mathbf{D}}\quad \|\mathbf{P} - \mathbf{D}\mathbf{Q}\|_F^2 \tag{12}$$

It is supposed that $\mathbf{q}_T^j$ is element in No. j line of sparse matrix $\mathbf{Q}$, in case dictionary form is $\mathbf{D} = (\mathbf{d}_1, \mathbf{d}_2, \cdots, \mathbf{d}_m)$, then $\mathbf{Q} = (\mathbf{q}_T^1, \mathbf{q}_T^2, \cdots, \mathbf{q}_T^m)^T$ can be obtained, which can further obtain

$$\|\mathbf{P} - \mathbf{D}\mathbf{Q}\|_F^2 = \left\|\mathbf{P} - \sum_{j=1}^{m}\mathbf{d}_j\mathbf{q}_T^j\right\|_F^2 = \left\|\left(\mathbf{P} - \sum_{j\neq j_0}^{\mathbf{d}_j\mathbf{q}_T^j}\right) - \mathbf{d}_{j_0}\mathbf{q}_T^{j_0}\right\|_F^2\,. \tag{13}$$

In combination of $\mathbf{E}_{j_0} = \mathbf{P} - \sum\limits_{j\neq j_0}^{\mathbf{d}_j\mathbf{q}_T^j}$, dictionary update process shall be:

$$\min_{\mathbf{D}}\ \left\|\mathbf{E}_{j_0} - \mathbf{d}_{j_0}\mathbf{q}_T^{j_0}\right\|_F^2\,. \tag{14}$$

According to equation (14), atom in the dictionary can be updated according to SVD method; its corresponding sparse coefficient can be synchronously updated; specific process is shown in literature [2]. Dictionary D can be obtained based on above-mentioned process.

3.3. Image de-noising

Texture feature $\hat{\mathrm{H}}$ of obtained image can be extracted based on self-adaptive noise bias of dictionary D; $\hat{\mathbf{X}}$ after de-noising of obtained image and texture feature $\hat{\mathrm{H}}$ can be obtained by using filtering guidance; then, image restoration $\mathbf{X}^*$ shall be conducted.

Texture feature $\hat{\mathrm{H}}$ shall be extracted; sparse expression form of dictionary $\mathbf{D}$ for image block $\mathbf{\Delta}_k \in R^n$ in noise bias shall be obtained; the method shall be unified sparse coding with the form of:

$$\forall k \quad \begin{cases} \min\limits_{\alpha_k} & \|\mathbf{\Delta}_k - \mathbf{D}\alpha_k\|_2^2 \\ s.t. & \|\alpha_k\|_0 \leq T_0 \end{cases} \tag{15}$$

Above-mentioned problem shall be subject to the minimal solving based on norm L_0 mentioned in Section 2.2 so as to obtain sparse expression α_k of image block; texture feature of image k within noise bias shall be $\hat{\mathrm{H}}_k = \mathbf{D}\alpha_k$. Image block shall be subject to split joint; overlapped area shall be subject to average filtering; then, texture feature form shall be:

$$\hat{\mathbf{H}} = \left(\sum_k \mathbf{R}_k^T \mathbf{R}_k\right)^{-1} \left(\sum_k \mathbf{R}_k^T \hat{\mathrm{H}}_k\right). \tag{16}$$

In equation (16), $\mathbf{R}_k$ is mainly used to conduct corresponding matrix extraction for k groups of image blocks; in case $\mathbf{R}_k\mathbf{Y}$ is obtained image block k of image $\mathbf{Y}$ through division, obtained texture feature is $\hat{\mathrm{H}}$ and obtained de-noising image of filtering guidance is $\hat{\mathbf{X}}$, then it can obtain

$$\mathbf{X}^* = \hat{\mathbf{X}} + \hat{\mathbf{H}}. \tag{17}$$

Features of above-mentioned texture feature preserving algorithm: 1. two groups of mutually independent features can be enhanced based on dictionary constraint and based on that the optimal update form of dictionary shall be superior to K-SVD, and other update forms; 2. sparse coding process coupling shall be in the middle of update processes of two groups of dictionaries; 3. in terms of non-convex problem in dictionary training process, it does not require to calculate the minimal accurate value point but requires several limited iteration times can be completed; 4. in combination of two groups of dictionaries, there is only involving a dictionary for dictionary change every time; the rest dictionaries shall be fixed, which can prevent dictionaries from being subject to structural pollution in other forms so as to realize effective separation for two groups of elements.

4. Algorithm description

Firstly, algorithm calculation process is described there; solving convergence for the minimal optimization problem of image restoration is analyzed based on norm L_0.

4.1. Algorithm step

Process for mentioned sparse image de-noising method for redundant dictionary of filtering guidance is shown in Algorithm 1 in detail:

Annotation:

Algorithm 1 Sparse Image De-noising for Noise Bias

Input: : Interference image for additional noise
Initial: Gauss matrix $\mathbf{D}^0$

Step1: De-noising of filtering guidance $\mathbf{Y}$ so as to obtain noise bias $\boldsymbol{\Delta}$ de-noising image $\hat{\mathbf{X}}$;

Step2: Redundant dictionary shall be subject to training based on noise bias;

(s2-1) Equation (6) shall be solved based on iteration (7); sparse coefficient $\mathbf{Q}$ shall be updated;

(s2-2) Equation (12) shall be solved based on the method of SVD; dictionary $\mathbf{D}$ shall be updated;

(s2-3) (s2-3) and (s2-2) shall be executed circularly until the convergence;

Step3 Image shall be restored based on dictionary $\mathbf{D}$ and $\hat{\mathbf{X}}$; (s3-1) Equation (13) shall be solved based on norm L_0 so as to obtain sparse coefficient α_k

(s3-2) $\hat{\mathrm{H}}_k = \mathbf{D}\alpha_k$ shall be calculated; in combination of equation (14), texture feature $\hat{\mathrm{H}}$ can be obtained

(s3-3) Obtained de-noising image form shall be $\mathbf{X}^*$ according to equation (15)

Output: : Restored image $\mathbf{X}^*$ can be obtained

(1) Guidance decision: taking advantage of filtering guidance to conduct noise remove for noisy image $\mathbf{Y}$;

(2) Selection of parameter u: optimization process of equation (13) can be regarded as multi-objective optimization process, which can use method α to determine parameter u.

4.2. Convergence analysis

It is mainly analyzed by aiming at convergence of iteration process for equation (7)

Theorem 1: sequence of the optimal solving for problem in iteration of equation (7) is convergent.

Proof: according to:

$$\nabla L_{\delta,\,u}(\mathbf{q}_l)^{\mathrm{T}} \nabla L_{\delta,\,u}(\mathbf{q}_l) > 0\,.$$

Given $\mathbf{d}_k = \nabla L_{\delta,\,u}(\mathbf{q}_l)$, it can obtain:

$$-\nabla L_{\delta,\lambda_k}(\tilde{\mathbf{x}}_k)^{\mathrm{T}} \mathbf{d}_k < 0\,.$$

As $\mathbf{d}_k$ is subject to gradient descent, thus it has step length t and conforms to condition:

$$L_{\delta,\,u}\left(\mathbf{q}_l - t\,H\,\nabla L_{\delta,\,u}(\mathbf{q}_l)\right) < L_{\delta,\,u}\left(\mathbf{q}_l\right)\,.$$

Therefore, obtained sequence of iteration in equation (16) is descending. Meanwhile, function $L_{\delta,\,u}(\mathbf{q}_l)$ has differentiable continuation property. Under the condition of initialization, above-mentioned iteration sequence is bounded. To sum up, obtained sequence of iteration in equation (7) is convergent. Q. E. D.

5. Experimental analysis

In terms of contrast algorithm, K-SVD algorithm is selected. Algorithm experiment is mainly divided into the following four groups: change of obtained PSNR value caused by noise due to different contrast mean square error in experiment 1; it is compared in the visual angle of image after de-noising in experiment 2; algorithm performance difference is compared under the overlapped pixel in experiment 3; algorithm performance difference is compared under the condition of different No. of dictionary atoms in experiment 4.

Parameter setting: noise bias amplitude of image block is 5×5; overlapped pixel is set to be 4; 20 thousand groups of image blocks are randomly selected to conduction training for dictionary. No. of atoms in dictionary D is set to be 150; $\mathbf{D} \in R^{25\times 150}$ can be obtained. Hardware setting: in terms of CPU, quad-core with 3.0GHz is selected; in terms of RAM, host with 8Gb is selected; in terms of algorithm evaluation indicator, PSNR is selected.

Experiment 1: texture feature effect preserving

Table 1. Comparison of PSNR values of three kinds of de-noising algorithms

σ	Barbara		Boat		House	
	K-SVD	MNSR	K-SVD	MNSR	K-SVD	MNSR
20	30.78	31.69	30.35	31.15	32.76	33.35
25	29.37	30.51	29.25	30.34	32.24	32.79
30	28.47	29.68	28.54	29.48	31.15	31.56
50	25.36	26.43	25.89	26.65	27.89	28.38
100	21.87	23.26	22.79	23.47	24.46	25.86

Firstly, three image samples of boat, Barbara, and house are selected to conduct comparison test. PSNR value obtained through contrast algorithm is selected in Table 1 under noise with different mean square error. It is known from data in Table 1 that PSNR indictor obtained in MNSR image restoration scheme in the thesis is superior to contrast scheme under the same setting.

Next, remote sensing change image in a certain place in Changping District from 2005 to 2010 is selected; extraction in changed area is conducted through forms of texture feature extraction and spectral feature extraction. Original image is shown in Fig. 1a and Fig. 1b. Extraction images are separately shown in Fig, 1c and Fig. 1d.

Image contrast of remote sensing change for texture feature extraction and spectral feature extraction in a certain place in Changping district from 2005 to 2010 is shown in Fig. 1; in terms of extraction effect of change area (areas marked with circle in Fig. 1c and Fig. 1d), it is shown in the contrast result that obtained extraction effect in change area in the way of texture feature extraction method is better than extraction result of spectral feature. The latter has obvious wrong extraction phenomena as different seasonal crops may disturb feature extraction.

Experiment 2: comparison of visual de-noising effect

Visual algorithm de-nosing performance is compared based on three groups of

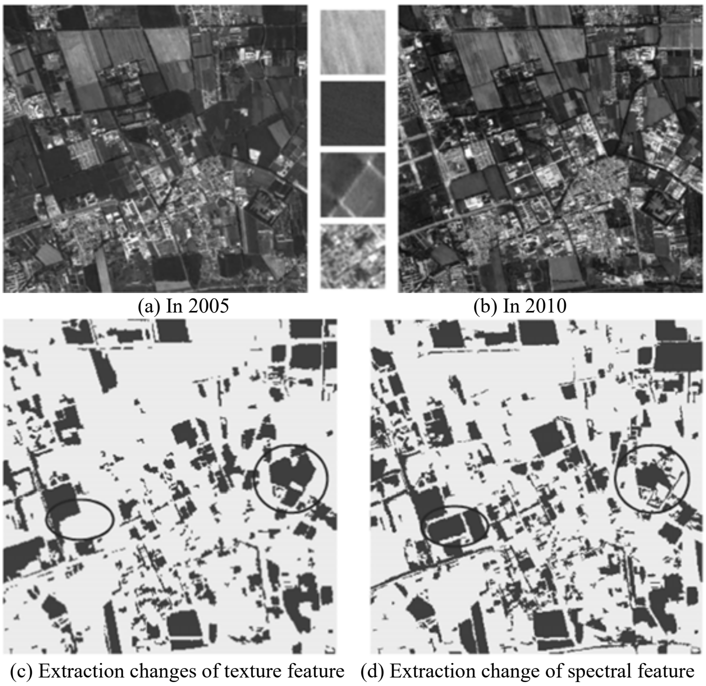

Fig. 1. Extraction effect of texture feature

remote sensing images. Mean square error indicator shall be selected to be $\sigma = 30$; visual de-noising performance of three remote sensing images is listed in Fig.1. It is known in Fig. 2 that image reconstruction effect of MNSR scheme designed in the thesis is more meticulous, which approximates to original image in visual sense.

Experiment 3: Comparison of Influence for No. of Overlapped Pixel

Influences of No. of overlapped pixel on algorithm image de-noising effect is shown there. Parameter shall be set to be $\sigma = 30$; comparison of PSNR indicators in MNSR scheme and K-SVD scheme with different No. of overlapped pixel is listed in Fig. 2. Above-mentioned PSNR indictors are mean value of three remote sensing images in Experiment 1. According to Fig. 3, PSNR indictors in MNSR scheme and K-SVD scheme shall be increased with increase of No. of overlapped pixel; in addition, MNSR scheme is always superior to K-SVD scheme.

Experiment 4: Comparison of Influence for No. of Atoms in a dictionary

Influence of No. of atoms in a dictionary on de-noising algorithm effect is listed in the contrast test. Parameter shall be set to be $\sigma = 50$; in case the rest simulation settings are unchangeable, change range of No. of atoms is between 100 and 1000. Comparison of PSNR indicators obtained from dictionary with different No. of atoms is listed in Fig. 4, which is similar to that in experiment 3; mean value of PSNR indicators in three groups of images are selected for comparison. According to data comparison in Fig. 3, when the No. of atoms in a dictionary is less than 150, PSNR indicators in MNSR scheme reach saturation point.

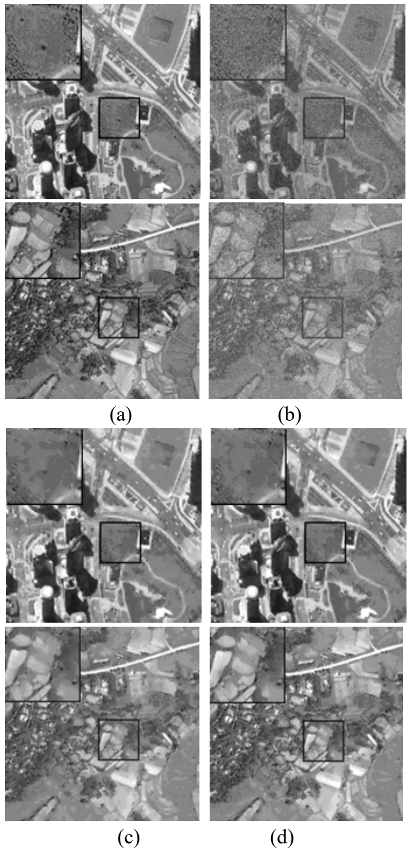

Fig. 2. De-noising algorithm visual effect [(a) image; (b) image noise; (c) K-SVD algorithm; (d) MNSR algorithm]

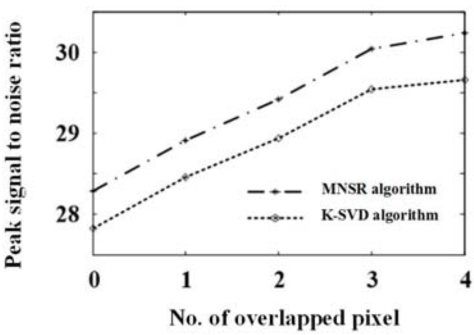

Fig. 3. Influence of the No. of pixels

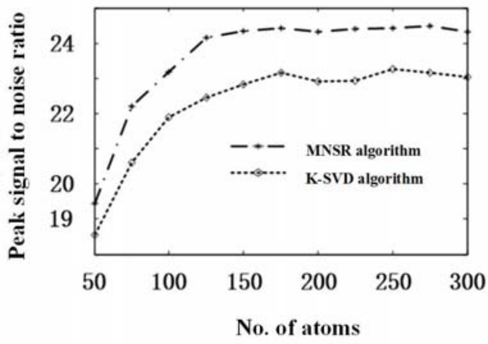

Fig. 4. Influence of the No. of atoms in a dictionary

6. Conclusion

In order to solve problems that it is hard to preserve image details after de-noising and it is insufficient to protect texture features in current de-noising scheme, a sparse image de-noising scheme based on redundant dictionary of filtering guidance is proposed. Firstly, image is subject to de-noising and noise bias is obtained based on filtering guidance in the scheme; then, image texture features contained in image noise are extracted based on dictionary training and sparse matrix expression so as to realize quality improvement for de-noising image details. Comparison test shows that the scheme mentioned in the thesis has better PSNR than contrast algorithm and it can protect image feature texture and detail feature so as to realize improvement of visual de-noising effect.

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References

[1] C. H. Wu, Y. Zheng, W. H. Ip, et al.: *A flexible H.264/AVC compressed video watermarking scheme using particle swarm optimization based dither modulation*[J]. AEUE - International Journal of Electronics and Communications, *65* (2011), No. 1, 27–36.

[2] Y. Zheng, X. Zhang, G. Zhou, et al.: *Automatic PMD compensation experiment with particle swarm optimization and adaptive dithering algorithms for 10-gb/s NRZ and RZ formats*[J]. Quantum Electronics IEEE Journal of, *40* (2004), No. 4, 427–435.

[3] C. T. Hsieh, Y. K. Wu, W. J. Chung: *Digital watermarking system for halftone images based on particle swarm optimization*[C]// First IEEE International Conference on Ubi-Media Computing. IEEE, 2008 (2008), 201–206.

[4] G. Vahdati, H. Khodadadi, M. Yaghoobi, et al.: *Fractal image compression based on spatial correlation and hybrid particle swarm optimization with genetic algorithm*[C]// International Conference on Software Technology and Engineering. IEEE, 2010 (2010), V2-185-V2-189.

[5] G. Vahdati, M. Yaghoobi: *Fractal image compression based on spatial correlation and chaotic particle swarm optimization*[C]// International Conference on Computational Intelligence and Communication Networks. IEEE, 2011 (2011), 62–67.

[6] C. M. Li, Y. Wang, H. M. Gao, et al.: *Band Selection for Hyperspectral Image Classification Based on Improved Particle Swarm Optimization Algorithm*[J]. Advanced Materials Research, *889-890* (2014), No. 21, 1073–1077.

[7] K. S. Chew, K. Zarrabi: *Non-contact displacements measurement using an improved particle swarm optimization based digital speckle correlation method*[M]. IEEE. (2011).

[8] D. U. Yazhi: *Digital image correlation method based on Newton-Raphson method and particle swarm optimization algorithm*[J]. Computer Engineering & Applications, *48* (2012), No. 34, 184–189.

[9] F. Q. Wang, Rong: *Study on Ice Regime Forecast Based on SVR Optimized by Particle Swarm Optimization Algorithm*[J]. Meteorological & Environmental Research, 2012(2012), No. 11, 36–40.

[10] Z. Liang, K. Wang, G. U. Guoqing, et al.: *Digital speckle image correlation method base on particle swarm optimization algorithm*[J]. Laser Technology. (2014).

[11] Y. Zhang, Z. M. Lu, D. N. Zhao: *An oblivious fragile watermarking scheme for images utilizing edge transitions in BTC bitmaps*[J]. Science China Information Sciences, *55* (2012), No. 11, 2570–2581.

[12] H. Bai: *Design of Non-Uniform Linear Array via Linear Programming and Particle Swarm Optimization and Studies on Phased Array Calibration*[J]. (2014).

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