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Method of Image De-Noising Based on Non-Noisy Atoms Self Adaptive and Sparse Representation

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Abstract

In allusion to the losses of image detail and texture structure information during image de-noising process, an image de-noising algorithm based on non-related dictionary learning is proposed in this paper. Firstly, this algorithm is adopted to obtain self-adaption redundant dictionary for the noisy image through the dictionary learning algorithm; secondly, HOG features and gray-level statistical features of each atom in the dictionary are extracted to form the feature set, and meanwhile the feature set of the atoms is adopted to divide the atoms into two types (non-noisy atoms and noisy atoms); finally, the non-noisy atoms are adopted to recover the image, thus to realize the de-nosing purpose. The experiment result shows: the proposed algorithm does not need to know the prior information of the noise and PSNR performance thereof is better than that of existing algorithms, and meanwhile the proposed algorithm can well keep the image detail and texture structure information, thus to improve visual effect.

Keywords*: Dictionary learning; Sparse representation; Redundant dictionary; K-mean clustering*

1. Introduction

Digital images are inevitably influenced by noises and accordingly have reduced image quality during the acquisition and transmission processes, but clear and high-quality images are needed in many application fields. Therefore, the image de-noising process has very important practical significance, thus becoming an important research subject in the image processing field. Therein, the classic noise reduction methods include neighborhood filter method, median method and frequency domain filter method, but it is difficult for these methods to keep image detail and texture structure information during the de-noising process.

In recent years, the de-noising method based on dictionary learning [1-4] and the de-noising method based on nonlocal self-similarity [5-8] in the image processing field are widely concerned by the scholars at home and abroad. The basic thought of the de-noising algorithm based on dictionary learning is to adopt the local sparseness of the image for de-noising, and the development of such method is benefited by the breakthrough progress of the sparse representation theory [11-13], such as K-SVD [1-2] algorithm and SOLD algorithm [4]. Specifically, K-SVD algorithm aims at dividing the original image into small image blocks, then establishing self-adaption redundant dictionary through SVD method and finally adopting the redundant dictionary for the sparse representation of the image blocks, thus to realize the de-noising purpose. SOLD algorithm aims at adopting the online dictionary learning algorithm to obtain the redundant dictionary so as to improve the calculation efficiency of the algorithm. The basic thought of the de-noising method based on nonlocal self-similarity is to adopt the feature that the non-neighboring parts in the image have nonlocal self-similarity to de-noise the image, such as NLM

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algorithm [5-6] and BM3D algorithm [7-8], wherein Euclidean distance is adopted in NLM algorithm to represent the similarity of the pixel neighborhoods and accordingly calculate the pixel reconstruction weight value for estimating the pixel value; the two-dimensional image blocks with similar structure are combined in BM3D algorithm to form three-dimensional data, and such data are afterwards processed by federal filter method, and meanwhile the overlapped blocks are weighted and averaged for image reconstruction. Additionally, the image de-noising algorithm based on sparse representation and nonlocal self-similarity is researched in literatures [9-10]. Although the above algorithms have obtained significant achievements in the image de-noising aspect, yet these algorithms still may lose some image texture structure information [14] during the de-noising process, thus including noise in the image structure information and causing visual effect reduction. Therefore, it is necessary to research the de-noising algorithm which can not only have the de-noising function, but also well keep image detail and texture information.

In allusion to the above problems, MCA (Morphological Component Analysis) image decomposition theory thought [12] is adopted to realize image decomposition and dictionary learning technology through dictionary classification. The image de-noising algorithm based on dictionary learning and atom clustering (DLAC) is proposed in this paper, and the basic thought thereof is to adopt HOG features and gray-level statistical features to form the feature set and then extract the non-noisy atoms in the redundant dictionary, thus to realize the de-noising purpose. Firstly, the dictionary learning algorithm is adopted to obtain the self-adaption redundant dictionary; secondly, HOG features and gray-level statistical features of each atom in the dictionary are extracted to form the feature set, and the features of atoms are divided into two types (non-noisy atoms and noise atoms); finally, the non-noisy atoms are adopted for image reconstruction, thus to keep image detail during the de-noising process. The experiment result shows: compared with existing algorithms, the proposed algorithm can well keep image detail and texture structure information and improve visual effect, without the need to know the prior information of the noise.

2. Dictionary Learning Technology

Firstly, we simply review the dictionary learning technology: for a group of given samples $\boldsymbol{\beta}=(\boldsymbol{\beta}_1,\cdots,\boldsymbol{\beta}_K)\in R^{n\times K}$, the purpose of dictionary learning is to find a redundant dictionary $\boldsymbol{A}\in R^{n\times m}$ through learning so that each sample can be sparsely expressed. The dictionary learning problem can be expressed as follows:

$$\min_{\boldsymbol{A},\boldsymbol{\Gamma}} \quad \|\boldsymbol{\beta}-\boldsymbol{A}\boldsymbol{\Gamma}\|_F^2+\lambda\|\boldsymbol{\Gamma}\|_1 \tag{1}$$

In the above formula, $\boldsymbol{\Gamma}=(\boldsymbol{\Gamma}_1,\boldsymbol{\Gamma}_2,\mathrm{L}\ ,\boldsymbol{\Gamma}_K)\in R^{m\times K}$ is the sparse representation coefficient matrix. Such methods as MOD algorithm, K-SVD algorithm [16] and online dictionary learning algorithm [17] are usually adopted to solve the dictionary learning problem.

2.1. Hyperspectral Image De-Noising Algorithm Based on Multitask Nonnegative Dictionary Learning`

The multi-task nonnegative learning model of the hyperspectral image is firstly established in this algorithm, and then the iterative scheme is established to find the redundant dictionary and the coefficient matrix of each band image of the model, and finally the obtained results are adopted for the reconstruction of each band image.

2.2. Multitask Nonnegative Dictionary Learning Model

Hyperspectral remote sensing image data are a nonnegative three-dimensional matrix. S band images in image $\boldsymbol{X} \in R^{W \times H \times S}$ are divided into P mutually overlapped image blocks with the same size as $\sqrt{n} \times \sqrt{n}$. The vector of the p th image block in the s th band image is represented as $\boldsymbol{x}_p^s$, the data matrix composed of the s th band image blocks is set as $\boldsymbol{X}_s = \left[\boldsymbol{x}_1^s, \cdots, \boldsymbol{x}_P^s\right] \in R^{n \times P}$ and the corresponding redundant dictionary is represented as $\boldsymbol{D}_s \in R^{n \times m}$. Since each band image has strong relevance with others, thus each band image can be assumed to have the same coefficient matrix $\boldsymbol{\alpha} \in R^{m \times P}$. Therefore, the dictionary learning model for S band images can be expressed as follows:

$$
\begin{aligned}
&\min_{\boldsymbol{D}_1, \boldsymbol{\alpha}} \quad \frac{1}{2}\left\|\boldsymbol{X}_1 - \boldsymbol{D}_1\boldsymbol{\alpha}\right\|_F^2 + \lambda_1 \left\|\boldsymbol{\alpha}\right\|_1 \\
&\min_{\boldsymbol{D}_2, \boldsymbol{\alpha}} \quad \frac{1}{2}\left\|\boldsymbol{X}_2 - \boldsymbol{D}_2\boldsymbol{\alpha}\right\|_F^2 + \lambda_2 \left\|\boldsymbol{\alpha}\right\|_1 \\
&\qquad \vdots \\
&\min_{\boldsymbol{D}_S, \boldsymbol{\alpha}} \quad \frac{1}{2}\left\|\boldsymbol{X}_S - \boldsymbol{D}_S\boldsymbol{\alpha}\right\|_F^2 + \lambda_S \left\|\boldsymbol{\alpha}\right\|_1
\end{aligned}
\tag{2}
$$

In the above formula, $\lambda_1, \cdots, \lambda_S$ is the weighting coefficient, and $\left\|\boldsymbol{\alpha}\right\|_1 = \sum_{i,j}\left|\alpha_{i,j}\right|$ is used for the sparse constraint of matrix $\boldsymbol{\alpha}$. The dictionary learning models (3) of S band images are combined together to obtain the multitask dictionary learning model as follows:

$$
\min_{\boldsymbol{D}_1 \cdots \boldsymbol{D}_s, \boldsymbol{\alpha}} \quad \sum_{s=1}^{S}\left(\frac{1}{2}\left\|\boldsymbol{X}_s - \boldsymbol{D}_s\boldsymbol{\alpha}\right\|_F^2 + \lambda_s \left\|\boldsymbol{\alpha}\right\|_1\right) \tag{3}
$$

Hyperspectral remote sensing image data are nonnegative. According to the nonnegative decomposition theory, $\boldsymbol{X}_s$ can be decomposed into the product of two nonnegative matrixes. Therefore, the nonnegative constraint can be considered to be added in the redundant dictionary and the coefficient matrix in the dictionary learning model in order to improve the calculation efficiency and the de-noising performance, thus to obtain the following multitask nonnegative dictionary learning model:

$$
\begin{cases}
\min\limits_{\boldsymbol{D}_1 \cdots \boldsymbol{D}_s, \boldsymbol{\alpha}} & \sum\limits_{s=1}^{S}\left(\frac{1}{2}\left\|\boldsymbol{X}_s - \boldsymbol{D}_s\boldsymbol{\alpha}\right\|_F^2 + \lambda_s \left\|\boldsymbol{\alpha}\right\|_1\right) \\
s.t. & \forall s : \boldsymbol{D}_s \geq 0, \boldsymbol{\alpha} \geq 0
\end{cases}
\tag{4}
$$

In Formula (4), common coefficient matrix $\boldsymbol{\alpha}$ represents the strong relevance of various band images, and nonnegative constraint of redundant dictionary $\boldsymbol{D}_s \left(s = 1, \cdots, S\right)$ and coefficient matrix $\boldsymbol{\alpha}$ reflects the non-negativity of hyperspectral remote sensing image data.

2.3. Solution of Multitask Nonnegative Dictionary Learning Model

In this section, the iterative scheme will be established to solve multitask nonnegative dictionary learning model (5) according to the basic thought of the nonnegative matrix factorization multiplication iteration algorithm [18]. The following two iteration steps are mainly included: fix redundant dictionary $\boldsymbol{D}_s \left(s=1,\cdots,S\right)$ and update coefficient matrix $\boldsymbol{\alpha}$; fix coefficient matrix $\boldsymbol{\alpha}$ and update redundant dictionary $\boldsymbol{D}_s \left(s=1,\cdots,S\right)$.

If redundant dictionary $\boldsymbol{D}_s \left(s=1,\cdots,S\right)$ is fixed, then multitask nonnegative dictionary learning model (5) can be simplified as follows:

$$\begin{cases} \min\limits_{\boldsymbol{\alpha}} & \sum\limits_{s=1}^{S}\left(\frac{1}{2}\left\|\boldsymbol{X}_s-\boldsymbol{D}_s\boldsymbol{\alpha}\right\|_F^2+\lambda_s\left\|\boldsymbol{\alpha}\right\|_1\right) \\ s.t. & \boldsymbol{\alpha}\geq 0 \end{cases} \tag{5}$$

If $L_{\boldsymbol{D}_1\cdots\boldsymbol{D}_s}(\boldsymbol{\alpha})=\sum\limits_{s=1}^{S}\left(\frac{1}{2}\left\|\boldsymbol{X}_s-\boldsymbol{D}_s\boldsymbol{\alpha}\right\|_F^2+\lambda_s\left\|\boldsymbol{\alpha}\right\|_1\right)$ is true, then the following formula can be obtained according to the inequality $\boldsymbol{\alpha}\geq 0$:

$$\partial L_{\boldsymbol{D}_1\cdots\boldsymbol{D}_s}(\boldsymbol{\alpha})/\partial\boldsymbol{\alpha}=\sum_{s=1}^{S}\left(\boldsymbol{D}_s^T\boldsymbol{D}_s\boldsymbol{\alpha}-\boldsymbol{D}_s^T\boldsymbol{X}_s+\lambda_s\boldsymbol{1}\right)$$

(6)

If $\partial L_{\boldsymbol{D}_1\cdots\boldsymbol{D}_s}(\boldsymbol{\alpha})/\partial\boldsymbol{\alpha}=0$ is true, then the following formula can be obtained:

$$\sum_{s=1}^{S}\left(\boldsymbol{D}_s^T\boldsymbol{D}_s\boldsymbol{\alpha}+\lambda_s\boldsymbol{1}\right)=\sum_{s=1}^{S}\left(\boldsymbol{D}_s^T\boldsymbol{X}_s\right) \tag{7}$$

If $\otimes$ is set to represent the multiplication of the corresponding elements in the matrix, then the following formula can be obtained:

$$\boldsymbol{\alpha}\otimes\sum_{s=1}^{S}\left(\boldsymbol{D}_s^T\boldsymbol{D}_s\boldsymbol{\alpha}+\lambda_s\boldsymbol{1}\right)=\boldsymbol{\alpha}\otimes\sum_{s=1}^{S}\left(\boldsymbol{D}_s^T\boldsymbol{X}_s\right)$$

Accordingly, the iterative scheme of coefficient matrix $\boldsymbol{\alpha}$ can be obtained as follows:

$$\boldsymbol{\alpha}\leftarrow\boldsymbol{\alpha}\otimes\left(\sum_{s=1}^{S}\boldsymbol{D}_s^T\boldsymbol{X}_s\right)\%\left(\sum_{s=1}^{S}\left(\boldsymbol{D}_s^T\boldsymbol{D}_s\boldsymbol{\alpha}+\lambda_s\boldsymbol{1}\right)\right) \tag{8}$$

In the above formula, % represents the division of the corresponding elements in two matrixes.

If coefficient matrix $\boldsymbol{\alpha}$ is fixed, then multitask nonnegative dictionary learning model (5) can be simplified as follows:

$$\begin{cases} \min\limits_{\boldsymbol{\alpha}} & \sum\limits_{s=1}^{S}\left(\frac{1}{2}\left\|\boldsymbol{X}_s-\boldsymbol{D}_s\boldsymbol{\alpha}\right\|_F^2\right) \\ s.t. & \boldsymbol{D}_s\geq 0 \quad s=1,\cdots,S \end{cases} \tag{9}$$

If $L_{\boldsymbol{\alpha}}(\boldsymbol{D}_1,\cdots,\boldsymbol{D}_S)=\sum_{s=1}^{S}\left(\frac{1}{2}\left\|\boldsymbol{X}_s-\boldsymbol{D}_s\boldsymbol{\alpha}\right\|_F^2\right)$ is true, then the following formula can be obtained:

$$\partial L_{\boldsymbol{\alpha}}(\boldsymbol{D}_1,\cdots,\boldsymbol{D}_S)/\partial\boldsymbol{D}_s=\boldsymbol{D}_s\boldsymbol{\alpha}\boldsymbol{\alpha}^{\mathrm{T}}-\boldsymbol{X}_s\boldsymbol{\alpha}^{\mathrm{T}} \tag{10}$$

If $\partial L_{\boldsymbol{\alpha}}(\boldsymbol{D}_1,\cdots,\boldsymbol{D}_S)/\partial\boldsymbol{D}_s=0$ is true, then the following formula can be obtained:

$$\boldsymbol{D}_s\otimes\left(\boldsymbol{D}_s\boldsymbol{\alpha}\boldsymbol{\alpha}^{\mathrm{T}}\right)=\boldsymbol{D}_s\otimes\left(\boldsymbol{X}_s\boldsymbol{\alpha}^{\mathrm{T}}\right) \tag{11}$$

Accoridng to the above formula, the iteration scheme of the redundant dictionary of each band can be obtained as follows:

$$\boldsymbol{D}_s\leftarrow\boldsymbol{D}_s\otimes\left(\boldsymbol{X}_s\boldsymbol{\alpha}^{\mathrm{T}}\right)\%\left(\boldsymbol{D}_s\boldsymbol{\alpha}\boldsymbol{\alpha}^{\mathrm{T}}\right) \tag{12}$$

The above two iteration steps (9) and (13) are repeated till algorithm convergence in order to obtain dictionary $\boldsymbol{D}_s\left(s=1,\cdots,S\right)$ and common coefficient matrix $\boldsymbol{\alpha}$. According to iteration schemes (9) and (13), if the initial values of dictionary $\boldsymbol{D}_s\left(s=1,\cdots,S\right)$ and coefficient matrix $\boldsymbol{\alpha}$ are nonnegative, then dictionary $\boldsymbol{D}_s\left(s=1,\cdots,S\right)$ and coefficient matrix $\boldsymbol{\alpha}$ after the iterative scheme is updated are also nonnegative.

2.4. Hyperspectral Remote Sensing Image De-Noising

Dictionary $\boldsymbol{D}_s\left(s=1,\cdots,S\right)$ and common coefficient matrix $\boldsymbol{\alpha}$ corresponding to each band image in hyperspectral remote sensing image can be obtained according to section 2.2. Dictionary $\boldsymbol{D}_s\left(s=1,\cdots,S\right)$ and coefficient matrix $\boldsymbol{\alpha}$ obtained thereby can be adopted to obtain the data matrix of de-noised band image as follows:

$$\boldsymbol{X}_s=\boldsymbol{D}_s\boldsymbol{\alpha}\qquad s=1,\cdots,S \tag{13}$$

Each column vector of data matrix $\boldsymbol{X}_s$ is corresponding to each image block of s bands, and the image blocks are jointed by positions and the overlapped parts are averaged to obtain the de-noised image $\hat{\boldsymbol{X}}_s\left(s=1,\cdots,S\right)$.

3. Detailed Algorithm Steps and Analysis

3.1. Detailed Algorithm Steps

The detailed steps of the proposed algorithm will be described in this section, as shown in Algorithm 1.

Algorithm 1: Hyperspectral Image De-noising Algorithm Based on Multitask Nonnegative Dictionary Learning

Algorithm Input: Input noisy hyperspectral image $\boldsymbol{X}\in R^{W\times H\times S}$, weighting parameters $\lambda_1,\cdots,\lambda_s$ and dictionary atom number m;

Initialization: Initialize dictionary $\boldsymbol{D}_s\left(s=1,\cdots,S\right)$ and initialize the elements in coefficient matrix $\boldsymbol{\alpha}$ as the random values in the interval of $[0,1]$;

Step 1 Divide S band images in hyperspectral remote sensing image $\boldsymbol{X} \in R^{W\times H\times S}$ into P mutually overlapped image blocks with the same size as $\sqrt{n}\times\sqrt{n}$;

Step 2 Estimate dictionary $\boldsymbol{D}_s\left(s=1,\cdots,S\right)$ of each band image and common coefficient matrix $\boldsymbol{\alpha}$ through solving multitask nonnegative dictionary learning model (5);

(2-1) Adopt iteration scheme (9) to update coefficient matrix $\boldsymbol{\alpha}$;

(2-2) Adopt iteration scheme (13) to update dictionary $\boldsymbol{D}_s\left(s=1,\cdots,S\right)$;

(2-3) Repeat Steps (2-1) and (2-2) till algorithm convergence;

Step 3 Adopt dictionary $\boldsymbol{D}_s$ and coefficient matrix $\boldsymbol{\alpha}$ to reconstruct each band image $\boldsymbol{X}_s\left(s=1,\cdots,S\right)$ through Formula (14);

Algorithm Output: De-noised hyperspectral remote sensing image $\hat{\boldsymbol{X}}=\left[\hat{\boldsymbol{X}}_1,\cdots,\hat{\boldsymbol{X}}_S\right]$.

Notes for Algorithm 1:

(a) Selection of atom number m of dictionary $\boldsymbol{D}_s$: set dictionary dimensionality as $2n\le m\le 4n$, wherein large dictionary dimensionality can cause the increment of calculation workload.

(b) Selection of parameter λ_s: parameter λ_s is a value related to the noise level of s band images and dictionary atom number m, wherein this parameter is set as $\lambda_s=\sqrt{2\log(m)}$ in this paper due to unknown δ_s.

4. Test and Analysis

The performance of the proposed algorithm will be verified in this section through test and analysis, and meanwhile the proposed algorithm will be compared with NLM algorithm [5], K-SVD algorithm [1] and Demons algorithm, wherein the first two comparison algorithms are based on dictionary learning algorithm and the third comparison algorithm is gradient algorithm. Test 1 aims at comparing PSNR values of the four different algorithms; Test 2 aims at comparing the de-noising effects of different de-noising algorithms; Test 3 aims at presenting the influence of the initial cluster center on algorithm performance; Test 4 aims at presenting the influence of different feature set dimensionalities on algorithm performance.

Test 1: Comparison of PSNR Values of Four De-Noising Algorithms

Barbara, boat and house are respectively adopted for the test. Table 1, shows the comparison of PSNR values of four algorithms under different mean square errors of the noise. When M and N are set as $M=N=8$, according to Table 1, PSNR value of DLAC algorithm under the same condition is more than those of other three algorithms.

Table 1. Comparison of PSNR Values of Three De-Noising Algorithms

σ	barbara				boat				house			
	NLM	K-SVD	Demons	DLAC	NLM	K-SVD	Demons	DLAC	NLM	K-SVD	Demons	DLAC
20	31.32	30.88	30.57	32.03	30.41	30.36	30.67	31. 29	32.98	32.86	33.14	33.67
25	29.63	29.30	29.86	30.67	29.76	29.15	29.69	30. 42	32.21	32.14	32.37	32. 83

30	29.19	28.57	29.01	29.53	28.90	28.44	29.08	29. 66	31.25	31.05	31.25	31. 58
50	25.74	25.46	26.18	27.19	26.11	25.99	26.32	26. 73	28.10	27.97	28.13	28. 32
100	22.30	21.95	22.16	23. 65	22.87	22.81	23.08	23. 46	24.49	24.37	24.96	25.78

Test 2: Comparison of De-Noising Effects of Four Algorithms

Classic peppers image and barbara image are selected for this test (mean square error σ=40) to compare the d-noising effects, wherein M and N are set as $M = N = 8$, namely: the feature set dimensionality is 16. Figure 2, shows the original image and the noisy image. According to Figures 3 and 4, DLAC algorithm is superior to NLM algorithm, K-SVD algorithm and Demons algorithm in the aspect of visual effect.

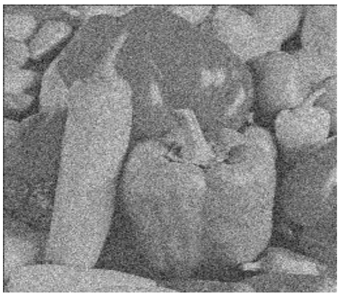
Test 3: Influence of Initial Cluster Center Selection on Algorithm Performance

Lena image is selected for this test in order to compare the performances of randomizing method [17], max-min method [18] and the atom variance method proposed in this paper for the selection of the initial cluster center. Under the condition of $M = N = 8$, Figure 5, shows the change of PSNR values of three initial cluster center selection methods along with mean square error σ. According to the figure, the initial cluster center selection has certain influence on the algorithm performance. The atom variance method adopted in this paper to select the initial cluster center is better than the classic randomizing method and max-min method.

Test 4: Influence of Feature Set Dimensionality on Algorithm Performance

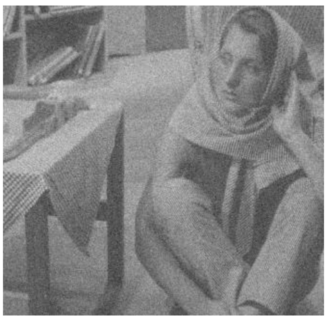
Lena image is selected for the test to compare the influence of different feature dimensionalities $M + N$ on algorithm performance. M and N are set as $M = N$, and the mean square errors are respctively set as 20, 30 and 50. Figure 6 shows the change of PSNR values along with the feature set dimensionality under different mean square errors: 20, 30 and 50. According to the figure, when the feature set dimensionality $M + N$ is more than 16, the performance of DLAC algorithm proposed in this paper tends to be stable.

(a) Original Image of Peppers



(b) Noisy Image of Peppers

(c) Original Image of Barbar



(d) Noisy Image of Barbar

Figure 1. Original Image and Noisy Image of Peppers and Barbara

(a) K-SVD Algorithm (b) NLM Algorithm (c) Demons Algorithm (d) DLAC Algorithm

Figure 2. Comparison of De-Noising Effects for Peppers Image

(a) K-SVD Algorithm (b) NLM Algorithm (c) Demons Algorithm (d) DLAC Algorithm

Figure 3. Comparison of De-Noising Effects for Barbara Image

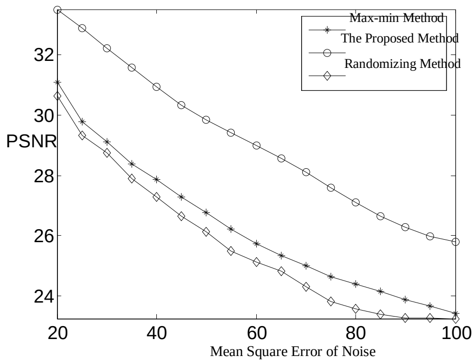


Figure 4. Influence of Initial Cluster Center on Algorithm

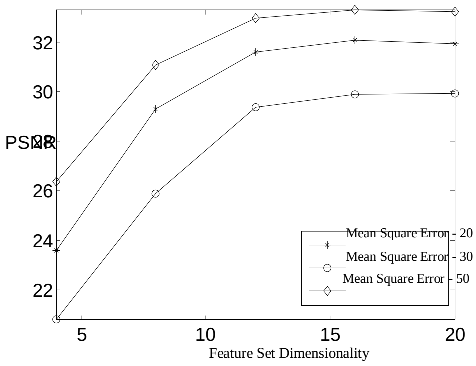


Figure 5. Influence of Feature Set Dimensionality on Algorithm

5. Conclusion

In allusion to the problems of the difficulty in keeping image detail and texture structure information during image de-noising process, an image de-noising algorithm based on dictionary learning and atom clustering is proposed in this paper. Firstly, K-SVD dictionary learning algorithm is adopted to obtain the self-adaption redundant dictionary; secondly, HOG features and gray-level statistical features of each atom in the dictionary are extracted to form the feature set, and meanwhile K-mean clustering algorithm is adopted to divide the atoms into two types (non-noisy atoms and noisy atoms) according to the feature set of atoms; finally, the non-noisy atoms are adopted to reconstruct the image, thus to realize the de-noising purpose. The experiment result shows: the proposed algorithm does not need to know the prior information of the noise and PSNR performance thereof is better than those of existing algorithms, and meanwhile the proposed algorithm can well keep the image detail and texture structure information, thus to improve visual effect. Since the proposed algorithm has large calculation workload, how to reduce algorithm time complexity will become the future research direction.

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