International Journal of Signal Processing, Image Processing and Pattern Recognition
Vol.8, No.10 (2015), pp.1-10
http://dx.doi.org/10.14257/ijsip.2015.8.10.01

A Study on Sparse Representation Model of Image Denoising Method

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Abstract

Image denoising is a basic problem in image processing, due to the image structure has the characteristic of self-similar, using the ideas of nonlocal, this paper proposes a non-local denoising method based on sparse representation, the structure information of image is improved after denoising, at the same time making similar image tiles have similar sparse representation, image reconstruction effect is better, through the numerical simulation the results show that the method has good application value.

Keywords: *Image denoising; Sparse representation. Nonlocal idea; Image construction*

1. Introduction

With the continuous development of social informatization and the enhanced ability of the computer processing, people now have entered the information era of life, images and more and more closely related to people's life and production, has been applied to the digital television, television, telephone, military, aerospace, medical, industrial, agriculture and other aspects. But the images in the process of acquisition and transmission will inevitably because of the influence of the equipment and the surrounding environment and mixed noise, such as electronic, speckle noise, photon noise and quantization noise, this will seriously affect the visual effect of image and the image of subsequent processing. As an important step of image preprocessing, denoising effect will largely determine the subsequent image feature extraction, image segmentation, image compression, such as the effect of the processing, if the signal-to-noise ratio is too low, can affect the quality of the image, which caused a big trouble to people's actual need. In order to improve the image quality and quality, provide convenience to people's production and life, in recent decades, image denoising has been scientific research one of the important research topic. A good denoising method is in does not affect the image under the premise of important details, as much as possible to remove noise.

Based on the human visual perception mechanism research has shown that the human eye vision system can be regarded as a kind of reasonable and efficient image processing system. In the human visual system, from the retina to the brain cortex exist a series of "receptive field" to (receptive field) to describe the pattern of cells. Receptive field of visual information processing in the system the basic structure and functional unit, by accepting the light and convert it into neural signals output to influence many outside geniculate ganglion cells, somatic cells and nerve cells in the visual cortex. Based on the mechanism of perception research shows that: in the primary visual cortex cells under the direction of the receptive field has very obvious sensitivity, only a single neuron to respond to in the feeling field stimulation, namely individual neurons only encodes a specific information, such as edge, line in a certain direction, stripes, and so on. Each neuron of image edge, the characteristics of endpoint, stripes and other side in a sparse coding strategy is described. Also, in auditory cortex, olfactory system and motor cortex neurons were also found that adopting the tactics of sparse coding. From mathematical

ISSN: 2005-4254 IJSIP

perspective, the sparse coding can be thought of as another way of describing the data, in this kind of describing mode is active, only a few components of the rest of the large component in inactive state.

Since the sparse representation model was proposed, has been widely used in various fields of image processing, including image denoising, to fuzzy, super resolution, compressed sensing, face recognition, image classification, image retrieval, etc. Based on sparse representation model research focuses on two aspects: the sparse coding method and dictionary learning method.

From the perspective of the sparse decomposition and sparse representation of image signal with noise include two parts, the clean image signal and noise. Because of the clean image signal is of a certain structure, its structural characteristics in conformity with the atomic properties, so the clean image signal is sparse, sparse representation through setting threshold can be preserved. The noise is random, is not relevant, so there is no structural characteristics. If it can be extracted from signal meaningful atoms, as signals are extracted part. If you can't continue to extracted from signal residual meaningful atoms, that is all the noise in the signal residuals. Through such principle can achieve the goal of image denoising.

From this perspective, image denoising can be converted to sparse representation and decomposition. Wavelet transform as a sparse representation, that is in a similar way to achieve the purpose of image denoising. After noise image signal into wavelet transform, because wavelet change is linear, the characteristics of wavelet domain noise remains unchanged. In general, we believe that the noise is high frequency signal and high frequency sub-band decomposition to three (HH and VV, VH) [1-3], the wavelet coefficients of noise is bigger, the images of the wavelet coefficient is smaller, by threshold, can achieve the goal of denoising.

For two-dimensional image signal, by one-dimensional wavelet expanding to two-dimensional wavelet didn't inherit the excellent characteristics of one-dimensional wavelet, two-dimensional wavelet transform is not optimal, said in search of better sparse. Had the Curvelet, Contourlet Wedgelet, Bandelet, Directionlet etc. multi-scale geometric analysis method [4-7]. On the other hand a dictionary of sparse representation in the field of sparse open another piece of space, and combining with multi-scale basis function, can construct wavelet dictionary, dictionary, mixed double redundant dictionary. With these tools in the field of denoising, achieved very good results, its performance is close to or even more than BMD algorithm. Both multiplicative and additive noise, image denoising could also benefit from this Angle to think.

2. Related Works

First briefly introduced the theory of sparse representation, defined as sparse signal, if the signal is only a finite number of X (K) nonzero sampling points, while the other sampling points are zero, called sparse signal X is K. Practice, usually the nature of time domain signals are sparse, strictly sparse signal is small, although some location value is small, but not necessarily equal to zero, then introduce the concept of compressible signal. Compressible signal is defined as, if a certain signal under the condition of not losing any information through some transformation can be sparse signal, that is the signal is sparse in some transform domain, is called a compressible signal.

There are two ways to get general dictionary: analytical learning and training. The analytical dictionary, such as DCT, Wavelet and Curvelet, Contourlet [8-10], the main characteristic of this kind of dictionary is simple and easy to implement, can quickly get signal sparse representation, but poor adaptability; And training learning dictionary have higher adaptability, can according to the current to deal with the input signal, and changes to solve problems, but the high complexity of analytical dictionary. Usually in order to achieve better treatment effect, we often learn the training to get the dictionary, so the dictionary learning algorithm is particularly important at present more popular dictionary learning algorithm have MOD, K - SVD, thin K - SVD, online learning, etc., a dictionary of K - SVD and its variant thin K - SVD is most commonly used.

Since while NLM algorithm was put forward, the natural image self-similarity has become one of the important basis of image processing. And denoising algorithm based on sparse representation on the denoising effect is more and more cause the attention of scholars, including K - SVD algorithm as representative, is the source of all kinds of improved algorithm, but K - the defect of SVD denoising algorithm, there are two more outstanding, it is a dictionary learning takes a long, complex algorithm, dictionary haven't high precision and quick way to learn, two is obtained dictionary structural training is not strong, it is difficult to apply so, also cannot deal with high-dimensional data.

BMD algorithm is a kind of denoising method based on block processing. USES the similarity of images, this method will have a similar structure of 2 d image block combined together to form 3 d data, then carries on the joint filter, finally by piece together, namely the overlapped block weighted average, restored image. Divided into two stages, each stage of block group and the combined filter two steps, but with different specific methods. The first stage to generate images of the initial estimate, the second phase of the initial estimate again denoising, form the final estimate. BMD fully tap the nonlocal structure of image redundancy, very good results have been achieved. It has been proved to be the one of the most optimal method of denoising performance.

In order to evaluate denoising effect, need effective evaluation index and method of common evaluation method of image denoising is divided into two kinds of subjective evaluation and objective evaluation, including subjective evaluation usually has two kinds: one is subjective evaluation as an observer, this is the image directly observed with the naked eye, and then respectively its image quality of the observation or good or bad. This is a qualitative method, quantitative standard, and by the observer the influence of subjective factors, the uncertainty of evaluation results have a certain. Another kind is with the development of fuzzy mathematics, the fuzzy comprehensive evaluation method can be used to minimize the influence of subjective factors, realize the approximate quantitative image quality evaluation, but it is still not completely eliminate the influence of subjective uncertainty and its quantitative calculation formulas of parameters often depend on expert experience. The common objective evaluation index for the peak signal-to-noise ratio (PNSR) and structural similarity (SSIM) two kinds.

3. Nonlocal Regularization Sparse Representation Model

We add in the denoising model of the original SCN regularization for correction coefficient of sparse representation, the new model are as follows [11]

$$\min_{\alpha}\{\|y-H\phi\alpha\|_2^2+\lambda\|\alpha\|_1+\|\alpha-\beta\|_1\} \tag{1}$$

In which β is sparse representation coefficient on the dictionary ϕ of a clear image, to estimate β by adopting the idea of NLM, referred to C_i as a collection of L image block index of similar to the structure of image block I, $a_{i,j}$ as the sparse coefficient of image block j, $j\in C_i$, then

$$\beta_i=\sum\nolimits_{j\in C_i}\omega_{i,j}a_{i,j} \tag{2}$$

In which $\omega_{i,j}$ is the weight that depends on the image block I and j similar degree [12], means

$$\omega_{i,j}=\exp(-\|a_i-a_j\|_2^2/h^2)/w \tag{3}$$

In which h is the constant related to the noise standard deviation, w is the normalized constant, can be realized through fast NLM algorithm on type.

Formula (1) using iterative threshold shrinkage algorithm, the iterative process is [13]

$$a_j^{i+1} = \begin{cases} S_{t1,t2,\beta_j}(v_j^{(i)}), \beta_j \geq 0 \\ -S_{t1,t2,-\beta_j}(-v_j^{(i)}), \beta_j < 0 \end{cases} \tag{4}$$

In which

$$v^{(i)} = \frac{1}{c}\phi^T(y - \phi a^{(i)}) + a^{(i)} \tag{5}$$

$$S_{t1,t2,\beta_j}(t) = \begin{cases} t + t1 + t2, t < -t1 - t2 \\ 0, -t1 - t2 \leq t \leq t1 - t2 \\ t - t1 + t2, t1 - t2 < t < t1 - t2 + b \\ b, t1 - t2 + b \leq t \leq t1 + t2 + b \\ t - t1 - t2, t > t1 + t2 + b \end{cases} \tag{6}$$

The algorithm steps are as follows:
The noise image Y in the form of overlap pixels extracting samples of size N * N as y_i, $i \in (1, m)$,
divided the sample using fast NLM algorithm into K classes, for each type of sample to use thin K - SVD dictionary learning algorithm solve the following formula[14]

$$\min_{D_m, \alpha_m} \|a_m\|_0, s.t. \|z_m - D_m A a_m\|_2 < \varepsilon \tag{7}$$

In which $\varepsilon = C \times \sqrt{n} \times \sigma_n$,C is noise gain, by the formula the dictionary $\phi_m = D_m A$ of the image block and sparse coefficient a_m are available.

In the case of type m, search for L image block of similar to the structure of image block I, estimate the value of β_m by formula (2), after ϕ_m and β_m have been certified, solve the following formula using iterative shrinkage algorithm, the revised sparse coefficient is available.

$$\min_{\alpha_m} \frac{1}{2}\|z_m - \phi_m a_m\|_2^2 + \lambda\|a_m\|_1 + \gamma\|a_m - \beta_m\|_1 \tag{8}$$

According to the above dictionary ϕ_m and revised sparse coefficient can reconstruct the denoising image.

4. Experiment and Analysis

This article selects the standard gray image Monarch, Lena, Barbara, House as test images, experiment, add four different standard deviation of the Gauss white noise respectively to verify the effectiveness of the algorithm and the denoising effect.

Table 1 for test images in the standard deviation of 10,25,50,75 respectively, K - SVD, BMD, CSR and PSNR value comparison algorithm in this paper, the SSIM value comparison to these algorithms in table 2 and figure 1 ~ 4 after add noise to the image denoising algorithm comparing the effect of different figure. In general, the algorithm in terms of PSNR and SSIM are superior to the traditional K - SVD algorithm, compared with the BMD algorithm, on the basis of guarantee the image structure information, the PSNR is generally less than 0.1 dB, PSNR value is very close to the CSR algorithm at the same time, in terms of time complexity, to add the mean, standard deviation of 0 to 25 Lena white Gauss noise images, for example, if the image size is 128 x 128, K - SVD algorithm takes 40.24 s, PSNR value of 25.89 dB, BMD algorithm takes 35 s, PSNR value of 26.98 dB, CSR algorithm of 152 s, PSNR value of 26.90 dB, this algorithm takes 83.24 s, PSNR value of 26.92 dB. If the image size is 256 x 256, the CSR algorithm processing time is 12.34 min, and the algorithm to the 224 s, if for parallel computing, it will be less than 180 s. Because this algorithm is not iterative calculation, the end of the clustering can be parallel computing, and CSR algorithm iterative result of each iteration needs to use the last time, and estimate the noise, thus causing the error is bigger, also relatively time consuming.

Table 1. Comparison of PSNR Value from Different Denoising Algorithms (dB)

standard deviation	Monarch				Lena			
	K-SVD	BMD	CSR	OURS	K-SVD	BMD	CSR	OURS
10	31.23	32.42	33.45	34.52	31.74	32.35	33.74	34.82
25	29.49	29.42	29.83	29.93	29.36	29.73	29.37	29.82
50	26.39	27.39	27.98	28.48	26.25	27.58	27.78	28.39
75	25.29	25.93	26.83	26.39	25.46	25.45	26.77	26.97
standard deviation	Barbara				House			
	K-SVD	BMD	CSR	OURS	K-SVD	BMD	CSR	OURS
10	33.53	33.72	34.65	34.62	32.54	33.65	34.34	33.92
25	28.49	27.32	29.13	29.11	27.46	28.43	28.77	28.62
50	25.39	25.69	26.38	26.28	25.25	25.18	25.08	25.59
75	24.59	24.53	25.13	25.19	24.36	24.45	24.67	24.47

Table 2. Comparison of SSIM Value from Different Denoising Algorithms

standard deviation	Monarch				Lena			
	K-SVD	BMD	CSR	OURS	K-SVD	BMD	CSR	OURS
10	0.953	0.954	0.946	0.956	0.934	0.936	0.941	0.950
25	0.887	0.879	0.896	0.898	0.865	0.867	0.868	0.867
50	0.789	0.768	0.786	0.787	0.745	0.746	0.739	0.747
75	0.675	0.685	0.677	0.685	0.647	0.651	0.648	0.652
standard deviation	Barbara				House			
	K-SVD	BMD	CSR	OURS	K-SVD	BMD	CSR	OURS
10	0.932	0.929	0.928	0.931	0.951	0.949	0.948	0.953
25	0.856	0.854	0.855	0.861	0.844	0.846	0.847	0.845
50	0.724	0.729	0.728	0.727	0.743	0.745	0.747	0.746
75	0.656	0.657	0.654	0.658	0.635	0.638	0.636	0.639

1 Original image

2 noise image

3 K-SVD denoising

4 BMD denoising

5 CSR denoising

6 OUR denoising

Figure 1. Monarch Image Denoising Comparison

1 Original image

2 Noise image

3 K-SVD denoising

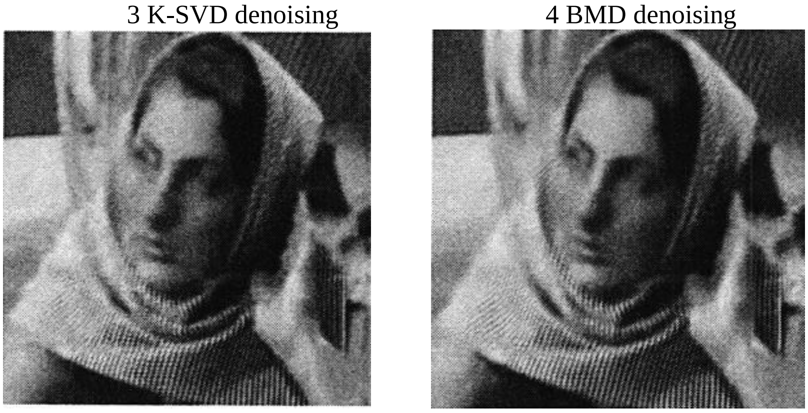
4 BMD denoising

5 CSR denoising   6 OUR denoising

Figure 2. Lena Image Denoising Comparison

1 original image   2 noise image

3 K-SVD denoising   4 BMD denoising



5 CSR denoising   6 our denoising

Figure 3. Barbara Image Denoising Comparison

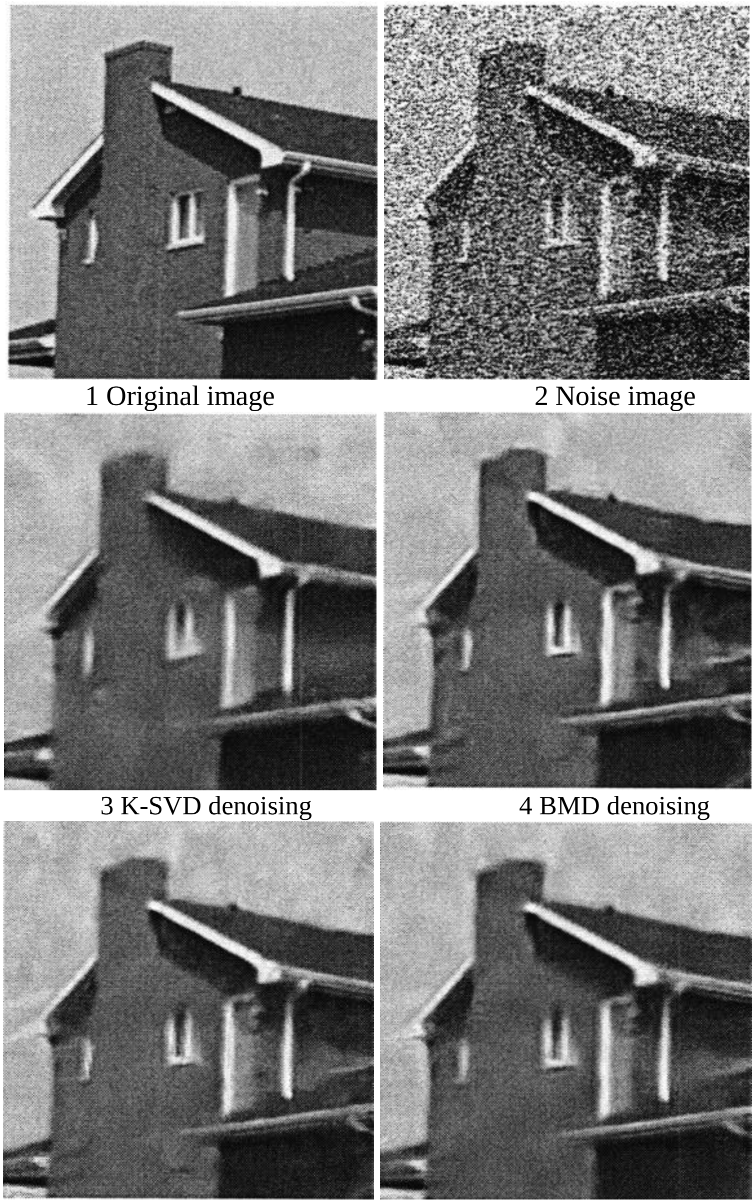


Figure 4. House Image Denoising Comparison

5. Conclusion

Algorithm of sparse representation based on CSR of sparse errors obey the Laplace prior distribution, the characteristics of the existing denoising model to add the regularization coefficient of sparse representation error, is proposed based on a nonlocal regularization sparse representation of image denoising algorithms. First of all, using the ideas of non-local denoising image block clustering structure similar, each image block independently dictionary learning, enhance the adaptability of the dictionary; Secondly, the use of thin K - K - SVD of SVD to replace the traditional dictionary within class learning, improve the structural the dictionary; Finally, the sparse regularization coefficient error are introduced to correct the sparse coefficient in order to further improve the image reconstruction effect. The experimental results show that compared with the traditional K - SVD algorithm, this algorithm can effectively maintain the structure of the image information, and enhance the denoising effect, at the same time, on the basis of not reducing SSIM, PSNR part is very close to or even better than the current advanced denoising algorithm.

Acknowledgements

This work was supported by a grant from the National Natural Science Foundation of Zhejiang (No. Y1100314).

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