An Improved Fast Nonlocal Means Filter Using Patch-oriented 2DPCA

Yuhui Zheng[1], Jianwei Zhang[2], Shunfeng Wang[3], Jin Wang[1] and Yunjie Chen[2]

[1]School of Computer and Software
[2]College of Math and Statistics
[3]College of Bin Jiang
Nanjing University of Information Science and Technology, Nanjing, China
zheng_yuhui@nuist.edu.cn, zhangjw@nuist.edu.cn,
wsfnuist@yahoo.com.cn, wangjin@nuist.edu.cn

Abstract

In former work [18], we propose a scheme to more efficiently preselect similar patches for the nonlocal means filter, based on the Patch-oriented two-dimensional principal component analysis (2DPCA) technique. Although the method can yield good results, the computational complexity remains high. For this reason, in this paper we proposed an improvement of the work, which is fast and directly employs features extracted by the patch-oriented 2DPCA to compute the weights. The new approach has been tested on a commonly-used standard test image database. The results demonstrate that our method can significantly improve the denoising effect.

Keywords: *nonlocal means filter, 2DPCA, image processing*

1. Introduction

Denoising is still a widely studied and largely unsolved problem in image processing and computer vision. The aim of denoising is to estimate the original image from a degraded noisy image. In the past decades, many methods for image denoising have been suggested, and a recent relatively complete review of them, especially in the spatial domain, can be found in [1].

It is well-known that linear smoothing methods have two important drawbacks: They blur and dislocate image structures. Therefore, it is natural to address the limitations of linear denoising methods by using advanced nonlinear filtering techniques which smooth the image while preserving important structures such as textures. Some of the sophisticated nonlinear spatial noise removal methods are based on functional minimization since they take the image geometry into account. Related partial differential equations (PDE) and variational methods, including recent anisotropic diffusion equations [2, 3] and total variation (TV) minimization [4, 5], have produced impressive results. Other nonlinear spatial denoising methods, such as the Yaroslavsky filter [6] and its iterative version [7] named bilateral filter, are neighborhood filters which incorporate a neighborhood of the pixel under consideration and perform some kind of averaging on the gray values. For studies on other filters, we refer to [8, 9, 19].

These nonlinear denoising methods are spatially local. Although they can preserve image structures in large scale, the small ones are always regarded as noise and are smoothed out. Lately, a very elegant nonlocal denoising method called NL-means filter has been proposed by Buades et. al., [1] which is inspired by studying on texture synthesis [10]. In this method, the restored gray value of the pixel under consideration is derived by the weighted average of the gray values of all pixels in the image. Each weight is proportional to the similarity between the patch around the pixel being processed and the patch corresponding to the other image pixels. Why the NL-means filter can produce astonishing results. Firstly, it is related to image redundancy, i.e. images contain repeated structures. Secondly, the NL-means filter employs patch-based technique to smooth image. Defined as local square neighborhoods of image pixels, patches provide one of the simplest ways to analyze and compare image structures. More recently, a similar image regularization method based on patches has also been proposed in [10] with excellent noise removal performance. Once again, this demonstrates the success of the patch-based denoising methods.

Unfortunately, although the denoising results in [1] are outstanding, the computational complexity of this method is quite a burden. This is a consequence of the fact that weights to all other pixels have to be calculated at each pixel. Hence, the complexity is quadratic in the size of image. Several acceleration methods have been suggested. The most popular way is to limit the weight computation to a subimage surrounding the pixel under consideration [11]. This approximation is at a quality cost, which has been observed in the literature [12]. Speedups without quality cost have been achieved in [13-15]. The basic idea underlying these high performance methods is to preselect the patches in entire image according to the patches' features. Only patches with similar features (we denote the collection of these patches as similar set) are used to compute the weights. An iterative version of the NL-means filter was proposed in [15]. This method used a cluster tree to preselect similar patches. In [12-14], it was suggested to preselect patches which have similar means and gradient directions or similar means and variances. It should be noted that the existing problems of these methods are threshold selections, which determine patches similar or dissimilar, and ultimately impact the noise removal effect.

In our former work [18], we propose a scheme to more efficiently preselect similar patches, based on the two-dimensional principal component analysis (2DPCA) technique [16]. Two important questions are addressed: how to provide a patch-oriented 2DPCA approach for preselection and how to adaptively determine the similar sets which contain very similar pixels. Although the method can yield good results, the computational complexity remains high. For this reason, we proposed a simple version of the 2DPCA NL-mean fliter [18], which directly employs features extracted by the patch-oriented 2DPCA to compute the weights.

The remainder of this paper is as follows: we start out with a review of the NL-means filter and its derivatives. In the following section, we introduce our new improved fast 2DPCA based NL-means filter in detail. Next, the new approach is tested on a standard test image database and real images. Finally, the conclusions close the paper.

2. NL-means Filter Methods

A Defined over a bounded domain $\Omega \subset R^2$, I and I^0 are respectively the restored and noisy images. The initially NL-means filter [1] can be defined as

$$I_i = \sum_{j \in \Omega} w(i,j) I_j^0 \tag{1}$$

where I_i is the value of restored image I at pixel i. I_j^0 is the value of noisy image I^0 at pixel j. Resored values I_i are derived by the weighted average of all gray values in the image. Weights $w(i,j)$ express the amount of similarity between the patches of each pair of pixels i and j involved in the computation

$$w(i,j) = \exp\left(-\left\|I^0\left(X_i^p\right) - I^0\left(X_j^p\right)\right\|_{2,a}^2 \Big/ h\right) \Big/ Z(i) \tag{2}$$

where $Z(i)$ is a normalizing factor, i.e. $Z(i) = \sum_{j\in\Omega} w(i,j)$. h is the decay parameter of the weights. X_i^p represents the square patch of size $(2p+1)\times(2p+1)$ centered at i. $\|\cdot\|_{2,a}^2$ is the Euclidean difference, weighted by a gaussian of zero mean and variance a.

The computational complexity of initially NL-means filter is $O\left(l^2N^2\right)$, where N is the number of pixels in the image, and $l = 2p+1$. For larger images this computation is a burden and is quite slow to be practically realizable.Therefore, one of the most popular acceleration ways is to restrict the search to patches in a subimage (or searching windows) thus turning the original filter into a semi-local one. Although the computational complexity of this filter is $O\left(l^2NL^2\right)$, where L^2 is the size of the square searching windows, a price may be payed for the speedup. Since the semi-local means filter only selects similar patches in a subimage, it cannot make sure that enough similar patches could be included in the computation. Several promising speedups have also been proposed in [4-6,18]. These methods are all preselcetion based NL-means filters which preselect relevant pixels using extracted features, and yield similar set for the NL-means computation. In the fact, the extracted features can be directly used to NL-means computation. Because of this, we presented an improved fast version of the former work [18].

3. The Fast 2DPCA based NL-means Filter

From the view of feature extraction, image patches' features such as means, variances and average gradient directions could not represent the image patches accurately. For instance, two patches with the same means and variances often contain different structures. In addition, noise can seriously affect gradient direction, thus feature like average gradient direction is not reliable. These problems enforce us to search new patch feature extraction method, which is efficient and robust. It is well-known that PCA is a classical feature extraction and data representation technique. As opposed to 1DPCA, 2DPCA [16] is based on 2D data rather than 1D vector so the matrix does not need to be transformed into a vector prior to feature extraction.

Based on the 2DPCA [16], we can obtain a feature matrix Y_i for each patch X_i^p.Then, the similar distance between the patch around current pixel i and the patch corresponding to the other image pixels j can be defined as

$$d_{i,j} = d\left(X_i^p, X_j^p\right) = \sum_{k=1}^{d} \left\|y_i^k - y_j^k\right\| \tag{3}$$

where $\left\| y_i^k - y_j^k \right\|$ denotes the Euclidean distance between the two principal component vector y_i^k and y_j^k. Lower value of $d_{i,j}$ shows higher similarity between the patches, and vice versa.

Then, we can carry out the NL-means computation using similar distance:

$$I_i = \sum_{j \in S_i} w'(i, j) I_j^0 \Big/ \sum_{j \in S_i} w'(i, j) \tag{4}$$

$$w'(i, j) = \exp\left(d_{i,j} / h\right) / Z'(i) \tag{5}$$

Where $Z'(i) = \sum_{j \in \Omega} w'(i, j)$ .When h is very high, all the pixels j will have the same weight with respect to the pixel i. The noisy image will be strongly moothed. When h is very low, since the exponential function will decay quickly, only few pixels will have a nonzero weight. The noisy image will be weakly smoothed. h is a sensitive parameter.

In [1], Buades et al. have pointed that the smoothing parameter h depends on the standard deviation of the noise σ. Recently, Coupe et al [14] have pointed that h needed to take into account $\left| \mathrm{N}_i^d \right|$ (the size of the patch), in order to making the filter indepentent of the patch size. Subsequently, they estimated the noise level σ via pseudo-residuals defined in [17] and proposed a automatical tuning of h for 3D image denoising. In this letter, we give the 2D version of the tuning technology. For each pixel i of the 2D noisy image I^0, firstly, let us define pseudo-residuals:

$$\varepsilon_i = \left(2I_i^0 - \left(I_{i+(1,0)}^0 + I_{i+(0,1)}^0\right)\right) / \sqrt{6} \tag{5}$$

After this, the standard deviation of noise $\hat{\sigma}$ is computed as fellow :

$$\hat{\sigma} = \sum_{i \in \Omega} \varepsilon_i^2 \Big/ N \tag{6}$$

Finally, we get $h = \beta \hat{\sigma}^2 \left| \mathrm{N}_i^d \right|$, where constant β allows to adjust the automatic estimation of h. In[14], it have been suggested that the best value of β is 0.5 for low levels of noise and 1 for high levels of noise.

4. Experimental Results

In the experimental evaluation, we compare the performance of six NL-means implementations: initially NL-means filter [1], the semi-local filter [11], the preselection method by mean and gradient direction [12], the preselection-based method by mean and variance [14], 2DPCA based NL-means filter [18], and our method. All methods were implemented in MATLAB and were test on a commonly-used image database including Lena, Barbara, Boat, House, and Pepper. As a quantitative evaluation for quality we stick to the peak signal-to-noise ratio (PSNR). In all experiments, we used the same Gaussian weighted 7×7 patches. Image intensities were in a range between 0 and 255. All computers times are on a Pentium IV 1.8 GHz.

Table 1. PSNRs of 5 NL-means Implementations for Standard Noisy Test Images with Standard Deviation 20

Image PSNR	Boat 22.12	Barbara 22.12	House 22.07	Lena 22.14	Pepper 22.11
NL-means filter	28.62	29.40	31.49	30.82	29.11
semi-local filter	28.28	28.92	29.72	29.40	27.63
Ref .12	28.06	30.43	32.87	31.04	30.07
Ref.14	30.10	30.38	33.04	31.36	30.49
Ref.18	32.21	32.52	35.20	33.32	32.52
Our method	32.02	32.31	34.97	33.09	32.35

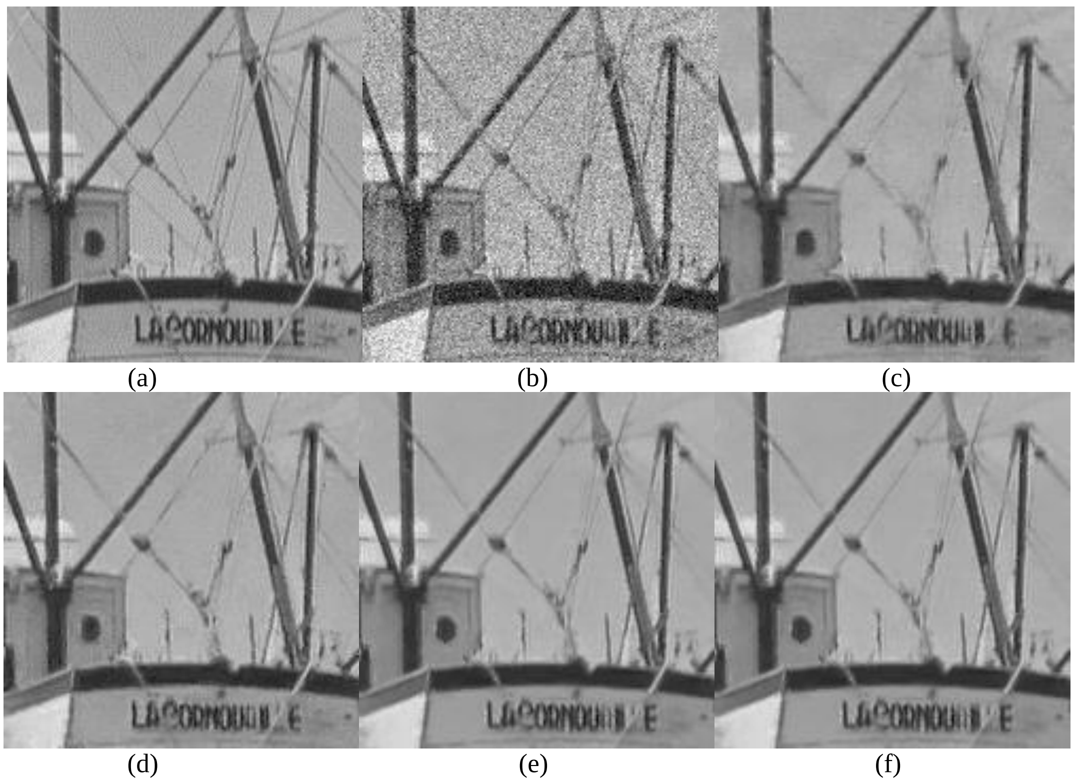

Figure 1. Boat Image ($\sigma = 20$). (a) Original Image; (b) Noisy Image ; (c)Method in [12] ; (d) Method in [14]; (e)2DPCA NL-means Filter; (f) Our Method

Table 1 quantitatively compares the 6 filters using the standard test images. For initially NL-means filter and its semi-local version, we used the parameters, like search window L and decay parameter h , given in [1] and [11]. We set the thresholds according to [12, 14] for the preselection-based filters [12, 14]. In facts, method in [12] used a larger search window to compute its filtering. While in our experiment, all the preseletion-based filters were restored to their true colors which had no search windows and implemented by the blockwise technique [10-12, 14] for speedup. From Table 1, we can see the PSNRs of original NL-means filter are higher than its semi-local version. As pointed in the literature, fast semi-local filter comes at a cost.

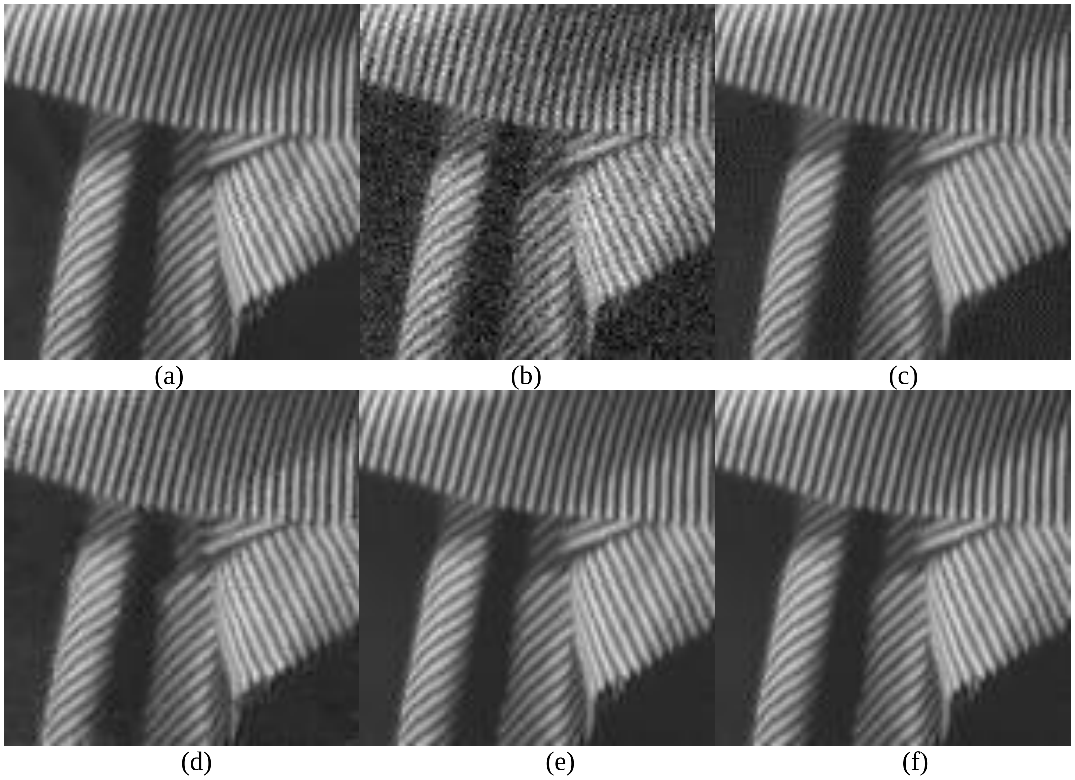

Figure 2. Barbara Image ($\sigma = 20$).(a) Original Image; (b) Noisy Image ; (c)Method in [12] ; (d) Method in [14] ; (e)2DPCA NL-means Filter; (f) Our Method

We focus on the comparison of the perselecion-based methods and our method. We can find that, in most cases, the four preselection-based filters are superior to two other filters in PSNR. The only exception is the method in [12]. The PSNR of this method for Boat image is low, even lower than the semi-local filter. Figure 1 shows the details. We could see from the denoising result of method in [12] (see Figure 5(c)) that the filter produces over smoothed denoising result, especially the weak edges. This is in that the direction information is very sensitive to noise, and moderate noise can seriously affect the direction of gradient vector. Comparison between Figure 5 (d) and Figure 1 (e) and Figure 2 demonstrates the two2DPCA-based filters excel the method in [14] in preserving image structures.

Figure 2 shows the filtering results of the three filters for Barbara in detail. In this experiment, the preseletion-based filter by mean and variance underperforms the method in [12]. Actually, the variance in [14] can reflect the degree of scatter of a signal, but cannot describe its direction. When two structures, which have the same variance but different direction, are included in an image, method in [14] would like to view them as one structure. Again, we observe that the 2DPCA based filters preserve the texture structures very well while efficiently removing the noise.

From Table 1, we can see that the PSNR values of Ref [18] and our method are close to each other. In terms of the computation times, for the test noisy images of size 256×256, i.e. House and Pepper, the average computation times of Ref. [12], Ref.[14] and our method are 164.5 s, 126.8 s and 226.6 s. For the noisy images of size 512×512, i.e. Barbara, Boat and Lena, the average computation times of Ref. [12], Ref.[14], Ref.[18] and our method are 237.1 s, 188.4 s,429.8 s, 214.6 s. Combined with a table1 ,it can be seen that Our method is relatively fast and effective.

5. Conclusion

In this paper, a new efficient and fast method using the patch-oriented 2DPCA was presented to improve NL-means filters. Based on the patch-oriented 2DPCA's abilities of feature extraction and filtering, our new method can efficiently select more similar features for the NL-means computation. The new approach has been tested on a commonly-used standard test image database. Experimental results show that our method can achieve better filtering results in a variety of images, such as weak gradient image, face image and texture image.

Acknowledgements

The authors wish to thank National Natural Science Foundation of China(61173072), the Academic Program Development of Jiangsu Higher Education Institutions, Natural Science Fundation of the Higher Education Institutions of Jiang su Province(10KJB520011), Natural Science Foundation of Jiangsu Province(BK2011824), and the Scientic Research Staring Foundation of Nanjing University of Information Science and Technology for supports.

References

[1] A. Buades, B. Coll and J. M. Morel, "A review of image denoising algorithms, with a new one", J. SIAM, vol. 2, no. 4, **(2005)**.
[2] D. Tschumperlé, "Fast anisotropic smoothing of multi-valued Images using curvature-preserving PDE's", Int. J. Comput. Vis., vol. 1, no. 68, **(2006)**.
[3] G. Plonka and J. W. Ma, "Nonlinear Regularized Reaction-Diffusion Filters for Denoising of Images with textures", IEEE Trans. Image Process, vol. 8, no. 17, **(2008)**.
[4] G. Gilboa, N. Sochen and Y. Y. Zeevi, "Variational denoising of partly textured images by spatially varying constraints", IEEE Trans. Image Process, vol. 8, no. 15, **(2006)**.
[5] B. Wohlberg and P. Rodriguez, "An iteratively reweighted norm algorithm for minimization of total variation functionals", IEEE Signal Processing letters, vol. 12, no. 14, **(2007)**.
[6] L. P. Yaroslavsky, "Digita Picture Processing-An Introdunction", New York, Springer, **(1985)**.
[7] C. Tomasi and R. Manduchi, "Bilateral filtering for gray and color images", Proceedings of International Conference Computer Vision, **(1998)** January 4-7, Bombay, India.
[8] P. Alli, P. Ramasubramanian and V. Sureshkumar, "Oil Spills Detection In SAR Images Using Nonlinear Fuzzy Filter", Journal of Advanced Science and Technology, vol. 25, **(2010)**.
[9] D. O. Aborisade, "A Novel Fuzzy logic Based Impulse Noise Filtering Technique", Journal of Advanced Science and Technology, vol. 32, **(2011)**.
[10] C. Kervrann and J. Boulanger, "Local adaptivity to variable smoothness for exemplar-based image regularization and representation", Int. J. Comput.Vis., vol. 1, no. 75, **(2008)**.
[11] A. Buades, B. Coll and J. M. Morel, "A non-local algorithm for image denoising", Proceedings of International Conference Computer Vision, **(2005)** October17-20, Beijing, China.
[12] M. Mahmoudi and G. Sapiro, "Fast image and video denoising via nonlocal means of similar neighborhoods", IEEE. Signal Processing letter, vol. 12, no. 12, **(2005)**.

[13] C. Kervrann, J. Boulanger and P. Coupe, "Bayesian non-local means filter, image redundancy and adaptive dictionaries for noise removal", Proceedings of the 1st international conference on Scale space and variational methods in computer vision, **(2007)** May30-June2, Ischia, Italy.
[14] P. Coupe, P. Yger, S. Prima P. Hellier, C. Kervrann and C. Barillot, "An optimized blockwise nonlocal means denoising filter for 3-D magnetic resonance images", IEEE Trans. Medical Imaging, vol. 4, no. 27, **(2008)**.
[15] T. Box, O. Kleinschmidt and D. Cremers, "Efficient nonlocal means for denoising of textural Patterns", IEEE Trans. Image Process, vol. 7, no. 17, **(2008)**.
[16] J. Yang, D. Zhang, A. F. Frangi, J. Y. Yang, "Two-dimensional PCA: a new approach to appearance-based face representation and recognition", IEEE Trans. Pattern. Anal. Mach. Intell, vol. 1, no. 26, **(2004)**.
[17] J. Boulanger, C. Kervrann, P. Bouthemy, P. Elbau, J. –B. Sibarita and J. Salamero, "Patch-based Nonlocal Functional for Denoising Fluorescence Microscopy Image Sequences", IEEE Trans. Medical Imaging, vol. 2, no. 29, **(2010)**.
[18] Y. H. Zheng, X. Z Wen and W. Tian, "2DPCA Based Nonlocal Means Filter", Proceedings of 10th IEEE International Conference on Signal Processing, **(2010)** October 24-28, Beijing, China.
[19] R. Vidhyalavanya and M. Madheswaran, "An Improved Denoising Algorithm using Parametric Multiwavelets for Image Enhancement", Journal of Advanced Science and Technology, vol. 16, **(2010)**.

Authors

Yuhui Zheng, Lecturer at the School of Computer and Software, Nanjing University of Information Science and Technology. His research interest covers image processing, pattern recognition, and remote sensing image restoration. Corresponding author of this paper.

Jianwei Zhang, Professor at the College of Mathematics and Physics, Nanjing University of Information Science and Technology. His research interest covers pattern recognition, artificial intelligence, and remote sensing information processing.