SCIENCE CHINA
Information Sciences

• LETTER •

April 2018, Vol. 61 049101:1–049101:3
https://doi.org/10.1007/s11432-017-9207-9

Nonlocal image denoising using edge-based similarity metric and adaptive parameter selection

Linwei FAN[1], Xuemei LI[1], Qiang GUO[2,3] & Caiming ZHANG[1,3*]

[1]*School of Computer Science and Technology, Shandong University, Jinan* 250101*, China;*
[2]*School of Computer Science and Technology, Shandong University of Finance and Economics, Jinan* 250014*, China;*
[3]*Shandong Provincial Key Laboratory of Digital Media Technology, Jinan* 250014*, China*

Received 16 March 2017/Revised 6 Jnue 2017/Accepted 19 July 2017/Published online 9 January 2018

Citation Fan L W, Li X M, Guo Q, et al. Nonlocal image denoising using edge-based similarity metric and adaptive parameter selection. Sci China Inf Sci, 2018, 61(4): 049101, https://doi.org/10.1007/s11432-017-9207-9

Dear editor,
We propose a nonlocal image denoising method with an edge-based similarity metric and adaptive parameter selection. The proposed denoising method uses a two-stage scheme to refine the denoising results. It first produces the central patch by the idea of nonlocal and then makes full use of the local structures to generate the central pixel. Consequently, the fine texture details can be effectively preserved using the proposed method.

Noise reduction is a necessary preprocessing step for high-level analysis and has been extensively studied for decades. Generally, denoising methods can be roughly classified into two categories: spatial domain methods [1–5] and transform domain methods [6–8]. The former utilize the spatial correlation of pixels to smooth the noisy image, and the latter exploit the sparsity of representation coefficients to distinguish the signal and noise. Among the spatial domain methods, the nonlocal means (NLM) filtering [2] performs spatial filtering by a nonlocal averaging of the pixels, using the spatial redundancy occurring in an image. However, analysis of the NLM shows that image details are often blurred. The main reason is that the similarity weights are calculated using only the simple Euclidean distance, and the influence of edge information is not well considered. In view of the spatial domain method being conceptually simple, we mainly focus on the spatial domain method based on NLM to further improve the performance.

We present a novel method to deal with this problem. As the edge information is an important feature for selecting similar patches, we provide a detection template with the 8-directional difference operator, which has a certain anti-noise capacity for edge extraction and can also effectively maintain the integrity of the edges. Meanwhile, a two-stage scheme is implemented to refine the denoising results, which are different from those of the traditional methods. Specifically, we first generate the central patch using the new patch-similarity metric. Then, the central pixel is determined using the selected neighboring patches, thereby preserving the local details. Moreover, to better protect the details, the filter parameters are adaptively determined according to the edge information.

Our denoising method consists of two major stages, which are described as follows.

Stage 1. First, we extract the edges SI of the noisy image using the anti-noise difference operator, which is used to guide the definitions of the patch-similarity metric and the filter parameters. To accurately detect the edges of the noisy image, a 5×5 template with the 8-directional difference operator is proposed in this article. The

* Corresponding author (email: czhang@sdu.edu.cn)

5×5 template has up to 8 directions, which include $0°$, $22.5°$, $45°$, $67.5°$, $90°$, $112.5°$, $135°$, and $157.5°$. More details of the weight determination of templates are provided in Appendix A (see supplementary materials).

After the edge information is obtained, we can obtain the central patch by the weighted mean method using all the similar patches in stage 1. The details of stage 1 are described as follows.

First, we find the similar patches in a search window and assign the patch-similarity weight as $w(N_i, N_j)^{\text{stage 1}}$. The foregoing analysis highlights the importance of the weight estimation of the image patch in effectively suppressing the influence of noisy pixels. Therefore, inspired by the PCA-based (principle component analysis) weight function being robust to noise [3], we integrate the distance-based edge similarity measure and the angle-based neighborhood similarity measure into the patch-similarity weight, which can be formulated as

$$w(N_i, N_j)^{\text{stage 1}} = w(N_i, N_j)^{\text{E}} \cdot R(N_i, N_j),$$

$$w(N_i, N_j)^{\text{E}} = \frac{1}{Z(i)} \exp(-(\|f_{\text{d}}(N_i) - f_d(N_j)\|_2^2/h^2) - (\|\text{SI}(N_i) - \text{SI}(N_j)\|_2^2/h')),$$

$$R(N_i, N_j) = \sin\left(\frac{\pi}{2} \frac{\Psi(N_i, N_j)}{\sqrt{\Psi(N_i, N_i)}\sqrt{\Psi(N_j, N_j)}}\right),$$

where $w(N_i, N_j)^{\text{E}}$ reflects the edge similarity between the image patches N_i and N_j, $R(N_i, N_j)$ is the neighborhood similarity, f_d represents the PCA subspace vector of projection coefficients, $\text{SI}(N_i)$ denotes the edge information in the image patch N_i, and both h and h' are filter parameters. Moreover, $\Psi(N_i, N_j) = \sum_k \sum_l i_{k,l} j_{k,l}$, and $i_{k,l}, j_{k,l}$ are the pixels of N_i, N_j, respectively. To simplify the implementation, the image patches are fixed at size 3×3 in the experiments.

Then, we obtain the filter parameters adaptively using the image structure IV. Intuitively, the filter parameter h is closely related to the noise variance σ, hence, we empirically define h as follows:

$$h \approx \sqrt{2}\beta\sigma^2,$$

where the parameter β can be determined using the image structure. Choosing a smaller h is suitable for reducing the degree of filtering and protecting details when the patches contain many textures. In contrast, a larger h is selected for a flat region to reduce noise as much as possible. Therefore, β is defined as a function relative to IV:

$$\beta = \begin{cases} 0.1 \times \text{IV}(i) + 2, & \text{IV}(i) \in [0, \text{th}], \\ 2, & \text{IV}(i) \in [\text{th}, 6], \end{cases}$$

where th is the optimal threshold value mapped into the interval $[0, 6]$. In the first stage, we assign filter parameter h' to $2h$ in our experiment.

After the new patch-similarity measures and the filter parameters are determined, we can obtain the central patch in a search window S_i by

$$\bar{u}(N_i) = \sum_{N_j \in S_i} w(N_i, N_j)^{\text{stage 1}} v(N_j),$$

where $\bar{u}(N_i)$ denotes the central patch and $v(N_j)$ denotes the noisy patch. In the edge regions, the ability of our method to maintain details is better than that of the conventional nonlocal denoising methods. This is because if the edge similarity between the current patch and its neighborhood is high, the patch-similarity is adjusted reasonably. The higher the structural similarity, the larger is the weight, and vice versa.

Stage 2. We now discuss the procedure to obtain the central pixel $\hat{u}(i)$ in stage 2. Many estimated values of the pixel i are acquired in the first stage, and are included in the central patches $\bar{u}(N_n)$. Thus, we can obtain the denoised central pixel $\hat{u}(i)$ by the weighted average of the values i in the selected neighboring patches.

In stage 2, the pixel-similarity weight $w(i, i^j)^{\text{stage 2}}$ is defined based on the similarity between the central patch and its neighboring patches. The weight function is given as

$$w(i, i^j)^{\text{stage 2}} = \exp(-\|\bar{u}(N_i) - \bar{u}(N_j)\|_2^2/(h'')^2),$$

where $\bar{u}(N_j)$ is the neighboring patch of central patch $\bar{u}(N_i)$, and h'' is the filter parameter which is set to 10σ.

Finally, the denoised central pixel $\hat{u}(i)$ is obtained by

$$\hat{u}(i) = \sum_{i^j \in N_j} w(i, i^j)^{\text{stage 2}} \bar{u}(i^j),$$

where pixel i^j denotes the neighboring pixel to pixel i in the selected neighboring patch $\bar{u}(N_j)$ and $\bar{u}(i^j)$ is the gray-value of pixel i^j obtained in stage 1. In this manner, the central pixel is estimated in stage 2. This method can accurately reflect the similarity between pixels and reduce pseudo-texture of the flat area. Moreover, setting the threshold at the edge regions improves the ability to maintain the edge structure.

Experiments. We apply the proposed method to images with Gaussian noise, and compare it with the state-of-the-art methods including the spatial domain and hybrid methods. For quantitative comparisons, the peak signal to noise ratio (PSNR) and structural similarity index metric (SSIM) are used as the evaluation criteria. As

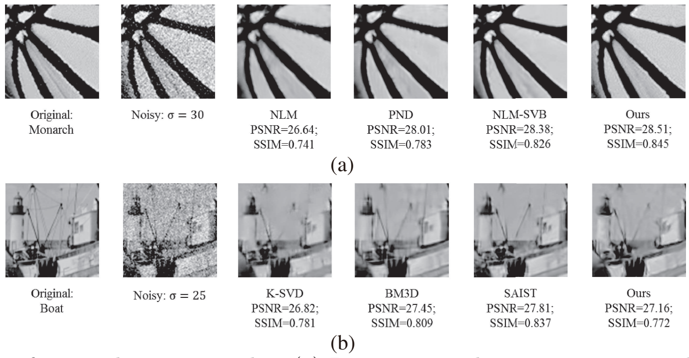

Figure 1 Enlarged parts of image denoising results. (a) Denoising results in comparison with spatial domain methods; (b) denoising results in comparison with hybrid methods.

shown in Figure 1(a), in terms of the visual quality of Monarch, the proposed method outperforms the spatial domain methods. It maintains more fine details than the others, without over-smoothing at the edge of the wings, thereby obtaining a denoised result much closer to the original image. Figure 1(b) provides a comparison of enlarged parts of the denoising results for Boat under $\sigma = 25$. It is obvious that our method is more accurate in detail preservation, and close to BM3D. Many experiments have been conducted to demonstrate the efficacy of the proposed method and validate the claims. The detailed experiment results are illustrated in Appendix B. Because the main goal of this study is to offer an improvement to the spatial filters, we do not claim to achieve a better PSNR than the hybrid methods.

Conclusion. For spatial image denoising, several key factors influence the denoising performance, such as the edge features, similarity measurement between image patches, and control parameters. Experimental results indicate that the effective usage of these key factors can significantly improve the accuracy of image denoising. Unlike existing nonlocal denoising methods, the proposed method uses a two-stage scheme to refine the denoising results. It first produces the central patch and then makes full use of the local structures to generate the central pixel. In addition, an anti-noise difference operator is presented for better reflecting the different directions of the edges, and thus the accuracy of detecting edges in noisy images is effectively improved. A patch-similarity weight is proposed by integrating the distance-based edge similarity and angle-based neighborhood similarity, which improves the accuracy of similar patch selection. Furthermore, to make the weight setting more reasonable, we adaptively adjust the filter parameters based on the image structure. On the basis of the above discussions, the proposed method can clearly improve the performance in preserving weak details and suppressing noise.

Acknowledgements This work was supported by National Nature Science Foundation of China (Grant Nos. 61373078, 61572292, 61472227, 61672327, 61472220), NSFC Joint Fund with Zhejiang Integration of Informatization and Industrialization under Key Project (Grant No. U1609218), and Fostering Project of Dominant Discipline and Talent Team of Shandong Province Higher Education.

Supporting information Appendixs A and B. The supporting information is available online at info.scichina.com and link.springer.com. The supporting materials are published as submitted, without typesetting or editing. The responsibility for scientific accuracy and content remains entirely with the authors.

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