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Two-stage non-local means filtering with adaptive smoothing parameter

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ABSTRACT

Non-local means (NLM) filtering is an efficacious algorithm in image denoising which searches the similar neighborhoods and estimates the pixel by averaging these neighborhoods. Some internal parameters such as patch size, search window size and smoothing strength have serious effects on filtering performance. This paper proposes an improved version of NLM by using weak textured patches based single image noise estimation and two-stage NLM with adaptive smoothing parameter. Our proposed method firstly applies weak textured patches based noise estimation to achieve the noise level of input noisy image. Then relying on the estimated noise level, we apply the first stage NLM with adaptive smoothing parameter to attain a basic denoised image. After that, the basic denoised image is refined by the second stage of NLM with smaller smoothing strength. Our experimental results show that the proposed algorithm outperforms the NLM and some NLM recent variants both in visual quality and numerical measures. Additionally, the potential halo effect is almost eliminated in the result images produced by our proposed method.

1. Introduction

Non-local means (NLM) filtering algorithm has received increasing attention in recent years which is introduced by Buades et al. in paper [1], and has impacted the field of image denoising. NLM searches for similar neighborhoods in the whole image and averages the corresponding pixels of these neighborhoods. NLM method belongs to the class of adaptive averaging filters, like the sigma filter [2], the Yaroslavsky filter [3], or the bilateral filter [4–6] as NLM relies on the use of overcomplete dictionaries which learned from the noisy image or from a larger data set and is the way of calculating the weights for the averaging process with the consideration of neighborhood information [7].

When applying NLM, the denoising performance is mainly decided by flowing key parameters: (1) the radius of the neighborhoods R_{sim}, which is used to find the similarity between two pixels; (2) the radius of a search window R_{win}; (3) the filtering parameter h that controls the decay of the exponential function. If the parameter R_{sim} is too large, no similar neighborhoods will be found while too small one leads rather redundant similar neighborhoods. For parameter R_{win}, since larger search window brings in a better result and intuitively should be as big as possible to have enough copies of the patch as we can which is also in the proof of convergence of the NLM procedure [8]. However, it is interesting to pick R_{win} as small as possible, since the computation time depends crucially on R_{win} [9]. The smoothing parameter h, which stands for the typical distance between similar patches, depends on the noise level. Duval et al. have proved that the relation between the optimal global smoothing parameter h and noise standard deviation σ is indeed approximately linear and the slope does not vary much between different images [10].

The acceptable denoising performance cannot be achieved by applying NLM filtering with default parameters under various noisy images. But by choosing the appropriate parameters, the quality of denoising image is able to be improved significantly. And some improved versions of NLM on parameter choice have been proposed in the past few years. By making the use of pair-wise hypothesis testing, R_{win} is chosen adaptively to each pixel in paper [11]. Based on Stein's Unbiased Risk Estimate, paper [10] proposes a way to locally set the radius of similar window R_{sim} and search window R_{win}. Relying on the feature metric which is capable of capturing local structures and local noise level, NLM with adaptive patch size and bandwidth is proposed in paper [12].

In this paper, a two-stage non-local means filtering with adaptive filtering parameter is proposed by making use of weak textured patches based noise level estimation and two rounds of NLM filtering with different smoothing parameter. It has been proved that the relation between the optimal global smoothing parameter h

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and image noise standard deviation σ is indeed approximately linear. Hence, we adopt noise level estimation from the single noisy image and then associate the estimated noise level with smoothing parameter h. After that, the first stage of NLM filtering with adaptive smoothing parameter is applied to obtain a basic denoised image. The final result can be achieved by performing the second stage of NLM with smaller smoothing parameter in the same way. The experimental results demonstrate that the proposed algorithm outperforms than NLM filtering and some NLM variants both in visual effects and numerical measure and works well especially for strong noisy image.

2. Weak textured patches based noise estimation

Given a nosiy image, it can be denoted as [13]:

$$\mathbf{y}_i = \mathbf{z}_i + \mathbf{n}_i \tag{1}$$

where $\mathbf{z}_i$ is the true image patch with i-th at its center written in a vectorized format and $\boldsymbol{y}_i$ is the observed vectorized patch corrupted by i.i.d zero-mean Gaussian noise vector $\mathbf{n}_i$ with variance σ^2.

By assuming that the signal and the noise are uncorrelated, the variance of the projected data on the unit vector $\mathbf{u}$, which is defined as the direction of the axis, can be expressed as:

$$V(\mathbf{u}^T\mathbf{y}_i) = V(\mathbf{u}^T\mathbf{z}_i) + \sigma_n^2 \tag{2}$$

where $V(\mathbf{y}_i)$ represents the variance of the dataset $\{\mathbf{y}_i\}$, σ_n is the standard deviation of the Gaussian noise. According to paper [14], the minimum variance direction $\mathbf{u}_{\min}$ can be defined similarly:

$$\mathbf{u}_{\min} = \arg\min_{\mathbf{u}} V(\mathbf{u}^T\mathbf{z}_i) = \arg\min_{\mathbf{u}} V(\mathbf{u}^T\mathbf{y}_i) \tag{3}$$

The minimum variance direction is the eigenvector associated to the minimum eigenvalue of the covariance matrix defined as:

$$\Sigma_y = \frac{1}{N}\sum_{i=1}^{N}(\mathbf{y}_i - \mu)(\mathbf{y}_i - \mu)^T \tag{4}$$

where N is the data number and μ is the average of the dataset $\{\mathbf{y}_i\}$.

By projecting the variance of the data onto the minimum variance direction, it equals the minimum eigenvalue of the covariance matrix. Then we can derive the equation:

$$\lambda_{\min}(\Sigma_{\mathbf{y}}) = \lambda_{\min}(\Sigma_{\mathbf{z}}) + \sigma_n^2 \tag{5}$$

where $\Sigma_{\mathbf{y}}$ signifies the covariance matrix of the noisy patch $\mathbf{y}_i$, $\Sigma_{\mathbf{z}}$ denotes the covariance matrix of the noise-free patch $\mathbf{z}_i$, and $\lambda_{\min}(\Sigma)$ represents the minimum eigenvalue of the matrix Σ.

The noise level can be easily estimated if the minimum eigenvalue of the covariance matrix of the noisy patches is decomposed. As the minimum eigenvalue of the covariance matrix of weak textured patches is approximately zero, the noise level then can be estimated as follows if the weak textured patches are selected from the noisy images.

$$\sigma = \sqrt{\lambda_{\min}(\Sigma_{\mathbf{y}'})} \tag{6}$$

where $\Sigma_{\mathbf{y}'}$ is the covariance matrix of the selected weak textured patch.

At the beginning, the initial noise level $\sigma^{(0)}$ is estimated from the covariance matrix, which is generated using all patches in the input noisy image. Then weak textured patches will be selected to estimate the final noise level.

As texture information can be reflected by the eigenvalue and eigenvector of the gradient covariance matrix $\mathbf{C}_{\mathbf{y}}$.

$$\mathbf{C}_{\mathbf{y}} = \mathbf{G}_{\mathbf{y}}^T\mathbf{G}_{\mathbf{y}} \tag{7}$$

$$\mathbf{G}_{\mathbf{y}} = [\,\mathbf{D}_h\mathbf{y} \quad \mathbf{D}_v\mathbf{y}\,] \tag{8}$$

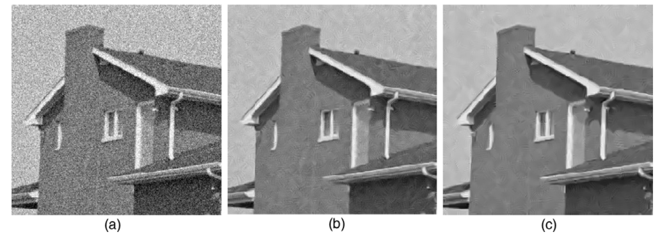

Fig. 1. The comparison of one-stage NLM and two-stage NLM. (a) Noisy house image (σ = 20); (b) filtered by one-stage NLM; and (c) filtered by two-stage NLM.

where $\mathbf{D}_h$ and $\mathbf{D}_v$ represent the matrix of horizontal derivative operators respectively. Weak textured patch, which has a smaller maximum eigenvalue and is smoother than rich texture patches, is selected if its maximum eigenvalue of the gradient covariance matrix is less than the threshold τ.

$$\tau = \sigma_n^2 F^{-1}\left(\delta, \frac{N}{2}, \frac{2}{N}tr(D_h^T D_h)\right) \tag{9}$$

where $F^{-1}(\delta,\alpha,\beta)$ is the inverse gamma cumulative distribution function with the given significance level δ, shape parameter α and scale parameter β, $tr(D_h^T D_h)$ is the trace of matrix $D_h^T D_h$.

By using the initial noise level $\sigma^{(0)}$, the first threshold $\tau_{(1)}$ is computed and the weak textured patches $W_{(1)}$ can be attained with threshold $\tau_{(1)}$. Then another estimated noise level is estimated according to the selected weak textured patches as Eq. (5). This process is iterated until the estimated noise level $\sigma^{(n)}$ is unchanged.

3. The proposed method

For a noisy image $y = (y_i)$, the noise level can be estimated by using the noise estimation procedures described in Section 2. Then the two-stage NLM with adaptive smoothing parameter is performed to the input noisy image. Based on the estimated noise, the smoothing parameter h_{basic} in the first stage of NLM is adopted automatically. And the basic denoised image $\hat{y}_{i,\text{basic}} = (\hat{y})$ at pixel i is computed as:

$$\hat{y}_{i,\text{basic}} = \sum_j w_{ij,\text{basic}} y_j \tag{10}$$

where $w_{ij,\text{basic}}$ is the weight depending on the similarity between the pixel i and j, and satisfies the usual conditions $0 \le w_{ij,\text{basic}} \le 1$ and $\Sigma_j w_{ij,\text{basic}} = 1$.

$$w_{ij,\text{basic}} = \exp\left(-\frac{1}{h_{\text{basic}}^2}||\mathbf{P}_i - \mathbf{P}_j||^2\right) \tag{11}$$

where $\mathbf{P}_i$ and $\mathbf{P}_j$ are the image patches of size $k \times k$ centered at pixel i and j, and $||\mathbf{P}||$ is the Euclidean norm of patch $\mathbf{P}$ as a point in $\boldsymbol{R}^{k^2}$ [15]. And h_{basic} is the smoothing parameter which controls the decay of the exponential function.

As shown in Fig. 1, most of the noise can be removed by using one-stage NLM with adaptive smoothing parameter. However, there is still much visually noise residual in the basic denoised image $\hat{y}_{i,\text{basic}}$, especially for strong noised image. Therefore, it is necessary to further process the denoising output for a better noise reduction [16]. Since the noise has been removed much after the first stage of NLM, the similar neighbors can be well identified in the second stage of NLM and the weights in the basic denoised image is computed more accuracy than those in the input noisy image. Both these advantages lead to much better results for two-stage NLM.

After the denoising procedure by the first stage of NLM, the basic denoised image $\hat{y}_{i,\text{basic}}$ is then refined by implementing the second