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Adaptive Nonlocal Means Algorithm for Image Denoising

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Abstract -- An adaptive image denoising technique based on the nonlocal means (NL-means) algorithm is investigated in this research. The proposed method first employs the singular value decomposition (SVD) method and the K-means clustering (K-means) technique for robust block classification in noisy images. Then, the local window is adaptively adjusted to match the local property of a block. Finally, a rotated block matching algorithm is adopted for better similarity matching. Experiment results are given to demonstrate the superior denoising performance of the proposed adaptive NL-means (ANL-means) denoising technique.

I. Introduction

Image denoising is one of the classical problems in digital image processing, and has been studied for nearly half a century due to its important role as a pre-processing step in various image and video applications. Its objective is to recover the best estimate of the original image from its noisy version. Several denoising methods have been proposed such as neighborhood filtering, total variation minimization, Wiener filtering, Gaussian scalar mixture, etc.

The recently proposed nonlocal means algorithm (NL-means) [1,2] has offered remarkably promising results. Unlike previous denoising methods that rely on the local regularity assumption, the NL-means exploits spatial correlation in the entire image for noise removal. It adjusts each pixel value with a weighted average of other pixels whose neighborhood has a similar geometrical configuration. Since image pixels are highly correlated while noise is typically independently and identically distributed (i.i.d.), averaging of these pixels results in noise cancellation and yields a pixel that is similar to its original value.

In this work, we propose an adaptive NL-means (ANL-means) algorithm that adjusts the similarity matching process based on the local structure of a pixel. It is shown that the ANL-means algorithm has a significant performance gain over the traditional NL-means algorithm for various test images, which is especially advantageous when the noise level is high.

II. Proposed Technique

A. Non local means (NL-means) algorithm

For given noisy image $f = \{ f(i) \mid i \in \Omega \}$, the NL-means denoised value $\hat{f}(i)$ at pixel i is obtained by a weighted average of all pixels in its neighborhood Ω_S [1]:

$$\hat{f}(i) = \frac{1}{C(i)} \sum_{j \in \Omega_S} w(i,j) f(j), \tag{1}$$

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where

$$C(i) = \sum_{j \in \Omega_S} w(i,j) \tag{2}$$

is a normalization constant and weight $w(i,j)$ is determined by the similarity of the Gaussian neighborhood between pixels i and j, which can be expressed as

$$w(i,j) = \exp\left(-\frac{\left\| N_i - N_j \right\|_{2,a}^2}{h^2}\right), \tag{3}$$

and where N_i denotes a square neighborhood centered at pixel i, $\|\cdot\|_{2,a}$ is a Gaussian weighted Euclidean distance function, a is the standard deviation of the Gaussian kernel, and h is the decay parameter.

The proposed adaptive technique consists of three steps: 1) employing the singular value decomposition (SVD) method and K-means clustering (K-means) technique for robust block classification; 2) adjusting the local window adaptively to match the local property of a block; and 3) applying a rotated block matching algorithm for better similarity matching. Step 1 will be described in Sec. II.B while Steps 2 and 3 will be detailed in Sec. II.C.

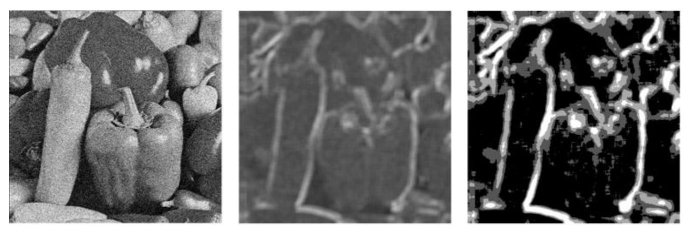

Figure 1: Example of block classification via SVD method and K-means clustering technique

B. Block classification

Adaption of the NL-means algorithm is conducted according to the block classification result. Here, block classification is achieved by applying the Singular Value Decomposition (SVD) to the gradient field of each block [3]. For a smooth region, there is no dominant direction and all eigenvalues are small. For an oriented edge/texture region, there is a dominant direction and the corresponding eigenvalue is significantly larger than others. For a block of size $nxn = N$, we can group its gradient values into matrix G of size Nx$2$and compute its SVD via

$$G = \left[\nabla f(1)^T \ \nabla f(2)^T \cdots \nabla f(N)^T \right]^T \ \text{and} \ G = USV^T \tag{4}$$

where

$$\nabla f(i) = \left[\frac{\partial f(i)}{\partial x} \quad \frac{\partial f(i)}{\partial y} \right]^T \tag{5}$$

is the gradient of image f at point i, U is an NxN orthogonal matrix, S contains singular values and V is an $2x2$ orthogonal matrix which describes the dominant orientation of the gradient field. The K-means clustering technique is employed to adaptively classify the acquired data. Since noise does not have any preferred direction, we can classify each noisy block effectively based on its singular value as shown in Fig. 1.

C. *Adaptive nonlocal (ANL) mean algorithm*

To exploit the block property and reduce noise in different regions, we adaptively choose the matching window size based on the block type, *i.e.* a small window (7x7) in the strong edge/texture region, a large window (25x25) in the smooth region, and a medium window (13x13) for other regions.

Furthermore, we employ a rotated block matching process to yield more similar image blocks. To speed up the matching process, we consider only a set of rotated blocks that have their dominant orientation aligned well with that of the target block. To be more specific, let $v_1 = [\upsilon_1\ \upsilon_2]^T$ be the first column of V in Eq. (5). We can obtain the dominant orientation of the gradient field of a given block by calculating

$$\theta = \arctan(\frac{\upsilon_1}{\upsilon_2}) . \quad (6)$$

Then, we can obtain four rotated blocks with dominant orientations equal to $\theta + 180$, $-\theta$ and $-\theta + 180$ degrees. Since the block rotation process takes a higher computational complexity, we apply this technique only to blocks that have a strong dominant orientation.

III. EXPERIMENTAL RESULTS

To compare performance of the traditional NL-means and the proposed ANL-means algorithms, we apply them to 7 representative test images which are corrupted by various additive white Gaussian noise (AWGN) with zero mean and standard deviation σ = 20, 30 and 40. We adopt the same parameters for the NL-means algorithm as given in [1]. For each case, three Gaussian noise patterns are generated and the averaged PSNR results of these three denoised images are reported in Table 1.

As compared with the NL-means algorithm, the ANL-means has an average PSNR performance gain of 0.63, 2.16 and 3.39 dB for σ = 20, 30 and 40, respectively. When the image is highly noisy, the traditional NL-means algorithm fails to find suitable matching blocks while the ANL-means algorithm can still find good matching blocks due to the employment of the SVD-based block classification technique, which is robust again AWGN.

In Fig. 2, we show the original Zelda image, the noisy image with σ = 40 and two denoised images using the NL-means and the ANL-means algorithms, respectively. We see clearly that the proposed NAL-means algorithm provides a much better denoised result, where noise is well suppressed in the smooth region while sharp edges around the object contour are well preserved.

IV. CONCLUSION

An adaptive NL-means algorithm was proposed in this work, which is shown to be effective in denoising highly noisy images. Based on the denoising results from various experimental settings, ANL-means algorithm is shown to have a superior performance in both PSNR and perceptual quality compared to the traditional NL-means algorithm.

Table 1: PSNR performance comparison of denoised images

Image	Average PSNR (dB)								
	σ = 20			σ = 30			σ = 40		
	NL	ANL	Δ	NL	ANL	Δ	NL	ANL	Δ
Lena	31.02	31.98	0.96	27.50	30.04	2.54	24.37	28.27	3.90
Zelda	31.85	32.83	0.98	28.18	30.72	2.55	25.06	28.76	3.70
Peppers	30.93	31.59	0.65	27.50	29.79	2.29	24.40	28.00	3.60
Airplain	30.52	30.93	0.41	27.20	29.05	1.85	24.34	27.41	3.07
Barbara	29.85	30.30	0.45	26.65	28.41	1.76	23.89	26.74	2.85
Elaine	30.40	30.82	0.42	27.30	29.58	2.28	24.32	28.10	3.78
Girlface	31.75	32.29	0.54	28.12	29.98	1.86	25.06	27.92	2.86
Average	30.90	31.53	0.63	27.49	29.65	2.16	24.49	27.89	3.39

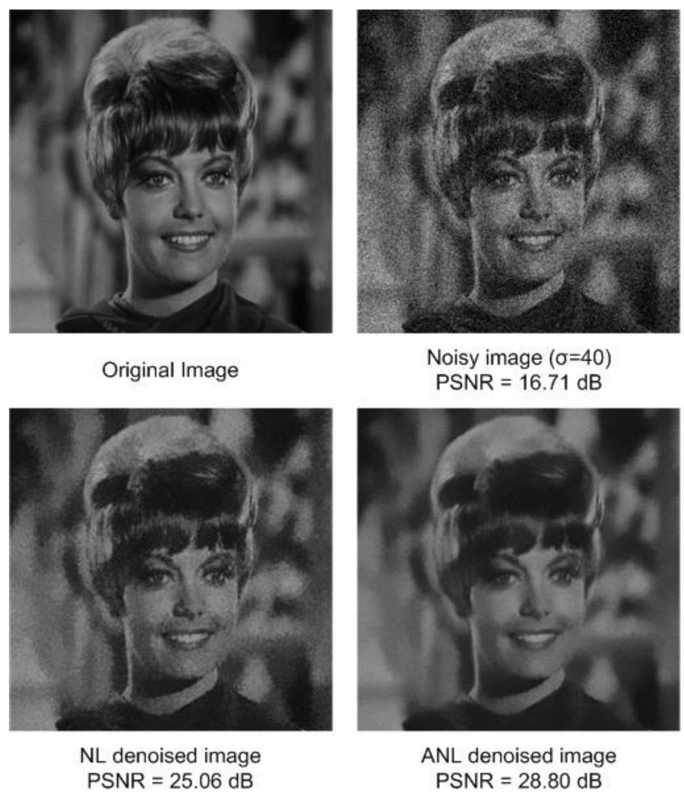

Figure 2: Perceptual quality comparison of two denoising algorithms.

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