VOL. 14, NO. 7, APRIL 2019 ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences
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www.arpnjournals.com

NONLOCAL MEANS SCHEME FOR IMAGE NOISE REDUCTION

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ABSTRACT

The nonlocal means (NLM) filtering scheme has gained an increasingly interest in the last decade for its great performance in image restoration. This scheme yields attractive results in removing Gaussian noise from an image by replacing the intensity value of each pixel by weighted average of the pixel intensities in a search neighborhood in the image. It is primarily based on repeated patterns that often exit in images. The selection of the kernel functions in such nonlocal means image restoration scheme is a major concern of researchers in order to improve the restored image quality. The Gaussian function is a standard kernel function commonly applied in the NLM filtering. In this paper, two functions for a nonlocal means image filtering scheme are proposed through a specific NLM method using an adaptive window size that varies according to the characteristics of the search regions in the image. Zero-mean Gaussian noise with different values of standard deviation corrupting various images of different characteristics has been used in the computer simulations. Mean squared error (MSE) and mean absolute error (MAE) have been used as measuring indices for the quality of the output restored image. Results show that these two functions work well and yield better performance mainly for images with a lot of details and edges than the conventional NLM scheme that uses the Gaussian kernel function and a fixed window size.

Keywords: nonlocal means, nonlocal filtering, Gaussian, kernel functions, adaptive window.

1. INTRODUCTION

Image denoising or restoration is one of the main areas in the literature of image processing where filters are designed to remove the noise that corrupts images, and thus to restore the original true images [1, 2]. Many of those proposed image filters use a defined local neighborhood or kernel around each pixel to produce an output image that is as close as possible to the original uncorrupted image [3-13]. For example, in the standard median filter with a 3x3 kernel size, each pixel value in the image is replaced by the median value of all pixels in a3x3 window around that particular pixel. This window is a sliding one that moves over the entire image such that all image pixels are covered. Similarly, the average filter replaces the pixel value at the center of the sliding window by the mean value of the window pixels.

In recent years, a new approach using nonlocal means filtering has raised and gained more attention by researchers for its efficient removal of Gaussian noise [14]. This approach takes advantage of the usual existence of similar patterns or regions in images to find estimates of the values of the restored intensities of the image pixels. Instead of using local regions around each pixel, this nonlocal scheme searches for similarities in regions or patches within a search bound in the image.

This scheme replaces the intensity value of each pixel in the image by a weighted average of the pixel intensities in a search neighborhood. This average is based on the similarity between the search and reference patches. Such similarity is measured through the Euclidian distance which measures the sum of square differences of distances between pixels in a patch. In order to have more weight for the pixels close to the center of the patch, a Gaussian weight distribution kernel function is commonly used.

One of the main challenging problems in nonlocal means filtering is the selection of the kernel functions. The conventional NLM algorithm uses the standard Gaussian function as the kernel function and a fixed size of the sliding window. This method has been improved from different perspectives by researchers.

The image denoising scheme proposed in [15] uses the NLM algorithm together with a principal component analysis to improve the complexity and performance of the standard NLM filtering. In [16], a probabilistic early termination (PET) approach is used to speed-up the NLM processing time. The Stein's unbiased risk estimate (SURE) together with the NLM method have been used in [17] for improvement of filtering performance and speed-up.

The Euclidian median is used in [18] and [19] to improve the performance of the conventional NLM method for large amounts of noise. In [20], a NLM method that primarily addresses the preservation of structure details of images is proposed. An adaptive-size window algorithm is proposed in [21] where the window size varies according to classification of the regions in the image.

The NLM filtering method introduced in [22] is focused on selection of pixel weights based on statistical shrinkage perspective and the James-Stein shrinkage estimator. In [23], the proposed method adapts the weight given to each pixel in the center of the window based on Stein's unbiased risk estimate principle. An improvement of the Local James Stein (LJS) method is introduced in [24] using direct bounds and re-parameterization based on the Baranchik's mini-max estimator.

In [25], and adaptive-size search window varies based on the edge gradient and direction of the noisy image. The NLM variant method introduced in [26]

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reduces the noise in magnetic resonance (MR) images by varying the size of the search window according to the edginess of an image. In [27], the proposed method is based on adaptive search window that varies depending on the characteristics of the search region. A small search window size is used for smooth or homogeneous regions in the image, and large size of such window is used for non-smooth or nonhomogeneous regions.

In this paper, two proposed kernel functions have been implemented in the adaptive NLM method [27], and their simulation results using several images of different features are investigated. The research method is introduced in section 2, results and discussion are shown in section 3 and conclusions are presented in section 4.

2. RESEARCH METHOD

The kernel or weighting functions, used to compute the weighting factors of a search neighborhood of pixels in the NLM filtering, have a primary impact on the quality of the restored filtered image. The two proposed kernel functions in this paper are defined as follows:

$$Function\ 1: \quad w(i,j) = e^{\frac{-\|N(i)-N(j)\|_2{}^3}{\lambda^3}} \tag{1}$$

$$Function\ 2: \quad w(i,j) = \left|\cos\left(\frac{\pi\|N(i)-N(j)\|_2}{3.5\lambda}\right)\right|, \tag{2}$$

where $N(i)$ and $N(j)$ definethe LxL search neighbourhood centred at pixels i and j, respectively, $\|.\|_2$ denotes the weighted Euclidean distance, and λ is a smoothing parameter that controls the smoothing degree of these weighting functions.

The Gaussian function typically used in the conventional NLM method is defined as follows:

$$w(i,j) = e^{\frac{-\|N(i)-N(j)\|_{2,a}{}^2}{2\lambda^2}}, \tag{3}$$

where $\|N(i)-N(j)\|_{2,a}{}^2$ is a Gaussian weighted Euclidian distance with a standard deviation = a.

The two proposed functions in Equations 1 and 2 have been used in the variant NLM method [27] where the size of the search window has been made adaptive based on the smoothness of the image region, the pixel to be denoised lies in. In particular, that size varies according to a gray level difference computed for each pixel using the conventional NLM method. The size of the search window is then determined to be small, medium or large based on the mean and standard deviation of this gray level difference image through using two threshold values.

The values of parameters used in the computer simulations are the same as those in [27]. In particular, for the conventional NLM algorithm, the size of the search window is chosen to be KxK=21×21, the neighbourhood size is 7×7 and λ = 0.75σ. For the proposed algorithm, the size of the search window is selected to be KxK=9×9, 15×15 and 21×21 for small, medium and large search windows, respectively. The size of neighbourhood is chosen as 7×7 and λ = 0.7σ for medium and large search windows and λ = σ for small search window.

The performance quantitative indices for measuring the quality of the restoration methods in this paper are the mean squared error (MSE) and the mean absolute error (MAE). These measuring indices are defined as follows:

$$MAE = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}\left|R_{i,j} - T_{i,j}\right| \tag{4}$$

$$MSE = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}\left(R_{i,j} - T_{i,j}\right)^2, \tag{5}$$

where $|.|$ stands for absolute value, MSE is the mean squared error between the restored image (R) and the uncorrupted true image (T), M and N are the total number of pixels in the horizontal and vertical dimensions of the image, $R_{i,j}$ is the pixel intensity value in the $(i,j)th$ location of the output restored image and $T_{i,j}$ is the pixel intensity value in the $(i,j)th$ location of the input true image.

It should be noted that that the commonly used peak signal-to- noise ratio as an quality measuring index is defined in terms of MSE as follows:

$$PSNR = 10\ log_{10}\left(\frac{(L-1)^2}{MSE}\right) \text{dB} \tag{6}$$

For an MxN image (total number of pixels =MN) with a dynamic range between 0 and L-1, the image pixel values lie between 0 and L-1, i.e., (L-1) is the maximum pixel value in the image. If each pixel in the image represents 8 bits per sample, then $L = 2^8$=256.

3. RESULTS AND DISCUSSIONS

The simulations in this paper were performed using MATLAB 8.6 (R2015b) on a laptop equipped with a 2.6-GHz Intel i7 CPU and 16 GB RAM.

Six images have been tested in the computer simulations, namely, Lax, Crowd, Pirate, Boats, Lake and Cameraman and are all shown in Figure 1. Those images were corrupted by Gaussian noise of zero mean and different values of standard deviation before being restored by the proposed filtering method and the traditional NLM image filtering algorithm.

The proposed method has two variants. The first one uses the function expressed in Equation 1 and the second variant uses function 2 expressed in Equation 2. Tables 1, 2 and 3 show the numerical results of both the proposed method with its two variants and the conventional NLM method in terms of MSE and MAE (detail preservation measuring index), for images contaminated with Gaussian noise of standard deviation =10, 15 and 20 respectively. The lower the values of MSE

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and MAE, the better the performance of the restoration method is.

Figure 2 shows the Lax image in three forms: before being corrupted by noise, after being subjected to Gaussian noise of standard deviation =20, and after being restored using the proposed method with Function 1. Figure 3 shows similar results for the Crowd image. The numerical (quantitative) results (Tables 1-3) and visual quality (Figure 2 and Figure 3) show that the two proposed functions in the adaptive NLM method work satisfactory and the results outperform that of the conventional NLM algorithm in terms of both MAE and MSE for such relatively small amount of Gaussian noise.

The significance of such improvement in the performance of the proposed scheme over the conventional NLM method varies based on the characteristics and details of the image being corrupted with noise. The more details and edges that exit in the image, the more significant the improvements are in the performance of the proposed method. In addition, the performance of the proposed method using Function 1 is slightly better than that using Function 2 in most cases as shown in Tables 1-3.

Figure 1. Tested Clean images (from left to right), first row: Lax, Crowd, and Pirate, second row: Boats, Lake and Cameraman.

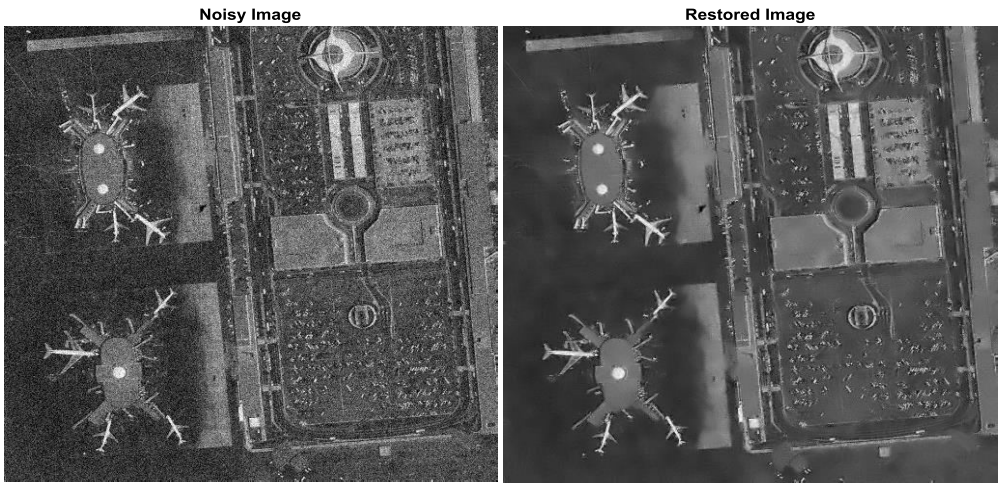

Figure 2. Lax image: Corrupted by Gaussian noise with σ=20 (left), and restored one using the proposed method with Function 1(right).

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Figure 3. Crowd image: Corrupted by Gaussian noise with σ=20 (left), and restored one using the proposed method with Function 1 (right).

Table 1. MSE and MAE of several restored images after being corrupted with zero mean Gaussian noise of standard deviation = 10.

Image	Conventional NLM		Proposed Method Using Function 1		Proposed Method Using Function 2	
	MSE	**MAE**	**MSE**	**MAE**	**MSE**	**MAE**
Lax	65.90	6.2523	64.68	6.2108	64.33	6.1959
Crowd	37.81	4.3874	34.69	4.2556	35.10	4.2856
Pirate	38.53	4.5744	36.62	4.4825	36.72	4.4878
Boats	29.71	3.6872	28.61	3.6552	28.58	3.6799
Lake	48.77	5.1794	46.54	5.0862	46.33	5.0979
Cameraman	21.99	3.1103	20.30	3.0717	20.53	3.0812

Table 2. MSE and MAE of several restored images after being corrupted with zero mean Gaussian noise of standard deviation = 15.

Image	**Conventional NLM**		**Proposed Method Using Function 1**		**Proposed Method Using Function 2**	
	MSE	**MAE**	**MSE**	**MAE**	**MSE**	**MAE**
Lax	107.56	7.7341	105.11	7.6946	104.67	7.6794
Crowd	59.31	5.4305	54.10	5.2506	54.67	5.3006
Pirate	61.86	5.7002	58.16	5.5838	58.17	5.5896
Boats	48.97	4.6542	46.58	4.6229	47.37	4.6894
Lake	76.16	6.2746	69.55	6.0616	71.05	6.1482
Cameraman	36.11	3.8953	33.10	3.8289	33.57	3.8771

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Table 3. MSE and MAE of several restored images after being corrupted with zero mean Gaussian noise of standard deviation = 20.

Image	Conventional NLM		Proposed Method Using Function 1		Proposed Method Using Function 2	
	MSE	MAE	MSE	MAE	MSE	MAE
Lax	154.55	8.9369	143.92	8.7697	142.10	8.7578
Crowd	82.12	6.3407	74.73	6.1723	75.52	6.2316
Pirate	84.15	6.5890	79.93	6.5106	79.62	6.5104
Boats	68.51	5.4922	67.10	5.5353	67.14	5.5784
Lake	100.91	7.0794	92.99	6.8973	95.00	7.0067
Cameraman	47.40	4.4693	45.60	4.4812	46.20	4.5420

4. CONCLUSIONS

The traditional NLM filtering method uses a fixed size search window and a standard Gaussian kernel function. In this paper, an adaptive NLM algorithm with two proposed kernel functions has been examined. Six images of different characteristics corrupted by Gaussian noise with zero mean and different values of standard deviation have been used in the computer simulations using MSE and MAE as performance measuring indices. The results show that the adaptive NLM method with either of the proposed kernel functions outperforms the conventional NLM method in terms of both numerical results and visual image quality mainly for images that have a lot of textures or details and edges corrupted with relatively small amounts of Gaussian noise.

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