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Analysis of Various Issues in Non-Local Means Image Denoising Algorithm

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Abstract: Denoising is still a fundamental, active and unsolved problem in image processing which affects the various high level computer vision tasks like image segmentation, recognition, and tracking etc. The basic goal of denoising is to estimate the original signal from the noisy observations while preserving the important details such as edges and textures. There is always a trade-off between the noise reduction and preserving the important image details. A wide collection of image denoising techniques have been proposed to deal with the denoising problem, but there is still requirement of improvement in the algorithms to enhance the performance of the algorithms. In recent years, the patch based image denoising algorithms like Non-Local Means (NLM) have drawn much more attention to tackle the denoising problem. This paper highlights the various issues of NLM algorithm and presents a review of significant contributions by the different authors to improve the performance of NLM image denoising algorithm.

Keywords: Image denoising, Non Local Means algorithm, Gaussian noise, peak signal to noise ratio

I. INTRODUCTION

Due to rapid development in imaging devices, digital images play an important role in daily life applications such as satellite television, traffic monitoring, signature validation, and medical sciences etc. Image recording systems are not perfect [1], [2]. As a result, all the digital images could be corrupted by noise during image acquisition and transmission due to improper functioning of camera sensors, transmission errors, faulty memory locations, and timing errors in analog-to-digital conversion. Modern image capturing devices are sensitive to noise due to rise in number of pixels per unit area of a chip. Camera manufactures depend on image denoising algorithms to reduce the effects of noise artifacts in the resultant image. Image noise is often assumed to be either impulse or Gaussian noise. It is considered as additive, zero-mean, white, Gaussian, independent and identical distributed (i.i.d). A digital image corrupted by noise leads to visible loss in image quality and can affect many advanced image processing and computer vision tasks such as tracking, recognition and segmentation etc. To acquire the useful information from noisy image, the denoising techniques are required [3], [4].

Image denoising remains an active and unsolved research problem in image processing and attracts the researchers to perform better restoration in presence of noise. The main goal of denoising is to remove the noise while preserving the important features of image such as edges and textures. There is usually a trade-off between noise reduction and the features preservation. Since image features usually involve high frequencies, linear low-pass filters produce poor results regarding the feature preservation. Thus, denoising is often a necessary and the first step to be taken before the images data is analyzed. It is necessary to apply an efficient denoising technique to compensate for such data corruption. Noise modeling in images is greatly affected by capturing instruments, data transmission media, image quantization and discrete sources of radiation [1]. Different algorithms are used to denoise the images depending on the noise model. The noise in digital images is either additive or multiplicative in nature [5], [6].

Most of the natural images are assumed to have additive random noise which is modeled as a Gaussian. Speckle noise is observed in ultrasound images [7] whereas Rician noise affects magnetic resonant imaging (MRI) images [8]. The scope of the paper is to focus on Gaussian noise removal techniques for natural images. A wide variety of image denoising techniques have been proposed to handle the denoising problem [9], [10]. Image denoising techniques are classified into two categories: spatial and transform domain. Spatial domain algorithms perform operations directly on the pixels, whereas the transform domain algorithms perform operations on transform coefficients in frequency domain. The spatial and transform domain methods can also be further classified as local and Non-local methods. The methods that only exploit the spatial redundancy in local neighbourhoods are referred as Local methods. Most of the transform based image denoising methods are local methods such as Visu-shrink, SURE-shrink, Neigh-shrink and Bayes-shrink etc [10], [11], [12]. Most of the spatial domain image denoising filters are mean, median, and Gaussian, and wiener filters etc [1]. which blurs the important image details. The methods that estimate pixel intensity based on the information from the whole image and thereby exploiting the presence of similar patterns and features in an image are referred as Non-local methods. Image denoising methods like non-local means (NLM) etc. are non-local methods. NLM algorithm [13] takes the advantage of redundancy present in an image to reduce the noise effectively. Various internal issues of NLM algorithm like search window size, patch size, central

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pixel weight smoothing parameter or bandwidth, weights calculation, and computational cost etc., are the critical issues which affect the denoising performance. Our focus is on the analysis of various issues in NLM image denoising algorithm on various images databases[i]. The performance of the algorithm can be analyzed in terms of visual quality and peak signal to noise ratio (PSNR) in dB which is defined as:

$$\mathrm{PSNR(dB)} = 10\log_{10}\left(\frac{U_{max}^2}{\mathrm{MSE}}\right) \qquad (1)$$

where, U_{max} represents the maximum gray scale value in clean image U of size $M \times M$ and MSE denotes the mean square error between the clean image U and denoised image $\widehat{U}$ which is expressed as:

$$\mathrm{MSE} = \frac{1}{M \times M}\sum_{i=0}^{M-1}\sum_{j=0}^{M-1}\left[U(i,j) - \widehat{U}(i,j)\right]^2 \qquad (2)$$

II. NOISE MODEL

1) Additive Noise Model:
In this model, noise signal is added to the original signal to produce a noisy signal and follows the following model:

$$y(i,j) = u(i,j) + \eta(i,j) \qquad (3)$$

where, $u(i,j)$ is the original image intensity and $\eta(i,j)$ denotes the zero mean Gaussian noise with some variance σ_n^2.

2) Multiplicative Noise Model:
In this model, noise signal gets multiplied to the original signal. The multiplicative noise model follows as:

$$y(i,j) = u(i,j) \times \eta(i,j) \qquad (4)$$

where, $u(i,j)$ is the original image intensity and $\eta(i,j)$ denotes the noise introduced to produce the corrupted signal $y(i,j)$ at (i,j) pixel location.

III.NON-LOCAL MEANS FILTER

Recently, Buades et al. presented the Non-Local Means (NLM) method which uses the neighborhood similarity for reduction of noise [13]. Non-local means (NLM) uses the redundant information of the image in pixel or spatial domain to reduce the noise effectively. The assumption is that every small neighborhood in a natural image have many similar copies in the same image.

Basically, the non-local means filter estimates a noise free pixel intensity as a weighted average of all the pixel intensities in the image, and the weights are proportional to the similarity between the local neighborhood of the pixel being processed and local neighborhood of surrounding pixels. Let $y(i)$ and $u(i)$ be the observed noisy and original image pixels, respectively, where i is the pixel index. It is assumed that the original image is corrupted by independent and identically distributed (i.i.d) Gaussian noise $\eta(0,\sigma_n^2)$ with zero mean and a known variance σ_n^2 such that

$$y(i) = u(i) + \eta(i) \qquad (5)$$

The estimated pixel values can be derived as the weighted average of all grey values within the whole image U or a predefined search region S_i as

$$\hat{u}_{NLM}(i) = \sum_{j \in U or S_i} w(i,j)y(j) \qquad (6)$$

where $\hat{u}_{NLM}(i)$ is the restored pixel value at pixel i. The weights $w(i,j)$ indicating the amount of similarity between the neighborhoods centered at pixel i and at pixel j in a predefined search region S_i are obtained as

$$w'(i,j) = \exp\left(-\frac{\|N(i) - N(j)\|_{2,\sigma_a}^2}{h^2}\right) \qquad (7)$$

and

$$w(i,j) = \frac{1}{z(i)}w'(i,j) \qquad (8)$$

where the normalizing factor z(i) is given as

$$z(i) = \sum_j w'(i,j) \qquad (9)$$

Figure 1: Cameraman image with a chosen search region S_i (marked in red) and respective similarity patches. The reference patch is marked in blue. Several compared patches within the search region, are marked by a light dashed yellow contour (for patches which resemble reference patch i.e., having a small dissimilarity measure value) and a heavy dashed white contour (for patches with high dissimilarity measure value)

Clean Image	Noisy image ($\sigma = 20$) PSNR = 22.1497 dB	NLM algorithm PSNR = 29.0170 dB

Figure 2: NLM denoising result for cameraman image

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Patch size: 3 × 3 PSNR = 29.2163 dB | Patch size: 5 × 5 PSNR = 28.7999 dB | Patch size: 7 × 7 PSNR = 28.3760 dB | Patch size:9× 9 PSNR = 28.1763 dB | Patch size: 11 × 11 PSNR = 28.1465 dB

Figure 3:Variation of PSNR(dB) w.r.t. patch size for cameraman image

The normalizing factor $z(i)$ ensures that $\sum_j w(i,j) = 1$ and the smoothing kernel width parameter h which controls the extent of averaging. Choosing a very small h leads to the noisy results, while a very large h gives an overly-smoothed image. In the above equation (7), $N(i)$ and $N(j)$ define the $P \times P$ square neighborhoods or patches centered on pixel i and j, respectively, S_i is a square search window of size $S \times S$ centered on pixel i. The vector norm used in equation (7) simply the Euclidean distance, weighted by a Gaussian kernel of varianceσ_n^2. Fig. 2 shows the denoising results of the conventional NLM algorithm in terms of PSNR(dB) and visual quality.

IV. ISSUES IN NLM ALGORITHM

In NLM algorithm, there are several issues such as search window size, patch size, smoothing parameter, central pixel weight, and computational cost etc. Several authors [13] -[25] have proposed new methods to handle these issues which are summarized as below:

A. Patch size

The size of the patch plays an important role in the performance of NLM algorithm. Fig. 3 and 4 show the plot of PSNR(dB) and the visual quality of denoised cameraman image for different patch sizes. As the patch size increases, the image details like edges and texture get blurred. The large patch size introduces the rare patch effect due to lack of redundancy in a search region. Several authors [14], [15], [16], [17] have proposed the NLM variants to select the adaptive patch size according to the region characteristics. Duvel et al. [14] improved the NLM algorithm by replacing the usual squared patches with the arbitrary shapes to take the advantage of local geometry of an image. W.L. Zeng et al. [17] classifies the image into several regions types using structure tensor and according to region type; a patch is adaptively adjusted to match the local property of a region. Zheng et al. [18] proposed an adaptive NLM algorithm based on the pixel seed region growing and merging.

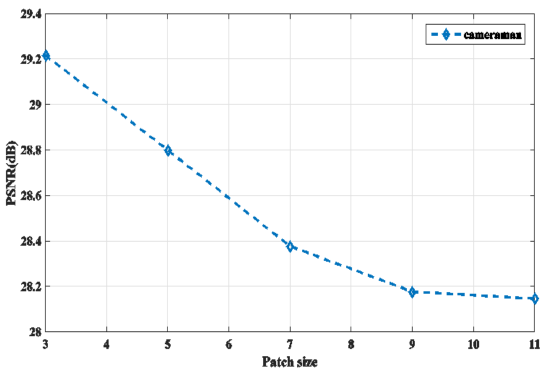

Figure 4: Plot of PSNR(dB) w.r.t. patch size for cameraman image

B. Search region size

In NLM algorithm, the size of search region also affects the performance of the algorithm. The size of search region in NLM algorithm is limited for all pixels in an image due to computational cost. Fig. 5 shows the variation of PSNR(dB) w.r.t. various search regions for cameraman image.

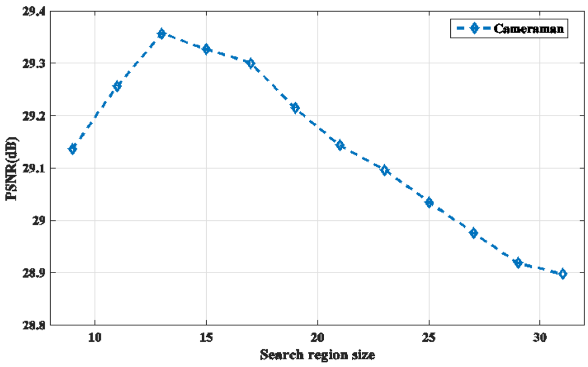

Figure 5: Variation of PSNR(dB) w.r.t. search region size

Ideally, the size of search region must be small for non-smooth regions and large for smooth regions. If the small size of the search region is chosen for a pixel lying in the smooth region, then the less number of relevant patches in averaging affects the performance. Similarly, if the large search region is selected for a pixel lying in non-smooth region, then the contribution of more irrelevant patches affects the NLM performance. It can be observed that if the size of search region is less or more than required, then the performance of NLM algorithm decreases due to biasing the estimation. Thus, the NLM algorithm can be improved by selecting the adaptive search region based on the region characteristics. Several authors [19], [20], [21] have proposed various variants of NLM algorithm by selecting the adaptive search region in an image. R verma et al. [22], [23] selects an adaptive search region based on the entropy and gray level difference of the region and improves the performance of the NLM algorithm.

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C. Central pixel weight

In NLM algorithm, the reference or central pixel participates in the averaging with all the other pixels in the search region. Several authors [24], [25] give suggestions on setting the central pixel weight. The central pixel weight is denoted by $w(i,j)$ for $i=j$. Y.Wu et al. [25] addressed the problem of central pixel weight (CPW) to improve the NLM algorithm. The different ways of assigning the central pixel weights are given as:

• $w(i,j)$ is one, before normalization.

• $w(i,j)$ is maximum of the other weights found in the search region and then normalize the weights. This choice gives better results in practice, but it not validated theory.

• $w(i,j)$ is zero i.e. do not consider the contribution of the central pixel weight in the averaging.

• Use Stein Unbiased Risk Estimator (SURE) for weight calculation. The weight of the central pixel in NLM is replaced by $\exp\left\{-\frac{2\sigma_n^2 M^2}{h^2}\right\}$ without modifying the other weights, before normalization.

TABLE I PSNR RESULTS FOR DIFFERENT CPW

Center pixel weight (CPW)	**Cameraman**	**Lena**
Zero	27.8815 dB	28.0244 dB
One	28.5321 dB	28.2453 dB
Max	29.0772 dB	28.8934 dB
SURE	29.1368 dB	28.4269 dB

Salmon et al. [24] compared the performance of NLM algorithm using different central pixel weights. Table 1 shows the variations in PSNR(dB) with respect to various weights assigned to central pixel for cameraman and Lena images. It can be observed that SURE based weight and maximal weights give the better results for most of the images with any noise level.

D. Smoothing parameter or Bandwidth

The smoothing parameter h quantifies how fast the weights decay with the increasing dissimilarity of the patches. It is generally proportional to the noise standard deviation. The performance of NLM algorithm is sensitive to h and it must be chosen carefully to denoise the image effectively. The relation between the global parameter h and the noise standard deviation is approximately linear for most of the images.

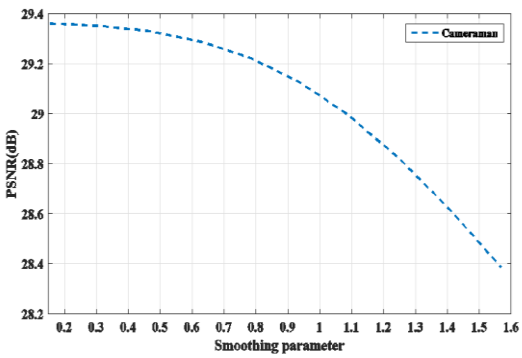


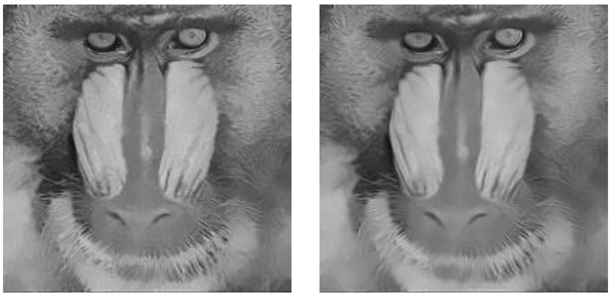
Figure 6: Variation of PSNR(dB) with respect to smoothing parameter h

A small value of h can cause grainy effect in smooth regions due to insufficient denoising, but it may retain the edges and texture effectively. Similarly, the large value of h results in over-smoothing of texture or edges regions [16]. The smoothing parameter h is also sensitive to image local structure. Fig. 6 shows the variation of PSNR(dB) with respect to smoothing parameter h for different image local structure. Duvel et al. [26] suggested the locally adaptive h which is linear with the noise standard deviation. This method runs the NLM algorithm with different values of h and selects the best value of h for which the PSNR is maximum.

E. Patch kernel

The distance or dissimilarity measure is calculated by using the vector norm of the difference between the reference patch and any compared patch (within a search region) weighted by a Gaussian or Box kernel of zero mean and variance σ_a. The Gaussian kernel is used to reduce the effect of differences in pixel values as they are further away from the center of a patch [13]. H. Berkovich et al. [27] proposed the selection of dissimilarity kernel to each pixel based on its local features. The Box kernel is used instead of the Gaussian kernel to improve the performance of the algorithm.

In general, simple or uniform kernel is used which assigns the same weights to all pixels in a patch. Fig. 7 shows that the denoising results of the Baboon image for different patch kernels. It can be observed that NLM algorithm using Box kernel gives better result than the uniform kernel for texture regions.



Box kernel Uniform kernel

Figure 7: Denoising of the image Baboon with σ_n=20

F. Computational cost

Let the size of an image is $M \times M$. For a search region size $S \times S$, and a patch size $P \times P$, the computational complexity of NLM algorithm is $O(M^2 S^2 P^2)$. The complexity of NLM algorithm depends upon the size of image, patch, and search region. According to true NLM principle, the search region must be an entire image to take the advantage of redundancy.

The complexity of NLM algorithm can be reduced by selecting the relevant patches in the search region. Several techniques [28], [29], [30], [31], [32] have been proposed to accelerate the NLM algorithm by preselecting the relevant patches based on the average gradient, mean and variance, principal component analysis (PCA), and higher order moments etc.

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TABLE II OVERVIEW OF ISSUES IN NLM ALGORITHM

Sr. no.	Issues	Problem Identity	References
A	Patch size	a) Large patch - rare patch effect b) Fixed patch size - unable to capture property of a region	[14], [17], [18]
B	Search region size	a) Large search region -Computational complexity increases b) Small search region - less number of similar patches c) Fixed search window size leads to biased estimation	[19], [20], [21], [22], [23]
C	Center pixel weight	It affects the averaging in NLM algorithm	[24], [25]
D	Smoothing parameter	a) large smoothing parameter leads to over-smoothing of image details b) small smoothing parameters results in grainy effect in smooth region	[16], [26]
E	Patch kernel	a) Uniform kernel - gives poor performance in smooth regions b) Box kernel - gives poor performance in texture regions	[3], [27]
F	Computational cost	It depends on the image size, search region and patch size	[28], [29], [30], [31], [32]

V. CONCLUSION

NLM algorithm is widely used to denoise the various images like natural, texture, satellite, ultrasound and MRI images etc. The internal parameters of the conventional NLM algorithm are discussed in this paper. The performance of the NLM algorithm depends on the proper selection of the parameters. To increase the denoising efficiency of NLM algorithm, the parameters can be made adaptive based on the region characteristics. The optimal selection of NLM parameters based on the region properties reduces the artifacts such as rare patch effect, jittering effect, and grainy effect etc.

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