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Optimum parameter estimation for non-local means image de-noising using corner information

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ABSTRACT

Non-local means (a.k.a. NL-means) method for image de-noising averages the similar parts of an image to reduce random noise. The de-noising performance of the algorithm, however, highly depends on the values of its parameters. In this paper, we introduce a method for finding the optimum parameters, present a linear estimation for the h parameter, and demonstrate that the most important parameter in this method is almost independent of the image and depends only on the noise. We also show that the de-noising performance can be increased by using corner information of noisy image. Our modifications result in better de-noising performance at less computational cost.

1. INTRODUCTION

Image and video de-noising (a.k.a. noise reduction) are challenging problems that are still open despite the considerable amount of research devoted to them. The importance of image restoration is due to increasing use of image and multimedia data and their transmission over lossy channels and networks, as well as the high demand for high quality and inexpensive media. Inexpensive acquisition, processing, and delivery of image and video, however, introduce undesirable artifacts to the media.

One of these conspicuous artifacts is additive zero-mean Gaussian noise. The zero-mean property of this noise that is added to all pixels of the image, allows for its reduction by local averaging of the pixel values. This averaging, however, causes blurring which reduces sharpness or effective resolution of the image -- another artifact that is most visible in the edges of the image. The main disadvantage of de-noising algorithms in general is lack of the ability to discriminate between image details and noise. As a result, in most cases, noise reduction leads to undesired effects in the image [1].

Baudes *et al* introduced non-local means (NL-means) de-noising method [1]. NL-means performs a weighted average on highly similar (overlapping) image blocks, to reduce noise and blurring at the same time. The major difference of NL-means and neighborhood filtering methods is that similarity is not measured based on the pixel value but it is measured based on the neighborhood of the pixel. Thus, the residual noise is reduced even further as compared to a conventional neighborhood filtering method. This improvement, however, comes at a higher computational cost.

In this paper we show how to optimize the parameters of non-local means algorithm with simple linear relationships and how to further improve the performance of the original non-local means by using corner information. In section 2, we introduce a simple way of optimizing the parameters of this algorithm, validated by numerous experiments (section 3). Utilization of corner information in enhancement of the algorithm is discussed in Section 4. Section 5 concludes the paper with a summary of contributions.

2. OPTIMAL PARAMETERS

2.1. Parameter Specification

NL-means has three parameters: Similarity window size, search window size (the region in which we are investigating similarity; Figure 1), and the *h* parameter. For a given image, good de-noising performance of NL-means highly depends on the values of these parameters.

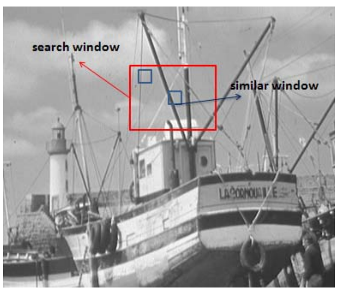

Figure 1. similarity and search windows in NL-means denoising.

Through numerous experiments, we observed that for all images the best de-noising performance occurs when the dimensions of the similarity window and search window are 3 × 3 or 5 × 5 independent of the value of *h*. That is, using larger or smaller windows results in lower de-noising performance in terms of Mean Square Error (MSE, or PSNR), and Structural Similarity Index (SSIM). In general, 3 × 3 search window size leads to acceptable performance, but for images that contain large smooth regions, 5 × 5 window size gives better results.

Figure 2 show the relationship between the search window size and PSNR for the two optimum similarity window sizes mentioned above.

2.2. Optimization of the *h* Parameter

Our experiments show that the optimum value of this parameter depends on window sizes and the standard deviation of the noise and does *not* depend on the model of the noise.

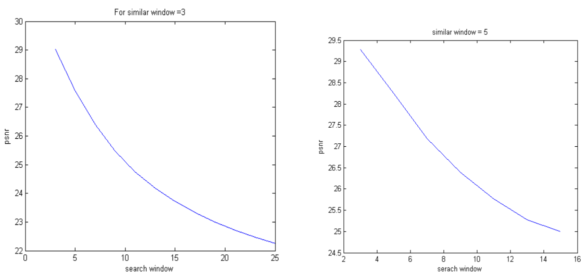

Figure 2. PSNR vs. search window size for similarity window of size 3 ×3 & 5 × 5.

For all of our test images, the relation between *h* and denoising performance is more or less similar to what is shown in Figure 3. It is observed that the image quality degrades with increasing the window size. It is also observed that for a given window size, the quality peaks at a certain value of *h*. The relationship between optimal $\sqrt{h}$ and the noise standard deviation is almost a linear one. Such relationship is shown for the two best window sizes in Figures 4, based on which the following estimations are derived. For 3×3 search and similarity windows, $h = (29.855\sigma - 0.0094)^2$, and for search window size 5×5 and similarity window 3×3, $h = (12.834\sigma + 0.0105)^2$.

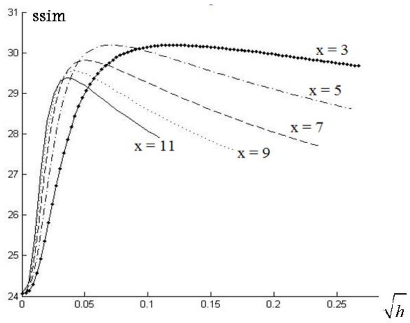

Figure 3. De-noised image quality (compared to the noise-free with SSIM) vs. $\sqrt{h}$ with varying search window size (x)

3. EXPERIMENTAL RESULTS

In our experiments, we used ten standard images [2], affected with different Gaussian noise standard deviations. The data in Table 1 is obtained using $\sqrt{h}$ which gives the best results. Table 2 compares the results acquired by experiment and formula. Table 3 shows the results for 3 × 3 search window.

4. UTILIZATION OF CORNER INFORMATION

Our technique gives better results if the image is composed of periodic parts (i.e., structured texture; highly redundant). Natural images are also redundant enough for satisfactory performance of this algorithm.

In order to reduce the computational cost of this method, one can compare some easily computable features of the two blocks (e.g., average or gradient direction) prior to measuring their similarities directly. If the difference is above a certain threshold, the weight of the corresponding block is set to zero [3].

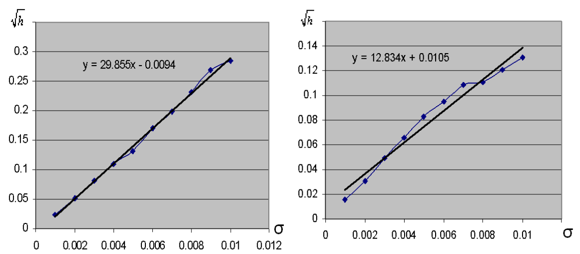

Figure 4. $\sqrt{h}$ vs. noise standard deviation for 3×3 work and similarity window sizes, and work window size 5×5 and similarity window 3×3.

In the original NL-means algorithm the similarity between two pixels i and j depends on the similarity between their neighborhoods $v(N_i)$ and $v(Nj)$, which is multiplied by a function with a Gaussian kernel. The similarity measure can be modified to consider the edge content [4]. It is also possible to set a threshold for larger weights, so that if the difference between the two blocks is greater than a pre-specified value, the weight of the corresponding block is set to zero.

The problem here is the unavailability of the original image and hence the true edge information. Therefore, the edge detection algorithm used should be as insensitive to noise as possible. One proper edge detection technique for this purpose is the Harris algorithm [5].

Table 1. Quality and processing times for various search and similarity window sizes for *pepper*

Search window size	Similarity window size	$\sqrt{h}$	MSE	SSIM (%)	Time (seconds)
3	3	0.1171	0.403	0.854	7.189
5	3	0.0691	0.436	0.863	18.946
7	3	0.0421	0.486	0.856	40.067
9	3	0.0351	0.521	0.850	65.381
11	3	0.0301	0.543	0.845	93.997
13	3	0.0241	0.55	0.837	140.510

Table 2. Comarison of the results obtained by experiment and formula

x	y	experiment	formula	Difference
3	3	.1171	.1100	.0071
5	3	0.0691	.0618	.0073

Table 3. Results for 3×3 search window

x	y	Image quality enhancement	Processing time improvement
3	3	----------	-----------
5	3	0%	163%
7	3	1.4677%	457%
9	3	2.29%	809%
11	3	2.97%	1207%
13	3	4.06%	1854%

$$w(i,j) = \frac{1}{Z(i)} \exp\left(-\frac{\| V(N_i) - V(N_j) \|_{2,u}^2}{h^2} - \frac{\| edge(N_i) - edge(N_j) \|_{2b}}{h'}\right) \quad (5)$$

Harris technique can be used for corner detection, edge detection and even detection of singular points (e.g., salt & pepper noise). In addition to the edges, corners can also be utilized for assigning the weights for improving the performance of the NL-means algorithm, because as stated above we do not have access to the original image and we have to extract edges and corners from the noisy image. Now that corner detection proves to be more robust against noise, it is obvious that it is preferable to edge detection.

The noise in the corner map can be easily removed by a simple process (e.g. masking), because it mostly appears as singular points, whereas this is not true for edge data. Hence, corners give more accurate information about a noisy image than edges. Table 4 contains the results of original NL-means and NL-means with corner-sensitive similarity measure.

5. CONCLUSION

The main problem of previous de-noising methods, which is removing high frequency information of the image, is to some extent solved by the NL-means algorithm. However, NL-means performance is very sensitive to its three parameters. We introduced a straightforward way to achieve this goal. We also showed that the performance of this technique can be improved by using corner information.

Table 4. Results of original NL-means and applying corner information in the NL-means method

	Original NL-means			NL-means with applying corner information		
MSE	.48109	.474473	.613861	.479766	.468312	.607678
PSNR	28.42073	28.46318	26.20439	28.43986	28.49417	26.29584
SSIM	.004395	.004394	.003541	.004395	.004394	.003541

6. REFERENCES

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