AN IMPROVED NON-LOCAL MEANS FILTER FOR IMAGE DENOISING

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Abstract—: Nonlocal means provide an efficient way of denouncing pictures by taking into account the self-similarity within the pixels of an picture. The Non Local Mean filter not only compares a pixel's intensity level, but also the entire neighborhood's geometric configuration. An enhanced non-local means algorithm was described in this document that can be seen as deriving from the amalgamation of non-local means ideas and bilateral filtering.

Keywords— Non local means, self-similarity, denoising, local filters.

I. INTRODUCTION

Denoising pictures have always been an significant component of signal processing, especially in the digitized globe of contemporary society. Local filters are one of the oldest techniques of denouncing that used only data about adjacent pixels with the concept that place meant resemblance. However, what local filters do not take into account is the nonlinear structure within the image, where similarities in an image can be shared spatially far apart between pixels. In perspective of this concept, the concept of non-local mean filtering was suggested by Buades et al.[5].

The initial non-local mean filters were intended to denoise single pixels, but moving on to split the picture into much narrower overlapping patches in the algorithm and use the patches to build the filter. If two patches are comparable, the middle point of one patch will be used to denoise the other. Furthermore, the research carried in showed that using the Euclidean average instead of the mean outcomes in a better filter which is more resistant to noise, leading to better outcomes. There are generally non-trivial relationships for a big information set between their information points. Formal denouncing technique “Dh”, can be described as a breakdown

$$v = Dhv + n(Dh,v) \qquad (1)$$

Here “v” is a noisy image and “h” is a kind of parameter of filterdepending on deflection of noise. Ideally, “Dhv” is smooth as compared to “v” and “n(Dh, v)” can be assumed to be a white noise realization. Thus, denoising can be defined as decomposition of image pixels between the range of smooth and non-smooth parts.

The primary distinction between the non-local means algorithm and frequency domain filters lies in the systematic usage of all possible self prediction inside the image pixels.. In order to remove the noise and restore the true image, several techniques have been suggested. Although they may be vary distinct in instruments, it must be stressed that the same fundamental comment is shared by a broad class: denouncing is accomplished through averaging. The average computation can be done locally as is done in Gaussian smoothing, the anisotropic filtering method and the neighborhood filtering method. Also it can be done by calculations of all variations like the Total Variation minimization. Another method can be the frequency domain models such as the Wiener empirical filters and the wavelet thresholding

Local Statistical Filter model is also a method of spatial filtering though it has the lacking that the edges and noise present in the some images are not identified correctly. Anisotropic Diffusion Filters can rectify this by the use of diffusion coefficient and can distinguish between corners and noise. The method however has the problem that it leads to blurry images and increased computation time on increasing the iteration.

Non Local Mean Filter has been developed to overcome many of these challenges posed by above discussed filtering algorithms. A novel approach to non-local means oriented denoising has been suggested in this study. Local statistics filter and anisotropic diffusion filter can not effectively suppress speckle noise. The non-local mean filter, therefore, is the remedial solution for the removal of speckles. Although, the Non Local Mean filter presents some difficulties. Therefore, the Non Local Mean filter needs performance enhancement.

II. LITERATURE REVIEW

Nezry et al. suggested a speckle filter that includes the benefits of a median speckle filter i.e. preservation of structure, adaptability of Lee or Frost filter to the local speckle, simplicity and efficiency of Lee-sigma filter to reduce speckles. A local adaptive median filter has been created to reduce or remove speckle noise adequately without sacrificing picture structures such as edges, linear characteristics, and fine details[11].

A. Baudes et al. created a non-local strategy in which pictures were denounced differently. This method was based completely on pixel resemblance in the pictures taking a large degree of redundancy benefit to suppress noise. Each window has a comparable window here. It increases many standard filters ' limitations[12]-[13].

P. Coupe et al. suggested a technique for replacing the local pixel comparison with the non-local patch comparison. The Non Local Mean filter makes no assumptions about the place of the most appropriate pixels used to denote the present pixel, unlike the techniques listed above. Rather than comparing the pixel intensity, which can be extremely damaged by noise, the Non Local Mean filter analyzes the patterns around the pixels[14]. They later implemented a technique for reducing the algorithm's complexity through a block-wise strategy. Volumes are split into blocks in the block wise strategy and then perform Non Local Mean to those blocks. Based on restored block intensities, the pixel values are returned. This strategy enables the complexity of the algorithm to be considerably reduced[15].

Porikli et al., suggested techniques that allow for continuous, sampling-free bilateral filtering. They used integral histograms in this technique to prevent redundant activities. Bilateral filtering according to the PSNR value denotes the color picture in the histogram technique. In case of blended noise, this technique is also efficient. This technique avoids over-smoothing[16]. .

III. NON LOCAL MEANS FILTER

Non Local Mean filter is based completely on the resemblance of pixels in pictures that take a large degree of redundancy benefit to suppress noise. Each window has a comparable window here. It increases many standard filters ' constraints. The Non Local Mean filter not only compares a pixel's intensity level, but also the entire neighborhood's geometric configuration. The pixel intensities restored are the weighted average of all image pixel intensities. Non Local Mean filter thus provides detailed conservation of noise suppression.

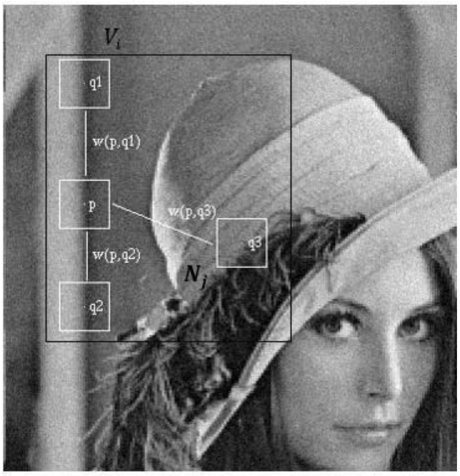

Figure 1: Non local filter window

Figure 1 demonstrates the similarity strategy to the non-local mean. It can be seen that the windows search and similarity windows are two kinds respectively. The search window has a bigger pixel size while the search window is lower. There's a center pixel in the search window. Here the search moves through the similarity window. Window and compare the search window pixel at each location. Wherever the distance between the two pixels is called the Euclidean distance based on the resemblance between the two pixels. Higher weights are given to comparable pixels and less weights are obtained from dissimilar pixels. Then the complete average requires account of all the pixels in the picture and is acquired the restored picture. The algorithm engaged in the Non Local Mean filter method was discussed in this chapter. The denounced value Y(i) for pixel I can be achieved for a noisy picture Y by calculating all pixels within Y as follows:

$$NLM(Y(i)) = \sum_{j \in Y} w(i, j) Y(j) \tag{2}$$

Here, w(i, j)holds the weights calculated depending on the resemblance between pixels I and j. It is as follows:

$$w(i,j)=\frac{1}{Z(i)}e^{-\frac{|Y(N_i)-Y(N_j)|_{2,\sigma}^{2}}{h^2}} \tag{3}$$

Where ‘h’ is the filtering parameter applied to the filter and ‘Ni’ and ‘Nj’ represent the neighborhood pixel, ‘i’ and ‘j’, respectively, ‘Z(i)’ reflects the constant of normalization, represented by:

$$Z(i)=\sum e^{-\frac{\left|Y(N_i)-Y(N_j)\right|_{2,\sigma}^{2}}{h^2}} \tag{4}$$

Non Local means method provides visually and statistically high quality outcomes at a high rate of noise. Here, compelling findings are achieved after correct tuning of parameters like search window, symmetry window and filtering parameters.

IV. IMPROVED NON LOCAL MEAN FILTER

The enhanced non-local means filter optimizes patch size selection using bilateral filtering. The following algorithm is as follows:

1. Calculate the size of the image [m, n] = size(image input)

2. Select the size of the kernel and the values of π1 and π2. 3. Spatial domain calculation Weights using formula:

$$d(i,j,k,l)=\exp\left(-\frac{(i-k)^2+(j-l)^2}{2\sigma_d^2}\right)$$

(5)

4. Pixels Normalization :

Input_Normalized= Input_image/255;

5. Calculation of Intensity Domain Weights:

$$r(i,j,k,l)=\exp\left(-\frac{\|f(i,j)-f(k,l)\|^2}{2\sigma_r^2}\right)$$

(6)

6. Bilateral Filter weights are obtained by multiplying intensity domain and pixel domain weights:

$$w(i,j,k,l)=\exp\left(-\frac{(i-k)^2+(j-l)^2}{2\sigma_d^2}-\frac{\|f(i,j)-f(k,l)\|^2}{2\sigma_r^2}\right)$$

(7)

7. The final output pixel is calculated as summation of weighted pixel values:

$$g(i,j)=\frac{\sum_{k,l} f(k,l)w(i,j,k,l)}{\sum_{k,l} w(i,j,k,l)}$$

(8)

V. CONCLUSION

The algorithm of Non Local Mean does not create the same assumptions as other techniques about the picture. Rather, it assumes that the picture includes a great deal of self-similarity. The local mean filters brings out smoothness in an image by computing the mean of the neighbourhood pixels, whereas in non-local means method the average of all the pixels in the image is taken into account, weighted by the similarity between these pixels and the target pixel. The method thus leads to better clarity after filtering and less detail loss in the image as compared to local mean algorithms.

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