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EFFICIENT NON-LOCAL AVERAGING ALGORITHM FOR MEDICAL IMAGES FOR IMPROVED VISUAL QUALITY

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Abstract

Image can be distorted by various ways including sensor inadequacy, transmission error, different noise factors and motion blurring. For controlling and maintaining the visual quality level of the image to be very high, it is very important to improve the image acquisition, image storage and image transmission, etc. Achieving high Peak Signal to Noise Ratio (PSNR) is essential goal of image restoration. This involves removing noises present in the image. Non-Local Means algorithm combined with Laplacian of Gaussian filter finds better results and produces good PSNR against impulse noise as well as Gaussian noise. Generally the effect of noise can be reduced using smooth filters for better results. Here, Laplacian of Gaussian (LoG) filter is applied for categorizing the edge and noisy pixels. Before that it is mandatory to obtain local smoothing of pixels. Finally the system performance is improved by averaging the non-local parameters. This is applicable to medical images also for removing impulse noise as well as Gaussian noise. The algorithm has been tested with MRI images and CT images efficiently. Better results are obtained in comparison with the previous methods with respect to better visual quality, PSNR and SSIM.

Keywords:

Non-Local Means Filtering, Image Denoising, Impulse Detector, Impulse Noise, LoG Filter

1. INTRODUCTION

The image quality has an important parameter as noise. Always the images are corrupted by impulse noise during the image acquisition and transmission process. For the reduction of this impulse noise, many algorithms are developed.

In [1] the switching filter and median filter are used to correct and identify the noisy pixels. PNSR and structural similarity index measures are measured. Compared to other methods this provides better performances. Up to 100% of the noise is removed from high-density noisy images.

A Non-local based universal noise suppression algorithm is proposed by [2].In this paper, a two-stage detection mechanism is performed. First, a robust outlyingness ratio (ROR) is used to measure the corrupted pixels. Then, the cluster-based pixel division is done. This method speaks about high PSNR and improved image quality.

Improved weighted averaged filtering [3] used for impulse noise removal algorithm. The original image is interpolated by the nearest neighborhood algorithm. The pure pixels and noisy pixels are computed to produce weights. Improved PSNR and good image quality are the results obtained by this method.

A switching based adaptive weighted mean filter is done [4] for salt and pepper noise removal. The neighbors and current pixels are compared to having an already known threshold to obtain noisy pixels. The available uncorrupted neighbor pixels replace the corrupted pixels with weighted mean. In this method, the computational efficiency is increased.

An unsymmetrical trimmed median filter is proposed in [5] for corrupted color images. Replacing of noisy pixels is either by trimmed median filter or mean value based on the presence of lowest and highest gray value based on the presence of lowest and highest gray values in the selected window.

An edge-preserving filter [6] is proposed for the removal of salt and pepper noise from the corrupted image. A review of modern techniques [7] insists on the latest technologies applied for removing the impulse noise [10] - [12].

2. IMPULSE NOISE REPRESENTATION

In noise corrupting of an image, there are various kinds. Impulse noise of type fixed value can be called salt and pepper noise and they are represented as in Eq. (1),

$$f(a,b) = \begin{cases} L_{\min} & \text{with Probability } 0.5P \\ L_{\max} & \text{with Probability } 0.5P \\ f(a,b) & 1-P \end{cases} \quad (1)$$

where, $f(a,b)$, $J(a,b)$, and P are the actual, noisy images and noise density respectively. (a,b) is the corresponding image coordinate. The values of L_{min} and L_{max} show that the image individual pixels have the probability of corrupting with two extreme values which are having the same probability. The impulse value of the pixel initially should be identified. To recover the noisy image, it is then located correctly and with the help of uncorrupted pixels, the original value of the corrupted pixels is calculated.

3. PROPOSED METHOD

Detecting the impulse and restoring the image are the two steps involved in the removal of noise. The two stages of noise removal procedure are as follows

3.1 DETECTING THE IMPULSE

Assuming all the pixels with extreme gray levels are noisy pixels may end in false detection. So, identifying corrupted pixels should be efficient. Specific impulse value in the original image is useful in identifying and estimating the noisy pixels.

Two extreme gray level values will have two equal probabilities in impulse noise. Thus, the Contrast between the original and noisy pixels can be identified by evaluating the orientation and coordination of the corrupted pixels with the adjacent pixels.

3.2 SELECTION OF WINDOW SIZE

Choosing the size of the optimum windows will estimate the accuracy of the proven algorithm. The binomial distribution says about the chosen window that it will contain noisy pixels equal to the value of $(W^2-1)(1-P)$ if the window size is W and the noise probability is P.

As per this equation, the number of noisy pixels is kept as 5 or 8. If we take the value as 8, then, the window size is represented as in Eq.(2) and Eq. (3),

$$\left(W^2-1\right)\left(1-p\right)=8 \tag{2}$$

$$W=\sqrt{\frac{1+8}{\left(1-p\right)}} \tag{3}$$

Decreasing the value will increase the detection error and increasing the value will decrease the detection accuracy. Therefore, the selection of noisy pixel values and the design of window size should be precise to maintain the accuracy and to improve the image quality. So, it is necessary to choose the window size greater than W.

The steps to find the noisy pixels are as follows:

- The set of noisy pixels V_N is constructed with L_{min} and L_{max} values indicates the logical OR.

$$V_N=\left(f\left(a,b\right)=L_{\min}\right)\|\left(f\left(a,b\right)=L_{\max}\right) \tag{4}$$

- The noise probability P and the window size are calculated as per the equation defined already.

$$W=\sqrt{\frac{1+8}{\left(1-p\right)}} \tag{5}$$

- The new sets $S_{min}(a,b)$ and $S_{max}(a,b)$ are formed with the neighboring pixel inclined at the coordinate (a,b), having the two extreme gray level values L_{min} and L_{max}.
- To calculate the set of noisy pixels,

$$V=V_N\cap\left[V_{N1}\cup V_{N2}\right] \tag{6}$$

$$V_{N1}=\left\{S_{\min}\left(a,b\right)+S_{\max}\left(a,b\right)=W^2\right\} \tag{7}$$

$$V_{N2}=\begin{pmatrix} f\left(a,b\right)=L_{\min}\ \&\&S_{\max}\left(a,b\right)\| \\ f\left(a,b\right)=L_{\max}\ \&\&S_{\min}\left(a,b\right) \end{pmatrix} \tag{8}$$

The two sets are calculated with a comparison of $S_{min}(a,b)$ and $S_{max}(a,b)$. But this may result in the wrong identification of original pixels as corrupted pixels and may reduce the accuracy.

- $V = V_N \cap [V_{N1} \text{ U } V_{N2}]$ is computed with the selected noisy pixels. Thus the noisy pixel identification procedure is done successfully leaving out the original pixels with the values of impulse values.

Then the mask is defined as

$$Mask\left(a,b\right)=\begin{cases}0 & if\left(a,b\right)\in V\\ 1 & otherwise\end{cases} \tag{9}$$

3.3 RETRIEVAL OF IMAGE

The study proposes a Non-local Mean filter. Developing the first stage image includes replacing the noisy pixel with the adjacent pixel available in the four corners. The same method is used to replace the noisy pixel by choosing the best impulse value [8]. Here, the Non-local mean filtering technique is used to give the best results.

4. RECONSTRUCTION OF THE ORIGINAL IMAGE

4.1 NON LOCAL MEANS FILTER

A powerful noise removal approach is known as Non -Local Means filter [9]. It was constituted on the basic theory of averaging all the non-local means pixels in the image. A specific pixel's gray level is compared with the geometrical composition in its entire surroundings.

When a distinct image i (consisting of some noise) is taken into consideration such that

$$i=\left\{i\left(a\right)|\,a\in 1\right\} \tag{10}$$

The approximate non-local means value $NL(i(a))$, for a pixel a, is calculated as

$$NL\left(i\left(a\right)\right)=\sum_{b\in 1}w\left(a,b\right)i\left(b\right) \tag{11}$$

where the set of weights $\{w(a,b)\}i(b)$ sis dependent upon the amount of similarity that exists between the pixels a and b and fulfill the given condition

$$0\le w\left(a,b\right)\le 1\text{and}\sum_b w\left(a,b\right)=1 \tag{12}$$

$NL(i(a))$ denotes the weighted average of the image pixels. The similarity that exists between the two pixels a and b are determined by intensity gray level vectors $i(N_a)$ and $i(N_b)$, where N_k correspond to the pixel neighborhood having a square configuration and centered at a pixel k and having a fixed size. The Euclidean distance d (a decaying function), which is also weighted in nature, is used for measuring the similarity between the pixels and is given by

$$d=\left\|i\left(N_a\right)-i\left(N_b\right)\right\|_{\frac{2}{p}}^{2} \tag{13}$$

where $p > 0$ depicts the standard deviation of the Gaussian kernel. If the gray level neighborhood of a pixel is similar to that of $i(N_a)$, then it possesses larger weights in computing the average as compared to other pixels in the image. The weights are determined as

$$w\left(a,b\right)=\frac{a}{Z\left(a\right)}e^{\left(\frac{d=\left\|i\left(N_a\right)-i\left(N_b\right)\right\|_{2P-1}^{2}}{h^2}\right)} \tag{14}$$

where $Z(a)$ is the normalizing constant

$$Z\left(a\right)=\sum_b e^{\left(\frac{d=\left\|i\left(N_a\right)-i\left(N_b\right)\right\|_{2P-1}^{2}}{h^2}\right)} \tag{15}$$

where parameter h represents the degree of filtering and it controls the decay of the exponential function. The Norm function is denoted by the symbol ||.

4.2 LAPLACIAN OF GAUSSIAN FILTER (LoG)

Laplace operator can detect edges and also the noise, first it can smooth the image by a convolution of a Gaussian kernel of width σ.

$$G_\sigma(a,b) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{a^2+b^2}{2\sigma^2}\right) \tag{16}$$

It reduces the noise before using Laplace for edge detection:

$$\begin{aligned} \Delta\left[G_\sigma(a,b) * f(a,b)\right] &= \left[\Delta G_\sigma(a,b) * f(a,b)\right] \\ &= LoG * f(a,b) \end{aligned} \tag{17}$$

The first equal sign is because

$$\begin{aligned} \frac{d}{dt}\left[h(t) * f(t)\right] &= \frac{d}{dt}\int f(T)h(t-T) \\ &= \int f(T)\frac{d}{dt}h(t-T)dT \\ &= f(T) * \frac{d}{dt}h(t) \end{aligned} \tag{18}$$

So, first Laplacian of Gaussian $\Delta g_\sigma(a,b)$ is obtained and then the input image is convolve. Consider,

$$\frac{d}{da}G_\sigma(a,b) = \frac{d}{da}e^{-\frac{(a^2+b^2)}{2\sigma^2}} = -\frac{a}{\sigma^2}e^{-\frac{(a^2+b^2)}{2\sigma^2}} \tag{19}$$

5. RESULTS OF NON LOCAL MEAN

The Fig.1 – Fig.5 represent the output of Non Local Mean Filter.

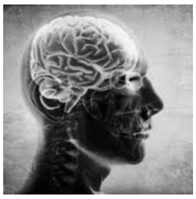

Fig.1. Original image

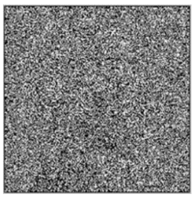

Fig.2: Noisy Image

Fig.3. Noisy image

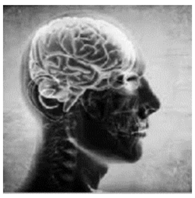

Fig.4. Total Variation

Fig.5. NLM filter O/P

The Fig.6 - Fig.8 represent the output of Non-Local Means Filter.

Fig.6. Original Image

Fig.7. Noisy Image

Fig.8. NLM filter O/P

Table.1. Comparison between different methods for run-time, PSNR and MSE values with 60% noise density.

Methods	Run time (s)	PSNR (dB)	MSE	SSIM
CM	0.6	22.13	68.8	0.81
AIM	0.016	21.8	65.34	0.85
EWA	0.075	27.4	42.56	0.86
Proposed NLM	0.073	32.2	39.14	0.89

For better performance study, 512×512 images with varying values of noise densities is taken into account and the values of PSNR and SSIM are compared with the best available methods for the removal of impulse noise. Various impulse noise patterns are added for testing purposes. NLM performs better compared to all other existing methods.

6. CONCLUSION

The proposed efficient Non-Local Means algorithm is a novel method to suppress the impulse noise using Non-Local Means Filter and LOG Filter using the nearest neighboring interpolation for constructing the initial image. Next, filtering technique is applied to remove the noise. Experimental results indicate that our method produces best PSNR value and compatible with the existing methods for run-time and MSE values. As the visual quality is enhanced better, this method suits many real-time applications.

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