A Glance At Image Denoising

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***Abstract*—This document is a brief literature survey based on given problem by Dr.Hamilton in order to evaluate author potential for undertaking graduate level research in the field of image processing. Image captured by different tools, including X-rays, SLR cameras, microscopic images of PCBs or stem-cells or fabric, or any other type of camera is often corrupted with noise. The first process before further application is "Image denoising" which involves different steps of the manipulation of image data to create a visually high-quality image. In the present survey the author tried to report a very limited aspects of noise addition and denoising techniques and verify his ability of writing and getting involved with new topics. At first he has listed some of additive noise models and after them, some of denoising methods. Finally, the author has wrote the answers of the given test.**

***Index Terms*—noise, denoising, Gaussian, isotropic, PDE, filter.**

I. Introduction

With the tremendous expansion in the capturing environment of digital images and variation of physical conditions like illumination and atmospheric conditions, image restoration methods are becoming indispensable tools [1]. Since all images are noisy, from the beginning of digital image era, numeric methods have been developed and introduced to reduce noise and improve SNR(signal-to-noise ratio) [2].

For example, a photograph of hockey player, many designs are used to get a clean and sharp photo of a player. These designs must use methods to get rid of blurring, electronic noises and motion inside the camera. After that digital storage will affect the picture and add some other noises. Compressing image in order to be sent over a network will affect it more and the list goes on and as mentioned before, "All images are noisy" [2].

The denoising process are done at filtering domain, transform domain and statistical domain. Based on different noise type, different methods are used to restore the image. At filtering domain, filters are categorized in to main group, linear or non-linear, and these methods affect the pixels of noisy image and their main disadvantage of is over-smoothing of edges in some of them. Transform domain filters are more complex but more effective on some noises.

In this article the main goal is discussing about behavior and implementation of 2-D diffusion equation filter which main idea behind it is edge preserving capability of this method. For this purpose some noises model and denoising methods are implemented and used for practice.

A 2-dimentional(2-D) image can be represented by a 2-D matrix of data image(x, y). Blank and whit or colorful picture can be shown with more dimensions. x and y represent pixel location and the value shows the brightness or intensity of pixel. Brightness for black and white picture take values of 0 for black and 1 for white and it can be called of binary images. In this paper, In order to maintain simplicity, all pictures are gray-scale and 2-D. Where value of brightness is between 0 to 255, '0' represent white and '255' is white and the range between is called gray levels [3].

II. Different types of noises

In an orderly noise model im(x,y) represents image and noisy_im(x,y) represent noisy one. A noisy picture can be shown as:

$$noisy\_im(x,y) = im(x,y) + n(x,y) \tag{1}$$

or:

$$noisy\_im(x,y) = im(x,y) * n(x,y) \tag{2}$$

The first one (1) is called additive noise and the second (2) one is known as multiplicative noise. The multiplicative noise is mostly caused by natural phenomena and adding random values to pixels. A very well known noise model is spatial domain:

$$noisy\_im(x,y) = conv(im(x,y), h(x,y)) + n(x,y) \tag{3}$$

as represented in (3), it is a mixture of additive and convolution and most images are degraded by this model. Equation (4) is an equivalent frequency domain representation [4].

$$NOISY\_IM(u,v) = IM(u,v).H(u,v)) + N(u,v) \tag{4}$$

"These two equations are the bases for most of the restoration material" [4].

In following sections, some important noise probability density functions(PDF) are demonstrated and the noise affection on an gray-scale image are pictured.

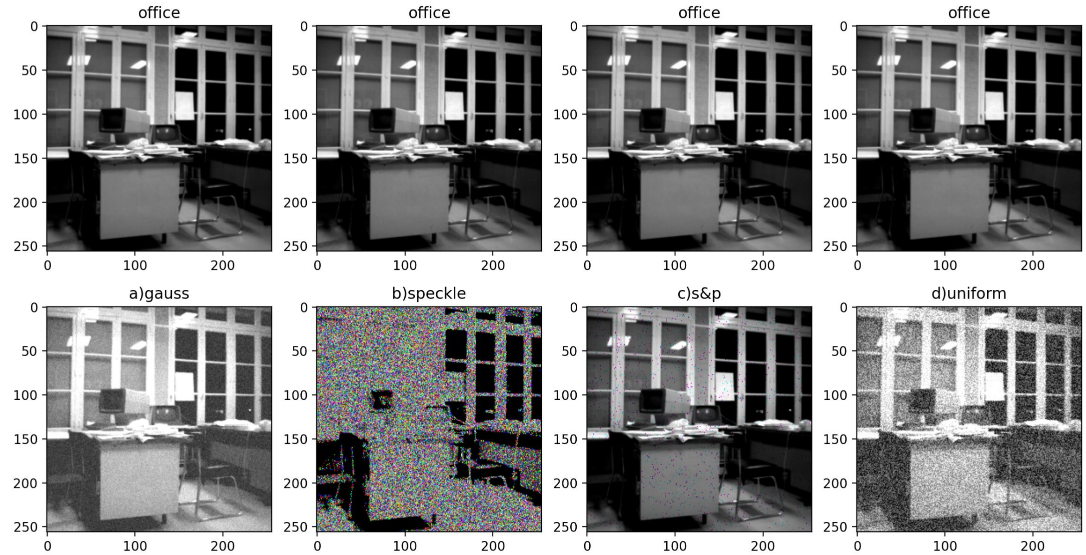

Fig. 1. Noise affection examples.

A. Gaussian noise

Gaussian noise(Normal noise) models are very well known in practice usage" [4]. This type is mostly caused by magnetic resonance of object's heat. The PDF for this model is :

$$p(z) = \frac{1}{\sqrt{2\pi\sigma}} e^{\frac{-(z-\bar{z})^2}{2\sigma^2}} \tag{5}$$

and equations (1) and (5) are used to generate the noisy image (a) at Figure 1.

B. speckle

Environment conditions effect on an image is called "Speckle noise" [5]. The noise is a multiplicative and can be demonstrated by a random matrix multiplications with the image. For this model (3) is used and the result is (b) at at Figure 1.

C. Salt-and-Pepper noise

The impulse noise(bipolar) is commonly known as salt-and-pepper noise. It is mostly caused by abrupt power surges and will appear as black or white pixels. The PDE is given by:

$$p(z) = \begin{cases} P_a & \text{for z = a} \\ P_b & \text{for z = b} \\ 0 & \text{otherwise} \end{cases} \tag{6}$$

and by using additive equation (1) it would generate a noisy image like (c) at Figure 1 [6].

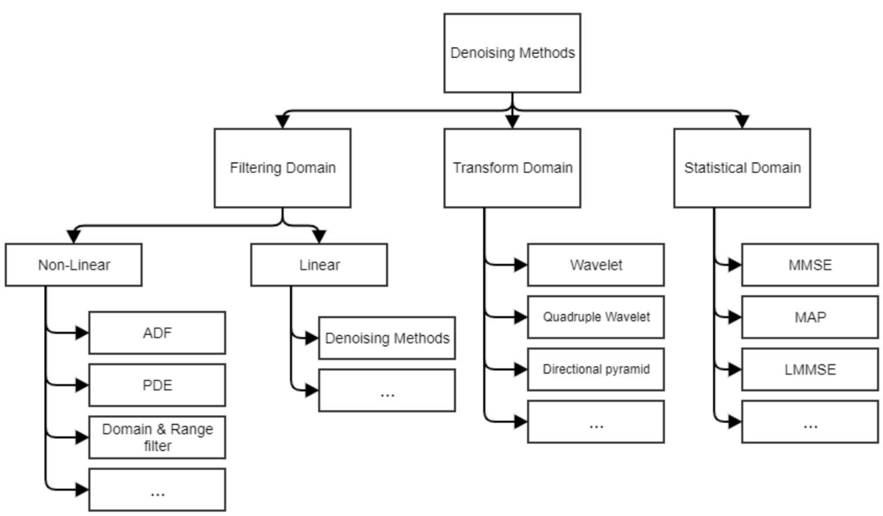

Fig. 2. Classification of Methods [6].

D. Uniform noise

The PDF of uniform noise is given by [4]:

$$p(z) = \begin{cases} \frac{1}{b-a} & \text{for } x \in [a, b] \\ 0 & \text{otherwise} \end{cases} \quad (7)$$

and equations (1) and (7) did result as (d) at Figure 1.

III. Image denoising and Restoration

Filtering domain, transform domain and statistical domain can be classified in subcategories like shown in Figure 2. The filtering domain can be classified as linear or non-linear, transform includes wavelet transform , quadruple wavelet, directional pyramid and some statistical domain methods are MMSE(Minimum Mean Square Error), LMMSE (Linear Minimum Mean Square Error) and ML(maximum likehood).

A. Statistical Domain

Maximum likelihood(ML) method is suggested to remove Rician noise [7]. Some methods use Linear Mean Square Error(LMMSE)estimator for Rician noise. these methods mostly use the local mean, local variance and local mean square [6].

B. Transform Domain

Wavelet-domain is important and advantageous for spatial variation and one of main advantages is preserving edges [8]. To handle high-dimensional data and sharp edges, which wavelet is insufficient, curvelet methods are developed [9]

C. Filtering Domain

As mentioned before, filters are two types, i.e., linear and non-linear.These filters are very effective against Gaussian noise, which are known as Gaussian filter. But will result in blurring image and edges and this is caused by averages pixels of non-similar patterns [6]. To overcome this problem filters like [10] are introduced, which is the main reference of this test is implementing Isotropic filter.

IV. Problem Answers

In next following sections questions 0 to 5 are answered and main references to solve the test were [10] and [11]. Python liberies including Matplotlib, OpenCv, Math and Numpy are used. Some pre-written codes are used and links are inserted at the related module files. For having a tool to numerically measure the effectiveness of processes, a PSNR(peak signal-to-noise ratio) module is implemented which computes the peak signal-to-noise ratio, in decibels, between two images. This ratio is used as a quality measurement between the original and a denoised image. The higher the PSNR, the better the quality of reconstructed image.

A. Question 0

Result of changing values was blurring the image as shown at Figure 3 and with larger values more smoothing happened, in general smoothing is fading edges

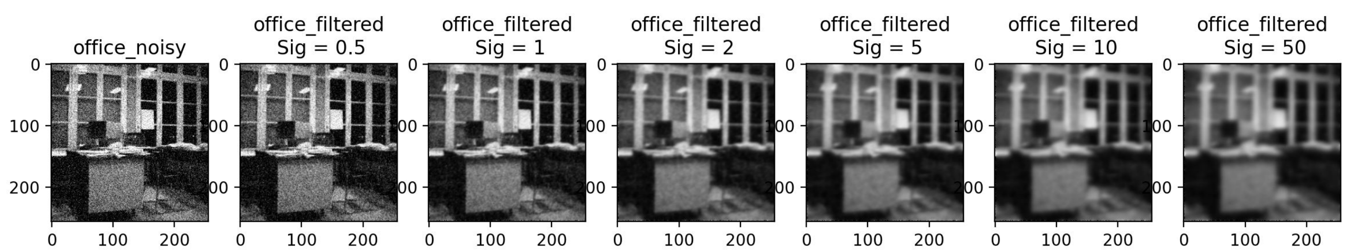

Fig. 3. Question 0 results.

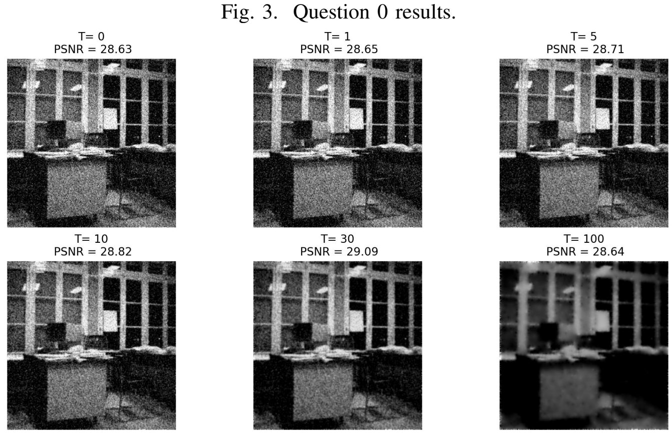

Fig. 4. Question 1 results.

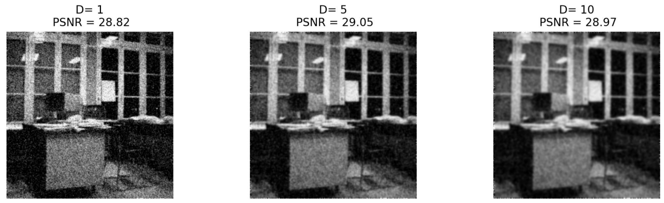

Fig. 5. Question 2 results.

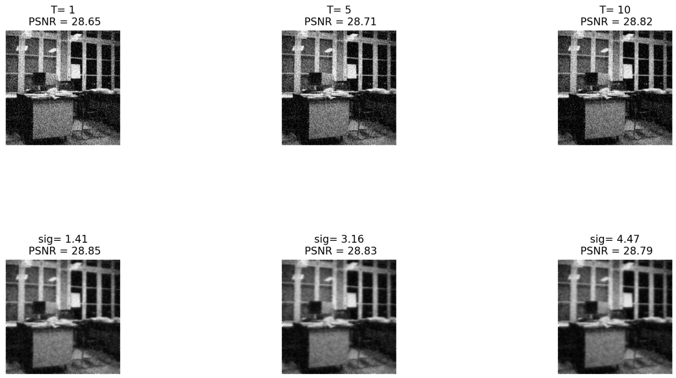

Fig. 6. Question 3 results.

B. *Question 1*

Numerical scheme for this question is:

$$\begin{aligned} u(i,j,t+1) = u(i,j,t) \\ + D.\Delta t(u(i-1,j,t) - u(i,j,t) \\ + u(i+1,j,t) - u(i,j,t) \\ + u(i,j-1,t) - u(i,j,t) \\ + u(i,j+1,t) - u(i,j,t)) \end{aligned} \tag{8}$$

Equation (8) represent gradient of a pixel placed at (i,j) at time of t+1. and by initial condition of:

$$u(i,j,0) = noisy\_image \tag{9}$$

and:

$$D = 1 \tag{10}$$

for:

$$t = 1, 5, 10, 30, 100 \tag{11}$$

is pictured at Figure 4. It is clear the output images are smoother than input image and diffusion process did reduce noise of input image. On another hand this process has sharper edges compared to Gaussian filter with more time iterations.

C. *Question 2*

Solving PDE using equation (8) for:

$$D = 1, 5, 10 \tag{12}$$

at

$$t = 10 \tag{13}$$

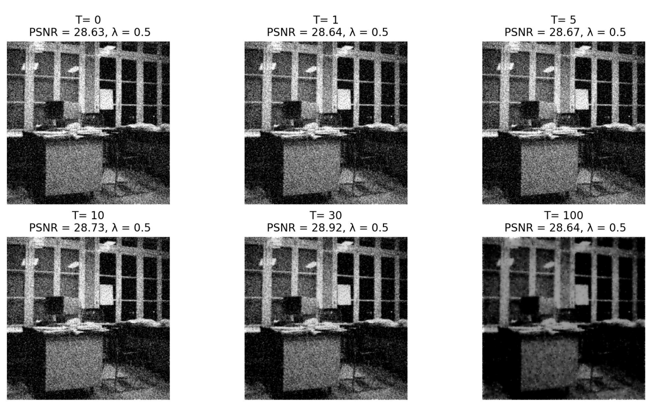

Fig. 7. Question 4 part 1 results.

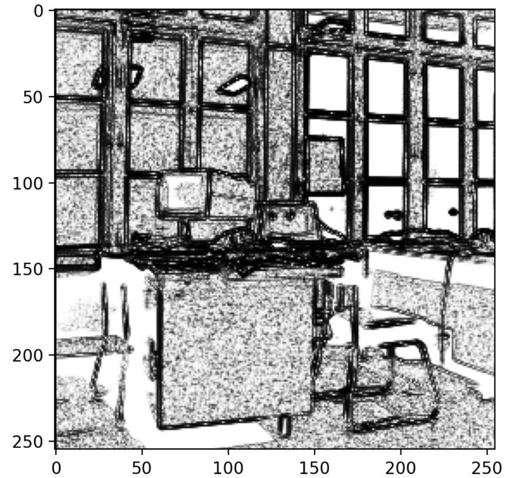

Fig. 8. Question 4 part 2 results.

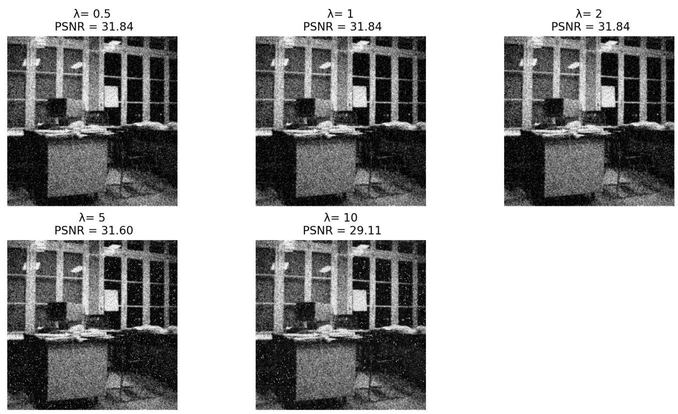

Fig. 9. Question 5 results.

has shown that with greater value of D, diffusion denoising process will be faster and same amount of time iterations. The output result is illustrated at Figure 5.

D. Question 3

The result of comparing these filters are shown at Figure 6. The result did not verify the equivalation of two equations.

E. Question 4

Solving PDE for:

$$t = 1, 5, 10, 30, 100 \tag{14}$$

and

$$\lambda = 0.5 \tag{15}$$

Shown the fact of smoother images with sharpest edges by considering pixel values at edges is shown at Figure 7 and PNSR confirm the noise reduction. Since edges are abnormality in values of background, they can be extracted as D(i,j) and an example is Figure8.

F. Question 5

Solving PDF for:

$$\lambda = 0.5, 1, 2, 5, 10 \tag{16}$$

showed that with greater $lambda noise reduction did not happened, Figure9.

V. Conclusion

Using 2-D diffusion PDE is a practical edge preserving method, and by extracting D(i,j), all edges are detectable in order to get processed later. Denoising and smothering was more powerful than Gaussian filter

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