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# IMAGE DENOISING AND THEIR COMPARISON USING VARIOUS FILTERS AND DIFFERENT TYPES OF NOISE

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**Digital Image Processing is a promising area of research in the fields of electronics and communication engineering, consumer and entertainment electronics, control and instrumentation, biomedical instrumentation, remote sensing, robotics and computer vision and computer aided manufacturing (CAM). For a meaningful and useful processing such as image segmentation and object recognition, and to have very good visual display in applications like television, photo-phone, etc., the acquired image signal must be deblurred and made noise free. The deblurring and noise suppression (filtering) come under a common class of image processing tasks known as image restoration.**

***Index Terms*—discrete wavelet transform , image processing , noise removal , median filter , PSNR**

## I. FUNDAMENTALS OF DIGITAL IMAGE PROCESSING

Digital image processing generally refers to the processing of a 2-dimensional (2-D) picture signal by a digital hardware. In a broader context, it implies processing of any signal using a dedicated hardware, e.g. an application specific integrated circuit (ASIC) or using a general-purpose computer implementing some algorithms developed for the purpose. An image is a 2-D function (signal), X( ) m,n , where m and n are the spatial (plane) coordinates. The magnitude of X at any pair of coordinates (m,n) is the intensity or gray level of the image at that point. In a digital image, m,n, and the magnitude of X are all finite and discrete quantities. Each element of this matrix (2-D array) is called a picture element or pixel. It is a hard task to distinguish between the domains of image processing and any other related area such as computer vision. Though, essentially not correct, image processing may be defined as a process where both input and output are images. At the high level of processing and after some preliminary processing, it is very common to perform some analysis, judgment or decision making or perform some mechanical operation (robot motion). These areas are the domains of artificial intelligence (AI), computer vision, robotics, etc. Digital image processing has a broad spectrum of applications, such as digital television, photo-phone, remote sensing, image transmission, and storage for business applications, medical processing, radar, sonar, and acoustic image processing, robotics, and computer aided manufacturing (CAM) and automated quality control in industries. Fig. 1 depicts a typical image processing system [1,2].

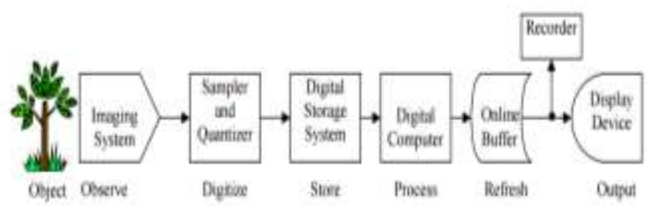


*Fig.1. A typical digital image processing system*

With the exception of image acquisition and display, most of the image processing functions are implemented in software. A significant amount of basic image processing software is obtained commercially. Major areas of image processing are [2]: (a) Image Representation and Modeling (b) Image Transform (c) Image Enhancement (d) Image Filtering and Restoration (e) Image Analysis and Recognition (f) Image Reconstruction (g) Image Data Compression (h) Color Image Processing, etc.

Image processing may be performed in the spatial domain or in a transform domain. To perform a meaningful and useful task, a suitable transformer, e.g. discrete Fourier transform (DFT), discrete cosine transform (DCT), discrete wavelet transform (DWT), etc., may be employed. Depending on the application, a suitable transform is used. Image enhancement tech niques are used to highlight certain features of interest in an image. Two important examples of image enhancement are (i) increasing the contrast, and (ii) changing the brightness level of an image so that the image looks better.

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It is a subjective area of image processing. On the other hand, image restoration is very much objective.

The restoration techniques are based on mathematical and statistical models of image degradation. Denoising (filtering) and deblurring tasks come under this category. Image processing is characterized by specific solutions; hence a technique that works well in one area may totally be inadequate in another. The actual solution to a specific problem still requires a significant research and development. 'Image restoration and filtering' is one of the prime areas of image processing and its objective is to recover the images from degraded observations. The techniques involved in image restoration and filtering are oriented towards modeling the degradations and then applying an inverse procedure to obtain an approximation of the original image. There are various types of imaging systems. X-ray, Gamma ray, ultraviolet, and ultrasonic imaging systems are used in biomedical instrumentation. In astronomy, the ultraviolet, infrared and radio imaging systems are used. Sonic imaging is performed for geological exploration.

Microwave imaging is employed for radar applications. But, the most commonly known imaging systems are visible light imaging. Such systems are employed for applications like remote sensing, microscopy, measurements, consumer electronics, entertainment electronics, etc. An image acquired by optical, electro-optical or electronic means is likely to be degraded by the sensing environment. The degradation may be in the form of sensor noise, blur due to camera misfocus, relative object camera motion, random atmospheric turbulence, and so on [1,2]. The noise in an image may be due to a noisy channel if the image is transmitted through a medium. It may also be due to electronic noise associated with a storage-retrieval system. Noise in an image is a serious problem.

The noise could be AWGN, SPN, RVIN, or a mixed noise. Efficient suppression of noise in an image is a very important issue. Denoising finds extensive applications in many fields of image processing. Conventional techniques of image denoising using linear and nonlinear techniques have already been reported and sufficient literature is available in this area and has been reviewed in the next section. Recently, various nonlinear and adaptive filters have been suggested for the purpose.

The objectives of these schemes are to reduce noise as well as to retain the edges and fine details of the original image in the restored image as much as possible. However, both the objectives conflict each other and the reported schemes are not able to perform satisfactorily in both aspects. Hence, still various research workers are actively engaged in developing better filtering schemes using latest signal processing techniques.

## II. DIFFERENT TYPES OF NOISE

### 2.1 Gaussian Noise

Gaussian noise is evenly distributed over the signal [Um98]. This means that each pixel in the noisy image is the sum of the true pixel value and a random Gaussian distributed noise value. As the name indicates, this type of noise has a Gaussian distribution, which has a bell shaped probability distribution function given by,

$$F(g) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-(g-m)^2/2\sigma^2},$$

where g represents the gray level, m is the mean or average of the function, and σ is the standard deviation of the noise. Graphically, it is represented as shown in Figure 2.1. When introduced into an image, Gaussian noise with zero mean and variance as 0.05 would look as in Image 2.1 [Im01]. Image 2.2 illustrates the Gaussian noise with mean (variance) as 1.5 (10) over a base image with a constant pixel value of 100.

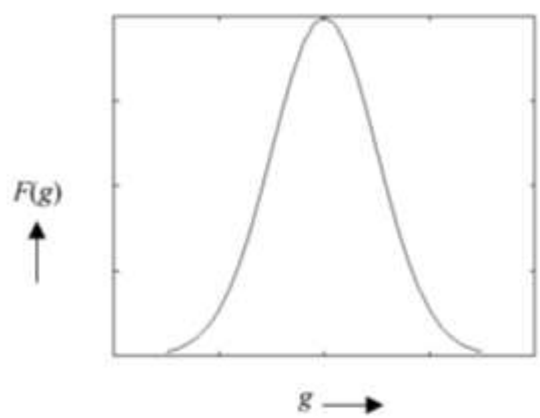


Fig. 2.1 Gaussian Distribution

### 2.2 Salt and Pepper Noise

Salt and pepper noise [Um98] is an impulse type of noise, which is also referred to as intensity spikes. This is caused generally due to errors in data transmission. It has only two possible values, a and b. The probability of each is typically less than 0.1. The corrupted pixels are set alternatively to the minimum or to the maximum value, giving the image a "salt and pepper" like appearance. Unaffected pixels remain unchanged. For an 8-bit image, the typical value for pepper noise is 0 and for salt noise 255. The salt and pepper noise is generally caused by malfunctioning of pixel elements in the camera sensors, faulty memory locations, or timing errors in the digitization process. The probability density function for this type of noise is shown in Figure 2.2. Salt and pepper noise with a variance of 0.05 is shown in Image 2.3 [Im01].

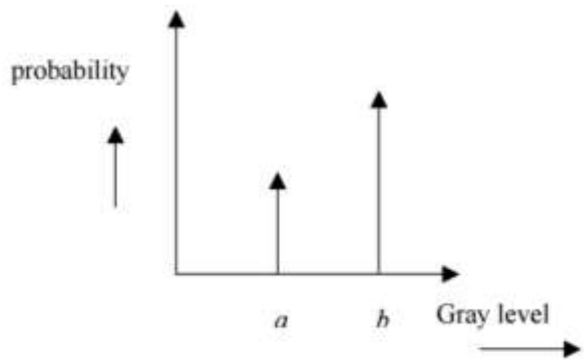


Figure 2.2: PDF for salt and pepper noise

**2.3 Speckle Noise**

Speckle noise [Ga99] is a multiplicative noise. This type of noise occurs in almost all coherent imaging systems such as laser, acoustics and SAR(Synthetic Aperture Radar) imagery. The source of this noise is attributed to random interference between the coherent returns. Fully developed speckle noise has the characteristic of multiplicative noise. Speckle noise follows a gamma distribution and is given as

$$F(g) = \frac{g^{\alpha-1}}{(\alpha-1)!a^{\alpha}} e^{-\frac{g}{a}},$$

where variance is $a^2\alpha$ and g is the gray level. On an image, speckle noise (with variance 0.05) looks as shown in Image 3.4 [Im01]. The gamma distribution is given below in Figure 3.3.

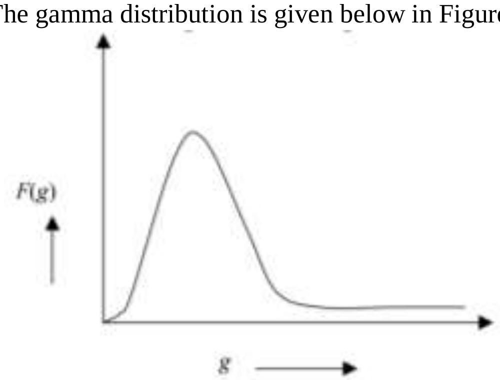


Fig. 2.3 Gamma distribution

## III FILTERING AND DENOISING

Most images are affected to some extent by noise, that is unexplained variation in data: disturbances in image intensity which are either uninterpretable or not of interest. Image analysis is often simplified if this noise can be filtered out. In an analogous way filters are used in chemistry to free liquids from suspended impurities by passing them through a layer of sand or charcoal. Engineers working in signal processing have extended the meaning of the term filter to include operations which accentuate features of interest in data. Employing this broader definition, image filters may be used to emphasise edges — that is, boundaries between objects or parts of objects in images. Filters provide an aid to visual interpretation of images, and can also be used as a precursor to further digital processing, such as segmentation.

Filters change a pixel's value taking into account the values of neighbouring pixels too. To take a simple example, Figs 3.1(b)–(d) show the results of applying three filters to the cashmere fibres image, which has been redisplayed in Fig 3.1(a).

- Fig 3.1(b) is a display of the output from a 5 × 5 moving average filter. Each pixel has been replaced by the average of pixel values in a 5 × 5 square, or window centred on that pixel. The result is to reduce noise in the image, but also to blur the edges of the fibres. A similar effect can be produced by looking at Fig 3.1(a) through half-closed eyes.
- If the output from the moving average filter is subtracted from the original image, on a pixel-by-pixel basis, then the result is as shown in Fig 3.1(c) (which has been displayed with the largest negative pixel values shown as black and the largest positive pixel values shown as white). This filter (the original image minus its smoothed version) is a Laplacian filter. It has had the effect of emphasising edges in the image.
- Fig 3.1(d) shows the result produced when output from the Laplacian filter is added to the original image, again on a pixel-by-pixel basis. To the eye, this image looks clearer than Fig 4.1(a) because transitions at edges have been magnified — an effect known as unsharp masking.

The above filters are all linear, because output values are linear combinations of the pixels in the original image. Linear methods are far more amenable to mathematical analysis than are nonlinear ones, and are consequently far better understood. For example, if a linear filter is applied to the output from another linear filter, then the result is a third linear filter. Also, the result would be the same if the order in which the two filters were applied was reversed. There are two,

complementary, ways of studying linear filters, namely in the spatial and frequency domains. These approaches are considered in §4.2 and §4.3 respectively.

**Nonlinear filters** — that is, all filters which are not linear — are more diverse and difficult to categorize, and are still an active area of research. They are potentially more powerful than linear filters because they are able to reduce noise levels without simultaneously blurring edges. However, their theoretical foundations are far less secure and they can produce features which are entirely spurious. Therefore care must be taken in using them. In §4.3, some nonlinear smoothing filters are considered, and in §4.4, nonlinear edge-detection filters are introduced.

**3.1 Linear filters in the spatial domain**

The moving average, or box filter, which produced Fig 4.1(b) is the simplest of all filters. It replaces each pixel by the average of pixel values in a square centred at that pixel. All linear filters work in the same way except that, instead of forming a simple average, a weighted average is formed. Using the terminology of chapter 1, let fij , for i, j = 1,...,n, denote the pixel values in the image. We will use g, with pixel values gij , to denote the output from the filter. A linear filter of size (2m+1)×(2m+1), with specified weights wkl for k,l = −m, . . . , m, gives

$$g_{ij} = \sum_{k=-m}^{m} \sum_{l=-m}^{m} w_{kl} f_{i+k,j+l} \qquad \text{for } i,j = (m+1),\ldots,(n-m).$$

For example, if m = 1, then the window over which averaging is carried out is 3 × 3, and

$$\begin{aligned} g_{ij} = \; & w_{-1,-1}\, f_{i-1,j-1} && + w_{-1,0}\, f_{i-1,j} && + w_{-1,1}\, f_{i-1,j+1} \\ & + w_{0,-1}\, f_{i,j-1} && + w_{0,0}\, f_{i,j} && + w_{0,1}\, f_{i,j+1} \\ & + w_{1,-1}\, f_{i+1,j-1} && + w_{1,0}\, f_{i+1,j} && + w_{1,1}\, f_{i+1,j+1}. \end{aligned}$$

For full generality, the weights (w) can depend on i and j, resulting in a filter which varies across the image. However, the linear filters considered in this chapter will all be spatially invariant. Also, all the filters will have windows composed of odd numbers of rows and columns. It is possible to have even-sized windows, but then there is a half-pixel displacement between the input and output images.

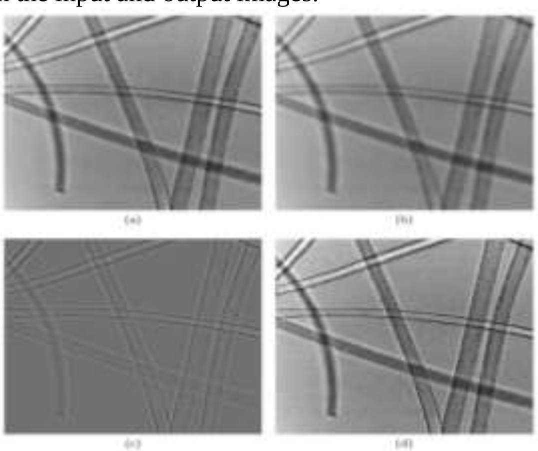

Figure 4.1: Application of linear filters to cashmere image: (a) original image, (b) output from 5 × 5 moving average filter, (c) result of subtracting output of 5 × 5 moving average filter from original image, (d) result of adding original image to the difference between the output from 5 × 5 moving average filter and the original image.

Note that the borders of g, that is

gij where either i or j = 1,...,m or (n − m + 1), . . . , n,

have not been defined above. Various possibilities exist for dealing with them:

1. They could be discarded, resulting in g being smaller than f.
2. The pixels in the borders of g could be assigned the same values as those in the borders of f.
3. The border pixels in g could be set to zero.
4. The filter could be modified to handle incomplete neighbourhoods, for example:

(a) by ignoring those parts of the neighbourhood which lie outside the image,

(b) by reflecting the input image (f) along its first and last row and column, so that pixel values fi,n+1 = fi,n−1 etc,

(c) by wrapping-round the input image so that fi,n+1 = fi,1 etc, as though it were on a torus.

**3.1 Smoothing**

For the moving average filter, wkl = 1/(2m + 1)2. Figs 3.2(a), (c) and (e) show the results of applying moving average filters with windows of size 3×3, 5×5 and 9×9 to the transformed Xray image in Fig 4.3(b). As can be seen, the bigger the window the greater the noise reduction and blurring. Computational efficiency is an important consideration in image analysis because of the size of data sets. In total, there are (2m + 1)2 additions and multiplications per pixel involved in deriving g from f. However, some filters can be computed more quickly. A filter is said to be separable if it can be performed by first filtering the image inside a (2m + 1) × 1 window, and then inside a 1×(2m+1) window. In other words, it can be separated into a column operation:

$$h_{ij} = \sum_{k=-m}^{m} w_k^c f_{i+k,j} \qquad \text{for } i = (m+1),\ldots,(n-m); \quad j = 1,\ldots,n,$$

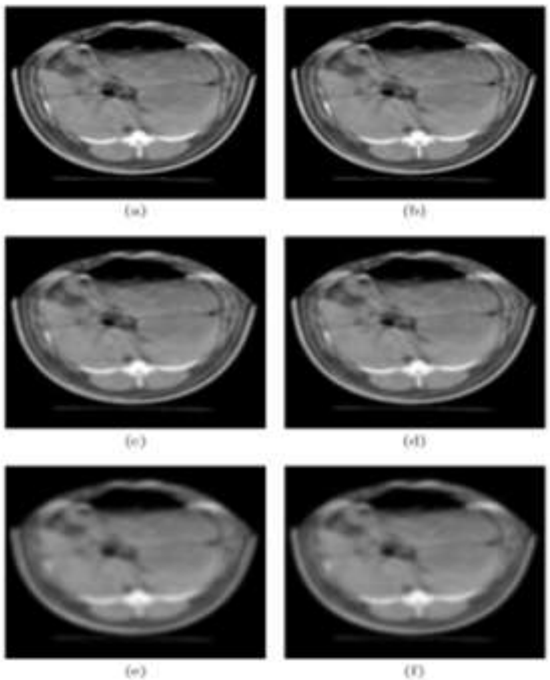

Figure 4.2: Linear smoothing filters applied to X-ray image: (a) 3 × 3 moving average, (b) Gaussian, $\sigma^2 = 2/3$ , (c) 5 × 5 moving average, (d) Gaussian, $\sigma^2 = 2$, (e) 9 × 9 moving average, (f) Gaussian, $\sigma^2 = 20/3$ .

Although the moving average filter is simple and fast, it has two drawbacks:

1. It is not isotropic (i.e. circularly symmetric), but smooths further along diagonals than along rows and columns.
2. Weights have an abrupt cut-off rather than decaying gradually to zero, which leaves discontinuities in the smoothed image.

## IV IMPLEMENTATION

A graphical user interface has been developed in matlab having the following features :-

- Types of noise
  - i) salt and pepper
  - ii) Gaussian
  - iii) speckle
- Types of filters
  - i) Average filter
  - ii) median filter
  - iii) Gaussian filter
  - iv) wiener filter
- Types of image color functions
  - i) Color images
  - ii) Grayscale images
  - iii) Inverted color images
- Comparison modes
  - i) 2d comparison
  - ii) 3d comparison
  - iii) comparison by means of MSE (mean square error)

The completed GUI has been shown below for ready reference

Fig. 4.1 Complete graphical user interface

We have compared these algorithms for several different parameters , the results of which are summarized below.

**5.3.1 Analysis for salt and pepper noise**

As clearly seen from the simulation that for salt and pepper noise median filter provides us the best mean square error in the image . But it must be noted that as the noise level in the image increases then in that case gaussian filter becomes utterly useless with our parameters . Until the value of sigma is increased , the gaussian filter fails to give any conclusive results.

**5.3.2 Analysis for speckle noise**

As clearly seen from the simulation that for peckle noise average filter provides us the best mean square error in the image . The gaussian filter on the other hand proves to be extremely successful as soon as the value of sigma is increased . Thus it can be said that for higher values of sigma Gaussian filter must be used for this type of noise else average filter must be used .

**5.3.3 Analysis for gaussian noise**

As clearly seen from the simulation that for gaussian noise there is no match to the results given by wiener filter in all the cases. In fact the MSE for wiener filter is so very less that it can be neglected also . It must however be interseting to naote that for gaussian noise the MSR for all the other filters are also quite low as compared to their respective MSE's for other noises.

## V CONCLUSION

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The purpose of this research work is to study and compare various noises present in digital images and methods to remove them . Our focus has been specifically on three types of noise i.e :-

- Salt and pepper noise
- Gaussian noise.
- Speckle noise

To remove thsese noiseds from the images we have chosen the following filters for compariosn :-

- Average filter.
- Median filter.
- Gaussian filter.
- Wiener filter.

It has been found in our research that for different parameters and noises , different filters are proven to be effective as compared to the others . thus one cannot conclude that any one filter outmatches the other under diversified conditions.

## VI

## RESULTS WITH DIFFERENT PARAMETER SETS

- Noise type :- Salt & pepper
- Noise level :- 5 %
- Filter :- Average
- Average level :- 3
- Gaussian level :- 0.25


(a) image without filter (b) image with filter

MSE = 18.05

- Noise type :- Salt & pepper
- Noise level :- 5 %
- Filter :- Gaussian
- Average level :- 3
- Gaussian level :- 0.25


(a) image without filter (b) image with filter

MSE = 6.21

- Noise type :- Gaussian
- Noise level :- 5 %
- Filter :- Average
- Average level :- 3
- Gaussian level :- 0.25


(a) image without filter (b) image with filter

MSE = 4.19

- Noise type :- Gaussian

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- Noise level :- 5 %
- Filter :- Gaussian
- Average level :- 3
- Gaussian level :- 0.25

( a) image without filter (b) image with filter

MSE = 25.5

We have compared these algorithms fir several different parameters the results of which are summarized in the tables given below

Table 6.1 Values of MSE for salt and pepper

| | Average level | Noise level | Gaussian Level | MSE value |
|---|---|---|---|---|
| Average filter | 3 | 5 | 0.25 | 18.43 |
| Gaussian filter | 3 | 5 | 0.25 | 6.5 |
| Median filter | 3 | 5 | 0.25 | 3.3 |
| Wiener filter | 3 | 5 | 0.25 | 13.6 |

Table 6.2 Values of MSE for Gaussian noise

| | Average level | Noise level | Gaussian Level | MSE value |
|---|---|---|---|---|
| Average filter | 3 | 5 | 0.25 | 4.09 |
| Gaussian filter | 3 | 5 | 0.25 | 25 |
| Median filter | 3 | 5 | 0.25 | 1.1 |
| Wiener filter | 3 | 5 | 0.25 | 0.8 |

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