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Denoising of Medical Images Using Virtual Instrumentation

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Abstract— ***The medical image (CT angiographic images) we obtained from various devices is corrupted with noise. The obtained image needs processing before it can be used for any diagnosis. Low contrast and poor quality are the main problems in the production of medical images. Denoising is the process with which we reconstruct a signal from a noisy one. Image denoising involves the manipulation of the image data to produce a visually high quality image. Good quality image should have a less CNR value when compared to SNR. Developing Image denoising algorithms is a difficult operation because fine details in a medical image embedding diagnostic information should not be destroyed during noise removal. In this paper a comparative study of different types of noises at different level are done. We have determined qualitative and quantitative analysis using Laboratory Virtual Instrumentation Engineering Workbench.***

Keywords— ***Noises, Angiography, LabVIEW***

I. INTRODUCTION

The process of removal of degradations that are incurred while the image is being obtained is known an image restoration. An electronic and photometric source causes degradation which is termed as noisy. A noise which is introduced in the transmission medium due to a noisy channel is termed as electronic noise and during quantization of the data from digital storage is digital quantization noise. MRI is the most common tool for diagnosis in Medical field. They are often affected by random noise arising in the image acquisition process. Noise which is obtained in the image not only produces undesirable visual quality but also lowers the visibility of low contrast objects. Therefore noise removal is essential in medical imaging applications in order to enhance and recover fine details that may be hidden in the data. The uncertainty in a signal due to random fluctuations in that signal is often defined as noise. There are many causes for these fluctuations. For example, an x-ray beam emerging from an x-ray tube inherently is statistical in nature. The number of photons emitted from the source per unit time varies according to a Poisson distribution. Some other reason for random fluctuations are introduced by the process of attenuation of the materials present in the path of the radiation beam (patient, x-ray beam filtration, patient table, film holder, and detector enclosure) is also Poisson processes.

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At last, the detectors themselves often introduce noise. In an image intensifier, both the intensifying screen and the film contain individual grains that are sensitive to the radiation or light. Hence, the exposure of the grains in the film produces random variations in film density on a microscopic level, which is a source of noise. When electronic detectors are used, the absorption of radiation by the detector is a random process. In addition, some detectors generate currents from thermal sources that introduce random fluctuations into the signal. Noise is therefore inherent in the radiographic imaging process and is influenced by a number of different processes. The noise term may be additive, multiplicative or combination of both. In case of medical images we have both additive and multiplicative noise depending upon the modalities used for image acquisition.[3] In general the noise generated due to the electronic components in an acquisition system is modeled with Gaussian noise which is an additive term. The general block diagram for Denoising technique is shown in figure 1. The "Linear operation" shown is the addition, multiplication, subtraction of the noise $n(x,y)$ to the signal $s(x,y)$. Once the corrupted image $w(x,y)$ is obtained, it is subjected to the denoising technique to get the denoised image $z(x,y)$. The point of focus in this thesis is comparing and contrasting several "denoising techniques.[1].

A. Signal to noise ratio

The most useful and simplest ways, to characterize noise in an imaging system is signal to noise ratio. Standard criteria reported in the literature for quantitative evaluation SNR

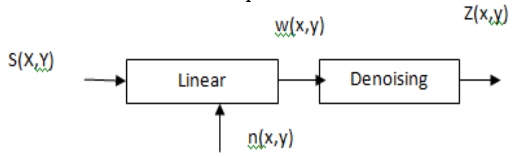

Fig 1. Denoising techniques

measures are used to measure the quality of the denoised image as well as visual quality of the images [5].However, for the description of noise to have physical meaning, it generally must be related to the signal size. The noise specifies the uncertainty in the signal; it generally is helpful to relate the noise to the signal size. SNR is not only used for electrical signals, it can be applied to any form of signal. If the ratio is higher than 1:1, it indicates more signal than noise. Signal-to-noise ratio is defined as the ratio between the desired signal, and the background noise. I f signal is less than noise, and then signal to noise ratio is negative. In this type of situation, reliable communication is generally not possible unless steps are taken to increase the signal level or decrease the noise level. It is given by

$$\text{SNR} = 20 \log \frac{A_{signal}}{A_{noise}}$$

$$= 20 \log \frac{Mean}{Standard\ deviation}$$

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where ,

A is root mean square (RMS) amplitude

A. Contrast to noise ratio

It is a measure used to determine image quality. CNR is similar to, signal-to-noise ratio (SNR), but subtracts off a term before taking the ratio. Thus this image may have a high SNR, but will have a low CNR metric. If it satisfies the above condition then the image is said to be good quality image.

It is defined as:

$$CNR = \frac{S_{max} - S_{min}}{\sigma_D}$$

Where

- S_{max} and S_{min} are signal intensities for maximum and minimum signal producing structures
- σ_D is the standard deviation of the pure image noise.

II. NOISE IN MEDICAL IMAGES

Many of these are introduced by the chemical or photographic limitations of our technology. However, there is a fundamental and unavoidable noise source against which we are always fighting in x-ray imaging, namely photon statistical noise or quantum noise. By photon statistical noise we mean the statistical imprecision introduced into a radiation signal by the random fluctuations in photon production and attenuation. These are naturally occurring, and cannot be avoided. For a detector, the photon statistical noise is calculated in terms of the photons absorbed by the detector and used to generate the image. Any photons which pass through the detector without being absorbed, or even those that are absorbed without generating image information, are wasted and do not contribute to reducing noise in the image. Since photons cannot be subdivided, they represent the fundamental quantum level of a system. It is common practice to calculate the statistical noise in terms of the smallest number of quanta used to represent the image anywhere along the imaging chain. The point along the imaging chain where the fewest number of quanta are used to represent the image is called the "quantum sink". The noise level at the quantum sink determines the noise limit of the imaging system. Without increasing the number of information carriers (i.e. quanta) at the quantum sink, the system noise limit cannot be improved

A. Gaussian noise

An evenly distributed noise over the signal is termed as Gaussian noise. The Gaussian-distributed pseudorandom sequence using a modified version of the Box-Muller method to transform uniformly distributed random numbers into Gaussian-distributed random numbers. It uses a triple-seeded very-long-cycle linear congruential generation (LCG) algorithm to generate the uniform pseudorandom numbers. Each pixel in the noisy image is the sum of the true pixel value and a random Gaussian distributed noise value. Our method is based on a probabilistic formulation that marginalizes depth maps as hidden variables and therefore does not require perfect depth estimation [2]. 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 expected standard deviation of the noise.

You can compute the expected values, $E\{\mathbf{x}\}$, using the formula,

$$E(x) = \int_{-\infty}^{\infty} x(f(x))\,dx$$

It can also expressed using expected mean value, μ, and the expected standard deviation value, σ, of the pseudorandom sequence are

$$\mu = E\{x\} = 0$$

$$\sigma = [E\{x - \mu\}^2]^{1/2} = s$$

where

'*s*' is absolute standard deviation

The Gaussian curve is shown in fig 2

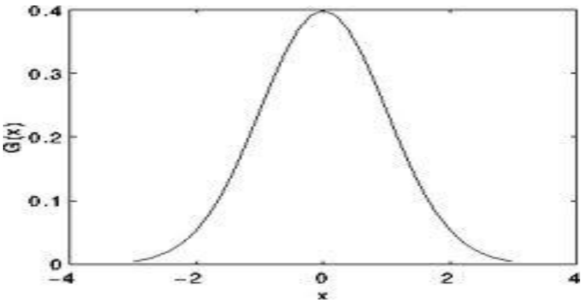

Fig. 2. The Gaussian curve

B. Poisson noise

A discrete probability distribution that expresses the probability of a given number of events occurring in a fixed interval of time is termed as Poisson noise. The Poisson distribution can also be used for the number of events in other specified intervals such as distance, area or volume. It generates a pseudorandom sequence of values that are the number of discrete events that occur in a given interval, specified by mean, of a unit rate Poisson process.

The following equation defines the probability density function of the Poisson noise**:**

$$P(X=k) = \frac{\lambda^k e^{-\lambda}}{k!} \qquad (k=0, 1\ldots)$$

Where,

- *e* is the base of the natural logarithm
- *k*! is the factorial of *k*.
- λ = λTwhen the number of events occurring will be observed in the time interval T=1.

The following equations define the mean value, μ, and the standard deviation value, σ, of the pseudorandom sequence:

$$\mu = E\{x\} = \lambda$$

$$\sigma = [E\{(x-\mu)^2\}]^{1/2} = \sqrt{\lambda}$$

Poisson noise is the result of the Poisson process. You can use the Poisson process to describe the probability of a certain number of events happening in a given period of time. The below diagram fig 3 shows the Poisson curve

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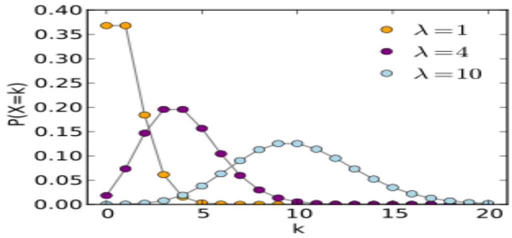


Fig3 Poisson curve

B. Binomial noise

The discrete probability distribution of the number of successes in a sequence of *n* independent yes or no experiments, each of which yields success with probability *p* is known as binomial distribution. Such a success/failure experiment is also called a Bernoulli experiment or Bernoulli trial; when *n* = 1, the binomial distribution is a Bernoulli distribution. The Binomial Noise generates a binomially-distributed, pseudorandom pattern whose values are the number of occurrences of an event. The following equation defines the probability density function of the binomial noise**:**

P(X=k) $=\frac{n}{k} p^k (1-p)^{n-k}$ (k=0,1,…,n)

where

- *n* is the number of trials**,**
- *p* is the trial probability**,**
- and $\frac{n}{k}$equals$\frac{n!}{(n!-k!)k!}$

To generalize, $P(X = k)$ is the probability that *k* of the *n* trials equals 1, and *n* – *k* equals zero. When *n* equals 1, the Binomial noise degenerates into Bernoulli noise.

The following equations define the mean value, μ, and the standard deviation value, σ, of the pseudorandom sequence:

$$\mu = E\{x\} = np$$
$$\sigma = [E\{(x-\mu)^2\}]^{1/2} = \sqrt{np(1-p)}$$

The below curve shows the probability mass function of binomial distribution and shown in figure 4.

III. PROBLEM FORMULATION

The estimation of the uncorrupted image from the distorted or noisy image, and is also referred to as image “denoising” is the basic idea behind this paper. There are various methods to help restore an image from noisy distortions. A major role in getting the desired image is selecting the appropriate method. The Denoising methods tend to be problem specific. For example, a method that is used to denoise satellite images may not be suitable for denoising medical images[1]. In this paper , a study is made on the various denoising algorithms and each is implemented in virtual instrument

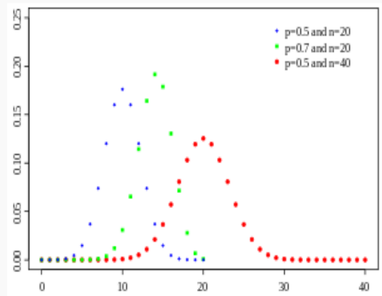


Fig 4. Binomial distribution curve

In order to quantify the performance of the various denoising algorithms, a high quality image is taken and some known noise is added to it. This would then be given as input to the denoising algorithm, which produces an image close to the original high quality image. The performance of each algorithm is compared by computing Signal to Noise Ratio (SNR) besides the visual interpretation. Three popular noises are studied in this project. Noise is often defined as the uncertainty in a signal due to random fluctuations in that signal. There are many causes for these fluctuations. For example, an x-ray beam emerging from an x-ray tube inherently is statistical in nature. That is, the number of photons emitted from the source per unit time varies according to a Poisson distribution. Other sources of random fluctuation introduced by the process of attenuation of the materials present in the path of the radiation beam (patient, x-ray beam filtration, patient table, film holder, detector enclosure) are also Poisson processes. Finally, the detectors themselves often introduce noise.

IV. SIMULATION RESULTS

The denoising technique is application dependent. So, it is necessary to learn and compare denoising techniques to select the technique that is apt for the application in which we are interested. By far there is no criterion of image quality evaluation that can be accepted generally by all. A technique to calculate the signal to noise ratio in images has been proposed. This method assumes that the discontinuities in an image are only due to noise. For this reason, all the experiments are done on an image with very little variation in intensity. Signal to Noise Ratio (SNR) for each of these outputs is computed. In this section, the performance of our proposed work is simulated using Lab VIEW (Version 10) software to test the feasibility and performance of our proposed tool. The real time dataset was collected from the hospital which includes the angiographic of coronary artery Figure 5 shows the phase image of coronary artery. Table 1, 2 and 3 shows the SNR and CNR values for Gaussian noise, binomial noise and poisson noise.

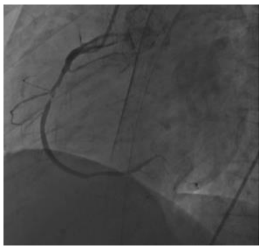
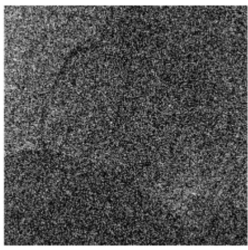
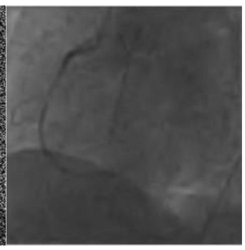


Fig. 5. Phase image



50% noisy image



50% denoised image

a

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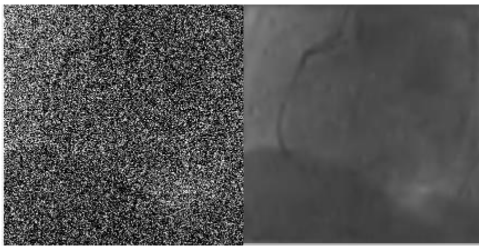
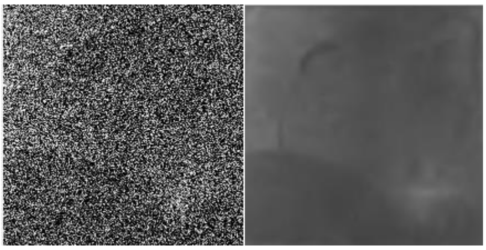


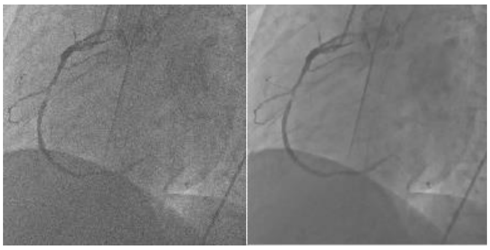
75% noisy image 75%denoised image

b



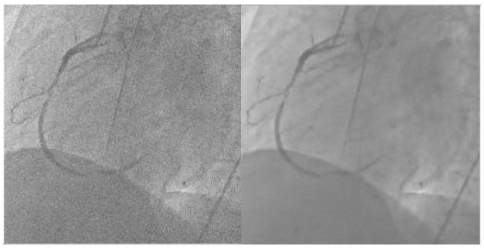
100% noisy image 100% denoised image

c



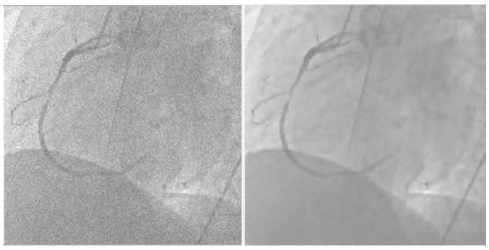
50% noisy image 50%denoised image

d



75% noisy image 75% denoised image

e

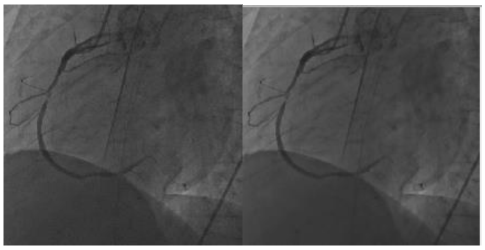


100% noisy image 100% denoised image

f

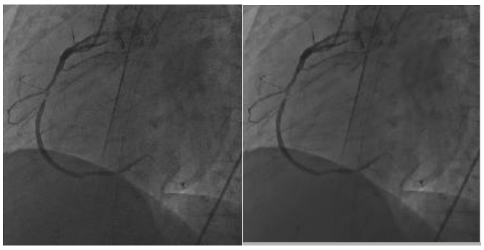
50% noisy image 50% denoised image

g



75% noisy image 75%denoised image

h



100% noisy image 100% denoised image

i

Fig.6.a) 50% noisy and denoised image for Gaussian noise b) 75% noisy and denoised image for Gaussian noise c) 100% noisy and denoised image for Gaussian noise d) 50% noisy and denoised image for Poisson noise e) 75% noisy and denoised image for Poisson noise f) 100% noisy and denoised image for Poisson noise g) 50% noisy and denoised image for Binomial noise h) 75% noisy and denoised image for Binomial noise i) 100% noisy and denoised image for Binomial noise.

Table 1 SNR and CNR for Gaussian noise

	Origina l	noisy image			denoised image		
		50%	75%	100%	50%	75%	100%
min	26	1	0	0	49	59	66
max	153	255	255	255	255	255	255
mea n	73.37	84.05	92.36	96.93	82.14	86.26	94.42
SD	16.19	45.17	52.05	51.75	36.79	34.81	38.54
SNR	13.13	5.39	4.98	5.45	6.98	7.88	7.78
CNR	7.8	5.6	4.9	4.9	5.6	5.6	4.9

Table 2 SNR and CNR for Binomial noise

	original	noisy image			denoised image		
		50%	75%	100%	50%	75%	100%
min	26	26	26	26	31	31	36
max	153	255	255	255	255	255	255
mean	73.37	81.06	80.64	80.73	80.47	80.38	80.51
SD	16.19	39.43	38.91	38.43	38.68	37.83	38.31
SNR	13.13	6.26	6.32	6.45	6.36	6.55	6.45
CNR	7.8	5.81	5.9	6.0	5.8	5.9	5.7

Table 3 SNR and CNR for Poisson noise

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	original	Noisy image			Denoised image		
		50%	75%	100%	50%	75%	100%
Min	26	81	103	123	86	110	134
max	153	255	255	255	255	255	255
mean	73.37	126.20	150.77	176.42	127.08	151.69	175.07
SD	16.19	25.13	22.80	23.12	24.69	22.86	18.981
SNR	13.13	14.02	16.41	17.65	14.23	16.44	19.29
CNR	7.8	6.9	6.6	5.7	6.8	6.3	6.4

V. CONCLUSION

In medical application it is better to see CNR rather than SNR. Because it gives high intensity for the medical images. From the experimental and mathematical results it can be concluded that poisson noise has good SNR and CNR value. Poisson noise is good for both quantitative and qualitative analyses. the selection of the right denoising procedure plays a major role, it is important to experiment and compare the methods. As future research, we would like to work further on the comparison of the denoising techniques. If the features of the denoised signal are fed into a neural network pattern recognizer, then the rate of successful classification should determine the ultimate measure by which to compare various denoising procedures. Besides, the complexity of the algorithms can be measured according to the CPU computing time flops. This can produce a time complexity standard for each algorithm. These two points would be considered as an extension to the present work done.

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