COMPARISION OF VARIOUS NOISE REMOVALS USING BAYESIAN FRAMEWORK

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ABSTRACT:
A noise is introduced in the transmission medium due to a noisy channel, errors during the measurement process and during quantization of the data. For digital storage each element in the imaging chain such as lenses, film, digitizer, etc. contributes to the degradation. Image noise removal is often used in the field of photography or publishing where an image was somehow degraded but needs to be improved before it can be printed. This paper reviews the Bayesian Estimation process for statistical signal processing. Different noise models including additive and multiplicative types are used. They include Gaussian noise, salt and pepper noise, speckle noise and Poisson noise. Selection of the denoising algorithm is application dependent. Hence, it is necessary to have knowledge about the noise present in the image so as to select the appropriate noise removal algorithm. The filtering approach has been proved to be the best when the image is corrupted with salt and pepper noise. The wavelet based approach finds applications in denoising images corrupted with Gaussian noise. In the case where the noise characteristics are complex, the multifractal approach can be used. Bayesian estimation process is used to optimize the removal of Poisson noise. A quantitative measure of comparison is provided by the signal to noise ratio of the image.

KEYWORDS: Bayesian estimator, prior Distribution, Posterior Distribution, Likelihood, Gaussian, salt and pepper, speckle, Poisson Noise.

1. INTRODUCTION

Visual information transmitted in the form of digital images is becoming a major method of communication in the modern age, but the image obtained after transmission is often corrupted with noise. The received image needs processing before it can be used in applications. Image noise removal involves the manipulation of the image data to produce a visually high quality image. For this type of application we need to know something about the degradation process in order to develop a model for it. When we have a model for the degradation process, the inverse process can be applied to the image to restore it back to the original form. This type of image restoration is often used in space exploration to help eliminate artifacts generated by mechanical jitter in a spacecraft or to compensate for distortion in the optical system of a telescope. Image denoising finds applications in fields such as astronomy where the resolution limitations are severe, in medical imaging where the physical requirements for high quality imaging are needed for analyzing images of unique events, and in forensic science where potentially useful photographic evidence is sometimes of extremely bad quality.

Nonlinear filtering is the process of estimating and tracking the state of a nonlinear stochastic system from non-Gaussian noisy observation data. In this technical memorandum, we present an overview of techniques for nonlinear filtering for a wide variety of conditions on the nonlinearities and on the noise. We begin with the development of a general Bayesian approach to filtering which is applicable to all linear or nonlinear stochastic systems. We show how Bayesian filtering requires integration over probability density functions that cannot be accomplished in closed form for the general nonlinear, non-Gaussian multivariate system.

2. ADDITIVE AND MULTIPLICATIVE NOISES

Noise is undesired information that contaminates the image. In the image denoising process, information about the type of noise present in the original image plays a significant role. Typical images are corrupted with noise modeled with either a Gaussian, uniform, or salt or pepper distribution. Another typical noise is a speckle noise, which is multiplicative in nature. The behavior of each of these noises is described below. The digital image acquisition process converts an optical image into a continuous electrical signal that is, then, sampled. At every step in the process there are fluctuations caused by natural phenomena, adding a random value to the exact brightness value for a given pixel.

2.1 GAUSSIAN NOISE

Gaussian noise is evenly distributed over the signal. 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,

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

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 Fig 1. The original image is shown in Fig 2 and the image after Gaussian Noise (variance = 0.05) addition is shown in Fig 3.

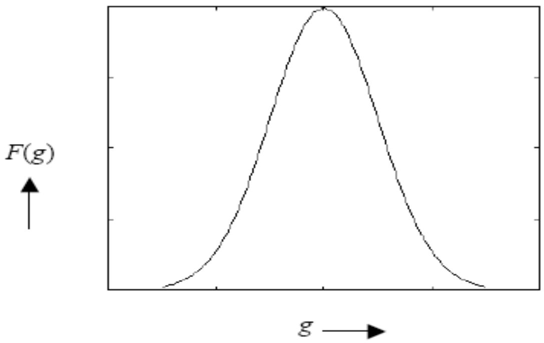

Fig1: PDF for Gaussian Noise

Gaussian noise can be reduced using a spatial filter. However, it must be kept in mind that when smoothing an image, we reduce not only the noise, but also the fine-scaled image details because they also correspond to blocked high frequencies. The most effective basic spatial filtering techniques for noise removal include: mean filtering, median filtering and Gaussian smoothing Crimmins Speckle Removal filter can also produce good noise removal. More sophisticated algorithms which utilize statistical properties of the image and/or noise fields exist for noise removal. For example, adaptive smoothing algorithms may be defined which adjust the filter response according to local variations in the statistical properties of the data.

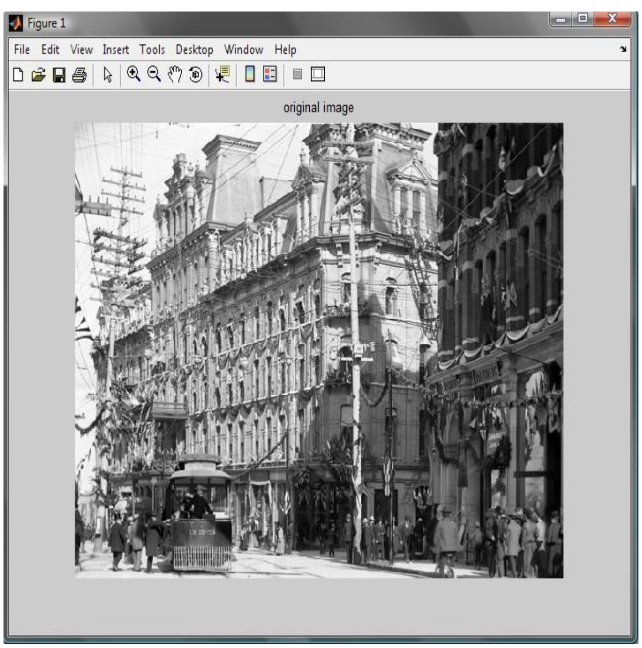

Fig 2: Original Image

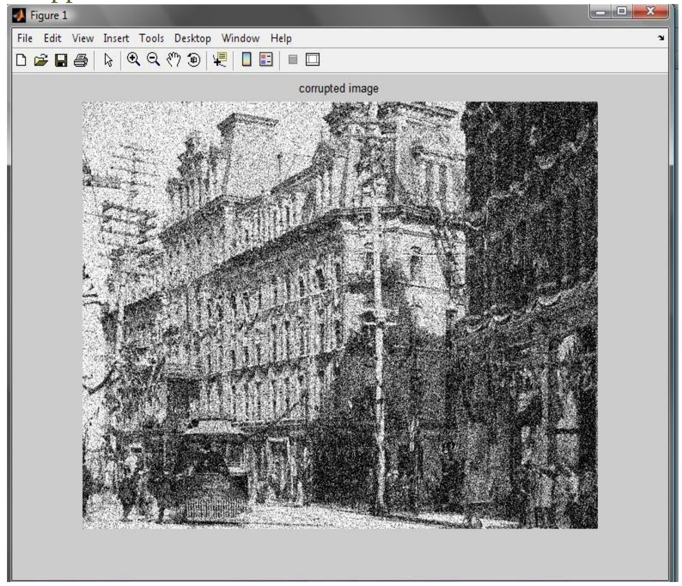

Fig 3: Image after Gaussian Noise addition
(Noise Variance = 0.05)

2.2 SALT AND PEPPER NOISE

For this kind of noise, conventional low pass filtering, e.g. mean filtering or Gaussian smoothing is relatively unsuccessful because the corrupted pixel value can vary significantly from the original and therefore the mean can be significantly different from the true value. A median filter removes drop-out noise more efficiently and at the same time preserves the edges and small details in the image better. Conservative smoothing can be used to obtain a result which preserves a great deal of high frequency detail, but is only effective at reducing low levels of noise. In salt and pepper noise (sparse light and dark disturbances), pixels in the image are very different in color or intensity from their surrounding pixels; the defining characteristic is that the value of a noisy pixel bears no relation to the color of surrounding pixels. Generally this type of noise will only affect a small number of image pixels. When viewed, the image contains dark and white dots, hence the term salt and pepper noise. Typical sources include flecks of dust inside the camera and overheated or faulty CCD elements.

Salt and pepper noise 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 Fig 4. Salt and pepper noise with a variance of 0.05 is shown in Fig 5.

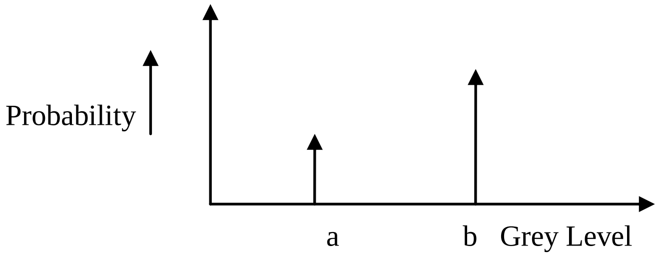

Fig 4: PDF for Salt and Pepper Noise

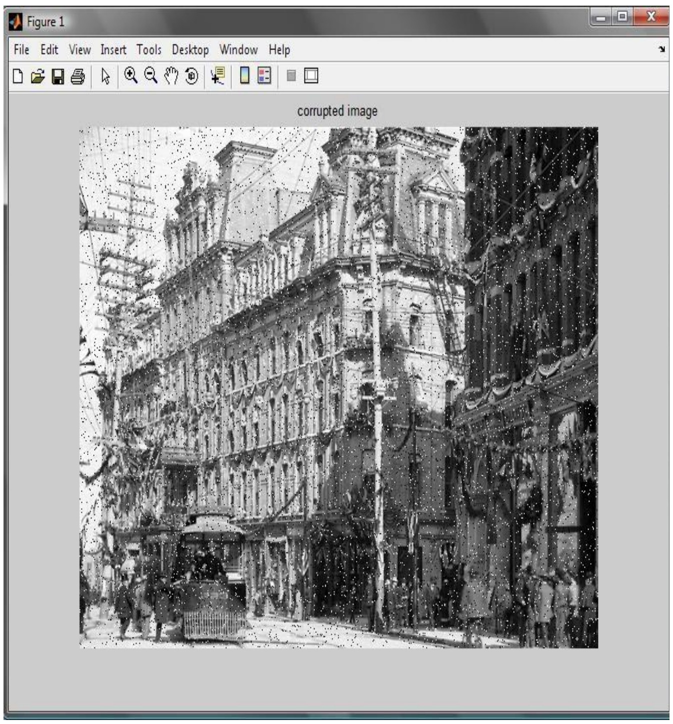

Fig 5: Image after Salt and Pepper Noise addition (Noise Variance = 0.05)

2.3 SPECKLE NOISE

Speckle noise 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,

$$F(g) = \frac{g^{\alpha-1}}{(\alpha-1)!\,a^{\alpha}} e^{-\frac{g}{a}}, \qquad (2)$$

where variance is $a^2\alpha$ and g is the gray level. The gamma distribution is given below in Fig 6. On an image, speckle noise (with variance 0.05) looks as shown in Fig 7.

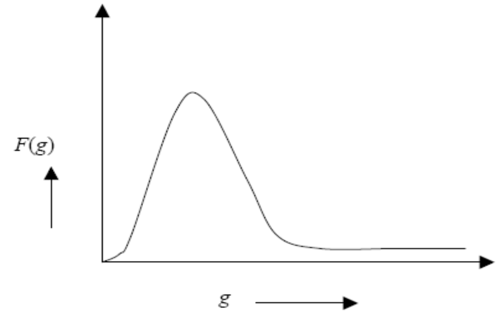

Fig 6: Gamma Distribution

Speckle noise is a granular noise that inherently exists in and degrades the quality of the active radar and synthetic aperture radar (SAR) images. Speckle noise in conventional radar results from random fluctuations in the return signal from an object that is no bigger than a single image-processing element. It increases the mean grey level of a local area. There are many forms of adaptive speckle filtering, including the Lee filter, the Frost filter, and the Refined Gamma Maximum-A-Posteriori (RGMAP) filter. They all rely upon three fundamental assumptions in their mathematical models, however:

1. Speckle noise in SAR is a multiplicative noise, i.e. it is in direct proportion to the local grey level in any area.
2. The signal and the noise are statistically independent of each other.
3. The sample mean and variance of a single pixel are equal to the mean and variance of the local area.

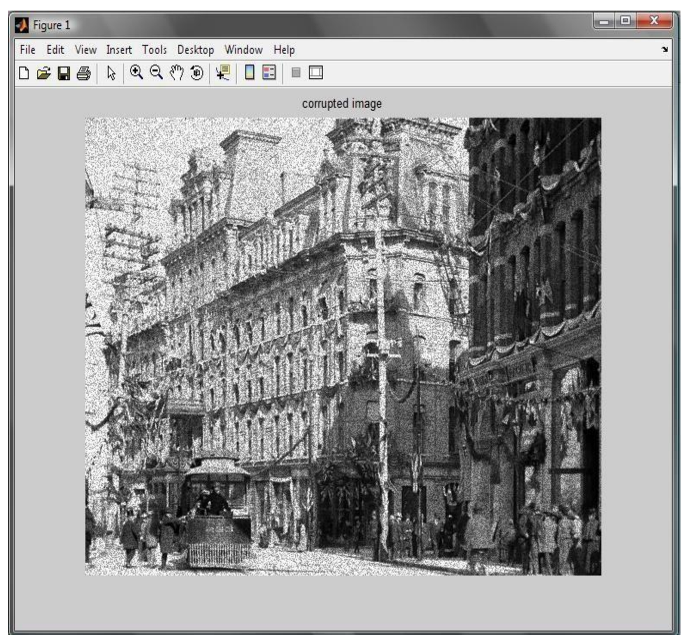

Fig 7: Image after Speckle Noise addition (Noise Variance = 0.05)

2.4 POISSON NOISE

The dominant noise in the lighter parts of an image from an image sensor is typically that caused by statistical quantum fluctuations, that is, variation in the number of photons sensed at a given exposure level; this noise is known as photon shot noise or Poisson Noise. Poisson noise has a root-mean-square value proportional to the square root of the image intensity, and the noises at different pixels are independent of one another. Poisson noise follows a Poisson distribution, which is usually not very different from Gaussian. Poisson noise is a type of electronic noise that may be dominant when the finite number of particles that carry energy (such as electrons in an electronic circuit or photons in an optical device) is sufficiently small so that uncertainties due to the Poisson distribution, which describes the occurrence of independent random events, are of significance. It is important in electronics, telecommunications, optical detection, and fundamental physics. The magnitude of shot noise increases according to the square root of the expected number of events, such as the electrical current or intensity of light. But since the strength of the signal itself increases more rapidly, the relative proportion of Poisson noise decreases and the signal to noise ratio (considering only Poisson noise) increases anyway. Thus Poisson noise is more frequently observed with small currents or light intensities following sufficient amplification. Since the standard deviation of Poisson noise is equal to the square root of the average number of events N, the signal-to-noise ratio is given by:

$$\mathrm{SNR} = N/\sqrt{N} = \sqrt{N} \qquad (3)$$

Thus when N is very large, the signal-to-noise ratio is very large as well.

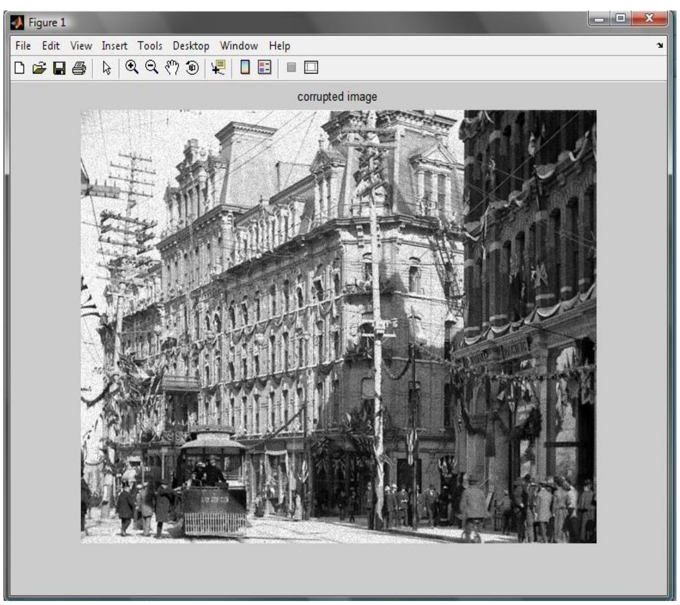

Fig 8: Image after Poisson Noise addition
(Noise Variance = 0.05)

3. BAYESIAN ESTIMATOR

Bayesian estimation is a framework for the formulation of statistical inference problems. In the prediction or estimation of a random process from a related observation signal, the Bayesian philosophy is based on combining the evidence contained in the signal with prior knowledge of the probability distribution of the process. Bayesian methodology includes the classical estimators such as maximum a posteriori (MAP), maximum-likelihood (ML), minimum mean square error (MMSE) and minimum mean absolute value of error (MAVE) as special cases. The hidden Markov model, widely used in statistical signal processing, is an example of a Bayesian model. Bayesian inference is based on minimization of the so-called Baye's risk function, which includes a posterior model of the unknown parameters given the observation and a cost-of-error function.

Estimation theory is concerned with the determination of the best estimate of an unknown parameter vector from an observation signal, or the recovery of a clean signal degraded by noise and distortion. For example, given a noisy sine wave, we may be interested in estimating its basic parameters (i.e. amplitude, frequency and phase), or we may wish to recover the signal itself. An estimator takes as the input a set of noisy or incomplete observations, and, using a dynamic model (e.g. a linear predictive model) and/or a probabilistic model (e.g. Gaussian model) of the process, estimates the unknown parameters. The estimation accuracy depends on the available information and on the efficiency of the estimator.

Bayesian theory is a general inference framework. In the estimation or prediction of the state of a process, the Bayesian method employs both the evidence contained in the observation signal and the accumulated prior probability of the process. Consider the estimation of the value of a random parameter vector θ, given a related observation vector y. From Baye's rule the posterior probability density function (pdf) of the parameter vector θ given y, $f(\theta/y)$ can be expressed as

$$f(\theta/y) = \frac{f(y/\theta)f(\theta)}{f(y)} \qquad (4)$$

Where for a given observation, f(y) is a constant and has only a normalizing effect. Thus there are two variable terms in the Equation 4. One term $f(y/\theta)$ is the likelihood that the observation signal y was generated by the parameter vector θ and the second term is the prior probability of the parameter vector having a value of θ. Conceptually Bayesian Estimator combines

1. The likelihood, i.e., the data, with

2. The prior

3.1 DYNAMIC AND PROBABILITY MODELS IN ESTIMATION

Optimal estimation algorithms utilize dynamic and statistical models of the observation signals. A dynamic predictive model captures the correlation structure of a signal, and models the dependence of the present and future values of the signal on its past trajectory and the input stimulus. A statistical probability model characterizes the random fluctuations of a signal in terms of its statistics, such as the mean and the covariance, and most completely in terms of a probability model. As an illustration consider the estimation of a *P*-dimensional parameter vector $\theta = [\theta_0, \theta_1, \ldots \theta_{p-1}]$ from a noisy observation vector $\boldsymbol{y}=[y(0), y(1), ..., y(N-1)]$ modeled as

$$y = h(\theta, \mathbf{x}, \mathbf{e}) + \boldsymbol{n} \quad (5)$$

In Fig 9, the distributions of the random noise $\boldsymbol{n}$, the random input $\boldsymbol{e}$ and the parameter vector θ are modeled by probability density functions, $f(\boldsymbol{n})$, $f(\boldsymbol{e})$, and $f(\theta)$ respectively. The pdf model most often used is the Gaussian model. Predictive and statistical models of a process guide the estimator towards the set of values of the unknown parameters that are most consistent with both the prior distribution of the model parameters and the noisy observation. In general, the more modeling information used in an estimation process, the better the results, provided that the models are an accurate characterization of the observation and the parameter process.

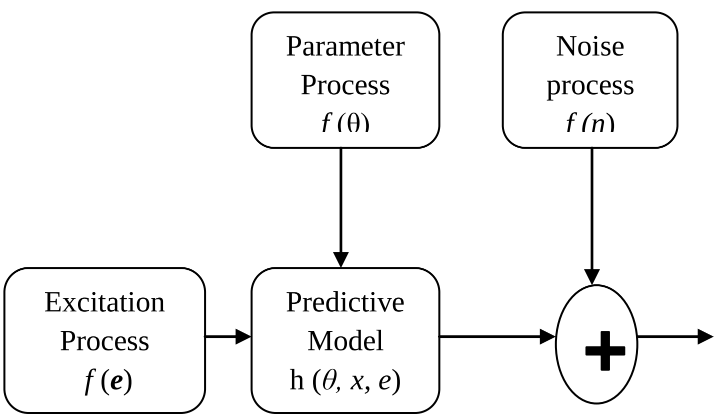

Fig 9. A random process **y** is described in terms of a predictive model h (·), and statistical models $f(\boldsymbol{e})$, $f(\theta)$ and $f(\boldsymbol{n})$

3.2 PARAMETER ESTIMATION AND SIGNAL RESTORATION

Parameter estimation and signal restoration are closely related problems. The main difference is due to the rapid fluctuations of most signals in comparison with the relatively slow variations of most parameters. For example, speech sounds fluctuate at speeds of up to 20 kHz, whereas the underlying vocal tract and pitch parameters vary at a relatively lower rate of less than 100 Hz. This observation implies that normally more averaging can be done in parameter estimation than in signal restoration. As a further example, consider the interpolation of a sequence of lost samples of signal given N recorded samples, as shown in Fig 10.

$$y = \boldsymbol{X}\theta + \mathbf{e} + n \quad (6)$$

Where $\boldsymbol{y}$ is the observation signal, $\boldsymbol{X}$ is the signal matrix, θ is the AR parameter vector, $\boldsymbol{e}$ is the random input of the AR model and $\boldsymbol{n}$ is the random noise. Using Equation 6, the signal restoration process involves the estimation of both the model parameter vector θ and the random input $\boldsymbol{e}$ for the lost samples. Assuming the parameter vector θ is time-invariant, the estimate of θ can be averaged over the entire N observation samples, and as N becomes infinitely large, a consistent estimate should approach the true parameter value.

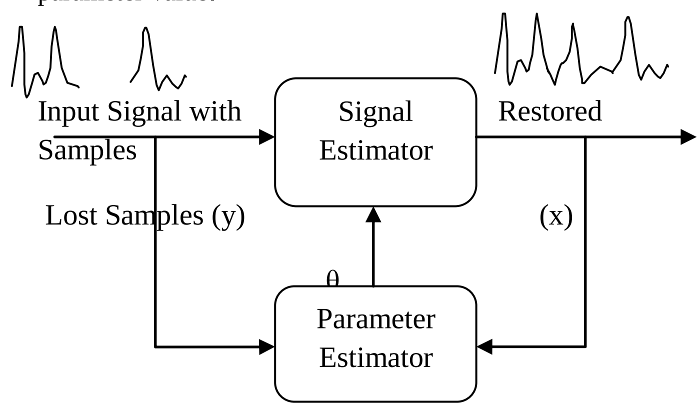

Fig 10 : Signal restoration using a parametric model of the signal process.

The difficulty in signal interpolation is that the underlying excitation $\boldsymbol{e}$ of the signal $\boldsymbol{x}$ is purely random and, unlike θ, it cannot be estimated through an averaging operation.

4. SNR:

Signal to Noise Ratio is probably the most well-known measure of them all. It is defined as the quotient between the signal and noise energy. If a signal is a scalar function $f(x)$, the energy is usually defined as:

$$E(f(x)) = \int (f(x))^2 \, dx \quad (7)$$

Consider an observed signal $X = S + N$, where S is the interesting part of the signal and N is the noise. SNR for X is usually defined as:

$$\mathrm{SNR}(X) = 20 \log_{10} \frac{E(S)}{E(N)} \text{ dB} \quad (8)$$

The list of problems with SNR can be made long. The most obvious problem is, however, that it can usually not be directly measured. If S and N are known, measuring SNR is no problem, but then noise reduction will not be needed. The noise free signal is already known. Various schemes of estimating SNR can be considered, but in doing so, we always need to decide what parts of the observed signal are interesting and what parts are noises.

5. RMSE

Another error measure of great importance is the Root Mean Square Error. RMSE is defined as:

$$\text{RMSE} = \sqrt{\frac{\sum i\ (xi - si)2}{N}} \qquad (9)$$

where *xi* is the sampled signal value at position *i* and s_i is the noise free value at the same position. It is obvious that if $x = s + n$, that is, if we add some uncorrelated noise n with zero mean to s and observe the resulting sum, RMSE will be equal to the standard deviation of the noise. RMSE is, in other words, an absolute measure of the noise amplitude. As with SNR, RMSE requires knowledge of the true noise free signal, which limits its use significantly.

6. RESULTS:

Comparison of SNR (Signal to Noise ratio) using Baye's Estimator (σ= 0.5):

	Gaussian Noise	Salt and Pepper Noise	Speckle Noise	Poisson Noise
SNR	22.2760	22.6158	24.8829	42.3882

Comparison of MSE (Mean Square Error) using Baye's Estimator (σ= 0.5):

	Gaussian Noise	Salt and Pepper Noise	Speckle Noise	Poisson Noise
MSE	0.2183	0.2061	0.1733	0.0327

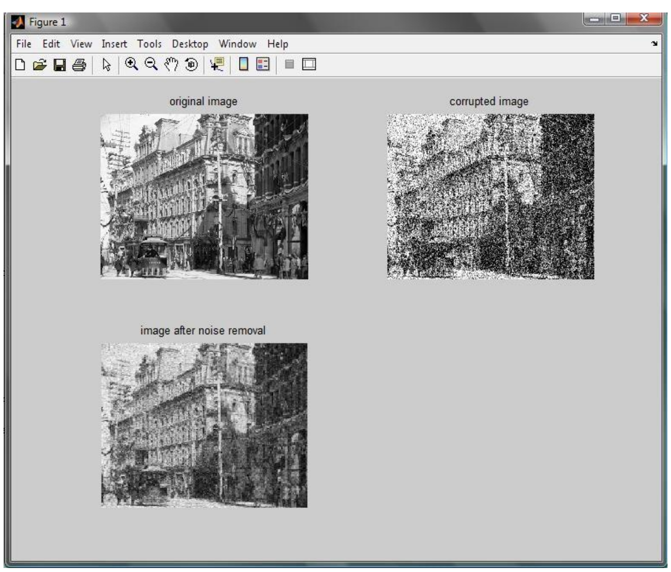

Fig 11: Removal of Poisson Noise by Bayesian estimator

7. CONCLUSION

The paper emphasizes on the SNR and MSE for various noises using Bayesian Estimator. The Results shows that Bayesian Estimator Optimizes the Poisson Noise removal as its Signal to Noise ratio (SNR) is maximum and least Mean square error (MSE). The SNR for Gaussian noise is minimum and also the MSE is maximum. Even if level of decomposition is increased the results becomes better.

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