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Performance Analysis And Optimization of Restoration Using Lorentzian Robust Estimator with Circular Spatial Mask To Diversified Field Images

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ABSTRACT

In this paper, a new robust statistical frame work for image restoration to images from diversified fields. Robust statistical approach the problem of estimation to the representation as better than reality assumptions about a system are occasionally violated. The degraded image is considered as a violation of the assumption of spatial intensities and is treated as an outlier random variable. A restored image is estimated by fitting a spatially co-herent still image model to the available degraded data using a robust estimator based regression technique within an optimal size of circular adaptive window. The robust formulation purpose at removing the noise outlier while preserving original contain in the restored image. We provide experimental result with synthetic degraded images and compare with the state-of-art techniques demonstrating with several examples.

KEYWORDS- image restoration, synthetic noises, outliers, robust restoration, robust statistics.

INTRODUCTION

Image restoration is an inverse problem whose aim is to recover an image from a version of that image which has degraded with noise. Images are likely to be degraded by the sensing environment when acquired through optical, electro optical. The degradation may be in the form of sensor noise, blur due to camera motion, random atmospheric turbulence. For digitally acquired images noise can be summarized as the visible effect of an electronic error in the captured image. Noise is the function of how well the image sensor and digital signal processing system inside a digital camera are prone to and can cope with or minimize these errors. Noise significantly degrades the image quality and creating the discrimination in the image. It also complicates further image understanding. The sensor noise generated by typical charge couple device, CMOS sensors and channels can be modeled as a Gaussian, Salt & Pepper, Speckle and Poisson distribution with zero mean and noise density can be estimated from the degraded images [1][2][3]. In particular imaging degradation such as those result in image quantitative parameters that can be considered in statistics context as outliers. The problem to remove the noise can be treated as to obtaining the original image using outliers.

In the following part of this paper, a detailed account of a simple technique for image restoration with robust statistics introduced with results showing its effectiveness at restoring at synthetic noise degraded images from various fields.

IMAGE RESTORATION

Statistical characteristics of images are fundamental importance in many fields of image processing. Incorporation of priori statistical knowledge of special correlation in an image, in essence, can lead to considerable improvement in many image processing techniques. For removing noise, the well-known mean filter and median filter for minimum quantitative measure estimation is derived from a measure or an estimation from spectrum of the image in the transform domain, as well as the system function of the spatial degradation phenomenon and the spectrum of the noise power [6][7].The linear filtering techniques are designed under the consideration wide sense of stochastic process [8]. Although the stationary consideration for additive and multiplicative zero mean, Gaussian noise is valid for most cases, it is not reasonable for most realistic images from particular field.

Noises removing filtering techniques have been designed in the past with stochastic process i.e. stationary assumption. All these have the effect of removing noise at the expense of the signal structure, such as the fixed pixel size wiener filter and fixed window mean and median noise removal techniques have been the standard in noise smoothing for the past four decades[9][10][11][12]. These filters typically smooth out the degradation, but destroy the high frequency structure of the image in the filtering technique. This is mainly due to the fact that all these restoration techniques deal with the particular window size having sample points that are to the same statistical ensemble. For image from natural field, any given part of the natural scenes generally differs sufficiently from the other part so that the stationary assumption over the natural image or even inside a fixed window region is not generally valid. In the past two or more decades, the attention of researchers has to developing non-linear adaptive restoration technique. That takes in an account the non-stationary of most realistic still images. These non-linear techniques have been used as an alternative to restore the image as much as possible [12]-[18]. However, do this at the expense of the proper noise reduction, where the high frequency area will be insufficiently restored, which will result in a large amount of high magnitude noise remaining around edges in the image. Some class of non-linear estimations that are gaining popularity for the problem of the image restoration are the robust estimation based techniques which draw their statistical base from the field of robust statistics filtering had adapted for restoring the image in the research work of kashyap and Eon, how develop a robust estimation technique for AWGN and Salt & Pepper noise [19], under the assumption of image model is locally stationary and divided into fixed window i.e.3x3, 5x5. They Recent research work involving robust statistics based image restoration include by Hamza and Krim [20][21][22]. These techniques show promising experimental result at filtering mixed noise. The mean and median filter, the mean –relaxed median filter and mean–log Cauchy filter is explained in [22]. Propose wavelet based estimator using a robust loss function [23]. In contrast, our restoration technique described in research work is initially concerned with restoration medium to severity AWGN, Speckle, Poisson and impulse noise degraded images from diversified fields (i.e. Natural, Medical, Arial images) .

The nonlinear anisotropic diffusion techniques [23]-[27] have been widely studied for the application of image restoration since the early work of Perona and Malik [28][29] whose technique will be used for comparison. In research work on robust anisotropic diffusion used to robust estimation to deal with intensity discontinuities in the image from various fields and apply their robust formulation to remove the noise while assuming the outliers in the spatial image are those due to the pixel intensity discontinuities under the consideration of an optimal size adaptive windowing framework (circular window) and assume the outliers are only due to synthetic degradations, thus facilitating its removal as will be present in the experimental result in this paper. Related restoration technique by Tomasi and Manduchi is bilateral image [31] filtering, where a nonlinear hybrid filter is proposed which combines both domain and range filtering, with the range filtering component acting as an adaptive windowing technique. A connection of robust diffusion, bilateral restoration technique and adaptive windowing has been established in research work by [32], which is similar result to [30] [31].

In the remainder of this paper, we take a look at the problem of recovering Natural, Medical and Arial images degraded by AWGN, Speckle, Poisson and Salt & Pepper noise respectively when the observed image model differs statistically from a stationary model. We propose a robust statistics based restoration technique that will be shown to be preserving vital image structure which is simple to implementation.

This paper is organized as follows, section II describes the literature review section III describes some special aspects of the robust statistics. Optimal size adaptive windowing frame work discussed in section IV and experimental results are shown in section V. Section VI presents conclusion and future research direction.

POBUST STATISTICS FOR OUTLIER DETECTION

The field of robust statistics was developed to address the fact that parametric models of classical statistics are often approximations of the phenomenon being modeled [33][34]. In particular, the field addresses how to handle outliers or gross errors, which do not conform to the assumptions [35]. It also indicated that the model used is idealization that are frequently violated in practice and that the least square solution are particularly sensitive to such violations. To improve the robustness, without sacrificing the model to minimization problems to account for outliers by the robust estimator [35].

Robust statistics addresses the problem of finding the most suitable model as shown $p=\{p_0, p_1, p_2, p_3, ..., p_{s-1}\}$, to a set of data measurements. $q=[q_0, q_1, q_{2,} q_3, ...q_{s-1}\}$, in case where the data differs statistically from the model assumption. In appropriate model, goal is to find for the parameter of ; p; that minimize the size of the residual error $(q-p)$ .This minimization can be written as

$$\underset{p}{Min}\sum_{s\in S} ° ((q_s - p_s), ±_s) ....(1)$$

Where $±_s$ is a scale parameter, and ' ° ' is an estimator function. When the errors in the measurement are Poisson, Speckle and Gaussian distributed, Bipolar fixed valued impulse distribution the optimal estimator is the quadratic [36].

$$° ((q_s - p_s), ±_s) = \frac{(q_s - p_s)^2}{2±_s^{\ 2}} ....(2)$$

Which gives rise to the standard least square estimation problem, the function ' ° ' is known as M-estimator because it corresponds to the maximum likelihood estimate. The robustness of particular estimator refers to its tolerance to outliers.

The useful parameter of robustness is the breakdown value [37], which is the largest percentage of outlier data points that will not cause a deviation. The least-squares approach has breakdown value of zero percent due to introducing single outliers in the data sample will cause a deviation in the estimate from the required values. Estimator, a robust technique may have a breakdown value up to fifty percent, that is the estimator can cope with up to fifty percent of the data being outliers [36]. The influence function is a second measure of robustness, which is the change in an estimate caused by insertion of outlying data as a function of the distance of the data from estimate. The influence function of least square estimator is proportional to the distance of the data point $'q'$ from the model ' p'. A plot of quadratic estimator in equation (2) as function of the distance $(p-q)$ is shown in [38]. The influence function is the derivative of the estimator and clearly shows that the influence of outliers increases linearly.

The robustness redescending estimators for influence function tends to zero with increases distance Black and Rangrajan [38], for reconstructing a smooth surface from degraded data using robust statistics and choose the lorentzian robust estimator for being continuously differentiable and redescending influence function [38][30].

ROBUST RESTORATION TECHNIQUE

The tool of robust statistics to develop a frame work for the robust estimation of the still image, when the information is degraded image. This robust estimation formulation is based on simple idea of rejecting noisy pixels appearing in the degraded still image. In this restoration technique we use an observed image model with additive and multiplicative noise as follows.

$$q = p + n..........(3)$$

In which q, p and n are images which represent, respectively, the degraded image and additive noise of non-zero mean, $m_q = m_p$ and variance $\pm_s^2$. We consider the basic assumption about image model $\hat{p}$ as wide sense of stationary type in spatial coherent domain. In addition the assumption that the both original image p_s and the noises (additive and multiplicative) $n_s; S \in [0, N-1]$ for N-size of image are ergodic random variables. The implication of this assumption is although a priori knowledge of the image signal and noise statistical variance and mean $(\pm_s^2, m_p, m_q)$ in turn to representative of their respective ensembles. The variance is estimated from a window in a flat area of the noisy image q_s [39].

In this technique, approach is to estimate degraded image signal by using a cost function 'E' that enforces the assumption about estimate and image pixels intensities at particular coordinate, s, belongs to neighborhood samples, M. Typically M is considered to be (5x5) and (7x7) mask for processing[38][30]. The shortcoming of using small radius of circular window is lack of enough samples to give an accurate estimate of the statistics process. An obvious alternate is to use an adaptive analysis circular window. A circular spatial coherent window, whose weight are derived from two independent functions, one is spatial distance and second gray level distance are employed for restoration. This image restoration technique is differing from bilateral filter [40]. In this particular image restoration technique consists of distance kernel and gray level kernel. The circular shape kernel is moved invariably throughout the image to remove the degradation. The weighting function is used in gray scale kernel of circular spatial. Coherent is similar to the weighting function used in range restoration technique. In developing an effective adaptive circular window to account for the nonstationary of image data, it's required for analysis window to have the maximum size possible at each pixel position without crossing over image structure and boundaries. The reason is that more the number of spatial signal samples are available in the analysis the more accurate their statistical characteristics can be estimated [41]. The weighting function is exponential whereas nonlinear function in case of distance kernel of this particular restoration technique.

The spatial distance between any arbitrary pixel in a particular window position at point (p_i, q_i) and center pixel at point (p, q) is shown as

$$d_s = \left[\sqrt{(p_i - p)^2 + (q_i - q)^2}\right]^{1/2} ....(04)$$

'w_d' Distance kernel is can be calculated as

$$w_d = 1 - \frac{d_s}{d_{\max}} ....(05)$$

And $d_{\max}$ is the distance from point (p, q). Thus, the window grows in size circularly symmetrical, increasing to maximum size $M_{\max}$ of the image and decreasing to minimum size near the boundary of objects in the image [17][42]. The distance between any arbitrary pixels $g(p_i, q_i)$ of a particular window at location (p_i, q_i) at the center $g(p, q)$ is shown by equation (6). Restrictions on near–edge pixels having to reduce their redial distance to a single pixel.

$$d_g = \sqrt{\left|g^2(p_i - q_i) - g^2(p, q)\right|} ....(06)$$

In statistical process for this adaptive window framework, the cost function is minimizing which can be given by equation (7).

$$E(\hat{p}) = \sum_{i \in M} {}^{\circ}(q_i - \hat{p}_s, \pm_s) \text{........}(07)$$

Where '$\hat{p}$' the restored signal. And is $i \in [0,(M-1)]$ is a pixel location in the adaptive local neighborhood to the current pixel at the location 's'. Thus minimizing this cost function, aim is to minimizing the noise signal in that particular region. The selection of cost function is to motivated by the fact that proposed research scheme deal with pixel vales discontinuities using the circular size adaptive windowing framework, for robust estimator $^{\circ}((q_s - p_s), \pm)$ depends on the optimization solution used to minimize the cost function to error argument $(q_s - p_s)$ of $^{\circ}((q_s - p_s), \pm)$ in adaptive region M. The scheme used, which will be requires the estimator to be twice differentiable; the lorentzian robust estimator satisfies this criterion.

$$^{\circ}((q_s - p_s), \pm) = \log\left(1 + \frac{1}{2}\left(\frac{(q_s - p_s)}{\pm}\right)^2\right) \text{......}(8)$$

Where '$\pm$' is scale parameter in the robust estimator formulation that under control the outlier rejection points [34]. Reducing '$\pm$' will cause the estimator to reject more measurements as outliers and vice versa. This is very significant as we are concerned with Gaussian, Speckle, Poisson and bipolar fixed value impulse noise distribution in original image. The influence function $\cdot((q_s - p_s), \pm)$ is the first derivative of $^{\circ}((q_s - p_s), \pm)$ with respect to $(q_s - p_s)$.

$$\cdot((q_s - p_s), \pm) = \frac{2q_s - 2p_s}{2\pm^2 + (q_s - p_s)^2} \text{......}(9)$$

The robust formulation of our cost function 'E' may cause it to be non-convex according to successive over relation minimization technique because of rapid convergence [35]. The iterative equation minimizing 'E' over still image are

$$\hat{p}^{(t+1)} = \hat{p}^{(t)} - \frac{\text{«}\partial E}{T\partial \hat{p}^t} \text{........}(10)$$

Where q_s is the iterative step and S is the relaxation value that controls convergence, and numerical technique to an image for optimization. The initial condition $t = 0$ for current element estimate at S, is set to the current corrupted pixel value q_s. The condition for stopping the iteration has been chosen such that the difference between the next estimate. The estimate $\left|\hat{p}^{(t+1)} - \hat{p}^{(t)}\right|$ falls below the current value of the outlier rejection point indicating that any outliers has been restored and that the ensemble average in the adaptive circular window. The 'T' is upper bound on the second partial derivatives of 'E' and calculated when $(q_s - p_s = 0)$, which yields

$$T = \frac{1}{\pm^2} \text{...........}(11)$$

A global minimum found by constructing an initially convex approximation to the cost function when greater than zero; by choosing initial values of the, $\pm$, to sufficiently large.

$$\pm = \frac{2_s}{\sqrt{2}} \text{.......}(12)$$

Where, 2_s is the maximum expected outlier in the argument of $^{\circ}(q_s = p_s)$, to degrading the 'E' for convex approximation. Large '$\pm$' values, the '$\cdot$' is approximately linear and '$^{\circ}$' is quadratic. We can select

$^{2}{}_{s}$ to be proportional to the estimation of the standard deviation within neighborhood set of pixels from region M as shown as

$$^{2}{}_{s} = \text{¸}\, \pm_{M} ......(13)$$

In image region, $\pm_{M}$ will be an estimate the degradation standard deviation $\pm_{n}$, $\pm_{M}$? $\pm_{n}$ in busy area. It is equal to the uncorrupted image standard deviation $\pm_{p}$. The value of $^{2}{}_{s}$ is variant according to size of adaptive circular window of the pixel located at position s , and '¸' is a scalar that affects the amount of smoothing and empirical chosen to provide better restoration result. If the value of ¸ is large then scheme reach to the standard least square estimation method. In the other side, the value of ¸ is less then reduce outlier contribution , at the risk of creating an initially nonconvex and gets to start the optimization process. An appropriate value of ¸ needs to be chose such that the initial minimization process uses enough samples from window [36]. Global minima using the Graduated nonconvexcity continuation technique helps to obtain the value of $\pm$ from one iteration to next, described in [43].

EXPERIMENTAL RESULTS

In this section, experimental results are presented to show the performance analysis of robust estimation for image restoration technique. In this particular scheme to applied additive white Gaussian noise, Poisson, Speckle and salt & Pepper noise corrupted digital still images and to compare its performance with few restoration technique available in literature. The bilateral restoration technique [32] and wavelet based restoration techniques considered to compare the results. The reason for choosing to compare our results with these techniques due to availability on www.csse.uwa.edu and evaluating the performance of individual restoration techniques. Comparing obtained result with NL Mean because that is nonlinear restoration technique to degraded images by AWGN, Poisson, speckle and salt & pepper noise respectively with diversified field images. All techniques are implemented in MATLAB 7.2.0 with the suitable combination according to the noise and restoration technique, as well as to find various quality metrics MSE and PSNR. Performance of schemes evaluated individually, its importance of objective and subjective analysis has taken under consideration. The universal quantitative measure mean square error is obtained between original image p and estimated image $\hat{p}$. The short coming of MSE is sensitive to minor changes in pixel intensities between the original and restored image. Robust quantitative measure of restoration technique performance that has been widely used by the digital image processing community is the Peak Signal to Noise Ratio as shown by

$$PSNR = 20\log_{10}\left(\frac{256-1}{\sqrt{\frac{1}{S}\sum_{s=0}^{S-1}(p_s-\hat{p}_s)^2}}\right)....(14)$$

The size of image 'S' is 256x256 gray level, PSNR is less sensitive to minor deviation and adapted for comparing the performance of various restoration methods. However, the objective measures like PSNR and MSE metrics are not necessarily correlated to our perception of a restored image [7]. The measure of fidelity will have to remain human perception, which is very subjective. For example, it is required extra smoothing of the restored image when the fine details are significant, in which case peak signal to noise ratio values in dB will not be optimum. Interest to preserve the most minute details the restored image, which contain some residual noise to remain after the restoration practice. In this subjective evaluation into an account, we test our scheme on seven standard set of Medical, Natural and Arial images commonly used for evaluation of performance in image processing as shown in Fig.1.

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Figure 1. Ideal Original Images of size 256 x 256, 256 gray levels, Medical Field: (a) Apperts (b) Bone (c) Brain; Natural Field; (d) Baboon (e) House; Arial Field: (f) Planet (g) Chemical Plant.

Table I summarize the result for all seven restored images from diversified fields, degraded by different four kinds of noise, Gaussian, Poisson, Speckle and salt & Pepper noise. We start by showing simulation result of performance of circular adaptive windowing robust restoration technique using the standard aperts gray level image in size of 256x256 from medical field as shown in Fig.2 (a) which was degraded by Gaussian noise (b) and after restoring the same PSNR=36.53dB as shown in (c). It is clear that NL-Mean filter is suitable because the PSNR=37.34dB after restoration process to Gaussian noise. The performance of our scheme is better than remaining three to Poisson noise (PSNR=40.43dB), Speckle (PSNR=36.03dB), and Salt & Pepper noise (PSNR=39.62dB).

In this experiment, we have applied medical image (Bone) in size 256x256 to restored by the robust technique, same scenario occurs, better performance showing to Poisson noise (PSNR=34.77dB), Speckle noise (PSNR=32.82dB), and Salt & Pepper noise (PSNR=34.44dB), not to Gaussian noise (PSNR=32.25dB). And same performance is showing to the Brain image also from medical field.

We now present the performance of our second experiment which involves restoring house and baboon images from natural field. In this experiment, it is clear that the performance of robust technique is better to Poisson noise, Speckle noise, and Salt & Pepper noise as shown in Table I. The performance of robust method to Gaussian noise is less than remaining three mentioned in Table I.

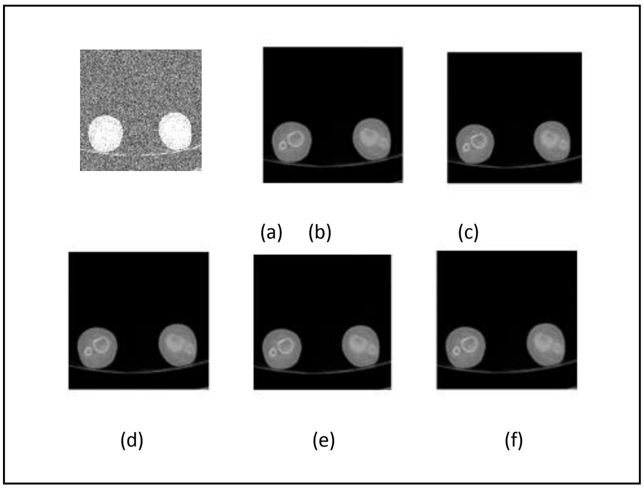

Figure 2. (a) Degraded version of the medical apperts image by AWGN of standard deviation (30) with PSNR 17.25dB. (b) Restored image of robust restoration technique with adaptive circular window size (5x5) neighborhood pixels (PSNR=36.53dB) (c) Restored image by Nl-mean (PSNR=37.34dB) (d) Restored image with PSNR=40.43dB (this is the highest PSNR value while reducing the Poisson noise) (e) Image while reducing the Speckle noise with PSNR= 36.03dB (f) Denoised image to Salt & Pepper noise with PSNR=39.62dB.

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We present the result of our third experiment which involves aerial images that was contaminated by Gaussian, Poisson, Speckle, and Salt & Pepper noise respectively. It is providing results objectively in terms of its PSNR values in dB and subjectively by direct visual perception. As we tackle the problem to balance between the maximum size of window $M_{\max}$ (5x5). If the size of window is increases performance decreases. In these experiments, we have chosen the values that are utilized to all images (« = 0.4 & ¸ = 0.3). Finally, we represent overall performance in comparison with other three restoration techniques for the Medical, Natural and Arial images with Gaussian, Poisson, Speckle and Salt & Pepper noise respectively as shown in Table I. The comparisons clearly show the merits of robustness technique both objectively in terms of its higher PSNR values in dB, compared to other three techniques at the same noise density.

CONCLUSION

This paper has presented a restoration technique based on the theory of robust statistics with the help of cost function. A cost function is robustified by using the Lorentzian robust estimator and minimized by a *Graduated Non-Convexity* (GNC) to obtain the global minima when the cost function is non-convex. A newly represented adaptive circular windowing frame work is adapted in the formulation of the robustness restoration restoration technique to improve the neighborhood statistical estimates. Experimental results are presented to show the performance analysis of the robust image restoration techniques and comparison are made with three other three restoration techniques. Results have shown the restoration technique to be highly effective to reduce the Poisson noise, Speckle noise, and Salt & Pepper noise from Medical, Natural and Arial field images. It is also showing the moderate effectiveness at reducing Gaussian noise from Natural and areal field images while restoring the fine details. In the future work, the research can be extended to produce the automatic system to all kind of images from diversified fields degraded by a mixture of noise distribution and synthetic noise.

TABLE 1: COMPARATIVE RESULT EXPRESSED AS MAXIMUM PSNR IN DECIBEL FOR THE VARIOUS RESTORATION TECHNIQUES. HIGHEST PSNR VALUES FOR EACH NOISE GAUSSIAN, POISSON, SPECKLE AND SALT & PEPPER NOISE RESPECTIVELY IN A BOLD FONT

Field	**Type of Image**	**Noise**	**Robustness (Proposed)**	**Diffusion**	**Bilateral Nonlinear**	**Non local (NL) Mean**
Medical	Bone	Gaussian	32.25	19.89	31.76	**36.88**
		Poisson	**34.77**	20.20	31.07	32.59
		Speckle	**32.82**	20.23	30.78	28.68
		Salt & Pepper	**34.44**	20.02	27.97	25.40
	Apperts	Gaussian	36.53	23.07	30.88	**37.34**
		Poisson	**40.43**	24.49	31.98	34.62
		Speckle	**36.03**	24.46	29.06	29.58
		Salt & Pepper	**39.62**	23.72	29.12	28.98
	Brain	Gaussian	31.25	20.57	31.44	**36.59**
		Poisson	35.56	20.76	30.17	**32.93**
		Speckle	**32.65**	20.75	29.13	28.92
		Salt & Pepper	**35.04**	20.63	27.20	23.10
Natural	Baboon	Gaussian	29.92	14.84	**31.25**	29.51

Field	Type of Image	Noise	Robustness (Proposed)	Diffusion	Bilateral Nonlinear	Non local (NL) Mean
		Poisson	**32.15**	14.86	27.33	27.52
		Speckle	**29.31**	14.84	25.34	27.30
		Salt & Pepper	**31.39**	14.82	26.20	30.66
	House	Gaussian	30.25	16.43	**31.98**	31.44
		Poisson	**34.18**	16.42	28.55	31.77
		Speckle	30.68	16.41	26.71	**32.20**
		Salt & Pepper	**33.24**	16.40	27.36	32.22
Arial	Plannet	Gaussian	30.33	16.27	32.08	**33.25**
		Poisson	**34.30**	16.28	28.09	33.72
		Speckle	**29.96**	16.27	29.50	29.23
		Salt & Pepper	**33.47**	11.24	29.50	25.25
	Chemical Plant	Gaussian	29.98	13.55	**31.79**	31.44
		Poisson	**32.36**	13.56	27.74	31.77
		Speckle	**29.35**	13.51	25.61	28.67
		Salt & Pepper	**31.79**	13.52	28.43	29.64

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REFERENCES

[1] F.Naderi, “Estimation and Detection of image degraded by film-grain noise,” Uni. Of Southern California, Los Angeles, Tech Rep. USCIPI690, Sep.,1976.
[2] ocieE.Haugh, “A structural theory of the selwyn granularity coeffiucient,” Journal of photo. s. Clerk Maxwell, A Treatise on ty, vol.11, no.65, 1963.
[3] G.Higgins, K. Slultz, “Experimental study of the RMS granularity as a function of scwnning spot size,” journal of opt.soc.Amer., vol.49,no. 925,1959.
[4] Hampel, “the enfluence curve and its role in robust estimation,” Journal of American Statistics Asso. Vol. 69, no. 346, pp. 383-393, 1974.
[5] M.J.Blak and P.R.Anandan, “A robust gradient method for determining optical flow,” yale Uinversity , Feb. 1992.
[6] N. Wiener, Extrapolatio, Interpolation and smoothing stationary time series, Cambridge , MA:MIT Press, 1942.
[7] K. Castleman, Digital Image Processing, Englewood Cliffs, Prentice hall, 1996.
[8] A. Papoulis, Probability, Ramdom variables, Stochastic Processes, Third Edition, New-York, Mgraw Hill 1991.
[9] A. Hillery and R. Chin, “Iterative wiener filter filter for image restoration,” IEEE Transaction, SP, Vol.39, no. 08, pp.1892-1899.
[10] M.Sonaka and V. Hlavac, and R, Boyl, Image processing analysis and Machine Vision, Second Ed., Boston MA: PWS-Kent, 1999.
[11] S. Rajala and R.DeFigueirredo, “ Adaptive nonlinear image restoration be a modified kalman filtering approach ,” IEEE Trans. ASSP, vol.29, no. 05, pp. 1033-1042, Oct. 1981.

[12] Anil L. Wanare, Dilip D. Shah, “Performance analysis and optimization of Nonlinear restoration techniques in spatial domain,” Inter National Journal of Image Processing, (IJIP), Vol. 06, no. 02, pp. 123-137, April 2012.
[13] Douglas S.C. , “Analysis and Implimentation of NLMS Adaptive filter,” comf., Signals & Systems, CA, pp. 659-663,
[14] C.Pomalaza-Raez, and C. Mcgllam, “An adaptive nonlinear edge preserving filter,” IEEE trans, Acoust. Speech, Signal Processing., vol.32, no. 03, pp. 571-576, June 1984.
[15] A. Flaig, G.R. Arce, and K.E. Barner, “Affine order statistic filters:A data adaptive filtering framework for nonstationary signals,” Proc. IEEE int. conf. ASSP, 1997, pp. 2145-2148, 1997.
[16] J.Park, W.Song, and W. pearlman, “Spekle filtering of sar images based on adaptive windowing.” Proeding Inst. Elect.Engg. vol.146, no4, pp 191-197, 1999.
[17] M. Black, D. Fleet, and Y. Yacoob, “Robustly estimating changes in image appearane,” Computer vision and image underatand, vol. 78, pp. 8-31, 2000,
[18] R. Kashyap, K.Eom, “Robust image modeling techniques with an image restoration application,” IEEE Trans, ASSP, vol. 36, no. 8, pp. 1313-1325, August 1988.
[19] A. Hamza, H.Krim, “Image denoising:A nonlinear robust statistical approach,” IEEE Trans. Signal Processing, vol. 19, no. 12, pp. 3045-3054, December 2001.
[20] H. Eng and K. Ma, “Noise adaptive soft-switching median filter,” IEEE Transaction Image Processing, vol. 10, no.02, pp. 241-252, 2001.
[21] V.I. Ponomaryov, F.J.G. Funes, O.B. Pogrebnyak, L.N. De Rivera, “Denoising robust image filter with retention of small size details in presence of complex noise mixture,” Proceding SPIE Conf, vol. 4671 II, pp. 877-887, CA, Jan. 2002.
[22] S. Sardy, P. Tseng, and A. Brace, “Robust wavelet denoising,” IEEE Transactio Signal Processing, vol. 49, no.06, pp. 1146-1152, Jun. 2001.
[23] C.Zhu, D.Mumford, “Prior learning and gibbs reaction-diffusion,” IEEE Trans. PAMI, vol. 19, no. 11, pp. 1236-1250, Nov.1997.
[24] J.Wieckert, “Application of nonlinear diffusion in image processing and computer vision,” proceding Algoritmy Acta Math. University of Comeneane, vol. LXX, pp.33-50, 2001.
[25] P.Mrazek, Nonlinear diffusion for image filtering and monotonicity enhancement ,”Ph.D. Thesis, Czech Tech. University Prague, Czech Republic , June 2001.
[26] D.Tschumperl, R.Deriche, “Vector valued image regularization with PDE,” IEEE conference computer vision pattern recognition, Madison, WI, June 2003.
[27] P. Perona, J. Malik, “Scale Space and edge detection using anisotropic diffusion,” IEEE Procedings workshop on computer vision,pp. 16-27, 1987.
[28] J.Baudin, A. Witkin, Badin, and R. Duda, “Uniqueness of the gaussian kernel for scale space filtering ,” IEEE Trans. On PAMT, Jan. 1986.
[29] M.Black, G.Sapira, D.Marimont, D.Heeger, “Robust anisotropic diffusion,” IEEE Transaction on IP, vol. 07, no. 3, pp. 421-432, March 1998.
[30] C. Tomasi, R. Manduchi, “Bilateral filtering for gray and color image,” IEEE conf. computer vision, Bombay, India,1998.
[31] D.Barash, D.Comaniciu, “A common framework for nonlinear diffusion, adaptive smoothing bilateral filtering and mean shift,” Image video computer, vol. 22, no. 01, pp. 73-81, 2004.
[32] P.Huber, Robust statistics., New York, Wiley, 1981.
[33] F.Hampel, E ronchetti, P.Rausseeuw, and W. Stahel, Robust statistics:The approach based on influence function. New York, Wiley 1986.
[34] M.Black, “Robust incremental optical flow,” Yale University, Technical Rep.YALEU/DCS/RR-923,1992.
[35] Sunghyun Cho, Jue Wong, Seunguong Lee, “Handling outliers in non-blind image deconvolution,” ICCV 2011.
[36] P.Rousseeuw, A. Leroy, “Robust regression and outliers detection. New York, Wiley 1987.
[37] M.Black and A. Rangarajan. The outlier process : Unifying line processes and robust statistics . IEEE Conference CVPR.
[38] P. Chan and J. Lim, One dimentional processing for adaptive image restoration,” IEEE transaction on ASSP, vol.33, no.01, pp. 117-129, 1985.
[39] R.Rockfellar, Convex Analysis, Princeton University Press. 1970.
[40] Y.Boykov, O.Veksler, R.Zabih, “A variable window approach to early vision,” IEEE transaction PAMI, vol. 20, no12, pp. 1283-1294, December 1998.

[41] K.Egiazarian, V.Katkovnik, J.Astola, "Adaptive window size image denoising based on ici rule," Procedings ICASSP, May 2001, pp. 1869-1872.
[42] A.Black, A.Zisserman, Eds, Visual Reconstruction. Cambridge MA: MIT Press, 1987.
[43] Pietro Perona, Jitendra Malik, "Scale –space and edge detection using anisotropic diffusion," IEEE trans. PAMI, vol.12, no.7, pp. 629-639, July 1990.
[44] J.Portilla, V.Strela, M.Wainwright, E. Simonselli, " Image denoising using Gaussian scale mixture in the wavelet domain." New York Technical repre. TR2002-831, 2002.
[45] R. Chan and C Hu, "An iterative Procedure for removing random valued impulse noise," IEEE Trans. SPL, vol.11, pp. 921-924, 2004.