Hybrid Noise Removal in Color Images using Wavelet Shrinkage Approaches of PURE-LET and Neighshrink SURE

P. Karthikeyan, S. Vasuki and G. Veera SenthilKumar

Abstract: Image denoising is an indispensable task where the complication of noise is prevalent and the contrast of low cost surveillance camera is more over low due to various image acquisitions. For the past two decades, denoising is performed by the Wavelet transform. The proposed work presents a novel approach of denoising by Poisson Unbiased Risk Estimate-Linear Expansion of Threshold (PURE-LET) and Neighshrink-Stein's Unbiased Risk Estimate (SURE) for mixed Poisson and Gaussian noise. Finally the potential of the proposed approach through extensive comparisons with state-of-the-art techniques that are specifically tailored to the estimation of Poisson intensities are demonstrated. Neigh Shrink is an efficient image denoising algorithm based on the Discrete Wavelet Transform (DWT).The observed results reported here are in encouraging agreement.

Keywords: Wavelet transform, mixed Poisson and Gaussian noise, PURE-LET, Neighshrink-SURE.

I. INTRODUCTION

Image noise comes from variety of sources. No imaging method is free of noise, but noise, but noise is much more prevalent in certain type of imaging procedures than in others. Solar Bust images are generally noisiest. The most significant factor is that noise can cover and reduce the visibility is especially significant for low-contrast objects.[1 2] Furthermore, noise can be introduced by transmission errors and compression. So it is necessary to apply an efficient denoising technique to compensate such data corruption. Image denoising still remains a challenge because noise removal introduces artifacts and causes blurring of the images. This paper describes different methodologies for noise reduction or denoising giving an insight as to which algorithm should be used to find the most reliable estimate of the original image length data given its degraded Version. Noise modeling in images is greatly affected by capturing instruments, data transmission media, image quantization and discrete sources are of radiation. Different algorithms are used depending on the noise model. Most of the natural images are assumed to have additive random noise which is modeled as a Gaussian. The two predominant sources of noise in digital image acquisition are:

1) The stochastic nature of the photon-counting process at the detectors;
2) The intrinsic thermal and electronic fluctuations of the acquisition devices.

Under standard illumination conditions, the second source of noise, which is signal-independent, is stronger than the first one. This motivates the usual Additive-White-Gaussian-Noise (AWGN) assumption. However, in many applications such as fluorescence microscopy or astronomy, only a few photons are collected by the photo sensors, due to various physical constraints (low-power light source, short exposure time, photo toxicity).Under these imaging conditions, the major source of noise is strongly signal-dependent. Consequently, it is more reasonable to model the output of the detectors as a Poisson-distributed random vector.

II. MULTISCALE ANALYSIS

Many directional wavelet transforms have been developed under the multi-scale analysis framework, including steerable wavelets, wedgelets, curvelets, contourlets, and directionlets. While these methods can accurately represent point wise singularities, they are weak in representing other discontinuities such as contours and edge in images. By using effective PURE-LET and Neighshrink SURE, both Poisson and Gaussian noise can be eliminated. Fast and high-quality nonlinear algorithms for denoising digital images corrupted by mixed Poisson-Gaussian noise [10] were proposed in this paper. The practical approximation of MSE estimate for the tractable optimization of arbitrary transform-domain thresholding is provided. A point wise estimator for undecimated filter bank transforms, which consists of sub band-adaptive thresholding functions with signal-dependent thresholds that are globally optimized in the image domain by PURE-LET.

PURE-LET proposed as noise removal strategy from Poisson-count images. Specifically, PURE is an unbiased estimate, defined in the Haar wavelet domain, of the mean-squared error between the original image and the estimated image. PURE-LET attempts to estimate the true image from the noisy image by minimizing PURE. PURE-LET involves inversion of a small size matrix.

III. THEORITICALBACKGROUND

A. White Gaussian Noise Modeling

Additive White Gaussian Noise (**AWGN**) is a channel model in which the only impairment to communication is a linear addition of wideband or white noise with a constant spectral density (expressed as watts per hertz of bandwidth) and a Gaussian distribution of amplitude. The model does not account for fading, frequency selectivity, interference, nonlinearity or dispersion. However, it produces simple and tractable mathematical models which are useful for gaining insight into the underlying behavior of a system before these other phenomena are considered. The Probability Density Function (PDF) of a Gaussian random variable, x, is given as

$$G(x) = \frac{1}{\sqrt{2\pi\sigma}} e^{-(x-\bar{x})^2/2\sigma^2} \quad (1)$$

Where x represents the intensity value, $\bar{x}$ is the mean value of x, and σ is the standard deviation. The noisy image model is expressed as

$$g(i, j) = f(i, j)+N(i, j), \quad (2)$$

Where g and f respectively represent noisy and noise-free images, and $N(i, j)$ is the AWGN noise.

B. Poisson Noise Model

The parameter λ is not only the *mean* number of occurrences $E[k]$, but also its variance

$$\sigma_k^2 = E[k^2] - [E[k]]^2 \qquad (3)$$

Thus, the number of observed occurrences fluctuates about its mean λ with a standard deviation $\sigma_k = \sqrt{\lambda}$. These fluctuations are denoted as Poisson noise or (particularly in electronics) as shot noise. The correlation of the mean and standard deviation in counting independent discrete occurrences is useful scientifically. By monitoring how the fluctuations vary with the mean signal, one can estimate the contribution of a single occurrence, even if that contribution is too small to be detected directly. For example, the charge e on an electron can be estimated by correlating the magnitude of an electric current.

IV. ALGORITHM STEPS TO DENOISE BY NEIGHSHRINK SURE

Following steps are involved in the denoising algorithm

1. Perform forward 2D wavelet decomposition on the noisy image.
2. Apply the proposed shrinkage scheme to threshold the wavelet coefficients using a neighborhood window and the universal threshold
3. Perform inverse 2D wavelet transform on the thresholding wavelet coefficients.

V. THE PURELET APPROACH

The fundamental tool is a statistical estimate of the Mean Square Error (MSE), or ‘‘risk’’, between the (unknown) noiseless image and the processed noisy image. Owing to the Poisson noise hypothesis, we refer to this result as the PURE; this is the equivalent of Stein’s unbiased risk estimate (SURE) which holds for Gaussian statistics. In particular, interscale PURE were developed. Minimization of this MSE estimate over a collection of ‘‘acceptable’’ denoising processes to find the best one, in the sense of the Signal-to-Noise Ratio (SNR), which is a widespread measure of restoration quality [8].To our knowledge, this is actually the first reported use of an (unbiased) MSE estimate in the Poisson-noise case for image processing. The efficiency of our method stems from the use of a simple normalized Haar-wavelet transform and from the concept of Linear Expansion of Thresholds (LET): the’ acceptable’’ denoising processes are expressed as a linear combination of elementary denoising processes, from which only the weights are unknown. It is these weights that are then computed by minimizing the PURE, through the resolution of a simple linear system of equations. This means that all the parameters of the algorithm are adjusted completely automatically, without requiring user input. For each sub band, our restoration functions involve several parameters, which provide more flexibility than standard single-parameter thresholding functions. Importantly, the thresholds are adapted to local estimates of the (signal-dependent) noise variance; this is a fundamental difference with our previous work [7]. These estimates are derived from the corresponding low-pass coefficients at the same scale; the latter are also used to incorporate inter-scale relationships into the denoising functions. The resulting procedure can be easily integrated into the wavelet decomposition, which is non-redundant. The MSE estimate is optimized independently for each sub band by exploiting the orthogonality of the Haar wavelet basis. As a result, our algorithm has low computational complexity and modest memory requirements. These are valuable features for denoising large data sets, such as those typically produced in biomedical applications. Importantly, this computational efficiency is not traded for quality. On the contrary, the algorithm yields improved results compared to traditional Gaussian-inspired approaches, and it performs competitively with state-of- the-art multiscale method that was specially developed for Poisson data[9].

VI. NEIGHSHRINK METHOD

VisuShrink is very simple, but its disadvantage is to yield overly smoothed images because the universal threshold T is too large. Just like VisuShrink, Sure Shrink also applies the soft shrinkage rule, but it uses independently chosen thresholds for each sub band through the minimization of the Stein’s unbiased Risk estimate (SURE). Sure Shrink performs better than VisuShrink, producing more detailed images.

They threshold the wavelet coefficients in overlapping blocks rather than individually or term by term as VisuShrink or Sure Shrink. The basic motivation of block thresholding remains: a coefficient is more likely to contain signal if neighboring coefficients do also. The applied NeighCoeff to image denoising and their method is called Neighshrink[4]. Neighshrink outperforms VisuShrink and Sure Shrink. It is well known that increasing the redundancy of Wavelet transforms can significantly improve the denoising performances. The vanishing moments is used for the wavelet decomposition. All detailed scales except the five coarsest scales are thresholded using the universal threshold. Note that this threshold is the same as Donoho’s threshold for 1D signal except the replacement of 1D signal with 2D image [3].

VisuShrink does not have any denoising power when the noise level is low. Under such a condition, VisuShrink produces even worse results than the original noisy images. However, Neighshrink performs very well in this case. When the noise level is low, the improvement is large. When the noise level is high, the improvement is low. By studying the denoised images, Neighshrink produces smoother and clearer denoised images. The wavelet coefficients are threshold by looking at the average value in the neighborhood window. Conducting this experiment in this paper taking the average of the wavelet coefficients in the neighborhood window is a natural choice. Unfortunately, it does not provide better performance. Hence these experiments are done using Neighshrink.

Let $g = \{g_{ij}\}$ will denote the matrix representation of the noisy signal. Then, $w=W_g$ denotes the matrix of wavelet coefficients of the signal under consideration. For every value of wij, let B_{ij} is a neighbouring window around $w_{ij,}$ w_{ij} denotes the wavelet coefficient to be shrinked. The neighbouring window size can be represented as L*L, where L is a positive odd number. A 3*3 neighbouring window centered at the wavelet coefficient to be shrinked is shown in Fig.1

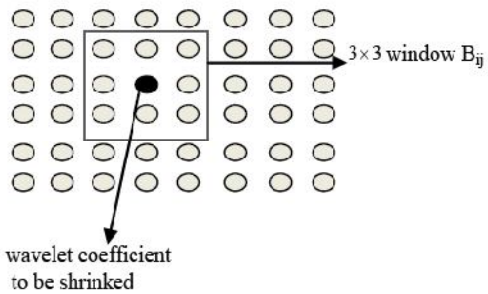


Fig.1 An illustration of the neighboring window of size 3*3 centered at the wavelet coefficient to be shrinked.

Let $S_{ij} = \sum_{(k,l)\in B_{ij}} w_{kl}^2$ (3)

Omit the corresponding terms in the summation when the above summation has pixel indexes out of the wavelet sub-band range. The shrinked wavelet coefficient according to the Neighshrink is given by this formula

$$w'_{ij} = w_{ij} w'_{ij} \quad (4)$$

The shrinkage factor βij can be defined as:

$$\beta_{ij} = (1 - T_{UNI}^2 / S_{ij}^2)_+ \quad (5)$$

Here, the + sign at the end of the formula means to keep the positive value while set it to zero when it is negative and T_{UNI} is the universal threshold, which is defined as

$$T_{UNI} = \sqrt{2\sigma^2 \ln(n)} \quad (6)$$

Where 'n' is the length of the signal.

Different wavelet coefficient sub-bands are shrinked independently, but the universal threshold T_{UNI} and neighbouring window size L kept unchanged in all sub-bands. The estimated denoised signal $f' = f'_{ij}$ is calculated by taking the inverse wavelet transform of the shrinked wavelet coefficients w'_{ij} i.e. $f' = W^{-1}w'$.

In order to determine the modified Neighshrink the optimal threshold and neighboring window size are calculated as,

$$(\lambda^s, L^s) = \arg_{\lambda,L} \min SURE(w_s, \lambda, L) \quad (7)$$

Where λ is optimal threshold, L is neighbouring window size , s is sub band and

$$SURE(w_s, \lambda, L) = Ns + \Sigma \|gn(wn)\|^2_2 + 2\,\Sigma \frac{\partial g_n}{w_n}$$

$$gn(wn) = \begin{cases} -\lambda^2 / w_n \\ -w_n \end{cases} \quad (8)$$

VII. The Proposed Noise Reduction Framework

The proposed work presents a novel approach of denoising by pure-let and Neighshrink sure for mixed Poisson and Gaussian noise.

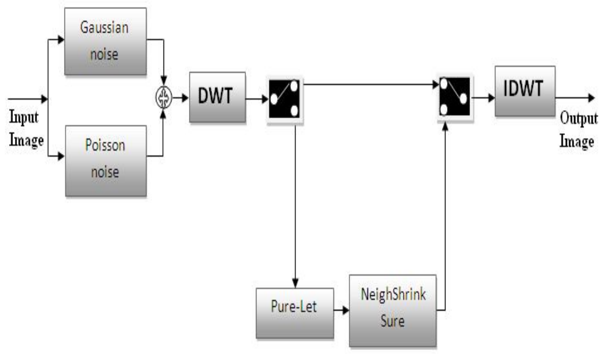


Fig.2.Proposed NeighShrink SURE with PURE-LET Method

Following steps are involved in the denoising algorithm in Fig.2

1. The Poisson and Gaussian noise are added to the input image.
2. Perform forward 2D wavelet decomposition on the noisy image.
3. Apply the Pure-Let to threshold the wavelet coefficients using minimum MSE.
4. Apply NeighShrink Sure to threshold the wavelet coefficients using neighbourhood window and optimum threshold.
5. Perform inverse 2D wavelet transform on the thresholded wavelet coefficients.

VIII. Evaluation

A. Evaluation Mehodology

Image enhancement quality is difficult to assess. Considerable literature exists relative to image quality estimation. However, this is most often in the context of image compression where the problem is to estimate the distortion or the loss of information, with criteria other than PSNR (peak signal to noise ratio), because PSNR does not reflect errors in the way that the human vision system does.References.

Number citations consecutively in square brackets [1]. The sentence punctuation follows the brackets [2]. Multiple references [2], [3] are each numbered with separate brackets [1]–[3]. When citing a section in a book, please give the relevant page numbers [2]. In sentences, refer simply to the reference number, as in [3]. Do not use "Ref. [3]" or "reference [3]" except at the beginning of a sentence: "Reference [3] shows.

Please note that the references at the end of this document are in the preferred referencing style. Give all authors' names; do not use "*et al.*" unless there are five authors or more. Use a space after authors' initials. Papers that have not been published should be cited as "unpublished" [4]. Papers that have been submitted for publication should be cited as "submitted for publication" [5]. Papers that have been accepted for publication, but not yet specified for an issue should be cited as "to be published" [6]. Please give affiliations and addresses for private communications [7].

B. *Qualitative Differences*

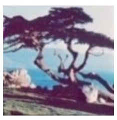
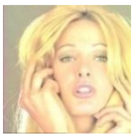
- The PSNR is the most commonly used as a measure of quality of reconstruction in image denoising. The PSNR for both noisy and denoised images were identified using the following formulae:

$$MSE=\frac{1}{mn}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}||I(i,j)-k(i,j)||^2 \qquad (9)$$

- Mean Square Error (MSE) which requires two *m* x *n* grey-scale images *I* and *K* where one of the images is considered as a noisy approximation of the other is defined as:
  The PSNR is defined as:
  Here, MAX_I is the maximum pixel value of the image).

$$PSNR=10.\ log_{10}\left(\frac{MAX_I^2}{MSE}\right)=20.\ log_{10}\left(\frac{MAX_I}{\sqrt{MSE}}\right)$$
(10)

TABLE 1:
COMPARISON RESULTS OF VARIOUS NATURAL IMAGES USING NEIGHSHRINKSURE PURE-LET METHOD

Input Images	**Methods**	**PSNR value in dB**			
		σ = 5	σ = 10	σ = 15	σ = 20
	PURE-LET	32.3375	28.3173	24.9452	22.3874
	Proposed Algorithm	33.8563	32.3935	31.1393	30.0787
	PURE-LET	32.8063	28.9574	25.4457	22.7284
	Proposed Algorithm	34.2982	33.1289	31.6475	30.4244
	PURE-LET	32.0768	28.9225	25.5195	22.8313
	Proposed Algorithm	33.2242	32.2226	31.0873	30.0687
	PURE-LET	29.7434	27.4226	24.7491	22.4042
	Proposed Algorithm	30.4194	29.2578	27.9214	26.7788
	PURE-LET	31.7988	29.1508	25.9120	23.1719
	Proposed Algorithm	32.7246	32.0206	31.2396	30.5521

- An examination of the details of the restored images is instructive. One notices that the decimated wavelet transform exhibits distortions of the boundaries and suffers substantial loss of important detail .The undecimated wavelet transform gives better boundaries, but completely omits to reconstruct certain ridges in the hatband. In addition, it exhibits numerous small-scale embedded blemishes; setting higher thresholds to avoid these blemishes would cause even more of the intrinsic structure to be missed.

IX. EXPERIMENTAL RESULTS

The experiments are conducted on several natural test images like Girl, House of size 256X256 and 512X512 at different noise levels σ = 5, 10, 15, 20. The experimental results are measured by the peak signal-to-noise ratio (PSNR) in decibels (dB) as mentioned in (10). Our proposed algorithm provides better result than PURE-LET method. The results are tabulated in table1. Fig.3 shows the resultant denoised Girl image with a noise variance of 20.

Fig.3. (a) Noise-free Image Girl. (b) Noisy Image: σ =20. (c) Result of Pure-let: PSNR = 23.1719dB. (d) Result of proposed algorithm : PSNR = 30.5521dB.

X. CONCLUSION

In this paper, a powerful method is proposed to address the issue of image recovery from its noisy counterpart. It is based on the generalized Gaussian and Poisson distribution modeling of sub band coefficients. The image is added with Gaussian and Poisson noise and denoising algorithm is implemented. As a result the wavelet coefficients are shrinked using the Neighshrink SURE. Thus noises are eliminated in the images. From the result it shows that the PSNR value in the proposed method is improved and the edges are preserved. Experiments are conducted and the performance of Pure-let and the proposed algorithm are tabulated.

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