A Review on Image Denoising over AWGN Channel

Pallavi Charde, Prof. P. S. Mohod

G.H.Raisoni College of Engineering and Technology for Women, Nagpur

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 process of removing noise from the original image is still a demanding problem for researchers. There have been several algorithms and each has its assumptions, merits, and demerits. The prime focus of this paper is related to the pre processing of an image before it can be used in applications. The pre processing is done by de-noising of images. Image denoising algorithms are applied on images to remove the different types of noise that are either present in the image during capturing or injected into the image during transmission. In this paper, we propose fast and high-quality nonlinear algorithm for denoising digital images corrupted by mixed Poisson-Gaussian noise over Additive White Gaussian Channel (AWGN) Channel. The proposed work presents a novel approach of denoising by Poisson Unbiased Risk Estimate-Linear Expansion of Threshold (PURE-LET) Stein's unbiased risk estimate-Linear Expansion of Threshold (SURE-LET).

Keywords: *Image, Noise, Image denoising, PURE-LET, SURE-LET.*

Introduction

An image is a two dimensional function f(x, y), where x and y are plane coordinates, and the amplitude of f at any pair of coordinates (x, y) is called the gray level or intensity of the image at that point. Digital images consist of a finite number of elements where each element has a particular location and value. These elements are called picture elements, image elements and pixels. There are two types of images i.e. grayscale image and RGB image. Gray scale image has one channel and RGB image has three channels i.e. red, green and blue. Image noise is unwanted fluctuations. There are various types of image noises present in the image like gaussian noise[4]. There are various noise reduction techniques which are used for removing the noise. The result is that it generally reduces the noise level. But the image is either blurred or over smoothed due to losses like edges or lines. Noise reduction is used to remove the noise without losing much detail contained in an image.

The two predominant sources of noise in digital image acquisition are the stochastic nature of the photon-counting process at the detectors and the intrinsic thermal and electronic fluctuations of the acquisition devices[1]. 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.

Image denoising is a process of removing the noise from an image without distorting the quality. In general, an image is often corrupted by noise during its transmission through a channel. Among various image-denoising strategies, the transform-domain approaches in general, and in particular the multiscale ones, are very efficient for AWGN reduction (e.g.,[2]–[3]). As many natural images can be represented by few significant coefficients in a suitable basis/frame, the associated transform-domain processing amounts to a (possibly multivariate) thresholding of the transformed coefficients, which results in a fast denoising procedure. Since the present work lies within this scope of transform-domain thresholding strategies, we discuss hereafter the main multiscale techniques that have been considered for Poisson intensity estimation. Note that there are also non-multiscale methods for Poisson denoising.

(PURE-LET) is to design and optimize a wide class of transform-domain thresholding algorithms for denoising images corrupted by mixed Poisson–Gaussian noise. We express the denoising process as a linear expansion of thresholds (LET) that we optimize by relying on a purely data-adaptive unbiased estimate of the mean-squared error (MSE), derived in a non-Bayesian framework (PURE: Poisson–Gaussian unbiased risk estimate)[1].

Unlike most existing denoising algorithms, using the SURE makes it needless to hypothesize a statistical model for the noiseless image. A key point of our approach is that, although the (nonlinear) processing is

IJERT

performed in a transformed domain typically, an undecimated discrete wavelet transform, but we also address nonorthonormal transforms this minimization is performed in the image domain.

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 Gaussian noise can be eliminated. Fast and high-quality nonlinear algorithm for denoising digital images corrupted by mixed Poisson Gaussian noise [1] were proposed in this paper.

During acquisition and transmission, images are often corrupted by additive noise. The main aim of an image denoising algorithm is then to reduce the noise level, while preserving the image features. Transform domain image denoising—the most popular approaches to process noisy images consist in first applying some linear often multiscale transformation, then performing a usually nonlinear and sometimes multivariate operation on the transformed coefficients, and finally reverting to the image domain by applying an inverse linear transformation. Among the many denoising algorithms to date, we would like to cite the following ones.

• Portilla et al. [2]: The authors' main idea is to model the neighborhoods of coefficients at adjacent positions and scales as a Gaussian scale mixture (GSM); the wavelet estimator is then a Bayes least squares (BLS). The resulting denoising method, consequently called BLS-GSM, is the most efficient up-to-date approach in terms of peak signal-to-noise ratio (PSNR).

• Pizurica et al. [14]: Assuming a generalized Laplacian prior for the noise-free data, the authors' approach called ProbShrink is driven by the estimation of the probability that a given coefficient contains significant information— notion of "signal of interest".

• Sendur et al. [15], [16]: The authors' method, called BiShrink, is based on new non-Gaussian bivariate distributions to model interscale dependencies. A nonlinear bivariate shrinkage function using the maximum a posterior (MAP) estimator is then derived. In a second paper, these authors have extended their approach by taking into account the intrascale variability of wavelet coefficients.

Theoritical Background

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 noisy image model is expressed as

$$g(i, j) = f(i, j)+N(i, j),$$

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

Noise in Image

Image noise is random variation of brightness or color information in images, and is usually an aspect of electronic noise. It can be produced by the sensor and circuitry of a scanner or digital camera. The sources of noise in digital images arise during image acquisition and/or transmission with unavoidable shot noise of an ideal photon detector[9].

Additive white Gaussian noise (AWGN)

The standard model of amplifier noise is additive, Gaussian, independent at each pixel and independent of the signal intensity, caused primarily by Johnson–Nyquist noise (thermal noise). In color cameras where more amplification is used in the blue color channel than in the green or red channel, there can be more noise in the blue channel. Gaussian noise is a noise that has its PDF equal to that of the normal distribution, which is also known as the Gaussian distribution. Gaussian noise is most commonly known as additive white Gaussian noise. Gaussian noise is properly defined as the noise with a Gaussian amplitude distribution[11]. Additive white Gaussian noise (AWGN) is random statistical noise in the background of a communication channel. Among various image-denoising strategies, the transform-domain approaches in general, and in particular the multiscale ones, are very efficient for AWGN reduction.

PURE-LET 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. 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

IJERT

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[10].

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[10].

Our driving principle is the minimization of a purely data-adaptive unbiased estimate of the mean-squared error (MSE) between the processed and the noise-free data. In a general PURE-LET framework, we first devise a fast interscale thresholding method restricted to the use of the (unnormalized) Haar wavelet transform. We then lift this restriction and show how the PURE-LET strategy can be used to design and optimize a wide class of nonlinear processing applied in an arbitrary (in particular, redundant) transform domain. We finally apply some of the proposed denoising algorithms to real multidimensional fluorescence microscopy images. Such in vivo imaging modality often operates under low-illumination conditions and short exposure time; consequently, the random fluctuations of the measured fluorophore radiations are well described by a Poisson process degraded by AWGN.

SURE-LET Approach

This approach is made possible by the existence of an excellent unbiased estimate of the mean squared error (MSE) between the noiseless image and its denoised version—Stein's unbiased risk estimate (SURE).

Our approach, thus, consists in reformulating the denoising problem as the search for the denoising process that will minimize the SURE—in the image domain. In practice, the process is completely characterized by a set of parameters. Now, to take full advantage of the quadratic nature of the SURE, we choose to consider only denoising processes that can be expressed as a linear combination of "elementary" denoising processes—linear expansion of thresholds (LET). This "SURE-LET" stategy is computationally very efficient because minimizing the SURE for the unknown weights gives rise to a mere linear system of equations, which in turn allows to consider processes described by quite a few parameters[13].There is, however, a tradeoff between the sharpness of the description of the process which increases with the number of parameters, and the predictability of the MSE estimate, which is inversely related to the number of parameters. We have already applied our approach within a nonredundant, orthonormal wavelet framework, and showed that a simple thresholding function that takes interscale dependences into account is very efficient, both in terms of computation time and image denoising quality.

Conclusion

IJERT

In this paper, a powerful method is proposed to address the issue of image recovery from its noisy counterpart. we will obtain denoised image using Image denoising technique PURE-LET and SURE-LET during the transmission of image over the AWGN channel. Thus noises are eliminated in the images.

References

[1] Florian Luisier, Thierry Blu and Michael Unser, "Image Denoising in Mixed Poisson-Gaussian Noise", IEEE TRANSACTIONS ON IMAGE PROCESSING, VOL. 20, NO. 3, pp. 696-708, MARCH 2011.

[2] J. Portilla, V. Strela, M. J. Wainwright, and E. P. Simoncelli, "Image denoising using scale mixtures of Gaussians in the wavelet domain," IEEE Trans. Image Process., vol. 12, no. 11, pp. 1338–1351, Nov. 2003.

[3] F. Luisier, T. Blu, and M. Unser, "A new sure approach to image denoising: Interscale orthonormal wavelet thresholding," IEEE Trans. Image Process., vol. 16, no. 3, pp. 593–606, Mar. 2007.

[4] T. Le, R. Chartrand, and T. J. Asaki, "A variational approach to reconstructing images corrupted by Poisson noise," J. Math. Imaging Vis., vol. 27, no. 3, pp. 257–263, Apr. 2007.

[5] S. Lefkimmiatis, P. Maragos, and G. Papandreou, "Bayesian inference on multiscale models for Poisson intensity estimation: Applications to photon-limited

image denoising," IEEE Trans. Image Process., vol. 18, no. 8, pp. 1724–1741, Aug. 2009.

[6] R. M.Willett and R. D. Nowak, "Multiscale Poisson intensity and density estimation," IEEE Trans. Inf. Theory, vol. 53, no. 9, pp. 3171–3187, Sep. 2007.

[7] B. Zhang, J. M. Fadili, and J.-L. Starck, "Wavelets, ridgelets, and curvelets for Poisson noise removal," IEEE Trans. Image Process., vol. 17, no. 7, pp. 1093–1108, Jul. 2008.

[8] P. Besbeas, I.D. Feis, T. Sapatinas, "A comparative simulation study of wavelet shrinkage estimators for Poisson counts", International Statistical Review 72 (2) (2004) 209–237.

[9]Suresh Kumar, Papendra Kumar, Manoj Gupta, Ashok Kumar Nagawat, "Performance Comparison of Median and Wiener Filter in Image De-noising "International Journal of Computer Applications (0975 – 8887) Volume 12– No.4, November 2010.

[10] H. Lu, Y. Kim, J.M.M. Anderson, "Improved Poisson intensity estimation: denoising application using Poisson data", IEEE Transactions on Image Processing 13 (8) (2004) 1128–1135.

[11] Gurmeet Kaur, Rupinder Kaur, "Image De-Noising using Wavelet Transform and various Filters" International Journal of Research in Computer Science eISSN 2249-8265 Volume 2 Issue 2 (2012) pp. 15-21

[12] F. Luisier, C. Vonesch, T. Blu, M. Unser, "Fast Interscale Wavelet Denoising of Poisson-Corrupted Images," Signal Processing, vol. 90, no. 2, pp. 415-427, February 2010.

[13] Thierry Blu, Senior Member, IEEE, and Florian Luisier, "The SURE-LET Approach to Image Denoising", IEEE TRANSACTIONS ON IMAGE PROCESSING, VOL. 16, NO. 11, pp. 2778-2786, Nov 2007.

[14] A. Pizurica and W. Philips, "Estimating the probability of the presence of a signal of interest in multiresolution single- and multiband image denoising," IEEE Trans. Image Process., vol. 15, no. 3, pp. 654 665, Mar. 2006.

[15] L. Sendur and I. W. Selesnick, "Bivariate shrinkage functions for wavelet-based denoising exploiting interscale dependency," IEEE Trans. Signal Process., vol. 50, no. 11, pp. 2744–2756, Nov. 2002.

[16] L. Sendur and I. W. Selesnick, "Bivariate shrinkage with local variance estimation", IEEE Signal Process. Lett., vol. 9, no. 12, pp. 438–441, Dec. 2002.

.

IJERT