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Comparison and study of different Image Denoising methodologies

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***Abstract*— Digital images are the best possible form of conveying visual information but they often gets debased with noise due to communication errors, poor illumination or sensor imperfection. Although there are a variety of methods established by various authors to denoise the corrupted images but the quest for new technique is still moving on.Removing such noise is useful in many applications, and this may explain the vast interest in this problem and its solution. Despite the complexity of the recently proposed algorithms, most of the methods have not yet achieved a pleasing level of applicability; each algorithm has its advantages and drawbacks. All these methods are extremely effective and give auspicious results in recent years. Behind a brief introduction, some of the popular methods are categorized into different sets and an overview of different algorithms and their performances are presented here. In this paper, our impulsion is to provide a brief overview of some of those techniques that may be used in image denoising and compare them qualitatively and quantitatively to understand the basic model of noise estimation and removal, to eliminate drawbacks and develop novel denoising scheme. Possible future work in the area of image denoising is also discussed.**

***Index Terms*—AWGN, LPG-PCA ,Po Edges,Wavelet.**

I. Introduction

Digital images are most suitable way of transmitting visual information from one place to another thus it is very useful,both in applications like television magnetic resonance imaging computer tomography and in field of science and technology such as geographical information system and astronomy. The devices like image sensors assemble the sets of data which is frequently contaminated by noise due to device failures. Also noise can lead due to communicationerrors and compression. Hence before image data is inspected and processed reduction of noise compulsory. Thus a technique is required to imitate the original image [1]. One of the most important challenges for researchers to developing a model, which better describes the degradation process. This model helps to determine the inverse process, which can be applied to the image to get it back into the original form.

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This paper is organized as follows. In section II, types of noise models in digital images are described. In section III various denoising schemes are discussed. Section IV devotes on results obtained by the image denoising algorithms discussed in section III. Finally, section V gives the conclusions of the work.

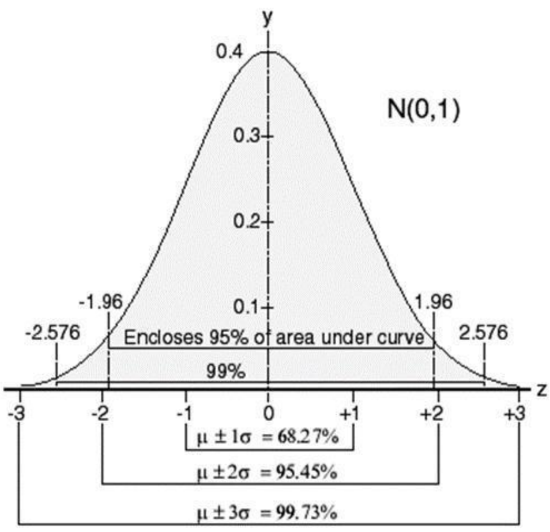
II. NOISE MODELS

Noise is any undesired information that infects an image. Noise appears in images from a variety of sources. The digital image retrieval process, which converts an optical image into a continuous electrical signal which is then sampled, is the process by which noise appears in digital images. At every step in the process there are variations caused by natural phenomena that count a random value to the exact brightness value for a given pixel. In typical images the noise can be formed with either a Gaussian (normal), uniform or salt-and-paper (impulse) distribution [2]. The shape of the distribution of these noise types as a function of gray level can be shaped as a histogram.

A. Gaussian Noise

The Gaussian model is most often used for natural noise processes, such as those occurring from electronic noise in the image acquisition system. The random electron fluctuations within resistive materials in sensor amplifiers or photo detectors results in thermal noise, which is the most common cause. This electronic noise is most problematic with poor lighting conditions or very high temperatures. The Gaussian model is also valid for film grain noise, if photographic film is part of the imaging process.

Fig.1: Probability density function for the Gaussian noise model.



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The Gaussian noise distribution described by

$$\textbf{HISTOGRAM}_{\textbf{Gaussian}} = \frac{1}{\sqrt{2\pi\sigma^2}} e^{\frac{-(g-m)^2}{2\sigma^2}} \quad (1)$$

where
g= gray level
m= mean (average)
σ = standard deviation
σ^2 =variance
About 70% of all the values fall within the range from one standard deviation (σ) below the mean (m) to one above, and about 95% fall within two standard deviations.

B. Uniform Noise

Uniform noise is very rare in real-world imaging systems, but provides a useful equivalence with Gaussian noise. For the mean of a uniform distribution, the linear average is a comparatively poor estimator. This implies that nonlinear filters should be preferred at removing uniform noise than Gaussian noise [2]. Equation (2) represents the uniform distribution.

$$\textbf{HISTOGRAM}_{\textbf{Uniform}} = \begin{cases} \frac{1}{b-a} & \text{for a} \le \text{g} \le \text{b} \\ 0 & elsewhere \end{cases} \quad (2)$$

$$\text{Mean} = \frac{a+b}{2}$$

$$\text{Variance} = \frac{(b-a)^2}{12}$$

With the uniform distribution, the gray-level values of the noise are uniformly distributed across a specific range, which can be the entire "'range (0-255 for 8-bits), or a smaller portion of the entire range.

C. Impulse Noise

Digital images mostly corrupted through Impulse noise. Nature of Impulse noise is independent and unrelated to the image pixels and is haphazardly distributed over the image. For an image corrupted through impulse noise, all the image pixels are not noisy, a group of image pixels will be noisy and the rest of pixels will be free from noise. There are different kinds of impulse noise. One is Salt and pepper noise whose distribution [2] is expressed by equation (3).

$$\textbf{HISTOGRAM}_{\textbf{Salt \& pepper}} = \begin{cases} A & for\, g = a\ (pepper) \\ B & for\, g = b(salt) \end{cases} \quad (3)$$

In the salt-and-pepper noise model there are only two possible values a and b and the probability of each is naturally less than 0.2 - with numbers greater than this the noise will swamp out the image. For an 8-bit image, the standard value for pepper noise is 0 and 255 for Salt noise.
The salt-and-pepper type noise [2] is typically caused malfunctioning pixel elements in the camera sensors, faulty memory locations, or timing errors in the digitization technique. Uniform noise is useful because it can be used to generate any other type of noise distribution and is often used to debase images for the evaluation of image restoration algorithms because it provides the most unbiased or neutral noise model.

III. DENOISING METHODOLOGY

Usually noise will be necessarily introduced in the image acquisition process. Hence it is necessary to remove noise by any means before using it in any application, to improve the quality of image. As a primary low-level image processing technique, it provides an expedient floor over which image processing ideas and techniques can be tested and perfected. From the earlier smoothing filters based and frequency domain denoising methods [1] to the lately developed wavelet [3-10], curvelet [11] and ridgelet [12] based methods, adaptive principle component analysis [13], bilateral filtering [14],[15], non-local mean based methods [16],[17], sparse representation [18] and K-SVD [19] methods, shape-adaptive transform [20], non-local collaborative filtering [21] and local pixel grouping with principle component analysis [22] and numerous, are some of the many directions and tools explored in studying this problem. With the rapid development of modern digital imaging devices and their progressively wide applications in our daily life, there are expanding requirements of new denoising algorithms for higher image quality.
Wavelet transform (WT) [23] has proved to be effective in noise removal. It decomposes the input signal into multiple scales, output represent various time-frequency components of the original signal. At every scale, some operations, such as thresholding [3],[4] and statistical modeling [5],[6],[7], can be performed to suppress noise. By converting back the processed wavelet coefficients into spatial domain denoising is accomplished. Late development of WT denoising includes ridgelet and curvelet methods for line structure conservation. Although WT has manifested its efficiency in denoising, it uses a fixed wavelet basis (with dilation and translation) to show the image. For natural images, notwithstanding, there is a wealthy amount of different local structural patterns, which cannot be well expressed by using only one fixed wavelet basis. Therefore, WT-based methods can propose many visual artifacts in the denoising output.
To blown away the problem of WT, in [13] Muresan and Parks proposed a spatially adaptive principal component analysis (PCA) placed denoising scheme, which measures the locally fitted basis to transform the image. Elad and Aharon [18],[19] proposed sparse redundant representation and K-SVD based denoising algorithm by guiding a highly over-complete dictionary. Foi et al. [20] applied a shape-adaptive discrete cosine transform to the district, which can achieve very sparse representation of the image and hence place to effective denoising. All these methods view better denoising performance than the conventional WT-based denoising algorithms.
Recently a novel denoising scheme named LPG-PCA [22] is developed. PCA is a classical de-correlation technique in statistical signal processing and it is extensively used in pattern recognition and dimensionality reduction. By converting the original dataset into PCA domain and keeping only the several most significant principal components, the noise can be removed. In [22], a PCA-based scheme was suggested for image denoising by using a moving window to compute the local statistics, from which the local PCA transformation matrix was estimated. However, this scheme

executes PCA directly to the noisy image without data selection and many noise residual and visual artifacts will appear in the denoised outputs. In this section we have no intention of providing a review of this immense activity on image denoising. Instead, we concentrate on few basic algorithms. These methods have been found in recent years to be highly effective and assuring, often leading to the best known performance in noise estimation and noise removal.

A. *Wavelet based image denoising*

Wavelet transform (WT) is a mathematical function that analyzes the data according to scale or resolution and converts that function or signal into another form which makes certain features of the original signal clearer to study or identify. The basic functions for the wavelet transform are more complicated called wavelets, mother(or analyzing) wavelets and scaling function. In wavelet analysis, the signal is broken into shifted and scaled versions of the original (or mother) wavelet. It has proved to be effective in noise removal [3-10]. Noise reduction using wavelets is performed by first decomposing the noisy image into multiple scales, which represent different time-frequency components of the original signal. At each scale, some shrinkage operations such as thresholding [3],[4] and statistical modeling [5],[6],[7] can be performed to suppress the magnitude of noisy coefficients. Finally, the reconstructed image is obtained by converting processed wavelet coefficients into spatial domain.

Mainly wavelet transform are two types: continuous wavelet transform (CWT) and Discrete wavelet transform (DWT). The CWT was developed to solve the resolution problem on the short time Fourier Transforms. It is used to divide a time function signal into wavelets with different scales and different levels of resolution by lengthening a single prototype function, which is also called mother wavelets. DWT Recall that in continuous wavelet transform, the process involves a correlation between the input signal and wavelets at different scales and translation. The DWT is considerably easier to implement when compared to the CWT.

The DWT decomposes the signal into various frequency bands with various resolutions. In wavelet filtering the original signal $x(n)$ is passed through two complementary filters and appears as two signals. The filtering process, if single stage wavelet filter is applied on a digital signal, then we end with twice as much data as we started with. The original signal $x(n)$ consists of M samples of data. The resulting approximation and detail coefficients are each of length M, for a total of $2M$.

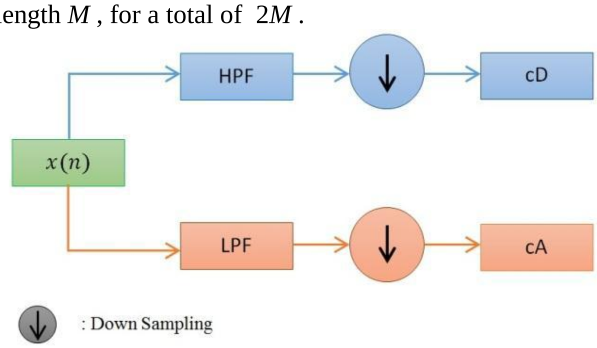

Fig. 2: Single stage wavelet filtering with down sampling.

There exists an alternative method to perform the decomposition using wavelets. By down sampling A and D to half of their lengths i.e. $M/2$, the total length of resulting signal can be maintained. The final output signals after down sampling are denoted as and cA and cD is shown in fig. 2. Similarly for Multistage wavelet filtering, the wavelet decomposition process can be iterated, so that one signal is broken down into several lower resolution components. This is termed as wavelet decomposition tree shown in fig. 3.

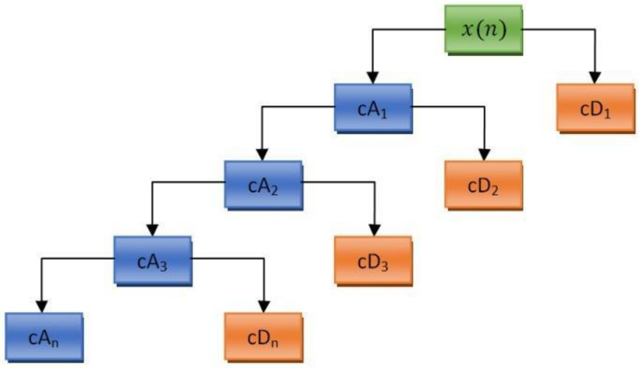

Fig.3: Multistage wavelet decomposition tree.

B. *PoEdges*

Product of Edgeperts (PoEdges) are a probabilistic model to model the statistical credencies between coefficients in wavelet decomposed images. It builds upon earlier work on wavelet statistics [1],[2]. PoEdges has long been recognized in the image processing community that wavelet transforms form an excellent basis for delegation of images. Within the class of *linear* transforms,it represents a compromise between many collising but desirable properties of image delegation such as multi-scale and multi-orientation representation, locality both in space and frequency, and orthogonality resulting in decorrelation.

C. *LPG-PCA Image denoising*

PCA is pervasively used in pattern recognition and dimensionality reduction, etc. [25]. In this scheme a pixel and its nearest neighbors are modeled as a vector variable, to preserve the local image structures. Training sample of vector variable is selected from the local window by using grouping. However, in a local window there can have very different structures; therefore, a training sample selection procedure is necessary.

Grouping the training sample is a classification problem, which can be realized by various techniques: Block matching, Correlation based matching, Fuzzy clustering [26], K- Means clustering [27], Self-organizing maps [28], Vector quantization [29], etc. Such an LPG procedure can use relatively small local window to group the similar contents for PCA training, so that the image local features can be well preserved after coefficient shrinkage by transforming the original dataset in the PCA domain, to remove the noise and trivial information. The above LPG-PCA denoising procedure was emphasized one more time that enhance the denoising performance, and the noise level is adaptively updated in the second stage.

As shown in Fig. 4, the proposed LPG-PCA algorithm has two stages. The first stage yields an initial estimation of the image by extracting most of the noise and then the second stage will further refine the output of the first stage. Both stages have the same procedures. only noise levels are different for both stages. Since the noise is significantly reduced in the first stage, the LPG accuracy will be much recovered in the second stage so that the final denoising result is visually much better.

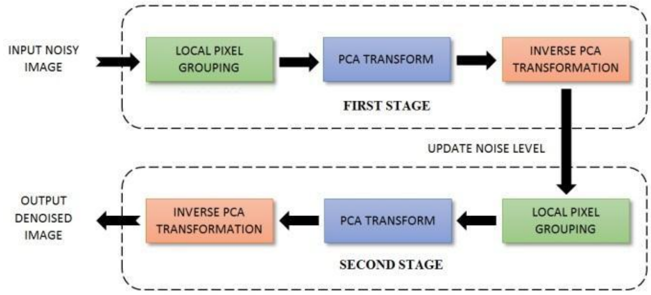

Fig. 4: Flowchart of the proposed two-stage LPG-PCA denoising scheme.

Compared with WT and PoEdges , the LPG-PCA method is a spatially adaptive image representation so that it can better describe the image local structures.

IV. RESULT OBSERVATION

In this section we will discuss the obtained results of our experiments. Tool required for the experimentation is MATLAB with Image Processing toolbox. Computations were performed with an Intel Dual Core 1.7x2 GHz and 2.5 GB memory, employing a 32-bit LINUX operating system. We used 4 different images to enumerate the performance of the algorithms discussed in section III. Our dataset includes standard test images selected from the CMU image database

Fig. 5: The set of noise free test images Baby, flower, Man and Ship.

We will evaluate the data for the image Baby, Flower, Man and Ship are shown in Fig. 5. All of our images are 8-bit gray scale images of dimension 256 x 256 and are converted to same image format (i.e. **TIF** in our experiment) using inbuilt functions of MATLAB. We compare our denoised images by two parameters PSNR and SSIM.

Fig. 6 shows the denoising results of the test image bay with noise level by different methods. The subfigure (a) is the original image; subfigures (b–d) are the denoised images by the methods in [8],[26],[22] respectively.

We see that although LPG-PCA has higher SSIM measures than PoEdges and they have much better visual quality than all the other methods. The wavelet based denoising methods [8] have the worst visual quality. This is because in WT, the fixed wavelet basis function is used to de-correlate the many different image structures. Often this is not adequate enough to represent the image content so that many denoising errors appear.

Fig. 6: The denoising results of image Baby by different schemes. (a) Noiseless Baby; denoised images by methods (b) [8]; (c) [26] and (d) [22].

PSNR and SSIM values of the algorithms discussed in section III are enlisted in Table I. On the observation of the result, we ensure that the algorithm LPG-PCA has the highest PSNR measures. The PSNR result of PoEdges is higher than the wavelet-based methods [8,10], and the wavelet-based method [10] has the lowest PSNR value. The value in the parenthesis is the SSIM measurement.

V. CONCLIUSION

In this review paper various denoising techniques are discussed and compared for the estimation and removal of AWGN signal. This paper reviews the existing denoising algorithms such as wavelet based denoising, PoEdges and LPG-PCA denoising. The wavelet based approach finds applications in denoising images depraved with Gaussian noise. Selection of the denoising algorithm is application dependent. Hence, it is necessary to have knowledge about the noise existence in the image so as to select the appropriate denoising algorithm. Our experimental results demonstrated that LPG-PCA has the highest PSNR and SSIM measures. The PSNR result of poEdges is higher than the wavelet-based Methods.

Table I. **The PSNR (dB) and SSIM results of the denoised images at different noise levels and by different schemes.**

Methods	Wavelet	PoEdges	LPG-PCA
Baby			
σ = 10	33.9(0.9050)	34.8(0.9202)	35.1(0.9523)
σ = 20	29.5(0.8054)	30.6(0.8505)	30.8(0.8909)
σ = 30	27.2(0.7302)	28.3(0.7865)	28.3(0.8215)

σ = 40	25.6(0.6757)	26.9(0.7503)	28.7(0.8042)
Flower			
σ = 10	33.3(0.9083)	34.5(0.9306)	35.0(0.9399)
σ = 20	29.0(0.8074)	30.4(0.8609)	30.9(0.8696)
σ = 30	26.9(0.7371)	28.1(0.7968)	28.7(0.8014)
σ = 40	25.3(0.6712)	26.6(0.7431)	26.6(0.7609)
Man			
σ = 10	33.1(0.8872)	33.9(0.9075)	34.0(0.9370)
σ = 20	29.3(0.7702)	30.1(0.8059)	30.2(0.8503)
σ = 30	27.5(0.6959)	28.3(0.7327)	28.2(0.7661)
σ = 40	26.4(0.6303)	27.1(0.6695)	27.0(0.6898)
Ship			
σ = 10	31.7(0.9290)	32.7(0.9447)	32.7(0.9434)
σ = 20	27.6(0.8551)	28.6(0.8849)	28.4(0.8742)
σ = 30	25.4(0.7922)	26.4(0.8235)	26.2(0.8042)
σ = 40	24.0(0.7332)	24.9(0.7716)	24.7(0.7362)

VI. References

[1] Rafael C. Gonzalez, Richard E. Woods, and Steven L. Eddins, Digital Image Processing , 2nd ed. Englewood Cliffs, NJ: Prentice- Hall, 2002.

[2] Scott E. Umbaugh, Digital image processing and analysis: human and computer vision applications with CVIPtools.: CRC press, 2010.

[3] D. L. Donoho, "Denoising by soft thresholding," IEEE Transactions on Information Theory, pp. 613–627, 1995.

[4] R. R. Coifman and D. L. Donoho, Translation-invariant de-noising, G. Oppenheim, Ed. Berlin, Germany: Springer, 1995.

[5] F. Luisier, T. Blu, and M. Unser, "A new SURE approach to image denoising: Interscale orthonormal wavelet thresholding," *IEEE Transactions on Image Processing*, vol. 16, no. 3, pp. 16(3), 593-606., 2007

[6] C.R. Mittermayr, S.G. Nikolov, H. Hutter, M. Grasserbauer" Wavelet denoising of Gaussian peaks: A comparative study", Volume 34, Issue 2, September 1996, Pages 187–202.

[7] Quan Pan, Lei Zhang, Guanzhong Dai, and Hongcai Zhang, "Two Denoising Methods by Wavelet Transform", ieee transactions on signal processing, vol. 47, no. 12, december 1999

[8] Hua Xie ; Dept. of Electr. Eng. & Comput. Sci., Michigan Univ., Ann Arbor, MI, USA ; Pierce, L.E. ; Ulaby, F.T., "SAR speckle reduction using wavelet denoising and Markov random field modeling" Volume:40 Issue:10.December 2002.

[9] P. Bao, X. Wu L. Zhang, "Multiscale LMMSE-based image denoising with optimalwavelet selection," IEEE Transaction on Circuits and Systems for Video Technology, vol. IV, no. 15, pp. 469–481, 2005.

[10] A. Pizurica and W. Philips, "Estimating the probability of the presence of a signal of interest in multiresolution single and multiband image denoising," IEEE Transaction on Image Processing, vol. III, no. 15, pp. 654–665, 2006.

[11] J. L. Starck, E. J. Candes, and D. L. Donoho, "The curvelet transform for image denoising," IEEE Transaction on Image Processing, vol. VI, no. 11, pp. 670–684, 2002.

[12] G. Y. Chen and B. Kegl, "Image denoising with complex ridgelets," Pattern Recognition, vol. II, no. 20, pp. 578–585, 2007.

[13] D. D. Muresan and T. W. Parks, "Adaptive principal components and image denoising," in Proceedings of the 2003 International Conference on Image Processing, vol. 1, 14–17 September 2003, pp. 101–104.

[14] C. Tomasi and R. Manduchi, "Bilateral filtering for gray and colour images," in IEEE International Conference on Computer Vision, Bombay, India, 1998, pp. 839–846.

[15] D. Barash, "A fundamental relationship between bilateral filtering, adaptive smoothing, and the nonlinear diffusion equation," IEEE Transaction on Pattern Analysis and Machine Intelligence, vol. VI, no. 24, pp. 844–847, 2002.

[16] A. Buades, B. Coll, and J. M. Morel, "A review of image denoising algorithms, with a new one,"Multiscale Modeling Simulation, vol. II, no. 4,2005.

[17] C. Kervrann and J. Boulanger, "Optimal spatial adaptation for patch based image denoising," IEEE Transaction on Image Processing, vol. X, no. 15, pp. 2866–2878, 2006.

[18] M. Elad and M. Aharon, "Image denoising via sparse and redundant representations over learned dictionaries," IEEE Transaction on Image Processing, vol. XII, no. 15, pp. 3736–3745, 2006.

[19] M Aharon, M Elad, and A M Bruckstein, "The K-SVD: an algorithm for designing of overcomplete dictionaries for sparse representation," IEEE Transaction on Signal Processing, vol. XI, no. 54, pp. 4311–4322, 2006.

[20] A. Foi, V. Katkovnik, and K. Egiazarian, "Pointwise shape-adaptive DCT for high quality denoising and deblocking of grayscale and color images," IEEE Transaction on Image Processing, vol. V, no. 16, 2007.

[21] K. Dabov, A. Foi, V. Katkovnik, and Egiazarian K., "Image denoising by sparse 3D transform-domain collaborative filtering," IEEE Transaction on Image Processing, vol. VIII, no. 16, pp. 2080–2095, 2007.

[22] L. Zhang, W. Dong, D. Zhang, and G. Shi, "Two-stage image denoising by principal component analysis with local pixel grouping," Pattern Recognition, vol. IV, no. 43, pp. 1531-1549, 2010.

[23] S. Mallat, A Wavelet Tour of Signal Processing. New York: Academic Press, 1998.

[24] L. P. Yaroslavsky, Digital Signal Processing—An Introduction. Berlin: Springer, 1985.

[25] K. Fukunaga, Introduction to Statistical Pattern Recognition, 2nd ed. New York: Academic Press, 1991. Symposium on Mathematical Statistics and Probability, Berkeley, 1967, pp. 281–297.

[26] E P Simoncelli Bayesian denoising of visual images in the wavelet domain. In *Bayesian Inference in Wavelet Based Models*, eds. P Müller and B Visakovic. Springer-Verlar, Lecture Notes in Statisitcs 141, 1999.