IMAGE NOISE QUALITY ASSESSMENT USING WAVELET TRANSFORMS

Mrs.Smita Sharma*

Prof. Gajendra Singh**

ABSTRACT-

Image noise quality assessment is a major issue found in various image processing and computer vision problems. It is always a challenge to preserve important features, such as corners, edges and other sharp structures, during the denoising process and wavelet analysis has been demonstrated to be a powerful method for performing image noise reduction. Wavelet transforms have been widely used for image denoising since they provide a suitable basis for separating noisy signal from the image signal.This paper describes a powerful image denoising method based on wavelet transforms . The decomposition is performed by dividing the image into a set of blocks and transforming the data into the wavelet domain. The estimation of the standard deviation of noise contaminating an image is a fundamental step in wavelet-based noise reduction techniques. Experimental results, compared to different approaches, it has been revealed that the proposed method is suitable for different classes of images contaminated by Gaussian noise.

KEYWORDS-

Image denoising , wavelet transforms.adaptive denoising; edge preservation, noise estimation, image processing.

* M.Tech Scholar Dept. of Computer Science , SSSIST SEHORE

** H.O.D. of Computer Science, SSSIST SEHORE

1 . INTRODUCTION

Image denoising plays a fundamental role in image processing, Digital images can be corrupted by noise during the process of acquisition and transmission, degrading their quality. A major challenge is to remove as much as possible of the noise without eliminating the most representative characteristics of the image. Several approaches [1-5] have been proposed to suppress the presence of noise in digital images, many of them based on spatial filters. These filters usually smooth the data to reduce noise effects however, this process can cause image blurring or edge removal [3]. The procedure for noise reduction is applied on the wavelet coefficients achieved using

the wavelet decomposition and representing the image at different scales. After noise is reduced, the image is reconstructed using the inverse wavelet transform. Decomposition and reconstruction are accomplished using two banks of filters constrained by a perfect reconstruction condition [6,13]. The structure of these filter banks is characterized by the frequency responses of two filters and by the presence or absence of sub/up-sampling, generating, respectively, decimated or undecimated wavelet transforms. Undecimated wavelet transforms have been considered for image noise reduction[6, 7,8,9,10, 11, 12] as well as the decimated transforms .

Donoho proposed a robust noise level estimator: the mean absolute deviation (MAD) of wavelet coefficients at the highest resolution [9, 14, 15, 16]. The common idea related to the suppression of noise based on the wavelet transform is to compute the wavelet decomposition of the noisy image and to

manipulate the obtained wavelet cofficients [19]. This paper describes a new method for noise sup-pression using wavelet transforms. we include an investigation of the problem of estimating the variance of the noise contaminating an image and we compare the novel algorithms, two of which based on training over a set of test images, with the MAD technique. During the application of the algorithm, only a noisy image is available for analysis, from which the level of the noise is estimated employing the parameters extracted during the training experiments.

Coefficients that are supposed to be affected by noise are replaced by zero or an adequate value. Reconstruction from these manipulated coefficients then generates the resulting denoised image.

The paper is organized as follows. We present the three new techniques for noise level estimation through wavelet transform , in Section.1.The experimental results are given tn Section 2. Finally, conclusions are drawn in Section 3.

2. IMAGE DENOISING METHOD

2.1 *Image Denoising through Wavelet Thresholding*

Wavelet thresholding is a common approach for denoising due to its simplicity. There are several studies on thresholding the wavelet coefficients [17,18,20,21,22,23]. The process, commonly called wavelet shrinkage, consists of the following main stages:

1. perform the discrete wavelet transform;
2. estimate a threshold;
3. apply the threshold according to a shrinkage rule;
4. perform the inverse wavelet transform using the thresholded coeffcients.

Suppose that a given image $i = \{ i_{x,y} ,\ x = 1,\dots, M ,\ y = 1 ,\dots, N \}$ has been corrupted by additive noise according to th e following model

$$g = i + n \qquad (1)$$

where g represents the observed image and n represents the noise .
A common assumption is that the noise is statistically independent and identically distributed. Most of the existing methods are designed for the case of additive white Gaussian noise.

The image g is decomposed into coefficients through a discrete wavelet transform W It can be expressed as

$$G = W(g) \qquad (2)$$

The execution of the discrete wavelet transform decomposes the input image into different frequency subbands, labeled LLj , LH_k , HL_k and HH_k, k = 1 , 2 ,……, J, where the subscript indicates the k-th resolution level of wavelet transform and J is the largest scale in the decomposition. These subbands contain different information about the image. The lowest frequency LL_j subband, obtained by low-pass filtering along he x and y directions, represents the coarse approximation of image signal. The LH_k and HH_k subbands correspond to horizontal, vertical and diagonal details of the image signal, respectively. The highest frequency HH_1 subband can contain a significant amount of noise . The LL_{k-1} subband can be further recursively decomposed to form the LH_k, HL_k and HH_k subbands.

After the selection of a threshold, the wavelet coefficients are modified according to a shrinkage function T, such that

$$I = T(G) \qquad (3)$$

The last step in the wavelet shrinkage is to transform the thresholded coefficients back to the original domain, expressed as

$$\hat{i} = \hat{W}^{-1}(I) \qquad (4)$$

where W^{-1} denotes the inverse discrete wavelet transform and f is the denoised image.

A global (universal) threshold is commonly used to filter small wavelet coefficients, in conventional thresholding schemes, However, this procedure can also remove high frequency components, such as edges. To improve the wavelet denoising method, an adaptive threshold is calculated in a subband-dependent manner to characterize local features of the image. A new thresholding scheme is proposed to threshold the small wavelet coefficients considered to be noise while preserving edges. This subband-dependent thresholding is obtained based on the calculation of noise level and edge strength.

Initially, the input image g, corrupted by Gaussian noise, is partitioned into m* m pixel blocks. Blocks are used in a manner that the denoising algorithm can exploit local noise characteristics and adapt thresholding to produce better results. Nevertheless, as information is often lost due to the thresholding, blocking effects between boundaries of neighbor blocks often arise. A larger region B_n of size n * n pixels (n > m), is used to avoid un-desirable effects. The discrete wavelet transform is then applied to each block B_n.

An edge detection algorithm is used to identify edges in the image. A multiscale edge detection based on Haar wavelet transform modulus maxima is used for this purpose , being applied separately to each block. Each coefficient identified as edge information , is compared to its neighbor ,in order to have a accurate edge localization and avoid noise . The coefficient is not identified as edge information, if there is no neighbor belonging to an edge. The multiscale edge detection produces an edge map for each subband, that is, a binary image where 1 represents an active edge element and 0 represents a non-edge element.

A shrinkage rule is applied taking into account the threshold according to the edge map. Coefficients related to active edge elements must be associated with smaller threshold values.

Finally, the inverse multiscale decomposition is performed over each external block B_n . The non- overlapping inner blocks B_m are used to reconstruct the denoised image ^i and reduce errors near block boundaries, since the blocks B_m, when concatenated, are much less likely of suffering blocking effects.

2.2 Image Denoising using Cumulative Distribution functions

This method is based on trying to exploit plane regions in the image. Consider a plane area of the image; the standard deviation of the image computed over that area is a direct estimate of the standard deviation of the noise. This method is applied to the wavelet components that, through construction, have a global zero mean. This means that by forming the sum of squared pixel values in a neighbourhood one obtains a localized estimate of the image variance.

In regions where there is image detail then the local variance will, on average, be the sum of the local image variance and the noise variance, assuming the noise and image are statistically independent. Hence in these regions the local variance will be greater than in plane areas. This implies that information about the noise variance can be obtained by examining areas with the smallest values of the local variance. To form an estimate based on this information, the cumulative distribution function n (cdf), $c(x)$, of the local pixel variances is formed. The value of $c(x)$ represents the number of pixels with a local variance less than x.

The character of the cdf depends upon both the image and noise statistics, but for small values of x the values of $c(x)$ are dominated by the noise. Computation of cdf for all possible values of x is burdensome and the solution adopted herein is designed with computational efficiency in mind.

Specifically, we will only measure the cdf for a particular value of $x = x0$. Mean values of $c(x0)$ are computed across the training set of images and are stored for a range of noise variances. This forms a lookup table of values of $c(x0)$ against noise variance. For every new image, the value of $c(x0)$ is computed and the lookup table is employed to infer the noise variance.

The effectiveness of the method depends upon the choice of $x0$. This point is chosen as the value that maximises a discrimination metric evaluated across the training set.

2.3 Image Denoising Using Trained Moments

The method of moment matching relies upon an assumed statistical model for the image and noise. This section describes how this method can be extended to avoid the need to assume a statistical model and instead employs training to form an estimate of the noise variance. The method used to achieve this is based on fitting a linear model based on a normalised set of moments. The algorithm is described in the context of the three moments, but it can be generalized to incorporate other moment information. The moments are used in a normalized form and are defined as

$$M1 = m1,$$
$$M2 = m2/\mathrm{m}1, \qquad (5)$$
$$M4 = m4/m1m2$$

The above choice of normalisations is not unique and similar schemes can be constructed employing different normalized moments. The noise standard deviation is then assumed to be related to these normalised moments through a linear equation

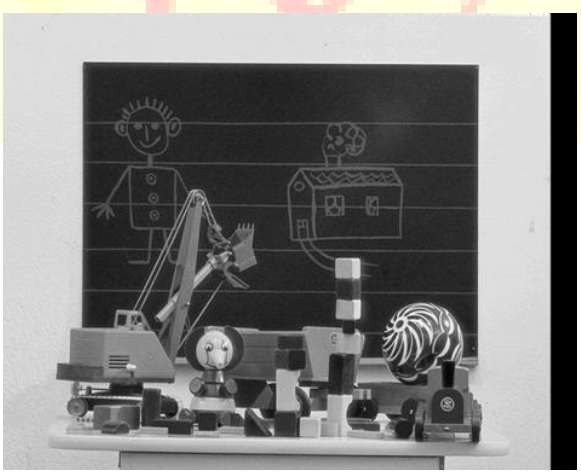
$\sigma v = \alpha 1M1 + \alpha 2M2 + \alpha 4M4,$ (6)

where αk are constant coefficients. The normalisation is designed to guarantee the dimensional consistency of (6). The K images in the training set are then used to evaluate the unknown coefficients αk. This is achieved by creating a library of images at different SNRs by adding noise with P different variances to each of the images. The noise variances are selected to cover the range of noise levels expected in practice. The coefficients αk that generate the best approximations, in the least squares sense, to the known noise variance across the training set can be computed using standard linear algebra techniques.

3. RESULT

To assess the performance of the noise estimation processes, a series of simulations was conducted. The three methods for noise estimation presented in Section 2 were implemented along with MAD. Those methods that needed training were trained on a set of six images (Figure 1). The performance of the methods was then evaluated using a selection of four images (Figure 2).The training and test sets contained no common images. Gaussian noise was added to each of the images using six different noise levels. The noise was estimated using only the highest frequency wavelet component. The mean squared error between the estimated noise variance and the true variance of the added noise is computed. For four noise levels the cdf method performs best and for the other two levels,the trained moment-based method achieves the best results. The grey level selected to estimate the noise level in the cdf

FIGURE 1 : IMAGES USED



FOR TRAINING

method performs particularly well when the contaminating noise level is clearly higher than the standard deviation of the image component . All the methods tend to perform better as the noise level increases, as one would anticipate. This test provides some evidence of the utility of training-based schemes.

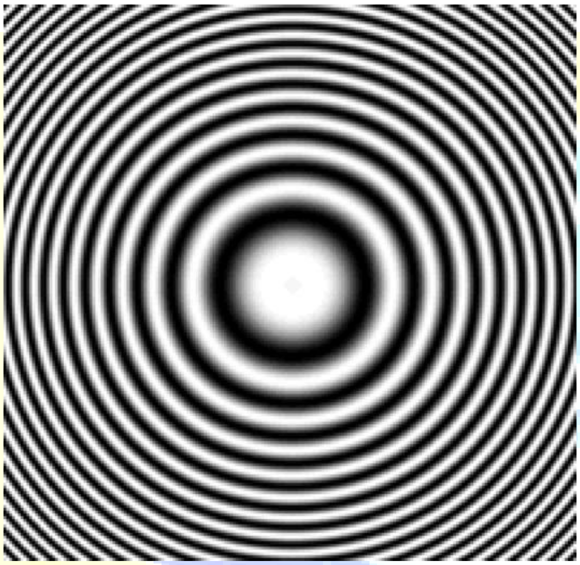
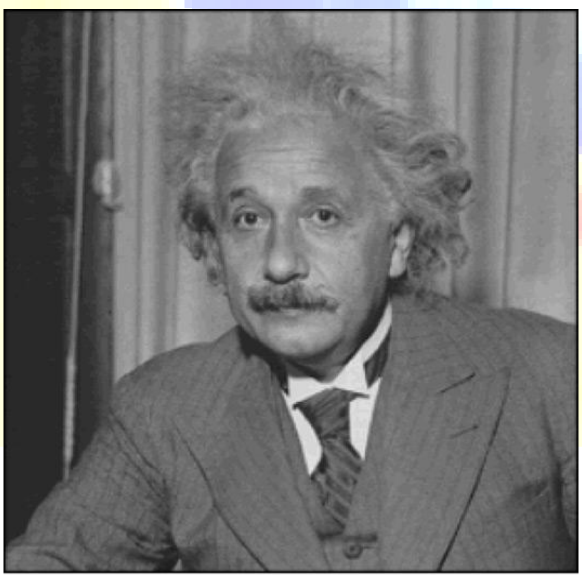


FIGURE 2 : IMAGES USED

The poor performance of the moment matching method can be attributed to the inadequacy of the Laplacian distribution for modelling . This has been verified by comparing the mean squared error between synthetically generated images with optimal3 Laplacian distribution .



FOR TESTING

4. CONCLUSION

The problem of the noise standard deviation level estimation over the wavelet component is considered in this work. Three novel methods have been proposed. A new thresholding scheme is proposed based on noise estimation on high frequency subbands and edge strength. The choice of thresholding functions integrated with edge detection can improve the performance of denoising methods. The techniques utilized to estimate the noise level are in general based on some type of assumption concerning image and noise characteristics. An alternative solution proposed here is to use training-based methods which do not rely on any prior assumption and utilise parameters extracted from a preliminary stage performed on a set of representative images.

Among the methods proposed here, two are training based, while the third is based on the assumption of specific statistical distributions for image and noise components. The results showed in this paper need to be generalized using larger sets of test images and different range noise levels. The techniques proposed seem also to be suitable for other classes of images and for non-spatially white Gaussian noise distributions.

REFRENCES

[1] E. Abreu, M. Lighstone, S. Mitra, K. Arakawa, A New Efficient Approach for the Removal of Impulsive Noise from highly Corrupted Images, IEEE Transactions on Image Processing 5 (6) (1996) 1012-1025.

[2] R. Garnett, T. Huegerich, C. Chui, W. He, A Universal Noise Removal Algorithm with an Impulse Detector, IEEE Transactions on Image Processing 14 (11) (2005) 1747-1754.

[3] R. C. Gonzalez, R. E. Woods, Digital Image Processing,Prentice-Hall, Inc., Upper Saddle River, NJ, USA, 2006.

[4] I. Pitas, A. Venetsanooulos, Nonlinear Digital Filters: Principles and Applications, Kluwer, Boston, MA, USA, 1990.

[5] M. Y • uksel, A. Bast • urk, Efficient Removal of Impulse Noise from Highly Corrupted Digital Images by a Simple

Neuro-fuzzy Operator, International Journal of Electronics and Communications 57 (3) (2003) 214-219.

[6] A. De Stefano, Wavelet based reduction of spatial video noise, Ph.D. thesis, ISVR, University of Southampton, Southampton, UK, 2000.

[7] M. R. Banham and A. K. Katsaggelos, "Spatially adaptive wavelet-based multiscale image restoration," *IEEE Trans.* Image Processing, vol. 5, no. 4, pp. 619–634, 1996.

[8] M. Lang, H. Guo, J. E. Odegard, C. S. Burrus, and R. O.Wells Jr., "Noise reduction using an undecimated discrete wavelet transform," IEEE Signal Processing Letters, vol. 3, no. 1, pp. 10–12, 1996.

[9] D. L. Donoho and I. M. Johnstone, "Ideal spatial adaptation by wavelet shrinkage," *Biometrika*, vol. 81, no. 3, pp. 425–455,1994.

[10] R. R. Coifman and D. L. Donoho, "Translation-invariant denoising," in *Wavelets and Statistics*, A. Antoniadis and G.

Oppenheim, Eds., vol. 103 of *Lecture Notes in Statistics*, pp. 125–150, Springer-Verlag, New York, NY, USA, 1995.

[11] A. De Stefano, P. R. White, and W. B. Collis, "An innovative approach for spatial video noise reduction using a wavelet based frequency decomposition," in *Proc. IEEE International Conference on Image Processing (ICIP '00)*, vol. 3, pp. 281–284,Vancouver, British Columbia, Canada, September 2000.

[12] A. De Stefano, P. R. White, and W. B. Collis, "Selection of thresholding scheme for video noise reduction on wavelet components using Bayesian estimation," in *Proc. 5th IMA International Conference on Mathematics in Signal Processing*, Warwick, UK, December 2000.

[13] G. Strang and T. Nguyen, *Wavelets and Filter Banks*, Wellesley Cambridge Press,Wellesley, Mass, USA, 1996.

[14] D. L.Donoho, "De-noising by soft-thresholding," *IEEE Transactions on Information Theory*, vol. 41, no. 3, pp. 613–627, 1995.

[15] A. Bruce, D. Donoho, and H. Gao, "Wavelet analysis [for signal processing]," *IEEE Spectrum*, vol. 33, no. 10, pp. 26–35, 1996.

[16] D. L. Donoho and I. M. Johnstone, "Wavelet shrinkage: asymptopia?," *Journal Royal Statistics Society B*, vol. 57, no. 2, pp. 301–369, 1995.

[17] S. Chang, B. Yu, M. Vetterli, Spatially Adaptive Wavelet Thresholding Based on Context Modeling for Image Denoising, IEEE Transactions on Image Processing 9 (9) (2000) 1522-1531.

[18] S. Chang, B. Yu, M. Vetterli, Adaptive Wavelet Thresholding for Image Denoising and Compression, IEEE Transactions on Image Processing 9 (9) (2000) 1532-1546.

[19] M. Malfati, D. Roose ,Wavelet-based Image Denoising using a Markov Random Field a Priori Model, IEEE Transactions on Image Processing 6 (4) (1997) 549-565.

[20] D. L. Donoho, I. M. Johnstone, Ideal Spatial Adaptation via Wavelet Shrinkage, Biometrika 81 (1994) 425-455.

[21] D. L. Donoho, I. M. Johnstone, Adapting to Unknown
Smoothness via Wavelet Shrinkage, Journal of the American Statistical Association 90 (432) (1995) 1200-1224.

[22] L. Sendur, I. W. Selesnick, Bivariate shrinkage with Local Variance Estimation, IEEE Signal Processing Letters 9 (12).

41. D. L. Donoho, De-noising by Soft-thresholding, IEEE
Transactions on Information Theory 41 (3) (1995) 613-
627.