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Enhancing an Image Corrupted with Speckle Noise by Using a Dictionary Technique

Daniel Owusu-Donkor[1] Dr. O. Uma Maheswari[2]
[1]Department of ECE College of Engineering, Anna University, Chennai 600 085, India
[2]Assistant Professor, Department. of ECE ,College of Engineering, Anna University,Chennai 600 085, India

***Abstract*— Images are corrupted by different types of noises in channel (wireless and wired in both cases) while transmitting or receiving the desired signal, so it is imperative that on the receiver side there should be an equipment/filter which can eliminate the existing noises and provide the actual image with actual size and actual shape. There are various techniques involved in the enhancement of a noisy image depending upon wavelet theory. One major advantage offered by wavelet is the ability to perform local analysis that is to analyze a localized area of a larger signal. Wavelet analysis can often compress or denoise a signal without appreciable degradation. So in this report, a dictionary technique is proposed for enhancing the image in the wavelet domain. The proposed technique o improves the efficiency of the denoising procedure.**

***Keywords* - Discrete Wavelet Transform, Median Filter, speckle noise, Peak Signal to Noise ratio**

I. INTRODUCTION

Images may be affected by noise in capturing and transmission stages. Noise sources cover a wide range of unwanted distortions from additive Gaussian noise in natural images to almost- multiplicative speckle noise in ultrasound and synthetic aperture radar (SAR) images. Image denoising is therefore a necessary step in image processing applications [1]. The first methods introduced for image denoising were based on statistical filters. It is now more than one decade that the wavelet transform has become an important tool to suppress the noise due to its effectiveness and producing better results. The wavelet transform has primary properties such as compression or sparsity which means that wavelet transforms of real-world signals tend to be sparse. Therefore, they have a few large coefficients that contain the main energy of the signal and other small coefficients which can be ignored. Moreover, the energy of the noise is spread among all the coefficients in the wavelet domain. Due to the fact that the wavelet transform of a noisy signal is a linear combination of the wavelet transform of the noise and the original signal, the noise power can be suppressed significantly with a suitable threshold while the main signal features can be preserved [1]. Different multiplicative noise reduction techniques are proposed in [2, 3, 4, 5]. In [6], hybrid order statistic filters for speckle noise reduction are proposed. Lee [7], Kuan [8], and Frost [9] filters are still widely used in many applications. In general, they succeed to reduce speckle noise in homogenous areas and failed in heterogeneous areas. This paper proposes a new image enhancement method based on dictionary learning and the use of a wavelet transform.

II. PROPOSED IMAGE ENHANCEMENT METHOD

Fig 1. shows the process by which the image is enhanced after obtaining or learning the dictionary of the image.

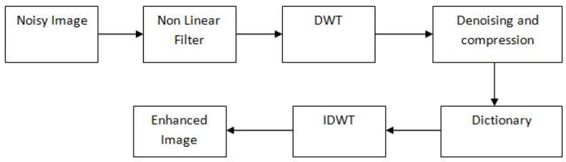

Figure 1. Proposed image enhancement method.

The input image used in this paper is of size 512 x 512, speckle noise (multiplicative noise) is then added to the input image. Median filtering is then applied to the corrupted image to smooth it and to also preserve the edges of the image. A 2-D discrete wavelet transform is applied to the filtered image to get a decomposed structure of the image as HH, HL, LH and LL. A denoising and compression tool is applied to the decomposed structure to further reduce the noise content in the image. The learned dictionary of the image is the applied to the denoised and compressed image to obtain the enhanced image and finally inverse discrete wavelet transform is applied to the enhanced image to get it's original size back.

III. DICTIONARY LEARNING

Yang et al. [13] and Zeyde et al. [14] developed methods for single image super-resolution (SR) based on sparse modeling. These methods utilize an over complete dictionary

$$D_h \in \mathbb{R}^{n \times K} \quad (1)$$

containing K "atoms" of size n. It is assumed that any patch $x \in \mathbb{R}^n$ in a high-resolution image can be expressed as a sparse linear combination of the atoms D_h as follows:

$$x \approx D_{h}\alpha, \text{ with } \|\alpha\|_0 \ll K, \alpha \in \mathbb{R}^K \quad (2)$$

A patch y in the observed low-resolution image can be represented using a corresponding dictionary D_l with the same

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sparse coefficient vector α. This is ensured by co-training the dictionary D_h with high-resolution patches and dictionary D_l with corresponding low-resolution patches. The observed low-resolution image is related to the original high-resolution image through a combination of known blur and down sampling operators.

Super-resolution reconstruction proceeds in a patch-by-patch manner and, for each observed patch y, starts by determining the sparse solution vector

$$\alpha^* = \min_{\alpha} ||FD_l\, \alpha - Fy||^2_2 + \lambda|| \alpha||_1 \quad (3)$$

Dictionary training starts by sampling patch pairs from corresponding high and low-resolution images (preserving the correspondence between spatial locations. High-resolution patches $X^h = \{x_1,x_2,...,x_m\}$ are concatenated with low-resolution patch features $Y^l = \{y_1,y_2,...y_m,\}$ and a concatenated dictionary defined by:

$$X_c = \begin{bmatrix} w_h X^h \\ w_l Y^l \end{bmatrix}, \quad D_c = \begin{bmatrix} D_h \\ D_l \end{bmatrix}, \quad (4)$$

with weights w_h, w_l. Optimized dictionaries are computed by:

$$\min_{D_h, D_l, Z} \quad ||X_c - D_c Z||_2^2 + \lambda ||Z||_1$$
$$\text{s.t.} \quad ||D_{c_i}||_2^2 \leq 1, \quad i = 1, \ldots, K. \quad (5)$$

This above process is used in finding the dictionary of the input image. In our proposed method, the learned dictionary is used to enhance the image which in comparison provides a better results than the other methods employed.

IV. Wavelet-Based Image Denoising

Wavelets are mathematical functions that cut up data into different frequency components, and then study each component with a resolution matched to its scale. They have advantages over traditional Fourier methods in analyzing physical situations where the signal contains discontinuities and sharp spikes. Wavelets were developed independently in the fields of mathematics, quantum physics, electrical engineering, and seismic geology. Interchanges between these fields during the last ten years have led to many new wavelet applications such as image compression, turbulence, human vision, radar, and earthquake prediction.

Wavelets have been successfully exploited in a multitude of signal processing applications. In recent years, there has been an amount of researches on wavelet-based image denoising [10]. The process of image denoising using wavelets consists of first applying the Discrete Wavelet Transform (DWT) to the noisy image, then performing wavelet shrinkage (thresholding the detail coefficients), and finally applying the Inverse Discrete Wavelet Transform (IDWT) to reconstruct the filtered image [11], therefore an estimation of the original image is obtained. However, when dealing with multiplicative noise, a logarithmic transformation is applied to the noisy image before wavelet decomposition in order to transform the multiplicative noise model into an additive model. Consequently, after the IDWT process, an exponential transformation is applied to reverse the logarithmic operation [12].

To construct a set of child wavelets from a mother wavelet, a scaling function and wavelet function are needed. These functions form a filter bank consisting of a low pass filter and a high pass filter. Therefore, the signal is decomposed to detail coefficients having low magnitude (at the output of the high pass filter) and approximation coefficients having high magnitude (at the output of the low pass filter). Since half the frequencies are removed, each filter's output is down sampled by 2 [12]. After first transforming the rows, the same process is applied on the columns of the resulting image and finally, four subbands are obtained; The approximation subband, the horizontal detail subband, the vertical detail subband and the diagonal detail subband. The use of the IDWT here is to perform the reverse operation of reconstructing the image in the spatial domain.

V. Practical Results

The experiments are conducted on several natural gray scale images like Cameraman, Lena and other converted gray scale images of size 512 × 512 at different noise levels σ=10, 20, 30 and 40. The noise added to these images is speckle noise and it is done at various levels. median filtering is employed to help smooth the image and also help in the preservation of the edges. 2-D discrete wavelet transform is applied to the filtered to get a 2 level decomposition of the image, the decomposition of the image gives us the following; HH, HL, LH, and LL. In order to help further reduce the amount of noise in the image a denoising and compression is applied to the decomposed image to further reduce the amount of noise in the image. The learned dictionary is applied to the image to obtain the enhanced image. The PSNR of the enhanced image are calculated. The PSNR calculated for the various test images are tabulated in Table 1.

In many practical applications it is very important to be able to suppress the amount of noise while enhancing the image. Comparing our image enhancement to other existing methods with images containing noise, the results obtained shows the suppression of noise better, while achieving a detail enhancement.

Figure 2. Lena image (up left), corrupted by speckle noise (up right), enhanced image (down left). σ=10

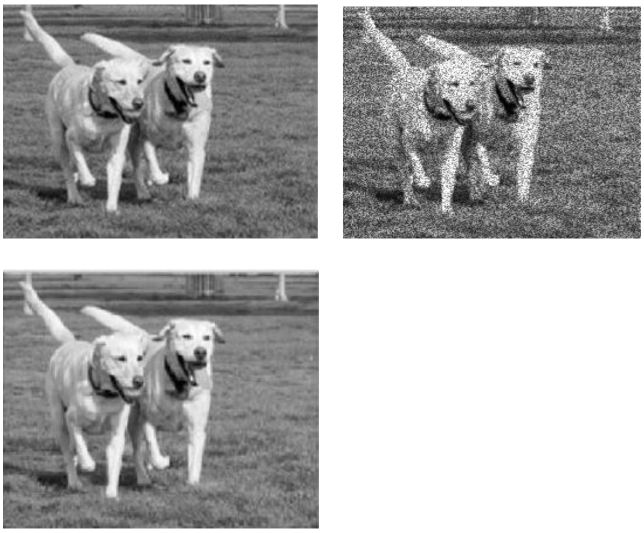

Figure 3. Dog image (up left), corrupted by speckle noise (up right), enhanced image (down left). σ=10

Figure 4. Flower image (up left), corrupted by speckle noise (up right), enhanced image (down left). σ=10

Image	Various Levels of Speckle Noise Intensity (σ)	PSNR (dB) of Noisy Image	PSNR (dB) of Enhanced Image
Lena			
	10	20.6114	33.557
	20	18.318	32.530
	30	16.281	30.735
Dog			
	10	21.853	34.375
	20	18.646	32.941
	30	15.642	31.654
Flower			
	10	19.461	31.900
	20	18.928	28.659
	30	16.421	27.096

Table 1. PSNR results for various test images

VI. CONCLUSION

In this paper, a method to perform a detail enhancement based on a dictionary and the use of a wavelet transform on images corrupted with speckle noise has been explained. The extended work of Yang et al was applied to an image to enhance a texture of fine detail without introducing any form of artifacts. The algorithm implemented here is preserves the edges resulting in the enhancement of the image without any significant loss of information.

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