Optimization Quality of Multi-resolution Image De-noising Schemes using Wavelet Transforms

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***Abstract* – Image de-noising is a central issue in picture handling.The primary goal is to eliminate noise from the deteriorated image while maintaining other image details. Lately, numerous multiresolution based approaches have achieved extraordinary progress in image denoising. In a nutshell, the wavelet transform provides the optimal representation of a noisy image, with noise caused by all remaining coefficients and information bearing signal from a small number of coefficients. The loud coefficients can be killed by thresholding system. Thus, there are three fundamental steps in every wavelet-based image denoising technique: to determine the inverse wavelet transform, threshold the wavelet coefficients, and compute the noisy image's wavelet transforms.**

The image's capacity for sparse representation determines how well the noisy coefficient separation works. The wavelet portrayal is ideally scanty, since the wavelets covering a peculiarity have a huge wavelet coefficient and any remaining coefficients are little. Only when the threshold value is chosen appropriately can the noise wavelet coefficient shrinkage be improved to its absolute best.

Keywords — Optimization, de-noising, wavelet transform, thresholding system, noisy image, wavelet-based image de-noising technique

I. INTRODUCTION

Computerized pictures assume an essential part in everyday life. This prompts the need of control of pictures. Image processing, image analysis, and image comprehension are the three types of image manipulation. Both the input and the output of image processing are data. The image is the input in image analysis, and the measurement of the image is the output. The image is the input in image understanding, and the high-level description of the image is the output. The fundamental manipulation of image processing is the focus of this thesis. The improvement of images' visual appearance or the extraction of their information is both examples of image processing [1, 2].

During the process of acquisition, transmission, and retrieval, noise typically corrupts images. Digital images are susceptible to a variety of noises, including shot noise, Gaussian noise, speckle noise, salt and pepper noise, and others. The noise can be further categorized as additive or multiplicative noise based on how it affects the image. Since the optical image is converted into a continuous electrical signal during image acquisition and then sampled to produce a digital image, the additive noise is taken into consideration here. The spatial space strategies are additionally characterized into straight and nonlinear strategies [3, 4].

Digital images are a crucial part of everyday life in today's scenario. As a result, image denoising requires a compromise between noise reduction and image detail preservation. In image processing, the discrete wavelet transform is an excellent tool. A countable set of coefficients in the transform domain is produced by the wavelet transform. As a result, a small portion of the signal's energy is dispersed across a large number of small wavelet coefficients, while the majority of the energy is contained in a few large wavelet coefficients. It has properties like inadequacy, grouping and connection between's adjoining wavelet coefficient. The real oriented dual tree discrete wavelet transform is yet another wavelet domain transform. Two simultaneous real separable 2D wavelet transforms can be used to accomplish this. By adding and subtracting sub-bands of two 2D separable Real wavelet transforms, this directional orientation transform can be realized. The change is liberated from checker board antiquity, however wavelet coefficients are not perplexing and subsequently it has not roughly moved invariance. In visual perception, details like edges and contours play a bigger role. The DTCWT is a useful tool for preventing all of these image details.

DTCWT is a more directional selective and computationally efficient method for shifting invariance. As a discrete wavelet transform, DTCWT makes use of separable filter banks, but it is superior because the magnitude and phase of a complex wavelet transform can be used to create new, efficient wavelet-based algorithms where DWT cannot. As a result, image denoising will perform better than DWT-based methods. This has roused to plan denoising calculations in view of wavelet changes [5].

The estimation of the threshold value determines how well each wavelet-based denoising method performs. To determine the threshold value, a variety of methods are available. The noise image's variances vary across the scale in the wavelet transform domain. To determine the threshold value using signal and noise variance, we take into account the dependencies that exist between the wavelet coefficients and their parent. The image's other sparse representations are also taken into consideration. Thus, bivariate shrinkage and SVD-based denoising algorithms; sub-band versatileVisuShrink and ideal NeighSurewith changing window strategies are created in wavelet space.

In the wavelet domain, block-based SVD are typically utilized. Sub-band coefficients and singular values are truncated in relation to the threshold value when SVD is applied in detail. When using wavelet, the amount of decomposition and image size increase, so do the computational requirements [6, 7].

II. Literature Review

Ozkan et al. proposed a linear filter that uses a mask on each pixel to reduce the intensity value between adjacent pixels to eliminate noise (1992). Gabbouj et al. dealt with the linear filters known as the median stack filter and the generalized median filter, both of which fail to preserve the edges. 1992), as well as Lee &Kassam Edge-preserving spatial filters like the SUSAN filter, which was proposed by Smith and Brady (1997), use distance as a measure of correlation between pixels as their foundation.

The fact that SUSAN filters only consider intensity rather than spatial locality is a drawback. Tomasi and Manduchi (1998) devised a bilateral filter that took into account both the intensity and the spatial distance between the pixels to overcome this issue. The parameter selection is the most significant issue with the bilateral filter, which works well to preserve edges but fails when the noise level is high.

Zhang &Gunturk (2008) addressed this as an empirical study of noise variance and explained how the bilateral filter is utilized in the wavelet domain. However, the bilateral filter flattens the gray level in the wavelet domain, giving the denoised image a cartoon-like appearance. A Shreyamshakumar-initiated combination of a Gaussian and a bilateral filter can overcome this limitation.

Acton & Bovik (1998), Gabbouj et al. address the non-linear methods that transform the image into smoothly varying regions with piecewise constant regions. 1992), as well as Lee & Kassam Andrews and Patterson (1976) introduced the nonlinear technique known as SVD, which can successfully denoise an image. While this approach applies SVD to the entire image in a single step, it does not distinguish between significant and non-significant singular values and only partially preserves edges. To save the edge halfway differential condition based techniques, utilize an edge identification term to smooth the edge structure was proposed by Arce and Encourage (1989). By independently enforcing geometric closeness and gray value from the well-known Bayesian approach, Smith & Brady (1997) and Tomasi&Manduchi (1998) developed a denoising method with edge preservation.

Due to its energy compaction property, which was first discovered by Mallat (1989), Raghuveer&Bopardikar (1999), and Mohideen et al. (), wavelet transform is regarded as one of the most effective transform domain methods for image denoising. 2008). The various discrete wavelet transforms can be correlated with the wavelet. This is because all other coefficients contain noise and the signal is contained in a small number.

Using a thresholding scheme, Donoho (1995) and Coifman&Donoho (1995) proposed a denoising method to filter these noisy coefficients. Donoho et al.'s SureShrink and Donoho& Johnstone's VisuShrink are two examples of threshold selection strategies. 1995), and Chang et al.'s BayesShrink(2000a), select the threshold value to produce a denoised image. Chen et al. (2004) proposed NeighShrink, a thresholding method that takes into account coefficients that are adjacent to one another. This technique utilizes just delicate thresholding approach and doesn't consider about multi wavelet coefficients. Utilizing a pre-filter, multi wavelet transform, thresholding scheme by neighboring multi wavelet coefficients, and then taking the inverse followed by post filtering were all suggested by Chen & Bui to alleviate this drawback. However, this plan only takes into account the immediate neighbors and does not take into account the larger neighborhoods. This issue was tended to by Dengwen and Wengang (2008) where an ideal edge and adjoining window size is still up in the air for each sub-band utilizing SURE. Cho et al. (The results of the NeighShrink approach for the parent wavelet coefficients and the neighbours in the proposed NeighLevel shrinkage (2009a) are quite satisfactory.

If a better adaptive threshold is used, the denoising result can be improved. Hari and Mantosh (2012 & 2015) proposed that the coefficients of a neighboring window for each sub-band can be used to determine the threshold value for each level.

Sendur and Selesnick (2002 & 2002) introduced Bayesian estimation theory, which is used to derive a bivariate shrinkage function from the dependencies between a coefficient and its parent. Denoising performance may be further enhanced by combining bivariate shrinkage with local adaptive methods. When the parent coefficient is lower, shrinkage is better. Zhang et al. suggested that, in order to denoise an image, a bivariate function can be combined with other transform domain methods. 2013).

Reconstruction of the noisy image suffers from shift invariance and directional selectivity, despite the ease of implementation of all methods. Kingsbury (1998, 1999, and 2001) and Selesnick et al. dealt with this issue (2005) to get the real and imaginary parts of complex wavelet coefficients by employing a dual tree wavelet filter. For 2D signals, the dual tree wavelet filter introduces a limited redundancy of 4:1. As a result, the transform results in directional selectivity and shift invariance. There are two DTDWT versions: The real 2D-DTDWT transform is the first, followed by the complex 2D-DTDWT. Khare et al. proposed Daubechies complex wavelet transforms (2010), which employs an adaptive threshold and shrinkage function for denoising, delivers improved performance when the noise level is high. However, the method is ineffective at any level of noise. Chen and co. (2012) has applied the dual tree complex wavelet transform to a noisy image with success by utilizing the wavelet coefficients across three scales in the thresholding process. Statistical dependencies between wavelet coefficients can still improve denoising performance. Remenyi et al. recently (2014) proposed a 2D scale blending complex wavelet change by laying out a covariance structure utilizing observational Bayesian strategy yields great denoising execution.

In the field of image denoising, spatial and transform domain-based strategies have both been extremely successful. Additionally, the denoising performance of the hybrid of the two domains has been improved. SVD, a well-known spatial domain method, can be utilized in conjunction with transforming domain methods like: Wongsawat et al. proposed applying SVD to a discrete cosine transformed image for denoising (2005). This method takes a long time and only keeps a small amount of high-frequency content with the original image.

Kakarala & Ogunbona (2001) also suggested SVD as a multi-resolution filter for signal analysis. In multi-resolution analysis, SVD compresses the signal's energy into the fewest possible coefficients. As a result, Zujun proposed that SVD can transform the noisy image into data and noise subspaces. Iqbal and others Using a non-local means filter, they proposed the Dual-tree complex wavelet transform and singular value decomposition for improving medical image resolution. To determine how well the proposed method works, both quantitative and qualitative analysis are used. Yu et al. propose a hybrid of SVD and DTCWT for detecting gas pipeline leaks while also reducing noise. 2016). In this work DTCWT is thought as a center to lead staggered disintegration and refining, for acoustic signs and SVD is used to eliminate clamor in non-trademark groups.

In view of the above study, it is obvious that all the denoisingtechniques have a similar objective, which is to get a commotion free picture by numerically limiting the blunder between the first and recuperated pictures. The survey shows that hybrid methods with spatial and sub-band adaptivity, sparse representation, and outperform existing denoising methods. This necessity has inspired to create denoisingcalculations in light of mixture approaches with multi-goal structures.

III. Methodology

Transmission and storage of raw images require huge quantity of disk space. Hence, there is an urgent need to reduce the size of image before sending or storing. The best possible solution to the problem is to use compression methods where the compression of data on digital images are made to reduce irrelevance and redundancy of the image data to be able to efficiently store or transmit data. Most of the existing compression techniques employed have their negatives and an enhanced technique which is faster, effective and memory efficient can definitely satisfy the requirements of the user.

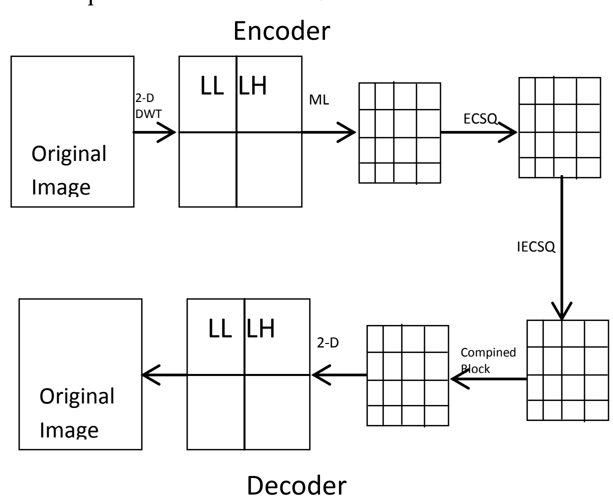

Figure 1: Methodology of image De-nosing

Image compression thrives to store or transmit the data in a proficient mode as well as to offer a best image quality at a specified bit-rate. Image compression can be done in lossy or lossless

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mode. Lossless compression is preferred for archival objectives and mainly used in medical imaging, technical drawings, clip art, or comics. This is due to the introduction of compression artifacts, low bit rates and also because the resources cannot be considerably saved by using image compression method. Lossy methods are especially suitable for natural images such as photographs in applications where negligible loss of fidelity is tolerable to attain a considerable reduction in bit rate. Here conciliated ensuing image quality devoid of much perception by the viewer is achieved.

This technique first decomposes an image into coefficients called sub-bands and then the resulting coefficients are compared with a threshold. Coefficients below the threshold are set to zero. Finally, the coefficients above the threshold value are encoded with a loss less compression technique. The compression features of a given wavelet basis are primarily linked to the relative scarceness of the wavelet domain representation for the signal. The notion behind compression is based on the concept that the regular signal component can be accurately approximated using the following elements: a small number of approximation coefficients (at a suitably chosen level) and some of the detail coefficients.

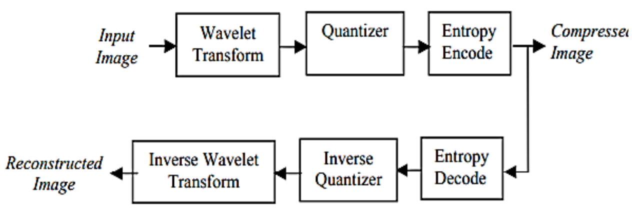

Figure 2: The structure of the wavelet transform based compression.

The steps of compression algorithm based on DWT are described below:

I. Decompose Choose a wavelet; choose a level N. Compute the wavelet. Decompose the signals at level N.

II. Threshold detail coefficients For each level from 1 to N, a threshold is selected and hard thresholding is applied to the detail coefficients.

III. Reconstruct Compute wavelet reconstruction using the original approximation coefficients of level N and the modified detail coefficients of levels from 1 to N.

Multi-level Block Truncation Code

The Encoder and decoder block of the multi-level block truncation code algorithm is shown if figure 2. Encoder part of the proposed algorithm shows that the original image is divided into three parts i.e. R component, G component and B component. Each R, G, B component of the image is divided into non overlapping block of equal size and threshold value for each block size is being calculated.

Threshold value means the average of the maximum value (max) of 'k × k' pixels block, minimum value (min) of 'k × k' pixels block and m_1 is the mean value of 'k × k' pixels block. Where k represents block size of the color image. So threshold value is:

$$T = \frac{\max + \min + m_1}{3} \quad (1)$$

Each threshold value is passing through the quantization block. Quantization is the process of mapping a set of input fractional values to a whole number. Suppose the fractional value is less than 0.5, then the quantization is replaced by previous whole number and if the fractional value is greater than 0.5, then the quantization is replaced by next whole number.

IV. Conclusion

Image de-noising is the fundamental problem in the image processing field. This is because images are often contaminated by noise during acquisition, transmission and storage. The spatial domains are restricted due to blurring the details of image while removing the noise. However, in transform domain wavelet transform have attained a great success in image processing applications, because wavelet transforms compress the energy of interest into a small number of large coefficients. The limitation of wavelet transform is shift invariance and directional selectivity.The intense of research work is to develop denoising techniques, to find better threshold value by combining the ideas of spatial and frequency domain techniques, to preserve the image details and visual appearance.

Generally the threshold values are found with the knowledge of noise variance, but the noise variance is not same across the scale. To overcome this sub-band adaptive VisuShrink is derived by using both the signal and noise variance. In the last method DTCWT is used along with SVD. Here the singular values are corrected by a Frobenius energy correction factor. A bivariate shrinkage function is used to remove the noisy information, and finally bilateral filter that uses geometric closeness and gray level value preserves the image details and smooth's the image.

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