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Denoising of Image by Wiener Filtering in Wavelet Domain

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Abstract—*Image de-noising is the process to remove noise from an image naturally corrupted by the noise. With Wavelet Transforms, various algorithms for de-noising in wavelet domain were introduced. Wavelet gave a superior performance in image de-noising due to its property such as multi-resolution. The DWT (Discrete Wavelet Transform) transforms noisy image into sub-bands, which consist of 4 sub-bands, namely the HH, HL, LH and LL sub-bands. The LL sub-band is the low resolution residual consisting of low frequency components and it is this sub-band which is further splitted at higher levels of decomposition. In this paper, an algorithm is designed based on wavelet thresholding and the Wiener filter technique. The sub-bands HH, HL, LH are filtered by wavelet thresholding and apply the Wiener filter on the sub-band LL. Finally perform inverse DWT transform to obtain a de-noised image. The results proved that the de-noised images using wavelets thresholding and Wiener filter has better balance between smoothness and accuracy than the DWT.*

1. INTRODUCTION

Ultrasonic imaging is a widely used medical imaging procedure because it is economical, comparatively safe, transferable and adaptable but it suffers from a main disadvantage i.e., contamination by speckle noise. Speckle noise is a multiplicative type whereas other noises, like Gaussian noise, are additive type. It is difficult to remove multiplicative noise from images.

Speckle noise is high frequency content in ultrasound images and appears in wavelet coefficients. It can be easily removed by using wavelet based thresholding technique [10]. In recent years, wavelet transform have been used as the powerful tools for noise removal applications. The motivation is that as the wavelet transform is good at energy compaction, the small coefficients are more likely due to noise and the large coefficients due to important signal features. These small coefficients can be thresholded without affecting the significant features of the image. Thresholding is a simple non-linear technique, which operates on one wavelet coefficient at a time. In its most basic form, each coefficient is thresholded by comparing against threshold, if the coefficient is smaller than threshold, set to zero; otherwise it is kept or modified. Replacing the small noisy coefficients by zero and inverse wavelet transform on the result may lead to reconstruction with the essential signal characteristics and less noise. Though wavelet thresholding method performs de-noising with edge preservation but in the smooth regions, it is not well de-noised. In this paper, Wiener filter and thresholding in discrete wavelet transform domain for de-speckling of ultrasound image is used. As the Wiener filter in the wavelet domain removes the noise pretty well in the smooth regions but performs poorly along the edges, it is applied in the low frequencies sub-band of the DWT (Discrete Wavelets Transform) of the noisy image and the wavelet thresholding method in the high frequencies sub-bands [10].

2. DISCRETE WAVELET TRANSFORM

The Discrete Wavelet Transform (DWT) of image signals produce a non-redundant image representation, which provides better spatial and spectral localization of image formation, compared with other multi-scale representations. The DWT can be interpreted as signal decomposition in a set of independent, spatially oriented frequency channels. A signal is passed through two complementary filters and emerges as two signals, approximation and Details. This is called decomposition. The components can be assembled back into the original signal without loss of information. This process is called reconstruction [2]. In decomposition process, the image is filtered in low and high pass filters along the rows and the outcomes of each filter are down-sampled by two. Those two sub-signals represent the low frequency component and high frequency component along the rows respectively and each of size N X N/2. Then each of these sub-signals is again high and low-pass filtered, along the columns. Then the outcomes obtained are down-sampled by two. As a result the original image is divided into four sub-images each of size N/2 X N/2 containing information from different frequency components. The LL sub-band is the result of low-pass filtering both the rows and columns and it contains a rough description of the image. Hence, the LL sub-band is also known as the approximation sub band. The HH sub-band is obtained by high-pass filtering in both directions and includes the high-frequency components along the diagonals as well.

The LH and HL sub-bands are the outcome of low-pass filtering along rows and high-pass filtering along column and vice versa. LH sub-band has typically the vertical detail information. HL represents the horizontal detail information. Decomposition steps are shown in Fig. 1. All three sub-bands HL, LH and HH are also known as the detail sub-bands, because they append the high-frequency information or details to the approximation sub-band. The sub-bands LL,LH,HL and HH may be called first average image, horizontal fluctuation, vertical fluctuation and the diagonal fluctuation respectively.

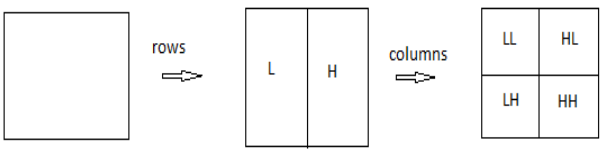

Fig. 1: Wavelet decomposition.

3. WIENER FILTER

The Wiener filter is used to remove the noise from a corrupted image based on statistics estimated from a local neighbourhood of each pixel [6]. This filter depends on the noise power (i.e. noise variance in a corrupted image). When the variance is large, the filter performs little smoothing and when the variance is small, the filter performs more smoothing. In this paper, the filter with local window n x n is applied on the DWT to remove the noise from each sub-band [5]. The Wiener filter is illustrated in the following equations.

$$\mu = 1/n^2 \sum_{i=1}^{n} \sum_{j=1}^{n} f(i,j) \quad \text{(i)}$$

$$\sigma^2 = 1/n^2 \sum_{i=1}^{n} \sum_{j=1}^{n} f^2(i, j) - \mu^2 \quad \text{(ii)}$$

where n = mask size =3

the above two equations are used to estimate local mean and local standard deviation, for local window nxn at noisy sub-band, respectively. The equation for the new de-noised coefficients D(i,j) is shown in the following equation.

$$D(i, j) = \mu + (\sigma^2 - \text{noise})\,(f(i, j) - \mu)/\sigma^2 \quad \text{(iv)}$$

where “noise” is power of noise in corrupted image and this value is estimated by using the following equation:

$$\text{Noise} = 1/MN\sum_{i=1}^{N} =1 \sum_{j=1}^{M} Variance(i,j\text{i, j}) \quad \text{(v)}$$

Where the N and M are the row and column values of the noisy image.

4. DENOISING ALGORITHM:

Procedures for image de-noising are as followed:

a. Input speckled-noised image.

b. Perform wavelet decomposition of the input image.

c. Apply soft thresholding to the sub-bands LH,HL and HH using the universal threshold value : T= σ√2logn, where σ is variance and n is the size of the image.

d. Apply Wiener filter to the LL sub-band for removal of noise coefficients.

Invert the wavelet decomposition to reconstruct the de-noised image.

5. EXPERIMENTAL RESULT

The performance of the wavelet thresholding with Wiener filter method that has been proposed in this paper is investigated with simulation. De-noising is carried out for image with speckle noise of variance 0.2. The de-noised image has been calculated by using Mean Square Error (MSE), which is defined as

$$\text{MSE} = 1/MN\sum_{i=1}^{M} \sum_{j=1}^{N} (X(i,j) - Y(i,j))^2 \quad \text{(v)}$$

The MSE value of the noisy image and de-noised image are found to be 0.0126 and 0.0048 respectively.

6. CONCLUSION

In this paper, a simple and efficient algorithm for speckle noise reduction is proposed, which combines the Wiener filtering and thresholding methods in the wavelet transform domain. As Wiener filter removes the noise pretty well in the smooth regions but performs poorly along the edges, thresholding method is applied to the high frequencies sub-bands (HH,HL,LH) and Wiener filtered to the low frequencies sub-band(LL). The outcome of this result reveals Wiener filter with thresholding scheme is more effective than both the Wavelet Wiener filter and the Wavelet thresholding scheme.

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