AN IMAGE DENOISING FRAMEWORK USING WAVELET SHRINKAGE AND DT-CWT

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Abstract –Non-stationary signal processing applications use standard non-redundant DWT (Discrete Wavelet Transform) which is very powerful tool. But it suffers from shift sensitivity, absence of phase information, and poor directionality. To remove out these limitations, many researchers developed extensions to the standard DWT such as WP (Wavelet Packet Transform), and SWT (Stationary Wavelet Transform). These extensions are highly redundant and computationally intensive. Complex Wavelet Transform (CWT) is also an impressive option, complex-valued extension to the standard DWT. There are various applications of Redundant CWT (RCWT) in an image processing such as Denoising, Motion estimation, Image fusion, Edge detection, and Texture analysis. In this work, the focused application is the image denoising using two innovative techniques and the images are considered which are corrupted by a random noise. The project presents that noise reduction of enhanced images using Dual tree complex wavelet transform double density dual tree wavelet transform filter. So the denoising process will be handled to reduce distortion under Dual tree complex wavelet transform domain. The measures used to assess the quality of the denoised image are the PSNR (Peak Signal to Noise Ratio). By denoising a noisy image with a standard deviation noise $\sigma = 40$, with the use of the threshold verifying $T2\log N(\sigma) = \sigma$ and the Haar wavelet and DT-CWT, we obtain a PSNR of 27.11 and 37.264 respectively.

Keywords –DT-CWT, Image Denoising, Thresholding, Wavelet Transform.

INTRODUCTION

Digital images play an important role both in daily life applications such as satellite television, computed tomography as well as in the field of research and technology such as astronomy and geographical information systems. In all actuality, an image is blended with certain measure of noise which diminishes visual nature of image. In this manner, evacuation of noise in an image is an exceptionally regular issue in late research in image processing. An image was defiled with noise during obtaining or at transmission because of channel errors or in storage because of faulty hardware. Image denoising is used to eliminate the noise while retaining as much as possible the important signal features. The function of image denoising is to calculate approximately the original image form the noisy data. Image denoising is a quiet undertaking for researchers on the grounds that noise evacuation presents artefacts and causes blurring of the images.

Noise can be presented in an image by discrete sources of radiation, image quantization, catching instruments and information transmission media. There are different sorts of image noise present in the image like shot noise, Gaussian noise, pepper noise, salt, speckle noise, and white noise. Image denoising is a course of action in digital image processing aimed at the removal of noise [1]. The most important reason to diminish noise is that extraneous features will
otherwise cause successive errors in recognition. Another motivation is that noise reduction reduces the size of the image file, and this in contrast reduces the time required for successive processing and storage. The purpose in the design of a filter to diminish noise is that it remove as much of the noise as possible while maintaining all of the image qualities [2].

Image denoising is used to eliminate the noise while retaining as much as possible the important signal features. The function of image denoising is to calculate approximately the original image form the noisy data. Image denoising still remains the challenge for researchers because noise removal introduces artefacts and causes blurring of the images [3].

It is assumed in image denoising methods that the characteristics of the corrupting the noises and the system are assumed to be known ahead of time. Through linear function the image \( s(x,y) \) is blurred and noise \( n(x,y) \) is superimposed or added to form the corrupted image \( w(x,y) \). This is convolved to generate the noise free image \( z(x,y) \).

As shown in the Figure 1 the “Linear operation” is the result of the addition or multiplication of the noise \( n(x,y) \) to the signal \( s(x,y) \). After obtaining the corrupted image \( w(x,y) \), it is exposed to the denoising method to get the denoised image \( z(x,y) \).

Denoising method based on Fourier transform method is localized in frequency domain and the wavelet transform method is localized in both frequency and spatial domain but both the methods are not data adaptive, however if the filtering approach is data adaptive it comes out with promising results. Data adaptiveness plays an important role in image denoising process because denoising of images is also dependent on the image (type) which is to be denoised [4].

I. PROPOSED METHODOLOGY

**Flow Diagram for Proposed Method**
Dual Tree Complex Wavelet Transform (DT-CWT)

It has been noted that, for some applications of the discrete wavelet transform, improvements can be obtained by using an expansive wavelet transform in place of a critically-sampled one. An expansive transform is one that converts an N-point signal into M coefficients with M > N. There are several kinds of expansive DWTs; here we describe the dual-tree complex discrete wavelet transform [5] [6].

The DT-CWT of a signal \( x \) is implemented using two critically-sampled DWTs in parallel on the same data. The transform is 2-times expansive because for an N-point signal it gives 2N DWT coefficients. If the filters in the upper and lower DWTs are the same, then no advantage is gained. However, if the filters are designed in a specific way, then the subband signals of the upper DWT can be interpreted as the real part of a complex wavelet transform, and subband signals of the lower DWT can be interpreted as the imaginary part. Equivalently, for specially designed sets of filters, the wavelet associated with the upper DWT can be an approximate Hilbert transform of the wavelet associated with the lower DWT. When designed in this way, the dual-tree complex DWT is nearly shift-invariant, in contrast with the critically-sampled DWT. Moreover, the dual-tree complex DWT can be used to implement 2D wavelet transforms where each wavelet is oriented, which is especially useful for image processing. (For the 2D DWT, recall that one of the three wavelets does not have a dominant orientation) The DT-CWT outperforms the critically-sampled DWT for applications like image denoising and enhancement.

One of the advantages of the DT-CWT is that it can be used to implement 2D wavelet transforms that are more selective with respect to orientation than is the 2D DWT [7]. Where \( w = (w_1, w_2), y = (y_1, y_2) \) and \( n = (n_1, n_2) \). The noise values \( n_1, n_2 \) are zero-mean Gaussian with variance \( \sigma \) [8, 9]. Based on the empirical histograms, the following non-Gaussian bivariate equation was used [8].
Figure 3: The Dual-Tree complex DWT of a signal $x$ [5]

$$ p_w(w) = \frac{3}{2\pi\sigma^2} \exp\left(-\frac{\sqrt{3}}{\sigma} \sqrt{w_1^2 + w_2^2}\right) $$

(1)

With this equation, $w_1$ and $w_2$ are uncorrelated, but not independent [9]. The MAP estimator of $w_1$ yields the following bivariate shrinkage function [10], [11].

$$ w_1 = \frac{\sqrt{y_1^2 + y_1^2 - \sqrt{3} \sigma^2}}{\sqrt{y_1^2 + y_1^2}} y_1 $$

(2)

In general, the DT-CWT has the following properties:
- Approximate shift invariance;
- Good directional selectivity in 2-dimensions (also true for higher dimensionality m-D);
- Perfect reconstruction (PR) using short linear-phase filters;
- Limited redundancy, independent of the number of scales, $2m:1$ for m-D; Efficient order-N computation- only twice the simple DWT for 1-D ($2m$ times for m-D).

To enhance the efficiency of the proposed algorithm, we have used double density dual tree complex wavelet transform.

**Wavelet Shrinkage Algorithm**

The process, commonly called wavelet shrinkage, consists of the following main stages:
- Perform the discrete wavelet transform;
- Estimate a threshold;
- Apply the threshold according to a shrinkage rule, in the three directions of the detail coefficients (horizontal, vertical, and diagonal);
- Perform the inverse wavelet transform using the thresholded coefficients.

Donoho and Johnstone proposed a nonlinear strategy for thresholding [12]. In their approaches, the thresholding can be applied by implementing either hard or soft thresholding method. Since the work of Donoho and Johnstone, there has been a lot of research on the way of defining the threshold levels and their type.

All the approaches require an estimation of the noise level. However the standard deviation of the data values may be used as an estimator, Donoho proposed a good estimator based on the median absolute deviation [12]:

$$ \sigma^2 = \left( \frac{\text{median} |y_{ij}|}{0.6745} \right)^2 $$

(3)

Where $y_{ij}$ are the coefficients of $HITH_1$ subband, which is the diagonal detail subband in the 1st level of the wavelet decomposition.
Algorithm & Flow Chart for Denoising using DWT & Hybrid Filters

I=Input Image
Taking I into the Denoising Block
Convert I from RGB to Gray Colour MAP say Igray
(Because the multidimensional matrix not supported by many digital filters & functions)
Let, \(dwt=\text{Wavelet transform and THfilt=Wavelet filtering with respect to threshold}\)
\((cA, cH, cV, cD)=dwt(Igray)\);
Here, \(cA, cH, cV\) and \(cD\) are approximation, Horizontal, Vertical and Diagonal Coefficients respectively.
Update the approximation coefficients by filtering it.
\(cA=\text{THfilt}(cA)\);
\(\text{THfilt}\) is the thresholding function that we considered, by taking following points as a filtering criteria
- Eliminate in the wavelet representation those elements with small coefficients, and
- Decrease the impact of elements with large coefficients.
- In mathematical terms, all we are doing is thresholding the absolute value of wavelet coefficients by an appropriate function.
Similar operation will be perform for multi-level decomposition
For second level
\((cA1, cH, cV, cD)=dwt(cA)\);
\(cA1=\text{THfilt}(cA1)\);
For third level
\((cA2, cH, cV, cD)=dwt(cA1)\);
\(cA2=\text{THfilt}(cA2)\);
After the transformation procedes, we have to apply inverse transform on the input medical image
Let, \(idwt=\text{Inverse Wavelet Transform of data}\)
\(Y2=idwt(\text{with respect to cA2 & other parameters are kept same});\)
\(Y1=idwt(\text{with respect to cA1 & other parameters are kept same});\)
\(Y=idwt(\text{with respect to cA and cDu& other parameters are kept same});\)
Here, Updated Diagonal coefficients are calculated as
\(cDu=\text{mean of cD&cH}\)
Let, median, average and diffusion are median, average and diffusion filters for data filtering.
\(Ym=\text{Median}(Y)\);
A median filter is more effective than convolution when the goal is to simultaneously reduce noise and preserve edges.
Create a filter structure for average filter, Say \(FSa\), after that, we have to perform multidimensional filtering on median filtered data, according to the specified options for average filter.
\(Ya=\text{Filter}(Ym, FSa)\);
Numerical gradient calculations is perform from average filtered output, say by function \(\text{Gradient}\)
\(fx, fy=\text{Gradient}(Ya)\)
After that, we have to calculate discrete Laplacian of the average filtered image, in order to pass it through diffusion approximation with two dimensional gradient functions.
Say, \(\text{Diffusion}\) is the function involving whole process of anisotropic diffusion which we have to apply on average filtered data, reducing image noise without removing significant parts of the image content, typically edges, lines or other details that are important for the interpretation of the image.
\(Yd=\text{Diffusion}(Ya)\);
Here, \(Yd\) is the final output that we are taking from denoising block which we use further in segmentation block.
As a consequence, the resulting medical images preserve linear structures while at the same time smoothing is made along these structures. Both these cases can be described by a generalization of the usual diffusion equation where the diffusion coefficient, instead of being a constant scalar, is a function of image position and assumes a matrix (or tensor).

II. Simulation and Results

PSNR is globally used to measure the quality that a reconstruction of lossy compression codecs (e.g., for image compression) has produced. The valid signal in this case is nothing but the original data, & the noise is the error got into it through compression. When comparing compression codecs, PSNR is an approximation to human observation of reconstruction quality. Although a higher PSNR in general indicates that the reconstruction is of superior quality, in some cases it will not. One need to be awfully careful with the range of validity of this metric; it is only decisively valid when it is used to make a comparisons of the results from the same codec (or codec type) and same content.

PSNR is defined by mean squared error (MSE). Given a noise-free $m \times n$ monochrome image $I$ and its noisy approximation $K$, MSE is given as:

$$MSE = \frac{1}{mn} \sum_{i=0}^{m-1} \sum_{j=0}^{n-1} [I(i,j) - K(i,j)]^2$$

(4)

The PSNR is defined as:

$$PSNR = 10 \log_{10} \left( \frac{MAX_i^2}{MSE} \right)$$

$$= 20 \log_{10} \left( \frac{MAX_i}{MSE} \right)$$

$$= 20 \log_{10}(MAX_i) - 10 \log_{10}(MSE)$$

(5)

Figure 4: Input Images for Image deoising

Table 1: Lena image with Gaussian Noise

<table>
<thead>
<tr>
<th>Standard Deviation of Noise</th>
<th>10</th>
<th>20</th>
<th>30</th>
<th>40</th>
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<tbody>
<tr>
<td>PSNR</td>
<td>34.11</td>
<td>30.32</td>
<td>28.01</td>
<td>26.36</td>
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<td>DWT-Visu shrink</td>
<td>35.42</td>
<td>32.39</td>
<td>30.59</td>
<td>29.26</td>
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<tr>
<td>DWT-Bayes shrink Sure</td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Proposed Method-1 (DT-CWT)</td>
<td>37.26</td>
<td>32.51</td>
<td>29.44</td>
<td>27.17</td>
</tr>
</tbody>
</table>

Table 2: Barbara image with Gaussian Noise

<table>
<thead>
<tr>
<th>Standard Deviation of Noise</th>
<th>10</th>
<th>20</th>
<th>30</th>
<th>40</th>
</tr>
</thead>
<tbody>
<tr>
<td>PSNR</td>
<td>31.21</td>
<td>29.32</td>
<td>26.31</td>
<td>23.43</td>
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<tr>
<td>DWT-Visu shrink</td>
<td>32.39</td>
<td>30.01</td>
<td>27.33</td>
<td>24.56</td>
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<td>DWT-Bayes shrink Sure</td>
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</tr>
<tr>
<td>Proposed Method-1 (DT-CWT)</td>
<td>35.26</td>
<td>31.23</td>
<td>29.56</td>
<td>26.45</td>
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</tbody>
</table>

In Table 1, on comparing with the other methods, the proposed method has shown great improvement in peak signal to noise ratio (PSNR) when Gaussian noise is considered. It was found that at the standard deviation of 10 the lowest PSNR is achieved by visu Shrink i.e. 34.11 dB and highest PSNR is accomplished by Proposed Method-1 i.e. 37.2642dB. Thus the proposed Method-1 outperforms other methods.

III. CONCLUSION

We have presented in this paper one of the applications of the wavelet analysis which is denoising by thresholding the wavelet coefficients. The result depends on the type of thresholding used: hard thresholding or soft thresholding. For the choice of threshold used: in this article the threshold used verifies the relation $T \leq 2 \log (N) \epsilon = s$. We have used Haar wavelet and dual tree complex wavelet transform. The most unfavourable case and it is possible to obtain information in a noisy image by a noise Standard deviation of up 40.

References


