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MRI Denoising Using 2-D Dual-Tree DWT

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Abstract—*In image processing, for denoising an image, wavelet thresholding (shrinkage) is one of the main techniques. In this work, we have denoised a Magnetic Resonance Image (MRI) using wavelet thresholding. MRIs are quite effective tool for diagnosis in medical world and its maximum possible denoising for better diagnosis is always a call of time. We have used three different methods for thresholding: separable 2-D discrete wavelet transform (DST), real 2-D dual-tree DWT (DTDWT), and complex dual tree 2-D DWT. Random noises in the images have been considered and results have been compared. To have better insight, we have performed our analysis by varying threshold levels. Apart from discussing the merits and demerits of different techniques, RMS errors obtained from these techniques have also been compared. Out of these techniques, best results were obtained through complex 2-D dual tree DWT.*

1. INTRODUCTION

One popular technique for image denoising is wavelet thresholding (or "shrinkage"). When we decompose data using the wavelet transform, we use filters that act as averaging filters, and others that produce details. Some of the resulting wavelet coefficients correspond to details in the data set (high frequency sub-bands). If the details are small, they might be omitted without substantially affecting the main features of the data set. The idea of thresholding is to set all high frequency sub-band coefficients that are less than a particular threshold to zero. These coefficients are used in an inverse wavelet transformation to reconstruct the data set [1]. Generally we can use three different methods to remove the noise from an image. These methods are using separable 2-D DWT, real 2-D dual-tree DWT, and complex 2-D dual-tree DWT. Infact, in medical field, various researchers use complex 2-D dual tree DWT alongwith other filters generally [2].

Classical discrete wavelet transform (DWT) provides a means of implementing a multiscale analysis, based on a critically sampled filter bank with perfect reconstruction [3]. However, questions arise regarding the good qualities or properties of the wavelets and the results obtained using these tools, the standard DWT suffers from the following problems described as below: Shift sensitivity: it has been observed that DWT is seriously disadvantaged by the shift sensitivity that arises from down samples in the DWT implementation [4]. Poor directionality: an m-dimension transform (m>1) suffers poor directionality when the transform coefficients reveal only a few feature in the spatial domain. Absence of phase information: filtering the image with DWT increases its size and adds phase distortions; human visual system is sensitive to phase distortion [5]. Such DWT implementations cannot provide the local phase information. In other applications, and for certain types of images, it is necessary to think of other, more complex wavelets, who gives a good way , because the complex wavelets filters which can be made to suppress negative frequency components. As we shall see the CWT has improved shift-invariance and directional selectivity [5]. The discrete complex dual tree wavelet transform (DT-CWT) was introduced by N. Kingsburg around in 1990. This implementation uses consists in analyzing the signal by two different DWT trees, with filters chosen so that at the end, the signal returns with the approximate decomposition by an analytical wavelet.

2-D Dual-Tree Wavelet Transform: One of the advantages of the dual-tree complex wavelet transform is that it can be used to implement 2D wavelet transforms that are more selective with respect to orientation than is the separable 2D DWT. There are two versions of the 2D dual-tree wavelet transform: the real 2-D dual-tree DWT is 2-times expansive, while the complex 2-D dual-tree DWT is 4-times expansive. Both types have wavelets oriented in six distinct directions. We describe the real version first.

1. Real 2-D Dual-tree Wavelet Transform: The real 2-D dual-tree DWT of an image x is implemented using two critically-sampled separable 2-D DWTs in parallel. Then for each pair of subbands we take the sum and difference.

2. Complex 2-D Dual-tree Wavelet Transform : The complex 2-D dual-tree DWT also gives rise to wavelets in six distinct directions, however, in this case there are two wavelets in each direction as will be illustrated below. In each direction, one of the two wavelets can be interpreted as the real part of a complex-valued 2D wavelet, while the other wavelet can be interpreted as the imaginary part of a complex-valued 2D wavelet. Because the complex version has twice as many

wavelets as the real version of the transform, the complex version is 4-times expansive. The complex 2-D dual-tree is implemented as four critically-sampled separable 2-D DWTs operating in parallel. However, different filter sets are used along the rows and columns. As in the real case, the sum and difference of subband images is performed to obtain the oriented wavelets.

2. METHODOLOGY

All the computational work has been performed on MATLAB (2008) software. We have used an MRI image of the brain of a female patient and have introduced a random noise in it with variance 20. Then RMS errors (with respect to original image) have been calculated for different thresholds (0-60) with three different wavelet techniques viz separable 2-D discrete wavelet transform, real 2-D dual tree discrete wavelet transform, and complex 2-D dual tree discrete wavelet transform. These errors have been tabulated (Table – 1) and plotted on a graph (Figure – 1) for better understanding. The denoised images through these techniques have been shown with noised image to compare visually (Figure – 2a, 2b, 2c, and 2d). The various steps used in this soft thresholding are:

A. Read an input image,

B. Add noise to the input image and compute RMS error, C. Use filter bank for first stage and remaining stages,

D. Set J (number of stages and T (threshold value),

E. Compute forward DTCWT,

F. Compute inverse DTCWT,

G. Extract output image and compute RMS error.

3. RESULTS AND CONCLUSIONS

RMS errors of noisy, denoised by separable DWT, 2-D real and complex dual tree DWT have been calculated with respect to the original image and have been shown in table 1. The same have been plotted in Figure 1 and from table and figure it is clear that least value (and hence best value) of RMS error comes for the image which has been denoised by 2-D complex dual tree DWT at threshold value 20. Comparing Figures 2a, 2b, 2c, and 2d make clear that the figure 2d which is denoised by 2-D complex dual tree DWT, is looking best and hence is the most usable.

Table 1: Values of RMS error (with respect to original image) with varying T

Threshold value (T)	RMS error (decibal) w.r.t. original image			
	Noisy image	Separable DWT	Real 2D DTDWT	Complex 2D DTDWT
0	20.191	19.9503	20.0220	20.0345
5	20.191	16.4779	15.1624	14.4497
10	20.191	13.5972	11.3788	10.0345
15	20.191	11.3558	8.9617	7.6580
20	20.191	9.7770	7.8554	7.1757
25	20.191	8.8340	7.6604	7.5567
30	20.191	8.4248	7.9135	8.1244
35	20.191	8.3970	8.3272	8.6802
40	20.191	8.5934	8.3330	9.1939
45	20.191	8.9039	9.2161	9.6655
50	20.191	9.2579	9.6283	10.1043
55	20.191	9.6192	10.0174	10.5149
60	20.191	9.9719	10.3851	10.9007

This makes us to conclude that the two dimensional dual tree complex discrete wavelet transform is best among the discussed denoising techniques.

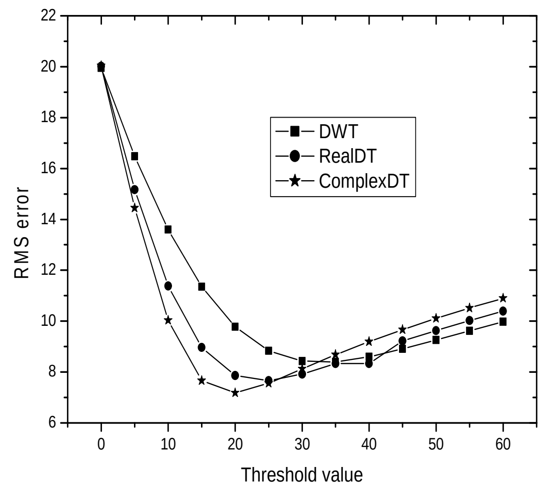

Figure 1: Plot of RMS error versus threshold values

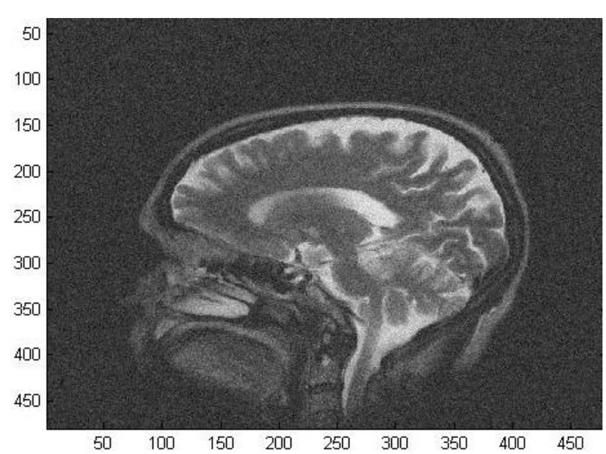

Figure 2a: Output of noisy image

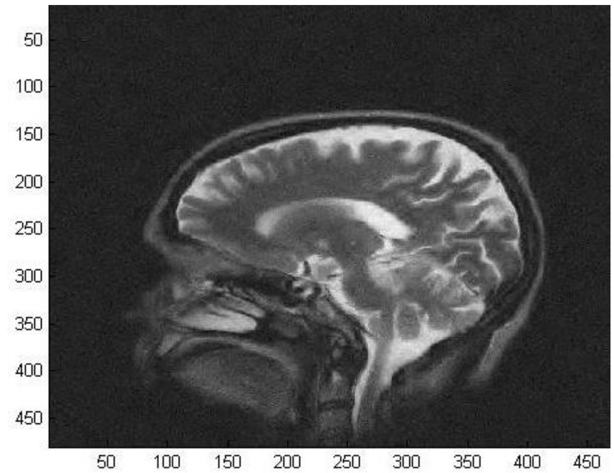

Figure 2b: Output of denoised image by separable DWT

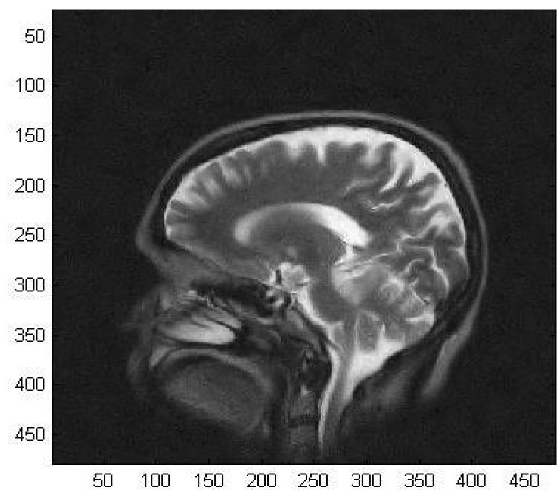

Figure 2c: Output of denoised image by 2D real dual tree DWT

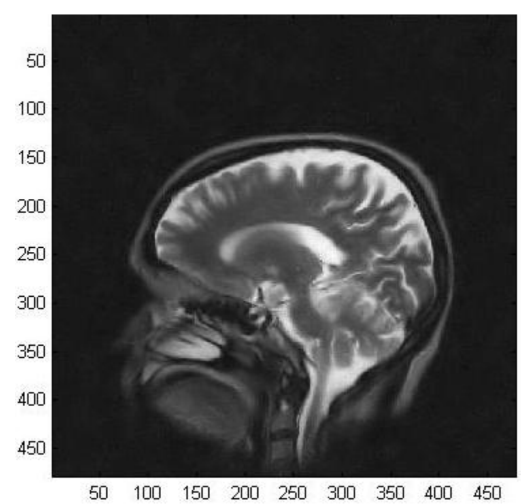

Figure 2d: Output of denoised image by 2D complex dual tree DWT

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