Image Denoising Using Complex Ridgelet Trasform

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Abstract

In this paper, we plan a new image denoising technique by integrating the dual-tree complex wavelets into the usual ridgelet transform. To make a new method for image donoising from approximate shift invariant property of the dual-tree complex wavelet and the high directional sensitivity of the ridgelet transform. We spread on the digital complex ridgelet transform to the image denoising of particular standard images added in white noise. In this procedure normal hard thresholding of the complex ridgelet coefficient is used. The results of this paper show better than VisuShrink, the ordinary ridgelet image denoising, and wiener2 filter, and also Complex ridgelets applied to curvelet image denoising.

***Keywords**: complex ridgelets Transform, Image denoising, wavelets, ridgelets, VisuShrink.*

1. INTRODUCTION(BACKGROUND)

The image processing scientific field normally wavelet transforms used for image denoising, image compression, signal processing, pattern recognition, many image applications and computer graphics. The Donoho and his coworkers pioneered a wavelet denoising scheme by performing soft thresholding, hard thresholding both. In this approach cover many number of image processing applications. Because wavelet transform can perfume compact the energy of the image to only a small number of large co-efficient and the majority of the wavelet coefficients are very small so that they can be set to be zero. The thresholding of the wavelet coefficients can be done by wavelet decomposition subbands. So that they are not thresholded because of a few low frequency wavelet subbands untouched. The Donoho's method used for advantages of smoothness and adaptation. However, as Coifman and Donoho pointed out, this algorithm exhibits visual artifacts: Gibbs phenomena in the neighbourhood of discontinuities. Consequently, they propose in a translation invariant (TI) denoising scheme to suppress such artifacts by averaging over the denoised signals of all circular shifts. The experimental results in confirm that single TI wavelet denoising performs better than the non-TI case. Bui and Chen [2] extended this TI scheme to the multiwavelet case and they found that TI multiwavelet denoising gave better results than TI single wavelet denoising. Cai and Silverman proposed a thresholding scheme by taking the neighbour co-efficient into account. Their experimental results showed apparent advantages over the traditional term-by-term wavelet denoising. Chen and Bui [3] extended this neighbouring wavelet thresholding idea to the multiwavelet case. They claimed that neighbour multiwavelet denoising outperforms neighbour single wavelet denoising for some standard test signals and real-life images. Chen et al. [6] proposed an image denoising scheme by considering a square neighbourhood in the wavelet domain.

Chen et al. [5] also tried to customize the wavelet filter and the threshold for image denoising. The above method results show and produce better denoising results. The ridgelet transform was developed to break the limitations of the wavelet transform. The large wavelet coefficients there in 2D wavelet transform, at every scale of the decomposition. With so many large coefficients, the denoising of noisy images faces a lot of difficulties. The following papers know that the ridgelet transform has been successfully used to analyze digital images. Unlike wavelet transforms, the ridgelet transform processes data by major computing integrals over different orientations and locations. A ridgelet is constant along the lines $x_1\cos\Theta + x_2\sin\Theta$ = constant. In the direction orthogonal to these ridges it is a wavelet. Ridgelets have been successfully applied in image denoising recently. In this paper, we combine the dual-tree complex wavelet in the ridgelet transform and apply it to image denoising. The approximate shift invariance property of the dual-tree complex wavelet and the good property of the ridgelet make our method a very good method for image denoising. The results show that by using dual-tree complex ridgelets, this algorithms obtain higher Peak Signal to Noise Ratio for all the denoised images including different noise levels.

2. COMPLEX RIDGELET

Both smooth objects and of objects with edges representation using in Discrete ridelet transform. It is same and near-optimal method of denoising for Gaussian noise. The ridgelet transform can resizing the energy of the image into a smaller number of ridgelet coefficients. In the same way, the wavelet transform produces many large wavelet coefficients on the edges on every scale of the 2D wavelet decomposition. These wavelet coefficients are needed in order to reconstruct the edges in the image. These are same approximate Radon transforms for digital data can be based on discrete fast Fourier transform. The ordinary ridgelet transform can be realized as shadows.

a). Find 2D FFT of the image first.

b). Change the sampled values of the Fourier transform achieved on the square lattice with sampled values of a polar lattice.

c). Find and compute the inverse FFT 1D on each angular line.

d). To make the 1D wavelet transform of resulting angular lines in order to obtain the ridgelet coefficients.

The ordinary discrete wavelet transform is not shift invariant because of the decimation operation during the transform. The small shift in the input signal can cause very different output wavelet coefficients. This overcome problem, Kingsbury introduced a new kind of wavelet transform, called the dual-tree complex wavelet transform, that exhibits approximate shift invariant property and improved angular resolution. Since the scalar wavelet is not shift invariant, it is better to apply the dual-tree complex wavelet in the ridgelet transform so that we can have what we call complex ridgelets. This procedure can be done by replacing the 1D scalar wavelet with the 1D dualtree complex wavelet transform in the last step of the ridgelet transform. In the way, we can association the good property of the ridgelet transform with the approximate shift invariant property of the dual-tree complex wavelets. The complex ridgelet transform can be applied to the total entire image or we can partition the image into a number of overlapping squares and we apply the ridgelet transform to each square. The decompose the original NxN image into smoothly overlapping blocks of sidelength R pixels so that the overlap between two vertically adjacent blocks is a rectangular array of size R=2 / R and the overlap between two horizontally adjacent blocks is a rectangular array of size R x R=2. For an NxN image, we count 2n/R such blocks in each direction. The above partitioning introduces a redundancy of 4 times. In order to get the denoised complex ridgelet coefficient, we use the average of the four denoised complex ridgelet coefficients in the current pixel location.

The thresholding for the complex ridgelet transform is similar to the curvelet thresholding. One difference is that we take the magnitude of the complex ridgelet coefficients when we do the thresholding. Let $y\lambda$ be the noisy ridgelet coefficients. We use the following hard thresholding rule for estimating the unknown ridgelet coefficients. When $|y\lambda| > k\sigma\tilde{\sigma}$ we let $y\lambda\hat{} = y\lambda$. Otherwise, $y\lambda\hat{} = 0$. Here, $\tilde{\sigma}$ is approximated by using Monte-Carlo simulations. The constant k used is dependent on the noise σ . When the noise σ is less than 30, we use k = 5 for the first decomposition scale and k = 4 for other decomposition scales. When the noise σ is greater than 30, we use k = 6 for the first decomposition scale and k = 5 for other decomposition scales.

Algorithm

i). Divide the image into RxR blocks with 2 vertically adjacent blocks overlapping R=2 / R
pixels and two horizontally adjacent blocks overlapping R x R=2 pixels.

ii). Each block, Apply complex ridgelets, threshold the complex ridgelet coefficients, and apply inverse complex ridgelet transform.

iii). Proceeds the average of the denoising image pixel values at the same place.

The above algorithm call as ComRidgeletShrink, however the algorithm using the ordinary ridgelets RidgeletShrink. The computational complexity of ComRidgeletShrink is similar to RidgeletShrink by by means of the scalar wavelets. The difference is that we replaced the 1D wavelet transform with the 1D dual-tree complex wavelet transform. The amount of computation for the 1D dual-tree complex wavelet is twice that of the 1D scalar wavelet transform. But, other steps of the algorithm keep the same amount of calculation. The experimental results show that ComRidgeletShrink outperforms V isuShrink, RidgeletShink, and wiener2 filter for all cases. In r some case, we obtain some improvement in

Peak Signal to Noise Ratio (PSNR) over RidgeletShrink. The development over V isuShink is even bigger for denoising all images. This shows that ComRidgeletShrink is an outstanding choice for denoising usual noisy images.

3 RESULTS

We use for famous image Lena. The from the free software package WaveLab developed by Donoho et al. at Stanford University. The above images with different noise levels are generated by adding Gaussian white noise to the original noise-free images. For comparison, we implement VisuShrink, RidgeletShrink, ComRidgeletShrink and wiener2. The VisuShrink is the universal soft-thresholding denoising procedure. The wiener2 function uses 5 x 5 neighborhood of each pixel in the image it is presented in the MATLAB Toolbox and applies a Wiener filter to an image adaptively, tailoring to the local image variance. The searching ,investigational results in the form of Peak Signal to Noise Ratio (PSNR). In that values to choose the partition block size of 64 x64 or 32 x32 is our best choice. The results for denoising image Lena with different noise levels and a fixed partition block size of 32 x 32 pixels. The first column of value is the PSNR of the original noisy images, and other columns are the PSNR of the denoised images by expending different denoising methods.

$$PSNR = -10\log_{10}\frac{\sum_{i,j}(\mathrm{N}(i,j)-\mathrm{M}(i,j))^2}{n^2 255^2}$$

Where M is the noise-free imageand N is the denoised image. The improvement of ComRidgeletShrink over V isuShrink is even more significant for all noisy levels and testing images. The figure shows the noise free image, the image with noise added, the denoised image with VisuShrink, the denoised image with RidgeletShrink, the denoised image with ComRidgeletShrink, and the denoised image with wiener2 for images Lena, at a partition block size of 32 x 32 pixels.

4. CONCLUSION

The paper complex ridgelet transform is obtained by execution 1D dual-tree complex wavelet onto the Radon transform coefficients. The Radon transform is done by resources of the projection-slice theorem. The complex ridgelet transform an outstanding best for image denoising because of we uses the approximate shift invariant property of the dual-tree complex wavelet transform. The complex ridgelet transform provides near-ideal sparsity of representation for both objects with edges and smooth objects.

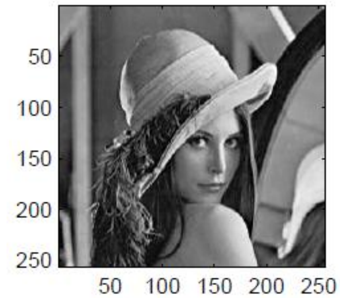

Figure 1. Original Image

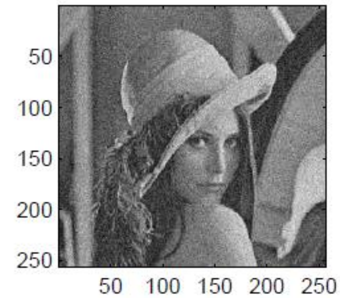

Figure2. Noisy Image

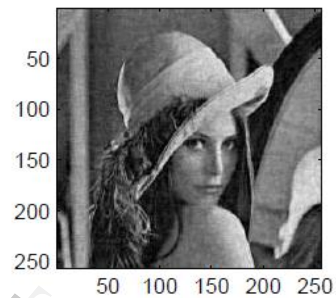

Figure 3. Redgelet Shrink

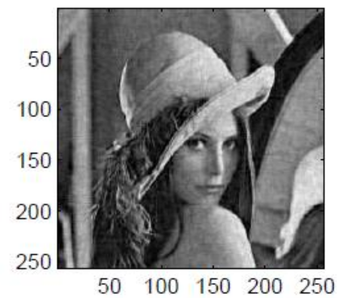

Figure 4: Complex RegeletShrink

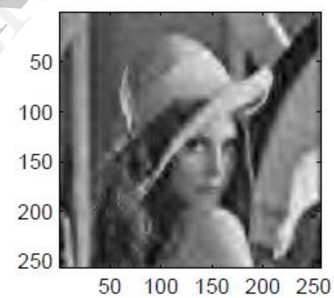

Figure5. VisuShrink

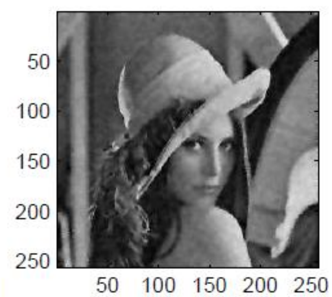

Figure 6. Resultant Image

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