ISSN 2229-5518

SLANT TRANSFORMATION AS A TOOL FOR PRE-PROCESSING IN IMAGE PROCESSING

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Abstract—The Slantlet Transform (SLT) is a recently developed multiresolution technique especially well-suited for piecewise linear data. The Slantlet transform is an orthogonal Discrete Wavelet Transform (DWT) with 2 zero moments and with improved time localization. It also retains the basic characteristics of the usual filterbank such as octave band characteristic and a scale dilation factor of two. However, the Slantlet transform is based on the principle of designing different filters for different scales unlike iterated filterbank approaches for the DWT. In the proposed system, Slantlet transform is implemented and used in Compression and Denoising of various input images. The performance of Slantlet Transform in terms of Compression Ratio (CR), Reconstruction Ratio (RR) and Peak-Signal-to-Noise-Ratio (PSNR) present in the reconstructed images is evaluated. Simulation results are discussed to demonstrate the effectiveness of the proposed method.

Index Terms—Discrete Wavelet transform, Compression ratio, Data Compresion, Peak-signal-to-ratio(PNSR), Coding Inter Pixel, Slantlet Coefficients, Choppy Images.

1 INTRODUCTION

For many decades, scientists wanted more appropriate functions than the sines and cosines, which comprise the basis of Fourier analysis, to approximate choppy images. By their definition, these functions are non-local (and stretch out to infinity). Therefore they do a very poor job in approximating sharp spikes. Wavelets are functions that satisfy certain mathematical requirements and are used in representing data or other functions.

This makes wavelets interesting and useful. But with wavelet analysis, approximating functions can be used that are contained neatly in finite domains. Wavelets are well suited for approximating data with sharp discontinuities [1].

The Discrete Wavelet transform (DWT) is usually carried out by filterbank iteration, but for a fixed number of zero moments it does not yield a discrete time basis that is optimal with respect to time localization. The Slantlet transform is an orthogonal DWT with 2 zero moments and with improved time localization. The Slantlet transform has been developed by employing the lengths of the discrete time basis function and their moments as the vehicle in such a way that both time-localization and smoothness properties are achieved. Using Slantlet transform it is possible to design filters of shorter length while satisfying orthogonality and zero moments condition. The basis function retains the octave-band characteristic. Thus Slantlet transform has been used as a tool in devising an efficient method for compression and denoising of various images.

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2. Literature survey

G.K. Kharate, A.A. Ghatol, et.al [2], proposed an algorithm based on decomposition of images using Daubechies wavelet basis. Compression of data is based on reduction of redundancy and irrelevancy. They have proposed an adaptive threshold for quantization, which is based on the type of wavelet, level of decomposition and nature of data.

Sos S. Agaian, Khaled Tourshan, et.al [3] proposes a novel approach for the parameterization of the slantlet transform with the classical slantlet and the Haar transforms are special cases of it is presented. The slantlet transform matrices are constructed first and then the filterbank is derived from them. The parametric slantlet transform performance in image and signal denoising is discussed.

Panda. G, Dash. P K, et.al [4] proposes a novel approach for power quality data compression using the slantlet is presented and its performance in terms of compression ratio (CR), percentage of energy retained and mean square error present in the reconstructed image is assessed.

Lakhwinder Kaur, Savita Gupta, et.al [5] proposed an adaptive threshold estimation method for image denoising in the wavelet domain based on the generalized Guassian distribution (GGD) modeling of subband coefficients.

Lei Zhang; Bao, P; Xiaolin Wu [8] proposed a wavelet-based multiscale linear minimum mean square-error estimation (LMMSE) scheme for image denoising is proposed, and the determination of the optimal wavelet basis with respect to the proposed scheme is discussed. The overcomplete wavelet expansion (OWE), which is more effective than the orthogonal wavelet transform (OWT) in noise reduction, is used.

3.The Slantlet Transform

The Slantlet filterbank is an orthogonal filter bank for the discrete wavelet transform, where the filters are of shorter support than those of the iterated D_2 filterbank tree. This filterbank retains the desirable characteristics of the usual DWT filterbank.

The Slantlet filter bank shown in Fig 3.1. is generalized as follows. The l-scale filter bank has 2l channels. The lowpass filter is to be called $h_l(n)$. The filter adjacent to the lowpass channel is to be called f_l (n). Both $h_l(n)$ & $f_l(n)$ are to be followed by down sampling by 2^l. The remaining 2l - 2 channels are filtered by $g_i(n)$ & its shifted time-reverse for i =1,…., l-1. Each is to be followed by down sampling by 2^{i+1}. x(n) Slantlet filter Coefficients

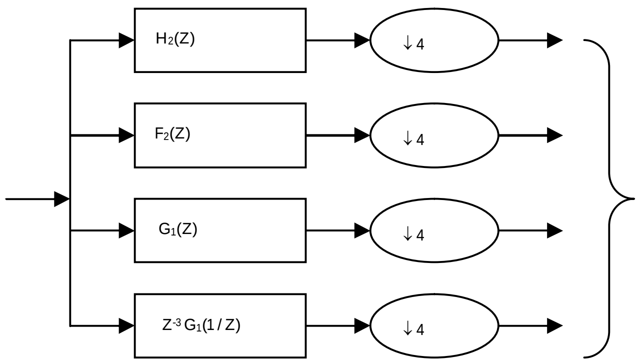

Fig 3.1. Slantlet filterbank

In the Slantlet filterbank, each filter $g_i(n)$ does not appear together with its time reverse. While $h_i(n)$ does not appear with its time reverse, it always appears paired with the filter $f_i(n)$. In addition, note that the l-scale and (l + 1) scale filterbanks have in common the filters $g_i(n)$ for i=1,…., l-1 and their time-reversed versions.

The Slantlet filterbank analyzes scale i with the filter $g_i(n)$ of length 2^{i+1}. The characteristics of the Slantlet filterbank:

1.Each filterbank is orthogonal. The filters in the synthesis filter bank are obtained by time reversal of the analysis filter.

2.The scale-dilation factor is 2 for each filterbank.

3.Each filterbank provides a multiresolution decomposition.

4.The time localization is improved with a degradation of frequency selectivity.

5.The Slantlet filters are piecewise linear.

4.Compression

The term data compression refers to the process of reducing the amount of data required to represent a

ISSN 2229-5518

given quantity of information. It is useful both for transmission and storage of information[7].

The encoder of the Fig 4.1 is responsible for reducing the coding interpixel and/or psychovisual redundancy of the input data. In the first stage of the encoding process the mapper transforms the input data into a format designed to reduce the interpixel redundancies.

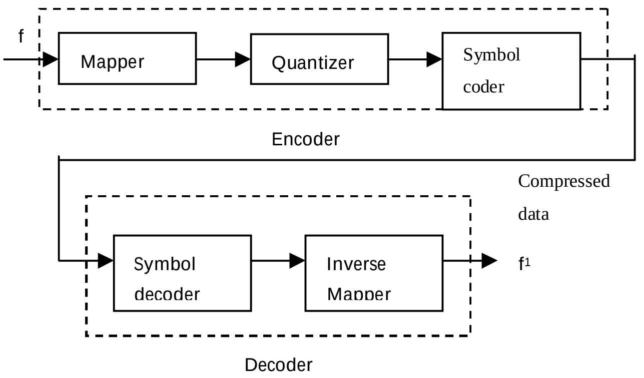

Fig4.1.General Block diagram for compression

The second stage, or quantizer block, reduces the accuracy of the mappers output in accordance with a predifined fidelity criterion- attempting to eliminate only psychovisually redundant data. This operation is irreversible and must be omitted when error-free compression is desired. In the third and final stage of process, a symbol coder creates a code (that reduces coding redundancy) for the quantizer output and maps the output in accordance with the code.

If n_1 and n_2 denotes the number of informations carrying units in the original and encoded data respectively, the compression that is achieved can be quantified numerically via the compression ratio

$$C_R = n_1/n_2$$

To view and/or use a compressed (i.e., encoded) data, it must be fed into a decoder, where a reconstructed output data is generated. Error can be defined between f and f^1

$$e = f^1 - f \qquad \ldots\ldots\ldots..4.1$$

The decoder contains only two components: a symbol decoder and an inverse mapper. The percentage of reconstruction ratio can be defined as

$$\frac{\text{Vector norm of the retained SLT Coefficients after threshold}}{\text{Vector norm of the original SLT coefficients}} \text{X100}$$

Compression of data without degradation of data quality is possible because the data contains a high degree of redundancy. The higher the redundancy the higher the achievable compression. The data compression methods can be broadly classified into

1. Lossless compression method
2. Lossy compression method.

5. Denoising

The de-noising objective is to suppress the noise part of the signal s and to recover f while retaining as much as possible the important signal features.

The noisy signal is basically of the form

$s(n) = f(n) + \sigma e(n)$, where e(n) is the gaussian white noise N(0,1) and time n is equally spaced.

In the recent years there has been a fair amount of research on wavelet threshold and threshold selection for image de-noising, because wavelet provides an appropriate basis for separating noisy signal from the data signal. Threshold is a simple non-linear technique, which operates on one wavelet coefficient at a time. Replacing the small noisy coefficients by zero and inverse wavelet transform on the result may lead to reconstruction with the essential signal characteristics and with less noise. The

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Peak-Signal-To-Noise-Ratio(PSNR) for any given data can be given as, PSNR=20*log10(1256/ (original data-de-noised data)).

6.Design Procedure

6.1.Algorithm for signal compression

The design procedure for signal compression contains three steps:

1. Decomposition

The Slantlet transform is used for decomposition and applied to each row and then again applied to the resulting information in each column. The steps used for decomposition

1.Find out whether the input signal is power of 2.

1.2. Separate the odd and even moment vectors along the length of the input signal.

1.3. Since the filters are piecewise linear, each filter can be represented as the sum of a DC and a linear term.

1.4. The DC and linear moments at scale i can be computed from the DC and linear moments at the next finer scale (i-1).

The image obtained after 2-D Slantlet transform can be shown as

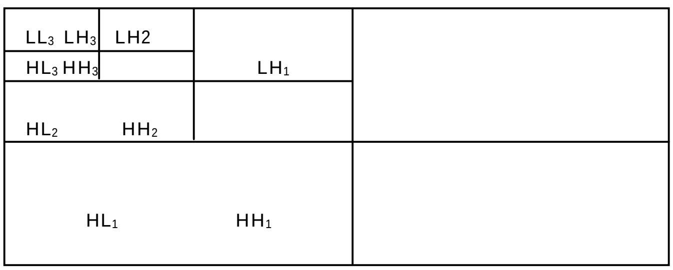

Figure 5.3. Decomposed image after 2-D Slantlet Transform

2. Threshold the coefficients

If a pixel in the image has intensity less than the threshold value, the corresponding pixel in the resultant image is set to white. Otherwise, if the pixel is greater than or equal to the threshold intensity, the resulting pixel is set to black. Soft threshold is used for image compression.

3.Reconstruction

Compute wavelet reconstruction based on the modified coefficients. This step uses the inverse Slantlet transform to perform the wavelet reconstruction.

3.1. Find out whether the signal is of finite duration (power of 2).

3.2. Initialize the moment vectors.

$\mu_0 = 1{:}N/2$

$\mu_1 = \mu_0$

3.3. Using DC and linear Slantlet coefficients, compute $\mu_0(n;l)$ and $\mu_1(n;l)$

m = 2^l;

$\mu_0(n;l)=s(1)/\sqrt{(m)}*s(2)*\sqrt{(3*(m-1)/(m*(m+1)))};$

$\mu_1(n;l) = s(2) * (-2 * \sqrt{(3/(m*(m^2 - 1)))})$

3.4. Then compute $\mu_0(n;i)$ and $\mu_1(n;i)$ for decreasing values of i by updating μ_0 and μ_1 using Slantlet coefficients.

6.2. Algorithm for signal De-noising

Input image is added with noise. For this noisy image, apply Slantlet transform. Steps 1 and 3 of the section 6.1 remains unchanged. But in the step 2, soft threshold is applied for de-noising. Soft threshold is an extension of hard threshold, first setting to zero the elements whose absolute values are lower than the threshold, and then shrinking the nonzero coefficients towards 0. The output of the step3 in section 6.1 is the de-noised version of the original input image.

7. Results and Analysis

Computer simulation study on Compression and De-nosing were carried out on some standard images to the Matlab programs of the Slantlet transform. Some 2D inputs include images of a cameraman, MRI and Testpart. Implementation is carried out using Matlab.

7.1. Simulation Results of Compression

International Journal of Scientific & Engineering Research Volume 2, Issue 4, April-2011
ISSN 2229-5518

The Compression Ratio (CR) and Reconstruction Ratio (RR) for different input images are tabulated as shown in the table 6.1 and table 6.2. The graphs are plotted against various threshold values and the ratios.

Thr value	Cameraman		MRI		Testpart	
	% CR	% RR	% CR	% RR	% CR	% RR
0	0	100	0	100	0	100
0. 5	14.73	100	52.95	99.99	11.68	100
5.0	64.68	99.99	70.10	99.97	54.25	99.99
10.0	76.02	99.99	79.92	99.87	69.92	99.99
100	98.02	99.80	98.86	96.66	95.97	99.69
500	99.81	99.24	99.81	89.28	99.60	98.07
5000	99.97	96.22	99.99	18.79	99.97	94.74

Table 7.1. Percentage of Compression Ratio(CR) and Reconstruction Ratio(RR) for different Images

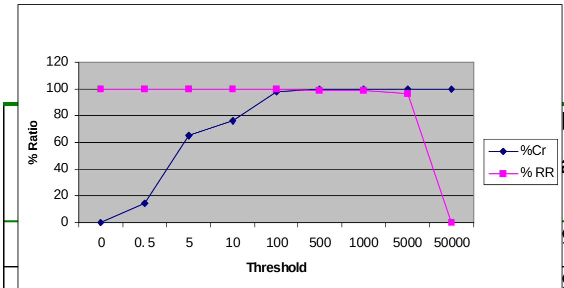

Figure 7.1. Graph for Cameraman

[illegible]	[illegible]	[illegible]	[illegible] R (...art)
[illegible]	[illegible]	[illegible]	[illegible]90
[illegible]	[illegible]	[illegible]	[illegible]90
5.0	20.0354	21.8754	16.8582
10.0	20.9197	22.7155	20.6429
20.0	22.4248	24.1644	21.9417
50.0	23.5620	25.2520	22.1960

7.2. Simulation results of de-noising

For the various threshold values, the percentage of signal to noise ratio for different images are tabulated as shown in the table 6.3 and 6.4. The graphs are plotted against various threshold values and the PSNR.

Table 7.2. Percentage of Signal to noise ratio (PSNR) for different Images

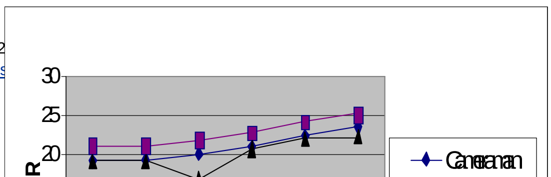

Figure 7.2. Graph between Threshold and PSNR for different Images.

8. Snapshots

The snapshots of the implementation of Compression & De-noising for different images are shown

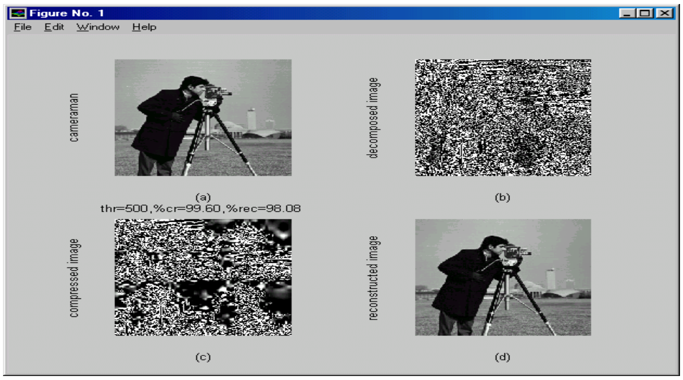

Figure 8.1. (a) Input image(cameraman) (b) Decomposed image (c) Compressed image (d) Reconstructed image.

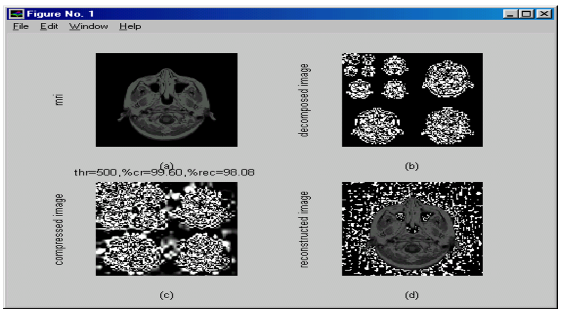

Figure 8.2. (a) Input image(MRI) (b) Decomposed image (c) Compressed image (d) Reconstructed image.

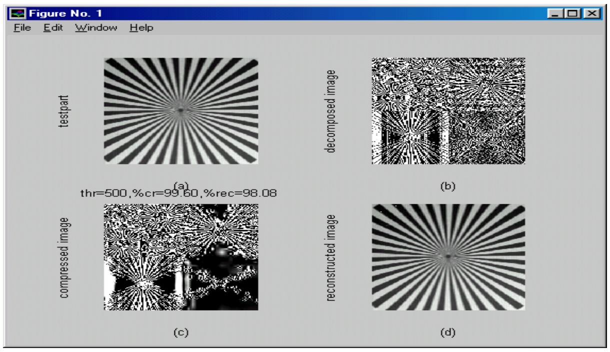

Figure 8.3. (a) Input image(testpart) (b) Decomposed image (c) Compressed image (d) Reconstructed image

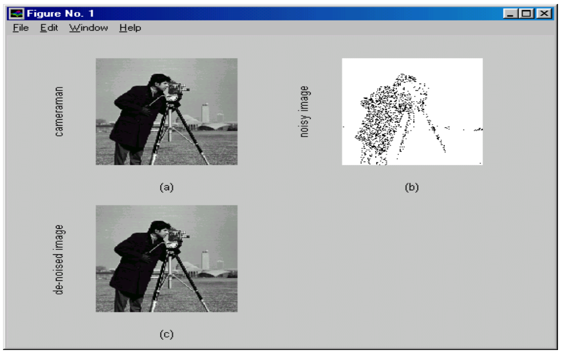

Figure 8.4. (a) Input image(cameraman)

(b) Noisy image (c) De-noised image .

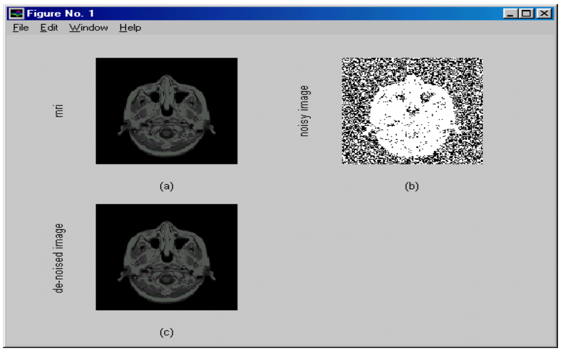

Figure 8.5. (a) Input image(MRI) (b) Noisy image (c) Denoised image.

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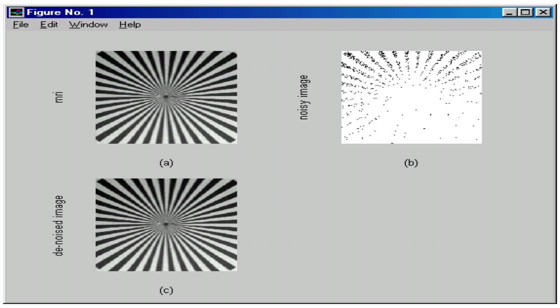

Figure 8.6. (a) Input image(Testpart) (b) Noisy image (c) De-noised image.

9.Conclusion

The Slantlet transform orthogonal filterbank uses the filters of shorter length as compared to iterated 2-scale DWT filterbank. The number of filters increases according to the order. The Slantlet transform gives better compression result for the piecewise linear data. The Slantlet transform has been applied for compression and de-noising of various images. The matlab programs for the Slantlet transform applied for compression and de-noising are developed and the computer simulation is carried out for some test images. It is observed that as the threshold level increases better compression ratio and PSNR can be achieved for the test data.

10. Future scope

The present work can be extended to compare the performance of applying Wavelet transform and Slantlet transform on images and also study the characteristics/performance benefits of Slantlet transform over Wavelet transform. This work can be enhanced to wavelet packets, which offers a more complex and flexible analysis, because the details as well as the approximations are split.

Acknoweledgements

Authors thank Singhania University Rajastan and Vidya Vikas Institute of Technology, Mysore.

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