

Shape Adaptive Discrete Wavelet Transform for Denoising of Images

T. Venkata Ramana, S. A. K. Jilani

Abstract— *The image acquired from a sensor is always degraded by some form of noise. The noise can be measured and eliminated by the process of denoising the image. Recently, Shape Adaptive methods of denoising have gained popularity. The Shape Adaptive Discrete Wavelet Transform (SADWT) transforms and codes the arbitrarily-shaped regions obtained by a segmentation of the image. The arbitrary shapes preserve the edges, artifacts and produce a high quality images. The features of the SADWT's include the number of pixels in the original visual images is same as the number of coefficients after SADWT's, the spatial correlation, locality properties of wavelet transforms and self-similarity across sub-bands are maintained well. For a rectangular region, the SADWT is similar to the traditional wavelet transforms. In this paper, the SADWT is evaluated for various images by comparing in terms of peak signal to noise ratio and improves the signal to noise ratio.*

Index Terms— *Denoising, ISNR, PSNR, Shape Adaptive Methods.*

1. INTRODUCTION

The Multimedia applications require noise free pictures for handling. The cutting edge visual coding benchmarks, for example MPEG-4[1]-[2] gives awesome adaptability in controlling visual protests in mixed media applications and could possibly enhance image quality in low piece rate coding. The discretionarily molded visual protest must safeguard its shape and surface i.e., the pixels inside the question district. The current strategies incorporate coding rectangular-molded pictures and video. The bouncing box straight away of the subjectively molded visual protest, at that point the qualities are cushioned in the pixel positions and the pixels inside the question are coded and are cushioned in the rectangle jumping box utilizing the customary strategies, which may be wasteful [3]-[7].

Consequently arbitrary molded locales are utilized, prevalently known as Shape Adaptive Methods. These incorporate SA-DCT Method, which creates an indistinguishable number of coefficients from the quantity of pixels in a subjectively formed picture square. The SA-DCT calculation accomplishes change effectiveness like the shape-versatile Gilge DCT [8], [10]. However it is executed with lower multifaceted nature. Since SA-DCT dependably changes tests in a self-assertively formed square to a specific edge of a rectangle jumping hinder before applying line or

section DCT changes, some spatial relationship might get lost. It isn't proficient in performing section DCT changes on an arrangement of coefficients that are from various recurrence groups after the column DCT changes [10], [11], [12], [13].

There are few strategies proposed for coding discretionarily molded picture objects utilizing the wavelet changes by cushioning methods [14], [15], [16], [17] i.e., the ordinary wavelet change is done in the cushioned rectangle area. Coding coefficient choice and coding coefficient inclusion procedures were utilized to enhance coding productivity. The other strategy utilized is macro block-district based wavelet coding [18], [23], [25] which first cushions indistinct locale with zeros, after that apply the wavelet changes to the cushioned rectangular area. So as to utilize zero-tree coding (ZTC), a subjective shape was quantized in the wavelet square limit. Hence the wavelet change unavoidably obscures the edges of the discretionarily formed protests and thus results in a larger number of coefficients are coded compared with the quantity of pixels in the question. These two strategies made a change on the clear cushioning techniques and don't take care of the key issue of how to productively perform wavelet change specifically to a subjectively formed locale and effectively code simply enough wavelet coefficients. Therefore, the execution of these systems isn't focused.

Li et al. [19] – [21], [24] proposed a novel shape versatile discrete wavelet change (SADWT) for discretionarily formed protest coding which can be specifically connected to the self-assertively formed district. The SA-DWT changes the examples in the self-assertively formed district into an indistinguishable number of coefficients from the sub-band area, while maintaining the spatial relationship, territory, and self-likeness crosswise over sub-bands. Methodologies applying the SADWT plan to install zero tree wavelet coding and vector wavelet coding plans were discussed [6].

The proposed paper evaluates the shape adaptive wavelet coding scheme as applied to denoise various images. Section II details about the Shape Adaptive Discrete Cosine Method, in Section III SA-DWT wavelet transform developed for arbitrarily shaped regions.

Results of SADWT with different images are compared with other coding schemes in Section IV. Section V conclude the paper.

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II. SHAPE ADAPTIVE DISCRETE COSINE TRANSFORM

In the event that a square with versatile size is to be supplanted by a more flexible versatile shape district, two issues promptly emerge i.e., How to proficiently change the information inside a locale which is certifiably not a square? How to locate these versatile shape areas from the uproarious perceptions? The conceivable arrangements can be Shape-Adaptive DCT (Sikora and Makai, 1995). A 2-D (orthonormal) change in view of 1-D DCT and can be connected on discretionarily molded areas. Great vitality compaction, low multifaceted nature, some portion of MPEG4 standard, can be thought as a speculation of the 2D square DCT and Anisotropic LPA-ICI which characterizes for each point in the picture, and versatile star formed neighborhood in which the fundamental flag is uniform (in polynomial sense). Extremely precise enables adjustment to the best structures in the picture. In light of convolutions, it is among the speediest point wise-versatile strategies for strong anisotropic filtering.

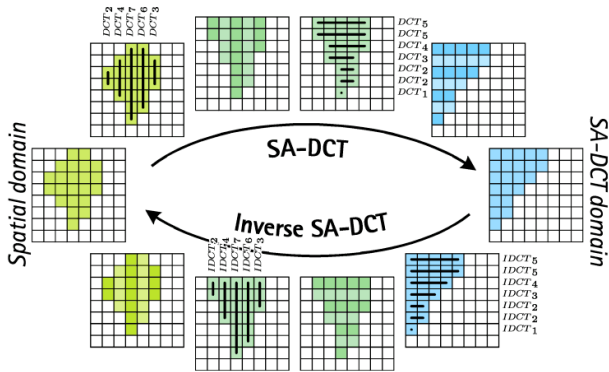


fig. 1: SA-DCT vs Spatial Domain

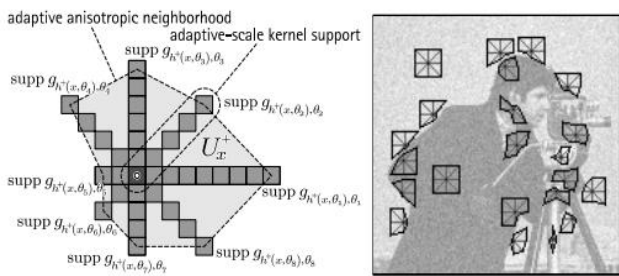


Fig. 2: Fast implementation of the LPA-ICI anisotropic neighborhoods.

"Linewise" 1-D LPA kernels were used in 8 directions. The anisotropic neighborhood $U^+ x$ was constructed as the polygonal hull of the adaptive scale kernel supports (left). Thus, the adaptive scales h^+ were required to construct the neighborhood. Some examples of the anisotropic neighborhoods $U^0 + x$ utilized for SADCT filtering of the noisy Camera man images (right) with $\sigma=25$.

Figure 1 shows the comparison of SA-DCT vs spatial domain. The SA-DCT [9], [10], [26], [27] gives better compression efficiency compared to that of much computationally complex transforms [20]. This improves de-correlation and energy compaction properties. The efficiency depends on the primary characteristics obtained for any transform domain noise removing method. Figure 2

shows a sample example of SA-DCT being used in shape adapting using neighborhood cells.

III. SHAPE ADAPTIVE DISCRETE WAVELET TRANSFORM

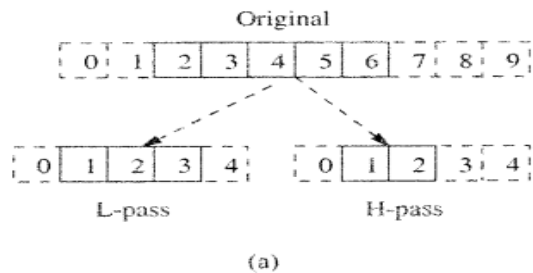
There are two segments in the SADWT. One is an approach to deal with wavelet changes in discretionary length picture fragments. The other is a sub-sampling technique to self-assertive length picture fragments at self-assertive areas. The SADWT permits odd or little length picture portions to be disintegrated in the change area in a comparative way to even- and long-length fragments, by keeping up the quantity of coefficients in the change space indistinguishable to the quantity of pixels in the picture area. The size of the coefficients of change area inside each sub-band is same to keep away from sharp changes in sub-bands.

An appropriate sub-sampling strategy is imperative to the SADWT as well. One thought is it could have the spatial connection and the self similarity property of wavelet changes. So 2-D divisible wavelet disintegrations and pyramid wavelet deteriorations should be connected to the discretionarily formed picture area without loss of spatial relationship. Another thought is that the impact of the sub-sampling technique on the proficiency of zero-tree coding.

Algorithm for two dimensional SADWT's:

Depending on the length of adaptive wavelet transform algorithms and sub-sampling strategies discussed above, the two dimensional SADWT for any visual images can be explained as

- 1) Use shape information within the bounding box to know the first row of pixels of the object to be transformed.
- 2) Find the first segment of next pixels within each row.
- 3) Apply the length adaptive one dimensional wavelet transform to this segment with correct sub-sampling strategy.
- 4) The coefficients of LP wavelet are kept in the corresponding row in the LP band. The coefficients of HP wavelet are kept in the corresponding row in the HP band (Fig. 3(a) and (b) explains the sub sampling strategy and ZTC gain also improved).
- 5) Do the above procedure to the next segment of consecutive pixels in the row.
- 6) Execute the above steps to the next row of pixels.
- 7) Execute the above procedure for each column of the low pass and high pass objects.
- 8) Execute the above processes to the LP band object until the level of wavelet decomposition was reached



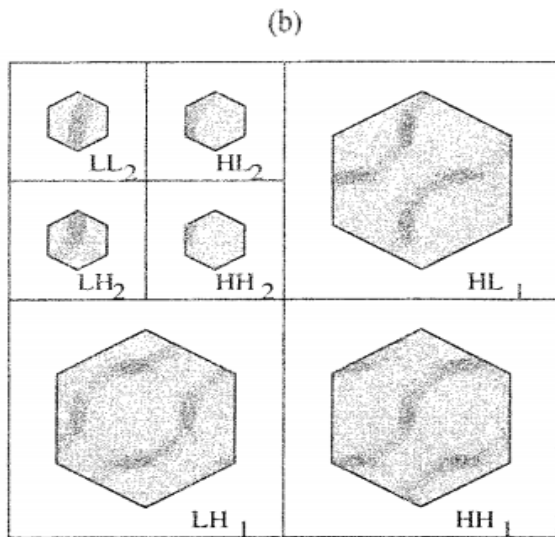
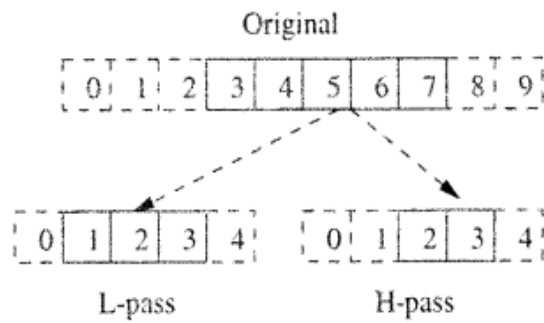


Fig.3: (a) 2-D SA-DWT.

(b) Examples of locations of the LP and HP objects in the transform domain.

(c) Multiresolution decomposition.

2-D SADWT calculation gives an approach to effectively break down a discretarily molded protest into a multi-determination question pyramid. The spatial connection, territory, and protest shape are all around safeguarded all through SADWT. In this way, it empowers multi-determination coding of discretarily formed articles. This technique guarantees that the quantity of coefficient to be coded in change area precisely same as in the picture space. The treatment of odd number of pixels in a portion guarantees no excessively vitality spilled in HP groups in pyramid wavelet decay. If the protest is a rectangle picture, the two dimensional SADWT is indistinguishable to a standard two dimensional wavelet change.

Table 1 Comparisons of memory requirements and computation complexity between SA-DWT and SA-DCT schemes

Table 1 shows the comparison of SA-DWT and SA-DCT for computational complexities. From that it is clear that SA-DWT complexities are less when compared to SA-DCT Method.

	Working buffer (words)	Main memory (words)	Memory access (words)	Computational complexity (additions(+) and multiplications (*))
SA-DWT	Max(W,H)	WH	(8/3)*(1-4 ^{-L}) WH (reads) (8/3)*(1-4 ^{-L}) WH (writes)	(40/3)*(1-4 ^{-L}) WH(+) (28/3)*(1-4 ^{-L}) WH(*)
SA-DCT	64	WH	WH (reads) WH (writes)	20/4 (WH) 11/4 (WH)

IV. RESULTS AND DISCUSSION

The Algorithms are coded and evaluated in MATLAB. The images considered for performance evaluation are Peppers, Lena, Cameraman, House, etc. The Performance of SA-DCT and SA-DWT are evaluated using PSNR and ISNR parameters.

The ratio of the maximum value (power) of a signal to the power of noise that affects the quality of its presentation is called PSNR (Peak Signal to Noise Ratio).

$$PSNR = 20 \log_{10} \left(\frac{MAX_f}{\sqrt{MSE}} \right)$$

where MSE is Mean Square Error given by

$$MSE = \frac{1}{mn} \sum_0^{m-1} \sum_0^{n-1} \|f(i, j) - g(i, j)\|^2$$

The PSNR must be as High as possible.

The degree that we need to evaluate the quality of the results of deblurring tests will increase signal to noise ratio (ISNR), below results shows the improvement in ISNR compared to the existing method.

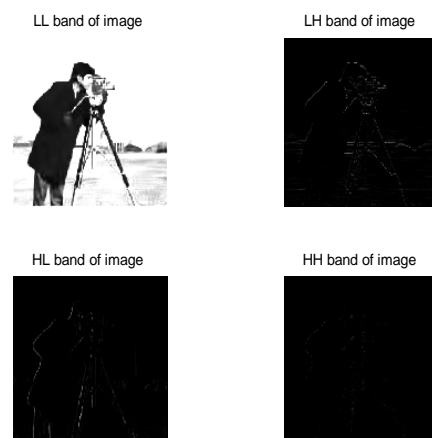


Figure 4: DWT Processed Cameraman Image

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SA-DWT Wiener-filter estimate, PSNR = 30.5165 dB, ISNR = 10.3387 dB



Fig.5: SA-DWT Processed Cameraman Image

Pointwise SA-DCT Wiener-filter estimate, PSNR = 33.4501 dB, ISNR = 13.2736 dB



Fig.6: SA-DCT Processed Cameraman Image

The Figure 4 shows the DWT processed image at level 1, which has four sub-bands LL, LH, HL, HH. Among these LL was considered for processing. Figure 5 shows the SA DWT processed Cameraman Image, which has better edge preservance than that of SA-DCT as shown in Figure 6.

Table 2: Comparison of SA-DCT and SA-DWT Methods for Denoising of Images

Method/ Images	SA-DCT PSNR (dB)	SA-DCT ISNR (dB)	SA-DWT PSNR (dB)	SA-DWT ISNR (dB)
Peppers	29.924	9.7792	33.4274	13.2509
Lena	35.7595	15.5824	31.7777	11.6045
Cameraman	33.7212	13.5447	30.5165	10.3387
House	31.9276	11.7828	33.3107	13.1332
TextureA	34.861	14.6845	34.3401	14.1636
TextureB	29.1169	8.9404	27.8043	7.6288
Couple	31.9311	11.754	31.4245	11.2473

Bridge 29.3293 9.1528 28.7458 8.5693
Boat 33.1851 13.0086 31.7728 11.5963

From Table 2, it is clear that the ISNR is maximum improved by 26% for Peppers Image and PSNR is improved by 10.4% when SA-DWT is used.

V.CONCLUSION

This paper describes shape-adaptive methods and their performance evaluation for denoising the images captured by sensors. The quantity of wavelet coefficients after SADWT is equal to the quantity of pixels in the image. The spatial correlation and wavelet transform properties, such as locality property and self-similarity across sub-bands are maintained in the SADWT. For a rectangle region, the SADWT is similar to the standard wavelet transform. From the output, it is evident that SA-DWT performs better than SA-DCT Method for denoising as it preserves artifacts and edges and also produces good quality of images.

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