An Enhanced Image Compression Codec using Spline-based Directional Lifting Wavelet Transform and an Improved SPIHT Algorithm

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Abstract: A novel lossy image-compression scheme is proposed in this paper. A two-step structure is embedded in this codec. A spline-based directional lifting wavelet transform is used to decorrelate the image data in the first step. Then in the second step, an improved Set Partitioning in Hierarchical Trees (SPIHT) algorithm based on binary tree is developed to code the wavelet coefficients. The numerical results demonstrated the efficiency of the proposed approach to achieve significant gains in terms of PSNR, BD-PSNR and SSIM for all test images. It offers better results compared to the existing ones.

1 INTRODUCTION

Image compression is important for many applications that imply enormous data storage, transmission and retrieval such as for multimedia (SerElkhetm and Heshmat, 2020), video conferencing (Wang et al., 2018), medical imaging (Kumar and Parmar, 2020) and so on.
During the past few years, several lossy image compression schemes have been developed. Usually, a three processing steps known as decorrelation, quantization and entropy coding (specially the arithmetic coding) are embedded in these schemes.
In the first step, the Discrete wavelet transform (DWT) has been successfully used in image-processing applications (Wu, 1997) ever since Mallat proposed the multiresolution representation of signals based on wavelet decomposition. The advantage of DWT over other transformations is that it performs multiresolution analysis with localization in both time and frequency (Saroya and Kaur, 2014). DWT has traditionally been implemented by convolution structure. However, this method requires both far more computations and large storage features that are not desirable for either high speed or low power image processing applications. Hence, the lifting based DWT (Daubechies and Sweldens, 1998) was proposed and it has become popular with less cost of computation, more efficient performance and easier hardware implementability. In (Boujelbene et al., 2016), a new biorthogonal wavelet transforms using splines performed in a lifting manner is proposed . Unlike conventional approaches which are limited to a few orders of splines, the proposed method uses several orders of filters in order to converge towards an optimal transformation. However, this approach does not faithfully represent the detailed information of the image. To adjust much better to the image orientation characteristics, a new kinds of wavelet-like transforms have been proposed such as grouplets (Mallat, 2009), tetrolets (Krommweh, 2010) and so on. These transforms require an edge-detection step and an adaptive decomposition (Saha et al., 2020). However, the edge-detection stage is generally a computationally-requiring process. Another series of methods (Chang and Girod, 2007) (Boujelbene and Jemaa, 2020) using the lifting scheme to embrace the flexibility of arbitrary directional transform e.g. adaptive directional lifting (ADL) have been proposed. These methods achieve higher compression performance.

After the image decomposition, an existing coding algorithm, such as EZW, SPIHT or SPECK, is usually followed directly. Some improved coding method like (Huang and Dai, 2012; Ke-kun, 2012; Jiang et al., 2018; Mander and Jindal, 2017) can be also used. Indeed, in (Huang and Dai, 2012), a scan method based on binary tree coding with adaptive scanning order (BTCA) is proposed. This algorithm has quality, position, and resolution scalability. However, it is only a little slower than SPIHT without arithmetic coding. In (Jiang et al., 2018), an image coding algorithm called SLCCA Plus which uses Non-Uniform Quantization, Extended Cluster Filtering, and Signi-

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fied Shared-Zerois is proposed. Although it raises the coding gain, this method requires more time. In order to speed up the encoding time, an improved SPIHT algorithm based on binary tree (Ke-kun, 2012) which raises the coding efficiency is proposed.

Unlike exsiting approachs which can have limited performance by considering only one compression stage either of decorrelation or coding, and in order to provide a good compression scheme, both the process of image decomposition and coding are considered in this paper. First, we employ a new spline wavelet transform based on directional lifting (ADL-SWT), which aims at further reducing the magnitude of the high-frequency wavelet coefficients. Then, after the ADL-SWT transform, an improved SPIHT coding algorithm based on binary tree (TSPIHT) is used, which can provide good coding performance with low complexity.
The remainder of this paper is organized as follows: In Section 2, the block diagram for the proposed codec is presented in detail. Here, we describe the principle of the spline-based directional lifting wavelet transform and the different steps of the TSPIHT coding algorithm. The experimental results are presented in Section 3, followed finally by a conclusion in Section 4.

2 PROPOSED CODEC SCHEME FOR WAVELET IMAGE COMPRESSION

We present here the block diagram of the proposed wavelet image compression scheme which is composed of two connected blocs as shown in Figure 1.

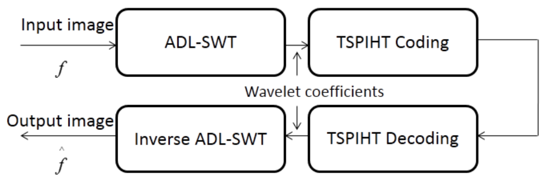

Figure 1: Block diagram for optimal codec.

A Spline wavelet transform based on adaptive directional lifting (ADL-SWT) represents the transform which combines the spline filter of order 5 with the adaptive directional lifting (ADL).
After the wavelet transform step, we try to get a way to code the wavelet coefficients into an effective result by taking into account the storage space , the redundancy and the speed. An improved SPIHT based on binary tree (TSPIHT) image coding is the best way which allows to raise the coding efficiency with decreasing the encoding time. In addition, this algorithm does not require arithmetic coding to improve its performance.
Once the input image has been coded, it is saved or sent through the communication channel to the receiver who needs to use this code in order to reconstruct the input image. This is the decoding process which consists of the TSPIHT decoding and the inverse ADL-SWT.

2.1 ADL-SWT

Instead of alternately using the lifting-based prediction in the horizontal or vertical direction, the ADL performs the prediction in windows of high pixel correlation. For lossy image compression, unlike conventional methods that use the ADL with the biorthogonal 9/7 filter, this technique mixes ADL with a spline wavelet filter. In fact, we have concentrated on the polynomial spline for the calculation of the filter taps. Lately, it was shown in (Boujelbene et al., 2016; Boujelbene et al., 2017) that the polynomial spline wavelet filter of fifth order provides the best performance as compared to the most efficient existing filters such as the biorthogonal 9/7.
Hence, to construct this performed scheme, the best spline filter of fifth order is combined with the ADL by incorporating the coefficients calculated by this filter into the ADL. Thus, the proposed ADL-SWT is employed as the representation of our image compression system. The proposed 2-D ADL-SWT involves two separable transforms. The schematic representation of this transform is shown in Figure 2.

Let X[m,n] be a 2-D signal, where m and n represent the row and column indices, respectively. Firstly, carry out 1-D ADL-SWT on each image column, producing a vertical low-pass subband (L) and a vertical high-pass subband (H). Secondly, carry out 1-D ADL-SWT on each row of L and H.
After one-level decomposition, one low-pass subband (LL) and three high-pass subbands (LH,HL and HH) are generated. In other words, the subband decomposition structure of 2-D ADL-SWT is the same that of 2-D DWT. The decomposition process of ADL-SWT can be extended to any desired level
For ADL-SWT, unlike DWT which does transform along the fixed direction, the selected filtering need to be encoded as side information. So, to reduce the overhead bits for the direction information, the image is divided into regions of approximately uniform edge orientations. All the pixels in the local region are predicted and updated along the uniform direction which is chosen in a rate-distortion optimal sense.

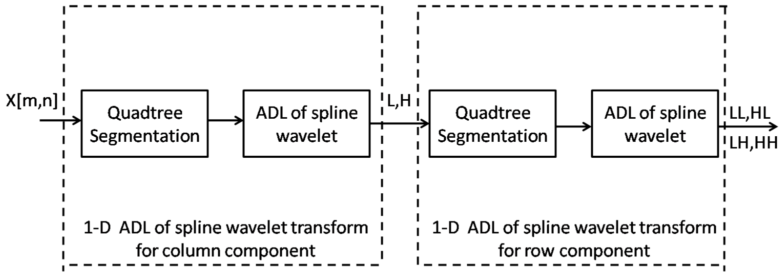

Figure 2: 2-D Adaptive Directional Lifting Spline Wavelet Transform.

The main steps of the ADL-SWT transform are illustrated by Algorithm 1.

Algorithm 1: ADL-SWT transform.

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The image is adaptively divided into blocks of variable sizes based on hierarchical quadtree segmentation.
Each block of 16x16 can be divided into three modes (16x16, 8x8 and 4x4).
Perform the ADL of spline wavelet filter on these modes
if The enegry metric (sum of absolute coefficients in high frequency subband) related to one of these block modes is smaller than the other then
    Select this mode
end if
The output is divided to variable-size regions based on hierarchical quadtree segmentation.
Each block of 16x16 can be divided into three modes (16x16, 8x8 and 4x4).
Perform the ADL of spline wavelet filter on these modes
if The enegry metric related to one of these block modes is smaller than the other then
    Select this mode
end if
The inverse transform is performed to reconstruct the image by giving the optimal lifting direction as side information
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2.2 TSPIHT Algorithm

Set Partitioning In Hierarchical Tree algorithm (SPIHT) (Said and Pearlman, 1996) is one of the most most powerful and efficient algorithms for image compression available. It is based on the same concepts: a progressive coding is applied, processing the image respectively to a lowering threshold. The difference is in the concept of zero trees : in SPIHT, a spatial orientation trees is used. This is an idea that takes into account bounds between coefficients across sub bands at different levels. The main steps of the SPIHT algorithm are as follows:

1. If there is a coefficient at the highest level of the wavelet transform in a certain subband which considered insignificant against a certain threshold, it is very probable that its descendants in lower levels will be insignificant too. So, we can code quite a large group of coefficients with one symbol.
2. Put the wavelet coefficients into a sorting pass that finds the significance coefficients in all coefficients and encodes the sign of these significance coefficients.
3. The significance coefficients that can be found in the sorting pass are put into the refinement pass that uses two bits to exact the reconstruct value for approaching to real value.
4. The threshold T is halved and the coding process will be repeated until the target is met or all the coefficients are coded.

In order to raise the performance of SPIHT algorithm and the encoding speed, a TSPIHT coding algorithm (Ke-kun, 2012) is used and incorporated in our compression codec. In this algorithm, the four coefficients splited by D-type sets (set of coordinates of all descendants of a node) are coded by binary tree. Through coding the significance of L-type (all descendants except the offspring) sets first, the algorithm can determine the significance of the root of the binary tree in advance with high probability, in a way to improve the coding efficiency.

3 EXPERIMENTAL RESULTS

To assess the efficiency of the proposed approach, a number of numerical experiments have been performed on a number of natural images using several performance measures.
For a fair comparison, the proposed codec has been compared with the codecs presented in (Boujelbene et al., 2017) and (Boujelbene and Jemaa, 2020) firstly and with the JPEG2000 standard secondly.

3.1 Test Images

The standard Waterloo 8-bit gray-scale image set containing twelve images (Lena: 512×512, Barbara: 512×512, Boat: 512×512, Mandrill: 512×512, Zelda: 512×512, Goldhill: 512×512, Peppers: 512×512, House: 512×512, Washsat: 512×512, France: 256×256, Montage: 256×256 and Library: 256×256) of different sizes, ranging from 256 to 512, has been considered to perform the required tests.

3.2 Performance Criteria

Peak Signal to Noise Ratio (PSNR), Structural Similarity Index Measure (SSIM) and Bjøntegaard Delta PSNR (BD-PSNR) were used in our experiments as a set of performance criteria.
The PSNR is defined as follows:

$$PSNR(dB) = 10log_{10}[\frac{(Peak)^2}{MSE}], \quad (1)$$

where *Peak* is equal to 255 for the images in 8 bits per pixel (bpp) and

$$MSE = \frac{1}{M \times N} \sum_{1}^{N} \sum_{1}^{M} (f(i,j) - \widehat{f}(i,j))^2, \quad (2)$$

where f, $\widehat{f}$ and $M \times N$ represent the original image, the reconstructed image and the total number of pixels in the image, respectively.

Besides PSNR, to further evaluate the quality and the distortion for the reconstructed image using the presented techniques, we use SSIM which is considered to be correlated with the quality perception of the human visual system (HVS). The SSIM is a decimal value between 0 (zero correlation with the original image) and 1 (exact same image). It is defined as follows:

$$SSIM = [l(f,\widehat{f})]^{\alpha}[c(f,\widehat{f})]^{\beta}[s(f,\widehat{f})]^{\sigma} \quad (3)$$

where: $(f,\widehat{f})$, $l(f,\widehat{f})$, $c(f,\widehat{f})$ and $s(f,\widehat{f})$ represent respectively two images, luminance comparison, contrast comparison and structural comparison between two images.
$\alpha > 0$, $\beta > 0$ and $\sigma > 0$ are used to adjust the importance of the three parameters.

To calculate the coding efficiency between different codecs based on PSNR measurements, a Bjøntegaard model was proposed by Gisle Bjntegaard (Bjontegaard, 2001). It is used to calculate the average PSNR and bit rate differences between two rate-distortion (R-D) curves obtained from the PSNR measurement when encoding a content at different bit rates. The Bjøntegaard delta PSNR (BD-PSNR), which corresponds to the average PSNR difference in dB for the same bit rate is used in our experiments.

3.3 Performance Results

A comparison between the proposed codec and the existing ones is presented in this section. Firstly, we have analysed and compared its performance to its obtained by the codecs 1 and 2.
The codec 1 which is presented in (Boujelbene et al., 2017), is constructed by the optimal spline wavelet transform (OSWT) with the TSPIHT algorithm. Indeed, OSWT is the optimal spline wavelet transform using conventional lifting and generated by a polynomial spline filter of order 5. On the other hand, the codec 2 which is presented in (Boujelbene and Jemaa, 2020), is constructed by the ADL-SWT transform with the SPIHT algorithm. As mentioned in the previous section, ADL-SWT is the proposed wavelet transform using directional lifting and a polynomial spline filter of order 5.

We present in Table 1 the PSNR and SSIM results of all the test images at different bitrates.
Obviously, Table 1 shows that the PSNR results obtained by the proposed codec for all test images are better than those obtained by the two codecs in most cases, and the improvement in PSNR is around 0.02-1.64 dB for all test images when compared to codec 1 and up to 0.43 dB when compared to codec 2.
Also, it is observed from Table 1 that the proposed codec produces high SSIM values when compared to the existing ones.

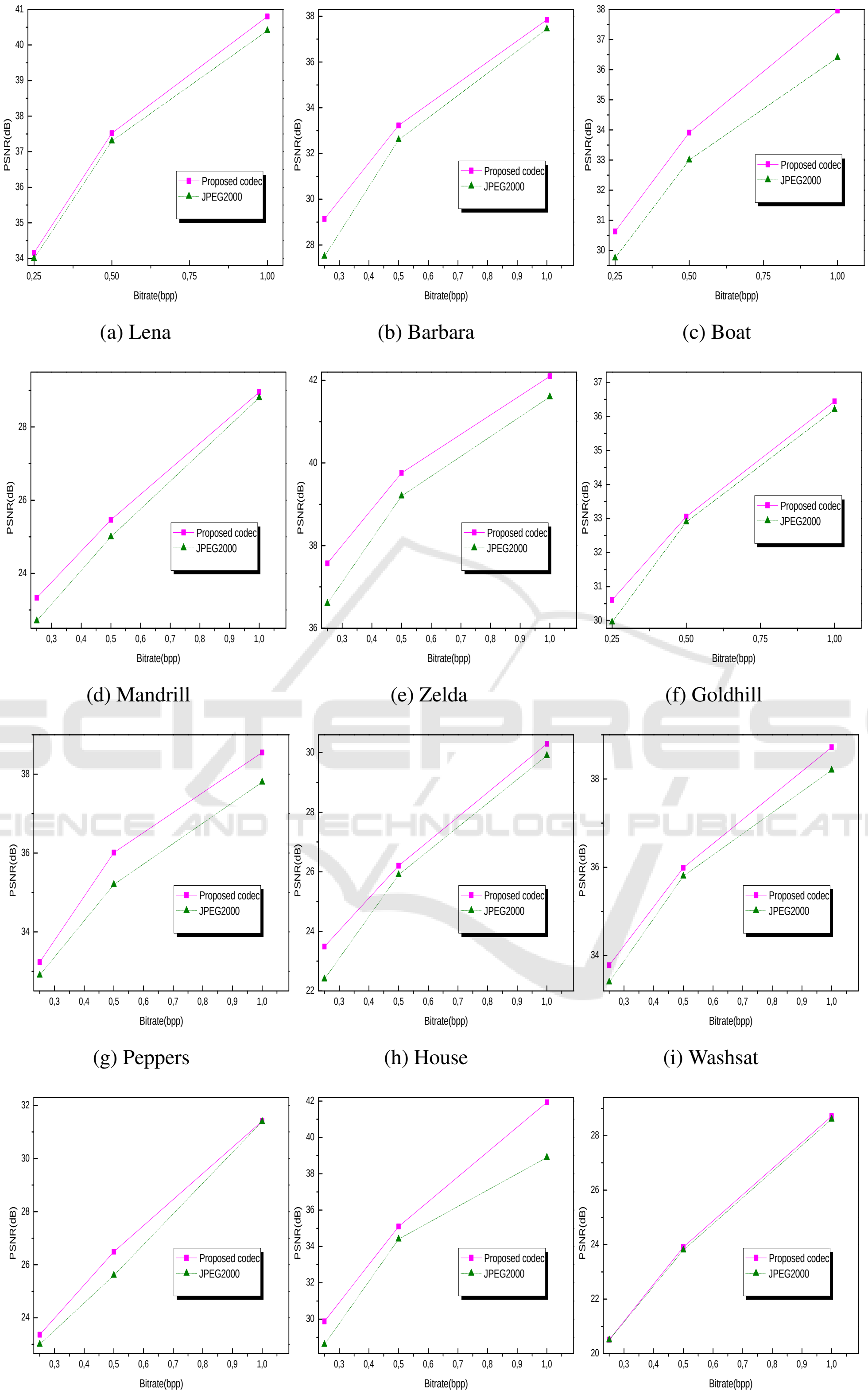
In addition, the coding efficiency was evaluated using the BD-PSNR gain measure. According to the simulation results shown in Table 2, we conclude that the proposed codec outperforms the two existing codecs for different test images. Indeed, the average PSNR gain against codecs 1 and 2 reaches 0.421 dB and 0.189 dB, respectively.

All these results justify the efficiency of the TSPIHT used in codec 1 as compared to the SPIHT coding algorithm as well as the efficiency of the transform using ADL employed in codec 2 over the one using the conventional lifting.
Moreover, in order to further evaluate the performance of the proposed codec, we compare its robustness with the JPEG2000 standard.
Figure 3 illustrates the results in terms of PSNR provided by the two codecs, and assessed at the same bitrates. Based on Figure 3, we can conclude that the results obtained by the proposed codec are better in most cases to those obtained by JPEG2000.

The performance, reported in Table 3, are computed in terms of BD-PSNR gain. It can be observed that for all images the proposed codec performs better than the JPEG2000 standard and the average PSNR gain can achieve up to 1.185 dB against JPEG2000.

Table 1: Comparison of the coding performance between the proposed and the existing codecs.

Image	Bitrate	Methods					
		Proposed codec		Codec 1		Codec 2	
		PSNR(dB)	SSIM	PSNR(dB)	SSIM	PSNR(dB)	SSIM
Lena	0.25	34.16	0.9701	34.08	0.9549	34.06	0.967
	0.5	37.52	0.989	37.2	0.9775	37.41	0.981
	0.75	39.38	0.993	38.99	0.985	39.25	0.989
	1	40.8	0.999	40.2	0.9897	40.62	0.997
Barbara	0.25	29.14	0.919	27.5	0.8933	29.03	0.912
	0.5	33.27	0.975	31.69	0.9542	33.14	0.969
	0.75	35.81	0.9829	34.59	0.9746	35.62	0.9815
	1	37.85	0.996	36.62	0.9848	37.77	0.994
Boat	0.25	30.63	0.9421	29.65	0.903	30.5	0.939
	0.5	33.91	0.671	33.01	0.9589	33.82	0.9698
	0.75	35.89	0.9861	35.1	0.9765	35.81	0.9856
	1	37.96	0.9981	36.5	0.9834	37.89	0.997
Mandrill	0.25	23.45	0.791	23	0.7894	23.21	0.7901
	0.5	25.46	0.8822	25.31	0.88	25.34	0.8812
	0.75	27.66	0.933	27.4	0.9227	27.59	0.9322
	1	28.95	0.9721	28.87	0.9471	28.91	0.971
Zelda	0.25	37.57	0.976	37.55	0.9755	37.52	0.9601
	0.5	39.76	0.9875	39.71	0.9866	39.71	0.977
	0.75	41.15	0.9921	41.01	0.9916	41.01	0.9901
	1	42.1	0.9946	42.02	0.9937	41.98	0.9931
Goldhill	0.25	30.61	0.9132	30.3	0.905	30.39	0.8215
	0.5	33.06	0.9641	32.83	0.9523	32.96	0.934
	0.75	34.97	0.972	34.77	0.9719	34.88	0.9486
	1	36.44	0.9832	36.23	0.9807	36.21	0.9629
Peppers	0.25	33.23	0.9621	33.15	0.951	33.07	0.9588
	0.5	36.21	0.9747	35.7	0.9728	35.81	0.9733
	0.75	37.41	0.9844	36.85	0.981	37.29	0.9822
	1	38.78	0.9891	38.1	0.9851	38.43	0.9885
House	0.25	23.49	0.8256	23.41	0.8175	23.31	0.8091
	0.5	26.2	0.9178	26.13	0.9059	26.04	0.909
	0.75	28.64	0.9513	28.59	0.9452	28.58	0.9448
	1	30.3	0.963	30.28	0.9621	30.17	0.9626
Washsat	0.25	33.78	0.8972	33.66	0.8965	33.66	0.8953
	0.5	35.99	0.9478	35.75	0.9458	35.91	0.9301
	0.75	37.93	0.9719	37.26	0.965	37.63	0.9715
	1	38.72	0.98	38.65	0.9787	38.59	0.98
France	0.25	23.36	0.7289	23.21	0.728	23.1	0.7093
	0.5	26.49	0.8438	26.01	0.8437	26.32	0.8331
	0.75	29.31	0.9119	29.16	0.9111	29.12	0.8899
	1	31.4	0.941	31.33	0.9399	31.29	0.9302
Montage	0.25	29.87	0.8899	29.75	0.8894	29.53	0.8721
	0.5	35.1	0.9567	34.99	0.9494	34.67	0.9423
	0.75	39.02	0.971	38.91	0.971	38.68	0.9688
	1	41.94	0.984	41.88	0.9812	41.59	0.9849
Library	0.25	20.51	0.6101	20.45	0.605	20.46	0.5966
	0.5	23.91	0.7488	23.39	0.7425	23.68	0.7452
	0.75	26.01	0.8215	25.39	0.8113	25.78	0.8106
	1	28.71	0.882	27.73	0.8675	27.98	0.8708



(a) Lena (b) Barbara (c) Boat

(d) Mandrill (e) Zelda (f) Goldhill

(g) Peppers (h) House (i) Washsat

(j) France (k) Montage (l) Library

Figure 3: PSNR (in dB) versus the bitrate (bpp) of the proposed and JPEG2000 codecs for all grayscale test images.

Table 2: BD-PSNR gain (dB) of the proposed codec against codecs 1 and 2 for all test images.

Image	BD-PSNR codec_1-Proposed_codec	BD-PSNR codec_2-Proposed_codec
Lena	0.327	0.12
Barbara	1.532	0.118
Boat	1.007	0.093
Mandrill	0.188	0.162
Zelda	0.05	0.062
Goldhill	0.24	0.142
Peppers	0.467	0.352
House	0.063	0.158
Washsat	0.192	0.095
France	0.357	0.175
Montage	0.103	0.402
Library	0.52	0.283
Average	0.421	0.189

Table 3: BD-PSNR gain of the proposed codec against JPEG2000 for all grayscale test images.

Image	BD-PSNR(dB)
Lena	0.24
Barbara	0.787
Boat	1.013
Mandrill	0.457
Zelda	0.618
Goldhill	0.255
Peppers	0.892
House	0.448
Washsat	0.277
France	0.655
Montage	1.185
Library	0.093
Average	0.577

To conclude, by analysing the results obtained, we can notice that our proposed approach is consistently more effective for all test images.

4 CONCLUSION

In this paper, a new wavelet image compression scheme which is constructed with a new spline wavelet transform based on adaptive directional lifting and an improved coding algorithm is presented. Experimental results have shown the superiority of the proposed codec over the exiting ones in terms of PSNR, BD-PSNR and SSIM for different test images. In the future, we plan to find a methodology for the integration of the encryption schemes with our compression codec.

REFERENCES

Bjontegaard, G. (2001). Calculation of average psnr differences between rd-curves. *VCEG-M33*.

Boujelbene, R. and Jemaa, Y. B. (2020). A new structure of spline wavelet transform based on adaptive directional lifting for efficient image coding. *Signal Image Video Process.*, 14(7):1451–1459.

Boujelbene, R., Jemaa, Y. B., and Zribi, M. (2016). Toward an optimal b-spline wavelet transform for image compression. In *13th IEEE/ACS International Conference of Computer Systems and Applications, AICCSA 2016, Agadir, Morocco, November 29 - December 2, 2016*, pages 1–8. IEEE Computer Society.

Boujelbene, R., Jemaa, Y. B., and Zribi, M. (2017). An efficient codec for image compression based on spline wavelet transform and improved SPIHT algorithm. In *2017 International Conference on High Performance Computing & Simulation, HPCS 2017, Genoa, Italy, July 17-21, 2017*, pages 819–825. IEEE.

Chang, C.-L. and Girod, B. (2007). Direction-adaptive discrete wavelet transform for image compression. *IEEE Transactions on Image Processing*, 16(5):1289–1302.

Daubechies, I. and Sweldens, W. (1998). Factoring wavelet transforms into lifting steps. *Journal of Fourier analysis and applications*, 4(3):247–269.

Huang, K.-K. and Dai, D.-Q. (2012). A new on-board image codec based on binary tree with adaptive scanning order in scan-based mode. *IEEE transactions on geoscience and remote sensing*, 50(10):3737–3750.

Jiang, X., Song, B., and Zhuang, X. (2018). An enhanced wavelet image codec: Slcca plus. In *2018 International Conference on Audio, Language and Image Processing (ICALIP)*, pages 163–167. IEEE.

Ke-kun, H. (2012). Improved spiht algorithm based on binary tree. *Comput Eng*, 15:063.

Krommweh, J. (2010). Tetrolet transform: A new adaptive haar wavelet algorithm for sparse image representation. *Journal of Visual Communication and Image Representation*, 21(4):364–374.

Kumar, P. and Parmar, A. (2020). Versatile approaches for medical image compression: A review. *Procedia Computer Science*, 167:1380–1389.

Mallat, S. (2009). Geometrical grouplets. *Applied and Computational Harmonic Analysis*, 26(2):161–180.

Mander, K. and Jindal, H. (2017). An improved image compression-decompression technique using block truncation and wavelets. *International journal of image, graphics and signal processing*, 9(8):17.

Saha, M., Naskar, M. K., and Chatterji, B. (2020). Advanced wavelet transform for image processing—a survey. In *Information, Photonics and Communication*, pages 185–194. Springer.

Said, A. and Pearlman, W. A. (1996). A new, fast, and efficient image codec based on set partitioning in hierarchical trees. *IEEE Transactions on circuits and systems for video technology*, 6(3):243–250.

Saroya, N. and Kaur, P. (2014). Analysis of image compression algorithm using dct and dwt transforms. *International Journal of Advanced Research in Computer Science and Software Engineering*, 4(2):897–900.

SerElkhetm, S. and Heshmat, S. (2020). A survey study on joint image compression-encryption methods. In *2020 International Conference on Innovative Trends in Communication and Computer Engineering (ITCE)*, pages 222–226. IEEE.

Wang, S., Gu, K., Zeng, K., Wang, Z., and Lin, W. (2018). Objective quality assessment and perceptual compression of screen content images. *IEEE computer graphics and applications*, 38(1):47–58.

Wu, X. (1997). Lossless compression of continuous-tone images via context selection, quantization, and modeling. *IEEE Transactions on Image Processing*, 6:656–664.