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Adaptive Image Compression Based Wavelet Using Space-Frequency Segmentation

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Abstract: We presented a new compression scheme by using the adaptive Space-Frequency Segmentation (SFS) decomposition method as the basis for context-based spatial entropy coders. The context-based entropy techniques were applied in the lossy coding for natural images. The proposed compression scheme for adaptive wavelet coding is combined with spatial encoding. Results showed that the proposed technique gives significantly better image quality compared with other compression rates.

Key words: Image compression, wavelet, segmentation

INTRODUCTION

The last years has shown a wide spread of image applications. These applications included the Internet, police departments, medical images, digital libraries and so on (Nelson, 1995; Salomon, 2000). Most of these applications used compression in order to reduce the size of the image files. Image compression aims to remove redundant data in order to reduce the size of a data file. The compression of an image into half of its original size implies that the storage area is doubled (Mandal, 2000). The same idea applies to the transmission of an image over the internet, which implies the reduction of bandwidth (Adler and Mitzenmacher, 2001; Wu and Coll, 1993). Currently, image compression is used very heavily in data storage and data transmission of images over the Internet. In these days, wavelet transform has a wide use in image compression (Chang and Yu, 2000). Wavelet improves pictures' quality at higher compression ratios mainly. In the last decade, a variety of wavelet-based schemes for image compression have been developed and implemented. Among these schemes JPEG (2000) is standard for still image compression of images and used the wavelet techniques.

The aim of this study, includes developing and applying an efficient SFS algorithm for image partition. Then using an appropriate entropy-coding algorithm that can be used with the developed segmentation to improve compression performance, particularly in the case of still image compression (Ji, 2001). Experiments conducted using the proposed approach produced encouraging results. The entropy-spatial coders used in the proposed system produced better results than those obtained by using the basic arithmetic coder. It provides more appropriate rate-distortion optimization for the SFS than the basic arithmetic coder does. The proposed compression scheme implies some control coding parameters. The effects of these parameters were investigated to determine the suitable range for each one of them.

MATERIALS AND METHODS

Image compression: Image compression research aims to reduce the number of bits needed to represent an image by removing the spatial and spectral redundancies as much as possible (Salomon, 2000; Xiong and Ramchandran, 1997). In general, there are two basic categories for image compression that is based on the information content of the reconstructed image. They are Lossless and Lossy (Salomon, 2000). A typical lossy image compression system is shown in Fig. 1. This system consists of 3 closely connected components: source encoder or linear transforms, quantizer and entropy encoder.

Compression is accomplished by applying a linear transform to decorrelate the image data, quantizing the resulting transform coefficients and entropy coding the quantized values. Currently, many linear transforms have been developed for this purpose. These transformations include Discrete Fourier Transform (DFT), Discrete Cosine Transform (DCT), Discrete Wavelet Transform (DWT) and many more (Salomon, 2000). Forward transform coding of Fig. 1a, is a coding scheme based on the

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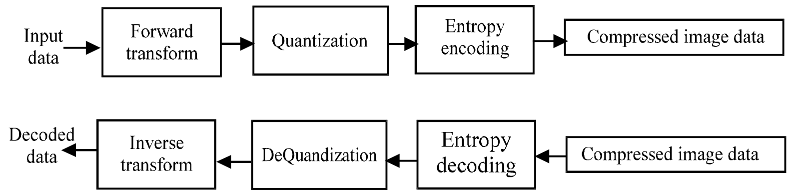


Fig. 1: Generic image encoder and decoder

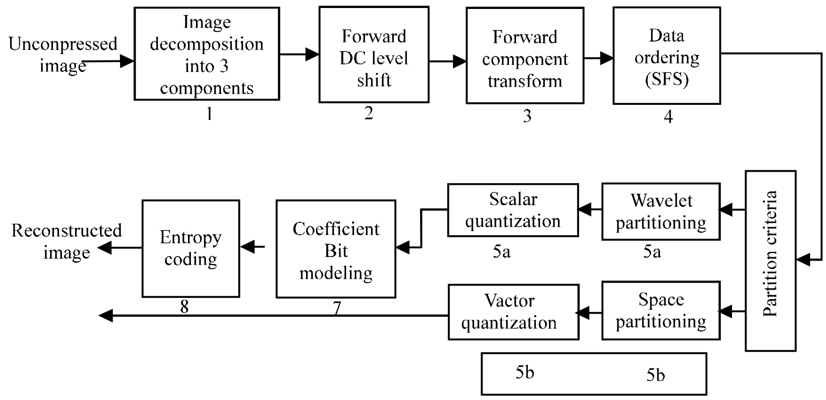


Fig. 2: Proposed Image compression coding scheme

utilization of interpixel correlation's (concerned with the correlation between pixels). In transform coding, the main idea is that if the transformed version of a signal is less correlated compared with the original signal, then quantizing and encoding the transformed signal may lead to data compression. The quantizer role in Fig. 1a, is to reduce the number of bits needed to store the transformed coefficients. The entropy encoder of Fig. 1a, further compresses the quantized values losselssly to give better overall compression. At the receiver site (Fig. 1 and b), the encoded data are decoded and transformed back to reconstruct the signal.

An image can be compressed by transforming its pixels (which are correlated) to a representation where they are de-correlated. Compression is achieved if the new values are smaller, on average, than the original ones. Lossy compression can be achieved by quantizing the transformed values. The decoder inputs the transformed values from the compressed stream and reconstructs the original data by applying the opposite transform. We used JPEG (2000) image compression standard that which supports the DCT-based coding mode and wavelet-based coding mode.

Proposed algorithm: The main processes for the designed compression algorithm are shown in Fig. 2, which consists of 8 stages. The input to this figure is the source image, which will do compression for it and the output is the compressed image. Following is a description of each stage.

Stage 1 (Image decomposition into 3 components): The proposed scheme supports multiple component images. The image components can be divided into tiles using SFS. These tiles are square arrays that include the same relative portion of all the components that make up the image. Thus, image tiling actually creates tile-components that can be decoded independently of each other. These tile-components can also be extracted and reconstructed independently. Different components need not have the same bit depths nor need all be signed or unsigned. For reversible (i.e., lossless) systems, the only requirement is that the bit depth of each output image component must be identical to the bit depth of the corresponding input image component. In the proposed scheme, the colored image is decomposed into 3 coloured components (i.e., Red, Green and Blue) and all steps of encoding and decoding are performed on each component. On the other hand, these 3 components are merged in the decoding stage to reconstruct the image.

Stage 2 (Forward discrete cosine level shift): Discrete Cosine (DC) level shifting is performed on samples of components that are unsigned only. It is performed prior to the computation of the forward Component Transform (CT). All samples of the image tile component are DC level shifted by subtracting the same quantity (i.e., 2^{P-1}) from the component samples, where P is the pixel depth. The inverse of this operation when it is performed during

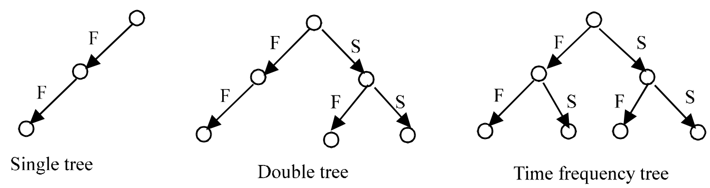


Fig. 3: Trees at depth two

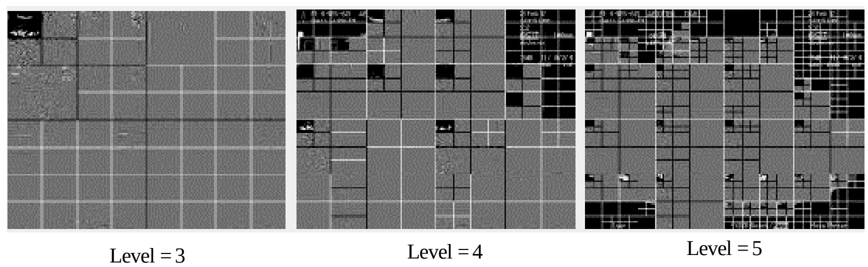


Fig. 4: SFS (Space Frequency Segmentation) partitions

the uncompression, is the inverse DC Level Shifting, which is executed on the reconstructed samples of components.

Stage 3 (Forwarded component transformation): The component transformation can be achieved by one of two methods. They are the Reversible Component Transformation (RCT) and the Irreversible Component Transformation (ICT). The RCT is a decorrelating transformation that is applied to the 3 coloured components of an image. The forward RCT is applied to all image color samples I_0 (x, y), I_1 (x, y), I_2(x, y), corresponding to the Red, Green and Blue components and produces the corresponding transformation. The 2nd method of forwarded component transformation is the ICT. The Forward ICT is applied to all image component samples I_0(x, y), I_1(x, y), I_2(x, y), corresponding to the Red, Green and Blue components and produces the corresponding transformations (Salomon, 2000; Skodras *et al*., 2001).

Stage 4 (Data ordering-SFS): The SFS method comes from the single-tree and double-tree wavelet packet algorithms. The double-tree library allows different wavelet packet single-trees over all quadtree segmentations of the image. SFS extends the double- tree segmentation scheme where the binary partition of two one-dimensional segments is replaced by the partition of four two-dimensional structures. Each space partition divides an image into four quadrants. General SFS applies the general time-frequency-pruning algorithm to choose between the four-way splits in space or frequency in a space-frequency tree. The SFS algorithm should generate a better optimal basis than both the single-tree and the double-tree. Its basis must be at least as good as the best double- tree/single-tree basis, because the set of possible double-tree/single-tree bases is a subset of the possible SFS bases. Figure 3 presents the 3 possible tree structures when the decomposition depth is set to 2, where F indicates frequency partition and S means time partition in one-dimensional signals.

In addition, to the implementation of SFS algorithm, the Delta Modulation Coder was applied to encode the Low Level (LL) subband. Other coders, were used to encode the contents of the high pass subbands, while a vector quantizer with fixed codebook was applied to encode the space-segments. An example, for SFS partition is shown in Fig. 4. It has maximum decomposition depth of 5. The white lines indicate that the sub-image is space split, while the black lines indicate that frequency segmentation is applied. The disappearance of lines inside a sub-image indicates that there is no splitting performed on the sub-image.

In the current research work, the operation of partitioning the image components (into tiles and performing the Discrete Wavelet Transform on some partitions) was performed by using adaptive SFS. This means, that the 2 sub-steps (tiling and DWT operations) are mixed in 1 combined step. The adaptive SFS work as follows:

- Decompose an image component into blocks of fixed size (say 128 or 64) and this size represents the Maximum size (MaxSiz). The selection of maximum size depends on the image details. Also, the minimum allowable size of the partitioning must be determined (MinSiz), where the MinSiz depends on the numbers of partitioning levels.

```
1) Initialization: /* Wid and Hgt are the width and height of image */
Nx=Wid div MaxSiz; Ny=Hgt div MaxSiz; L=0; Input Rat and Thr by the user
2) For each (Iy,Ix) where, Iy=0 to Ny-1 : Ys=Iy*MaxSiz and Ix=0 to Nx-1 : Xs=Ix*MaxSiz; do:
        2.1) read all the fields of initialized partitions:
                Part[L].X=Xs;
                Part[L].Y=Ys;
                Part[L].Siz=MaxSiz;
                Part[L].Typ=0;
                Part[L].Nxt=L+1;
        2.2) increment L by 1
  end foror
3) Put –1 at the last field Nxt of the last partition.
4) Compute the minimum size: MinSiz=MaxSiz/2^levels
5) Initialize J = 0.
6) Repeat the flowing operations:
        If Part[J].Siz>MinSiz then put the coefficients in A[].
                6.1) Send A[] to the MED of space with its size and return the Error E1.
                6.2) Apply wavelet transformation A[] and return B[].
                6.3) Send B[] to the MED of frequency with its size and return the Error E2.
                6.4) if (E1>Thr) or (E2>Thr) then
                        if (E1<=Rat*E2) then partition the block with space segmentation else partition the block
                          after applying DWT.
                        else J=part[j].nxt.
        while, (j … -1)
exit
```

Fig. 5: Space-frequency segmentation algorithm

- If the size of the considered subblock is greater than MinSiz then this subblock must be tested to determine whether it requires further partitioning or not.
- Initial subblocks will be partitioned, by using SFS, either as spatial (space) partitioning or as frequency (DWT).
- The Median Adaptive Predicator (MED) is utilized to evaluate whether the partitioning is performed in space or frequency. The MED is selected because it is the best appropriate causal context model.
- The algorithm can decide, which type of partitioning will be performed (space or frequency). There are 2 parameters have a great effects on selecting an appropriate partitioning types (the ratio and threshold). This operation is performed after doing the space and frequency partitioning on the same block and then selecting partitioning type whose error is less than other and it is higher than a selected threshold.
- According to, these conditions, the partitioning operation is done on all the image block. These operations continue until the block size reaches the MinSiz or they are uniform and the error of MED predictor doesn't exceed the threshold value. The formal description of SFS operation is given in Fig. 5.

To reconstruct the image partitioning in the decoder, the inverse of each step must be performed directly. Only the types of all partitions need to be registered from the encoder and from it and the maximum size, the decoder can build all the partitions starting from the smallest blocks (calculated from the maximum size and number of levels) to build the largest ones (parents) and this will continue until reaching the reconstruction of the whole image partitions.

Stage 5 (Wavelet transform): Wavelet transform is used for the analysis of the frequency-segmentation components into different decomposition levels. These decomposition levels contain a number of subbands, which consist of coefficients that describe the horizontal and vertical spatial frequency characteristics of the original tile component. To perform the forward DWT we have used a one-dimensional (1-D) subband decomposition of a 1-D set of samples into low-pass and high-pass samples. Low-pass samples represent a down-sampled, low-resolution version of the original set. High-pass samples represent a down-sampled residual version of the original set, needed for the perfect reconstruction of the original set from the low-pass set. The DWT can be irreversible or reversible where we implemented the irreversible transform in this study.

Stage 6 (Adaptive quantization and classification): After that each of the transform coefficients $a_b(u, v)$ is quantized to the value $q_b(u, v)$ according to, the following equation:

$$q_b(u,v) = \mathrm{sign}(a_b(u,v)).\left\lfloor \frac{|\alpha_b(u,v)|}{\Delta_b} \right\rfloor$$

The quantization step-size $)_b$ depends on the subbands number, its dynamic range and the required number of compression. In other words, the proposed scheme supports separate quantization step-sizes for each subband. The dynamic range depends on the number of bits used to represent the maximum coefficients in the specific subbands and on the choice of the frequency or space partitioning. All quantized transform coefficients are signed values even when the original components are unsigned. These coefficients are expressed in a sign-magnitude representation prior to coding. For reversible compression, the quantization step-size is required to be known.

In proposed algorithm, the step size for the LL-subband was taken equal 1 because of their importance which means that their coefficients are distorted significantly. Also, the proposed system combines the partition classification and adaptive quantization together in a uniform coding scheme. For each subband, types of partitioning are made on the initial partition of MaxSiz until reaching MinSiz. These sequences must be recorded and according to them, a quantization step size is computed. This quantization model tries to give a more precise step size for the subband coefficient.

Also, the proposed algorithm gives a different consideration for the quantizer sets. First, they separate the subbands into different classes; then they apply different quantization to each class using a bit allocation strategy. In adaptive scheme, the operations of calculation quantization step-size depend relatively on the subband size and types of partitioning occurred on the initial partition until reaching current size. The magnitudes of these step-size also help us to determine the value of LowBit which is needed in the entropy coder step.

Stage 7 (Coefficient bit modeling): The next stage was to do coefficient bit modeling (Bit Slicing). In this stage, the wavelet coefficients are arithmetically coded by bit-plane. The coding is done from most significant bit-plane to least significant bit-plane. The basic idea behind using this method is based on decomposing the quantized transform coefficients into binary component (i.e., bitmap layers), such that the ith layer represents a (0-1) bitmap, each point represents the ith bit value of the corresponding transform coefficient. The resulting layers may imply different spatial and statistical characteristics. If these characteristics are considered to choose the suitable coding method and to encode each layer separately, then the resulting code size may, probably, be compact in a smaller size than that of the original image, consequently the image compression task will be achieved. In our case, the bitmap slicing is performed upon the quantized coefficients. These coefficients first are expressed in a sign magnitude representation by splitting the sign of each coefficient repairing it to another state. The sign bit is taken (1) for the positive or a zero coefficient and (0) for the negative coefficients. The magnitude coefficients are valued the same as the transform coefficients regardless of the sign. For a particular subband, there is a maximum number of magnitude bits M_b. Thus, it is important to know the maximum value of the transform coefficients for each subband in order to determine the maximum number of bits needed to represent each subband. The proposed scheme suggests the following equation:

$$\text{Plan}(I, X, Y) = (q(X, Y) \text{ shr } I) \text{ and } 1$$

Where,

q(x, y) : The quantized transform coefficient.

I : The bit-plane index, whose value laies between (LowBit-HiBit).

HiBit : Maximum number of bits needed to represent each subband.

LowBit : The lower bound of the bit-planes will be considered throughout the codingstage of each plane. In the proposed scheme the value of LowBit is considered variable and, mainly, depends on the partitioning information.

This formula will check how the value of coefficient q(x, y) in the subband can be represented as a bitmap (i.e., in terms of 0,1 bit-planes).

Stage 8 (Adaptive spatial encoders): The mapping operations are those process which tend to map the original image data from the pixel domain to another domain, such that the output data will show suitable characteristics (e.g., energy compactness, highly peaked bandwidth, small variance or entropy). The adapted mapping methods in the proposed coding scheme are divided into 4 principal categories, they could be merged through different steps and produce hybrid methods, which show a progressive compression performance. A brief description will be devoted for presenting the major concepts accompanied with the principal mapping methods. In this study, 3 different coding schemes for compression of images have been constructed and evaluated. The 1st scheme is based on applying vector quantization with fixed codebook on the space-segments. The 2nd one is based on applying Differential Pulse Code Modulation (DPCM) on the low subbands of frequency-segments and the 3rd is based on applying the bitmap slicing followed either by Run-length Coder or Chaining Coder on high subbands of frequency-segmentations.

Table 1: The criteria of choosing the spatial coder type

Size	Bits	Max no. for feasible encoding Run-length	Chaining	Total no. of bits using bitmapencoder
4×4	4	3	2 chain	4
8×8	6	10	3 chain	6
16×16	8	31	6 chain	8
32×32	10			10
64×64	12			12

An important considerations, which must be taken when choosing mapping process, is the history of each partition, since the history of subbands is used to calculate the step-sizes of quantizer and to choose the appropriate coder. The partition, which generated from a sequence of space-segmentation, differs in coding and quantization from those generated from sequence of frequency-segmentation and also differs from another one, which came from sequence, mixed between space-frequency of segmentation. Before applying any of the coders for any subband yielded from a frequency-segmentation, a bit-plane is generated by finding the maximum number of bits for each subband. The decision of choosing an appropriate coder depends at 1st on the types of partitioning used to construct the considered lock (partition), on the size of subband and finally on the nature of the contents of bit-planes. The last 2 factors are important to determine the type of spatial encoders used to represent the content of the bit-planes. Table 1 presents the relationship between the block size and the maximum allowed number of runs and chains, which might exist in the bit-plane.

To calculate the total number of bits needed by the Run-Length decoder, the following equation will determine the required bits:

$$\text{Total-Bits} = \text{Bits}\times\text{No. of Ones} + (\text{Bits}-1)$$

where:

Bits : Number of bits need to represent a specific subband.

No. of ones : Number of bits in bit-plane whose value equals (1).

To calculate the total number of bits needed by the chaining encoder, we suggest the following equation to determine the required number of bits:

$$\text{Total-Bits} = \text{No. of Chains}\times\text{Bits} + (\text{No. of Ones} - \text{No. of Chains})\times 3$$

where, No. of Chains is the number of sequence of ones in the bit-plane.

RESULTS

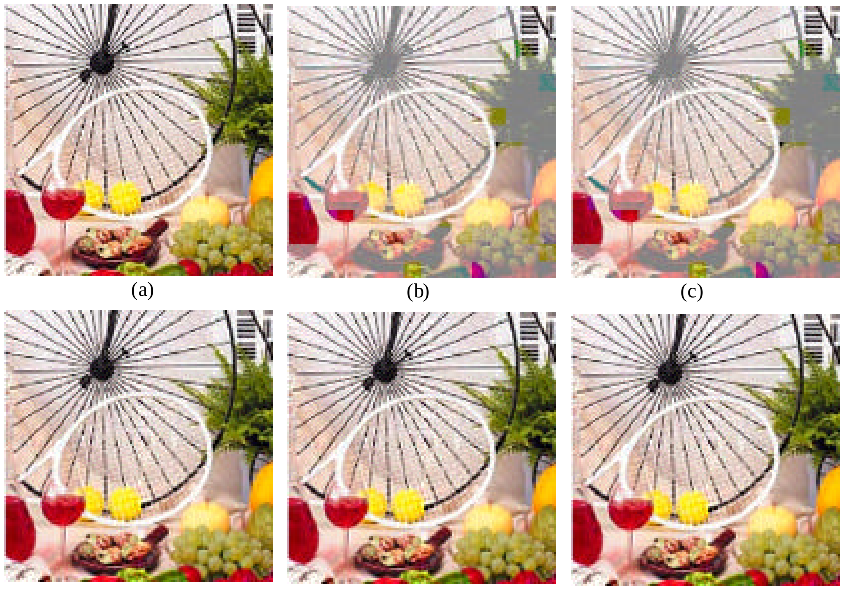
This study suggests using the adaptive SFS scheme as a partition utility. This partition is followed by applying either the vector or scalar quantization according to the partitioning history of the considered sub-block. Also, the types of the entropy coder which are applied depend on the partitioning history of the considered sub-block and on the nature of the sub-block. The proposed scheme has been tested on many images until we are able to get the conclusions. A sample of these tests will be demonstrated in this section. The experiments use the maximum partition (block) size a value that is powers of two. The measurement distortions that are used are MSE and PSNR. The value of Bits Per Sample (BPS) is used as a performance indicator. BPS represents the average number of bits used to represent each sample of the original signal. The size of the images that were considered in the experiments is 256 by 256 and all of them are continuous true colored images with 24-bits per pixel. The suggested scheme performs compression directly on the RGB color components. The experiments research as follows:

- Input the source image to the encoder.
- Partition the image into initial blocks of maximum size and call this variable "MaxSize".
- Perform partition using SFS method.

Results showed that "MaxSize" has a considerable effect on the Mean Square Error (MSE) and peak signal to noise PSNR measurements of the constructed image. In addition, it has an effect on the compression ratio. The larger the maximum size value generates higher compression ratio and less distortion for MSE and PSNR. As mentioned in previous study, the proposed scheme used SFS (Space- Frequency Segmentation) in partitioning an image. It partitions an image either in spatial domain or frequency domain depending on some control factors whose values are given by the user for the encoder. After calculating a MSE of two partitioning, the adaptive algorithm first check if the two errors greater than this threshold value, if it is greater than this threshold, then check if the result of multiplying one of error by a ratio greater than other. Depending on this checking, the coder chooses an appropriate partitioning. The ratio factor is considered an important factor in the proposed algorithm of partitioning, because its value will have effect directly on the compression ratio, quality of output images (degradation) and PSNR. Table 2 and Fig. 6 shows the objective measures of applying the

Table 2: Image 'Bike' of size 256*256. CR is a compression ratio and C.size is the compressed size

C. image	Ratio	Thresh	CR	PSNR	MSE	C. size
Figure (6.b)	0.70	8	4.25	16.02	1624.45	46275
Figure (6.c)	0.65	8	2.84	17.78	1083.23	69025
Figure (6.d)	0.60	8	2.77	26.24	144.100	70950
Figure (6.e)	0.50	8	3.27	27.53	117.030	60052
Figure (6.f)	0.40	8	3.27	27.53	117.030	60052



(a) (b) (c)

(d) (e) (f)

Fig. 6: Image 'Bike' of size 256×256, where (a) is the original image

proposed scheme to a random image with a different ratios and the corresponding figure for the constructed image.

The previous experiment and other experiments showed that a ratio (0.5) is a good ratio to get a relatively good compression ratio, image quality and quality measurement (MSE and PSNR). Another factor, which was investigated is the threshold factor. Results shoed that the threshold factor has a small effect on the subjective quality of the reconstructed image on a noticeable effect on the compression ratio and PSNR. Table 3 shows an example of the effect of change in the threshold factor on the compression results of a random image.

The 3rd parameter, which was investigated is the quantization step-size. Test results showed that quantization step-size has a major influence on the compression performance and consequently, on the reconstructed image. The increase of quantization step-size will lead to a decreasing in the constructed image but will cause an increase in the compression ratio. In the proposed coding scheme, different quantization steps values are used for each partition (sub-block), its value depends on the initial quantizer value allocated by the user at the initial step. The values change of the quantizer depend on the history of partitioning applied to produce the consider sub- block. Table 4 presents the effect of the initial quantization step-size on the quality of the constructed random image and on the compression ratio.

The result showed, that the quantizatition step-size has a great effect on the compression ratios and it causes a monotonic increase in compression ratio as the magnitude of the initial quanitization step-size is increased.

The 4th parameter which was investigated is the number of partitioning levels. The levels of decomposition of an image (starting with tiles that have certain maximum size) have a great effect on the reconstructed image quality and also on the compression ratio. In the previous experiments, we used the same number of decomposition levels (i.e., 4), but in the following experiment we used the number of levels to be 5. The reason for this is to see the effect of this on the compression performance. Table 5 gives the effect of this for a certain image entitled "Ski".

Note that all the previous experiments depend on changes one of the parameters, whose values have a significant effect on the quality compression measurements of the compressed image. We run our program, but with changing more than one parameter at the same time. The results of this experiment, are listed in Table 6 and Fig. 7. This table lists these parameters according to the compression ratio measurement factor, while the MaxSize and Levels of wavelet partitioning are fixed (128 and 5, respectively).

From Table 6, once can notice the following:

- The best magnitude of ratio has the range of 0.5- 0.6.
- The magnitude of the quantization step size must be greater than or equal to 2.
- The value of the quantization factor is within the range 0.8-0.9.
- When the value of the threshold becomes greater than 3, the MSE increases and PSNR decreases although the compression ratio is increased (This can be noticed in row 1 and row 7 of the Table 6).

Table 3: The effect of the threshold parameter on the compression results for a random image of size 256×256; CR is a compression ratio and C.Size is the compressed size

Ratio	Thresh	CR	PSNR	MSE	C. size
0.5	4	5.05	29.86	69.178	38910
0.5	2	5.26	29.67	70.065	37383
0.5	1	5.27	29.87	70.241	37251

Table 4: The effect of the initial quantization step-size (QNT) on the compression performance parameters for a random image

Ratio	Thr	Qnt	CR	PSNR	MSE	C. size
0.5	1	1	7.708	31.06	50.90	25514
0.5	1	2	14.616	28.49	92.05	13455
0.5	1	3	20.154	27.27	121.74	9758
0.5	1	4	25.507	26.47	146.37	7710

Table 5: The effect of the quantization step size on the compression performance factor for "Ski" image

Ratio	Level	Qnt	CR	PSNR	MSE	C. size
0.5	5	1	7.1200	25.491	153.606	27598
0.5	5	2	16.453	21.730	436.581	11953
0.5	5	3	24.124	20.357	598.985	81520
0.5	5	4	29.538	19.668	701.972	66580

Table 6: The compression ratio sorted as a result of performing the suggested scheme with maximum size 128 and decomposition level 5

Threshold	Ratio	Quant step size	Quant factor	Compression ratio	MSE	PSNR
5	0.5	2	0.8	14.57	171.16	25.79
5	0.6	2	0.8	14.57	171.16	25.79
4	0.5	2.5	0.7	15.94	158.18	26.13
4	0.6	2.5	0.7	15.94	158.18	26.13
1	0.5	2.5	0.7	16.01	158.47	26.13
3	0.5	1.5	0.9	16.47	175.97	25.67
3	0.6	1.5	0.9	16.47	175.97	25.67
4	0.5	2	0.8	16.55	172.38	25.76
4	0.6	2	0.8	16.55	172.38	25.76
2	0.5	1.5	0.9	16.92	176.25	25.66
2	0.6	1.5	0.9	16.92	176.25	25.66
1	0.5	1.5	0.9	17.12	176.31	25.66
1	0.5	3	0.7	18.74	179.48	25.59
1	0.6	3	0.7	18.74	179.48	25.59
2	0.6	3	0.7	18.81	179.45	25.59
3	0.5	3	0.7	18.90	179.38	25.59
3	0.6	3	0.7	18.90	179.38	25.59
4	0.6	2	0.9	21.41	223.65	24.89
4	0.6	2.5	0.8	20.95	210.62	24.89
1	0.5	2.5	0.8	21.08	210.94	24.88
1	0.6	2.5	0.8	21.08	210.94	24.88
5	0.6	3	0.8	21.14	238.85	24.34
2	0.5	2.5	0.8	21.17	210.90	24.89
2	0.6	2.5	0.8	21.17	210.90	24.89
3	0.5	2.5	0.8	21.26	210.80	24.89
3	0.6	2.5	0.8	21.26	210.80	24.89
5	0.6	2.5	0.9	22.88	272.15	23.78
4	0.5	3	0.8	24.05	240.05	24.32
4	0.6	3	0.8	24.05	240.05	24.32
1	0.5	3	0.8	24.11	240.45	24.32
1	0.6	3	0.8	24.11	240.45	24.32
2	0.5	3	0.8	24.23	240.42	24.32
2	0.6	3	0.8	24.23	240.42	24.32
3	0.5	3	0.8	24.37	240.37	24.32
3	0.6	3	0.8	24.37	240.37	24.32
5	0.5	3	0.9	25.29	301.74	23.33
2	0.6	2.5	0.9	26.33	273.66	23.75
3	0.5	2.5	0.9	26.51	273.54	23.76
3	0.6	2.5	0.9	26.51	273.54	23.76
1	0.5	3	0.9	29.56	303.40	23.31
3	0.5	3	0.9	29.97	303.34	23.31
3	0.6	3	0.9	29.97	303.34	23.31

Fig. 7: Output of performing the suggested compression system with parameters is listed in Table 6, where the numbers in the bottom of images denote to row number

The same experiment was repeated, but with Maximum size and levels to be 128 and 4, respectively. The results verified our previous notes. Following is the reconstructed images whose parameters values are taken from Table 5, where the rows are shaded.

CONCLUSION

We proposed an adaptive image compression scheme that is based on wavelet using space-frequency segmentation. The suggested approach is a flexible scheme. In addition, the suggested approach has higher energy of frequency partitioning than the space partitioning from the point of view of quality of compressed image. Experimental results showed that ratio, threshold, the quantization step size and the quantization factor (weight) should be selected very carefully. The experiential results showed that the use of MED predictor produces better PSNR than other predictors from simplest model (Sp1) and Sp2. In addition, the spatial encoders used in the proposed algorithm (Run-Length encoder and Chain Encoder) have a positive effect on the proposed scheme by reducing its complexity and speeding up the compression time, while the use of vector quantization and DPCM have the effect of increasing the compressed image quality (increasing PSNR). The above adaptive encoding mechanism has made the proposed system more effective than other popular entropy coders discussed in this thesis.

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