Image Compression Using Advanced Optimization Algorithms

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Abstract —In this paper, a new image compression technique that uses three-dimensional Discrete Cosine Transform and relies on Two-Dimensional Discrete Wavelet Transform, for image classification, is proposed. The proposed technique utilizes a modified quantization table and a method for converting a three-dimensional image cube into a one-dimensional array, which provides better coding efficiency in the run length coding step. To ensure faster performance, the proposed technique uses parallel computation-based algorithms. The first one utilizes computations parallelization process using SPMD (Single Program Multiple Data) and the other method utilizes Graphics Processor Unit (GPU) programming with CUDA language. Several images have been used to test the proposed algorithm. Experimental results demonstrate that the proposed algorithm outperforms previous compression methods in terms of Peak-Signal-to-Noise Ratio with a lower compression bit rate.

Index Terms—DCT, JPEG, DWT, parallel computation

I. Introduction

Image coding and compression techniques have become a highly active research area over the past decades [1]. The main purpose of image compression is reducing the redundancy in images in order to store or transmit data in an efficient form [2]. One common characteristic in most images is that neighboring pixels are highly correlated and consequently contain a lot of redundant information. To find an image representation in which pixels are less-correlated, various image compression schemes that utilize image transformations can be used. There are two compression techniques that are used for image compression (Lossless and Lossy compression [3]). When the reconstructed image after compression becomes numerically identical to the original image, it is called lossless image compression. Conversely, when the reconstructed image after compression becomes more distorted compared to the original image, it is called lossy image compression. To perform compression, a linear transformation is first applied to make the pixels of the image less-correlated. Then, the quantization process is performed to the coefficients that result from the transform. Discrete Cosine Transformation (DCT) [4] is the most easily and widely used transform in image compression schemes. It has excellent compaction for highly correlated data. It provides a good tradeoff between information packing ability and computational complexity. JPEG-based compression [5] is the well-known algorithm that uses the DCT and achieves high compression with less data loss. In addition, video compression MPEG [6] is one of the best algorithms to compress videos in with low bit-rate and high quality. In image watermarking field [7], a lot of researches use the DCT to achieve better results. Image processing using parallel computation [8] is proposed in many techniques [9] that depend on multicore systems instead of a single processor system to overcome the high computation complexity. For example, the method in [10] proposed a parallel technique for image segmentation using CPU and GPU. In [11], [12], parallel processing techniques are used in video compression. In [13]-[15], different image compression methods that use CPU and GPU parallel computing were presented.

In this paper, a new image compression technique using 3D-DCT is proposed. The proposed technique utilizes a modified quantization table and a method for converting a 3D image cube into a 1D array. The proposed algorithm provides better coding efficiency in the run length coding step. In order to improve the performance of the image compression algorithm, a 2D-DWT based classification is used [16] to determine the type of the image. The resultant 2D image is converted into 3D cubes of sizes that are determined based on the image type (low or high detail). The 3D-DCT is then applied on the constructed cubes. A parallel implementation of the proposed algorithm is used to improve the computation time in two ways: the first one utilizes computation parallelization process using SPMD (Single Program Multiple Data) and the other method utilizes graphics processor unit (GPU) programming with CUDA language. The performance of proposed algorithm is evaluated using some of the most commonly used test images in the compression literature. Test results demonstrate that the proposed algorithm outperforms several compression methods in terms of Peak-Signal-to-Noise Ratio (PSNR) and compression bit rate.

The paper is organized as follows. In Section II, the 2D-DCT and 3D-DCT compression techniques are previewed. In Section III, the proposed image compression algorithm is described in detail. In Section IV, the proposed parallel computation technique is presented. In Section V, experimental results of testing the proposed method are reported and discussed. Finally, conclusions are drawn in Section VI.

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II. 3D-DCT BASED TECHNIQUES

3D-DCT has been used in many techniques. Some of these techniques focus on integral images [17], [18], where image elements are placed along the third dimension before applying the 3D-DCT. This is commonly used in video compression [19], [20], in which, the temporal domain is used as the third dimension.

In visual tracking [21], 3D-DCT is frequently used to represent the object appearance model that is robust to variations in illumination, pose, etc. Furthermore, 3D-DCT is used in many image processing applications, such as video watermarking, denoising, and fingerprinting [22], [24]. 3D-DCT sequential coding is used for specific classes of images like medical images [25]. In [26], 3D spiral JPEG image compression is used, where it uses spiral scanning to format the multi-dimensional constellation, in order to get a more effective compression scheme [27]. For hyperspectral space images, different techniques are proposed, as in [28], [29].

In video compression, 3D-DCT is used by taking the two-dimensional frames and the temporal dimension (the sequence of frames) as the basis. DCT coefficients can be determined as:

$$F(u,v) = C(u)C(v)C(p)K \sum_{x=0}^{N-1} \sum_{y=0}^{M-1} \sum_{z=0}^{L-1} f(x,y,z)\, A_{ux} A_{vy} A_{pz} \quad (1)$$

where A_{ij} and K are determined as

$$A_{ij} = \cos\left[\frac{(2j+1)i\,\pi}{2N}\right] \quad (2)$$

$$K = \sqrt{\frac{8}{MxNxL}} \quad (3)$$

and $x = 0,1, ..., N-1$; $y = 0,1,...,M-1$; $z = 0,1,...,L-1$; $C(u)$ and $C(v)$ are determined as

$$C(\varepsilon) = \begin{cases} \frac{\sqrt{2}}{2} & if \quad \varepsilon = 0 \\ 1 & otherwise \end{cases} \quad (4)$$

III. THE PROPOSED IMAGE COMPRESSION ALGORITHM

The main goal of the proposed compression algorithm is to achieve a high compression ratio with minimum information loss. In the following subsections, the main steps of the proposed 3D-DCT based compression technique are described.

A. 3D Cube Formation

A 2D input image is first mapped into a set of 3D data cubes. This is done by grouping NxN blocks. These blocks are processed from left-to-right and top-to-bottom. Eight NxN blocks are used to construct a 3D data cube. In our technique, we used two cube-dimensions: 8x8x8 cubes and 4x4x4 cubes, depending on the image classification which is determined as discussed in the following sub-section.

B. Image Classification

When the correlation between the pixels (The similarity between blocks [30]) is high, DCT coefficients get smaller and, consequently, it yields a better compression. Images can be classified into two types: high-detail and low-detail images. The similarity ratio in the low-detail images is more than that in high–detail images. Based on that, we suggest that the 8x8x8 cube size would be more suitable for low details images because it has high similarity ratio, while the 4x4x4 cube size would be more suitable for the high details images because of its low similarity ratio.

In the proposed algorithm, an image classifier is used to determine the type of the image. Such image classifier decreases the dimension of the image by using Discrete Wavelet Transform (DWT) and then uses the details images to determine its type and to decide the appropriate cube size. The result of 2D-DWT is decomposed into four quadrants:

LL: The upper left quadrant represents the approximated version of the original at half the resolution.

HL/LH: The lower left and the upper right blocks. The LH block contains the vertical edges. In contrast, the HL blocks shows the horizontal edges.

HH: The lower right quadrant. We can interpret this block as the area where we find diagonal edges of the original image.

The GxG image (512 x512 or any other size) is decomposed by 1-level 2D-DWT, then take the inverse DWT with only the LH sub-band (it is chosen experimentally based on the vertical edges of image) and the other sub bands are set to zero. We take the 2D-DFT (Discrete Fourier Transform) [31] to compute the mean of the inversed image. The computed mean is compared to a certain threshold T (decided experimentally). If it is lower than T, then the image is a low detail image. Otherwise it is a high detail image. The block diagram for this stage is shown in Fig. 1.

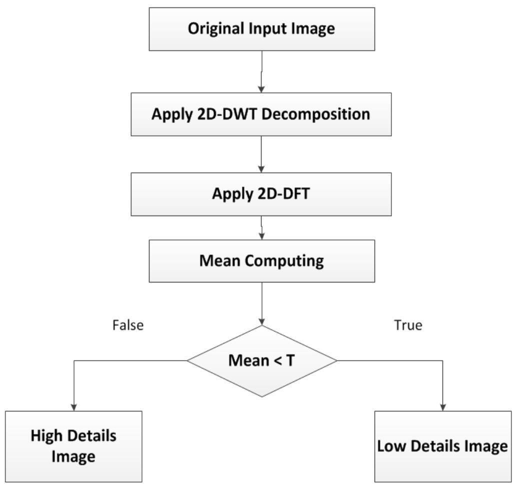


Fig. 1. Block diagram of the 2D-DWT based classifier

C. 3D-DCT Transformation

The 3D-DCT, using eqn. (1), is performed on each cube.

D. 3D Quantization

The quantization matrix that is used is MxMxM matrix and can be determined by

$$Q(x,y,z) = 3x + 6y + 1z \qquad (5)$$

where x = 0, 1, ..., $M-1$, y = 0, 1, ..., $M-1$, and z = 0, 1,...,$M-1$.

Although it is not optimized, based on our experiments this formula has provided the best results. The proposed quantization table can be multiplied by a scalar to get varying levels of compression rates and picture quality.

E. 3D Zig-Zag Scanning

It is necessary to convert a 3D cube into a 1D vector before the variable length Huffman coding is applied. The 3D scan for 8x8x8 cube can be performed using four techniques: (3D-Zig-Zag, 3D-Horizontal, 3D-Vertical and 3D-Hilbert Scanning) as illustrated in Fig. 2.

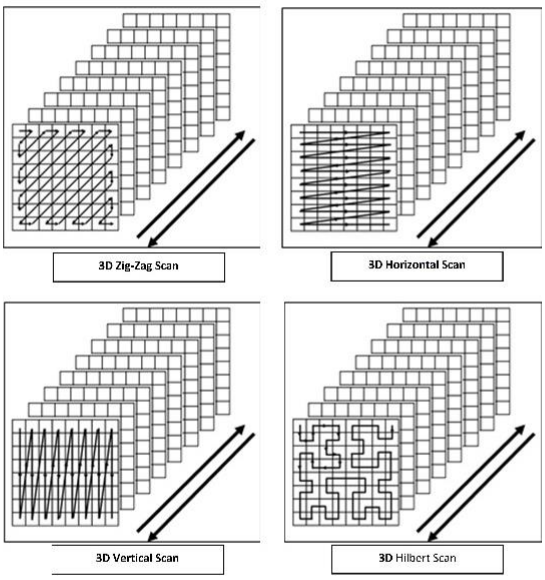


Fig. 2. 3D Zig-Zag scanning

F. Huffman Encoding

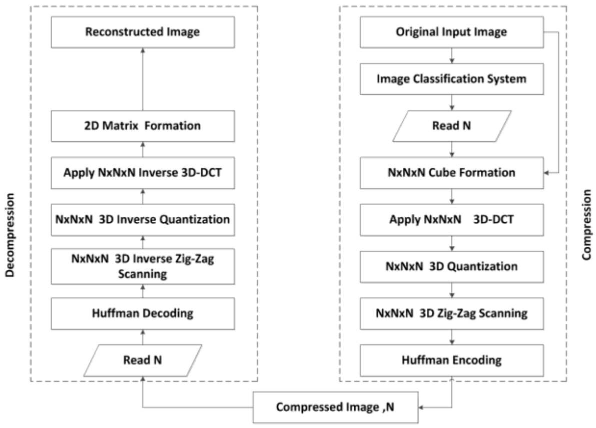


Fig. 3. Encoder and decoder block diagram.

Huffman coding is combined with reducing the image redundancy using DCT to help in compressing the image data to a better level. The block diagram for the full proposed system is shown in Fig. 3.

IV. The Proposed Parallel Computation Technique

In this paper, we used two methods for computations parallelization:

A. SPMD (Single Program Multiple Data)

The main idea of SPMD technique depend on that we have one block code and have several data that is used by that code. In the SPMD technique, there are number of workers that would be defined. So, by running identical code on all workers, each worker can have different, unique data for that code.

This proposed image compression using SPMD is performed as in the following steps:

1- Divide the original image blocks into four sub-images.
2- The proposed image compression algorithm (Single Code) is run on the four sub-images simultaneously in parallel.
3- The four decompressed sub-images are reassembled in the final decompressed image.

The block diagram for the proposed system using SPMD is shown in Fig. 4.

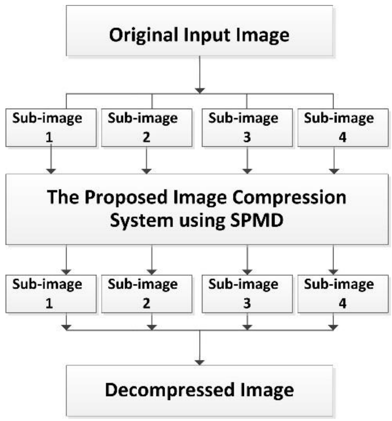


Fig. 4. Block diagram of the proposed image compression using SPMD.

B. CUDA Parallel Processing

Graphics Processor Unit (GPU) programming with CUDA language can be utilized in the computations parallelization process.

Using NVIDIA GPU) the CUDA programming language re-define some phases of MATLAB code into C-like language to re-evaluate it into parallelization process. The improvement of the proposed image compression algorithm consumption time is evaluated in the experimental result.

1) 3D cube formation parallelization

In the 3D Cube formation code, there are a high number of iteration (for-loops). Each iteration creates one cube of NxNxN blocks, so we parallelize these iterations in threads as shown in Fig. 5.

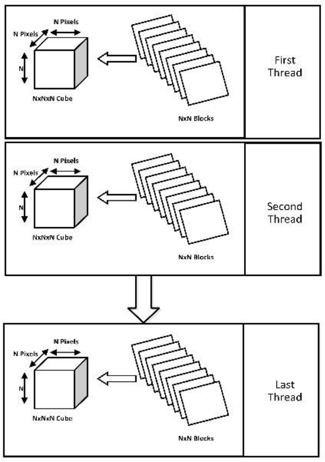


Fig. 5. Block diagram of 3D cube formation parallelization.

2) 3D-DCT and 3D-quantization parallelization

In these steps, each iteration has NxNxN cube and on which, the main processes of the proposed image compression are performed, where 3D-DCT and 3D-Quantization are applied. So, we will parallelize these iterations in threads as shown in Fig. 6.

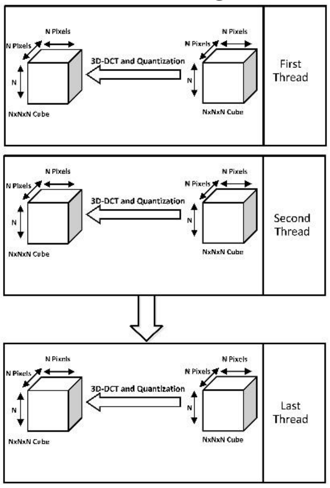


Fig. 6. Block diagram of 3D-DCT-quantization parallelization.

3) Proposed scanning parallelization

The Proposed scanning depends on performing four different scanning patterns (Zigzag, Horizontal, Vertical and Hilbert Scanning), to achieve the best results.

So, we parallelize these four methods in threads as shown in Fig. 7.

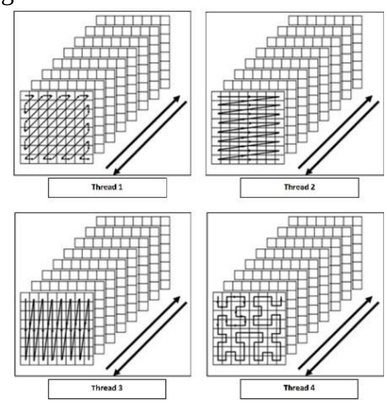


Fig. 7. Block diagram of the proposed scanning parallelization.

V. Performance Evaluation and Experimental Results

A. Experimental Results of the Proposed Image Compression Technique

The performance of the algorithm is evaluated in terms of image quality and compression ratio. To evaluate the image quality in image compression systems, reliable quality measures should be used. A set of objective image quality measures for image compression systems were investigated in [32] and emphasized the correlation between these measures and the subjective image quality measures. The most commonly used measures are the PSNR and the Compression Ratio (CR). The PSNR is determined as follows:

$$PSNR = 10x\ \log_{10} \frac{255^2}{MSE} \tag{6}$$

where Mean Square Error (MSE) is determined as

$$MSE = \frac{\sum_{M,N} [I_1(m,n) - I_2(m,n)]^2}{MxN} \tag{7}$$

where I_1 is the original image, I_2 is the compressed image and MxN is the total number of pixels in the original image.

The Compression Ratio (CR) is determined as follows:

$$CR = \frac{B_0}{B_1} \tag{8}$$

where, B_0 is the number of bits before compression, and B_1 is the number of bits after compression. Alternatively, the bit rate, which measures the number of bits per pixel (BPP) can be determined by

$$BPP = \frac{B_1}{MxN} \tag{9}$$

where B_1 is number of bits after compression and MxN is the total number of pixels in an image.

1) Bit rate

The proposed algorithm was tested using several test images of dimension 512 x512. The results are shown in Tables I and II, in terms of PSNR and BPP. Results obtained using the proposed 3D-DCT algorithm is compared with a standard JPEG compression system and the results is shown in Table I. Low-detail images such as (Lena, Cameraman, Pepper, Elaine and Barbara) and high-detail images such as (Baboon, Bridge, Hildebrandt, City, Cartoon) were compressed using 4x4x4 and 8x8x8 cubes. It can be seen in Table I that results of using 8x8x8 Cubes and 4x4x4 Cubes show that 8x8x8 cube formation gives better bit rate than the JPEG algorithm in case of low-details images (have a low bit rate and a high PSNR). Also, it can be seen that 4x4x4 cube formation gives better bit rate than JPEG algorithm in case of high-detail images (have a high bit rate and a high PSNR). Fig. 11 shows some images that were used in the experimental testing for different PSNRs. Lena and Baboon images were selected as examples for low and high-detail images and tested with different PSNR values and the results are shown in Fig. 8 and Fig. 9.

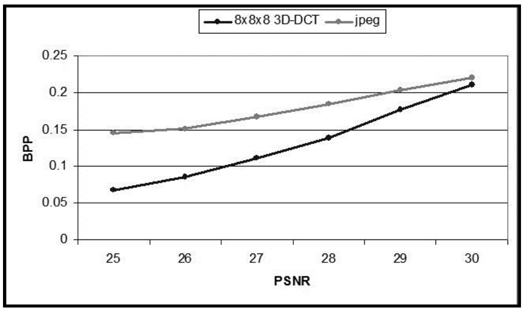


Fig. 8. PSNR vs BPP in Lena image.

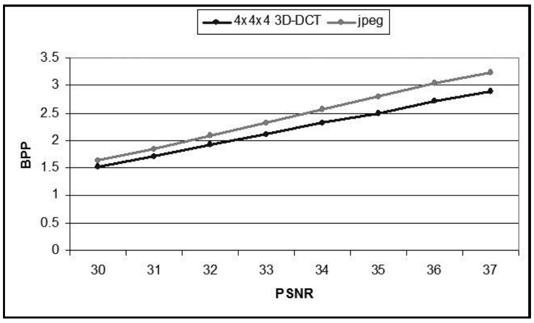


Fig. 9. PSNR vs BPP in baboon image

In Fig. 8, it can be noticed that the bit rate improves with high PSNR in case of 8x8x8 cube. While, in Fig. 9, it can be shown that the bit rate improves for high PSNR in case of the 4x4x4 cube formation. Table II shows a comparison of the results obtained using the proposed 3D-DCT algorithm, JPEG standard algorithm, and the Spiral JPEG algorithm.

TABLE I: COMPARISON BETWEEN JPEG-BASED METHOD AND THE PROPOSED 3D-DCT ALGORITHM (USING 8X8X8 AND 4X4X4 CUBE SIZE).

Image	Low /High N=8 or N=4	JPEG (BPP)	JPEG (BPP)	8x8x8 Cube (BPP)	4x4x4 Cube (BPP)
Lena	N=8	30	0.22	0.21	0.24
		27	0.165	0.11	0.13
		26	0.151	0.085	0.11
Cameraman	N=8	30	0.20	0.18	0.21
		27	0.15	0.10	0.13
		25	0.14	0.06	0.09
Baboon	N=4	35	2.79	2.59	2.50
		33	2.32	2.17	2.11
		30	1.63	1.56	1.52
		28	1.18	1.16	1.14
Bridge	N=4	37	3	2.87	2.78
		35	2.57	2.48	2.39
		32	1.87	1.84	1.81

Quantization equation that used in the proposed algorithm is derived to deal with cube formation method, by changing the quantization equation that used in the 3D-Spiral compression algorithm and using the proposed quantization equation. From Table II, it can be noticed that 8x8x8 cube formation have slightly better bit rate than 3D-Spiral JPEG algorithms, in the case of low-details images like Lena and Flower. Furthermore, it can be seen that 4x4x4 cube formation have slightly better bit rate than the 3D-Spiral JPEG algorithm, in case of high-details images, like Baboon.

TABLE II: COMPARISON BETWEEN JPEG, 3D-SPIRAL JPEG, AND 3D-DCT USING TWO SIZES FOR CUBES.

Image	PSNR	JPEG (BPP)	Spiral (BPP)	8x8x8 Cube (BPP)	4x4x4 Cube (BPP)
Lena	27.65	0.17	0.13	0.128	0.153
Baboon	37.68	3.38	3.13	3.10	3.05
Flower	29,73	0.127	0.04	0.036	0.046
House	24.41	0.17	0.11	0.11	0.16

2) Time comparison

In terms of time, when using the two methods, we observed that the compression system with 8x8x8 cube formation is faster than the compression system with 4x4x4 cube formation and this is due to the large size of blocks that used in the formation of the cube, the larger the number of cubes, the less time the compression process. And it also proved by results for different images, as shown in Fig. 10.

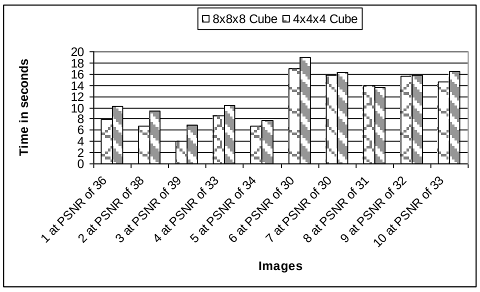
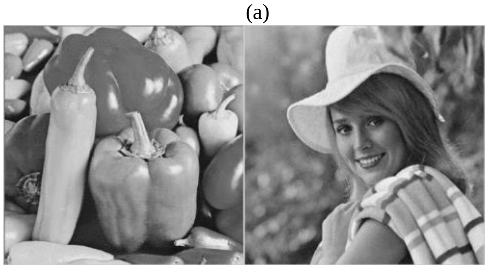


Fig. 10. Time comparison for different images using the proposed two ways of compression

(a)

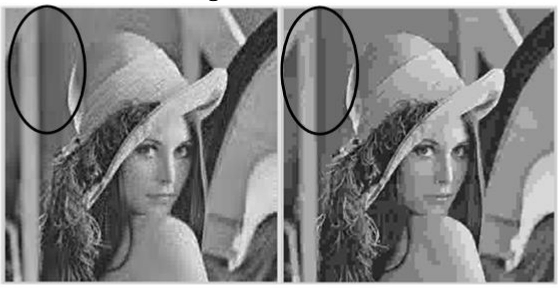


(b)

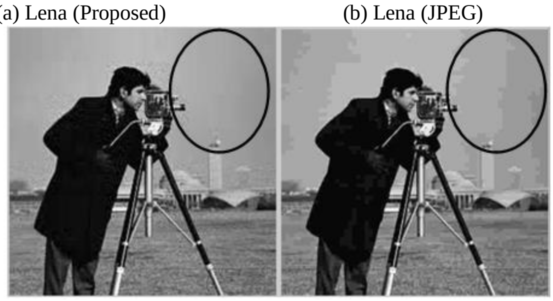
Fig. 11. (a) Original images (Pepper, Elaine, Bridge, City), (b) Decompressed images (Pepper at PSNR=33.7 dB, Elaine at PSNR= 32.4 dB, Bridge at PSNR= 31.2 dB, City at PSNR=30.6).

3) Blocking artifact effects

Because of compression, the decompressed images may exhibit various kinds of distortion artifacts such as blocking, blurring and ringing [33]. The human visual sensitivity to several types of artifacts is very different. The blocking artifacts are usually the most significant among them, especially at low bit rate compression. The reduced blocking artifact effect in the proposed algorithm can be illustrated in Fig. 12.



(a) Lena (Proposed) (b) Lena (JPEG)



(c) Cameraman (Proposed) (d) Cameraman (JPEG)

Fig. 12. Comparisons of the resulting compression artifacts: (a) Proposed method using Lena (PSNR=27 for 0.11bpp), (b) JPEG method using Lena (PSNR=27 for 0.165bpp), (c) Proposed method using Cameraman (PSNR=30 for 0.18bpp), (d) JPEG method using Cameraman (PSNR=30 for 0.20bpp).

B. Parallel Computation Experimental Result

1) SPMD parallelization

The proposed algorithm was tested using several test images of dimensions 512 x512. The results are displayed in Table III and Fig. 13 in terms of Q (Quality of compression), the consumption time in terms of S (Serial Time, SPMD Time, and CUDA Time) in seconds and the Efficiency of parallelization.

2) CUDA parallelization

The CUDA parallelization was tested on some phases of the algorithm (phase 1: The 3D Cube formation, phase 2: The 3D-DCT-Quantization, and phase 3: The proposed scanning).

The results are shown in Table III, Table IV and Fig. 14, in terms of compression quality, consumption time (in seconds), and the efficiency of parallelization.

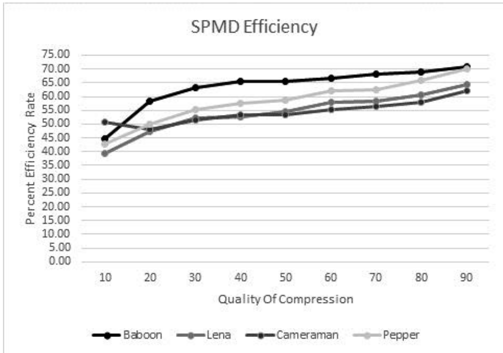


Fig. 13. Efficiency of SPMD for different qualities

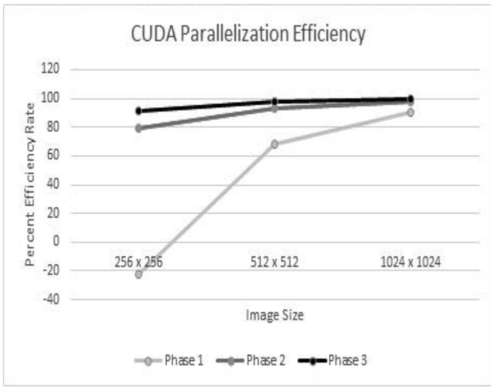


Fig. 14. Efficiency of GPU-CUDA for different image sizes.

TABLE III: COMPARISON BETWEEN THE EXECUTION TIME OF THE PROPOSED SERIAL ALGORITHM, THE PROPOSED PARALLEL SPMD ALGORITHM, AND THE PROPOSED PARALLEL CUDA WITH THE EXECUTED FOUR PHASES OF THE ALGORITHM

Q	Images											
	Baboon			Lena			Cameraman			Pepper512		
	Serial Time	SPMD Time	CUDA Time	Serial Time	SPMD Time	CUDA Time	Serial Time	SPMD Time	CUDA Time	Serial Time	SPMD Time	CUDA Time
10	2.95	1.629	2.306	2.335	1.412	1.750	2.748	1.351	2.163	2.448	1.401	1.863
20	5.988	2.505	5.344	3.516	1.859	2.931	3.393	1.768	2.808	3.614	1.805	3.029
30	9.132	3.343	8.488	4.546	2.173	3.961	4.325	2.104	3.740	4.681	2.090	4.096
40	11.932	4.122	11.288	5.535	2.614	4.950	5.210	2.439	4.625	5.668	2.413	5.083
50	14.552	5.023	13.908	6.424	2.911	5.839	6.008	2.807	5.423	6.588	2.718	6.003
60	17.569	5.868	16.925	7.529	3.168	6.944	6.910	3.100	6.325	7.731	2.944	7.146
70	22.064	7.059	21.420	9.129	3.790	8.544	8.236	3.588	7.651	9.455	3.548	8.870
80	29.717	9.247	29.073	12.115	4.758	11.530	10.561	4.430	9.976	12.809	4.380	12.228
90	45.569	13.242	44.925	20.303	7.221	19.718	16.788	6.346	16.203	23.153	6.904	22.568

TABLE IV: COMPARISON BETWEEN THE TIME OF THE SERIAL ALGORITHM AND THE PARALLEL GPU-CUDA ALGORITHM FOR SPECIFIC PHASES OF PROPOSED ALGORITHM.

Time	Image Size								
	256 x 256			512 x 512			1024 x 1024		
	Phase 1	Phase 2	Phase 3	Phase 1	Phase 2	Phase 3	Phase 1	Phase 2	Phase 3
Serial Time	0.004	0.0365	0.1242	0.0176	0.1458	0.4468	0.0669	0.5669	1.7777
CUDA Parallel Time	0.0049	0.0074	0.0112	0.0056	0.0101	0.0103	0.0067	0.0123	0.0104

VI. CONCLUSIONS

In this paper, a new image compression technique that uses 3D-DCT and relies on 2D-DWT based classification has been proposed. The proposed technique has two cube formation methods (8x8x8 and 4x4x4 cube formations), to be used depending on the image type that classified by the 2D-DWT Classification Technique.

Several images have been used to test the proposed algorithms. Experimental results show that the proposed algorithm outperforms previous compression methods in terms of PSNR with a lower bit rate and it has less blocking artifacts than JPEG compression. To overcome the time consumption problem, two techniques with parallel computation have been proposed. The first one utilizes computations parallelization process using SPMD while the other method utilizes GPU programming with CUDA language. The results showed that the time consumption was decreased.

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