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Combination of DCT & DWT techniques for image compression

A. Hadj Brahim*, A. Ali Pacha, N. Hadj Said

[1]*Laboratory of Coding and Security of Information. University of Sciences and Technology of Oran Mohamed Boudiaf Oran-Algeria.*
[2]*Laboratory of Coding and Security of Information*
University of Sciences and Technology of Oran Mohamed Boudiaf Oran-Algeria.

***Corresponding author:** abderrahmene.hadjbrahim@univ-usto.dz*

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Abstract. The compression of images is one of the most important processes in image processing. The compression reduces the storage space of the images, which is used to increase the performance of storage or transmission of images. For good compression techniques, not only the size of the compressed images is important, but also the quality of the decompressed images. In this paper, two classical techniques of compression are combined to develop a new compression, the first one is the Discrete Cosine Transform (DCT), and the second one is the Discrete Wavelet Transform (DWT). The results of the proposed compression are compared with the classical techniques by using several tests such as Mean square error (MSE), Peak Signal to Noise Ratio (PSNR), and Structural similarity index measurement (SSIM.

Keywords. DCT, DWT, PSNR, MSE, SSIM, Image compression.

INTRODUCTION

With the growing up of digital images, the quality is increasing rapidly, which causes an increase in the data needed for storage or transmission. To solve this problem, compression is applied to the images to reduce their space storage. The compression of images becomes one of the important processes in different fields such as medical images, military images, satellite images…etc, which can reduce the size of images needed for the storage of the transmission, which leads to a decrease in the time of transmission. The compression of images is based on minimizing the pixels needed to represent an image without decreasing the quality of the decompressed image.

Compression can be classified into two categories, lossless compression, and lossy compression. In lossless compression, the decompressed images are the same as the original image, and no information is lost. The lossless compression is used in the domains where no information should be lost such as medical images where a small loss can cause misdiagnosis.

In lossy compression, some information about the original image is discarded without significantly impacting the quality of the decompressed image. However, to the human eye, the difference between the decompressed image and the original image is often imperceptible since many elements in the image are ignored with minimal effect on the overall visual perception. Various lossy compression techniques exist, including DCT, DWT, and others.
In this paper, a new compression technique is proposed by combining the DCT and DWT in one compression. Firstly, the original image is compressed by using the DCT technique. Then, the result of the first compression is quantified by using the quantification matrix of JPEG. Secondly, the second compression is applied in the quantified image by using the DWT technique to obtain the final compressed image.

METHODOLOGY

Discrete Cosine Transform (DCT)

The Discrete Cosine Transform (DCT) technique is one of the most common compression techniques in lossy compression that is used in many algorithms such as JPEG (Raid et al., 2014). The DCT compression is an orthogonal transform where the pixels of the image are converted into sets of spatial frequencies.
The compressed matrix of the image is obtained by (Parmar, 2014):

$$D(i,j) = \frac{2}{\sqrt{nm}} C(i)C(j) \sum_{x=0}^{n-1} \sum_{y=0}^{m-1} I(x,y) \cos\frac{(2x+1)i\pi}{2n} \cos\frac{(2y+1)j\pi}{2m} \quad (1)$$

Where m and n are the number of rows and columns of the plain image I, respectively, $i, x = 0,1, \ldots, n-1$, and $j, y = 0,1, \ldots, m-1$, and

$$C(i), C(j) = \begin{Bmatrix} \frac{1}{\sqrt{2}} & for\ i,j = 0 \\ 1 & otherwise \end{Bmatrix} \quad (2)$$

The inverse DCT (IDCT) can be given by (Parmar, 2014):

$$I(x,y) = \frac{2}{\sqrt{nm}} \sum_{k=0}^{n-1} \sum_{v=0}^{m-1} C(i)C(j)D(i,j) \cos\frac{(2x+1)i\pi}{2n} \cos\frac{(2y+1)j\pi}{2m} \quad (3)$$

The plain image is divided into 8 x 8 or 16 x 16 pixel blocks and DCT is applied to each. Then, the quantization is applied where parts of compression actually occur, and the less important frequencies are discarded, and the most important frequencies that remain are used to retrieve the image in the decomposition process, hence the use of the lossy. The quantization is applied by using a matrix named quantification matrix, and the most known matrix is the standard quantification matrix of JPEG that is given in table 1 (Zhou, 2011).

Table 1. The JPEG quantification matrix.

16	11	10	16	24	40	51	61
12	12	14	19	26	58	60	55
14	13	16	24	40	57	69	56
14	17	22	29	51	87	80	62
24	22	39	56	68	109	103	77
26	35	55	64	81	104	113	92
49	64	78	87	103	121	120	101
72	92	95	98	112	100	103	99

Thus, the algorithm of DCT compression can be given as follows:

- The plain image is divided into 8x8 or 16x16 pixel blocks.
- The DCT is computed for each block by using equation 1.
- The DCT coefficients are quantized by using the quantification matrix.

The DCT algorithm has many advantages such as (Britanak et al., 2010):

- It can be implemented in a single integrated circuit.
- It can assemble the most information about the image in the fewest coefficients.

Discrete Wavelet Transform (DWT)

Another common technique in lossy compression for image compression is the Discrete Wavelet Transform (DWT). The DWT represents pixels of the image in terms of functions that are localized both in time and frequency, which transforms a discrete-time signal into a discrete wavelet representation. The 2D-DWT is applied to the image by applying 1D-DWT on the row-wise of the image to obtain low (L) and high (H) bands. After that, the 1D-DWT is applied on the column-wise of the image to obtain four sub-bands LL, LH, HL, HH, the LL band provides the approximation coefficients. Whereas the LH, HL, HH bands provide information about horizontal, vertical, diagonal components respectively (Maghari, 2019).

The DWT can be written by:

$$\psi_{j,n}(t) = \frac{1}{\sqrt{2^j}}\psi\left(\frac{t-2^j n}{2^j}\right) \quad (4)$$

where$j, n \in Z$, and Z represent the set of integers. There are many transforms of DWT, and one of the most used is the Haar wavelets (Gupta, 2015).

The DWT has many properties (Shapiro, 1993). First, wavelets are effective to represent non-stationary signals due to the adaptive time-frequency window. Second, the wavelets have high decor relation and compaction efficiency. Third, blocking artifacts and mosquito noise are reduced in a wavelet-based image coder. Fourth, the wavelet basis functions match the human visual system characteristics, which means a superior image representation.

Compared to the DCT, the DWT has the following advantages (Parmar, 2014):

- Allows good localization both in the time and spatial frequency domain.
- DWT uses a more optimal set of functions to represent sharp edges than cosines.
- Wavelets are finite in extent as opposed to sinusoidal functions.

PERFORMANCE EVALUATION

To determine if the compression technique is good and can be applied in the actual application, several tests are used to measure the performance of the compression technique, such as Compression ratio (CR), Mean square error (MSE), Peak Signal to noise ratio (PSNR), and Structural similarity index measurement (SSIM)…etc.

Compression ratio (CR)

The compression ratio (CR) is measured by dividing the number of bits of the compressed image by the number of bits of the original image. It can also be described as the ratio of the size of the original image to the size of the compressed image.

CR can be calculated by:

$$CR = \frac{N_c}{N_i} \times 100 \quad (5)$$

Where N_i is the number of bits of the original image, and N_c is the number of bits of the compressed image. The lower the ratio is, the better is the compression technique.

Mean square error (MSE)

In order to measure the quality of the decompressed image compared to the original image, the mean square error (MSE) is one of the most tests in the image compression techniques. MSE is a measure of image quality index, which is used to measure the classical error estimate. A high value of MSE means that the decompressed image has poor quality compared to the original image.

MSE can be given by Mehra (2016):

$$MSE = \left(\frac{1}{M * N}\right)\sum_{i=1}^{M}\sum_{j=1}^{N}\left(X(i,j) - Y(i,j)\right)^2 \quad (6)$$

Peak signal to noise ratio (PSNR)

One of the important test in compression techniques is the Peak signal to noise ratio (PSNR) which measure the quality of the decompressed image after image processing, and its equation can be given by (Hore and Ziou, 2010) :

$$PSNR = 10\log\frac{255 * 255}{\left(\frac{1}{M * N}\right)\sum_{i=1}^{M}\sum_{j=1}^{N}\left(X(i,j) - Y(i,j)\right)^2} \quad (7)$$

The higher the PSNR means that the decompressed image has less difference compared to the plain image.

The relation between PSNR and MSE can be given by:

$$PSNR = 10\log\frac{255 * 255}{MSE} \quad (8)$$

Thus, the low MSE value means the high PSNR value and vice versa.

Structural similarity index measurement (SSIM)

Structural similarity index measurement (SSIM) measures the similarity between the original image and the decompressed image by taking three aspects of brightness, contrast, and structure. The value of the SSIM is between 0 and 1, the more similar the decompressed image is to the original image the closer the SSIM is to 1.

The SSIM equation is defined by (Hadj Brahim et al., 2020) :

$$SSIM = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)} \quad (9)$$

Where $C_1 = (k_1 \times L)^2$, $C_2 = (k_2 \times L)^2$, $k_1 = 0.01$, $k_2 = 0.02$, $L = 255$, and μ_x , μ_y , σ_x , σ_y , σ_{xy} represent the mean, variances, and covariances of the original image and decompressed image, respectively.

PROPOSED METHOD

Compression process

The proposed method for the compressed image is illustrated in figure 1, and it is described as follows:

1) The original image is divided into blocks of the same size 8 x 8.
2) Each block of the original image is compressed by using DCT to obtain the compressed bloc.
3) Each compressed block is quantified by using the JPEG quantification matrix to obtain the quantified bloc.
4) All quantified blocks are combined to obtain the first compressed image.

5) The first compressed image is recompressed by using the DWT to obtain the final compressed image.

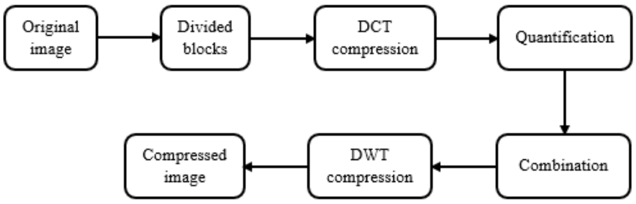


Fig. 1. Proposed image compression.

Decompression process

The decompression process is the inverse operation of the compression process as shown in figure 2, and it is described as follows:

1) The compressed image is decompressed by using the DWT to obtain the first decompressed image.
2) The first decompressed image is divided into blocks of the same size 8 x 8.
3) Each bloc is unquantified by using using the JPEG quantification matrix to obtain the unquantified block.
4) The unquantified block is decompressed by using the DCT to obtain the decompressed bloc.
5) All decompressed blocks are combined to obtain the final decompressed image.

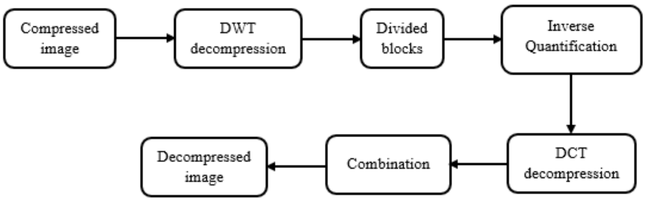
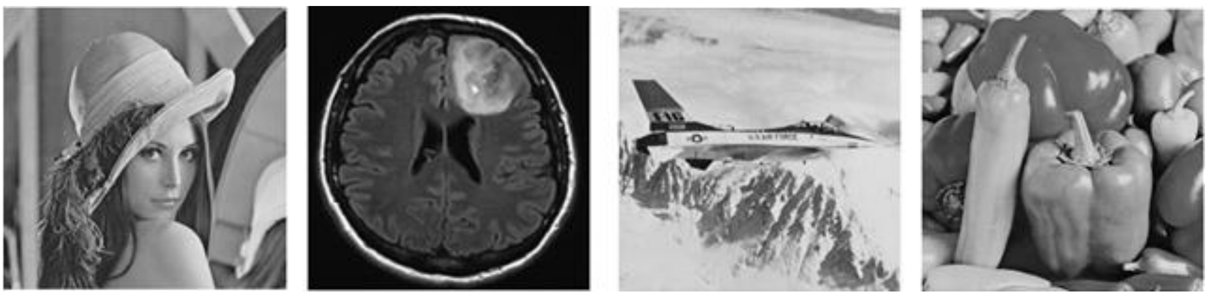


Fig. 2. Proposed image decompression.

THE SIMULATION RESULTS

This section presents the simulations implemented using Matlab 2017a on a 64-bit computer with an Intel (R) Core (TM) i3 CPU @2.13 GHZ with 4.00 GHZ RAM and Microsoft Windows 7 operating system. The test images of the simulation results include 256 x 256 images: "Lena", "Brain", 512 x 512 images: "Jet-Plane" and "Peppers", these figures are shown in figure 3.



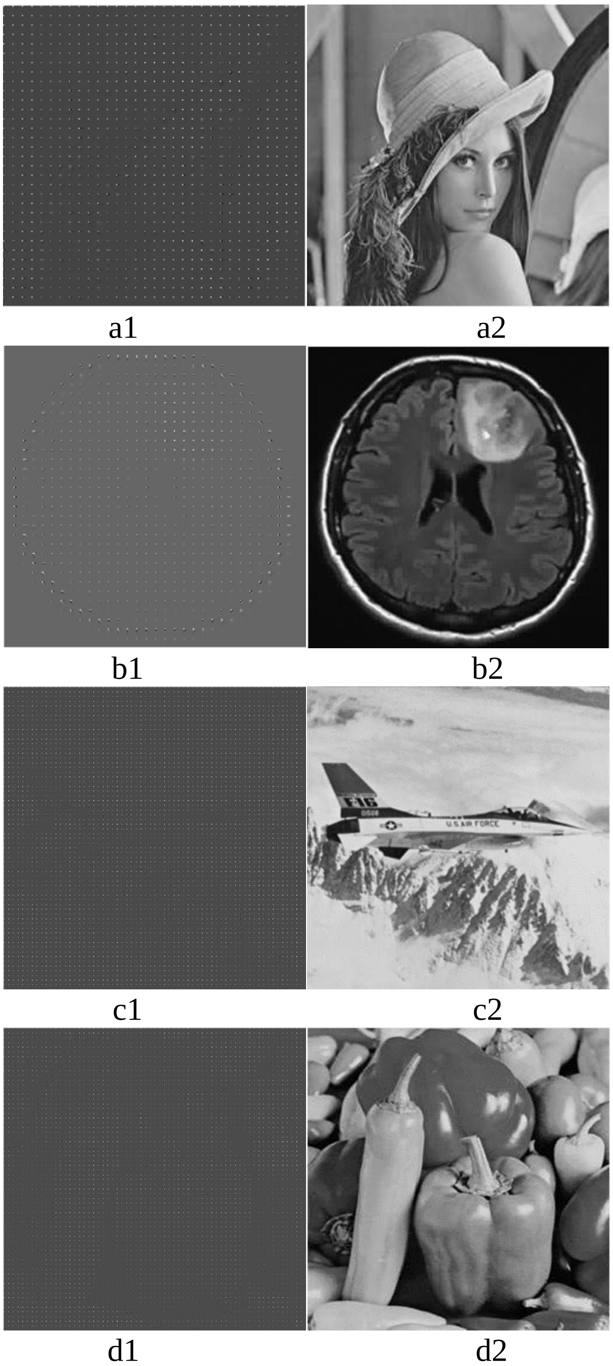
a b c d

(a) Lena image, (b) Brain image, (c) Jet-Plane image, (d) Peppers image.

Fig. 3. Plain images.

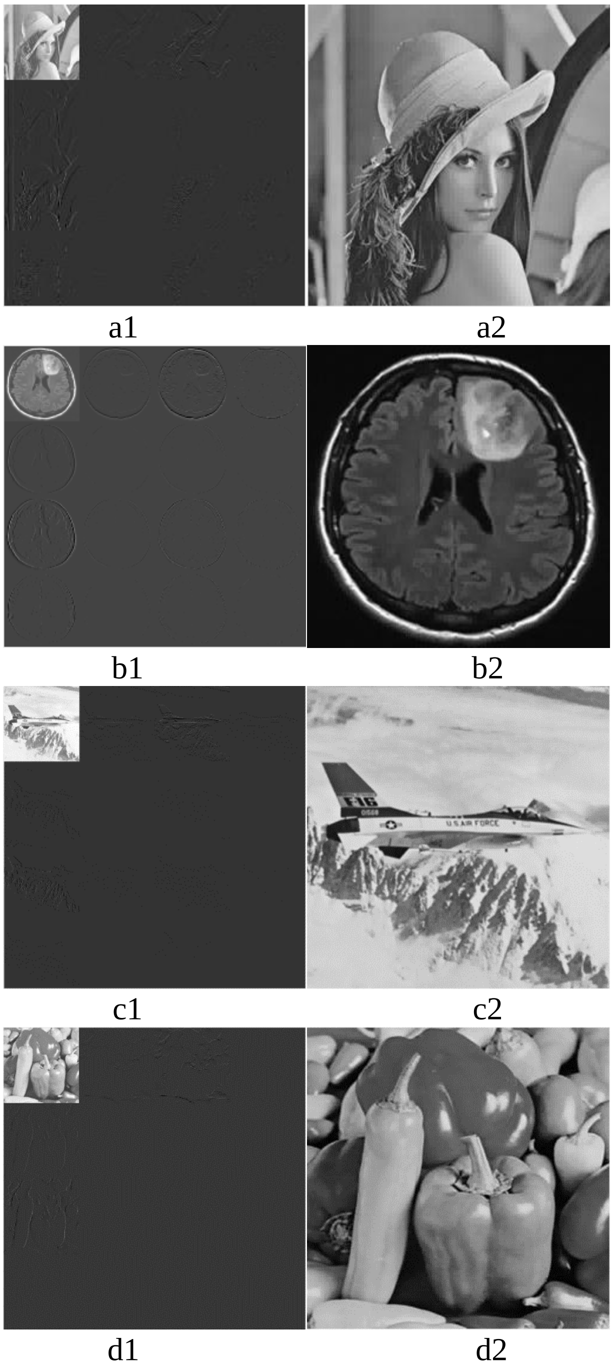
Compression and decompression results

This section presents the outcomes of employing various compression techniques, where figure 4 displays the results of DCT compression, figure 5 illustrates the outcomes of DWT compression, and figure 6 showcases the results of the proposed compression method.



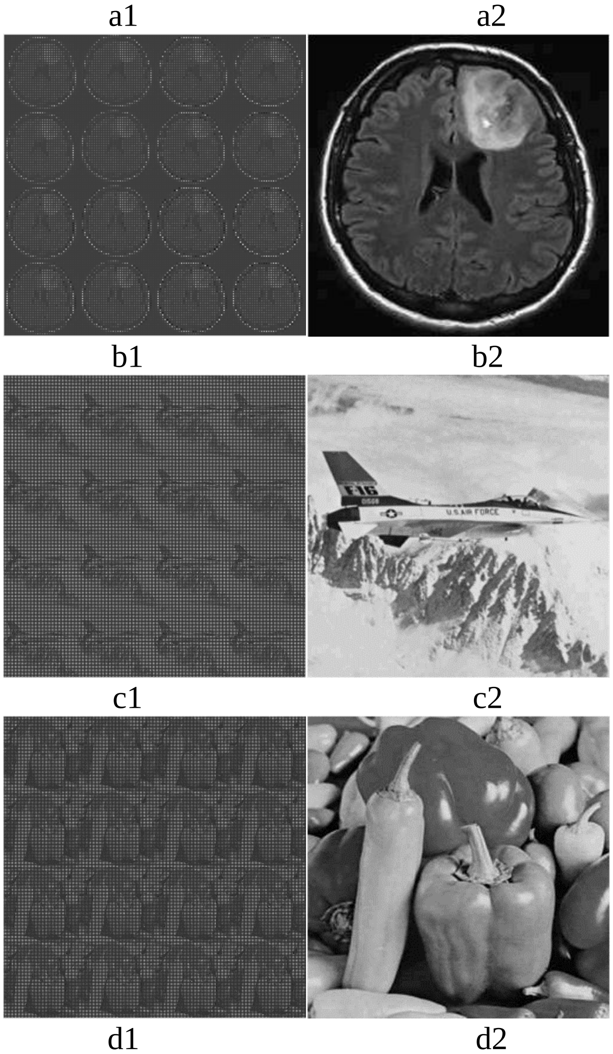
(a1-a2) compression and decompression of Lena image, (b1-b2) compression and decompression of Brain image, (c1-c2) compression and decompression of Jet-Plane image, (d1-d2) compression and decompression of Peppers image.

Fig. 4. DCT compression results.



(a1-a2) compression and decompression of Lena image, (b1-b2) compression and decompression of Brain image, (c1-c2) compression and decompression of Jet-Plane image, (d1-d2) compression and decompression of Peppers image.

Fig. 5. DWT compression results.



(a1-a2) compression and decompression of Lena image, (b1-b2) compression and decompression of Brain image, (c1-c2) compression and decompression of Jet-Plane image, (d1-d2) compression and decompression of Peppers image.
Fig. 6. Proposed compression results.

As depicted in figure 6, the decompressed images generated by utilizing the proposed compression technique retain the essential information from the original images. The human eye is unable to discern any noticeable difference between the original and decompressed images. Consequently, the proposed compression technique demonstrates excellent performance in reconstruction, preserving the key details of the original images effectively.

Tests results

To measure the performance of the proposed compression technique, several tests are used such as CR, MSE, PSNR, and SSIM. The results are compared with the classical compression DCT and DWT.

Table 2 shows the MSE, PSNR, and CR values of different images when we use DCT, DWT, and the proposed compression technique. From table 2 we can see that for: an image with size 256 x 256, the average PSNR is 32dB which is close to the PSNR of the DCT compression, but the CR is very low compared to the DCT and DWT (average of PSNR is 32dB for average CR 51%, while for DCT average of PSNR is 35dB for average CR 77%). For the images with size 512 x 512, the average PSNR is 37dB which is close to the PSNR of the DWT compression, but the CR is very low compared to the DCT and DWT (average PSNR is 37dB for average CR 28%, while for DWT average of PSNR is 38dB for average CR 42%) which mean with a lower CR, a good PSNR is obtained by the proposed image compression.

Table 2. The CR, MSE, and PSNR results using different techniques.

Images	Compression	CR	MSE	PSNR(dB)
Lena	DCT	72.03%	11.6871	33.9203
	DWT	75.10%	8.8340	35.8001
	Proposed	46.58%	23.4301	30.7933
Brain	DCT	82.03%	5.3681	37.7524
	DWT	82.75%	7.2390	36.6005
	Proposed	56.80%	15.0857	33.7605
Jet-Plane	DCT	47.07%	2.7454	40.7767
	DWT	43.64%	5.0122	38.4189
	Proposed	27.84%	8.9944	37.0157
Peppers	DCT	47.14%	2.0562	42.0391
	DWT	41.45%	4.8389	38.5777
	Proposed	28.45%	7.7927	37.8556

Table 3 shows the SSIM, and CR values of different images when we use DCT, DWT, and the proposed compression technique. From table 3 we can see that for: an image with size 256 x 256, the average SSIM is 0.9 which means that the decompressed image has a good similarity to the original image with only 51% of CR, while for the DWT, the average SSIM is 0.94 with 78.9% of CR. For the images with size 512 x 512, the average SSIM is 0.94 which means that the decompressed image has a high similarity to the original image with only 28% of CR. Moreover, the SSIM value of the proposed compression technique is close to the SSIM value of the DWT compression which has 0.95 for 42.5% of CR.

Table 3. The CR, and SSIM results using different techniques

Images	Compression	CR	SSIM
Lena	DCT	72.03%	0.9373
	DWT	75.10%	0.9355
	Proposed	46.58%	0.8932
Brain	DCT	82.03%	0.9660
	DWT	82.75%	0.9489
	Proposed	56.80%	0.9249
Jet-Plane	DCT	47.07%	0.9754
	DWT	43.64%	0.9610
	Proposed	27.84%	0.9474
Peppers	DCT	47.14%	0.9800
	DWT	41.45%	0.9526
	Proposed	28.45%	0.9499

CONCLUSION

This paper proposes a new compression technique by combining the two classical compression DCT and DWT. Firstly, the original image is compressed by using DCT. Then the result is quantified by using the quantification matrix of the JPEG compression. Secondly, the quantification image is recompressed by using the DWT to obtain the final compressed image. Simulation results and performance analyses show that our proposed compression technique has a good performance) in terms of MSE, PSNR, and SSIM. Moreover, the performance of our proposed compression technique is close to the performance of the classical compression technique (DCT and DWT) but with a compression ratio less than the classical ones. Therefore, the proposed compression can achieve higher compression than the classical ones.

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