OPTIMUM COEFFICIENTS OF DISCRETE ORTHOGONAL TCHEBICHEF MOMENT TRANSFORM TO IMPROVE THE PERFORMANCE OF IMAGE COMPRESSION

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ABSTRACT

This paper proposes an improved image compression scheme which utilizes optimum coefficients of discrete orthogonal Tchebichef moment transform. In the conventional moments-based-compression techniques, after making a trade-off between the conflicting factors, namely the quality of the reconstructed image and the compression ratio, the moments are chosen sequentially up to the desired order for reconstruction. But, as far as this proposed method is concerned, for reconstruction, it utilizes the optimally selected Tchebichef Moment Transform coefficients that yield better quality output image with a reasonable peak-signal-to-noise ratio for a desired value of compression ratio. Standard test images of different classes with various sizes (128x128, 256x256, 512x512 and 1024x1024) have been subjected to the proposed compression method for the block sizes 4x4 and 8x8 in order to assess its performance. The standard performance measures such as compression ratio, mean square error and peak-signal-to-noise ratio are considered in this study. The results reveal that the proposed method vis-à-vis the task of compression performs invariably well for the different classes of input images of above-mentioned sizes.

Keywords: Image compression, optimisation, orthogonal moments, discrete Tchebichef moments

1.0 INTRODUCTION

Image compression is one of the most important topics in the realm of image processing as it plays a vital role in reducing the memory requirements for storing multimedia images and significantly saves transmission time for a given bandwidth channel. In the recent past two decades, many researchers reported quite a few compression techniques for binary, gray and colour still images as well as for video images. Different transforms and statistical means have long been employed in developing more and more efficient image compression algorithms [1-3]. JPEG and JPEG 2000 are the most popular compression standards which are still in use for still images of different classes as they yield a reasonable compression ratio (CR) sans much compromising the quality of reconstructed images [4, 5]. Huffman coding together with either Discrete Cosine Transform (DCT) or Discrete Wavelet Transform (DWT) respectively forms the above said standards [6-9].

In the past few decades, moment functions have also been employed in a broad spectrum of applications of image processing which includes image segmentation, computer vision, image segmentation, image analysis, image compression etc [10-17]. Moments are derived from polynomial functions and computed for a digital image. They are statistical values that represent both low frequency information and high frequency details of an image. Unlike geometric moments, orthogonal moments, on the other hand, represent independent features of the image and thus have near zero or very minimum information redundancy in a set. The invariant property of orthogonal moments with respect to image translation, rotation and sizing invites the scientists/researchers to make use of them for various image processing applications [13, 17-19]. Since the continuous moments are severely suffering from discretisation error when they are numerically implemented in the domain of the discretised image coordinate space [20-22], recently Abu et al [23], Hunt and Mukundan [24], and Yap et al [12] have introduced and studied discrete orthogonal moments namely, the Tchebichef and Krawtchouk moments respectively. These moments possess discrete basis sets and have been well proven to be very useful as pattern features in the analysis of two-dimensional images.

Zhu et al proposed a general form for obtaining discrete orthogonal moments such as Tchebichef, Krawtchouk, Hahn, Charlier and Meixner very recently [25]. They evaluated these discrete orthogonal moments in terms of the ability of image reconstruction and image compression. Of the three moments namely, Tchebichef, Krawtchouk and Hahn considered for their study vis-à-vis the compression, the Tchebichef outperformed others by reaching the highest value of PSNR for the same compression ratio and ranked the Hahn next to it. For a desired compression ratio, Zhu et al have arranged the absolute value of all moment values in downward order and have chosen a part of them to reconstruct the original image. In order to improve the performance of the moments based compression methods further, a simple selection procedure based on random optimization technique is comfortably employed in this present work to choose the TMT coefficients required for reconstruction. The discrete orthogonal Tchebichef moment is considered in this study as its compression efficiency has already been proven [20, 25, 26]. Different classes of benchmark images of various sizes are subjected to the proposed optimum-TMT coefficients-based compression scheme in order to test its performance. The results of the proposed compression method reveal that for the block size 4x4, the statistical quality measures of the reconstructed images are much better than that of the methods reported by Lang et al [27], Zhu et al [25] and Abu et al [28].

2.0 THEORY OF PROPOSED COMPRESSION METHOD

Fig.1 depicts the various functional modules that are employed in the proposed compression scheme. Before compression process is instigated, the non-square input image is resized into a nearest possible square by replicating required number of additional rows and columns in such a way that the resulted size (NxN) should be an integral multiple of the desired block size (nxn) for further processing. In this work *n* is equal to either 4 or 8. Based on the desired block size (nxn) chosen, the resized image is divided into non-overlapping square blocks. Orthogonal discrete coefficients of TMT are, then, computed for each block up to the maximum possible order i.e. n+n. For a desired compression ratio, optimum TMT coefficients, which contribute significantly for better quality reconstructed image, are selected by numerically minimizing the Mean Square Error (MSE) function from each block using the random optimization method. Compressed image is then obtained by concatenating the optimal blocks horizontally and then vertically.

During decompression process, the compressed image is divided into non-overlapping square blocks in the same way as it was performed during the compression process. Subsequently, inverse orthogonal discrete moment transform is performed for each block. Finally, the image of original size (NxN) is simply constructed by concatenating the inversely transformed blocks horizontally and then vertically.

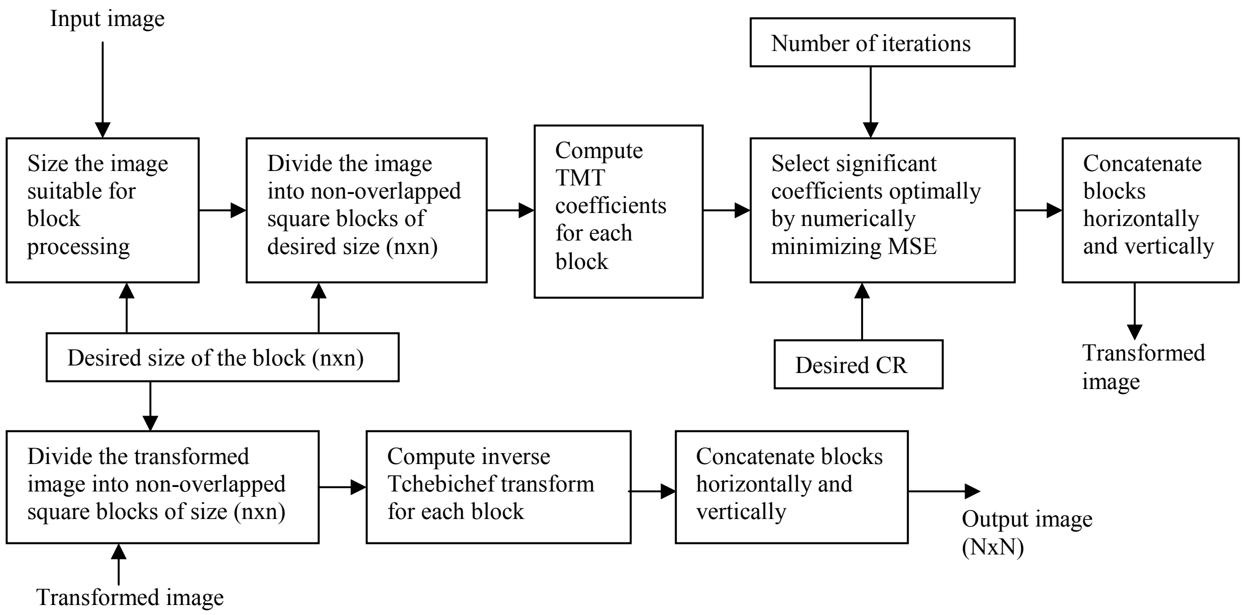

Fig. 1. Functional modules of proposed compression / decompression scheme

3.0 COMPUTATION OF 2-D DISCRETE ORTHOGONAL TCHEBICHEF MOMENT

The numerical errors occurred due to the numerical instability problem while computing the Tchebichef moment transform coefficients in higher orders particularly for large image will seriously affect the quality of image reconstruction to a greater extent. To circumvent this problem, Mukundan proposed a phenomenal solution to compute Tchebichef polynomials [20, 21]. The Tchebichef moments of order $p+q$ of an image intensity distribution $f(x,y)$ of a square image of size NxN are defined based on the scaled orthogonal Tchebichef polynomials $t_p(x)$ and $t_q(y)$, as

$$T_{pq} = \frac{1}{\rho(p,N)\rho(q,N)} \sum_{x=0}^{N-1} \sum_{y=0}^{N-1} t_p(x) t_q(y) f(x,y) \tag{1}$$

$p,q = 0,1,2,\ldots N\text{-}1.$

The inverse moment transform for exact reconstruction of the image is

$$f(x,y) = \sum_{p=0}^{N-1} \sum_{q=0}^{N-1} T_{pq} t_p(x) t_q(y) \tag{2}$$

$x,y = 0,1,2,\ldots N\text{-}1.$

Where,

$$t_p(x) = \frac{(2p-1) t_1(x) t_{p-1}(x) - (p-1)\left(1 - \frac{(p-1)^2}{N^2}\right) t_{p-2}(x)}{p} \tag{3}$$

where $p = 2,3,4,\ldots N\text{-}1.$

Similarly, $t_q(y)$ can be obtained by straightforwardly substituting q and y respectively for p and x in (3). The polynomials $t_p(x)$ and $t_q(y)$ in (1) satisfy the recurrence formula given in (3). The initial conditions for the recurrence relations referred in (3) are

$$t_o(x) = t_o(y) = 1$$
$$t_1(x) = \frac{(2x - N + 1)}{N} \text{ and } t_1(y) = \frac{(2y - N + 1)}{N} \tag{4}$$

The squared – norm $\rho(p,N)$ in (1) are expressed by

$$\rho(p,N) = \frac{N\left(1 - \frac{1}{N^2}\right)\left(1 - \frac{2^2}{N^2}\right)\ldots\left(1 - \frac{p^2}{N^2}\right)}{2p+1} \tag{5}$$

$p = 0,1,2,\ldots N\text{-}1.$

Similarly, $\rho(q,N)$ in (1) can be obtained by simply substituting q for p in (5).

4.0 PROPOSED COMPRESSION ALGORITHM

The proposed compression algorithm is explained through the flowchart shown in Fig. 2. The image of size NxN, which is to be compressed, is inputted. The desired compression ratio (CR), size of sub-image (nxn) and number of iterations (NI) are keyed in for dividing the image into non-overlapped sub-images so-called blocks and calculating the number of TMT coefficients to be selected from each block. Then, the Tchebichef polynomials $t_p(x)$ and $t_q(y)$, and square-norm $\rho\ (p,N)$ and $\rho\square(q,N)$ are computed for the block of size (nxn).

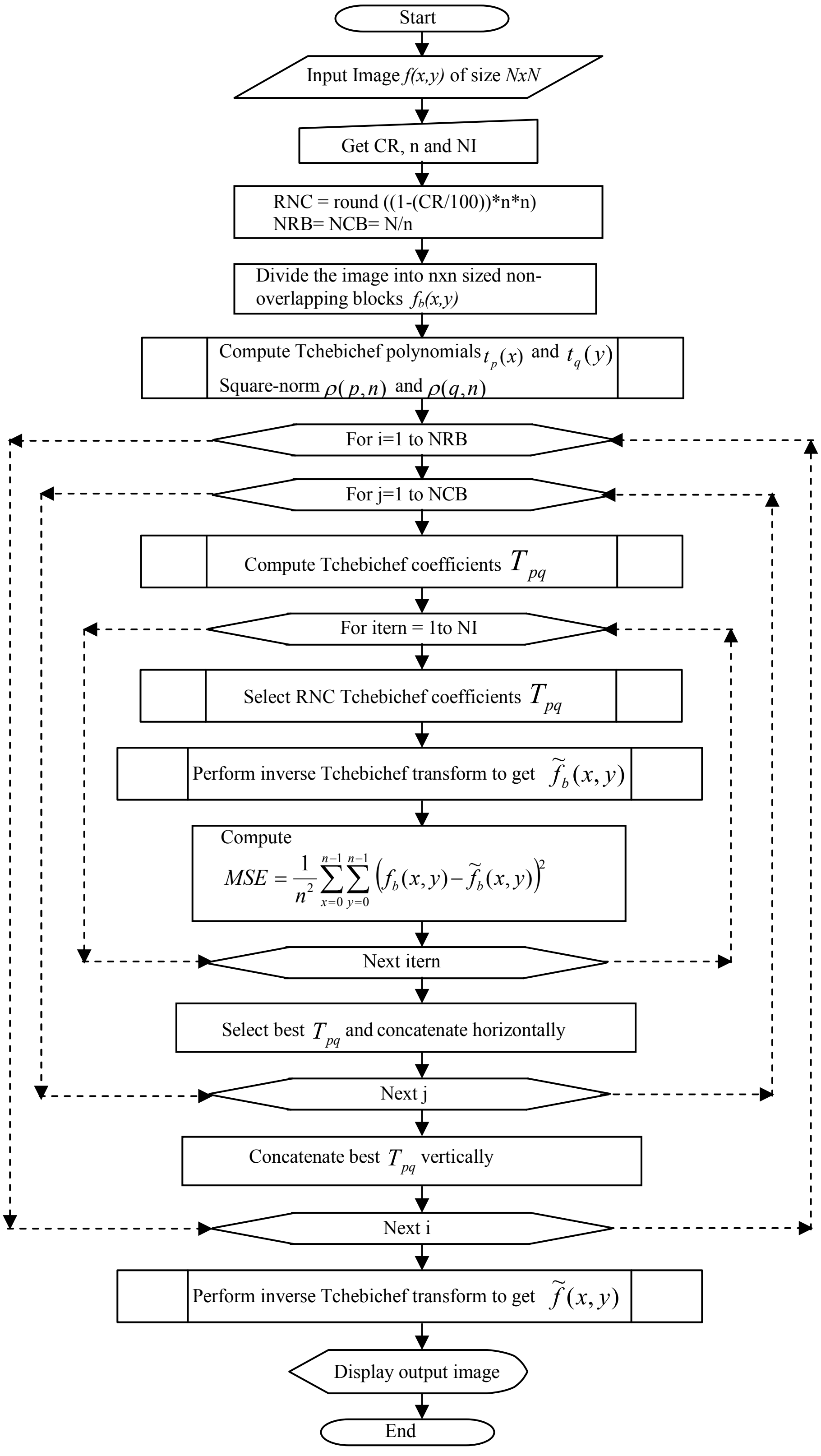

Fig. 2. Flowchart of the proposed compression algorithm

The blocks are processed horizontally from the topmost-left one. The Tchebichef coefficients are computed for each block. NRB and NCB are number of row and column blocks respectively. Subsequently, the required number of coefficients (RNC) is selected from each block using the subprogram which is discussed in detail in the next section. Concatenation of chosen blocks with optimal coefficients is done horizontally and then vertically in order to represent the input image in the transformed-compressed domain. During the process of decompression, the transformed image is block-processed and for each block, the inverse TMT is performed. Finally, the decompressed image of size NxN is displayed. The intensity distributions of input and reconstructed block are denoted as and respectively.

5.0 SELECTION OF TMT COEFFICIENTS

As the moments based on discrete polynomials exhibit a reasonable energy compaction for quiet a few classes of images, they are generally used for image compression applications. Conventionally, TMT coefficients are chosen sequentially up to certain order based on the desired compression ratio. In general, it is felt that few coefficients of moment transform yield a very high compression ratio and vice versa [25]. However, if optimum coefficients are properly chosen, the most of the energy in an image will be concentrated on a relatively few number of moment transform coefficients. The following steps elaborately describe the proposed random optimization method for selecting optimum coefficients of TMT in order to yield a better quality reconstructed image sans sacrificing the compression ratio.

Step 1: Compute TMT coefficients using (1) for a chosen block ($f_b(x,y)$) of size nxn.

Step 2: Generate integers from 1 to n^2 randomly without any repetition using random permutation function and stored in a one dimensional array.

Step 3: Calculate $RNC = \left(1 - \frac{CR}{100}\right) \times n^2$.

Step 4: Select required number (i.e. as many as RNC) of integers sequentially from the integer array which is obtained in the previous step and sort them in ascending order.

Step 5: Create an array of size $1\text{x}n^2$ with all zeros.

Step 6: Replace the zeros in the above array by '1' where the index of zeros equals to the value of integers in the sorted array.

Step 7: Convert the resulted one dimensional array of size $1\text{x}n^2$ into a two dimensional array of size nxn so-called window.

Step 8: Perform element-by-element multiplication between the window and the block of TMT coefficients.

Step 9: Perform inverse TMT using (2) to get $\tilde{f}_b(x, y)$.

Step 10: Compute the MSE using (6).

Step 11: Repeat steps 2 to 10 till the specified number of iterations (NI) elapsed.

Step 12: Select the optimum block of coefficients, for which the MSE is minimal, from the NI number of block of coefficients.

6.0 RESULTS AND DISCUSSIONS

To prove the performance of the presented compression algorithm, it is applied to various benchmark images of different sizes. The images namely, Lena and Baboon of 128x128 size, Lady and House of 256x256 size, Lena and Baboon of 512x512 size, and, Man and Sandiego of 1024x1024 size are considered in this study. Most of the above said images were obtained from University of Southern California – Signal and Image Processing Institute (USC-SIPI) [29]. The chosen image is divided into sub-images so-called blocks of different sizes such as 4x4 and 8x8. The quality measures, which numerically quantify the fidelity of the reconstructed image, such as MSE and PSNR (dB) are computed using (6) and (7) respectively for the three different compression ratios (50%, 75% and 87.5%) in order to precisely assess the performance of the proposed method.

$$MSE = \frac{1}{N^2}\sum_{x=0}^{N-1}\sum_{y=0}^{N-1}\left(f(x,y)-\hat{f}(x,y)\right)^2 \tag{6}$$

$$PSNR(dB) = 10\log_{10}\left[\frac{255^2}{\frac{1}{N^2}\sum_{x=0}^{N-1}\sum_{y=0}^{N-1}\left(f(x,y)-\hat{f}(x,y)\right)^2}\right] \tag{7}$$

To find the optimal TMT coefficients of the chosen block, the proposed random search optimization algorithm is employed due to its simplicity and effectiveness. The number of iterations, required for the algorithm, is set as 50. In order to compare the performance of the proposed algorithm on the compression application, the sequential selection algorithm has been considered [25]. The proposed algorithm was coded using MATLAB version 7.0.0.19920 (R14), and 200 runs were conducted with different random initial solutions in every run for each block of an image in a PC (Intel® Pentium® D Processor 945 @ 3.4 GHz, 800 MHz FSB, 2 × 2 MB L2 cache with 512 MB RAM).

To prove the efficiency of the proposed compression algorithm, the statistical performance measures of both the algorithms were computed and are given in Tables 1, 2, 3 and 4 respectively for all the chosen images of sizes 128x128, 256x256, 512x512 and 1024x1024. The MSE and PSNR values shown clearly indicate the marked improvement in the performance of the proposed algorithm over the existing sequential selection algorithm for the chosen block size 4x4 and in most of the cases for the block size 8x8 also. For the block size 4x4, the ability of the present algorithm is high in selecting optimum moment transform coefficients irrespective of the size of the images. Though the sequential selection method got proud about its shorter computation time, it shed tears for its inability in minimizing the MSE to the extent achieved by the proposed technique. Since optimization is carried out offline, the proposed method does not need to worry about its trudging vis-à-vis the task of selecting the best TMT coefficients.

Table 1: A comparison of performance measures of the proposed method with a recently reported method for the images of size 128x128

Size of the image = 128 x 128									
Block size	CR (%)	Sequential selection method				Proposed selection method			
		Lena		Baboon		Lena		Baboon	
		MSE	PSNR (dB)	MSE	PSNR (dB)	MSE	PSNR (dB)	MSE	PSNR (dB)
4 x 4	50	23.94	34.33	25.33	34.10	13.36	36.87	9.19	38.50
	75	86.93	28.74	67.04	29.87	49.96	31.14	31.03	33.21
	87.5	115.83	27.49	79.09	29.15	102.61	28.02	58.89	30.43
8 x 8	50	21.96	34.71	24.10	34.31	36.28	32.53	23.19	34.48
	75	74.50	29.41	62.26	30.19	100.23	28.12	57.37	30.54
	87.5	177.16	25.65	111.07	27.68	172.22	25.77	90.75	28.55

Table 2: A comparison of performance measures of the proposed method with a recently reported method for the images of size 256x256

Size of the image = 256 x 256									
Block size	CR (%)	Sequential selection method				Proposed selection method			
		Lady		House		Lady		House	
		MSE	PSNR (dB)	MSE	PSNR (dB)	MSE	PSNR (dB)	MSE	PSNR (dB)
4 x 4	50	7.30	39.50	22.79	34.55	1.51	46.35	2.37	44.39
	75	30.67	33.26	61.60	30.23	9.07	38.55	14.98	36.38
	87.5	39.35	32.18	67.54	29.84	30.98	33.22	43.19	31.78
8 x 8	50	5.65	40.61	16.02	36.08	5.38	40.82	8.68	38.75
	75	21.71	34.76	53.59	30.84	25.66	34.04	37.75	32.36
	87.5	85.71	28.80	119.41	27.36	62.71	30.16	69.12	29.73

Table 3: A comparison of performance measures of the proposed method with a recently reported method for the images of size 512 x 512

Size of the image = 512 x 512									
Block size	CR (%)	Sequential selection method				Proposed selection method			
		Lena		Baboon		Lena		Baboon	
		MSE	PSNR (dB)	MSE	PSNR (dB)	MSE	PSNR (dB)	MSE	PSNR (dB)
4 x 4	50	5.59	40.65	107.34	27.82	2.88	43.54	24.81	34.18
	75	27.37	33.76	207.35	24.96	12.79	37.06	82.16	28.98
	87.5	34.73	32.72	227.71	24.56	30.43	33.30	153.51	26.27
8 x 8	50	4.92	41.21	103.04	28.00	9.01	38.59	60.95	30.28
	75	22.33	34.64	208.04	24.95	30.32	33.31	143.72	26.56
	87.5	64.74	30.02	284.88	23.58	56.15	30.64	211.42	24.88

Table 4: A comparison of performance measures of the proposed method with a recently reported method for the images of size 1024 x 1024

Size of the image = 1024 x 1024									
Block size	CR (%)	Sequential selection method				Proposed selection method			
		Man		Sandiego		Man		Sandiego	
		MSE	PSNR (dB)	MSE	PSNR (dB)	MSE	PSNR (dB)	MSE	PSNR (dB)
4 x 4	50	12.01	37.34	66.32	29.91	4.59	41.51	24.13	34.30
	75	45.19	31.58	138.56	26.71	17.93	35.60	69.61	29.70
	87.5	53.96	30.81	160.62	26.07	40.02	32.11	119.60	27.35
8 x 8	50	10.86	37.77	65.24	29.99	12.87	37.04	53.07	30.88
	75	37.83	32.35	134.96	26.83	38.73	32.25	114.97	27.52
	87.5	95.19	28.45	209.29	24.92	70.17	29.67	166.24	25.92

The reconstructed images of various sizes of proposed and sequential method are shown in Figures 3, 4, 5 and 6 for the chosen block size 4x4. In spite of the fact that the TMT coefficients which have been selected by either the proposed algorithm or the sequential method indeed compresses the input images to a desirable extent, both the visual quality of the images shown in the Figures 3, 4, 5 & 6 and the performance measures given in the Tables 1, 2, 3 & 4 strongly confirm that the proposed algorithm outperforms the sequential selection-based method for all the chosen images. The percentage reduction in the MSE and percentage increase in the PSNR values, computed using (8) and (9), of the proposed method over the sequential selection method for the chosen block size 4x4 are given in the Tables 5 and 6 respectively. This substantial reduction in MSE and appreciable increase in PSNR values certainly portray that the proposed method globally ameliorates the quality of the reconstructed images for the compression ratios 50%, 75% and 87.5%.

$$Percentage\,reduction\ in\ MSE = \frac{MSE\,(sequential) - MSE\,(proposed)}{MSE\,(sequential)}\,X\,100 \quad (8)$$

$$Percentage\ increase\ in\ PSNR = \frac{PSNR\,(proposed) - PSNR\,(sequential)}{PSNR\,(proposed)}\,X\,100 \quad (9)$$

Table 5: Percentage reduction in the MSE of the proposed method over the sequential selection method for the block size 4x4

CR (%)	Percentage reduction in MSE							
	128x128		256x256		512x512		1024x1024	
	Lena	Baboon	Lady	House	Lena	Baboon	Man	Sandiego
50	44.19	63.72	79.32	89.60	48.48	76.89	61.78	63.62
75	42.53	53.71	70.43	75.68	53.27	60.38	60.32	49.76
87.5	11.41	25.54	21.27	36.05	12.38	32.59	25.83	25.54

Table 6: Percentage increase in the PSNR of the proposed method over the sequential selection method for the block size 4x4

CR (%)	Percentage increase in PSNR							
	128x128		256x256		512x512		1024x1024	
	Lena	Baboon	Lady	House	Lena	Baboon	Man	Sandiego
50	6.89	11.43	14.78	22.17	6.64	18.61	10.05	12.80
75	7.71	10.06	13.72	16.91	8.91	13.87	11.29	10.07
87.5	1.89	4.21	3.13	6.11	1.74	6.51	4.05	4.68

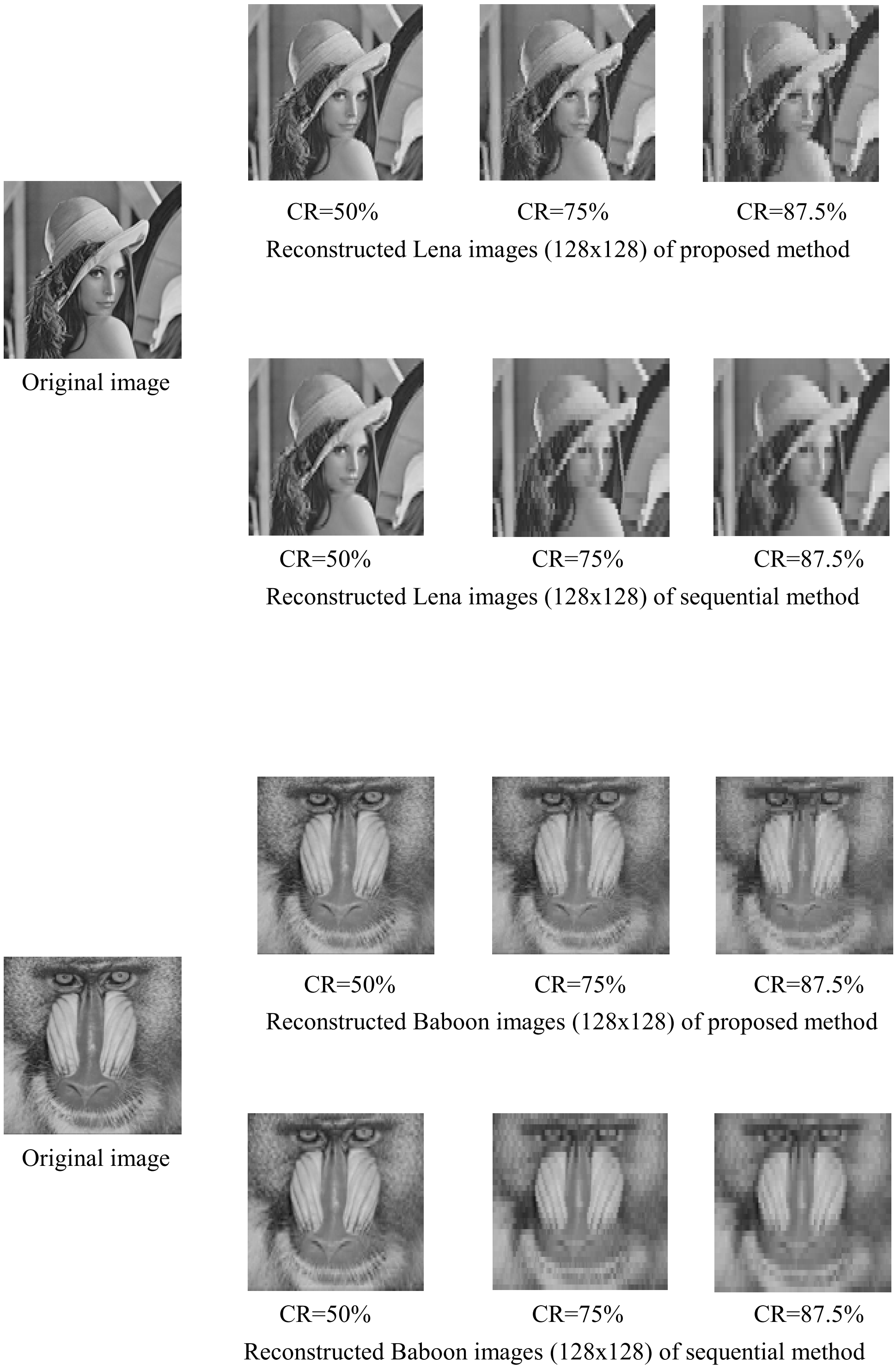

Fig. 3. Reconstructed Lena and Baboon images (128x128) of proposed and sequential methods for the block size 4x4

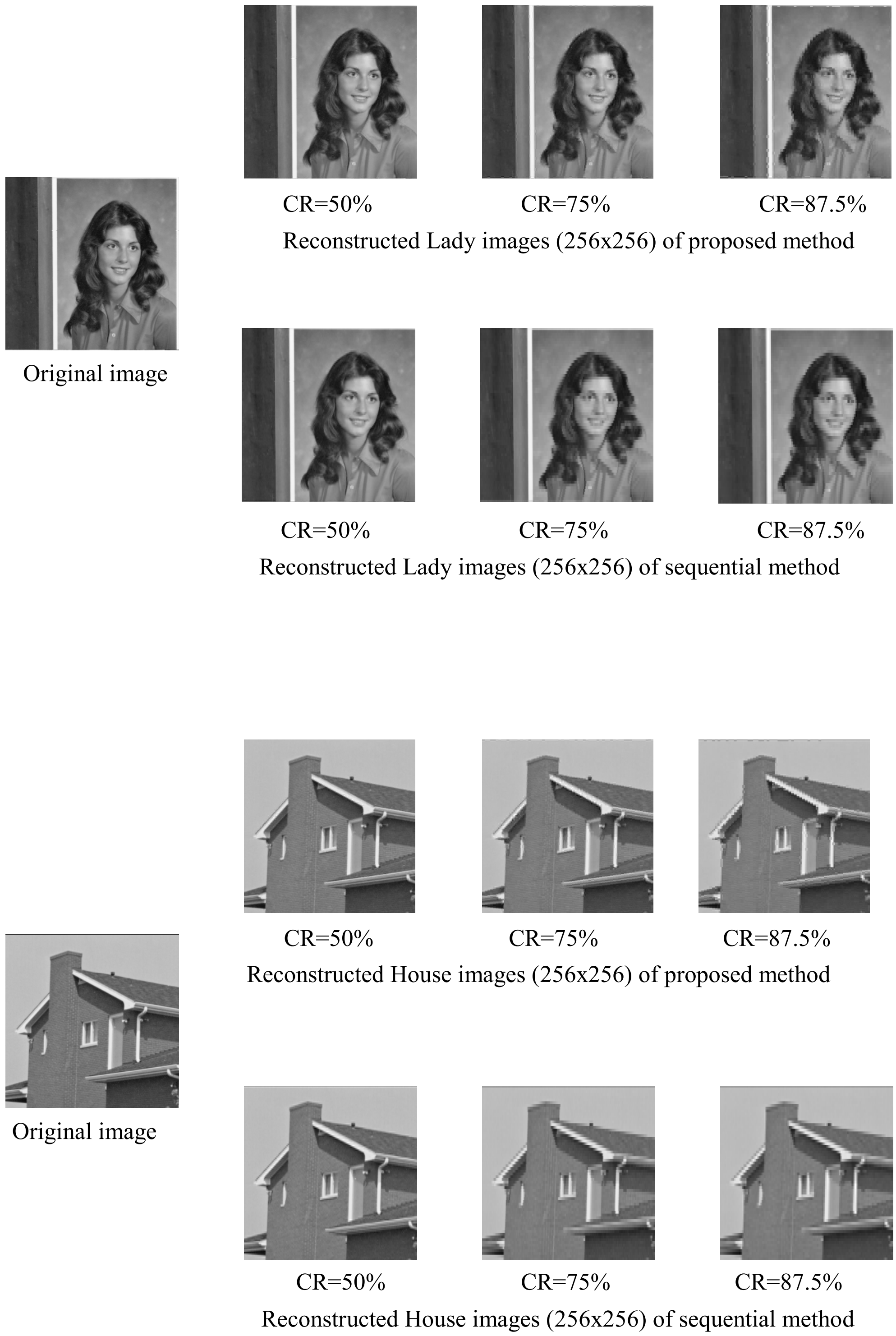

Fig. 4. Reconstructed Lady and House images (256x256) of proposed and sequential methods for the block size 4x4

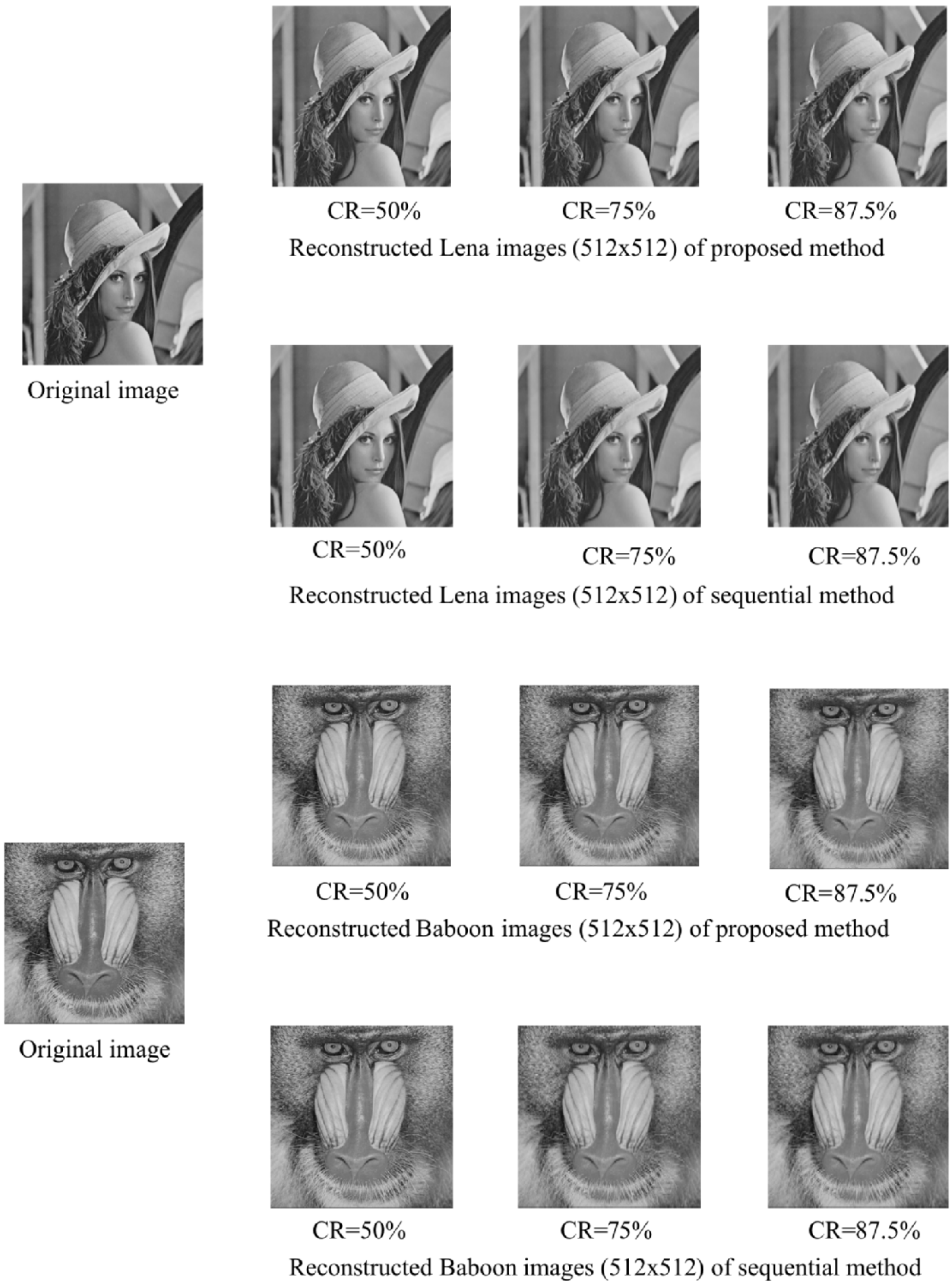

Fig. 5. Reconstructed Lena and Baboon images (512x512) of proposed and sequential methods for the block size 4x4

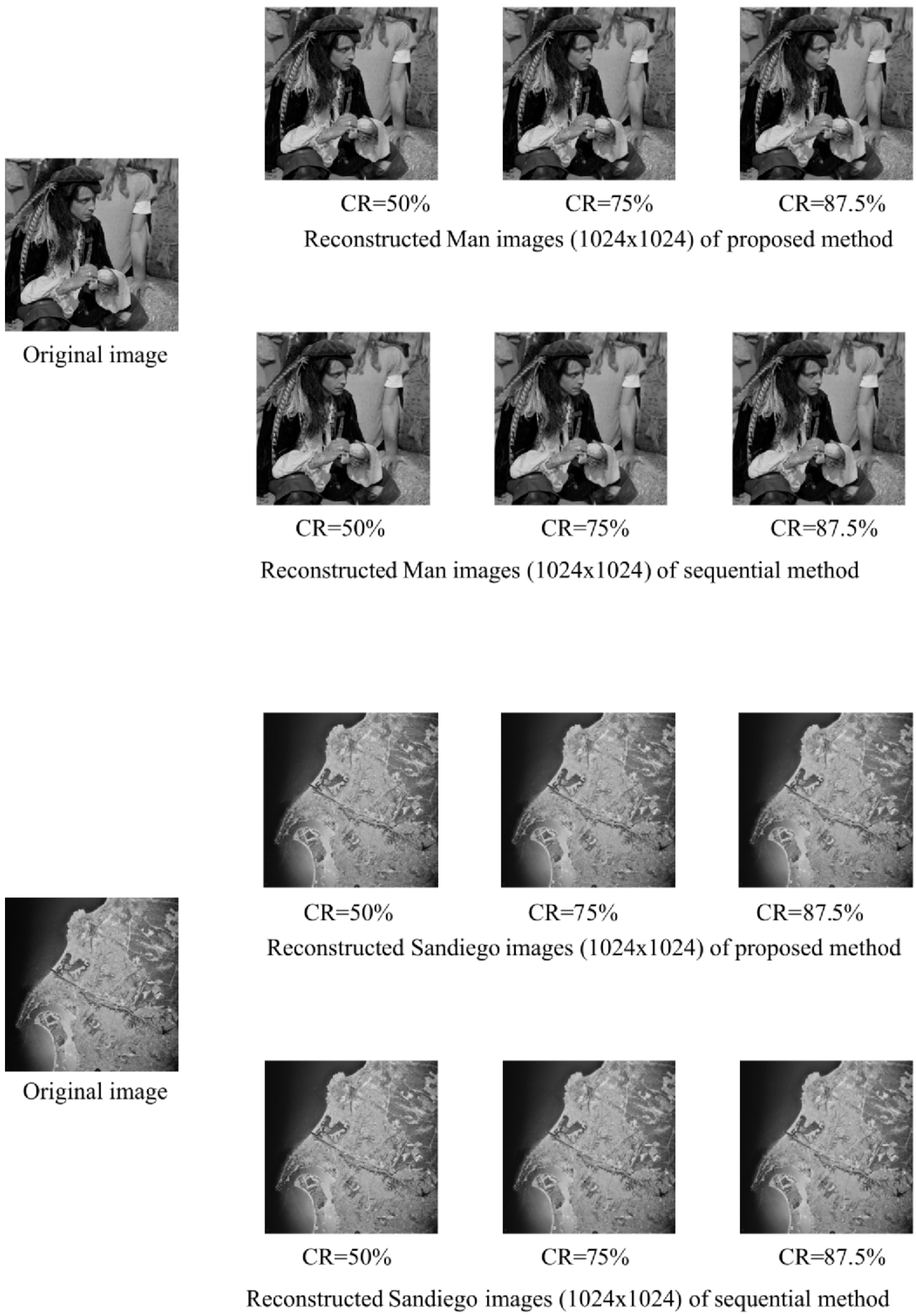

Fig. 6. Reconstructed Man and Sandiego images (1024x1024) of proposed and sequential methods for the block size 4x4

The quality measure, which portrays the human visual perception, Mean Structural SIMilarity (MSSIM) index has also been computed using the algorithm given in [30] for both the methods and given in Table 7. It is observed that the standard conventional metrics such as MSE and PSNR are also in consistent with the MSSIM vis-à-vis assessing the image quality information.

Table 7: A comparison of MSSIM of the proposed method over the sequential selection method

Image size	Image	Block size	MSSIM					
			Sequential selection			Proposed selection		
			Compression Ratio (%)			Compression Ratio (%)		
			50	75	87.5	50	75	87.5
128x128	Lena	4	0.9505	0.8406	0.7778	0.9697	0.8975	0.7977
		8	0.9013	0.7462	0.6201	0.9044	0.7792	0.6671
	Baboon	4	0.9023	0.7355	0.6781	0.9609	0.8638	0.7129
		8	0.9041	0.7451	0.5865	0.9011	0.7604	0.6277
256x256	Lady	4	0.9750	0.9167	0.8903	0.9881	0.9552	0.8952
		8	0.9718	0.9216	0.8365	0.9650	0.8855	0.7972
	House	4	0.9211	0.8321	0.8111	0.9834	0.9377	0.8711
		8	0.9190	0.8284	0.7336	0.9507	0.8622	0.7934
512x512	Lena	4	0.9601	0.8864	0.8565	0.9806	0.9352	0.8743
		8	0.9612	0.8953	0.8001	0.9512	0.8750	0.8038
	Baboon	4	0.8219	0.6143	0.5566	0.9514	0.8378	0.6954
		8	0.8193	0.6148	0.4558	0.8843	0.7202	0.5786
1024x1024	Man	4	0.9381	0.8241	0.7874	0.9723	0.9107	0.8304
		8	0.9404	0.8382	0.6995	0.9318	0.8321	0.7381
	Sandiego	4	0.8423	0.6620	0.5863	0.9417	0.8200	0.6862
		8	0.8408	0.6635	0.5154	0.8759	0.7207	0.5925

The proposed algorithm to select optimum coefficients has been applied to 24 images (6 number of each 128X128 size, 256X256 size, 512X512 size and 1024X1024 size) in order to assess its performance for a given Compression Ratio (CR) with different block sizes using t-test. As the objective performance measure PSNR ameliorates when the CR is decreased for a given block size and also when the block size is decreased for a given CR for all the chosen images, the results are given only for eight images of four different sizes. The statistical performance of both the proposed selection method and sequential selection method are assessed using t-test. The ranges of MSE and PSNR for 95% confidence interval of the mean have been computed using the one sample t-test module which is available in the XLSTAT 2013.1.01 software. The results of the t-test given in Table 8 reveal that the proposed method outperforms the sequential selection method irrespective of the compression ratio.

Table 8: Results of t-test of the proposed method and sequential selection method

CR (%)	95% confidence interval on the mean			
	Sequential selection		Proposed selection	
	MSE	PSNR (dB)	MSE	PSNR (dB)
50	]5.24, 17.81[	]36.02,40.51[	]1.35, 20.11[	]36.03, 43.28[
75	]22.68, 63.84[	]30.41, 34.21[	]10.97, 60.19[	]30.96, 36.56[
87.5	]48.63, 103.04[	]27.52, 31.52[	]30.99, 110,33[	]28.20, 32.53[

7.0 CONCLUSIONS

The proposed compression scheme certainly improves the efficiency of the moments based conventional compression technique to a reasonable extent. The proposed algorithm that utilized optimally selected TMT coefficients is found to be more suitable for compression of different classes of images with various sizes. Optimal TMT coefficients required for compressing the images, namely the Lena, Baboon, Lady, House, Man and Sandiego, are obtained using the simple optimization algorithm. The presented compression method was implemented using MATLAB Version 7.0.0.19920 (R14) and yielded satisfactory results. In this work, the method for selecting optimum TMT coefficients does its job phenomenally by numerically minimizing the objective function. The results of the proposed method were compared with the results reported earlier by other investigators. It is clearly found that for all the chosen images, the proposed method gives better results than TMT based conventional compression methods reported by Zhu et al and Abu et al. The proposed compression algorithm is especially useful when different classes of images are stored and analysed in a common data base. Since the basis functions of discrete TMT and Discrete Cosine Transform (DCT) are orthogonal, the former one can be straightforwardly deployed instead of later in the JPEG baseline technique. In order to achieve improved compression performance of JPEG, the optimal TMT coefficients of the 4x4 blocks can be quantized and coded using Huffman tables so that the header information during compression process can be uniquely decoded during decompression process. This algorithm with slight modification and use of a multi-core digital processor can offer an efficient online compression engine for multimedia applications. It is right to mention that this technique is not only applicable to the images which were considered in this work but also for others having wide spectral variations of any nature. This method is inherently slow when compared with sequential selection method which is conventionally employed for moments based compression because for the desired compression ratio, quite a few iterations are to be inevitably elapsed to select the optimum TMT coefficients. However, it is quite attractive due to its effective compression ability and versatility. The use of high speed digital processors employed grid computing system to select the optimal TMT coefficients hopefully justifies the real-time implementation of the proposed compression method.

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