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ENHANCING THE QUALITY OF RECONSTRUCTED IMAGE USING A COHESIVE DIGITAL IMAGE COMPRESSOR

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ABSTRACT

The high-dimensional representation of image data poses huge challenges for effective transmission and archival of image files over the Internet. Dimensionality reduction and data decorrelation are two important tasks in the domain of signal and digital image processing. In this work, we propose a novel cohesive image compressor to reduce the size of the image and enhance the quality of the reconstructed image. Our proposed compressor exploits (i) principal component analysis (PCA) technique that reduce the size of the input picture by selecting an appropriate number of principal components (PCs); and (ii) discrete Tchebichef transform (DTT) to decrease the dimension of the picture further and enhance the quality of image acquired from PCA approach. We implement our cohesive image compressor technique on various digital images to achieve quality image compression. Extensive experimental results establish that our cohesive approach considerably outdoes other prevailing compression methods such as PCA, DTT, discrete cosine transform (DCT), integer approximate DTT (IA-DTT), and cohesive PCA-DCT methods. We evaluate our proposed cohesive digital image compressor in terms of compression performance measures (e.g., compression ratio, compression time), and image quality metrics (e.g., structural similarity index measure, peak signal-to-noise ratio, and universal quality index). The experimental results reveal that the reconstructed pictures using our proposed digital image compressor constantly exhibit improved perception qualities than other methods used for comparison regardless of the pictures.

Keywords: Discrete Tchebichef transform; image compression; image quality; performance metrics; principal component analysis; quality metrics;

I.INTRODUCTION

Dimensionality reduction of still images and videos has become an important research issue as image processing applications and systems come of age [1]. A tremendous amount of image data like videos, pictures, diagrams, and webpages are generated and transferred worldwide due to the progress of High definition (HD) technology as well as the Internet. This has contributed robust requirements towards the progress of noble methods of image compression, which precisely reduce and recover pictures, exploiting precise demands on the image compression techniques. The goal of dimensionality reduction is to decrease redundancy and irrelevance of data in a picture to be able to transmit or archive effectively. It is focused on reducing the number of bits needed to signify a picture. Modern multimedia applications with stringent requirements of processing capacity, archival, and transmissions are making image compression feasible. Hence, compression techniques are mostly incorporated into all multimedia applications to realize lucrative results.

Image compression can be classified into lossless or lossy methods [2]. Lossy compression has been extensively applied on image data in which the quality loss of the resultant image is not visible but the dimension of the image can be decreased considerably. These lossy techniques, particularly when employed at lower bit rates, create compression artifacts. They are appropriate for usual pictures where the slight (occasionally unnoticeable) loss of picture quality is tolerable to realize a considerable decrease in bit rate. The lossy compression is also known as the visually lossless method since it creates invisible variances. Conversely, lossless compression preserves the quality of the input image while the image is reconstructed [3]. Lossless compression techniques are developed for storage purposes and frequently used to compress technical drawings, medical imaging, comics, or clip art.

Two-dimensional discrete transformation is used to decorrelate the input color pictures. These approaches convert interrelated statistics into uncorrelated values. Amongst the popular discrete transformation techniques, the PCA approach, also known as Karhunen–Loève transform (KLT), is recognized as the optimal method for data decorrelation [4, 5]. It is generally employed to decrease the data dimensionality, where the data contained in all the coefficients are replaced by the data variability statistics of the preliminary PCs. The accuracy of such calculation hinges on the number of PCs utilized and the amount of variance described, or energy reserved, by each of them. In the domain of signal as well as image processing, PCA is recognized as an ideal transform technique for data decorrelation when the input follows the first-order Markov function [6].

The important characteristics of the PCA method are as follows: (i) PCA decorrelates the original data in the transform domain completely; (ii) PCA focuses the energy (difference) in limited variables of the resultant vector; and (iii) PCA reduces the MSE (i.e., mean square error) in dimensionality reduction. Since the PCA matrix hinges on the variance and covariance matrix of the given input information, developing effective compression techniques for practical applications becomes a challenging endeavor. If the given input follows a fixed interrelated function [7], then the PCA is very closely approximated by the discrete cosine transform (DCT) [8]. Normal photographs fall into this specific type. Consequently, DCT takes over the compaction and decorrelation features of the PCA, with the benefit of having a closed-form expression independent of the input data.

The DCT-based compression method was developed as an alternate to the PCA method [9], introducing the static transform method, data decorrelation, and energy compaction features [10]. As the DCT method does not rely on the given input information, fast techniques can be appropriately developed. Video and image processing research groups generally use the DCT in their most popular standards for dimensionality reduction, including MPEG [11], JPEG [12], H.263 [13], H.264/AVC [14], and H.265/HEVC [15]. In spite of being broadly espoused for dimensionality reduction, the DCT is not the single choice for transformation technique [16]. Especially, JPEG-based dimensionality reduction methods using DTT have been proved to be accurate options [17]. The DTT depends on the estimation of the Tchebichef coefficients, which create a group of orthogonal moment functions and can eliminating redundancy in the given picture [18].

Cohesive compression approaches involve two or more dimensionality reduction methods to realize an efficient image compression. The basic tenet of the cohesive compression methods is to combine transform techniques with spatial domain to improve the compression performance and the quality of recovered pictures with decreased noise rate. One more possibility is realizing two transformation techniques on input pictures. The combination of the two techniques provides enhanced illustrations of images, better treatment of curved contours, and improved reconstructed pictures. The total reimbursements of the cohesive techniques are improving the quality of pictures and decreasing error as well as artifacts in compressed pictures.

In this work, we aim at developing a cohesive digital compressor to reduce the dimensionality of the input color image while preserving the reasonable visual quality of the given image. Hence, the PCA method is employed to reduce the size of the picture, and DTT is employed to maintain the quality of the recovered picture. We carried out a complete analysis based on renowned figures of merit in the context of compression and quality performance metrics. We proved that our proposed technique outdoes other prevailing techniques. The remaining sections of this article are structured as follows: Section 2 reviews the related works about compression of images. In Section 3, we take an in-depth look at the proposed method to describe correctly how each step performs. Then the experimental evaluation is described, and the results are displayed and related to other methods in Sections 4 and 5 respectively. Finally, conclusions are drawn from the results in Section 6.

II. RELATED WORK

Recently, innumerable research works have been adapted several dimensionality reduction techniques. These techniques are relatively deprived of the picture quality to reduce the computational overhead. On the other hand, it is more useful to maintain lower complexity or lower energy depletion and concurrently provide improved results. Kishk et al. proposed a compression technique that combines PCA and discrete wavelet transform. This approach is based on using PCA with wavelet factors of the 3D pictures to enhance the quality of the reconstructed pictures while providing higher compression performance. The wavelet constants of the specific picture are weighted and rationalized before using the PCA technique. The PCA is realized to each sub-band individually to improve the compression ratio. The qualities of the recovered pictures and given inputs are measured [19]. Abbas et al. proposed an image compression method using PCA and analyzed the quality performance of the reconstructed image [20]. The authors proved that PSNR values upturn with the number of PCs. Further, they demonstrated that the compression ratio (CR) and mean square error (MSE) reduces more number of PCs are selected enlarged.

Ng proposed a technique to assess the use of PCA on dimensionality reduction of pictures and relate the quality of the compressed output using different performance metrics. The author proved that the PCA method successfully decreases the dimension of pictures by preserving the essential features of the input picture. This method realized 35.3% compression for the best performance. The transmission time of pictures over the Internet has realized important enhancement, particularly for the downloading activity using portable expedients [21]. Amin et al. discussed PCA as an image compression method [22].

Of late, different low-power DCT techniques have emerged. Amongst these approaches, utilization of approximated DCT to reduce its computational cost, and consequently, its energy consumption has been expected. A complete appraisal of DCT-based compression techniques, which can be established for maximum performance or minimum energy depletion, is observed in the literature [23]. In recent times, the DTT is proved to be improved than DCT regarding compression enactment. Mukundan introduced an image compression model using the DTT method and obtained numerical results demonstrating that the DTT-based dimensionality reduction has similar performance to the DCT in [24]. Likewise, in [25], a lossy compression using the DTT method is suggested under the JPEG standard. It enables analogous results for lossy compression such as JPEG compression using the DCT method; however, it does not perform well for the lossless operation.

Yuting et al. introduced an integer approximate DTT to find out the quantization as well as the inverse quantization matrices equivalent to integer transform [26]. The proposed IA-DTT is used to reduce the dimension of a gray-scale image considerably. Since the resultant IA-DTT matrix is not normal, it is required to multiply a diagonal matrix to its left. While the integer matrix is used to achieve the transformation, the diagonal matrix has to be combined into the quantization procedure. The authors calculated the corresponding quantization as well as the inverse quantization matrix. The results revealed that IA-DTT provides low quality images with extremely low complexity as compared to JPEG.

Recently, the DTT has been established as a lower-cost approach with features related to the DCT for reducing the dimension of the picture and video coding [27]. This method enables a polynomial kernel, whose features such as high energy compaction, and decorrelation, make it equivalent to the DCT, especially when specific features of a picture, for instance, the content and structure, strongly affect the feature of the reconstructed picture is taken into account. On the other hand, the above mentioned approaches cannot provide a finite resolution and consume higher computational time to decrease the dimension of a certain picture. Hence, we propose a hybrid image compression method to achieve better compression performance and improved quality metrics.

III. PROPOSED METHOD

Discrete transform-based dimensionality reduction is a method of decreasing picture size by transforming the given input image in one domain into another more influenced domain and eliminating less important components to reduce the size of the input image. More precisely, picture data is originally specified in the spatial domain with luminous or color values. Then, the data is converted so that the picture is represented by the different structures of information in an alternative domain (frequently in the frequency domain). Finally, some features that indicate less important properties of the picture are neglected.

1.1 Image compression using PCA

The PCA technique is based on the orthogonal Eigenvectors and covariance matrix of the input data. It decorrelates the pixels of an original picture. Once executing the linear transformation, higher energy associated with the transformed variables is packed within the earliest few PCs that reveal the energy compaction property of PCA. Hence, it is usually employed in clustering analysis and dimensionality reduction approaches since it reduces the size of a dataset or a picture [28]. This type of image compression method reduces a large number of correlated coefficients [5]. Dimensionality reduction is accomplished by recovering the picture with the first few PCs of the Eigenvalues. It can be found that after applying the PCA technique the less important features of the picture information have been dropped but the picture still keeps its main features. The dimensionality reduction by PCA is performed by means of the following steps:

1. Derive the vector values of the input picture (V)
2. Calculate the covariance matrix $C(V)$.
3. Compute Eigen values and Eigen vectors by resolving the characteristics equation.
4. Normalize each Eigenvector.
5. Construct the PCA transform matrix (P) using normalized Eigenvectors as their columns
6. As a final point, calculate the PCA transform of the original picture using the following expression

$$I = VP \qquad (1)$$

7. The original picture is recovered from the transformed coefficients using the following formula

$$R = VP^T \qquad (2)$$

1.2 Discrete Tchebichef Transform

The DTT is a novel transform that exploits the Tchebichef moments to construct a basis matrix [18]. DTT is realized by calculating the orthonormal Tchebichef polynomials [29]. For a picture of dimension $D_X \times D_Y$, the forward DTT of order $r + s$ is denoted as

$$T_{rs} = \sum_{x=0}^{D_x-1} \sum_{y=0}^{D_y-1} t_r(x) t_s(y)\, g(x,y) \qquad (3)$$

where $r, s = 0,1, \dots . D - 1$. The inverse transform of DTT is defined by

$$g(x,y) = \sum_{r=0}^{D_x-1} \sum_{s=0}^{D_y-1} t_r(x) t_s(y)\, T_{rs} \qquad (4)$$

where $x, y = 0,1, \dots . D - 1$. From (3) and (4), $t_r(x)$ and $t_s(y)$ are rth- and sth-order Tchebichef polynomials, correspondingly. Generally, qth-order Tchebichef polynomial is defined using the following recurrence relation as

$$t_q(x) = (\eta_1(x) + \eta_2) t_{q-1}(x) + \eta_3 t_{q-2}(x) \qquad (5)$$

$$\eta_1 = \frac{2}{q} \sqrt{\frac{4q^2 - 1}{D^2 - q^2}} \qquad (6)$$

$$\eta_2 = \frac{1 - D}{q} \sqrt{\frac{4q^2 - 1}{D^2 - q^2}} \qquad (7)$$

$$\eta_3 = \frac{q - 1}{q} \sqrt{\frac{2q + 1}{2q - 3}} \sqrt{\frac{4q^2 - 1}{D^2 - q^2}} \qquad (8)$$

The initial values of $t_q(x)$ for $q = 0, 1$ is defined as

$$t_0(x) = \frac{1}{\sqrt{q}} \qquad (9)$$

$$t_1(x) = \frac{2x + 1 - D}{\sqrt{\frac{3}{D(D^2 - 1)}}} \qquad (10)$$

Now, Equation (4) can be rewritten as follows

$$g(x,y) = \sum_{r=0}^{D_x-1} \sum_{s=0}^{D_y-1} \vartheta_{rs}\, T_{rs} \qquad (11)$$

where $x, y = 0,1, \dots . D - 1$, and ϑ_{rs} is known as the basis matrix. The basis matrix ϑ_{rs} can be defined as follows

$$\vartheta_{rs} = \begin{bmatrix} t_r(0)t_s(0) & t_r(0)t_s(1) & \dots . & t_r(0)t_s(7) \\ t_r(1)t_s(0) & t_r(1)t_s(1) & \dots . & t_r(1)t_s(7) \\ \dots . & \dots . & \dots . & \dots . \\ t_r(7)t_s(0) & t_r(7)t_s(1) & \dots . & t_r(7)t_s(7) \end{bmatrix} \qquad (12)$$

Hence, the DTT of a square image

$$I = \{g(x,y)\}_{x,y=0}^{x,y=D-1} \qquad (13)$$

as in (3) can be viewed as the projection of the image I on the basis image ϑ_{rs}, which is the product of the vectors t_r and t_s, where $t_r = t_r(0) t_r(1) \dots t_r(D - 1)$ and $t_s = t_s(0) t_s(1) \dots t_s(D - 1)$. Equation (12) can be written a

$$\vartheta_{rs} = [t_r]'[t_s] \qquad (14)$$

In other words, Tchebichef transform T_{rs} estimates the correlation between the image I and basis image ϑ_{rs}. It stores a high positive value if there is a strong similarity between them. It shows that when the order of the transform is increased, the basis images are changed from low spatial frequency to high spatial frequency. This proves that there will be neither large variation in the dynamic range of transformed values is numerical instabilities that occur for large values of D

1.3 A cohesive PCA-DTT digital image compressor

This work proposes a cohesive method for image compression applications. In this digital compressor, PCA is combined with DTT to reduce the dimensionality of the image and enhance the quality of reconstructed images. Our method follows two steps. In each step, the size of the original picture is reduced and then recovered with the corresponding inverse transform method. First, the size of the original picture is reduced and recovered by PCA. The feature-reduced image obtained from the PCA technique is further reduced using DTT. PCA is a data-dependent approach whose basic function is unbalanced. This restriction can be overwhelmed by DTT whose base function is static.

Moreover, DTT is an input independent approach and divides a picture into blocks; each block is reduced by appropriate quantization method and then recovers the picture through inverse DTT (IDTT). Several studies proved that the DTT provides improved results related to other compression techniques such as PCA. Therefore, the size of the recovered picture from PCA is again reduced by the DTT technique. Due to the utilization of DTT, recovered picture from PCA-DTT provides superior quality and provides greater PSNR value. Our cohesive compressor outperforms other techniques found in literature such as PCA [30], DTT [31], DCT [32], IA-DTT [26], and PCA-DCT [33] methods.

IV. EXPERIMENTAL EVALUATION

The effectiveness of our proposed compressor is verified using MATLAB R2018a software running on Intel Core Duo CPU, 3 GHz platform. The experiments are carried out on 15 color images such as human face images, object images, and vegetable images. The dimensionality of each picture is 512 × 512. Our cohesive compressor provides improved quality of the recovered picture. The compression performance and visual quality measures of the reconstructed images, by means of the presented approach, have been calculated and related with achieved results from PCA, DTT, DCT, IA-DTT, and PCA-DCT. The compression and quality metrics of the proposed method are better than other existing approaches. The output picture quality of our cohesive compressor is approximate or closer to the input picture. The sample inputs and corresponding recovered pictures using PCA-DTT are shown in Figures 2 and 3, correspondingly. The quality of a picture mainly hinges on the structural similarity index measure and the universal quality index of the picture. SSIM and UQI are measures that define the structural nature of a picture.

Figure 1: Input images used to evaluate our algorithm

V. RESULTS AND DISCUSSION

In order to reconstruct the output picture, the inverse transform method was carried out. The dequantized block was achieved by multiplying each quantized block by the quantization matrix. The inverse transformation was calculated. We implement our cohesive image compressor technique on various digital images to realize better-quality image compression.

Figure 2: Output images obtained from PCA-DTT algorithm

Our experimental results establish that the cohesive approach considerably outdoes other prevailing compression methods in terms of compression performance measures such as compression ratio (CR), compression time (CT), and image quality metrics such as structural similarity index measure (SSIM), peak signal-to-noise ratio (PSNR), and universal quality index (UQI). These measures reflect the features of the picture professed by the human visual system, where the higher values denote flawless restoration while lower values represent deprived picture quality. The average value for all output pictures is calculated. Table 1 depicts the results.

In Table 1, a numerical evaluation is carried out between our cohesive digital image compressor and some of the best-known algorithms such as PCA, DCT, DTT, IA-DTT, and PCA-DCT in terms of CR, CT, PSNR, SSIM, and UQI. The average results of compression performance and quality measures of human face images, object images, and vegetable images using different compression methods are given in Figure 3. It is witnessed that PCA-DTT has the maximum compression performance and quality metrics than other existing digital compression methods in most of the images. For all the images, PCA-DTT exhibits greater compression and quality performances.

Table 1: Comparison of performance and quality measures

Input Image	Method	CR	CT	PSNR	SSIM	UQI
Human face	PCA	5.12	8.40	19.36	0.71	0.67
	DCT	5.6	7.2	24.1	0.73	0.6

		6	1	2		9
	DTT	5.97	6.34	26.89	0.81	0.74
	PCA-DCT	6.55	5.42	29.07	0.83	0.76
	IA-DTT	7.50	4.23	30.14	0.85	0.77
	PCA-DTT	7.90	3.92	31.54	0.95	0.84
Object images	PCA	4.74	8.31	19.89	0.72	0.67
	DCT	4.45	6.95	24.78	0.75	0.69
	DTT	5.18	5.96	27.62	0.83	0.74
	PCA-DCT	8.62	5.31	29.86	0.85	0.76
	IA-DTT	10.11	5.22	30.58	0.87	0.78
	PCA-DTT	10.40	4.21	32.40	0.97	0.84
Vegetable images	PCA	5.13	7.03	20.35	0.73	0.64
	DCT	4.20	4.58	27.35	0.75	0.66
	DTT	5.50	4.25	27.79	0.84	0.70
	PCA-DCT	9.40	5.30	30.55	0.86	0.72
	IA-DTT	10.22	7.92	31.74	0.91	0.76
	PCA-DTT	11.00	3.21	33.15	0.98	0.80

Figure 3 shows the bar plot for the performance metrics of our compressor and prevailing methods on different standard test pictures and Table 1 demonstrated that our cohesive compressor provides superior quality of the recovered picture in terms of CR value.

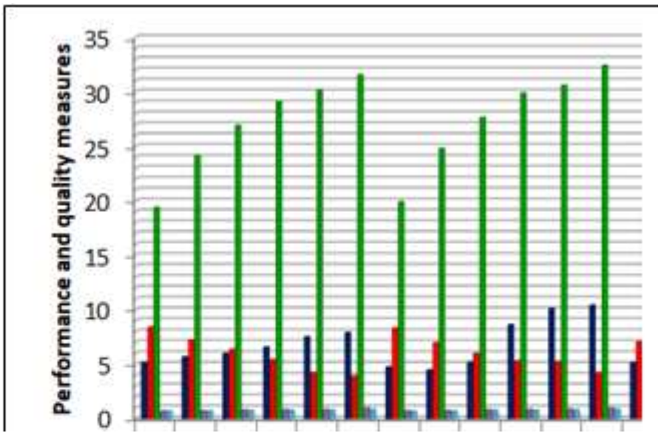

Figure 3: Comparison of compression performance and quality metrics of different images

Our cohesive digital compressor using PCA-DTT displays a noteworthy coding performance (PSNR). This can be evaluated by analyzing the compressed images given in Figure 2. The reconstructed images using PCA-DTT exhibit fewer artifacts. Hence, PCA-DTT follows closely or even superior to PCA-DCT. Our proposed method achieves closely and even improved than PCA-DCT. Thus, it concluded that PCA-DTT exhibits enhanced coding performance for different pictures. Nevertheless, PCA-DTT has similar or improved compression competence to PCA-DCT. Figure 3 shows the perception qualities (SSIM and UQI) of different images using various compression algorithms. It can be observed that the reconstructed pictures using PCA-DTT constantly exhibit improved perception qualities of reconstructed pictures than other methods used for comparison regardless of the pictures.

VI. CONCLUSIONS

In this paper, a cohesive digital compressor is proposed by integrating PCA and DTT compression approaches. More precisely, the two major goals of our research are (i) to design and implement a new hybrid compression technique to compress color images; and (ii) to compare our algorithm with other compression methods such as PCA, DCT, DTT, IA-DTT, and PCA-DCT experimentally. To realize the first goal the input image is compressed and reconstructed using PCA. The feature-reduced image obtained from the PCA technique is further compressed using DTT. Then the method is analyzed and related to the methods found in the literature in terms of compression and coding performance to realize our second goal.

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