SINGULAR VALUE DECOMPOSITION BASED CLASSIFIED VECTOR QUANTIZATION IMAGE COMPRESSION METHOD USING DISCRETE SINE TRANSFORM

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ABSTRACT

An efficient image compression technique using singular value decomposition (SVD) based classified vector quantization (CVQ) and Discrete Sine Transform (DST) for the efficient representation of still images was presented. The proposed method combines the properties of SVD, CVQ, and DST; while avoiding some of their limitations. A simple but efficient classifier based gradient method in the spatial domain, which employs only one threshold to determine the class of the input image block into one of finite number of classes, and uses three AC coefficients of the DST coefficients to determine the orientation of the block without employing any threshold that results in a good image quality was utilized. The proposed technique was benchmarked with the conventional approach based VQ, existing methods using CVQ; and JPEG-2000 image compression techniques. Simulation results indicated that the proposed approach alleviates edge degradation and can reconstruct good visual quality images with higher Peak Signal-to Noise-Ratio (PSNR) than the benchmarked techniques.

Keywords: singular value decomposition, DST, classified vector quantizer, image compression.

1. INTRODUCTION

Transform coding is a central component in image compression. Wavelet techniques have been in use for multiresolution image processing. Discrete Cosine Transform is also extensively used for image compression. Similar to the Discrete Wavelet and Discrete Cosine Transform it is now found that Discrete Sine Transform also possess some good qualities for image processing. Discrete Sine Transform (DST) is now seen to possess multiresolution property. Multiresolution refers to characteristics of the image analysis such that a feature in an image can appear at different resolutions and scales [1, 3]. In multiresolution analysis, some features that go undetected at one resolution may be easy to spot at another resolution.

Images are very important representative objects. They can represent transmitted television or satellite pictures, medical or computer storage pictures and many more. When a two-dimensional light intensity signal is sampled and quantized to create a digital image, a huge amount of data is produced. The size of the digitized picture could be so great that results in impractical storage or transmission requirements. Image compression deals with this problem such that the information required to represent the image is reduced while maintaining an acceptable image quality thus making the transmission or storage requirements of images more practical.

Transform coding is a widely applied method for lossy image compression. Image transforms effectively decorrelate the pixels so that pixels representing similar events in the image are grouped together according to their spatial or spectral properties. After transformation, the useful information is concentrated into a few of the low-frequency coefficients and the Human Visual System is more sensitive to such low spatial frequency information than to high spatial frequency. This is achieved through several different orthogonal transforms. Thus coding of transform coefficients can lead to substantial data reduction and it is currently one of the best coding techniques known. Among these transforms, the DST has some more desirable properties; it has high energy compaction and sparse representation. Further, DST coefficients are real, symmetric and orthogonal. Symmetric and orthogonal property indicates that for forward and reverse transformation, computation is same except for normalization. As DST is a separable transform, the 2D DST can be implemented using twice the 1D DST.
On the other hand, there are several lossy image compression techniques. Singular value decomposition (SVD) is a well-known method in linear algebra. It plays an interesting fundamental role in many different applications such as digital image processing, dimensionality reduction and image compression [4-5]. The use of SVD in image compression is motivated by its excellent energy compaction property in the least square sense [6-7]. As a result, the use of SVD technique in image compression has been widely studied [8-9].

Another image compression technique is based on vector quantization (VQ). VQ is a well-known and very efficient approach to low bit-rate image compression [10-11]. A serious problem in ordinary VQ is edge degradation caused by employing the distortion measure, such as the mean square error (MSE), in searching for the closest codeword in the codebook, as mean square error does not accurately preserve the edge information. To tackle this problem, classified VQ (CVQ) based on a composite source model, has been introduced by Ramamurthi and Gersho [12]. A variety of CVQ techniques, in which the classification is carried out in the spatial domain [12-13] or in the frequency domain [14-15]; have been proposed in the literatures to solve the poor edge reproduction problem.

This paper proposes a combined approach for image compression scheme based on SVD based CVQ and DST. This approach combines the strengths of the SVD based CVQ and the DST, while avoiding some of their limitations. The SVD generally relies on "global" information derived from all the vectors in the dataset, which is more effective for datasets consisting of homogeneously distributed vectors. For databases with heterogeneously distributed vectors, more efficient representation can be generated by subdividing the vectors into various groups characterized by a different set of statistical parameters. Finally, the excellent energy compaction property of the DST can simplify the block classification problem for the CVQ. Classification using transform domain, in which a few energy-compacted transform coefficients are used to distinguish edge direction and location, and hence it is computationally simpler than classification in the spatial domain.

The remainder of the paper is as follows. In Section 2, a brief description of DST and SVD concepts and their application to image compression is introduced. The main features of VQ and CVQ are shown in Section 3. Section 4 describes the proposed method including the methodology to classify the image into different classes. Experimental results are given in Section 5 to demonstrate the potential of the proposed image compression scheme as well as a comparison between the proposed methods, conventional approach based VQ, existing methods using CVQ; and JPEG-2000 image compression techniques. Finally, Section 6 presents some conclusions.

2. DISCRETE SINETRANSFORM (DST) AND SINGULAR VALUE DECOMPOSITION (SVD)

A. Discrete Sine Transform (DST)

Discrete Sine transform (DST) is a kind of Sinusoidal unitary and separable Transform developed by Jain [16]. As DST is a separable transform, the 2D DST can be implemented using twice the 1D DST. The 1D DST is first applied column wise and its result is used as the input for a second 1D DST now row wise. It is a fast transform and hence computation time is less.

The most common DST definition of a 1-D sequence of length N is

$$S(u) = \alpha(u)\sum_{x=0}^{N-1} f(x)\sin\left[\frac{\pi(2x+1)u}{2N}\right] \tag{1}$$

For u = 0,1,2,. . . ,N-1 . Similarly, the inverse transformation is defined as

$$f(x) = \sum_{u=0}^{N-1} \alpha(u)S(u)\sin\left[\frac{\pi(2x+1)u}{2N}\right] \tag{2}$$

For x = 0,1,2,. . . ,N-1 . in both equation of DST and its inverse $\propto (u)$ is defined as

$$\alpha(u) = \begin{cases} \sqrt{\frac{1}{N}} foru = 0 \\ \sqrt{\frac{2}{N}} foru \neq 0 \end{cases} \tag{3}$$

And, the 2-D DST is a direct extension of the 1-D case and is given by

$$S(u,v) = \alpha(u)\alpha(v)\sum_{x=0}^{N-1}\sum_{y=0}^{N-1} f(x,y) Sin\left[\frac{\pi(2x+1)u}{2N}\right] Sin\left[\frac{\pi(2y+1)v}{2N}\right] \tag{4}$$

For $u, v = 0,1,2,..., N-1$ and $\alpha(u)$ and $\alpha(v)$ are defined in eq (3). The inverse transform is defined as

$$f(x,y) = \sum_{u=0}^{N-1}\sum_{v=0}^{N-1} \alpha(u)\alpha(v)S(u,v) Sin\left[\frac{\pi(2x+1)u}{2N}\right] Sin\left[\frac{\pi(2y+1)v}{2N}\right] \tag{5}$$

For $y = 0,1,2,..., N-1.$

B. Singular Value Decomposition (SVD

Singular Value Decomposition is well-known method in linear algebra [4] to diagonalise a rectangular m×n matrix A by factorizing it into three matrices U, S, and V, such that,

$$A = USV^T \tag{6}$$

where S is a diagonal m×n matrix (the same dimensions as A) with elements si along the diagonal and zeros everywhere else. U and V are orthonormal matrices with sizes m×m and n×n, respectively.

The matrix U is called the left singular matrix (the columns ui of U are called the left singular vectors), V is called the right singular matrix (the columns vi of V are called the right singular vectors), and the diagonal matrix S is the singular values matrix (the diagonal elements si of S are called the singular values). The singular vectors form orthonormal bases and lead to the following relationship:

$$Av_i = s_i u_i \tag{7}$$

SVD is an approximation technique which effectively reduces any matrix into a smaller invertible and square matrix. Thus, one special feature of SVD is that it can be performed on any real m × n matrix. If the matrix A is a real matrix, then U and V are also real. Equation (7) can be expressed as:

$$A = \sum_{i=1}^{p} u_i s_i v_i^T \tag{8}$$

Where u_i and v_i are the ith column vectors of U and V respectively, s_i are the singular values, and p=min{m,n}. If the singular values are ordered so that $s_1 \geq s_2 .... \geq s_p$, and if the matrix A has a rank r < p, then the last p – r singular values are equal to zero, and the

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matrix A can be approximated by a matrix A* with rank r (i.e. the SVD becomes A*) as the following equation

$$A^* = \sum_{i=1}^{r} u_i s_i v_i^T \qquad (9)$$

Hence, the approximation error matrix E_r is dependent on the performance accuracy of the quantisation and/or truncation by parameter r, which can be described as $E_r = A - A^*$.The 2-norm of a matrix may be calculated from the singular values. The 2-norm of approximation error is calculated by

$$E_r^2 = \left\|A - A^*\right\|_2 = \left\|\sum_{i=1}^{p} u_i s_i v_i^T - \sum_{i=1}^{r} u_i s_i v_i^T\right\|_2 = \left\|\sum_{i=r+1}^{p} u_i s_i v_i^T\right\|_2$$

$$= \sum_{i=r+1}^{p} (s_i)^2 \qquad (10)$$

As the singular values are in descending order, it can be seen that the error decreases towards zero in the 2-norm sense.

The property of SVD to provide the closest rank r approximation for a matrix A as shown in equation (9) can be used in image processing for compression and noise reduction. By setting the small singular values to zero, matrix approximations whose rank equals the number of remaining singular values can be obtained [17].

3. VECTOR QUANTIZATION AND CLASSIFIED VECTOR QUANTIZATION

Image quantization is the process of reducing the image data by removing some of the detail information by mapping groups of data points to a single point.

Mathematically, a vector quantizer Q of dimension k and size N is a mapping of a vector in k-dimensional Euclidean space, Rk, to a finite subset Y of Rk containing N reproduction points, called codevectors or codewords [10]. Thus,

$$Q : \mathrm{R}^k \to Y \qquad (11)$$

The finite set $Y = \{y_i : i = 1,2,..., N\}$, where N is the size of the set Y, is called a VQ codebook, and yi represents the ith codevector (codeword) in the codebook Y. The most popular form of vector quantizer is the Voronoi or nearest neighbor vector quantizer[10], where for each input vector, x, a search is done through the entire codebook to find the nearest codevector, yi, which has the minimum distance .

$$Q(x) = y_i \quad \text{if} \quad d(x, y_i) < d(x, y_j) \forall i \neq j \qquad (12)$$

Where d (x, y) is a distance measure between the vectors, x and y. This measure is given by

$$d(x, y) = \sqrt{\left(\sum_{j=1}^{k} (x_j - y_j)^2\right)} \qquad (13)$$

Where xj and yj are the jth elements of the vectors x and y, respectively. Figure-1 depicts the basic processing steps of VQ system.

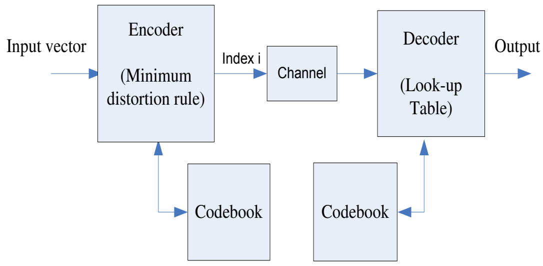

Figure-1. Basic processing steps of VQ system.

Edge is one of the most important features of visual information. An edge or an abrupt change in the gray level is a very important in the perception of image quality. Since the human visual system is highly sensitive to edges [18], human eyes are very susceptible to the degradation along edges [19], even though edges constitute only a small portion of the entire image. This suggests that edges can provide an efficient image representation, making edge-based compression techniques very useful, even at high compression ratios. Furthermore, the mean squared of the error (MSE) is a poor distortion measure for coding edges, that is, even if the codebook contains edge codevectors, the MSE criterion does not ensure that an edge vector will be coded with an edge vectors. To improve edge fidelity, classified VQ (CVQ), which is based on a composite source model, was proposed by Ramamurthi and Gersho [12] as a solution to the edge degradation problem of the conventional VQ. A CVQ coder consists of a classifier and separate codebooks for each class. The possible classes are typically: shade, horizontal edge, vertical edge and diagonal edge classes. Each image block is classified into one of the appropriate classes by a classifier.

4. THE PROPOSED METHOD

A. Block classification

The proposed method assumes that any edge information within a small image block can be described by a straight line across the block with an abrupt change of intensity in the spatial domain. However, the assumption that any edge segment within a block is a straight line starts to fail for 6×6 blocks and bigger [20], and therefore a block size of 4×4 was utilized in the proposed technique to achieve good subjective quality images. The discrete gradient of the block is used as a measure of the edge content of the block in the spatial domain. The orientation of the edge is used to further classify the edge blocks in the frequency domain. Normally, for 4×4 image blocks, the orientations are restricted to four types: horizontal,

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vertical and two diagonals. Only three AC coefficients of DST coefficients are employed to determine the orientation of the edge block.

At the outset, the block mean value is calculated and subtracted from each pixel in the block.

Let B = {bij; 1 ≤ i, j ≤ 4} represents a 4x4 image block. In this case bij is the gray level pixel value corresponding to position (i, j) of row i and column j in the image block B. The discrete gradients of the block B in the x and in the y directions are determined as follows:

$$\left.\begin{aligned} G_x &= \tfrac{1}{8}\left[\sum_{i=1}^{2}\sum_{j=1}^{4} bij - \sum_{i=3}^{4}\sum_{j=1}^{4} bij\right] \\ G_y &= \tfrac{1}{8}\left[\sum_{i=1}^{4}\sum_{j=1}^{2} bij - \sum_{i=1}^{4}\sum_{j=3}^{4} bij\right] \end{aligned}\right\} \qquad (14)$$

In general, for an even numbers n×m block size, the directional derivatives are:

$$G_x = \frac{2}{m\times n}\left[\sum_{i=1}^{\frac{m}{2}}\sum_{j=1}^{n} bij - \sum_{i=\frac{m}{2}+1}^{m}\sum_{j=1}^{n} bij\right] \qquad (15a)$$

$$G_y = \frac{2}{m\times n}\left[\sum_{i=1}^{m}\sum_{j=1}^{\frac{n}{2}} bij - \sum_{i=1}^{m}\sum_{j=\frac{n}{2}+1}^{n} bij\right] \qquad (15b)$$

Where i = 1, 2,…, m; j = 1, 2,…, n. The gradient magnitude within each image block is defined by:

$$|G| = \sqrt{\left(G_x^2 + G_y^2\right)} \qquad (16)$$

If the gradient magnitude |G| in equation (16) of the block B is smaller than a threshold T, the block contains no significant gradient and it is classified as a shade block; otherwise, it will be classified as an edge block. Once a block is classified as an edge block, the orientation of the edge pattern within the block will be computed using DST. Three AC coefficients of DST coefficients will be used to determine the orientation of the edge block, namely S(0,1), S(1,0), and S(1,1) as follows:

Compute each of the edge direction β_θ for $\theta \in \{0, \frac{\pi}{4}, \frac{\pi}{2}, \frac{3\pi}{4}\}$ such that

$$\left.\begin{aligned} B_0 &= 2|V| \\ B_{\frac{\pi}{4}} &= (4/3)\max\{|H+V+D|, |H+V-D|\} \\ B_{\frac{\pi}{2}} &= 2|H| \\ B_{\frac{3\pi}{4}} &= (4/3)\max\{|H-V+D|, |H-V-D|\} \end{aligned}\right\} \qquad (17)$$

Where,

$$H = \tfrac{1}{2}S(0,1), V = \tfrac{1}{2}S(1,0), D = \tfrac{1}{2}S(1,1)$$

The θ value whose measure is the largest will be selected as the block edge orientation of the block.

Once the block classification process has been completed, five different sub-codebooks are generated, representing the different orientations of edge block information and the shade block. SVD-based CVQ is used for designing the sub-codebooks corresponding to each class. Different rank values have been used in the codebook generating process according to the type of the codebook. Figure-2 shows the classification process.

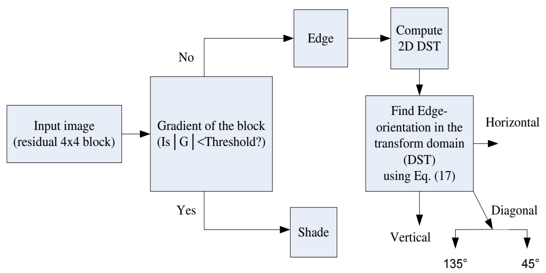

Figure-2. Block diagram of the classification process.

B. Construction of the codebook

Two standard 512×512 monochromatic images, Barbara and Peppers, are used for codebook constructions. The selected training images are divided into small non-overlapping blocks of size 4×4 pixels making the vector dimension equal to 16. The block mean value is computed and subtracted from each pixel in the block and then the classification process is performed as shown before. The process is resulted in a better utilization of codevectors for encoding shade blocks because they are mapped into small regions near the origin where they can be encoded efficiently. Visually sensitive edge blocks and shade blocks are encoded with a codebook specifically designed for that class of blocks so that distortion is minimized. The value of the threshold T is determined experimentally and set to 15 to obtain a reasonable percentage of the shade blocks. Once the block classification process has been completed, different sub-codebooks corresponding to the different classes are generated, using SVD-based CVQ technique with different rank values. The different five sub-codebooks corresponding to the classified classes were generated by projecting the n dimensional dataset of a class to the space spanned by the m (m < n) most

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significant singular vectors of the m (m < n) largest singular values. That is, the sub-codebooks were generated from the eigenvectors of a set of image in a corresponding class.

C. Encoder

The encoder of the proposed method operates on the residual blocks where the mean value of the input image block is subtracted from each pixel in the block to yield a residual block (vector). The mean values are then encoded separately via scalar quantization with 6-bits value for a 256 level gray scale image based on both the desired quality and rate, using prediction method together with an improved greyscale (IGS) quantization method [21]. Figure-3 shows the block diagram of the proposed method encoder.

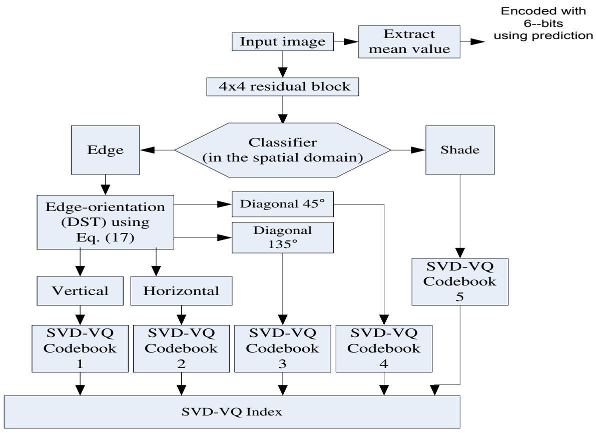

Figure-3. Block diagram of the proposed method encoder.

As one of the classified codebook design problems is concerned with deciding the set of sizes of the codebook classes to minimize the overall distortion, approximately the same number of codevectors for all the edge classes has been selected. This assumption is motivated by the fact that all the edge classes are perceptually have equal importance. This implies that an edge block will appear equally distorted to the eye irrespective of its class. The shade class, however, can be given a less number of codevectors in comparison to the edge classes as it is an easily coded class.

Decoder

The decoder performs simple table look-up operations to retrieve the corresponding codeword from the same codebook as the encoder used, and computes the inverse of the used transforms. As the residual block is used in the encoding process, the block mean value is added to the reconstructed image block.

Simulation Results

Simulations were carried out to test the performance of the proposed approach, and presented to assess the objective quality of the coded images. MATLAB code was written for the generation of the proposed method performed on Pentium (R) Core i7-4700MQ CPU@2.40GHz Windows 8.1 pro 64-bit. A database of five grey level images was developed to systematically evaluate the application of the proposed system. The training set used is obtained from two 512×512 monochromatic images of 8-bit intensity, Barbara512 and Peppers512. Three test images outside the training set that have different spatial and frequency characteristics: Baboon512, Lena512 and Goldhill256 as well as the two images inside the training set: Barbara512 and Peppers512 were used to evaluate the performance of the proposed method. These test images were coded by the proposed method employing the same codebooks that were used for coding the images Barbara512 and Peppers512. The performance of this scheme is usually characterized using different image quality metrics, the MSE and the Peak Signal- to Noise- Ratio (PSNR) as image quality metrics based error, as well as the Structural Similarity Index (SSIM) based approach proposed by Wang *et al.* [22].
The PSNR is defined as follows:

$$PSNR = 10\log_{10}\left[\frac{(255)^2}{MSE}\right] \tag{18}$$

Where MSE is the mean square of the error between the original and the reconstructed images, and it is defined as:

$$MSE = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}\left(x_{ij} - y_{ij}\right)^2 \tag{19}$$

Where MN is the total number of pixels in the image.

The SSIM based approach used first and second order statistics of the original and distorted images and has been defined as follows [22].

$$SSIM(X,Y) = \frac{\left(2\mu_x\mu_y + C_1\right)\left(2\sigma_{xy} + C_2\right)}{\left(\mu_x^2 + \mu_y^2 + C_1\right)\left(\sigma_x^2 + \sigma_y^2 + C_2\right)} \tag{20}$$

Where $C_1 = \left(K_1 L\right)^2$ and $C_2 = \left(K_2 L\right)^2$

Where L is the dynamic range of the pixel values (255 for 8-bit images). The constants C1 and C2 are small positive constants where K1 and K2 are the same as in [22]: K1 = 0.01 and K2 = 0.03. The quantities μ_x, σ^2_x be the mean and variance of the reference image $X = \{x_i | i = 1,2,..., N\}$, and μ_y, σ^2_y be the mean and variance of the distorted image $Y = \{y_i | i = 1,2,..., N\}$ while σ_{xy} be the covariance of the reference and distorted images and are given by

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$$\left.\begin{aligned} \mu_x &= \frac{1}{N}\sum_{i=1}^{N} x_i \\ \mu_y &= \frac{1}{N}\sum_{i=1}^{N} y_i \quad \text{(21a)} \\ \sigma_x^2 &= \frac{1}{N-1}\sum_{i=1}^{N}(x_i-\mu_x)^2 \end{aligned}\right\}$$

$$\left.\begin{aligned} \sigma_x^2 &= \frac{1}{N-1}\sum_{i=1}^{N}(x_i-\mu_x)^2 \\ \sigma_{xy} &= \frac{1}{N-1}\sum_{i=1}^{N}(x_i-\mu_x)(y_i-\mu_y) \end{aligned}\right\} \text{(21b)}$$

The overall image quality is measured by the Mean SSIM (MSSIM) index which is given by

$$MSSIM(X,Y) = \frac{1}{M}\sum_{j=1}^{M} SSIM(x_j, y_j) \qquad (22)$$

Where xj and yj are the image contents at the j-th local window; and M is the number of local windows in the image.

Tables 1 and 2 show the performance of the proposed method characterised by the PSNR and the MSSIM based approaches respectively, while Figure-4 shows some of the reconstructed compressed images of the proposed method and their corresponding reconstructed error.

Table-1. Reconstruction performance for the proposed method trained on the top two images (Barbara512 and Peppers512) and generated to the rest of the images. This test is calculated by using approximately the same bitrate.

	Proposed method		**VQ**		**JPEG-2000**	
Image	**Bitrate** (bpp)	**PSNR** (dB)	**Bitrate** (bpp)	**PSNR** (dB)	**Bitrate** (bpp)	**PSNR** (dB)
Barbara512	0.5625	33.3686	0.5604	27.3250	0.5654	33.1516
Peppers512	0.5427	35.8856	0.5446	28.5478	0.5333	35.8340
Lena512	0.5257	36.1862	0.5282	28.7617	0.5114	36.7676
Baboon512	0.6526	30.8762	0.6229	25.5914	0.6534	30.2985
Goldhill256	0.7511	32.8406	0.7124	26.7216	0.7554	31.4860

Table-2. Reconstruction performance for the proposed method trained on the top two images (Barbara512 and Peppers512) and generated to the rest of the images. This test is calculated by using approximately the same bitrate.

	The proposed method		**VQ**		**JPEG-2000**	
Image	**Bitrate** (bpp)	**MSSIM**	**Bitrate** (bpp)	**MSSIM**	**Bitrate** (bpp)	**MSSIM**
Barbara512	0.5625	0.8664	0.5604	0.1973	0.5654	0.9100
Peppers512	0.5427	0.9230	0.5446	0.2761	0.5333	0.9208
Lena512	0.5257	0.9312	0.5282	0.4742	0.5114	0.9427
Baboon512	0.6526	0.7897	0.6229	0.1223	0.6534	0.7836
Goldhill256	0.7511	0.8549	0.7124	0.1429	0.7554	0.8207

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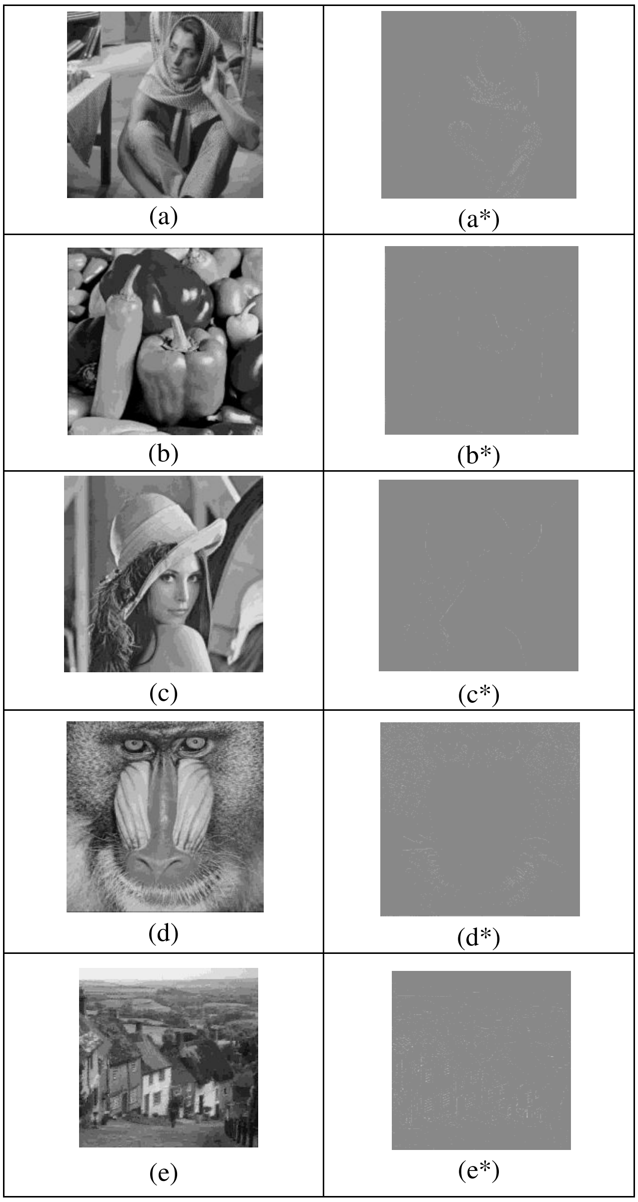

Figure-4. Some of the reconstructed compressed images by the proposed method.
(a) 512 × 512 reconstructed image Barbara512 at bitrate 0.5625bpp and psnr = 33.3686dB, (b) 512 × 512 reconstructed image Peppers512 at bitrate 0.5427bpp and psnr = 35.8856dB, (c) 512 × 512 reconstructed image Lena512 at bitrate 0.5257bpp and psnr=36.1846dB, (d) 512 × 512 reconstructed image Baboon512 at bitrate 0.6526bpp and psnr = 30.8762dB, (e) 256 × 256 reconstructed image Goldhill256 at bitrate 0.7511bpp and psnr = 32.8406dB. The images a*, b*, c*, d*, e* are the differences between the original images and their reconstructed images a, b, c, d and e plus 128, respectively.

The results in Tables 1 and 2 show that, in all cases, the proposed method outperformed ordinary VQ using the k-means algorithm [10] and show competitive results in comparison to JPEG-2000 standard which was generated using MATLAB [21] in terms of both the PSNR and the MSSIM. However, the proposed model outperforms JPEG-2000 in some cases where the test images were of high detail type (the images Baboon512 and Goldhill256). This is because of the good approximation of the edge blocks which lie far away from the densely region near the origin, that result from the mean-removed process, so that the high amplitude vectors may be adequately represented. On the other hand, popular transform-based lossy compression techniques tend to introduce artifacts at high frequency signal components since such details often represent high frequency components in frequency domain.

It is noted that the edge direction is highly correlated with the corresponding DST coefficients. This means that DST coefficients appear along the direction perpendicular to the edge direction. This is together with the excellent energy-compaction property of DST, the used classifier provides high accuracy in terms of determining each of the strength and the edge-orientation of a given input image block. The properties of DST together with the compact energy and low-rank approximation properties provided by SVD transform led to high image quality for the proposed method at reasonable bitrate.

The quality of the reconstructed images by the proposed scheme is preserved. Additionally, by comparing the proposed scheme with more conventional CVQ methods [12], [23], [24], [25], and [13], it has been noted that the proposed method maintains higher PSNR values for the same images at the same bitrate. For example, for the image Lena512, the comparisons are summarized in Table-3.

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Table-3. Comparison results between the proposed method and more conventional CVQ for the image Lena512. This comparison is calculated by using approximately the same bitrate.

	PSNR (dB) values for the image Lena512 by different methods. This comparison is calculated by using approximately the same bitrate.					
Bitrate (bpp)	**Reference [12]**	**Reference [23]**	**Reference [24]**	**Reference [25]**	**Reference [13]**	**Proposed Method**
0.625	-	31.26	-	32.65	36.7972	36.8793
0.688	-	31.79	-	33.27	37.1509	36.9019
0.70	29.79	-	-	-	37.1885	37.3191
0.750	-	32.23	-	33.80	37.4166	37.4463
0.530	-	-	34.14	-	36.0838	36.3245
0.572	-	-	34.49	-	36.4723	36.6729
0.600	-	-	34.74	-	36.6557	36.8693

6. CONCLUSIONS

An efficient coding method for accurate reconstruction of still images at low bit-rates was presented. The method combines SVD based CVQ as well as the DST in both the spatial and transform domains. The classification algorithm uses only one threshold value on the magnitude of the gradient across the image block to classify the each non-overlapping section of the image into a shade or edge block. An edge-oriented classifier using only three AC coefficients of DST are utilized to determine the direction of the edge block. The method also shows an advantage in PSNR and MSSIM over the standard VQ method using the k-means algorithm and the existing methods using CVQ scheme; and competitive to the JPEG-2000, for similar values of the bit-rate.

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