Engineering Journal of University of Qatar, Vol. 9, 1996, p.105-121

A HADAMARD TRANSFORM FUZZY SEGMENTATION AND CLASSIFICATION TECHNIQUE FOR IMAGE COMPRESSION

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ABSTRACT

A new technique for image data compression based on fuzzy segmentation, classification and properties of sequency ordered Hadamard Transform (HT) is presented. Using a pyramidal data structure, an image is segmented into blocks of variable sizes. The size of each block is determined using a fuzzy procedure depending on the amount of information contained. Regions with low details are divided into blocks of variable size, while regions containing more information are successively segmented into smallest size of 4*4 blocks. Only a small number of more energetic components of HT are used for the coding of the uniform blocks, while a fuzzy edge oriented classifier is designed for the coding of the high-detail blocks. The classifier employs several prototype edge patterns in HT blocks and the fuzzy techniques for recognition of the direction of edges. The low-detail regions are coded with very low bit rate on the expense of small reduction in the visual quality of images, while the coding process for high-detail regions results in an acceptable image quality. Decoded images of high quality are obtained for encoding rates of 1 bit per pixel.

INTRODUCTION

Vector Quantization (VQ) is a well known technique for image data compression (1). In this technique the image is partitioned into uniform and equal size blocks and each block is coded with a low bit rate (1). It has been suggested that segmentation of an image into smaller blocks results in a better image quality and several algorithms have been presented for fixed block size of 4*4 (2). However, frequently considerable parts of an image are uniform and contain less new information. Therefore using a fixed block size technique will not give the least possible bits for coding.

Intensive researches have been focused on coding techniques based on variable size blocks. Each segment is then coded with different bit rate, depending on the information content of that segment (3,4). The quadtree data structure technique is often employed in order to account for the size as well as the position of the segmented blocks (5). The edge degradation problem with the classical VQ method has been addressed by introducing the Classified VQ (CVQ) (6). This technique essentially uses a separate classifier with more bits for representation of edges (5). However design of an edge oriented classifier in the spatial domain is not simple and give rise to several different thresholds for pattern matching. The use of CVQ in the transform domain has also been reported by several authors particularly the use of Discrete Cosine Transform (DCT) which has been shown to be simpler and more efficient than other methods (7,8). A significant advantage of the DCT includes a good approximation to the optimal Karhunon-Loeve (K-L) transform and higher capability in energy compacting. This technique is often applied as a satisfactory method for image data compression (8). An excellent survey on VQ schemes in transform domain is given by Blain and Fisher (9). Lee and Crebbin (7) have applied the CVQ for image segmentation and used only a small number of high energy DCT components in order to detect the edges and to classify the blocks.

In this paper the pyramid data structure and a fuzzy segmentation technique is applied to obtain variable block size with different amount of details. Blocks with low details are coded with very low bit rate and for highly detailed blocks, a fuzzy edge oriented classifier (FEOC) is designed. The classifier utilizes the properties of the model of the edges in the HT domain. The main reason for using pyramidal data structure is the requirements of successively dividing the image into smaller and addressable blocks with different sizes. The decision on the block segmentation depends on properties of the block which is often associated with uncertainty. As a simpler and more efficient decision making mechanism for block segmentation, a fuzzy logic approach is employed. The FEOC uses different edge patterns of the HT for the 4*4 blocks. Based on the direction of the edges, a particular block is classified as the destination edge class. Since the occurrence of an ideal edge is less likely, the fuzzy based classifier is shown to be a more efficient for edge detection.

In order to illustrate the effectiveness of the proposed image compression technique, results of an extensive simulation studies are presented. It is shown that an encoding bit rate of less than 1 bit per pixel (bpp) is obtained for an acceptable visual quality image.

The paper proceeds as follows. In section II the sequency ordered HT is briefly reviewed. Section III describes the actual quantization procedure using pyramidal segmentation and fuzzy classification of regions. In Section IV, the FEOC algorithm and the coder design is presented. Section V describes the smoothing algorithm while in Section VI the results obtained from simulation studies are discussed followed by Section VII, in which conclusions are drawn.

SEQUENCY ORDERED HADAMARD TRANSFORM

The Hadamard matrix H is an orthogonal matrix consisting of elements with values of +1 and -1. The rows of the Hadamard matrix can be reordered to give a sequency ordered Hadamard matrix.

Given a rectangular digital image represented by $f(i,j)$, the two dimensional HT is given by:

$$F(m,n) = H(m,n)\, f(i,j)\, H(m,n) \qquad (1)$$

where $H(m,n)$ is Hadamard matrix. Taking a HT of a sampled image, the result is a pattern in terms of its sequency and is expressed as the weighted sum of $H(m,n)$. The weights tend to get smaller as the sequency indices increase (10).

High spatial sequencies in HT domain are introduced by the occurrence of sharp edges in the original image. Thus, a low pass filtering is expect to remove sharp edges and hence produce blurred images. A high pass filter is characterized by a spectrum having a relatively large weight for sequencies far from the origin, and low weight values for sequencies near the origin.

The sequency ordered HT weights of order four is shown in Figure 1 and their corresponding basis planes in Figure 2.

sequencies	0	1	2	3
0	F_{00}	F_{01}	F_{02}	F_{03}
1	F_{10}	F_{11}	F_{12}	F_{13}
2	F_{20}	F_{21}	F_{22}	F_{23}
3	F_{30}	F_{31}	F_{32}	F_{33}

Fig. 1. Sequency ordered HT weights

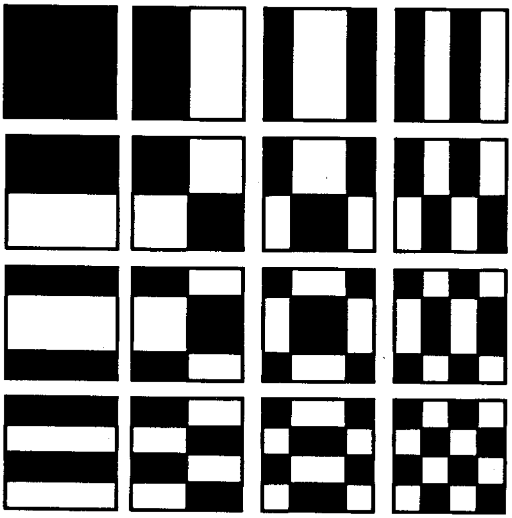


Fig. 2. Hadamard basis planes

Upon Hadamard transformation, the actual object in the frame will be reflected in the value of the weights, F_{ij} . For example, if the input pattern is symmetrical about either the x or y coordinate, then certain weights equal zero.

PYRAMIDAL SEGMENTATION AND FUZZY CLASSIFICATION

A hierarchical processing follows the operation of the Human Visual System (HVS) in that processing proceeds from level to levels of increasing refinement. The pyramidal approach also uses a hierarchical structure and is applicable to the task of segmentation and edge feature extraction. One of the most significant benefits of this approach is the reduced computational complexities. To construct all levels of the pyramid, the original image matrix of size N*N is partitioned into sub-matrices with dimensions half that of the original matrix. This procedure is repeated until a 1*1 matrix is obtained at the top of the pyramid (10,11). Note that a quadtree is a node structure that is generated from a pyramid and the nodes correspond directly to the cells of a pyramid. Many researchers have used quadtree based CVQ for image compression (7,12).

In this paper, image segmentation is based on pyramidal data structure and fuzzy techniques, such that blocks with less details are specified in larger sizes and those with more details are represented in smaller sizes. The variance of pixels is used as the criterion for the amount of information contained in each block and according to the degree of presence of details, fuzzy values are assigned. The normalized variance is calculated for each segment and given a fuzzy label based on the assignment of the simple triangular membership function shown in Figure 3.

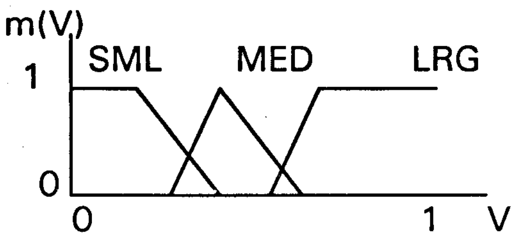


Fig. 3. Fuzzy-set values of fuzzy variable V

The information content of each block may have one of the three values SML, MED and LRG, which means that perceptual blocks are classified as small-detail, medium-detail and large-detail respectively. The SML and MED blocks may be directly coded with low bit rate. The LRG blocks are divided into four sub-blocks, reducing the dimension by half each time. For the acceptable reasons given by Ngan and Koh (13), the maximum size of blocks is 16*16 and the pyramidal segmentation is successively applied until the smallest size blocks of 4*4 are obtained. Considering the dimension of blocks in three sizes 16*16, 8*8 and 4*4 and using fuzzy linguistic values SML, MED and LRG, the pyramidal fuzzy segmentation algorithm classifies the image into seven super-classes. The characteristics of each block super-class is determined by the size and the degree of information content. Codes for super-classes are shown in Table 1.

Since block size directly effects the visual quality of the restored image, different membership functions are assigned to blocks of different sizes. Figure 4 shows three different membership functions for fuzzy variables X, O and Q which are used for classification of the block sizes 16*16, 8*8 and 4*4 respectively.

Table 1. Super-classes and their Assigned Codes

Super-class Number	Block Size	Fuzzy-value	Type of Information	Coding Bits b_7 b_6 b_5
1	16 * 16	SML	low-detail	0 0 0
2	16 * 16	MED	medium-detail	0 0 1
3	8 * 8	SML	low-detail	0 1 0
4	8 * 8	MED	medium-detail	0 1 1
5	4 * 4	SML	low-detail	1 0 0
6	4 * 4	MED	medium-detail	1 0 1
7	4 * 4	LRG	high-detail	1 1 0

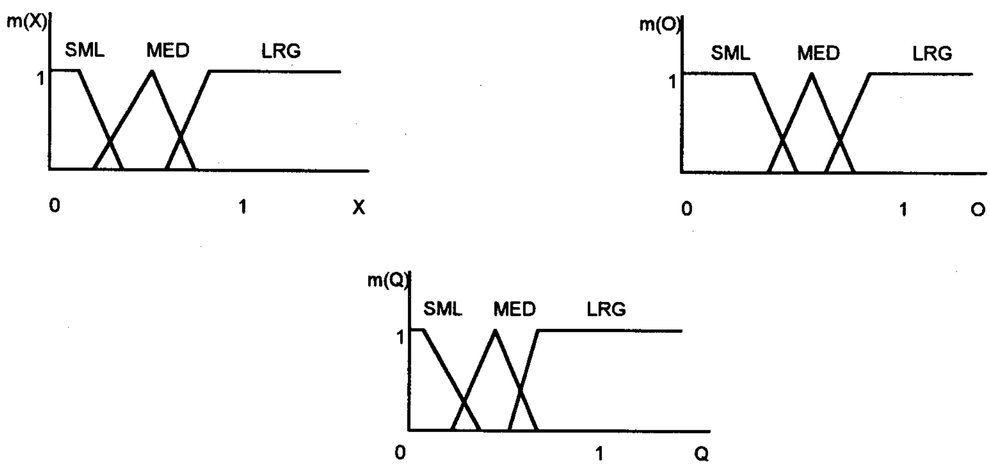


Fig. 4. Fuzzy-set values of fuzzy variables X, O and Q

The membership functions are assigned such that fewer blocks are categorized as super-class 1, hence reducing the undesired blocking effects on the image quality. In order to increase the efficiency of the classifier while preserving good image quality, several blocks are assigned to super-class 7.

FUZZY EDGE ORIENTED CLASSIFIER AND CODING SCHEME

After segmentation of the image blocks into three perceptual blocks and knowing that the first group of blocks (super-classes 1, 3 and 5) contain less information, the mean of block for coding is sufficient. Codes for super-class in association with the mean of block is utilized for coding these type of blocks.

For coding the second group of blocks (super-classes 2, 4 and 6), only a few components of HT with larger information content are selected and coded with the lowest possible bits.

The largest magnitude values of HT components are around the low sequencies and near to the DC term. It is observed that in a low detail region, the position of the HT coefficients needed for coding the equal size blocks are in the same position. Thus, choosing a few high energy coefficients in HT domain are sufficient for coding them. In this paper, different coefficients from top-left corner of the HT block are used for compression in a staircase fashion. In practice, 27 coefficients for block size of 16*16, 14 for 8*8 and 5 for 4*4 are used, respectively. The remaining coefficients do not have enough information to affect the result of compression and are set to zero.

The DC and AC coefficients of HT in each block with respect to their specific features are coded separately. The DC coefficients in the pyramid are inter-related and are compressed and coded using D differential Pulse Code Modulation.

However, for the third group of blocks (super-class 7) which may contain different, distorted and complicated edge patterns, the FEOC is used. In designing this classifier, several known edge patterns with different position, orientation and polarity are first defined, then a pattern matching technique is used to extract edge features in a block. As the pattern comparison methods are not very efficient in the spatial domain, most frequently, the transform domain is used for this purpose. Several methods of CVQ in which the classification is based on the transform domain have been reported (2,8). Most of these techniques employ DCT. Since the elements of DCT are non-integer and require more bits for coding, in this research HT is used for block classification and it is shown to be computationally less demanding in addition to easier feature extraction.

The HT F(m,n) of an image f(i,j) for i,j = 0,1,2,3 is obtained as

$$F = HfH = \begin{bmatrix} F_{00} & F_{01} & F_{02} & F_{03} \\ F_{10} & F_{11} & F_{12} & F_{13} \\ F_{20} & F_{21} & F_{22} & F_{23} \\ F_{30} & F_{31} & F_{32} & F_{33} \end{bmatrix} \tag{2}$$

The coefficient represents F_{00} the DC term of the original image and all other weights may have positive or negative signs. The signs of weights represent the change of intensities of pixels in the original image. For example, if F_{01} has larger value than other weights (except F_{00}) and its sign is negative, then in the original image, there is an intensity transition from low value to a high and its direction is from left to right. Consequently, a straight vertical edge is present.

For an image size of 4*4, there are a total of 15 distinct coefficients (except the DC term) in HT domain and the total pattern of the intensity changes can be calculated as

$$P = \sum_{r=0}^{15} \binom{15}{r} = \sum_{r=0}^{15} \frac{15\,!}{r!\,(15-r)!} = 2^{15} \tag{3}$$

As it would not be practical to use all these class patterns, to simplify the result, the histogram of HT coefficients is utilized. It is observed that the histogram components other than the first row and the first column do not have significant information, so they can be ignored. For the remaining coefficients, however, significant features can be extracted for the purpose of FEOC design. These features are :

$$\begin{aligned} &\text{Horizontal features}: \; H = \{h_i \, ; i = 0,1,2,3\}, \; h_i = F_{i0} \\ &\text{Vertical features}: \; V = \{v_j \, ; j = 0,1,2,3\}, \; v_j = F_{0j} \end{aligned} \tag{4}$$

Figure 5 shows all the significant features used for FEOC with their corresponding information.

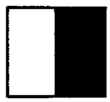
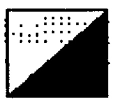
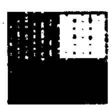
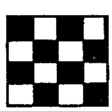
Properties of HT Weights	Edge notation (ICON)	Edge Type and Direction	Class Code $b_4\ b_3\ b_2$	Class No.
$v_1 = v_2 = v_3 = 0$		Straight horizontal	000	1
$v_1 = v_3 = 0,\ v_2 \neq 0$		Curved horizontal	001	2
$h_1 = h_2 = h_3 = 0$		Straight vertical	010	3
$h_1 = h_3 = 0,\ h_2 \neq 0$		Curved vertical	011	4
$h_1 = v_1,\ h_2 = v_2,\ h_3 = v_3$		45^{o}	100	5
$h_1 = -v_1,\ h_2 = v_2 = h_3 = v_3 = 0$		L shape	101	6
$h_1 = -v_1,\ h_2 = v_2,\ h_3 = -v_3$		135^{o}	110	7
—		Unknown	111	8

Fig. 5. FEOC classes

Based on the consideration of the edge position and polarity, several different sub-classes may be defined for each class of Figure 5. Different conditions of edge occurrence for the class 1 are shown in Figure 6.

HT of Edge Sample	Edge Sample	Edge Polarity	Edge Position	Subclass Number
$\begin{bmatrix} 280 & 0 & 0 & 0 \\ -40 & 0 & 0 & 0 \\ -40 & 0 & 0 & 0 \\ -40 & 0 & 0 & 0 \end{bmatrix}$	$\begin{bmatrix} 10 & 10 & 10 & 10 \\ 20 & 20 & 20 & 20 \\ 20 & 20 & 20 & 20 \\ 20 & 20 & 20 & 20 \end{bmatrix}$	+	up	1
$\begin{bmatrix} 480 & 0 & 0 & 0 \\ -320 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}$	$\begin{bmatrix} 10 & 10 & 10 & 10 \\ 10 & 10 & 10 & 10 \\ 50 & 50 & 50 & 50 \\ 50 & 50 & 50 & 50 \end{bmatrix}$	+	middle	2
$\begin{bmatrix} 360 & 0 & 0 & 0 \\ -200 & 0 & 0 & 0 \\ 200 & 0 & 0 & 0 \\ -200 & 0 & 0 & 0 \end{bmatrix}$	$\begin{bmatrix} 10 & 10 & 10 & 10 \\ 10 & 10 & 10 & 10 \\ 10 & 10 & 10 & 10 \\ 60 & 60 & 60 & 60 \end{bmatrix}$	+	down	3
$\begin{bmatrix} 360 & 0 & 0 & 0 \\ 200 & 0 & 0 & 0 \\ 200 & 0 & 0 & 0 \\ 200 & 0 & 0 & 0 \end{bmatrix}$	$\begin{bmatrix} 60 & 60 & 60 & 60 \\ 10 & 10 & 10 & 10 \\ 10 & 10 & 10 & 10 \\ 10 & 10 & 10 & 10 \end{bmatrix}$	–	up	4
$\begin{bmatrix} 480 & 0 & 0 & 0 \\ 320 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}$	$\begin{bmatrix} 50 & 50 & 50 & 50 \\ 50 & 50 & 50 & 50 \\ 10 & 10 & 10 & 10 \\ 10 & 10 & 10 & 10 \end{bmatrix}$	–	middle	5
$\begin{bmatrix} 280 & 0 & 0 & 0 \\ 40 & 0 & 0 & 0 \\ -40 & 0 & 0 & 0 \\ 40 & 0 & 0 & 0 \end{bmatrix}$	$\begin{bmatrix} 20 & 20 & 20 & 20 \\ 20 & 20 & 20 & 20 \\ 20 & 20 & 20 & 20 \\ 10 & 10 & 10 & 10 \end{bmatrix}$	–	down	6

Fig. 6. Sub-class of class 1 (straight horizontal edges)

It is clear that the components v_1, v_2 and v_3 for all straight horizontal edges are zero. This indicates the important properties of the elements of HT as an edge classifier in that they are independent of the edge position and polarity. Since only the elements of HT is used for coding in the final stage, there is no need for including the position and polarity of edges.

Although the HT domain facilitates an easy method for feature extraction, the probability of occurrence of ideal edges is low and the difference of only one pixel in a block is enough to change the components of HT. For this reason the algorithm for edge feature extraction based on HT would not be appropriate and may result in an increased number of unknown classes which reduces the compression rate considerably. As a more suitable feature extraction algorithm, a fuzzy technique is used for this purpose.

In the proposed edge classification technique, horizontal and vertical features (h_i and v_j) of a block which directly influence the type of the edges are taken as fuzzy variables. Each of these variables are labeled S (small) or L (large) according to the triangular membership function shown in Figure 7.

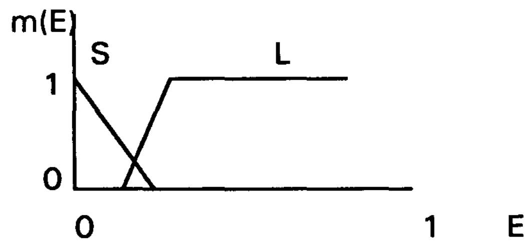


Fig. 7. Fuzzy-values of edge feature

The next step is the design of inference mechanism (IF ... THEN ... rules) which classifies the type as well as the class of edges. The set of fuzzy rules for the FEOC which have been generated are given in Figure 8. The rule base is obtained from the inspection of the HT weights associated with the type of edges as shown in Figure 5.

Therefore, for coding the third and the most important group of blocks, it is only necessary to keep the code for super-classes and for the class as the characteristic of the edge. In addition to the type of the edge, some horizontal and vertical features that are required for restoring the edges together with the DC term are coded. Obviously, when coding a block, each of the features h_i

and v_j which have the fuzzy value S, are replaced by zero and will not be coded; also a complete block with unknown edge may be coded directly.

if	$S(v_1)$ & $S(v_2)$ & $S(v_3)$	then	Classify block to class 1.
else if	$S(v_1)$ & $S(v_2)$ & $L(v_3)$	then	Classify block to class 2.
else if	$S(h_1)$ & $S(h_2)$ & $S(h_3)$	then	Classify block to class 3.
else if	$S(h_1)$ & $S(h_2)$ & $L(h_3)$	then	Classify block to class 4.
else if	$S(h_1 - v_1)$ & $S(h_2 - v_2)$ & $S(h_3 - v_3)$	then	Classify block to class 5.
else if	$S(h_1 + v_1)$ & $S(h_2)$ & $S(h_3)$ & $S(v_2)$ & $S(v_3)$	then	Classify block to class 6.
else if	$S(h_1 + v_1)$ & $S(h_2 - v_2)$ & $S(h_3 + v_3)$	then	Classify block to class 7.
else			Classify block to class 8.

* S(x) means if absolute value of x is small.
L(x) means if absolute value of x is large.

Fig. 8. IF ... THEN ... rules for FEOC

THE SMOOTHING ALGORITHM

One common problem with basic VQ is that low rates often cause the boundaries between blocks to be visible even when the fidelity within each block is high. These blocking effects can easily be removed by using a smoothing algorithm. A heuristic smoothing scheme to generate a smoothed output from the reconstructed image is used (10).

A simple approach to smoothing would be to directly post process the image with a low-pass filter; however, such a filter unacceptably blurs high detail regions of the image. Since many of the blocks causing the blocking effect must belong to the low- and medium-detail classes, these blocks can be selectively smoothed without introducing artifacts. We thus implement smoothing by forcing each low- and medium-detail block to fit with neighboring regions of image by interpolating only the boundary pixels of the block itself. Since the interpolation is only done within low- and medium-detail blocks, it is not possible to adversely affect any surrounding high-detail blocks.

The smoothing algorithm take place in two stages. The task of the first stage is to use data from reconstructed image to smooth the pixels forming the block boundaries, while that of the second is to process the pixels one position

away from the boundary. The second stage operates on the output of this first stage; however, due to their small size, the 4*4 blocks are omitted from the second stage. If we describe the pixels in reconstructed image by $f(i,j)$, those in the smoothed image $g(i,j)$, and call the set of pixels to be smoothed ψ, then the smoothing operation can be described as follows.
For the first stage we have

$$g(i,j) = \begin{cases} f(i,j) & (i,j) \notin \psi \\ s(i,j) & (i,j) \in \psi \end{cases} \tag{5}$$

where the $s(i,j)$ are the smoothed pixels given by

$$s(i,j) = \frac{[f(i,j) + f(i,j+1) + f(i,j-1)]}{3} \tag{6}$$

if (i,j) is on the top or bottom of a block;

$$s(i,j) = \frac{[f(i,j) + f(i+1,j) + f(i-1,j)]}{3} \tag{7}$$

if (i,j) is on a block side; or

$$s(i,j) = \frac{[f(i,j) + f(i+1,j) + f(i-1,j) + f(i+1,j+1)]}{4} \tag{8}$$

where (i,j) is a corner pixel of a block. The second stage is implemented in a similar manner, except that the pixels interpolated are different. The smoothing is done only in the direction perpendicular to the block boundary in order to avoid problems when a neighboring block having a sharp edge comes up to the block boundary.

EXPERIMENTAL RESULTS

Two 64 gray level test images of size 320 × 200 ('Eagle' and 'Lady'), as shown in Figure 9 are used to test the proposed encoding procedures.

Fig. 9. 'Eagle' and 'Lady' test images

To measure the reconstructed image quality, the peak signal to noise ratio (PSNR) as defined as follows.

$$PSNR = 10 \log 10 \left[L^2 / \frac{1}{M \times N} \sum_{i=0}^{M-1} \sum_{j=0}^{N-1} [f(i,j) - \hat{f}(i,j)]^2 \right] [dB] \quad (9)$$

Where $f(i,j)$ and $\hat{f}(i,j)$ are the (i,j)th pixels of the original and reconstructed images respectively. M and N are the size of image matrix and L is the maximum gray level in the image. Table 2 shows the result of segmentation using the pyramid based fuzzy techniques.

As it can be observed from Table 2, the number of low, medium and high-detail blocks depends on the nature of the image with regard to the information content. In order to obtain better results the membership functions are adjusted for each block separately because, tuning the membership functions for a particular image may not suite the others.

Table 3 shows the quality of reconstructed images, the mean square error (MSE) and the number of bits per pixel for each test image is also given. Figure 10 shows reconstructed test images.

Table 2. Results of Pyramidal Image Segmentation

Super-class Number	Information Type	Block Size	No. of Blocks (Image percent) 'Eagle'	'Lady'
1	low	16 * 16	83 (0.346)	41 (0.171)
2	medium	16 * 16	41 (0.171)	72 (0.300)
3	low	8 * 8	172 (0.179)	338 (0.352)
4	medium	8 * 8	167 (0.174)	142 (0.148)
5	low	4 * 4	18 (0.005)	8 (0.002)
6	medium	4 * 4	226 (0.059)	77 (0.020)
7	high	4 * 4	256 (0.067)	27 (0.007)

Table 3. The Result of Image Compression Using the Proposed Algorithm for Two Different Test Images.

PSNR [dB] for		MSE for		Bit per Pixel	
'Eagle'	'Lady'	'Eagle'	'Lady'	'Eagle'	'Lady'
32.09	33.53	2.4515	1.7601	1.12	0.96

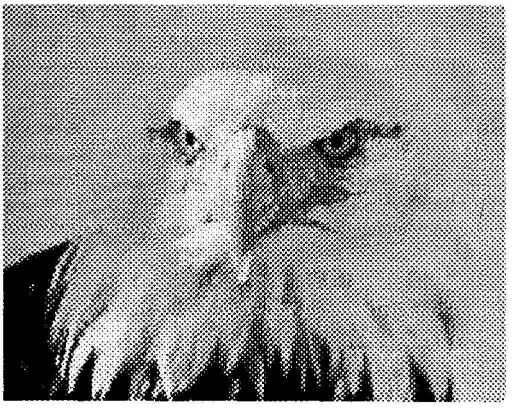


Fig. 10. Reconstructed 'Eagle' and 'Lady' test images

CONCLUSIONS

Fuzzy techniques and the properties of sequency ordered Hadamard transform is utilized to design an edge-oriented classifier for the purpose of image compression. It is shown that pyramid-based fuzzy image segmentation can be an effective and efficient mechanism for isolating blocks of distinct perceptual significance and thereby achieving low bit rates for image compression with an acceptable quality. A fuzzy algorithm is employed to segment an image into various sized blocks, in which larger blocks are classified into the low-detail classes and are encoded at very low bit rates. The high-detail blocks are classified using fuzzy edge-oriented classification. Two different test images are used to illustrate the effectiveness of the proposed approach for digital image compression.

REFERENCES

1. **Nasrabadi, N. M. and King, R. A., 1988.** Image Coding Using Vector Quantization: A Review. IEEE Trans. Commun. COM-36, pp. 957-971.

2. **Panchanathan, S. and Goldberg, M., 1991.** Mini-Max Algorithm for Image Adaptive Vector Quantization. IEE Proc. 1, Commun. Speech Vis., 138, pp. 53-60.

3. **Nasrabadi, N. M. and Feng, Y., 1990.** A Multilayer Address Vector Quantization Technique. IEEE Trans. Circuits Syst. CAS-37, pp. 912-921.

4. **Vaisey, J. and Gersho, A., 1992.** Image Compression with Variable Block Size Segmentation. IEEE Trans. Signal Process. 40, pp. 2040-2060.

5. **Kim, J. W. and Lee, S. U., 1992.** A Transform Domain Classified Vector Quantizer for Image Coding. IEEE Trans. Circuits Syst. Video Technol., 2, pp. 3-14.

6. **Ramamurthi, B. and Gersho, A., 1986.** Classified Vector Quantization Of Images. IEEE Trans. Commun. COM-34, pp. 1105-1115.

7. **Lee, M. H. and Crebbin, G., 1994.** Classified vector quantization with variable block size DCT models. IEE Proc. Vis-Image signal processing, vol. 1.

8. **Kim, D. S. and Lee, S. U., 1991.** Image vector quantizer based on a classification in the DCT domain. IEEE Trans. Commun. COM-39, pp. 549-556.

9. **Blain, M. E. and Fisher, T., 1991.** A comparison of vector quantization techniques in transform and subband coding of imagery. Signal Processing and Image Communication, 3 (1), pp. 91-105.

10. **Schalkoff, R. J., 1989.** Digital image processing and computer vision. John wiley & sons Inc., New York.

11. **Kim, S. H. and Rao, K. R., 1992.** Pyramid VQ for image coding using DCT classifier based on HVS. Proceedings of ICIP-92, pp. 151-155, Singapore.

12. **Lee, M., Atikiouzel, H. Y. and Crebbin, G., 1992.** Quadtree based classified vector quantization for image coding. Proceedings of ICIP-92, pp. 26-29, Singapore.

13. **Ngan, K. N. and Koh H. C., 1992.** Predictive Classified vector quantization. IEEE Trans. Image Process. 1, pp. 269-280.