A new fuzzy gradient-adaptive lossy predictive coding system for still image compression

Abstract - **In this paper a new fuzzy logic-based lossy predictive coding system for gray-scale still image compression is developed. The proposed coder employs a recently introduced adaptive fuzzy prediction methodology in the predictor design. In addition, it adopts a novel fuzzy gradient-adaptive quantization scheme. The proposed coding technique possesses superior performance over its non-fuzzy counterparts especially at low bit quantization. This is due to the inherent adaptivity in the fuzzy prediction methodology as well as the gradient-adaptive quantization scheme. Simulation results are provided to demonstrate the efficient performance of the proposed fuzzy predictive coding system.**

Keywords - **Image Coding, Lossy Predictive Coding, Adaptive Prediction, Switched Quantization, Fuzzy Gradient Classification**

I. Introduction

Rapidly growing demand for the transmission and storage of high quality imagery data has motivated researchers to develop advanced image compression techniques. The main objective of image compression or coding is to achieve a low bit rate representation of dgital images while maintaining minimum perceived loss of image quality. Research activity in the field of image coding has resulted in a multitude of coding paradigms, including transform coding, subband coding, vector quantization and predictive coding, naming only a few. Predictive coding offers an attractive, efficient yet computationally simple technique for encoding of high-resolution imagery data. Medical imaging, image archiving, remote sensing, preservation of artwork and historical documentation are all candidate fields for predictive coding

In predictive coding [l-2], also called *differential coding*, such as differential pulse code modulation (DPCM), the transmitter and the receiver process the image in some fixed order (say raster order, row by row and left to right within a row). The current pixel is predicted from the preceding pixels, which have been reconstructed. The difference between the current pixel $P(x,y)$ and its predicted value $\hat{P}(x,y)$, *prediction error* $d(x,y)$, is then quantized, encoded and transmitted to the receiver. A block diagram of a general lossy DPCM coding system is depicted in Figure (l) where the codeword assignment in the encoder and its counterpart in the decoder are not included.

In the lossless coding mode of predictive coding, the quantizer is not included and the output of the predictor is restricted to be integer numbers and the difference is coded

with an entropy-coding algorithm. In this case, differential coding is referred to as *information-preserving* or *lossless* differential coding.
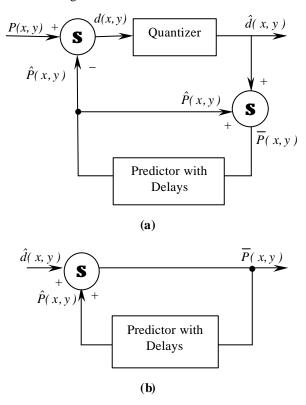

(a)

(b)

Fig. 1. Block diagram of a general lossy DPCM scheme
(a) Encoder part   (b) Decoder part

The underlying notion beyond predictive coding is to remove mutual redundancy between successive pixels by coding prediction errors. If the prediction is well designed, then the distribution of the prediction error is concentrated near zero and has substantially lower first order entropy than the entropy of the original image.

The design of a lossy predictive coding scheme involves two main stages, which are predictor design and quantizer design. The interaction between the predictor and the quantizer is quite complex but it significantly affects the performance of lossy predictive coding. Although such interaction must be taken into consideration, the predictor and the quantizer are often separately designed. With a well-designed predictor, if the quantizer is not properly designed, the overall performance will deteriorate especially at low bit quantization. Similarly, employing a properly designed quantizer and inefficient prediction scheme will increase the quantization errors and hence the efficiency of the coding scheme is significantly reduced.

Extensive research activity has been devoted to predictor design. The multitude of prediction schemes can be generally categorized into linear and nonlinear schemes. Another classification is adaptive and nonadaptive schemes. Linear predictors [1-2] exploit a linear combination of a set of previously decoded pixels to estimate the predicted value of the current pixel. However, images are highly nonstationary and large prediction error occurs at image edges and contours. In order to improve the prediction efficiency, adaptive predictors that adapt to local image properties are employed [3-4]. On the other hand, nonlinear predictors [5-7,13] yield superior performance over linear counterparts with respect to minimizing the mean square error. It is thus desirable that the predictor should enjoy the adaptivity as well as the nonlinearity characteristics for increased performance of predictive coding.

Quantizer design significantly affects the performance of lossy predictive coding. It is to some extent a challenging task to achieve high perceptual quality of decoded images especially at low bit quantization. The prediction error distribution is generally not uniform. The probability of occurrence of small prediction errors (smooth regions) is greater than the probability of occurrence of large prediction errors (edge regions). Nonlinear quantizers [1-2] are thus necessary to achieve minimum mean squared quantization error by distributing decision levels according to the probability density function of the prediction error. Decision levels are densely distributed in the regions of high probability and coarsely distributed in the regions of low probability.

However, images are highly nonstationary, thus using a single fixed nonlinear quantizer for a given image will reduce the efficiency of performance. Smooth regions will be reconstructed with less granular noise. However, edge regions will not be instantaneously reconstructed because of the slope overload quantization distortion. This leads to blurred edges and reduced perceptual quality of decoded images especially at low bit quantization. Adaptive nonlinear quantization schemes are thus very attractive and effective solutions to make the quantizer design adaptive to image characteristics to achieve better performance. Examples of adaptive quantization schemes are forward adaptive quantization, backward adaptive quantization and switched quantization [1-2]. Adaptive predictor can be advantageously combined with a switched nonuniform quantizer to achieve improved performance with respect to prediction as well as quantization.

In the past decade, there has been a significant amount of research activity in the field of fuzzy image coding. This has resulted in a variety of coding schemes in adaptive transform coding [8-11], subband coding [12] and predictive coding [13], naming only a few. With respect to lossy predictive coding, Yu [13] developed an adaptive fuzzy logic-based prediction scheme that adapts to the image local structures to improve the predictor design. In this scheme, five local patterns are assumed for the image. The fuzzy membership functions characterizing these patterns are derived using a gradient-based methodology. The predicted value of the current pixel is obtained based on the membership functions and the defined predicted values for the different patterns. This fuzzy prediction scheme results in better reconstruction of edges as well as smooth regions. However, the performance of the fuzzy coding system, which employs this fuzzy prediction methodology, deteriorates at low bit quantization because quantization errors are sometimes so large as to mislead the membership functions.

In this paper a new adaptive fuzzy predictive coding system is introduced. The proposed coder employs the adaptive fuzzy prediction methodology developed in [13]. This results in better prediction of smooth as well as edge regions. In addition, the proposed coder adopts a novel fuzzy gradient-adaptive quantization scheme that switches between three well-designed nonuniform quantizers depending on the local gradient of the pixel to be coded. This, in turn, leads to reduced quantization errors in both smooth and edge regions and consequently higher perceptual quality of reconstructed images is achieved.

The rest of the paper is organized as follows. The proposed coding system is described in details in section II. Simulation results are provided in section III to evaluate the performance of the proposed coder and the paper concludes in section IV.

II. The Proposed Coding System

A. The Adaptive Fuzzy Prediction Scheme

In the proposed coding system, the adaptive fuzzy prediction methodology developed in [13] is adopted in order to solve the problem of imprecise image local structures in the prediction. In this scheme, five local patterns of the image are assumed which is uniform area, horizontal edge, vertical, 45° diagonal edge and 135° diagonal edge patterns. The prediction values of the current pixel in the highly-defined five local patterns can be defined in terms of the $(p_1 - p_{10})$ neighborhood, Figure (2), using extrapolation as follows [13]:

$$P_0(x,y) = p_7 + k_1(p_7 - p_3) \tag{1}$$

$$P_{90}(x,y) = p_8 + k_2(p_8 - p_5) \tag{2}$$

$$P_{45}(x,y) = p_9 + k_3(p_9 - p_{10}) \tag{3}$$

$$P_{135}(x,y) = p_6 + k_4(p_6 - p_1) \tag{4}$$

$$P_{uniform}(x,y) = 0.25 \times (P_0(x,y) + P_{90}(x,y) + P_{45}(x,y) + P_{135}(x,y)) \tag{5}$$

where $k_1 - k_4$ are constants to be determined.

p_1	p_4	p_5		p_{10}	
p_2	p_6	p_8	p_9		
p_3	p_7	p_0			

Fig. 2. The neighborhood of the current pixel $p_0(x,y)$

Image local patterns are not highly defined and hence fuzzy sets can be exploited successfully in defining these local patterns and in classifying the image local structures into these patterns, efficiently. The five local patterns are thus characterized by five fuzzy membership functions, which are computed as follows[13]:

$$m_0(x,y) = \frac{|f_{90}(x,y)|^a}{|f_0(x,y)|^a + |f_{90}(x,y)|^a + |f_{45}(x,y)|^a + |f_{135}(x,y)|^a + 2d}$$

$$m_{90}(x,y) = \frac{|f_0(x,y)|^a}{|f_0(x,y)|^a + |f_{90}(x,y)|^a + |f_{45}(x,y)|^a + |f_{135}(x,y)|^a + 2d}$$

$$m_{45}(x,y) = \frac{|f_{135}(x,y)|^a}{|f_0(x,y)|^a + |f_{90}(x,y)|^a + |f_{45}(x,y)|^a + |f_{135}(x,y)|^a + 2d}$$

$$m_{135}(x,y) = \frac{|f_{45}(x,y)|^a}{|f_0(x,y)|^a + |f_{90}(x,y)|^a + |f_{45}(x,y)|^a + |f_{135}(x,y)|^a + 2d}$$

$$m_{uniform}(x,y) = \frac{2d}{|f_0(x,y)|^a + |f_{90}(x,y)|^a + |f_{45}(x,y)|^a + |f_{135}(x,y)|^a + 2d}$$

Where a and d are positive constants and $f_{90}(x,y)$, $f_0(x,y)$, $f_{45}(x,y)$ and $f_{135}(x,y)$ are the first order gradient in the horizontal, vertical, 45° diagonal and 135° diagonal directions respectively, and are approximately computed within the neighboring pixels of the current pixel $p_0(x,y)$ as follows[13]:

$$|f_0(x,y)| = \left|\frac{p_1 + p_2 + p_3 - p_4 - p_6 - p_7}{3}\right| + \left|\frac{p_4 + p_6 + p_7}{3} - \frac{p_5 + p_8}{2}\right|$$

$$|f_{90}(x,y)| = \left|\frac{p_1 + p_4 + p_5 - p_2 - p_6 - p_8}{3}\right| + \left|\frac{p_2 + p_6 + p_8}{3} - \frac{p_3 + p_7}{2}\right|$$

$$|f_{45}(x,y)| = \left|\frac{p_4 + p_8 - p_6 - p_1}{2}\right| + \left|\frac{p_6 + p_1 - p_2 - p_7}{2}\right|$$

$$|f_{135}(x,y)| = \left|\frac{p_4 + p_2}{2} - \frac{p_3 + p_6 + p_5}{3}\right| + \left|\frac{p_3 + p_6 + p_5}{3} - \frac{p_7 + p_8}{2}\right|$$

These membership functions have been derived knowing that the directional gradient assumes a local maximum in the direction perpendicular to the contour direction. Finally, the fuzzy prediction value of the current pixel $\hat{P}(x,y)$ is defined as:

$$\hat{P}(x,y) = P_0(x,y) \times m_0(x,y) + P_{90}(x,y) \times m_{90}(x,y) + P_{45}(x,y) \times m_{45}(x,y)$$
$$+ P_{135}(x,y) \times m_{135}(x,y) + P_{uniform}(x,y) \times m_{uniform}(x,y)$$

The main computational complexity associated with this fuzzy prediction scheme consists in computing the membership functions, $m_0(x,y)$, $m_{90}(x,y)$, $m_{45}(x,y)$ and $m_{135}(x,y)$ in terms of the first order gradient values $|f_{90}(x,y)|^a$, $|f_0(x,y)|^a$, $|f_{135}(x,y)|^a$ and $|f_{45}(x,y)|^a$, and $2d$. In Reference [13], the author has presented an efficient methodology for reducing the implementation complexity associated with the computation of the membership functions. The reader is kindly referred to [13] for more details in this respect.

The parameters of the adaptive fuzzy prediction scheme, a, d, k_1, k_2, k_3 and k_4, are optimized for a given image such that entropy of the prediction error is minimized. To further reduce the complexity of the fuzzy prediction scheme, the set of the predictor parameters are optimized only once using a proper training image. Then the fuzzy predictor is used for all images without any modification in its parameters. A proper training image must have a multitude of edge patterns. In the context of the proposed coding system, that image is chosen to be the standard Barbara image. The parameters optimized for the standard Barbara image are: $k_1 = k_2 = 0.5$, $k_3 = k_4 = 0.05$, $a = 4$ and $d = 40,000$.

B. The Proposed Fuzzy Gradient-Adaptive Quantization Scheme

B.1. Motivation

Quantizer design significantly affects the performance of lossy predictive coding in terms of image quality especially at low bit rates. This is due to the fact that the reconstruction errors in lossy predictive coding are equal to the errors resulted from the quantization process. Hence, if the quantizer is well-designed, the quantization errors will be reduced and an improved image quality is achieved. Unlike uniform quantizers, nonuniform counterparts, such as the Lloyd-Max quantizer [1-2], have superior performance with respect to minimizing the mean squared quantization error. Employing one quantizer for the whole image; however, reduces the coding efficiency especially at low bit quantization. Smooth regions will be reconstructed with less granular noise. On the other hand, edge regions will not be reconstructed instantaneously leading to edge blurring. It is thus imperative that for increased quantization performance, the quantizer should enjoy the nonuniformity as well as the adaptivity characteristics.

In the proposed coding system, a novel fuzzy gradient-adaptive switched nonuniform quantization scheme is proposed. This scheme switches between three well-designed nonuniform quantizers depending on the local gradient of the pixel to be coded. The underlying notion of the proposed scheme is summarized as follows. The image gradient is first estimated, then a proposed fuzzy gradient classification technique called *Maximum Entropy-based Fuzzy Gradient Classification* (MEFGC) algorithm, is adopted to classify the image gradient into three classes, namely, *low gradient*, *medium gradient* and *high gradient* classes. A gradient-adaptive nonuniform Lloyd-Max quantizer is then designed for each class separately. The design is based on a novel exponential weighting strategy of the prediction error estimated form a preceding fuzzy lossless predictive coding stage. After the three quantizers have been well-designed, the quantization process switches from one quantizer to the other depending on the local gradient of the current pixel to be coded. The proposed quantization scheme adapts to image activity by proper selection of step size values in accordance with image gradient and hence quantization errors are significantly reduced in both smooth and edge regions. This, in

turn, leads to high perceptual quality even with low bit quantization. In the subsections that follow, the MEFGC algorithm is introduced. Then the proposed quantization scheme is described in details.

B.2. Maximum Entropy-Based Fuzzy Gradient Classification Algorithm

Recently, we have developed a new automatic fuzzy edge detection technique [11,14-15]. The underlying notion of that technique is that the problem of edge detection is viewed as a three-level thresholding problem. The goal of which is to classify the image domain according to the gradient value into three fuzzy classes. These classes constitute pixels having *low local gradient* (smooth region), *medium local gradient* (weak edges) and *high local gradient* (strong edges), respectively. These classes (regions) are characterized by membership functions whose parameters are determined using an efficient search technique [16]. Since in edge detection it is desired to obtain the best compact representation of image edges, the criterion upon which the parameters are chosen is to minimize the fuzzy entropy. In the proposed fuzzy predictive coding system, a modified version of that technique is developed. The modification consists in two aspects. The first is that the maximum entropy is chosen rather than the minimum entropy

motivation beyond this choice is to retain most of the gradient information after the thresholding process. The second modification is that the output of the technique is not the edge map but the classification itself of the image gradient. Hence, this technique is referred to as *Maximum Entropy-Based Fuzzy Gradient Classification* (MEFGC) algorithm.

The purpose of the MEFGC algorithm is to classify the image gradient into three classes, namely, *low gradient*, *medium gradient* and *high gradient* classes. These classes are characterized by three fuzzy membership functions, m_{low}, m_{medium} and m_{high}, respectively. Figure (3) demonstrates the three fuzzy membership functions corresponding to the three fuzzy classes of image gradient combined with a hypothetical image gradient normalized histogram. The three membership functions are characterized by four parameters, a_1, c_1, a_2 and c_2 which satisfy the conditions $a_1 \le c_1$ and $a_2 \le c_2$. These parameters are found using the effective search scheme introduced in [16]. The basis for that scheme in the context of the proposed coding system is that the parameters are selected such that the fuzzy entropy of image gradient is maximized after the thresholding process. The reader is kindly referred to [16] for a detailed description of the search scheme.

The fuzzy entropy function is defined by:

$$H(a_1, c_1, a_2, c_2) = -p_{low} \log p_{low}$$
$$- p_{medium} \log p_{medium} - p_{high} \log p_{high} \quad (6)$$

where $p_{low} \equiv \sum_{k=0}^{G_{max}} h_k \cdot m_{low}(k)$, $p_{medium} \equiv \sum_{k=0}^{G_{max}} h_k \cdot m_{medium}(k)$,

and $p_{high} \equiv \sum_{k=0}^{G_{max}} h_k \cdot m_{high}(k)$

Where h_k is the probability distribution of the image gradient (gradient histogram), G_{max} is the maximum gradient value and $k = 0,1,2,....,G_{max}$.
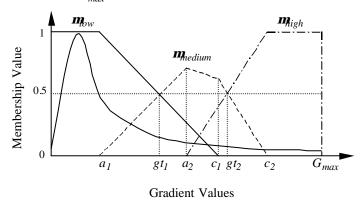

Fig. 3. The membership functions of the three fuzzy classes of image gradient combined with a hypothetical image gradient normalized histogram

After the membership parameters have been determined, the gradient thresholds gt_1 and gt_2 are automatically found as follows:

$$gt_1 = (a_1 + c_1)/2 \quad \text{and} \quad gt_2 = (a_2 + c_2)/2 \quad (7)$$

A pixel is classified into *low gradient* class if its computed gradient value is lower than gt_1 and is classified into *medium gradient* class if its gradient value is lower than gt_2 and higher than gt_1. Otherwise, it is classified into *high gradient* class.

B.3. Description of the Proposed Quantization Scheme

The design of the proposed quantization scheme is described in a four-step procedure as follows.

1. The gradient of the image is estimated using Sobel operator [2] then the MEFGC algorithm is adopted to classify the image domain according to the gradient values into three classes, namely, *low gradient*, *medium gradient* and *high gradient* classes, respectively.

2. A prediction error image $PE(x,y)$ is obtained from a preceding stage of the fuzzy lossless predictive coding scheme described in Section II.A.

3. A set of three probability density functions (PDFs), corresponding to the *low gradient*, *medium gradient*, and *high gradient* classes, is created using a novel gradient-adaptive exponential weighting strategy of $PE(x,y)$ as follows:

$$PDF_k = PDF\{PE_k\} \quad k=1,2,3$$

Where

$$PE_k = \left\{ PE(x,y)\, exp\left(\left[\frac{G(x,y)}{Gmax}\right]^{g_k}\right) \quad \forall\, (x,y) \in class\ k \right\} \quad (8)$$

Where $G(x,y)$ is the gradient at the pixel at location (x,y), G_{max} is the maximum image gradient, g_k is a class-dependent coefficient that has a suggested value of 0.25. from experimental simulations and $k = 1,2$ and 3 refer to the *low gradient*, *medium gradient* and *high gradient* classes, respectively.

4. For the set of three PDFs, PDF_k, three optimal Lloyd-Max quantizers, Q_L, Q_M and Q_H which correspond to *low gradient*, *medium gradient* and *high gradient* classes respectively, are designed for a specified number of quantization levels/bits.

In this manner, a quantizer is efficiently and separately designed or each class of image gradient. Consequently, the step sizes of the quantizer are properly changed according to the gradient of the current pixel to be coded. Finer step sizes will be used for low gradient regions while coarser step sizes will be used for high gradient regions. In addition, the step sizes are adaptively changed within each gradient class due to the adopted optimal quantization scheme (Lloyd-Max quantization scheme). This allows efficient adaptation to image content and hence higher perceptual quality especially at low bit quantization due to reduced quantization errors in both smooth and edge regions. Figure (4) depicts a block diagram for the proposed quantization design procedure.

To further reduce the complexity associated with the proposed fuzzy gradient-adaptive quantization scheme, the set of the gradient-adaptive nonuniform quantizers are designed only once using a proper training image. Again the standard Barbara image is chosen to be that image. After the quantizers have been designed, they are used for all images without any modification in their parameters. In this manner, the complexity of the quantization scheme is prohibitively reduced, yet maintaining the gradient-adaptive characteristic.

III. Simulation Results

In this section, the performance of the proposed fuzzy gradient-adaptive lossy predictive coding technique is evaluated through simulation results on a set of test images, namely, Barbara, Lena, Peppers and CameraMan images. A comparison between the proposed coding system with a set of three linear predictive coding systems is provided. In linear prediction, the predicted value is computed as a linear weighted sum of the previously reconstructed values. The predicted value $\hat{P}(x,y)$ is defined as follows:

$$\hat{P}(x,y) = A \times \overline{P}(x-1,y) + B \times \overline{P}(x-1,y-1) + C \times \overline{P}(x,y-1)$$

where A, B and C are the predictor coefficients and $\overline{P}(x-1,y)$, $\overline{P}(x-1,y-1)$ and $\overline{P}(x,y-1)$ are the previously reconstructed pixel values. In this paper, three linear predictors are considered and are defined as follows:
LP1 (Linear Predictor # 1): A = 0.50, B = 0.0, and C = 0.50
LP2 (Linear Predictor # 2): A = 0.75, B = -0.5, and C = 0.75
LP3 (Linear Predictor # 3): A = 0.90, B = -0.8, and C = 0.90

The set of linear predictive coding systems, LP1, LP2 and LP3 utilizes nonuniform Max-Lloyd quantizers for the quantization stage. Tables (I) provides a comparison between the proposed coding scheme and the linear predictive coding systems LP1, LP2 and LP3 at 3-bit, 2-bit and 1-bit quantization for the set of test images with respect to the *peak signal-to-noise ratio* (PSNR) values. It is shown how superior is the proposed coding system over its nonfuzzy linear counterparts. This is due to the employed adaptive prediction as well as the novel adaptive quantization schemes. Figure (5) demonstrates the decoded Lena images at 2-bit quantization using the proposed and LP2 coding systems (in the top row of the figure) and their associated enhanced coding error images (in the bottom row of the figure). It is observed how the proposed system yields higher perceptual quality. In addition, it is depicted how the coding errors are significantly reduced in both smooth and edge regions.
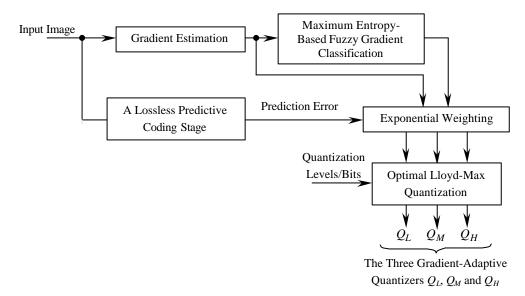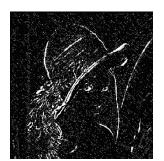

Fig.4. A block diagram for the design procedure of the proposed fuzzy gradient-adaptive quantization scheme

Table I: Coding results in terms of the PSNR values for the proposed coder and the set of linear predictive coders

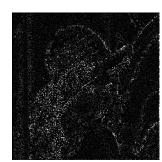| Images	Quant. Bits	PSNR in dB			
		LP1	LP2	LP3	Proposed
Barbara		23.435	25.732	25.304	25.7331
Lena		19.701	21.572	22.478	25.8570
Peppers	1	19.292	21.379	23.230	25.6995
Camera Man		17.935	19.802	21.135	23.6480
Barbara		29.430	29.589	28.067	29.9006
Lena		25.733	26.364	26.063	32.0865
Peppers	2	24.936	26.477	28.853	32.1627
Camera Man		24.107	24.877	25.042	29.9407
Barbara		34.823	34.344	32.848	35.7949
Lena		33.062	34.554	33.093	38.8073
Peppers	3	31.561	35.031	34.571	38.8606
Camera Man		31.435	32.639	31.612	35.7232

Fig.5. Coding results of the proposed coder at 2-bit quantization (Left: LP2, Right: The proposed coder)

IV. Conclusions

Throughout the paper, a new fuzzy predictive coding system is developed. The proposed system adopts a recently introduced fuzzy prediction scheme. This results in better prediction of edges with different orientations as well as smooth regions. In addition, the proposed coder adopts a novel fuzzy gradient-adaptive quantization scheme that switches between three well-designed nonuniform quantizers depending on the local gradient of the pixel to be coded. This, in turn, leads to reduced quantization error in edge and smooth regions and consequently higher quality. The proposed coding system possesses superior performance over its linear counterparts even at low bit quantization, which is exercisable both objectively and subjectively from the simulation results.

References

[1] N. S. Jayant, *Digital Coding of Waveforms*, Prentice Hall, Englewood Cliffs. NJ, 1984.

[2] R. C. Gonzalez and R. E. Woods, *Digital Image Processing*, Third Edition, Addison-Wesley, 1992.

[3] P. A . Maragos, R. W. Schafer and R. M. Mersereau,"Two dimensional linear prediction and its application to adaptive predictive coding of images," *IEEE Trans on ASSP*, vol. ASSP-32, pp. 1213-1239, December 1984.

[4] W. Zschunke,"DPCM picture coding with adaptive prediction,"*IEEE Trans on Comm*, vol. COM-25, pp. 1295-1302, November 1977.

[5] C. N. Manikopoulos,"Neural network approach to DPCM system design for image coding,"*Proc. Inst. Elect. Eng.-I,* vol. 139, no.5, pp. 501-507, October 1992.

[6] S. Chakravarti, T. P. Jung, S. C. Ahalt and A. K. Krishnamurthy,"Comparison of prediction methods for differential image processing applications,"in *Proc. IEEE Int. Conf. Syst. Eng.,* Dayton, OH, August 1991, pp. 210-213.

[7] J. Salo and Y. Neuvo,"A new two-dimensional predictor design for DPCM coding of video signals,"in *Signal Processing of HDTV*. North-Holland, 1988, pp. 207-211.

[8] B. Kosko, *Neural Networks and Fuzzy Systems,* Englewood Cliffs, NJ: Prentice Hall, 1992.

[9] S. G. Kong and B. Kosko,"Fuzzy sub-image classification in image sequence coding," in *Proc. Int. Conf. ASSP*, vol. III, March 1992, pp. 517-520.

[10] Said E. El-Khamy, Ibrahim A. Ghaleb and Noha A. El-Yamany,"A new fuzzy adaptive perceptual image coding system," in *Nineteenth National radio Science Conference NRSC 2002*, Alexandria, Egypt, March 2002.

[11] Noha A. El-Yamany, *New Applications of Fuzzy Logic Techniques for Image Segmentation, Edge Detection and Compression*, M.Sc. Thesis, Department of Electrical Engineering, Faculty of Engineering, Alexandria University, July 2002.

[12] B. Kosko, *Fuzzy Engineering*, Englewood Cliffs, NJ: Prentice hall, 1997.

[13] Tian-Hu Yu," A fuzzy logic-based predictor for predictive coding of images," *IEEE Trans. Fuzzy Syst.*, vol. 6, no.1, pp. 153-162, February 1998.

[14] Said E. El-Khamy, Ibrahim A. Ghaleb and Noha A. El-Yamany,"Fuzzy edge detection with minimum fuzzy entropy criterion," in *Eleventh Mediterranean Electrotechnical Conference MELECON 2002*, Cairo, Egypt, May 2002.

[15] Said E. El-Khamy, Ibrahim A. Ghaleb and Noha A. El-Yamany," Minimum Entropy based fuzzy edge detection," in *XXVIIth General Assembly URSI GA 2002,* Maastricht, the Netherlands, August 2002.

[16] Mansuo Zhao, Alan M. N. Fu and Hong Yan,"A technique for three-level thresholding based on probability partition and fuzzy 3-partition," *IEEE Trans on Fuzzy Syst,* vol. .9, no.3, pp. 469-479, June 2001.