Neuro-Statistical Vector Quantizer (NSVQ) Design in the Spatial Domain

*P. Arockia Jansi Rani[1] V. Sadasivam[2]

Abstract

Image compression is the process of reducing the number of bits required to represent an image. To enhance the performance of image compression, an efficient and intuitive technique is proposed based on a Neuro-Statistical model taking into account the psycho visual features in the spatial domain. First, Competitive Learning Algorithm is used to generate the codebook. Then, each code vector of the codebook is modelled by the Savitzky–Golay polynomial, for obtaining better perceptual fidelity of the reconstructed images. Simulation results show that the proposed Neuro-Statistical Vector Quantization technique provides better perceptual quality in terms of BSMI and PSNR ratio while maintaining compression ratio similar to that of the existing methods.

Keywords : Competitive Learning; codebook; Savitzky-Golay Polynomial; Vector quantization; Image compression.

* Corresponding author: Tel. +91-9487-99704; Fax: +91-462-2334363; Mobile: +91-9486-666667

[1] Lecturer, Department of Computer Science and Engineering, Manonmaniam Sundaranar University, Tirunelveli-627012, Tamil Nadu, India (email: jansi_msu@yahoo.co.in)

[2] Professor and Head, Department of Computer Science and Engineering, Manonmaniam Sundaranar University, Tirunelveil-627012, Tamil Nadu, India (email: sadamsu@yahoo.co.in)

1. Introduction

The fundamental goal of data compression is to reduce the bit rate for transmission or data storage while maintaining an acceptable fidelity or image quality. Compression is achieved by transforming the data, projecting it on a basis of functions, quantizing, and then encoding these quantized coefficients. This paper is concerned with the image compression system that uses a Vector quantization (VQ) task. Vector quantization provides a means of converting the input signal into bits in a manner that takes advantage of remaining inter and intra-band correlation. It is a relatively new coding technique that has aroused wide interest for researchers in computer science. When applied to image compression, VQ for images provides many attractive features in applications where high compression ratio is desired.

The key to VQ [14] based image compression is a good codebook. The method used most often for developing a codebook is the Linde – Buzo - Gray (LBG) algorithm [19]. It is a practical suboptimal clustering analysis algorithm. The Pair wise Nearest Neighbor algorithm [6] is a well-known method for the codebook construction in vector quantization, and for clustering of data sets. Research in neural networks [4] is a rapidly expanding area that has attracted the attention of scientists and engineers. A large variety of artificial neural network has been developed, based on a multitude of learning techniques and different topologies. Chang and Gray [13] introduced an online technique for VQ design using the stochastic gradient algorithm, which shall be considered a special case of the self-organizing map (SOM) algorithm

[16], and it is shown to perform slightly better than LBG. Nasrabadi and Feng [12] also used SOM for VQ design and demonstrated that performance is better than or similar to LBG. Yair et al. [5] used a combination of SOM and stochastic relaxation and obtained consistently better performance than LBG. Amerijckx et al. [2] used SOM algorithm to design a VQ for the coefficients of discrete cosine transform of the image blocks. The output of VQ encoder is further compressed using entropy coding. The reported performance is equivalent to or better than standard Joint Photographic Experts Group (JPEG) algorithm.

In this paper, a new technique called Neuro-Statistical Vector Quantization (NSVQ) is proposed for designing a vector quantizer for image compression using Competitive learning (CPL) Algorithm and Savitzky-Golay smoothing technique. An initial codebook is generated by training the Competitive learning Network with the training vectors. Then, to achieve better psycho-visual fidelity, each code vector is replaced with the best-fit coefficients generated by the Savitzky-Golay polynomial. This technique exploits the psycho-visual as well as statistical redundancies in the image data, enabling bit rate reduction. One unique feature of VQ is that the decoder is very simple to implement, which makes VQ attractive for single–encoder, multiple–decoder applications such as videotext and archiving.

This paper is organized as follows: The proposed scheme is presented in section II. The architecture of the artificial neural network used for the Vector Quantizer codebook design is discussed in the beginning. The remainder of the section formally defines the objective function upon which the proposed image-compression algorithm is based, and outlines the approach for minimizing this objective function. Section III describes the image-compression algorithm developed from the formulation of Section II. Simulation results of the algorithm on standard images are given in Section IV. Peak signal-to-noise ratio (PSNR) is one of the performance measures used for the evaluation of the VQ performance. Conclusion and future enhancement are given in section V.

II. Vector Quanitization

According to Shannon's rate distortion theory, better results are always obtained when vectors are encoded. Therefore, the present application uses vector quantization. Vector quantization has proven to be a powerful tool for digital image compression [3], [11]. The principle involves encoding a sequence of samples (vector) rather than encoding each sample individually. VQ procedure is as follows:

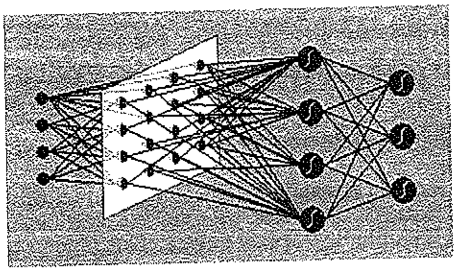
Let $C = \left\{C_i, \quad i = 1.......n\right\}$ be a codebook of size n, where $C_i = \left\{c_{i1}, c_{i2}, ...c_{ik}\right\}$ is a k-dimensional code vector. For a given input vector $X = (x_{i1}, x_{i2}, ...x_{ik})$, find the code vector $Y(X)$ which is almost similar or closest (in some sense) to X. The distance between X and a code vector C_i is denoted by $d(X, C_i)$. CPL Algorithm is used to generate the codebook.

A. The Competitive Learning (CPL) Algorithm

This algorithm reduces the dimensions of data using winner-take-all feature. The network consists of two layers of neurons: an *input layer* and a *competition layer*, as shown in Fig. 1. The weights of the connections from the input neurons to a single neuron in the competition layer are interpreted as a reference vector in the input space. Each neuron in the input layer is trained using competitive learning. When an input pattern is presented to the network, the neuron in the competition layer, for which the reference vector is closest to the input pattern, is determined. This neuron is called the winner neuron and it is the focal point of the weight changes. Given the winning node i, the weight update is given by,

$$w_k(\text{new}) = w_k(\text{old}) + \mu\delta(i,k)(x - w_k) \qquad (1)$$

Where μ is the learning parameter and $\delta(i,k)$ is called the neighborhood function that has value 1 when $i = k$ and falls off with the distance $|r_k - r_i|$ between units i and k in the output array. x is the input vector and w_k is the reference(weight) vector.



Input Layer   Competition Layer

Fig.1. Competitive Learning Network

Weights associated with output nodes other than the winning neuron do not change. The above rule drags the weight vector w_i of winninig neuron towards the input. This scheme when repeated many times usually preserves spatial order. In addition, the distribution of the weight vectors in the output resembles closely the distribution of the training vectors. Therefore, the weight vectors approximate the distribution of the training data as well as preserve topology of input data on the viewing plane. These features make this algorithm attractive for VQ design because if there are many similar vectors, unlike a clustering algorithm, which will place only one prototype, this network will generate more code vectors for the high-density region, consequently preserving finer details.

B. Savitzky – Golay polynomial for 2D Images

Once the CPL network is trained, the codebook can readily be designed using the weight vectors as the reconstruction vectors. Images can be encoded by finding out, for each image vector, the code vector with the least Euclidean distance. However, all spatial vector quantizers produce some checker- board pattern in the reconstructed image [18], [7], [10]. Even though the reconstructed image shows quite good PSNR, this effect often had some adverse psycho-visual impact. In the proposed method, a scheme of polynomial surface smoothing is used to modify the code vectors generated by CPL Algorithm, which reduces the blocking artifacts in the reconstructed image and improves the psycho-visual quality. In this case, the computational overhead occurs only at the codebook design stage only, and not during encoding or decoding of each image. Although, in computer graphics, polynomial surfaces serve as standard tools for modelling the surface of graphical objects [17], in image coding, their application is mostly restricted to image segmentation and representation of segmented patches. Low degree polynomials are used for local approximation of segmented patches [9] [8] while Bezier- Bernstein polynomials [15] and bi-cubic surfaces [1] are used for image compression.

In the proposed work, the Savitzky- Golay polynomial surfaces are used to refine the code vectors of the codebook. Surfaces of degree 2, 3 and 4 do not improve the performance significantly for test images. So, the Savitzky-Golay polynomial surfaces of order 5 are used throughout the work. The linear Savitzky-Golay polynomial fitting is a convolution of the image with the least squares fitting of a polynomial.

The fundamental idea is to fit a different polynomial to the data surrounding each data point. The smoothed points are computed by replacing each data point with the value of its fitted polynomial. Numerical derivatives come from computing the derivative of each fitted polynomial at each data point. While fitting polynomials for these purposes is obvious, the surprising part is that the polynomial coefficients can be computed with a linear filter. For smoothing, only one coefficient of the polynomial is needed, so the whole process of least squares fitting at every point becomes a simple process of applying the appropriate linear filter at every point.

To find the coefficients of the polynomials corresponding to the code vectors generated by the Competitive Learning network, the training vectors are divided into groups such that a training vector belongs to the i^{th} group is mapped to the i^{th} code vector. The smoothed points are found by replacing each code vector with the value of its fitted polynomial. The process of Savitzky – Golay polynomial fitting is to find the coefficients of the polynomial that are linear with respect to the data values. Therefore, the problem is reduced to find the coefficients for fictitious data and applying this linear filter over the complete data. For example, if the size of the smoothing window is given as $n \times n$ where n is odd, and the order of the polynomial to fit is k, where $n > k+1$, the polynomial coefficient corresponding to each pixel is computed as follows:

$$d(i) = f(x_i, y_i) = a_{00} + a_{10}x_i + a_{01}y_i + a_{20}x_i^2 + a_{11}x_i y_i + a_{02}y_i^2 + \ldots + a_{0k}y_i^k \qquad (2)$$

Where, $k = 5; n = 7$, the coefficient of (x_i, y_i) is a and (x_i, y_i) is the pixel coordinate of $d(i)$; is the pixel value. Next step is to fit a polynomial of type in Eq (2), to the data. By solving the least squares, the polynomial coefficients can be found. Eq (3) is used to solve the least squares.

$$d = Xa \qquad (3)$$

Where, is defined by the following matrix:matrix:

$$\begin{matrix} 1 & x_0 & y_0 & x_0^2 & x_0y_0 & y_0^2 & x_0^3 & x_0^2y_0 & x_0y_0^2 & y_0^3 & \ldots y_0^k \\ 1 & x_1 & y_1 & x_1^2 & x_1y_1 & y_1^2 & x_1^3 & x_1^2y_1 & x_1y_1^2 & y_1^3 & \ldots y_1^k \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 1 & x_{n^2} & y_{n^2} & x_{n^2}^2 & x_{n^2}y_{n^2} & y_{n^2}^2 & x_{n^2}^3 & x_{n^2}^2y_{n^2} & x_{n^2}y_{n^2}^2 & y_{n^2}^3 & \ldots y_{n^2}k \end{matrix} \qquad (4)$$

a is the vector of polynomial coefficients given by

$$a = (a_{00}\ a_{10}\ a_{01}\ a_{20}\ a_{11}\ a_{02}\ a_{30}\ a_{21}\ a_{03} \ldots a_{0k})^T \qquad (5)$$

and the column vectorrepresents block image data, i.e. data, i.e. $d = (d(0)\ d(1) \ldots d(n^2))^T$ (6)

Equation (7) simply reproduces the polynomial for each pixel in the image patch.

Rewriting Eq (3) gives us,

$$a = (X^T X)^{-1} X^T d \qquad (7)$$

Where, $C = (X^T X)^{-1} X^T$ is the pseudo – inverse of X,

and it is independent of the image data. Each polynomial coefficient is computed as the inner product of one row of and the column of pixel values. This is the surprising part about Savitzky–Golay model: the polynomial coefficients are computed using a linear filter on the data. Just as one can reassemble d back into a rectangular patch of pixels, one can also assemble each row of into the same size rectangle to get a traditional looking image filter. The advantage of the Savitzky–Golay model is its ability to preserve higher moments in the data and thus reduce smoothing on peak heights. The coefficient vector is calculated for all code vectors obtained from competitive Learning network. Once the coefficient vectors are available, the codebook can be designed by reconstructing the code vectors using them. The effectiveness of this method is tested using several images.

III. The Proposed Coding Producere

In the proposed system, the codebook whose size is equal to one third of the size of the input image is initialized randomly. This initial codebook trained using CPL Algorithm. The trained code vectors are statistically smoothened using fifth order Savitzky–Golay polynomial. The input image is now subject to vector quantization that uses the proposed codebook to reduce psycho-visual redundancy. The compressed image is decompressed using code vector reassignment procedure to reconstruct the image. Fig.2a shows 256 x 256 Baboon input image. Fig.2b shows the respective reconstructed images using the proposed NSVQ codebook design while Figs.2c and 2d depict the same using CPL Algorithm's codebook design and the Linde – Buzo - Gray (LBG) algorithm's codebook design respectively. It is evident that the proposed work not only increases the PSNR for this image, but also reduces blocking effect thereby improving the psycho-visual quality.

IV Result Analysis

Experimental simulations were performed to compare the performance of the proposed technique with that of the generalized VQ techniques. The performance of the proposed technique is measured using Boundary Smoothness Mismatch Index (BSMI) measurements that can access the preservation of psycho visual quality with respect to the blocking effect. The *BSMI* [Eq (8)] measures the smoothness per pixel across the block boundary due to vector quantization.

$$BSMI = \frac{\sum_{(i,j) \in P_B} X_{ij} L(i,j)^2}{P_B} \qquad (8)$$

L (i, j) is the mask where (i, j) denotes the coordinate of the pixel on which the mask is applied. The mask is shown in Fig 3. denotes the set of pixels at the block boundaries in an image respectively. BSMI ratio is the ratio of input image's BSMI index value to the reconstructed image's index value. For perfect reconstruction, this ratio is one. Another quantitative measure is the Peak Signal to Noise Ratio (PSNR). PSNR measures are estimates of the quality of a reconstructed image compared with an original image. The formula is given in [Eq.(9)].

PSNR=10*log10 ((256^2)/MSE) (9)

Where, MSE is the mean squared error.

The effectiveness of the proposed work is tested for test images by varying the order of the polynomial used in the codebook design. The results are tabulated in Table 1. The PSNR increases with the increase in the polynomial order until fifth order. The PSNR value decreases for polynomials of order greater than 5. Therefore, polynomial of order 5 is used in the proposed work.

Table 2 shows the result of the proposed work for test images of varying file sizes. It is clear that the algorithm performs better as the image file size increases. Moreover, since the computation time increases with the increase in file size 256 x 256 size images are used for analysis of the work.

The performance of the proposed work (NSVQ) is compared with existing CPL and LBG image compression algorithms. Table 3 shows the result of comparison. It is practically proved that the proposed work yields superior reconstructed psycho-visual image quality than the existing techniques in terms of better PSNR ratio while maintaining same compression ratio. The proposed technique gives compression ratio to about 3:1, above 66% space saving and compression rate in the order of 2.6 bits/ pixel. In addition, the BSMI ratio is roughly nearer to 1 and PSNR values around 40db for 512 x 512 images (Table 2) implies good quality of the reconstructed images.

V Conclusion

In this correspondence, a new Image Compression technique using Neuro – Savitziky – Galoy polynomial based vector quantization has been presented. The proposed NSVQ technique provides superior compression performance. Simulation results show that the Savitzky Galoy codebooks produce reconstructed images with better psycho visual quality with respect to the blocking effect and good compression ratio. The algorithm may be modified to compress multimedia data also.

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Authors Biography

Arockia Jansi Rani .P. received the B.E. Degree in Electronics and Communication Engineering in 1996 and the M.E. degree in Computer Science and Engineering (with distinction) in 2002, both from Manonmaniam Sundaranar University, TamilNadu, India. In 1997, she joined the faculty of the Department of Electronics and Communication Engineering, Karunya Institute of Technology, TamilNadu and worked for a period of two years. In December 2003, she joined Manonmaniam Sundaranar University, TamilNadu, where she is currently working as Associate Professor in the Department of Computer Science and Engineering. Her research interests include image processing, Neural Networks, Data Mining, Image Security, Wavelets and Vector Quantization. [Email-id: jansi_msu@yahoo.co.in]

Dr.V.Sadasivam received the B.E. Degree in Electrical Engineering in 1973 from Madurai University and the M.Sc.(Engg) degree in Power Systems in1975, from Madras University, TamilNadu, India.. He received the Ph.D. degree in Computer science and Engineering from Anna University, TamilNadu, India, in 1993. He has 36 years of teaching experience and he is currently Professor and Head of the Department of Computer Science and Engineering in Manonmaniam Sundaranar University. His research interests include image processing, Artificial Intelligence, Neural Networks and Expert Systems. [Email-id: sadamsu@yahoo.co.in]

Figure Captions:

Fig.1. Competitive Learning Network

Fig.2. Input image and respective reconstructed images obtained using the proposed NSVQ, CPL, and LBG methods (Compression Ratio 2.9:1)

Fig.2a. 256 x 256 input image

Fig.2b. Reconstructed Image using the proposed method

Fig.2c. Reconstructed Image using CPL method

Fig.2d. Reconstructed Image using LBG method

Fig.3.The Mask

Table Captions:

Table 1: Performance analysis of the proposed work for various degrees of polynomial surfaces for a compression ratio of 2.9:1

Table 2: Analysis of the proposed work for Zelta image with various file sizes for a compression ratio of 2.9:1

Table 3: A Comparative Analysis of the Performance of the Proposed Work with Existing Algorithms for a compression ratio of 1: 2.9

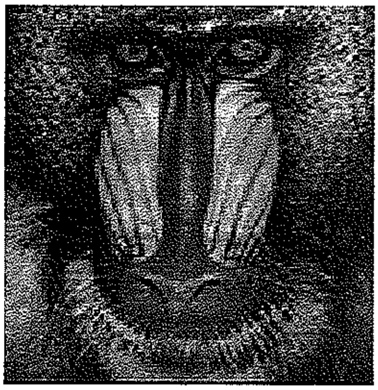

Fig.2a. 256 x 256 input image

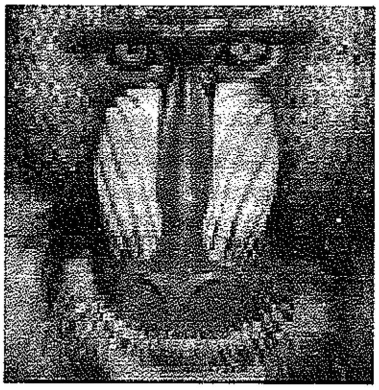

Fig 2b Reconstructed Image using the proposed method

Fig 2c Reconstructed Image using CPL method

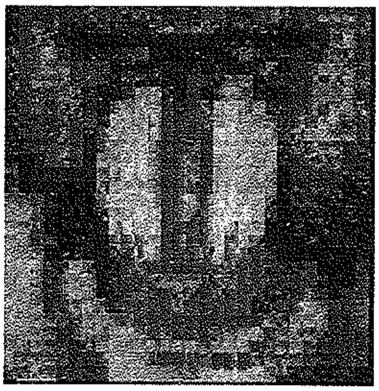

Fig 2d Reconstructed Image using LBG method

Fig.2. Input image and respective reconstructed images obtained using the proposed NSVQ, CPL, and LBG methods (Compression Ratio 2.9:1)

0	-1	0
-1	4	-1
0	-1	0

Fig.3 The Mask

Table 1: Performance analysis of the proposed work for various degrees of polynomial surfaces for a compression ratio of 2.9:1

S.No	Image (size:256 x 256)	Polynomial order	MSE	PSNR (db)	BSMI Ratio
1	Baboon	2	139.06	26.65	2.11
		3	140.35	26.65	2.12
		4	103.25	27.94	1.71
		5	103.21	27.99	1.69
		6	143.64	26.55	2.00
2	Lighthouse	2	330.06	22.94	1.88
		3	329.83	22.94	1.87
		4	235.27	24.41	1.68
		5	235.27	24.41	1.68
		6	238.83	24.34	2.14
3	Boy	2	1495.9	16.38	2.05
		3	1495.9	16.38	2.05
		4	118.19	27.40	1.08
		5	117.86	27.42	1.08
		6	119.4	27.35	2.00

Table 2: Analysis of the proposed work for Zelta image with various file sizes for a compression ratio of 2.9:1

S.No	Zelta Image Size	MSE	PSNR (db)	BSMI Ratio	Computation Time (sec)
1	64 x 64	413.22	21.96	2.14	0.51
2	128 x 128	229.66	24.52	1.83	1.51
3	256 x 256	127.03	27.09	1.58	7.26
4	512 x 512	6.65	39.90	1.00	55.22

Table 3: A Comparative Analysis of the Performance of the Proposed Work with Existing Algorithms for a compression ratio of 1: 2.9

S.No	Image	Algorithm	MSE	PSNR(db)
1	Baboon	NSVQ	103.21	27.99
		CPL	143.64	26.55
		LBG	438.22	21.71
2	Zelta	NSVQ	127.03	27.09
		CPL	212.04	24.86
		LBG	384.60	22.28
3	Lighthouse	NSVQ	235.62	24.41
		CPL	238.84	24.34
		LBG	570.52	20.56
4	Bird	NSVQ	81.61	29.01
		CPL	176.05	25.67
		LBG	210.64	24.89
5	Boat	NSVQ	300.00	23.36
		CPL	487.89	21.24
		LBG	644.50	20.03
6	Boy	NSVQ	117.86	27.42
		CPL	337.42	22.84
		LBG	513.48	21.02
7	Lion	NSVQ	97.92	28.22
		CPL	132.72	26.90
		LBG	403.78	22.06