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CODEVECTOR MODELING USING LOCAL POLYNOMIAL REGRESSION FOR VECTOR QUANTIZATION BASED IMAGE COMPRESSION

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Abstract
Image compression is very important in reducing the costs of data storage and transmission in relatively slow channels. In this paper, a still image compression scheme driven by Self-Organizing Map with polynomial regression modeling and entropy coding, employed within the wavelet framework is presented. The image compressibility and interpretability are improved by incorporating noise reduction into the compression scheme. The implementation begins with the classical wavelet decomposition, quantization followed by Huffman encoder. The codebook for the quantization process is designed using an unsupervised learning algorithm and further modified using polynomial regression to control the amount of noise reduction. Simulation results show that the proposed method reduces bit rate significantly and provides better perceptual quality than earlier methods.

Keywords:
Wavelet Transform, Savitzky-Golay Polynomial, Vector quantization and Huffman Coding

1. INTRODUCTION

Wavelet coders for images have been implemented both with Scalar Quantization [1] and Vector Quantization [2]. The process of wavelet decomposition has localization properties in both the time and the frequency domains. In wavelet based image coders [3], [4] the image is decomposed into several sub images prior to the encoding stage. As a result it is usually more efficient to encode a transformed image than to directly encode the pixels. In this paper, the use of Statistical-Neural net based vector quantizer with discrete wavelet transform has been presented. Vector quantization (VQ) provides a means of converting the decomposed 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 [5] when applied to image coding. VQ provides many attractive features in applications where high compression ratios are desired. Linde, Buzo and Gray known as the LBG algorithm [6] is the well known iterative technique for the codebook design phase in the VQ process. This algorithm is conceptually simple but involves computational complexity. The algorithm requires an initial codebook. The performance of this algorithm is based on the selection of this initial code book. To overcome this problem, Jeyanthi et.al.[7] suggests a Modified Generalized Lloyd algorithm in this paper. This algorithm identifies and replaces the unused code vector with a training vector. This training vector has the highest distortion in the Voronoi region of training vectors. Chun-Wei Tsai et.al.[8] presents an Enhanced Generalized Lloyd Algorithm (GLA) using Pattern Reduction. This algorithm reduces the computational complexity using the pattern reduction approach. The quality of the reconstructed image is not affected because the size of the codebook is not reduced. This algorithm reduces the computation time from 29.45% up to about 77.98% as compared to those of the standard GLA and other fast GLA-based algorithms. The generalized K-means algorithm takes very long time to converge. Kekre's Fast Codebook Generation algorithm [9] reduces the convergence time in order to optimize the vector quantized codebook. The algorithm generates unique minima for each code vector. As a result it takes less number of iterations as compared to LBG codebook.

Neural networks seem to serve the purpose of initializing a code book for the VQ process. Naserbadi and Feng [10] proposed a Self-Organizing Map (SOM) based VQ algorithm. This algorithm performs better than the early VQ techniques. A unified approach [11] that combines SOM and stochastic gradient techniques promises good quality reconstructed images. Arijit [12] uses Self-Organizing Map (SOM) to construct a generic codebook. Further cubic surface fitting technique is applied on the code vectors of this codebook in order to enhance the codebook. The aim of generic codebook design method is to reduce the compression bit rate. It is reported that the algorithm performs better in the spatial domain than in the transform domain. Amerijckx et. al. [13] applied SOM based VQ technique in a discrete cosine transform domain. This method improves the compression ratio significantly. Kwang-Back Kim et.al. [14] presents an Enhanced Self-Organizing Map algorithm for medical image compression in the wavelet domain. With this approach the weight updation is done in two ways: based on the frequency of the winner node and based on the ratio of the present change in weight to the previous change in weight. This enhanced SOM algorithm is used in the codebook generation phase of VQ. In VQ searching the codebook, to find the best matching code vector for an input vector, is a time consuming problem. To reduce this computational overhead a fast codebook searching method for a Self-Organizing Map (SOM) based vector quantizer [15] is proposed in this paper. A non-exhaustive search method is used to find a matching code vector from the code book for an input vector instead of the exhaustive search in a large codebook with high dimensional vectors.

In this paper, a scheme for designing a vector quantizer for image compression using Kohonon's SOM algorithm and Savitzky-Golay polynomial modeling is proposed. An initial codebook is generated by training an SOM with the training vectors. Then, to achieve better psycho-visual fidelity, each code vector is replaced with minimum distortion polynomial coefficient generated by statistical modeling process. The set of code indices produced by the quantizer is further compressed using Huffman encoder. This technique exploits the psycho-visual as well as statistical redundancies in the image data, enabling bit rate reduction.

The paper is organized as follows: The proposed scheme is presented in section 2. Section 2.1 begins by the algorithm of SOM used for the Vector Quantizer codebook design. Section

2.2 formally defines the objective function upon which this image coding algorithm is based, and outlines the proposed approach for minimizing this objective function. Section 3 describes the image coding algorithm developed from the formulation of Section 2. Finally, Section 4 Presents simulation results of the algorithm on standard images. Peak Signal-to-Noise Ratio (PSNR) is used as one of the performance measures of the VQ. Conclusion and future enhancement are given in section 5.

2. VECTOR QUANITIZATION

VQ is an effective technique for performing image compression. VQ is always better than scalar quantization because it fully exploits the correlation between components within the vector. Also, its decoding procedure is very simple since it only consists of table lookups. This paper uses VQ to encode the wavelet coefficients. The principle of VQ is defined as follows:

Let $C = \{C_i,\ i = 1 \ldots\ldots\ldots\ldots n\}$ be a codebook of size n, where $C_i = \{c_{i1}, c_{i2}, \ldots\ldots c_{ik}\}$ is a k – dimensional code vector. For a given input vector $x = (x_{i1}, x_{i2}, \ldots\ldots x_{ik})$, 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 $d(x, C_i)$.

2.1 SELF-ORGANIZING MAP (SOM)

Design of an initial code book is a crucial step in the VQ process. This paper employs SOM for the initial codebook design. SOM is a fully interconnected unsupervised Neural Network. The network consists of two layers namely the input layer and the output layer. Competitive learning rule is used to train the network. The input vector (transform coefficients) is presented at the input layer and propagated to the competitive layer. Euclidean distance measure is used to determine the neuron in the competitive layer to which the input vector is the closest. This neuron is called the winning neuron or the firing neuron. The weight values associated with this neuron and its neighbors are updated using the competitive learning rule.

Algorithm for Kohonon's Self Organizing Map:

- Assume output nodes are connected in an array (usually 1 or 2 dimensional)
- Assume that the network is fully connected – all nodes in input layer are connected to all nodes in output layer.
- Use the competitive learning algorithm as follows:

1. Randomly choose an input vector $x = (x_{i1}, x_{i2}, \ldots\ldots x_{ik})$
2. Determine the "winning" output node i with the minimum distance measure min(d_i).

$$d_i = \sum_{j=1}^{k} \left(x_j - w_j\right)^2 \tag{1}$$

3. Given the winning node i, determine all neurons within a certain neighborhood $N_{i*}(d)$ of the winning neuron. The neighborhood contains the indices for all of the neurons that lie within a radius d of the winning neuron i given by, $N_{i*}(d) = \{j, d_{ij} \le d\}$ (2)

4. Update all such neurons $i \in N_{i*}(d)$ as follows:

$$w_k(\text{new}) = w_k(\text{old}) + \mu\delta(i,k)(x\text{-}w_k) \tag{3}$$

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.

This procedure is repeated by changing the learning rate parameter. This process brings the weight vectors closer to the distribution of the input vector. Also, input topology is preserved. 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, SOM will generate more code vectors for the high-density region. Consequently, finer details will be better preserved.

2.2 SAVITZKY – GOLAY POLYNOMIAL FOR 2-D IMAGES

Once SOM 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. Even though the reconstructed image shows quite good PSNR, this effect often had some adverse psycho-visual impact. The proposed method adopts a scheme of polynomial rendering to modify the code vectors generated by SOM algorithm that reduces the checker-board pattern in the reconstructed image and improves its psycho-visual quality. The computational overhead occurs only at the codebook design stage and not during encoding or decoding of each image.

The use of linear Savitzky-Golay polynomial modeling proposed in this work is a convolution of the image with the least-squares fitting of a polynomial. The process of Savitzky–Golay is to find the coefficients of the polynomial which are linear with respect to the data values. Therefore the problem is reduced in finding the coefficients for fictitious data and applying this linear filter over the complete data. The size of the smoothing window is given as n x n where n is odd, and the order of the polynomial to fit is k, where $n > k + 1$; $k = 4$, $n = 7$; 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. The polynomial given in Eqn. (4) is used to fit the data.

$$d(i) = f(x_i, y_i) = a_{00} + a_{10}x_i + a_{01}y_i + a_{20}x_i^2 + a_{11}x_iy_i + a_{02}y_i^2 + \ldots\ldots + a_{0k}y_i^k \tag{4}$$

By solving the least squares, the polynomial coefficients can be found. Eqn. (5) is used to solve the least squares.

$$d = Xa \tag{5}$$

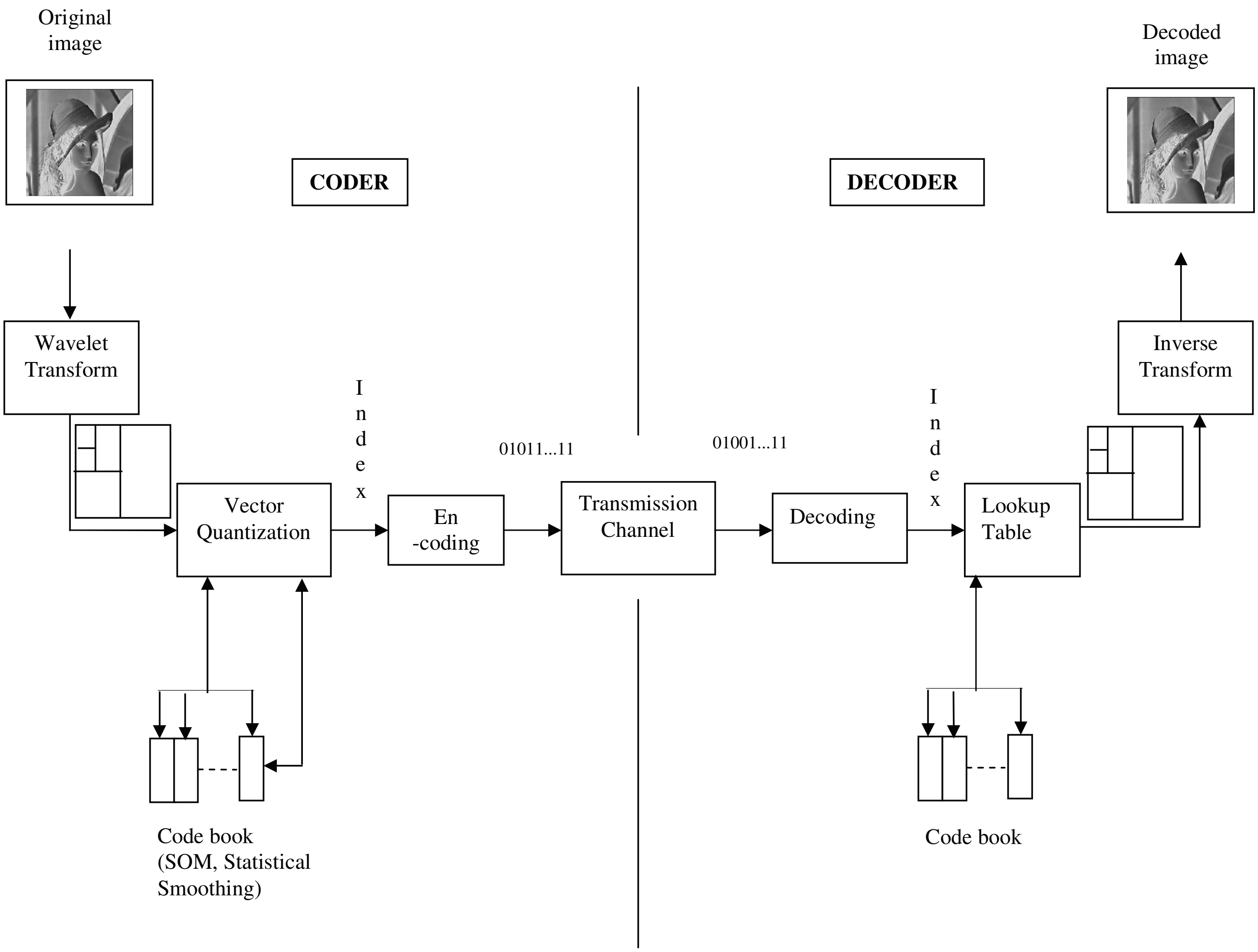


Fig.1. The Proposed Still Image Compression System

Where, X is defined by the following matrix:

$$\begin{bmatrix} 1 & x_0 & y_0 & x_0^2 & x_0y_0 & y_0^2 & x_0^3 & x_0^2y_0 & x_0y_0^2 & y_0^3 & \ldots y_0^k \\ 1 & x_1 & y_1 & x_1^2 & x_1y_1 & y_1^2 & x_1^3 & x_1^2y_1 & x_1y_1^2 & y_1^3 & \ldots y_1^k \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 1 & x_{n^2} & y_{n^2} & x_{n^2}^2 & x_{n^2}y_{n^2} & y_{n^2}^2 & x_{n^2}^3 & x_{n^2}^2y_{n^2} & x_{n^2}y_{n^2}^2 & y_{n^2}^3 & \ldots y_{n^2}k \end{bmatrix} \quad (6)$$

a is the vector of polynomial coefficients given by Eqn.(7)

$$a = (a_{00}\, a_{10}\, a_{01}\, a_{20}\, a_{11}\, a_{02}\, a_{30}\, a_{21}\, a_{03} \ldots\ldots a_{0k})^T \quad (7)$$

and the column vector d represents $n\ x\ n$ block image data, (i.e.)

$$d = (d(0)\ d(1) \ldots\ldots d(n^2))^T \quad (8)$$

Rewriting Eqn. (5) gives us,

$$a = (X^T X)^{1} X^T d \quad (9)$$

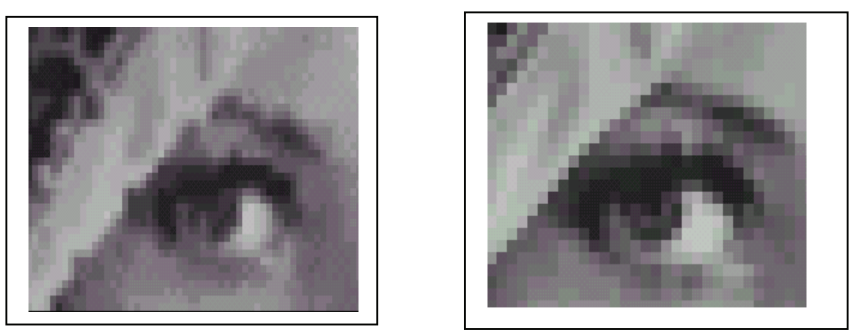
The term $(X^T X)^{1} X^T$ is the pseudo inverse of X.

Polynomial coefficients are computed using Eqn. (9) and the image data covered by the window are replaced with these coefficients. This procedure computes the coefficient vector a for all code vectors obtained from SOM. The advantage of the Savitzky–Golay model is its ability to preserve higher moments in the data and thus reduce smoothing on peak heights. Once the coefficient vector is available, the codebook can be designed by reconstructing the code vectors. The effectiveness of this method is tested using several images. Although the quality improvement in terms of PSNR appears marginal, significant improvement in terms psycho-visual quality is observed consistently.

Fig.2. Original Lena image of size 256x256

(a) (b)

Fig.3. Comparison of the Proposed Work based on Neuro-Statistical Modeling and The Generalized SOM based Image Coder for Lena Image. (a) Generalized SOM method (b) Proposed method



(a) (b)

Fig.4. (a) Enlarged right eye portion of Lena Image shown in Fig. 3(a).
(b) Enlarged right eye portion of Lena Image shown in Fig. 3(b).

3. THE PROPOSED CODING PROCEDURE

An efficient image coding scheme (Fig.1.) is introduced by the authors. In the first step, a bi-orthogonal wavelet transform with multi-resolution scale factor of 2 is preferred to the usual dyadic wavelet transform since it is more isotropic and yields fewer artifacts. In the second step, the code book is created using the proposed neuro-statistical approach. An index is assigned to each code vector in this codebook. Then, the transformed coefficients are compared with the code vectors in the codebook. The indices of the minimum distortion code vectors corresponding to each input vector are sent to the encoding stage. Huffman encoder is used to encode the quantized output.

4. RESULT ANALYSIS

Fig.2. shows the original Lena image. Figure 3(a). Shows the reconstructed Lena image using SOM codebook while Figure 3(b), depicts the same obtained using the proposed codebook. The images used are sampled 256 x 256 black and white images.

The intensity of each pixel is coded on 256 gray levels (8bpp). It is evident from the images shown in Figure 4. that, the image obtained by the proposed algorithm is quite superior to the resultant image of the existing algorithm in terms of psycho visual quality. Figure 4 shows the enlarged right eye portion of the images shown in Figures 3(a) and (b).

The choice of a suitable polynomial order for the proposed work is based on the observations tabulated in Table1. It shall be noted that the bit rate is not influenced by the application of the modeling process. However, the PSNR increases with the increase in the polynomial order until fourth order and the value decreases for polynomials of order greater than 5. Therefore, fourth order polynomial is used in the proposed work. Further, the effectiveness of the proposed algorithm is tested with various images of same size and different sizes. It shall be observed from Table 2. that the quality of the reconstructed image is improved as the size of the original image is increased. Also the Bit Rate decreases with the increase in image size. But the computation time is increased gradually as the image size is varied from 64 x 64 to 256 x 256. And for the 512 x512 size images the computation time is increased drastically which is an undesirable characteristic. Therefore images of size 256 x 256 are used for the analysis of the proposed work. Experimental simulations were performed to compare the performance of the proposed work with that of the generalized SOM based VQ technique.

Table.1. The impact of Polynomial modeling on various image compression measures for Woman-dark hair image

Sl. No.	Polynomial Order	MSE	PSNR(db)	Ratio	Space (%)	Rate (bits/pixel)
1	2	876.29	18.70	12.73	92.14	1.25
2	3	175.04	25.69	12.85	92.22	1.24
3	4	117.90	27.41	12.85	92.22	1.24
4	5	120.75	27.31	12.84	92.21	1.24
5	6	131.14	26.95	12.82	92.20	1.24

Table.2. Performance of the proposed work for various sizes of Russian Lady Image

Image Size	MSE	PSNR(db)	Ratio	Space (%)	Rate (bits/pixel)	Computation Time (Sec)
64 x 64	314.25	23.15	4.88	79.54	3.27	0.24
128 x128	241.98	24.29	9.51	89.48	1.68	0.36
256 x 256	179.67	25.58	13.19	92.41	1.21	0.84
512 x 512	125.77	27.13	14.84	93.26	1.07	3.93

Table.3. Analysis of the proposed work to illustrate the impact of polynomial modeling using various test images

Sl. No.	Image	Algorithm	MSE	PSNR(db)	Ratio	Space (%)	Rate (bits/pixel)
1	Tracy girl	Proposed	148.79	26.40	14.06	92.89	1.13
		Wavelet-SOM	393.78	22.17	15.07	93.36	1.06
2	Rose	Proposed	361.84	22.54	12.38	91.92	1.29
		Wavelet-SOM	422.09	21.87	12.42	91.95	1.28
3	Lena	Proposed	207.85	24.95	12.88	92.24	1.24
		Wavelet-SOM	213.48	24.83	12.89	92.24	1.24
4	Woman-Dark hair	Proposed	117.90	27.41	12.85	92.22	1.24
		Wavelet-SOM	131.14	26.95	12.82	92.20	1.24
5	Bird	Proposed	92.74	28.45	13.16	92.40	1.21
		Wavelet-SOM	110.02	27.71	13.43	92.55	1.19
6	Boat	Proposed	269.77	23.82	13.23	92.44	1.20
		Wavelet-SOM	282.79	23.61	13.21	92.43	1.21
7	Russian Lady	Proposed	179.67	25.58	13.19	92.41	1.21
		Wavelet-SOM	183.00	25.50	13.18	92.41	1.21

Table.4. Performance comparison of the proposed work with existing methods for the 256 x 256 size Zelta image

Sl. No.	Algorithm	MSE	PSNR(db)	Ratio	Space (%)	Rate (bits/pixel)
1	Proposed	110.02	27.71	13.43	92.55	1.19
2	Wavelet-SOM	117.21	27.24	13.41	92.54	1.19
3	Wavelet-CPL	161.01	26.06	12.75	92.15	1.26
4	Wavelet-Kmeans	229.05	24.53	11.96	91.64	1.33

Table.3. shows the overall performance of the proposed work for various test images. The proposed work gives reconstructed images with 20-30db quality factor at a compression rate of 1bpp. In addition, it is inferred that the proposed work results in a 2db gain in quality in comparison with the generalized VQ technique. The performance of the proposed work is compared with the existing wavelet based SOM, CPL and Kmeans Coders. The observations for the Zelta image are tabulated in Table 4. The proposed work outperforms the existing image coders in terms of good reconstructed image quality.

5. CONCLUSIONS

In this correspondence, a new wavelet based coding technique using Neuro-Savitziky-Galoy polynomial modeling based vector quantization has been presented. The proposed technique exploits superior coding performance at low bit rate. Simulation results show that the Savitzky-Galoy codebooks produce images with better psycho visual quality with respect to the blocking effect.

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