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IMAGE COMPRESSION USING SELF-ORGANIZING FEATURE MAP AND WAVELET TRANSFORMATION

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Abstract

In this paper, a new method of vector quantizer design for image compression using Generic codebook and wavelet transformation is proposed. In the proposed method, Self Organizing Feature Map (SOFM) is used for initial codebook generation. A new scheme of wavelet transformation based Vector Quantization (VQ) technique is proposed to replace the SOFM code vectors by VQ code vectors. The proposed wavelet transform is used to generate wavelet coefficients which are then converted into VQ code vectors. Discrete Cosine Transformation based vector quantization technique is proposed in the existing image compression algorithms with low quality images with greater amount of information loss. Hence to increase the psycho visual quality of the reconstructed image wavelet transformation based vector quantization technique is proposed in this paper. Performance of the proposed work is tested with varying codebook size and various training images. Experimental results show that the reconstructed images obtained by the proposed method are of good quality with better compression ratio and higher Peak Signal–to–Noise Ratio.

Keywords:

Vector Quantization, Self-Organizing Feature Map, Image Compression, Wavelet Transformations

1. INTRODUCTION

Image Compression has been the major area of research due to the increasing demand for visual communications in entertainment, medical and business applications over the existing band limited channels. In this paper, a new novel method for image compression by vector quantization [7] of the image using self organizing map [10] and wavelet transformation is proposed. A vector quantizer is a structure that implements many to one mapping of data from one domain to another. VQ has been used for image compression by many researchers. The most commonly used algorithm is the Generalized Lloyd Algorithm (GLA) [4] also called K–means algorithm. VQ is used for replacing the SOFM code vectors in the initial codebook by the VQ code vectors obtained through wavelet based vector quantization technique. The recent interest in Artificial Neural Networks (ANNs) motivated a large number of researchers in the field of VQ based Discrete Cosine Transform (DCT) [18] and Discrete Wavelet Transform (DWT) [3] methods. The above methods are based on a three–layer linear perceptron in which the first two layers can acts as an encoder and the third layer (output layer) acts as a decoder. Typically, the network is trained by a set of small sized image blocks (say 8×8 or 4×4).Self–Organizing Feature Map based neural network technique is used for initial codebook generation. SOFM is a clustering technique having several desirable features and consequently it has attracted the attention of researchers in the field of vector quantization [15] [20]. The learning scheme of self-organizing feature map is based on Least Mean Square (LMS) [1] algorithm. In LMS algorithm the weights of the neurons are modified 'On the fly' for each input vector as opposed to the batch update scheme of GLA. SOFM will generate more code vectors for the high density region. The wavelet coefficients obtained through wavelet decomposition are converted into VQ code vectors by vector quantization technique. The term wavelet [9] was introduced in 1984. Discrete wavelet transform can be used in image compression for sub-band decomposition. Wavelet based coding provides substantial improvement in picture quality at higher compression ratios. Wavelet transforms have been proven to be an extremely powerful tool for image coding [5] [19]. Wavelet coding schemes at higher compression avoid blocking artifacts and yields high quality reconstructed image.

1.1 MOTIVATION AND JUSTIFICATION OF THE PROPOSED WORK

Shapiro [17] first introduced the notation of embedded coding called as Embedded Zero tree Wavelet coding (EZW) which yields output of low psycho visual quality image. Lewis and Knowles [11] constructed a wavelet function which uses the piecewise constant function. The wavelet function used by Lewis failed to produce image without blocking effects. Daubechies [6] introduced a family of compactly supported orthogonal wavelet systems with fixed regularity. The wavelet method proposed by Daubechies yields output with PSNR value ranges from 22 dB to 36 dB for various wavelet coefficients. Mallat [14] proposed the theory of multi resolution wavelet analysis known as Mallat algorithm which reduces the dimensionality with higher computational load. Pavlidis [16] introduced the scheme of polynomial surface fitting for modifying the code vectors generated by SOFM which failed to reduce the blockiness and dimensionality of the reconstructed image. Lloyd [13] constructed an algorithm for incremental update through competitive learning with higher loss of data. Therefore to overcome the above mentioned drawbacks, a new method of compressing the image using wavelet transformation and self organizing feature map is proposed.

1.2 OUTLINE OF THE PROPOSED WORK

In this paper, Vector Quantizer based compression using SOFM and wavelet transformation is proposed. Fig.1 shows the block diagram of the proposed work. Initially SOFM is trained with the randomly initialized weight vectors and generate an initial codebook as shown in dotted lines in Fig.1. To increase the psychovisual quality, each SOFM code vectors in the initial codebook is replaced with VQ code vectors. The wavelet coefficients are obtained by applying wavelet transform on the image. The image is then decomposed into four sub bands namely LL, LH, HL and HH by using one level operation [8].LL, LH and HL are termed as low-frequencies bands and HH band is called as high frequency band. Low frequencies band consists of the special feature of the image and hence these bands are collected together to form the wavelet coefficients. Then the coefficients are quantized using vector quantization and are converted into VQ code vectors. The encoder finds the closest VQ code vectors by finding the closest distance between the weight vectors and VQ input vectors. Once the closest VQ code vectors are found, the index of the VQ code vectors are passed to the decoder side through a transmission channel. In the decoder, the index of the VQ code vectors are replaced with the associated code vectors obtained from the encoder and a codebook is generated. By applying Vector Re Quantization (RVQ) techniques, the VQ code vectors are converted into blocks. Then by using block reconstruction technique the blocks are decomposed into wavelet coefficients and are obtained in four sub bands. With the help of Inverse Wavelet Transform (IWT) the coefficients at each band is up sampled. The low pass images and high pass images are filtered by low pass filter and high pass filter respectively. The output of these two filters are summed together to produce the corresponding Reconstructed Image (RI).

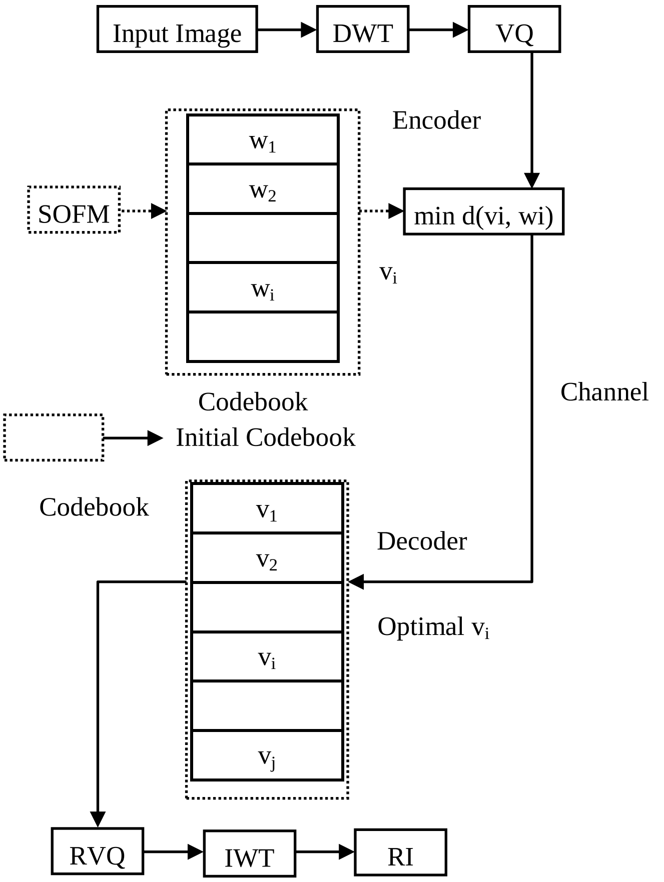

Fig.1. Block Diagram of the Proposed Work

1.3 ORGANIZATION OF THE PAPER

This paper is organized as follows. Section 2 describes about the methodology of the proposed work. Experiments and Results are carried out in section 3. Section 4 explains about the analysis work. Section 5 deals with the conclusion and section 6 discuss about the future work of the proposed work.

2. METHODOLOGY

The method for compressing the gray scale images using Self Organizing Feature Map and Wavelet Transformation is discussed below.

2.1 INITIAL CODEBOOK GENERATION USING SOFM

The architecture of SOFM is shown in Fig.2. SOFM architecture for vector quantization depends on the size of the codebook [2]. The codebook size is chosen to be M. A Self-Organizing Feature Map consists of components called nodes and a position in the map space [12]. The input layer consists of N nodes and the output layer consists of M nodes arranged in M x N nodes in the output layer. The weights of the neurons are initialized to small random values. The network must be fed with large number of training vectors. When a training sample is fed to the network, the Euclidean distance measure to all weight vectors is computed. The neuron with weight vector similar to the input is called the Best Matching Node (BMN). The update formula for a neuron with weight vector $W_v(t)$ is,

$$W_v(t + 1) = W_v(t) + \Theta(v, t) + \alpha(t)(D(t) - W_v(t)) \quad (1)$$

where, $\alpha(t)$ is a monotonically decreasing learning coefficient and $D(t)$ is the input vector. The neighborhood function $\Theta(v, t)$ depends on the lattice distance between the BMN and neuron v. This process is repeated for each input vector until convergence. During mapping, there will be only one single winning neuron: the neuron whose weight vector lies closest to the input vector. After training the winning weight vectors are treated as SOFM code vectors. The set of all SOFM code vectors are termed as initial codebook.

Initial Codebook Generation algorithm is summarized as follows:

1. Initialize the nodes' weight vectors with random values.
2. Get an input vector.
3. Traverse each node in the map
   3.1 Use Euclidean distance formula to find the similarity between the input vector and weight vector.
   3.2 Find the node that produces the smallest distance.
   3.3 Update the nodes in the neighborhood of BMN until convergence.

2.2 WAVELET TRANSFORMATION

The original image of size say M×N is first decomposed in the horizontal direction into two halves by the low pass filter $L_h(z)$ and high pass filter $H_h(z)$. The output of each filter is then down sampled with a factor of 2. Then the output is further partitioned in the vertical direction into two halves by the same filters. The output of each filter is again down sampled with a factor of 2, which yields four image bands LL, LH, HL and HH of the first scale as shown in Fig.3. LL, LH and HL are termed as low-frequencies bands and HH band is called as high frequency band. After wavelet decomposition, the lower frequencies bands are adopted as the bands with noteworthy features. Hence these bands are collected together to form the wavelet coefficients. Then the coefficients are quantized by vector quantization technique with respect to an expected compression rate.

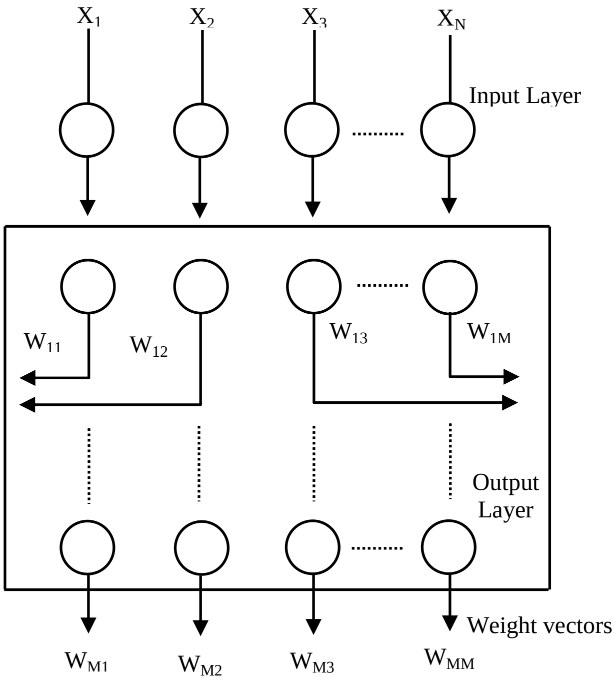

Fig.2. SOFM Architecture

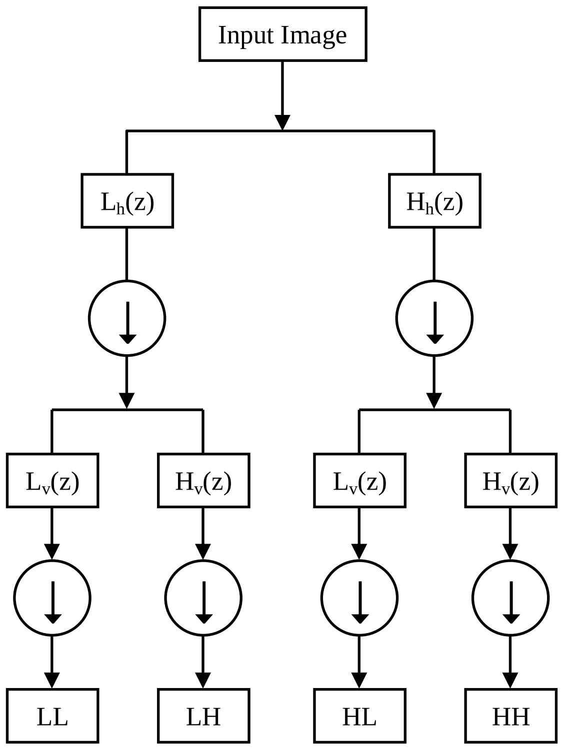

Fig.3. Wavelet Analysis Filters Bank

2.3 VECTOR QUANTIZATION

Vector quantization is one of the commonly used techniques for data compression. Fig.4 shows the block diagram of vector quantizer. A vector quantizer maps k-dimensional vectors in the vector space R^k [8] into a finite set of vectors $Y = \{Y_i: i = 1, 2... N\}$ each vector Y_i is called a code vector or a code word, and the set of all the code words is called a codebook. The wavelet coefficients obtained at the wavelet decomposition level are converted into blocks. Then by applying vector quantization technique the blocks are converted into VQ code vectors. In the encoding stage, the VQ code vectors are compared with every SOFM code vectors in the initial codebook using Euclidean distance formula. Euclidean distance is computed as follows:

$$D(t, w_i) = \sqrt{\sum_{j=1}^{k} (t_j - w_{ij})^2} \tag{2}$$

The VQ code vectors found to be the closest in distance given by Eq.(2) from the input vector to the vector block is declared as the winning VQ code vectors. The indices of the winning VQ code vectors will be stored. These indices will be passed through a channel to the decoder.

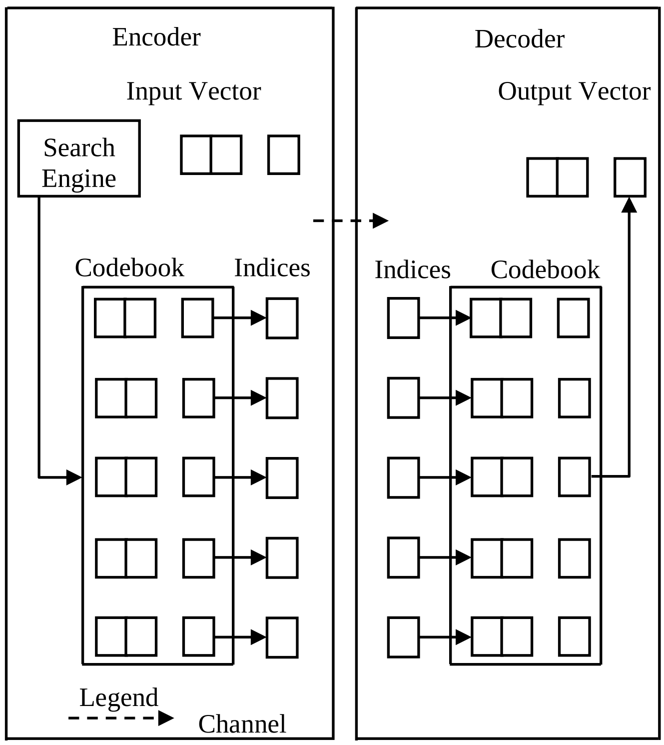

Fig.4. Block Diagram of Vector Quantizer

2.4 DECODING

The decoder receives the indices of the VQ code vectors. It can be decoded by replacing the index with the associated VQ code vectors obtained from the encoder. In vector re quantization process, the VQ code vectors will be converted into blocks. Then with the help of block reconstruction technique the blocks will be reconstructed to wavelet coefficients. The coefficients at each band are up sampled with a factor of 2. The low pass images and high pass images are filtered by low pass filter $L_0(z)$ and high pass filter $H_0(z)$ respectively. The output of these two filters are summed together to produce the corresponding reconstructed image which is shown in Fig.5.

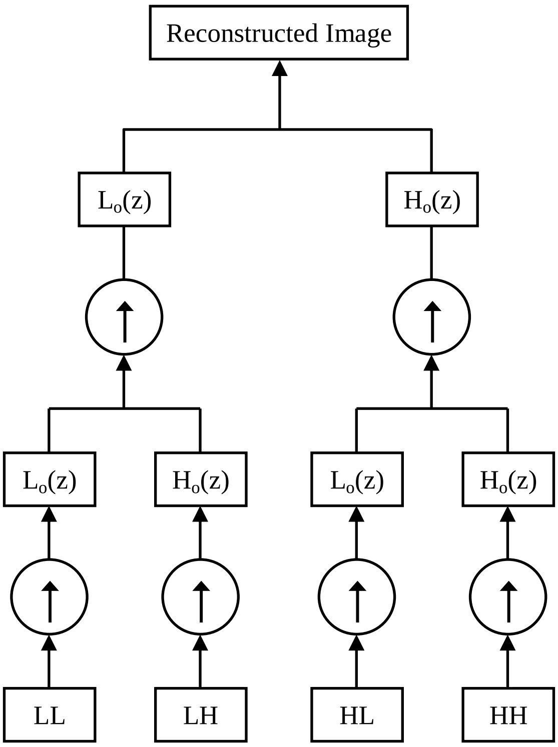

Fig.5. Inverse Wavelet Transform

3. EXPERIMENTS AND RESULTS

The performance of the proposed work is tested with various evaluation parameters and the work is compared with other conventional compression methods.

3.1 PERFORMANCE EVALUATION MEASURES

For performance evaluation, it is necessary to define objective measurement parameters. Two commonly used parameters, Root Mean Square Error (RMSE) as in Eq.(3) and Peak signal to Noise Ratio (PSNR) as in Eq.(4) are used in this paper to evaluate the performance of the proposed work. If the size of the original image is M x N, then the parameter RMSE is defined as,

$$RMSE = \frac{1}{M \times N} \sum_{i=1}^{M} \sum_{j=1}^{N} \left(\hat{f}(i,j)^2 - f(i,j)^2 \right) \tag{3}$$

where, $f(i,j)$ is the original image and $\hat{f}(i,j)$ is the reconstructed image. Then PSNR can be defined as,

$$PSNR = 10 \text{ x } \log_{10}(255^2/RMSE^2) \tag{4}$$

where, 255 is the peak signal value.

Compression Ratio is defined as the ratio of the total number of bits needed to code the original image to the total number of bits needed to code the compressed image. Thus the CR is defined as,

$$CR = \frac{B_0}{B_e} \tag{5}$$

where, B_0 is the total number of bits needed to code the original image data and B_e is the total number of bits needed to code the compressed data.

3.2 EXPERIMENT 1: COMPRESSION OF CAMERAMAN IMAGE

In the proposed work, the classical cameraman image shown in Fig.6(a) was used as the test image. Initially the codebook was generated using SOFM. The input image was decomposed using Haar wavelet structure. Experiment was also carried out with another wavelet structure called DB2. The reconstructed image obtained using SOFM followed by DB2 wavelet is shown in Fig.6(b) and the reconstructed image obtained using SOFM with Haar wavelet is shown in Fig.6(c). The performance is evaluated with parameters PSNR, RMSE, CR and it is shown in Table.1.

(a) (b) (c)

Fig.6(a) Original Image (b) Reconstructed image using SOFM+DB2 Wavelet (c) Reconstructed image using SOFM + Haar Wavelet

From Table.1, it is inferred that the proposed scheme works well for SOFM followed by Haar wavelet method with a PSNR value of 35.72 of codebook size say 256 for a compression ratio of 10.14. The performances of the proposed work are evaluated with the parameter RMSE and PSNR for various codebook sizes, and are shown in Fig.7 and Fig.8.

Table.1 SOFM Compression for Cameraman Image

Wavelet Type	Codebook Size	RMSE	PSNR	CR
SOFM+DB2 wavelet	64	8.3021	26.45	15.65
	128	7.6285	27.24	13.23
	256	6.5674	34.87	10.25
SOFM+Haar wavelet	64	5.3010	27.25	14.75
	128	5.2524	28.30	12.22
	256	4.3041	35.72	10.14

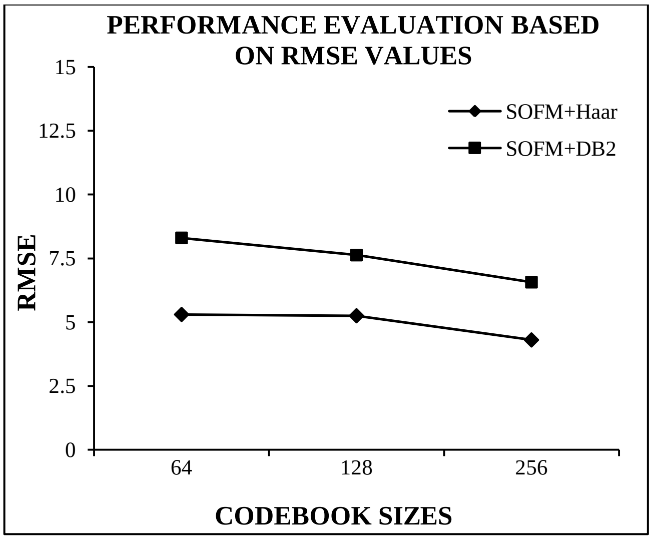

Fig.7. Performance Evaluation chart for Cameraman image based on RMSE Value

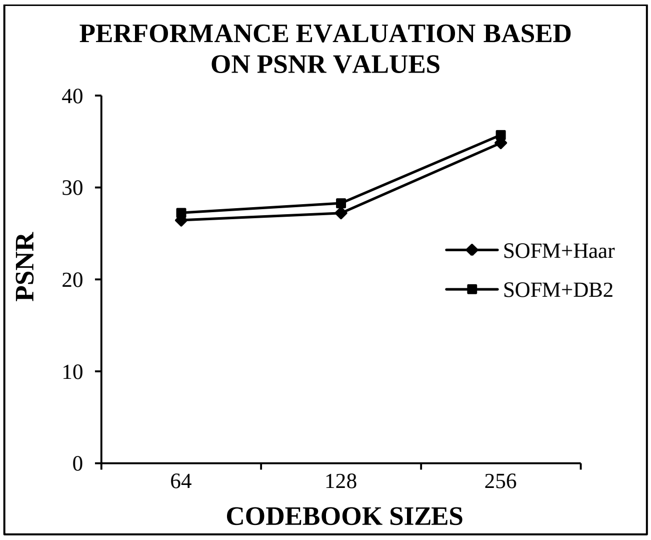

Fig.8. Performance Evaluation chart for Cameraman image based on PSNR Values

3.3 EXPERIMENT 2: COMPRESSION OF HOUSE IMAGE

This experiment was conducted with house image shown in Fig.7(a). Initially the codebook is generated using SOFM. The input image was decomposed using Haar Wavelet. Experiment was carried out with another wavelet called DB2. The reconstructed image obtained using SOFM followed by DB2 wavelet is shown in Fig.9(b) and the reconstructed image obtained using SOFM with Haar wavelet is shown in Fig.9(c). The performance is evaluated with parameters PSNR, RMSE, CR and are presented in Table.2. From Table.2, it is inferred that the proposed scheme produces better quality reconstructed image with a PSNR value of 35.87 and CR of 10%.

(a) (b) (c)

Fig.9(a) Original Image (b) Reconstructed image using SOFM+DB2 Wavelet (c) Reconstructed image using SOFM + Haar Wavelet

Table.2. SOFM Compression with House Image

Compression Methods	Codebook Size	PSNR	CR
LBG	256	27.42	13.25
DCT + SOFM	256	33.25	12.36
SOFM + Haar wavelet	256	35.87	10.06

4. RESULT ANALYSIS

In this section the proposed work is compared with the conventional VQ compression methods like LBG and DCT with SOFM and the performance is evaluated with the parameters like PSNR and CR.

4.1 EXPERIMENT 1: COMPARISON OF VARIOUS VQ METHODS

From Table.1 and Table.2, it is observed that SOFM with Haar wavelet greatly improves the quality of the reconstructed image. It is identified that the method produces the reconstructed image with a greater PSNR value. In this experiment cameraman image and house image as shown in Fig.6(a) and Fig.9(a) were used as test images. Performance of the proposed work was evaluated with various conventional compression methods like LBG, DCT+SOFM and it is given in Table.3. From Table.3, it is shown that the proposed work using Haar wavelet yields highest PSNR with better psycho visual quality reconstructed image as shown in Fig.6(c) and in Fig.9(c). The performance of various compression methods are evaluated with the parameters PSNR, CR and the evaluation chart is given in Fig.10 and Fig.11.

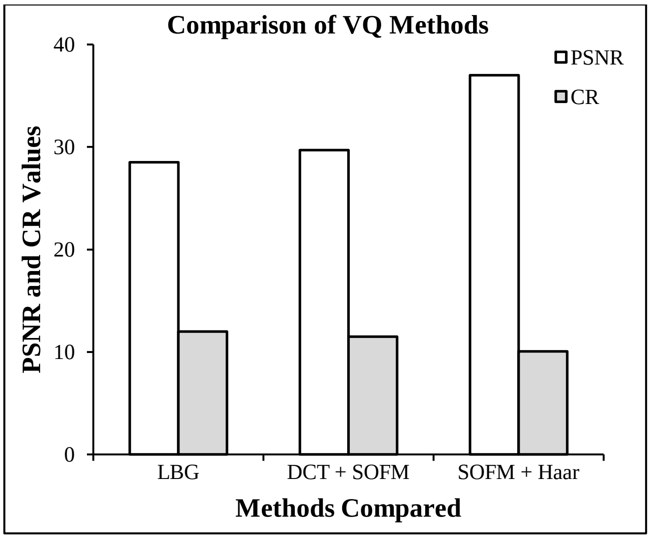

Fig.10. Performance Evaluation Chart for cameraman Image

Table.3. Comparison of various VQ methods for Cameraman Image

Wavelet Type	Codebook Size	RMSE	PSNR	CR
SOFM+DB2 wavelet	64	7.4216	27.64	13.29
	128	6.2311	28.45	12.18
	256	5.3201	34.76	10.72
SOFM+Haar wavelet	64	5.2101	28.25	12.05
	128	5.1054	29.75	11.03
	256	5.0011	35.87	10.06

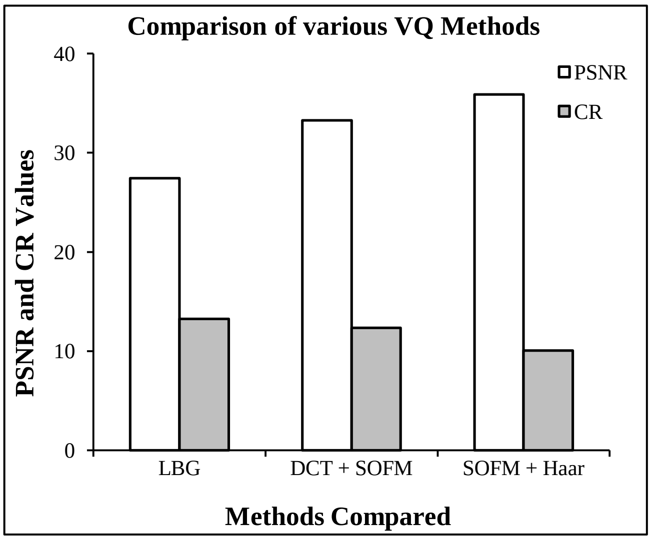

Fig.11. Performance Evaluation Chart for house image

5. DISCUSSION AND CONCLUSION

A novel method for designing vector quantizer for image compression that produces the reconstructed image with better quality is proposed. The method uses the SOFM based neural network techniques for initial codebook generation. In order to reduce the blocking effects in the reconstructed image, Haar wavelet based vector quantization scheme is used. From Table.3 it is evident that the proposed work achieves higher PSNR value of 35.72 and CR of 10% when compared to other proposed yields a better quality reconstructed image as shown in Fig.6(c) and Fig.7(c). SOFM based compression technique required lesser number of bits to compress the coded image. Hence the quality of the decompressed image obtained using proposed work is much better than the other conventional compression methods. This work can be applied in real time image processing applications.

In future, it is proposed to evaluate the performance of SOFM based compression technique with other neural networks based schemes such as Back Propagation algorithm to improve the mapping between the training vectors and weight vectors by reducing the computational load and there by generating an accurate codebook. Further, the method can also be extended for progressive compression of images using other feed forward techniques like Adeline networks. The proposed work can also be extended to other soft computing techniques like fuzzy C means clustering algorithms, genetic algorithms to achieve high psycho visual quality image with less information loss. The proposed may also be extended to various lossless compression techniques and in various applications like medical image processing and in biometrics area.

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