

January 2011

DESIGN OF NEURO-WAVELET BASED VECTOR QUANTIZER FOR IMAGE COMPRESSION

Rasmita Lenka

1Lecturer , KISD, rasmitalenka@yahoo.co.in

Swatika Padhi

Final yr Student, ITER, swatikapadhi@gmail.com

Minakshee Behera

Final yr Student, ITER, menakhseebehera@gmail.com

Naresh Patnaik

Final yr Student, ITER, nareshpatnaik@gmail.com

Mihir N. Mohanty

Asst.Prof. H.O.D,ITER,SOAU, Bhubaneswar, mihir.n.mohanty@gmail.com

Follow this and additional works at: <https://www.interscience.in/ijcct>

Recommended Citation

Lenka, Rasmita; Padhi, Swatika; Behera, Minakshee; Patnaik, Naresh; and Mohanty, Mihir N. (2011) "DESIGN OF NEURO-WAVELET BASED VECTOR QUANTIZER FOR IMAGE COMPRESSION," *International Journal of Computer and Communication Technology*. Vol. 2 : Iss. 1 , Article 10.

DOI: 10.47893/IJCCT.2011.1070

Available at: <https://www.interscience.in/ijcct/vol2/iss1/10>

This Article is brought to you for free and open access by the Interscience Journals at Interscience Research Network. It has been accepted for inclusion in International Journal of Computer and Communication Technology by an authorized editor of Interscience Research Network. For more information, please contact sritampatnaik@gmail.com.

DESIGN OF NEURO-WAVELET BASED VECTOR QUANTIZER FOR IMAGE COMPRESSION

Rasmita Lenka¹, Swagatika Padhi², Minakshee Behera³, Naresh Patnaik⁴, Mihir N. Mohanty^{5*}

¹Lecturer , KISD. ^{2,3,4} Final yr Student, ITER. ^{5*} Asst.Prof. H.O.D,ITER,SOAU, Bhubaneswar

rasmitalenka@yahoo.co.in, *mihir.n.mohanty@gmail.com.

Abstract: *This paper presents a novel approach to design a vector quantizer for image compression. Compression of image data using Vector Quantization (VQ) will compare Training Vectors with Codebook that has been designed. The result is an index of position with minimum distortion. Moreover it provides a means of decomposition of the signal in an approach which takes the improvement of inter and intra band correlation as more lithe partition for higher dimension vector spaces. Thus, the image is compressed without any loss of information. It also provides a comparative study in the view of simplicity, storage space, robustness and transfer time of various vector quantization methods. In addition the proposed paper also presents a survey on different methods of vector quantization for image compression and application of SOFM.*

Keywords: *Neural Networks (NN), Image compression using Vector Quantization, application of wavelet, vector quantization using SOFM.*

1. INTRODUCTION

Day by day the use of multimedia, images and the other picture formats are rapidly increasing in a variety application. Type of technique that is used to store in multimedia data is an important although storage is bigger than ever, however it is not enough. Hence, the data compression particularly the image compression plays a vital role.

The compact representation of an image while maintaining all the necessary information without much loss of data is referred to as Image compression. It can be classified into two types:

- (i) Lossless and
- (ii) Lossy compression.

Again lossy compression can be broadly classified into two types, namely Scalar Quantization (SQ) and

Vector Quantization (VQ)[1]. A popular technique for source coding of image and speech data, since 1980 is VQ. VQ involves processing the input samples in groups into a set of well-defined vectors using some distortion measure.

Most of the benefits of image compression include less required storage space, quicker sending and receiving of images i.e., the transfer rate is high, and less time lost on image viewing and loading. One of the example to illustrate this, is in medical application. The constant scanning and/or storage of medical images and documents take place. Image compression offers many other benefits, as information can be stored without placing large loads on system servers . Depending on the type of compression applied, images can be compressed to save storage space, or to send to multiple places for particular application. At the destination, these images can uncompress when they are ready to be viewed, retaining the original high quality.

Image compression also plays an important role to any organization that requires the viewing and storing of images to be standardized, such as a chain of retail stores or a federal government agency. In the retail store example, the introduction and placement of new products or the removal of discontinued items can be much more easily completed when all employees receive, view and process images in the same way. Federal government agencies that standardize their image viewing, storage and transmitting processes can eliminate large amounts of time spent in explanation and problem solving. The time they save can then be applied to issues within the organization, such as the improvement of government and employee programs.

2. DESIGN OF VECTOR QUANTIZATION

In this method, an input image is divided into small blocks called Training Vectors, say $(x_j(k))$. This Training Vectors can be closely reconstructed from applying a transfer function ‘Q’ to a specific region of an input image itself, which is called Codebook $(\hat{x}_i(k))$. Thus, only the set of transfer functions, which have fewer data than an image, were required for reconstruct the input image back.

A vector quantizer [3] maps k-dimensional Euclidean space R^k into a finite subset of vectors $Y = \{x_i; i = 1, 2, \dots, N\}$ of R^k . Y is the set of reproduction vector and vector y_i is called a code vector or a codeword and the set of all the codewords are called a codebook. Associated with each codeword, y_i , is a nearest neighbor region called Voronoi region, and it is defined by:

$$V_i = \{x \in R^k; \|x - y_i\| \leq \|x - y_j\| \text{ for all } j \neq i\}$$

(a) The set of Voronoi regions partition the entire space R^k such that:

$$\bigcup_{i=1}^N V_i = R^k \text{ ----- (b)}$$

$$V_i \cap V_j = \emptyset \text{ for all } i \neq j \text{ ----- (c)}$$

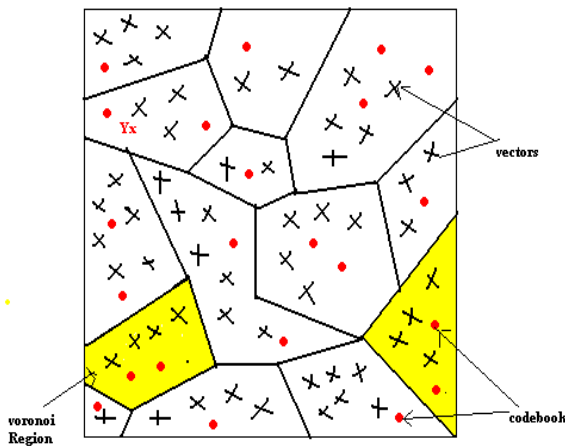


FIG 1: Codewords in 2-dimensional space. Input vectors are marked with an x, codewords are marked with red circles, and the Voronoi regions are separated with boundary lines

Vector Quantization is a combination of two functions: an encoder, which views the input vector x and generates the address of the reproduction vector specified by $Q(x)$, and a decoder, which uses the address to generate the reproduction vector \hat{x} . If a distortion measure $d(x, \hat{x})$ which represents the penalty or cost associated with reproducing vectors x by \hat{x} is defined, then the best mapping Q is the one which minimizes $d(x, \hat{x})$. Vector quantization is the process of dividing the original image into blocks of size $(l*m)$ where the $(l*m)$ block of pixels can be ordered to form an n $(l*m)$ dimensional vector. A local codebook $C = \{\hat{x}_1, \hat{x}_2, \hat{x}_3, \dots, \hat{x}_n\}$ of a fixed size, having N codewords of the same dimension n , is generated using all the vectors present in the image. Each vector X in the image is represented by its best match from the codebook \hat{X}_k such that minimum distortion occurs, i.e.,

$$D(X, \hat{X}_k) < D(X, \hat{X}_i), \text{ for } i=1,2,3,\dots,N, \text{ where } D$$

is the chosen distortion measure.

Usually, the mean-squared error (MSE) is chosen as the measure for distortion due to its computational simplicity, though it does not correlate closely with the visual quality of the image.

3. IMAGE COMPRESSION USING VQ

In Vector Quantization [3][4] an input image is divided into small blocks called Training Vector $(x_j(k))$. This Training Vectors can be closely reconstructed from applying a transfer function (Q) to a specific region of an input image itself, which is called Codebook $(\hat{x}_i(k))$. Thus, only the set of transfer functions, which have fewer data than an image, were required for reconstruct the input image back. A transfer function (Q) is defined as follows.

$$Q : R^k \rightarrow Y,$$

Where $Y = \{x_i; i = 1, 2, \dots, N\}$ that recreate and N is the number of vectors in Y . VQ consists of 2 parts.

- i) Encoder
- ii) Decoder

The encoder takes an input vector and outputs the index of the codeword that offers the lowest distortion. In this case the lowest distortion is obtained by evaluating the Euclidean distance between the input vector and each codeword in the codebook, once the closest codeword is found, the index of that codeword is sent through a channel. When the decoder receives the index of the

codeword, it replaces the index with the associated codeword. In this method a problem arises, i.e, the image quality is not better but as the index is transmitted less channel bandwidth is required.

But image quality can be improved by application of wavelet transform and more it can be efficient by using SOFM for vector quantization. These are described in section

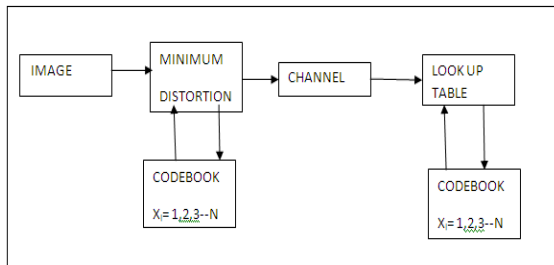


FIG2. Image Compression Using VQ

4. APPLICATION OF WAVELET TRANSFORM IN IMAGE COMPRESSION USING VECTOR QUANTIZATION

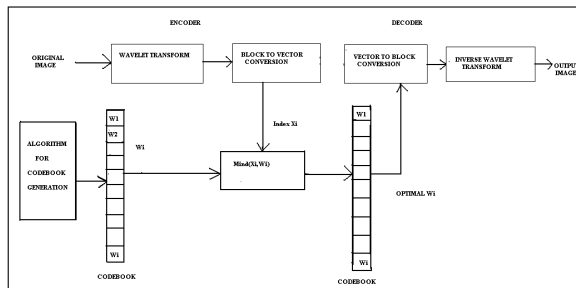


Fig.3. Block Diagram of proposed method

Encoder and Decoder consist of the following things, an input image 8-bit gray scale images with are solution of 256 × 256 pixels. Wavelet transform [8] decompose the original image to one level decomposition, then we divide these decomposition level into vector blocks (Block to Vector Conversion) as seen in Fig.3. Then the vector block is compared with every codeword in the cookbook [12][14]. The representative codeword is determined to be the closest in Euclidean distance from the input vector block. The Euclidean distance is defined by:

$$d(x_i, w_j) = \sqrt{\sum_{k=1}^n (x_{i,k} - w_{j,k})^2}$$

Once the closest codeword is found, the index of that codeword is sent through a channel. When the

decoder receives the index of the codeword, it replaces the index with the associated codeword, and then these codewords are converted to blocks (Vector to Block Conversion) as seen in Fig.3. Then block reconstruction collected to reconstruct one level decomposition wavelet coefficient, Then Inverse Wavelet transform transformed these coefficients and generates the reconstructed image. In this proposed method the artifacts are removed but little amount of haziness remains because of not updating codebook. The overall process is represented in terms of flow chart in Fig.6

METHOD 1: Algorithm for selection of codebook from wavelet coefficient.

- 1) The input image is subdivided into blocks and from that training vector is obtained in form a column vector(N*1).
- 2)Then wavelet transform is applied to the image for 2 level decomposition .From the approximation coefficient the codebook of size (1*16) is selected .
- 3)The minimum distortion(Euclidean distance) between the training vector and the codebook is calculated .
- 4) Then the index which has minimum distortion is transmitted.
- 5) At the decoder the codebook is recovered from the transmitted index .A matrix which has the dimension equal to the wavelet coefficient is generated.
- 6) Then IDWT is applied to this new matrix

METHOD 2: Algorithm for selection of codebook from image.

- 1) The input image is subdivided into blocks and from that a codebook is randomly selected of size(1*N)
- 2)Then wavelet transform is applied to the image for 2 level decomposition .From the approximation coefficient the Training vector is found and converted to a column matrix of size(N*1)
- 3) The minimum distortion(Euclidean distance) between the training vector and the codebook is calculated .
- 4) Then the index which has minimum distortion is transmitted.

5) At the decoder the codebook is recovered from the transmitted index .A matrix which has the dimension equal to the wavelet coefficient is generated.

6) Then IDWT is applied to this new matrix.

The result is better in case of TYPE 1

As the result obtained from all the methods related to VQ for image compression in the previous section a has proved not to be optimal because of random selection of codebook and not updating it which generates an image not 100% approximate the original image.

Vector quantization an effective algorithm for updating the codebook and is applied i.e, SOFM (Self Organization Feature Map) [9],[10].

In the following section application of SOFM is combined with wavelet to increase the quality of the reconstructed image.

5. DESIGN OF CODEBOOK

The code vectors [5] are generated by evaluating the characteristics of the specific image sub samples, which are determined through rigorous mathematical operations and training the selected samples by Kohonen’s SOFM artificial neural network with adjustable learning rate and initializations conditions followed by application of discrete wavelet transform (DWT). The testing of the codebook is done with variety of images and the compression performance is evaluated by using objective and subjective quality measures. Unlike many researcher’s who use only Peak Signal to Noise Ratio (PSNR) for determining the quality which is deceptive many times, we have employed other quality measures such as Image fidelity, structural content, mean structural similarity index, universal quality index, spatial frequency measure and spectral activity measure along with PSNR.

5.1 SOFM Architecture and Algorithm

A self-organizing feature map [4],[10] is a neural network clustering technique having several desirable features, and, consequently ,it has attracted the attention of the researchers in the field of vector quantization SOFM networks exhibit the interesting properties of topology preservation and density matching. The self-organizing feature map is denoted here by $Asof m: R^k \rightarrow V(R^k)$. This is often advocated for visualization of metric-topological relationships and matching density property of feature vectors (signals) $X = \{x_1, x_2, x_3, \dots, x_N\}$ in R^k . Usually X is transformed into a display lattice of

dimensions. .SOFM is realized by a two-layer network, as shown in Fig.(4)The first layer is the input layer or fan-out layer with k neurons and the second layer is the output or competitive layer. The two layers are completely connected. There are lateral inhibitory connections and self-excitatory connections between the neurons in layer two, which enable the neurons to compete among themselves to find the winner node given an input signal. An input vector $x \in R^k$, when applied to the input layer, is distributed to each of the $(m \times n)$ output nodes in the competitive layer. Each node in this layer is connected to all nodes in the input layer; hence, it has a weight vector prototype W_{ij} attached to it. SOFM begins with a (usually) random initialization of the weight vectors W_{ij} . Then weight factor is updated after some iteration. It is given as $W_{new} = W_{ij-1} + \alpha_t \sum g_t(x - W_{ij-1})$ ----- (d)

Where α_t is learning parameter and $g_t = \frac{-d(x, W_{ij})}{\sigma_t}$
 σ_t and α_t both decreases with time

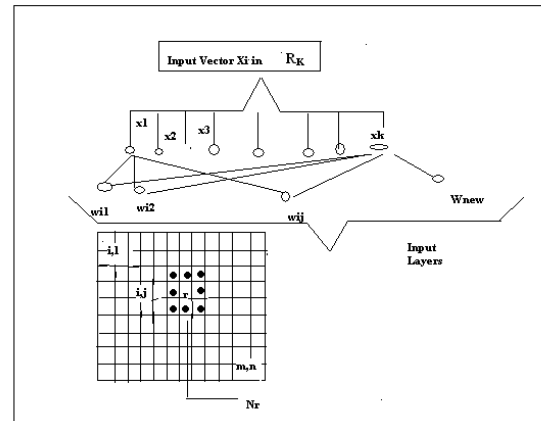


Fig 4. SOFM Architecture

The topological neighborhood also decreases with time. This scheme when repeated long enough usually preserves spatial order in the sense that weight vectors which are metrically close R^k in generally have, at termination of the learning procedure, visually close images in the viewing plane. Also, the distribution of the weight vectors in resembles closely the distribution of the training vectors X. So, 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, SOFM will generate more code vectors for the high density region.

5.2 PROPOSED ALGORITHM

- 1) The 256x256 pixel image in 4x4 pixel blocks in order to generate a 16-element vector, which acts as input to SOFM neural network
- 2) Statistical operations on pixel blocks such as calculation of mean, standard deviation, variance is performed
- 3) Depending upon the standard deviation change the initialization of weights, since weights of SOFM neural net serves as code-vectors in codebook, learning rate and possibly number of epochs are changed in order to prevent over training of certain input vectors
- 4) The generated code-vectors are transformed using 'haar' or 'db1' mother wavelet up to one decomposition level. Thus every code-vector is transformed into LL, LH, HL and HH i.e. into low frequency approximation coefficients, horizontal, vertical and diagonal coefficients. The size of code-vector is reduced to 4 elements from 16 elements due to down sampling.
- 5) The approximation coefficients and horizontal coefficients are combined together to form 16 element vector, similarly the vertical and diagonal coefficients are combined to form another 16 element code-vectors. Thus due to such combination, two code vectors corresponding to one SOFM-generated code-vector are generated. So two codebooks are generated. The size of the codebooks is 1K each
- 6) In this method compression is more and the result is better than other VQ method and effect of artifact is very less.

5.2.1 QUALITY MEASURES

We have employed few quality measures that are normally used for the quality analysis of decompressed images.

1. Mean Square Error (MSE):

$$MSE = \frac{\sum_{j=1}^M \sum_{k=1}^N [X(j, k) - \hat{X}(j, k)]^2}{MN}$$

Where X is the input vector and \hat{X} is a codebook vector. M*N is the image size in

pixels. MSE should be low for less distortion which means better quality images

2. Peak Signal To Noise ratio (PSNR):

$$PSNR = 10 \log \left(\frac{255^2 - MSE}{MSE} \right) \text{ dB}$$

For perfect reconstruction it should approach to infinity. Normally it is in the range of 35 to 55 dB.

3. Structural Content (SC):

$$SC = \frac{\sum_{j=1}^M \sum_{k=1}^N X(j, k)^2}{\sum_{j=1}^M \sum_{k=1}^N \hat{X}(j, k)^2}$$

4. Image Fidelity (IF):

$$IF = \frac{1 - \frac{\sum_{j=1}^M \sum_{k=1}^N [X(j, k) - \hat{X}(j, k)]^2}{\sum_{j=1}^M \sum_{k=1}^N [X(j, k)]^2}}{\sum_{j=1}^M \sum_{k=1}^N [X(j, k)]^2}$$

5. Normalized-Correlation-Coefficient

$$NK = \frac{\sum_{j=1}^M \sum_{k=1}^N [X(j, k) - \bar{X}] [\hat{X}(j, k) - \bar{\hat{X}}]}{\sqrt{\sum_{j=1}^M \sum_{k=1}^N [X(j, k) - \bar{X}]^2} \sqrt{\sum_{j=1}^M \sum_{k=1}^N [\hat{X}(j, k) - \bar{\hat{X}}]^2}}$$

Normally SC, IF and NK are in the range of 0 to 1. A value very near to or equal to one is the best.

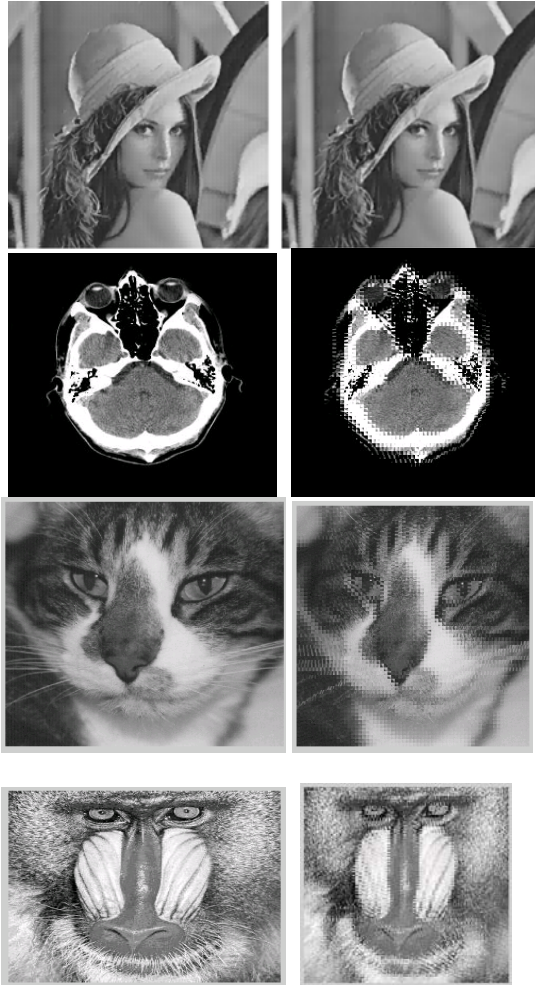


Fig 5. Original image(left) and Reconstructed image (right) with VQ using Proposed Method .

FLOW CHART OF IMAGE COMPRESSION TECHNIQUE BY VECTOR QUANTIZATION USING SOFM,WAVELET

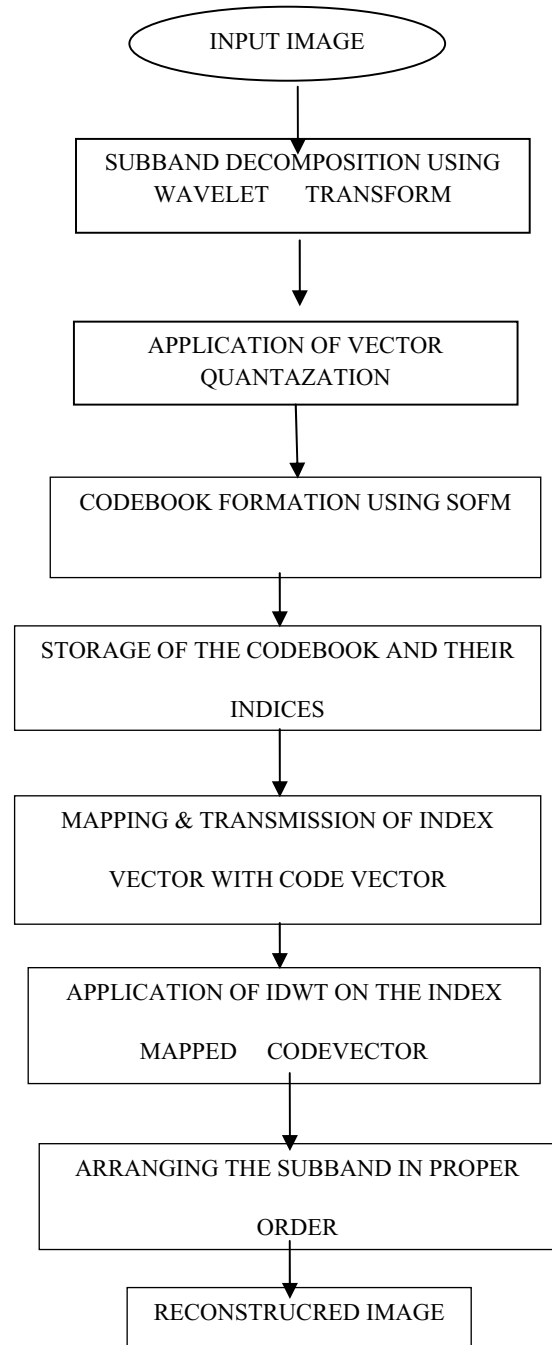


Fig.6. Flow Chart for Image Compression

IMAG E	PSNR (in dB)	MSE	IF	NK	SC
Lena	49.3705	266.6020	0.9626	0.9813	1.0000
CT_sc an	39.6940	1.2280e+003	0.8739	0.9369	1.0000
Camer aman	44.3177	273.3692	0.9570	0.9785	1.0000
House	52.6755	235.2827	0.9842	0.9921	1.0000
Pepper s	45.4993	287.1783	0.9618	0.9809	1.0000
Mrisca n	56.2118	235.4140	0.8793	0.9397	1.0000
Baboo n	38.1759	1.4293e+003	0.9458	0.9729	1.0000
Cat_1	56.7074	224.0311	0.9850	0.9925	1.0000
Face	52.2225	250.8215	0.9586	0.9793	1.0000
Source	51.4870	277.5963	0.9743	0.9871	1.0000
Vince _c	44.6435	248.5782	0.9278	0.9639	1.0000

TABLE 1: QUNALITY ANALYSIS OF IMAGE COMPRESSION USING NEURO-WAVELET BASED CODEBOOK

The Table.1 shows that there is much variation relate to PSNR and MSE .So improved in image clarity can be achieved by some change in algorithm relate to generation of codebook for designing VQ.

CONCLUSION

We have presented a comprehensive scheme for designing vector quantizers for image compression using generic codebooks that produce reconstructed images with good psychovisual quality. From the Table.1 The scheme exploits the special features of SOFM for codebook generation. Another attractive feature is that the proposed approach is of low computational complexity and constitutes a promising starting issue in the development of an integrated image compression/transmission system over Rayleigh and Rician channels (encountered in mobile communication systems). Actual studies are conducted in order to extend the proposed approach to higher block dimensions (4x4) and to the VQ video images. There is no single algorithm or methodology that satisfies all the requirements that use the vector quantization for image compression as every algorithm has its own merits and demerits.

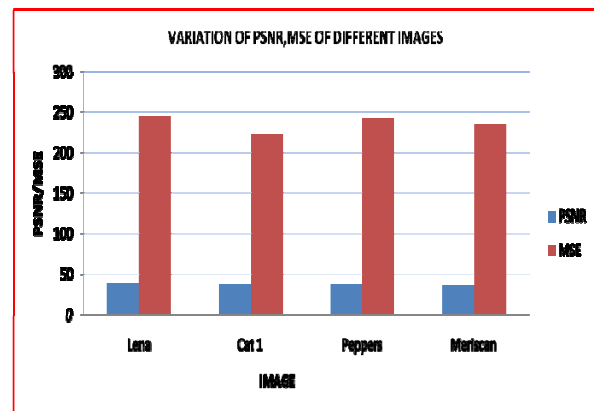


FIG.6 Variation in Psnr & Mse of different image in Image compression using Neuro-Wavelet VQ Method

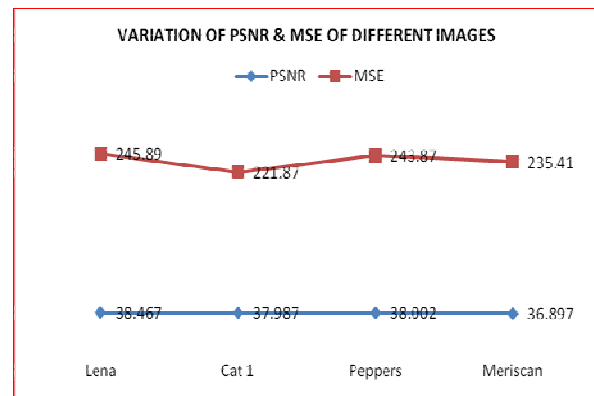


FIG.7 Variation in PSNR & MSE of different images by Image compression using VQ with wavelet

REFERENCES

- [1] Y. Linde, A. Buzo, and R. M. Gray, "An Algorithm for Vector Quantizer Design," *IEEE Trans. on Commun.*, vol. COM-28, pp. 84-95, 1980.
- [2] Nasrabadi NM and Yushu Feng (1990) Image compression using address vector quantization. *IEEE Trans. Commun.* 38 (2), 2166-2173.
- [3] Amerijckx C, Michel Verleysen, Philippe Thissen, and Jean-Didier Legat (1998) Image Compression by self organized Kohonen map. *IEEE Trans. Neural Networks.* 9 (3), 503-509.
- [4] Amerijckx C (2003) Image compression using self organizing maps. *J. System Analysis Modeling Simulation.* 43(11) 1529-1547
- [5] Laha A, Pal NR and Chanda B (2004) Design of vector quantizer for image compression using self organizing feature map and surface fitting. *IEEE Trans. Image Processing.* 13. 1291-1302.
- [6] Y. Linde, A. Buzo and R.M.Gray, —An algorithm for vector quantizer design, *IEEE Trans. Commun.*, vol.28, pp.84-95, Jan.2003.
- [7] Ahmet M. Eskicioglu and Paul S. Fisher (1995) Image quality measures and their performance. *IEEE Trans. Commun.* 43(12), 2959-2965.
- [8] S.Mallat, "A theory for multi resolution signal Decomposition: The wavelet representation," *IEEE Trans. on Pattern and Machine Intell.*, Vol. (PAMI-11), 1989, pp.674-693.
- [9] T.Kohonen, "Things you haven't heard about the Self-Organizing Map," "in *Proc. ICNN'93, Int. Conf. Neural Networks*, 1993, pp. 1147–1156.
- [10] Improved Versions Of Learning Vector Quantization, Teuvo Kohonen Helsinki University of Technology
- [11] Image Compression by Self-Organized Kohonen Map Christophe Amerijckx, Associate Member, IEEE, Michel Verleysen, Member, IEEE, Philippe Thissen, Member, IEEE, and Jean-Didier Legat, Member, IEEE
- [12] Sudhakar R, Karthiga R and Jayaraman S (2006) Image compression using coding of wavelet coefficients— a survey. *GVIP J.* 6 (1), 1-14.
- [13] Simon Haykin (2001) *Neural networks: a comprehensive foundation*. 2nd ed., Pearson Education. India
- [14] P. C. Cosman, R. M. Gray, and M. Vetterli, "Vector Quantization of Image Subbands: A Survey" *IEEE Trans. on Image processing* Vol. (5), No.(2) , Feb.1996, pp. 202-225.