IOSR Journal of Electronics and Communication Engineering (IOSR-JECE)
e-ISSN: 2278-2834,p- ISSN: 2278-8735.Volume 9, Issue 4, Ver. V (Jul - Aug. 2014), PP 13-20
www.iosrjournals.org

Image Compression using ANFIS in Wavelet Domain

Pravin B. Pokle#, Dr. Narendra.G. Bawane*
#Ph.D.Research Scholar, Deptt. of Electronics Engineering, B.D.College of Engg, Sewagram, Dist. Wardha.
**Principal, S.B.Jain Institute of Engineering, Management and Research, Nagpur.*
pbpokle@rediffmail.com
* narendra.bawane@yahoo.com

***Abstract**: Image compression is backbone in the field of communications and multimedia. The objective of Image compression is to minimize the size in bytes of a file by reducing the redundancy of the image data without degrading the quality of image, resulting in reduction of file size so that more images can be stored in a given amount of disk or memory space and also reduces the time required to send the images over the network [1]. In this paper we present a novel approach towards image compression based on Adaptive Neural Fuzzy inference system(ANFIS) with Differential Pulse code modulation(DPCM) in Wavelet domain so that better compression ratio can be achieved with minimum error. The overall implementation of the work consists of four steps: first, seven band wavelet. Based upon statistical properties of sub bands, different quantization and coding schemes are used. Second, first sub band is compressed using differential pulse code modulation (DPCM), the coefficient corresponding to other sub bands are compressed using Adaptive Neural Fuzzy Inference system (ANFIS). In the third stage, the result obtained is fed as input to the fuzzy vector quantizer and in fourth stage the output obtained from third stage is fed to the K means quantizer for further compression. Finally the results are compared for MSE, PSNR and the visual appearance after decoding of image.*

***Keywords:** Image Compression, Fuzzy vector quantization, Wavelet Transform, Peak Signal to Noise Ratio, Adaptive Neural Fuzzy Inference System(ANFIS), DPCM,peak signal to noise ratio, mean square error.*

I. Introduction

In day to day life, image compression is in demand since last few decades and since ever its demand has not fallen down. The key factor of image compression is reducing the number of bits by minimizing the redundancy between neighboring pixels in an image file. Many researchers have been presented different ideas and algorithms to improve the performance measures in past decade in order to achieve the better performance and quality. However every algorithm has its own advantages and disadvantages due to nature of each scheme. It is clear that amongst all the proposed schemes, discrete cosine transform is easy for implementation, understanding and more advantages if it is applied to JPEG standards. Another technique which is more recently developed is Vector Quantization. The performance of Vector Quantization is directly proportional to the vector size and codebook size [2]. This means with increase in vector size, the codebook size also increases which results in exponential increase in encoding complexity. Despite the fact that vector quantization is theoretically possible, the vector size should be limited for practical purposes. Vector Quantization techniques applied to image compression are broadly divided into two categories based on either a hard or soft decision in membership function viz K-means and Fuzzy K- means[3]. One of the most popular minimization technique used is K-means using a descent algorithm. K- means strongly depends upon selection of initial codebook but is easy to implement [4]. K means ignores the possibility that the training vector may be a member of different clusters and therefore is based on hard decisions. Artificial neural network is gaining popularity in the fields where high computational rates are required [5]. In the domain of image processing, applications can be found in concurrent parallel processing structures, in the recognition of characters or 2-D patterns, in some 2-D signal processing tasks and more recently, in data compression for image coding systems. Recent researches have resulted in several advancement in the signal processing tools such as wavelets. Wavelet transforms exhibits the orientation and frequency selectivity of images as shown by studies in the area. Image coding using wavelets uses bi-orthogonal wavelets to obtain a set of bi-orthogonal sub bands. The original image was decomposed at different scales or sub-bands of frequency using Mallat's pyramidal architecture in which horizontal and vertical orientations are considered preferential [6]. After the decomposition of the image wavelet coefficients were vector quantized resulting in set of multi resolution codebooks. The main objective of this paper is to develop an Adaptive Neuro Fuzzy inference system network in order to achieve high compression ratio without degrading the original image quality.

Wavelet Transform

The term wavelet has been used for decades in digital signal processing and exploration geophysics[7]. The equivalent French word ondelette meaning "small wave" was used by Morlet and Grossmann in the early 1980s. A wavelet is a wave-like oscillation with amplitude that begins at zero slowly increases and then decreases again back to zero. In wavelet transformation, image is represented as sum of wavelets with different locations and scales. All wavelet transforms considers the forms of time-frequency representation for continuous-time (analog) signals and hence they are related to harmonic analysis. It is seen that, almost all practically useful discrete wavelet transforms use discrete-time filter banks [8]. These filter banks are called the wavelet and scaling coefficients in wavelets nomenclature. Wavelet transforms are broadly divided into three classes: continuous wavelet, discrete wavelet and multiresolution-based wavelets.

1) Continuous wavelet transforms (continuous shift and scale parameters)

In this the signal of finite energy is projected on a continuous family of frequency bands (or similar subspaces of the L^p function space $L^2(\mathbf{R})$). For instance the signal may be represented on every frequency band of the form [f, 2f] for all positive frequencies f > 0. Then, the original signal can be reconstructed by a suitable integration over all the resulting frequency components [9].

The frequency bands or subspaces (sub-bands) are scaled versions of a subspace at scale 1. In most of the situations, this subspace is generated by the shifts of one generating function ψ in $L^2(\mathbf{R})$, the mother wavelet. For the example of the scale one frequency band [1, 2] this function is:

$$\psi(t) = 2\,\mathrm{sinc}(2t) - \mathrm{sinc}(t) = \frac{\sin(2\pi t) - \sin(\pi t)}{\pi t} \qquad (1)$$

With the (normalized) sinc function. That, Meyer's, and two other examples of mother wavelets are:
The subspace of scale a or frequency band [1/a, 2/a] is generated by the functions (sometimes called child wavelets)

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right), \qquad (2)$$

Where ‗a' is positive and defines the scale and b is any real number and defines the shift. The pair (a, b) defines a point in the right half plane $\mathbf{R}_+ \times \mathbf{R}$.

The projection for a function x onto the subspace of scale a then has the form

$$x_a(t) = \int_{\mathbb{R}} WT_\psi\{x\}(a,b)\cdot\psi_{a,b}(t)\,db \qquad (3)$$

with wavelet coefficients

$$WT_\psi\{x\}(a,b) = \langle x, \psi_{a,b}\rangle = \int_{\mathbb{R}} x(t)\psi_{a,b}(t)\,dt. \qquad (4)$$

Discrete Wavelet Transform

It is very difficult to analyze a signal computationally using all wavelet coefficients; the solution of this problem is to reconstruct a signal from the corresponding wavelet coefficients by picking a discrete subset of the upper half plane. One such system is affine system for some real parameters a > 1, b > 0. The corresponding discrete subset of the half plane consists of all the points (a^i, ja^ib) with i, j in **Z**. The corresponding baby wavelets are now given as:

$$\Psi_{i,j}(t) = a^{-i/2}\,\Psi(a^{-i}t - jb) \qquad (5)$$

A sufficient condition for the reconstruction of any signal *x* of finite energy by the formula is that the functions $\{\psi_{i,j} : i, j \in Z\}$ form a tight frame of $L^2(\mathbf{R})$.

$$x(t) = \sum_{i \in Z}\sum_{j \in Z} \langle x, \psi_{i,j}\rangle \cdot \psi_{i,j}(t) \qquad (6)$$

Discrete wavelet transform is a linear transform operates on a data vector whose length is an integer power of two transforming it into numerically different vector of same length [10].Data can be separated into different frequency components, further this data studies each component with resolution matched to its scale. Using wavelet analysis, perfect reconstruction filter bank could be formed with coefficients sequences aL(k) and aH(k) as shown in figure 1 below.

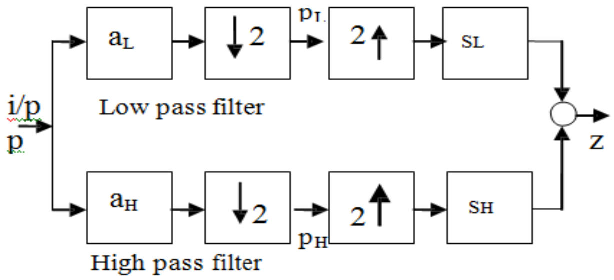

Fig. 1: Two channel filter bank

In the above figure, the input sequence p is convolved with low and high pass filter (LPF and HPF) aL(k) and aH(k).The result from filter is then down sample by two, giving the transformation signal pL and pH. The reconstruction of signal is achieved by up sampling by two and convolution with high and low synthesis filters sH(k) and sL (k). The signal is reconstructed exactly for properly designed filters. Digital signal decomposition with dyadic frequency scaling known as discrete wavelet transform (DWT) can be formed by cascading the analysis filter bank with itself a number of times[11]. Discrete wavelet transform for an image as a 2-Dimensional signal can be derived from 1-Dimensional Discrete wavelet transform. In order to easily obtain scaling and wavelet function for two dimensions, two 1-Dimensional functions are multiplied. The scaling function for two dimensional discrete wavelet transform can be obtained by multiplying two 1-Dimensional scaling functions $(p,z) = \varphi(p) * \varphi(z)$. Wavelet functions for 2-Dimensional Discrete wavelet transform can obtained by multiplying two wavelet functions or wavelet and scaling function for 1-Dimensional analysis. With 2-Dimensional case there exists three wavelet functions that scan details in horizontal $\Psi(p,z)(I) = \varphi(p) * \Psi(z)$, vertical $\Psi(p,z)(II) = \Psi(p) * \varphi(z)$ and diagonal directions $\Psi(p,z)(III) = \Psi(p) * \Psi(z)$. This may be represented as a four-channel perfect reconstruction filter bank as shown in Fig. 2 below.

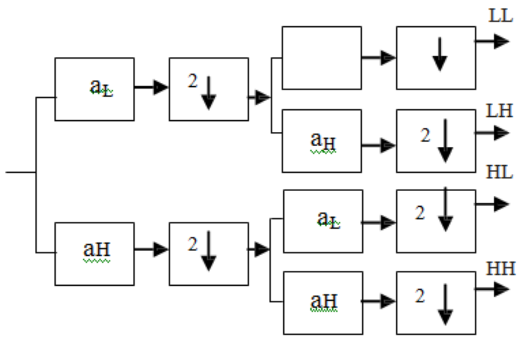

Fig. 2: One filter stage in 2-Dimesional DWT

The pyramidal structure of wavelet decomposition is as shown in the figure below:-

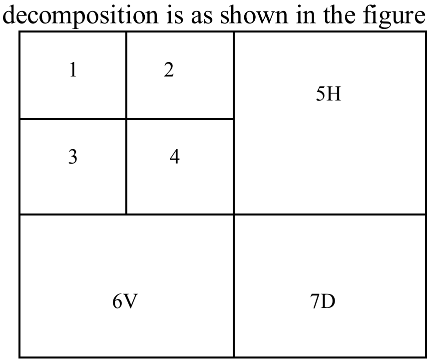

Fig. 3: Pyramidal structure of wavelet decomposition

Wavelet decomposition of image results in division of image into seven bands as shown in the figure 3.

II. Proposed Work

In this paper we proposed image compression using wavelet in combination with Artificial Neural network and Fuzzy inference system (ANFIS) so that we can achieve better compression. Figure 4 below shows the complete image compression system.

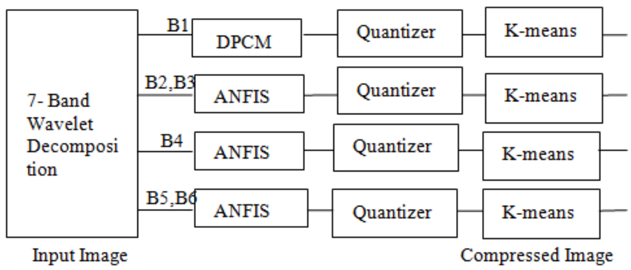

Figure 4 - Complete Image Compression

In this work, the input image is first decomposed using seven band wavelet decomposition. After decomposition we get seven different bands each of with different frequency and characteristics. Since most of the information is in lowest frequency band i.e.B1, therefore it is encoded with Differential pulse code modulation (DPCM) [12]. After this the coefficient are scalar quantized. The remaining frequency bands are coded using Adaptive Neural Fuzzy Inference System (ANFIS). The information of Band 7 is discarded as it contains little information to contribute to the image from the stand that this band can be assumed to be zero with little effect on the quality of reconstructed image. The output of Artificial Neural network and Fuzzy inference system (ANFIS) is then quantized. Finally these quantized values are subjected to k-means to achieve further compressions. It is seen that we achieved a better compression up to 78.83% compared to original image as well as Peak Signal to Noise ratio (PSNR) obtained of the output image is high and comes out to be around 50dB and the minimum mean sequence error (MMSE) is very low and comes out to be 0.02 which is a lot more than a better value.

7-Band Wavelet Decomposition

The first step is to decompose the input image into 7 sub bands using wavelet decomposition. As most of useful frequency contents are in band 1, it is encoded using DPCM, Bands 2 and 3 contain the same frequency contents for different orientations therefore both the bands are quantize separately using ANFIS also the frequency contents for bands 5 and 6 are same thus these bands are quantize with another quantizer via ANFIS structure. The coefficients of Band-4 are different thus it is coded using separate quantizer. Since Band-7 contains less information thus it is discarded. The output of the ANFIS network is then quantized. Finally these quantized values are applied to K-means clustering for achieving better compression [13].

Differential Pulse code Modulation (DPCM)

Differential **p**ulse **c**ode **m**odulation (DPCM) is a method of converting analog signal into digital signal where the analog signal is sampled and then difference between actual sample value and its predicted value is quantized and then encoded forming digital value. DPCM is form of predictive coding because it is necessary to predict sample value. Image compression using DPCM depends on prediction technique since well-conducted prediction techniques leads to good compression rates [14].

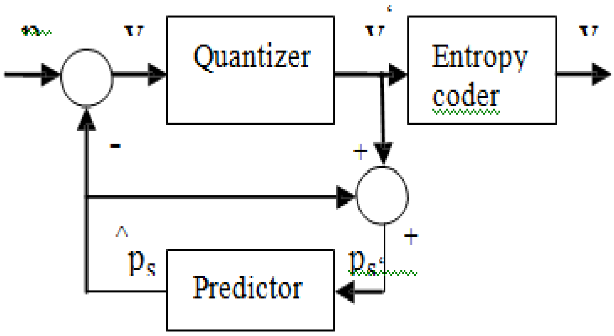

Figure 5: DPCM encoder

DPCM encoder is shown in figure 5, it is the combination of quantizer, entropy enceoder and a predicator.Here p_s is the current sample and $\hat{p}_s$ is predicted value, $\hat{p}_s$ is formed using prediction factors and previous samples, for this linear prediction is used, thus predicted value can be given as a weighed linear combination of ‗m' previous samples using x_i , weighting factors:

We choose weighting factors x_i

$$\hat{p}_s = \sum_{i=0}^{m-1} x_i \cdot p_s(i) \qquad (7)$$

Then the difference in signal is given by:

$$v = p_s - \hat{p}_s = \sum_{i=0}^{m-1} x_i \cdot p_s(i) \qquad (8)$$

In order to minimize some function of error between p_s and $\hat{p}_s$ (like mean-squared) this leads us to minimization of quantization noise (better signal-to-noise ratio). In this paper we use DPCM because it gives image with a continuous-tone which mostly contains smooth tone transitions. Also using DPCM we can assign short code words to achieve a good compression ratio.

Adaptive Neuro-Fuzzy Inference system (ANFIS).

The main problems while using fuzzy system is when we apply ‗if-then' rules to fuzzy system it takes more time for evaluation also a fuzzy set is fully determined by its membership function. Thus using a given input/output data set, the function anfis constructs a fuzzy inference system (FIS) whose membership function parameters are adjusted using either a back propagation algorithm or back propagation in combination with a least squares type of method[15]. This will allows the fuzzy systems to learn from the data they are modeling. The ANFIS approach learns the rules and membership functions from data. ANFIS is an adaptive network consists of network of nodes and directional links [16]. Associated with the network is a learning rule - for example back propagation. The name adaptive come from the fact that here some or all, of the nodes have parameters which affect the output of the node. These networks are usefull for learning a relationship between inputs and outputs. Architecture of ANFIS for a two rule Sugeno system is shown in figure 6 below.

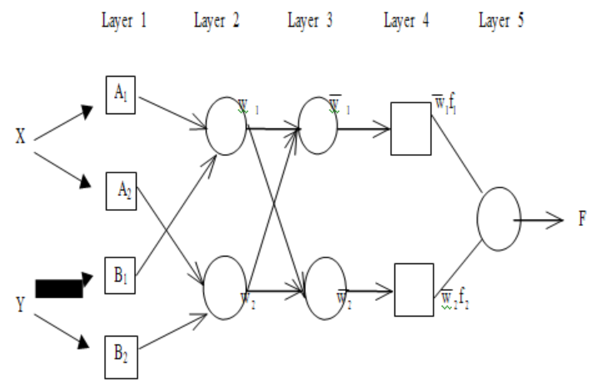

Figure 6: Two level ANFIS structure

In ANFIS both forward and a backward pass is used for the training of the network, here the input vector is propagated through the network layer by layer in forward pass while, in the backward pass, similar to the back propagation the error is sent back through the network .

In this paper, Similar to neural network, ANFIS network is train using back propagation algorithm for training the data set. Compression is done in three steps i.e. first the data set for various frequency bands after decomposition is train by proper setting of error tolerance and epochs. In this paper in order to minimize the error we set epochs to 100 and error to 0. Second step is to test the data set by loading data from workspace and finally generate fuzzy inference system[17]. After generating a FIS file will be generated which will then applied to quantizer for further compression via k- means algorithm. Quantization is a compression technique achieved by compressing a range of values to a single quantum value. In quantization, a signal is mapped into a series of k discrete messages. The optimal thresholds are equidistant from the values, for a given set of quantization values. The concept of quantizing data can be extended from scalar or one dimensional data to vector data of arbitrary dimension. Vector Quantization employs a set of representation vectors (for one dimensional cases) or matrices for two dimensional cases. The set therefore is referred as codebook and entries as codeword's. As we use vector quantization, as k- means clustering is used since it can easily be used to choose k different but prototypical objects from a large data set for further compression. Figure 6 shows the structure generated for given input.

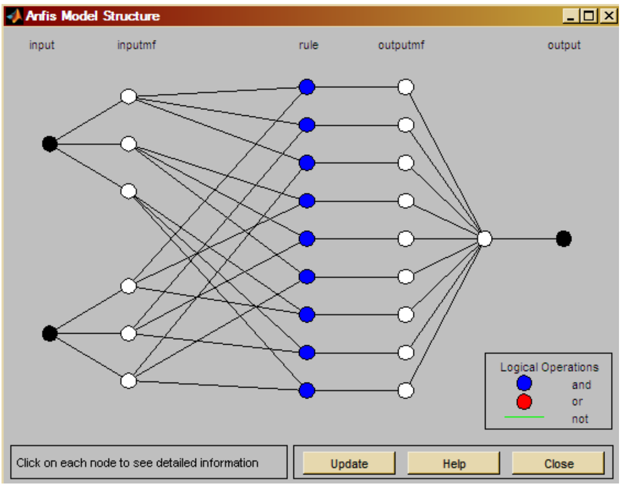

Figure 7: ANFIS structure for given input

III. Modeling Results

In this section, we present the experimental results of the proposed method based on several experiments involving real image data. The set of experiments evaluate the effect of different wavelet filters on the quality of the reconstructed image. Experiments were conducted using the standard data base such as images _lena‘, _hydrangeas‘ and _woman_darkhair‘. Images were decomposed using Haar and Daubechies filters (db2, db4, db6 and db18) Band -1 is coded using DPCM and remaining bands are coded using ANFIS. After those coefficients are vector quantize using k-means algorithm for better compression.

The performance measures for analysis used is mainly Mean square Error (MSE), Peak Signal to Noise Ratio (PSNR), Compression Ratio and Image Quality. Where MSE is the cumulative squared error between the compressed and the original image. Whereas PSNR is a measure of the peak error.

Figure 8 shows the input image and the compressed Lena image using Haar and different wavelet filters with $\lambda = 5$. In the other set of experiment shown in figure 9 and 10, we set $\lambda = 5$ with different wavelets applied on the Hrdranges and woman_darkhair. It is seen that from both the set of experiment, the result obtained by Haar wavelet is better compared to Daubechies family[19]. It is seen from both the set of experiments, High compression ratio and high PSNR is obtained with nearly same visual appearance with minimum error can be achieved using Haar wavelet [20]. Table 1 shows comparative analysis for different parameters for different filters applied to different image samples.

Figure 8: (a) Original lena image (b) Reconstructed image using Haar wavelet (c) Reconstructed image using db2 (d) Reconstructed image using db4 (e) Reconstructed image using db6 (f) Reconstructed image using db18

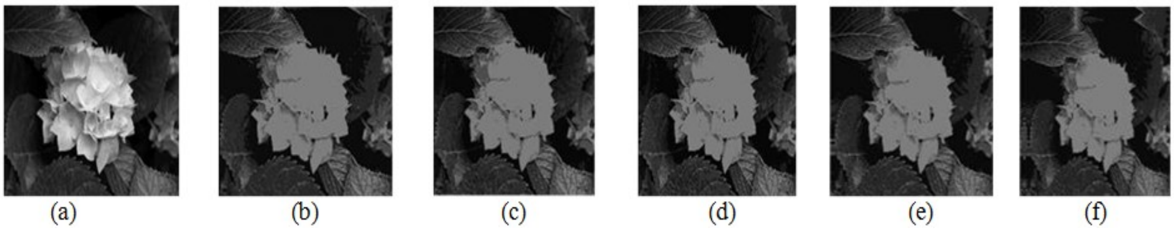

Figure 9: (a) Original Hydrangeas image (b) Reconstructed image using Haar wavelet (c) Reconstructed image using db2 (d) Reconstructed image using db4 (e) Reconstructed image using db6 (f) Reconstructed image using db18, λ= 5

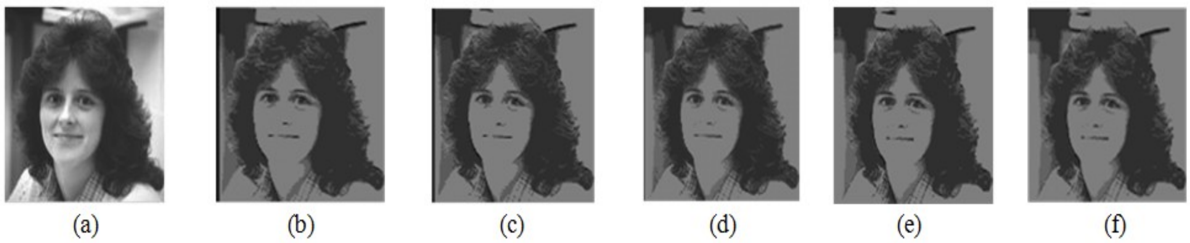

Fig.10:(a) Original Hydrangeas image (b) Reconstructed image using Haar wavelet (c) Reconstructed image using db2 (d) Reconstructed image using db4 (e) Reconstructed image using db6 (f) Reconstructed image using db18, λ= 5

Image	Performance Measures	Haar Wavelet	Daubechies2	Daubechies4	Daubechies6	Daubechies18

Lena.bmp	MMSE(dB)	2.53	2.60	3.17	3.51	5.03
	PSNR(dB)	44.11	43.97	43.12	42.68	41.12
	Compression Ratio	78.13	77.73	77.08	76.42	72.21
Hydrangeas.jpg	MMSE(dB)	1.09	1.24	1.45	1.63	2.41
	PSNR(dB)	47.76	47.20	46.52	46.01	44.30
	Compression Ratio	78.11	77.90	77.52	77.14	74.79
Woman_darkhair.tif	MMSE(dB)	3.69	3.50	3.55	3.91	5.56
	PSNR(dB)	42.46	42.69	42.63	42.21	40.68
	Compression Ratio	78.15	77.53	77.18	76.44	72.10

Table1: Comparative analysis of proposed method with different wavelet filters for three image samples

IV. Conclusion

For compression of images many researchers have been proposed various algorithms and techniques. It is seen that in conventional methods it is very difficult to recover the missing pixels at the decoder side. The proposed method works very efficiently and effectively and the results obtained are extremely good. From table 1 it is clear that the results obtained by proposed method using Haar wavelet achieves high compression up to 78.13% which is a very high compression rate. Also the visual quality of output image is intact and hence is nearly same as input image. Moreover, the Peak Signal to Noise ratio (PSNR) value obtained is very high at a cost of small minimum mean square error (MMSE) value.

References

[1] R. C. Gonzalez and R. E. Woods, "Digital Image Processing", 2nd Ed., Prentice Hall, 2004.

[2] Alpcan, T., Kesal, M. and Deliç, H. (1998) Wavelet Based Subband Vector Quantization Algorithm for Gray Images', Proceedings of the IASTED International Conference on Signal and Image Processing, Las Vagas, Nevada, Oct.28-31,1998, pp.720-724.

[3] Nobuhara H. and Hirota, K. (2004), ‗Color image compression/reconstruction by YUV fuzzy wavelets‘, IEEE Annual Meeting of the Fuzzy Information, Vol.2, Pp. 774 – 779.

[4] Khalid W. Alnaji and Waseam M.Ashour(2011), ‗A Novel Clustering Algorithm Using K-means (CUK)‘, International Journal of Computer Applications © 2011 by IJCA Journal,1 - Article 3.

[5] Mrs. S.Sujata, Mrs. A. Shanthi Sona(2013), ‗New Fast K-Means Clustering Algorithm using Modified Centroid Selection Method‘, International Journal of Engineering Research & Tech., Vol.2/Issue 2.

[6] Liu H, Zhai L, Gao Y, Li W and Zhou J (2005) ―Image compression based on biorthogonal wavelet transform‖, proceedings of ISCIT, pp 578–581

[7] Averbuch A, Lazar D and Israeli M (1996) ―Image compression using wavelet transform and multiresolution decomposition,‖ IEEE Trans. Image Processing 5:4–15

[8] Y. Tanaka, M. Ikehara, T.Q. Nguyen, ―Multiresolution image representation using combined 2-D and 1-D directional filter banks,‖ IEEE Trans. Image Proc., Vol. 18, pp. 269-280, 2009.

[9] Sudhakar, R., Karthiga, R and Jayaraman, S. (2005) Image Compression using Coding of Wavelet Coefficients – A Survey, ICGST-GVIP Journal, Vol. 5, Issue 6, Pp.25-38.

[10] C.-L. Chang and B. Girod, ―Direction-adaptive discrete wavelet transform for image compression,‖ IEEE Trans. Image Process., vol. 16, no. 5, pp. 1289– 1302, May 2007.

[11] R. Eslami, H. Radha, ―A new family of nonredundant transform using hybrid wavelets and directional filter banks,‖ IEEE Trans. Image Proc., Vol. 16, No. 4, 2007.

[12] Vipula Singh . Navin Rajpal . K. Srikanta Murthy, ‗Design of a Neuro Fuzzy Model for Image Compression in Wavelet Domain‘, J. Indian Soc. Remote Sens. (June 2009) 37:185–199-springer

[13] F. C. A. Fernandes, R. L. C. van Spaendonck, and C. S. Burrus, ―Multidimensional, mapping-based complex wavelet transforms,‖ IEEE Trans. Image Process., vol. 14, no. 1, pp. 110–124, Jan. 2005.

[14] A. Habbi, ―Comparison of Nth-order DPCM encoder with linear transformation and block quantization techniques,‖ IEEE Trans. Commun., vol. COM-19, pp. 948-956, Dec. 1971.

[15] Y.Chakrapani , K.Soundararajan, ‗Adaptive Neuro-Fuzzy Inference System based Fractal Image Compression‘, ACEEE International Journal on Signal and Image Processing Vol 1, No. 2, July 2010

[16] Zhibin Liu, Tong Li and Fengshan Xiong, ‗An Improved ANFIS Method and Its Application on Agricultural Information Degree Measurement‘, MMIT- 08 proceeding on Int. conference on Multimedia & Information Technology, IEEE Computer Society Washington, DC, USA

[17] Shohel Ali Ahmed, Snigdha Dey, Kandarpa Kumar Sarma ―Image Texture Classification Using Artificial Neural Network (ANN)‖ 978-1-4244-9581- 8/11/$26.00 © 2011 IEEE.

[18] Arun Vikas Singh Srikanta Murthy K, ‗Neuro-Wavelet based Efficient Image Compression using Vector Quantization‘ , international Journal of Computer Applications © 2012 by IJCA Journal Volume 49 - Number 3 .Year of Publication: 2012

[19] Adnan Khashman, Kamil Dimililer, "Image Compression using Neural Networks and Haar Wavelet" WSEAS Transactions on Signal Processing, vol. 4, may 2008, pp. 330–339.

[20] Anuj Bhardwaj and Rashid Ali, "Image Compression Using Modified Fast Haar Wavelet Transform," World Applied Sciences Journal, vol. 7, 2009, pp.647-653.