Analysis of Image Compression Approaches Using Wavelet Transform and Kohonen's Network

MOURAD RAHALI[1,2], HABIBA LOUKIL[1], MOHAMED SALIM BOUHLEL[1]
[1]Sciences and Technologies of Image and Telecommunications
High Institute of Biotechnology, University of Sfax, TUNISIA
[2]National Engineering School of Gabes, University of Gabes, TUNISIA
rahali.mourad@yahoo.fr, loukil_habiba@voila.fr, medsalim.bouhlel@enis.rnu.tn

Abstract: - Since digital images require a large space on the storage devices and the network bandwidth, many compression methods have been used to solve this problem. Actually, these methods have, more or less, good results in terms of compression ratio and the quality of the reconstructed images. There are two main types of compression: the lossless compression which is based on the scalar quantization and the lossy compression which rests on the vector quantization. Among the vector quantization algorithms, we can cite the Kohonen's network. To improve the compression result, we add a pre-processing phase. This phase is performed on the image before applying the Kohonen's network of compression. Such a phase is the wavelet transform. Indeed, this paper is meant to study and model an approach to image compression by using the wavelet transform and Kohonen's network. The compression settings for the approach to the model are based on the quality metrics rwPSNR and MSSIM.

Keywords - Image compression, Kohonen's networks, wavelet transform, learning algorithm, rwPSNR, MSSIM.

1 Introduction

The compression techniques are divided into two main categories. First, the lossy compression in which some of the information in the original image is lost. Second, the lossless compression exploits the information redundancy in the image to reduce its size. The lossy compression methods [1] are more likely to achieve higher compression ratio than those obtained by the lossless methods [2]. The methods of image compression by neural networks [3] yield acceptable results. Yet, these methods have a limit on the compression ratio and the reconstructed image quality. To improve the reconstructed image quality, we combine the discrete wavelet transform (DWT) [9] and the quantization by Kohonen’s networks [4]. Thereafter, we use the Huffman coding to encode the quantized values [5][12]. In this paper, we are interested in the study of an approach to image compression through the use of the wavelet transform and Kohonen’s network. We will, in particular, detail the learning process of image compression and evaluate the compression result with a new quality metric rwPSNR. To develop and improve the assessment, we will use another quality metric; namely, the MSSIM. Next, we test the image compression by using the wavelet and Kohonen’s network together. Lastly, we make a comparison by using Kohonen’s network only without the wavelet transform and the second comparison between the proposed approach and various compression methods.

2 Proposed approach

2.1.Image compression

Image compression is carried out through the following steps:

- Apply a wavelet transform [7] to an original image depending on the decomposition level and the wavelet type.
- Decompose the image into blocks according to a block size (for example 2x2, 4x4, 8x8 or 16x16).
- Search the codebook for each block and the code word with a minimum distance from the block. The index of the selected word is added to the index vector that represents the compressed image.
- Code the index vector by a Huffman coding [12].
- Save the index vectors coded for use during decompression.

The Figure 1 depicts the steps of compression.

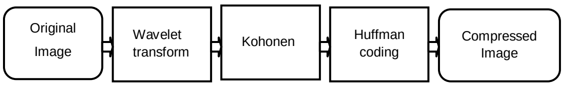


Fig. 1. Image compression Steps

2.2.Learning phase

In fact, learning [6] is deemed to be a very important step to compress images by the neural network. The goal is to construct codebooks to be used during compression. The learning process is described in Figure 2.

The first step of learning is the wavelet transform of an original image to obtain four sub-images: an approximation image and three detail-images (figure 4) in different resolutions depending on the decomposition level and the wavelet choice. The second step is to decompose the four sub-images in blocks according to the block sizes (2x2, 4x4, 8x8 or 16x16). The blocks are arranged in linear vectors to be presented in the Self-Organizing Map (SOM) [4] one after the other. The third step is to adjust the weight-coupling according to an index vector. The weights obtained at the end of learning represent the codebook which will be used for compression. The codebook obtained depends on several settings such as the choice of the learning image, the type of the wavelet transform, the decomposition level, the block size and the size of the self-organizing map. Therefore, we should create several codebooks to improve the compression.

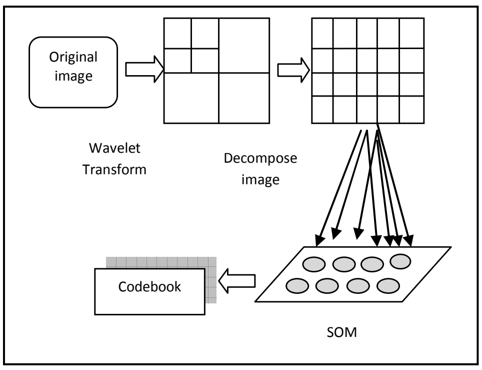


Fig.2. Learning phase

2.3.Image Decompression

Image decompression is realized throughout these steps:

- Replace each code by the corresponding index to obtain the index vector. This is the decoding step.
- Find the three detail-images and the approximation image by replacing each element of the index vector by the corresponding block in the codebook. In order to improve the reconstructed image quality, in our approach, we keep the approximation image un-indexed by the self organization map.
- The inverse transform is applied to the sub-images obtained after de-quantization to display the reconstructed image.

The Figure 3 described the decompression steps.

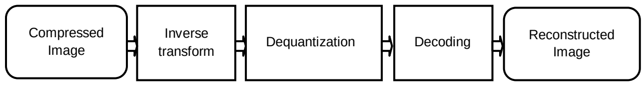


Fig.3. Image decompression Steps

The same codebook is used during both compression and decompression.

2.4.Kohonen's network algorithm

Kohonen's network algorithm [8] [4] follows these steps:

- Find the winning neuron of the competition

$$d(X, w_c) \le d(X, w_i), \forall i \ne c \tag{1}$$

Where, X is input vector, w_c is weight vector of the winning neuron c and w_i is weight vector of the neuron i

- Update weight w_i

$$w_i(t+1) = w_i(t) + h(c,i,t) * \left[X - w_i(t)\right] \tag{2}$$

Where, w_i is the weight vector of the neuron i in instant t and h is a function defined by :

$$h(c,i,t) = \begin{cases} \alpha(t), i \in N(c,t) \\ 0, \text{ else if} \end{cases} \; with \;\; \alpha(t) \in [0,1] \tag{3}$$

The function h defined the extent of the correction to the winning neuron c and its neighborhood.

In instant t, the neighbors of winning neuron c are determined by the function $N(c,t)$. The final neighbors of a neuron consist of the neuron itself. The function $h(c,i,t)$ assigns the same correction $\alpha(t)$ for all neurons belonging to the neighbors of the winning neuron at instant t.

2.5.Image pretreatment using wavelet transform

The two-dimension-wavelet transform [7][9] is adopted in our approach. Figure 4 shows the image division into sub-images for the case of seven-band decomposition. The sub-image LL2 represents the lowest frequency of the original image. As a matter of fact, the restoration of the wavelet coefficients in the sub-image LL2 will directly affect the image quality.

The sub-images HH1, LH1, HL1, HH2, LH2, and HL2 contain detail information of the edge, the outline and the vein of the image at different decomposition layers. Concretely, the sub-image HL2 and the sub-image HL1 denote the image-coefficient at the vertical edge after the first and the second layers wavelet decomposition. The sub-image LH2 and the sub-image LH1 indicate the image coefficients at the horizontal edge. The sub-image HH1 and the sub-image HH2 signify the image coefficients on the cross edge.

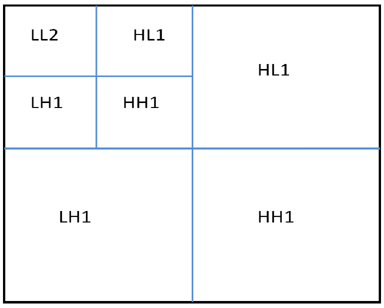


Fig.4. Decomposition on the frequency by wavelet

3 Objective assessments : The quality index

To improve our method, we use tow quality metric: rwPSNR and MSSIM.

3.1. The relative weighted Peak Signal to Noise Ratio rwPSNR

The PSNR quantifies an intensity of the distortion. It does not adjust to the dynamic characteristics of the image. Indeed, the deterioration is more visible in less textured zones (weak variance) and is less visible in more textured zones (stronger variance). Accordingly, we take the variance of the picture into consideration. Hence, it increases when the variance is high and decreases in the opposite case. We will have a new definition of the MSE.

Let X = {xij| I = 1,..,M; j=1,..,N}and Y = { yij| I=1,..,M ;j=1,.., N} be the original image and the test image, respectively. The wMSE is given as:

$$wMSE = \frac{1}{MN}\sum_{m=0}^{M-1}\sum_{n=0}^{N-1}\left(\frac{\left|\left(x_{m,n}-y_{m,n}\right)\right|}{1+Var\left(M,N\right)}\right)^2 \quad (4)$$

Where Var (M,N) is the test image variance. The human eyes do not have an equal sensitivity across the different intensities. In fact, there is a threshold of sensitivity that must be exceeded before an increase of the intensity so that it can be detected. So, as a complement to the wPSNR, we introduce our rwPSNR [10] "relative weighted PSNR" which takes account of the relative difference of the image-gray levels because the noticeable difference of the two stimuli is roughly proportional to the intensity of the stimulus. Actually, an error between two pixels of two images can not translate the same error deviation between two pixels of two other images with the same intensity difference. Indeed, if the intensity difference (10) between the pixels is 10 and 20, it remains numerically the same as that between a pair of pixel values 110 and 120. However, the perception differs on the visual plan. In the first case, the error is quantified at 100% (20 to 10). But, in the second case, the error is quantifiable at 10% (120-110). Therefore, one has to think about the necessity of introducing the relative difference notion in the calculation of the wPSNR from which rwPSNR is derived. So, we have a new definition of the MSE noted as rwMSE "relative weighted Mean Square Error" which takes account of the variance and the image intensity. Our rwMSE is defined as follows:

Let X = {x | i = 1, ... ,M; j = 1, ... , N} and Y ={y | i = 1, ... ,M; j = 1, ... , N} respectively be the original image and the test image. The rwMSE is given as:

$$rwMSE = \frac{1}{MN}\sum_{m=0}^{M-1}\sum_{n=0}^{N-1}\left(2*\frac{\left|\left(x-y\right)/\left(x+y\right)\right|}{1+Var\left(M,N\right)}\right)^2 \quad (5)$$

The expression of our relative weighted peak signal to noise ratio is given by:

$$rwPSNR = 10*\log_{10}\left(\frac{x^2{}_{\max}}{rwMSE}\right) \quad (6)$$

3.2. The Structural similarity means MSSIM

The new image quality measurement design is based on the assumption that the human visual system is highly adapted to extract the structural information of the visual field. The measurement of the structural information change can provide a good approximation of the distortion of the perceived image. The error sensitivity approach estimates the perceived errors to quantify the image degradation; whereas, the new philosophy considers the degradation of the image as the perceived changes in the structural information. The luminosity of the surface of the observed object is the product of illumination and reflection. But the structures of the objects in the scene are independent of illumination. Therefore, to explore the structural information in an image, we have to eliminate the influence of illumination. Therefore, the structural information in an image is defined as the attributes that represent the structures of the objects. Since luminosity and contrast may vary across the scene, we use luminosity and the local contrasts in our definition.

The system breaks the task of similarity measurement into three comparisons: Luminosity $L(x, y)$, Contrast $C(x, y)$ and Structure $S(x, y)$. The combination of the three comparisons determines the structural similarity index (SSIM) [11].

$$SSIM(x,y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C1)(\sigma_x^2 + \sigma_y^2 + C_2)} \quad (7)$$

When applying, only one total quality measurement of the whole image is required; whence, a means SSIM index (MSSIM) to assess the overall quality of the image is determined.

$$MSSIM(X,Y) = \frac{1}{M}\sum_{i=1}^{M} SSIM(x_i, y_i) \quad (8)$$

4 Subjective assessments

The objective assessment is insufficient to assess the visual quality of the compression methods. The subjective assessment analyzes the degradation of visual quality of images. Also, the human eye can judge the compression quality to compare the result between compression methods. In our work, we compare tow compression methods with and without wavelet transform.

4.1.Quantitative assessments of results

In our work, we change the compression parameters: the decomposition level (j) of the wavelet, the input block size (BS), the wavelet type and the size of the self organizing map (SOM). To evaluate the performance of our approach in image compression, we use the following measures: bits per pixel (Nbpp), the means square error (MSE), the relative weighted peak signal to the noise ratio (rwPSNR) and the structural similarity means (MSSIM) and we compare our approach to image compression without using the wavelet transform (Table 1and 2)

Table 1. With wavelet transform

	Nbpp	rwPSNR	MSE	MSSIM	Parameters
Lena	4.60	66.98	41.60	0,954	J=1; BS=4; SOM=256
	4.17	66.87	43.43	0,946	J=1; BS=4; SOM=64
	3.02	62.94	66.88	0,933	J=1; BS=16; SOM=256
	1.94	61.06	175.21	0,785	J=2; BS=16; SOM=256
	0.59	60.76	208.31	0,732	J=2; BS=256; SOM=16
	0.34	58.06	502.25	0,526	J=3; BS=64; SOM=16
Cameraman	4.71	61.75	90.08	0,932	J=1; BS=4; SOM=256
	3.90	61.47	93.58	0,928	J=1, BS=4, SOM=64
	2.79	60.04	114.65	0,899	J=1, BS=16, SOM=256
	2.32	59.82	120.43	0,892	J=1, BS=16, SOM=64
	1.82	59.20	135.9	0,859	J=1, BS=16, SOM=4
	1.29	58.08	385.75	0,724	J=2, BS=16, SOM=64
	0.57	57.72	403.24	0,664	J=2, BS=256, SOM=64
Barbara	4.14	62.82	155.29	0,899	J=1, BS=4, SOM=64
	2.96	61.18	204.50	0,857	J=1, BS=16, SOM=256
	2.42	60.49	246.09	0,813	J=1, BS=4, SOM=4
	1.83	60.13	258.69	0,770	J=1, BS=256, SOM=4
	1.36	57.60	394.86	0,650	J=2, BS=16, SOM=64
	0.59	57.68	469.14	0,526	J=2, BS=64, SOM=4
	0.21	56.42	624.43	0,369	J=3, BS=256, SOM=4

Table 2. Without wavelet transform

	Nbpp	rwPSNR	MSE	MSSIM	Parameters
Lena	3.92	63.45	92.43	0.938	BS=4; SOM=256
	2.54	61.14	133.26	0.869	BS=4; SOM=64
	1.91	60.70	151.82	0.845	BS=16; SOM=64
	1.66	59.73	175.75	0.753	BS=16; SOM=16
	0.82	61.03	248.99	0.738	BS=64; SOM=16
	0.31	57.47	566.33	0.486	BS=256; SOM=16
Cameraman	3.72	60.43	120.62	0.898	BS=4; SOM=256
	2.23	59.86	177.74	0.863	BS=4; SOM=64
	2.01	56.04	253.46	0.833	BS=16; SOM=64
	1.39	57.21	211.84	0.739	BS=16; SOM=16
	0.75	57.65	415.16	0.703	BS=64; SOM=16
	0.42	55.79	454.63	0.661	BS=256; SOM=64
	0.39	55.65	530.23	0.502	BS=256; SOM=16
Barbara	3.23	61.53	156.83	0.865	BS=4; SOM=256
	2.99	60.09	181.62	0.837	BS=4; SOM=64
	2.36	57.56	265.42	0.792	BS=16; SOM=64
	1.56	56.61	316.59	0.687	BS=16; SOM=16
	0.75	58.62	366.85	0.643	BS=64; SOM=16
	0.47	55.61	507.30	0.541	BS=256; SOM=64
	0.33	54.83	563.21	0.364	BS=256; SOM=16

Table 3 shows an objective assessment of the relative weighted peak signal to the noise ratio (rwPSNR) depending on the number of bits per pixel (Nbpp). The blue curve represents the rwPSNR of the compressed images using the discrete wavelet transform and Kohonen’s network. The green curve represents the rwPSNR of the compressed images using only Kohonen’s network without the wavelet transform. Thus, we see very well that the image quality calculated by our metric (rwPSNR) has been improved by the compression approach using the wavelet transform compared to the other approach without wavelet transform. Table 4 shows an objective assessment of the structural similarity means (MSSIM) depending on the number of bits per pixel (Nbpp). The blue curve represents the MSSIM of the compressed images using the discrete wavelet transform and Kohonen's network. The green curve represents the MSSIM of the compressed images using only Kohonen's network without the wavelet transform.

Table 3. Curves of rwPSNR=f(Nbpp)

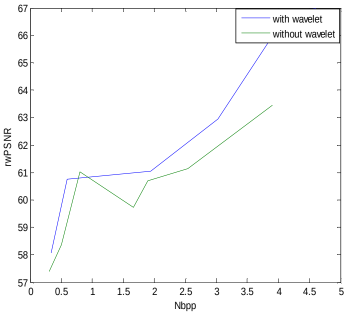
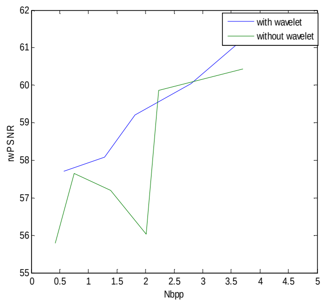
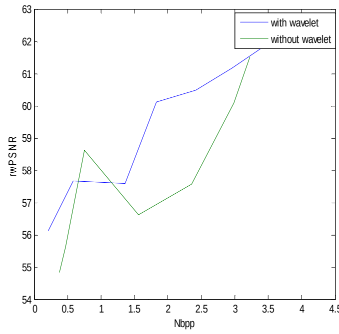
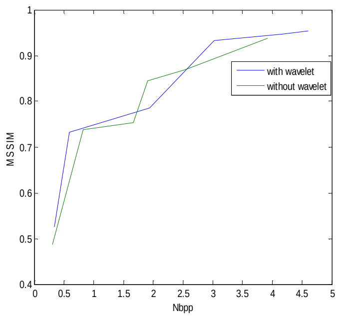
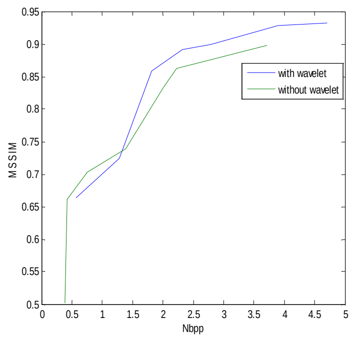
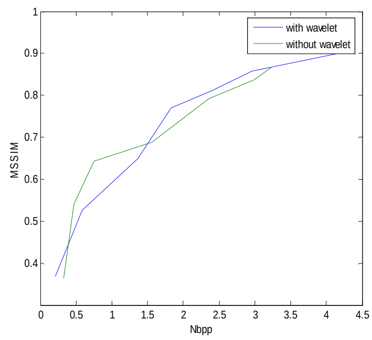
Lena	Cameraman	Barbara
		

Table 4. Curves of MSSIM=f(Nbpp)

Lena	Cameraman	Barbara
		

4.2.Assessment of the images visual quality

The figure 5 to10 provide the assessment of the visual quality of three images (Lena, Cameraman and Barbara) which are compressed by our approach.

(a) MSE=41.60, rwPSNR=66.98, mssim = 0,954

(b)MSE=175.21, rwPSNR=61.06, mssim= 0,785

(c)MSE=502.25, rwPSNR=58.06, mssim= 0,526

Fig. 5. The visual quality With wavelet transform of Lena

(a')MSE=92.43, rwPSNR=63.45, mssim= 0.938

(b')MSE=175.75, rwPSNR=59.73, mssim= 0.753

(c')MSE=566.33, rwPSNR=57.47, mssim= 0.486

Fig. 6. The visual quality without wavelet transform of Lena

(a)MSE=93.58, rwPSNR=61.47, mssim= 0,928

(b)MSE=135.972, rwPSNR=59.20, mssim= 0.859

(c)MSE=403.24, rwPSNR=57.72, mssim= 0,664

Fig. 7. The visual quality with wavelet transform of Cameraman

(a')MSE=120.62, rwPSNR=60.43, mssim= 0.898

(b')MSE=211.84, rwPSNR=57.21, mssim= 0.739

(c')MSE=530.23, rwPSNR=55.65, mssim= 0.502

Fig. 8. The visual quality without wavelet transform of Cameraman

(a)MSE=246.09, rwPSNR=60.49, mssim=0,813

(b)MSE=258.69, rwPSNR=60.13, mssim=0,770

(c)MSE=469.14, rwPSNR=57.68, mssim=0,526

Fig. 9. The visual quality with wavelet transform of Barbara

(a')MSE=265.42, rwPSNR= 57.56, mssim= 0.792

(b')MSE=316.59, rwPSNR=56.61, mssim= 0.753

(c')MSE=507.3, rwPSNR=55.61, mssim= 0.541

Fig. 10. The visual quality without wavelet transform of Barbara

4.3.Comparison between our approach and various methods

To evaluate our result, we use the standard image quality metrics for comparisons with other methods. The standard metrics is Peak Signal to Noise Ratio (PSNR) and Compression Ratio (CR). Table 8 and 9 show the comparison between the proposed approach and various methods [8][13][14]. The methods were applied on standard images 256*256 (Lena and Cameraman) : Neural Network one level, Neural Network two level [13], standard and modified Self-Organization Map SOM [8] and wavelet transform combined by Vector Quantization VQ [14].

Table 8. Comparison Results for Lena Image

Methods	Nbpp	CR	PSNR
Proposed method	1.39	82.59	25.18
	1.8	78	27.39
Neural Network one level	2.32	71	27.3
Network neuron two levels	1.49	81.3	24.7
Modified SOM	1.84	77	22.15
Standard SOM	1.7	79	19.15
Wavelet transform + Vector Quantization	3.2	60	26.2

Table 9. Comparison Results for Cameraman Image

Methods	Nbpp	CR	PSNR
Proposed method	1.77	77.8	25.44
Modified SOM	2.32	71	23.65
Standard SOM	1.79	77.6	20.67

4.4.Simulation and results

Our work is based on the comparison of different compression methods. The performance evaluation using various image quality metrics like PSNR, rwPSNR, MSE and MSSIM indicates that the best method is the wavelet transform and kohonen's network. After comparing the two compression methods with and without wavelet transform, we can show the importance of using the wavelet transform in compression. In fact, the wavelet transform allows reducing the entropy of the image and separating its details to improve the quality of the reconstructed image according to the number of bits per pixel (table 3 and 4). The reconstructed image quality is acceptable; i.e. for rwPSNR it is more than 59 and for MSSIM it is between 0.7 and 1. The block effect is remarkable if the block size (BS) is higher than 256 and the degradation of the visual quality if the level of decomposition of the wavelet (J) is superior or equal to 2.

For performance evaluation, the proposed method is compared with various methods [8][13][14]. The comparison is done using various measures such as PSNR, the number of bits per pixel Nbpp and compression ratio CR. From Table 8 and 9, we can be deduced that the PSNR according of bits per pixel compression ratio of our method is better than of the some compression methods. From table 8, the PSNR of our method is 25.18 and the CR is 82.59% but the PSNR of NNs with two levels [13] is 24.7 and CR is 81.3%. So, the PSNR and CR are better in proposed approach

5 Future scope and conclusion

In this paper, we use an image compression approach based on the wavelet transform and the vector quantization by Kohonen's network and the Huffman coding. We use two metrics to assess the reconstructed image quality: rwPSNR and MSSIM. We compare our method with other compression methods. The comparison is done using various standard measures such as PSNR and CR, it can be recognized that the PSNR according to CR of our method is better than some of the methods. To improve the reconstructed image quality and the compression ratio, we will add a phase of pre-treatment before the wavelet transform. We will use Weber-Fechner law and the A-law, which are used in the field of telephony, to quantify an image through the semi-logarithmic method.

References

[1]. D. Koff and H. Shulman, "An Overview of Digital Compression of Medical Images: Can We Use Lossy Image Compression in Radiology?", Canadian Association of Radiologists Journal,Vol 57, N°4, October 2006.

[2]. N. Zhang and X. Wu "Lossless compression of color mosaic images", Image Processing, IEEE Transactions on Vol 15, Issue 6, pages 1379 – 1388, June 2006.

[3]. J Jiang, "Neural network technology for image compression", International Broadcasting Convention, 14-1, Conference Publication N° 413, IEEE, September 1995.

[4]. T. Kohonen, "The self-organizing map", proceeding of the IEEE, Vol 78, N° 9, September 1990.

[5]. J. Pujar and L. Kadlaskar, " A New Lossless Method Of Image Compression And Decompression Using Huffman Coding Techniques", Journal of Theoretical & Applied Information Technology, Vol. 15 Issue 1/2, p18-23, 2010.

[6]. J. Ribés, B. Simon and B. Macq "Combined Kohonen neural networks and discrete cosine transform method for iterated transformation theory", Vol 16, Issue 7, Pages 643-656, April 2001.

[7]. P. Raghuwanshi and A. Jain "A Review of Image Compression based on Wavelet Transform Function and Structure optimization Technique", International Journal Computer Technology and Applications, Vol 4, pages 527-532, June 2013.

[8]. G. Boopathi, "An Image Compression Approach using Wavelet Transform and Modified Self Organizing Map", International Journal of Computer Science Issues, Vol. 8, Issue 5, N° 2, September 2011.

[9]. A. S. Lewis, G. Knowles, "Image compression using the 2-D wavelet transform", IEEE Transactions on Image Processing, Vol 1, Issue 2, pp 244-250, April 1992

[10]. H. Loukil, M. H. Kacem and M. S. Bouhlel, "A New Image Quality Metric Using System Visual Human Characteristics", International Journal of Computer Applications, Vol 60, N° 6, December 2012.

[11]. Alan C. Brooks, Xiaonan Zhao and Thrasyvoulos N. Pappas, "Structural Similarity Quality Metrics in a Coding Context: Exploring the Space of Realistic Distortions", IEEE Transactions On Image Processing, Vol. 17, N° 8, August 2008.

[12]. M. K. Mathur, S. Loonker, D. Saxena, "Lossless Huffman Coding Technique for image Compression And Reconstruction Using binary Trees" international journal of computer technology and applications,Vol 3, N°1, pp76-79,Feb 2012.

[13]. S. A. Alshehri, "Neural Network Technique for Image Compression" IET Image Processing, pp. 1–5, September 2015.

[14]. H. Wang, L. Lu, D. Que, X. Luo, "Image Compression Based Om Wavelet Transform And Vector Quantization", International Conference on Machine Learning and Cybernetics, Beijing, 45 November 2002.