Effect of Two Dimensional Image Compression on Statistical Features of Image using Wavelet Approach

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ABSTRACT
The wavelet based approach becoming most common for image compressions and de-noising. The level of decomposition during image compression may be optimized to retain use full energy contents. In this paper we are analyzing the effect of image compressions on its statistical features. These statistical features will be utilized for image recognition and analysis. This analysis will help us in the designing of recognition techniques where image compression will be a prime requisite to save memory and channel space with enhanced speed. The real time image processing is the main application area of the proposed concept.

Categories and Subject Descriptors
Image Processing and Computer Vision

General Terms
Algorithms, Performance, Reliability, Experimentation, Theory

Keywords
DWT, De-noising, Histogram, IDWT, Image Compression, LPF, HPF, Decomposition Tree

1. INTRODUCTION
The image compression techniques involve chain decomposition. The two dimensional image can be decomposed up to any level but to identify the optimized decomposition level is a very tough job. We have tried to analyze the effects of various decomposition levels on their statistical parameters.

The statistical parameters have unique characteristics about the two dimensional images. The image compression techniques are of two kinds lossless and lossy. The lossless techniques are BMP, TIFF,DPCM, GIFF,PNG and MNG where as lossy techniques are chroma sampling, transform coding such as Fourier, wavelet etc. and fractal compressions. The image compression is basically the removal of coding, psycho visual and inter-pixel redundancies [2], [4], [5], [8], [9].

2. METHODOLOGIES

2.1 Image compression through wavelet

2.1.1 Wavelet analysis
Let $\boldsymbol{W} = \{W_{ij}$; i, j = 1, 2…N$\}$ denote the N×N matrix of the original image to be recovered and N is integer power of 2. During transmission the signal $\boldsymbol{W}$ is corrupted by distributed (*i. j. l*) zero mean, white Gaussian Noise $\boldsymbol{k}_{ij}$ with standard deviation σ i.e. $\boldsymbol{k}_{ij} \sim \mathbf{M}(0, \sigma^2)$ and the noisy observations $\mathbf{a}_{ij} = \boldsymbol{W}_{ij} + \sigma\, \mathbf{k}_{ij}$ is obtained. Also for faithful transmission, the signal $\boldsymbol{W}$ from noisy observations $\boldsymbol{k}_{ij}$ should be such that the mean squared error be minimum. Let W_x and W_y denote the 2D discrete wavelet transform (DWT) matrix and its inverse respectively [1], [5], [6]. Then $\mathbf{X} = W_a$ represents the matrix of wavelet coefficients of a having four sub bands (LL, LH, HL and HH). The sub-bands HH_s, HL_s, LH_s are called details, where s is the scale varying from 1, 2 …… *d* and *d* is the total number of decompositions. The size of the sub band at scale **s** is $M/2^s \times M/2^s$. The sub band LL_d is the low-resolution residue. The wavelet thresholding de-noising method processes each coefficient of **X** from the detail sub bands with a soft threshold function to obtain $\hat{Y}$. The de-noised estimate is the inverse transform $\hat{\mathbf{W}} = W_x\hat{Y}$ [3], [4], [6], [7], [8], [9]. The block diagram of wavelet based image compression method is shown in figure2.

2.1.2 Multistep decomposition and reconstruction
A multi step analysis-synthesis process can be represented as shown in figure 1. These processes have two aspects: breaking up a signal to obtain the wavelet coefficients and reassembling the signal from the coefficients [3].

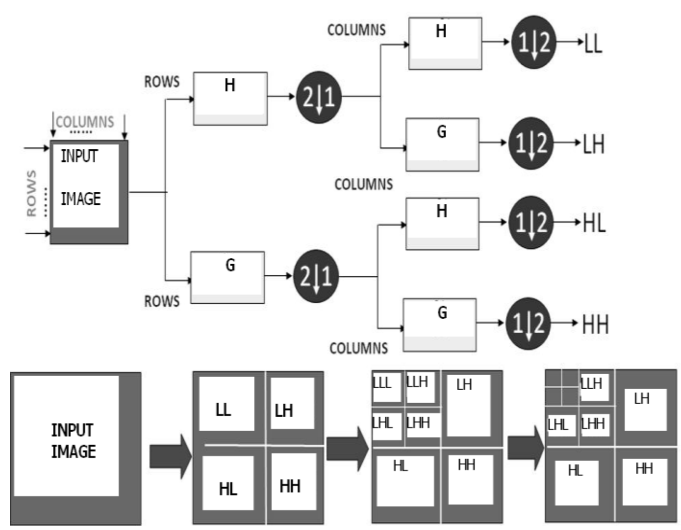


Figure 1. Various decomposition levels of 2D image

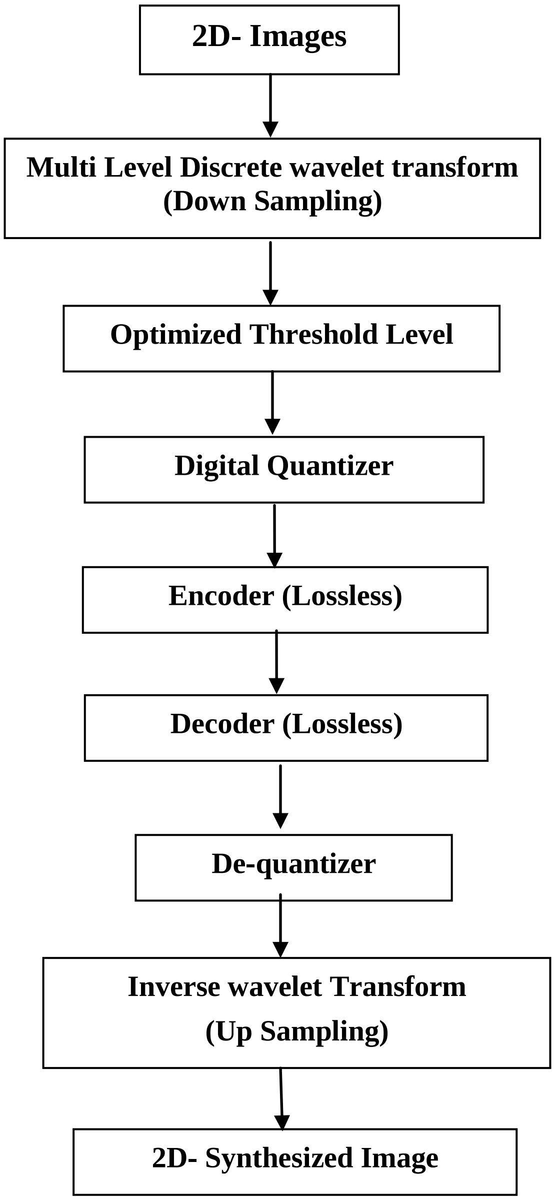


Figure 2. Process of 2D image compression through wavelet

2.2 Image de-noising algorithm

The image de-noising algorithm achieves optimal soft thresholding in the wavelet domain for recovering original signal from the noisy one [3], [4], [6], [7], [8]. This algorithm:

a) Performs multi-scale decomposition (MDWT) of the image corrupted noise using wavelet transform.

b) Estimates the noise variance σ^2 using equation (1), where X_{ij} Є HH_s

$$\sigma^2 = \left\{ \frac{Median(X_{ij})^2}{0.6755} \right\} \quad \textbf{(1)}$$

c) Computes scale parameters for each level.

d) Computes the standard deviation σ for each sub band, except low pass residual.

e) Computes the threshold T_N using:

$$T_N = \frac{\beta \sigma^2}{\sigma_y} \quad \textbf{(2)}$$

f) Apply soft thresholding to the noisy coefficients.

g) Invert the multi scale decomposition (IDWT) to reconstruct the de-noised image *W*.

2.3 Image fusion

The image fusion is used to improve the spatial resolution, geometric precision, enhancement of image features display, accuracy, and capability to change detection and replace or repair the defected image data [3]. Here, we are applying HPF fusion method. In this method, the high frequency component of high-resolution image is superimposed on low-resolution multispectral image, to obtain the enhanced spatial multispectral image. Let, $\mathbf{W}_k$ (i, j) is the fusion value of the band **k** pixel (i, j), L_k (i, j) is the value of multi-spectral of band **k** pixel (i, j), and **H** (i, j) shows the high frequency information of the high-resolution image. This phenomenon is well illustrated through equation 3.

$$W_k\,(i,j) = L_k(i,j) + H(i,j) \quad \textbf{(3)}$$

3. IMPLEMENTATION AND RESULTS

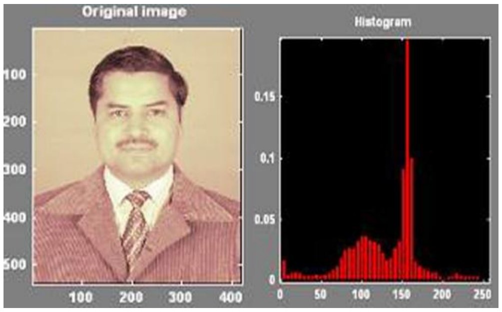
The statistical information obtained from all domains of two dimensional images using Haar wavelet will be used for developing image recognition techniques through fuzzy logic, or neuro-fuzzy approach. Figure 4, 5, and 6 are few examples, showing statistical information with corresponding histograms. The table1 can further be extended to accommodate more information about the image using different wavelets.

The image, which we want to process could be of any kind such as JPEG,TIFF, GIF, PNG, BMP, synthesised, denoised, reconstructed or resudues of image. Each of these will have unique statistical information. e.g. if we want to analyze an image through its detail diagonal coefficient and detail vertical coefficient then we could have the following statistical data respectively (refer table-1 for further details):

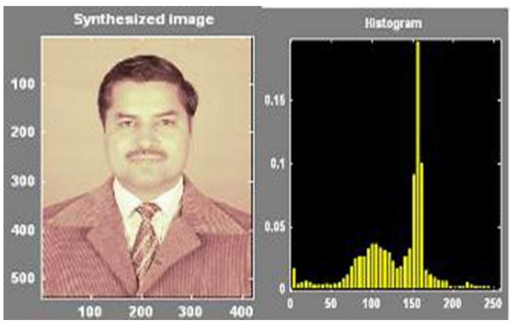
Mean	**Median**	**Mode**	**Max**	**Min.**	**Range**	**Standard Deviation**	**Median Absolute Deviation**	**Mean Absolute Deviation**
0.181	*0*	*3*	*150*	*-150*	*300*	*13.38*	*2*	*6.674*
0.284	*0*	*2.63*	*303*	*-310*	*613*	*44.46*	*3.75*	*17.82*

From above information, we may observe the uniqueness of statistical data obtained from analyzing same image with different wavelet approach. These informations are very much useful to distinguish and characterize an image. The reliable rcognition system can only be developed with sufficient knowledge base information about the object.We can integrate these informations to form fuzzy inference rule for image classification and processing.

3.1 Statistical analysis of 2D image using histogram

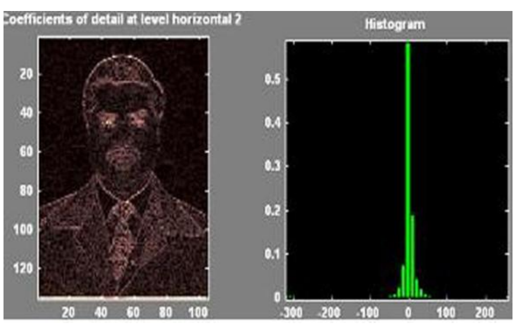


(a)

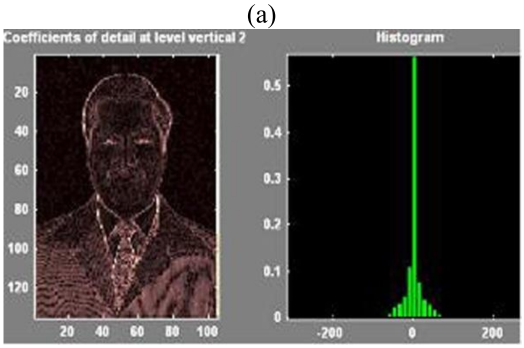


(b)

Figure 3. (a) Original 2D image
(b) Synthesised 2D image with statistical graph

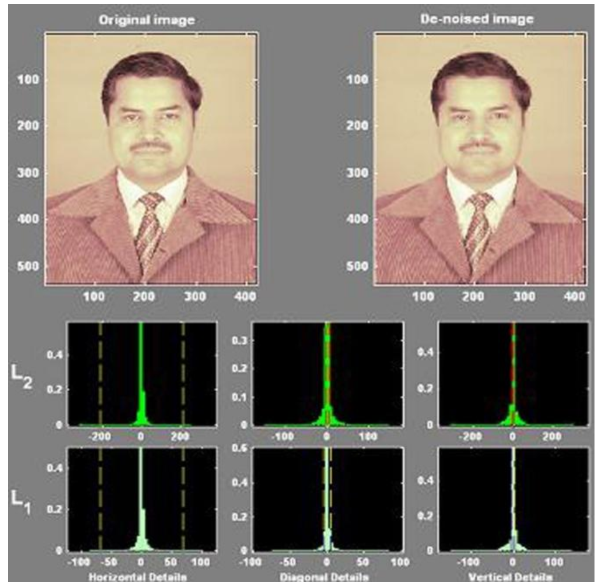


(a)

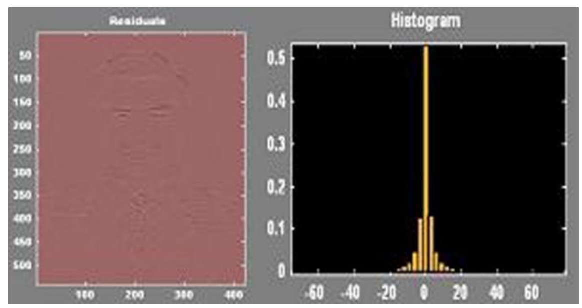


(b)

Figure 4. (a) Coefficient of details at level horizontal-2
(b) Coefficient of details at level vertical-2



(a)

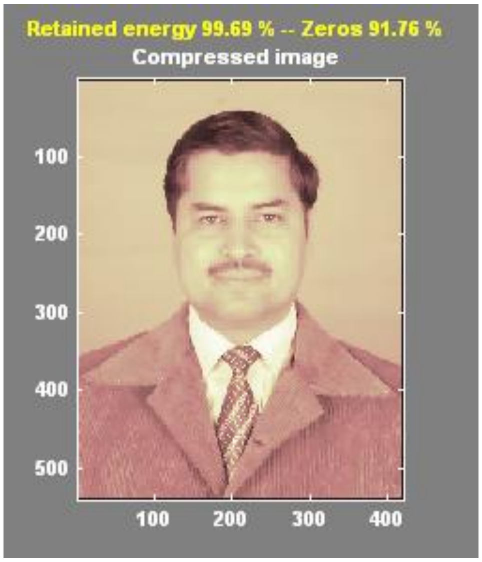


(b)

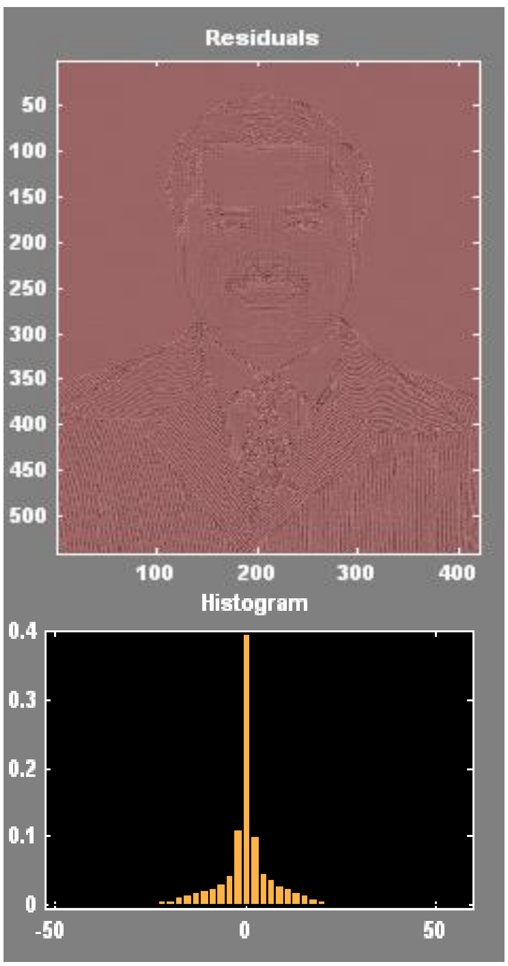
Figure 5. (a) Denoised 2D image with statistical information
(b) Residue of de-noised image and its statistica information

3.2 Effect of image compression

The effect of compressions at various level is summarized in table 2. From this table we can observe the tremendous changes in the statistical features of an image.The compressed image and its residual with histogram are shown in figure 6. On observing the table 2 we found that the mean and median deviation increses as we increse the decomposition level for any thresholding method. Also there is an effect of compression on retained energy content and zeros of the compressed image. On incresing the number of decomposition the energy content reduces and zeros increses. The effects of image compression on statistical features as summarised in table 2 is graphically illustrated in figure 9. These representation will be helpful while designing of image recognition techniques. The optimized decomposition level may also be formulated based on these statistical informations and graphs. Generally, the wavelet compression methods belongs to lossy compression techniques hence the optimised decomposition level is a prime requisite to retain usefull information about an image.



(a)



(b)

Figure 6. (a) Compressed image (b) Residual of compressed image with histogram

3.3 Two dimensional image fusion

The principle of image fusion using wavelets is to merge the wavelet decompositions of the two original images using fusion. This method is applied to the approximation and details coefficients of the images (refer figure 7). The fused image is obtained by fusion of the two original images X_1 and X_2. The image matrices X_1 and X_2 must be of the same size and associated with indexed images on a common color map. In the figure 8, the two images of same size are fused using wavelet decomposition to get synthesized image. The decomposition is done using DWT and synthesis of image is through IDWT. The image fusion technique is useful during template matching and reconstruction of image from image features.

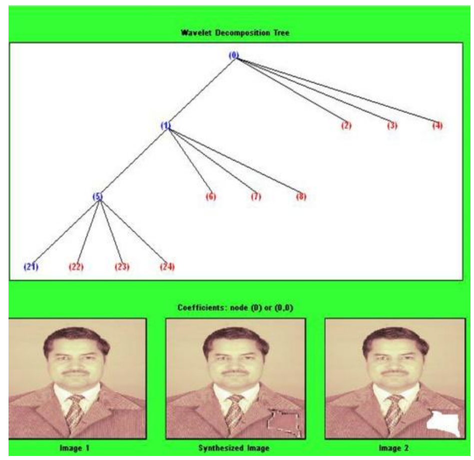


Figure 7. Wavelet decomposition tree for image fusion

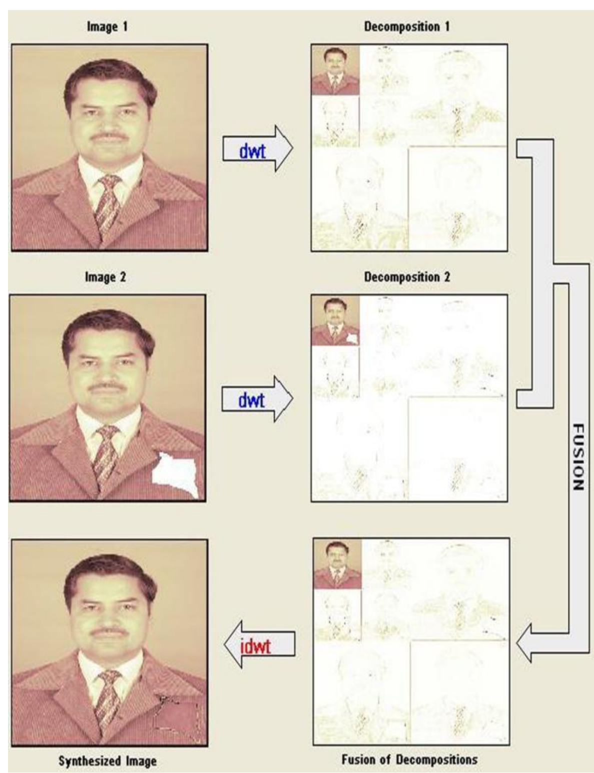


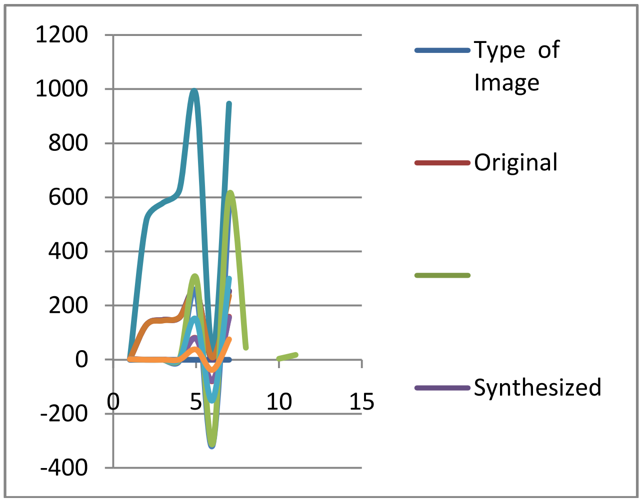
Figure 8. Image fusion using wavelet

Table 1. Statistical information contained in an image

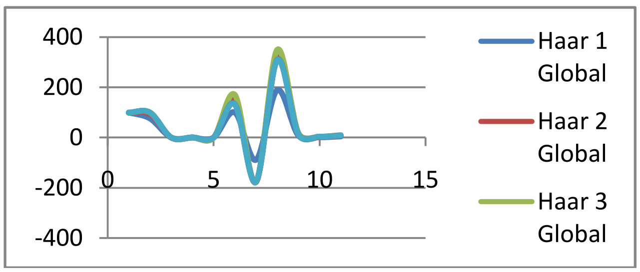
Type of Image	Data Size	Wavelet	Level of Decomp.	Mean	Median	Mode	Max	Min	Range	SD	Median AD	Mean AD
Original	JPEG; 540 x 420	Haar	2	128.7	147	155.9	255	1	254	44.27	20	35.71
Synthesized	JPEG; 540 x 420	Haar	2	128.7	147	155.9	255	1	254	44.27	20	35.71
Coeff. of Approx.	JPEG; 540 x 420	Haar	2	514.6	579	627.1	977	31.25	945.8	164.2	90.75	137.8
Reconst. Approx.	JPEG; 540 x 420	Haar	2	128.7	144.8	156.8	244.3	7.813	236.4	41.04	22.69	34.46
Coeff. of Details (Horizontal)	JPEG; 540 x 420	Haar	2	-0.487	0	-3.5	253	-317	570	35.41	3	11.95
Reconst. Details (Horizontal)	JPEG; 540 x 420	Haar	2	0	0	1.585	79.25	-79.25	158.5	8.853	0.75	2.978
Coeff. of Details (Vertical)	JPEG; 540 x 420	Haar	2	0.284	0	2.63	303	-310	613	44.46	3.75	17.82
Reconst. Details (Vertical)	JPEG; 540 x 420	Haar	2	0	0	1.55	77.5	-77.5	155	11.11	0.9375	4.455
Coeff. of Details (Diagonal)	JPEG; 540 x 420	Haar	2	0.181	0	3	150	-150	300	13.38	2	6.674
Reconst. Details(Diag.)	JPEG; 540 x 420	Haar	2	0	0	0.75	37.5	-37.5	75	3.34	0.5	1.667

Table 2. Effect of compression on statistical data of an image

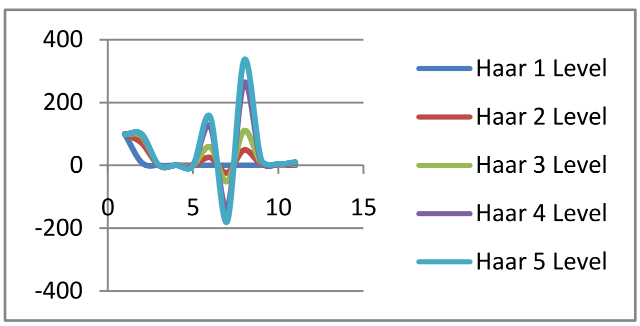
Size & Type of Image	Wavelet	Level	Thresh. Method	Retained Energy%	Zeros%	Statistical Information about Residuals								
						Mean	Median	Mode	Max	Min	Range	SD	Median AD	Mean AD
JPEG; 540X 420	Haar	1	Global	99.67	75.67	0	0	-0.17	100	-89.00	189	7.85	1.25	4.253
JPEG; 540X 420	Haar	2	Global	98.54	93.75	0	0.0625	-0.1975	156	-176.70	333	16.5	2.313	8.297
JPEG; 540X 420	Haar	3	Global	98.33	98.33	0	0.1094	-0.9516	170	-178.70	348.6	17.6	3.219	9.384
JPEG; 540X 420	Haar	4	Global	99.08	99.08	0	0.1055	-0.1406	133	-176.40	309.2	13.1	3.301	7.768
JPEG; 540X 420	Haar	5	Global	99.17	99.17	0	0.1406	-0.8401	132	-176.40	308	12.6	3.485	7.627
JPEG; 540X 420	Haar	1	Level	100	8.46	0	0	-1.68E-13	0	0.00	0	0	0	0
JPEG; 540X 420	Haar	2	Level	99.92	70.54	0	0	0.1375	25	-23.75	48.75	3.86	1	2.417
JPEG; 540X 420	Haar	3	Level	99.69	91.76	0	0	0.1006	58.5	-51.69	110.2	7.57	1.75	4.686
JPEG; 540X 420	Haar	4	Level	99.28	97.76	0	0.0625	1.712	125	-137.60	262.8	11.6	2.5	6.76
JPEG; 540X 420	Haar	5	Level	98.12	99.4	0	0.1523	-2.004	156	-179.70	335.3	18.6	4.172	10.39



(a)



(b)



(c)

Figure 9. Graphical representation of an image from its statistical data (a) Characteristics features, (b) After compression with global thresholding (c) After compression with level thresholding

4. CONCLUSION AND FUTURE SCOPE

The properties of wavelet transforms are very suitable for exploring statistical information contained in two dimensional images. The information can further be utilized to differentiate the required image from bulk images. By using wavelet based histogram method, we can identify unique image features. The histogram based approach is very efficient method to identify image features quickly. This paper presents an innovative approach to identify the effect of image compression on statistical image features using wavelets and also suggests a path to develop reliable image recognition techniques. The optimized decomposition level may be obtained to retain useful information about the image. The future scope of these approaches is in the field of real time image processing, machine vision, remote sensing and recognition e.g. automatic visual inspection systems, computer vision, video compression, and fault identification etc.

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