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A New Compression Method based on Jpeg2000 and Contourlet Transform

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Abstract

This paper presents a new coding method for image compression based on jpeg2000 and contourlet transform. Jpeg2000 standard is a common standard that uses Discrete Wavelet Transform (DWT) in the compression process. The main problems of DWT are failure to detect curved edges in image and its shortage representation of the ridge and furrow patterns which cause deficiency and block artifacts remain in the decompressed image. Contourlet transform however, is a new two dimensional extension of the wavelet transform with multidirectional and multiscale filter banks. In this paper, jpeg2000 standard is improved by using contourlet transform and scalar quantization. The results obtained are compared with those of the wavelet based ones which show the superiority of the proposed method. In addition for images containing fine-textured, PSNR obtained by contourlet transform is higher than that of the wavelet transform, while texture and edge are reconstructed better than that of the Jpeg2000 standard.

Keywords: *Image Compression, Wavelet Transform, Contourlet Transform, Scalar Quantization.*

1. Introduction

In recent years, communication extension led to increasing attention to the problem of data transform volume. Reducing the amount of information improves the capacity of storage devices and also increases the data transfer rate. One of the most important strategies for reducing the size of the image is the image compression techniques. There are two types of image compression methods: lossy and lossless. In lossless compression, the original image is obtained accurately after decompression. This type of compression is generally used in medical images, genuine signature and where quality degradation cannot be tolerated. Lossy schemes remove unnecessary picture information witch the viewer will not notice and can achieve very high compression ratio. Picture quality is reduced as much as the image data are eliminated [1]-[3].

Jpeg2000 standard is one of the common lossy standards that use discrete wavelet transform (DWT) in the compression process with an excellent result in compression [4]. This standard now used extensively in the computer world. Despite of the relatively good properties, wavelet transform has some internal limitations that affect the final compression quality. The restrictions in capturing the geometry of image edges are well identified because wavelet transformation can only extract a single point in the image, that in this case the extracted edges lacks required coherency [5]. While in real world, most of the images contain curves and arcs that must be preserved in compression process. In addition block artifacts is another anomaly that is considered in this compression standard.

In this paper, a new compression method based on contourlet transform and scalar quantization is proposed to improve the quality of Jpeg2000 standard. The proposed method uses an architecture which is compatible with existing Jpeg2000 standard. The contourlet transform instead of DWT provides different and flexible number of directions at each scale. Contourlet advantages in contradiction of wavelet can be explained by the fact that contourlet transform produces five properties including multiresolution, localization, sampling, directional, and anisotropy to show a good image [6]-[7]. It was shown to deal with images having smooth contours effectively. Finally, at the end of this paper, the results of the proposed method are compared with those of wavelet based to show the effectiveness of the proposed method.

There are not many previous researches carried out on improving Jpeg 2000 using contourlet transform. Swamy and et al in [8] used the combination of contourlet transform and scalar quantization for image compression. However in their method, pre-processing and post-processing steps are not clearly defined. While in the proposed method, all details and all pre-processing and post-processing stages are clarified similar to jpeg 2000 standard. In addition, Huffman coding in last step for image compression is used. Vasuki and Vanathi in [9], used wavelet based contourlet transform for compressed image and Esakkirajan in [10] used the hybrid method based on contourlet transform and multistage vector quantization. But despite all these methods the innovation of the proposed method in this article over other past methods is that in the proposed method the implementation is quite similar to the jpeg 2000 standard which makes the improvement more clear. It is also investigated the effect of contourlet transform on improving jpeg 2000. That's why we try to compare the results of the proposed method with jpeg 2000 standard.

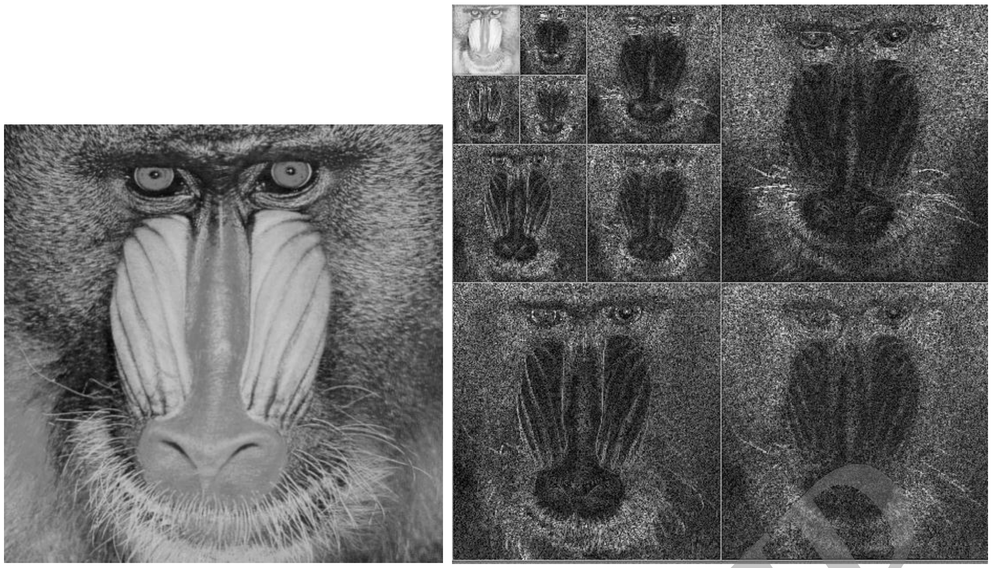
The remainder of the paper is organized as follows: in Section 2, Jpeg 2000 standard, contourlet transform and wavelet transform are explained. In Section 3, the new proposed approach for image compression is discussed. Experimental results are given in Section 4. Finally, in Section 5 conclusions are explained.

2. Background

In this Section, wavelet transform, contourlet transform and Jpeg 2000 standard are explained.

2.1 Wavelet Transform

Wavelet transformation is the technique that provides both spatial and frequency domain information. DWT represents image as a sum of wavelet function (wavelets) on different resolution levels. In wavelet transform, a signal passes through low pass and high pass analysis filter banks. Finally, the image has been broken into four bands[11]. Figure 1 shows an example of a real image and its directional sub-bands. The wavelet transform is a separable transform which is optimal at isolating the discontinuities at horizontal and vertical edges[11]. The choice of wavelet function for image compression depends on the image application and the content of image[4]. Discrete Wavelet Transform (DWT) was used in most of the image compression applications,(for example used in jpeg2000 standard)[12].



(a) (b)

Figure 1. (a) original image (b) the result of 3 level of wavelet transform

Wavelet transform is a powerful transform to represent images that contains smooth areas separated with edges, but is not an efficient means in presenting sharp edges and singularities in many nature images[13]. Another transform which use in image processing is contourlet transform. The contourlet transform is development of the wavelet transform that represents image contours and image textures. This transform is explained further.

2.2 Jpeg 2000

Jpeg 2000 is based on DWT, which is applied on image tiles. The block diagram of jpeg 2000 standard is shown in figure 2. At the first step wavelet transform is applied to the input image. After applying the wavelet transform, coefficients are quantized. At the final step the quantized coefficients are encoded. The jpeg 2000 image coding standard employs the 9/7 filters as the default wavelet filters for lossy compression [14-17].

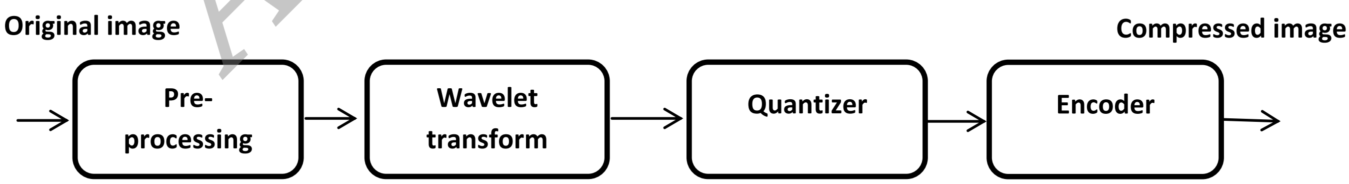


Figure 2. Block diagram of the jpeg2000

Although the wavelet transform is powerful in representing images, it cannot perform well when the edges are smooth curves. But contourlet transform that have the property of capturing contours and fine details in images can address this issue[11]. For this reason, the use of another multidirectional and multiscale transform instead of wavelet transform(such as contourlet transform), may improve this standard.

2.3 The Contourlet Transform

The contourlet transform is a two-dimensional development of the wavelet transform. This transform proposed by Do and Vetterli (Do & Vetterli, 2002). Contourlet transform use multiscale and directional filter banks. The contourlet is composed of basic images oriented at various directions in multiple scales that can effectively catch smooth contours of images [5],[18]. In this transform, at first the laplacian pyramid (lp) is used to catch the point discontinuities, and then the directional filter bank (dfb) is used to link discontinuous point into linear structures.

Figure 3 shows a multiscale and directional decomposition using a combination of a LP and a DFB [5]. At first, the LP decomposes images into subbands and then DFB analyzes each detail image. Since the directional filter bank (DFB) was designed to capture the high frequency directionality of the input image and it is poor on handling low frequency content, therefore the DFB is added with the laplacian pyramid, where low frequency of the input image is removed before applying DFB. Figure 4 shows an example of a real image and its corresponding four levels pyramidal contourlet transform with 28 directional sub-bands [5],[13],[18-23].

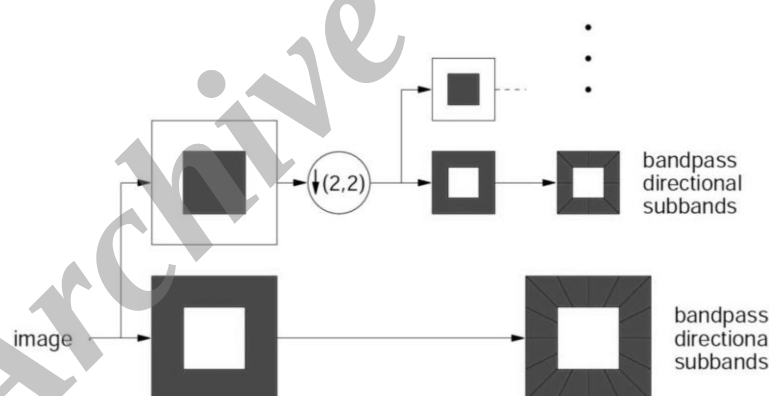
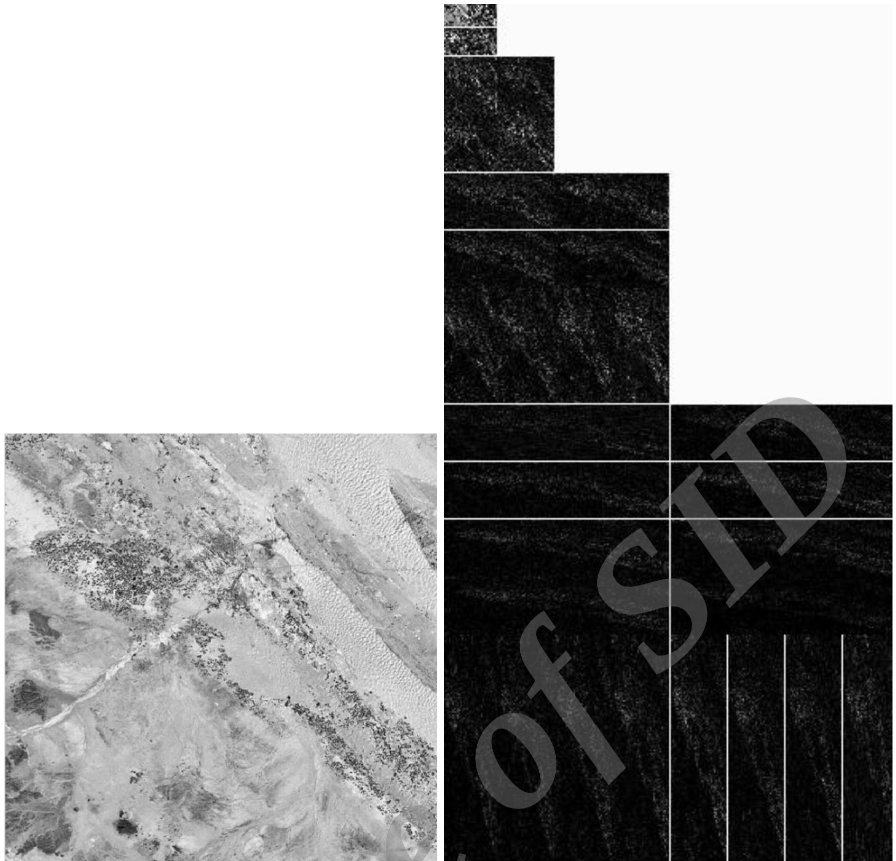


Figure 3. Contourlet filter bank. First, the LP decomposes images into subbands and then DFB analyzes each detail image [5]



(a) (b)

Figure 4. (a) original image. (b) the result of 4 level of contourlet transform with 28 directional sub-bands (1 at level 1, 3 at level 2, 8 at level 3 and 16 at level 4)

Contourlet transform have two important properties. The first is directionality and the second is anisotropy that can capture smooth contours in image [18],[23]. The contourlet transform is one of the image transforms that represents images containing contours and textures. Contourlet transform has good approximation characters for smooth 2D functions and finds a direct discrete-space construction and is so computationally efficient [11].

3. The Proposed Method

In proposed method the combination of contourlet transform and scalar quantization is used to compress image. Figure 5 shows the block diagram of the proposed method.

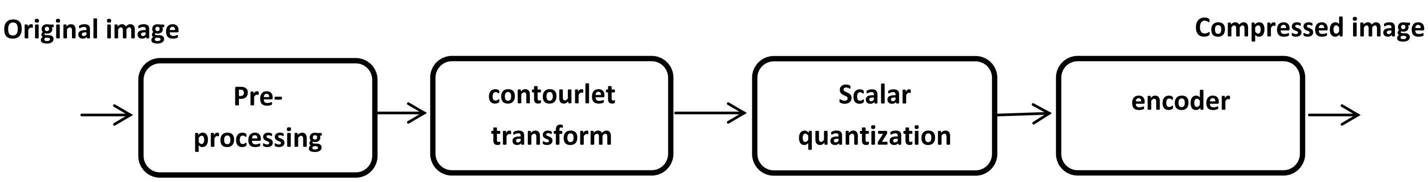


Figure 5. Block diagram of the proposed method

The first step of the encoding process is to level shift the pixels of the image by subtracting 2m-1, where 2m is the number of gray levels in the image. Then two-dimensional contourlet transform is applied to the input image in order to decorrelate the relationship between the pixels. At this stage contourlet transform is applied to image output from the previous stage. Contourlet transform parameters should also be specified. The number of disintegration levels of laplacian pyramid, number of disintegration per level and filters that are used in each of these analyzes should be specified. In contourlet transform "9-7" ، "5-3" ، "Burt" ، "Pkva" and "Haar" filters can be used to build a laplacian pyramid.

As contourlet is defined, in this transform, a Laplacian pyramid(LP) is employed in the first step, while directional filter banks (DFB) are used in the angular decomposition stage. For an L-level DFB, we have 2Ldirectional subbands with $G_K^{(l)}$, 0≤k<2l equivalent syntheses filters and the overall down sampling matrices of $S_K^{(l)}$, 0≤k<2l defined as:

$$S_K^{(l)} = \begin{cases} \begin{bmatrix} 2^{l-1} & 0 \\ 0 & 2 \end{bmatrix}, & 0 \le k < 2^{l-1} \\ \begin{bmatrix} 2 & 0 \\ 0 & 2^{l-1} \end{bmatrix}, & 2^{l-1} \le k < 2^l \end{cases} \tag{1}$$

Then, $\{g_k^l\left[n - S_k^{(l)} m\right]\}$, 0≤k<2l, m∈Z2is a directional basis for L2(Z2) where $g_k^{(l)}$ is the impulse response of the synthesis filter $G_k^{(l)}$.

Coefficient distribution of contourlet transform is shown in figure 6. For 4-level, the original low-frequency sub-band coefficients of even numbered lines are arranged to a corresponding position in the horizontal virtual level of low-frequency sub-band (for example subband01-08). The odd trip is a corresponding position in the vertical virtual level of low-frequency sub-band (for example sub-band 09-16). The low-frequency sub-band is as big as the original one.

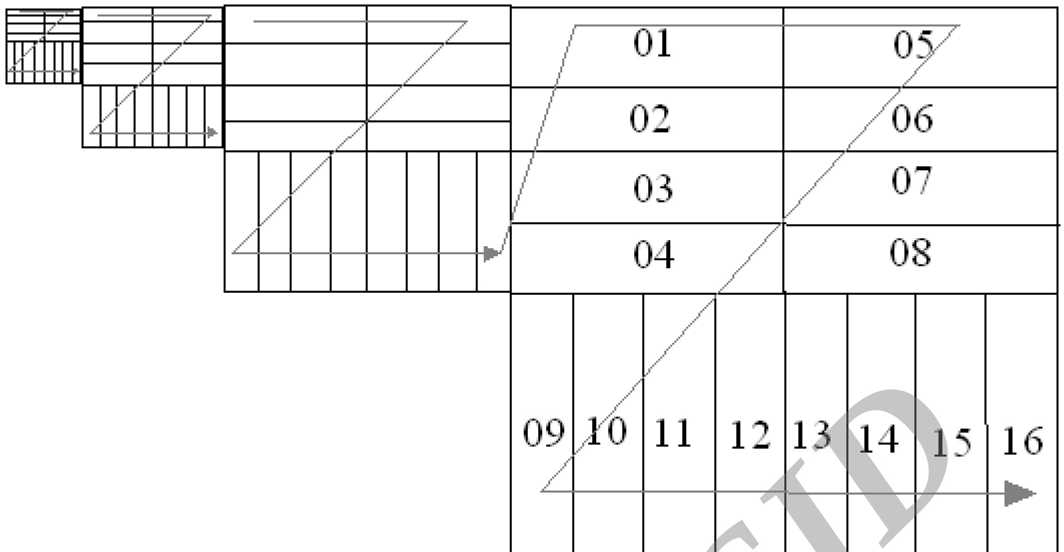


Figure 6. Coefficient distribution of contourlet transform

After contourlet transform has been computed, the total number of transform coefficients is equal to the number of samples in the original image, but the important visual information is concentrated in a few coefficients. To reduce the number of bits needed to represent them, coefficient x is quantized to value Q.

$$q=Q(x) \tag{2}$$

Quantization is the element of lossy compression systems and responsible for reducing the accuracy of data in order to make them more compressible. In this system, first a transformation is performed on the image and then transformation coefficient are quantized and encoded. Scalar quantization is the simplest form of quantization. In this step, scalar quantization is used and ab(u,v) coefficient of b subband is quantized to qb(u,v) coefficient. For a given step size Δ, qb(u,v) coefficient is calculated as:

$$q_b(u,v) = sign[a_b(u,v)].floor\left[\frac{|a_b(u,v)|}{\Delta_b}\right] \tag{3}$$

Step size Δ is calculated as follows:

$$\Delta_b = 2^{R_b-\varepsilon_b}\left(1+\frac{\mu_b}{2^{11}}\right) \tag{4}$$

R_b is a nominal dynamic range of subband b, ε_b and μ_b, respectively, are the number of bits allocated to the exponent and mantissa of subband coefficients. Nominal dynamic range of subband b (R_b) is the total number of bits used to represent bits of the original image.

To reconstruct compression image, inverse quantizer is used. The inverse quantizer is determined by

$$\hat{x} = \overline{Q^{-1}}(q) = \begin{cases} 0, & q = 0 \\ sign(q)(|q|+\delta)\Delta & q \neq 0 \end{cases} \tag{5}$$

Where δ is a parameter that user can select in the range $0 \le \delta < 1$ (typically δ=1/2). δ can be chosen to obtain the best quality at reconstruction .

The final step of the encoding process is to code the quantized coefficients arithmetically. In this step we use Huffman encoding augmented by zero run-length coding.

3.1 Performance Measurement

In order to compare the execution of proposed method with other methods, compression ratios (CR), Mean Square Error (MSE) and peak signal to noise ratio (PSNR) are measured. CR is defined as the ratio between the uncompressed size and the compressed size of an image and MSE is the distortion measure between the original image and reconstructed. The PSNR is used as a measure of quality of reconstruction of lossy image compression. A higher value of PSNR is good because it means that the ratio of signal to noise is higher. Therefore a compression method having a lower MSE (and a high PSNR) is better one. CR, MSE and PSNR are used as three quality comparison scale. These are defined as:

$$CR = \frac{the\ number\ of\ bits\ in\ the\ original\ image}{the\ number\ of\ bits\ in\ the\ compressed\ image} \tag{6}$$

$$MSE = \frac{1}{MN}\|x - \hat{x}\|_2^2 = \frac{1}{MN}\sum_{i,j}\left|x_{i,j} - \hat{x}_{i.j}\right|^2 \tag{7}$$

x is the original image and $\hat{x}$ is the reconstructed image.

$$PSNR = 10\log_{10}\frac{255^2}{MSE}\ (dB) \tag{8}$$

Another parameter that we use to compare the execution of proposed method with other method is SSIM parameter. The structural similarity (SSIM) index is a method for measuring the similarity between two images. The SSIM metric is calculated on various windows of an image. The measure between two windows *x* and *y* of common size *N*×*N* is:

$$SSIM(x,y) = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)} \tag{9}$$

With μ_x the average of *x*; μ_y the average of *y*; σ_x^2 the variance of *x*; σ_y^2 the variance of *y*; σ_{xy} the covariance of *x* and *y*; $c_1 = (k_1 l)^2$, $c_2 = (k_2 l)^2$ two variables to stabilize the division with weak denominator; *L*the dynamic range of the pixel-values (typically this is $2^{bits\ per\ pixel} - 1$); $k_1 = 0.01$and $k_2 = 0.03$ by default.

The resultant SSIM index is a decimal value between -1 and 1, and value 1 is only reachable in the case of two identical sets of data [24].

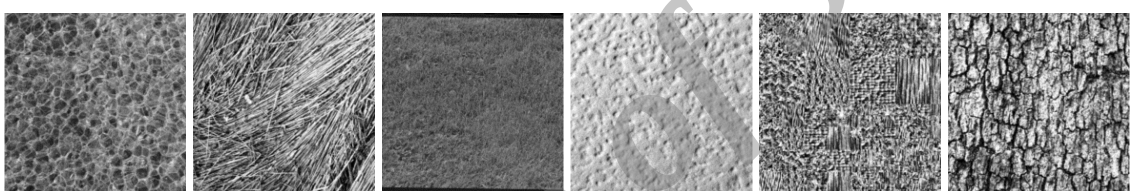
4. Experimental Results

In this section, standard images of Brodatz database have been used in order to test the proposed method and to obtain results. Figure 7 shows these standard pictures. The size of images is *512*512*. This system was tested on a portable 2.0 GHz PC using MATLAB platform.

The results of the proposed method on two standard images with different filters (P-filter stands for Pyramidal filer and D-filter stands for Directional filter) are shown in table 1 and table 2. In the case of test images, the '9-7' and 'pkva' as the pyramidal and directional filter combination gives better PSNR and MSE results when compared to other pyramidal and directional filter combinations therefore in proposed method these filters have been used.

Lena Peppers Barbara Pirate Mandril Cameraman

(a)



1.1.13 1.2.03 1.4.10 1.5.03 texmos2.p512 1.2.02

(b)

Figure 7. Standard images of brodatz database(a) standard images (b) texture images

Table 1. PSNR and MSE parameters for different filters of contourlet transform for lena image in 10:1 compression ratio

filter	MSE	PSNR
Wavelet:	4.4022	41.694
contourlet:		
pfilter= Haar' dfilter= '9_7'	6.3154	40.127
pfilter= Haar' dfilter= '5_3'	6.5733	39.953
pfilter= Haar' dfilter='pkva'	6.1832	40.219
pfilter= '9_7' dfilter='pkva'	4.2422	41.855
pfilter= '9_7' dfilter= '5_3'	4.5263	41.573
pfilter= pkva' dfilter= '9_7'	5.1792	40.988

pfilter= pkva' dfilter= '5_3'	5.5245	40.708
pfilter= '5_3' dfilter='pkva'	4.6088	41.495
pfilter= '5_3' dfilter= '9_7'	4.6638	41.443

Table 2. PNSR and MSE parameters for different filters of contourlet transform for cameraman image in 10:1 compression ratio

filter	MSE	PSNR
Wavelet:	3.1005	43.216
contourlet:		
pfilter= Haar' dfilter= '9_7'	6.5403	39.975
pfilter= Haar' dfilter= '5_3'	7.1979	39.559
pfilter= Haar' dfilter= 'pkva'	6.3381	40.111
pfilter= '9_7' dfilter= 'pkva'	3.5139	42.673
pfilter= '9_7' dfilter= '5_3'	4.0397	42.067
pfilter= 'pkva' dfilter= '9_7'	4.6576	41.449
pfilter= 'pkva' dfilter= '5_3'	4.9973	41.143
pfilter= '5_3' dfilter= 'pkva'	4.1279	41.974
pfilter= '5_3' dfilter= '9_7'	4.033	42.075

In figure 8 and figure 9 the results of performance of jpeg 2000 standard and the proposed method have been evaluated and compared with each other. PSNR and MSE parameters are used to evaluate and compare the performance of two methods in fix compression ratio. In figure 8 and figure 9, six standard images (Lena, Peppers, Barbara, Pirate, Mandrill, and Cameraman) are used to evaluate the proposed method. As shown in figure 8 and figure 9, in some cases the proposed method compared with jpeg 2000 didn't create higher PSNR. This is due to the fine texture of some images. For images that contain a finer texture and more curved lines (for example: Mandrill), the proposed method gives better results. For this reason, in figure 10 and figure 11, six standard texture images (1.1.13, 1.2.03, 1.4.10, 1.5.03, texmos2.p512, and 1.2.02) are used to evaluate the proposed method and compared this method with jpeg 2000 standard.

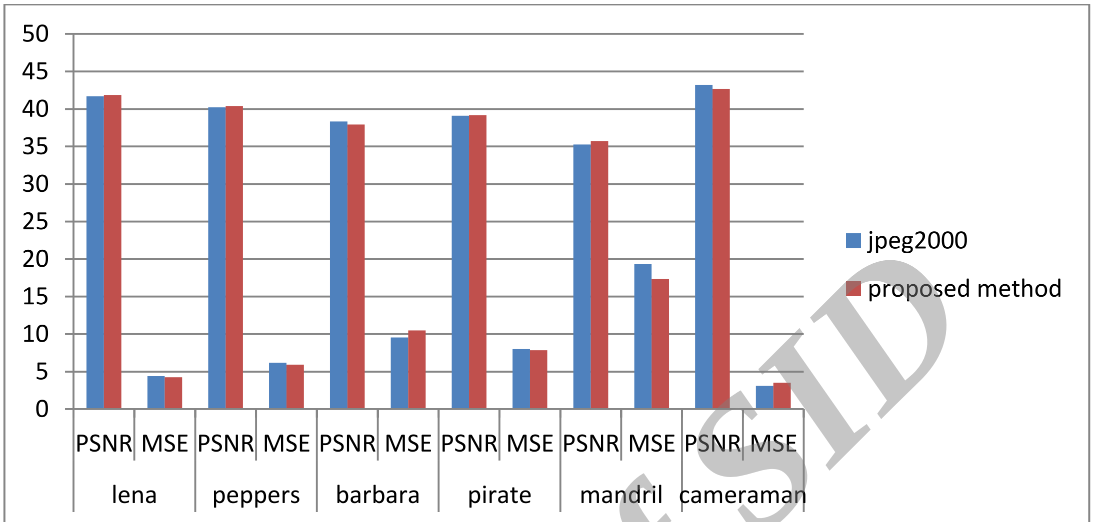


Figure 8. Implementation results of jpeg2000 and proposed method on standard test images for 10:1 compression ratio

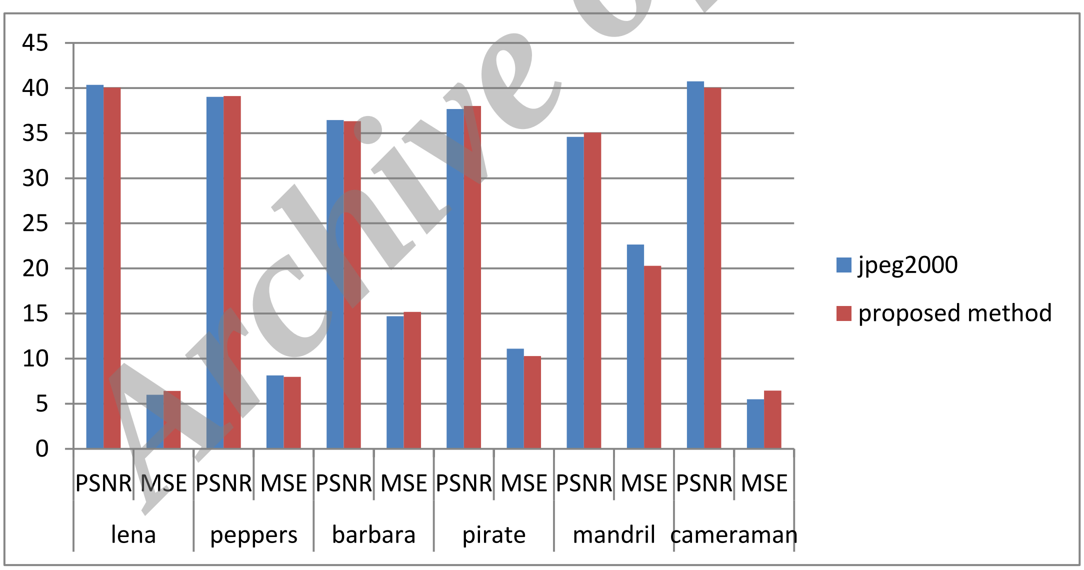


Figure 9. Implementation results of jpeg2000 and proposed method on standard test images for 20:1 compression ratio

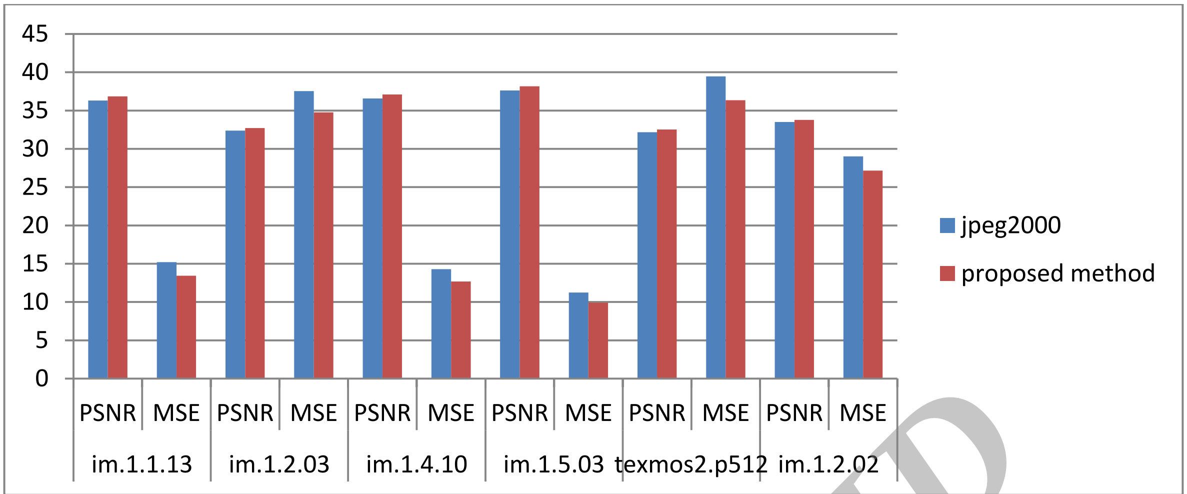


Figure 10. Implementation results of jpeg2000 and proposed method on standard texture image for 10:1 compression ratio

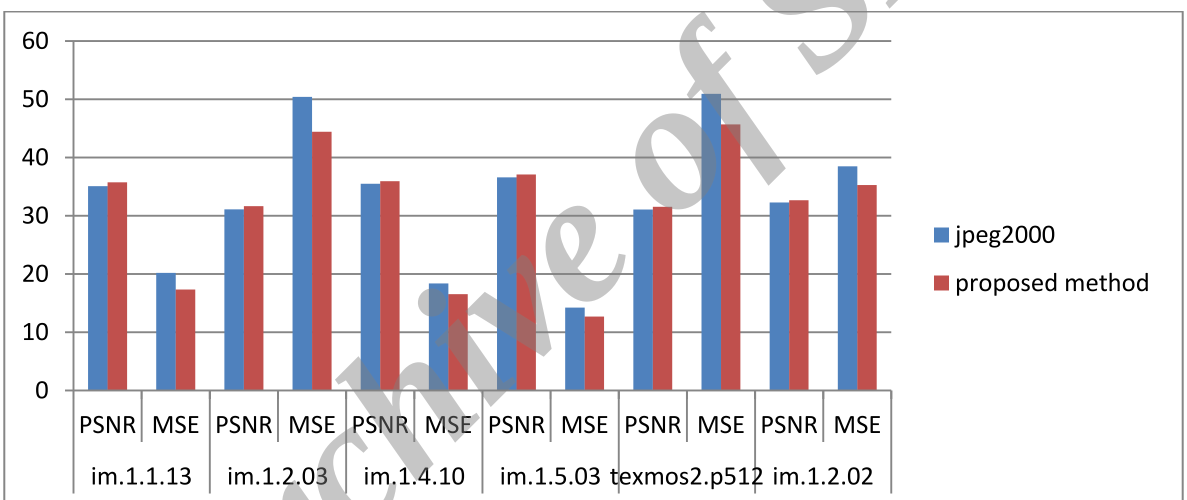


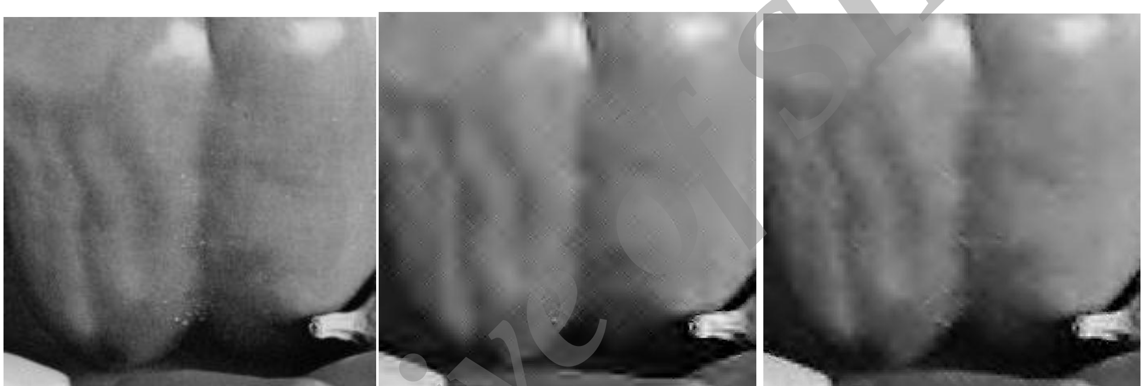
Figure 11. Implementation results of jpeg2000 and proposed method on standard texture images for 20:1 compression ratio

From the figure 10 and figure 11, it is evident that the PSNR of the reconstructed image in the proposed method is better than jpeg 2000. So, the proposed method has better results for images with finer texture and more curved lines.

The comparison of proposed method with jpeg 2000 is shown in figure 12 and figure 13 for first group of images. Figure 12(c) and figure 13(c) show the reconstructed image using contourlet transform based on the proposed method, while figure 12(b) and figure 13(b) show the same for wavelet transform in jpeg 2000 standard. From figure 12 and figure 13, it is completely obvious that contourlet transform compared to wavelet transform provides better results in preserving minutiae; although the amount of PSNR for the proposed method in lena is less than jpeg 2000.

(a) *(b)* *(c)*

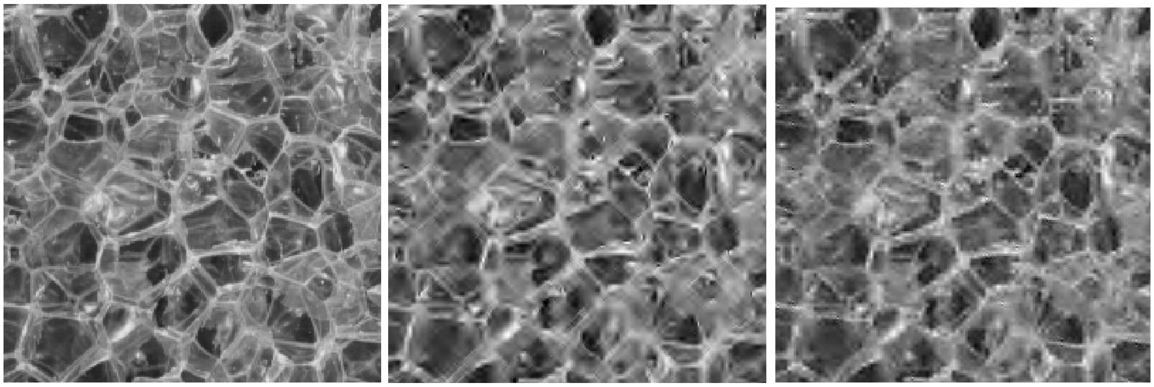
Figure 12. Implementation of jpeg2000 and proposed method on lena image (10:1 compression ratio): (a) original image (b) jpeg 2000 (c) proposed method



(a) *(b)* *(c)*

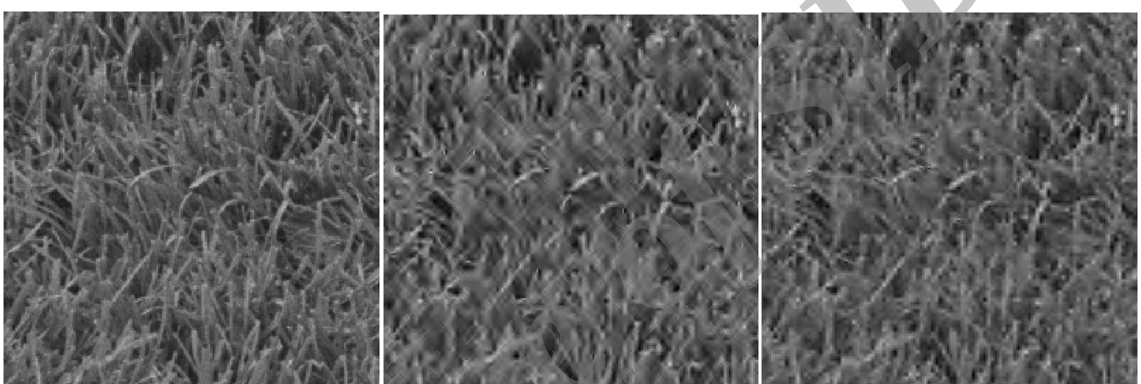
Figure 13. Implementation of jpeg2000 and proposed method on peppers image (20:1 compression ratio): (a) original image (b) jpeg 2000 (c) proposed method

Figure 14 and figure 15 shows the reconstructed images for tow images of second group of images (standard texture images). According to figure 10 and figure 11, in all performances, a new method has higher PSNR parameter than jpeg 2000 method and also image quality is improved in the performance of the proposed method. As shown in figure 14(b) , 15(b), 14(c) and 15(c) can be seen, in the new method, some parts of image texture that was fading in jpeg 2000 method has been reconstructed and demonstrated.



(a) (b) (c)

Figure 14. Implementation of jpeg2000 and proposed method on 1.1.13 image (10:1 compression ratio): (a) original image (b) jpeg 2000 (c) proposed method



(a) (b) (c)

Figure 15. Implementation of jpeg2000 and proposed method on 1.4.10 image (20:1 compression ratio): (a) original image (b) jpeg 2000 (c) proposed method

Figure 16 and figure 17 show the results of performance of two methods which have been evaluated and compared with each other. SSIM is used to evaluate and compare the performance of two methods in fix compression ratio. From figure 16 and figure 17 it is evident that the SSIM of proposed method is higher than jpeg 2000. Therefore, compressed image by proposed method is more similar to the original image than compressed image with jpeg 2000.

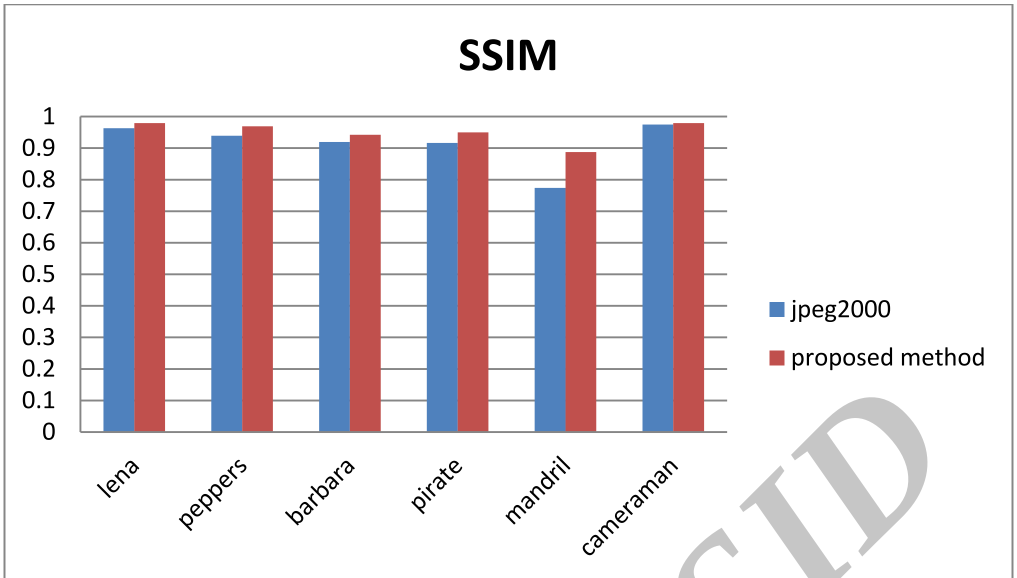


Figure 16. SSIM value for standard images in 10:1 compression ratio

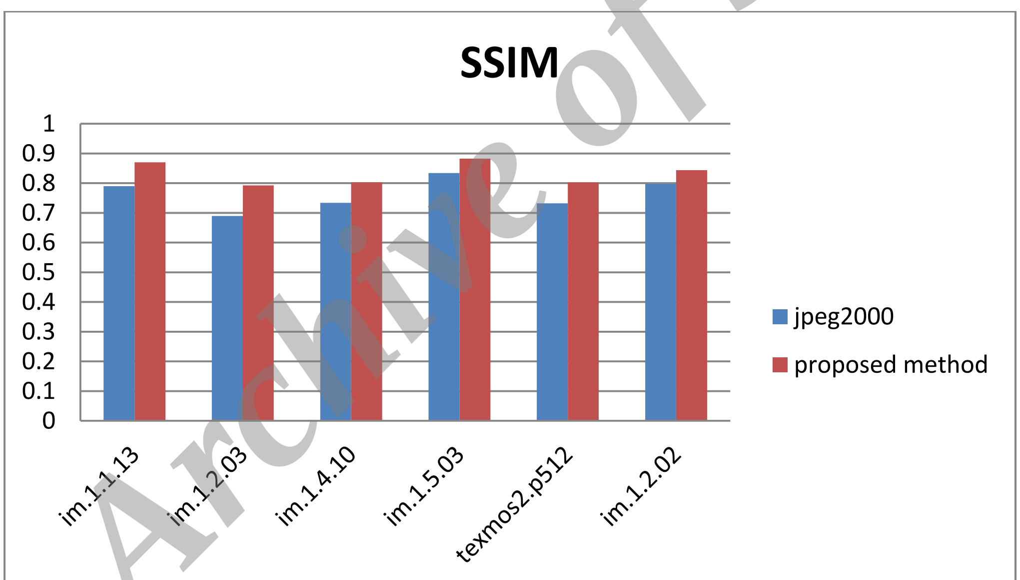


Figure 17. SSIM value for texture images in 20:1 compression ratio

5. Conclusion

In this paper, a new method based on contourlet transform for image compression is proposed. Contourlet transform is a multi-scale and directional transform that used to describe curves and delicate details in the image. In this study, implementation results of the jpeg 2000 and the proposed method on test images show that in jpeg 2000 standard due to the use of wavelet transform, the details of the image is fading. By implementing new method on sample images, these details were restored and displayed. In most performances, the new method has a higher PSNR parameter than the jpeg 2000 method. Also in all performances, the proposed method has a higher SSIM parameter than the other one. This is due to the fine texture of the some images. For images that contain a finer texture and more curved lines, the proposed method gives better results. The experimental results reveal the fact that the proposed method is suitable for images that contain a finer texture and more curved lines. It should be mentioned that, in the new method, due to using contourlet transform, parts of the texture of the image that was faded before, reconstructed and appeared. For the future works other multiscale transforms such as ridgelet or curvelet transform can be used instead of contourlet transform. Also, adding some encode task can improve the performance of the system. Combining contourlet transform with other methods or encode systems may obtain superior results.

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