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Visually Lossless JPEG2000 Image Compression

KEYWORDS Images compression, visually lossless coding, visually lossless compression, JPEG2000, visual masking effects, human visual system, reversible color transform, visibility threshold.

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ABSTRACT *Conventional lossless image compression methods aim to compress images such that every single bit of decompressed image data is identical to the original and yield moderate compression ratios. Generally, the sensitivity of the human visual system to quantization distortion produced by the JPEG2000 image compression standard is investigated and a visual distortion model is then proposed and incorporated into a JPEG2000 image encoder to yield visually lossless compression. This method uses the visibility thresholds (VTs) for image compression. The VTs are obtained by quantization distortion that is based on distribution of wavelet coefficients and the dead-zone quantizer. A visual masking model adjusts the resulting VTs. Compared with numerically lossless compression of JPEG2000; the visually lossless compression method achieves significant reduction in bit-rate without visual quality degradation. Resulting code-streams obtained by this method are fully JPEG2000 part-I compliant.*

I. Introduction

The image compression techniques are mainly classified into two categories: 1) lossless and 2) lossy techniques. The lossless compression methods compact the image data using fully reversible transformations. Numerically lossless compression techniques are facing difficulties with today's exponential growth in image sizes, due to their limited compression ratios. The lossy methods perform much better; however, they discard information during the process of compression. The particularities of the human vision system are often not taken into account and not used to the advantage. This will degrade noticeably the image quality and unwanted artifacts may be introduced. Lossy compression is further categorized into visually lossless and visually lossy compression depending on the visibility of compression artifacts. The popularity of visually lossless for JPEG2000 is increased because of lossless encoding mode, high compression efficiency, high visual quality, absence of block based artifacts, scalability, and error resiliency. A visually lossless algorithm involves the identification and removal visually irrelevant information in images prior to encoding. Properties of the human visual system are incorporated into the design of the encoder to obtain better visual quality. JPEG2000, a wavelet-based image compression standard, is widely used to encode a variety of images such medical images, geospatial images and natural images because of its superior compression performance over JPEG and various other functionalities. In JPEG2000, a discrete wavelet transform decomposes each component into several sub-bands, which have diferent frequencies and orientations. In order to hide compression artifacts caused by quantization, visibility thresholds are measured and used for quantization of sub-bands in JPEG2000. Visibility thresholds applied in the visually lossless coding methods are measured at the near-threshold level where distortion is just noticeable. Previous research in the area of image compression is summarized in [3-9]. The human vision model is used to enhance the JPEG2000 compression standard and outstanding compression results are achieved. The goal of similar approaches is to maximize the compression ratio while maintaining acceptable image degradation. In our work, the goal is to preserve the appearance of images and discard only visually insignificant data.

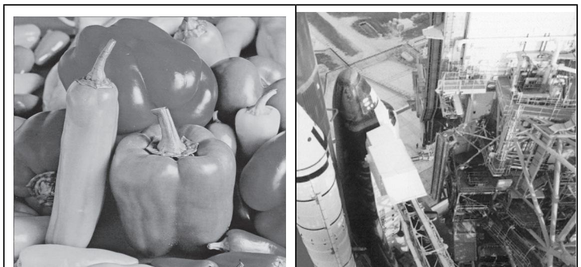
Visually lossless compression offers the potential for using higher compression levels without noticeable artifacts. The human visual system (HVS) is the end user of most image information. Therefore, any imaging system that reflects human image processing needs should be designed with the characteristics and behavior of the HVS taken into consideration. This will ensure that only information that is relevant for the HVS is stored. One important property of the HVS is that the human eyes selectively understand the image by frequency and orientation. The sensitivity of human eyes to frequencies and orientations is represented by the contrast sensitivity function (CSF), or VT which is the inverse of the CSF. The CSF is obtained by experimentally measuring the threshold of contrast visibility in a stimulus image, which has been decomposed using discrete wavelet transform. Here the HVS is embedded in quantization stage. A perceptually tuned step size is computed and the resulting visibility thresholds are used as quantization step size to quantize each wavelet sub-bands at visually lossless level [10].

This paper is organized as follows. The materials and methods are described in Section II. Section III is focused on results and discussions. Conclusions are drawn in Section IV.

II. Materials and methods

A. Database

Images are collected from the USC database [11], LIVE database [12], Kodak PhotoCD [13], and ISO JPEG2000 test suite. Databases consist of 8-bit monochrome and 24-bit color images as shown in Fig. 1 and Fig. 2.



(a) Pepper   (b) Onthepad

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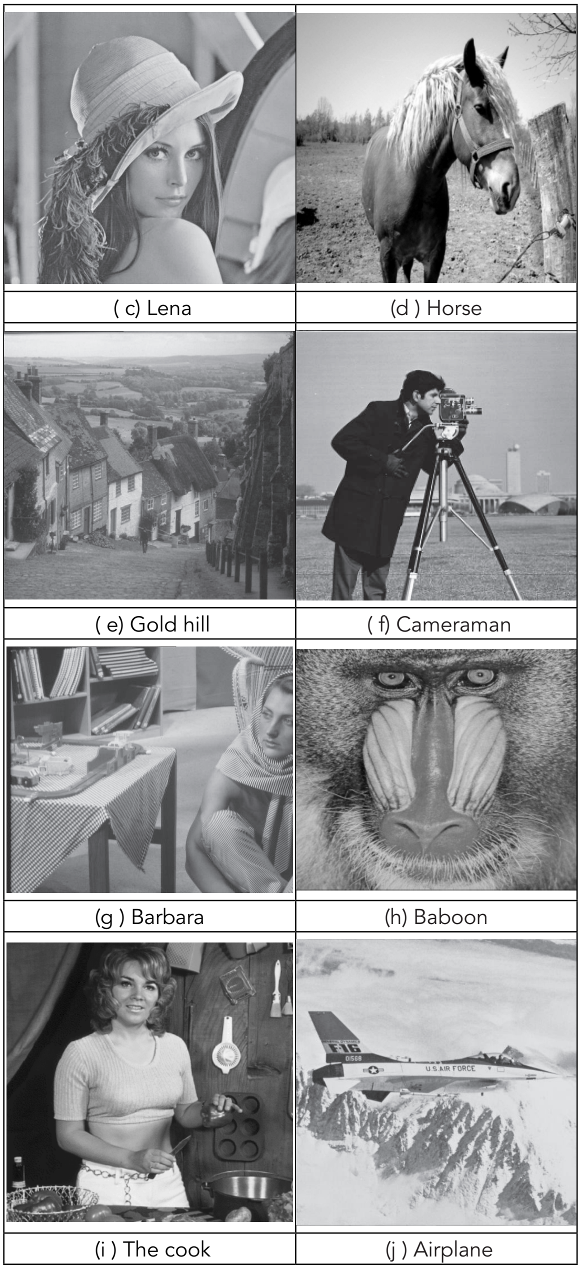
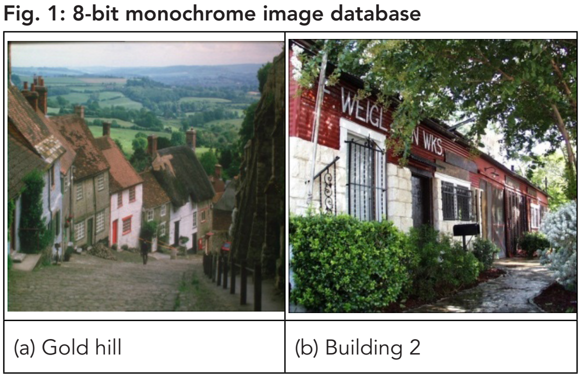


(c) Lena | (d) Horse | (e) Gold hill | (f) Cameraman | (g) Barbara | (h) Baboon | (i) The cook | (j) Airplane

Fig. 1: 8-bit monochrome image database



(a) Gold hill | (b) Building 2

(c) Buildings | (d) Bikes | (e) Barbara | (f) Stream | (g) Baboon | (h) Pepper | (i) Lena | (j) House

Fig. 2: 24-bit color image database

B. Proposed visually lossless image compression scheme

Visually lossless compression algorithms aim to encode images at the minimum bit-rate such that the original and reconstructed images are indistinguishable when viewed by a human. Flow diagram for proposed visually lossless image compression scheme is shown in Fig. 3.

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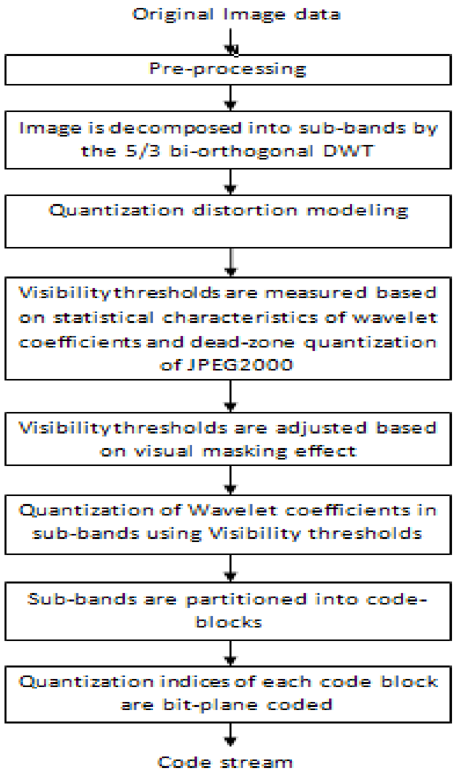

Fig. 3: Flow diagram for visually lossless encoding for JPEG2000

The HVS has varying sensitivity to different color components, spatial frequencies, orientations and underlying background images. Using this fact, a visually lossless coding algorithm has been presented for 8-bit monochrome and 24-bit color images. Visibility thresholds are measured for statistically modeled quantization distortion, and have different values depending on the local variances within each sub band. Since quantization distortion appears on various background images, the threshold values are adjusted using a self-masking model and a texture-masking model to cope with spatially changing visual masking effects. The resulting thresholds are used to determine the maximum quantization for visually lossless coding.

1. Pre-processing

The first step in pre-processing is to partition the input image into rectangular and non-overlapping tiles of equal size. Each tile is compressed independently using its own set of specified compression parameters. Then unsigned sample values in each component are level shifted by subtracting a fixed value of 2^{B-1} from each sample to make its value symmetric around zero. Signed sample values are not level shifted. Finally, the level-shifted values can be subjected to a forward point wise inter-component transformation to decorrelate the color data. Two transform choices are allowed: 1) irreversible color transform (ICT), which is identical to the traditional RGB to YCbCr color transformation and can only be used for lossy coding, 2) reversible color transform (RCT), which is a reversible integer-to-integer transform that approximates the ICT for color decorrelation and can be used for both lossless and lossy coding [14]. This work is focused on reversible color transform.

2. Discrete wavelet transform (DWT)

The DWT inherently provides a multi-resolution image representation while also improving compression efficiency due to good energy compaction and the ability to decorrelate the image across a larger scale. Furthermore, integer DWT filters can be used to provide both lossless and lossy compression within a single compressed bit-stream. Here, the bi-orthogonal CDF 5/3 wavelet transform is used [15].

3. Quantization distortion modeling

After the wavelet transform, the coefficients are scalar-quantized to reduce the number of bits to represent them. The output is a set of integer numbers which have to be encoded bit-by-bit. The parameter that can be changed to set the final quality is the quantization step: the greater the step, the greater is the compression and the loss of quality. The quantization distortion in JPEG2000 is the difference of wavelet coefficients between the encoder and the decoder generated by the dead-zone quantizer of JPEG2000 and mid-point reconstruction. The maximum quantization step sizes where quantization distortion remains invisible indicate the visibility threshold. Visibility thresholds are measured for the quantization distortion. The quantization distortion model is created based on the statistical characteristics of wavelet coefficients and the dead-zone quantizer. Generalized Gaussian distribution with probability density function (PDF) models [1] wavelet coefficients and is given by Eqn. (1).

$$f(y) = \frac{\alpha.A(\alpha,\sigma)}{2\Gamma(1/\alpha)} \exp\left(-A(\alpha,\sigma)|y-\mu|\right)^{\alpha} \quad (1)$$

where

$$A(\alpha,\sigma) = \sigma^{-1}\left(\frac{\Gamma(3/\alpha)}{\Gamma(1/\alpha)}\right)^{1/2} \quad (2)$$

Here Γ (.) is the Gamma function.

The parameters μ and σ are the mean and standard deviation, respectively. The parameter α is called the shape parameter. JPEG2000 quantizes each wavelet coefficient 'y' using the following scalar dead-zone quantizer:

$$q = Q(y) = sign(y).\left\lfloor\frac{|y|}{\Delta}\right\rfloor \quad (3)$$

Here, q is the quantization index, which is subsequently encoded using embedded bit-plane coding. The de-quantization procedure in the decoder is expressed by

$$\hat{y} = Q^{-1}(q) = \begin{cases} 0 & q = 0 \\ sign(q)(|q|+\delta)\Delta & q \neq 0 \end{cases} \quad (4)$$

Where, δ = 1/2 corresponds to mid-point reconstruction. A more appropriate model for quantization distortions produced by the dead-zone quantizer and mid-point reconstruction is given by the probability density function:

$$f(d) = \begin{cases} \frac{1}{\sqrt{2}\sigma} e^{-\frac{\sqrt{2}|d|}{\sigma}} + \frac{1-p1}{\Delta} & 0 \le |d| \le \frac{\Delta}{2} \\ \frac{1}{\sqrt{2}\sigma} e^{-\frac{\sqrt{2}|d|}{\sigma}} & \frac{\Delta}{2} < |d| \le \Delta \\ 0 & otherwise \end{cases} \quad (5)$$

Where,

$$p1 = \int_{-\Delta}^{\Delta} \frac{1}{\sqrt{2}\sigma} e^{-\frac{\sqrt{2}|y|}{\sigma}} dy = 1 - e^{\frac{\sqrt{2}\Delta}{\sigma}} \quad (6)$$

The second term of the first line in Eqn. (5) follows from assuming that the quantization distortion is uniform only for wavelet coefficients whose magnitudes are larger than Δ. Wavelet coefficients in the LL sub-band are often modeled by the Gaussian distribution with $\mu = 0$ and α = 2 in Eqn. (1). The quantization distortion of the LL sub-band being modeled by

$$f(d) = \begin{cases} \frac{1}{\sqrt{12\sigma}} + \frac{1-p2}{\Delta} & 0 \le |d| \le \frac{\Delta}{2} \\ \frac{1}{\sqrt{12\sigma}} & \frac{\Delta}{2} < |d| \le \Delta \\ 0 & otherwise \end{cases} \quad (7)$$

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where, $p2 = \frac{\Delta}{\sqrt{3}\sigma}$

It is important to note that the uniform model depends only on the parameter, while the model of Eqn. (5) depends on as well as the coefficient variance .

4. Visibility thresholds for quantization distortions

A color image having RGB components is first converted into an image with one luminance and two chrominance components using RCT. Each component is then transformed using cohen-daubechies–feauveau 5/3 DWT. A K- level dyadic wavelet decomposition has 3K + 1 sub bands [16]. Since K = 5 is usually sufficient to obtain near optimal compression performance, VTs are estimated for 16 sub bands in each of the three color components in this work.

To measure the visibility threshold for a given sub-band a two-alternative forced-choice method is used [1]. In this method, an image that contains a stimulus and an image that does not contain a stimulus are displayed sequentially and a human subject is asked to decide which image contains the stimulus. A stimulus is an RGB image obtained by applying the inverse wavelet transform and the inverse RCT to wavelet data containing quantization distortions. Stimuli are displayed on a LCD monitor in ambient light. The display time for each image is 2 seconds with an interval of 2 seconds between subsequent images. The subject is then given an unlimited amount of time to select which image contains the stimulus. The experiment is iterated while varying Δ in order to find the largest value of Δ for which the stimulus remains invisible. The obtained value of Δ is then the VT of the sub band.

5. Visibility threshold adjustment

In actual image coding, all sub-bands are quantized simultaneously and quantization distortion is superimposed on a background image. Visibility of quantization distortions from similar sub-bands is known to increase linearly when the distortion is highly visible. VTs can vary significantly with image background. Here, the image background is called the masker, while the distortion is referred to as the target. The change of threshold values according to the contrast of the image background is represented by the target threshold versus masker contrast (TvC) function. As the contrast of the masker increases, the threshold decreases slightly and then begins to increase [17-18]. The masking effect is considered in this work and visibility thresholds are modified to exploit the masking effect. Since masking occurs most strongly when the target and masker have a similar frequency and orientation, the model employed here considers spatial-masking only within the sub-band of interest. The visually lossless masked threshold $_b$ is defined as

$$\hat{t}_b = t_b * m_b \tag{8}$$

where, is the base threshold value and m_b is a masking factor calculated from the magnitudes of wavelet coefficients in sub-band b.

$$t_b = a_b * \sigma_b^2 + r_b \tag{9}$$

Where, is the variance of coefficients in subband b. The linear parameters and are obtained by least squares fitting of the threshold values measured for different assumed values of for each subband.

$$m_b = \left(\frac{1}{\|B\|}\sum_{n\in B}(s_b[n].\tau_b[n]^{\beta}\right)^{\frac{1}{\beta}} \tag{10}$$

where is the number of coefficients in code block *B*. The parameter β lies between 0 and 1 and controls the degree of overall masking.

The masking factor m_b is calculated using two visual masking models, the self-contrast masking model and the texture-masking model. The self-contrast masking model approximates the change of threshold in the TvC function according to the magnitude of wavelet coefficients. The corresponding self-contrast masking factor, $s_b[n]$, at two-dimensional location n in sub-band b is defined by

$$s_b[n] = max\,\{1, w_1\left(\frac{|y[n]|}{y_b^{\mp}+\epsilon}\right)^{\rho 1}\} \tag{11}$$

where, *y*[n] is the wavelet coefficient at location n and is the conditional expectation of *y* given *y* ≥ 0. The small constant is included for stability of the equation. The parameterreflects nonlinearity of self-contrast masking and has a value between 0 and 1. The parameter adjusts the degree of self-contrast masking and together with prevents over-masking. The self-contrast masking factor takes a value of 1 (no masking) for small values of |*y*[n]|. On a log-log scale, it increases linearly with slope when log |*y*[n]| exceeds log b by more than. Thus to ensure visually lossless quality in all regions, care is needed in selecting the parameters and [19]. In addition to self-contrast, texture activity can significantly affect distortion visibility. Specifically, VTs increase as the texture beneath the distortion becomes more difficult to predict. The texture masking factor, , for the texture activity of small local texture-block *j* is given by

$$\tau_b[n] = \max\left\{1, w_2\left(\hat{\sigma}_j^2\right)^{\rho 2}\right\} \tag{12}$$

here, is the variance of reconstructed wavelet coefficients in texture-block j. Every location in the texture-block is then assigned the same value. Brighter intensities represent higher masking effects. The self-masking $s_b[n]$ is strong along prominent edges, and the texture-masking $\tau_b[n]$ is more pronounced in complex textures. The value of $s_b[n] \cdot \tau_b[n]$ is 1.0 in flat background areas, such as the sky and horse body. Masking values in a sub-band are affected by the orientation of maskers.

6. Visually Lossless Encoding

After quantization, the sub-band is partitioned into code blocks, and the quantization indices of each code block are bit-plane coded. Each bit-plane is coded in three coding passes, except the most significant bit-plane (MSB), which is coded in one coding pass. First, the variance $\sigma^{2,}$ for code block i in sub-band b is calculated. Then a base threshold $t_{b,i}$ for that code block is determined. The self-masking factor $s_{b,\,i}$ [n] is calculated for each wavelet coefficient in the code block. During the bit-plane coding, the texture-masking factor $\tau_{b,i}$ [n] is calculated for each coefficient in the code block, followed by $m_{b,i}$ and. The maximum absolute error for the code block is calculated at the end of each coding pass z as [2]

$$D^{(z)} = \max_{n\epsilon\beta}\left(\left|y[n] - \hat{y}^{(z)}[n]\right|\right) \tag{13}$$

Where, denotes the reconstructed value of *y*[n] using the quantization index , which has been encoded only up to coding pass *z*. Coding is terminated when *D(z)* falls below the masked threshold.

3. Results and discussions

Visually lossless compression is performed on ten different images. This method significantly reduces encoding time while maintaining superior visual quality compared with conventional JPEG2000 encoders. This scheme successfully yields compressed images, whose quality is indistinguishable to those of the original images, at significantly lower bitrates than those of numerically lossless coding and other visually lossless algorithms in the literature. The four output filters are decomposition low-pass, decomposition high-pass, reconstruction low-pass and reconstruction high-pass filters. These four filters associated with the Daubechies wavelet are shown in Fig. 5.

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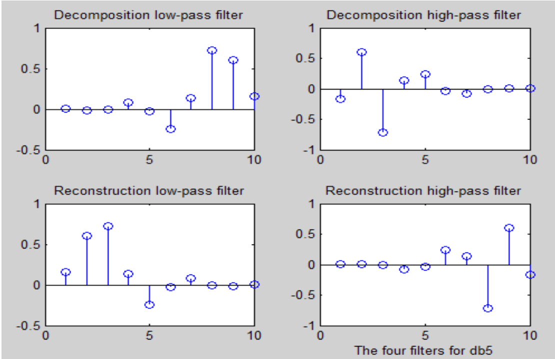


Fig 5: Four filters associated with the Daubechies wavelet 'db5'

The mean square error (MSE) and the peak signal to noise ratio (PSNR) are the two error metrics used to compare image compression quality. The MSE represents the cumulative squared error between the compressed and the original image, whereas PSNR represents a measure of the peak error. The PSNR in decibel is evaluated as follows:

To compute the PSNR, first the mean-squared error is calculated using the following equation:

$$MSE = \frac{\sum_{M,N}[I_1(M,N)-I_2(M,N)]^2}{M*N} \quad (14)$$

I_1 and I_2 denote the original image and decoded image. M and N are the number of rows and columns in the input images, respectively. Then PSNR is computed using the following equation:

$$PSNR = 10\,\log_{10}\left(\frac{255^2}{MSE}\right) \quad (15)$$

The higher the PSNR, the better the quality of the compressed or reconstructed image. Typical values for lossy compression of an image are between 30 and 50 dB and when the PSNR is greater than 40 dB, then the two images are indistinguishable. The lower the value of MSE, the lower the error. BPP(bits per pixel) value is used to compare the amount of compression applied to a particular image. The bits per pixel value vary for different images. Compression ratio is a measure of the reduction of detail coefficient of data which is the ratio of discarded data and original Data. In the process of image compression, it is important to know how much important coefficient one can discard from input data in order to preserve critical information of the original data.

Tables 1 and 2, respectively, show the bitrates obtained for encoding 8-bit monochrome and 24-bit color images using proposed coding scheme. For comparison, bitrates obtained for numerically lossless JPEG2000 compression are also included. The images reconstructed from the compressed data appear identical to the originals. For monochrome images, the numerically lossless coding method of JPEG2000 yields an average bit rate of 5.063 bits-per-pixel (bpp), while this visually lossless coding method achieves an average bit rate of 1.887 bpp, an improvement in compression ratio of 2.68 to 1, without any perceivable quality degradation.

Image	Dimension (W*H)	Lossless (bpp)	Proposed (bpp)	PSNR (db)
Airplane	512*512	3.99	1.87	46.76
Baboon	512*512	6.11	2.04	43.67
Barbara	512*512	4.78	1.90	39.98
Camera man	512*512	4.99	1.82	45.71
Goldhill	512*512	4.61	1.70	42.08
Horse	512*512	5.25	1.90	45.75
Lena	512*512	4.30	1.83	50.79
Onthepad	512*512	6.50	2.00	43.75
Peppers	512*512	4.62	1.86	39.83
Thecook	512*512	5.48	1.95	41.62
Average		5.063	1.887	43.94

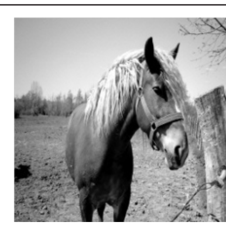
Table 1: Bitrates and PSNR'S for the proposed visually lossless Jpeg2000 encoder for 8-bit monochrome images.

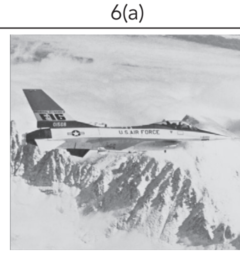
Image	Dimension (W*H)	Lossless (bpp)	Proposed (bpp)	PSNR (db)
Baboon	512*512	9.59	1.92	46.27
Barbara	720*576	10.50	1.65	36.58
Bikes	512*512	10.81	1.94	35.23
Building	768*512	11.13	1.59	37.96
Building2	512*512	13.90	1.93	34.06
Goldhill	720*576	9.67	1.74	37.18
House	512*512	10.08	1.86	49.47
Streams	768*512	11.86	1.89	36.39
Lena	512*512	8.98	1.67	38.36
Peppers	512*512	13.56	1.73	36.83
Average		11.08	1.792	38.93

Table 2: Bit-rates and PSNRS for the proposed visually lossless Jpeg2000 encoder for 24-bit color images .

In the case of color images, the numerically lossless coding method and the proposed visually lossless coding method achieve, respectively, 11.08 bpp and 1.792 bpp on average, with an improvement in compression ratio of 6.18 to 1. As seen from the tables, different images encoded in the proposed visually lossless manner have significantly different bitrates. In particular, the resulting bitrates range from 1.70 bpp to 2.04 bpp for monochrome images, and from 1.59 bpp to 1.94 bpp for color images. The monochrome images have a minimum PSNR of 39.83 dB and a maximum PSNR of 50.79 dB. The luminance PSNR values for color images are similar. The results of proposed visually lossless image compression for some images are shown in Fig. 6 and Fig. 7.


6(a)


6(b)


7(a)


7(b)

Fig. 6: (a) Original image 'Horse' and (b) visually lossless compressed image (1.90 bpp), PSNR = 45.75db)
Fig. 7: (a) Original image 'airplane' and (b) visually lossless compressed image (1.87 bpp), PSNR = 46.76db)

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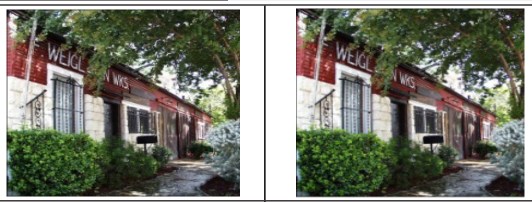
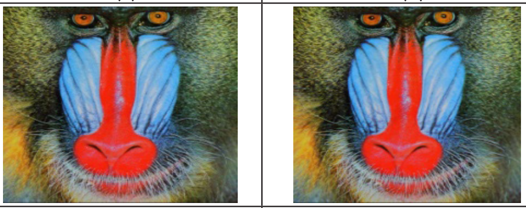


8(a) 8(b)



9(a) 9(b)

Fig. 8: (a) Original image 'Building 2' and (b) visually lossless compressed image (1.59 bpp), PSNR = 37.96db)
Fig. 9: (a) Original image 'Baboon' and (b) visually lossless compressed image (1.92 bpp), PSNR = 46.27 db)

Fig. 6 shows an original monochrome image 'Horse' together with a version that has been encoded by the proposed method. The encoded image exhibits a PSNR of 45.75 dB, bits per pixie (bpp) value= 1.90 and no differences are visible when the images are displayed using a 1:1 scale. Similarly, compressed images for 24-bit color images are shown in Fig. 8 and Fig. 9. This scheme encodes images much faster than conventional encoders schemes.

4. Conclusions

This work proposes a method of encoding images in a visually lossless manner using JPEG2000. Visually lossless coding shows the compression of images without any perceptible degradation in image quality. The human visual system has varying sensitivity to different color components, spatial frequencies, orientations, and underlying background images. A distortion model is developed using the distribution of wavelet coefficients and the dead-zone quantizer employed in JPEG2000 and provides higher accuracy than the conventional model. The sensitivity of each sub-band is obtained via psychophysical experiments using random noise generated by a JPEG2000 quantization distortion model and the inverse wavelet transform. In order to hide coding artifacts caused by quantization, visibility thresholds are measured and have different values depending on the local variances within each sub-band. Since quantization distortion appears on various background images, the threshold values are adjusted using a self-masking model and a texture-masking model to cope up with spatially changing visual masking effects. These image visibility thresholds, along with visual masking models, provide the maximum quantization step sizes that still provide visually lossless quality. The resulting quantization step sizes enable visually lossless coding at significantly lower bitrates compared with numerically lossless coding methods. The proposed JPEG2000 Part-I compliant coding scheme successfully yields compressed images, whose quality is indistinguishable to those of the original images, at significantly lower bitrates than those of numerically lossless coding and other visually lossless algorithms in the literature. This quantization scheme encodes images much faster than conventional encoder's scheme.

The compression performance of visually lossless encoder can be further improved in future by decreasing the bits per pixel value and visual quality is improved by improving the PSNR value.

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