Journal of Applied Technical and Educational Sciences
jATES
ISSN 2560-5429
http://jates.org

Analysis of JPEG Digital Image Compression Process

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Abstract

JPEG is the most often used image compression standard that is used since 1992. It is a lossy compression method, and is widely used in digital cameras and mobile phones. Depending on the parameters and user needs, it can achieve a compression ratio between 10 and 50. Memory for digital image storage is saved on the expense of decompressed image quality. The method is based on the Discrete Cosine Transform (DCT) that separates the image into different frequency components. This paper shows how different parameters of the algorithm influence the performance of the compression. In the end, ideas are given how to either increase the compression ratio keeping the same decompressed image quality, or to improve the quality without decreasing the compression ratio. The quality between the original and the decompressed images is measured using two objective criteria: the Peak Signal-to-Noise Ratio (PSNR) and the structural similarity index (SSIM). Different types of 8x8 image blocks (flat, impulse, ramp, ...) and their DCT transforms are analysed so the reader can anticipate the frequency content of the blocks. Understanding of the frequency content helps in creating customized algorithms for improving the basic JPEG.

Keywords: digital image compression, JPEG, quantization

1. Introduction

Digital image compression is an important operation to save memory space when storing digital images or videos. Compression algorithms take advantage of the presence of redundant data in digital images and reduce them. The point of the compression is to eliminate the redundancy without losing information from the image. Compression methods can be divided into two main categories: 1/ lossless, where the original image can be restored without any loss, and 2/ lossy, where the reconstructed image is only the approximation of the original. Current standards allow compression ratios around 1:3 for the lossless case and between 1:10 and 1:50 for the lossy case.

The importance of digital image compression can be shown with the following example. For a 512x512 pixel 8-bit single colour digital image, the memory needed to store the image is

768kB. One minute of full HD 1080x1920 pixel resolution video with 30 frames per second would need around 12GB of storage space, so the importance of compression is obvious.

This paper focuses on the most widely used digital image compression standard - the JPEG algorithm, which is based on the discrete cosine transform. Since this transform is well documented and used since 1974 (Pennebakker, Mitchell, 1992; JPEG group, 1992; Ahmed, Natarajan, Rao, 1974), it will not be explained in detail. A typical 256x256 pixel digital image that without compression occupies 64kB of memory space is shown in Fig. 1(a). Figures 1(b), 1(c) and 1(d) show the same image with different levels of compression. Image sizes are listed below. As it can be observed, compression ratio of 10 can be easily achieved without noticeable loss in quality. For higher compression ratios (lower bitrate) the degradation in decompressed image becomes visible. The intensity of the degradation can be controlled with quantization that will be explained in the next section.

(a) (b) (c) (d)

Fig. 1. Test image Lena with different compression ratios. (a) Original Lena image, Size: 64kB, bitrate: 8bpp, (b) Lena test image compressed with compression ratio 11, Size: 5.8kB, bitrate: 0.73bpp, (c) Lena test image compressed with compression ratio 30, Size: 2.1kB, bitrate: 0.27bpp, (d) test image Lena compressed with compression ratio 46. Size: 1.4kB, bitrate: 0.17bpp.

2. The JPEG process

The JPEG algorithm starts by dividing the digital image into blocks of size NxN. The size of the block can be different, where N usually equals 8. Other block sizes are possible, but rarely used. The same sequence of steps is then performed on each block. First, the original image range is shifted from [0, 255] to [-128, 127] by subtracting 128 from each entry of the 8x8 block. This step is followed by the discrete cosine transform (DCT) of the block and this is the core of the JPEG compression algorithm. The DCT compacts the energy of the block into only few coefficients(Wallace, 1992). So, the block of 8x8 pixels is transformed into a block of 8x8 coefficients that represent the frequency components of the block. The upper left value is the DC component, and it represents the average value of the block, the remaining 63 values in the transformed block are the AC components and they represent the frequencies from low to high. The basic idea behind compression is to preserve the DC and the low frequency coefficients, and to ignore the high frequency coefficients, since the human eye will not be capable to recognize the degradation. The operation that will zero out the high frequency components is quantization. The trick is to find the optimal measure of degradation that will not be visible for the human eye, since JPEG is optimized for humans.

2.1. Discrete Cosine Transform (DCT)

The Discrete Cosine Transform converts the NxN matrix into another NxN matrix. In the case of digital image processing, these matrices represent digital images. The formulas for the forward and inverse transformations are given in Eq. (1).

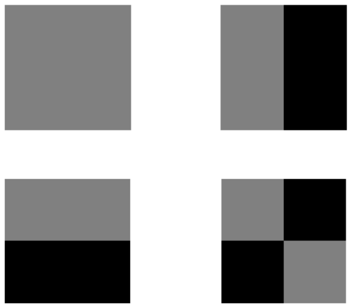
$$C(u,v)=\alpha(u)\alpha(v)\sum_{x=0}^{N-1}\sum_{y=0}^{N-1} f(x,y)\cdot\cos\left[\frac{(2x+1)u\pi}{2N}\right]\cdot\cos\left[\frac{(2y+1)v\pi}{2N}\right]$$

$$f(x,y)=\sum_{u=0}^{N-1}\sum_{v=0}^{N-1}\alpha(u)\alpha(v)C(u,v)\cdot\cos\left[\frac{(2x+1)u\pi}{2N}\right]\cdot\cos\left[\frac{(2y+1)v\pi}{2N}\right] \tag{1}$$

$$\alpha(u)=\begin{cases}\sqrt{1/N} & \text{for } u=0\\ \sqrt{2/N} & \text{for } u=1,2,\ldots,N-1\end{cases}$$

As it can be seen, the core of the transform is the cosine function. The original matrix is decomposed into its frequency components using the cosine function. The transformation is real, there is no imaginary part as in the Fourier transform. The 2-D DCT is also separable, so it can be obtained by two subsequent 1-D DCTs. The 2x2 basis functions for the 2-D DCT along with their numeric values are shown in Fig. 2. For example, a 2D-DCT transform of the 2x2 matrix $M=\begin{bmatrix}3 & -7\\ 8 & 6\end{bmatrix}$ is a 2x2 matrix $MDCT=\begin{bmatrix}5 & 6\\ -9 & 4\end{bmatrix}$. It means that matrix *M* can be obtained from the four basis function using Eq. (2). 4x4 and 8x8 blocks are decomposed in similar way using 16 and 64 basis functions, respectively.

$$5\cdot\begin{bmatrix}0.5 & 0.5\\ 0.5 & 0.5\end{bmatrix}+6\cdot\begin{bmatrix}0.5 & -0.5\\ 0.5 & -0.5\end{bmatrix}-9\cdot\begin{bmatrix}0.5 & 0.5\\ -0.5 & -0.5\end{bmatrix}+4\cdot\begin{bmatrix}0.5 & -0.5\\ -0.5 & 0.5\end{bmatrix}=\begin{bmatrix}3 & -7\\ 8 & 6\end{bmatrix} \tag{2}$$



(a)

$$\begin{bmatrix} 0.5 & 0.5 \\ 0.5 & 0.5 \end{bmatrix} \quad \begin{bmatrix} 0.5 & -0.5 \\ 0.5 & -0.5 \end{bmatrix}$$

$$\begin{bmatrix} 0.5 & 0.5 \\ -0.5 & -0.5 \end{bmatrix} \quad \begin{bmatrix} 0.5 & -0.5 \\ -0.5 & 0.5 \end{bmatrix}$$

(b)

Fig 2. (a) 2x2 basis functions, (b) Numeric values of the transform matrices

2.2 Quantization

Quantization is the operation that degrades the digital image in a controlled way. Quantization is done by dividing each transform coefficient by an appropriate value. Quantization can be uniform when all quantization matrix entries have the same value, and non-uniform when each component is quantized differently. Since the human eye has different sensitivity to different frequency components, usually the non-uniform type of quantization is preferred (Thai, Cogranne, Retraint, 2017). The standard Q_{50} quantization matrix that is used in many applications is shown in Fig. 3. Quantization with this matrix can achieve very high compression ratio, with excellent decompressed image quality. This quantization matrix was discovered experimentally by image processing experts who made subjective tests over many different digital images (Wang, Lee, Chang, 2001). Other quantization matrices can be derived from the Q_{50}. If the user needs higher quality, the Q_{50} should be multiplied by *(100-quality level)/50*. Higher quality also means more bits for representation and lower compression ratio. On the other hand, if the user wants to save extra bits and to sacrifice quality, the Q_{50} should be multiplied by *50/quality level*. The higher the index of matrix Q, the higher the quality, but the compression ratio also drops.

Two typical quantization matrices are shown in Fig. 3: the Q_{10} and the Q_{90}. By using the Q_{10} most of the coefficients will be zeroed out, and only few coefficients will remain. On the other hand, by using the Q_{90} whose entries are quite small, most of the frequency components will survive the quantization (Tan, Gan, 2015). Typical block of DCT coefficients quantized with different quantization matrices is shown in Fig. 4.

$$Q_{10} = \begin{bmatrix} 80 & 60 & 50 & 80 & 120 & 200 & 255 & 255 \\ 55 & 60 & 70 & 95 & 130 & 255 & 255 & 255 \\ 70 & 65 & 80 & 120 & 200 & 255 & 255 & 255 \\ 70 & 85 & 110 & 145 & 255 & 255 & 255 & 255 \\ 90 & 110 & 185 & 255 & 255 & 255 & 255 & 255 \\ 120 & 175 & 255 & 255 & 255 & 255 & 255 & 255 \\ 245 & 255 & 255 & 255 & 255 & 255 & 255 & 255 \\ 255 & 255 & 255 & 255 & 255 & 255 & 255 & 255 \end{bmatrix} \quad Q_{90} = \begin{bmatrix} 3 & 2 & 2 & 3 & 5 & 8 & 10 & 12 \\ 2 & 2 & 3 & 4 & 5 & 12 & 12 & 11 \\ 3 & 3 & 3 & 5 & 8 & 11 & 14 & 11 \\ 3 & 3 & 4 & 6 & 10 & 17 & 16 & 12 \\ 4 & 4 & 7 & 11 & 14 & 22 & 21 & 15 \\ 5 & 7 & 11 & 13 & 16 & 12 & 23 & 18 \\ 10 & 13 & 16 & 17 & 21 & 24 & 2 & 21 \\ 14 & 18 & 19 & 20 & 22 & 20 & 20 & 20 \end{bmatrix}$$

$$Q_{50} = \begin{bmatrix} 16 & 11 & 10 & 16 & 24 & 40 & 51 & 61 \\ 12 & 12 & 14 & 19 & 26 & 58 & 60 & 55 \\ 14 & 13 & 16 & 24 & 40 & 57 & 69 & 56 \\ 14 & 17 & 22 & 29 & 51 & 87 & 80 & 62 \\ 18 & 22 & 37 & 56 & 68 & 109 & 103 & 77 \\ 24 & 35 & 55 & 64 & 81 & 104 & 113 & 92 \\ 49 & 64 & 78 & 87 & 103 & 121 & 120 & 101 \\ 72 & 92 & 95 & 98 & 112 & 100 & 103 & 99 \end{bmatrix}$$

Fig. 3. Quantization matrices Q_{10}, Q_{50} and Q_{90}

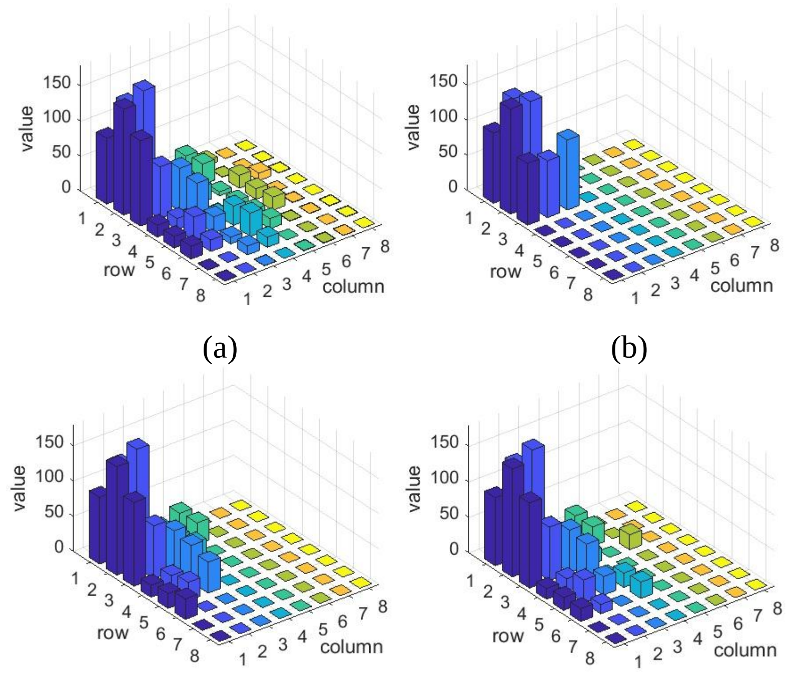
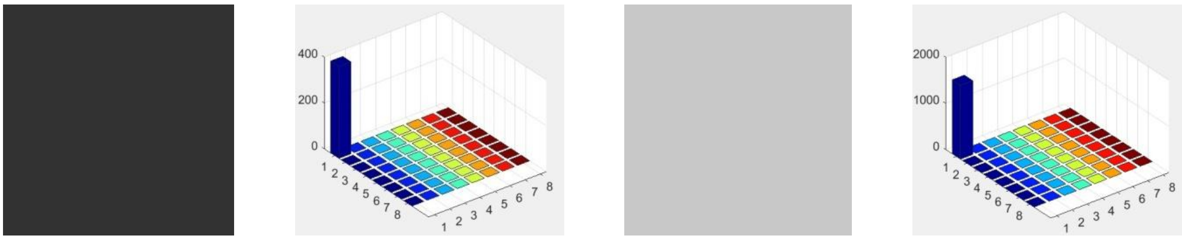


Fig. 4. (a) Original 8x8 block of DCT coefficients, (b) Quantized and dequantized block using quantization matrix Q_{10} – 7 coefficients remained, (c) Quantized and dequantized block using quantization matrix Q_{50} – 20 coefficients remained, (d) Quantized and dequantized block using quantization matrix Q_{90} – 25 coefficients remained

2.3. Block transforms

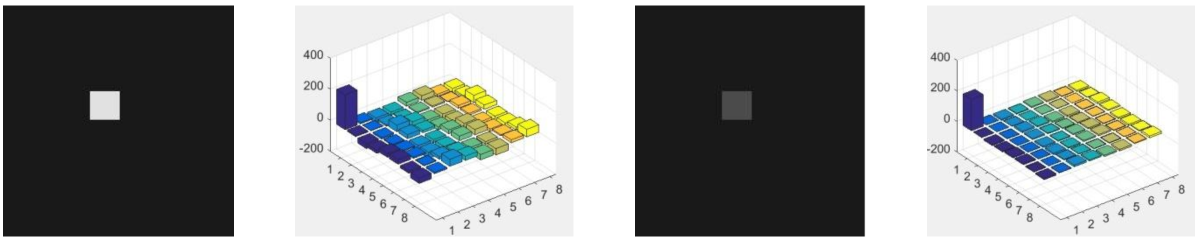
To get better insight what happens during the transformation of the *8x8*image block, typical blocks along with their transform are presented. The simplest block is a flat block where no variation in intensity is present inside the block, Fig. 5. The DCT of this block contains only the DC component that represents the average value of the block, Fig. 5(b) and (d). The DC component of the darker block is smaller because the average intensity of the block is smaller.



(a) (b) (c) (d)

Fig.5. (a) Flat block, intensity 50, (b) DCT2 (a), (c) Flat block, intensity 200, (d) DCT2 of (c)

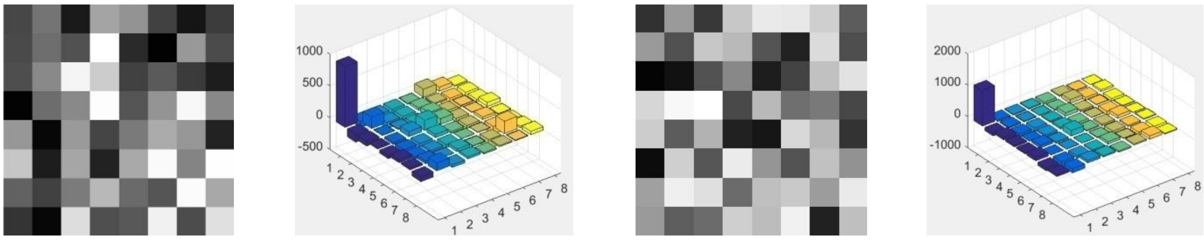
Fig. 6 shows a block that contains only one pixel impulse in the middle of the block. Transform of the block shows that horizontal, vertical and diagonal frequency components will appear. The intensity of these components depends on the contrast of the block to be transformed. Higher contrast will result in appearance of greater intensities of high frequency components. Fig. 6(a) shows a block with contrast 200 (intensity of the flat area is 25, and intensity of the impulse is 225). Fig. 6(c) also shows an impulse, but with a much lower contrast of 50 (intensity of the flat area is 25, and the intensity of the impulse is 75 as in the previous case). The difference in the frequency content is obvious. While both DC components are almost equal (225 and 206 respectively, the difference is caused by the different impulse intensity), AC components of the high contrast block are higher. The low contrast block more remind to the flat block, and this observation also holds for the frequency content.



(a) (b) (c) (d)

Fig. 6. (a) Impulse image block, contrast=200, (b) DCT2 of (a), (c) Impulse image block, contrast=50, (d) DCT2 of (c)

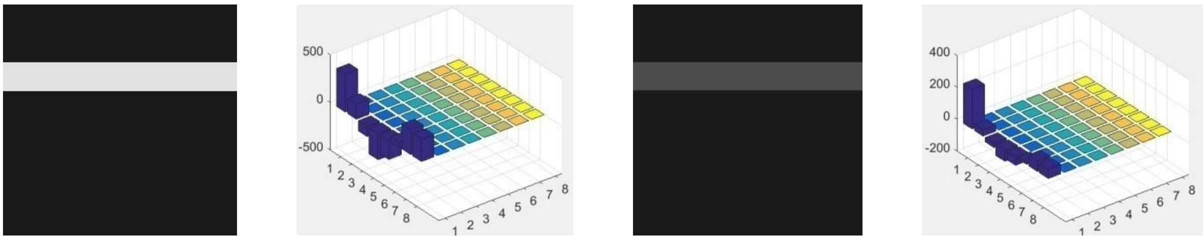
The next block analysed was a random texture block, Fig. 7. The block contains 64 random values between 0 and 255. The randomness of the block implies random frequency content for all spatial frequencies. The DC component that represents the average of the block will remain dominant in comparison with the other frequency components for both different random texture blocks.



(a) (b) (c) (d)

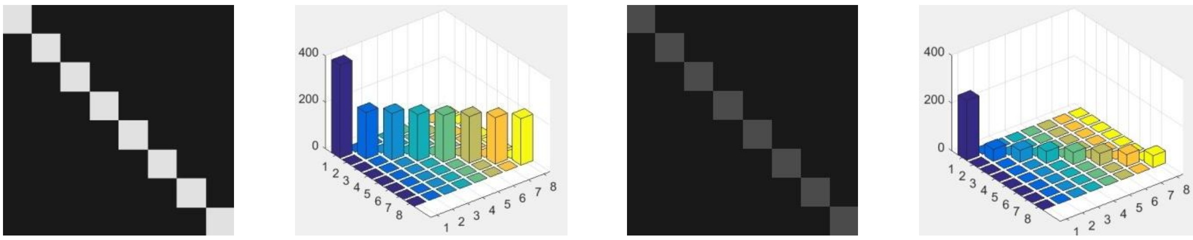
Fig. 7. (a) Random texture block 1, (b) DCT2 of (a), (c) random texture block 2, (d) DCT2 of (c)

The block that contains a horizontal line is shown in Fig. 8. Changes in intensity occur only in the vertical direction of the block, and that is the reason why only vertical frequency components are contained in the transformed image. The intensity of the transform coefficients also depends on the contrast between the line and the flat area. Higher contrast in the original block will result in higher intensities of the frequency components.



(a) (b) (c) (d)

Fig. 8. (a) High contrast horizontal line, (b) DCT2 of (a), (c) Low contrast horizontal line (d) DCT2 of (c)

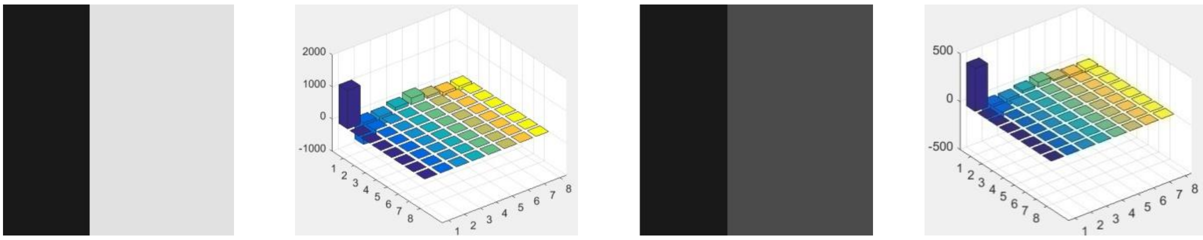


(a) (b) (c) (d)

Fig. 9. (a) High contrast diagonal line image block, (b) DCT2 of (a), (c) Low contrast diagonal line image block, (d) DCT2 of (c)

Next, the low contrast and high contrast diagonal line is analysed, Fig 9. After the transformation of both blocks, only the diagonal frequency components remained. This is because of the same change in both horizontal and vertical directions. Again, the intensity of the frequency components depends on the contrast between the line and the flat area of the block.

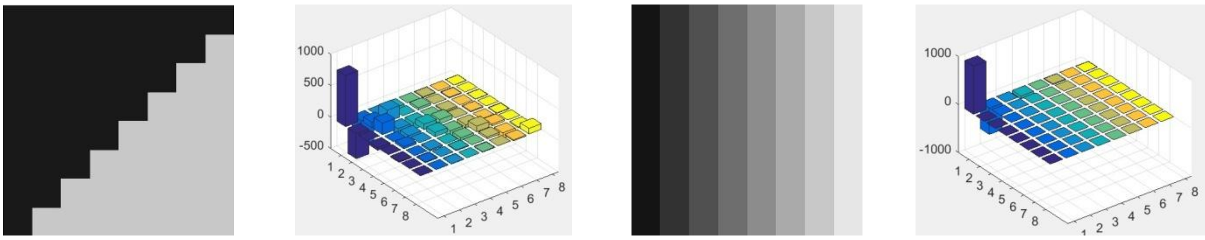
Fig. 10 shows the transformation of the low contrast and high contrast vertical edges. Both frequency plots show similar shape, dominant DC component and minor AC components. The DC component of the high contrast block is much bigger because the average value of the high contrast block is higher than the average value of the low contrast block.



(a) (b) (c) (d)

Fig. 10. (a) High contrast image block, (b) DCT2 of (a), (c) Low contrast image block, (d) DCT2 of (c)

Finally, Fig. 11 shows a diagonal edge and slope blocks before and after their corresponding DCT representations. Similarly as in the case of a diagonal line, the spectra of the diagonal edge contains only diagonal components. For the slope block where the intensity change occurs only in horizontal direction, the spectral components also appear in one direction (only the first row has entries different from zero).



(a) (b) (c) (d)

Fig. 11. (a) Diagonal edge image block, (b) DCT2 of (a), (c) Slope image block, (d) DCT2 of (c)

The above examples provide better insight into the nature of the transform. The important thing to remember is that the DC component represents the average of the block, and contains the highest portion of block energy. By moving further away from the DC component, frequency rises, and the energy of the components drops (Thyagarajan, 2011).

3. Experimental results

Thumbnails of standard test images where our tests were performed on are shown in Fig. 12. Two objective measures were used to evaluate the quality of the compression process: peak signal-to-noise ratio (PSNR) and the structural similarity index (SSIM). Values obtained express the PSNR and SSIM between the original image and the image after the compression and decompression processes. While the PSNR measures the difference between images on a pixel base, the SSIM measures the difference in image structure. The PSNR ranges between 0 and high values (in *dB*), and the SSIM ranges between 0 and 1. Higher values of both measures mean better quality. Table I shows the results for all test images compressed and decompressed using quantization matrix Q_{50}.

Fig.12. Test images used in the research: Baboon, Barbara, Boat, Cameraman, Clock, F16 (top row), Lake, Lena, Moon, Peppers and Pirate (bottom row)

Table 1. Compression parameters for 11 test images, CR is the Compression Ratio, PSNR is expressed in decibels (dB), and SSIM is the Structural Similarity Index

	Bitrate (bpp)	CR	PSNR	SSIM
Baboon	0.84	9.49	29.63	0.66
Barbara	0.89	8.99	33.52	0.86
Boat	0.94	8.49	31.96	0.81
Cameraman	0.77	10.36	31.57	0.59
Clock	0.58	13.91	34.95	0.56
F16	0.83	9.66	32.71	0.74
Lake	1.05	7.60	31.14	0.80
Lena	0.72	11.10	33.79	0.79
Moon	0.72	11.07	32.19	0.64
Peppers	0.77	10.33	34.29	0.82
Pirate	0.96	8.30	31.70	0.82

4. Discussion

This paper analysed the DCT of different types of 8x8 pixel image blocks. Depending on the block type, the frequency content in the transformed domain is also changing. By analysing the transformed blocks the reader can get a good estimate what to except after transforming real image blocks. This is important because the transformation is followed by quantization which is the irreversible step of the process. The decision which quantization matrix to use can be reached if the user knows what to expect after the transformation. Many improved JPEG algorithms exploit this property, and adapt the quantization step to the block content.

5. Conclusion

In this paper we have analysed the JPEG process, explained how the discrete cosine transform works, and how quantization degrades the image quality. We also showed how the compression process saves memory space for storing digital images. By doing the experiments with test images we showed what are the typical values for the quality measures. In the future, it is planned to find a connection between image content and compressed digital image quality to get higher compression ratio with no change in decompressed image quality.

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