

EQ2330 Image and Video Processing

Project 2

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Summary

The goal of this task is to implement two kinds of image transformation technology, DCT(Discrete Cosine Transform) and DWT(Discrete Wavelet transform). Then uniform quantizer with different step size is applied to two sets of transform coefficients respectively to investigate the relationship between bit-rate and peak signal-to-noise ratio and thus measure the quality of reconstructed image.

1 Introduction

Image compression is a method through which we can reduce the storage space of images, videos which will be helpful to increase storage and transmission process's performance. In image compression, we do not only concentrate on reducing size but also concentrate on doing it without losing quality and information of image. In this project, two types of image compression techniques are implemented. The first technique is based on Discrete Cosine Transform (DCT) and the second one is based on Discrete Wavelet Transform (DWT). The performance of both transformation is measured through the distortion and the bit rate-PSNR curve.

2 System Description

2.1 DCT-based Image Compression

2.1.1 DCT

DCT is the short of Discrete Cosine Transformation. It is the basic transformation used in JPEG 2000 standards. There are four types of DCT and one of the most widely used one is DCT-II, which is a orthonormal transformation and a unitary transformation. DCT transform of a size $M \times M$ block can be implemented by the following method:

$$y = Ax A^T \quad (1)$$

where A is a $M \times M$ matrix whose elements is

$$a_{ij} = \alpha_i \cos\left(\frac{(2k+1)i\pi}{2M}\right) \quad (2)$$

with

$$\alpha_i = \begin{cases} \sqrt{\frac{1}{M}}, & i = 0 \\ \sqrt{\frac{2}{M}}, & \forall i > 0 \end{cases} \quad (3)$$

2.1.2 IDCT

IDCT is the inverse transform of DCT. It can be implemented by the following method:

$$x = A^T y A \quad (4)$$

The implementation of the DCT and IDCT can be found in section A.2.1.

2.2 FWT-based Image Compression

2.2.1 The Two-Band Filter Bank

For the FWT implementation, We use the lifting scheme to design the filter bank. Lifting implementation of the 5/3 filter bank is illustrated in figure 1:

The forwarding lifting scheme of 5/3 filter bank consists of the following steps:

1. The splitting step, where the signal vector is separated into even and odd samples
2. The prediction step, associated with the predict operator $P_1(z) = -\frac{1+z}{2}$
3. The update step, associated with the update operator $U_1(z) = \frac{1+z^{-1}}{4}$
4. The scaling step, indicated by the scaling factors $\sqrt{2}$ and $\frac{1}{\sqrt{2}}$

For each pair of input samples, $2n$ and $2n + 1$, the lifting equations of the analysis filter bank are written as follows:

$$HP[n] = x[2n + 1] - \frac{x[2n] + x[2n + 2]}{2} \quad (5)$$

$$LP[n] = \sqrt{2}(x[2n] + \frac{\sqrt{2}(HP[n] + HP[n - 1])}{4}) \quad (6)$$

where x are the signal samples, HP denotes the high-frequency output coefficient, and LP denotes the low-frequency output coefficient. Note that we use a periodic extension of the signal to obtain signal values whose indices are less than 0 or larger than the signal length. In the MATLAB implementation, this extension is achieved by $x[\text{mod}(k, l)]$, where l is the length of x and mod denotes the modulo operation.

The corresponding synthesis step is the inverse transform of the analysis step. The input signal sets are the low frequency coefficients and high frequency coefficients. After the synthesis step, we obtain the reconstructed even samples and odd samples. Finally, by concatenating them, we obtain the reconstructed image. The liftings equations of the synthesis filter bank are written as follows:

$$\hat{x}[2n] = \frac{1}{\sqrt{2}}LP[n] - \frac{\sqrt{2}HP[n] + \sqrt{2}HP[n - 1]}{4} \quad (7)$$

$$\hat{x}[2n + 1] = \sqrt{2}HP[n] + \frac{\hat{x}[2n] + \hat{x}[2n + 2]}{2} \quad (8)$$

The implementation of the FWT and IFWT can found in section 3.1[3].

2.2.2 The FWT

In this section, we use the Row-Column(RC) computation schedule to implement the 2D DWT. Firstly, we implement 1D FWT through x coordinate (to every column), thus obtaining the low band and high band. Then we implement 1D FWT through y coordinate (to every row) to these two bands respectively, thus obtaining four subbands which represent the approximation coefficients, horizontal coefficients, vertical coefficients and diagonal coefficients respectively. Lastly, we concatenate all the coefficients in a single image. This is the process of 1D-FWT.

After that, we do the 2D-FWT four times. Since most energy is concentrated in the approximation coefficients. In each step, we extract the approximation part as the input signal of the following 2D-FWT procedure. The whole procedure is illustrated in figure 2 [2].

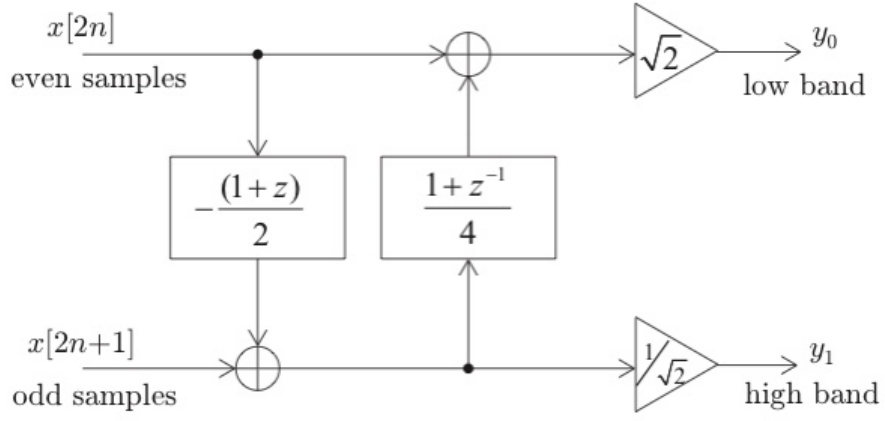


Figure 1: Lifting implementation of the 5/3 filter bank (Image source: [3])

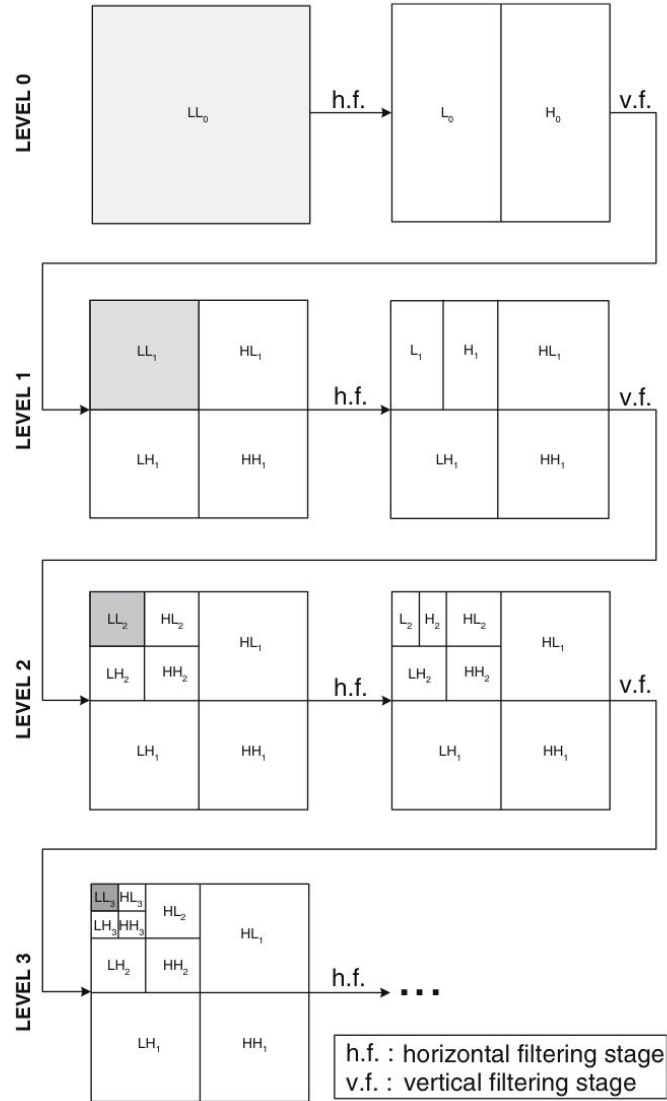


Figure 2: 2D FWT(Image source: [2])

2.3 Quantization and Performance analysis

2.3.1 Uniform Quantizer

Rounding a real number x to the nearest integer value forms a uniform quantizer. A mid-tread uniform quantizer has the following mapping format.

$$Q(x) = \Delta \cdot \left\lfloor \frac{x}{\Delta} + \frac{1}{2} \right\rfloor \quad (9)$$

where $\lfloor \cdot \rfloor$ denotes the floor operator, Δ denotes the quantization step size.

$Q(x)$ is the equalized value of real number x . By implementing this quantizer, all coefficient values are mapped to the midpoint of the range, and all equalization steps are equally spaced. Figure 3 shows the quantizer function for a step size $\Delta = 4$.

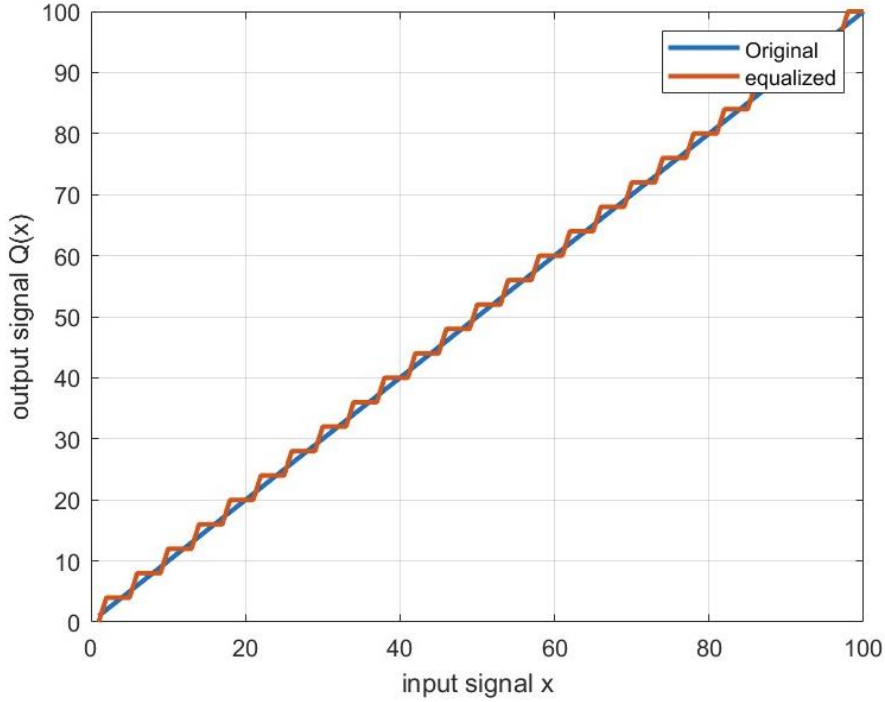


Figure 3: Mid-tread uniform equalizer(step size $\Delta = 4$)

2.3.2 Distortion and Bit-Rate Estimation

Given an image \mathbf{I} with size $m \times n$, and the reconstructed output image \mathbf{Q} after the equalization to the coefficients, the MSE (mean square error) is defined as follows:

$$\text{MSE} = \frac{1}{mn} \sum_{i=0}^{m-1} \sum_{j=0}^{n-1} [\mathbf{I}(i, j) - \mathbf{Q}(i, j)]^2 \quad (10)$$

The PSNR(Peak Signal-to-Noise Ratio) is defined as:

$$\text{PSNR} = 10 \cdot \log_{10} \left(\frac{\text{MAX}_I^2}{\text{MSE}} \right) \quad (11)$$

Where MAX_I denotes the maximum pixel value of the image, in this case, $\text{MAX}_I = 255$.

For the DCT coefficients, different VLCs (Variable-length code), are uses depending on the position of the coefficient in the 8×8 blocks. That means all coefficients which are at position (1, 1) in their respective block use the same VLC and all coefficients at position (2, 1) use a different one and so on.

For the FWT coefficients, We uses a special code for each of the four subbands (approximation, horizontal, vertical, diagonal coefficients). The four subbands are encoded individually according to different types of VLC.

For the distortion analysis, we vary the quantizer step-size over the range $2^0, 2^1, 2^2, \dots, 2^9$. For different step-sizes, the coefficient values are mapped to different representative levels. Average distortion is a measurement of the reconstruction quality, which is the mean square error between the original and the reconstructed image. Intuitively, if the step-size is smaller, there will be more representative levels, thus the average distortion is smaller which will lead to better reconstruction quality. The quality of the quantization can be predicted by the 6 dB rule. According to this rule of thumb, the SNR of a quantized signal increases with 6 dB per bit.

Then, to calculate the bit-rate, due to the fact that the shannon entropy is the lower bound of any variable-length code, we assume that the shannon entropy is a reasonable approximation of the ideal code word length of a VLC. Since different VLCs are used for different coefficient types, we calculated the entropy for each coefficient type individually. The bit-rate is the weighted average of these entropies.

3 Results

3.1 DCT

We are able to derive the A matrix of the blockwise 8×8 DCT:

$$A = \begin{bmatrix} 0.3536 & 0.3536 & 0.3536 & 0.3536 & 0.3536 & 0.3536 & 0.3536 & 0.3536 \\ 0.4904 & 0.4157 & 0.2778 & 0.0975 & -0.0975 & -0.2778 & -0.4157 & -0.4904 \\ 0.4619 & 0.1913 & -0.1913 & -0.4619 & -0.4619 & -0.1913 & 0.1913 & 0.4619 \\ 0.4157 & -0.0975 & -0.4904 & -0.2778 & 0.2778 & 0.4904 & 0.0975 & -0.4157 \\ 0.3536 & -0.3536 & -0.3536 & 0.3536 & 0.3536 & -0.3536 & -0.3536 & 0.3536 \\ 0.2778 & -0.4904 & 0.0975 & 0.4157 & -0.4157 & -0.0975 & 0.4904 & -0.2778 \\ 0.1913 & -0.4619 & 0.4619 & -0.1913 & -0.1913 & 0.4619 & -0.4619 & 0.1913 \\ 0.0975 & -0.2778 & 0.4157 & -0.4904 & 0.4904 & -0.4157 & 0.2778 & -0.0975 \end{bmatrix} \quad (12)$$

3.2 FWT

By implementing the FWT and the inverse FWT of scale 6, we could get the reconstructed image. By comparing the reconstructed image with its original version in figure 4, we could conclude that the lifting scheme allows for perfect reconstruction with arbitrary scale since the MSE between the reconstructed image and original image equals zero.



Figure 4: original(left) versus reconstructed(right)

By applying the 2D-FWT four times to the image "harbor", the wavelet coefficients for scale 2 and 4 of the image **harbor** are illustrated as figure 5. We could conclude that the main energy is concentrated in the approximation coefficients (upper left).

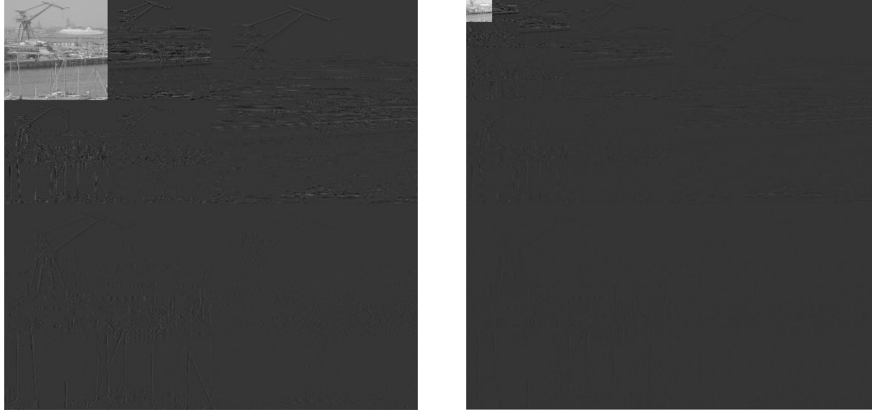


Figure 5: wavelet coefficients of harbor(scale 2 and 4)

3.3 Quantization and Performance analysis

3.3.1 DCT

First, we compared the mean squared error of the reconstructed image with the mean squared of the quantized coefficients. We observed that both distortions are always equal. To explain this behaviour, let $C \in \mathbf{R}^{512 \times 512}$ be the coefficients, $C_q = C + E$ the quantized coefficients with additional quantization noise E and I and I_r the original and reconstructed image, respectively. Then, we have

$$I_r = \text{IDCT}(C) = \text{IDCT}(C_q + E) = \text{IDCT}(C_q) + \text{IDCT}(E) = I + \text{IDCT}(E), \quad (13)$$

because the IDCT is linear. Therefore, the distortion in the reconstructed image is the quantization noise that was transformed by the IDCT. Since the IDCT is unitary, the energy of this distortion is equal to the energy of E . Hence, the mean square errors are also equal.

The result of the distortion analysis for the DCT transformation are shown. Figure 6 shows the PSNR of the quantized image with respect to the bit-rate that is necessary to encode the quantized image. The PSNR increases with the bit rate. For bit rates above 1 bit per pixel, the slope of the curve is approximately 6 dB per bit. This behaviour can be motivated by the 6 dB per bit rule. Since the DCT is an orthonormal transformation, the quantization noise stays the same after back transformation and hence, the 6 dB per bit rule also holds for the PSNR of the reconstructed image.

3.3.2 FWT

It could be observed that the entropy of the approximation coefficients is always higher than that of the horizontal, vertical, diagonal coefficients since the low frequency part carries more information. For example, when step size equals 1. The entropy of approximation coefficients is 6.9455, while the entropy of horizontal, vertical, diagonal coefficients are 5.7850, 5.2386, 4.4330 respectively.

The result of the distortion analysis for the FWT transformation are shown in table 1 and 2. Figure 6 shows the PSNR of the quantized image with respect to the bit-rate that is necessary to encode the quantized image. The PSNR increases with the bit rate. For bit rates above 1 bit per pixel, the slope of the curve is approximately 6 dB per bit. The rate distortion performance of the compression with the FWT compression is similar to the DCT compression.

Table 1: Average distortion and MSE for the quantized images (Part 1)

MSE \ Step size	2^0	2^1	2^2	2^3	2^4
Average distortion	0.1036	0.3956	1.4114	4.9249	16.3830
MSE(coefficients)	0.0842	0.3260	1.1874	4.1820	14.3805

Table 2: Average distortion and MSE for the quantized images (Part 2)

MSE \ Step size	2^5	2^6	2^7	2^8	2^9
Average distortion	48.9955	128.5811	277.9681	447.3449	589.7516
MSE(coefficients)	45.2450	126.6955	297.3768	533.9498	780.9233

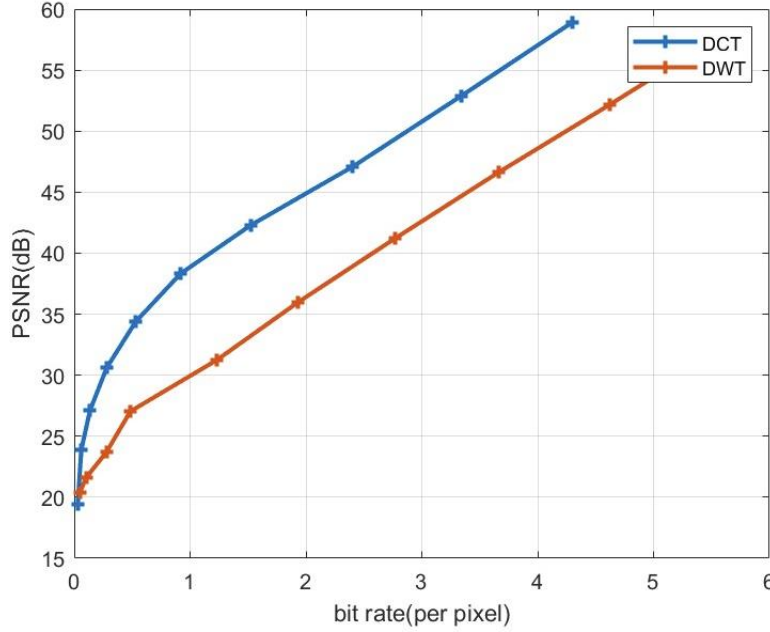


Figure 6: When using DCT and FWT transformation, PSNR of the quantized image plotted over the bit rate per pixel needed to encode the quantized image with a variable length code.

4 Conclusions

By implementing the algorithms of DCT and FWT respectively, we find that DCT and FWT transformation both allow for perfect reconstruction. When doing the performance analysis, it could be observed that the rate-PSNR curves of two transforms both adhere to the 6 dB per bit rule. By comparing the two rate-PSNR curves, it could be observed that the DCT outperforms the DWT due to its higher PSNR with respect to the same bit rate. However, in practice, FWT technique is more efficient than DCT technique in quality and efficiency wise.

A Appendix

A.1 Who Did What

Chenting Zhang: FWT implementation and performance analysis

Lukas Rapp: FWT implementation and performance analysis collaboratively with Chenting Zhang and part of DCT performance analysis

Shaotian Wu: DCT part, including DCT implement, DCT uniform quantizer and part of DCT performance analysis

A.2 MatLab code

A.2.1 Implementation DCT and IDCT using matrix multiplications

```

1 im=imread("images/boats512x512.tif");
2 im=double(im);

```

```

3  im_size=length(im);
4  block_size=8;
5
6  %Calculate A matrix in DCT
7  A=DCT_Mat(block_size);
8
9  %Implement of DCT to the image
10 s=im_size/block_size;
11 for i=0:s-1
12     for k=0:s-1
13         C=im(block_size*i+1:block_size*(i+1),block_size*k+1:block_size*(k+1)
14             ↪ );
15         D=A*C*A';
16         im_conv(block_size*i+1:block_size*(i+1),block_size*k+1:block_size*(k
17             ↪ +1))=D;
18     end
19 end
20
21 %Implement of IDCT to the image
22 for i=0:s-1
23     for k=0:s-1
24         C=im_conv(block_size*i+1:block_size*(i+1),block_size*k+1:block_size
25             ↪ *(k+1));
26         D=A'*C*A;
27         im_rec(block_size*i+1:block_size*(i+1),block_size*k+1:block_size*(k
28             ↪ +1))=D;
29     end
30 end
31
32 function A=DCT_Mat(block_size)
33 for i=0:block_size-1
34     for k=0:block_size-1
35         s=i+1;
36         t=k+1;
37         A(s,t)=cos(i*(2*k+1)*pi/16);
38         if i==0
39             A(s,t)=A(s,t)*sqrt(1/8);
40         else
41             A(s,t)=A(s,t)*sqrt(2/8);
42         end
43     end
44 end
45 end
46 end

```

A.2.2 Uniform Quantizer and plot

```

1  step_size_list=[2^0,2^1,2^2,2^3,2^4,2^5,2^6,2^7,2^8,2^9];
2
3  xhead=biggest(im_conv,im_size);
4  for digit=0:9
5      %Implement Uniform Quantizer
6      stepsize=step_size_list(digit+1);
7      for i=1:512
8          for k=1:512
9              im_conv_qua(i,k)=sign(im_conv(i,k))*stepsize*floor(abs(im_conv(i
10                 ↪ ,k))/stepsize+0.5);
11          end
12      end
13      %Plot the uniform quantizer

```



```

14     x=-xhead:0.01:xhead;
15     y=x;
16     for i=1:length(x)
17         y(i)=sign(x(i))*stepsize*floor(abs(x(i))/stepsize+0.5);
18     end
19     figure();
20     plot(x,y);
21     title('Quantizer function');
22     xlabel('x');
23     ylabel('Q(x)');
24 end
25
26 function xhead=biggest(Mat,size)
27 xhead=0;
28 if length(Mat)~=size
29     error("Wrong matrix size");
30 end
31 for i=1:size
32     for k=1:size
33         if xhead<Mat(i,k)
34             xhead=Mat(i,k);
35         end
36     end
37 end
38 end

```

A.2.3 Performance Analysis

```

1
2 close all;
3 clear;
4
5 im=imread("images/boats512x512.tif");
6 im=double(im);
7
8 im_size=length(im);
9
10 block_size=8;
11 step_size_list=[2^0,2^1,2^2,2^3,2^4,2^5,2^6,2^7,2^8,2^9];
12
13 im_conv=DCT(im,im_size,block_size);
14
15 for index_step_size=1:length(step_size_list)
16     disp(index_step_size);
17     stepsize=step_size_list(index_step_size);
18     im_conv_qua_int = sign(im_conv).*floor(abs(im_conv)/stepsize+0.5);
19     im_conv_qua = stepsize * im_conv_qua_int;
20
21     im_rec=ones(512);
22     for i=0:63
23         for k=0:63
24             C=im_conv_qua(8*i+1:8*(i+1),8*k+1:8*(k+1));
25             D=idct2(C,[8 8]);
26             im_rec(8*i+1:8*(i+1),8*k+1:8*(k+1))=D;
27         end
28     end
29
30     dist_fig=sum((im-im_rec).^2, 'all')/512^2;
31     disp(dist_fig);
32

```

```

33     PSNR=10*log10(255^2/ dist_fig);
34     PSNR_list(index_step_size)=PSNR;
35
36     entropy_im_conv_qua = 0;
37     for m = 1:8
38         for n = 1:8
39             % Extracts all coefficients which are at position m, n in each
40             % block
41             coefficients_m_n = im_conv_qua(m:8:end, n:8:end);
42
43             % Get probabilities for coefficients
44             [numbers, values] = groupcounts(reshape(coefficients_m_n, [], 1)
45                 ↪ );
46             probs = numbers / sum(numbers);
47
48             % Calculate entropy of all coefficients at position m, n in each
49             entropy_coefficients_m_n = sum(-log2(probs) .* numbers, 'all');
50             entropy_im_conv_qua = entropy_im_conv_qua +
51                 ↪ entropy_coefficients_m_n;
52         end
53     end
54     bitr = entropy_im_conv_qua / (size(im_conv_qua,1) * size(im_conv_qua, 2)
55         ↪ );
56
57     bitr_list(index_step_size)=bitr;
58 end
59
60 figure();
61 plot(bitr_list, PSNR_list, '+-', 'LineWidth', 2);
62
63 % correct
64 function A=DCT_Mat(block_size)
65 for i=0:block_size-1
66     for k=0:block_size-1
67         s=i+1;
68         t=k+1;
69         A(s,t)=cos(i*(2*k+1)*pi/16);
70         if i==0
71             A(s,t)=A(s,t)*sqrt(1/8);
72         else
73             A(s,t)=A(s,t)*sqrt(2/8);
74         end
75     end
76 end
77 end
78
79 % correct
80 function im=DCT(im, im_size, block_size)
81 if mod(im_size, block_size)
82     error("Wrong block size");
83 end
84 s=im_size/block_size;
85 for i=0:s-1
86     for k=0:s-1
87         C=im(block_size*i+1:block_size*(i+1), block_size*k+1:block_size*(k+1)
88             ↪ );
89         D=dct2(C, [block_size block_size]);
90         im(block_size*i+1:block_size*(i+1), block_size*k+1:block_size*(k+1))=
91             ↪ D;
92     end
93 end

```

```

89 end
90 end

```

A.2.4 FWT

```

1
2 function DWT=FWT2(im, layer, max_layer)
3 % layer: always start with 0
4 % max_layer: the number of transformations that are applied
5     disp(size(im)); % display in the command line
6     if layer >= max_layer
7         DWT = im;
8     else
9         [a,d_hor, d_ver, d_diag] = FWT2_step(im); % one-step 2-D FWT
10
11         a = FWT2(a, layer + 1, max_layer); % recursive, using the
12         ↪ previous approximation as input
13
14         DWT = cat(1,[a d_hor],[d_ver d_diag]); % concatenate coefficients
15         ↪ in a single image
16
17         % approximation | horizontal detail
18         % -----
19         % vertical detail | diagonal detail
20     end
21 end
22
23 function [a,d_hor, d_ver, d_diag] = FWT2_step(im)
24     for n = 1:size(im,2) %apply to single columns
25         [a_col(:,n), d_col(:,n)] = analysis_step(im(:,n));
26     end
27
28     for m = 1:size(a_col,1)
29         [a(m,:), d_ver(m,:)] = analysis_step(a_col(m,:)); %get LP and
30         ↪ vertical details
31     end
32
33     for m = 1:size(d_col,1)
34         [d_hor(m,:), d_diag(m,:)] = analysis_step(d_col(m,:)); %get
35         ↪ horizontal and diagonal details
36     end
37 end
38
39 function [low_band, high_band] = analysis_step(signal)
40 % 5/3 lifting scheme
41     even_samples = signal(2:2:end);
42     odd_samples = signal(1:2:end);
43
44     odd_samples_tmp = zeros(size(odd_samples));
45     for time=1:length(odd_samples)
46         odd_samples_tmp(time) = odd_samples(time) - 1/2 * (even_samples(time
47         ↪ ) + even_samples(mod(time+1, length(even_samples))));
48     end
49
50     low_band = zeros(size(even_samples));
51     for time=1:length(even_samples)
52         low_band(time) = sqrt(2) * (even_samples(time) + 1/4 * (
53         ↪ odd_samples_tmp(time) + odd_samples_tmp(mod(time-1,

```

```

        ↪ length(odd_samples_tmp)))));
50     end
51
52     high_band = 1/sqrt(2) * odd_samples_tmp;
53 end
54
55
56 function new_time = mod_time(time, L)
57     new_time = mod(time - 1, L) + 1;
58 end

```

A.2.5 IFWT

```

1  function im_rec=FWT2_inv(fwt, layer)
2      for l = (layer-1):-1:0
3          s = size(fwt, 1) / 2^l;
4          fwt(1:s, 1:s) = FWT2_inv_step(fwt(1:s, 1:s));
5      end
6      im_rec = fwt;
7  end
8
9
10 function im_rec = FWT2_inv_step(fwt)
11     s = size(fwt, 1) / 2;
12
13     a = fwt(1:s, 1:s);
14     d_hor = fwt(1:s, (s+1):end);
15     d_ver = fwt((s+1):end, 1:s);
16     d_diag = fwt((s+1):end, (s+1):end);
17
18     d_col = zeros(size(a,1), 2*size(a,2));
19     for m = 1:size(a, 1) %apply to rows
20         d_col(m,:) = synthesis_step(d_hor(m,:), d_diag(m,:)); %get LP and
        ↪ vertical details
21     end
22
23     a_col = zeros(size(a,1), 2*size(a,2));
24     for m = 1:size(a,1) %apply to rows
25         a_col(m,:) = synthesis_step(a(m,:), d_ver(m,:)); %get LP and
        ↪ vertical details
26     end
27
28     im_rec = zeros(2*size(a, 1), 2*size(a, 2));
29     for n = 1:size(fwt,2) %apply to single columns
30         im_rec(:, n) = synthesis_step(a_col(:, n), d_col(:, n));
31     end
32 end
33
34
35 function signal_rec = synthesis_step(low_band, high_band)
36     even_samples = zeros(length(low_band), 1);
37     odd_samples = zeros(length(low_band), 1);
38
39     low_band_sc = 1/sqrt(2) * low_band;
40     high_band_sc = sqrt(2) * high_band;
41
42     for time = 1:length(low_band)
43         even_samples(time) = low_band_sc(time) - 1/4 * (high_band_sc(time) +
        ↪ high_band_sc(mod_time(time - 1, length(high_band_sc))));
44     end

```

```

45
46     for time = 1:length(high_band)
47         odd_samples(time) = high_band_sc(time) + 1/2 * (even_samples(time) +
48             ↪ even_samples(mod_time(time + 1, length(even_samples))));
49     end
50     signal_rec = zeros(2*length(low_band), 1);
51     signal_rec(1:2:end) = odd_samples;
52     signal_rec(2:2:end) = even_samples;
53 end

```

A.2.6 Equalization, performance analysis

```

1  clear;
2  close all;
3  clc;
4  im=imread('harbour512x512.tif');
5  imshow(im);
6  im = double(im);
7
8  DWT = FWT2(im, 0, 2); %coefficient
9  DWT_img = mat2gray(DWT);
10 imshow(DWT_img, []); %show scale 4 DWT coefficients
11
12 %% mid-tread quantizer
13 step_size = [2^0, 2^1, 2^2, 2^3, 2^4, 2^5, 2^6, 2^7, 2^8, 2^9];
14
15 % 3-D matrix(2-D coefficients for different step_size)
16 DWT_q = zeros(size(DWT,1), size(DWT,2), length(step_size));
17 for k = 1:length(step_size)
18     DWT_q(:, :, k) = mid_tread(DWT, step_size(k));
19 end
20
21 for k = 1:length(step_size)
22     Appro(:, :, k) = DWT_q(1:256, 1:256, k);
23     Horizontal(:, :, k) = DWT_q(1:256, 257:512, k);
24     Vertical(:, :, k) = DWT_q(257:512, 1:256, k);
25     Diagonal(:, :, k) = DWT_q(257:512, 257:512, k);
26 end
27
28 im_rec = zeros(size(im,1), size(im,2), length(step_size));
29 for i = 1:length(step_size)
30     im_rec(:, :, i) = FWT2_inv(DWT_q(:, :, i), 4);
31 end
32 % test when k = 4
33 figure;
34 im_rec_temp = FWT2_inv(DWT_q(:, :, 4), 4);
35 imshow(uint8(im_rec_temp));
36
37 %% calculate the MSE
38 mse_coef = zeros(1, length(step_size));
39 mse_image = zeros(1, length(step_size));
40
41 for i = 1:length(step_size)
42     mse_coef(i) = MSE(DWT, DWT_q(:, :, i));
43 end
44
45 for i = 1:length(step_size)
46     mse_image(i) = MSE(im, im_rec(:, :, i));
47 end

```

```

48
49 %% bit-rate versus PSNR
50 PSNR_image = zeros(1,length(step_size));
51 for i = 1:length(step_size)
52     PSNR_image(i) = 10.*log10(255^2./mse_image(i));
53 end
54
55 Appro_vect = reshape(Appro, 1,[],10);
56 Horizontal_vect = reshape(Horizontal,1,[],10);
57 vertical_vect = reshape(VERTICAL,1,[],10);
58 Diagonal_vect = reshape(Diagonal,1,[],10);
59
60 num_bins_appro = zeros(1,length(step_size));
61 num_bins_hori = zeros(1,length(step_size));
62 num_bins_vert = zeros(1,length(step_size));
63 num_bins_diag = zeros(1,length(step_size));
64
65 for i = 1:length(step_size)
66     num_bins_appro(i) = ceil((max(Appro_vect(:, :, i))-min(Appro_vect(:, :, i)))
        ↪ ./step_size(i));
67     num_bins_hori(i) = ceil((max(Horizontal_vect(:, :, i))-min(Horizontal_vect
        ↪ (:, :, i)))./step_size(i));
68     num_bins_vert(i) = ceil((max(vertical_vect(:, :, i))-min(vertical_vect
        ↪ (:, :, i)))./step_size(i));
69     num_bins_diag(i) = ceil((max(Diagonal_vect(:, :, i))-min(Diagonal_vect
        ↪ (:, :, i)))./step_size(i));
70 end
71
72
73 % bit rate(ideal code word length of a VLC) entropy
74 entropy = cal_pro(Appro_vect, Horizontal_vect, vertical_vect, Diagonal_vect,
        ↪ step_size);
75 bitrate = entropy;
76 figure;
77 plot(bitrate, PSNR_image, '+', 'LineWidth',2);
78 title('bit rate versus PSNR(dB)');
79 grid on;
80 xlabel('bit rate(per pixel)');
81 ylabel('PSNR(dB)');
82
83
84 function quantized = mid_tread(input_signal, step_size)
85     quantized = input_signal;
86     for i = 1 : size(quantized,1)
87         for j = 1 : size(quantized,2)
88             quantized(i,j) = step_size.*floor(quantized(i,j)./step_size
            ↪ +1/2);
89         end
90     end
91 end
92
93 function value = MSE(input, output)
94     temp = 0;
95     for i = 1:size(input,1)
96         for j = 1:size(input,2)
97             temp = temp + (output(i,j)-input(i,j)).^2;
98         end
99     end
100     value = temp./(size(input,1).*size(input,2));
101 end
102

```

```

103
104 function entropy = cal_pro(Appro_vect, Horizontal_vect, vertical_vect,
    ↪ Diagonal_vect, step_size)
105 num_bins_appro = zeros(1, length(step_size));
106 num_bins_hori = zeros(1, length(step_size));
107 num_bins_vert = zeros(1, length(step_size));
108 num_bins_diag = zeros(1, length(step_size));
109
110 for i = 1:length(step_size)
111     num_bins_appro(i) = ceil((max(Appro_vect(:, :, i)) - min(Appro_vect(:, :, i)))
    ↪ ./ step_size(i));
112     num_bins_hori(i) = ceil((max(Horizontal_vect(:, :, i)) - min(Horizontal_vect
    ↪ (:, :, i))) ./ step_size(i));
113     num_bins_vert(i) = ceil((max(vertical_vect(:, :, i)) - min(vertical_vect
    ↪ (:, :, i))) ./ step_size(i));
114     num_bins_diag(i) = ceil((max(Diagonal_vect(:, :, i)) - min(Diagonal_vect
    ↪ (:, :, i))) ./ step_size(i));
115 end
116
117
118 % calculate the probability
119 pro_appro_1 = histcounts(Appro_vect(:, :, 1), num_bins_appro(1), '
    ↪ Normalization', 'probability');
120 pro_hori_1 = histcounts(Horizontal_vect(:, :, 1), num_bins_hori(1), '
    ↪ Normalization', 'probability');
121 pro_vert_1 = histcounts(vertical_vect(:, :, 1), num_bins_vert(1), '
    ↪ Normalization', 'probability');
122 pro_diag_1 = histcounts(Diagonal_vect(:, :, 1), num_bins_diag(1), '
    ↪ Normalization', 'probability');
123 entropy_appro_1 = -sum(pro_appro_1.*log2(pro_appro_1+eps)); % +eps
    ↪ cus if pro = 0, it will lead to NAN
124 entropy_hori_1 = -sum(pro_hori_1.*log2(pro_hori_1+eps));
125 entropy_vert_1 = -sum(pro_vert_1.*log2(pro_vert_1+eps));
126 entropy_diag_1 = -sum(pro_diag_1.*log2(pro_diag_1+eps));
127 entropy_1 = 1/4*(entropy_appro_1+entropy_hori_1+entropy_vert_1+
    ↪ entropy_diag_1);
128 ... repeat 10 times ...
129 entropy=[entropy_1, entropy_2, entropy_3, entropy_4, entropy_5, entropy_6,
    ↪ entropy_7, entropy_8, entropy_9, entropy_10];

```

References

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