Daljit Singh, Sukhjeet Kaur Ranade / International Journal of Engineering Research and Applications (IJERA) ISSN: 2248-9622 www.ijera.com
Vol. 2, Issue 5, September- October 2012, pp.1736-1741

Comparative Analysis of Transform based Lossy Image Compression Techniques

Daljit Singh*, Sukhjeet Kaur Ranade**
*(Department of Computer Science, Punjabi University, Patiala)
** (Asst.Prof. Department of Computer Science, Punjabi University, Patiala)

ABSTRACT

We undertake a study of the performance difference of the discrete cosine transform (DCT) and the wavelet transform for gray scale images. Wide range of gray scale images were considered under seven different types of images. Image types considered in this work are standard test images, sceneries, faces, misc, textures, aerials and sequences. Performance analysis is carried out after implementing the techniques in Matlab. Reconstructed Image Quality values for every image type would be calculated over particular bit rate and would be displayed in the end to detect the quality and compression in the resulting image and resulting performance parameter would be indicated in terms of PSNR , i.e. Peak Signal to Noise Ratio. Testing is performed on seven types of images by evaluating average PSNR values. Our studies reveal that, for gray scale images, the wavelet transform outperforms the DCT at a very low bit rates and typically gave a average around 10% PSNR performance improvement over the DCT due to its better energy compaction properties. Where as DCT gave a average around 8% PSNR performance improvement over the Wavelets at high bit rates near about 1bpp and above it. So Wavelets provides good results than DCT when more compression is required.

Keywords - JPEG standard, Design metrics, JPEG 2000 with EZW, EZW coding, Comparison between DCT and Wavelets.

1. INTRODUCTION

Data compression is the technique to reduce the redundancies in data representation in order to decrease data storage requirements and hence communication costs. Reducing the storage requirement is equivalent to increasing the capacity of the storage medium and hence communication bandwidth. Thus the development of efficient compression techniques will continue to be a design challenge for future communication systems and advanced multimedia applications. Data is represented as a combination of information and redundancy. Information is the portion of data that must be preserved permanently in its original form in order to correctly interpret the meaning or purpose of the data. Redundancy is that portion of data that can be removed when it is not needed or can be reinserted to interpret the data when needed. Most often, the redundancy is reinserted in order to generate the original data in its original form. A technique to reduce the redundancy of data is defined as Data compression [1]. The redundancy in data representation is reduced such a way that it can be subsequently reinserted to recover the original data, which is called decompression of the data.

Data compression can be understood as a method that takes an input data D and generates a shorter representation of the data c(D) with less number of bits compared to that of D. The reverse process is called decompression, which takes the compressed data c(D) and generates or reconstructs the data D' as shown in Figure 1. Sometimes the compression (coding) and decompression (decoding) systems together are called a "CODEC"

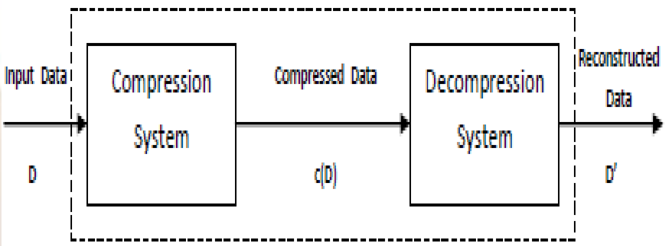


Fig.1 Block Diagram of CODEC

The reconstructed data D' could be identical to the original data D or it could be an approximation of the original data D, depending on the reconstruction requirements. If the reconstructed data D' is an exact replica of the original data D, the algorithm applied to compress D and decompress c(D) is lossless. On the other hand, the algorithms are lossy when D' is not an exact replica of D. Hence as far as the reversibility of the original data is concerned, the data compression algorithms can be broadly classified in two categories – lossless and lossy [2].

Transform coding has become the de facto standard paradigm in image (e.g., JPEG [3], [4]) where the discrete cosine transform (DCT) is used because of its nice decorrelation and energy compaction properties [5]. In recent years, much of the research activities in image coding have been focused on the discrete wavelet transform. While the good results obtained by wavelet coders (e.g., the embedded zerotree wavelet (EZW) coder) are partly attributable to the wavelet transform.

In this paper, we will study the Transform based lossy image compression techniques and basic concepts to keep in mind for the transform based image coding.

The rest of the paper is organized as follows. In section 2 we discuss the design metrics. Then we discuss JPEG Standard Image Compression in section 3. Then in section 4, we describe JPEG 2000 with EZW coding in detail. The comparison between DCT and Wavelets is explained in section 5. Finally conclusions are made in section 6.

2. DESIGN METRICS

Digital image compression techniques are examined with various metrics. Among those the most important one is Peak Signal to Noise Ratio (PSNR) which will express the quality. There exists another property which expresses the quality, that is, Mean Square Error (MSE). PSNR is inversely proportional to MSE. The other important metric is Compression Ratio, which express the amount of compression embedded in the technique. The given below are equations for PSNR and MSE:

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

$$(\text{MSE}) = \frac{1}{N}\sum_{j,k}(f[j,k]-g[j,k])^2$$

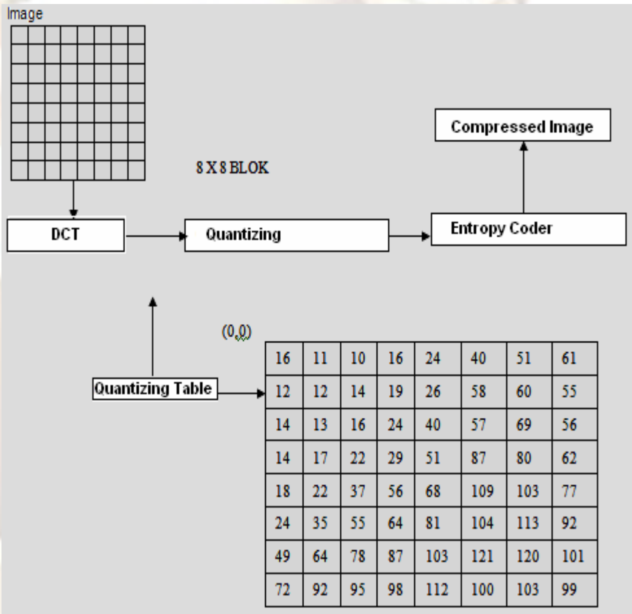
The higher the compression ratio reduces the image quality. The given below is the formula to find the compression ratio:

Comp ratio = Original_size/compressed_size

3. JPEG STANDARD

All the compression algorithms depend on the human eye filtering. Human eye can not perceive from a proper level. Therefore, the gray level values in the original image can be moved to the frequency base. Some kind of coefficients will appear in the transformation that we use in the frequency base. It's possible to obtain the original image by using these coefficients again. However, it's unnecessary to benefit from infinite frequency component. High frequency coefficients can be abandoned by taking the risk of some losses. The number of the frequency abandoned shows the quality of the image obtained later. In the applications done, despite very little quality losses, it's possible to make the image smaller in 1:100 ratio. JPEG used commonly in the compression algorithms works as shown in figure 2.

As summarized in the figure 2, JPEG Compression separates the image into the parts containing 8x8 gray values. Discrete cosine transformation is applied on each part to pass the frequency base on each. The reason why this transformation is chosen is coefficients are not complex but real numbers. The numbers obtained are quantized by utilizing a table due to the ratio of the quality. QUANTIZER table determines how many of the high frequency numbers will be abandoned. Some of the 64 pairs of the frequency coefficient obtained by discrete cosine transformation after QUANTIZING process will get the zero value. The fact that these coefficients are compressed by Huffman coding provides more place seriously. When the image is intended to be obtained again, the reverse of this process will be applied again. At first, Huffman code is encoded and the block including 64 coefficients with the zeros are obtained. This block is multiplied by quantizing table. Most of the coefficients will get the value closer to its initial value but the ones multiplied by zero will be zero again. This process determines the losses that exist after discrete cosine process. So if we pay more attention, the losses occur in the quantizing process.



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

Fig.2 JPEG compression

Quantization is the main factor of compression. JPEG process uses varying levels of image compression and quality are obtainable through selection of specific quantization matrices [6]. This enables the user to decide on quality levels ranging from 1 to 100, where 1 gives the poorest quality and highest compression, while 100 gives the best quality and lowest compression.

For a quality level greater than 50 (less compression, Higher image quality), the standard quantization matrix is multiplied by (100-qualitylevel)/50. For a quality level less than 50 (more compression, lower image quality), the standard quantization matrix is multiplied by 50/quality level.

The given below is the original image and reconstructed images after applying 2D – DCT at varying levels of quantization matrices Q_1, Q_{10}, Q_{30} and Q_{50} with PSNR values. The test is performed on standard image cameraman to explain this concept. The Q_1 level gives more compression but lower quality but the Q_{50} level gives less compression but higher quality.


Original image


Q=1, PSNR=16.89


Q=10, PSNR=27.81


Q=30, PSNR=31.91


Q=50, PSNR=33.87

The table 1 given below shows the average compression ratio and average PSNR of 7 different types of images, each type having a different number of images. The Q_1 level have higher compression but poor image quality i.e. lower PSNR value and Q_{50} level have the lower compression but higher PSNR value.

Table1. DCT Results

Img Type	No. of imgs	Q=10		Q=30		Q=50	
		Av. PSNR (db)	Av. Comp	Av. PSNR (db)	Av. Comp	Av. PSNR	Av. Comp
Standard imgs	7	29.49	17.23	33.65	9.51	35.46	7.21
Sceneries	20	26.70	15.18	29.85	7.62	31.97	5.84
Faces	21	29.25	19.48	31.92	10.24	33.02	7.16
Sequences	23	26.38	11.65	29.83	5.75	31.32	4.49
Textures	20	22.09	7.95	25.69	4.14	27.72	3.38
Misc	15	28.75	16.43	32.85	9.65	34.64	7.95
Aerials	20	27.71	16.56	30.96	7.89	32.45	5.91

4. JPEG 2000 WITH EZW CODING

The JPEG committee has released its new image coding standard, JPEG 2000, which will serve as a supplement for the original JPEG standard introduced in 1992. Rather than incrementally improving on the original standard, JPEG 2000 implements an entirely new way of compressing images based on the wavelet transform, in contrast to the discrete cosine transform (DCT) used in the original JPEG standard.

The state of wavelet-based coding has improved significantly since the introduction of the original JPEG standard. A notable breakthrough was the introduction of embedded zero-tree wavelet (EZW) coding by Shapiro [7]. The EZW algorithm was able to exploit the multi resolutional properties of the wavelet transform to give a computationally simple algorithm with outstanding performance. Improvements and enhancements to the EZW algorithm have resulted in modern wavelet coders which have improved performance relative to block transform coders. As a result, wavelet-based coding has been adopted as the underlying method to implement the JPEG 2000 standard [8].

4.1 EZW Coding Algorithm

The EZW coding algorithm can now be summarized as follows.

1) Initialization: Place all wavelet coefficients on the dominant list. Set the initial threshold to $T_0=2^{floor(\log_2 x_{max})}$.

2) Dominant Pass: Scan the coefficients in mortan scan order using the current threshold Ti . Assign each coefficient one of four symbols:
   - positive significant (ps): meaning that the coefficient is significant relative to the current threshold Ti and positive.
   - negative significant (ns): meaning that the coefficient is significant relative to the current threshold Ti and negative.
   - isolated zero (iz): meaning the coefficient is insignificant relative to the threshold Ti and one or more of its descendants are significant.
   - zero-tree root (ztr): meaning the current coefficient and all of its descendant are insignificant relative to the current threshold Ti.
.

Any coefficient that is the descendant of a coefficient that has already been coded as a zero-tree root is not coded, since the decoder can deduce that it has a zero value. Coefficients found to be significant are moved to the subordinate list and their values in the original wavelet map are set to zero. The resulting symbol sequence is entropy coded.

3) Subordinate Pass: Output a 1 or a 0 for all coefficients on the subordinate list depending on whether the coefficient is in the upper or lower half of the quantization interval.
4) Loop: Reduce the current threshold by two, $T_i = T_i/2$. Repeat the Steps 2) through 4) until the target fidelity or bit rate is achieved.

The pseudocode for the embedded zerotree coding is shown in the table 2 given below:

Table2. EZW pseudocode

```
Initialization
   T0=2^floor(log2(max(coefficients)))
   k=0
   Dominant List=All coefficients
   Subordinate List=[]

Significant Map
   for each coefficients in the Dominant List
       if |x| ≥ Tk
           if x> 0
             set symbol POS
     else
            set symbol NEG
       else if x is non-root part of a zerotree
            set symbol ZTD(ZeroTree Descendant)
       if x is zerotree root
            set symbol ZTR
       otherwise
            set symbol IZ

Dominant Pass
  if symbol(x) is POS or NEG(it is significant)
         put symbol(x) on the Subordinate List
         Remove x from the Dominant List

Subordinate Pass
  for each entry symbol(x) in Subordinate List
         if value(x) ϵ Bottom Half of [Tk , 2Tk]
                   output "0"
         else
                   output "1"

Update
   Tk+1 = Tk/2
    K = K+1

Go to Significance Map
```

The compression ratio and quality of the image depends on the quantization level, entropy coding and also on the wavelet filters used[9]. In this section, different types of wavelets are considered for image compression. Here the major concentration is to verify the comparison between Hand designed wavelets. Hand designed wavelets considered in this work are Haar wavelet, Daubechie wavelet, Biorthognal wavelet, Demeyer wavelet, Coiflet wavelet and Symlet wavelet. Except Coiflet and Symlet wavelet, all the Hand designed wavelets produced less PSNR around 28dB and compression ratio around 1bpp. Coiflet and Symlet wavelet produced high PSNR around 29 dB, at same compression ratio. The Cameraman images experimental results are shown in figure3 to 8. A

Number of test images are considered and the results on cameraman image are presented in the table 3.

Fig3: Original image

Fig4: Haar wavelets

Fig5: Daubechie

Fig6: Coiflets

Fig7: Symlet

Fig8: Dymer

Table3. Comparison between Filters

Filters	Haar	Daubechie	Biorthognal	Dymer	Coiflet	Symlet
Org size	524288	524288	524288	524288	524288	524288
Comp size	91368	121872	87360	93288	90832	91656
Comp ratio	5.7738	4.3020	6.0015	5.6201	5.7721	5.7382
PSNR	25.11	27.89	27.55	27.59	28.82	28.93

5. COMPARISON BETWEEN DCT AND WAVELETS

Wavelet based techniques for image compression have been increasingly used for image compression. The wavelet transform achieves better energy compaction than the DCT [10] and hence can help in providing better compression for the same Peak Signal to Noise Ratio (PSNR).A comparative study of DCT and wavelet based image coding can be found in [11]. This section describes the comparison between DCT and Wavelets. Testing is performed on seven types of images at a bit rate of 0.25 bpp and 1.00 bpp. The results are shown in the tables 4 and 5 :

Table4. Comparison between DCT and Wavelets at a Bit rate of 0.25 bpp

Image Types	No. of imgs	DCT	Wavelets
		Av. PSNR (db)	Av. PSNR (db)
Stand imgs	7	25.46	28.01
Sceneries	20	23.76	25.16
Faces	21	28.62	29.82
Sequences	23	23.08	25.01
Textures	20	17.15	18.62
Misc	15	21.07	27.36
Aerials	20	24.39	25.01

Table5. Comparison between DCT and Wavelets at Bit rate of 1.00 bpp

Image types	No. of imgs	DCT	Wavelets
		Av. PSNR (db)	Av. PSNR (db)
Stand imgs	7	33.87	31.12
Sceneries	20	29.59	26.20
Faces	21	32.52	30.34
Sequences	23	28.14	27.13
Textures	20	21.39	20.05
Misc	15	33.06	30.17
Aerials	20	30.07	28.59

6. CONCLUSION

In this paper, we studied the two common schemes used in JPEG. We considered the modular design of the scheme and considered various possible cases. The non-block schemes gave better performance but they were less computationally efficient. The performance of algorithm with two common transforms used was considered. It was observed that the wavelet transform gave a average around 10% PSNR performance improvement over the DCT due to its better energy compaction properties at very low bit rates near about 0.25 bpp. While DCT transform gave a average around 8% PSNR performance over wavelets at high bit rates of 1 bpp. So Wavelets provides good results than DCT when more compression is required. The methods of encoding such as Embedded Zero tree and our implementation of JPEG 2000 were considered. A comparative study based on transform filters, computational complexity and rate-distortion tradeoff is also presented. Some terms related to Transform based lossy image compression are explained in very simple language to help the beginners to have clear understanding of the topic.

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