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Comparison of Jpeg Compression Technique with Shape Adaptive DCT Technique (SA-DCT)

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Abstract: Image compression is the application of Data compression on digital images. The discrete cosine transform (DCT) is a technique for converting a signal into elementary frequency components. It is widely used in image compression. A formal compression standard "Joint Photographic Experts Group" JPEG, has been discussed and its SNR graph is compared with another compression technique using shape adaptive DCT (SA-DCT) transformation. In JPEG technique the original image is transformed into 8*8 blocks and then inverse transformed in 8*8 blocks to create the reconstructed image. One coding method that has been attracting much attention recently is the shape-adaptive DCT (SA-DCT), which was first proposed by Sikora et al in 1995 [5]. It is based on predefined orthogonal sets of DCT basis functions that operate on arbitrarily shaped image segments [1]. The number of DCT coefficients generated is identical to the number of pixels contained in the boundary segment. The SA-DCT algorithm shifts image pixels toward the block boundary and each column is then transformed vertically using DCT basis functions. The same procedures are later repeated in the horizontal direction. At the decoder side, the processes are reversed to recover the image. The simulation results shows that the SNR of a compressed image using SA-DCT coding techniques has a larger value as compared to a JPEG compressed image.

Keywords: DCT, JPEG, SA-DCT

I. INTRODUCTION

Data compression is the technique to reduce the redundancies in data representation in order to decrease data storage requirements and hence communication costs [3]. 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 re-inserted to interpret the data when needed. Most often, the redundancy is re-inserted in order to generate the original data in its original form. A technique to reduce the redundancy of data is defined as Data compression. The redundancy in data representation is reduced in such a way that it can be subsequently re-inserted to recover the original data, which is called as 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 as "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. Usually lossless data compression techniques are applied on text data or scientific data. Sometimes data compression is referred as coding, and the terms noiseless or noisy coding, are usually referred to as lossless and lossy compression techniques respectively. The term “noise" here is the “error of reconstruction" in the lossy compression techniques because the reconstructed data item is not identical to the original one.

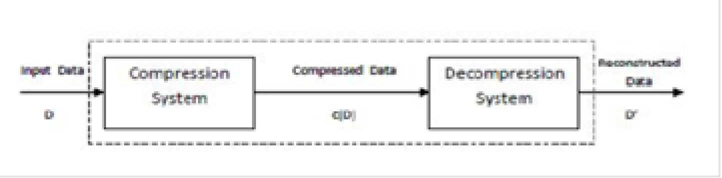

Figure 1: Block Diagram of CODEC

II. Discrete Cosine Transform (DCT)

The discrete cosine transform (DCT) helps separate images into parts [2] (or spectral sub-bands) of differing importance (with respect to the image's visual quality). The DCT is similar to the discrete fourier transform: it transforms a signal or image from the spatial domain to the frequency domain. A discrete cosine transform (DCT) expresses a sequence of finitely many data points in terms of a sum of cosine functions oscillating at different frequencies. DCT’s are important to numerous applications in science and engineering.

The 2-D discrete cosine transform (DCT) is an invertible linear transform and is widely used in many practical image compression systems because of its compression performance and computational efficiency [4]. DCT converts data (image pixels) into sets of frequencies. The first frequencies in the set are the most meaningful; the latter, the least. The least meaningful frequencies can be stripped away based on allowable resolution loss. DCT-based image compression relies on two techniques to reduce data required to represent the image. The first is quantization of the image's DCT coefficients; the second is entropy coding of the quantized coefficients. Quantization is the process of reducing the number of possible values of a quantity, thereby reducing the number of bits needed to represent it. Quantization is a lossy process and implies in a reduction of the color information associated with each pixel in the image. Entropy coding is a technique for representing the quantized coefficients as compactly as possible.

The DCT can well approximate the Karhunen-Loeve transform (KLT) and has high ability for decorrelation. After performing the DCT, most energy is concentrated in the low frequency region, which is very beneficial for compression. Although JPEG is widely used in image compression, it has a problem. Many objects have irregular shapes and cannot be well approximated by the combination of rectangular blocks. Therefore, after dividing an image into 8*8 blocks, many blocks contain the edges of some objects. The edge region has a lot of high frequency components, which are not good for compression. Therefore, it is more rea-sonable to divide an image according to the shape of objects. Based on this concept, some shape adaptive image compression algorithms were proposed. For example, in the MPEG-4 standard, an image is divided according to the shape of the objects and the shape-adaptive discrete cosine transform (SA-DCT) is used for transforming and encoding each block.

III. Joint Photographic Experts Group (JPEG)

In 1992, the Joint Photographic Experts Group (JPEG) established the first international standard for still image compression where the encoders and decoders are Discrete Cosine Transform (DCT) based. JPEG is primarily a lossy method of compression. JPEG was designed specifically to discard information that the human eye cannot easily see. Slight changes in color are not perceived well by the human eye, while slight changes in intensity (light and dark) are. Therefore JPEG's lossy encoding tends to be more frugal with the gray-scale part of an image and to be more frivolous with the color. DCT separates images into parts of different frequencies where less important frequencies are discarded through quantization and important frequencies are used to retrieve the image during decompression.

The DCT is used in JPEG image compression. There, the two-dimensional DCT of N*N blocks are computed and the results are quantized and entropy coded. In this case, N is typically 8 and the two-dimensional DCT formula is applied to each row and column of the block. The result is an 8*8 transform coefficient array in which the (0,0) element (top-left) is the DC (zero frequency) component and entries with increasing vertical and horizontal index values represents higher vertical and horizontal spatial frequencies. The DCT based encoder works by segmenting the image into 8*8 blocks. Each block makes its way through each processing step, and yields output in compressed form into the data stream. As image pixels are highly correlated, the DCT achieves data compression by concentrating most of the signal in the lower spatial frequencies. For a typical 8*8 sample block from a typical source image, most of the spatial frequencies have zero or near-zero amplitude and need not be encoded. In principle, the DCT introduces no loss to the source image samples; it transforms them to a domain in which they can be more efficiently encoded.

IV. Conclusion Shape Adaptive DCT (SA-DCT)

Discrete cosine transform (DCT) has been extensively used in image compression because of its efficiency: ease of implementation and superior energy compaction property. It has been adopted in several block-based coding standards such as JPEG and MPEG-1/2. However, regular block-based DCT transform cannot be performed on non-rectangular objects that are normally boundary blocks of the foreground or background objects segmented from an original image. Modern applications require new coding techniques that can handle both rectangular and arbitrarily shaped objects. This object-based coding is also an important image coding scheme for content-based manipulation, scalability and interactivity, which are the major requirements in MPEG-4 standardization. Many techniques for coding arbitrarily shaped image segments have been proposed. One of the earliest approaches is to calculate the DCT basis functions for all the different segment shapes using a generalized orthogonal transformation. Another method is to use zero padding and modify the boundary blocks so that they can be transformed by conventional two-dimensional DCT. Other examples uses a variable block-partitioning scheme to reduce the number of coding blocks of the segmented image and a mixture of boundary block merging (BBM) and padding techniques to minimize the number of boundary blocks to be coded.

One coding method that has been attracting much attention is the shape-adaptive DCT (SA-DCT). It is based on predefined orthogonal sets of DCT basis functions that operate on arbitrarily shaped image segments. The number of DCT coefficients generated is identical to the number of pixels contained in the boundary segment. Figure 2 illustrates the concept of the modified SA-DCT working in boundary blocks of an arbitrarily shaped image object. The segmented foreground image is partitioned into M*N blocks, which are later classified as foreground, background and boundary blocks. The foreground blocks will be processed by conventional 2-D DCT.

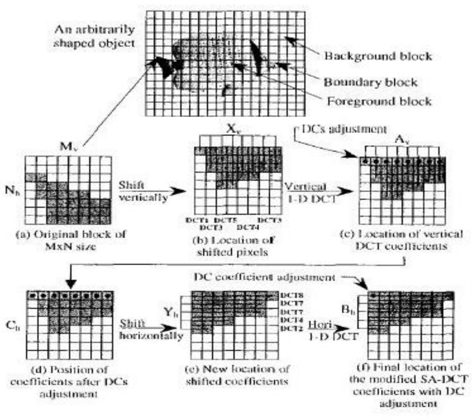

Figure 2: Coding of Arbitarily shaped image using modified SA-DCT

V. EXPERIMENTAL RESULTS

The performance of the JPEG and the SA-DCT for image compression is compared.

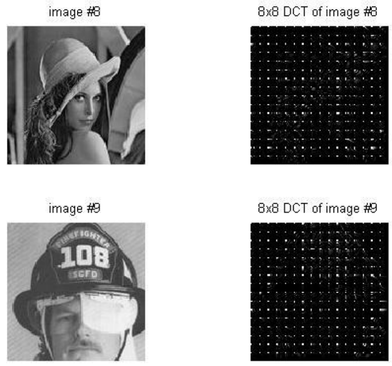

*Figure 3: A 8*8 DCT of image*

The 8*8 DCT of the two tested image is shown in figure 3. Then first image i.e, Lena image is taken for compression, and then it is reconstructed back as shown in figure 4.

Figure 4: Reconstructed image using JPEG

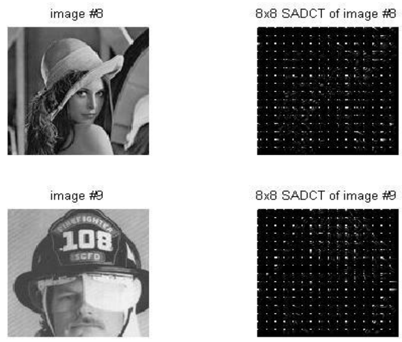

*Figure 5: A 8*8 SA-DCT of image*

The 8*8 SA-DCT of the two tested images is shown in figure 5. Then the first image i.e, Lena image is taken for compression, and then it is reconstructed back as shown in figure 6 using SA-DCT.

Figure 6: Reconstructed image using SA-DCT

If the two reconstructed images of JPEG and SA-DCT is compared, it is evident that JPEG suffers from ringing artifacts. These are the artifacts that appear as spurious signals near sharp transitions in a signal. Visually, they appear as bands or ghosts near edges; audibly, they appear as echos near transients, particularly sounds from percussion instruments; most noticeable are the pre-echoes.

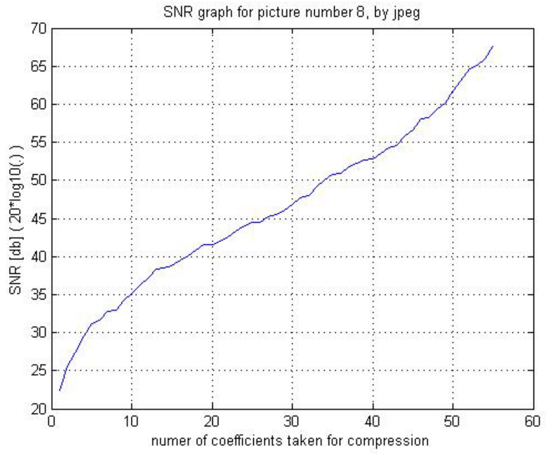

Figure 7: SNR graph using JPEG

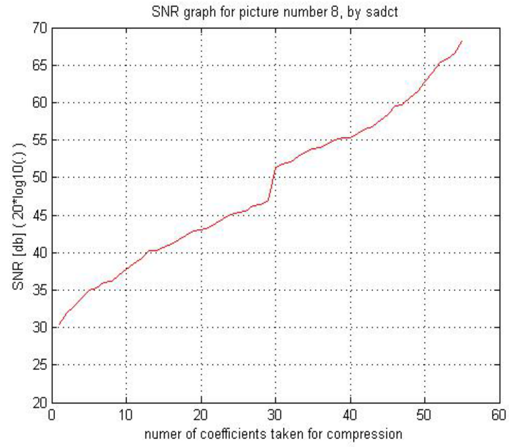

Figure 8: SNR graph using SA-DCT

The SNR graphs for the compressed lena image using JPEG and SA-DCT against the number of coefficients used for compression is plotted graphically. It can be easily seen from the graph that for the same image, SA-DCT has higher SNR value as compared to JPEG.

VI. CONCLUSION

JPEG suffers from block-shaped artifacts at higher compression ratio. In DCT, images are broken into blocks of 8*8 or 16*16 or bigger. The problem with these blocks is that when the image is reduced to higher compression ratio, these blocks become visible. This has been termed as the Blocking Artifacts. In Shape Adaptive DCT (SA-DCT) techniques besides image compression, this method is also effective in dealing with those artifacts which are often encountered in block-DCT compressed images and videos. Blocking artifacts are suppressed while salient image features are preserved. Here in order to construct the graph the first image i.e lena's image is taken as the test image. It is clear from the constructed SNR graphs that an image compression using SA-DCT technique has a greater SNR value as compared to the JPEG compression of the same image. The SNR graphs for various images were plotted and it was found that SA-DCT techniques outperforms JPEG in terms of SNR.

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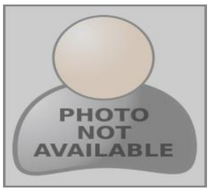

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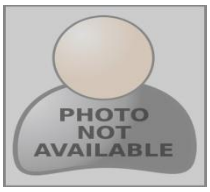

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