

Image Compression Using the Discrete Wavelet Transform and Implementation

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Abstract—The discrete wavelet transform (DWT) is a technique for converting a signal into elementary frequency components. It is widely used in image compression. Here some functions for compression of both gray scale and color images with DWT and its implementation in MATLAB have been developed.

Keywords— Image compression; DWT; quantization; SPIHT; entropy coding; DCT.

I. INTRODUCTION

A digital image obtained by sampling and quantizing a continuous tone picture requires an enormous storage. For instance, a 24 bit color image with 512x512 pixels will occupy 768 Kbyte storage on a disk, and a picture twice of this size will not fit in a single floppy disk. To transmit such an image over a 28.8 Kbps modem would take almost 4 minutes. The purpose for image compression is to reduce the amount of data required for representing sampled digital images and therefore reduce the cost for storage and transmission. Image compression plays a key role in many important applications, including image database, image communications, remote sensing (the use of satellite imagery for weather and other earth-resource applications), document and medical imaging, facsimile transmission (FAX), and the control of remotely piloted vehicles in military, space, and hazardous waste control applications. In short, an ever-expanding number of applications depend on the efficient manipulation, storage, and transmission of binary, gray-scale, or color images.

An important development in image compression is the establishment of the JPEG 2000 standard for compression of color pictures. Using the JPEG2000 method, a 24 bit/pixel color images can be reduced to between 1 to 2 bits/pixel, without obvious visual artifacts. Such reduction makes it possible to store and transmit digital imagery with reasonable cost. It also makes it possible to download a color photograph almost in an instant, making electronic publishing/advertising on the Web a reality. The DWT is an improvement over the discrete Fourier transform (DFT). Here we have computed some codes in MATLAB for compression of images using DWT. The results have been observed in the laboratory for both the compression of gray scale and color images.

II. DISCRETE WAVELET TRANSFORM

A wavelet is defined as a “small wave” that has its energy concentrated in time to provide a tool for the analysis of transient, non-stationary, or time-varying phenomena. It has the oscillating wave-like properties but also has the ability to allow simultaneous time and frequency analysis. Wavelet Transform has emerged as a powerful mathematical tool in

many areas of science and engineering, more so in the field of audio and data compression. The DWT is very similar to a Fourier series, but in many ways, is much more flexible and informative. It is a tool which breaks up data into different frequency components or sub bands and then studies each component with a resolution that is matched to its scale. Unlike the Fourier series, it can be used on non-stationary transient signals with excellent results. The Fourier Transform is given by:

It involves the breaking up of a signal into sine waves of various frequencies. The advantages of Wavelets over Fourier methods in analyzing physical situations stem from the fact that sinusoids do not have a limited duration but instead extend from minus to plus infinity.

In Fourier transform domain, we completely lose information about the localization of the features of an audio signal. Quantization error on one coefficient can affect the quality of the entire audio file. The wavelet expansion allows a more accurate local description and separation of signal characteristics. A wavelet expansion coefficient represents a component that is itself local and is easier to interpret. The Fourier basis functions have infinite support in that a single point in the Fourier domain contains information from everywhere in the signal. Wavelets, on the other hand, have compact or finite support and this enables different parts of a signal to be represented at different resolution.

Wavelets are adjustable and adaptable and can therefore be designed for adaptive systems that adjust themselves to suit the signal. Fourier Transform, however, is suitable only if the signal consists of a few stationary components. Also, the amplitude spectrum does not provide any idea how the frequency evolve with time.

All wavelets tend to zero at infinity, which is already better than the Fourier series function. Furthermore, wavelets can be made to tend to zero as fast as possible. It is this property that makes wavelets so effective in signal and audio compression.

III. PASSWORD IMAGE

We have tried to make our GUI efficient by application of password before compression. The main emphasis is given to fact that image compression does not start till the password is entered.

IV. THE WAVELET CODING AND SPIHT

Discrete Wavelet Transform (DWT) provides a Multiresolution image representation and has become one of the most important tools in image analysis and coding over the last two decades. Image compression algorithms based on DWT provide high coding efficiency for natural (smooth) images. As dyadic DWT does not adapt to the various space-frequency properties of images, the energy compaction it achieves is generally not optimal. However, the performance can be improved by selecting the transform basis adaptively to the image. Wavelet Packets (WP) represent a generalization of wavelet decomposition scheme. WP image decomposition adaptively selects a transform basis that will be best suited to the particular image. To achieve that, the criterion for best basis selection is needed. Coifman and wickerhauser proposed entropy based algorithm for best basis selection [1]. In their work, the best basis is a basis that describes the particular image with the smallest number of basis functions. It is a one-sided metric, which is therefore not optimal in a joint rate-distortion sense. A more practical metric considers the number of bits (rate) needed to approximate an image with a given error (distortion) [2] but this approach and its variation presented in [1] can be computationally too intensive. In [3] a fast numerical implementation of the best wavelet packet algorithm is provided. Coding results show that fast wavelet packet coder can significantly outperform a sophisticated wavelet coder constrained to using only a dyadic decomposition, with a negligible increase in computational load. The goal of this paper is to demonstrate advantages and disadvantages of using WP decomposition in SPIHT-based codec. SPIHT algorithm was introduced by Said and Pearlman [4], and is improved and extended version of Embedded Zerotree Wavelet (EZW) coding algorithm introduced by Shapiro [5].

Both algorithms work with tree structure, called Spatial Orientation Tree (SOT) that defines the spatial relationships among wavelet coefficients in different decomposition sub bands. In this way, an efficient prediction of significance of coefficients based on significance of their “parent” coefficients is enabled. The main contribution of Shapiro’s work is zerotree quantization of wavelet coefficients and introduction of special zerotree symbol indicating that all coefficients in a SOT are found to be insignificant with respect to a particular quantization threshold. An embedded zerotree quantizer refines each input coefficient sequentially using a bit plane coding scheme, and it stops when the size of the encoded bit stream reaches the target bit-rate. SPIHT coder provides gain in PSNR over EZW due to introduction of a special symbol that indicates significance of child nodes of a significant parent and separation of child nodes (direct descendants) from second-generation descendants. To date, there have been numerous variants and extensions to SPIHT algorithm. For example: 3-D SPIHT for video coding [1], SPIHT for color image coding, and scalable SPIHT for network applications. Since the SPIHT algorithm relies on Spatial Orientation Trees (SOT) defined on dyadic sub band structure, there are a few problems that arise from their

adaptation to WP decomposition. First is the so-called parental conflict, that happens when in the wavelet packet tree one or more of the child nodes are at the coarser scale than the parent node. It must be resolved in order that SOT structure with well-defined parent-child relationships for arbitrary wavelet decomposition can be created. Xiong et al. [6] avoided the parental conflict by restricting the choice of the basis. In their work the Space-Frequency Quantization (SFQ) algorithm is used. SFQ algorithm employs a rate-distortion (R-D) optimization framework for selecting the best basis and to assign an optimal quantiser to each of the wavelet packet sub bands. Rajpoot et al. Defined a set of rules to construct the zerotree structure for a given wavelet packet geometry and offered a general structure for an arbitrary WP decomposition. In their work a Compatible Zerotree Quantisation (CZQ) is utilized, and it does not impose restriction on the selection of WP basis. A comparison of PSNR obtained with CZQ-WP and SPIHT shows that SPIHT provides gain in PSNR over CZQ-WP for the standard test images, while CZQWP offers better visual quality than SPIHT. This observation motivated us to use SPIHT with WP in order to exploit strengths of both methods. This extension of SPIHT we call Wavelet Packet SPIHT (WP-SPIHT).

The suitability of wavelet transforms (WT) for use in image analysis is well established: a representation in terms of the frequency content of local regions over a range of scales provides an ideal framework for the analysis of image features, which in general are of different size and can often be characterized by their frequency domain properties. In numerical analysis and functional analysis, a discrete wavelet transform (DWT) is any wavelet transform for which the wavelets are discretely sampled. As with other wavelet transforms, a key advantage it has over Fourier transforms is temporal resolution: it captures both frequency and location information. Digitized versions of rolled ink fingerprint images were used at 480 x 480 resolutions, 8 bits per pixel. These are losslessly transformed using a DWT. To do this, we make use of SPHIT algorithm in which the image is decomposed into four sub bands by cascading horizontal and vertical two-channel critically-sampled filter banks. To obtain the next scale of wavelet components, the lowest frequency sub band is further decomposed and critically sampled. The process continues until some chosen final scale is reached.

A basis that spans a space does not have to be orthogonal. In order to gain greater flexibility in the construction of wavelet bases, we resort to relaxing the orthogonality condition and allowing non-orthogonal wavelet bases. For Example, it is well-known that the Haar wavelet is the only known wavelet that is compactly supported, orthogonal, and symmetric. In many applications, the symmetry of the filter coefficients is often desirable since it results in linear phase of the transfer function. So in order to construct more families of compactly supported, symmetric wavelets, in this section we forego the requirement of orthogonality, and, in particular, we introduce the so-called biorthogonal wavelets.

V. NUMERICAL RESULTS

Input Image =256 kb



Fig. 1. Test image leena.tif.

PSNR=5.65(dB), C.R=31.25%

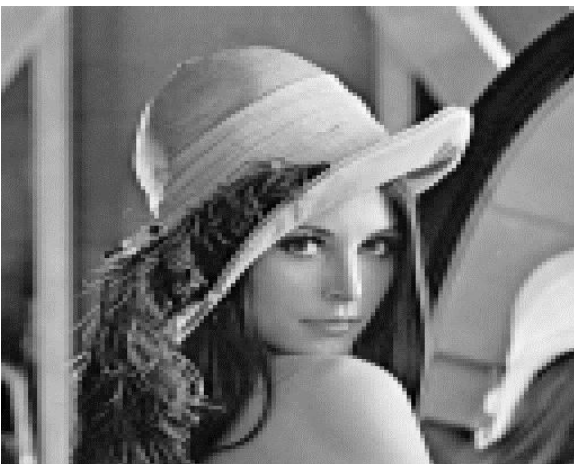


Fig. 2. Compressed image.

Input Image = 257kb

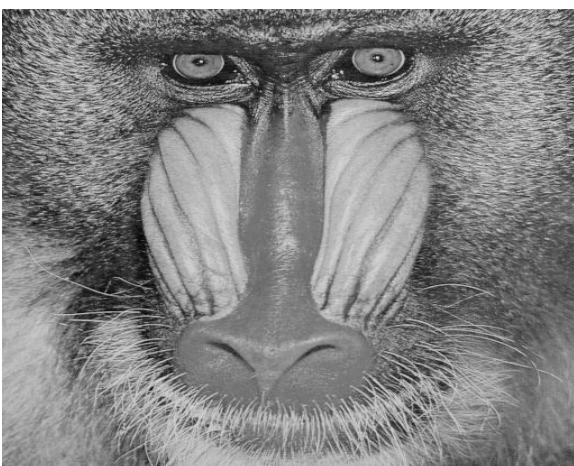


Fig. 3. Test image baboon.

PSNR=5.51(dB), C.R=29.05



Fig. 4. Compressed image.

Input Image Size=260kb for Image Lena with Noise



Fig. 5. Compressed image of lena with noise.

PSNR=5.45, C.R=30.15

VI. RESULT

Following are the filter outputs for the input image and the compressed image on which we have worked

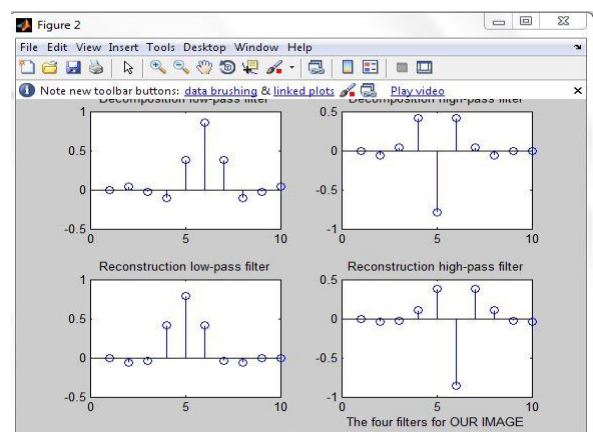


Fig. 6. Filter values.
PSNR=5.65dB

BPP = 31.25%

| Image Name | Compression Ratio | PSNR (dB) |
|------------------|-------------------|-----------|
| Leena | 31.25 | 5.65 |
| Barbara | 36.39 | 6.64 |
| Baboon | 29.05 | 5.51 |
| Goldhill | 36.45 | 6.74 |
| Leena with noise | 30.12 | 5.45 |

VII. CONCLUSION

Image compression aims at reducing the number of bits needed to represent an image by removing the spatial and spectral redundancies. For still image compression, the 'Joint Photographic Experts Group' or JPEG2000 is used which gives a good performance. It uses discrete wavelet transform. The DWT-based image coders perform very well at moderate bit rates. As the compression ratio increases the image quality degrades because of the artifacts resulting from the block based scheme. JPEG2000 is designed for compressing full-color or gray-scale images of natural, real-world scenes. It works well on photographs, naturalistic artwork, and similar material; not so well on lettering, simple cartoons, or line drawings. JPEG2000 handles only still images, but there is a related standard called MPEG for motion pictures.

JPEG2000 is designed to exploit known limitations of the human eye, notably the fact that small color changes are perceived less accurately than small changes in brightness.

Thus, JPEG2000 is intended for compressing images that will be looked at by humans. If you plan to machine-analyze your images, the small errors introduced by JPEG2000 may be a problem for you, even if they are invisible to the eye. Another important aspect of JPEG2000 is that decoders can trade off decoding speed against image quality, by using fast but inaccurate approximations to the required calculations. Some viewers obtain remarkable speedups in this way. Encoders can also trade accuracy for speed, but there's usually less reason to make such a sacrifice when writing a file.

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