

Wavelet based JPEG like Image Coding Scheme

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Abstract: As the Joint Photographic Experts Group (JPEG) has become an international standard for image compression; we present techniques that allow the processing of an image in the “JPEG-compressed” domain. The goal is to reduce memory requirements while increasing speed by avoiding decompression and space domain operations. In each case, an effort is made to implement the minimum number of JPEG basic operations. In this paper we are reviewing the Wavelet Transform Technique for coding the images. We use the Wavelet Transform instead of Discrete Cosine Transform (DCT) and the compressed data is analysed for the size of file on disk. While most of the results apply to any image, we focus on scanned images as our primary source.

Keywords: JPEG, DPCM, RLE, CWT

1. INTRODUCTION

1.1 IMAGE REPRESENTATION

A digital image is a two dimensional signal. It simply specifies a color value for every pixel within its space. Images signals require large amounts of storage space. Images storage requirements are a function of dimensions and color depth.

The human eye is generally said to be able to distinguish between a maximum of 2^{24} colors. This level of color depth is known as *true color* since any color visible in the real

More common is 8-bit color, which offers 256 different colors. Grayscale images are also 8-bit, with 256 shades of gray. 8-bit images are often stored with color values from 0 to 255. The mapping of these values to their RGB counterparts is stored in a color map. It is this 8-bit image format which will be considered for this project. Images of this sort are smaller in size and therefore easier to process. In addition, the hardware requirements for 24-bit color display far exceed those necessary for display of 8-bit color. The size of this image, in bits, would be equivalent to the color depth in bits multiplied by the image size:
Size = $512 \times 512 \times 8 = 2079152$ bits = 262144 bytes = 256 kilobytes

1.2 DIFFERENT CLASSES OF COMPRESSION TECHNIQUES

Two ways of classifying compression techniques are mentioned here.

1.2.1 Lossless vs. Lossy Compression

In a lossless compression algorithm, compressed data can be used to recreate an exact replica of the original; no information is lost to the compression process. This type of compression is also known as entropy coding.

Lossy compression means that the original signal cannot be exactly reconstructed from the compressed data. In practical image compression algorithms very fine details

are lost, but image size is drastically reduced. They consist of the following basic steps:

1. The image is preprocessed
2. An invertible transform is performed on an image
3. The transform coefficients are decimated (quantized)
4. The quantized coefficients are entropy coded (lossless compression).

There exist several different kinds of transforms which can be used, including the Discrete Cosine Transform and the Fractal Transform, but for the purposes of this reports only the wavelet transform will be implemented.

1.2.2 Predictive vs. Transform Coding

In predictive coding, information already sent or available is used to predict future values, and the difference is coded. Differential Pulse Code Modulation (DPCM) is one particular example of predictive coding.

Transform coding first transforms the image from its spatial domain representation to a different type of representation using some well-known transform and then codes the transformed values (coefficients).

1.3 Entropy Encoder

An entropy encoder compresses the quantized values losslessly to give better overall compression. It uses a model to accurately determine the probabilities for each quantized value and produces an appropriate code based on these probabilities so that the resultant output code stream will be smaller than the input stream.

The most commonly used entropy encoders are the Huffman encoder and the arithmetic encoder, although for applications requiring fast execution, simple run-length encoding (RLE) has proven very effective.

1.4 Image Compression

Traditional lossless compression methods (Huffman, LZW, etc.) usually don't work well on image compression.

1.5 Steps for Compression

This report proposes the creation of a wavelet based image transform coder. As outlined above a transform coder consists of four steps. These will be explained here in context of the implementation in this thesis.

1.5.1 The Image is Preprocessed

This stage involves "adjusting" the image to make it more suitable. This includes any methods of presenting the image data to the transform algorithm in different ways. This report will implement rudimentary preprocessing techniques to make the image more suitable for transformation. Various preprocessing steps will be studied, including:

- breaking the image apart into squares of different sizes
- overlaying
- averaging
- color smoothing

1.5.2 An Invertible Transform is Performed on an Image

At the core of the compression program is a wavelet transform. This transform is a lossless stage. The suitability of various types of wavelets (Bi-Orthogonal, Daubechies, etc...) to image processing will be examined and the results will be plotted as a function of the overall compression ratio and the quality of the reconstructed image.

1.5.3 The Transform Coefficients are Decimated (Quantized)

This step is where the actual reduction of data takes place. There are various techniques used to zero the wavelet coefficients.

1.5.4 The Quantized Coefficients are Entropy Coded (Lossless Compression)

There exist a great many lossless compression packages, all of which are well developed. The output from stage 3 will be written to a file and a system compression tool (such as the UNIX *compress* command) will be used to reduce the file size.

1.6 Wavelet-Based Compression

Despite all the advantages of JPEG compression schemes based on DCT namely simplicity, satisfactory performance, and availability of special purpose hardware for implementation; these are not without their shortcomings.

Since the input image needs to be "blocked", correlation across the block boundaries is not eliminated. This results in noticeable and annoying "blocking artifacts" particularly at low bit rates.



Figure 1: Original Lena Image



Figure 2: Reconstructed Lena with DC component only, to show blocking artifacts

1.7 THE CONTINUOUS WAVELET TRANSFORM

The continuous wavelet transform (CWT) is defined as the sum over all time of the signal multiplied by scaled, shifted versions of the wavelet function ψ :

$$C(\text{scale}, \text{position}) = \int_{-\infty}^{\infty} f(t)\psi(\text{scale}, \text{position}, t)dt$$

The results of the CWT are many wavelet coefficients C , which are a function of scale and position. Multiplying each coefficient by the appropriately scaled and shifted wavelet yields the constituent wavelets of the original signal:

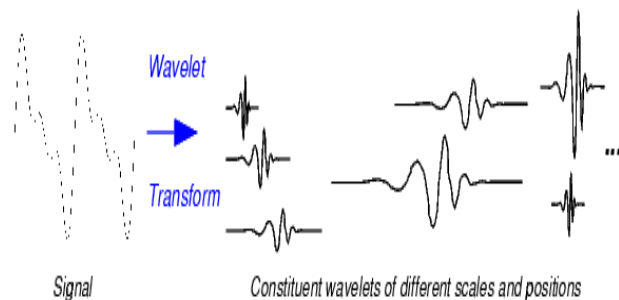


Figure 3: Continuous Wavelet Transform

1.8 THE DISCRETE WAVELET TRANSFORM

Calculating wavelet coefficients at every possible scale is a fair amount of work, and it generates an awful lot of data. It turns out, rather remarkably, that if we choose scales and positions based on powers of two—so-called dyadic scales and positions—then our analysis will be much more efficient and just as accurate.

We obtain such an analysis from the discrete wavelet transform (DWT). An efficient way to implement this scheme using filters was developed in 1988 by the Mallat algorithm is in fact a classical scheme known in the signal processing community as a two-channel subband coder. This very practical filtering algorithm yields a fast wavelet transform — a box into which a signal passes, and out of which wavelet coefficients quickly emerge.

1.9 Wavelet Reconstruction

The other half of the story is how those components can be assembled back into the original signal without loss of information called reconstruction, or synthesis. The mathematical manipulation that effects synthesis is called the inverse discrete wavelet transforms (IDWT).

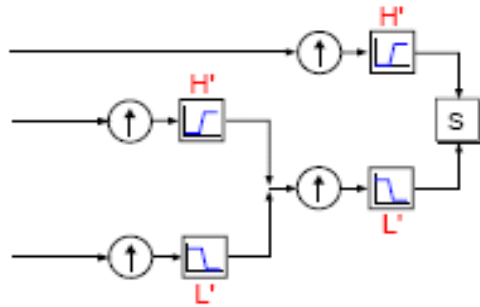


Figure 4: Wavelet Reconstruction

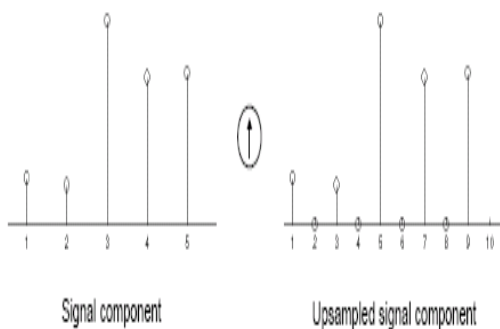
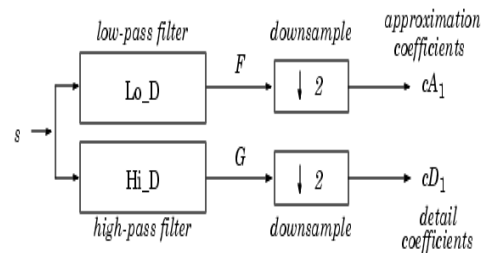


Figure 5: Up Sampling

2.1 ALGORITHMS USED

Given a signal s of length N , the DWT consists of $\log_2 N$ stages at most. Starting from s , the first step produces two sets of coefficients: approximation coefficients cA_1 , and detail coefficients cD_1 .

These vectors are obtained by convolving s with the low-pass filter Lo_D for approximation, and with the high-pass filter Hi_D for detail, followed by dyadic decimation. More precisely, the first step is



where \boxed{X} Convolve with filter X.
 $\boxed{\downarrow 2}$ Keep the even indexed elements (see dvaddown).

Figure 6: Single Level Decomposition

The length of each filter is equal to $2N$. If $n =$ length (s), the signals F and G are of length $n + 2N - 1$, and then the coefficients cA_1 and cD_1 are of length

$$\text{floor}\left(\frac{n-1}{2}\right) + N$$

The next step splits the approximation coefficients cA_1 in two parts using the same scheme, replacing s by cA_1 and producing cA_2 and cD_2 , and so on.

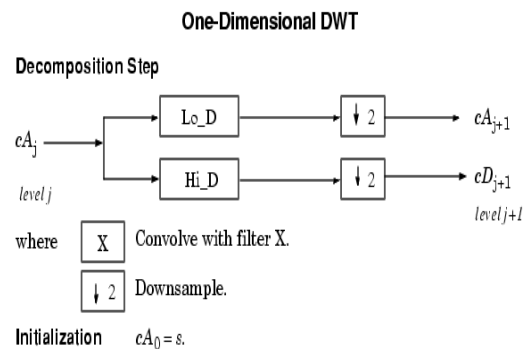


Figure 7: 1-D DWT

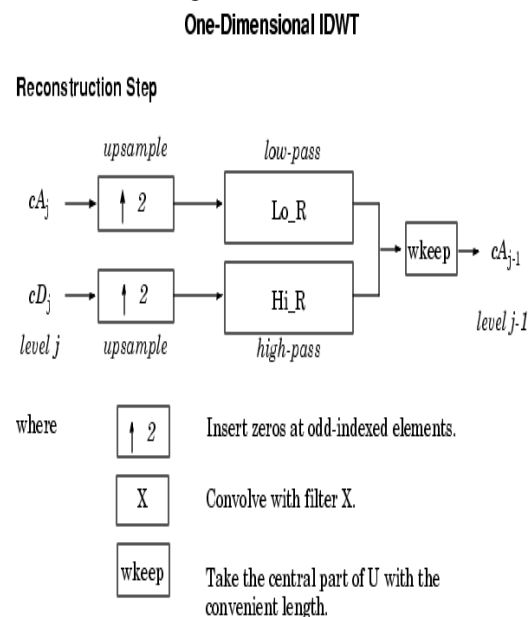
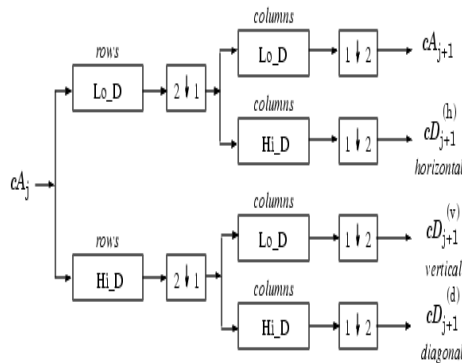


Figure 8: 1-D IDWT

For images, a similar algorithm is possible for two-dimensional wavelets and scaling functions obtained from one-dimensional wavelets by tensorial product. This kind of two-dimensional DWT leads to a decomposition of approximation coefficients at level j in four components: the approximation at level $j + 1$ and the details in three orientations (horizontal, vertical, and diagonal). The following charts describe the basic decomposition and reconstruction steps for images.

Two-Dimensional DWT

Decomposition Step



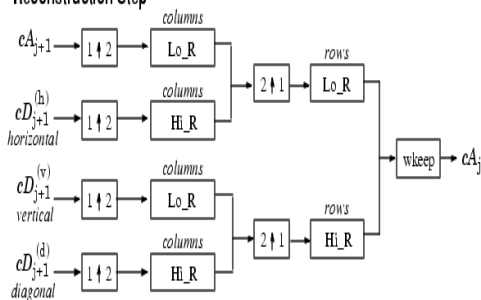
where $\begin{bmatrix} 2 & \downarrow & 1 \\ \end{bmatrix}$ Downsample columns: keep the even indexed columns.
 $\begin{bmatrix} 1 & \downarrow & 2 \\ \end{bmatrix}$ Downsample rows: keep the even indexed rows.
 $\begin{matrix} \text{rows} \\ \boxed{X} \end{matrix}$ Convolve with filter X the rows of the entry.
 $\begin{matrix} \text{columns} \\ \boxed{X} \end{matrix}$ Convolve with filter X the columns of the entry.

Initialization $cA_0 = s$ for the decomposition initialization.

Figure 9: 2-D DWT

Two-Dimensional IDWT

Reconstruction Step



where $\begin{bmatrix} 2 & \uparrow & 1 \\ \end{bmatrix}$ Upsample columns: insert zeros at odd-indexed columns.
 $\begin{bmatrix} 1 & \uparrow & 2 \\ \end{bmatrix}$ Upsample rows: insert zeros at odd-indexed rows.
 $\begin{matrix} \text{rows} \\ \boxed{X} \end{matrix}$ Convolve with filter X the rows of the entry.
 $\begin{matrix} \text{columns} \\ \boxed{X} \end{matrix}$ Convolve with filter X the columns of the entry.

Figure 10: 2-D IDWT

2.2 FUNCTIONS USED

2.2.1 DWT (Single-Level Discrete 1-D Wavelet Transform)

Syntax: $[cA, cD] = \text{dwt}(X, \text{'wname'})$

Description: The dwt command performs a single-level one-dimensional wavelet decomposition with respect to either a particular wavelet or particular wavelet decomposition filters (Lo_D and Hi_D) that you specify. $[cA, cD] = \text{dwt}(X, \text{'wname'})$ computes the approximation coefficients vector cA and detail coefficients vector cD, obtained by a wavelet decomposition of the vector X. The string 'wname' contains the wavelet name.

2.2.2 IDWT (Single-Level Inverse Discrete 1-D Wavelet Transform)

Syntax: $X = \text{idwt}(cA, cD, \text{'wname'})$

Description: The idwt command performs a single-level one-dimensional wavelet reconstruction with respect to either a particular wavelet or particular wavelet reconstruction filters (Lo_R and Hi_R) that you specify. $X = \text{idwt}(cA, cD, \text{'wname'})$ returns the single-level reconstructed approximation coefficients vector X based on approximation and detail coefficients vectors cA and cD, and using the wavelet 'wname'.

2.2.3 Imread (Read Image From Graphics File)

Syntax: $[X, \text{map}] = \text{imread}(\text{filename})$

Description: $[X, \text{map}] = \text{imread}(\text{filename})$ reads the indexed image in filename into X and its associated colormap into map. The colormap values are rescaled to the range [0, 1].

2.2.4 Imwrite (Write Image to Graphics File)

Syntax: $\text{imwrite}(X, \text{map}, \text{filename})$

Description: imwrite(X, map, filename) writes the indexed image in X and its associated colormap map to filename in the format specified. If X is of class uint8 or uint16, imwrite writes the actual values in the array to the file. If X is of class double, the imwrite function offsets the values in the array before writing, using uint8(X-1). The map parameter must be a valid MATLAB colormap. Note that most image file formats do not support colormaps with more than 256 entries.

2.2.5 DWT2 (Single-Level Discrete 2-D Wavelet Transform)

Syntax: $[cA, cH, cV, cD] = \text{dwt2}(X, \text{'wname'})$

Description: The dwt2 command performs a single-level two-dimensional wavelet decomposition with respect to either a particular wavelet or particular wavelet decomposition filters (Lo_D and Hi_D) you specify. $[cA, cH, cV, cD] = \text{dwt2}(X, \text{'wname'})$ computes the approximation coefficients matrix cA and details coefficients matrices cH, cV, and cD (horizontal, vertical, and diagonal, respectively), obtained by wavelet decomposition of the input matrix X. The 'wname' string contains the wavelet name.

2.2.11 IDWT2 (Single-Level Inverse Discrete 2-D Wavelet Transform)

Syntax X = idwt2(cA, cH, cV, cD, 'wname')

Description: The idwt2 command performs a single-level two-dimensional wavelet reconstruction with respect to either a particular wavelet or particular wavelet reconstruction filters (Lo_R and Hi_R) that you specify. X = idwt2(cA, cH, cV, cD, 'wname') uses the wavelet 'wname' to compute the single-level reconstructed approximation coefficients matrix X, based on approximation matrix cA and details matrices cH, cV and cD (horizontal, vertical, and diagonal, respectively).

SIMULATION RESULTS

Results obtained after performing DWT with MATLAB code are shown below. Figure (11) shows original Lena image. Figure (12) & (13) show compressed images for various threshold values. As threshold value increases blurring of image continues to increase.

Figure 11: Original Lena Image



Figure 12: Compressed Image for threshold = 2



Figure 13: Compressed Image for threshold = 5

Figure 11 shows the original image and figure 12 and 13 shows compressed image signal for threshold value of 2 and 5 respectively.

CONCLUSION

Thus we see that the proposed algorithm that is wavelet based image compression technique compresses the original Lena image as shown in Figure 12 and 13. The size of the Original Lena Image is 62.7KB, the size of the compressed Lena Image for threshold =2 is 60.7KB and the size of the compressed Lena Image for threshold =5 is 54.3 KB.

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BIOGRAPHIES



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