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Image Compression Using Wavelet Technique

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Abstract: ***Image compression is now essential for applications such as transmission and storage in data bases. A variety of new and powerful algorithms have been developed for image compression over the years. Among them the wavelet-based image compression schemes have gained much popularity due to their overlapping nature which reduces the blocking artifacts that are common phenomena in JPEG compression and multi resolution character which leads to superior energy compaction with high quality reconstructed images. In this paper we discuss about the image compression, wavelet based techniques and algorithm of image compression.***

Keywords: image compression, wavelet based techniques, wavelet family, compression algorithm, compression ratio

1. Introduction

Image compression is the application of data compression on digital images. In effect, the objective is to reduce redundancy of the image data in order to be able to store or transmit data in an efficient form. Uncompressed multimedia (graphics, audio and video) data requires considerable storage capacity and transmission bandwidth. Despite rapid progress in mass-storage density, processor speeds, and digital communication system performance, demand for data storage capacity and data transmission bandwidth continues to outstrip the capabilities of available technologies. The recent growth of data intensive multimedia-based web applications have not only sustained the need for more efficient ways to encode signals and images but have made compression of such signals central to storage and communication technology.

1.1 Image compression basics

The neighboring pixels of most natural images are highly correlated and thus contain lot of redundant information. A less correlated representation of the image is the result of any compression algorithm. The main task of image compression algorithms is reduction of redundant and irrelevant information. In the present scenario, various methods of compressing still images exist. In any data compression scheme, three basic steps are involved: Transformation, Quantization and Encoding.

1.2 Transformation

In image compression, transform is indented to de-correlate the input pixels. Selection of proper transform is one of the important issues in image compression schemes. The transform should be selected in such a way that it reduces the size of the resultant data set as compared to the source data set. Few transformations reduce the numerical size of the data items that allow them to represent by fewer binary bits. The technical name given to these methods of transformation is mapping. Some mathematical transformations have been invented for the sole purpose of data compression; others have been borrowed from various applications and applied to data compression. These include the Discrete Fourier Transform (DFT), Discrete Cosine Transform (DCT), Walsh-Hadamard Transform (WHT), Hadamard-Haar Transform (HHT), Karhune-Loeve Transforms (KLT), Slant-Haar Transform (SHT), Short Fourier Transforms (SFT), and Wavelet Transforms (WT). Transform selection process still remains an active field of research.

1.3 Quantization

The procedure of approximating the continuous set of values in the image data with a finite, preferably small set of values is called quantization. The original data is the input to a quantizer and the output is always one among a limited number of levels. The quantization step may also be followed by the process of thresholding. Each sample is scaled by a quantization factor in the process of quantization, whereas the samples are eliminated if the value of the sample is less than the defined threshold value, in the process of thresholding. These two methods are responsible for the introduction of error and leads to degradation of quality. The degradation is based on selection of quantization factor and the value of threshold. If the threshold value is high, the loss of information is more, and vice versa. The value of threshold or the quantization factor should be selected in a way that it satisfies the constraints of human visual system for better visual quality at high compression ratios. Quantization is a process of approximation. A good quantizer is the one which represents the original signal with minimum distortion. If lossless compression is desired this step should be eliminated.

1.4 Encoding

Encoding process reduces the overall number of bits required to represent the image [1]. An entropy encoder compresses the quantized values further to give better overall compression. This process removes the redundancy in the form of repetitive bit patterns at the output of the quantizer. It uses a model to precisely determine the probabilities for each quantized value and produces a suitable code based on these probabilities so that the resultant output code stream will be smaller than the input. Commonly used entropy coders are the Huffman encoder and the Arithmetic encoder. The Huffman procedure needs each code to have an integral number of bits, while arithmetic coding techniques allow for fractional number of bits per code by grouping two or more similar codes together into a block composed of an integral number of bits. This makes arithmetic codes to perform better than Huffman codes. Therefore, arithmetic codes are more commonly used in wavelet based algorithms. The decoding process involves the reverse operation of the encoding steps with the exception of de-quantization step that cannot be reversed exactly.

2. Wavelet Based Coding Schemes

Wavelet compression schemes allow the integration of various compression techniques into one. With wavelets, a compression ratio of up to 300:1 is achievable. A number of novel and sophisticated wavelet-based schemes for image compression have been developed and implemented over the past few years. These include Embedded Zero Tree Wavelet (EZW) [2], Set-Partitioning in Hierarchical Trees (SPIHT) [3], Set Partitioned Embedded Block Coder (SPECK) [4], Embedded Block Coding with Optimized Truncation (EBCOT) [5], Wavelet Difference Reduction (WDR) [6], Adaptively Scanned Wavelet Difference Reduction (ASWDR) [7] , Space – Frequency Quantization (SFQ) [8], Embedded Predictive Wavelet Image Coder (EPWIC), Compression with Reversible Embedded Wavelet (CREW) [9], the Stack- Run (SR) [10], the recent Geometric Wavelet (GW) [11] and improved GW [12].

A. Wavelet family

Here are several wavelet family members which are discussed below.

B. Crude wavelets

Wavelets – Gaussian wavelets (gaus), Morlet, Mexican hat (mexihat).

a) Properties
  - *Phi* does not exists
  - The analysis is not orthogonal
  - *Psi* is not compactly supported
  - Reconstruction property is not insured

b) Possible analysis
  - *Continuous decomposition is possible*

c) Main Nice properties
  - Symmetry, Psi has explicit expression

d) Main difficulties
  - Fast algorithm and Reconstruction unavailable

C. Infinitely Regular wavelets

Wavelet – Meyer (meyr)

a) Properties
  - *Phi and Psi are indefinitely derivable*
  - *Phi exists and analysis is orthogonal*
  - *Psi and Phi not compactly supported*

b) Possible analysis
  - *Continuous transform*
  - *Discrete transform but with non FIR filters*

c) Main Nice properties
  - *Symmetry, infinite Regularity*

d) Main difficulties
  - *Fast algorithm unavailable*
  - *Wavelets – Discrete Meyer wavelet (dmey)*

e) Properties
  - *FIR approximation of the Meyer wavelet*

f) Possible analysis
  - Continuous transform
  - Discrete transform

D. Orthogonal and compactly supported wavelets

Wavelets –Daubechies (dbN), Symlets (symN), Coiflets (coifN)

a) Properties
  - Psi has given number of vanishing moments
  - Phi exists and analysis is orthogonal
  - Psi and Phi are compactly supported

b) Possible analysis
  - Continuous transform
  - Discrete transform using FWT

c) Main Nice properties
  - Support, vanishing moments, FIR Filter

d) Main difficulties
  - Poor Regularity

E. *Biorthogonal and compactly supported wavelet pairs*

Wavelets – B-splines biorthogonal wavelets

a) Properties
  - Phi and Psi both for decomposition and reconstruction are compactly supported
  - Phi function exists and analysis is biorthogonal
  - Psi and Phi for decomposition have vanishing moments
  - Psi and Phi for reconstruction have known regularity

b) Possible analysis
  - Continuous transform
  - Discrete transform using FWT

c) Main Nice properties
  - Symmetry with FIR and nice allocation is possible

d) Main difficulties
  - Orthogonality is lost

F. Complex wavelets

Wavelets – complex Gaussian wavelets(cgauN), complex morlet wavelet(cmorFb-Fc), complex Shannon wavelet(shanFb-Fc), complex frequency B-spline wavelet(fbspM-Fb-Fc)

a) Properties
  - Phi does not exists
  - The analysis is not orthogonal
  - Psi is not compactly supported
  - Reconstruction property is not insured

b) Possible analysis
  - Complex Continuous decomposition

c) Main Nice properties
  - Symmetry, psi has explicit expression

d) Main difficulties
  - Fast algorithm and reconstruction unavailable

3. Implementation Overview

In this section discussed the implementation overview of the concept. The following implementation steps have been made for the devised algorithm, which is based on 2D-wavelet.

Step 1- Reading an image of either gray scale or RGB image
Step 2- Converting the image into grayscale if the image is RGB

Step 3-Decomposition of images using wavelets for the level N
Step 4- Selecting and assigning a wavelet for compression
Step 5- Generating threshold coefficients
Step 6- Performing the image compression using wavelets
Step 7- Computing and displaying the results such as compressed image, retained energy and Zero coefficients
Step 8- Decompression the image based on the wavelet decomposition structure.
Step 9- Plotting the reconstructed image
Step 10- Computing and displaying the size of original image, compressed image and decompressed image

In this algorithm it calculates size and displays the results for original, compressed and decompressed image. It also shows the compression ratio for the desired result. Some other facilities also it going to display like file format, file mode, width and height, color-type, bit depth, byte order etc Below showing the results for some wavelet family members.

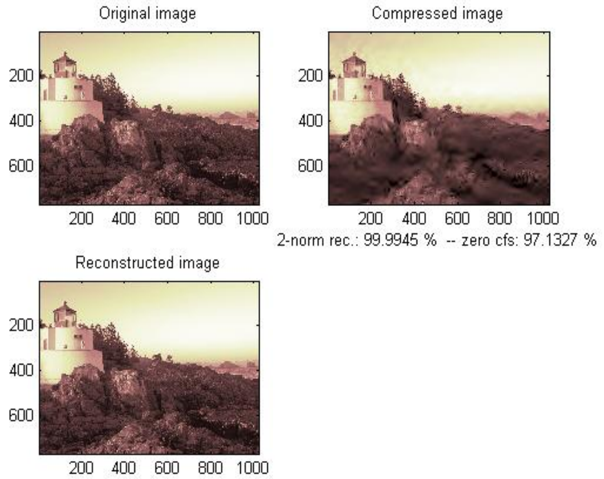

Figure 1: Output for Infinitely Regular Wavelets using discrete Meyer wavelet (dmey).

Figure 1 shows the result for infinite regular wavelet using discrete Meyer wavelet which is member of above family. It gives the compression of 99.9945%.which is almost original image.

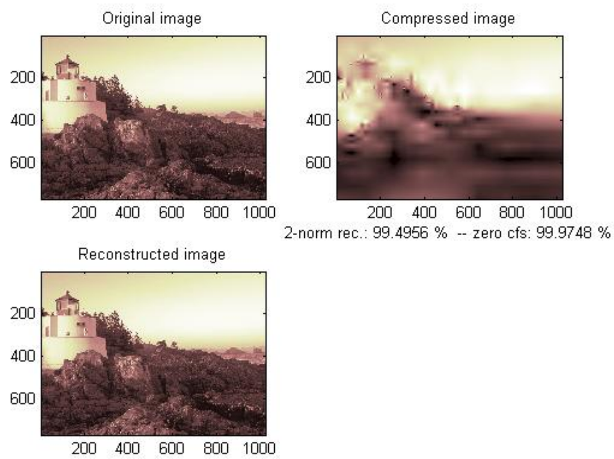

Figure 2: Output for Orthogonal and Compactly Supported Wavelet

Figure 2 shows the result for orthogonal and compactly supported wavelet using Daubechies (dbN) family member which gives compression of 99.4956%.

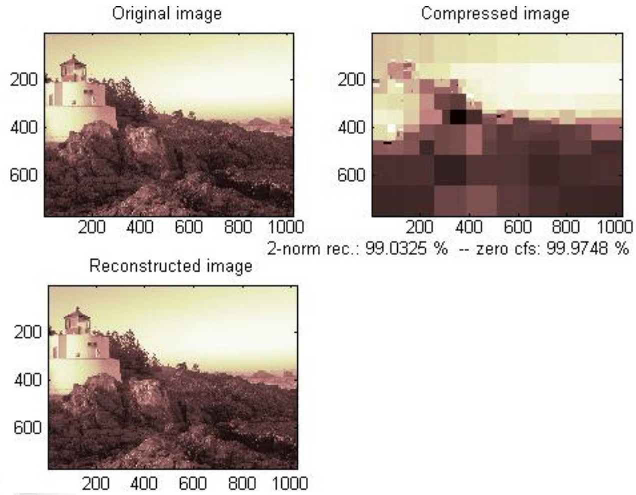

Figure 3: gives the result for biorthogonal and compactly supported wavelet pairs by B-Splines biorthogonal wavelet (biorNr.Nd and rbiorNr.Nd) gives compression of 99.03%.

4. Conclusion

The wavelet-based image compression has gained much popularity because of their overlapping nature that reduces the blocking artifacts. The multi resolution character of wavelet-based schemes which leads to superior energy compaction with high quality reconstructed images. We have shown the wavelet family member results also the effect on compression ratio.

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