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EFFICIENT LOSSY IMAGE COMPRESSION TECHNIQUE BASED ON SEAM IDENTIFICATION AND SPIHT CODING

Angothu Govind*[1], Mr.B.Vijay Kumar[2]

[1]Student, Department of ECE, Vaagdevi College of Engineering Sangem, Warangal (AP), India.

[2]Asst. Prof, Department of ECE, Vaagdevi College of Engineering Sangem, Warangal (AP), India.

ABSTRACT

The project proposes the seam based efficient image compression using integer wavelet transform and Lossy encoding techniques. In mobile multimedia communications, image retargeting is generally required at the user end. However, content-based image retargeting is with high computational complexity and is not suitable for mobile devices with limited computing power. The work presented in this paper addresses the increasing demand of visual signal delivery to terminals with arbitrary resolutions, without heavy computational burden to the receiving end. In this paper, the principle of seam carving is incorporated into a wavelet codec (i.e., SPIHT). For each input image, block-based seam energy map is generated in the pixel domain and the integer wavelet transform (IWT) is performed for the retargeted image. Different from the conventional wavelet-based coding schemes, IWT coefficients here are grouped and encoded according to the resultant seam energy map. The bit stream is then transmitted in energy descending order. At the decoder side, the end user has the ultimate choice for the spatial scalability without the need to examine the visual content; an image with arbitrary aspect ratio can be reconstructed. Experimental results show that, for the end users, the received images with an arbitrary resolution preserve important content while achieving high coding efficiency for transmission.

Keywords: Image Compression, Wavelet Transform, Seam Curving, Spatial scalability.

INTRODUCTION

Image Compression

Digital Image compression addresses the problem of reducing the amount of data required to represent a digital image. The underlying basis of the reduction process is removal of redundant data. From the mathematical viewpoint, this amounts to transforming a 2D pixel array into a statically uncorrelated data set. The data redundancy is not an abstract concept but a mathematically quantifiable entity. If n1 and n2 denote the number of information-carrying units in two data sets that represent the same information, the relative data redundancy R_D of the first data set (the one characterized by n1) can be defined as,

$$R_D = 1 - \frac{1}{C_R} \qquad \text{------ (1.1)}$$

Where C_R called as compression ratio [2]. It is defined as

$$C_R = \frac{n1}{n2} \qquad \text{--------(1.2)}$$

In image compression, three basic data redundancies can be identified and exploited: Coding redundancy, interpixel redundancy, and phychovisal redundancy. Image compression is achieved when one or more of these redundancies are reduced or eliminated.

The image compression is mainly used for image transmission and storage. Image transmission applications are in broadcast television; remote sensing via satellite, air-craft, radar, or sonar; teleconferencing; computer communications; and facsimile transmission. Image storage is required most commonly for educational and business documents, medical images that arise in computer tomography (CT), magnetic resonance imaging (MRI) and digital radiology, motion pictures, satellite images, weather maps, geological surveys, and so on.

There are two types of image compression techniques.

- Lossy Image compression
- Lossless Image compression

Lossy Image compression

Lossy compression provides higher levels of data reduction but result in a less than perfect reproduction of the original image. It provides high compression ratio.

Lossy image compression is useful in applications such as broadcast television, videoconferencing, and facsimile transmission, in which a certain amount of error is an acceptable trade-off for increased compression performance.

Lossless Image compression

Lossless Image compression is the only acceptable amount of data reduction. It provides low compression ratio while compared to lossy. In Lossless Image compression techniques are composed of two relatively independent operations: Devising an alternative representation of the image in which it’s inters pixel redundancies are reduced and Coding the representation to eliminate coding redundancies.

Lossless Image compression is useful in applications such as medical imaginary, business documents and satellite images.

WAVELET APPROACH

Storage constrains and bandwidth limitations in communication systems have necessitated the search for efficient image compression techniques. For real time video and multimedia applications where a reasonable approximation to the original signal can be tolerated, lossy compression is used. In the recent past, wavelet based image compression schemes have gained wide popularity. The characteristics of the wavelet transform provide compression results that outperform other transform techniques such as discrete cosine transform (DCT). Consequently, the JPEG2000 compression standard and FBI fingerprint compression system have adopted a wavelet approach to image compression.

The wavelet coding techniques is based on the idea that the co-efficient of a transform that decor relates the pixels of an image can be coded more efficiently than the original pixels themselves. If the transform’s basis functions in this case wavelet- packs most of the important visual information into small number of co-efficient, the remaining co-efficient can be coarsely quantized or truncated to zero with little image distortion.

The still image compression, modern DWT based coders have outperformed DCT based coders providing higher compression ratio and more peak signal to noise ratio (PSNR) due to the wavelet transforms multi-resolution and energy compaction properties and the ability to handle signals.

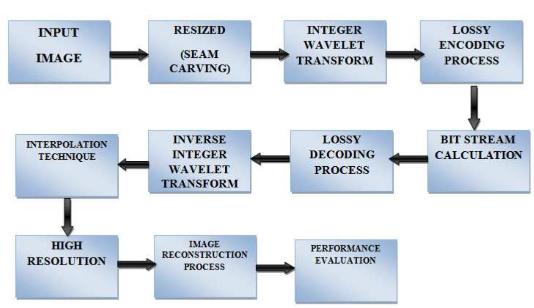

Fig 1: Block Diagram

The image to be compressed is transformed into frequency domain using wavelet transform. In wavelet transform the images are divided into odd and even components and finally the image is divided into four levels of frequency components. The four frequency components are LL, LH, HL, HH, and then the image is encoded using SPIHT coding. Then the bit streams are obtained. The obtained are decoded using SPIHT decoding. Finally inverse wavelet transform is taken and the compressed image will be obtained.

Seam Carving For Image Retargeting

The process allows the user to resize an image by removing a continuous path of pixels (a seam) vertically or horizontally from a given image. A seam is defined as a continuous path of pixels running from the top to the bottom of an image in the case of a vertical seam, while a horizontal seam is a continuous line of pixels spanning from left to right in an image.

Algorithm implementation

The first step in calculating a seam for removal or insertion involves calculating the gradient image for the original image. The gradient image is a common image that is used in both horizontal and vertical seam calculation, and can be calculated either from the luminance channel of a HSV image, or calculated for each of the R, G, and B channels, then averaging the three gradient images.

Fig 2: Image with vertical seam

Figure 3 is included as an example gradient image. The sobel operator was chosen for calculation of the gradient image in this project, but other gradient operators may be used.

Fig 3: Resized Image

The process can be repeated to remove a set of seams, horizontally or vertically and will result in an image with reduced dimensions, but with the overall scene content intact. An example of this is included as Figure 7, where the image was resized to 320x240 pixels, from 640x480 pixels and as can be seen, the resulting image will have artifacts if a large number of seams are removed.

PROGRESSIVIE IMAGE TRANSMISSION

After converting the image pixels into wavelet coefficient SPIHT is applied. We assume, the original image is defined by a set of pixel values $p_{i,j}$, where (i, j) the pixel coordinates. The wavelet transform is actually done to the array given by,

$$c(i, j) = DWT\{p(i, j)\}.$$

Where c (i, j) is the wavelet coefficients.

In SPIHT, initially, the decoder sets the reconstruction vector $\hat{c}$ to zero and updates its components according to the coded message. After receiving the value (approximate or exact) of some coefficients, the decoder can obtain a reconstructed image by taking inverse wavelet transform, called as “progressive transmission”.

$$\hat{p}(i, j) = IDWT\{\hat{c}(i, j)\}$$

A major objective in a progressive transmission scheme is to select the most important information-which yields the largest distortion reduction-to be transmitted first. For this selection, we use the mean squared-error (MSE) distortion measure

$$D_{MSE}(p-\hat{p}) = \frac{1}{N}\|p-\hat{p}\|^2 = \frac{1}{N}\sum_i\sum_j (p_{i,j}-\hat{p}_{i,j})^2$$

Where Nis the number of image pixels. $p_{i,j}$ is the Original pixel value and $\hat{p}_{i,j}$ is the reconstructed pixel value.

RESULTS AND DISCUSSION

Quality Measures For Image

The Quality of the reconstructed image is measured interms of mean square error (MSE) and peak signal to noise ratio (PSNR) ratio. The MSE is often called reconstruction error variance σ_q^2. The MSE between the original image f and the reconstructed image g at decoder is defined as:

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

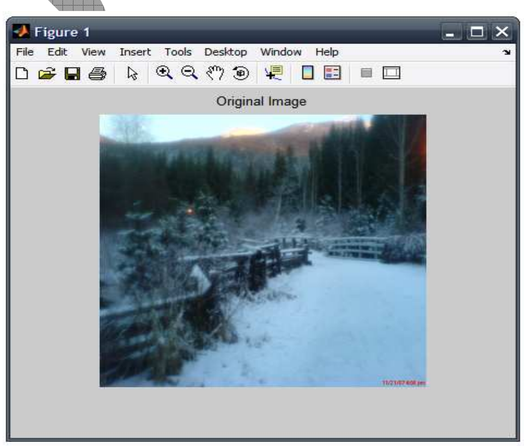

Fig 4: Original Images

Where the sum over j, k denotes the sum over all pixels in the image and N is the number of pixels in each image.

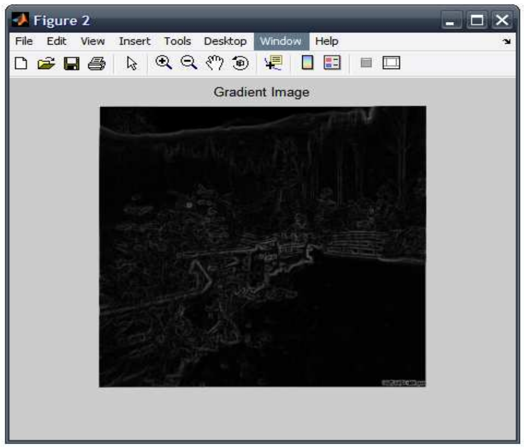

Fig 5: Gradient image

From that the peak signal-to-noise ratio is defined as the ratio between signal variance and reconstruction error variance. By using the received side information and bit stream, the reconstructed image with a different resolution can be generated.

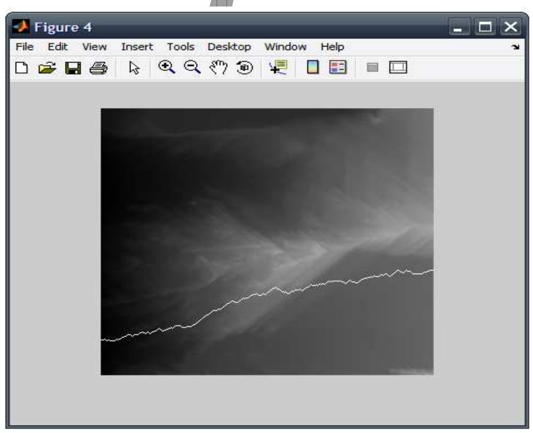

Fig 6: Energy Map Calculations

However, due to the DWT architecture, an SOT with scale DWT represents neighboring pixels in the original image.

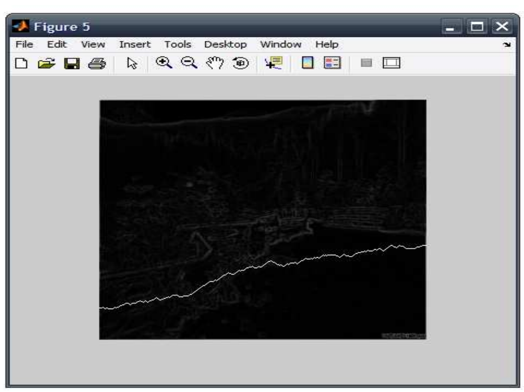

Fig 7: Image by removing vertical seams

If one vertical or horizontal seam is deleted, neighboring columns or rows of the original image are deleted accordingly. Generally when PSNR is 40 dB or greater, then the original and the reconstructed images are virtually indistinguishable by human eyes. In such a case, the retargeted size must be the integer times of 2^L.

The PSNR between two images having 8 bits per pixel in terms of decibels (dBs) is given by:

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

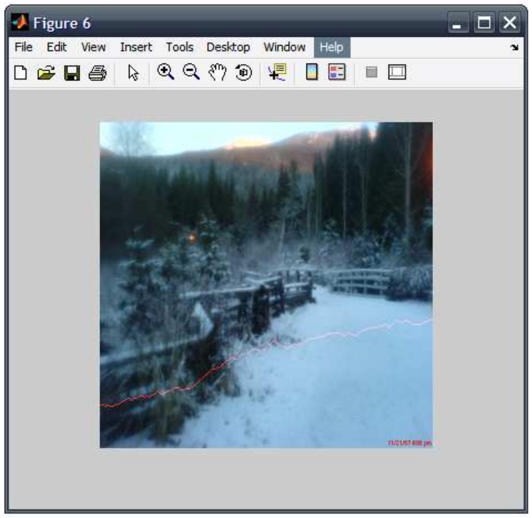

Fig 8: Increase image size by adding horizontal seams

For the ROI-Seam, the ROIs were encoded loss lessly using SPIHT (five-level DWT is performed); the pixel value and the position information of each seam in the non-ROIs were quantized and encoded using the adaptive arithmetic coding (AAC). The overall PSNR of the seams was set as 40 dB. At the decoder side, the seams corresponding to an image with near but smaller size than the targeted size was received and the seam insertion was performed to generate the images with the demanded aspect ratio.

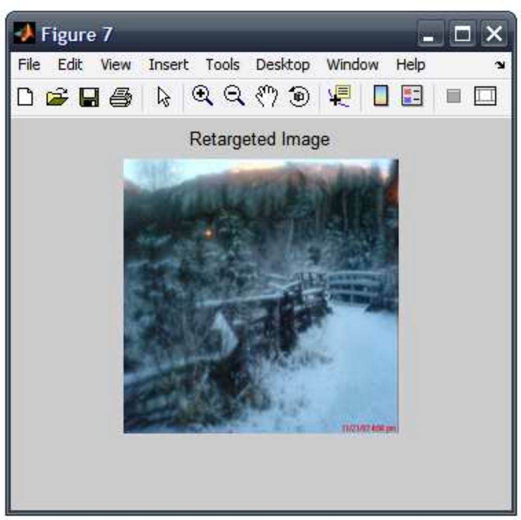

Fig 9: Retargeted Image

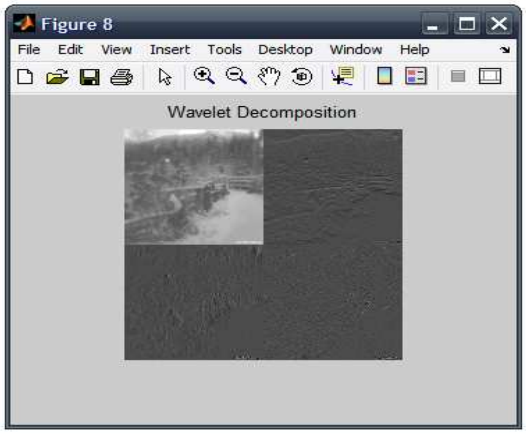

Fig 10: Integer Wave Let Transform

Overhead of side information for 672 X 672 image reconstruction. We can see that much less overhead was needed for the proposed Seam-SPIHT and CD-SPIHT in comparison with the ROI-Seam. The reason is that for the Seam-SPIHT and CD-SPIHT, SC was performed in a block or pillar manner and the number of seams are much less than that of original image pixels.

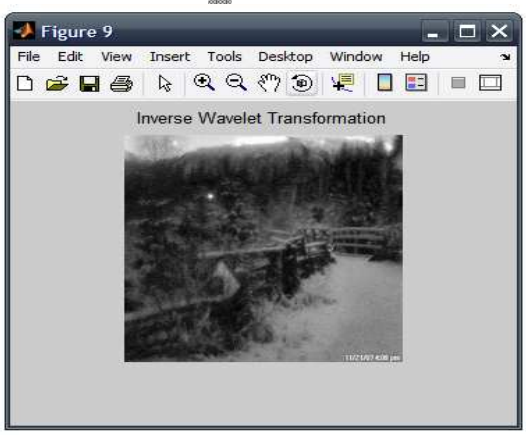

Fig 11: Inverse Wavelet Transform

For a vertical (or horizontal) seam, the positions of a seam are encoded from top (or left) to bottom (or right), and only coordinates (or -coordinates) are required to identify the positions.

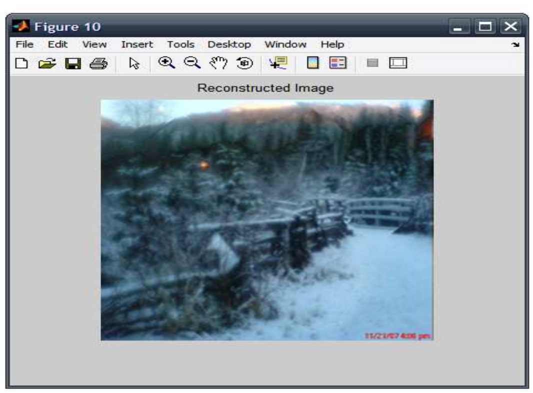

Fig 12: Reconstructed Image

We would like to point out that, due to the alternative seam transmission order, one more bit is needed to indicate the status of the first transmitted seam (i.e., vertical or horizontal seam). Considering each N X M input image with L-scale DWT, the size of seam block unit would be 2^l X 2^l, in this case, N/2^l and M/2^l (i.e., the size of wavelet coefficients in the Low frequency sub band) positions are encoded in the first pair of vertical and horizontal seams; then, for each new pair of seams, the number of positions needed to be encoded is reduced by one.

CONCLUSION

This project presented to provide solutions for increasing the compression ratio with various quantization levels and reduce the processing time based on seam carving technique followed by integer wavelet transform and set partitioning in hierarchical tress coding. Also, the seam carving process was presented to retarget the image corresponding to display set size. Here lossy embedded coding ie., spiht coding to increase the CR and reduce the information loss. In this project, performance will be analyzed through determining the image quality after decompression, compression ratio and execution time. The project can be further enhanced by modifying the transformation technique and encoding process to curvelet and modified spiht algorithm for improving the efficiency of the technique.

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