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

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ABSTRACT:

The project proposes the seam primarily based on economical compression. In mobile multimedia system communications, image retargeting is mostly needed at the user end. However, content-based image retargeting is with high machine quality and isn't appropriate for mobile devices with restricted computing power. The work conferred during this paper addresses the increasing demand of signal delivery to terminals with discretionary resolutions, while not serious machine burden to the receiving end. During this paper, the principle of seam carving is incorporated into a wave codec (i.e., SPIHT). For every input image, block-based seam energy map is generated within the pel domain and therefore the whole number wave rework (IWT) is performed for the retargeted image. These are encoded in keeping with the resultant seam energy map. Experimental results shows that, the retargeted images shows better PSNR and MSE values as well as good compression ratios without loss of data.

1. INTRODUCTION:

In recent years, the development and demand of multimedia product grows increasingly fast, contributing to insufficient bandwidth of network and storage of memory device. Therefore, the theory of data compression becomes more and more significant for reducing the data redundancy to save more hardware space and transmission bandwidth. In computer science and information theory, data compression or source coding is the process of encoding information using fewer bits or other information-bearing units than a unencoded representation. Compression is useful because it helps reduce the consumption of expensive resources such as hard disk space or transmission bandwidth. Most of the existing application requires the images to compress in an efficient manner due the limitations in storage space and resources. Larger size images require large bandwidth to transmit, so the cost communication is difficult in the available bandwidth. So the term data compression became more and more significant to save the storage space and bandwidth. The image compression [1] is the process of data compression to reduce the amount of redundancy. It is the main process of coding information fewer bits than the un-encoded source and allows the users to obtain quality images with given bits. It is important to remove the unwanted regions in an image without complexity. The hospital image needs to transmit without losing important information while keeping high compression ratio. The proposed method is useful for obtaining high compression ratio with less complexity in most of the applications. The images can obtain at receiver side by applying the reverse process that has performed for encoding. The compression techniques are categorized in to lossy and lossless compression. Lossless compression as name implies compresses the data without losing any information. Lossy compression involves the loss of data during compression. The advantages over lossless is that it can achieve high compression ratio.

By applying Discrete Cosine Transform (DCT), the data in time (spatial) domain can be transformed into frequency domain. Because of the less sensitivity of human vision in higher frequency, we can compress the image or video data by suppressing its high frequency components but do no change to our eye [2]. But because of the blocks in the dct there are many chances of occurring blocking artifacts which may cause the loss of content. There are several representatives of wavelet based image coders such as: Embedded zero tree wavelet coder (EZW) [3], Set partitioning in hierarchical trees (SPIHT) [4], Morphological representations of wavelet data (MRWD)

[5] And Significance-linked connected component analysis (SLCCA) [6]. These methods provide excellent rate-distortion performances. Although wavelets are

capable of more flexible space frequency resolution tradeoffs than DCT, DCT is still widely used in many practical applications because of its compression performance and computational advantages. Recently, DCT based coders with innovative data organization strategies and representations of DCT coefficients have been reported with high compression efficiency.

An additional image retargeting process (e.g., down-sampling, cropping, warping [7] or seam carving (SC) [8], [9]) is needed in the receiving end.\

II SEAM CURVING

A seam is a connected path of low energy pixels in an image. On the left is the original image with one horizontal and one vertical seam. In the middle the energy function used in this example is shown (the magnitude of the gradient), along with the vertical and horizontal path maps used to calculate the seams. By automatically carving out seams to reduce image size, and inserting seams to extend it, we achieve content-aware resizing. The example on the top right shows our result of extending in one dimension and reducing in the other, compared to standard scaling on the bottom right.

III 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.

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. 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.

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.

IV INTEGER WAVELET TRANSFORM

Integer wavelet transform maps an integer data set into another integer data set. In discrete wavelet transform, the used wavelet filters have floating point coefficients so that after processing the image the image quality may be lost forever. The floating point values of the pixels that should be integers may cause the loss of the actual data which may lead to the failure of the lossless compression. To avoid problems of floating point precision of the wavelet filters when the input data is integer as in digital images, the output data will no longer be integer which doesn't allow perfect reconstruction of the input image and in this case there will be no loss of information through forward and inverse transform. Due to the mentioned difference between integer wavelet transform (IWT) and discrete wavelet transform (DWT) the LL sub band in the case of IWT appears to be a close copy with smaller scale of the original image while in the case of DWT the resulting LL sub band is distorted.

PROGRESSIVIE IMAGE RANSFORMATION:-

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,

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

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

In SPIHT, initially, the decoder sets the reconstruction vector $\widehat{c}$ 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".

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

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

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

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.

V SPIHT Algorithm

SPIHT algorithm keeps track of the state of sets by means of three lists, i.e, list of insignificant sets (LIS), list of significant pixels (LSP) and lists of insignificant pixels (LIP). The algorithm uses the following sets to code a bitmap effectively: $O(i, j)$ is the set of coordinates of all offspring of node (i, j), $D(i, j)$ is set of coordinates of all descendents of node (i, j), $L(i, j)$ is the set of coordinates defined as $D(i, j) - O(i, j)$, $H(i,j)$ is set of all tree roots. The significance test of the wavelet coefficient is defined as follows:

$$S_n(\Gamma) = \begin{cases} 1, \max\limits_{(i,j\epsilon\Gamma)} |(T(i,j)| \geq 2^n \\ 0, otherwise. \end{cases}$$

Where, $T(i, j)$ is the coefficient at node (i, j). Γ is the testing coordinate set in (11). Briefly, SPIHT coding method is described in the following two passes:

1. Initialization: LSP=φ. LIP contains all tree roots at coarsest scale. LIS contains all tree nodes. Choose the threshold according to above equation.

2. Sorting pass: Output $Sn(i, j)$ for all the nodes (i, j) of LIP. If $Sn = 1$, move the node (i, j) to the LSP and output the sign of $T(i.j)$. For all the nodes of (i, j) of LIS, if the nodes belongs to type A, output $Sn(D(i, j))$. If $Sn(D(i.j)) = 1$, output $Sn(k, l)$ for any node (k, l) _ $O(i, j)$. If $Sn(k, l) = 1$, append node (k, l) to the LSP and output its sign.

Otherwise, move (k, l) to the LIP. If $L(i, j)$_= φ, then move (i, j) from LIS, while marking as type B. Otherwise, remove the node (i, j) from LIS. If the node belongs to type B, then output $Sn(L(i, j))$. If $Sn(L(i, j)) = 1$, append the four direct subsequent nodes to the LIS as type A.

3. Refinement pass: For each elements (i,j) in the LSP, output the n-th most significant bit except those added above.

4. Update: Decrement n by 1, and go to sorting pass.

VI 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:

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

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. From that the peak signal-to-noise ratio is defined as the ratio between signal variance and reconstruction error variance. The PSNR between two images having 8 bits per pixel in terms of decibels (dBs) is given by:

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

Generally when PSNR is 40 dB or greater, then the original and the reconstructed images are virtually indistinguishable by human eyes.

Fig 1: original image

Fig 2: gradient image

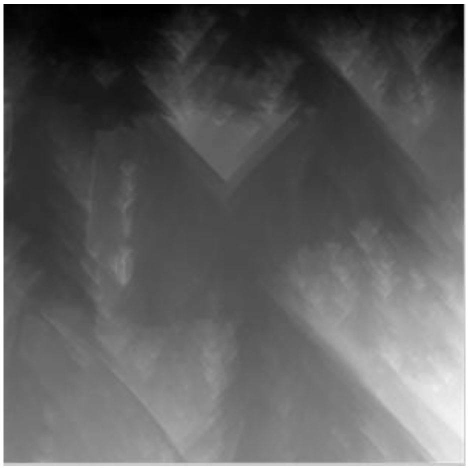

Fig 3: energy map

Fig 4: energy map with horizontal seam

Fig 5: gradient image with horizontal seam

Fig 6: original image with horizontal seam

Fig 7: retargeted or compressed image

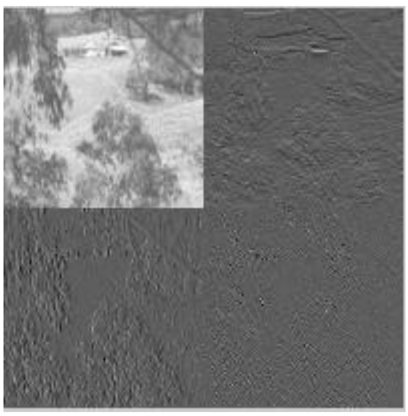

Fig 8: integer wavelet transform

Fig 9: inverse transformed image

Fig 10: decompressed image

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 i.e., 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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