Automated Identification Based On Seam Carving Technique and Set Partioning Technique In Hierarchical

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Abstract— **The efficient seam based image compression using Integer wavelet Transform (IWT) and Lossy encoding techniques. In mobile multimedia communications, image retargeting is generally required at the user end. In this novel, the principle of seam carving is incorporated into a wavelet codec. For each image seam energy ma is generated in the pixel domain and integer wavelet transform is performed for retargeted image. The bit stream is then transmitted in seam energy map. At the decoder side the ultimate choice for the spatial scalability without the need to examine the visual content; an image with arbitrary aspect ratio can be reconstructed and achieving high coding efficiency for transmission.**

Keywords: Seam carving, Energy map, Integer wavelet transform, Reconstruction.

I. INTRODUCTION

Image compression based on adaptive wavelet decomposition is presented. Image compression is done to reduce irrelevant and redundancy of the image data in order to be able to store or transmit in an efficient form. Wavelet transform is a representation of square integrable (real or complex) valued function by a certain orthonormal series generated by wavelet. It is the most popular candidate of time frequency transformation. Seam carving also known as image retargeting, is an algorithm for image resizing by removing number of seams to reduce image, automatically or manually. The SPIHT algorithm used for image compression is algorithm that exploits the inherent similarities across the sub-band in wavelet decomposition of an image. EZW is one of the SPIHT algorithm used here.

II. ENCODING TECHNIQUES

EZW Encoding

When searching through wavelet literature for image compression schemes it is almost impossible not to note Shapiro's Embedded Zero-tree Wavelet encoder or EZW encoder for short. An EZW encoder is an encoder specially designed to use with wavelet transforms, which explains why it has the word wavelet in its name. The EZW encoder was originally designed to operate on images (2D-signals) but it can also be used on other dimensional signals. By considering the transformed

Dimensional signals. By considering the transformed coefficients as a tree with the lowest frequency coefficients at the root node and with the children of each tree node being the spatially related coefficients in the next higher frequency sub-band, there is a high probability that one or more sub-trees will consist entirely of coefficients which are zero or nearly zero, sub-trees are called zero-trees. It exploits the zero-tree based on the observation that wavelet coefficient decrease with scale. Of course the zero-tree rule will be violated often, but as it turns out in practice, the probability is still very high in general.

Algorithm

If we assume that always the same wavelet transform will be used. Additionally we can send the image dimensions and the image mean. Sending the image mean is useful if we remove it from the image before coding. The first step in the EZW coding algorithm is to determine the initial threshold. If we adopt coding our initial threshold t0 will be

$$t0 = 2[\log 2 (\text{Max}(|\gamma(x, y)|))]$$

Here MAX (.) means the maximum coefficient value in the image and (x,y) denote the coefficient.

PROPOSED SYSTEM

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.

BLOCK DIAGRAM

The step by step process of this is based on image compression and reconstruction is given in a form of block diagram as shown in fig. 1. This explains about the input image is seam carved using integer wavelet transform at

encoded side in which the bit streams are inverse IWT is applied at decoder side. Hence the image is retrieved and reconstructed with high performance.
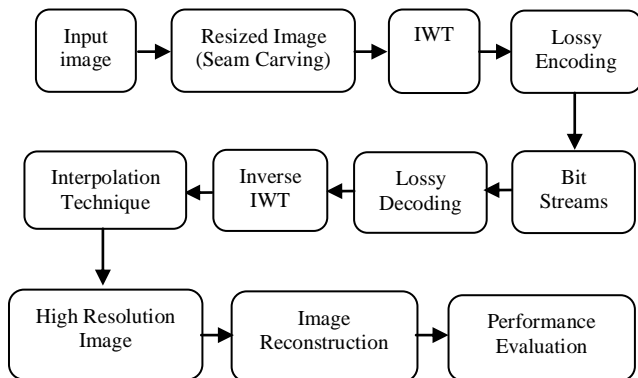

Fig. 1 Block Diagram of proposed system

Algorithm

STEP1: Calculating a seam for removal or insertion and calculating gradient image for original image.

STEP2: calculate for each RGB or HSV images and calculate the gradient image.

STEP 3: Once the gradient image is calculated the next is to calculate the energy map image.

STEP 4: Calculate the horizontal and vertical seam case in the energy map.

STEP 5: Once the energy map is calculated next to find the optimal seam and to find the minimum value in the last row (I,j) pixel.

STEP 6: After the optimal seam is found the path of pixels that make up the seam are removed from both the gradient image and the original RGB image and remaining pixels are shifted right or up.

STEP 7: The process is repeated to remove a set of seams, horizontally or vertically and will result in an image with reduced dimensions.

STEP 8: If the desired image size is to be increased by N pixels in a given direction, the computation of the first N seems to be removed along that direction must be first completed. This method of calculating N seams is used to avoid inserting pixels along the same seam repeatedly.

III. WAVELET TRANSFORM

2-D WAVELET TRANSFORMS

The 1-D DWT can be extended to 2-D transform using separable filters. With separable filters, applying a 1-D transform to all the rows of the input and then repeating on all of the columns can compute the 2-D transform. When one-level 2-D DWT is applied to an image, four transform coefficient sets are created. As depicted in fig. 2 the four sets are LL, HL, LH, HH, where the first letter corresponds to

applying either a low pass or high pass filter to the rows, and the second letter refers to the filter applied to the columns.
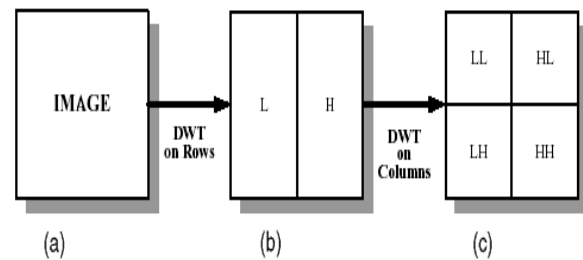

Fig. 2 Block Diagram of DWT (a) Original Image (b) Output image after the 1-D applied on Row input (c) output image after the second 1-D applied on row input.
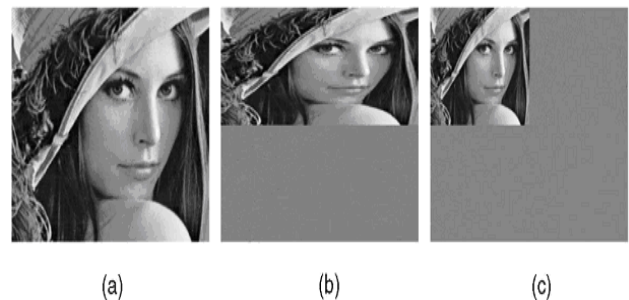

Fig. 3 DWT for Lena image (a) Original Image (b) Output image after the 1-D applied on column input (c) Output image after the second 1-D applied on row input

The Two-Dimensional DWT (2D-DWT) converts images from spatial domain to frequency domain. At each level of the wavelet decomposition, each column of an image is first transformed using a 1D vertical analysis filter-bank. The same filter bank is then applied horizontally to each row of the filtered and sub sampled data. One-level of wavelet decomposition produces four filtered and sub sampled data. One-level of wavelet decomposition produces four filtered and sub sampled images, referred to as sub bands. The upper and lower areas of Fig.3b, respectively, represent the low pass and high pass coefficients after vertical 1D-DWT and sub sampling. The result of the horizontal 1D-DWT and sub sampling to form a 2D-DWT output image is shown in fig.3c.

Specifically, the LL sub band in fig.2c can be transformed again to form LL2, HL2, LH2, and HH2 sub bands producing a two-level wavelet transform. An alternative implementation of the 1D-DWT, known as the lifting scheme, provides significant reduction in the memory and the computation complexity. Nevertheless, the lifting approach computes the same coefficients as the direct filter-bank convolution.

2-D TRANSFORM HEIRARCHY

The 1-D wavelet transform can be extended to a two-dimensional (2-D) wavelet transform using separable wavelet filters. With separable filters the 2-D transform can be

computed by applying a 1-D transform to all the rows of the input, and then repeating on all of the columns.

LL1	HL1
LH1	HH1

Fig. 4 Sub-band Labeling Scheme for a one level, 2-D Wavelet Transform

The original image of a one-level (K=1), 2-D wavelet transform, with corresponding notation is shown in fig.4. In all of the discussion K represents the highest level of the decomposition of the wavelet transform.

LL$_1$	HL$_1$	HL$_2$	HL$_3$
LH$_1$	HH$_1$		
LH$_2$		HH$_2$	
LH$_3$			HH$_3$

Fig. 5 Sub-band labeling Scheme for a Three Level, 2-D Wavelet Transform

The 2-D sub-band decomposition is just an extension of 1-D sub-band decomposition. The entire process is carried out by executing 1-D sub-band decomposition twice, first in one direction (horizontal), then in the orthogonal (vertical) direction. For example, the low-pass sub-bands (L1) resulting from the horizontal direction is further decomposed in the vertical direction, leading to LL1 and LH1 sub-bands. Similarly, the high pass sub-bands (H1) is further decomposed into HL1 and HH1.Since they represent the horizontal, vertical and diagonal residual information of the original image. To obtain a 2-DWT, the 1-D transform is applied first along the rows and then along the columns to produce four sub-bands. The final configuration contains a small low-resolution sub-band. In addition to various transform levels, the phrase level 0 is used to refer to the original image data.

WAVELET COMPUTATION

In order to obtain an efficient wavelet computation, it is important to eliminate as many unnecessary computations as possible. A careful examination of the forward and reverse transforms shows that about half the operations either lead to data which are destroyed or are null operations (as in multiplication by 0).
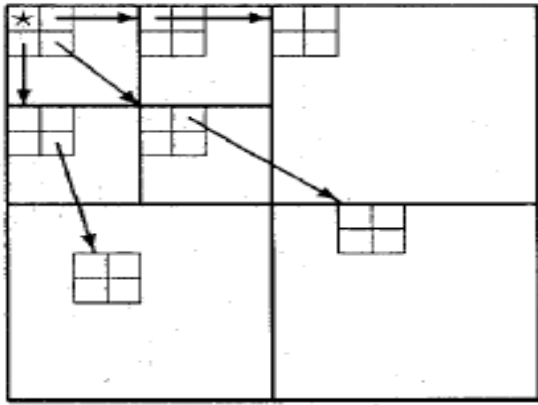
The 1-DWT is computed by separately applying two analysis filters at alternating even and odd locations. The inverse process first doubles the length of each signal by inserting zeros in every other position, then applies the appropriate synthesis filter to each signal and adds the filtered signals to get the final reverse transform.

SPIHT CODING

The SPIHT coder is a powerful image compression algorithm that produces an embedded bit stream from which the best reconstructed images in the mean square error sense can be extracted at various bit rates. The perceptual image quality, however, is not guaranteed to be optimal since the coder is not designed to explicitly consider the human visual system (HVS) characteristics. Extensive HVS research has shown that there are three perceptually significant activity sensitivity of the HVS to these regions in image compression schemes such as SPIHT, the perceptual quality of the images can be improved at all bit rates. The differing activity regions are used to assign perceptual weights to the transform coefficients prior to SPIHT encoding.

The progressive transmission method outlined above can be implemented with the following algorithm to be use by the encoder:

Algorithm I

Output $n = \left\lfloor \log_2 (\max_{(i,j)} \{ |c_{i,j}| \}) \right\rfloor$ to the decoder.

Output μ_n, followed by the pixel coordinates $\eta(k)$ and sign of each of the μ_n coefficients such that $2^n \leq |c_{i,j}| < 2^{n+1}$ (sorting pass).

Output the nth most significant bit of all the coefficients with $|c_{i,j}| \geq 2^{n+1}$ (i.e., those that had their coordinates transmitted in previous sorting passes), in the same order used to send the coordinates.

Decrement n by one, and go to Step 2).

SPATIAL ORIENTATION TREES

Spatial orientation tree naturally defines the spatial relationship on the hierarchical pyramid. Spatial orientation tree is defined in a pyramid constructed with recursive four sub-band splitting. Each node of the tree corresponds to a pixel and is identified by the pixel coordinate. The tree is defined in a such a way that each node has either no offspring or four offspring, which always form a group of 2 x 2 adjacent pixels. In the fig.6 the arrows are oriented from the parent node to its four offspring.

Fig. 6 Examples of parent-offspring dependencies in the Spatial-orientation tree

Fig. 7 Original Image

Fig. 8 Gradient Image

Fig. 9 Energy Map With Vertical Seam

Fig. 10 Energy Map With Horizontal Seam

IV. RESULTS AND DISCUSSION

The quality of the reconstructed image is measured in terms of mean square error (MSE) and peak signal to noise ratio (PSNR) ratio. The MSE is often called reconstruction error variance $\sigma q2$. The MSE between the original image f and the reconstructed image g at decoder is defined as:

$$MSE = \sigma q2 = \frac{1}{N} \sum_{j,k} (f[j,k] - g[j,k])^2$$

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.

The compression ratio of the image is given by:

$$CR = \frac{\text{No of bits in original image}}{\text{No of bits in compressed image}}$$

V. PERFORMANCE EVALUATION

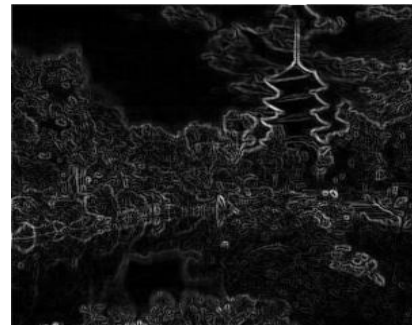The performance evaluation result of the images are shown below.
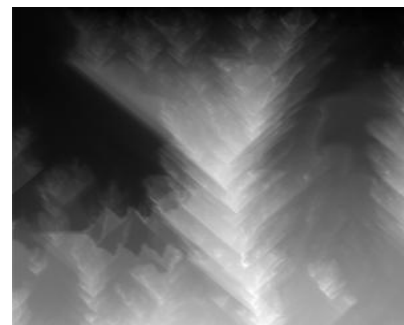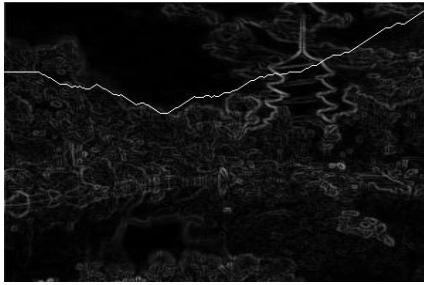
Fig. 11 Seams In Original Image

Fig. 12 Seams With RGB

Fig. 13 Retargeted Image

Fig. 14 Wavelet Decomposition

Fig 15 Reconstructed images
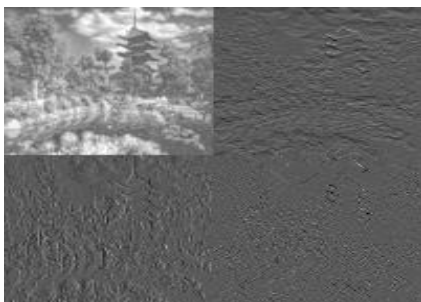
VI. CONCLUSION

This paper presented to provide solution for increasing the compression ratio with various quantization levels and reduce the processing time based on seam carving techniques followed by integer wavelet transform and ser partitioning in hierarchical trees 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 paper, performance will be analyzed through determining the image quality after decompression, compression ratio and execution time.

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