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Retargeted Image Compression Using Wavelet Codec

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Abstract– In recent years, the development and demand of multimedia product grows progressively fast, contributing to inadequate bandwidth of network and memory storage for device. Therefore, the term called compression becomes more and more significant. There are many image compression methods which compress the image as a whole and not considering the device storage and resources. Therefore, content aware image compression with low computational complexity is a bottleneck problem in the field of facility limited multimedia devices. The image coding method which already exists cannot support content-based high compression. In this paper, the image resizing technique, seam carving is combined with SPIHT. Block-based seam is generated on each input image and then carved out, which results a retargeted image, but the resultant output does not have good picture quality. To improve the picture quality of the image a simple linear resize operation is done. Then a multilevel discrete wavelet transform (DWT) is performed on the improved retargeted output. Then SPIHT coding technique is applied, which results in a series of bit stream. There is an ultimate choice for the end user at the decoder side for spatial scalability without the need to examine the visual content. As a result, an image can be recreated with arbitrary aspect ratio in a content-aware manner, with the help of the side information of seam energy map.

Keywords-Seam Carving, Discrete Wavelet Transform (DWT), Set Partitioning in Hierarchical Tree (SPIHT), Image Compression.

I. INTRODUCTION

There are various display devices like mobile phone, PDA's, laptop, etc. Each and every display devices varies with its arbitrary ratio. So that the size of the image also varies, as the results quality of the image becomes poor. The ultimate aim is to preserve the quality of the image from one display device to another. One solution to this problem is to resize and compress the content aware information.

The main goal of such system is to reduce the storage quantity as much as possible.The reduction in image size allows more images to be stored in a given amount of disk or memory space. It also reduces the time required for images to be sent over the Internet or downloaded from Web pages. Compression is achieved by the removal of one or more of the three basic data redundancies

1. Coding Redundancy
2. Inter pixel Redundancy
3. Psycho visual Redundancy

Coding redundancy is present when less than optimal code words are used. Inter pixel redundancy results from correlations between the pixels of an image. Psycho visual redundancy is due to data that is ignored by the human visual system (i.e. visually non essential information). Image compression techniques reduce the number of bits required to represent an image by taking advantage of these redundancies.

An inverse process called decompression (decoding) is applied to the compressed data to get the reconstructed image. The objective of compression is to reduce the number of bits as much as possible, while keeping the resolution and the visual quality of the reconstructed image as close to the original image.

In this paper, based on Region of Interest (ROI) concept image is resized with the technique called seam carving. The process of seam carving is done by generating a block based seam path which is a connected path of low energy pixel value and after the seam path is found it will be carved out from that corresponding image.

The seam carved image is given to the multilevel discrete wavelet transform (DWT). Then wavelet coefficients are incorporated with a wavelet codec called SPIHT. Their compression efficiency for e.g. on image compression is widely acknowledged. The already used JPEG2000 standard will be based on wavelet transforms too. The well known algorithm of Pearlman Set Partitioning In Hierarchical Trees (SPIHT) is to restrict the necessity of random access to the whole image to a small sub images only.

The main idea is based on partitioning of sets, which consists of coefficients or representatives of whole sub trees. The decoder duplicates the execution path of the encoder to ensure this behavior; the coder sends the result of a binary decision to the decoder before a branch is taken in the algorithm. Thus, all decisions of the decoder are based on the received bits. The name of the algorithm is composed of the words set and partitioning.

The compression performance is measured with peak signal to noise ratio and Mean Square Error (MSE) and the Peak Signal to Noise Ratio (PSNR), which are defined as below,

$$\text{PSNR}= 20 \log_{10} \frac{255}{MSE} \quad (1)$$

$$\text{MSE}=\sqrt{\frac{\sum_{x=0}^{W-1} \sum_{y=0}^{H-1}[f(x,y)-f'(x,y)]^2}{WH}} \quad (2)$$

The compression ratio is defined as follows:

$$\text{Cr} = \frac{n1}{n2} \quad (3)$$

II. GENERAL DESCRIPITION

A. *Seam Carving*

Nowadays with the increasing number of display devices, web contents can be displayed with various sizes for different devices. This imposes new demands on digital media which require designers to create different alternatives and design different layouts for these devices. Therefore, there is great need for displaying images on various media like cell phones or PDAs without distortion.

Normal scaling does not work very well because content of the image have been distorted, which makes the image less visually pleasing. Cropping also has certain drawbacks since some of the important image contents could have been discarded. Hence, it is necessary to develop a more effective resizing approach which considers the image contents instead of geometric constraints. Seam Carving is the technique which satisfies the content-aware image resizing. The essence of seam carving is to find the optimal seam that is least content-aware in the image.

For image of size $n \times m$, a vertical seam is defined as a set of pixels of the form

$$\{(i, (s(i))\}_{i=1}^{n} \quad (4)$$

Where S is a mapping S: [1, … , n] → [1, … , m], such that *S*□*i*□□□□*S*□*i* □1□□□1 for all *i*, i.e. all the pixels along the path are 8-connected. Similarly, horizontal seam is defined as the set

$$\{(\, s(i), (i))\}_{i=1}^{m} \quad (5)$$

Such that *S* □*i*□□□□*S* □*i* □1□□□1 for all *i*. The process on vertical seams and horizontal Seams are similar, hence to avoid redundancy, the following parts will mainly focus on vertical seams.

To find a continuous path across the image that can go through areas of image that are less content-aware and avoid major content of the image, it is necessary to search for seams with minimal energy. The basic energy function commonly used for an image is defined as the total gradient of the image:

$$e_1(\text{I}) = \left|\frac{\partial}{\partial x}\,\text{I}\right| + \left|\frac{\partial}{\partial \text{y}}\,\text{I}\right| \quad (6)$$

which can be approximated for each pixel (i,j) by

e□*i*, *j* □□□|*x*□*i* □1, *j* □□□□*x*□*i*, *j* □|□□□|*x*□*i*, *j* □1□□□*x*□*i*, *j* □|□□ □□□□□□□□□□□□ (7)

There are several possible image importance measures, such as entropy, segmentation, Histogram of Gradients (HoG), or other norms of total gradient. For this project, $e1$ is used as the energy function. $e(i,j)$ is also known as the cost of a single pixel at (i,j), hence the cost of a seam is defined as

$$\textstyle\sum_k e(k, S(k)) \qquad \text{for vertical seam} \quad (8)$$

$$\textstyle\sum_k e(S(k), k) \qquad \text{for horizontal seam} \quad (9)$$

Therefore, given an energy function e, the optimal seam is the one that minimizes the cost of the seam. The optimal seam can be found using dynamic programming. Given e and a direction, say vertical, the cumulative minimum energy M can be defined as,

$$M(i,j) = \; min_{S(i)=j} \textstyle\sum_{k=i}^{end} e\left(k, S(k)\right) \quad (10)$$

which is the minimum cost of the vertical seam starting from pixel (i,j) and going down to the bottom of the image. Thus the minimum entry of the first row of M indicates the final pixel of the optimal seam.

In order to find the whole optimal seam, dynamic programming algorithm can be used. This method is depending upon the information of seam energy map and the center pixel value of the image which is taken. The algorithm for the dynamic program is shown as steps in below:

1. The last row of M is equal to the last row of e, i.e.
   M □*n*, *j* □□□□*e* (*n*, *j*)
2. For $1 \le i \le n - 1$ and $1 \le j \le m$,
   M □*i*, *j* □□□□*e* □*i*, *j* □□+ min {*M* (*i* +1, *j* □1□, *M* (*i* □1, *j*), *M* (*i*□1, *j*□1)}
3. For pixels at edges of the image, the above equation is replaced with
   M (*i*,1)□=□*e*(*i*,1)□+□min {*M* (*i* +1,1),*M* (*i* +1,2)}□□

Or

$M(i,1) = e(i,1) + \min\{M(i+1, j), M(i+1,1), M(i+1,2)\}$

Once the optimal seam is found, the image can either be shrink without distorting the major content of image.

B. Set Partitioning In Hierarchical Tree

SPIHT was designed for optimal progressive transmission, as well as for compression. One of the important features of SPIHT (perhaps a unique feature) is that at any point during the decoding of an image, the quality of the displayed image is the best that can be achieved for the number of bits input by the decoder up to that moment. Another important SPIHT feature is its use of embedded coding.

It is important to have the encoder and decoder test sets for significance in the same way, so the coding algorithm uses three lists called *list of significant pixels* (LSP), *list of insignificant pixels* (LIP), and *list of insignificant sets* (LIS). These are lists of coordinates (i, j) that in the LIP and LSP represent individual coefficients, and in the LIS represent either the set $D(i, j)$ (a type A entry) or the set $L(i, j)$ (a type B entry).

1. SPIHT Coding Algorithm

The algorithm for SPIHT is shown in below:

a. Initialization: Set n to $\lfloor \log_2 max_{(i,j)} c(i,j) \rfloor$ and transmit n. Set the LSP to empty. Set the LIP to the coordinates of all the roots $(i,j) \in H$. Set the LIS to the coordinates of all the roots $(i,j) \in H$ that have descendants.

b. Sorting pass:
   - b.1 for each entry (i,j) in the LIP do:
     - b.1.1 output $S_n(i,j)$;
     - b.1.2 if $S_n(i,j) = 1$, move (i,j) to the LSP and output the sign of $c_{i,j}$;
   - b.2 for each entry (i,j) in the LIS do:
     - b.2.1 if the entry is of type A, then
       - output $S_n(D(i,j))$;
       - if $S_n(D(i,j)) = 1$, then
         - for each $(k, l) \in O(i,j)$ do:
           - · output $S_n(k,l)$;
           - · if $S_n(k,l) = 1$, add (k, l) to the LSP, output the sign of $c_{k,l}$;
           - · if $S_n(k,l) = 0$, append (k, l) to the LIP;
       - if $L(i,j) \neq 0$, move (i,j) to the end of the LIS, as a type-B entry, and go to step b.2.2; else, remove entry (i,j) from the LIS;
     - b.2.2 if the entry is of type B, then
       - output $S_n(L(i,j))$;
       - if $S_n(L(i,j)) = 1$, then
         - ·append each $(k, l) \in O(i,j)$ to the LIS as a type-A entry:
         - ·remove (i,j) from the LIS:

c. Refinement pass: for each entry (i,j) in the LSP, except those included in the last sorting pass (the one with the same n), output the nth most significant bit of $|c_{i,j}|$;

d. Loop: decrement n by 1 and go to step b if needed

III. METHODOLOGY

In order to obtain an efficient compression of an image with less computational complexity, the retargeting technique with an effective compression technique, like SPIHT is required. There are mainly two parts; one is the image resizing part and another one is compression part. For the resizing part, a color image is taken as input and energy of the image is calculated. From this method, ROI and non-ROI region can be known. With the help of the energy map function and by using dynamic programming technique the path to connect low energy pixels are detected. These processes are applicable for both horizontal and vertical manner. After the seam path is found in both horizontal and vertical manner, it will be carved out and rejoined in the image. This process will continue until the required arbitrary resolution is obtained. As the result of these processes image quality is not good. To improve the picture quality, from the beginning point, a simple linear resizing operation has to be performed. If the original size of image is 500×500 and it is targeted to the size 200×200, it has to be first resized to 300×300. This is because the image fills the entire width and the heights. Then use the seam carving to retarget the image.

As for the second part, on compression side, the retargeted image is given as input to Discrete Wavelet Transform (DWT) for wavelet decomposition and the resulted wavelet coefficients are given as input for the SPIHT encoding process. SPIHT codec gives a series of bit streams. At the decoder side, with the help of the seam energy map side information image and inverse discrete wavelet transform (IDWT) content, image can be reconstructed with less computational complexity. The block diagram of our proposed system is shown in Figure 1 below.

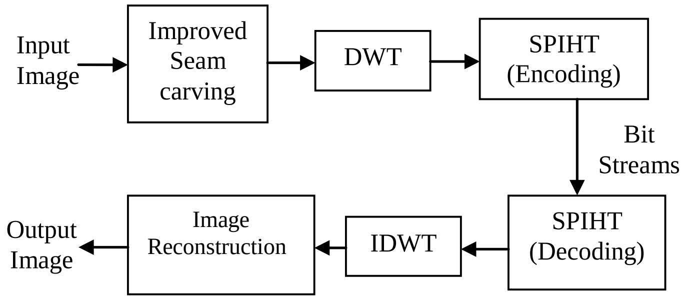


Figure 1. Block diagram of our proposed method.

IV. RESULTS AND DISCUSSIONS

The results of experiments conducted to perform content based color image compression and to retarget the image with optimum display size. Experiments conducted in MATLAB 7.10.0 (R2010a). Color image (shown in figure 2) of size 500 ×500 is used as input image for conducting the experiments.

A. Results of Seam Carving

The results of image retargeting seam carving technique are shown below:

Original image has taken with the size of 500 ×500, which is then gradient and energy is calculate for that particular image which gives the side information using seam energy map.

Figure 2. Original Image before resizing of size 500×500.

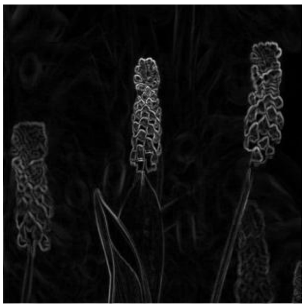


Figure 3.Gradient of Image.

The energy for that image is calculated in both horizontal and vertical direction which is shown in the Figure 4, 5 and 6. The seam path is the connected path of low pixel values, which are generated by the dynamic programming technique. With the content of seam energy map side information and the center pixel with neighboring pixel of value of image are combined to find low pixels. This method of finding seam path will be repeated in both horizontal and vertical manner. The seam path on energy, gradient, and RGB original image is detected which is shown in the following Figure 6, 7, 8.

Figure 4. Vertical Energy Map.

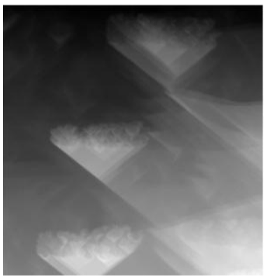


Figure 5. Horizontal Energy Map.

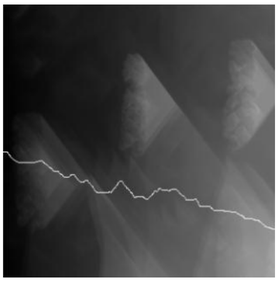
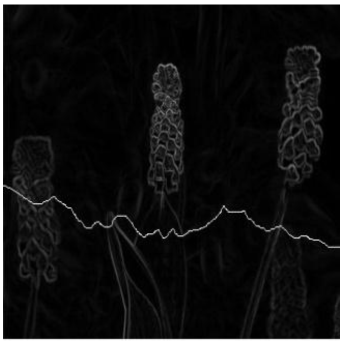


Figure 6. Seam path on Energy image



. Figure 7. Seam path on Gradient image.

Figure 8. Seam path on RGB image.

After the gradient and energy seam path is generated on the image, it will be removed from that image and then all the pixels of the image are shifted left (or up) to compensate for the missing path. The visual impact is noticeable only along the path of the seam, leaving the rest of the image intact. Without resizing the retargeted image will be looks like Figure 9.

Figure 9. 500×500 image retargeted to size of 200×200.

Figure 10. 300×300 image retargeted to size of 200×200.

From above Figure 9, the quality of image is not good it is visually not so clear in order to obtain a good visual quality a resizing technique is applied which provides thre following output which is shown in the Figure 10. From both Figure 9 the gap between each bunch of flower is reduced which differs from original information to preserve the quality and resize the image using seam carving a simplified resizing technique is used that image is shown in the above Figure 10.

(a) (b) (c)

Figure 11: Comparing aspect ratio change. From left to right: (a) Original image of size 500×500; (b) Seam carved image of size 200×200 before applying resizing operation; (c) our proposed method to seam carve the image of size 200×00.

B. Result of DWT-SPIHT codec

For the compression part the improved retargeted image is given as input to the wavelet decomposition which results in sub images shown in figure 11. Wavelet coefficients are encoded and then decoded using a wavelet codec method called SPIHT. With the help of seam energy map side information and inverse DWT coefficient values image can be reconstructed with the required arbitrary ratio without any information loss. At the receiver side images reconstructed at the receiver with resolution 200 ×200 which is shown in Figure 13.

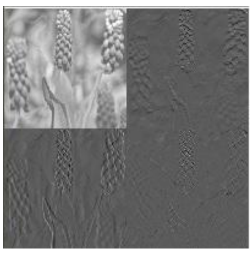


Figure 11. Wavelet Decomposition.

Figure 12. Inverse Wavelet Transform.

Figure 13. Reconstructed image.

The peak signal-to-noise ratio (PSNR) is commonly used as a measure of the quality of the reconstructed image. From the acquired PSNR, the necessary MSE value can be found out. At lower bit rates, the PSNR is almost identical for the original and modified versions but at higher bit rates, the PSNR is higher for the modified algorithm than the original one.The performance of MSE, PSNR and Compression ratio (CR) are evaluated in Figure 14, Figure 15, Figure 16.

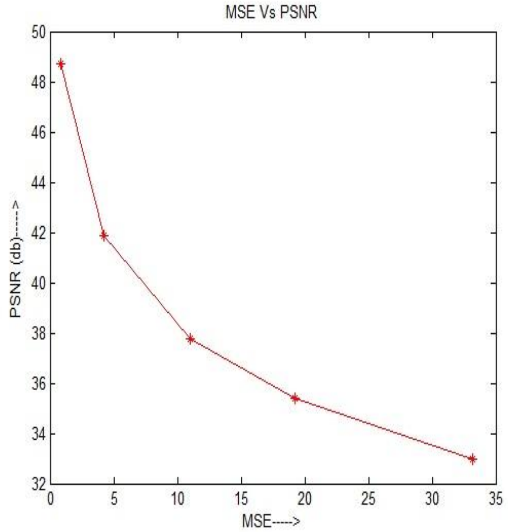


Figure 14. Mean Square Error (MSE) Vs

Peak Signal to Noise Ratio (PSNR).

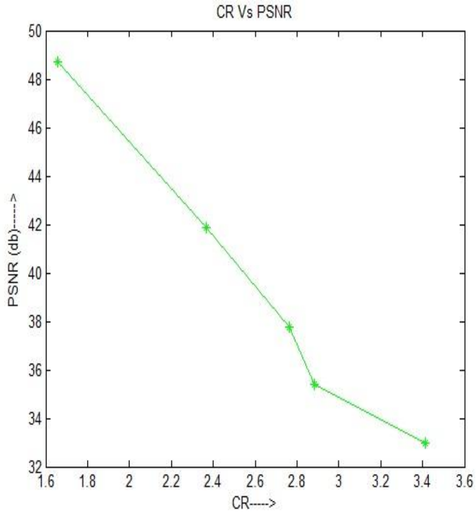


Figure 15. Compression Ratio (CR) Vs

Peak Signal to Noise Ratio (PSNR).

Mean Square Error.

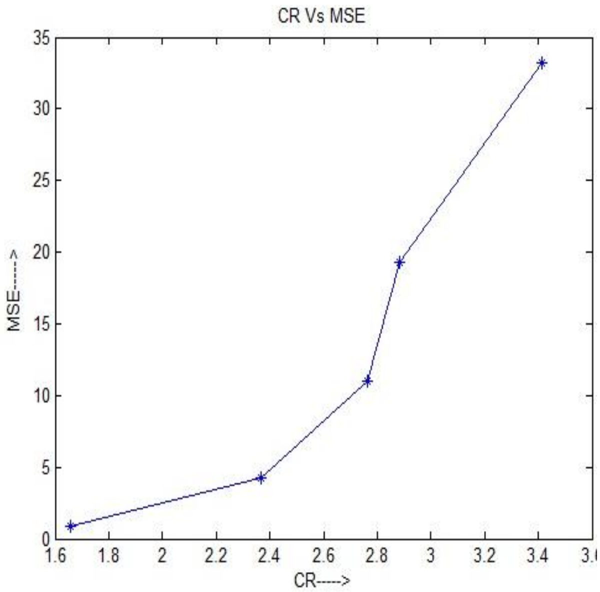


Figure 16. Compression Ratio Vs

In the Figure 16, Mean Square Error (MSE) decreases with respect to increase in PSNR (db), MSE is inversely proportional to PSNR. Similarly in Figure 17 Compression ratio (CR) increase with respect to the PSNR (db) decreases, when compression ratio increases picture quality will be decreased. In Figure 18 Compression ratio increases with respect to the Mean Square Error (MSE) increases. Compression Ratio (CR) is defined is ratio of size of the input image to size of the output image. Compression Ratio is also called bpb (bit per bit), since it equals the number of bits in the compressed stream needed, on average to compress one bit in the input stream.

The compression performance is measured with peak signal to noise ratio and Mean Square Error (MSE) and the Peak Signal to Noise Ratio (PSNR) which are tabulated as follows:

TABLE I- PARAMETERS AND VALUES

Parameter	Value
Encode Time	4.6528
Decode Time	2.0529
Compression Ratio	1.6571
Mean Square Error	0.8781
Peak Signal to Noise Ratio	48.69

V. SUMMARY AND CONCLUSION

In this paper, the concept of Seam carving and the improvement which is done by using a simplified linear resizing operation is discussed and also the combination of improved seam carving and wavelet codec is can be combined together to provide better compression results for mobile multimedia devices. The performances of these combined techniques are measured by Peak Signal to Noise Ratio (PSNR) which results 48.69 dB. This method is computationally less complex and also allows the user to retarget the images with appropriate resolution.

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