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A Performance Analysis for Seam Carving Algorithm

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***Abstract*— Seam carving, which sometimes referred to as content aware resizing is one of the successful methods for resizing the images with small deteriorations in image quality. This approach eliminates most of the disadvantages of resizing operation and provides better visual quality. Apart from the size of the image to be processed, the performance of the seam carving algorithm is highly dependent on the number of seams and the image content. In this paper, we presented a detailed performance analysis for seam carving algorithm. The experiments are realized according to image type, image size and the number of seams. According to comparative results, in addition to the image size, the number of seam and image content is one of the factors that affect the performance of the algorithm.**

Keywords-seam carving; content-aware image resizing; performance evaluation

I. INTRODUCTION

Transforming images to their new sizes is a basic and a useful tool for many image processing operations. Saving image content and important foreground objects inside an image while resizing it, is one of the most popular research topics in image processing subject. Traditional resizing operations such as cropping and scaling are not satisfactory since they cause data losses (cropping) and visible distortions (scaling) in image content. Therefore, researchers started to search for content-aware resizing methods recently. Avidan and Shamir proposed an impressing approach for this purpose [1]. Their suggestion is to remove the least important pixel paths one by one to reduce image size or similarly to add new pixel paths which are placed in between two less important pixel paths. This approach eliminates most of the disadvantages of resizing operation and provides better visual quality.

With the proliferation of digital image devices, resizing images, especially content-aware resizing, is used more in smart phones, monitors, and HTML in which images are need to be resized dynamically. Images can be enlarged/straighten to different sizes via scaling and even weight and height can be processed with different rates. But since this scaling operation is realized equally on every object of the image and since this will damage or will not reflect image content, it is not a good method. On the other hand, seam carving only adds/removes seam(s) which includes less information for enlarging/shrinking. Therefore, a content-aware resizing of images is performed.

"A seam is an optimal 8-connected path of pixels on a single image from top to bottom, or left to right, where optimality is defined by an image energy function" [1]. Main idea of seam carving is to add seams to the image for enlarging or to remove seams from image for lessening. As a result, this method removes the most negligible pixels and preserves fundamental features of the image.

Since there are some calculations during resizing in seam carving, operation speed is slower when compared with other resizing methods. Clipping is the fastest method in image resizing because pixels which are in the outside of clipping window are directly thrown and no calculation is performed to end the operation. As for scaling, it is necessary to add intermediate pixels whose values are average of neighbor pixels (for enlarging) or combine/remove some pixels to reduce image size. Seam carving is much more complex than those traditional resizing methods because it is required to constitute an energy map and this can be very time consuming depending on the energy function used. After the optimal seam is removed, the optimal seam and shift pixels are determined. The performance even may change by some parameters inside this algorithm. Some applications of seam carving and some performance enhancement efforts appear in the literature are given below.

An enhancement is done for some deterioration caused by seam carving method in [2]. Proposed approach uses an extra energy function except the one in seam carving. Once a seam is found secondary energy map is checked on that seam and if the threshold value is exceeded at any point, then this seam cannot be removed and marked as irremovable. The process goes until the target size is obtained or the stopping criterion is satisfied. The minimum size that an image can be transformed without any distortion is obtained in the mentioned paper, but there may be some distortions if the image is expected to be lessened to a size less than the found minimum size.

Unlike many of the content-aware image resizing method, [3] provides a method based on supervised learning. Seam carving method is applied after important borders of the content are determined. Therefore, the number of seams that may pass over the important objects of image content is reduced. This provides a better protection of the image content when compared to classical seam carving method. New border model for related region of interest (ROI) is learned over the images in the training set. Next, these borders of the input image are used as a key while seam carving is applied for obtaining target output image.

In reference [4] an approach is given to extract text lines in gray-scaled or binary images without dependence to the language. Energy map is established by signed distance transform on binary images and by gray distance transform on gray-scaled images. Medial seams and separating seams are computed for each text line. Medial seams pass over supposed texts and separating seams determine bottom and top borders of the text line and this determines the local borders of the seam map. So, seam map and discrete transforms are calculated again just for related part of the image and the operation cost is minimized.

More than one image resizing operator is used to preserve image structure and important objects in [5]. Unlike multi-operator former methods which give shrinkage and stretching effects on the images, content-aware resizing is evaluated both horizontally and vertically in the proposed method. Shrinkage/stretching effect is tried to be reduced by combining this multi-operator structure with seam carving. The cost of deciding to change the operator is reduced by applying a new image pattern measure. In addition, an enhancement to seam carving method about improving the preservation of general structure is proposed. Vertical and horizontal seam carving is combined and a better preservation of important objects is provided.

Another study on improving the effectiveness of seam carving method is given in [6]. While classical seam carving method removes seams one by one, seams can be removed as a group in the proposed approach. Greater filters are used for this purpose. Required iteration number to achieve the goal size is significantly minimized. Also, the distortions on seam edges are reduced thanks to the filters used. Although it is not realistic, this approach assumes that the selected seams are the optimal ones.

An importance diffusion scheme based approach is proposed in [7]. The effects of the removed pixels are disseminated to their neighbors to save the visual context and to prevent from shrinkage formed on unimportant parts. Basic row/column extraction and seam carving methods are applied to reveal visually nice results.

Gradient based methods usually cause visual distortions on the blended scenes having complex backgrounds. To avoid this, [8] uses a method which emphasizes the visually salient parts. Importance maps of the images are constituted taking the advantage of advanced statistics. A reasonable content-aware resizing is realized with the proposed mapping.

This paper is organized as follows: The Background for seam carving algorithm is detailed in section II, Detailed experimental results are given in Section III, and the brief conclusions about the results are given in Section IV.

II. BACKGROUND

The most important issue in the method is to find the optimal path. Energy function is used at this point and a seam that has minimum energy value is determined as the optimal seam. Different energy functions can be used to obtain energy map of an image and one of them proposed by the inventors of seam carving [1] is gradient magnitude. Flow chart of seam carving operation when an input image is given for reducing width is as follows:

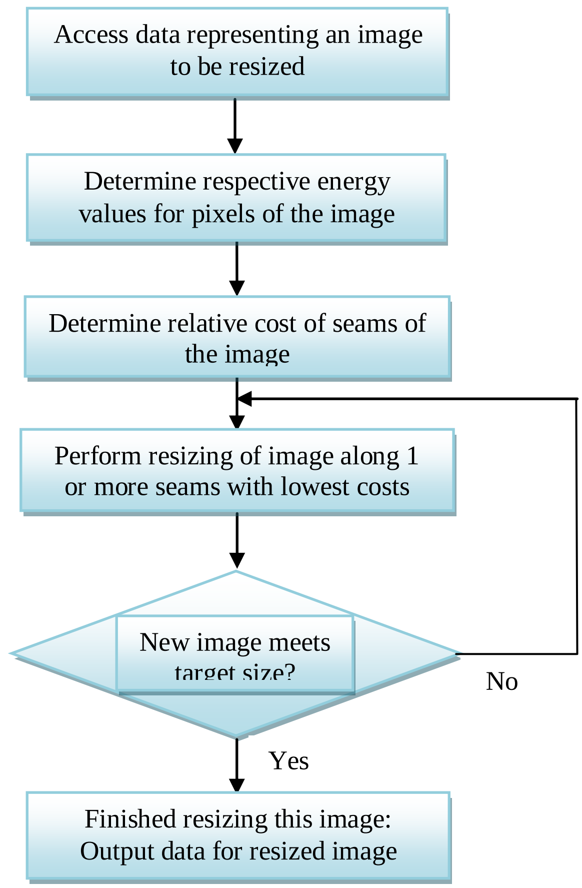

Figure 1. Flow chart to reduce image size[9]

The logic for scaling height is also the same, but seams from left to right are found and the height is decreased by one in each loop. For enlarging (or narrowing) an image, artificial pixels whose values are between its left and right (or top and bottom) neighbors are constituted and added to the image after the optimal seam is found. Stretching effect may occur after this extension operation. To prevent from this effect, for example if the image is supposed to be enlarged by k seam, first k seams that have minimum energy value are selected and artificial seam addition is done for k seams. If both width and height of an image are supposed to be updated, then primarily direction of the operation must be determined. At this stage, the seam in the vertical or horizontal directions must be determined at the beginning. This evaluation is again done based on energy values.

Pixel Costs					Min. Costs			
2	3	5	4		2	3	5	4
6	1	7	8		6+2	1+2	7+3	8+4
2	7	1	2					
10	6	7	8					
2nd Row Iteration					Finished Min. Costs			
2	3	5	4		2	3	5	4
8	3	10	12		8	3	10	12
2+3	7+3	1+3	2+10		5	10	4	12
					15	10	11	12

Figure 2. Forming minimum cost table

Figure 2 shows an example for finding an optimal seam. A minimum cost table in which energy values of each pixel is calculated to find minimum-cost path. To form this table, it is assumed that we are intended to find seams from up to down, top three neighbor pixels of the current pixel are benefited. The least pixel value of those three neighbors is added to current pixel's value and the cost of the corresponding pixel is obtained as that sum. Operation goes as follows:

Minimum seam is determined after the minimum cost table is established. The pixel which has the minimum value at the bottom row of the table will be the bottom pixel of the optimal seam. Then, a pixel which has the minimum value among above three neighbors of that pixel is chosen as a new part of the seam and the pixel selection goes so.

Identify Min.					Backtrack for Seam			
2	3	5	4		2	3	5	4
8	3	10	12		8	3	10	12
5	10	4	12		5	10	4	12
15	10	11	12		15	10	11	12

Figure 3. Determining minimum (optimal) seam

III. Experimental Results

A. Testing Environment

In this analysis we used a PC with Intel Core2 Duo 3GHz CPU. We run the algorithm on Octave which is free and high level software designed especially for numerical calculations [10].

B. Energy Functions

There are four energy functions used to evaluate the performance. Filters applied to obtain energy map are Sobel, Laplacian, Canny, and LoG.

Filters in image processing are mostly used for the extraction of the edges and the definition of an edge is "a line between adjacent regions of distinctly different intensity" [11]. Sobel filter is a derivative mask to detect edges both in horizontal and vertical directions [12]. Its horizontal and vertical convolution kernels are

$$W_{vertical} = \begin{bmatrix} 1 & 0 & -1 \\ 2 & 0 & -2 \\ 1 & 0 & -1 \end{bmatrix}, \quad W_{horizontal} = \begin{bmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix} \qquad (1)$$

The other energy function, Laplacian, Laplacian filter uses second derivative of an image and used to emphasize the areas with high intensity difference. Its kernel is

$$W = \begin{bmatrix} 0 & 1 & 0 \\ 1 & -4 & 1 \\ 0 & 1 & 0 \end{bmatrix} \qquad (2)$$

Laplacian kernel is very sensitive to noise since they approximate a second derivative measurement on the image [12]. To eliminate this deficiency, image is first smoothed with Gaussian operator and then Laplacian filter is applied. Instead of two convolution operation, LoG kernel is calculated first and then this composite kernel is applied to image, i.e. only one convolution is performed. 2D LoG function centered at zero with Gaussian standard deviation σ is

$$LoG_{xy} = -\frac{1}{\pi\sigma^4}\left[1 - \frac{x^2+y^2}{2\sigma^2}\right] e^{-\frac{x^2+y^2}{2\sigma^2}} \qquad (3)$$

Canny filter detects edges in images by using a multi-stage algorithm [12]. Gaussian filter is also applied in this filtering to eliminate noises and non-maximum suppression is applied after intensity gradients of the image are found. Non-maximum suppression is a technique to discard unwanted parasitic points on the edges .

TABLE I. EXECUTION TIMES FOR 512X512 IMAGES

Number of seams	Image1 (sec.)				Image2 (sec.)				Image3 (sec.)			
	Sobel	Laplacian	LoG	Canny	Sobel	Laplacian	LoG	Canny	Sobel	Laplacian	LoG	Canny
10	1.3539	0.68	4.503	8.12	1.31	0.62	4.23	7.99	1.35	0.64	4.4920	7.170
50	6.3136	3.19	18.90	28.94	6.29	3.16	20.02	32.06	6.34	3.08	22.31	32.71
100	12.0455	6.08	35.37	57.79	11.99	6.07	39.28	63.03	11.88	6.05	40.90	59.80
250	25.5079	12.92	79.86	126.34	25.58	12.68	87.51	127.14	25.41	12.88	87.38	130.30

TABLE II. EXECUTION TIMES FOR 768X1024 IMAGES

Number of seams	Image1 (sec.)				Image2 (sec.)				Image3 (sec.)			
	Sobel	Laplacian	LoG	Canny	Sobel	Laplacian	LoG	Canny	Sobel	Laplacian	LoG	Canny
10	3.75	2.20	13.73	19.88	3.72	2.03	12.76	23.27	3.75	1.63	12.52	20.46
50	18.20	9.484	63.71	102.39	18.56	9.46	62.87	103.97	18.10	8.12	62.75	103.59
100	35. 47	18.361	119.04	190.77	36.13	17.95	122.94	197.76	35.19	16.33	128.21	196.74
250	82.14	41.561	277.72	449.40	83.57	41.43	284.85	458.40	82.09	36.96	295.12	456.68

TABLE III. EXECUTION TIMES FOR 1080X1920 IMAGES

Number of seams	Image1 (sec.)				Image2 (sec.)				Image3 (sec.)			
	Sobel	Laplacian	LoG	Canny	Sobel	Laplacian	LoG	Canny	Sobel	Laplacian	LoG	Canny
10	9.72	4.84	31.75	50.70	9.47	5.06	37.27	60.20	9.38	6.18	32.07	50.13
50	47.95	23.68	157.29	259.69	47.32	24.15	170.54	294.23	46.64	27.86	165.17	246.63
100	93.03	46.16	335.54	494.20	93.46	49.26	330.50	576.00	91.05	52.78	358.48	489.93
250	224.64	109.12	808.21	1284.93	224.96	122.51	766.60	1283.34	232.89	121.35	754.00	1179.35

In this study, performance analyses are performed for image width reduction. Seam removal is applied to the images. The logic is the same for height reduction in which the transpose of image matrix is dealt with. For resizing in both directions, the same is done after the order of operation is decided (first width then height or vice versa). The most time consuming computation for processor is to evaluate energy function for each pixel of the image and therefore, the complexity of the algorithm mostly comes from it.

The difference of using different energy functions is shown in Table 1, 2, and 3 clearly. Using Laplacian filter as an energy function gives the best performance in terms of execution time. If the visual quality is considered as a main performance metric, then applying Canny becomes the most suitable filter for content-aware image resizing (see Figure 6).

All the images in Table 2 are in different file formats, i.e. image 1 is a .tif file, image 2 is a .jpg file and image 3 is a .png file. It can be seen from Table 2 and Figure 4 that file type has a negligible effect on seam carving performance.

Figure 5 shows that execution time grows linearly with number of removed seams. The reason of this is straightforward. In order to reduce image width more, this means that after the image is updated, it is necessary to compute the energy map, determine optimal seam, and remove it. There is a loop which will continue until desired image size is reached. Variation of average execution time with number of removed seams in Figure 5 for 512x512, 768x1024, and 1080x1920 RGB images shows that average execution time increases by the increase in image size.

Resizing can be completed in a shorter time period in smaller images. Because greater image size means more energy value calculation to complete energy map and this makes the CPU work harder. Therefore, image size and total execution time is directly proportional with each other.

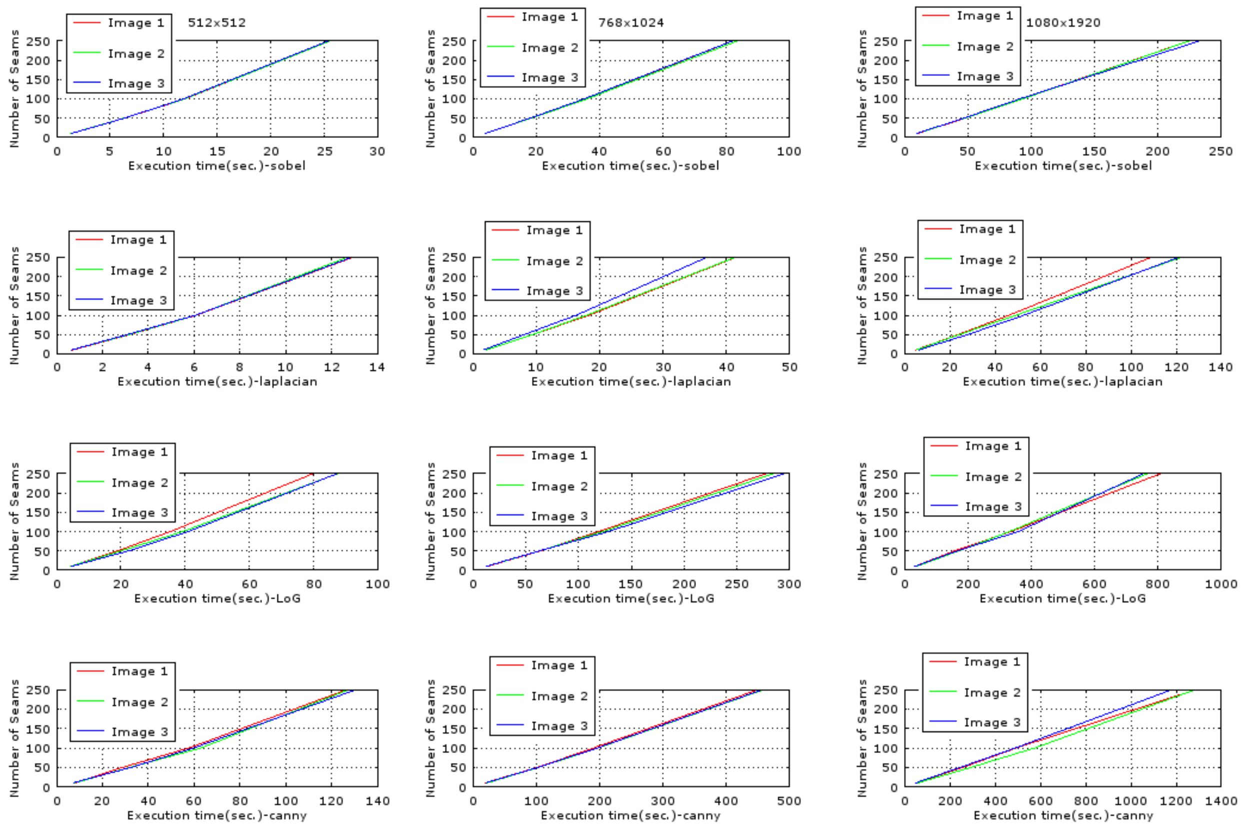

Figure 4. Average execution times vs. removed seam numbers. Colunms of the figure show plots for 512x512, 768x1024, and 1080x1920 images respectively. Rows of the figure shows results for Sobel, Laplacian, LoG, and Canny respectively.

It is trivial to conclude that the most important part in content aware image resizing by seam carving is to decide energy function for the calculation of energy map. Because after the energy map is constituted, operations are the same for every case.

On the other hand, the algorithm is run for the images with different complexity levels. It is shown in Table 1, 2, and 3 that intricacy of the objects in an image has an affect up to 12% to execution time of the algorithm. For example, the execution time of removing 250 seams in Image 1 of Table 3 is 12% faster than Image 2 which is in the same image size with Image 1 but its content is more complex. Content of an image is also directly related to visual result of seam removal/addition, i.e. size reduction/enlargement. Distortions after resizing are more negligible in the images with plain content (see Figure 6).

There are glittering differences in execution times of energy functions as seen in Figure 4. The difference is sometimes more than 12 times. The reason of that much time interval for performing seam carving is the calculation of energy function. Canny applies multiple operations to obtain an edge map instead of applying just a simple kernel convolution. Noises in the image are first removed by Gaussian filter and then unnecessary pixels around edges are ejected. As a result, a clearer edge map is obtained. Since there are more operations in Canny when compared with other energy functions its execution time is higher than the others. In terms of visual quality, although its average execution time is the greatest, Canny provides better visual results after the image is resized as seen in Figure 6.

IV. CONCLUSIONS

In this study, a performance analysis is given experimentally. The effects of image size, energy function, file format, complexity of images, and the number of removed seams to the execution time of seam carving algorithm are shown by running the algorithm for the images with different properties. We can conclude that the selected energy function is the most important criteria for the performance of seam carving. While execution time is proportional to image size,visual complexity of images may also affect seam carving performance up to 12 %. As a future work, the analysis can be extended to the order of seam removal or addition. In addition, the ways of increasing the performance can be searched and efficient energy functions can be extracted. Compliance of the algorithm with parallel programming can also be investigated and different parallel strategies can be considered to accelerate the execution time of the algorithm.

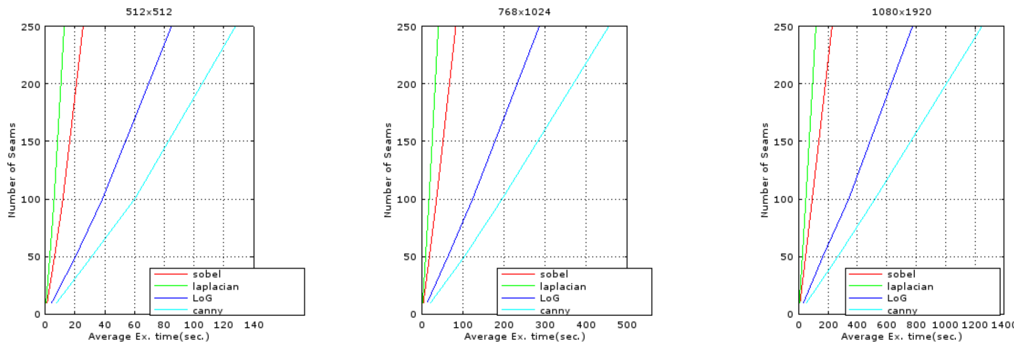

Figure 5. Average execution times vs. removed seam numbers for 512x512, 768x1024, and 1080x1920 based on different energy functions.

Figure 6. Original image on the left and 250 seam removal based on Sobel, Laplacian, LoG, and Canny respectively.

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