IJE TRANSACTIONS B: Applications Vol. 31, No. 5, (May 2018) 684-692

International Journal of Engineering

Journal Homepage: www.ije.ir

Improved Content Aware Image Retargeting Using Strip Partitioning

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PAPER INFO

Paper history:
Received 19 November 2016
Received in revised form 22 January 2018
Accepted 08 Febraury 2018

Keywords:
Seam Carving
Image Resizing
Image Retargeting
Dijkstra Method
Strip Partitioning

ABSTRACT

Based on rapid upsurge in the demand and usage of electronic media devices such as tablets, smart phones, laptops, personal computers, etc. and its different display specifications including the size and shapes, image retargeting became one of the key components of communication technology and internet. The existing techniques in image resizing cannot save the most valuable information of images on display devices with different resolutions. Seam carving is a standard technique for content-aware resizing of images and videos with negligible distortion. However, seam carving resize high-resolution videos and high quality images with high computational complexity; this limits its real-time applications. In this paper, we present a novel approach to reduce seam carving process time. In the proposed technique, the image was split into three equal parts: upper-middle-lower (or right-middle-left) using horizontal or vertical strips. The middle strip was analyzed by original seam carving technique. For other strips (upper-lower), the seam was obtained employing Dijkstra fixed start point technique. In our proposed technique, unlimited Dijkstra depth search was replaced with a limited depth search. It enhances the computational efficiency of Dijkstra technique for the upper and lower strips. The experimental results showed much better computational efficiency than the current enhanced seam carving techniques. These results indicate that computational complexity is superior, while still maintaining the output quality of the original seam carving method.

***doi**: 10.5829/ije.2018.31.05b.01*

1. INTRODUCTION

In this research paper, two limitations are considered. One is removing or adding low energy pixels without considering the real human visual system. This may carve out the regions of interest (ROI) with relatively low energy [1, 2].

Another limitation is in computing cumulative energy and finding minimal seam. In fact, this process is computationally intensive and makes the method unusable in real time applications. In surmounting the first limitation, literature [3] divided the image into several strips. Thereafter, it computes the importance of each strip separately using a saliency value. This saliency value helps to find seam with minimum cumulative energy and visual distortion. Zhiwei He et al. [4] used a hybrid energy function to obtain the importance of each pixel. This energy function combines saliency value with gradient energy. It has been reported in literature [5] that a hybrid energy function in frequency domain depends on the saliency map and gradient energy. Then, the image is partitioned into several strips such that each strip has pixels with similar energy levels. Kumar et al. [6] described a distortion-sensitive energy function for image resizing that enhances edge preservation and decreases aliasing artifacts. In fact, Kumar et al. [6] combined a gradient descriptor with anti-aliasing filter improves quality. It has been defined in literature [7] a weighted energy function based on saliency map and that it enhances retargeting. The main advantage of reported method [7] is reserving more resolution to salient objects even when the aspect ratio is unchanged. Shen et al. [8] employed depth information of kinect sensor as a modern depth camera. In fact, they combined the depth information with gradient energy to ascertain the important objects. The performance of this technique in determining the important objects is superior to original seam carving method. Dahan et al. [9] used depth and

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color information in image retargeting algorithm for layered images to enhance quality after retargeting. Dekkers et al. [10] suggested a new concept as a geometry feature to specify important areas of the image. Luo et al. [11] proposed a novel energy function for seam carving that enhance global structure preservation. Meanwhile, Luo et al. [11] tried to improve the quality by combining multiple image resizing operators. Lin et al. [12] suggested a patch-based retargeting scheme that combines content based image retargeting with an extended feature to maintain salient objects and structure lines of images simultaneously. Zhang et al. [13] used fisheye transformation to resize an image. The fundamental idea of Zhang and his coworkers [13] was emphasis on the salient objects without totally discarding unnoticeable contents. All of the above-mentioned techniques attempted to discover superior unnoticeable pixels than simple seam carving. To obtain better seams, they used extra features that imposed extra computational cost on seam carving. In seam carving, the computation of extra features lengthens the process time. This poses a problem, which is yet to be solved for the entire seam carving based techniques. To solve the time-consuming challenge, some heuristic methods have provided to accelerate these techniques. Lee et al., [14] updated the energy maps around the removed seam after the first iteration. In addition, they removed several seams in each cumulative energy map computation. This technique causes a poor resizing quality compared to the improved seam carving method. Additionally, this technique has some unknown parameters like the number of deleted seams for each cumulative energy map. Due et al., [15] employed gradient value and direction of each pixel to remove several seams in each computation. In this work, the resizing quality is roughly better than the results reported in literature [14]. Kim et al. [5] reported that images are divided into several strips with different levels of importance and each strip is processed independently. Cao et al., [16] split the image into some equal strips. Thereafter, they described the importance of each strip using the saliency value of its pixels. For a specified target size, number of removed seams for each strip is measured in relation to its importance. The low resizing quality and unknown parameters such as the number of strips are the disadvantages of this technique. Wu et al., [3] combined the technique of Cao et al., [16] using correlation and neighboring probability of seams. Finally, the resizing quality obtained was better than the results reported in the literature [16]. Ajorian et al., [17] proposed a technique that removes several seams in each cumulative energy map. The main unsolved problem of all the methods is the issue of the best value for parameters such as number of removed seams at each computation. Chang and Yang [18] proposed a technique that employs graph cut algorithm in video frame instead of dynamic programming. This technique also enhance quality without increasing computations. The graph cut is much simpler than dynamic programming with a speed that is about two times faster, but in single images, the results are poor compared to the original seam carving technique.

In this research, an improved approach was developed to reduce the process time of the seam carving technique. Initially, we divided the image into three equal parts, upper-middle-lower (or right-middle-left) using horizontal or vertical strips. Thereafter, we analyzed the middle strip by original seam carving technique. For the other strips (upper-lower), the seam was obtained using Dijkstra Fixed Start Point (DFSP) method. In order to speed up the DFSP method in the upper and lower strips, unlimited Dijkstra depth search was replaced with a depth limited search. Clearly, the computational cost in the upper and lower strips was much lower than the simple seam carving. As a matter of fact, our proposed method speeds up dynamic programming component and the energy for each pixel can be computed using the original or any improved seam carving method. Our approach can be viewed as an improvement on the state-of-the-art seam carving algorithms. Additionally, all methods that employed Dijkstra algorithm in large graphs were valued.

This paper was organized into sections. In section 2 mathematical model is briefly discussed. Then, the proposed method is explained in section 3. Comparison with improving seam carving algorithms using standard dataset is presented in section 4 and in section 5 conclusion is drawn.

2. MATHEMATICAL MODEL

The main idea behind seam carving algorithm is to remove unnoticeable pixels while maintaining the significant content of the image. The importance of the pixel can be measured by some metric measures such as gradient operator, entropy operator, saliency map, etc. Using one or some of these criteria, algorithm generates a cumulative energy matrix (energy map) of the input image. The seam is defined as an optimal, 8-connected path of pixels on a single image from top to bottom (left to right) containing one pixel in each row (column) of the image, which is the minimum cumulative energy.

2. 1. Original Seam Carving There are different ways of extracting the unnoticeable pixels from an image. In original seam carving technique, an energy value is assigned to each pixel using the gradient energy function.

This value can easily be computed employing Sobel masks in both the horizontal and vertical directions [1].

A vertical seam for an N×M image is defined as follows [1]:

$$S^x = \{S_i^x\}_{i=1}^{n} = \{(x(i), i)\}_{i=1}^{n} \quad (1)$$
$$where\ \forall i,\ |x(i) - x(i-1)| \leq 1$$

where x is a mapping x: [1, 2, ...,n] → [1, 2, ...,m]. S is a vertical seam in the image from top to bottom and subscript i is the number of rows.

Similarly, a horizontal seam can be defined. The cost of the seam is defined as the sum of the energies along the seam path [1]. An optimal seam would have the minimum cost. Dijkstra algorithm [11] is the best method for obtaining this seam. Based on Dijkstra algorithm, the cumulative minimum energy map M for the second row to last row is defined as follows: [1]:

M(i,j)=e(i,j)+min(M(i-1,j-1),M(i-1,j),M(i-1,j+1)) (2)

Thereafter, the optimal seam was located by taking the minimum pixel value in the last row, which represents the end of the optimal seam path. Then, the optimal seam path is tracked by going upwards towards matrix M and finding the minimum value among the three adjacent pixels right above that. The steps described above are for vertical seams. For horizontal seams, all the procedures can simply be done on the transposed version of the image.

2. 2. Some Fast Seam Carving Methods

The aforementioned methods may be classified into three main categories based on seam carving:

- Methods based on strips that divide image into a few sections [3, 16]
- Methods that use ROI (Region of Interest), and saliency map that eliminate number of seams simultaneously [15, 17].
- Hybrid and heuristic methods that combine the above methods [3, 11, 14].

2. 3. Seam Carving with Partial Updating

In original seam carving technique, all pixels' energy should be computed after removing each seam. In this method, a large amount of time is spent to compute this map. After removing a seam, is not all that necessary to recompute energy map for all the pixels. Figure1 shows that the energy map in the triangular-like region has actually been transformed [14], starting from the top point of the removed seam. For example, as is reported in literature [14] only the energy map of the dark pixels is computed while the white pixels maintain their values. This optimized algorithm reduces the computational time and enhances the efficiency of the system; however, it is still computationally intensive.

3. PROPOSED METHOD

In this section, a novel idea on reducing the computational cost of the seam carving techniques is presented. In these methods, cumulative energy map checking is employed to obtain the optimal seam. In previous methods, Dijkstra algorithm was used to check the cumulative energy map. The computational cost of these methods depends on Dijkstra algorithm. For high resolution images, this procedure is very intensive. The proposed method consists of two steps. In order to maintain consistency, we only described the proposed technique for vertical seam carving. This method is also applicable to horizontal seam carving.

3. 1. The Strips and Modified Dijkstra Algorithm

In our method, each image was divided into some strips e.g. three strips, as is the case in some previous seam carving methods. In previous methods, the image was divided into three equal strips and the strips obtained were called top strip, middle strip and bottom strip (Figure 2). In these methods, only the middle strip was used for energy updating [14, 16, 17]. But, in our proposed technique, the seam of the middle strip was used to obtain the seam in other strips. Thus, the start point (pixel) of the seam in the middle strip is presumed as the end point of the seam in the upper strip, while in the lower strip, the start point of the seam is presumed to be the end point of the middle strip.

The fixed start point in the upper and lower strips reduces the number of computations in Dijkstra algorithm. For each pixel, it is imperative for Dijkstra to consider the values of the three pixels in order to obtain the cumulative minimum energy.

In regular methods, such as in an M×N image, the total computations for obtaining an optimal seam is 3M×N. However, in our method, using Dijkstra in the middle strip only, the computations was about 33% of the complexity previously mentioned.

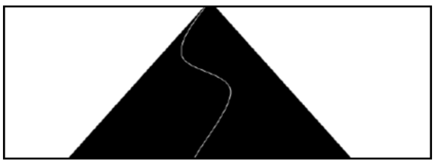

Figure 1. The region is actually amended. The dark region may change the pixel's energy map value after one seam is removed [4]

Figure 2. Image is divided into three equal strips

In an M×N image in which the seam's start point is known, Dijkstra only computes the cumulative minimum energy in the triangular area (e.g. white pixels in Figure 3). The number of pixels that the process does not apply to are M, N, and the start point location in the first row.

For example, in Figure 3 the location of the start points is considered in the middle of the first row. In Figure 3a, the height of image M is smaller than half of the image's width (N/2), while in Figure 3b, M is equal to N/2 and in Figure 3c, M is bigger than N/2. Thus, the number of white pixels in Figure 3a is smaller than half of the total pixels (smaller than 50% of all pixels), in Figure 3b, this value is equal to 50% and in Figure 3c it is greater than 50%.

Note that, in the proposed method, the image is divided into three equal strips and the height of each strip is equal to M/3. In standard size images, the value of M would be in the range of [1.5N-2N] and its strips are usually in the form of Figure 3c. Finally, the percentage of the white pixels in standard size images is equal to a value in the range of 50-70%. In fact, the sum of the initial M×N process for middle strip and the next 2×M×N×α for upper and bottom strips gives the total calculations for which α is a coefficient and it affects the percentage of white pixels' number in the upper and lower strips. Thus, the total computations of the proposed method for obtaining the minimum cumulative map is equal to M×N+2α×M×N which is smaller compared to 3×M×N. For example, suppose that α is set at 0.6, then, the total computations would be equal to 2.2×M×N, which is about 27% lower than the standard Dijkstra method's total computations.

3. 2. Limited Depth Search In order to enhance DFSP, the unlimited Dijkstra depth search was replaced with a limited depth. The ideal Dijkstra algorithm searches all candidates' pixels each time. With a known start point, the search domain has three pixels in the second row while the next row 2 pixels are added to the domain sequentially (one pixel in each side). The unlimited Dijkstra depth search causes an increase in the search domain continuously until the entire row is occupied or the image matrix is completed. In the proposed method, an increase in domain is restricted to the first 5 rows (discussion about the right size of this parameter is in section 3.3).

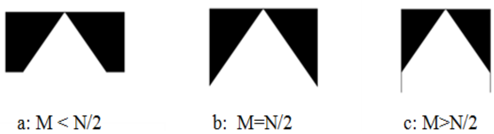

Figure 3. With a known start, Dijkstra only compute cumulative minimum energy map for white pixels

The candidates' pixels which are checked to obtain the optimal seam in these 5 rows are called X_c and the other pixels are called X_d (e.g. Figure 4 shows an example of an increase in the first 5 rows: white pixels are X_c and dashed pixels are X_d). Furthermore, energy value was computed for X_c and the optimal seam was obtained. For the next rows or columns, a new search (restricted to the 5 rows) at the end of the seam obtained commences.

Moreover, owing to the detected start point and the limited depth search, the total process of algorithm decreased significantly in comparison with the original seam carving method. In this case, Dijkstra algorithm only computed the cumulative minimum energy in the area shown in Figure 4. In this case, the total number of pixels in the five rows is 3+5+7+9+11, respectively; which is equal to 35 pixels. For an M×N image, the total number of processes is:

$$M \times N + 2 \times \frac{M}{5} \times 35 = M(N+14) \qquad (2)$$

The coefficient 3 in Equation (2) shows 3 processes for each pixel. M/5 is the value of the five rows in the M rows of the image and 35 is the number of pixels in the five rows. Equation (2) shows that the number of processes is independent of N (number of columns). The total computations for obtaining the minimum cumulative map in an M×N image that is divided into 3 equal strips are M×N for middle strip and 21×M/3 for upper and lower strips, which are much smaller than 3×M×N and M×N+2×M×N×α. If α is assumed to be 0.6, N=600 and M=800, the total computations for standard Dijkstra algorithm with dynamic programming would be 3×M×N=1440000, for DFSP, which is equal to 1056000. Lastly, in the proposed method, the limited depth search which had a value of 491200, decreased about 54% in comparison with the modified Dijkstra method and about 66% in comparison with standard method. Clearly, in combination with partial updating [14], this method is still a lot better than standard and modified seam carving algorithm.

3. 3. The Effect of Parameters in the Proposed Method The proposed method has three adjustable parameters, number of rows in depth search, number of strips and height of each strip. To adjust these parameters, different types of images were tested in order to obtain an appropriate value for these parameters.

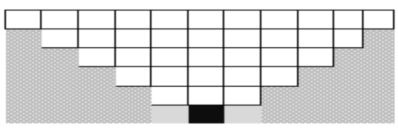

Figure 4. Start point is shown as dark pixel; white pixels show the area for tracking optimal seam from down to top

Due to the result obtained, depth search was not considered a critical parameter because the value of this parameter was much smaller than the number of columns. If depth search is set to one (the minimum value), each pixel will only be compared with three pixels in the next row or column (this is good for run time). However, if the image contains a similar texture in the upper or lower strips, output would have a low quality and maybe a sharp cutting area (see Figure 5). Thus, depth search must be adjusted by values higher than one, which is assumed to be five. Another important adjustable parameter of the proposed method is the number of strips, which is assumed to be three. Note that, if the number of strips is set at a higher value, the complexity of the method would increase. Firstly, the number of strips was assumed an odd number.

At this state, the middle strip is odd and the ideal seam carving can be applied to the middle strip as well as the odd strips (e.g. dark areas in Figure 6). Then, for even strips, the DFSP must be modified to obtain a seam with two fixed end points (e.g. white areas in Figure 6). If the upper and lower strips do not belong to even strips, the normal DFSP must be applied to these strips (e.g. grey areas in Figure 6). In the meantime, the odd strips that were analyzed by ideal seam carving (except middle strip) require a constrained start point. Suppose A1 and A2 are the start and end points of the seam in the middle strip (Figure 7); therefore, the height of strips No 2 and 4 would be $M\times m$. It is clear that the seam in strip 1, should be started from a pixel in the range of [A1-$M\times m$ A1+$M\times m$], otherwise the 8-connected path of the seam would be lost. For strip 5, the seam should be started in the range of [A2-$M\times m$ N]. The last adjustable parameter is the height of each strip. It is obvious that when the middle strip height is increased, the upper and lower strips height consequently decreased.

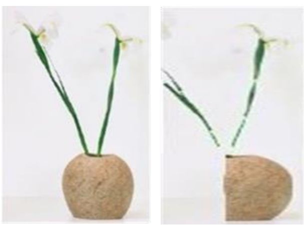

Figure 5. Original image and result of proposed method. Depth search is supposed as 1

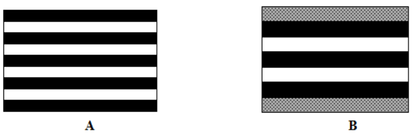

Figure 6. Ideal seam carving for dark strips and a modified Dijkstra with known start and end points for white strips. In image B, the upper and lower strips should be analyzed by DFSP

As a result, the computational time and output quality increases and the proposed method tend towards the original seam carving method. If the height (length) of the middle strip is set lower than the top and bottom strips, computational time decreases and the output's quality will be poor. The heights (lengths) of the upper and lower strips can be differentiated, but due to the unknown category and type of images, these values were chosen to be equal.

Before analyzing computational complexity of proposed method it is be noted that memory requirement is not an important issue in seam carving methods. In the proposed method the memory requirement is similar to other seam carving methods and approximately equal to image size that used for storing image gradient values and computing optimal seam.

3. 4. Computational Complexity

To evaluate computational complexity of the proposed method some details are given in this section.

Discarding the gradient calculation that is similar in seam carving methods, the original seam carving method need $3\times M\times N$ process to obtain an optimal seam (see section 3.1 for details), by partitioning and some other modifications [2, 14] improved seam carving methods decrease this value to $M\times N+2\times M\times N\times\alpha$ that α is a selectable value lower than 1 (see section 3.1 for details). In the proposed method using partitioning and limiting search depth to the first 5 rows (see section 3.2 for details) the total computations decrease to $M\times(N+14)$. It is obvious that this value is much lower than previous methods. For example, in a 600×800 image, the proposed method has about 54% lower computations in comparison to improved seam carving methods.

4. SIMULATION RESULT

The proposed method, original seam carving and fast seam carving methods [2, 14] were implemented on a PC with Core i5 CPU, 2.66 GHz, 4 GB RAM and tested on 100 images with different categories much of which is from MIT image retargeting dataset[2].

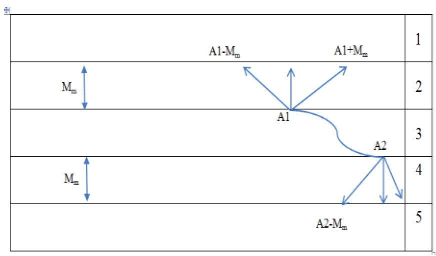

Figure 7. Constrained start point for odd strips

[2] http://people.csail.mit.edu/mrub/retargetme/download.html#datase

All images were divided into three equal strips and the proposed method resized the length of all images to 65% of its normal length (height was assumed constant). The fast seam carving method with partial updating [2, 14] was applied to the middle strip and the seam was computed for lower and upper strips using the proposed method. The depth search was assumed to be 5. Figure 8 shows two selected images in normal scale and the results of the proposed method and fast seam carving with partial updating [2, 14] method. Obviously, the quality of the proposed algorithm performed better or at least as well as the seam carving method. It can be seen from the temple image in the first row that our approach can generally maintain salient objects such as the temple structure, which is much better than seam carving method. The runtime of improved seam carving was 6.8 seconds and that of the proposed method was about 5.2 seconds, which means our method had about 24% lower run time.

It is to be noted that all methods were implemented on a similar hardware. In the second row, all details in the right corner of the image (branches of tree) were maintained in the proposed method but in the normal method, they were distorted. The runtime for normal seam carving image is 7.1 seconds but in our proposed method, it was 5.6 seconds. In the second step, to evaluate the performance of the proposed method and to determine the effect of all the selected parameters, all database images were resized to 600×800 images, and the algorithm was tested on this new database in three different positions.

4. 1. Depth Search Influence To evaluate this parameter, the proposed method was applied to all the database images tagged with three different values, which are 5, 7, and 9.

Figure 8. Performance comparison between original seam carving and proposed method with selected values

TABLE 1. Ratio of runtime in proposed method to runtime in original and fast seam carving

	Original seam carving	The best reported score [14, 2]	Proposed method
Runtime	100%	83.32%	78.54%

The minimum value for depth search was selected as five because for depth search lower than 5, the sharp cutting area (as described in Figure 6) could occur. All images were divided into three equal strips. The original image was resized from 600×800 pixels to 400×800 pixels. The original seam carving method with partial updating was applied to the middle part and the seam was computed for other strips using the proposed method. As can be seen in Figure 9, three selected images of different categories were resized using both the proposed method and seam carving method. Despite the fact that the results obtained have low differences, it can be seen that the output quality of the proposed algorithm is similar to the seam carving method. In the mean time, for all the depth search values, the output quality is similar.

Table 2 shows the ratio of runtime in the proposed method to runtime in the original seam carving method. As shown in Table 2, the proposed method has much lower runtime (about 30%) in all cases compared to the original method. Consequently, the depth search that is equal to 5, which has the lowest runtime, was selected as the best value for this parameter.

4. 2. The Height (length) of Middle Strip The proposed method can induce variations in the height of the middle strip, and as such, the height of the other strips was selected as an equal value. The height of the middle strip was assumed to be 50, 33 and 25% of the total height of the image. Similar to section 4.1, all images were divided into three strips and all the original images were resized from 600×800 pixels to 400×800.

The depth search was selected to be 5 based on the results obtained in previous sections. As can be seen in Figure 10, six selected images of different categories were resized using both the proposed method and seam carving method.

TABLE 2. Ratio of runtime in the proposed method to runtime in the conventional seam carving method

Image name	**Runtime decreasing efficiency**		
	Depth search		
	5	**7**	**9**
A	0.68	0.69	0.70
B	0.70	0.70	0.71
C	0.69	0.69	0.70

Obviously, based on the results presented in Figure 10, this parameter affected the output quality. As shown in the images of Figure 10, the overall performance of the middle strip with height equal to 33% was better or at least equal to the seam carving method in most cases. Table 3 shows the ratio of runtime in the proposed method to runtime of seam carving method. As shown in Table 3, the column with middle strip height = 25% has much lower runtime (about 34%) in all cases compared to the original method. However, with respect to the results of the value obtained at height 33% which had a few higher runtime in comparison with 25% (and showed better quality), the 33% was selected as the height of the middle strip.

Figure 9. Performance comparison between seam carving and proposed method with three different depth search values (Normal imageseam carvingProposed methodProposed methodProposed method. Depth search=5Depth search=7Depth search=9)

Normal image | Original seam carving | Proposed method | Proposed method | Proposed method

Middle part height | 25% | 33% | 50%

Figure 10. Performance comparison between original seam carving and proposed method with three different middle part values

TABLE 3. Ratio of runtime in proposed method to runtime in seam carving method

Image name	Runtime decreasing efficiency		
	middle part height		
	25%	33%	50%
A	0.65	0.68	0.70
B	0.67	0.70	0.72
C	0.66	0.69	0.71

4. 3. Simulation with Selected Values To better illustrate the strength and weakness of the proposed method, see the results of Figure 8 again (depth search = 5 and middle strip height = 33). In row C, the quality of the proposed method is lower compared to the original seam carving method. In fact, when the image is heterogeneous or the middle strip is so different from other strips and the region of interest is out of the middle strip, the quality of the proposed method is decreased.

5. CONCLUSION

In this paper a new method is proposed for improving computational complexity of the seam carving method. In the proposed algorithm, the image is divided into some horizontal or vertical strips and the original seam carving method is applied only to some strips (first group). In other strips (second group), algorithm estimated seam in a limited depth search with respect to the computed seam in the first group. In the second group, the computational cost and storage space was much lower than the first group so the total computational cost of the proposed method is superior to the seam carving method.

The proposed method was tested on a database of 100 images of different categories to determine unknown parameters of the algorithm. Based on the results of this study, the best values for parameters were selected.

Simulation results with respect to the selected values showed that the proposed seam carving method is about 30% faster than the seam carving method without losing the quality of the retargeted image. Conclusively, the proposed method is a framework and can be combined with all improved seam carving methods that employs Dijkstra and dynamic programming to decrease their computational complexity.

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Improved Content Aware Image Retargeting Using Strip Partitioning

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P A P E R I N F O

Paper history:
Received 19 November 2016
Received in revised form 22 January 2018
Accepted 08 Febraury 2018

Keywords:
Seam Carving
Image Resizing
Image Retargeting
Dijkstra Method
Strip Partitioning

چکیده

با توجه به گسترش سریع تقاضا برای رسانه‌های دیجیتال و تجهیزاتی مانند تبلت و گوشی های هوشمند، نیاز مبرم به روشهای که بتوانند ابعاد تصویر را به سرعت با اندازه صفحه نمایشگر تجهیزات مختلف تطبیق دهد به شدت احساس می‌شود. روش های موجود در تغییر ابعاد تصاویر عمدتا قادر به حفظ اطلاعات دارای محتوای بالای بصری نبوده و از روش های هندسی برای تغییر ابعاد استفاده می‌کنند. سیم کاروینگ به عنوان یک روش مبتنی بر محتوا در تغییر ابعاد تصویر و ویدئو گسترش نسبتاً زیادی در سال‌های اخیریافته است. یکی از چالش‌های نسبتا بالا در این روش، محاسبات مورد نیاز است که کاربرد آن را در روشهای آنلاین محدود می‌کند. با توجه به این موارد در این مقاله یک روش جدید برای کم کردن حجم محاسبات روش سیم کاروینگ پیشنهاد شده که در آن با شکسته شدن تصویر به سه نوار و اعمال الگوریتم اصلی به نوار میانی و تعمیم نتیجه آن به نوارهای بالا و پایین تصویر، حجم محاسبات کاهش بسیار مشهود یافته بدون آنکه کیفیت نسبت به روش اصلی کاهش چندانی پیدا کند. علاوه بر این کار برای کم شدن حجم محاسبات عمق جستجو در نوار های بالا و پایین نیز محدود شده است. در نهایت نتایج پیاده سازی کاهش زمان اجرای بسیار قابل توجه و به صورت همزمان حفظ کیفیت خروجی را به صورت قابل قبولی نشان می‌دهد. نتایج تغییر پارامترهای موجود در الگوریتم نیز بر خروجی به تفکیک آورده شده تا کاربر بتواند بر اساس نظر خود پارامترهای مناسب را انتخاب کند.

***doi**: 10.5829/ije.2018.31.05b.01*