An Analysis Of Hybrid Techniques Of Seam Carving

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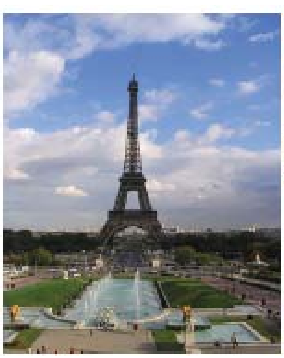
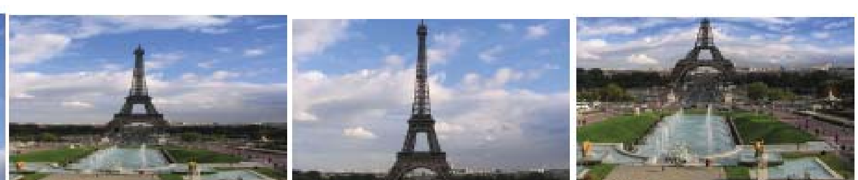
Abstract— Diversified display devices and advancement in image processing techniques have increased the need for content aware resizing of images to fit into display devices of varying resolutions. Traditional resizing methods scaling, cropping, warping are all content unaware methods. Seam Carving has gained popularity in this scenario but it is not without any setbacks. Instead of searching for a single best operator a combination of multiple operators are proposed to benefit from each of these techniques. In this paper we survey such techniques combined with seam carving, which we term Hybrid techniques. We also analyze their efficiencies based on parameters such as content preservation, global visual impacts and computational complexities.

Keywords-Seam Carving;Scaling; Cropping; Warping; Monotonic

I. INTRODUCTION

With the blossom of too many display devices and advancement in image processing techniques, has grown the interest for adopting images to different types of display devices of varying resolutions. A feasible resizing algorithm should be able to preserve the important content in an image as well as the global visual effect. The diversity and versatility of display devices poses a challenge on retargeting images. Seam carving, a content aware image resizing technique has greatly gained popularity in this scenario. It proves to be superior to other resizing methods like scaling, cropping and warping. However it is not without any drawbacks. It uses an energy based strategy to remove or insert seams (connected path of pixels) of low energy to/from the image to achieve the desired size. This frequently damages the local structure or global visual effect. Moreover the denser image contents and at times the orientation of the objects in the image reduce the extent of applicability of seam carving. Fig.1.shows the distortion caused by seam carving compared to scaling and cropping. Several researches are in progress to optimize seam carving. No single operator proves to be the best for all images. So combination of multiple operators is proposed to profit from the advantages of each technique and minimize the negative impacts of one another. Researches had shown that using several operators can potentially give better results for retargeting, than using a single operator.





(b) (c) (d)

Fig. 1. Example of image distortion by Seam Carving compared with Scaling and Cropping
a) Original image b) Scaling c) Cropping d) Seam Carving

(a)

II. BACKGROUND

Recently, seam carving proposed by Avidan and Shamir [1] to resize images in a content aware fashion is gaining much popularity. Using dynamic programming they computed an optimal 8-connected path of pixels across the image which they termed 'seam'. Seams are composed of pixels of low energy gradients which when removed or inserted causes less deviation to the visual impact of the image. The seams can be removed for image size reduction, or duplicated for expanding them. Later, this work was extended by Rubinstein et al. [2] for video retargeting in which graph cut approach was used instead of dynamic programming. Backward energy computation [1] was replaced by new Forward image energy [2] to take into account the energy inserted into the image during resizing, rather than only the removed energy, which lead to better results of resizing. Graph cuts was also used in [3] for temporally resizing of video. Fuzzy segmentation techniques was used to enhance seam carving by identifying and preserving the image contents[4]. Parallel algorithms were applied to improve the speed of computation[5][6]. In cases where one of these operators does not perform well, it might be better to use another or revert to simpler resizing methods such as cropping, scaling and warping. These methods are not content aware, but they can be considered less harmful as they do not distort the media. See result of these methods in Fig.1 and Fig.2. Wang et al. [13] presented a "scale-and stretch" warping method that updates a warped image that matches optimal local scaling factors. A layered image resizing is used in latest versions of Photoshop to provide content aware scaling. This decomposes the image into foreground content and the background layer. The seam carving technique is applied to the image content to preserve its information saliency and background is scaled or cropped. Ongoing researches to combine the content preserving resizing technique, seam carving with technique that preserve the global visual effect has resulted in many hybrid multioperator techniques. These methods take the advantages of both discrete and continuous methods and give better results for retargeting than using a single operator. However each has their own merits and demerits. This aroused within us the interest in conducting a survey on the hybrid techniques of seam carving with a view to analyze their efficiencies. Comparison of single operator methods with hybrid method (A) is shown in Fig 2.

This survey is organized as follows: The original seam carving is detailed in section III, Hybrid techniques are explained in section IV. Here we compare three papers using hybrid techniques. Multioperator media retargeting[7] is discussed in (A), Optimized Image Resizing Using Seam Carving and Scaling[8] in (B) and Fast Multioperator Image Resizing[9] is discussed in (C). The parameters that measure their efficiencies are the 1)Content preservation, 2)Visual impact, and 3)Computational complexities. Their results and discussions are elaborated in section V and conclusion in section VI.

III. OVERVIEW OF SEAM CARVING

Seam Carving [1], proposed by Ariel Shamir and Shai Avidan alters the size of an image by generously removing or inserting pixels in an image. It uses a simple image operator called seam. Seam is an optimal 8-connected path of pixels on a single image from top to bottom (vertical seam), or left to right (horizontal seam).

The seams should be

- monotonical, - one and only pixel in each row/column for a vertical/ horizontal seam.
- 8 connected – Being found a pixel on the seam, the next pixel that constitute the seam is one of its three neighbours on the next row/column.

Removal / Insertion of such a seam do not cause much visual attention. By repeatedly carving out or inserting seams we can change the aspect ratio of an image or retarget the image to a new size. The optimality of pixels is defined by an image energy function.

$$e_1(\mathbf{I}) = |\frac{\partial}{\partial x}\mathbf{I}| + |\frac{\partial}{\partial y}\mathbf{I}|$$

Let I be an image of size nxm, then a vertical seam is defined to be:

$s^x = \{s_i^x\}_{i=1}^{n} = \{(x(i),i)\}_{i=1}^{n}$, s.t for all i, $|x(i)-x(i-1)| \leq 1$, where x is a mapping $x:[1,\ldots,n] \rightarrow [1,\ldots.m]$.

And similarly a horizontal seam is defined to be:
$s^y = \{s_j^y\}_{j=1}^{m} = \{(j,y(j))\}_{j=1}^{m}$, s.t. for all j, $|y(j)-y(j-1)| \leq 1$, where y is a mapping $y:[1,\ldots,m] \rightarrow [1,\ldots.n]$.

Energy of a Seam = Sum of Energy of pixels that constitute the seam

$$E(s) = E(I_s) = \sum_{i=1}^{n} e(I(s_i))$$

The optimal seam can be found using dynamic programming.

$$s^* = \min E(s) = \min \sum e(I(s_i))$$

i) Demerits

- This algorithm always removes or inserts low energy pixels until the desired image size is achieved, without considering the real visual effect.
- The ROI’s with relatively low energy cannot sustain from being carved out.
- Denser regions of interest (ROI) in the image and sometimes the orientation of the image make it unavoidable that the seams bypass the important regions thereby distorting it. Fig .1(d)

IV. MULTI OPERATOR TECHNIQUES

(A) In [7] the author defines a resizing space as a conceptual multi-dimensional space combining three resizing operators namely cropping, scaling and seam carving. The resizing space of n operators spans along two directions - width and height. Hence, the dimension of this space is atmost 2n. A sequence of operations used to retarget the image called the multioperator sequence, defines a directed path in this space beginning at the origin and following the path’s operator sequence using integer steps either in the positive or negative direction of the respective operator axis, which can change either the width or the height of the image. Positive and negative coordinate values signify enlargement or reduction of size. The path may be regular or mixed. A regular path is composed of consecutive single operator sequences, one per operator (e.g. first apply seam carving, then cropping and finally scaling). In regular paths the order of operators is fixed ahead of time. In mixed path, the order of the operations, as well as the number of times each operator is used is not fixed. In this paper the author restricts the paths to be monotonic (all operators either increase the size of the image, or decrease it, but not both). The main goal therefore, is to find the best path from the origin to one of these points, subject to some global objective function. To switch between seam carving and scaling seam cost[1] shall be used to find the optimal “multioperator” sequence. Seam cost is a monotonically increasing function and not very indicative of the quality of retargeting. Moreover for cropping and scaling, an effective cost function is not defined. In this paper Rubinstein et al. defines the cost of applying an operator as the difference between the resulting image and the original image. To compare and evaluate different retargeting results a global similarity measure termed Bi-Directional Warping (BDW), a non-symmetric variant of Dynamic Time Warping (DTW) is used with dynamic programming algorithm that maximizes this measure by finding the best path to the respective point in resizing space. BDW measures the similarity between every row (or column) and then takes the maximum alignment error as the distance. This is extended to work on a row (or column) of patches instead of pixels, as patches can better capture spatial information. The optimal cost and optimal sequence including the order of applying the operators are all stored in a dynamic programming table. It is assumed that the ratio of operators is more important than their orders in the sequence. The search space is sampled in higher rates than 1 pixel, applying each operator multiple times between stages. Fig 2. shows that the result of this method is very impressive than the results of single operator techniques.

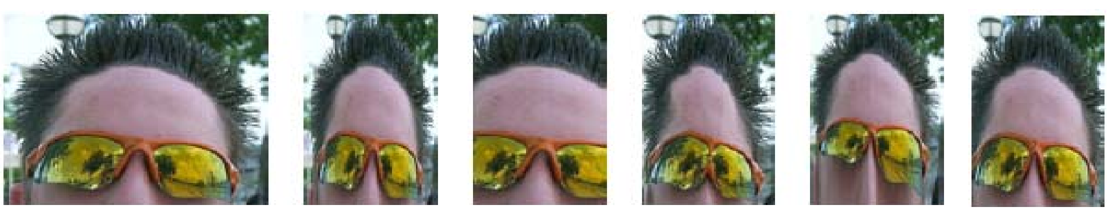


Fig. 2. a) Original image b) Scaling c) Croping d) Seam Carving d) Warping [13] e) Result of (A)

(B) In [8] the authors combine seam carving and scaling. This algorithm removes partial pixels with seam carving operation on the original image. After each seam is removed, the current image is scaled to the target size and the distance to the original image is computed. The resized image with the minimum distance to the original image is the final result. The appropriate ratio between seam carving and scaling, is controlled by the seam carving number (NSC-V, NSC-H). The goal of this algorithm is to find the feasible NSC numbers (i.e how many width/height ratios should be first reduced by seam carving and how many others then by scaling) in both vertical and horizontal directions, to obtain a resized image of best visual effect. Similarly to enlarge an image, as suggested also by [1], probable seam number k that indicates the number of "homogeneous" seams in the image is proposed. Then the optimal NSC-V value in the domain of [0, k] is found using the distance measure and is duplicated. This method is more effective and accurate than setting the seam numbers manually. For quantifying and evaluating the quality of a resizing result, the author formulated an image distance measure which is a combination of patch-based bidirectional Image Euclidean Distance (IMED) [10],[13], image dominant color (DCD) [11] similarity and seam energy variation.

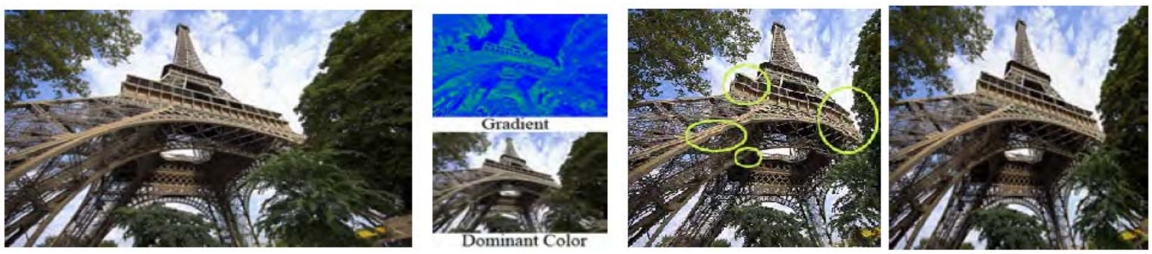


Fig.3. (a) Original Image (b) (c) Seam Carving (d) Result of (B) with DCD

Fig. 4. (a) Original Image (b)Seam Carving (c) Scaling (d) Only IMED (e) IMED + DCD (f) DCD of e.

IMED considers the spatial relationship between the pixels of different images and Is therefore robust enough to withstand small perturbations. The patch distance is measured in YIQ color space and normalized by the patch size. Since scaling operation is used to protect the global visual effect and some local structures, this will increase the patch-based bidirectional distance more quickly than using pure seam carving[12]. Due to similar reason, IMED can also be affected in particular for images with strong structured parts. To solve this problem, damage caused by seam carving to the global visual effect and energy variation during the seam carving process is estimated and the distance measure is revised accordingly. This may be ignored if resizing is done in both directions. The computation speed is accelerated by avoiding distance calculations for every pixel of the patch. The algorithm cannot obtain a good result by comparing only the IMED. However, the global visual effects are also important. Color features are commonly used to represent the global information of images, which are relatively independent of the viewing angle, translation, and rotation of the objects and regions of interest. The similarity of the dominant color descriptors (DCD) between the original image and the resized image, widely used in content-based image retrieval was used to describe the dominant colors in a region of interest or in the whole image. It also provides percentage of pixels in the image corresponding to each dominant color. A DCD that specifies a small number of dominant color values and their statistical properties: distribution and variance [11] was used to detect the fine changes that occur while gradually resizing an image. Fig.3. compares the original seam carving and hybrid technique (B) with DCD. Fig.4. shows how DCD improves visual effect when compared to resizing using only IMED.

(C) An image similarity measure based on Dynamic Time Warping (DTW) [7] or Euclidean Image Distance (IMED)[8] is very slow. The computation of patch matching in BDW and IMED makes it inefficient for interactive usage. Although the seam cost is not very intuitive for evaluating the quality of resizing, the effectiveness of using energy based measure to estimate pixel importance has been demonstrated in previous works [1], [13]. Therefore in [9] the author introduces a new, operator cost-based approach combining Image energy and Dominant Color Descriptor (DCD). Image energy is used to detect the loss of the prominent information during the resizing process. The energy can indicate the presence of local structures. A dominant color descriptor (DCD) is used to describe the global information of the original image. Dong et al.'s method [8] is used to extract DCD. An objective function is also formulated to optimize the resizing process. The best path (i.e. sequence of operators) is found by minimizing the objective function according to the cost functions. Moreover, a new optimization algorithm is proposed, which dramatically increases the speed of multioperator resizing without damaging the visual quality.

During the resizing process, an operator O is employed to reduce or enlarge an image either in its width or its height. In this paper, seam carving, bi-cubic scaling and cropping are used as the resizing operators. Each time one pixel is removed or added to the width or height of the image. Cropping is used only for reducing image size by removing pixels along the side with lower cost separately for width and height. For scaling, a scale-by-k time is performed rather than applying one pixel scaling k-times. Cost function is defined as the sum of products of all operators energy information cost and DCD information cost.

Energy information cost is to estimate the damage to the local object structures of the image to be resized and the DCD information cost evaluates the global visual information loss. The energy information cost is computed from the energy of (max) number of pixels that are affected by the operator, in the operational field s, For seam carving, s is the seam which is proposed to be removed or inserted. For scaling, we set s to be the whole image because all the pixels will be affected by the scaling operator. For cropping, s only needs to count boundary pixels. DCD information cost is calculated by considering the distance between the pixels in s and their corresponding dominant colors. DCD helps to achieve a nice balance between several visually-important objects.

A dynamic programming scheme is used as in [7] to optimize the search for the best mixed operator sequence and same as the discrete search schemes in [7] and [8], the search space is sampled at higher rates than 1 pixel, applying each operator 5 times between stages. The forward energy takes into account the energy inserted into the image during resizing, rather than only the removed energy, which leads to better results for many examples especially in preserving the object boundaries[2]. To profit from this advantage, the scaling and cropping energy is adjusted by a weight coefficient equivalent to the ratio between the total forward energy to the backward energy. ($w_f = E_f / E_b$). When using forward energy for seam carving, it was observed that a carefully-designed random selection scheme tends to achieve better results than the standard min operator due to the approximation nature of cost adjustment. Specifically, the stochastic scheme is based on a statistical analysis of the operator costs. This method can smooth the deviations during the operator cost calculations. Results of resizing using the three methods discussed above are shown in Fig.5.

Fig. 5. (a) Original Image (b)Seam Carving (c) Scaling (d) Reuslt of (B) (e) Result of (A) (f) Result of (C)

V. REUSLTS AND DISCUSSIONS

Seam Carving caused greediness effects but warping methods[13] well protect the aspect ratio of separate objects. Optimizing seam carving combining with other techniques however has reduced the adverse effect of seam carving and therefore gives good results. Of all the three methods discussed above the (C) produce better results than (A) and (B), the patch matching resizing sometimes fail to preserve contents in some patches as in Fig. 6. Similarly use of DCD in (B) and (C) preserves the global visual effect better. In (A) a regular path is applied and in (B) also the order of seamcarving and scaling is fixed. (C) proves that switching the order of resizing operators may generate better results than current ones. Comparing the computational complexities of the algorithms proves that (C) is much faster than the other two methods.

The dimension of the resizing space is 2n for n operators. Even if we use monotonic sequences there are still O(nm) different multioperator sequences. This means the search space is exponential in the size change m. Reducing width of the image I by m pixels, using n operators in dynamic programming, (using mixed path), the time and space complexities are O(mn), which is polynomial in the amount of size change, while exponential in the number of operators to be used. One possible method to accelerate the resizing process is to use regular paths [7],[8]. It means that the order of operators is fixed ahead of time. This allows us to find the optimal result using exhaustive search in O(mn-1), which is polynomial in the size change m while exponential in the number of operators n. Since n is usually small (say, three or four operators) and m is sampled in discrete steps, this search is feasible. In C a stochastic operator selection is used to enhance the speed. A direct mixed path method was also proposed in (C) which do not guarantee to find the global optimal result, but is well enough for many examples. The time and space complexities of the algorithm are O(mn) which is quadric in both the amount of size change and the number of operators.

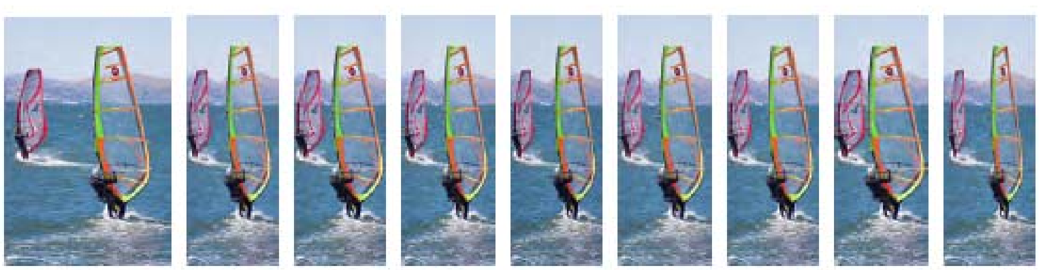
In (B) the computation time is greater than that of A and C. The author states that computation time could be minimized using an optimization scheme such as gradient descent. Also the computation speed is accelerated by avoiding distance calculations for every pixel of the patch. In (A), BDW is employed to compare the similarity between the result and the original image. In (B) IMED-based measure is directly applied to find the best result, while the BDW in (A) cannot. The running time will be dramatically increased if the two-dimension BDW is used.

Fig.6 (a) Original Image (b) Patch Match Resizing (c) Resizing without patch matching

VI. Conclusion

The computation of patch matching in BDW in (A) and IMED in (B) becomes the main bottleneck of the efficiency. Moreover, because the optimization computation grows exponentially with the number of operators, it will also slow the resizing processing when more operators are employed (2-10 minutes for 2 operators, 10-20 minutes for 3 or 4 operators). So (B) (3 operators) tends to be slower than (A) and (C). Using energy based measure to estimate pixel importance has been demonstrated in previous works [1],[13]. Moreover the forward energy takes into account the energy inserted into the image during resizing, rather than only the removed energy, which leads to better results in preserving the contents[2]. Therefore in (C) the author combines Image energy and Dominant Color Descriptor (DCD) to determine the operator cost and apply forward energy to adjust the cropping and scaling energy cost. The stochastic operator selection scheme based on a statistical analysis of the operator costs further enhances the resizing. The snowman in Fig. 7. is resized in 20 seconds using (C), while (A) and) (B) takes 28 and 32 seconds respectively. Therefore (C) is a fast approach, straightforward to implement, and can generate equivalent results as (A) and (B). Fig.8. compares the results of resizing using different methods discussed above.

Fig. 7. a) Original Image b)Seam Carving c) Scaling d) Cropping e) Reuslt of (A) d) Result of (C)



(a) Original image (b) (c) (d) (e) (f) (g) (h) SC (i) SL

Fig . 8 Compariing the results of using different methods.
(a) Original Image, (b) Result of (A) mixed path, (c – e) Results of (C) : (c) using mixed path (d) mixed path with stochastic operator selection, (e) direct mixed path with stochastic operator selection, (f) Result of (A) regular path, (g) Result of (C) regular path, (h) Seam Carving (h) Scaling.

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