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Image Seam Carving Based on Content Importance and Depth Maps

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Abstract— **In many occasions images are transferred from one device to another with a different display size. In such situations images need to be resized. Image seam carving algorithms attempt to change the size of images while preserving image salient contents with minimum distortion. For this purpose energy map production is an important factor that can help determining the important objects and reducing distortion. Existing methods have some limitations and disadvantage. Due to lack of proper energy map that take advantage of both saliency and depth these methods could not attain proper results. In this paper, we develop a seam carving method based on object importance map. By jointly considering gradient, saliency and depth maps, we develop an efficient energy map. Furthermore, we proposed an edge preservation algorithm to avoid passing of seams through salient pixels. By taking advantage of both object importance map and edge preservation, our method achieved better seam carving performance. Experimental results show that the proposed approach produces better images than previous depth-aware and content-aware seam carving methods. Moreover, our results show that we can maintain both geometrical structures and salient objects while reducing visual artifacts.**

Keywords-Seam carving; retargeting; energy function; saliency map; depth map

I. INTRODUCTION

The diversity of modern displays with different sizes and aspect ratios has increased the importance of image retargeting techniques in recent years. Image retargeting algorithms aim to adapt the image contents and structures of salient objects to the size of screen without distortion. Traditional approaches such as cropping and scaling usually cannot achieve satisfactory resizing results [1]. Scaling only considers the output size and can be used to uniformly change the image aspect ratio. Other standard operations, such as cropping can select the most interesting parts of an image while discarding other important regions. In order to address the above problems and effectively resize an image, several content-aware image retargeting approaches have been proposed.

Seam carving is an intelligent technique in content-aware image retargeting, which is first proposed by Avidan *et al.* [2]. The main idea of this method is preservation of important content with minimizing the distortion during the retargeting process. To satisfy the target image size, seam carving iteratively reduces the input image size by removing seams with least vertical or horizontal energy according to an energy map. Optimal seams are computed by the gradient information and dynamic programming. Rubinstein *et al.* [3] extend this technique by utilizing the graph cut based energy optimization. Rubinstein *et al*. [4] also improved the original image seam carving method by using the optimal sequence of different operators to reach better visual quality in the target image. Despite the improvements, these methods may distort the shape and or the geometry of important objects. Because they do not consider structure preservation and can produce undesirable results. To make some improvement, Battiato *et al.* [5] presented a method that uses the Gradient Vector Flow (GVF) of the image to exactly select the seams to be carved away from the image. Using of GVF can create a vector field that attempts to preserve salient information.

Saliency is one of the important measures that can be helpful in preservation of the image content. For instance, Jiang *et al.* [6] proposed a technique for creating a saliency map that operates based on the difference between color histogram of a region and its adjacent regions. Some methods attempt to maintain the saliency of image objects. Chuang *et al.* [7] proposed an automatic target-preserving content-aware method that utilizes a saliency map to extract the important regions of an image. Then the content-aware interpolation technique is applied to resize the image according to attractiveness of regions. He *et al.* [8] proposed an improved seam carving content aware image resizing technique to solve the disadvantages of gradient based energy of the original seam carving. This improved technique combines both of the gradient energy and saliency map to calculate the energy function and uses a multi-thread program to increase the computational efficiency.

The depth information can have an important contribution in determination of important objects of a scene. Mansfield *et al.* [9] extended seam carving to scene carving by using a map of the image that is determined by user to decompose the scene into several layers. They assume that the inputs to the algorithm are an image and its relative depth map. The corresponding depth information of each object is provided by the user-defined depth map of the scene. Then foreground of the image is distinguished from other regions based on applied depth decomposition. However, user-defined depth maps may be different because the users' ideas are not the same and it can lead to different target results. Shen *et al.* [10] demonstrated that using depth information to evaluate importance of the image pixels can produce satisfactory seam carving results. For instance, a seam may cross important regions which will introduce visual artifacts in important objects of that scene. Therefore depth map can provide extra meaningful information in the energy function. In addition, the just noticeable distortion (JND) model helps improving seam carving by preserving important image contents. This method attempts to remove fewer seams in near objects than in distant objects.

In this paper we present a novel seam carving algorithm using a new combined energy map. This energy map utilizes three different maps including gradient map, saliency map and depth map. Combination of these three maps can generate a satisfactory resized image. On the other hand, we have proposed an edge preservation algorithm that tries to protect as much of the visual saliency pixels as possible. Our results are either better or comparable with the state-of-the-art image seam carving methods. The framework of the proposed method is illustrated in Figure 1.

The remaining sections of this paper are organized as follows: Section II presents the framework of proposed image seam carving method. In section III the experimental results are detailed and inspected to explain the effectiveness of the proposed scheme. Finally, conclusion is given in Section IV.

I. PROPOSED METHOD

To overcome the limitations and disadvantages of the naive image retargeting algorithms, we proposed a new combined energy map formation for seam carving algorithm. The new method is based on the energy map that is contained gradient map, saliency map and depth map. This energy map can be used to determine the importance of pixels of the image.

Figure 1 shows the framework for our proposed scheme. In the first step, three maps are extracted using the input images information. An energy map is defined based on these three maps. Then seam selection is applied. An optimal seam is calculated and carved using dynamic programming. After a seam is removed, size of the resized image is compared with the target's size. If the resized image is larger than the target image, then the energy map is computed again. In this energy map updating, gradient map must be re-calculated. This process is repeated until the resized image is equal to the target image. In the followings we describe the steps of algorithm in details.

A. Gradient Map Extraction

Existing seam carving methods mostly use the gradient maps to determine visual importance of pixels which was first proposed by Avidan *et al.* [2] based on Equation (1).

$$e(I) = \left|\frac{\partial}{\partial x} I\right| + \left|\frac{\partial}{\partial y} I\right| \quad (1)$$

where I is the given input image. Although gradient energy function has good efficiency for many images but it may cause serious distortions due to sensitivity to noise and allocation of higher energy to edge pixels. In addition, many pixels with high gradient values in the image may not be important. Therefore, this map alone may not be sufficient.

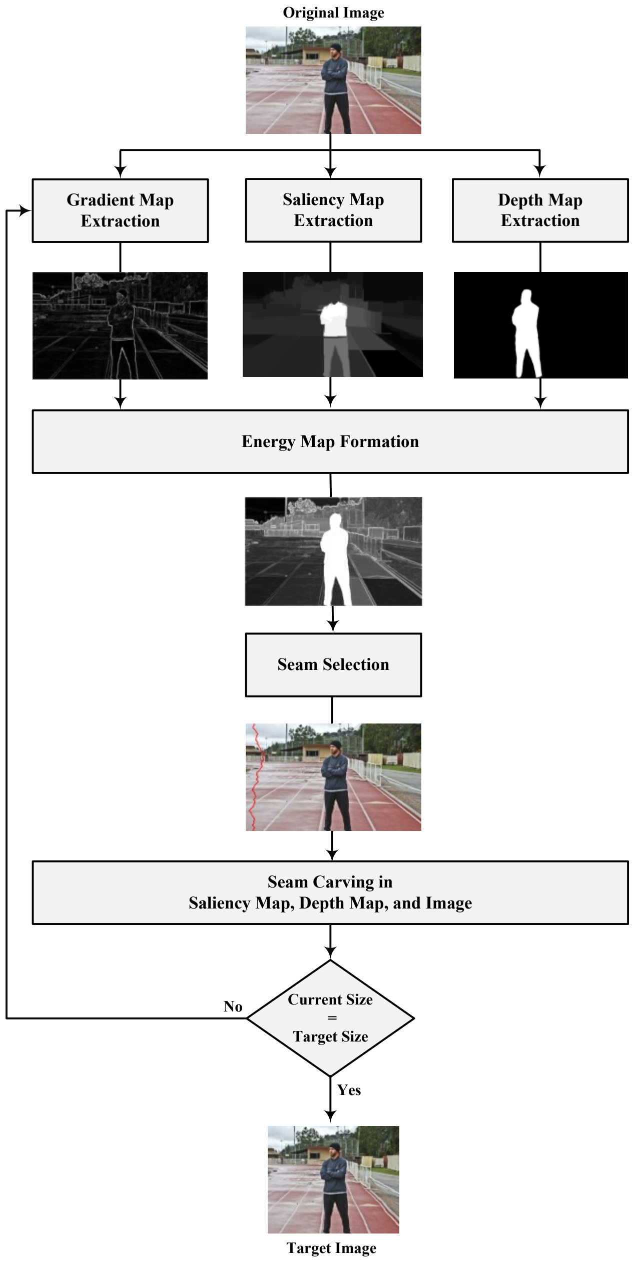

Figure 1. Framework of proposed algorithm.

B. Saliency Map Extraction

The distinction between noticeable regions and other regions can be done by the saliency map that uses color, intensity and orientation features in an image. We use salient object segmentation based on context and shape prior [6]. This method associates the bottom-up saliency information with object-level shape prior. The segmentation is done by performing energy minimization based on the initial irregular estimation. Then, the exact saliency map and shape prior can be created from the recent segmentation.

C. Depth Map Extraction

Closer objects usually have more importance and people pay more attention to them in a scene. On the other hand, distant objects often produce the background pixels and are mostly good candidates to be removed in the seam carving stage. Therefore the depth map of image can get useful clues for image seam carving and can be used as extra information in the energy function. In order to protect closer objects, the largest depth energy is assigned to their pixels. In contrast, the smallest depth energy is assigned to the pixels of far objects in the scene. Different methods exist to provide the corresponding depth information of an image. For instance, the depth map can be obtained directly by user from the scene [10] or be captured by a depth camera such as the Kinect sensor [11]. When stereo image pairs are utilized, the disparity map can give an estimation of depth information [12]. In this paper, we consider two ways for obtaining the depth information. Depth information is obtained either through user-defined depth map or disparity from stereo imaging is used as a depth map.

D. Energy Map Formation

We need an energy map to efficiently determine important regions in an image, but each energy map has some shortcomings by itself. Therefore, we introduce a new energy map based on saliency map, gradient map and depth map to extract their combined advantages.

Depth map provides us with the information about object distance to camera. We usually expect that the near objects are more important and give more weights to them. But it is not always the case. There are situations that some objects in the background might also be important. On the other hand, the saliency map determines outstanding objects in the image and combining it with the depth map will improve the results.

Gradient map gives the information about objects edges and that is important to keep the image undistorted. But it fails to detect the edges exactly when the contrast between objects is not high. Hence, by combining these three maps we try to save the image contents and avoid visual artifacts. Equation (2) defines our combined energy map for each pixel.

$$EM_{i,j} = \max\left(DM_{i,j}, SM_{i,j}\right) + GM_{i,j} \tag{2}$$

where $DM_{i,j}$, $SM_{i,j}$, $GM_{i,j}$ and $EM_{i,j}$ are the values of pixel (i,j) in the depth, saliency, gradient and combined maps respectively. All these maps are normalized.

E. Seam Selection

A seam is defined as an 8-connected path of pixels that can be top-to-bottom (vertical) or left-to-right (horizontal). Let I be an $n \times m$ image. Then a vertical seam is defined to be:

$$\begin{aligned} &S^x = \{s_i^x\}_{i=1}^n = \{(x(i), i)\}_{i=1}^n, \\ &s.t.\ \ \forall i, |x(i) - x(i-1)| \le 1, \end{aligned} \tag{3}$$

where x is a mapping $x\colon [1, \ldots, n] \to [1, \ldots, m]$. Similarly if y is a mapping $y\colon [1, \ldots, m] \to [1, \ldots, n]$ then a horizontal seam is defined as follows:

$$\begin{aligned} &S^y = \left\{s_j^y\right\}_{j=1}^m = \{(y(j), j)\}_{j=1}^m, \\ &s.t.\ \ \forall j, |y(j) - y(j-1)| \le 1. \end{aligned} \tag{4}$$

The cost of removing each pixel $e\left(I(s_i^x)\right)$ is determined from combined energy map. The cost of a vertical seam $E(S^x)$ is the sum of costs of all pixels on that seam and is calculated from Equation (5).

$$E(S^x) = \sum_{i=1}^{n} e\left(I(s_i^x)\right) \tag{5}$$

This equation is the same for vertical and horizontal seams. The optimal seam S^* (e.g. vertical seam) is the seam that has the minimum cost.

$$S^* = arg\min_S E(S) = arg\min_S \sum_{i=1}^{n} e\left(I(s_i)\right) \tag{6}$$

This optimal seam is calculated using dynamic programming. In each step in the dynamic programming, the memorization table entry $M_{i,j}$ is updated according to (7).

$$M_{i,j} = EM_{i,j} + \min\left(M_{i-1,j-1}, M_{i-1,j}, M_{i-1,j+1}\right) \tag{7}$$

At the end of this process, the entry at the last row in $M_{i,j}$ that contains the lowest value, will determine the end of the optimal seam. Then, the optimal seam path is obtained by backtracking from this minimum entry in the last row to the first row in M.

(a)

(b)

(c)

(d)

Figure 2. Images with shown seams for resizing, (a) without edge preservation, (b) with edge preservation, (c) and (d), resizing of image (a) and (b) respectively.

(a) (b) (c) (d) (e)

Figure 3. (a) Origin image, (b) energy map of origin image, (c) result of reducing width in 10 percent, (d) result of 25 percent width reduction, (e) result of 30 percent width reduction.

F. Seam carving

After specifying the vertical optimal seam in previous section, we should remove it from the image. By removing this seam all of the pixels on the right of the seam are shifted to the left by one pixel. Therefore, width of the image is reduced by one pixel. We do not need to recalculate the saliency and depth maps. The same seam is removed from these maps and they are resized same as the image. In contrast, we should calculate a new gradient map because removing a seam will affect the gradient. Then we calculate a new energy map. If several removed seams are close to each other, a large area of the image is omitted. If this happens on strong edges of the image, it will cause a big distortion in the image. Figure 2 shows this situation.

To avoid this distortion in our proposed method, where a seam crosses a strong edge, we assign a penalty to adjacent pixels to prevent other seams from crossing them. This penalty is actually an extra weight that is added to the energy map and reduces the tendency of other seams to cross those regions. Figure 2 shows the effect of adding such penalty. Yellow color in this figure is where a seam crosses a strong edge. Increasing the weight of pixels in those regions forces the seams to be far from each other and hence reduces the image distortion.

III. Experimental Results

We tested our algorithm on several datasets that contain indoor and outdoor scenes. The algorithm was implemented in MATLAB R2012a. In all experiments, we used the user-defined depth information [9] and disparity map [10] for depth map of the energy function. However, we can obtain the depth maps with different ways [11].

A. Datasets

Flickr is one of the outdoor datasets that we tested. This dataset contains a set of images with different and large depth ranges. For instance, *Man* (Figure 2) is one of the images in this dataset. Preserving the perspective of the running track is one the challenges in resizing of this image. Thus, we chose this image for our comparisons.

The *All-2views* stereo dataset also has many images with different and large depths which is suitable for testing of our proposed method. In this dataset we chose *Baby* stereo image because this image is highly textured and contains objects in different depths. Preserving textured area and salient objects are challenges of this image for seam-carving methods.

B. Main Test

We test our proposed algorithm on many different images to determine the ability of our method for resizing in different challenges. The major contributions of resizing methods are preserving of geometrical structure, avoiding of visual artifacts and maintained of salient objects. Besides these challenges, the method should reduce the size of the image by a reasonable percent. For assessing these key issues, we test our proposed resizing method for shrinking the width of the image by different values.

As an example, we select the *People* image which contains both geometrical structures and different salient objects in different depths. Figure 3 demonstrate our resizing results in which we shrink the image width by 10, 25 and 30 percent. The original image and the corresponding energy map, shown in Figure 3 parts (a) and (b). The results of resizing for these values are shown in parts (c), (d) and (e), respectively. From the given results, we see that by reducing the width size the geometrical structures in the background could be highly preserved. Moreover, salient objects are minimally distorted.

C. Comparison with other methods

We compare our algorithm with the two similar and comparable methods which are presented in [2] and [9]. In [2] a seam carving for content-aware image resizing is presented. In [9] two scene consistent image retargeting algorithms are presented for resizing. The first one is seam carving with object protection and the second one is seam carving with object protection with edge cropping.

Figure 4 shows our proposed energy maps. As shown in Figure 4 each column illustrates corresponding maps of the original image of the first row. These maps include gradient, depth, and saliency. The combination of these maps by the method proposed in section II-D produces the final energy map. Based on this energy map, we produce the final results.

In our approach we compared our results with different resized images. Figure 5 shows comparison of our method with other methods that mentioned above for reducing the width by 30 percent. From the given results, we have found that salient objects in our method are preserved better than other methods.

For the *Man* image while the man has good visual appearance, the perspective of the running tracks is preserved (Figure 5 (b)). In contrast, as shown in Figure 5 (c) for the method of [2], the body of the man is totally deformed and has unrealistic distortions. Moreover, the running tracks in the left side are severely distorted. From the given results, we see that our method by diffusing different important map could protect

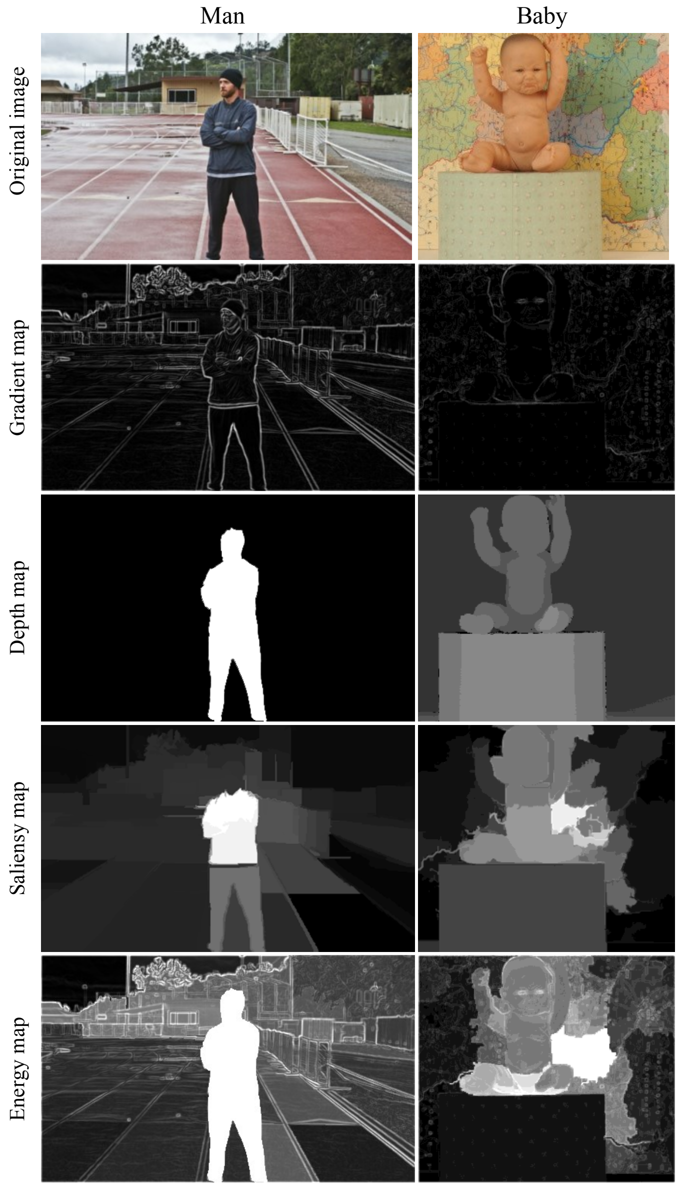

Figure 4. Original images with corresponding maps.

these lines from reshaping. Also the results of both methods in [9] that are shown in parts (d) and (e) indicate that their method could preserve the body shape but they destroy perspective of the running tracks.

Figure 5 shows another example of our results in which *Baby* image after resizing has a good visual quality. As seen in this result, the content-aware image resizing presents in [2] completely destroy the baby doll and preserve map behind it. The paper map behind the baby doll is the background and is not important. Our method by combining different maps produces an effective energy map. This energy map helps us to maintain the important objects even with small depth values. The methods of [9] damage the body of the doll and have lower visual quality in comparison with our method. For instance, in part (d) both hands of the doll are completely reshaped and in part (e) the left hand is distorted. Furthermore, both methods deformed the shape of the cylinder in the left side but our method completely retains its shape.

IV. CONCLUSION

In this paper we proposed a new algorithm for effectively resizing of a source image by maintaining important contents of the image intact. This was achieved by simultaneous consideration of edge content of the image as well as the saliency and depth of the objects in that image. This means that we evaluated the importance of image pixels. Furthermore the proposed edge protection played an important role in conservation of strong edges. The experimental results demonstrated that the proposed algorithm produced better resizing results than previous comparable methods and succeed in minimizing distortions of the image. The proposed method could also be used for video sequences [13] for changing of frame sizes. Furthermore, in some biomedical images [14,15] the background of image could be eliminated by the proposed resizing method.

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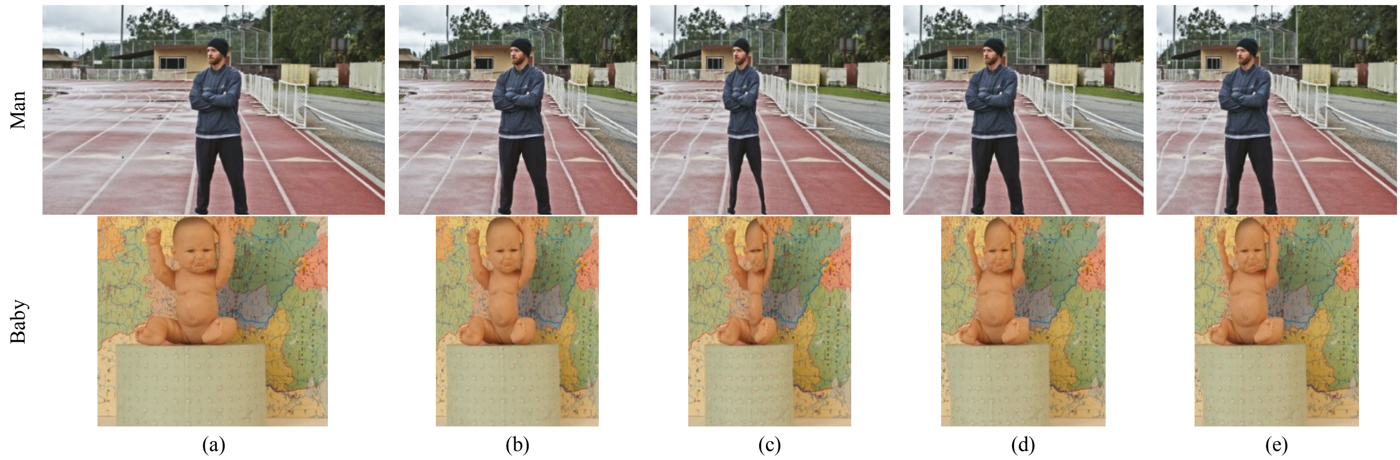

Figure 5. (a) Original image, (b) our results, (c) results of Avidan et al. [2], (d) results of Mansfield et al. [9] with object protection, (e) results of Mansfield et al. [9] with object protection and edge cropping.

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