Integrated Content-aware Image Retargeting System

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Abstract

In recent years, image retargeting has been an active research topic due to the rapid growth of mobile devices and display screens with different resolutions and aspect ratios. To address this problem, various content-aware image-retargeting approaches have been proposed to retarget images while preserving important regions and minimizing distortions. In our research, the goal is to propose a new integrated content-aware image retargeting system that outperforms other traditional approaches. At the beginning, an improved context-aware saliency detection approach is applied for detecting low-level saliency. Then, a high level salient feature—human faces—is also incorporated using an improved Viola-Jones face detector with a skin color detector as a post-processing stage, to construct the final importance map. Finally, a non-uniform image scaling approach is employed as the retargeting stage. Experimental study over a set of 74 benchmark images demonstrated that the proposed system overcomes most of the drawbacks of other existing approaches.

Keywords: *content-aware image retargeting; saliency map; face detection; skin color detection*

1. Introduction

Digital images are captured in different resolutions and aspect ratios, and most of the time they must be retargeted to arbitrary sizes and aspect ratios in order to cope with the requirements of various media distributions, such as newspaper, website, television or small mobile devices. Besides, image retargeting can also be applied to produce thumbnails. Moreover, rapid growth of mobile devices with limited resolutions and network services has boosted the significance of image retargeting technology. High-resolution images need to be adapted for small screens of mobile devices. On the other hand, due to the limited processing powers of mobile devices, the efficiency of an image retargeting approach is a key challenge.

Image retargeting problem is defined by Vaquero *et al.* [1] as: given an image I of size $m \times n$ and a new size $m' \times n'$, the goal is to produce a new image J with size $m' \times n'$ that will be a good representative of the image I. In addition, Shamir *et al.* [2] summarized the main objectives of image retargeting as follows:

(1) Preserving important contents

In an image retargeting system, an importance map is used to represent the importance of individual pixels within the image. For compact images (i.e. images with too much details), preserving important contents is a challenge, as some significant features have to be removed in the retargeting process.

(2) Limiting visual artifacts in the retargeted images

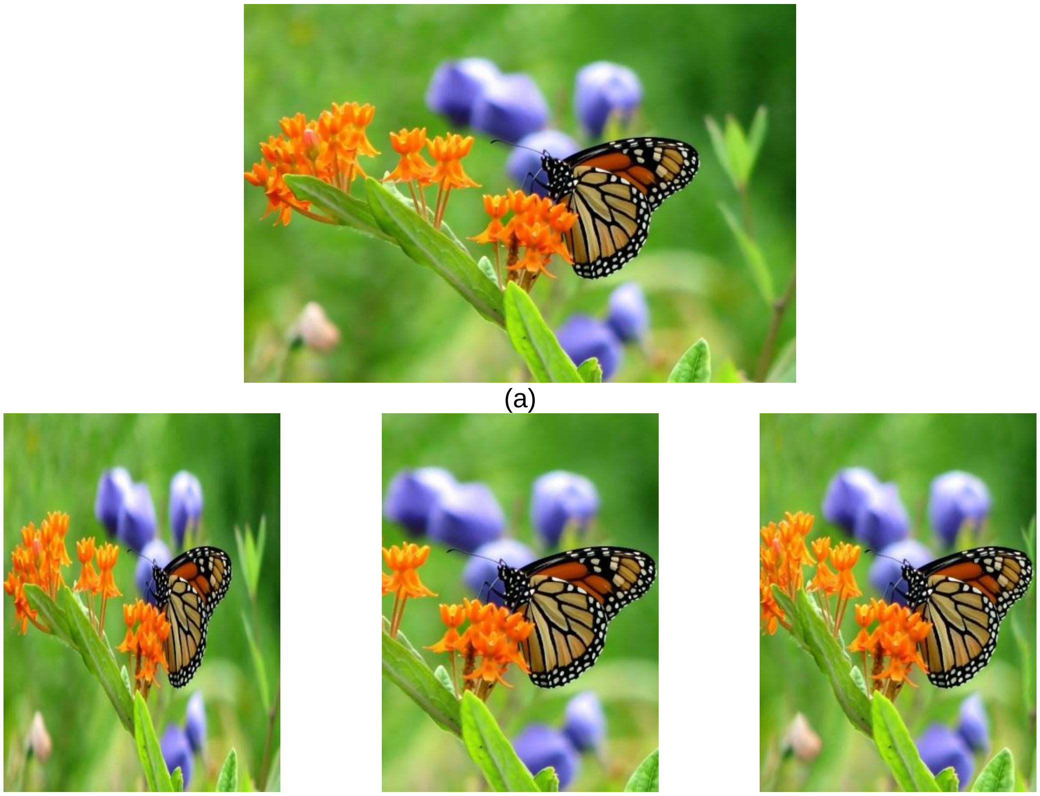
Retargeting may produce obvious visual artifacts for some images, such as object stretching or deformation, aliasing and object removal.

(3) Preserving internal structures of the original images

Distortions of internal structures - such as symmetry and geometric structures (lines, edges etc.) produced by retargeting stages- are obvious to human vision even if they exist in background.

Evaluating whether a retargeted image *J* is a ***good*** representative of an input image *I* remains a challenge. Evaluation measures are classified into two categories: objective analysis and subjective analysis. An objective analysis depends on measuring the distance between the input image and the retargeted one using computational image distance metrics, which are designed to compare image content under varying sizes or aspect ratios, such as Bidirectional similarity (BDS) [3], Bidirectional Warping (BDW) [4], SIFT-flow [5] and Earth-Mover's Distance (EMD) [6]. In general, distance metrics are less accurate in judging the quality of the retargeted image, since they may fail to detect structural distortions in the retargeted image that can be extremely obvious for human vision. On the other hand, a subjective analysis depends on the use of the visual perception of different human viewers to a set of image attributes. While it is susceptible to different viewers' perceptions, subjective analysis is still the most widely used in the image-retargeting arena. In an attempt to unify the test images used by various researchers, Rubinstein *et al.* [7] proposed a benchmark of images and listed 16 categories of reasons for rejecting a retargeting result.

Various automatic retargeting techniques have been proposed. They can be broadly classified into two directions: brute force and content-aware retargeting. Brute force approaches, such as scaling and fixed-window cropping, are the oldest and simplest image retargeting techniques. While, scaling can produce perfect results when the aspect ratio is not changed, it tends to squeeze (or stretch) the images' objects when retargeting to a different aspect ratio (see Figure 1(b)). On the other hand, fixed-window cropping maintains the relative dimensions of objects within the image, but unfortunately it eliminates portions of the original image. This may have a severe impact in the retargeted image, particularly in the case of multiple scattered objects spanning a wide range in the original image (see Figure 1(c)). To overcome the drawbacks of brute force retargeting techniques, various content-aware image-retargeting approaches have been proposed in recent years. These approaches aim at adaptively retargeting the image based on its contents (see Figure 1(d) for an example of an image retargeted using one technique from the class of content-aware image retargeting). To achieve this goal, an importance map is employed to guide the retargeting stage. The importance map is constructed by computing the importance of every pixel within the image. Computing a robust importance map for image retargeting is an active research area. Common image importance measures found in literature include gradient, saliency map, entropy, segmentation, and Histogram of Gradients (*HoG*). Saliency map has recently emerged as a promising direction, as they attempt to imitate the human visual system. Then under the guidance of the importance map, the retargeting stage is employed to construct the retargeted image.



(a)

(b) (c) (d)

Figure 1. Results of brute force and content-aware image retargeting techniques. From (a) to (d) are a sample input image and the results of reducing the original image by 50% in the horizontal direction, by scaling, cropping, and seam carving, respectively.

Content-aware image retargeting approaches were classified by Vaquero *et al.* [1] into at least six categories: cropping-based, segmentation-based, patch-based, seam carving, warping-based and multi-operator approaches. **Cropping-based** approaches [8, 9] search for the optimal cropping window, based on a pre-specified importance measure. These approaches avoid distortions of the objects within the image. However, some portions of the image are totally removed, especially in dense and (or) images with scattered objects. **Segmentation-based** approaches [10] depend on segmenting the image to extract relevant objects. Then, the background with the target size is generated by inpainting techniques. Finally, segmented objects are placed in the retargeted image, taking into consideration their spatial relationship in the original image. However, both segmentation and inpainting stages are challenging. **Patch-based** approaches [3]3, 11] divide the original image into small patches. Then, they try to minimize a similarity measure of patches between the original and the retargeted images. Reserved patches are reconstructed in the retargeted image. This method can preserve both global and complete visual features. However, it is computationally expensive and may produce incoherent results. **Seam carving** is proposed by Avidan *et al.* [12], which reduces the image width (or height) by removing seams. A seam is a vertical (or horizontal) 8-connected path of pixels with the lowest energy, based on an importance map. The optimal seams are computed using dynamic programming. Seam carving produces good results in some cases. However, it may cause distortions when removing seams that go across important areas and/or internal structures. In order to reduce distortions and artifacts, Avidan *et al.* [13] applied forward energy in seam carving to consider the energy inserted into the retargeted image when a seam is removed. Moreover, various researchers [14, 15, 16] extended the seam-carving algorithm by employing different importance maps to preserve specific features (e.g. edge detector, face detector, saliency map etc.). **Warping-based** approaches [17, 18] are continuous methods, which nonlinearly distort all image contents based on their importance. Less distortion is constrained in important areas, while more distortion is allowed in less significant regions. The main advantage of warping-based approaches is that it can produce more coherent and smoother results compared to discrete methods [13, 4]. However, warping-based approaches may cause noticeable distortions in object regions and change relative proportions of objects. Moreover, they are computationally expensive and prone to optimization challenges. Up till now, no single algorithm can produce satisfactory results in all cases. As a result, **multi-operator** approaches [4, 19] try to switch between various retargeting algorithms during the retargeting stage. The major challenges are the selection of the appropriate approach for each stage as well as the metric for the switching points. Rubinstein *et al.* [4] presented a multi-operator approach combining scaling, cropping and seam carving to obtain more pleasing results than using a single operator. To combine those three operators in a multi-dimensional resizing space, they used an algorithm based on dynamic programming to find the best path, which maximizes the bi-directional warping (*BDW*) between the original image and the retargeted one. Apparently, multi-operator approaches can yield better results provided that the sequence of applying these operators is properly selected.

In this paper, a new integrated content-aware image retargeting system is presented. The proposed system is based on our non-uniform scaling scheme [20]. Moreover, it employs both our improved context-aware saliency detection [21], and our improved Viola-Jones face detector [23] to compute a robust importance map. Experimental results demonstrate that, in most cases, the proposed integrated system produces better results compared to other common retargeting schemes found in literature.

The rest of this paper is organized as follows. Section 2 presents the proposed integrated content-aware image retargeting system, as well as brief descriptions of our recent contributions [20, 21, 23], which are employed in the proposed system. Interested readers are advised to consult [24] for full details. Then, experimental results are demonstrated in Section 3. Finally, Section 4 offers the conclusions of our work and highlights the major directions to extend this research in future.

2. Proposed Integrated Content-aware Image Retargeting System

Figure 2 shows the block diagram for the proposed system. It contains two major stages. While the first stage computes an importance map for the input image, the second stage retargets the input image to the desired dimensions using our proposed non-uniform scaling scheme [20]. It is worth mentioning that, the importance map is constructed as a linear combination of the image gradient map (a measure of the energy within the image) and the saliency map (a measure of attracting the human visual system) produced by our improved context-aware saliency detection approach [21]. Then, for images containing human faces, a face map is computed by our improved *Viola-Jones* face detector [23], with 1’s representing face regions and 0’s representing non-face ones. The face map is used as a mask to increase the saliency values of pixels in the detected face regions in the final saliency map by a pre-specified factor. In our experiments, we set this factor to two. More details, regarding the techniques employed in our system, are briefly presented in the following subsections.

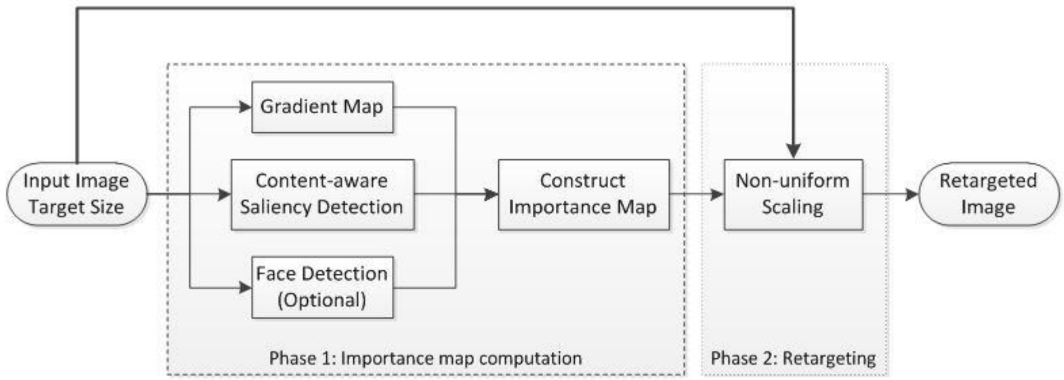


Figure 2. Proposed Integrated Retargeting System

2.1. Improved Context-aware Saliency Detection

The objective of this step is to produce a saliency map for the input image. Saliency map presents sensory information in an attempt to imitate the human visual system. It aims at highlighting image's regions, which attract an observer. The attraction level of a region depends upon how different it is from its surrounding context using various features: e.g. color, orientation, motion or other high-level features. Saliency detection has been an active research direction over the past decade. Please, refer to [25] for a comprehensive survey of existing approaches.

Recently, Goferman *et al* proposed their pioneer Context-aware saliency detection approach [14]. In this approach, the saliency of a pixel is computed by the distance of the patch centred at that pixel to all neighbouring patches. It can accurately detect the prominent objects and their surrounding contexts. Yet, this approach is computationally expensive due to the necessity to exhaustively search the entire image to find similar patches. This drawback severely limits its use in practical retargeting applications.

In our contribution [21], we successfully improved the running time for the approach in [14]. This goal was achieved by employing a local search window surrounding the pixel under consideration. The proposed local search window limits the search space, when looking for similar patches. The principal of spatial locality was the motivation to propose this window. Note that, an object generally spans a local area within the image. Hence, similar patches (belonging to the same salient object) tend to cluster in neighboring regions. This claim was experimentally validated using 86 images from the benchmark proposed in [7]. Moreover, the research investigated the effect of the size of the local window in both the quality of the generated saliency map and the computational time. The research recommended that using a window size of 85×85 produces saliency maps with almost the same quality as the original maps, while at the same time, it significantly improves the computational time (the improved algorithm executes in 21.7% of the time of the original algorithm). Please refer to [21] for more details regarding the conducted experiments, as well as, full statistical analysis to support our hypothesis.

2.2. Improved *Viola-Jones* Face Detector

Face detection is the core of all facial analysis, e.g., face localization, facial feature detection, face recognition, face authentication, face tracking, and facial expression recognition. Moreover, it is a fundamental technique for other applications such as content-based image retrieval, video conferencing, and intelligent human computer interaction (*HCI*).

Up till now, Viola-Jones face detector [22] has the most impact in face detection research during the past decade. It has become the *defacto* standard of face detection in real applications such as digital cameras, and digital photo management software.

In order to reduce the false positive rate, while keeping the high detection rate of the original *Viola-Jones* face detector, we proposed the use of an explicit skin color detector to detect candidate face regions [23]. The proposed skin color detector was employed as a post-processing stage to filter out candidate faces based on their color profile. This stage uses the *RGB* color space, with the threshold values proposed in [26]. The proposed improvement was experimentally tested over a set of 100 images with 867 faces from the *Bao* color face image database [27]. The statistical analysis showed significant improvement in the precision rate (0.98 compared to 0.86 for the original *Viola-Jones* face detector), at the expense of a little reduction on the detection rate (0.94 compared to 0.96). For more details and experimental results, please refer to our recent contribution [23].

2.3. Non-uniform Scaling

The objective of this stage is to map the input image to the required dimensions using the importance map constructed in the previous stage. We limit our discussion on reducing the image width. Reducing the image height uses the same concept in the vertical direction. Similarly, increasing the image size, in either the vertical or the horizontal directions, uses the same approach. This stage is composed of two steps, which are briefly explained in the sequel.

The first step maps the input image to a temporary map with continuous column coordinates. Each column in the input image is allocated a slot – with varying width – in the temporary map. The width of each slot is proportional to the energy (or importance values) of the image's column, compared to the overall energy within the image. The energy of each column is defined as the summation of the importance values of the individual pixels forming that column. Note that, this step represents a non-uniform scaling operation, where different regions within the original image are scaled differently based on their relative importance values.

The second step resamples the temporary map at discrete intervals to yield the final retargeted image. Each column in the final image is constructed as a weighted sum of the columns that exist in a certain neighborhood around this column in the temporary map. Resampling weights should decay as the distance between the discrete coordinate and continuous coordinate increases. Various decay functions can be used (e.g. Gaussian, logarithmic, linear). However, a linear decay function would be the appropriate choice when dealing with small devices with limited processing powers.

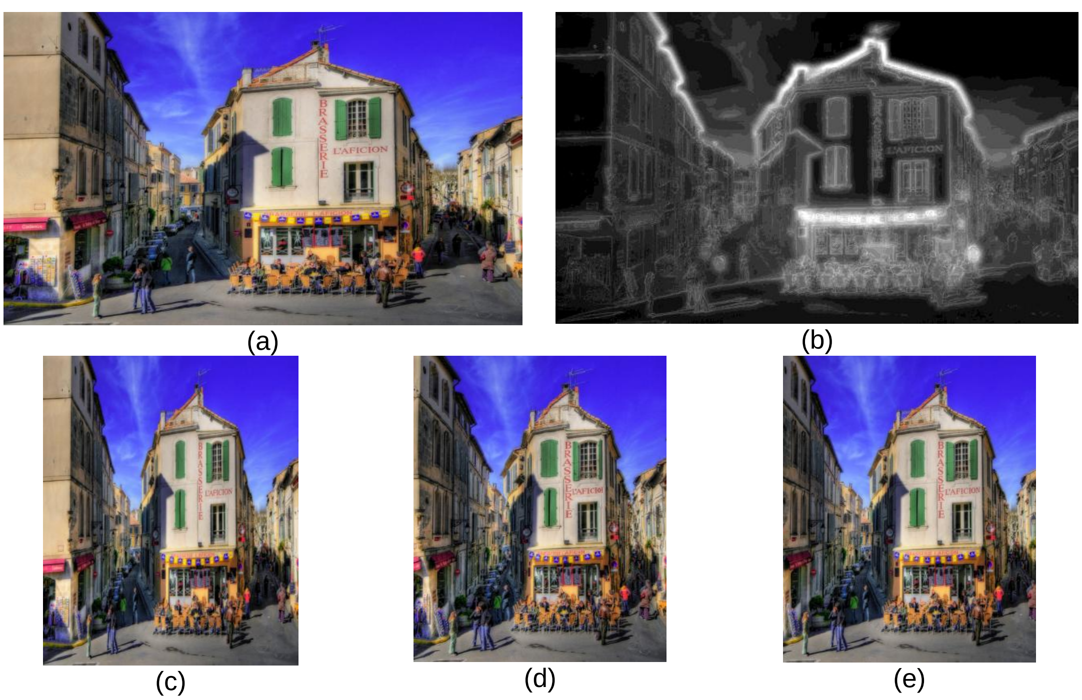
Note that, unlike seam carving, the unit of operation in the proposed scheme is a column (or row in case of height reduction). As a result, if a column is changed, all columns to its right will be shifted by the same amount. This feature significantly reduces distortions that may be produced by seam carving when the image contains straight lines in the direction of reduction (vertical lines in this case). Moreover, the computational complexity of the non-uniform scaling is $O(N)$, where N is the total number of pixels in the original image. This low time complexity, compared to other existing schemes, makes our scheme more attractive for both small devices and online applications. Please refer to our contribution [20] for full mathematical derivations, implementation details, and experimental results.

3. Experimental Results

The proposed system was evaluated on a set of 74 images from the benchmark proposed by Rubinstein *et al.* [7]. It is worth mentioning that, content-aware retargeting methods generally work better on images containing some removable contents (e.g. sky, water, grass, etc.). As a result, we focused on more challenging images which contain various relevant features (e.g. dense information, global and local structures, people, faces, lines and sharp edges, buildings, etc.). Such challenging cases represent solid basis to check the robustness of any image retargeting system.

In the conducted experiments, the width of the test images was reduced with reduction ratio set to 25% or 50% of the original width. Furthermore, the proposed system was compared to uniform scaling, conventional seam carving [13], Multi-operator (*MULTIOP*) [4], and our proposed non-uniform scaling [20]. During the experiments, test images sharing common attributes were grouped together. In the following paragraphs, a representative case from each group will be discussed.

Figure 3 shows a sample test image containing a main object (the middle building) surrounded by a complex background (other buildings and pedestrians). Moreover, both the main object and the surrounding background contain straight lines and sharp edges. The major challenge in such a case is to preserve the main object while, at the same time, limit the artifacts in lines/edges in all buildings. While uniform scaling (Figure 3(c)) maintains all contents of the original image, it considerably compresses the width of the main building. Seam carving, Figure 3(d), produces noticeable distortions in the roof of the middle building and removes some parts of the wall of the left building. Similarly, *MULTIOP* operator (Figure 3(e)) also removes the wall of the left building. Our proposed non-uniform scaling scheme (Figure 3(f)) preserves more content of the left building without any noticeable line distortion. However, our integrated retargeting system (Figure 3(g)) can better preserve the size and shape of the middle building compared to all other approaches. It also maintains the completeness of background as well.



(f)

(g)

Figure 3. Retargeting results for the input image (a) in the horizontal direction: (b) importance map combining our improved context-aware saliency map with gradient map; (c) uniform scaling; (d) conventional seam carving [13]; (e) *MULTIOP* [4]; (f) non-uniform scaling [20]; (g) our final approach. The reduction ratio is 50%.

Figure 4 shows a test image representing a class of images containing mainly one big object as the focus of interest. In this class of images, the major challenge is to preserve this big object with minimum distortions. For this class of images, uniform scaling severely compresses the main object (Figure 4(c)). Seam carving produces noticeable distortions in the retargeted image (notice the line/edges distortions in the windshield of the boat and deformation of the head of the boat in Figure 4(d)). At the same time, both *MULTIOP* (Figure 4(e)) and our non-uniform scaling (Figure 4(f)) successfully avoid the above two artifacts. However, the body of the boat is still slightly compressed. On the other hand, our proposed retargeting system (Figure 4(g)) preserves more content of the boat compared to others, due to the fact that the non-uniform scaling is cooperated with our improved context-aware saliency map.

(a)

(b)

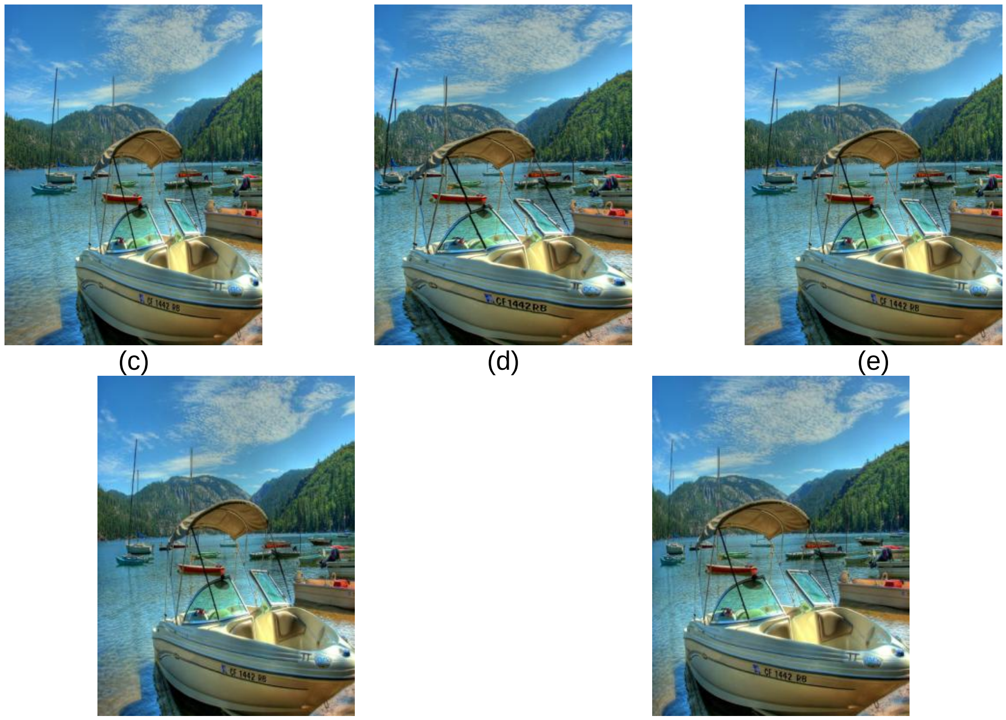


Figure 4. Retargeting results for the input image (a) in the horizontal direction: (b) importance map combining our improved context-aware saliency map with gradient map; (c) uniform scaling; (d) conventional seam carving [13]; (e) *MULTIOP* [4]; (f) non-uniform scaling [20]; (g) our final approach. The reduction ratio is 50%.

Figure 5 shows a test image representing a class of images containing one big object with low details (uniform color with no relevant features: e.g. texture, edges, etc.) surrounded by complex background. In such a class of images, uniform scaling in Figure 5(c) outperforms all other content-aware retargeting approaches, including our proposed system. This result was expected in advance, since the complex background mistakenly attracts the attention of content-aware retargeting approaches. As a result, they tend to minimize distortions to the background instead of focusing on the object of interest. This observation is evident in Figure 5(g), where our proposed system maintains the background better than all other approaches.

(a) (b)


(c)


(d)


(e)


(f)

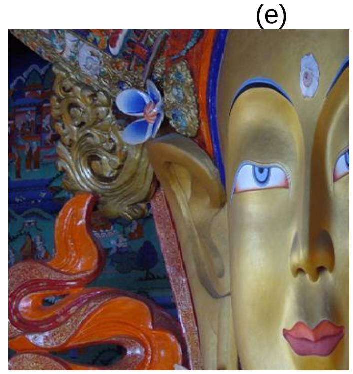
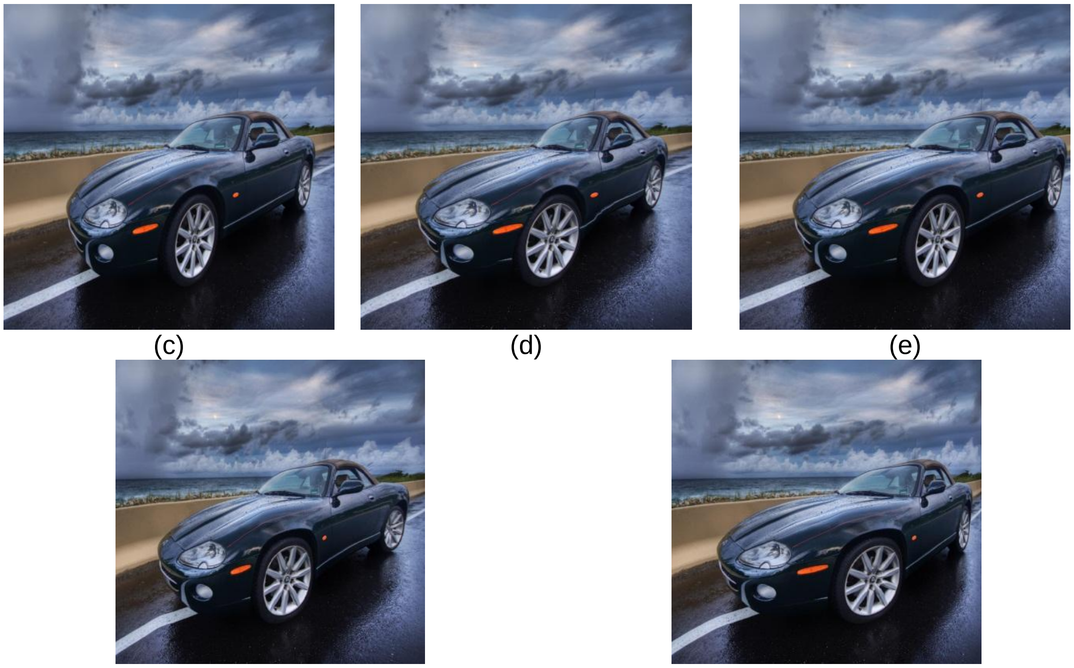

(g)

Figure 5. Retargeting results for the input image (a) in the horizontal direction: (b) importance map combining our improved context-aware saliency map with gradient map; (c) uniform scaling; (d) conventional seam carving [13]; (e) *MULTIOP* [4]; (f) non-uniform scaling [20]; (g) our final approach. The reduction ratio is 50%.

Figure 6 shows a test image representing a class of images containing objects with low color contrast compared to background. In the input image (Figure 6(a)), the car has low color contrast compared to the road and the sky colors. Since our improved context-aware saliency is based on color contrast, it fails to detect the whole car as a salient object (Figure 6(b)). As a result, our proposed system, Figure 6(g), degenerates to our non-uniform scaling approach (Figure 6(f)). Both produce distortion to the white street line at the lower left corner of the image. Seam carving produced noticeable line distortion at the side of the car (Figure 6(d)). Nevertheless, uniform scaling (Figure 6(c)) and *MULTIOP* (Figure 6(e)) produce satisfactory result in this case.


(a)


(b)

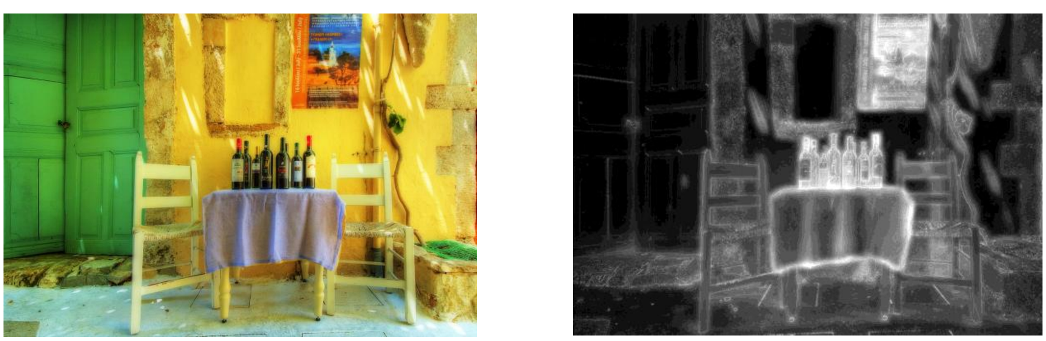


(c) (d) (e)

(f) (g)

Figure 6. Retargeting results for the input image (a) in the horizontal direction: (b) importance map combining our improved context-aware saliency map with gradient map; (c) uniform scaling; (d) conventional seam carving [13]; (e) *MULTIOP* [4]; (f) non-uniform scaling [20]; (g) our final approach. The reduction ratio is 50%.

Figure 7 shows a test image representing a class of images containing multiple objects with almost same importance levels. Both uniform scaling (Figure 7(c)) and our proposed non-uniform scaling (Figure 7(f)) compress all objects in the horizontal direction. They considerably reduce the size of the middle table and the bottles. Seam carving (Figure 7(d)), as well as *MULTIOP* (Figure 7(e)), causes noticeable distortions in the two chairs. Yet, our proposed system (Figure 7(g)) maintains better size of the middle table and the bottles, while at the same time, it produces less distortion in the two chairs compared to other approaches.



(a) (b)

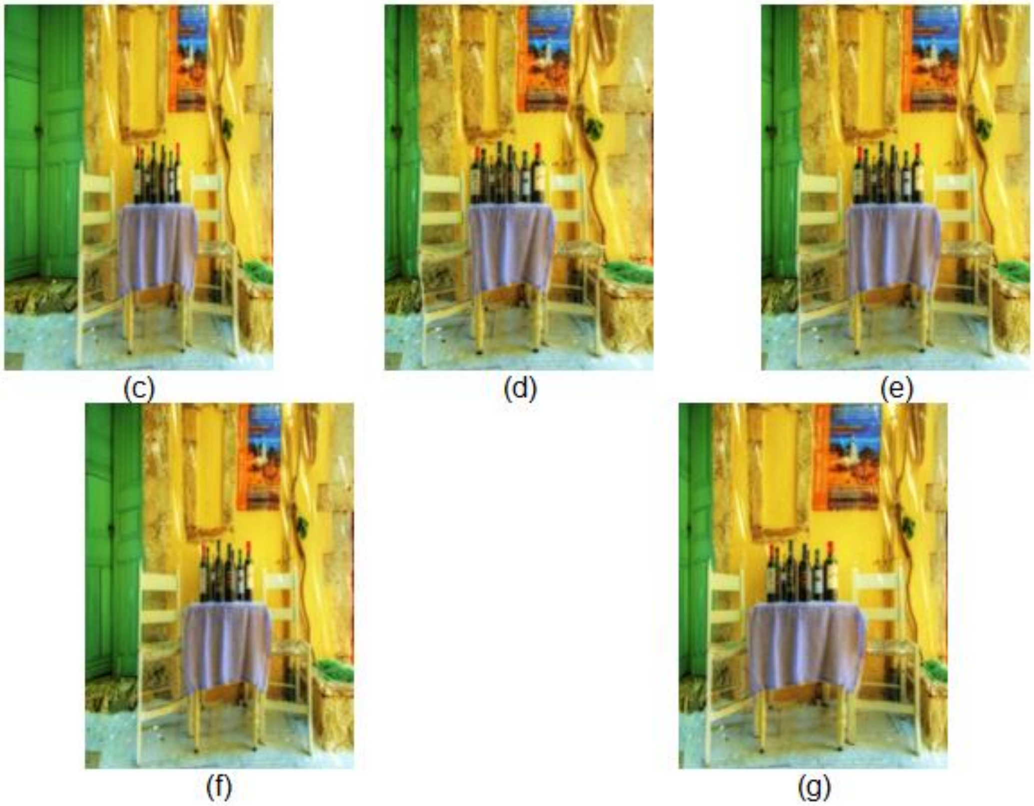


Figure 7. Retargeting results for the input image (a) in the horizontal direction: (b) importance map combining our improved context-aware saliency map with gradient map; (c) uniform scaling; (d) conventional seam carving [13]; (e) *MULTIOP* [4]; (f) non-uniform scaling [20]; (g) our final approach. The reduction ratio is 50%.

Figure 8 shows a test image representing a class of images including a group of people, as well as a big building with various sharp edges. In this case, the building and three front people represent the focus of interest for human vision. Uniform scaling (Figure 8(c)) compresses both the three people and the building. Seam carving (Figure 8(d)) produces distortions in the road line, left edges of building, the windows at the right side of the building, and the body of the middle person with an orange shirt. Both, *MULTIOP* (Figure 8(e)) and our proposed non-uniform scaling (Figure 8(f)), produce less distortion to the building. However, they compress the three persons at the middle of the image. Yet, our proposed system (Figure 8(g)) produces the best result compared to all other approaches. It not only preserves the details of the building, but it also produces a natural look for the three persons at the middle of the image.

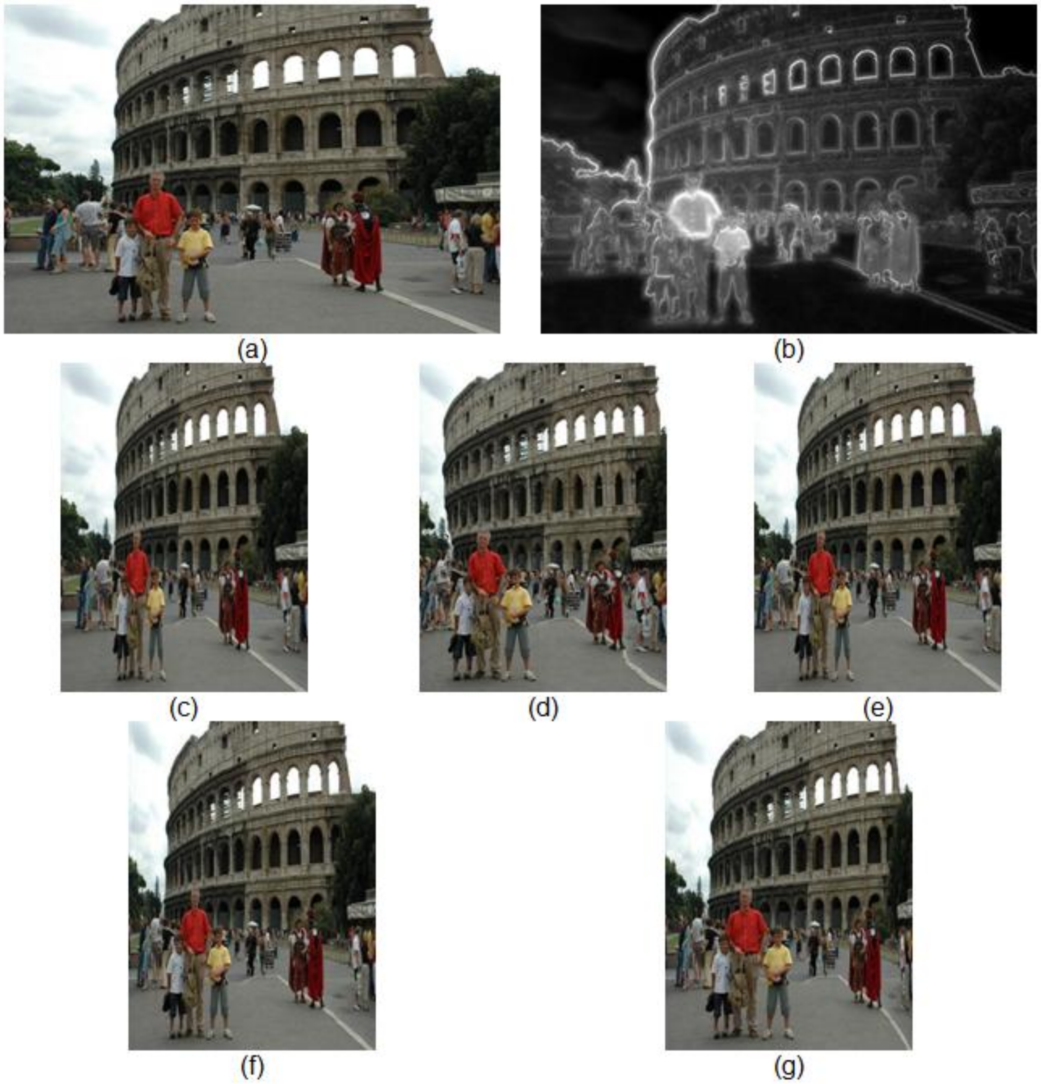


Figure 8. Retargeting results for the input image (a) in the horizontal direction: (b) importance map combining our improved context-aware saliency map with gradient map; (c) uniform scaling; (d) conventional seam carving [13]; (e) *MULTIOP* [4]; (f) non-uniform scaling [20]; (g) our final approach. The reduction ratio is 50%.

Figure 9 shows a test image representing a class of images containing human faces. Uniform scaling (Figure 9(c)), MULTIOP (Figure 9(e)), and our non-uniform scaling (Figure 9(f)) compress the face of the person in the middle of the image, compared to the original image (Figure 9(a)). Seam carving (Figure 9(d)) produced the worst result, where the face and the body of the person were severely distorted. Yet, our proposed system (Figure 9(g)) maintains a better size for the person, compared to all other approaches.

Figure 9. Retargeting results for the input image (a) in the horizontal direction: (b) importance map constructed by our improved context-aware saliency map, gradient map and face map of our improved *Viola-Jones* face detector; (c) uniform scaling; (d) conventional seam carving [13]; (e) *MULTIOP* [4]; (f) non-uniform scaling [20]; (g) our final approach. The reduction ratio is 50%.

4. Conclusion and Future Work

We proposed an integrated image retargeting system composed of two main stages. The first stage employs both our proposed improved context-aware saliency detection scheme and our improved *Viola-Jones* face detector to construct an importance map to guide the next retargeting stage. The second stage employs our proposed non-uniform scaling scheme to retarget the image to the desired dimensions. Experimental results demonstrate that, in most cases, our proposed system produces better results compared to common retargeting schemes found in literature. However, the major shortcoming of our proposed system is that it may produce noticeable distortions when dealing with images containing objects with low color contrast relative to the background. This shortcoming is believed to be a direct consequence of using color dissimilarity as a measure when detecting salient regions in the image. Incorporating other features (e.g. texture) is a good candidate to overcome this problem. We plan to investigate this improvement direction during our future studies. Another improvement direction is to try various methods to combine the image gradient, the saliency map, and the face map into the final importance map. In our experiments, we assigned equal weights to the image gradient and the saliency map. Moreover, we used the face map to double the importance values of face regions in saliency map. We believe that more experiments are still needed to find optimal parameter settings for better results.

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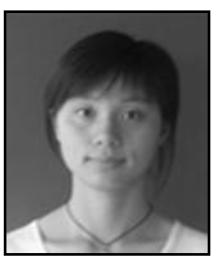

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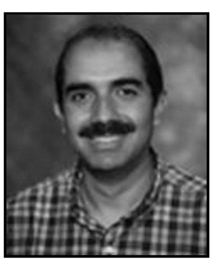

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