Adaptive image retargeting using saliency-based continuous seam carving

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1 Introduction

With the rapid growth of diverse mobile devices with a broad range of display resolutions, it becomes increasingly important to efficiently display large images on small-sized screens of mobile devices. The resolution of the original image is changed to adapt to the dimension of the target display, and such a resolution adaptation, usually termed image retargeting (or image adaptation, or image resizing) can be realized using a variety of approaches. Scaling is the most straightforward approach, but it is totally unaware of image content and especially degrades the readability of small but important objects in the scaled image. In contrast, there have been several classes of content-aware image retargeting approaches, as briefly described in the following.

Cropping-based approaches1–4 are effective for displaying one major object or a concentration of multiple objects in the image, but cannot correctly handle scattered multiple objects. Recomposition-based approaches5–7 need to segment salient objects from the image and repair the background using the image inpainting method, and then synthesize the retargeted image using a smaller scaling ratio for objects than for the repaired background. However, salient object segmentation without any user intervention is still very unreliable for achieving acceptable quality of retargeting, and object segmentation is usually time-consuming. Warping-based approaches8–11 nonuniformly scale regions with different importance in order to minimize the distortion of important regions, but may introduce noticeable distortions in background regions. A patch-based approach using bidirectional similarity to measure the redundancy of image patterns is proposed in Ref. 12 to gradually resize the image, but its iterative process causes very high computational complexity.

Recently, a promising approach called seam carving13 was proposed primarily for image retargeting, and later improved by introducing forward energy and extended to video retargeting in Ref. 14. Using seam carving, the image width (or height) is reduced by one pixel each time through removing a seam, which is a vertical (or horizontal) connected path of pixels with the lowest energy. Although

Abstract. This paper presents an adaptive image retargeting approach using saliency-based continuous seam carving to efficiently display images on small screens. A multiscale contrast-based saliency map is first generated and used as the energy map for conventional discrete seam carving, and a reasonable number of seams are adaptively extracted. Then the reduced dimensions allocated to continuous seam carving (CSC) and possible scaling are determined by the analysis of the energy curve of the extracted seams. The proposed CSC assigns to each extracted seam a reserving ratio in accordance with the corresponding seam energy and the reduced dimension, and the retargeted image is generated using an efficient scheme of mapping and resampling based on the reserving ratio map. Experimental results demonstrate better retargeting performance of the proposed approach under different reduction ratios. © 2010 Society of Photo-Optical Instrumentation Engineers.

Subject terms: image retargeting; reserving ratio map; saliency map; seam carving.

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seam carving generally shows superior results to those of previous retargeting approaches, it unavoidably distorts salient objects when the reduction ratio is high. The reason is that the operation of removing a seam in Refs. 13 and 14 is a discrete one, and thus seams across salient objects have to be removed once seams with lower energy have all been removed. For this reason, we call the conventional seam carving discrete seam carving (DSC). In addition, the energy map used in Refs. 13 and 14 can only highlight object boundaries and edges, and thus seams may traverse salient objects even under a lower reduction ratio. In Ref. 15, the saliency map generated using a bottom-up visual attention model\(^1\) is used as the energy map to improve the retargeting performance of DSC.

With the main motivation to overcome the drawbacks of DSC, we present an adaptive image retargeting approach, which mainly exploits the proposed continuous seam carving (CSC) and multiscale contrast-based saliency map, and combines the merits of seam carving and scaling in a uniform way. In comparison with DSC and other classes of retargeting approaches mentioned, the main contribution of our approach is twofold:

1. In contrast with the conventional DSC, the proposed CSC method becomes a continuous retargeting operation with the introduction of a reserving ratio map, and thus can generate a smoothly retargeted image for a better viewing experience. Compared with DSC, the increased computation load is negligible due to the use of an efficient scheme of mapping and resampling in CSC, and thus CSC still maintains the processing efficiency of DSC and a lower computational complexity than time-consuming recomposition-, warping-, and patch-based approaches.\(^2\)

2. Although some retargeting approaches\(^9,15\) have exploited the saliency map of the image to guide their retargeting operations and achieved better performance, we demonstrate that our multiscale contrast-based saliency map is more useful for image retargeting than the adopted spotlight saliency map in previous approaches.

The rest of this paper is organized as follows. Section 2 describes our adaptive image retargeting approach in detail. Experimental results and conclusions are given in Secs. 3 and 4, respectively.

## 2 Adaptive Image Retargeting

The proposed adaptive image retargeting approach mainly consists of three stages as outlined in Fig. 1. First, a multiscale contrast-based saliency map is constructed and used as the energy map for seam carving. Then, based on the target dimension, a reasonable number of seams are extracted by DSC to generate the seam map, and the reduced dimensions allocated to CSC and possible scaling are adaptively determined by analysis of the energy curve of these extracted seams. Finally, our CSC method computes the reserving ratio for each seam, and exploits an efficient scheme of mapping and resampling to generate the retargeted image with an optional scaling operation. In the following, seam carving and our observations are briefly described in the first subsection, and then the three stages of our approach are detailed in the following three subsections.

### 2.1 Seam Carving and Our Observations

Seam carving is a recently developed image-retargeting operator, which has been proven to be the most favorable approach in terms of computation efficiency and visual quality of retargeting images. A seam is defined as a connected path of pixels with the thickness of single pixel in the vertical or horizontal direction of the image. By removing or inserting a seam, we can reduce or enlarge the height (width) of the image by one row (column). Therefore, we can achieve any amount of shrinkage or enlargement through repeated seam removal or insertion. Formally, let \( I \) be the original image with size \( w \times h \) (width by height). A vertical seam \( S^y \) is defined as

\[
S^y = \{ s^y_i \}_{i=1}^h = \{(x(i),i)\}_{i=1}^h, \quad \forall i \mid |x(i) - x(i-1)| \leq 1, \tag{1}
\]

where \( (x(i),i) \) denotes the coordinates of the \( i \)th pixel of the seam \( S^y \). Similarly, a horizontal seam \( S^x \) is defined as

\[
S^x = \{ s^x_j \}_{j=1}^w = \{(j,y(j))\}_{j=1}^w, \quad \forall j \mid |y(j) - y(j-1)| \leq 1, \tag{2}
\]

where \( (j,y(j)) \) denotes the coordinates of the \( j \)th pixel of the seam \( S^x \).

Given an energy function \( E \) to measure the importance of each pixel, the vertical seam with the lowest energy is determined as follows:

\[
S^y_{\text{min}} = \arg \min_{S^y} E(S^y) = \arg \min_{S^y} \sum_{i=1}^h E(I(s^y_i)), \tag{3}
\]

where the energy function, used in Refs. 13 and 14, is defined as the sum of the horizontal and vertical gradient magnitudes,

\[
E(I(x,y)) = \left| \frac{\partial I(x,y)}{\partial x} \right| + \left| \frac{\partial I(x,y)}{\partial y} \right|. \tag{4}
\]
The vertical seam with the lowest energy can be efficiently determined by the dynamic programming method. By repeatedly removing the vertical seam with the currently lowest energy of the image, the image width is reduced by one pixel each time to gradually reach the target width of the retargeted image. The image height can be reduced using a similar operation on horizontal seams.

An example of seam carving is illustrated in Fig. 2. For the original image with a size of 720×540 shown in Fig. 2(a), the gradient-based energy map calculated using Eq. (4) is shown in Fig. 2(b). Based on the energy map, the first 200 vertical seams are extracted and superposed on the original image as shown in Fig. 2(c). Using DSC, the image width is reduced by 200 pixels by carving these 200 seams, and the retargeted image with a size of 520×540 is shown in Fig. 2(d). For a comparison, the scaled image with the same size is shown in Fig. 2(e). It can be seen that the two human objects are better retained using DSC than using scaling, and this testifies to the better performance of important content preservation using seam carving.

Based on our observation from experiments on a variety of images, retargeted images using DSC with a small reduction ratio (less than 30%) are usually acceptable for most images, e.g., Fig. 2(d). Nonetheless, we can observe from Fig. 2(c) that a few seams have already traversed the two human objects while there are still considerable homogeneous background regions that are not traversed by a seam. The reason is that a gradient-based energy map such as Fig. 2(b) only highlights distinctive edges such as object boundaries, and thus it is inadequate to guarantee the performance of DSC with a moderate or large reduction ratio.

For the example image shown in Fig. 2(a), if its width is reduced by a half, the 360 seams extracted using DSC are overlapped on the original image as shown in Fig. 2(f), and we can see that more seams traverse the two human objects. The correspondingly retargeted image with size 360×540 is shown in Fig. 2(g), which exhibits noticeable distortions, including the obviously narrowed shapes of the two human objects and the visually distorted region marked in the blue rectangle (it is shown magnified in the bottom right corner).

The energy map used in DSC is crucial for the visual quality of the retargeted image. For a given number of seams, the ideal energy map for DSC should be able to choose for extraction many seams that traverse unimportant background regions while choosing few seams that traverse salient regions. In Ref. 15, the performance of DSC is improved by incorporating a bottom-up visual attention model,16 which is exploited to generate a spotlight saliency map. Using the saliency map as the energy map in DSC, the visual distortions of the retargeted images are alleviated within a range of reduction ratios. However, the spotlight saliency map can only highlight the locations of visually salient objects; it cannot sufficiently highlight the whole region of salient objects. By performing DSC on hundreds of images containing salient objects, we found that such a spotlight saliency map is not adequate for seam carving.

For the example image in Fig. 2(a), its spotlight saliency map is shown in Fig. 3(a). Using Fig. 3(a) as the energy map, the 360 vertical seams extracted by DSC are superposed on the original image as shown in Fig. 3(b), and the correspondingly retargeted image with size 360×540 is shown in Fig. 3(c). Compared with Fig. 2(f), although a large number of seams in Fig. 3(b) have been directed to bypass the two human objects, quite a few seams still traverse them. Compared with Fig. 2(g), the aspect ratio of human objects is well preserved in Fig. 3(c), but there is still similar noticeable artifact in the region marked by the blue rectangle (a magnified view is also shown in the bottom right corner). The main reason for such distortions is that salient objects still cannot be sufficiently highlighted in the spotlight saliency map. Therefore, we first need to propose an efficient saliency map generation method to overcome the drawbacks of the spotlight saliency map when used as the energy map for seam carving. The following subsection describes the generation of the proposed multiscale contrast-based saliency map.

### 2.2 Multiscale Contrast-Based Saliency Map

Assume that the original image I has size \( w \times h \) (width × height), and its three color channels in the RGB color space are denoted as \( r, g, \) and \( b \). Based on the color decomposition method suggested in Ref. 16, four broadly...
tuned color channels \( R, G, B, \) and \( Y \) for red, green, blue, and yellow and one luminance channel \( L \) are obtained as follows:

\[
R = r - (g + b)/2, \\
G = g - (r + b)/2, \\
B = b - (r + g)/2, \\
Y = (r + g)/2 - |r - g|/2 - b, \\
L = (r + g + b)/3. 
\]  
(5)

For each pixel at \((x,y)\), a 5-D feature vector \( f(x,y) \) is composed of the four chrominance components and the luminance component calculated using Eq. (5), i.e., \( f(x,y) = [R \ G \ B \ Y \ L]^T \). The saliency for the pixel at \((x,y)\) is defined as the average of the contrast evaluated at multiple scales,

\[
SAL(x,y) = \frac{1}{n-1} \sum_{k=0}^{n-1} SAL_k(x,y) = \frac{1}{n-1} \sum_{k=0}^{n-1} |F_k(x,y) - F'_k(x,y)|, 
\]  
(6)

where \( SAL_k(x,y) \) denotes the contrast evaluated at the \( k \)th scale, and \( F_k(x,y) \) and \( F'_k(x,y) \) represent the average feature vector of the center region \( R_k(x,y) \) and the surrounding region \( R'_k(x,y) \) around \((x,y)\) at the \( k \)th scale, respectively. Specifically, \( F'_k(x,y) \) is defined as

\[
F'_k(x,y) = \sum_{(x',y') \in R'_k(x,y)} f(x',y') / |R'_k(x,y)|, 
\]  
(7)

where \( |R'_k(x,y)| \) is the area of the center region \( R'_k(x,y) \). The vector \( F_k(x,y) \) is calculated using a formula similar to Eq. (7). Figure 4 shows a pictorial illustration of the center region \( R_k(x,y) \) and the surrounding region \( R'_k(x,y) \). Let \( W_k(x,y) \) and \( W_{k+1}(x,y) \) denote the square windows centered at \((x,y)\) with size \((2^k + 1) \times (2^k + 1)\) and \((2^{k+1} + 1) \times (2^{k+1} + 1)\), respectively. Then \( R'_k(x,y) \) and \( R_k(x,y) \) are defined as

\[
R'_k(x,y) = W_k(x,y), \\
R_k(x,y) = W_{k+1}(x,y). 
\]  
(8)

As shown in Fig. 4, the surrounding region \( R'_k(x,y) \) is the gray band that belongs to \( W_{k+1}(x,y) \) while not belonging to \( W_k(x,y) \). The total number of scales, \( n \), is determined when either of the following two conditions is first satisfied: (1) it is the maximum integer such that \( 2^n \leq \min(w,h)/2 \); (2) the surrounding region \( R'_k(x,y) \) has violated the image boundary.

Using the multiscale contrast-based saliency map as the energy map, salient objects are highlighted more adequately, and thus early traversing seams on them can be avoided. The multiscale contrast-based saliency map generated for the example image in Fig. 2(a) is shown in Fig. 5(a). Using Fig. 5(a) as the energy map, the 360 vertical seams extracted using DSC and the retargeted image with size \( 360 \times 540 \) are shown in Fig. 5(b) and 5(c), respectively. Compared with the corresponding results shown in Figs. 2 and 3, we can see that the distribution of seams in Fig. 5(b) is more reasonable for seam carving, and thus the visual distortion in Fig. 5(c) is insignificant.

2.3 Adaptive Seam Extraction and Analysis

To simplify the description of the following two stages of our approach, we describe the retargeting process in the horizontal direction to reduce the image width (the retargeting process in the vertical direction can be performed in a similar way). Assuming that the width of the finally retargeted image is \( w_r \), a reasonable number of vertical seams are first extracted by DSC, which uses our multiscale contrast-based saliency map as the energy map. The number of extracted seams, \( n_s \), is defined as

\[
n_s = \text{round}[(w - w_r) / (w - w_r)^{1/\alpha}], 
\]  
(9)

where the parameter \( \alpha \) is defined as

\[
\alpha = \max \left( \frac{\sum_{y=1}^{h} \sum_{x=1}^{w} \text{SAL}(x,y)}{\sum_{y=1}^{h} \sum_{x=1}^{w} \text{SAL}_0(x,y)}, 1 \right). 
\]  
(10)

The parameter \( \alpha \) is actually dependent on the homogeneity of the input image. If the image is rich in homogeneous regions such as sky, grassland, and water, \( \alpha \) acquires a greater value and thus \( n_s \) is not too much greater than the desired width reduction \( w - w_r \). Otherwise, if salient objects are abundant in the image, their significant edges lead to a smaller value of \( \alpha \) and thus a larger value of \( n_s \). Therefore, \( n_s \) is adapted not only to the desired width reduction but also to the image content.
For the example image in Fig. 2(a), if the target width $w_t$ is 180, and $w - w_t = 540$ (a high reduction ratio of 75%), then $n_s$ is calculated as 638 using Eq. (9). All 638 vertical seams are sequentially extracted by DSC to generate the vertical seam map $SM_v$ as shown in Fig. 6. Each seam in $SM_v$ is identified by labeling its associated pixels with the sequential extraction number represented using spectral colors from blue to red. It can be seen that the unlabeled white region in Fig. 6 overlaps most of the salient object regions.

It should be noted that the later-extracted seams with higher energy have to traverse salient regions when the reduction ratio is too high. Compared with DSC, the proposed CSC, which is detailed in the next subsection, can generally improve the visual quality of retargeted images for low to medium reduction ratios. However, for a small retargeted image whose dimensions have been sufficiently reduced, we found that the most reasonable operation is to further uniformly scale it to fit the target width. Although uniform scaling on a sufficiently small image is unaware of the image content, it can preserve the scene layout and introduce no local artifacts, which are very likely to be introduced by nonuniform retargeting operations, including warping-based approaches and our CSC.

Based on the preceding analysis, we need to determine a suitable reduced width for CSC, and possibly perform scaling to reduce the remaining width to fit the target width. The reduced width allocated to CSC, $n_c$, is determined by the analysis of the energy curve of the $n_s$ extracted seams. Let the energy value for each extracted seam $S_y^i$ ($i=1,\ldots,n_s$) be denoted as $e_y^i$, and the average value of the energy map $SAL$ be denoted as $e_y$. We calculate the average energy value $ase_y$ around each $e_y^i$ within a sliding window, whose half width is set to 5 in our implementation. We check the average energy values $ase_y^i$ ($i=1,\ldots,n_s$) in turn, and assign $n_c$ as the minimum sequential extraction number of the seam whose average energy value is greater than $e_y$. If all $ase_y^i$ ($i=1,\ldots,n_s$) are smaller than $e_y$, then $n_c$ is set equal to $n_s$, which means only CSC is used to reduce the image width.

Figure 7 shows the corresponding energy curve for the extracted seams shown in Fig. 6. It can be seen that the energy curve is basically a rising curve, but not strictly monotonic, due to the greedy property of the dynamic programming used in DSC. Using the average energy value of a sliding window smooths the energy curve. For this example, the reduced width allocated to CSC is determined as 426. After performing CSC, scaling is performed to further reduce the width by 114 pixels to obtain the finally retargeted image with size $180 \times 540$.

### 2.4 Continuous Seam Carving

This subsection details the proposed CSC method, which first computes the reserving ratio for each seam of the generated seam map, and then exploits an efficient scheme of mapping and resampling to obtain the retargeted image with the determined dimension.

The reserving ratio $r_i$ for each seam $S^i$ ($i=1,\ldots,n_s$) in the seam map $SM_v$ is determined as follows:

$$
r_i = \begin{cases} 
(n_s - n_c) \frac{se_y^i}{\sum_{k=1}^{n_s} se_y^k}, & n_c < n_s, \\
(w_t + n_c - w) \frac{se_y^i}{\sum_{k=1}^{n_s} se_y^k}, & n_c = n_s.
\end{cases}
$$

The reserving ratio map $RRM_v$ is then generated by assigning to each pixel the reserving ratio of its associated seam. The reserving ratios for unlabeled pixels in the seam map are set to 1.0, i.e., those white pixels in the seam map $SM_v$ will be completely reserved in the retargeted image after CSC. Based on $RRM_v$, the pixel located at the integer coordinates $(x,y)$ in the original image $I$ is mapped to a new coordinates $(x',y)$ in an unevenly sampled image $I_u$. The fractional coordinate $x'$ is defined as

$$
x' = x + \frac{r_i(x,y)}{1 - r_i(x,y)} 
$$

Fig. 8 Comparison of retargeted images using our approach, DSC, and scaling: (a) image $(294 \times 540)$ retargeted using CSC, (b) image $(294 \times 540)$ retargeted using DSC, (c) image $(180 \times 540)$ retargeted using our approach, (d) image $(180 \times 540)$ retargeted using DSC, (e) image $(180 \times 540)$ retargeted using scaling.
For the example image in Fig. 2(a), the retargeted image using the proposed CSC method with the reduced width of 426 pixels is shown in Fig. 8(a), and the retargeted image using DSC with the same reduced width is shown in Fig. 8(b). The visual quality of the image retargeted using CSC is obviously better than that using DSC. Scaling is then performed on the retargeted image shown in Fig. 8(a) to further reduce the width by 114 pixels, and the final retargeted image is shown in Fig. 8(c). For a comparison, the images retargeted using DSC and scaling with the same target width of 180 pixels are shown in Fig. 8(d) and 8(e), respectively.

3 Experimental Results

We evaluate the proposed adaptive image retargeting approach on a collection of 150 images. Retargeting with three reduction ratios of 25%, 50%, and 75% is performed in our experiments. To demonstrate the effectiveness of our retargeting approach and especially the improvements on the conventional seam carving approach, we compare our results with those of scaling, scale-and-stretch\(^\text{11}\) (a warping-based approach), conventional DSC,\(^\text{14}\) and DSC using our saliency map (DSC-SAL). Figure 9 shows six representative test images used in our experiments. Under the three reduction ratios, the retargeting results on the horizontal direction, the vertical direction, and both directions are shown in Figs. 10 and 11, Figs. 12 and 13, and Figs. 14 and 15, respectively. For the retargeting results on both directions shown in Figs. 14 and 15, we perform the proposed retargeting approach twice with two different orders (width first and height first), and then choose the result with the less energy loss as the final retargeting result. We can see from Figs. 10–15 that our approach can generally preserve not only salient objects but also the scene layout much better than other approaches under all three reduction ratios. It is obvious that scaling on only one direction introduces distortion in the form of aspect ratio change of salient objects, especially for high reduction ratios. The scale-and-stretch method can avoid obvious distortions of salient objects, but it can also cause an obvious distortion of background regions, e.g., the significant change of the scene layout in Figs. 11(b) and 15(b). DSC can distort the salient objects in the image even if the re-
Fig. 11 Retargeting results for Fig. 9(b) on the horizontal direction: (a) scaling, (b) scale-and-stretch, (c) DSC, (d) DSC with our saliency map, (e) our approach. In each part, the reduction ratios for the top, bottom left, and bottom right images are 25%, 50%, and 75%, respectively.

Fig. 12 Retargeting results for Fig. 9(c) on the vertical direction: (a) scaling, (b) scale-and-stretch, (c) DSC, (d) DSC with our saliency map, (e) our approach. In each part, the reduction ratios for the top, middle, and bottom images are 25%, 50%, and 75%, respectively.

Fig. 13 Retargeting results for Fig. 9(d) on the vertical direction: (a) scaling, (b) scale-and-stretch, (c) DSC, (d) DSC with our saliency map, (e) our approach. In each part, the reduction ratios for the top, middle, and bottom images are 25%, 50%, and 75%, respectively.

Fig. 14 Retargeting results for Fig. 9(e) on both directions: (a) scaling, (b) scale-and-stretch, (c) DSC, (d) DSC with our saliency map, (e) our approach. In each part, the reduction ratios for the top, bottom left, and bottom right images are 25%, 50%, and 75%, respectively.
duction ratio is only 25%, e.g., Figs. 10(c) and 13(c). Using our saliency map as the energy map, DSC-SAL performs better for some images, but can still distort salient objects at a high reduction ratio due to its discreteness, e.g., Figs. 12(d) and 15(d).

The retargeting results with a reduction ratio of 75% in Fig. 15 indicate that Fig. 9(f) is rather challenging for image retargeting approaches. The scaled image is not suitable for recognizing the four persons, and the retargeted images generated by the other three approaches are totally unacceptable, while our approach can still obtain a visually acceptable result. The retargeting results shown in Fig. 14 indicate that our approach can obtain a better balance between preserving the scene layout and emphasizing the salient objects.

To further evaluate the performance of different retargeting approaches with respect to subjective visual quality, we performed a user study to verify whether our retargeting results are more desirable than the results of the other four approaches. In our user study, we used the retargeting results of 24 images from our test set, and each image contains at least one salient object. The user study consisted of three sessions for the three reduction ratios, and each session consisted of four separate parts, viz., our approach versus scaling, our approach versus scale-and-stretch, our approach versus DSC, and our approach versus DSC-SAL. The source image was first shown in the center region of a 21-in. LCD monitor for 3 s, then a pair of retargeted images using our approach and one other approach was simultaneously shown on the monitor for 6 s, and finally a gray screen was shown for 3 s. As shown in Fig. 16, both retargeted images were displayed on a virtual mobile phone screen in order to provide the user with the viewing experience on a mobile device. The position for showing our result (left or right, up or down) was randomly determined.

We invited 20 graduate students (12 males and 8 females) to participate in our user study. Each participant was asked to determine which one of the two retargeted images was preferred, and write the position (L/R, U/D) of the preferred image on the answer sheet during the period of gray screen. After we collected the answer sheets from all 20 participants, for each part of each session, we counted the total number of times that our results were selected as preferable to those of the other method, and calculated the selection ratio of our results.

The statistical data from the user study are shown in Table 1. On average, the selection ratio of our results is 85.38% with respect to scaling, 78.28% with respect to scale-and-stretch, 86.62% with respect to DSC, and 75.16% with respect to DSC-SAL. We can conclude from Table 1 that the retargeted images using our approach generally provide the observer with a better viewing experience than other approaches. We also see from Table 1 that selection ratios of our results with respect to scale-and-stretch, DSC, and DSC-SAL increase with the reduction ratio, and thus can infer that the superiority of our approach is more significant for higher reduction ratios. We further find that our retargeting results with reduction ratios of 50% and 75% for some test images, which contain multiple salient objects and a complex background, are definitely preferred by all participants.

<table>
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<th>Method for comparison</th>
<th>Reduction ratio 25%</th>
<th>Reduction ratio 50%</th>
<th>Reduction ratio 75%</th>
<th>Average selection ratio (%)</th>
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participants. Besides, the effectiveness of the proposed multiscale contrast-based saliency map for seam carving is also verified in that the selection ratios of our results with respect to DSC-SAL are the lowest under each reduction ratio.

4 Conclusion
We have presented an adaptive image retargeting approach using saliency-based continuous seam carving. The multiscale contrast-based saliency map is used as the energy map to sufficiently highlight salient objects. By analysis of the energy curve of extracted seams using DSC, the reduced dimensions allocated for CSC and possible scaling are adaptively determined. The proposed CSC introduces the resolving ratio map and exploits an efficient scheme of mapping and resampling to overcome the inherent drawbacks of DSC. Experimental results demonstrate that the images retargeted using our approach can preserve salient objects and maintain scene layout better than previous retargeting approaches under different reduction ratios, and thus can provide end users with a more comfortable viewing experience on mobile devices.

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