Multimed Tools Appl
DOI 10.1007/s11042-012-1242-6

Optimized image resizing using flow-guided seam carving and an interactive genetic algorithm

Jong-Chul Yoon · Sun-Young Lee · In-Kwon Lee · Henry Kang

Abstract In this paper, we introduce a novel method for content-aware image resizing based on flow-guided seam carving. It extends the existing seam carving framework by replacing the conventional energy field with a "structure-aware" energy field that takes into account the feature orientations in the image. Guided by this new energy field, our approach excels in preserving (i.e., avoiding the distortion of) important structures in the image, such as shape boundaries. We also present a simple user interface to further optimize the resizing result based on the genetic selection process among multiple resizing operators such as scaling, cropping, and flow-guided seam carving. We show that such simple user interaction, coupled with the genetic algorithm, dramatically increases the chances of producing the user-desired outcome.

Keywords Image resizing · Structure-aware energy field · Interactive genetic algorithm

J.-C. Yoon (✉)
Department of Broadcasting Visual Arts Technology & Entertainment,
Kangwon National University, Samcheok, Korea
e-mail: media19@kangwon.ac.kr

S.-Y. Lee · I.-K. Lee
Department of Computer Science, Yonsei University, Seoul, Korea

S.-Y. Lee
e-mail: shepherd@cs.yonsei.ac.kr

I.-K. Lee
e-mail: iklee@yonsei.ac.kr

H. Kang
Department of Computer Science, University of Missouri, St. Louis, MO, USA
e-mail: kang@cs.umsl.edu

Published online: 13 October 2012

1 Introduction

With the recent advances in digital image processing, images have become an common material for media distribution and display devices such as PDAs, cell phones, televisions, computer monitors, and laptops comprise more than 70 % of communication devices today. An image display using these various devices derives new problem: images should be resized for its display and application. Typically, each device is limited by its own fixed resolution and aspect ratio, which calls for proper image resizing to fit the given image to the display. Furthermore, printing documents with embedded image need resizing to comply with the overall layout.

Traditional approaches, which are known as image retargeting or resizing, modify the ratio and size of the image in order to best satisfy the target display device. However, straightforward resizing operators, such as scaling, produce distorted image contents because they are oblivious to image content. To overcome this limitation, a class of techniques is used to attempt resizing the images using a content-aware energy function. Seam carving [2, 17] and grid warping-based methods [21, 23] are representative approaches for content-aware image resizing methods. These methods first estimate the important regions of the image and then resize the image but preserve of the content of important regions. However, since the energy function for important region typically reflects feature strength without considering feature orientation, some prominently shaped boundaries of arbitrary orientations might be poorly protected. Furthermore, these techniques do not take into account the aesthetic appeal of the resized image because the user can control only the target size of the image. The resizing system does not allow for interactions with the user.

In this paper, we introduce a novel method of interactive image resizing that protects prominent feature lines and shape boundaries during the generation of the energy field, and provides a better way of choosing a resizing operator. We first extract a direction field that describes the orientation of salient features in the image, and then obtain local derivatives in the perpendicular direction of the recorded orientations in the field. The magnitudes of these directional derivatives, which can be viewed as "orientation-aware" or 'structure-aware' gradient magnitudes, will comprise our new energy field. We then apply the conventional image resizing algorithm using this new energy function. Additionally, we use an interactive genetic algorithm (IGA) to determine the parameter values of the image resizing technique so as to meet users' preferences. Users select operators and then order the results by visual merit. The system collects the scores and the genetic algorithm then repeatedly changes the parameter values in response to these scores. This process is repeated until a satisfactory result is obtained.

We will demonstrate that our "structure-aware" energy function outperforms conventional ones in preventing unwanted distortion of important structures of arbitrary orientation. We will also show that the interactive interface can produce results that satisfy users.

The rest of this paper is organized as follows: In Section 2, we illustrate some limitations of the existing seam carving framework, which leads to the motivation of our approach. Section 3 describes how the structure-aware energy field is constructed and incorporated into the seam carving algorithm. In Section 4, we evaluate resizing results from our structure-aware energy field. In Section 5, we explain how an IGA is used in our system. In Section 6, we present some experimental results, and we draw conclusions in Section 7.

2 Related work

Image resizing has often been conducted by brute-force scaling along horizontal and vertical axes, resulting in the distortion of image contents when they are converted to a different aspect ratio. Cropping methods [1, 3, 6, 20] reduce such distortion by discarding unimportant content, which is followed by uniform scaling. However, they may inadvertently remove some important structures near the image boundary.

Seam carving [2, 17] was recently proposed for content-aware image resizing. It employs dynamic programming to eliminate (or insert) vertical or horizontal seams that pass through the insignificant (preferably homogeneous) image regions using an energy function based on gradient magnitude or saliency measures. However, the shortage of homogeneous regions could lead to shape distortion or jaggedness. Moreover, since the energy function reflects feature strength only along to the axes of image coordinate, it cannot protect some prominent shape boundaries of arbitrary orientations.

Grid warping-based methods [21, 23] place a grid mesh on the image and perform adaptive scaling of the grids such that the distortion is minimized in important regions. Unlike seam carving, it does not discard any pixel information and thus reduces jaggedness in the end result. However, as pointed out by Wang et al. [21], such adaptive warping of grids may lead to severe contraction or stretching of certain image contents. It may also fail to preserve the shapes of prominent image lines in arbitrary orientations.

To overcome the this problem, additional functions have been considered for image resizing. Wu et al. [24] used a translational symmetric which promoted better understanding of the image semantics of the image. Kim et al. [12] minimized the overall distortion of resized image by detecting a partitioned scale distortion function in the frequency domain. However, these approaches only protected image contents which have symmetrically or directionally structured shapes, whereas our structure-aware energy can preserve the arbitrary shapes.

A recent trend is to apply different operators sequentially, such as scaling, cropping, and resizing, to the image. since no single operator performs well in every case. Rubinstein et al. [18] recently presented an image-resizing algorithm in which bi-cubic scaling, cropping, and seam carving are combined. Liu et al. introduced the continuous seam carving (CSC) operator and combined it with uniform scaling to generate the final retargeted result. However, these results do not always agree with users' preferences [18] since they do not consider users' satisfaction.

3 Observation

To illustrate the limitations of the existing seam carving framework [2, 17], we prepared an image with some obvious directional features (see Fig. 1a). Based on the method of [2], let us attempt to resize this image in the horizontal direction. Here, we use $I(\mathbf{x})$ to denote the input image, where $\mathbf{x} = (x, y)$. Figure 1b shows the accumulated energy map using the conventional gradient magnitude as the energy function: $e(\mathbf{x}) = \sqrt{g_x^2 + g_y^2}$, where $g_x = \partial I/\partial x$ and $g_y = \partial I/\partial y$. This input image does not contain strong horizontal features and thus exhibits relatively low energy in g_y; this leads to the distortion of the vertical features (see Fig. 1c). On the other hand,

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

Fig. 1 Resizing with/without orientation information: **a** input image with vertically-biased features; **b** accumulated energy map using conventional gradient magnitude; **c** resizing based on **b**; **d** accumulated energy map using horizontal gradient only; **e** resizing based on **d**; **f** proposed method

if we use only the horizontal gradient component $e(\mathbf{x}) = |g_x^2|$ as an energy function the accumulated energy map fully appreciates the vertical features (see Fig. 1d); this leads to better protection of prominent feature lines (see Fig. 1e).

This experiment suggests we can improve the quality of image resizing by incorporating feature orientation information. Since the feature orientations generally vary from pixel to pixel, we must design an energy function that adaptively conforms to the local structure and orientation. We therefore generalize this idea of directionally-biasing the energy function by first extracting the feature direction field from the image and then computing gradient magnitudes *in the perpendicular direction to* the local feature orientations recorded in the field. Figure 1f shows the results obtained using our approach.

4 Flow-guided seam carving

We define an energy function such that both feature strength and feature orientation are taken into account. We first construct a vector field that represents prominent feature orientations in the image. In particular, we look for a smooth direction field in order to reduce the influence of noise and to maintain consistent and coherent feature flow all around. There are a variety of techniques to obtain a smoothed direction field from an image, including scattered orientation interpolation [7, 13], PDE-based orientation diffusion [15, 19, 25], structure tensor [16, 22], and non-linear orientation filtering [10, 11, 14]. We choose the method of [11] to construct a directional field known as an edge tangent flow (ETF). An ETF is constructed by non-linear smoothing of tangent vectors that describe the directions of minimum color variation, that is, the vectors perpendicular to the image gradients ∇I.

Using ETF, we now define the orientation-adaptive gradient magnitude. Let $\mathbf{t}(\mathbf{x}) = [t_x(\mathbf{x}), t_y(\mathbf{x})]$ be the normalized tangent vector recorded in the ETF at $\mathbf{x}$. Also, let $\mathbf{t}^{\perp}(\mathbf{x})$ denote its perpendicular vector. We then compute the 'oriented' gradient magnitude as a directional derivative of I along $\mathbf{t}^{\perp}(\mathbf{x})$:

$$g^o(\mathbf{x}) = |\nabla_{\mathbf{t}^{\perp}} I(\mathbf{x})|. \tag{1}$$

As opposed to the conventional gradient magnitude $|\nabla I|$ obtained in a non-biased fashion (see Fig. 2a), our method measures the feature strength only in the direction of the biggest color variation, and therefore produces a more "structure-aware" energy field.

Image resizing is typically conducted in either a horizontal or a vertical direction. As we demonstrated in Fig. 1, vertical structures are vulnerable to horizontal resizing.

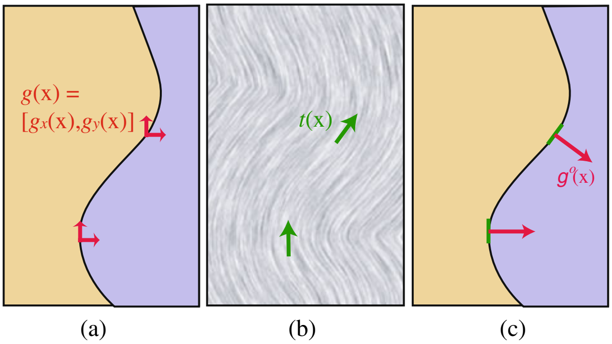


Fig. 2 Oriented-axis-based gradient acquisition: **a** conventional method; **b** ETF; **c** proposed method

Similarly, horizontal structures are easily distorted by vertical resizing. To address this, we make further adjustments to our structure-aware energy term. For vertical seams, we introduce the structure-adaptive weight $w_v(\mathbf{x})$ as follows:

$$w_v(\mathbf{x}) = |\mathbf{e}_y \cdot \mathbf{t}(\mathbf{x})|, \tag{2}$$

where $\mathbf{e}_y = (0, 1)$, that is, the unit vector along the y axis. This adjustment leads to better protection of vertical feature lines under horizontal resizing. The weight for horizontal seams, denoted as $w_h(\mathbf{x})$, is similarly obtained.

The new energy function for finding vertical seams is now defined as:

$$e_v(\mathbf{x}) = |w_v(\mathbf{x})g^o(\mathbf{x})|. \tag{3}$$

Similarly, the energy function $e_h(\mathbf{x})$ for finding horizontal seams is defined as $e_h(\mathbf{x}) = |w_h(\mathbf{x})g^o(\mathbf{x})|$. We thus use e_v under horizontal resizing and e_h under vertical resizing. Figure 3 compares the energy field based on conventional gradient magnitude versus ours.

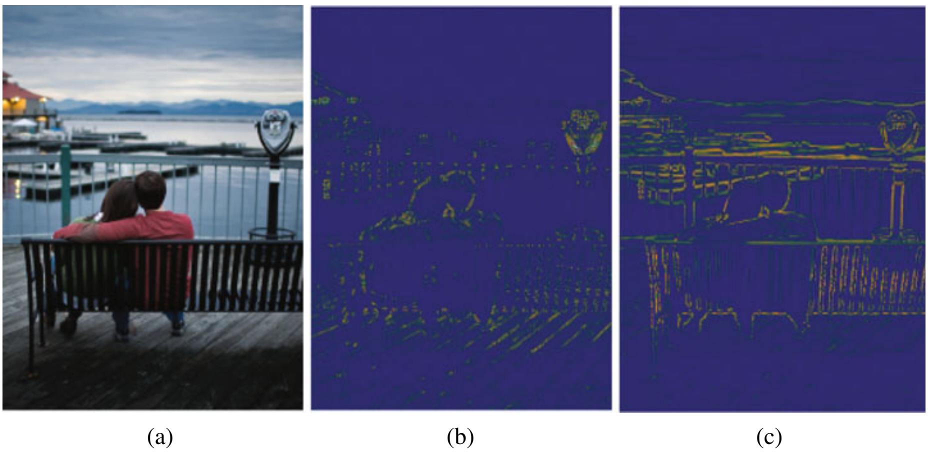


Fig. 3 Structure-aware energy field: **a** input image; **b** conventional gradient magnitude; **c** magnitude of structure-adaptive gradient

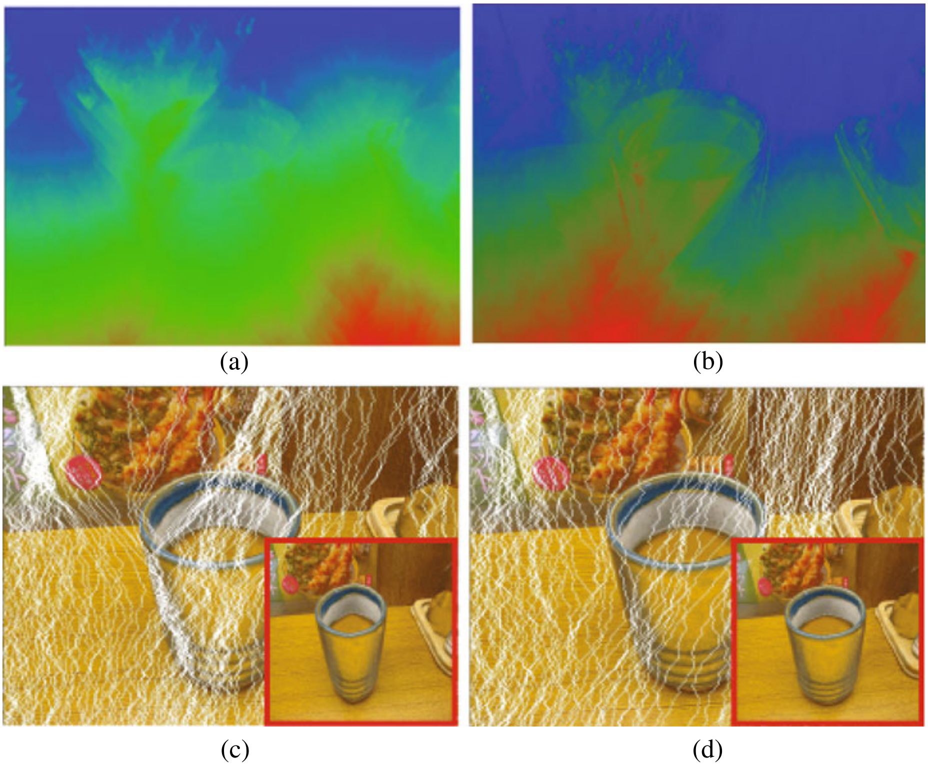


Fig. 4 Seam detection and image resizing: **a** gradient-based accumulated energy field; **b** our accumulated energy field; **c** seam detection (and resizing) using **a**; **d** seam detection (and resizing) using **b**

Using our new energy function, we perform dynamic programming [2] to construct the accumulated energy map and find the optimal seams. The forward energy [17] has also been added in this process.

Our approach enables interactive image resizing just like these predecessors [2, 17]. However, the key difference is in the energy function setup, which is part of the preprocessing.

Figure 4 compares the accumulated energy field of the original seam carving with ours. Notice that our approach does a better job of protecting the curved boundary of the cup.

5 Evaluation of the structure-aware energy field

In our experiments, we use a set of images from [5], many with directional features. Figure 5 shows comparisons with [17]. Again, notice that the prominent shape boundaries are preserved better with our approach. Figure 6 shows a comparison with the grid warping-based resizing method [21]. Since each grid has a quad form, it

Fig. 5 Comparisons with Rubinstein et al. [17]. Our method better preserves prominent feature lines

may have a problem handling features not aligned with the grid, such as diagonally oriented lines (as shown in Fig. 6a). Our flow-guided approach has no such problem, and protects prominent outlines as well as avoids over-stretching of grid warping (as shown in Fig. 6b). In several of these comparisons, it is clear that flow-guided seam carving produces a more readable image at the new aspect ratio.

We also demonstrate applying a flow-based energy field to the grid warping method [21]. Figure 7 shows a comparison of gradient-based energy-based grid warping and flow-based energy-based grid warping. Our method better preserves the circle shape boundary of the bowl and portion of each wood (as shown in Fig. 7c and e). As shown in Figs. 7b and d, flow-based energy has a field with more structure-aware properties than the gradient-based energy field, such as the circle boundary of the bowl and the veining of the wood.

Fig. 6 Results by Rubinstein et al. [17], Wang et al. [21], and ours

To verify our results, we determine the quality of our results using image similarity measures. Recently, Dong et al. [4] proposed a bi-directional similarity function called Image Euclidean distance (IMED). Image Euclidean distance considers the spatial relationship between pixels in different images and is robust enough to withstand small perturbations. We compare IMED values for flow-guided seam carving with Rubinstein et al. [17] and Wang et al. [21] (see Table 1). For most images, the similarity measure is better for flow-guided seam carving. However, if we look at the IMED cost measures for Figs. 5d and 6a in Table 1, it becomes apparent there are exceptions. However, it seems pretty clear from these pictures that flow-guided seam carving produces a better result. Rubinstein [18] observes that the results of automatic resizing by similarity distance do not coincide with user preferences. This is why we make provision for our system to be modified interactively, using a genetic algorithm.

6 Interactive generic algirothm (IGA)

An IGA [8] uses human subjective evaluation instead of the fitness function used by a standard GA. Interactive genetic algorithms are useful for finding solutions to problems related to emotional and subjective factors. We use an IGA, to construct

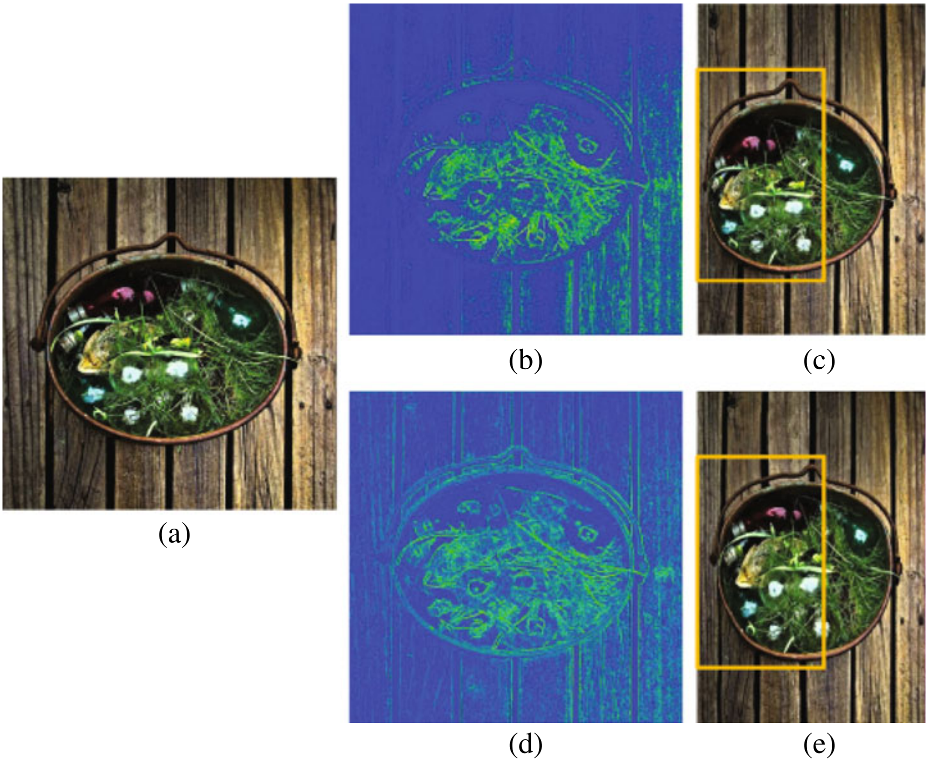


Fig. 7 Grid warping-based image resizing [21] using different energy fields: **a** input image; **b** gradient-based significant map; **c** grid warping-based image resizing using [21] with gradient-based energy; **d** flow-based significant map; **e** grid warping-based image resizing [21] with flow-based energy

a multi-operator system that combines flow-guided seam carving with an approach to scaling and cropping similar to that of Rubinstein [18]: we replace the similarity metric they used to compare images with the IGA.

Table 1 IMED similarity values for seam carving [17], grid warping-based resizing [21] and flow-guided seam carving

Images	[RSA08]	[WTSL08]	Structure-aware energy
(a) IMED similarity values for Fig. 5			
Figure 5a	5.66		4.78
Figure 5b	2.11		1.00
Figure 5c	1.21		0.81
Figure 5d	0.53		0.67
Figure 5e	1.82		1.65
(b) IMED similarity values for Fig. 6			
Figure 6a	0.49	0.58	0.51
Figure 6b	0.21	0.32	0.20

Table 2 Chromosome encoding

Parameter	Lower	Upper	Bits
p_1: number of operator	1	3	2
p_2: types of operator	1	3	2
p_3: order of operators	1	6	3
p_4: portion of operator	1	9	4

6.1 Chromosome encoding

The resizing of an image using the multi-operator scheme is controlled by a list of pre-defined parameters. A chromosome p_i consists of a choice of parameters and image resizing methods as follows:

1. The parameter p_1 is the number of operators used for image resizing. We can use between one and three operators, chosen from flow-guided seam carving (FSC), scaling (SL), and cropping (CR).
2. The parameter p_2 represents a combination of operators and its meaning depends on p_1. If p_1 is 1, then p_2 determines which of the three possible operators will be used. If p_1 is 2, then p_2 specifies the pair of operators that will be used, chosen from (FSC, SL), (FSC, CR) or (SL, FSC) without regard for operator order.
3. The parameter p_3 is the order in which the operators are applied. It is only relevant if p_1 is 2 or 3. If p_1 is 3 and p_2 is (FSC, SL, CR), then p_3 makes the six samples of gene combination, and these samples correspond to values between 1 and 6.
4. The parameter p_4 is the influence of the chosen operator, and its effect is also relative to p_1. The influence of each operators can vary between 10 % and 90 %.

Table 2 and Fig. 8 show the domain of each parameter and the number of bits required in a chromosome.

6.2 Interactive resizing

Figure 9 illustrates the GUI of our system. The interactive image resizing procedure using our GUI is as follows:

– Initialization: First, the user assigns a target size for resizing and then the system presents the user with six resized images, which are computed using six randomly selected operators.
– User Interaction: Six images are shown to a user with a slider located below the images to assign a fitness value to each generated image. We assumed that 10 indicates the greatest satisfaction and 1 indicates the lowest satisfaction with the resized image. After the user assigns a score from 1 to 10 for each image, he or

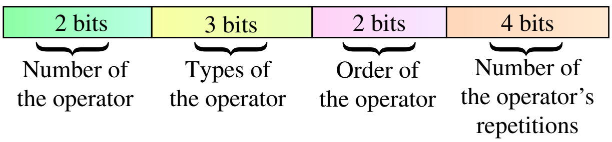


Fig. 8 Chromosome representation of our system

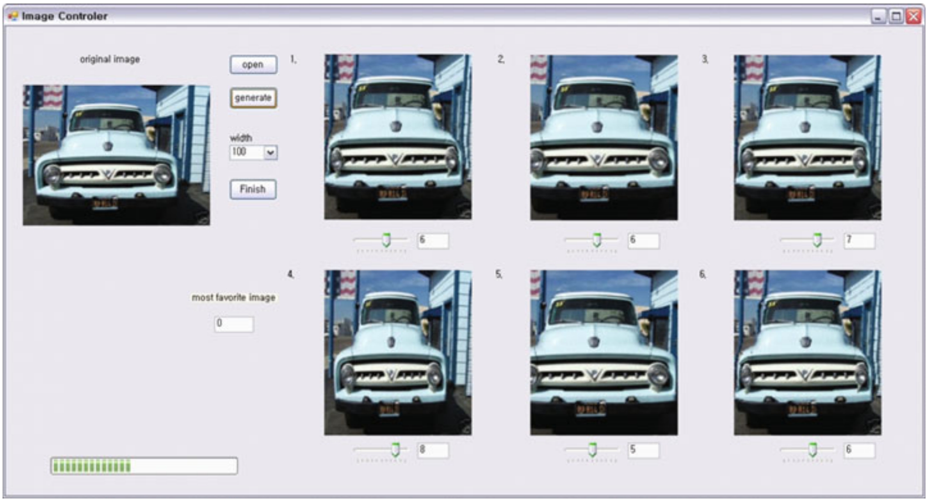


Fig. 9 Interface used in the experiments

she presses the 'generate' button. The system then finds three chromosomes with the highest value in the first generation.

– Reproduction: From the three highest-ranked chromosomes in the first generation, two parent chromosomes are randomly selected to produce one chromosome. The crossover operator swaps the part of the bit-string in the parent chromosomes determined by a crossover point. We use a single crossover point on both parents' chromosomes, and generate six child chromosomes using different combination of parent set. After the crossover, the system applies the mutation operator to the six child chromosomes. This process inverts 2 % of the total number of bits to introduce randomness. By trial and error, we found that mutation values are suitable. A new set of resized images is then computed using the new parameters and presented to the user. Figure 10 illustrates the interactive evolution process.
– Repetition and Termination: The interaction and next-generation processes are repeated until the user feels that no further progress can be made and presses

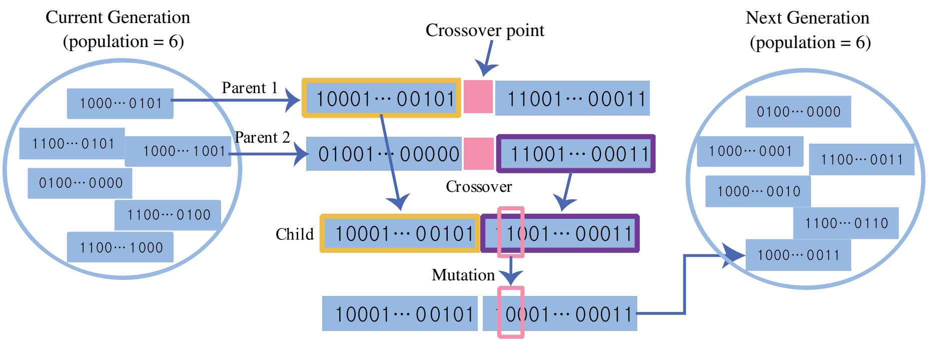


Fig. 10 The genetic operation process: selection, crossover, mutation, and reproduction

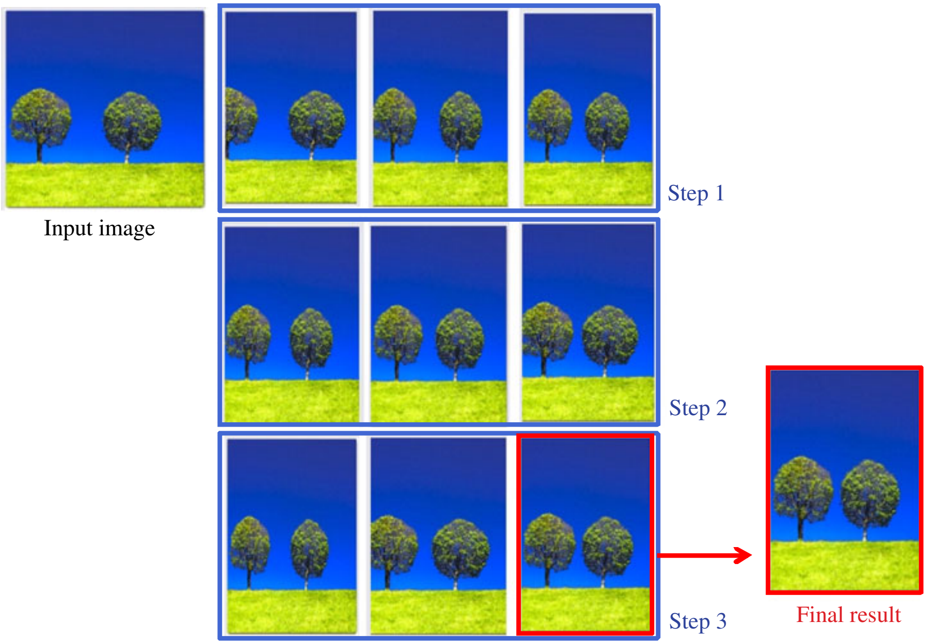


Fig. 11 Steps in the evolution of an image resizing filter

"finish" button. Figure 11 shows an example of the evolution process, although only the three highest-ranked images are reproduced. In this case, the user achieves an acceptable result in three iterations.

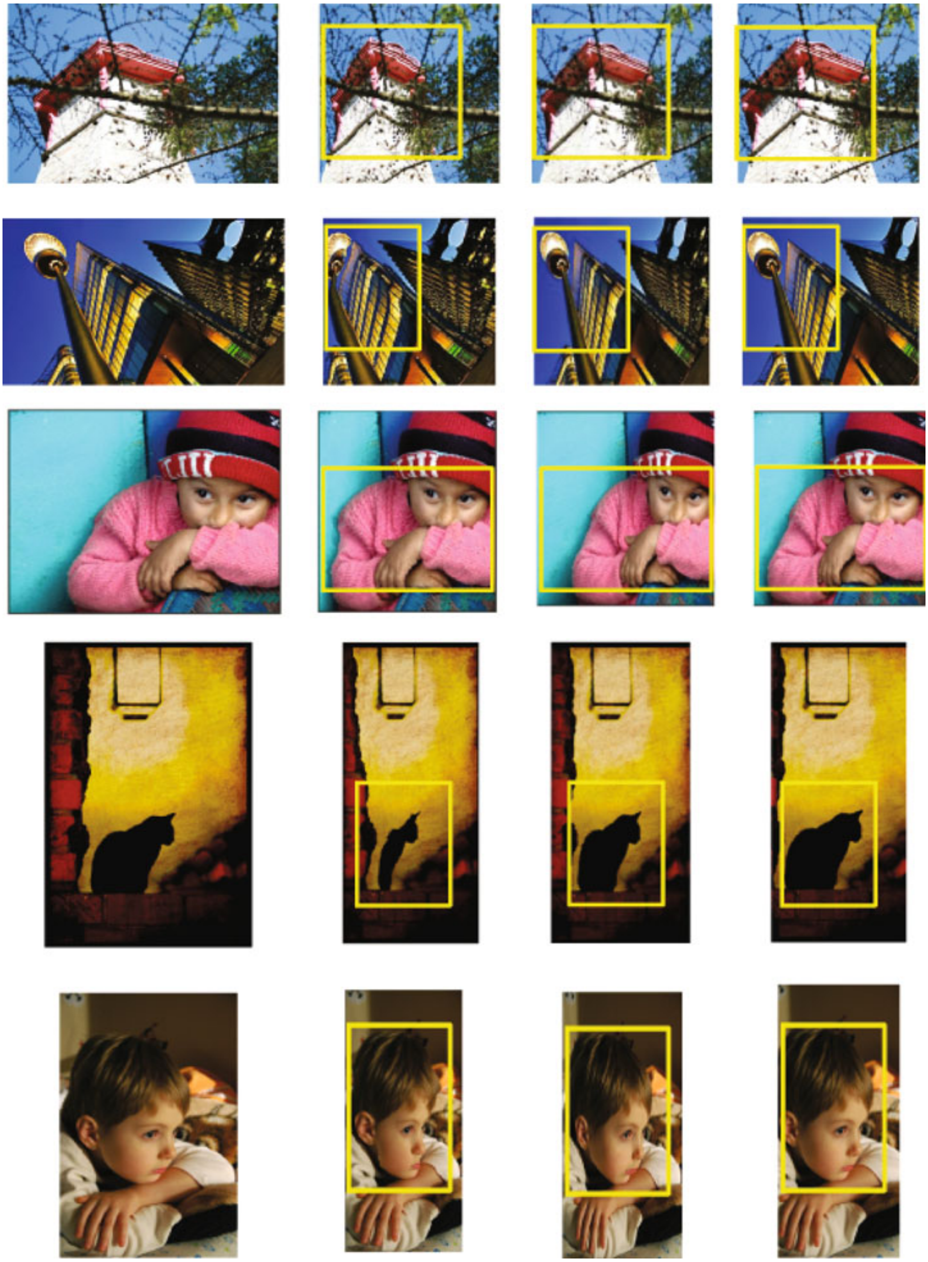
Our system is implemented by MFC with OpenCV 2.3, and the test environment is a PC with an Intel Core i-5 2500S processor and 2Gb of memory. Performance mainly depends on the resolution of the image.

7 Experimental results

We compare our result with the multi-operators in [18] with flow-guided energy and seam carving in Fig. 12. In comparison with seam carving, flow-guided energy applied to multi-operators in [18] produces images that contain better preserved contents and less distortion. To prove the advantage of our system, we conducted a user evaluation and system usability test. Twenty-one users participated in our experiments. Most participants were computer science students or experienced users of graphic editing tools. We experimented with the ten photographic images shown in Fig. 13.

7.1 User evaluation

We measured the users' degree of satisfaction and the processing time with the results produced automatically [18] and by interactive optimization. Before the experiment, we explained an interface of our IGA based system with single example image. We fixed resizing ratio as an 80 % of width size, and firstly showed an original



Input image

Rubinstein et al. 2008 [7]

Rubinstein et al. 2009 [10] with flow-guide energy

Our results

Fig. 12 Comparison of results from our system with those from seam carving and multi-operator

Fig. 13 Input images

image and automatically resized result. Then, user resized an original image using our system, and compared the satisfaction of resized result. The degree of satisfaction was determined by scores between 0 and 100. Figure 14a shows the users' preference for the interactive and automatic systems, averaged over all the images. The overall preference for the interactive approach is 73 %: this means users get a preferred result using the interactive system for 73 % of the image. Generally, users can recognize the important things in the image, but the energy field cannot. Therefore, the user gives a high score when the important things are preserved, despite the fact that the image's background has disappeared due to cropping. We also compared

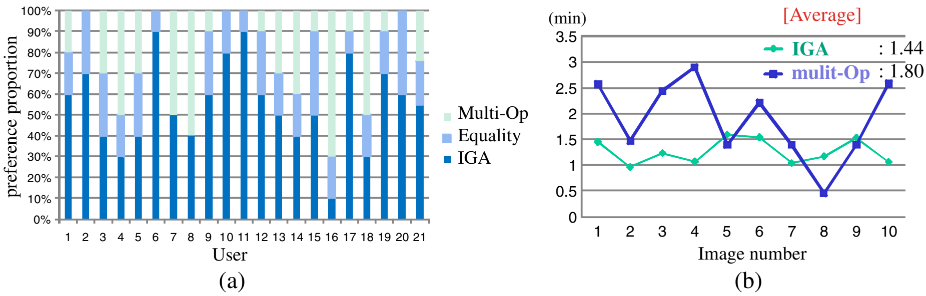
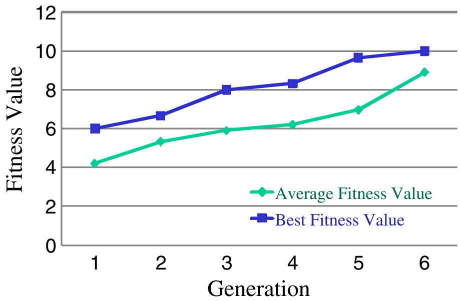


Fig. 14 Results of user evaluation: **a** preference for the results of each system by each user; **b** processing time

Fig. 15 Changing fitness during the search for a resized image



the processing times: the results shown in Fig. 14b indicate our interactive approach is faster than the automatic system.

We then carried out a convergence test based on the users' preferences that we measured. Figure 15 shows the average and best changes of fitness. The average and

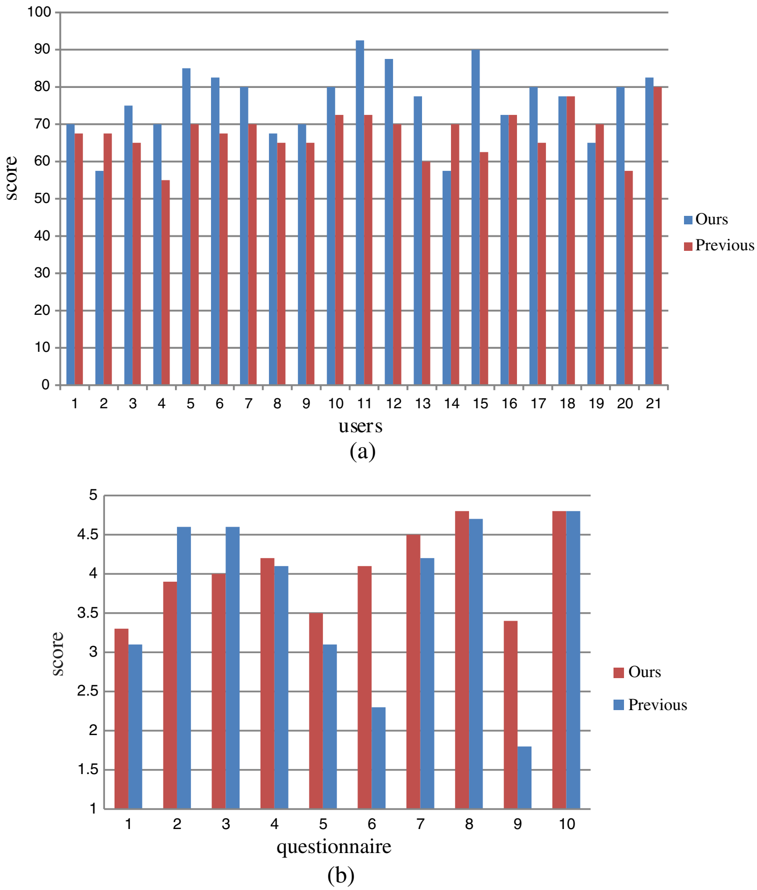


Fig. 16 Result of usablity test: **a** usability Scale by each user; **b** 5-point Likert scale by each item

best value of fitness is calculated based on the preferences of selected users who finished IGA processing over the six generation step. These figures show the steady improvements of the results over generations.

7.2 System usability test

We assessed and compared the usability of our system and original seam carving method [2, 17] using the SUS (System Usability Scale) [9] tool. An user is asked to rate 10 items using a 5-point Likert scale (strongly disagree to strongly agree). Figure 16a shows the results of the SUS. While the average score of original seam carving is about 67.7 with a distribution range from 57.5 to 80, the average score of our system is about 76.1 with a distribution range from 65 to 92.5, which means that our system is more usable than the original seam carving. Figure 16b shows the results of the SUS by item using a Likert scale. Using a conversion formula, we controlled all scores to have positive phases. That is, the higher the score, the more usable the system. Figure 16b shows our system scored more points for systematic stability and function, but scored fewer points for ease of use. Our system, which requires iterative steps, cannot give feedback to users in real time. However, the resulting images from our system are preferred over those of the original seam carving by users. The average preference score of our system is about 88.8, while that of the original seam carving is about 54.8.

8 Conclusion

We have presented an enhanced seam-carving technique that improves the quality of photograph resizing. Guided by the structure-adaptive energy field, which can effectively be applied to any resizing algorithm, we improved the state-of-the-art photograph resizing algorithms based on seam carving and grid warping, in terms of protecting prominent feature lines and the boundaries of shapes. Furthermore, we made use of an IGA to provide users with more acceptable resized images. This addresses the problem of the inconsistency between users' preferences and automatically produced results. To prove the advantage of our interactive system, we conducted user evaluation and convergence tests, and the results showed that users find interactively resized image more satisfactory. We also showed that users can resize an image much faster using this technique than with a multi-operator system. Therefore, our method not only improves the quality of image resizing but also replaces the previous image resizing interface mechanism.

One limitation of our approach is that the accuracy of ETF may be compromised when there are blurry shape boundaries surrounded by a complex background. This could lead to an inappropriate resizing result. Using an adaptive kernel size for ETF construction based on texture might alleviate this problem.

Another limitation of our approach is the risk of falling into a local minimum due to errors in the user's input. An IGA cannot convert inconsistent input to a useful result. Furthermore, fitness is expressed only as scores rather than reflecting any specific criterion of resized images. We plan to study how we might incorporate more sophisticated fitness values.

Although the current paper mainly focuses on photograph resizing, our approach may be applicable to video resizing by extracting a 3D directional field that extends to the temporal axis. The next logical step is to experiment with various 3D orientation fields extracted from a 3D video cube, such as work by [26], and extend our scheme to video resizing followed by some comparative analysis vs. [17].

Acknowledgement This study was supported by 2011 Research Grant form Kangwon National University and the National Research Foundation of Korea (NRF) grant funded by the Korea government (MEST) (No. 2011-0028568).

References

1. Anthony S, Maneesh A, Doug D, David S, Michael C (2006) Gaze-based interaction for semi-automatic photo cropping. In: Proceedings of the SIGCHI conference on human factors in computing systems, pp 771–780
2. Avidan S, Shamir A (2007) Seam carving for content-aware image resizing. In: Proceedings of ACM SIGGRAPH '07, p 10
3. Chen L, Xie X, Fan X, Ma W, Zhang H, Zhou H (2003) A visual attention model for adapting images on small displays. ACM Multimedia Syst 9(4):353–364
4. Dong W, Zhou N, Paul JC Zhang X (2009) Optimized image resizing using seam carving and scaling. ACM Trans Graph 28(5):1–10
5. FLICKR (2008) Share your photos. Watch the world. http://f\/lickr.com
6. Hao L, Xing X, Wei-Ying M, Hong-Jiang Z (2003) Automatic browsing of large pictures on mobile devices. In: Proceedings of the 11th ACM international conference on multimedia, pp 148–155
7. Hays J, Essa I (2004) Image and video-based painterly animation. In: Proc. non-photorealistic animation and rendering, pp 113–120
8. Interactive Evolution (1998) An introduction to genetic algorithms. MIT Press
9. Jordan PW, Weerdmeester B, Thomas A, Mclelland IL (1996) Sus: a quick and dirty usability scale. In: Usability evaluation in industry, pp 189–194
10. Kang H, LEE S, Chui C (2007) Coherent line drawing. In: Proceedings of ACM symposium on non-photorealistic animation and rendering, pp 43–50
11. Kang H, Lee S, Chui C (2009) Flow-based image abstraction. IEEE Trans Vis Comput Graph 15(1):62–76
12. Kim JS, Jeong SG, Juu YH, Kim CS (2011) Content-aware image and video resizing based on frequency domain analysis. IEEE Consum Electron 57(2):615–622
13. Litwinowicz P (1997) Processing images and video for an impressionist effect. In: Proc. ACM SIGGRAPH, pp 407–414
14. Paris S, Briceño H, Sillion F (2004) Capture of hair geometry from multiple images. ACM Trans Graph 23(3):712–719
15. Perona P (1998) Orientation diffusions. IEEE Trans Image Process 7(3):457–467
16. Pham TQ (2006) Spatiotonal adaptivity in super-resolution of undersampled image sequences. Delft University of Technology
17. Rubinstein M, Shamir A, Avidan S (2008) Improved seam carving for video retargeting. In: Proceedings of ACM SIGGRAPH '08, pp 1–9
18. Rubinstein M, Shamir A, Avidan S (2009) Multi-operator media retargeting. ACM Trans Graph 28(3):1–11
19. Tschumperlé D, Deriche R (2002) Orthonormal vector sets regularization with PDE's and applications. Int J Comput Vis 50(3):237–252
20. Viola P, Jones MJ (2004) Robust real-time face detection. Int J Comput Vis 57(2):137–154
21. Wang Y-S, Tai C-L, Sorkine O, Lee T-Y (2008) Optimized scale-and-stretch for image resizing. In: Proceedings of ACM SIGGRAPH Asia '08, pp 1–8
22. Weickert J (1996) Anisotropic diffusion in image processing. Dept of Mathematics, University of Kaiserslautern, Germany
23. Wolf L, Guttmann M, Cohen-Or D (2007) Non-homogeneous content-driven video-retargeting. In: Proceedings of IEEE ICCV, pp 1–6

24. Wu H, Wang YS, Feng KC, Wong TT, Lee TY, Heng PA (2010) Resizing by symmetry-summarization. ACM Trans Graph 29(6)159:1–9
25. Xu C, Prince JL (1998) Snakes, shapes, and gradient vector flow. IEEE Trans Image Process 7(3):359–369
26. Yoon JC, Lee IK, Kang H (2012) Video painting based on a stabilized time-varying flow field. IEEE Trans Vis Comput Graph 18(1):58–67

Jong-Chul Yoon received the BS and MS degrees in media from Ajou University, Korea, in 2003 and 2005, respectively, and the PhD degree in computer science from Yonsei University, Korea, in 2010. He is a Full time lecture in Dept. of Broadcasting Visual Arts Technology and Entertainment at the Kangwon National University, Korea. His research interests include non-photorealistic rendering, image and video processing, and procedural modeling.

Sun-Young Lee received her BS degree in Computer Engineering from Hongik University in 2006 and earned her MS in Computer Science from Yonsei University in 2008. She is currently a PhD student in the Computer Science from Yonsei University. Her research interests include multimedia technology.

In-Kwon Lee received his BS degree in Computer Science from Yonsei University in 1989 and earned his MS and PhD in Computer Science from POSTECH in 1992 and 1997, respectively. Currently, he is teaching and researching in the area of computer animation, geometric modeling, and computational music in Yonsei University.

Henry Kang received the BS degree in computer science from Yonsei University, Korea, in 1994 and the MS and PhD degrees in computer science from the Korea Advanced Institute of Science and Technology (KAIST) in 1996 and 2002, respectively. He is an Associate professor of computer science at the University of Missouri, St. Louis. His research interests include nonphotorealistic rendering and animation, illustrative visualization, image and video processing, image-based modeling and rendering, and facial expression animation.