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Review:

A survey for image resizing*

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Abstract: Image resizing is a key technique for displaying images on different devices, and has attracted much attention in the past few years. This paper reviews the image resizing methods proposed in recent years, gives a detailed comparison on their performance, and reveals the main challenges raised in several important issues such as preserving an important region, minimizing distortions, and improving efficiency. Furthermore, this paper discusses the research trends and points out the possible hotspots in this field. We believe this survey can give some guidance for researchers from relevant research areas, offering them an overall and novel view.

Key words: Image resizing, Saliency measures, Cropping, Seam carving, Warping

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1 Introduction

With the rapid development of Internet technology and the broad applications of multimedia, more and more images and videos are available on the Internet. Various display devices such as televisions, notebooks, personal digital assistants (PDAs), and cell phones, however, have different resolutions and aspect ratios. In such scenarios, image/video resizing is a natural choice, and thus the image/video resizing techniques are urgently important for display device manufacturers and web page designers. Due to the obvious importance and broad applications of the image/video resizing technologies, researchers have made great efforts in this field.

There are two traditional solutions to fulfill image/video resizing: uniform scaling and cropping. Although both of the solutions are pretty simple and easy to implement, they however have some obvious drawbacks. For example, the uniform scaling method always distorts the important regions especially when the change in the aspect ratio is large. On the other hand, the cropping method always loses important regions especially when the target size is reduced sharply. In short, both of solutions are not (well) applicable for display devices with different aspect ratios. To alleviate this challenge, the idea of seam carving (Avidan and Shamir, 2007) was proposed. Its basic principle is to resize the image while considering the important content. From then on, the content-aware image resizing technique has attracted much attention in the communities of computer graphics and image processing.

The content-aware methods contain two main steps: (1) measuring importance (a.k.a., saliency measures), and (2) resizing images using the importance-based resizing operator. This survey starts with an overview of saliency measures, and then introduces various content-aware methods such as content-aware cropping, seam carving, warping, and multi-operator methods. For intuition, Fig. 1 shows the classification of existing image resizing methods.

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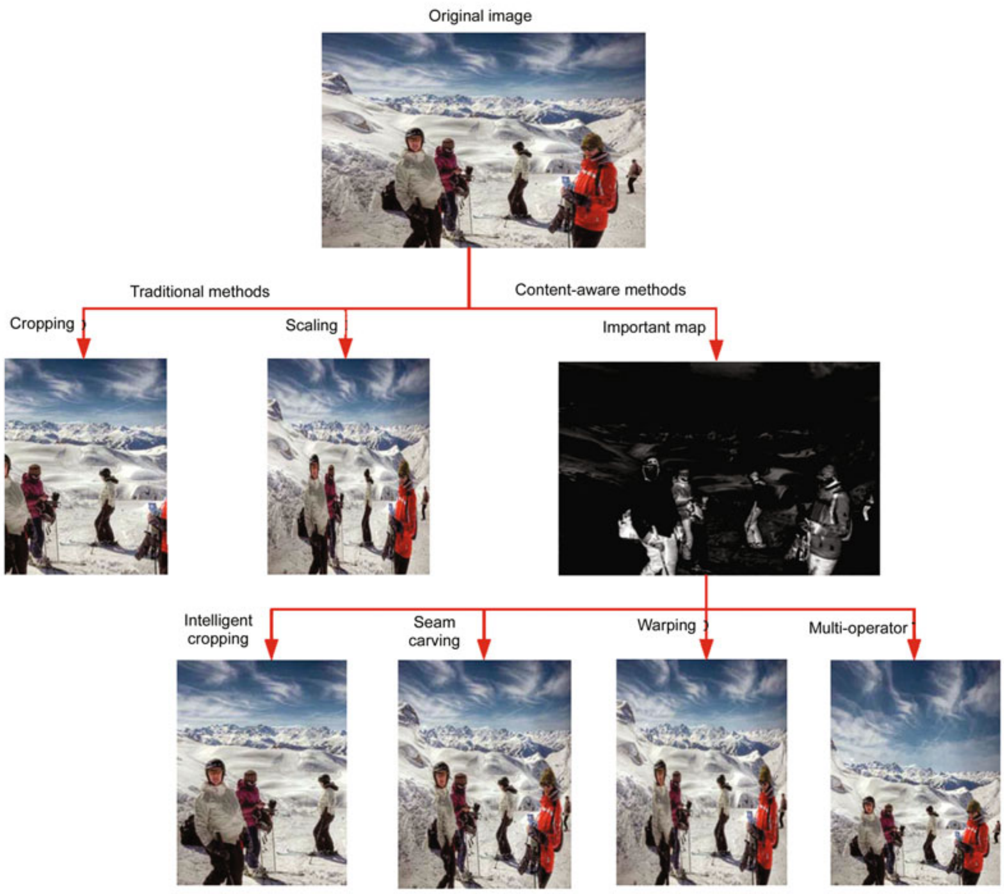

Fig. 1 Classification of image resizing methods

2 Saliency measures

To preserve the salient regions of the image during resizing, the saliency measure becomes a vital step for image resizing. The saliency measure is accomplished by mapping each pixel of an image to the interval [0, 1], where '1' represents the most important (salient) region. According to the saliency, each pixel is ranked in the mapping image. The saliency map represents the image areas, which draw more human attention. The saliency measure is an important research area in computer vision.

The approaches to measure saliency can be generally classified into two categories, namely bottom-up methods and top-down methods. Bottom-up methods are based on low-level features, such as color, orientation, and intensity, while top-down methods utilize semantic information, such as face and text. The saliency measure in image resizing uses mainly bottom-up methods, so in the following section, we focus only on bottom-up methods.

The edge map is widely used in image resizing, which preserves prominent objects by maintaining strong contours, while ignoring smooth areas. The edge map assigns high or low importance values to edges or smooth areas respectively. The l_1-norm or l_2-norm of the grayscale gradient vector at a single pixel, e.g., the Canny edge detector, can be used in solving the edge map. Avidan and Shamir (2007) used the l_1-norm of the grayscale intensity gradient to compute their energy map. However, this method fails when the edge map contains noisy regions. In this case, the noisy regions are always mistaken for the saliency regions.

Itti *et al.* (1998) proposed an approach to compute the saliency map for images based on the bottom-up idea. They used pyramid technology to compute three feature maps for three low-level features, namely color, orientation, and intensity. For each feature, the saliency was detected by separating the feature from neighboring regions. These feature maps were combined together to form a single saliency map. After several iterations, salient regions converged to a few key points. Other low-level measures include Harris corners, histograms of gradients, and entropy. To consider image regions containing texture and isolated features, a combined corner and edge detector based on the local auto-correlation function was utilized (Harris and Stephens, 1988; Dalal and Triggs, 2005). Wang *et al.* (2008) defined the significance map as the product of the gradient magnitude and the saliency measure (Fig. 2). The significance map characterizes the visual attractiveness of each pixel, and noisy gradients are filtered out by Itti's saliency.

Pixel energy computed from simple l_1-norm or l_2-norm of the grayscale intensity gradient suffers from certain drawbacks: it does not consider the complete salient regions or color information, and it is sensitive to noise. To overcome these shortcomings, some researchers proposed some enhanced methods. Lin *et al.* (2012) improved the energy map by using the Gabor operator and the saliency map. Frankovich and Wong (2011) introduced an absolute energy cost function that incorporates energy gradient information into the optimization framework to better account for areas characterized by high detail concentration. Achanta and Susstrunk (2009) proposed a saliency map obtained by evaluating the Euclidean distance of the average Lab vector value of an input image. They used the Lab color space, since Euclidean distances in this color space were approximately perceptually uniform. These saliency maps had uniformly highlighted salient regions with well-defined boundaries. By using the improved energy map, their methods achieved better results without the usual artifacts in normal and noisy images.

Graph-based visual saliency (GBVS) was proposed as a new bottom-up visual saliency model. It contains two steps: forming activation maps on certain feature channels at first and secondly, normalizing activation maps in a way which highlights conspicuity and admits combination with other maps. The model is biologically plausible as it is naturally parallelized (Harel *et al.*, 2006). Walther and Koch (2006) proposed a biologically plausible model of forming and attending to proto-objects in natural scenes. This method focuses on local saliency and low-level features. Hou and Zhang (2007) proposed a model which is independent of features, categories, or other forms of prior log-spectrum of an input image, and they extracted knowledge of the objects. By analyzing the spectral residual of an image in the spectral domain, they proposed a fast method to construct the corresponding saliency map in the spatial domain. This method also focuses on global features. Liu *et al.* (2011) formulated the salient object detection problem as a binary labeling task where they separated the salient object from the background. They proposed a set of novel features, including multi-scale contrast, center-surround histogram, and color spatial distribution, to respectively describe a salient object locally, regionally, and globally. Cheng *et al.* (2011) proposed an algorithm to extract saliency based on regional contrast, which simultaneously evaluates global contrast differences and spatial coherence. Goferman *et al.* (2012) proposed a new type of saliency-context-aware saliency. They unified local and global saliencies by measuring the similarity between each image patch and other image patches, both locally and globally. Their detection algorithm is based on four principles observed in the psychological literature. Fig. 3 shows the saliencies of different approaches. Yan Q *et al.* (2013) used a hierarchical model to deal with the images that contain small-scale high-contrast patterns. This method achieves high performance and broadens the feasibility of applying saliency detec-

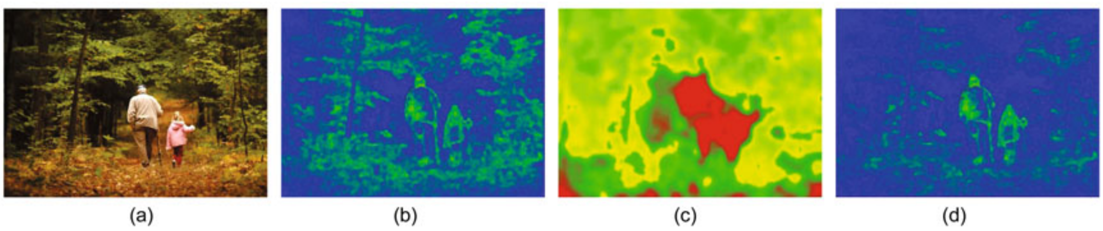

Fig. 2 Wang's significance map (image adapted from Wang *et al.* (2008)): (a) original image; (b) gradient map; (c) saliency map; (d) Wang's significance map (product of (b) and (c))

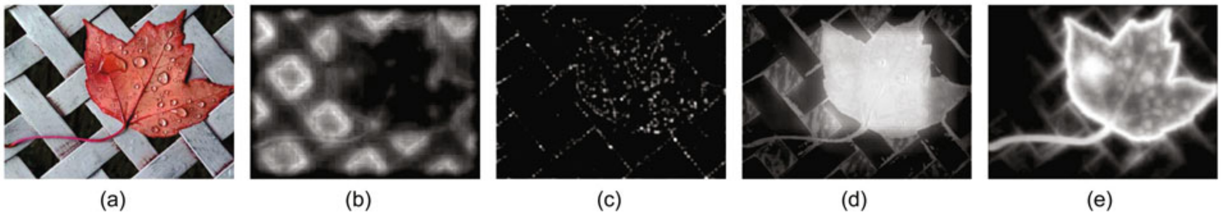

Fig. 3 Saliency based on different approaches (image adapted from Goferman *et al.* (2012)): (a) input image; (b) Walther and Koch (2006)'s method; (c) Hou and Zhang (2007)'s method; (d) Liu *et al.* (2011)'s method; (e) Goferman *et al.* (2012)'s method

tion to more applications handling different natural images.

Because importance measures are subjective, users can interactively specify the important regions. Santella *et al.* (2006) minimized information about the location of important content provided by eye tracking. They used fixation data to identify important content. Users were requested to mark those parts on the image whose shapes should be preserved (Gal *et al.*, 2006).

3 Image resizing techniques

Image resizing techniques mainly include scaling, cropping, seam carving, warping, multi-operator, and other methods. Intelligent cropping, seam carving, warping, and multi-operator resizing are corresponding to content-aware resizing methods. In this section, we briefly describe the basic theories of these methods and some new methods in recent years.

3.1 Scaling

Scaling is defined by a homogeneous map between pixels of the original image and pixels of the target image. The most common approach for scaling adopts the interpolation of original image pixels. Nearest neighbor interpolation, bilinear interpolation, and bi-cubic interpolation are the three most commonly used interpolation methods. Image scaling can be performed in real time and the global visual effects can be preserved when interpolation methods are employed. However, these interpolation scaling methods can bring artifacts, such as an artificial block and aliasing. Scaling causes obvious distortion if the aspect ratio of the input image is obviously different from that of the output image.

3.2 Cropping

The cropping method extracts a rectangular window with a desired size from the original image. The content within the window is kept and others are discarded. The traditional cropping method simply crops a cropping rectangle from the center of the image as its output resizing result. This method is very simple. However, it has a limitation of losing those important contents lying on the periphery of an image. So, the effect is seriously damaged.

To preserve important contents of an image, a user can directly draw a crop rectangle around them. However, it is time-consuming and burdensome. So, content-aware intelligent cropping is proposed to solve the problem. The intelligent cropping method usually includes two steps, i.e., main content detection and cropping. Suh *et al.* (2003) used a saliency map to express important information. They also considered the semantic information such as face detection to enhance the result of automatic thumbnail cropping. This method is substantially more recognizable than the original cropping method, but it depends on the detection algorithm which often produces inaccurate results. Chen *et al.* (2003) introduced an image attention model which has three attributes, i.e., region of interest (ROI), attention value (AV), and minimal perceptible size (MPS). An attention object (AO) often represents a semantic object, such as a human face and a text sentence. Three attention models (saliency, face, and text) were used to calculate their attention values respectively. They classified an image into five different categories. Then different rules were used to adjust the AV weights for different classes. Finally, a branch-and-bound algorithm was developed to find the optimal adaptation efficiently. However, this method heavily relies on semantic extraction techniques. If the corresponding semantic technique is not available, it is hard to obtain a good result. Combined with the AO model, some large images were browsed on small devices by using rapid serial visual presentation (RSVP) technology (Fan *et al.*, 2003a; Liu *et al.*, 2003). Santella *et al.* (2006) semi-automatically determined the region of attention by estimating the gaze of a user looking at each photo. Ciocca *et al.* (2007) first classified the image into three broad classes according to the classification and regression trees (CART) methodology. Then they used a self-adaptive image cropping algorithm by visual and semantic information for each class of image. Amrutha *et al.* (2009) used ROI detection framework for intelligent automatic cropping so as to obtain more recognizable thumbnails.

With the rapid development of digital camera, digital photos have been used extensively in daily life. The resizing of a digital photo becomes more and more important. Zhang *et al.* (2005) formulated auto cropping as an optimization problem. They defined an objective function by using the composition submodel, conservative submodel, and penalty submodel. Then particle swarm optimization (PSO) was employed to obtain an optimal solution by maximizing the objective function. So, the optimal result was obtained for digital photographs. According to the belief map, Luo (2007) maximized the subject content, and developed an efficient global search algorithm using the concept of the integral image to locate the best cropping window which satisfies multiple constraints. These automatic photo cropping techniques search for important regions from the original photo. However, not taking account of the quality of the cropped region, these methods are always disagreeable to users. Nishiyama *et al.* (2009) used a quality classifier to assess whether a cropped region is pleasant to users. By automatically distinguishing high-quality regions from low-quality ones in a photo, they ensured a high-level agreeable cropped region. Results could be tailored to users' preferences. Cavalcanti *et al.* (2010) used four feature extractors to analyze images and estimate relevant content areas. A genetic algorithm (GA) optimization problem was set up to obtain the outputs of these extractors. However, this method seriously depends on feature extractors. Yan JZ *et al.* (2013) proposed an automatic image cropping method that directly accounts for changes resulting from removing undesirable areas. Tang *et al.* (2013) presented content-based photo quality assessment using both regional and global features.

All the above-mentioned methods achieve impressive results, but they rely on traditional image cropping operations, which may lose some interesting information of images if the output resolution is significantly lower than the input resolution.

3.3 Seam carving

Seam carving is an image processing operator for content-aware image resizing including reduction and expansion (Avidan and Shamir, 2007). A seam is defined as an optimal 8-connected path of low energy pixels crossing the image from top to bottom, or left to right. The importance of a pixel is defined by an energy function based on the image gradient.

The energy function is

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

Suppose that there is an image I with size $n\times m$. A vertical seam is defined as follows:

$$\begin{aligned} &L^x = \{L_i^x\}_{i=1}^n = \{(x(i), i)\}_{i=1}^n \\ &\text{s.t. } |x(i) - x(i-1)| \le 1, \ \forall\ i, \end{aligned} \tag{2}$$

where x is a mapping $x : [1, 2, ..., n] \to [1, 2, ..., m]$. A horizontal seam is defined as follows:

$$\begin{aligned} &L^y = \{L_j^y\}_{j=1}^m = \{(j, y(j))\}_{j=1}^m \\ &\text{s.t. } |y(j) - y(j-1)| \le 1, \ \forall\ j, \end{aligned} \tag{3}$$

where y is a mapping $y : [1, 2, ..., m] \to [1, 2, ..., n]$.

So, the pixels of the path of vertical seam $\{L_i\}$ are as follows:

$$I_L = I(L_i)_{i=1}^n = I(x(i), i)_{i=1}^n. \tag{4}$$

If E is an energy function, the cost of a seam is the sum of the energy of its pixels:

$$E(L) = E(I_L) = \sum_{i=1}^n e(I(L_i)). \tag{5}$$

The optimal seam L^* is obtained by minimizing the following seam cost:

$$L^* = \operatorname*{argmin}_L E(L) = \operatorname*{argmin}_L \sum_{i=1}^n e(I(L_i)). \tag{6}$$

By using a dynamic programming algorithm, the optimal seam can be found. The image size is changed by carving out or inserting a seam in one direction. Seam carving is repeatedly performed until the desired size is reached. Seam carving is an effective algorithm for image resizing which contains large areas with low energy.

However, this method has an inherent problem. When the intensity variation of background is larger than that of the main interesting objects, it causes a distorted image. In addition, the amount of contents and the layout can influence the effect of this method and even lead to certain distortion. The traditional seam carving method uses backward energy, which ignores energy inserted into the resized image after seams are removed. So, forward energy was proposed. By altering energy which was created by those new neighbors produced from previously non-adjacent pixels because of removing a seam, the result of image resizing was improved (Rubinstein *et al.*, 2008; Shamir and Avidan, 2009; Shamir and Sorkine, 2009). Noh and Han (2012) also proposed an improved backward energy method. Combined with Rubinstein's method, they focused on forward gradient differences in both orientation and magnitude before and after removing a seam. By this improvement, Noh and Han (2012) preserved regular structures, such as straight lines and smooth curves.

Both backward and forward seam carving methods have advantages. Firstly, the implementation is simple. Secondly, it can preserve important contents and avoid obvious distortions when changing the aspect ratio. Finally, removed seams determine the resizing image, which provides continuous changes between different resolutions.

However, in spite of these benefits, seam carving methods have some limitations. Damage to local structure and the global visual effect frequently occurs in seam carving methods (Fig. 4). The reason originates from the energy-based strategy of the algorithm. This algorithm iteratively removes the seams until the desired image size is achieved, without considering the real visual effect, so it frequently damages the local structure or global visual effect.

Many researchers attempt to improve the efficiency of seam carving by either its computation speed or the quality of the resizing image.

Seam carving methods are usually time-consuming because dynamic programming uses many iterations. Huang *et al.* (2009) presented a real-time image resizing algorithm, which searches seams by establishing the matching relation between adjacent rows or columns. Their contribution was to enhance the efficiency of the resizing method. Mishiba and Ikehara (2011a) proposed a block-based seam carving method, where a seam element is a pixel block, and a seam is a path of blocks. The blocks of a seam are down-sampled in the step of image shrinking. By this method they created resized images with less distortion, which ran faster than seam carving.

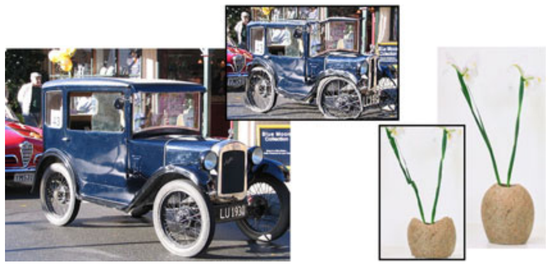

Fig. 4 Distorted map of seam carving (image adapted from Avidan and Shamir (2007))

The original seam carving method uses a gradient-based energy map, which highlights only distinctive edges. So, a seam is inadequate for traversing important objects. To overcome this kind of deformation, some researchers improved seam carving methods by enhancing energy functions or salience maps. Frankovich and Wong (2011) combined backward energy, forward energy, and an additional energy gradient cost function into the optimization process to determine appropriate seams. Zhou *et al.* (2012) proposed a new energy function with object geometry constraints to optimize seam carving. Tan *et al.* (2013) improved energy by a perceptually relevant energy function and this improvement better preserved original structures for seam carving. Seam carving was introduced by using a saliency map instead of gradient magnitude. A saliency map was generated by assigning visual importance to each pixel in terms of global color and intensity contrast (Achanta and Susstrunk, 2009). This method is noise-robust and artifacts-free. Domingues *et al.* (2010) merged several features such as gradient magnitude, saliency, face, edge, and straight line detection to form an adaptive importance map. Liu *et al.* (2010) adopted a multi-scale contrast-based saliency map by using red, green, blue, yellow, and luminance channels. They introduced the reserving ratio map and exploited an efficient scheme of mapping and resampling to overcome inherent drawbacks of seam carving. Using continuous seam carving (CSC) methods, a resizing image could preserve salient objects and maintain the scene layout better. Cao *et al.* (2012) used several non-overlapping strips to constrain seam carving. This method improves the effect of image resizing and reduces the deformation to some extent. However, this method still has some limitations. They adopted the minimum accumulated energy to determine the seam searching algorithm in one strip. So, Wu *et al.* (2013) made some improvements on the basis of Cao's algorithm. They determined the removed seams by both the accumulated energy and the neighboring probability. By this improvement, removed seams were scattered. The resizing image had fewer artifacts (Fig. 5).

Since wavelet analysis is similar to human visual system operators, Han *et al.* (2009a) proposed wavelet based seam carving, which estimates the local energy map by weighing multi-scale subbands appropriately. Semantic information of images could be preserved faithfully in the resizing process. Mishiba and Ikehara (2011b) also proposed seam carving in the wavelet transform domain to avoid breaking the spatial continuity. Conger *et al.* (2010) presented a generalized seam carving algorithm from the perspective of filter banks and developed a multi-scale analysis model. Seams could avoid passing important image features by using various filter banks. This method is less sensitive to fine texture, so it could preserve important image contents. Mansfield *et al.* (2010b) applied a visibility map to formulate resizing as a binary graph labelling problem. To some extent, all the methods above could reduce deformation and keep saliency content, but they could not solve the situation in which an image contains a certain special structure, such as a straight line.

When homogeneous information in the orthogonal direction runs out, seam carving may lead to serious distortion. The proportional constraint for seam carving was proposed by developing proportional lines, which were optional line objects arranged in straight lines to reduce straight-line distortions (Utsugi *et al.*, 2009). A piecewise seam carving method was proposed which separates an image into several parts, and each of these parts is carved by seams individually. So, it could preserve interesting objects (Thilagam and Karthikeyan, 2011). On the basis of piecewise seam carving, parallel programming algorithms are profitable in improving the speed of image resizing (Thilagam and Karthikeyan, 2012).

The original seam carving and its corresponding improved methods adopt pixel importance, as the energy function ignores information of the structure of the image. Therefore, shapes of objects in the original image are often distorted. To well preserve visual contents and avoid over-shrinkage of unimportant parts, an importance diffusion method was used to propagate the importance of removed pixels to their neighbors (Cho *et al.*, 2009). To preserve structure, Mishiba and Ikehara (2011c) proposed seam merging and a new merging energy criterion. However, this method could not preserve important contents due to

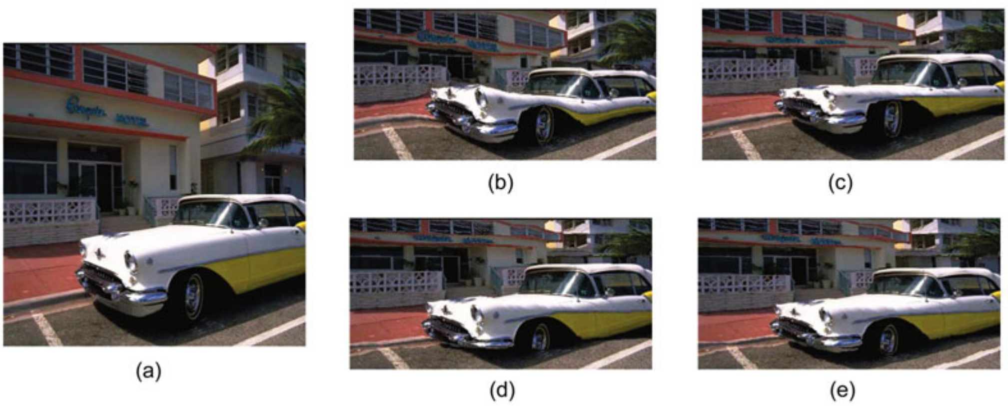

Fig. 5 Results comparison (image adapted from Wu *et al.* (2013)): (a) original image; (b) improved seam carving (Rubinstein *et al.*, 2008); (c) real-time image resizing (Huang *et al.*, 2009); (d) strip constraints method (Cao *et al.*, 2012); (e) improved strip constraints method (Wu *et al.*, 2013)

the lack of use of pixel importance. So, Mishiba and Ikehara (2012) used importance and structure energies to improve seam merging to preserve important contents and structures. They preserved the main structures by using a cartoon version of the original image when calculating its structure energy. In addition, they introduced a new energy term to suppress the distortion generated by excessive reduction or enlargement during iterative merging or inserting (Mishiba *et al.*, 2013, Fig. 6).

3.4 Warping

The warping method can be described by the warping function, which maps positions in a source image to positions in a target image. The warping function is nonlinear and shows different magnifications in different parts of the image. The warping resizing method emphasizes the ROI and does not discard other parts of the image completely.

To emphasize the important parts and retain the surrounding context, Liu and Gleicher (2005) proposed automatic image resizing with fisheye-view warping. Firstly, they found the ROI, and then used a nonlinear fisheye-view warping to warp the rest of the image. This method could maintain required details and necessary contexts, but it considers only a single ROI. To solve an image with multiple ROIs, Zhang *et al.* (2013) presented image resizing with a multi-focus fisheye transformation. They designed three fisheye transformation methods and their corresponding implemented multi-focus conflict solution schemes. Because this method locates the focus areas clearly, it could not solve images without obvious focus areas. Wang and Abdel-Dayem (2012) applied non-uniform scaling to a content-aware image resizing system which preserves important regions and minimizes distortions. They adopted a gradient map, content-aware saliency detection, and face detection to construct the importance map.

Image warping has been proposed to resize images non-homogeneously (Gal *et al.*, 2006; Wolf *et al.*, 2007). Gal *et al.* (2006) warped an image into arbitrary shape and preserved user-specified features. They used the Laplacian editing optimization to accommodate similarity constraints. By an inhomogeneous 2D texture mapping method they preserved the shape of masked regions and warped the rest of the image. These methods attempts to keep prominent regions as they are while distorting only homogeneous regions. However, homogeneous regions would have obvious distortion with the resizing direction. Instead of strengthening the salient image unchanged, Wang *et al.* (2008) proposed optimized scale-and-stretch for image resizing by iteratively computing the optimal scaling factor in every local region, and then deformed each region on the basis of the significance map. They optimized important regions to scale uniformly and distorted homogeneous regions. This method distributes distortion in all spatial directions, so it could minimize noticeable distortion of objects with prominent features and structures. Some objects might be so excessively distorted that their global spatial structures are damaged.

The above methods do not consider the image structure, so they may damage shapes of some important objects. Zhang *et al.* (2009) presented a novel shape-preserving method by using a grid mesh and optimally diffusing distortion in less important regions in all directions. Inspired by conformal energy, they constructed quadratic distortion energy

Fig. 6 Results comparison (image adapted from Mishiba and Ikehara (2012)): (a) original image; (b) improved seam carving (Rubinstein *et al.*, 2008); (c) diffusion method (Cho *et al.*, 2009); (d) seam merging (Mishiba and Ikehara, 2011a); (e) improved seam merging (Mishiba and Ikehara, 2012)

to measure shape distortion. By minimizing the sum of weighted quadratic distortion energies, the resizing result has better performance in maintaining large prominent objects and image edge structures, while, for adopting soft constraints, this method could not guarantee to preserve edges strictly, which might cause the slight rotation of prominent objects. Krähenbühl *et al.* (2009) proposed a streaming resizing system using non-uniform, pixel-accurate warping. Guo *et al.* (2009) presented an image resizing method using mesh parameterization incorporating boundary, saliency, and structure constraints which could easily preserve image structures. They used irregular triangular meshes which perform a better approximation of structured edges, especially for slant edges. However, this method does not consider semantic and topological relations among objects. Karni *et al.* (2009) proposed image resizing using a shape deformation approach based on energy minimization. Wang *et al.* (2010) presented saliency-driven shape preservation for image resizing with a mesh deformation technique, which ensures important regions undergoing a similarity transformation. This method preserves a better shape of important regions. However, when the size of the resizing image remains unchanged, or it is changed uniformly in both vertical and horizontal directions, the mesh-based method degenerates to simple linear interpolation scaling. Wang *et al.* (2011) proposed a saliency-weighted scaling factor energy for image resizing. They defined a quadric energy to establish the relationship between the scaling factor of a local region and its saliency. Furthermore, a triangle similarity quadric energy was introduced to prevent salient regions from distortion. This method could lend more pixels to salient objects in the target image even when the source image is equally scaled in vertical and horizontal directions (including the case in which the image remains unchanged). Panozzo *et al.* (2012) presented robust image resizing via axis-aligned deformation, which has robustness, smoothness, and real-time performance.

To preserve the global image configuration, non-homogeneous mesh warping methods were proposed. Bao and Li (2011) sampled mesh vertices according to the saliency map, and used different quadratic error metrics including shape, orientation, and scale distortion to measure distortion. By applying a patch-linking scheme, the global visual effect could be better preserved. Niu *et al.* (2012) also applied a non-homogeneous warping resizing method. They defined quadratic metrics to measure image distortion and introduced a patch-linking scheme. This method solves the energy minimization problem for the resizing mesh, which could better preserve the global image configuration. However, this method would be ineffective as an image is full of salient features.

Image warping methods place a grid mesh on an image, and optimize its geometry for a desired scale. These methods usually need to solve large linear systems, so they are time-consuming. To improve efficiency, researchers proposed some improved methods. Kim *et al.* (2009) proposed image resizing based on Fourier analysis. They used gradient information to divide the input image into several strips, and then scaled each strip adaptively as a constrained optimization problem, which could be solved by using the Lagrangian multiplier technique. Similarly, Kim *et al.* (2011) proposed image resizing based on the frequency domain analysis. They used gradient and saliency information to construct an importance map, and partitioned image pixels into several strips according to similar importance levels. Then, they adaptively scaled each strip to minimize the whole image distortion. Computational complexity of these methods is lower. Zhang *et al.* (2008) employed per-pixel cumulative shrinkability maps by using a random walk model to accelerate the resizing process and decrease storage requirements. Ren *et al.* (2009) proposed a novel multi-map constrained region warping approach. The original image is decomposed into many homogeneous regions and represented by curved-edge trapezoid meshes. Image resizing is formulated as a constrained optimization problem of mesh vertexes relocation. Because the curve-edge mesh requires much less vertexes, the computing cost is reduced efficiently. Jin *et al.* (2010) presented real-time image resizing using non-homogeneous scaling optimization. They used a triangular mesh and warped it using a quadratic optimization. The optimization is performed by solving a sparse linear system, and thus it has a high efficiency.

3.5 Multi-operator

No single resizing operator is proved to be optimal for all images, so some researchers proposed multi-operator methods, which will potentially give better results for the resizing image. These multi-operator methods benefit from the advantages of each technique, and avoid the shortcomings of these operators.

Before the multi-operator was put forward, some researchers have been combining multiple operators for image resizing. Hwang and Chien (2008) proposed perceptual seam carving by using face and saliency maps to obtain a more accurate energy function according to the human attention model. When the average of the minimum-energy seam is greater than the threshold, seam carving degenerates to traditional resampling. Han *et al.* (2009b) improved seam carving by exploiting a wavelet-based energy function to preserve content and shape. When the difference in energy is larger than the experimental threshold, seam carving is switched to scaling to resize the rest of the image. Kumar *et al.* (2011) proposed a distortion-sensitive seam carving algorithm. They applied the seam carving method by using local gradient information to select the seam, and replaced the seam carving method with some other algorithms when they reach the stopping criteria. Resampling or cropping was used instead of seam carving for the rest of the image. These methods could avoid distortion caused by seam carving excessively. Transition methods between these operators could be viewed as preliminary ideas of the multi-operator method.

Rubinstein *et al.* (2009) proposed multi-operator media resizing. They combined several resizing operators, such as cropping, scaling, and seam carving to define a resizing space as a conceptual multi-dimensional space by using a dynamic programming algorithm to look for the best (or optimal) path in this space. Bi-directional warping (BDW) was used as a global similarity measure to compare and evaluate different resizing results between the source and target images. The multi-operator methods avoid the drawbacks of a single operator, i.e., removing too much important information about cropping, distorting many structured media of scaling, and inserting artifacts of seam carving in some cases. However, this algorithm has high complexity and does not always agree with users' preference.

Following Rubinstein *et al.* (2009), Dong *et al.* (2009) proposed optimized image resizing using seam carving and scaling. They defined the distance measure objective function by combining patch-based bi-directional image Euclidean distance (Wang *et al.*, 2005), image dominant color similarity, and seam energy variation to compare and evaluate resized images quantitatively. This optimized image resizing method could protect the global visual effect and some local structures, especially when the size of the resized image is smaller than that of the original image (Fig. 7).

Above-mentioned multi-operator methods are time-consuming and do not consider users' preferences. So, Dong *et al.* (2012) proposed fast and interactive multi-operator image resizing. They used the image energy function and dominant color descriptor to formulate operator cost functions. To meet users' preferences, they used a coefficient to revise the operator costs. Also, they designed an interactive multi-operator image resizing framework to integrate users' real visual preferences tightly. However, this method might damage the global spatial structure of the image. Dong *et al.* (2014) proposed summarization-based image resizing by intelligent object carving on the basis of a multi-operator framework, which could handle similar objects in scenes.

The above methods use unidirectional seam

Fig. 7 Results comparison (image adapted from Dong *et al.* (2009)): (a) original image; (b) seam carving; (c) scaling; (d) cropping; (e) multi-operator (Rubinstein *et al.*, 2009); (f) optimized image resizing (Dong *et al.*, 2009)

carving and do not utilize homogeneous information along the resizing direction. In principle, they resize an image only along one direction. To avoid this situation, Shi *et al.* (2010) proposed a bi-directional seam carving method considering horizontal and vertical directions simultaneously. They defined a significance map by the weighted average of gradient magnitude and saliency measure, which was calculated by a multi-resolution saliency model based on incremental coding length (ICL). They decided the number and the order of the vertical and horizontal seam carving according to the objective function. In the bi-directional resizing method, arbitrary image resizing combines three sub-operations: unidirectional seam carving in the horizontal or vertical direction, and uniform scaling. This method could avoid destroying prominent features and structure objects. Consequently, it decreases staircase effects. Qu *et al.* (2012) proposed a unified framework to fuse three popular resizing strategies, i.e., warping, cropping, and scaling, for thumbnail generation. Luo *et al.* (2012) proposed multi-operator image resizing with automatically integrating direct and indirect seam carving. They defined a quantitative measure, artifacts measure (ATF), to estimate the seam artifacts. Whether or not to change the operators is determined according to ATF, by which the cost of decision-making would be reduced. By using accumulated energy seam carving (ACESC) as a basic operator, they improved global structure preservation (Fig. 8).

3.6 Other methods

The aforesaid cropping, seam carving, warping, and multi-operator methods are commonly used methods. In addition, some researchers proposed some new algorithms to solve problems occurring in some special cases.

3.6.1 Segmentation-based method

Many techniques deal with an image with a single object. Important information may be lost when the original image consists of multiple objects. To address multiple important objects in an image, Setlur *et al.* (2005) developed a non-photorealistic

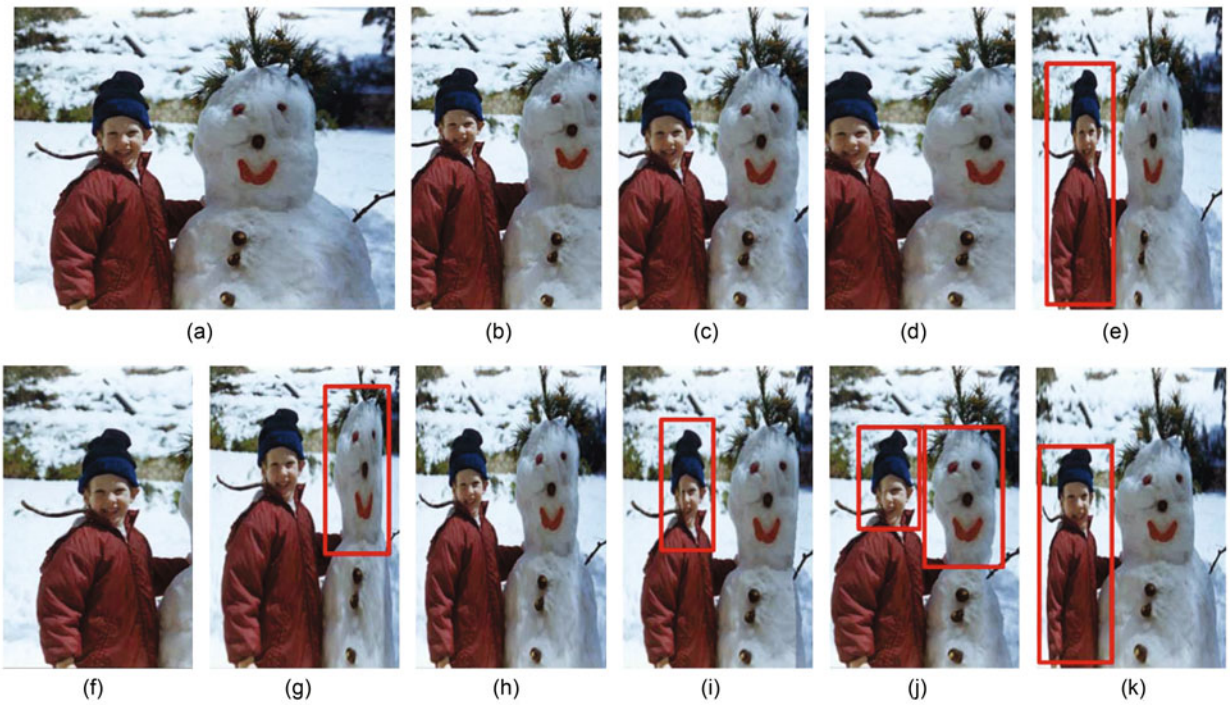

Fig. 8 Results comparison (image adapted from Luo *et al.* (2012)): (a) original image; (b) multi-operator (Luo *et al.*, 2012); (c) multi-operator (Rubinstein *et al.*, 2009); (d) cropping; (e) scaling; (f) shift-map (Pritch *et al.*, 2009); (g) optimized scale-and-stretch (Wang *et al.*, 2008); (h) streaming resizing (Krähenbühl *et al.*, 2009); (i) non-homogeneous (Wolf *et al.*, 2007); (j) improved seam carving (Rubinstein *et al.*, 2008); (k) shape deformation approach (Karni *et al.*, 2009)

image resizing method, which segments prominent objects and recomposes them into the background to be resized. This method could better keep regions of importance and background information of the original image simultaneously. However, it relies on image segmentation and restoration to a large extent.

3.6.2 Patch-based method

The patch-based method divides an image into non-overlapping patches, and then modifies or rearranges the patch domain using global optimization. Cho *et al.* (2008) defined terms in a Markov network to specify a good image reconstruction from patches. Barnes *et al.* (2009) used a new randomized algorithm for quick finding of approximate nearest-neighbor matches among image patches. Liang *et al.* (2012) separated the original image into unimportant patches and important patches, which contain the salient areas, and then presented a new similarity image distance to measure similarity between the former and the resized images. Lin *et al.* (2013b) used a similarity transformation constraint to deform visually salient content and performed an optimization process to smoothly propagate distortions. These methods could preserve visually salient objects and global contexts. However, creating the patch is computationally expensive.

3.6.3 Shift-map method

Because the patch-based method reduces the flexibility of rearrangement, Pritch *et al.* (2009) presented shift-map image editing which considers the relative shift of each pixel. They used an optimal graph labelling to represent this operation and a graph cut to solve this graph labelling. Moving individual pixels could increase flexibility, finally improving the resizing result (Fig. 9).

3.6.4 Symmetry-summarization method

In the real world there are a lot of images with translational symmetry structure. Considering image semantics information, Wu *et al.* (2010) proposed a method to resize the image by symmetry-summarization. They adopted a fast symmetry detection method to detect multiple disjoint symmetry regions, even when the lattices are curved and the perspective viewed. Afterwards they resized the symmetry region by summarization and the non-symmetry region by warping. Finally, symmetry and non-symmetry regions are merged by a seamless cut path that uses a graph-cut to hide the discontinuity artifact (Fig. 10).

3.6.5 Depth-aware method

The above existing methods address resizing of a single image. In recent years, with the development of depth cameras, pixel depth information is easier to obtain. Depth-aware resizing methods were proposed. Combining a 2D image and depth map could preserve structures of the important objects (Ramachandra *et al.*, 2009; Choi, 2012). Mansfield *et al.* (2010a) used a user-provided relative depth map to preserve scene consistent image resizing. Dahan *et al.* (2012) used depth and color information to better resize the image with many condensed details. This method is used in stereo image resizing. It has been explored preliminarily by some researchers (Utsugi *et al.*, 2010; Basha *et al.*, 2011; 2013; Yue *et al.*, 2013; Zhang *et al.*, 2013).

Fig. 9 Results comparison (image adapted from Pritch *et al.* (2009)): (a) original image; (b) shift-map (Pritch *et al.*, 2009); (c) non-homogeneous (Wolf *et al.*, 2007); (d) optimized scale and stretch (Wang *et al.*, 2008); (e) improved seam carving (Rubinstein *et al.*, 2008)

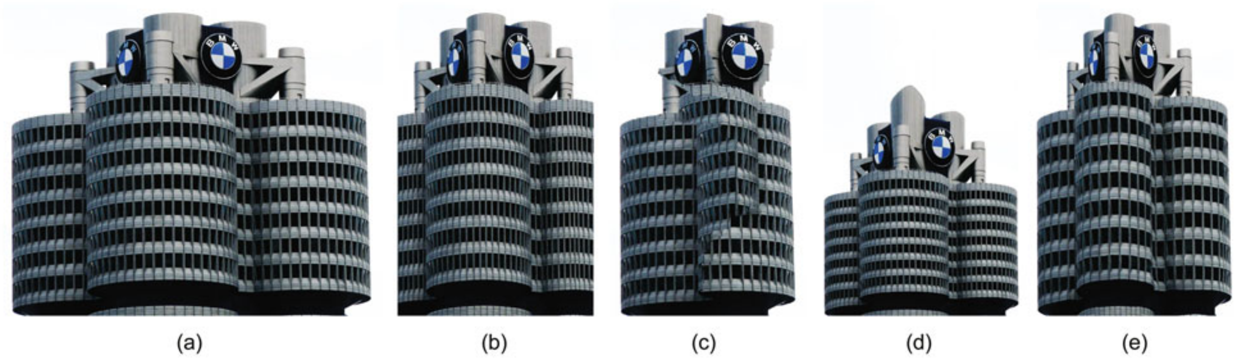

Fig. 10 Results comparison (image adapted from Wu *et al.* (2010)): (a) original image; (b) multi-operator (Rubinstein *et al.*, 2009); (c) shift-map (Pritch *et al.*, 2009); (d) warping (Wang *et al.*, 2008); (e) symmetry-summarization (Wu *et al.*, 2010)

3.6.6 Multi-layered method

Image resizing technology distorts the important parts when it is shrunken too much. To solve this problem, Sugimoto *et al.* (2012) proposed multi-layered image resizing. They designed a novel 3D space domain image resizing, which rearranged objects with occlusions and deformed objects. This method could be applied in more complicated scenes with many objects.

4 Video resizing techniques

Video is the sequence of continuous image frames. Compared with image resizing, video resizing is much more challenging due to the additional temporal constraint. This section simply introduces some methods of video resizing.

Video resizing techniques can be roughly categorized into three classes: cropping based methods, seam carving based methods, and warping based methods.

Cropping based video resizing methods could be described as finding the optimal cropping windows (Fan *et al.*, 2003b; Liu and Gleicher, 2006; Tao *et al.*, 2007; Deselaers *et al.*, 2008; Li *et al.*, 2010). Generally, the cropping based approaches sacrifice the contents in the borders of the frames to protect salient regions from distortion.

Seam carving based video resizing methods are separated into volumes based and frame based methods. The volumes based method views the video as video volumes. Rubinstein *et al.* (2008) improved the seam carving method for video resizing. They removed 2D seams from 3D space-time volumes, which were determined by graph cut. Han *et al.* (2009) constructed a 4D graph. Then they detected multiple 3D surfaces by a global optimization process which could be solved via s-t graph cuts. Finally, video resizing was achieved by removing or inserting these multiple 3D surfaces. The frame based method resizes video by using frame-by-frame processing based on the temporal coherence formulation. Kopf *et al.* (2009) proposed fast seam carving for size adaptation of videos. Grundmann *et al.* (2010) introduced discontinuous seam carving for video resizing, which relies on a novel appearance-based temporal coherence formulation that allows for frame-by-frame processing and results in temporally discontinuous seams. Chao *et al.* (2011) proposed coarse-to-fine temporal optimization for video resizing based on seam carving. Yan B. *et al.* (2013) improved the seam carving based video resizing to preserve the temporal smoothness of seams by matching the frame pixels with the key points. Wang *et al.* (2014) proposed a deformable shape preserving video resizing scheme where salient curves extracted from frames are protected from deformation by minimizing the matching cost of curves in the original frames and the resized frames. Obviously, seam carving based methods change the aspect ratio of the video by compressing the un-salient regions where the distortion is less noticeable to the viewer. However, they often bring severe deformation when the video has few textureless regions.

Warping based video resizing methods extend image-based warping methods to warp the video. Wolf *et al.* (2007) proposed non-homogeneous content-driven video resizing by solving a sparse linear system of equations. Zhang *et al.* (2008) proposed shrinkability maps for content-aware video resizing by using a random walk model. Krähenbühl *et al.* (2009) proposed a non-uniform, pixel-accurate warp to the target resolution which considers automatic as well as interactively defined features. Because the motions in videos are not given enough consideration, these methods usually produce unsatisfactory results when videos contain complex motions. Wang *et al.* (2009) proposed motion aware temporal coherence for video resizing by estimating inter-frame camera motion. Niu *et al.* (2010) proposed warp propagation for video resizing which achieves temporal consistency by introducing a motion history map that propagates information about the moving objects between frames. Wang *et al.* (2011) proposed scalable and coherent video resizing with per-frame optimization by considering the optical flow as additional information. Yen *et al.* (2011) used a panoramic mosaic to guide the scaling of corresponding regions of video frames in a video shot to ensure good temporal coherence. Lin *et al.* (2013a) proposed an object-preserving warping scheme with object-based significance estimation to reduce this unpleasant distortion. Chen and Luo (2013) proposed video resizing by preserving motion-tolerant contextual visual saliency. Nie *et al.* (2013) presented a video resizing approach combining the advantages of both content-aware warping and patch-based summarization. They developed a mean value coordinate (MVC) (Shen *et al.*, 2012) warping method due to its simplicity and efficiency used in the initialization. Qu *et al.* (2013) proposed context-aware video resizing via a graph model. Li *et al.* (2014) proposed a video resizing method that divides a video into spatio-temporal grid flows, for which content consistency between grids is maximized. They utilized grid flows to select key-frames, and then resized these key-frames via quadratic programming. The limitation of warping based methods is that they can cause the waving and jittering effect caused by the warping on the frames.

In addition to the above methods, some researchers also tried other methods. A hybrid method was proposed. The warping was combined with cropping (Wang *et al.*, 2010; 2011). However, the temporal coherence of regions in the video was calculated independently of each other, which usually causes noticeable artifacts in output. Kiess *et al.* (2014) presented a fast parallel algorithm for the resizing of videos, which combines seam carving and cropping. Yan *et al.* (2014) presented a video resizing method with the assessment of the jittery artifact. Ding *et al.* (2012) proposed a novel framework to efficiently re-compress massive Internet images. On the basis of this method, Zhang *et al.* (2014) presented a compressed-domain video resizing solution that operates without compromising the resizing quality.

5 Discussion

This paper summarizes the recent academic achievements in the image resizing field. We discuss advantages and disadvantages of these approaches in various applications. Traditional scaling and cropping methods consider only geometric constraints while ignoring the information of important regions. Scaling can be applied only uniformly. If the resized image is smaller than the original one, the important objects may not be recognized. The scaling method causes certain distortion on condition that the aspect ratio varies between the original image and resized image. The cropping method can retain image details and contents without distortion, but it inevitably loses some information outside the cropping window. Content-aware resizing algorithms usually preserve the important content better, by maintaining the structural and semantic information. Still some drawbacks exist. As is known to all, the definition of importance is subjective. That is to say, different consumers focus on different contents even in the same image. Content-aware image resizing methods will sometimes generate unsatisfactory results when the important content is not suitable. Although many improved methods have been proposed, the existing methods cannot effectively solve users' preferences.

Despite the fact that the theory and algorithms used for these existing methods are different, they have some common ground. Each type of method attempts to optimize a proper energy function to achieve the best resizing result. They remove or shrink unimportant content in order to obtain well-preserved important information without distortion. In other words, seam carving methods use pixel manipulation to remove unnecessary information or continuous background of the image, such as sky, water, and sand. These methods easily produce discontinuity artifacts and cannot solve the condition if the image contains dense and complex structures, especially for complex images with people. Warping methods shrink unnecessary information by deformation. These methods easily retain the geometric structure smoothly and may fail occasionally when the image is full of salient features. Multi-operator methods make full use of the advantages of each algorithm, so they can preserve the contents and structures of the image. However, they are time-consuming on account of the conversion measures among different operators.

Image resizing researchers focus their attention on content preservation, global visual impacts, and computational complexities. So far, there is no resizing method that satisfies all resizing problems of an image in all conditions. Resizing quality severely depends on the image itself. Usually, the cropping method is suitable when a single salient object occupies a small part of the image and background information is not preserved. Uniform scaling is appropriate when the image is full of salient information and a complex structure, especially for scenery images, for a scene is presented in the entire picture of a scenery image, and important information is spread out in the whole image. Seam carving is the most desirable algorithm for the image that contains large areas of low energy and small areas of high energy. Warping is applicable when the image needs to maintain structural information better. A multi-operator is used to preserve important objects and the global structure of the image without much time consumption.

Based on the study of a large amount of image resizing methods, we summarize the advantages and disadvantages of various methods in different situations. On the basis of existing research, we have proposed a seamlet carving method for shape-aware image resizing (Lin *et al.*, 2012). In that paper, we made two prominent improvements. Firstly, we improved the energy map by considering Gabor filter banks and the saliency theory. Combining the gradient map and saliency map with Gabor features, we established the final energy map (Fig. 11). Secondly, we proposed a seamlet carving operator. Our method breaks the 8-connect of seam carving. It can handle the discontinuous pixels and further achieve an optimized image resizing result with shape-preservation (Fig. 12).

6 Conclusions and future work

Image resizing has been one of the hottest research topics in recent years. In this paper, we summarize advantages and disadvantages of existing methods for image resizing. In comparison with the previous related work on image resizing (Rubinstein *et al.*, 2010; Vaquero *et al.*, 2010), we focus on content-based cropping, seam carving, warping, and multi-operator methods. Information loss is inevitable in the process of image resizing. The key problem is to preserve the most attractive regions and useful information, minimize visual distortion, achieve real-time resizing, and satisfy user preferences under the constraint of topological relations and the global context.

In conclusion, the trends and possible directions for future research are listed below:

1. Since all content-aware resizing methods are based on salience detection, the saliency measure algorithm will be further researched, especially video saliency. Li *et al.* (2013) have proposed temporally coherent video saliency using regional dynamic contrast, but this method is under preliminary study and needs to be improved. Due to the restriction of spatial and temporal consistency, video resizing

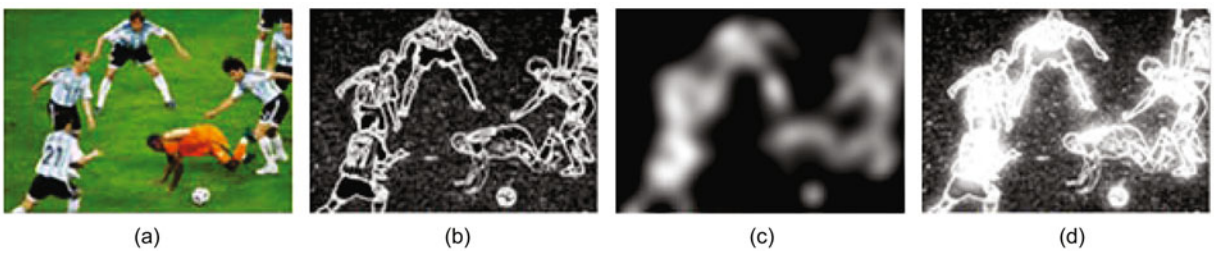

Fig. 11 Energy comparison map (image adapted from Lin *et al.* (2012)): (a) original image; (b) gradient map; (c) saliency map; (d) total energy map

Fig. 12 Seamlet carving for image resizing: (a) original image; (b) seam carving; (c) seamlet carving

techniques are currently immature and need further investigation. Video resizing based on the video saliency measure will be an important research direction in the future (Hu *et al.*, 2013).

2. Resizing methods for images with a more semantic, complex structure and different topology relationship could be researched to retain their importance contents and prevent deformation during the resizing process.

3. Resizing techniques can be applied in some special occasions, such as irregularly-shaped images. Qi and Ho (2012) have proposed resizing image domains with non-rectangular boundaries. In accordance with this idea, some stereo irregularly-shaped resizing technologies will be studied. With the development of the stereo camera, stereo image resizing becomes increasingly important. Therefore, more attention will be paid to a stereo resizing method.

4. Current image resizing methods have a common shortcoming of lower efficiency, so a GPU acceleration technique will be taken into account for image resizing to enhance the resizing efficiency. Nowadays image resizing criteria are generally subjective. More objective criteria will be considered to evaluate resizing quality.

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