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Realtime Aesthetic Image Retargeting

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Abstract

Humans have always sought to achieve aesthetics in art. In this paper, we present a novel approach for retargeting images to different aspect ratios while improving the composition aesthetics of the results. A simpler computational aesthetic energy is proposed and used to drive the salient objects and prominent lines to move towards their corresponding optimal positions. A mesh-based warping scheme is presented to transform the images while protecting the visual appearance of salient objects. The objective function is quadratic and thus it can be quickly minimized by solving a sparse linear system. The retargeting results are generated in realtime while the user changes the aspect ratios of the target images. A variety of experiments have shown the applicability and effectiveness of our algorithm.

Categories and Subject Descriptors (according to ACM CCS): I.3.3 [Computer Graphics]: Picture/Image Generation—Display algorithms

1. Introduction

An aesthetic photo taken by an expert photographer can evoke an emotional response from the viewer that transcends mere visual appreciation. In recent years, there is an explosive growth of research field, called *Computational Aesthetics*, which studies the computational methods for making applicable aesthetic decisions in a similar fashion as humans can [Hoe05].

Mobile video displays such as cellular phones, PDAs, and hand-held PCs become more popular. Images generally have much higher resolutions and different aspect ratios than the small screens of these mobile devices. Image retargeting addresses the issue of displaying images on various screen sizes. However, uniform rescaling the original image according to the target screen size normally introduces large distortion on the important objects in image and make them unrecognizable. It may be desirable to warp different parts of the image differently, depending on the image content. In particular, visually important objects in the image are expected to be preserved at a sufficient size so that they can be easily recognized in the retargeting result. This idea is typically referred to as *content-aware image retargeting/resizing* [STR*05, AS07, SS09].

Composition represents the final harmony of a picture and the way it is perceived by others. Photo having strong composition effectively forces the viewer to focus on the things the artist wants them to see. A recent work [LCWCO10] has developed a computational model for evaluating the composition aesthetics of a given image based on measuring a few well-grounded composition guidelines. However, this method is much slow and not suitable for realtime applications as it searches the optimal result in a 4D space.

In this work, we develop a novel technique for retargeting an image while improving the composition aesthetics of the image. First, we construct a triangular mesh over the image that is consistent with the salient objects and prominent lines. We then define an aesthetic energy to measure the composition aesthetics of the salient elements in the image by applying some basic composition guidelines. Minimization of the aesthetic energy pushes the salient elements to move towards their corresponding optimal positions. Then a warping energy and a smooth energy are respectively defined to warp the mesh to protect the visual appearance of salient objects and make the warping as smooth as possible. The total objective function has the *quadratic form* and thus

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the optimization can be obtained via solving a sparse linear system in real time. Our system is able to retarget the image into well-composed results with any frame sizes and aspect ratio. It allows the user to adjust the aspect ratio and obtains the aesthetic retargeting results in an interactive manner, as shown in the accompany video.

2. Related work

We briefly reviewed the techniques developed for image editing including content aware image retargeting and image composition and aesthetics.

2.1. Content aware image retargeting

Content-aware image resizing and retargeting has become a hot research topic in recent years [SS09]. Two categories of approaches are mesh warping methods [WGCO07, WTSL08, KFG09, JLW10] and synthesis methods [BSFG09, PKVP09]. An intensive survey is beyond the scope of this paper.

Liu and Gleicher [LG05] propose an image retargeting approach by using a nonlinear fish-eye transformation to protect the visual appearance of the important content in the image. The work of [STR*05] cuts the important regions from the image and pastes them back on the resized background. Gal et al. [GSCO06] present a warping method that preserves the important features by constraining their deformation to be a similarity transformation. Avidan and Shamir [AS07] introduce a seam-carving operator to carve out pixels in unimportant regions. The retargeting result is then obtained by successively applying the seam-carving operators. The seam-carving operator is extended to video retargeting and media retargeting [RSA08, RSA09]. There are also other works on video retargeting [WGCO07, KLHG09]. The retargeting can be performed using quad meshes [WTSL08, KFG09] or triangular meshes [GLS*09, JLW10]. Recently, a skeleton-aware retargeting technique is introduced to reshape the human bodies in images [ZFL*10].

2.2. Aesthetic image composition

Composition is the arrangement of visual elements in the image frame, which is an essential aspect in the creation of a vast variety of artistic work. Only a little work related to photo composition has been published in the literature. The work of [SLBJ03] develops fully automated image cropping techniques using a visual salience model based on low-level contrast measures and an image-based face detection system. The rule of thirds has been used to position automatically detected features of interest in an automatic robot camera [BDSG04]. The same kind of approach, using the rules of thirds and fifths, has been used to place silhouette edges in automated view selection of 3D models [GRMS01]. Another compositional heuristic that specifies how features should be balanced from left to right has been used to arrange images and text objects in a window [LFN04]. The work of [ZZS*05] proposed 14 templates that utilize composition rules to crop photos by using face detection results. Santella et al. presented an interactive method based on eye tracking for cropping photographs given minimal information about the location of important content [SAD*06].

Recently, Liu et al. [LCWCO10] propose an algorithm for optimizing the composition of images. A computational means for evaluating the composition aesthetics of a given image based on measuring several well-grounded composition guidelines, including rule of thirds, diagonal, visual balance, and region size. An optimization method for automatically producing a maximally aesthetic composition in image is also presented. However, the optimized composition is searched in a high dimensional (4D) space which makes the algorithm much slow and impractical.

3. Overview

Achieving an aesthetic retargeting result requires a content-aware image warping. Specifically, our approach warps the input image by pushing the salient objects and the prominent lines towards their corresponding target positions to gain higher aesthetic appearance. See Figure 1 for an overview of our retargeting algorithm.

First, we detect the salient objects and the prominent lines in the image, as shown in Figure 1(b,c). We then build a triangular mesh over the image with constraints that the underlying salient features and prominent lines align with its edges, as shown in Figure 1(d). The triangular mesh will be used as a controlling mesh to warp the image domain. The reason why we use triangular mesh instead of quad mesh is that the former is more flexible to satisfy the various constraints than the latter.

Then we use a nonhomogeneous warping technique to warp the mesh to a target mesh. The warping is driven by preserving the visual appearances of salient objects and prominent lines and by modifying the interrelation among these entities, i.e., improving the composition of the image. The result image is obtained by texture mapping. See Figure 1(f,g,h) for a few warped meshes and result images with different target frame sizes.

The warping is formulated as a quadratic optimization problem on mesh vertices which can be minimized by solving a sparse linear system. Thus our algorithm runs efficiently and supports real-time manipulation feedback for image retargeting (see the accompanying video).

4. Preliminaries

We briefly review a set of basic guidelines for composing aesthetic images and introduce the construction of the controlling triangular mesh.

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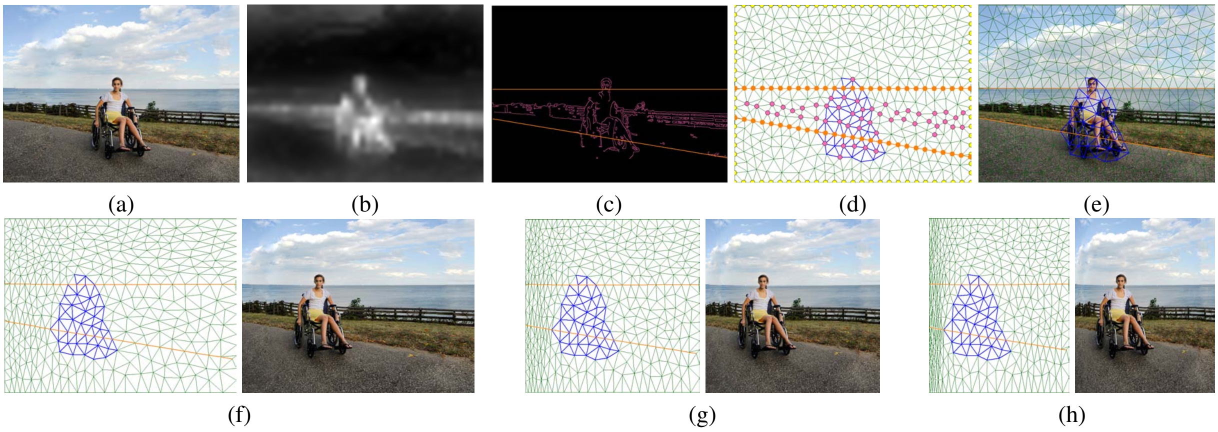

Figure 1: *Overview of our aesthetic retargeting approach. (a) The original image; (b) saliency map of (a); (c) detected feature edges (in purple) and prominent lines (in orange); (d) the sampling points from prominent lines (in orange), detected feature edges (in purple), and boundaries (in yellow), and then a triangular mesh is generated with constrained Delaunay triangulation method with the sampling points as its vertices; the blue triangles denote the salient object in the image; (e) the triangular mesh over the image; (f-h): aesthetic retargeting results from (a) with same size, 75% width, and 60% width respectively. Left: the warped meshes; right: the result images.*

4.1. Basic composition guidelines

Professional photographers generally adopt various guidelines for shooting aesthetic photographs [GS90, Kra05]. Many of the aesthetic rules are objective. We only consider a limited set of basic composition guidelines, see more details in [LCWCO10]. Note that by "aesthetics" we mean the aesthetic composition in well-composed images in this paper.

Rule of thirds. The best known guideline of photo composition is the rule of thirds. By partitioning the canvas into thirds (both vertically and horizontally) and then placing the salient objects and prominent lines of the photo near these lines, artists can obtain well-composed photos. The four intersections formed by these thirds lines are referred to as "power points".

Diagonal dominance. A salient diagonal element is encouraged to be located along the corresponding diagonal line, which is also aesthetically significant. The two diagonal lines as well as the four thirds lines are called the "power lines".

Visual balance. The salient objects are suggested to be distributed evenly around the center of the image frame to achieve a visually balanced image.

4.2. Visual elements and triangulation

Like [JLW10], we identify visual elements including salient objects and prominent lines in the source image and construct a triangulation over it. The prominent lines can be automatically detected by Hough transformation [FO08] or optionally be specified by the user (see Figure 1(c)). Then a triangular mesh is constructed, as shown in Figure 1(d). We compute a saliency map [HKP06] of the image (see Figure 1(b)). Important triangles with saliency values larger than some threshold (0.6) are regarded as salient objects and are marked in blue (Figure 1(d,e)). Either the saliency map or the salient objects may be provided in semi-automatic mode by the user.

4.3. Notations

The set of four power points and the set of six power lines are denoted by $\mathcal{P}$ and $\mathcal{L}$, respectively.

Denote $\mathcal{I}^I$ and $\mathcal{I}^O$ as input image and output image respectively. Their corresponding triangular meshes are denoted by $\mathcal{M}^I$ and $\mathcal{M}^O$. The target image $\mathcal{I}^O$ can either have the same size or have a different aspect ratio with $\mathcal{I}^I$. The scale factors of $\mathcal{I}^O$ with respect to $\mathcal{I}^I$ in the x- and y-directions are denoted by s^x and s^y, respectively.

Denote $\mathcal{T}$ as the triangle set of $\mathcal{M}^I$ and $\mathcal{B}$ and $\mathcal{D}$ as the set of salient objects and prominent lines in $\mathcal{I}^I$, respectively.

For each geometric entity e (such as triangle, salient object, or prominent line), $\sigma(e)$ represents its saliency value which is computed by averaging the saliency values of all pixels in it. $A(e)$ represents the normalized area of e if $e \in \mathcal{T}$ or $e \in \mathcal{B}$. $C(e)$ represents the center of e. For a salient object $e \in \mathcal{B}$, $C(e)$ is computed as the average of the vertices of e. For a prominent line $e \in \mathcal{D}$, $C(e)$ is actually its midpoint.

5. Algorithm

We now describe our technique for retargeting an input image $\mathcal{I}^I$ into an aesthetic output image $\mathcal{I}^O$. The retargeting

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operation warps the mesh $\mathcal{M}^I$ into a target triangular mesh $\mathcal{M}^O$. We then obtain the target image $\mathcal{I}^O$ by texture mapping between corresponding triangles of $\mathcal{M}^I$ and $\mathcal{M}^O$. To accomplish the retargeting, we employ an optimization framework. We evaluate the quality of the retargeting using three energy functions: aesthetic energy, warping energy, and smoothness energy, which are described in detail in the following three sections.

5.1. Aesthetic energy

The first criterion is to improve the aesthetics of the result image. Specifically, the salient objects and prominent lines should be as close as possible to their corresponding nearest power points or power lines respectively, according to the composition rules. We define three error terms as in the work of [LCWCO10]. However, different from their work, we use quadratic forms in the error functions such that the energy function can be easier to be minimized.

Point error term. For each object $B \in \mathcal{B}$, we find the nearest power point $P(B) \in \mathcal{P}$ to its center $C(B)$. According to the rule of thirds, the center of object B should be as close as possible to the target power point $P(B)$. To this end, we define an objective term E_p as the sum of the squared distances between $C(B)$ and P:

$$E_p = \sum_{B \in \mathcal{B}} \sigma(B) A(B) \|C(B) - P(B)\|^2 \tag{1}$$

Line error term. For each prominent line $D \in \mathcal{D}$, we find the nearest power line $L(D) \in \mathcal{L}$ to D. Note that if the prominent line D has an angle with x-axis which is less than 15 degree, we regard it as a horizontal line; if it has an angle with y-axis which is less than 15 degree, we regard it as a vertical line; otherwise, it is regarded as a diagonal line. The distance between two lines is computed by the distance between their midpoints. According to the rule of thirds and diagonal guideline, the prominent line should be as close as possible to its corresponding target power line. Thus, we define an objective term E_l as follows.

$$E_l = \sum_{D \in \mathcal{D}} \sigma(D) \|C(D) - C(L(D))\|^2 \tag{2}$$

Visual balance error term. To make the arrangement of all salient objects visually balanced within the image frame, the center of mass of all the objects should be close to the image center $C(\mathcal{I}^O)$. We define an objective term E_v to measure the visual balance as follows.

$$E_v = \|\sum_{B \in \mathcal{B}} A(B) C(B) / \sum_{B \in \mathcal{B}} A(B) - C(\mathcal{I}^O)\|^2 \tag{3}$$

Total aesthetic energy. The aesthetic energy is then defined as

$$E_a = \xi E_p + \eta E_l + \gamma E_v \tag{4}$$

where ξ, η and γ are weights.

5.2. Warping energy

We use a content-aware warping technique to warp $\mathcal{M}_I$ [JLW10]. We would like to preserve the aspect ratio of salient contents and the prominent line features during warping.

For each triangle $t \in \mathcal{T}$, we assign it an auxiliary linear transformation (2×2 matrix) G_t taken from some family of allowed transformations. We constrain the transformations as nonhomogeneous scales. Specifically, each triangle t will be assigned a matrix as $G_t = \begin{pmatrix} s_t^x & 0 \\ 0 & s_t^y \end{pmatrix}$ where s_t^x is the x-scale factor and s_t^y is the y-scale factor.

On the other hand, each triangle t is equipped with a unique affine mapping from itself to its counterpart in $\mathcal{M}^O$. The linear portion of the affine mapping is denoted as a 2×2 Jacobian matrix J_t which is constant per triangle. It is easy to see that the elements of matrix J_t are linearly dependent on vertices of (triangles in) $\mathcal{M}^O$.

We define the warping energy as:

$$E_w = \sum_{t \in \mathcal{T}} \sigma(t) A(t) \|J_t - G_t\|_F^2 \tag{5}$$

where $\|\cdot\|_F$ is the Frobenius norm.

Minimization of the warping term E_w makes the linear part of the affine mapping be as close as possible to the selected transformation G_t.

5.3. Smoothness energy

To avoid the discontinuity in the result image, we introduce a smoothness error term. We require the scaling transformations applied within a region of the mesh to be as similar as possible. We formulate this constraint to apply between every two triangles that are adjacent in the mesh [JLW10]:

$$E_s = \sum_{s,t \in \mathcal{T},\ s,t\ are\ adjacent} \sigma(s,t) A(s,t) \|G_s - G_t\|_F^2 \tag{6}$$

where $A(s,t) = (A(s) + A(t))/2$ and $\sigma(s,t) = (\sigma(s) + \sigma(t))/2$.

5.4. Total energy

The total energy is defined as the weighted sum of the three energies:

$$E = E_a + \lambda E_w + \mu E_s \tag{7}$$

where λ and μ are weights.

5.5. Constraints

We need to add some constraints in the energy to perform the optimization [JLW10].

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Boundary constraints. We have to ensure that the coordinates of points on the boundaries of the original image frame remain on the boundaries of the result image. We have two types of constraints on the boundary. For the vertices v on the left side of $\mathcal{M}^O$ we have the positional constraint: $v_x = 0$. For the triangle t with an edge on the left side of $\mathcal{M}^O$ we have the scale constraint: $s_t^y = s^y$. The other 3 sets of boundary constraints are similar.

Salient object constraints. The triangles in salient objects should better preserve their aspect ratios. Therefore, we assign the expected scale transformation matrices for these triangles as

$$M_t = \begin{pmatrix} \beta s^* & 0 \\ 0 & \beta s^* \end{pmatrix}, \; t \in B, B \in \mathcal{B} \qquad (8)$$

where $s^* = \max\{s^x, s^y\}$, and β is a scalar to determine how large would we preserve the size of the salient objects in the retargeted image $\mathcal{I}^O$. If we want to enlarge the salient objects in $\mathcal{I}^O$, we can set large value of β.

Prominent line constraints. The prominent lines should be preserved in the target images. First, we determine the direction (slope) n of the line $D \in \mathcal{D}$ based on the aspect ratio of the image frames. Suppose there are k successive line segments $v_i v_{i+1} (i = 0, 1, \ldots, k-1)$ on D. We add the following constraints to preserve the linearity of D as

$$v_i v_{i+1} \cdot n^{\perp} = 0, i = 0, 1, \ldots, k-1 \qquad (9)$$

where $n^{\perp}$ is a unit vector perpendicular to n.

5.6. Implementation

It is easy to see that the objective function (7) is quadratic with respect to the vertices of $\mathcal{M}_O$ and the scale factors $\{s_t^x, s_t^y | t \in \mathcal{T}\}$ of all triangles. The boundary constraints and the salient object constraints are regarded as hard constraints and the prominent line constraints are regarded as soft constraints to the minimization problem. Minimization of (7) with these constraints can be obtained by solving a sparse linear system. Note that although we solve for both the mesh vertices of $\mathcal{M}_O$ and the scale factors of all triangles, we are interested only in $\mathcal{M}_O$ while the scale factors play an auxiliary role only.

6. Experimental results

All the examples presented in this paper were made on a PC with Duo CPU 1.8GHz and 2GB memory. We employed Intel MKL [Int] to solve the sparse linear system in our system. The averaged edge length of triangulations is within 15-35 pixels. It takes about 20-80ms to obtain one retargeting result for an image with resolution of 1024×768. In our system, the user can adjust the aspect ratio of the image and obtain the aesthetic retargeting results in an interactive rate, as shown in the accompanying video.

There are a few of parameters in our approach. The values of parameters are selected experimentally. We set $\xi = 1, \eta = 2$ and $\gamma = 0.2$ in (4) and $\lambda = 1$ and $\mu = 0.5$ in Eq. (7) by default.

The scalar parameter β in (8) emphasizes how important the salient objects are compared to the image size. By default we set $\beta = 1$. Setting larger value of β encourages salient objects to be larger in the result. Fig. 2 shows various results of setting different values of β in an example. Larger β enlarges the salient objects (the two goats) in the retarget results (Fig. 2(e,f)) while smaller β makes the goats shrinkage in the results (Fig. 2(b,c)).

The prominent line is preserved by the line constraints in Eq. (9). The prominent line is distorted in the result if no line constraints are added in the optimization, as shown in Figure 3(b).

We adopt the similar composition guidelines proposed in [LCWCO10] to improve the aesthetics of images in our approach. The differences are two folds. First, our objective function is a quadratic form which can be minimized by solving a sparse linear system. Thus, our approach is much faster than [LCWCO10] which needs to search the optimal solution in a 4D space. The retargeting can be operated in an interactive manner in our system, as shown in the accompanying video. Second, unlike [LCWCO10] our approach does not perform cropping and hence our retargeting results contain all contents in the original images. Figure 4 show two examples to compare with the approach of [LCWCO10]. It can be seen that our approach also obtain visually pleasing results.

Our system allows the user to change the aspect ratios of the image and obtain the retargeting results in an interactive manner. Figure 5 shows some retargeting results with different image sizes. Figure 6 shows more retargeting results produced by our approach.

Limitations. Like [LCWCO10], our technique also has a few limitations. Our technique only follows the basic guidelines to recompose the image without discretion and does not apply inspiration or creativity. In some cases, professional photographers do not use the predefined composition guidelines in their art works and often disobey them. Furthermore, image aesthetics includes much more aspects such as color harmony, lighting, pattern, textures, than composition [GS90, Kra05]. As the images are warped in the retargeting results, distortion might be noticeable in some results, as demonstrated in Figure 7.

7. Conclusions

We have presented a novel approach for retargeting images while improving the composition aesthetics. The optimization is performed by solving a sparse linear system and thus is able to be achieved with high efficiency. The aesthetic retargeting results can be obtained in an interactive rate. A

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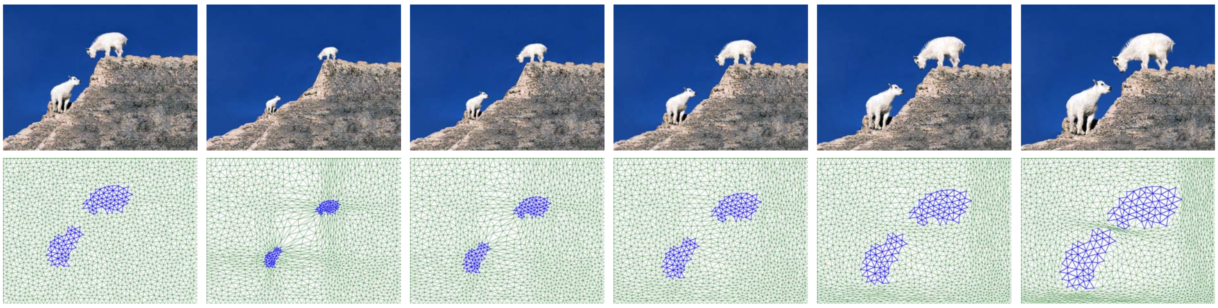
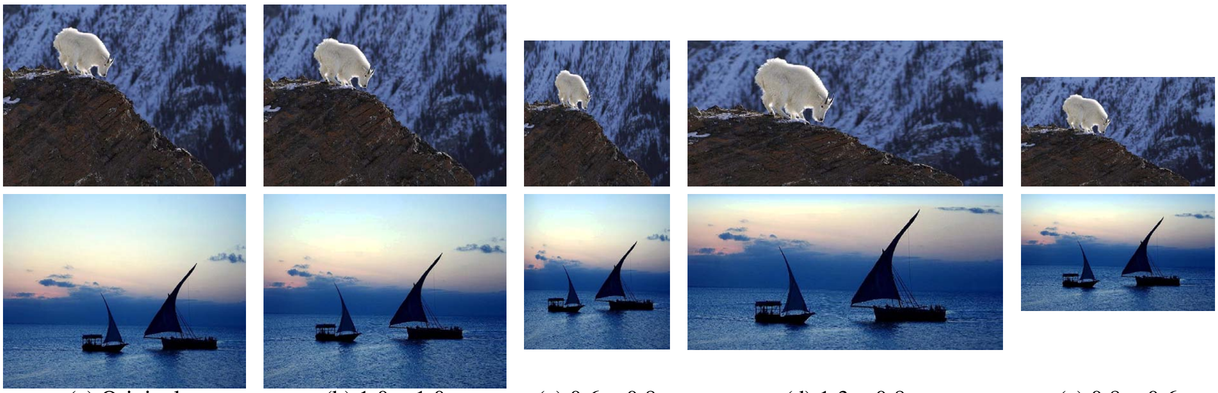


(a) (b) (c) (d) (e) (f)

Figure 2: *Retargeting images with different values of β in (8). The two goats are the salient objects in the original image (a). (b-f): retargeting results with different β of 0.5, 0.75, 1.0, 1.25, 1.5, respectively.*



(a) Original (b) 1.0×1.0 (c) 0.6×0.8 (d) 1.3×0.8 (e) 0.8×0.6

Figure 5: *Retargeting the images into different frame sizes. The numbers shown below the images denote the width and height ratios of target frames with respect to original frame.*

number of experimental results have shown the applicability and effectiveness of our approach. In the future, we will consider more guidelines for composing aesthetic images like color, structure, lighting etc [DW10].

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

Figure 6: *More results of aesthetic retargeting the original images (a) into 100%(b), 60%(c), 80%(d), 120%(e) of original frame width, respectively.*

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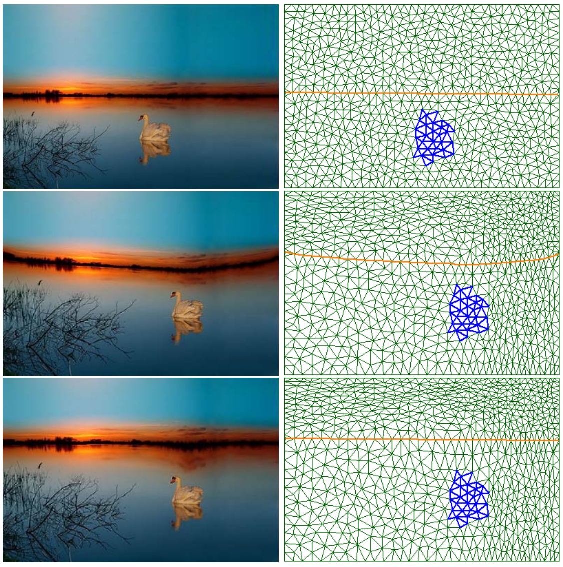

Figure 3: *The prominent line is preserved by adding the line constraints in Eq. (9). Upper row: original image; middle row: retargeting result without line constraints; lower row: retargeting result with line constraints.*

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Figure 4: *Compare with [LCWCO10]. Upper row: original images; middle row: results by [LCWCO10]; lower row: retargeting results by our approach ($\beta = 1.5$). Our results contain all content in original images without cropping anything.*

Figure 7: *Our warping based retargeting technique might suffer noticeable distortions in the results. The distortions in water regions in both examples are remarkable due to the large scales of warping operation. Left: original images; right: aesthetic retargeting results.*

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