In this paper, we propose a novel content-aware image resizing method based on grid transformation. Our method focuses on not only keeping important regions unchanged but also keeping the aspect ratio of the main object in an image unchanged. The dual conditions can avoid distortion which often occurs when only using the former condition. Our method first calculates image importance. Next, we extract the main objects on an image by using image importance. Finally, we calculate the optimal grid transformation which suppresses changes in size of important regions and in the aspect ratios of the main objects. Our method uses lower and upper thresholds for transformation to suppress distortion due to extreme shrinking and enlargement. To achieve better resizing results, we introduce a boundary discarding process. This process can assign wider regions to important regions, reducing distortions on important regions. Experimental results demonstrate that our proposed method resizes images with less distortion than other resizing methods.

Key words: content-aware image resizing, grid transformation, warping method, aspect ratio preservation

1. Introduction

Currently, users access multimedia contents using a wide variety of devices, such as televisions, mobile phones and portable media players. Their screens have a variety of aspect ratios. For optimal display, the aspect ratios of images need to be changed because those of screens and images are not necessarily the same. There are traditional resizing techniques such as cropping and uniform scaling. Cropping images, however, discards important content such as human faces and foreground objects, and scaling images distorts important content when the aspect ratio is changed.

In recent years, research on content-aware image resizing methods has been carried out actively for overcoming these limitations [1]. Seam carving [2]–[4] is one of approaches for content-aware image resizing. Seam carving methods change the size of an image by gracefully carving out or inserting paths of pixels. Cho et al. [5] combined the seam carving approach with importance diffusion for avoiding over-shrinkage of unimportant parts. Resizing methods with combination of seam carving and depth information were proposed in [6], [7]. Warping methods [8]–[10] are other approaches for content-aware image resizing. They place a mesh onto an image and then deform the mesh by computing a new geometry for the mesh. Sun and Ling [11] use seam carving to guide the warping transformation.

Many content-aware image resizing methods focus on only preventing important content from changing because keeping important content unchanged can reduce the possibility of making visually implausible images. However, if the target image width is smaller than the width of important content on an original image, these methods fail to prevent important content from changing. Instead of enforcing the size of important content to remain unchanged, the optimized scale-and-stretch approach [8], which is categorized as a warping method, determines an optimal scaling rate for each local region on a mesh. Their method distributes the distortion to image regions with homogeneous content.

In this paper, we propose a new resizing method, which is based on grid transformation. Like other warping methods, our method places a grid onto an image and then deforms the grid for resizing (see Fig. 1). While many warping methods move vertices on a mesh in any directions, our method moves each vertical and horizontal grid line in the perpendicular direction to itself. In other words, our proposed method changes the distances between the grid lines. It preserves the orientation of the mesh edges which compose grid lines. The reason we use this approach is the following. In the warping methods that allow vertices to move to any directions, the grid lines are likely to bend. This causes large distortion as described in [8]. To minimize the bending of the grid lines, Wang et al. [8] tried to retain the edge orientations during mesh deformation. In the resizing results of [8], the edge lengths are changed while many edges are linearly aligned. From this observation, we can see the advantage of our mesh transformation, which changes the distances between the grid lines. Our approach
suppresses distortion because it preserves the orientation of the mesh edges.

Optimal grid transformation is found to solve an energy minimization problem. To obtain a favorable resizing result, we introduce two energies: energy for keeping important regions unchanged, and energy for preserving the aspect ratios of objects. These details are shown in Sect. 2.2. The latter energy is the central idea in our method. This energy helps to keep the aspect ratios of main objects unchanged. Especially when the target image width is smaller than the width of main objects, using this energy leads to plausible resizing results. Figure 2 is an example to show this fact. Figure 2(b) is the resizing result by our proposed method without the energy and (c) with the energy. In the case without the energy, the width of the main object is reduced because the width is wider than of the target image. Similarly, in the case with the energy, the width of the main object is reduced. At the same time, the height is also reduced by the effect of the energy. As a result, we can obtain the resizing result in which the figure of the original object is preserved as much as possible.

To successfully preserve the aspect ratios of objects, we first extract main objects, and then perform grid transformation. To obtain more satisfactory results, our method adds a condition to the scaling rates of meshes. In conventional warping methods, the lower thresholds of the scaling rates of meshes are not set or set to 0. It leads to distortion due to convergence of unimportant regions. To avoid such distortion, our method uses lower thresholds. However, using lower thresholds causes other distortion. Lower thresholds maintain the scaling rates of unimportant regions above a certain level. It means reduction of area for important regions, causing distortion on important regions. To suppress such distortion, our method discards boundary regions whose scaling rates are small. It gives more area for important regions. This approach is like an adaptive cropping method.

From another viewpoint, our proposed method combine adaptive cropping with piecewise scaling. Although cropping may discard main contents in an image, it does not create any artifacts by definition. As described in [12], adaptive cropping methods have the potential to produce satisfactory results compared with recently-proposed resizing methods. Scaling in one direction changes the aspect ratios of contents, leading to artifacts. Our piecewise scaling approach can scale local regions in horizontal and vertical directions. This approach has the potential to keep the aspect ratios of main contents, avoiding artifacts. Because of these potentials, it can be expected that the combination of adaptive cropping and piecewise scaling produces satisfactory results compared with conventional resizing methods.

2. Grid-based Image Resizing

Our method places a grid divided by vertical and horizontal lines onto an original image of $m \times n$. Let us denote a region between neighboring grid lines in the same direction by grid section $O_i$ and the distance between these lines by section width $l_i$. Here $\sum_{i \in H} l_i = m$, $\sum_{i \in V} l_i = n$, and $I_H$ and $I_V$ are sets of all section indices in horizontal and vertical directions, respectively. To resize an image of $m \times n$ pixels into an arbitrary size of $m' \times n'$ pixels, our method changes the section widths $l_i$ to $l'_i$ satisfying $\sum_{i \in H} l'_i = m'$, $\sum_{i \in V} l'_i = n'$, and $d_i \leq l'_i \leq u_i$, where $d_i$ and $u_i$ are thresholds to suppress distortion due to extreme shrinking and enlargement. Figure 3 is an example of section widths before and after transformation. Our goal is to find optimal widths $l'_i$ of grid sections.

Our proposed method attempts to satisfy the following two conditions as much as possible. First, important regions are kept unchanged. This condition is required on many content-aware image resizing methods. Second, the aspect ratios of main objects are kept unchanged. To find optimal transformation satisfying these conditions, we solve this problem as an energy minimization problem. The definitions of our proposed energies are shown in Sect. 2.2, and the energy minimization problem is shown in Sect. 2.3.

2.1 Image Importance and Main Object

Unlike homogeneous scaling methods, many content-aware resizing methods scale each region inhomogeneously at a rate corresponding to its importance. Avidan and Shamir [2] use the $L_1$-norm of the grayscale intensity gradient as image importance. Visual saliency, which indicates perceptual quality, is useful for image importance. Itti et al. [13] introduce a brain-like model to generate a saliency map by extracting color, intensity and orientation features. Achanta’s method [14] calculates the Euclidean distance in $Lab$ color space between the pixel vectors in a Gaussian filtered im-

![Fig. 2](image) The effect of the energy for preserving the aspect ratios of objects. (a) Original image. (b) Our resizing result without the energy. (c) Our resizing result with the energy.

![Fig. 3](image) Example of section widths before and after transformation.
In this paper, we set \( T \) parameter and \( \psi \) as the total importance \( \Psi \). \( \psi \) \( i \) is the number of elements of \( \Psi \). We define the energy for keeping important regions unchanged as

\[
E_C = \sum_{i \in I} \omega_i \left( 1 - \frac{l'_i}{l_i} \right)^2
\]

where \( I \) is a set of all grid sections on the grid. The change of the scaling rate at a more important region makes larger energy. Figure 5 is examples of this energy.

Next, we define the energy for keeping the aspect ratios of objects unchanged. For simplicity, first we discuss the case where there is only one object on an image. Figure 6 is examples of deformation in the case of changing and keeping an aspect ratio of an object. As shown in this figure, an aspect ratio of an object is kept when the widths of all grid sections intersecting with the object are scaled at equal rate. From this observation, we define the energy for keeping aspect ratio in a way that becomes larger when the scaling rates of the grid sections have varied more widely.

Let us denote an index set of the grid sections intersecting with object region \( \Psi_j \) by \( I_{\Psi_j} \), and a function to calculate an average scaling rate of a section by

\[
R(I_{\Psi_j}) = \frac{1}{|I_{\Psi_j}|} \sum_{i \in I_{\Psi_j}} \frac{l'_i}{l_i}
\]

2.2 Energy Definition

Optimal transformation of a grid is calculated by solving an energy minimization problem. To obtain favorable resizing results, we use two energies, which is defined for keeping important regions unchanged, and for keeping the aspect ratios of objects unchanged. The definitions of these energies are shown below.

First, we define the energy for keeping important regions unchanged. The ideal condition to obtain a satisfactory resizing result is that all important regions are untouched in a resizing process. However it is hard to satisfy the condition when the target image width is smaller than the width of important regions. In addition, we cannot completely ignore distortions on unimportant regions. To solve these problems, each grid section is scaled depending on its importance. Let us denote the importance of grid section \( \Omega_i \) by \( \omega_i = \sum_{j \in I} S \). We define the energy for keeping important regions unchanged as
the energy for keeping the aspect ratio of $\Psi_j$ by

$$E'_A = \sum_{i \in \Psi_j} I_i \left( R(I_{\Psi_j}) - \frac{l_i}{l_i'} \right)^2.$$  

Next we discuss the case where there are more than one object on an image. When a grid section intersects with multiple objects, the widths of all grid sections intersecting with all the objects need to be scaled at equal rate in order to keep the aspect ratios of all the objects. Therefore, our method merges these objects to treat as one object. After merging, our method calculates the total energy for keeping aspect ratio by summing together:

$$E_A = \sum_{\Psi \in \Psi_j} \sum_{i \in \Psi} I_i \left( R(I_{\Psi_j}) - \frac{l_i}{l_i'} \right)^2.$$  

where $\Psi$ is a set of all objects.

In Eq. (4), the term in the bracket indicates the difference between the scaling rate of one interval and the average scaling rate among the corresponding intervals. The term $l_i$ multiplied by the bracketed term has a role to prevent $E_A$ from largely depending on the initial mesh intervals. If $E_A$ is calculated by using only the bracketed term without multiplying $l_i$, a finer division of the initial mesh makes larger energy after resizing. In $E_C$, $\omega_i$ has the same role, which is the sum of importance on grid section $\Omega_i$, implicitly including the term $l_i$.

### 2.3 Total Energy Minimization

To calculate optimal transformation of a mesh, we wish to minimize the weighted sum of two energies:

$$E_{\text{total}} = E_C + \lambda E_A$$  

subject to $\sum_{i \in \Psi_j} l_i' = m'$, $\sum_{i \in \Psi_j} l_i = n'$, and $0 < l_i' < u_i$. Here, $\lambda$ is a weight factor, and $d_i$ and $u_i$ are lower and upper thresholds to suppress distortion due to extreme shrinking and enlargement, respectively. We use the following threshold:

$$d_i = \tau^{-1} l_i \min\{s_v, s_h\},$$

$$u_i = \tau l_i \max\{s_v, s_h\}$$

subject to $\sum_{i \in \Psi_j} l_i' = m'$, $\sum_{i \in \Psi_j} l_i = n'$, and $0 < l_i' < u_i$. Here, $\lambda$ is a weight factor, and $d_i$ and $u_i$ are lower and upper thresholds to suppress distortion due to extreme shrinking and enlargement, respectively. We use the following threshold:

$$d_i = \tau^{-1} l_i \min\{s_v, s_h\},$$

$$u_i = \tau l_i \max\{s_v, s_h\}$$

where $s_h = m'/m$ and $s_v = n'/n$ are the horizontal and the vertical scale of a target image, respectively, and $\tau$ is a parameter to adjust the thresholds. We solve the energy minimization problem of Eq. (5) by using active set method. In conventional warping methods, the lower thresholds of the scaling rates of meshes are not set or set to 0. It leads to distortion due to convergence of unimportant regions. Figure 7 (a) is an example of convergence. The red box regions have artifacts because of extremely reduction. The lower threshold we defined above can avoid such distortion. However, using the lower threshold causes other distortion. The lower threshold maintains the scaling rates of unimportant regions than a given level. It means reduction of area for important regions, causing distortion on important regions. In Fig. 7 (b), the red box region, which is unimportant, occupies a certain space. Therefore, human figures are highly deformed because of smaller space. To suppress such distortion, we use an additional process.

If the optimal scaling rate at a section in contact with an image boundary is small, it indicates that the section may contain many unimportant regions. Our method discards such sections, and then recalculates the energy minimization problem (see Fig. 8). This discarding process can assign wider regions to important regions, reducing distortions on important regions. All boundary grid sections satisfying the following condition are eliminated: $l_i' = d_i$. The scaling rates of the eliminated sections are set to be 0. This process has an effect like adaptive cropping on a resizing image. Figure 7 (c) indicates the effect of this additional process.

Finally, we outline the whole process of our proposed method in Algorithm 1.
Algorithm 1 Resizing process

1. Initialization:
   a) Input an original image.
   b) Project a grid on the image.
   c) Set a target image size to be \( m' \times n' \).

2. Compute importance and extract main objects:
   a) Compute image importance \( S \) and obtain initially-segmented regions by using Achanta’s method [14].
   b) Eliminate unimportant regions from the segmented regions to leave main objects with a threshold.

3. Compute optimal transformation of the grid:
   a) Solve the energy minimization problem of Eq. (5) by using active set method [15].
   b) If boundary grid sections satisfy \( l_i' = d_i \), discard these boundary regions and then do Step 3 again.

4. Output a resized result.
   a) Calculate a resized image based on the optimal grid transformation by using bilinear interpolation.

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3. Content Amplification

Our method can be used to amplify contents of an image while preserving its size. To achieve it we replace the energy for keeping important regions unchanged by

\[
E_C = \sum_{i \in \Omega} \omega_i \left( s - \frac{l_i'}{\tau} \right)^2
\]

(8)

where \( s \) is an amplification parameter and we update parameter \( \tau \) to \( s \tau \). The energy expressed in Eq. (8) becomes zero if all grid sections are scaled by \( s \). It is, however, not satisfied because the image size does not change in this content amplification process. Thus grid sections with higher importance are enlarged and grid sections with lower importance are shrinked to minimize the total energy expressed in Eq. (5). It results in amplification of important content. Figure 9 shows examples of content amplification with our method. As shown in this figure, the main objects are amplified depending on the amplification parameter.

4. Evaluation Method

In this section, we describe how to evaluate the effectiveness of our method.

4.1 Resizing Methods

The choice of the methods for comparison is important for validating the effectiveness of our method. One of the main ideas of our method is piecewise scaling for unimportant regions. An approach similar to this is shown in [2], which removes image columns with minimal energy. It leads to an effect similar to reduction of the width of a grid section in our method. To prevent excessive removal of unimportant columns, Cho et. al. [5] proposed importance diffusion approach, which propagates importance of removed pixels to their neighbors. Whereas the column removal approach produces a scaling-like effect for local regions in only a horizontal direction, our proposed method can scale local regions in horizontal and vertical directions. Therefore the comparison to the column removal approach is suitable for showing the efficacy of our piecewise scaling approach. The seam carving method [2] is one of flexible resizing methods. We used the method [5] for comparison, which combines the seam carving method with the importance diffusion. We should compare a method categorized as a warping method. Wang’s warping method [8] is appropriate for comparison.

To summarize, we compared our method (OUR) with column removal with importance diffusion (CR), seam carving with importance diffusion (SC) and Wang’s warping method (WW). Importance criteria on the image are often not easily separable from the approach itself. In WW, the procedure for calculating image importance is one of the essential idea. Therefore we followed the procedure written in [8] for WW. In CR and SC, importance criteria can be separate from these approaches. To focus on comparing the difference in these resizing approaches, we used the same procedure for calculating image importance [13] in CR, SC and our method.

Our method used the following empirically-determined parameters, which produce sufficiently good results: \( \lambda = 100 \), \( \tau = 1.25 \) and the initial grid divided by 10 pixels.

4.2 Resized Images

To conduct our experiment, we chose a set of 24 images from Flickr (http://www.flickr.com/). Figure 10 is a list of the images. They have wide variety of types, e.g. images with people, animal, salient objects, structures and...
landscape. We assigned the following attributes to these images: lines, main objects (people/animal/foreground objects), background, and landscape. Note that one image has several attributes. These attributes were used for the questions in the user study described later. We rescaled the widths of all the images down to 50%.

4.3 User Study Design

To evaluate our proposed method, we conducted a user study. Our evaluation method and system are based on the image retargeting survey system [12], which has web-based interface. The participants were shown two resized images side-by-side, and are asked to select the one they preferred. Although we are interested only in the comparison between our method and other methods, we compared all the possible 6 combinations of comparisons, i.e., not only OUR-CR, OUR-SC and OUR-WW but also CR-SC, CR-WW and SC-WW. The reason is for avoiding bias in frequency of appearance of images to ensure a fair comparison. Given the 24 images tested, the number of possible paired comparisons is 144. This is too large comparisons to conduct a test with attention at a time. Therefore, we divided the 24 images into 2 sets (1–12 and 13–24 of images in Fig. 10). Each participant is assigned 72 comparisons.

In our experiment, the original image was not shown. This situation reflects the real-world context, where images are often edited and the original images are unknown to people who view the edited images.

For examining characteristics affecting the user preference, our evaluation system occasionally asked the participants to pick one or several reasons for choosing a result. Table 1 is the list of reasons by image attribute. For example, when the participants are asked a question for image Fig. 10-1, which is assigned attribute of main objects (M) and background (B), our system offers the reasons ID 2, 3 and 4 (and 5 and 6 common to all images) shown in Table 1. In order to maintain the participant’s attention, this question appeared randomly with a probability of 1/4.

Table 1 Proposed reasons for choosing a result. Common attribute was assigned to all images. Thus the last two questions were always offered.

| Attribute          | Reason                                      | ID |
|--------------------|---------------------------------------------|----|
| lines              | Lines were less distorted                   | 1  |
| main objects       | Objects were less distorted                 | 2  |
| background/landscape| Background/Landscape was less distorted      | 4  |
| Common             | Cannot put my finger on it.                 | 5  |
| Common             | This result was simply more appealing.      | 6  |

Table 2 Preference matrix for all images. An entry $n$ in the $i$-th row and the $j$-th column means that the participants chose the result with the $i$-th method $n$-times over the $j$-th method.

|        | CR   | SC   | WW   | OUR  |
|--------|------|------|------|------|
| CR     | -    | 119  | 61   | 31   |
| SC     | 25   | -    | 23   | 11   |
| WW     | 83   | 121  | -    | 45   |
| OUR    | 113  | 133  | 99   | -    |

Fig. 11 Selected rate of the reasons for choosing our method over CR (1), SC (2) and WW (3).

5. Experimental Results

The user experiment consisted of 12 subjects, who were in ages of 20 to 25, and were undergraduate and graduate students. The preference matrix of the experiment is shown in Table 2. The results of our method were favored in 78.5% (113 of 144) of the comparisons with CR, in 92.4% (133 of 144) of the comparisons with SC, and in 68.8% (99 of 144) of the comparisons with WW. Given a null hypothesis that
a total vote for our method is the same as one for another method because there is no significant difference between them, all $p$-values of the $\chi^2$ test are less than 0.01, rejecting the null hypothesis at the 1% level.

We discuss the advantages and the limitations of our proposed method by the resized results and the reasons for
choosing a result. Figure 12 is a part of the resized results, where the results of our proposed method in (1)–(4) are preferred to of other methods by most or all participants, and the result of our proposed method in (5) has relatively few votes. Figure 11 shows the selected rates of the reasons for choosing our method over another. As shown in Fig. 11 (2), distortion of objects is the main reason for choosing the result of our method over the result of SC. The results in Fig. 12 support the fact that the resized images with SC have many distortions. While the seam carving approach has a relatively-high transformation flexibility, this flexibility may cause distortions. As shown in Fig. 11 (1) and (3), the reasons for choosing the result of our method over the result of CR and WW show a similar tendency. The main reason is “Objects looked more natural in size and shape”. It can be said that our approach for keeping the aspect ratio of the main objects makes a large contribution to produce satisfactory results. For example, compared to CR in Fig. 12 (1), which reduced only the width of the car, our method reduced the width and height of the car, preventing an unnatural change of the aspect ratio of the car. The comparison of our method to WW in Fig. 12 (1) shows the efficacy of the constraint on the section width of the mesh. Our method and WW properly deformed the car with less distortion. WW, however, excessively extended the sky background because WW does not set the upper threshold of the scaling rates of meshes. Our method avoids such distortion due to the upper threshold. The boundary discarding process of our proposed method played an important role in producing satisfactory results. This process was expected to assign wider regions to important regions, reducing distortions on important regions. In fact, the efficacy was confirmed in many results. A prominent result is found in Fig. 12 (2). Our method cropped the left side regions, resulting in the assignment of wider space to other regions. It led to an acceptable result with less distortion. The advantage of our mesh transformation, which preserves the orientation of the mesh edges, is apparent in Fig. 12 (3). The results with WW and our method look similar but many participants favored our method over WW. The reason is that whereas WW distorted vertical lines on

Fig. 13  Results of extreme resizing. Left: original image (768×512 pixels). Upper right: Wang’s warping method (WW). Middle right: our method. Lower right: main objects and grids after transformation in our method.
background, our method maintained them because it does not distort vertical lines in principle. Many structures are designed with horizontal and vertical elements, e.g., buildings. Thus many images enjoy the advantage of our method. The original image of Fig. 12 (4) includes no eye-catching objects. Object extraction could not function efficiently for such images. Despite this, our method resized the image with less distortion than other methods. If there is not much importance difference on an image, our method performs like uniform scaling, which causes some distortions but does not causes extreme distortion. Figure 12 (5) represents the limitation of our method. Saliency detection and important object extraction have a great influence on our resizing results. In Fig. 12 (5), human figures are expected to be extracted as important objects. Our method, however, fails to extract them, leading to the unsatisfactory result.

Finally, we show the comparison of extreme resizing between WW and our method in Fig. 13. Even in this severe condition, our method produces a plausible result.

6. Conclusions

We proposed a novel method for content-aware image resizing based on grid transformation. We first calculate image importance. Next, we extract main objects on an image by using image importance. Finally, we calculate the optimal grid transformation which suppresses changes in size of important regions and the aspect ratios of main objects. Our method uses lower and upper thresholds for transformation to suppress distortion due to extreme shrinking and enlargement. We introduced a boundary discarding process to avoid distortion. This process can assign wider regions to important regions, reducing distortions on important regions. Experimental results demonstrate that our proposed method resizes images with less distortion than other resizing methods. We showed that our proposed method can be used to amplify contents of an image.

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