Improved Seam Merging for Content-Aware Image Resizing

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SUMMARY In this paper, we propose an improved seam merging method for content-aware image resizing. This method merges a two-pixel-width seam element into one new pixel in image reduction and inserts a new pixel between the two pixels in image enlargement. To preserve important contents and structure, our method uses energy terms associated with importance and structure. Our method preserve the main structures by using a cartoon version of the original image when calculating the structure energy. In addition, we introduce a new energy term to suppress the distortion generated by excessive reduction or enlargement in iterated merger or insertion. Experimental results demonstrate that the proposed method can produce satisfactory results in both image reduction and enlargement.

key words: content-aware image resizing, seam carving, seam merging

1. Introduction

With the diversity of display device sizes and aspect ratios, studies on the automatic resizing of images are becoming more important. Cropping and scaling are common approaches to change aspect ratios and resolutions. Cropping, however, can discard important parts on an image, and scaling produces distortion in the case of changing aspect ratios. For effective image resizing, several content-aware image resizing methods have been proposed [1], [2]. Seam carving [3] is one of the approaches for content-aware image resizing. It repeatedly removes an 8-connected path of pixels, called seam, from top to bottom or from left to right. In terms of removal, the optimal seam is the one with the least total energy. To preserve important contents, the original seam carving and many improved methods [4]–[6] use pixel importance as the energy. These methods, however, may distort object shapes because they ignore structure preservation. To solve this problem, we proposed seam merging [7], [8], which merges a two-pixel-width seam that minimizes structural distortion to reduce image size. We provide a brief description of this method in Sect. 2. See [7], [8] for more details. The seam merging method provides satisfactory results in many images. This method, however, has the following problems to solve. First, it cannot enlarge images because it was designed only to reduce image size. Second, it may fail to preserve important contents due to the lack of using pixel importance. Last, it may fail to preserve main structures like object outlines for preserving many small structures like texture components.

In this paper, we propose an improved seam merging method to address these problems. The rest of this paper is organized as follows: Section 2 represents the detail of the improved seam merging. Experimental results are provided in Sect. 3. Finally, the conclusion is given in Sect. 4.

2. Proposed Method

This section describes our proposed method. We first provide a brief description of the features of our method.

The conventional seam merging method reduces image size by repeatedly merging a two-pixel-width seam into a one-pixel-width seam. While it only defines image reduction, the improved seam merging method can reduce and enlarge image size. This method not only merges a two-pixel-width seam element into one new pixel, but also inserts a new pixel between the two pixels. The former reduces image size, and the latter enlarges.

To calculate pixel values on a resized image and energy to select seams, seam merging uses a merging history, which is a record listing which pixels are merged into a pixel in the resizing process. Seam carving ignores formerly removed parts in each resizing process, and that leads to large distortion generated by the accumulation of small distortion. Seam merging prevents such distortion by referring formerly merged parts using merging histories. In the conventional seam merging method, a merging history is defined as a set of pixel coordinates. In the improved seam merging method, it is defined as a multiset, which allows duplicate elements. It enables us to enlarge image size using a seam merging approach.

The conventional seam carving and many improved methods used importance energy to preserve important contents. The conventional seam merging introduced structure energy to preserve structure. To preserve important contents and structure, the improved seam merging combines importance and structure energies. The structure energy is calculated by using the cartoon image of an original image for better structure preservation. In addition, we introduce a new energy term to suppress the distortion generated by excessive reduction or enlargement in iterated merger or insertion.

To summarize, the differences between the conventional seam merging and the improved seam merging are
as follows.

- The improved seam merging can enlarge image size.
- In the improved seam merging, the structure energy is calculated by using the cartoon image of an original image for better structure preservation.
- The improved seam merging uses not only an energy term to preserve structure but also energy terms to preserve important contents and to suppress the distortion generated by excessive reduction or enlargement.

In the following subsection, we explain the energy definitions in our proposed method. For simplicity, the discussion is limited to the case of resizing images in a horizontal direction. An upper index in brackets (e.g. $s^{(k)}$) indicates $k$-th merging/inserting process.

2.1 Improved Seam Merging

A vertical seam is defined as a connected path of seam elements (two-pixel pairs) from top to bottom that contains only one seam element per row. Let $s$ be a seam, which is a set of seam elements $s_r$. Here $s_r$ is a seam element which creates a new pixel at $r$ after the merging/inserting process (see Fig. 1). New pixels form a connected path like a seam of seam carving. Given that $r_i = (x_i, i)$ is a coordinate of a seam element in the $i$-th row, $x_i$ satisfies $|x_i - x_{i-1}| \leq 1$. The pixel value of a newly created pixel is defined by using its merging history, which is a multiset. Merging history $Q^{(0)}(r)$ initially has its coordinate $r$ and is updated in the resizing process. The merging history of newly created pixel $r$ is updated by combining merging histories of pixels constituting seam $s_r$. Note that a merging history can contain duplicate elements in the inserting process. In the case where pixel $r$ and $q$ are merged, the merging history is updated as follows:

$$Q^{(k)}(r) = Q^{(k-1)}(r) \cup Q^{(k-1)}(q)$$

(1)

where $Q^{(0)}(r) = \{r\}$. The merging histories of pixels located on the left of the newly created pixels remain unchanged. To compensate for the coordinate change due to merging/inserting, the merging histories of pixels located on the right of the newly created pixels are shifted to left in the merging process and to right in the inserting process.

Let $I^{(k)}(r)$ be a pixel value at $r$ on a resized image after $k$-th merging/inserting process. $I^{(k)}(r)$ is calculated as the average of pixels listed in a merging history:

$$I^{(k)}(r) = \frac{1}{N(Q^{(k)}(r))} \sum_{q \in Q^{(k)}(r)} I^{(0)}(q)$$

(2)

where $N(Q^{(k)}(r))$ is the number of elements listed in $Q^{(k)}(r)$ and $I^{(0)}(q)$ is a pixel value at $q$ on an original image.

An optimal seam has the least total energy required to create new pixels. Let $E^{(k)}(s_r)$ be an energy required to create a new pixel at $r$ in $k$-th merging/inserting process. An optimal seam is expressed by

$$s^{(k)} = \arg \min_{s_r \in S} E^{(k)}(s_r).$$

(3)

The conventional seam merging method uses structure energy for preserving local structures on an original image. The energy is calculated by using pixel context which expresses a local structure defined as the intensity differences between a pixel and its surrounding pixels. Pixel context is expressed as

$$d^{(k)}(r, n) = I^{(k)}(r) - I^{(k)}(r + n)$$

(4)

where $n$ is a relative coordinates. In this paper, we use 4-connected coordinates as $n$, i.e., $n \in N$ where $N = \{(0, 1), (1, 0), (0, -1), (-1, 0)\}$. An example of pixel context is shown in Fig. 2. A large change of pixel context makes structure distorted. To prevent such distortion, the energy to create a new pixel grows when the change of pixel context is large after merging. Structure energy is expressed using the change of pixel context as

$$E^{(k)}(s_r) = \sum_{q \in Q^{(k)}(r), n \in N} (d^{(k)}(r, n) - d^{(0)}(q, n))^2.$$  

(5)

Using this structure energy produces plausible images.

In some images, however, it may fail to produce satisfactory results. Figure 3 (b) is a resized image using the energy expressed by Eq. (5). As shown in this figure, body outlines are distorted while unimportant background parts are left. The cause is that the background texture has complicated local structures. Although structure change in areas having many small edges like texture is unnoticeable, structure energy becomes large because of complicated structures. As a result, a seam passes through main structure parts because they have less energy than texture parts have. It leads to significant structure distortion. To obtain better resized images, we need to use structure energy which is little affected by texture components.

Our proposed method calculates structure energy using pixel context on the cartoon image of luminance image $Y$ of original image $I^{(0)}$. $Y$ can be decomposed into two components $Y = u + v$, such that $u$ represents a cartoon or

![Fig. 1](image1.png)  
**Fig. 1** Our method reduces image size by merging a seam and enlarges by inserting a seam.

![Fig. 2](image2.png)  
**Fig. 2** An example of pixel context. A number in a square indicates a pixel intensity. The pixel context of the gray pixel is expressed as $d(r, n_1) = -4$, $d(r, n_2) = 0$, $d(r, n_3) = 2$, $d(r, n_4) = -1$. 

![Diagram](image3.png)
simplification of $Y$, while $v$ represents noise or texture of $Y$. To obtain a cartoon image, we use the TV/L2 model, also known as the Rudin, Osher, and Fatemi model [9]:

$$\inf_u \left\{ F(u) = \int |\nabla u| + \lambda \int |v|^2 \, dxdy, Y = u + v \right\}. \quad (6)$$

Cartoon image $u$ is an image formed by homogeneous regions and with sharp boundaries. Using $u$, pixel context is rewritten as

$$d^{(k)}(r, n) = u^{(k)}(r) - u^{(k)}(r + n). \quad (7)$$

The update rule of $u$ is as follows.

$$u^{(k)}(r) = \frac{1}{N(Q^{(k)}(r))) \sum_{q \in Q^{(k)}(r)} u^{(0)}(q). \quad (8)$$

Figure 3 (d) is a resized image using the cartoon image (Fig. 3 (c)) as calculating structure energy. As shown in this figure, using a cartoon image reduces the effect of texture components and keeps main structures on an image.

Keeping important parts is as needed as keeping structure to obtain satisfactory resized results. The conventional seam carving and many improved methods use an importance map to prevent important parts from distortion. These methods, however, may produce distorted results because they repeatedly remove the least important seams ignoring which parts were removed before. It leads to excessive removal of unimportant parts and introduces distortion. To prevent such distortion, Cho et al. [6] proposed the use of importance diffusion, which propagates importance of removed pixels to their neighbors. Our proposed method uses an importance map and calculates importance energy using merging histories to prevent such distortion. Using importance map $T$, importance energy to create new pixel $r$ is expressed as

$$E_T^{(k)}(s_r) = \sum_{q \in Q^{(k)}(r)} T(q). \quad (9)$$

As shown in this equation, image importance is accumulated in the resizing process. Pixel importance can be measured by intensity gradient, saliency measure, object detections, user inputs, and many other criteria [3]. The determination of which criteria should be used as image importance depends on context. To make a fair comparison with conventional methods, in our experiments all the methods including our proposed method use the same importance map, which is the $L_1$-norm of the intensity gradient of a luminance image:

$$T = \left| \frac{\partial}{\partial x} Y \right| + \left| \frac{\partial}{\partial y} Y \right|. \quad (10)$$

Figure 4 (a) shows an importance map of the original image (Fig. 3 (a)). Figure 4 (b) expresses accumulated importance in the resizing process. In this figure, importance on the outline of bodies increases very little while importance on the background region is accumulated. As shown in this example, the importance energy can preserve important contents and prevent excessive reduction on unimportant regions.

To obtain more satisfactory results, we introduce an additional energy. In many cases, using the foregoing structure and importance energies can prevent excessive merging/inserting in an area because of energy accumulation. However, they fail to prevent it in smooth areas because there is a little energy accumulation. To solve this problem, we introduce the following energy which grows when merging/inserting is repeated.

$$E_U^{(k)}(s_r) = N(Q^{(k)}(r)). \quad (11)$$

$N(Q^{(k)}(r))$ is 1 at all pixels of an original image. This energy is especially effective in image enlargement. Figure 5 (a) is an enlarged image in horizontal direction. In this image, background pixels seem to be naturally stretched. The reason is as follows. $N(Q^{(k)}(r))$ at an inserted pixel is larger.
than at adjacent pixels. Therefore, the inserted pixel decreases the probability of pixel insertion at adjacent positions. As a result, new pixels are nearly equally inserted in unimportant regions. Figure 5 (b) is the distribution of \( N(Q^k(r)) \) of the enlarged image. As shown in this figure, the concentration of pixel insertion on one area can be avoided.

Finally, to define the energy in Eq. (3) for selecting an optimal seam with the three energies \( E_s^k \), \( E_r^k \), and \( E_u^k \), we need to normalize these energies, which are defined in different measures. Before starting the resizing process, we calculate the following maximum energy on each of the three energies individually, and then divide each energy by the corresponding maximum energy in the resizing process.

\[
E_s = \max_s \sum_{s, s'} E_s^{(1)}(s_r).
\]

Using normalized energies, the total energy to create a new pixel at \( r \) is expressed as

\[
E_s^k(s_r) = E_s^k(s_r) + E_r^k(s_r) + E_u^k(s_r).
\]

An optimal seam expressed Eq. (3) can be found using dynamic programming.

3. Experimental Results

To validate our method, we implemented our proposed method and tested it on a variety of images. Figure 6 shows all images for our simulation.

Firstly we discuss the case of image reduction. Figure 7 shows some results of image reduction with improved seam carving methods [4], [6], the conventional seam merging method [8], and the improved seam merging method. The original image of Fig. 7 (1) can be relatively well-resized with all methods. The reason is that this image consists of broad background region with smooth texture and foreground objects with sharp edges and texture. There are some silhouettes in the foreground of the original image of Fig. 7 (2). It is hard to resize such an image with less distortion because objects without texture like silhouettes are generally not regarded as important. The conventional methods [4], [6] regard the background with texture as important. As a result, the silhouettes are excessively reduced. In the result of the conventional seam merging method, the silhouettes are preserved better than of [4], [6] but seems unnatural. Our proposed method reduces unimportant background, preserving the silhouette. The reason is as follows. In a cartoon image of the original image of Fig. 7 (2), the background is almost homogeneous. Therefore, our method can preserve the silhouettes, which have clear structure. The original images of Fig. 7 (3) and (4) have some texture on the backgrounds. In these images, our proposed method preserves figures of foreground objects well while the other conventional methods reduce figures. In Fig. 7 (5), our proposed method keeps the shape of the straight edge of the cup while the other conventional methods distort.

We next show the results of image enlargement with [4] and our method. As shown in Fig. 8, our method keeps main objects and structures, while seam carving based approach [4] distorts some objects. In image enlargement, seam carving once removes seams, and then duplicates corresponding seams on an original image. The reason is straightforward pixel inserting creates a stretching artifact [3]. Additionally, seam carving needs to break the pro-
cess into several steps in the case of excessive image enlarging (for instance, greater than 50%). As shown in this process, seam carving selects seams optimized for image reduction, not for image enlargement. In contrast, our method enlarges images straightforwardly without excessive stretching artifact thanks to the accumulation of energies.
Table 1  BDW distances [×10^3] and maximum BDW distances [×10^4]. Numbers in brackets indicate ranking order.

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|             | 0.0648(1) 0.373(1) |

4. Conclusion

In this paper, we have proposed the improved seam merging method for content-aware image resizing. This method merges a two-pixel-width seam element into one new pixel in image reduction and inserts a new pixel between the two pixels in image enlargement. To preserve important contents and structure, our method uses energy terms associated with importance and structure. Our method preserve the main structures by using a cartoon version of the original image when calculating the structure energy. In addition, we introduce a new energy term to suppress the distortion generated by excessive reduction or enlargement in iterated merger or insertion. Experimental results demonstrate that the proposed method can produce satisfactory results in both image reduction and enlargement.

Our future work is to extend our proposed method for video resizing.

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References

Appendix: Bi-directional Warping

Bi-Directional Warping (BDW) is an algorithm for measuring a distance between two images [10]. The following is how to calculate the BDW distance in this paper. Let $S$ and $T$ be given images divided into $h$ rows, and $S_i$, $T_i$ be respectively row $i$ in $S$ and $T$ (see Fig. A.1(a)). The BDW distance is given by

$$
BDW(S, T) = \frac{1}{N_S} \sum_{i=1}^{h} A\text{-DTW}(S_i, T_i) + \frac{1}{N_T} \sum_{i=1}^{h} A\text{-DTW}(T_i, S_i)
$$

(A.1)

where $N_S$ and $N_T$ are the total number of elements (patches) in $S$ and $T$ respectively, and function $A\text{-DTW}$ is an Asymmetric Dynamic Time Warping measure ($A\text{-DTW}$). $A\text{-DTW}$ is an algorithm for measuring similarity between two one-dimensional signals. Let $S'$ and $T'$ be two one-dimensional signals, and $S'_i$ and $T'_i$ patches in $S'$ and $T'$, respectively. We use the following $A\text{-DTW}$:
Fig. A-1  Calculation of BDW. (a) Images $S$ and $T$ are divided into rows, and then the A-DTW measure from rows of $S$ to rows of $T$ is calculated. (b) The A-DTW measure is the sum of the minimum distance between two one-dimensional signals (patches in this case).

$$A-DTW(S', T') = \min \sum_{i=1}^{s} d(S'_i, T'_{x(i)}),$$

$$s.t. \forall i, 1 \leq x(i-1) \leq x(i) \leq t,$$

(A-2)

where $s$ and $t$ are the total number of patches in $S'$ and $T'$ respectively, $x$ is a mapping $x : [1, \ldots, s] \rightarrow [1, \ldots, t]$, and $d(S'_i, T'_{x(i)})$ is a distance between patch $S'_i$ and $T'_{x(i)}$ (see Fig. A-1(b)). We use $n \times n$ patches with overlap of $n - 1$ pixels between adjacent patches. The distance $d(S'_i, T'_{x(i)})$ is given by the mean squared differences of pixel values. As shown above, the BDW distance expresses the average similarity between corresponding two patches.

The maximum BDW distance is the sum of the maximum alignment errors of $S \rightarrow T$ and $T \rightarrow S$. The maximum alignment error is the maximum distance of $d(S'_i, T'_{x(i)})$ in Eq. (A-2). In seam-carving-like image resizing, most elements are usually well aligned, yet a small number of deformed elements are enough to cause a visual artifact [10]. Therefore, the maximum BDW distance can measure the most noticeable artifact.

We use four scales of patch size, $n = 4, 8, 16, 32$, and use the average to calculate the BDW distance and the maximum BDW distance.

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