IMAGE RETARGETING USING IMPORTANCE DIFFUSION

Sunghyun Cho[1], Hanul Choi[1], Yasuyuki Matsushita[2], and Seungyong Lee[1]

[1]POSTECH [2]Microsoft Research Asia

ABSTRACT

This paper presents a simple and effective image retargeting method that preserves visually important parts while reducing unwanted distortions of an image. Our approach is based on a novel importance diffusion scheme, which propagates importance of removed pixels to their neighbors for preserving visual contexts and avoiding over-shrinkage of unimportant parts. Importance diffusion enables even a simple row/column removal method, which removes the least important rows/columns repeatedly, to produce visually pleasant results. It also provides control over the trade-off between uniform and non-uniform sampling for the row/column removal and seam carving methods. Experimental result demonstrates that importance diffusion successfully improves the retargeting results of row/column removal and seam carving.

Index Terms— Image processing, image sampling, image retargeting

1. INTRODUCTION

With increasing diversity of display devices and availability of images, effective utilization of display space is becoming more and more important. When viewing images on a smaller display than originally intended, a naïve scaling would not perform well because important parts in the image could become too small. Image retargeting methods aim at shrinking the spatial size of an image while maintaining important parts so that screen utilization is maximized.

For effective image retargeting, several approaches have been introduced. One major approach is based on image cropping that finds the region-of-interest (ROI) [1, 2]. These methods successfully achieve their goal, and the results are shown to be superior to simple image scaling. However, they completely lose the information outside ROIs.

The second approach is based on image warping [3, 4, 5], which places a grid mesh on an image and optimizes its geometry for a desired scale. These methods need to solve large linear systems, and they can be time- and storage-demanding for devices with limited computing power, which usually have small displays.

The third approach is the seam carving method introduced by Avidan and Shamir [6]. The seam carving method finds the least significant seam crossing the image vertically or horizontally. By removing or inserting seams in a sequential manner, it successfully resizes an image while keeping important parts. Rubinstein et al. [7] further improved the seam carving method for reducing visual distortions. They define forward energy of a seam as the energy computed after removing the seam, instead of the energy of removed pixels. The seam carving method has many benefits. First, the implementation is simple, so several open-source codes are already available on internet. Second, it provides continuous changes between different scales, where the retargeted size of an image is determined by the number of removed seams. Third, the computation is not expensive, taking time complexity of $O(n)$ for finding the optimal seam, where n is the number of pixels.

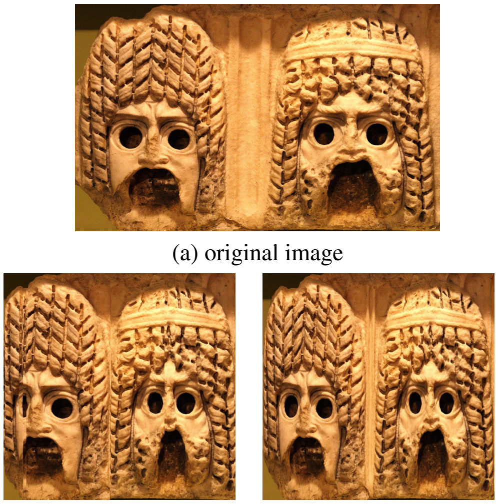
However, in spite of these benefits, the seam carving method often produces distorted results, because it repeatedly removes the least important seams ignoring the contextual information carried by the removed parts.This results in excessive removal of unimportant parts, and introduces distortions and loss of contextual information around important parts.

This paper presents a novel importance diffusion scheme that addresses these problems. In order to preserve the image context and avoid excessive removal of unimportant parts, importance diffusion elevates importance of the neighbors of removed pixels by propagating the importance of removed pixels to their neighbors after removing a seam. As a result, images can be retargeted with less artifacts.

The importance diffusion scheme has several nice properties. With importance diffusion, as well as seam carving, even a simple method that repeatedly removes the least important rows/columns from an image can produce visually pleasant results. Moreover, the simple method equipped with importance diffusion often produces better results than the original seam carving as we show in the discussion. This simple row/column removal method can be very useful for environments with limited computing power, such as mobile devices with small displays. In addition, importance diffusion bridges the gap between uniform and non-uniform sampling of image pixels and provides control over the trade-off between preserved saliency and distortion in a retargeted image.

2. IMPORTANCE DIFFUSION

This section describes our importance diffusion scheme. For better description, we first explain the scheme with the case



(a) original image

(b) R/C removal (c) R/C removal with ID

Fig. 1: While simple row/column (R/C) removal results in discontinuous blocks of important parts, row/column removal with importance diffusion (ID) successfully retargets the image by avoiding excessive removal of unimportant parts.

of row/column removal and later extend it to seam carving.

2.1. Row/Column removal

One of the simplest idea for retargeting is to remove unimportant rows and columns from an image. Denoting a pixel importance as $v(x, y)$, the row and column importance $v_r(y)$ and $v_c(x)$ are computed by summing pixel importance along the x and y directions, respectively. The pixel importance can be computed in various ways; for example, using image gradients and using forward energy proposed by Rubinstein et al. [7]. Sequential removal of the least important rows and columns leaves more important parts of the image.

However, repeated removal of unimportant rows and columns often produces unwanted artifacts, since excessive removal of unimportant lines results in discontinuous blocks of important parts (Fig. 1(b)). This problem is caused by not preserving the context of removed parts during row/column removals. To resolve this problem, the neighbors of removed parts should evidently carry the information about the removed parts as well as their own pixel information. In other words, the importance of the neighbors should increase reflecting the importance of the removed parts.

With this idea, our method updates the importance of the neighbors of removed parts by diffusing importance of the removed rows and columns by

$$\begin{aligned} v_r(y') &\leftarrow v_r(y') + w(y, y')p(v_r(y)), \\ v_c(x') &\leftarrow v_c(x') + w(x, x')p(v_c(x)), \end{aligned} \tag{1}$$

where x' and y' are indices of neighbors of the removed column x and row y, w is a weighting function for diffusion, and p is the diffusion function. The weighting function w regulates the amount of importance passed to its neighbors. We use $w(x, x') = 1$ if x' is either $x' = x + 1$ or $x' = x - 1$, and $w(x, x') = 0$ otherwise, which means only the immediate neighbors have increase of importance. The diffusion function p can be defined as any monotonically increasing function of v, such as $p(v) = v/2$.

Although the row/column removal approach is extremely simple, when combined with importance diffusion, it effectively produces visually pleasing results (Fig. 1(c)). In the implementation, finding the least important row/column can be accelerated using a heap data structure. The simplicity and computational efficiency of this method can be useful for devices with low computing power, such as mobile phones.

2.2. Seam carving

The seam carving method [6, 7] is one of the most effective image retargeting tools. In the method, a vertical seam is defined by

$$S = \{(s_y, y)\}, \tag{2}$$

where $y = \{1, ..., H\}$, $s_y = \{1, ..., W\}$, and $|s_y - s_{y+1}| \leq 1$. A horizontal seam is defined in a similar manner. The backward energy function f of a vertical seam S, which was introduced in [6], is defined as

$$f(S) = \sum_y v(s_y, y), \tag{3}$$

and the forward energy of S, which was introduced in [7], is defined by new pixel difference after removing the seam S. The seam carving method repeatedly finds the least important seams from an image by a dynamic programming based optimization method and carves them out to retarget the image.

While the seam carving is very effective, it has the same problem with the simple row/column removal (Figs. 2(b) and 2(d)). It can excessively carve less important parts of an image and result in unwanted visual distortions. Similar to row/column removal, our importance diffusion can improve the seam carving method. After finding the least important seam, we diffuse importance of every pixel on the seam to its neighboring pixels. For example, for a seam element (s_y, y) of a vertical seam S, we diffuse its importance to neighbors as

$$v(x, y) \leftarrow v(x, y) + w(x, s_y)p(v(s_y, y)). \tag{4}$$

With the importance diffusion, we can reduce discontinuity artifacts and image deformation in seam carving (Fig. 2(c) and (e)).

2.3. Non-uniform and uniform sampling

The importance diffusion method enables to bride the gap between uniform and non-uniform sampling by changing the

(a) original image (b) backward SC (c) backward SC with ID (d) forward SC (e) forward SC with ID

Fig. 2: Results of seam carving (SC) with importance diffusion (ID) show less artifacts, while the results of the original seam carving show severe artifacts on the left part of the image. Forward/backward SC mean seam carving with the forward/backward energy, respectively.

(a) $p(v) = 0$ (b) $p(v) = v/4$ (c) $p(v) = v/2$ (d) $p(v) = v$ (e) uniform scaling

Fig. 3: Effect of importance diffusion with row/column removal. By changing the importance diffusion function $p(v)$, the sampling ratio between important and unimportant parts can be controlled. From (a) to (d), the retargeting result becomes more similar to uniform scaling.

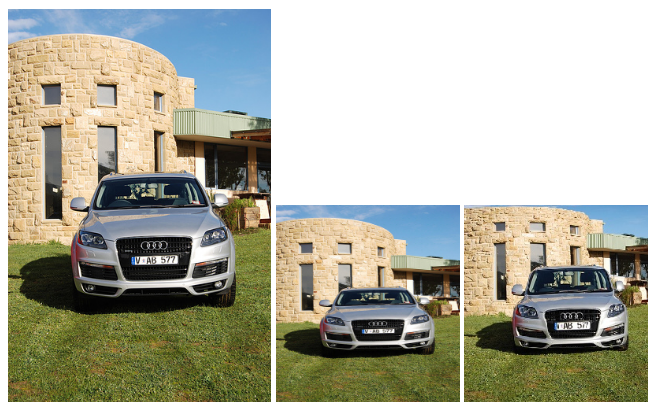
diffusion function $p(v)$ (Fig. 3). For example, $p(v) = 0$ makes the sampling process totally non-uniform, i.e., it sequentially removes the least important rows and columns without importance diffusion. On the other hand, using $p(v) = M$, where M is a value greater than the maximum importance value, preserves neighbors of removed rows and columns, and the sampling process becomes similar to uniform sampling. When the function p lies within these two bounds, the sampling process becomes the midst of uniform and non-uniform sampling. By controlling function p, we can balance between uniform and non-uniform sampling.

3. RESULTS

We used diffusion functions $p(v) = v/4$ for Fig. 1, $p(v) = v$ for Fig. 5, and $p(v) = v/2$ for the others. For pixel importance values for row/column removal and backward seam carving, we used $|g_x| + |g_y|$, where g_x and g_y are horizontal and vertical gradient components for each pixel, respectively.

Fig. 4 shows a result of the simple row/column removal combined with importance diffusion. While the car is shrunken too much in the result of simple scaling, the result of row/column removal combined with importance diffusion preserves the car well without visual distortion.

Fig. 5 shows results of seam carving. The result of seam carving without importance diffusion shows distorted features. Because of the amount of information in the original image, unimportant regions are removed too much causing the distortion. However, importance diffusion avoids exces-

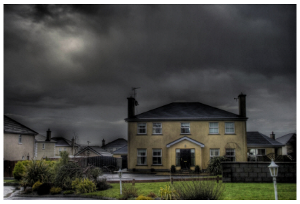


(a) original image (b) uniform scaling (c) R/C removal with ID

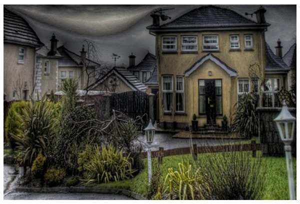
Fig. 4: Result of row/column removal. Row/column removal preserves the car better than uniform scaling.

sive removal of unimportant regions, so the result of seam carving with importance diffusion shows less artifacts.

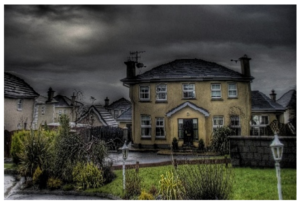
We also measured the processing time of row/column removal with importance diffusion to show the computational efficiency of the method. We implemented the method in C++, and our testing environment is a PC running MS Windows XP 32bit version with Intel Core2 Quad CPU 2.66 GHz. The original sizes of Figs. 1, 4, and 6 are 1024×637, 334×500, and 500×377, respectively. Their retargeted sizes are 750×637, 233×250, and 250×188, and their processing times were 3.91, 0.62, and 0.79 milliseconds, respectively.



(a) uniform scaling



(b) forward SC

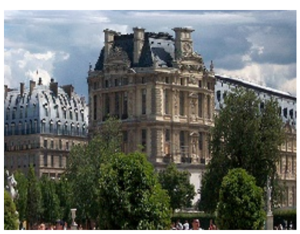


(c) forward SC with ID

Fig. 5: Result of seam carving with importance diffusion. Seam carving with importance diffusion preserves the image context better and produces less artifacts than the original seam carving.

(a) uniform scaling

(b) forward SC



(c) R/C removal with ID

Fig. 6: Comparison between the original seam carving and row/column removal with importance diffusion. Row/column removal with importance diffusion often preserves the image structure better than seam carving without importance diffusion.

4. DISCUSSION

Similar ideas to the importance diffusion scheme have been used in different contexts. Error diffusion based dithering methods update attributes of neighbors of half-toned pixels to compensate the quantization error [8]. Keeping unimportant parts for providing better understanding was also considered in the image warping based method of Liu and Gleicher [9].

The reason why importance diffusion reduces distortions is that importance diffusion makes non-uniform sampling of pixels, which seam carving does, more uniformly. Uniform sampling or scaling of an image does not break the image structure, even though it does not preserve the original detail and scale of important parts. With importance diffusion, we can take the advantage of uniform sampling as well as of non-uniform sampling.

Interestingly, when combined with importance diffusion, the simple row/column removal often preserves the structure of the image content better than the original seam carving method, especially when the image contains much structural information. For example, the source image shown in Fig. 6 contains dense and complex structure. In such an example, row/column removal combined with importance diffusion gives a better result (Fig. 6(c)) in comparison with the original seam carving method (Fig. 6(b)). This is because row/column removal maintains the horizontal and vertical structures of an image, while seam carving does not.

5. ACKNOWLEDGEMENTS

We thank the following Flickr users for sharing their images: Alaskan Dude, berther, Swami Stream, thomasrdotorg, Roomic Cube and Matti Mattila. This work was supported by the IT R&D program of MKE/MCST/KEIT (2008-F-031-01, Development of Computational Photography Technologies for Image and Video Contents).

6. REFERENCES

[1] Bongwon Suh, Haibin Ling, Benjamin B. Bederson, and David W. Jacobs, "Automatic thumbnail cropping and its effectiveness," in *Proc. of UIST*, 2003, pp. 95–104.

[2] Li-Qun Chen, Xing Xie, Xin Fan, Wei-Ying Ma, Hong-Jiang Zhang, and He-Qin Zhou, "A visual attention model for adapting images on small displays," *ACM Multimedia Systems Journal*, pp. 353–364, 2003.

[3] Feng Liu and Michael Gleicher, "Automatic image retargeting with fisheye-view warping," in *Proc. of UIST*, 2005, pp. 153–162.

[4] Lior Wolf, Moshe Guttmann, and Daniel Cohen-Or, "Non-homogeneous content-driven video retargeting," in *Proc. of Int'l Conf. on Comp. Vis. (ICCV)*, 2007.

[5] Yu-Shuen Wang, Chiew-Lan Tai, Olga Sorkine, and Tong-Yee Lee, "Optimized scale-and-stretch for image resizing," *ACM Trans. on Graphics*, vol. 27, no. 5, 2008.

[6] Shai Avidan and Ariel Shamir, "Seam carving for content-aware image resizing," *ACM Trans. on Graphics*, vol. 26, no. 3, pp. 10, 2007.

[7] Michael Rubinstein, Ariel Shamir, and Shai Avidan, "Improved seam carving for video retargeting," *ACM Trans. on Graphics*, vol. 27, no. 3, 2008.

[8] Robert Ulichney, *Digital Halftoning*, MIT Press, 1987.

[9] Feng Liu and Michael Gleicher, "Video retargeting: automating pan and scan," in *Proc. of ACM Multimedia*, 2006, pp. 241–250.