IMAGE RETARGETING BASED ON GLOBAL ENERGY OPTIMIZATION

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ABSTRACT

This paper proposes a novel image retargeting technique based on global energy optimization. Most existing methods enhance the high energy parts of the original image by pre-defined strategies or local optimization based iterations. They can not achieve the global optimal effect in energy retainment. To solve this problem, our approach formulates image retargeting as a global optimization problem on energy. We first calculate the energy map of the original image. Then, we utilize a constrained linear programming to maximize the retained energy in retargeting. Finally, we propose a pixel fusion based method to generate the retargeted image. To make it more feasible in implementation, we further provide two strategies to reduce the time cost of our approach. We demonstrate the proposed approach by comparing with typical image retargeting methods.

***Index Terms*—** image retargeting, energy retainment, global optimization, pixel fusion

1. INTRODUCTION

Advancement of multimedia technology leads to the significant requirement in convenient data access using portable devices, such as mobile phone and PDA, for transmitting, sharing and exchanging information [1]. The existing digital images, such as those taken by digital cameras, usually have high resolution and fixed aspect ratio. They should be adapted for effective viewing on a screen with small size and arbitrary aspect ratio [2]. This adaptation is commonly referred to as *image retargeting*.

Traditional image resizing methods, such as uniform scaling, letter boxing and static cropping, usually have weak performance in image retargeting, for they only consider the display space limitation but not the image content. Fig. 1 shows an example of the retargeting results of these methods. Uniform scaling (Fig. 1(b)) causes serious distortion of the objects, letter boxing (Fig. 1(c)) makes the objects too small to recognize, and static cropping (Fig. 1(d)) only retains the central part of the original image. They all cause serious information loss in the retargeted images.

To address this problem, some content-aware methods are proposed. They calculate the energy (i.e. the importance) of each pixel in the original image and try to reduce the information loss by preserving high energy pixels in retargeting. To achieve acceptable effect in display, some aspects are also considered, for example, avoiding distortion in the retargeted image. In this way, the objective of image retargeting is treated as retaining the high energy pixels in the original image with some constraints.

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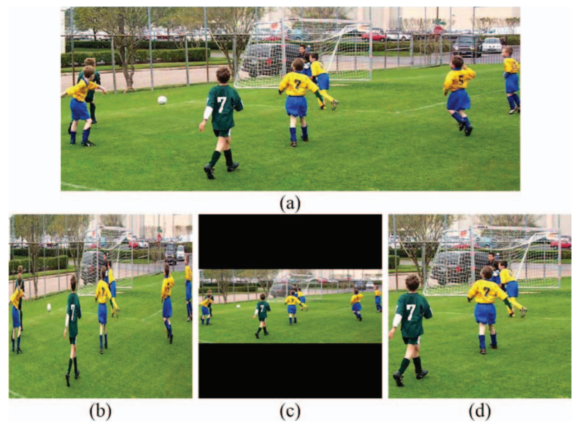

Fig. 1. Retargeting results of traditional image resizing methods. (a) Original image; (b) Result of uniform scaling; (c) Result of letter boxing; (d) Result of static cropping.

Existing typical content-aware image retargeting methods can be roughly classified to two categories. The first one enhances the high energy parts of the original image by pre-defined strategies. Chen et al. [3] proposed an attention based cropping method, which retains the minimum region covering important objects by cropping and then resizes the retained region by scaling. Liu et al. [1] improved the method by displaying the different objects in image successively with an optimal path, which is applicable to the condition when there are many objects should be retained. Liu et al. [2] proposed a fisheye-view warping method, which warps the original image to the target screen by pre-defined non-linear functions. Setlur et al. [4] proposed a recomposition based method, which decomposes the original image into objects and background, scales each one of them independently and then recombines them to generate the retargeted image. Though their strategies for object enhancement are different, the effects of them are all influenced by whether the pre-defined strategies are suitable for the original image. To overcome this problem, the second category treats image retargeting as an energy optimization problem, i.e., retaining the high energy pixels by optimization algorithms. Avidan et al. [5] proposed a significant method named "seam carving", which utilizes dynamic programming algorithm to iteratively remove the unnoticeable pixels from the original image.

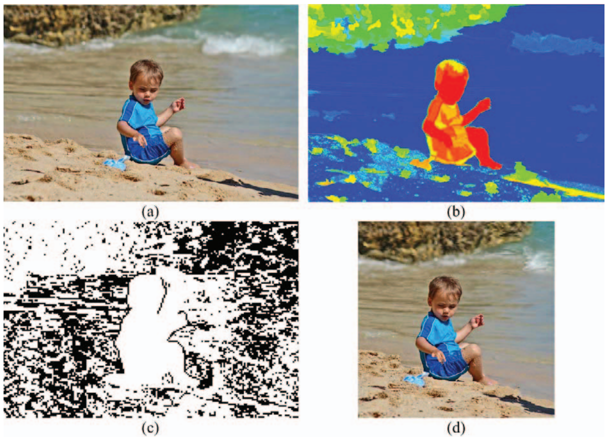

Fig. 2. Procedure of our approach. (a) Original image; (b) Energy map; (c) Optimal new width of pixels; (d) Retargeted image.

Ren et al. [6] formulated the original image to a directed graph and sampled the image by using minimum-cost flow algorithm on the graph. These methods usually have good performance, but they are only local energy optimal in each step of iteration. Furthermore, these iteration based methods are usually time-consuming, especially when there are many pixels to remove.

In this paper, we propose a novel image retargeting approach that realizes global optimal energy retainment in the retargeted image. The core of our approach is formulating energy retainment to a constrained 0-1 integer programming problem. To solve the problem in polynomial time, we relax it to a linear programming problem, and propose a corresponding pixel fusion based method to generate the retargeted image. Moreover, we further improve the feasibility of our approach in implementation by combining with preliminary scaling and relaxing the pixel position constraints.

The rest of paper is organized as follows: Section II proposes a global energy optimization based image retargeting approach. Section III provides two strategies to improve the feasibility of our approach in implementation. Section IV shows the experiment results in comparison with existing typical image retargeting methods. The paper is closed with conclusion and future work.

2. GLOBAL ENERGY OPTIMIZATION BASED RETARGETING

Fig. 2 illustrates the procedure of our approach. First, the energy map of the original image is calculated (Fig. 2(b)), where the energy from low to high is colored by from blue to red. Then, the optimal new width of each pixel is computed by linear programming (Fig. 2(c)), where the new width from 0 to 1 is represented by from black to white. Finally, a pixel fusion based method is proposed to generate the retargeted image (Fig. 2(d)).

2.1. Energy map calculation

In image retargeting, energy indicates the importance of the pixels. Similar to previous methods [1]-[4], the energy e_{ij} of each pixel p_{ij} is considered in two aspects, static saliency and face existence. It can be calculated as follows:

$$e_{ij} = w_1 * e_{ij}^S + w_2 * e_{ij}^F , \tag{1}$$

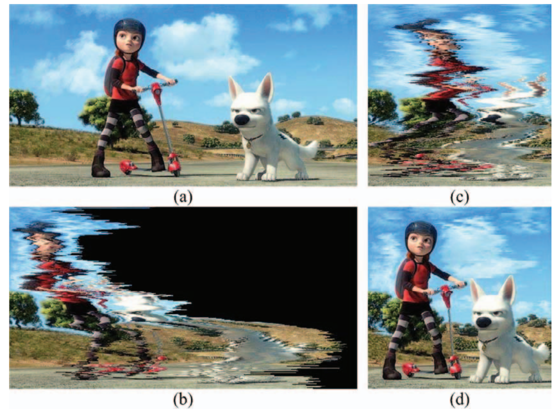

Fig. 3. Constraints in retargeting. (a) Original image; (b) Result without any constraints; (c) Result with constraint in image shape; (d) Result with constraints in image shape and pixel positions.

iteratively

where, e_{ij}^S and e_{ij}^F denote the importance of pixel p_{ij} in the aspects of static saliency and face existence respectively; w_1 and w_2 are positive weights, and their sum equals to one.

In our experiment, we utilize the attention model in [7] to evaluate the static saliency, and detect the faces with the algorithm in [8]. The weights w_1 and w_2 are both assigned to 0.5.

2.2. 0-1 integer programming based energy optimization

Based on the energy map, we retarget the original image by removing the pixels with low energy.

Assume W and H are the width and height of the original image, and W' and H' are the width and height of the retargeted image. To simplify the problem, we only consider the horizontal resizing in the following discussion, i.e., $W' < W$ and $H' = H$. The vertical resizing can be dealt with in the same way.

In horizontal resizing, we define a $W \times H$ matrix $\mathbf{X}$ to represent which pixels are retained in the result. Its element is defined as:

$$x_{ij} = \begin{cases} 1, & p_{ij} \text{ is retaind} \\ 0, & p_{ij} \text{ is removed} \end{cases} \tag{2}$$

The retained energy after retargeting can be represented as:

$$\sum_{i=1}^{W} \sum_{j=1}^{H} \left(e_{ij} x_{ij} \right) \tag{3}$$

According to the above analysis, image retargeting can be treated as a problem to maximize the value of Equation (3). However, the generated retargeted image may be unreadable (Fig. 3(b)) based on the maximal value which is calculated without any constraints. To obtain a readable retargeted image, some constraints are added. First, the number of retained pixels in each row should be equal to the required width of the retargeted image, which can keep the regular shape of the result (Fig. 3(c)). Second, the new positions of pixels in the same column of the original image should be similar, which can avoid serious distortion in the retargeted image (Fig. 3(d)).

We formulate the constraints and represent image retargeting as the following optimization problem:

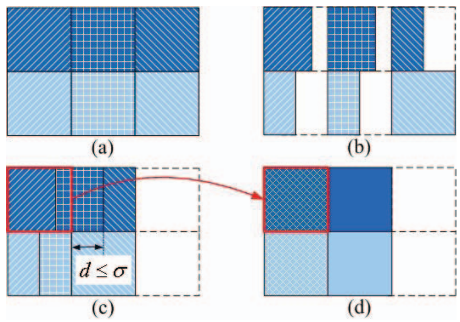

Fig. 4. Pixel fusion based method for horizontal retargeting. (a) Initial components; (b) Resized components; (c) Relocated components; (d) New components generated by fusion.

$$\max \sum_{i=1}^{W} \sum_{j=1}^{H} \left(e_{ij} x_{ij} \right) \tag{4}$$

$$s.t. \ \sum_{i=1}^{W} x_{ij} = W', \ \ \forall j \tag{5}$$

$$\left| \sum_{n=1}^{i} x_{nj} - \sum_{n=1}^{i} x_{n(j+1)} \right| \le \sigma, \ \ \forall i \forall j \tag{6}$$

$$x_{ij} \in \{0,1\}, \ \ \forall i \forall j \tag{7}$$

where, σ is a small positive threshold. In our experiments, σ equals one.

2.3. Pixel fusion based retargeted image generation

In subsection 2.2, image retargeting is formulated to a 0-1 integer programming problem. Unfortunately, it is a NP hard problem. It is extremely time-consuming to solve the problem directly, even using some methods to reduce the solution space, i.e., implicit enumeration method [9]. Hence, we propose a pixel fusion based method, with which the above optimization problem can be approximately solved.

We relax the constraint in Equation (7) as follows:

$$0 \le x_{ij} \le 1, \ \ \forall i \forall j \tag{8}$$

With this relaxation, the optimization problem is transformed to a constrained linear programming problem, which can be solved effectively. Based on the result of linear programming, the retargeted image is generated as follows: First, each pixel in the original image is treated as a component whose width can be changed (Fig. 4(a)); second, the new width of each component is assigned to x_{ij} in the result of linear programming (Fig. 4(b)); third, the components in the same row are jointed together (Fig. 4(c)); finally, the new component is generated by calculating its color value in RGB space with a linear combination of the components (or component parts) in its range (Fig. 4(d)), and treated as the corresponding pixel in the retargeted image.

3. FEASIBILITY IMPROVEMENT IN IMPLEMENTATON

Linear programming is time-consuming when the numbers of variables and constraints are huge [9]. In our approach, each pixel of the original image will bring in one variable and two constraints to the optimization problem. In practice, a high quality original image usually contains millions of pixels. It is hard to directly apply our approach in practical application. Hence, we propose two strategies to make our approach more feasible in implementation.

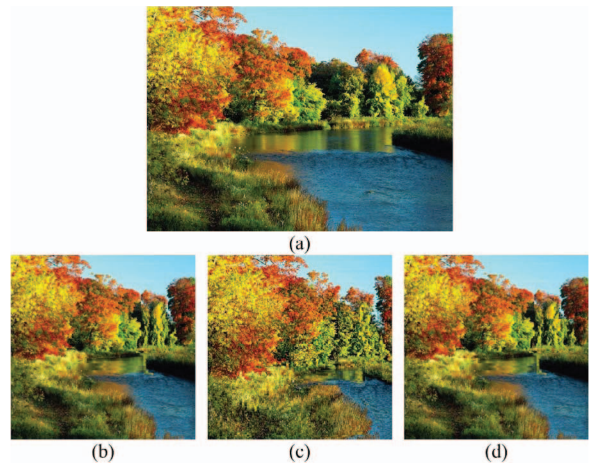

Fig. 5. Results with different strategies in feasibility improvement. (a) Original image; (b) Result with preliminary scaling; (c) Result with pixel position constraint relaxation; (d) Result with preliminary scaling and pixel position constraint relaxation.

3.1. Combination with preliminary scaling

Considering scaling is an effective method to down-sample image without any distortion, we reduce the variable number in optimization by combining a preliminary scaling to our approach. In our implementation, the ratio of preliminary scaling is determined in the following way. First, the original image is roughly segmented into several regions, and the mean of pixel energy values for each region is treated as the energy of this region. Then, the region with highest energy is selected. If its energy is larger than a pre-defined threshold, the preliminary scaling ratio is equal to $\max\{W'/W_k, H'/H_k\}$, where W_k and H_k are the width and height of the region with the highest energy, respectively. Otherwise, the preliminary scaling ratio is assigned to $\max\{W'/W, H'/H\}$.

Fig. 5 shows an example of the combination with preliminary scaling. The size of the original image is 1024*768 and the required size of the retargeted image is 300*300. Fig. 5(b) shows the result generated by preliminarily down sampling the original image to the size of 400*300. The result is acceptable, and the number of variables is only 15% of the original problem.

3.2. Relaxation in pixel position constraint

We further reduce the number of constraints to improve the feasibility of our approach in implementation.

Equation (6) describes the constraint on pixel position in the retargeted image. For edges are crucial visual feature in image, we consider the position constraints are more important to the pixels in edges. Hence, we calculate the gradient of each pixel, and only retain the position constraints to the pixels with high gradient values. Fig. 5(c) shows the retargeted image generated by only retaining the position constraints corresponding to the top 3% pixels with the highest gradient values. Though it has some jitters, the general structure of the original image is well kept. Fig. 5(d) shows the retargeted image with both preliminary scaling and pixel position constraint relaxation. Compared with Fig. 5(b), it shows comparable result with only little unnoticeable jitters.

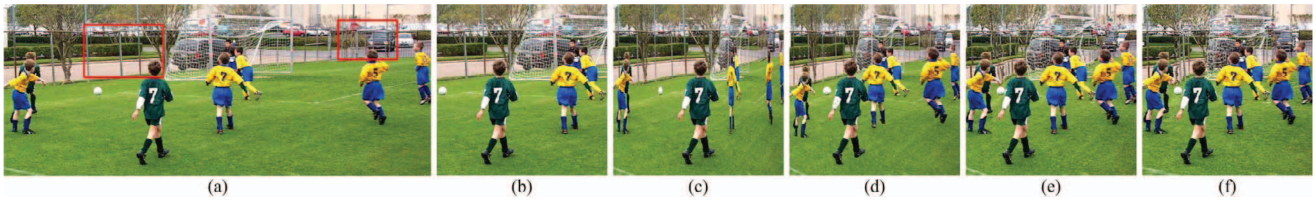

Fig. 7. Comparison with the existing typical image retargeting methods. (a) Original image; (b) Result of attention base cropping; (c) Result of fisheye-view warping; (d) Result of recomposition based method; (e) Result of seam carving; (f) Our result.

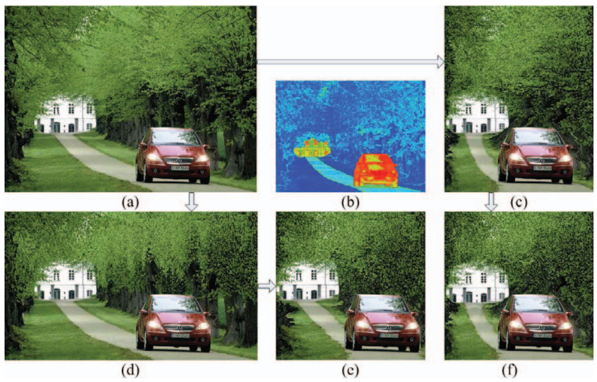

Fig. 6. Results with different resizing orders. (a) Original image; (b) Energy map; (c) and (f) Result of horizontal-vertical resizing; (d) and (e) Result of vertical-horizontal resizing.

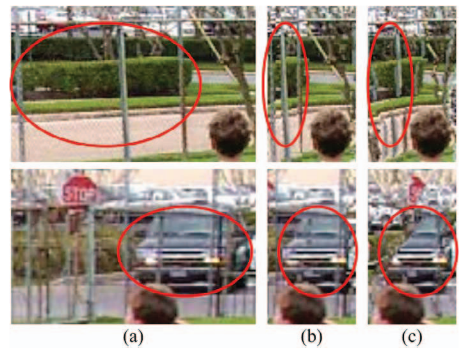

Fig. 8. Comparison with seam carving. (a) Regions in original image (marked with red rectangles in Fig. 7(a)); (b) Corresponding regions in our result; (c) Corresponding regions in result of seam carving.

4. EXPERIMENTS

To illuminate our performance, we implement our approach and test it in several aspects. Fig. 6 shows the retargeted images generated from the same original image but with different resizing orders. Experiment shows our approach is robust to the order of horizontal and vertical resizing and suitable for retargeting an image to various aspect ratios.

Fig. 7 shows the results of comparing our approach with existing typical image retargeting methods, including attention based cropping [3], fisheye-view warping [2], recomposition based method [4], and seam carving [5]. In comparison, the energy map and the required size of retargeted image are same to each method. Attention based cropping (Fig. 7(b)) can not contain all the football players. Fisheye-view warping (Fig. 7(c)) retains all content in the original image but distorts the players except player 7. Recomposition based method (Fig. 7(d)) deals with the players in the center well, but artificially scales the most left and right players for its limitation in object scaling ratio decision. Seam carving (Fig. 7(e)) shows similar performance to our result (Fig. 7(f)), but it still has some problems in details, such as the objects in background may be destroyed (Fig. 8).

With the improvement in section 3, the original image can be efficiently retargeted by our approach. We implement the algorithm with MATLAB, and experiment in the PC with CPU P4 3.0. When retarget the original images to the size 320×320 (screen resolution of PDA), the average time cost is 2.93 seconds.

5. CONCLUSION

In this paper, we propose a novel image retargeting approach based on global energy optimization. Image retargeting is formulated as a constrained 0-1 integer programming on energy, and transformed to a linear programming with a corresponding pixel fusion based method to generate the final retargeted image. Moreover, two strategies are provided to improve the feasibility of our approach in implementation by reducing the numbers of variables and constraints in the optimization.

Our future work focuses on extending our approach to other types of media, such as video.

6. REFERENCES

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