FAST RETARGETING WITH ADAPTIVE GRID OPTIMIZATION

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ABSTRACT

Effective and efficient retargeting techniques may enrich users' browsing experiences in mobile devices. Existing mesh-based retargeting solutions put less efforts in making well-tuned meshes. In this paper, we propose a novel adaptive grid based optimization method to retarget an image. First, we present an entropy based measure to guide the grid construction. Then we employ the quadtree structure to adjust the grid granularity adaptively. Furthermore, to reduce the inappropriate deformation from inconsistent importance assignment, we build a global optimization model to alleviate serious shape deformation in retargeting. Comparison experiments show our method’s superiority over the state-of-the-art approaches.

Index Terms— image retargeting, adaptive grid

1. INTRODUCTION

With the prevalence of mobile devices, consumers often browse large images (e.g., high resolution photos/paintings) on the versatile screens. However, the resolution of a mobile device is fixed while the resolution and aspect ratio of images differ from each other. To optimize the screen use is essential for displaying the source image. Image retargeting adapts the images of various aspect ratios to the target screen and maximizes the viewer experience. Many content-aware retargeting methods have been proposed such as seam carving\cite{1, 2, 3, 4}, multi-operator\cite{5}, mesh-based retargeting\cite{6, 7, 8, 9, 10}. Seam carving [1, 2, 3] tries to carve a group of optimal seams iteratively based on an energy map of images/videos. Rubinstein proposes to combine different retargeting methods including scaling, cropping, seam carving in [5]. In addition, mesh-based methods \cite{6, 7, 8, 9} attempt to partition source images/videos, where more or less deformation is allowed in non-important regions, while, the meshes are kept well for important regions.

Generally speaking, the computation cost of seam carving depends on the image resolution. Removing seams probably break the structure of an object, which is disallowed in browsing a large image.

For mesh-based methods, there is a tradeoff between efficient computing and important content preserving. Dense meshes may better preserve important content but incur more time and memory. In retargeting large images, adjusting mesh size may seek a compromise in terms of computation complex, as the computation load increases with the number of mesh vertices. However, interesting objects would be distorted after retargeting, as the object’s meshes could be assigned inconsistent importance value due to coarse mesh partition.

In particular, the resulting mesh often covers both important regions and less important regions. Such kind of meshes with inconsistent importance assignment is considered as uncertain one. In detail, if unimportant regions occupy a larger area than salient objects contained in uncertain meshes, the importance value of these meshes would be low. Thus, salient objects would be distorted when unimportant regions are shrunk/stretched to make room for salient objects as shown in Fig.1.

We propose a novel grid-based retargeting method with adaptive grid partition. With the quality measurement in grid partition, we propose to perform adaptive grid construction, aiming to make optimal partition satisfying the composition of visual content. Thus, those uncertain grids with lower importance are minimized. Despite the coarse grid, our approach may preserve the important objects as they are covered by the grid with high importance (see Fig.2). Moreover, to reduce the improper deformation from inconsistent importance assignment within remaining uncertain grids, we build a global optimization model to elegantly reallocate distortions to the grids as well as put the constraint of rectangular grids rather than arbitrary quadrangle. Specially, the rectangular grid based transformation enables us to reduce the number of variables of the optimization modal in the proposed new objective function. The model complexity just depends on the number of horizontal and vertical partitions rather than the
the same width. So the edge is simply denoted by $E$.

have the same height while the grids in each column have

the constraint of rectangular grids, all the grids in each row

$f$ are the edges of grids. Each grid is denoted by $g_{i,j}$. We can divide into $N_w$ grids, and the grids are denoted by $G = \{g_{11}, \ldots, g_{ij}, \ldots, g_{NN}\}$ with its location $i, j$. Owing to the constraint of rectangular grids, all the grids in each row have the same height while the grids in each column have the same width. So the edge is simply denoted by $E = \{(w_{1}, h_{1}), \ldots, (w_{N}, h_{N})\}$, and $w_{i}, h_{j}$ is the width and the height of the grid $g_{i,j}$ respectively.

Importance determination: We employ canny operator to calculate the importance map of the image. Each grid’s importance $s_{i,j}$ is computed by averaging the pixel-wise importance values in that grid $g_{i,j}$.

Uncertainty of Grid Importance We apply the entropy of grid’s importance to evaluate the uncertainty of grid’s importance, formulated as:

$$H(g_{i,j}) = s_{ij} \log_{r} \frac{1}{s_{ij}} + (1 - s_{ij}) \log_{r} \frac{1}{1 - s_{ij}}$$

Grid Measure A high quality grid should minimize the proportion of uncertain grids on the premise of the speed requirement. Note that more uncertain grids with large area ratio to the image in the grid partition, more distortion will be brought for image retargeting.

An ideal grid partition is to adaptively generate the grids based on the image structure and content distributions. However, this process involves accurate image segmentation and recognition which is a challenge topic in the field of computer vision. Clearly, regardless of the importance map’s accuracy, if a grid only cover the salient objects or unimportant regions, the entropy of the importance is low, otherwise is high. Therefore, the uncertain grids with low importance can be discriminated and discarded according to the uncertainty (i.e., entropy) of grid’s importance. This motivates us to measure the quality of grid partition by the entropy of grid importance. Hence, we address the optimal grid construction problems as minimizing the total information entropy of grid importance in this paper.

2. ADAPTIVE GRID CONSTRUCTION

2.1. Measuring the Quality of Grid Representation

Image Representation With grid construction, an image is divided into $N \times K$ grids, and the grids are denoted by $M = \{V, E\}$ in which $V$ is the 2D grid coordinate, $E$ are the edges of grids. Each grid is denoted by $G = \{g_{11}, \ldots, g_{ij}, \ldots, g_{NN}\}$ with its location $i, j$. Owing to the constraint of rectangular grids, all the grids in each row have the same height while the grids in each column have the same width. So the edge is simply denoted by $E = \{(w_{1}, h_{1}), \ldots, (w_{N}, h_{N})\}$, and $w_{i}, h_{j}$ is the width and the height of the grid $g_{i,j}$ respectively.

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2.2. Adaptive grid construction Algorithm

To obtain a adaptive grid with high quality, we minimize Eq.2, which is a fractional nonlinear optimization. For the purpose of efficiency, our algorithm approximate the solution of the optimization by means of employing quadtree decomposition. The uncertain grids with low importance are subdivided iteratively to minimize the total proportion of uncertain grids with low importance. Once the importance of uncertain grids is close to other grids from the same salient objects, adaptive grid is constructed.

Algorithm 1 Adaptive grid construction.

Input: An importance map $imMap \{W_{S}, H_{S}\}$ : the maximum depth of quad tree: maxP.

Output: grid $M = \{V, E\}$

1: Pre-Computing: uniformly resizing the $imMap$
   $W_S = W_S \cdot 2^{maxP}$, $H_S = H_S \cdot 2^{maxP}$, $d = 1$

2: create the root node, the root node $imMap$

3: while $d < maxP$ do
   4: Go through nodes at the depth $d$ of quadtree
   5: Calculate each grid $g(i,j)$’s importance $s_{i,j}$
   6: Calculate entropy $H(s_{i,j})$ of grid $g(i,j)$
   7: if $H(s_{i,j}) > \theta$ then
     8: subdivide $g_{i,j}$ into four leaf node
   end if

10: $d = d + 1$
11: end while
12: assign leaf nodess $x$ coordinate to $x$ coordinate of each
   vertices, and the same with the leaf nodess $y$ coordinate
13: calculate each grid’s edge.
14: return Grid $M = \{V, E\}$

We measure the quality of grid with the following rule:

$$GQ = \sum_{i=1,j=1}^{f} H(g_{i,j}) \cdot f(P_{i,j})$$

where $P_{i,j}$ is the ratio of grid $g_{i,j}$’s area to the whole image’s. The function $f(x)$ is an increasing function on $x \in [0, 1]$.

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We summarize our adaptive grid construction in Alg.1. For the importance map $imMap \{W_{S}, H_{S}\}$, in which $H_S$, $W_S$ are the height and width of the importance map respectively, we apply the algorithm and obtain the grid automatically. As illustrated in Fig.3, the objects are covered by important grids completely, which means that the grids as well as their importance represent the meaningful importance of image’s content. Moreover, the size of adaptive grid depends
on the content of image. This is robust to handle various types of images with different aspect ratio, resolution etc.

3. GRID BASED RESIZING MODEL

3.1. The Nonlinear Optimization Model

Based on the importance values of grids, the optimization model[10] is employed to optimally allocate image aspect distortion to each grid. The constraints of rectangular grids are employed to avoid serious shape transformation in resizing. All grids’ aspect ratio changes are summed up to measure distortion energy in retargeting. The objective function as well as boundary constraints are formulated as follows:

**Objective Function** To minimize the sum of grid distortion energy, the objective function is defined as:

$$\min \sum_{i,j} DG_{ij}$$

where \(n > 1\), \(s_{ij}\) is the grid \(g_{ij}\)’s importance, calculated by averaging pixel-wise importance values in the grid. \(DG_{ij}\) is the distortion energy of grid \(g_{ij}\).

**Distortion Energy of the Grid** As we constrain the grid-based shape transformation over rectangular grids, the change of grid’s aspect ratio is used to measure distortion energy in retargeting. Thus, we use the edges of grids rather than the coordinates of vertices to measure the distortion energy of each grid. The distortion energy \(DG_{ij}\) is defined as:

$$DG_{ij} = (h_i - ar_{i,j} \cdot w_j)^2$$

where \(ar_{i,j}\) is the aspect ratio of the original grid, \(w_j, h_i\) is the width and height of the target grid \(g_{ij}\), respectively. Clearly, our model has fewer parameters to optimize than [7].

**Boundary Constraints** We introduce the boundary constraints as follows:

$$\sum_{j=1}^{N} h_j = H_T$$
$$\sum_{i=1}^{K} w_j = W_T$$

where \(H_T, W_T\) are the height and width of the target image, respectively. The minimum height or length of a grid is set to one pixel, as adjacent grids should not overlap each other.

**Global Optimal Solution** Our grid based resizing model is a convex quadratic programming. The objective function \(\sum_{i,j} (y_{ij} - ar_{i,j} \cdot x_i)^2 \cdot s_{ij}^0\) is a convex one. Moreover, the equality constraints are linear functions and the inequality constraints can be seen as concave functions. The solutions satisfying equality and inequality constraints form a convex set. When a local solution is resolved, the global solution is yielded.

We employ an active-set method to solve this optimization problem. With the width and height of a target image \(W_T, H_T\), the initial guess is \((\frac{H_T}{w_1}, \ldots, \frac{W_T}{w_N}, \ldots)\) satisfying the equality constraint. Then, the nonlinear program can be solved iteratively to get global solutions in feasible region.

For the convex programming, the Hessian matrix of the objective function is positive semidefinite. The complexity is similar to a linear programming that depends on the number of the model variables \(O(N + K)\) (i.e. the division of width and height).

**4. EXPERIMENTS**

To evaluate the effectiveness and efficiency of our retargeting method, we collect 45 testing images, which are subjectively categorized into simple, multiple, and complex by object/scene complexity, to conduct our experiments. Our experiments involve two parts: (1) assess the effects of grid construction on the retargeting; (2) evaluate the effectiveness of adaptive grid retargeting.

**Table 1:** Preference statistics of ten participants in user study.

<table>
<thead>
<tr>
<th></th>
<th>simple/15</th>
<th>multiple/15</th>
<th>Complex/15</th>
</tr>
</thead>
<tbody>
<tr>
<td>Scaling</td>
<td>0.8%</td>
<td>1.4%</td>
<td>3.1%</td>
</tr>
<tr>
<td>Seam Carving[2]</td>
<td>34.1%</td>
<td>26.6%</td>
<td>23.2%</td>
</tr>
<tr>
<td>Wang’s method[7]</td>
<td>32.2%</td>
<td>27.8%</td>
<td>28.5%</td>
</tr>
<tr>
<td>Our results</td>
<td>32.9%</td>
<td>53.5%</td>
<td>44.3%</td>
</tr>
</tbody>
</table>

**Assess the effects of grid construction on the retargeting**

We run our proposed approach and Wang’s method[7] using grids of different density. As illustrated in Fig.1, Fig.4, the grid construction heavily affects the retargeted result.

Note that the font/style of some characters are distorted in Fig.4b, Fig.4c. As the two density of grid contain some uncertain grids which covers less area of the characters than unimportant region, these uncertain grids are assigned low importance value and heavily deformed. Moreover, due to our adaptive grid providing meaningful importance, our methods retained the character’s shape well (as Fig.4d). Therefore, our adaptive grid partition is advantageous for the mesh-based method to retarget the image.
Evaluate the effectiveness of grid-based retargeting method our method are compared with other two representative methods [7][2]. As illustrated in Fig.5, we can see that the seam carving method [2] brings about considerable shape artifacts of an object, since, at object regions, some seams with lower importance are falsely removed. For Wang’s method [7], when an important object covers several grids but the importance of these grids are different from each other, most grids with low importance become irregularly quadrilateral after retargeting, so that the structure of an object are distorted (see Fig.5c). For our approach, even if our method and Wang’s method using the same coarse grids containing uncertain grids with low importance, the distortion is smoother and more unnoticeable in our results than Wang’s method [7] (see Fig4b, Fig4c). Therefore, our method is more effective on preserving the consistence of objects and the continuity of unimportant regions.

User Study A subjective evaluation is further performed by the user study. The results of several popular methods are provided to subjects. By means of user preference and scoring evaluation, the effectiveness is measured quantitatively. In total 10 students and teachers participated in our user study. We showed each participant an original image and a randomly ordered sequence of retargeting results with different methods including scaling, seam carving[5], Wang’s method[7], and our method. Each participant is required to choose the results that are most visually similar to the original image. As listed in Tab.1, most participants prefer our results.

On Efficiency Our experiments were performed on a standard laptop with 2.26 GHz duo core CPU, 2GB memory. The image size ranges from 288×240 to 8500×5000. Our retargeting method take 30ms to process a image of resolution 1600×1200 pixels using grid 90×70 averagely. The complexity of our grid-based resizing model is $O(N + K)$ instead of depending on real resolution of an image or number of vertices $NK$ [7]. As show in Tab.2, our resizing model is significantly efficient to handle large images.

In this paper, a novel fast adaptive grid retargeting approach is proposed. A entropy based measure is introduced to evaluate the quality of grid partition. Then we employ the quadtree algorithm to adaptive construct content based grids to minimize the number of uncertain grids. Finally, we build a global optimization model to reduce the inappropriate deformation from inconsistent importance assignment within salient regions. Due to meaningful grid representation and the low computational cost in solving model, our retargeting method performs fast and effectively, which could be used in real application.

6. REFERENCES


Table 2: Average running time for solving resizing model.

<table>
<thead>
<tr>
<th>$N + K$</th>
<th>20</th>
<th>40</th>
<th>60</th>
<th>80</th>
<th>100</th>
<th>120</th>
<th>140</th>
<th>160</th>
</tr>
</thead>
<tbody>
<tr>
<td>time (ms)</td>
<td>0.29</td>
<td>1.25</td>
<td>2.2</td>
<td>3.0</td>
<td>5.95</td>
<td>9.0</td>
<td>12.2</td>
<td>15.5</td>
</tr>
</tbody>
</table>

Fig. 4: Comparisons of retargeted results using different grids, (a) Source image, (b)-(d) in the first row: results of Wang’s method [7] using uniform grid 24×15, 28×19, 35×26, respectively; (b)-(d) in the second row: our results using uniform grid 24×15, 28×19 and adaptive grid 37×35 generated by adaptive partition, respectively.

Fig. 5: Comparison Results: (a) Original image, (b) Scaling, (c) Wang’s method [7], (d) Seam carving [2], (e) Our results.

5. CONCLUSION