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Contour Sensitive Saliency and Depth Application in Image Retargeting

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ABSTRACT

Image retargeting technique requires important information preservation and less edge distortion during increasing/decreasing image size. The major existed content-aware methods perform well. However, there are two problems should be improved: the slight distortion appeared at the object edges and the structure distortion in the non-salient area. According to psychological theories, people evaluate image quality based on multi-level judgments and comparison between different areas, both image content and image structure. The paper proposes a new standard: the structure preserving in non-salient area. After observation and image analysis, blur (slight blur) is generally existed at the edge of objects. The blur feature is used to estimate the depth cue, named blur depth descriptor. It can be used in the process of saliency computation for balanced image retargeting result. In order to keep the structure information in non-salient area, the salient edge map is presented in Seam Carving process, instead of field-based saliency computation. The derivative saliency from x- and y-direction can avoid the redundant energy seam around salient objects causing structure distortion. After the comparison experiments between classical approaches and ours, the feasibility of our algorithm is proved.

Keywords: Image retargeting, seam carving, saliency computation, blur depth descriptor, structure information.

1. INTRODUCTION

With the development of multimedia technology, image retargeting, displaying digital images on different sizes and resolutions, becomes one of the hotspots in image processing research. The size of the image can be automatically resized according to the screen of the display device, such as, mobile phone, digital monitor, camera, tablet and so on, preserving the important information. Content-aware method is widely used to solve this problem. Avidan et al. [1,2] proposes the Seam Carving (SC) algorithm by calculating the 8-connected minimum energy line to resize the image. As the well performance and easy implementation, there are many methods based on SC with fusion.

Additional features, e.g. saliency [3] and depth [4] features, reduce the probability of lost important parts decreasing effectively. Zhou et al. [5] propose the WSM model (Wall-seam Model) in 2016, combining the salient feature and image edge using bidirectional retargeting to maintain the completeness of salient parts, with the price of distortion of image background. In 2017, Shafieyan et al. [6] propose a depth field map algorithm to improve the image retargeting quality. The application of depth filed is helpful to improve the edge integrity but extra equipment to measure the depth distance is required. Because the conventional depth filed is not sensitive to the image contour, the distortions of non-significant area are generated. With the increasing of high resolution images in people's lives, non-significant information plays vital role gradually. How to maintain the contours of significant objects as well we the image structure becomes the emergent issue required to be solve recently.

To overcome difficulties mentioned above, the paper proposes a novel approach combining saliency and depth computation for more reasonable image retargeting. Compared with the existed methods, the proposed approach estimates the depth of field based on the blurness that widely exists in the high-resolution image. Then, the saliency map is calculated at the basis of depth field. The computation of derivative in horizontal and vertical direction is used to preserve the contour completeness. Therefore, the contour-based saliency map is helpful to reduce the distortion in non-salient area.

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2. RELATED WORK

The SC algorithm is originally proposed by Avidan and Shamir in 2007. After that, many researchers propose improvement algorithms for better resizing effects [7, 8, 9, 10]. At present, SC algorithm has been applied to various fields, including image retargeting, video retargeting, image shaping, stereo vision and three-dimensional rendering. Aimed at achieving good performance for various image categories, multi-method fusion algorithms are illustrated. Rubinstein et al. [11] proposed a BDW (Bi-Directional Warping) function to measure the similarity between the resized image and the original one by combining SC, scaling and cropping methods. Dong et al. [12] proposed patch-based bidirectional similarity function, using Euclidean distance, principle color similarity and minimum energy line. Another way to improve the performance is to use auxiliary features, such as saliency [5] and depth of field features [13]. In the saliency way, the common methods are the GBVS (Graph-based Visual Saliency) model [14] and the Itti model [15]. However, they are regional model, cannot preserve the integrity of the boundary well after retargeting. Shafieyan et al. [6] use an adaptive algorithm to find the optimal ratio between saliency and depth, which is perform well on the preservation of important area. In this paper, inspired by those, we propose a novel contour-based saliency model combined with depth filed computation. It can handle both the saliency contour at important area as well as the structure information at non-salient area.

3. OUR APPROACH

3.1 Contour-based Saliency Computation

The saliency computation improves the integrity of essential information during retargeting. The traditional approaches (gbvs model and itti model) are regional computation to calculate the image characteristics of the important features to find important regions without considering the object contour, as shown in Fig. 1. The red region is the significant area, but it is independent of the people contours. In this way, the contour information will be broken after image retargeting.

In our approach, the watershed algorithm is used to preprocess the image, which can generate ridge line at the object edges for the integrity of the contour information in Equation 1.

$$G(x,y) = Max(grad\{f(x,y)\}, g\theta), \tag{1}$$

in which, $f(x, y)$ is the original image, g_θ is the threshold, and *grad {.}* represents the gradient operation.

Figure 1. GBVS model

a.gbvs saliency b.our saliency

Figure 2. saliency computational

After image pre-processing, the image will be segmented into several small areas G_i. According to the psychological theory, human visual cognitive system is not a one-time process to make the conclusion, but through different levels of iteration to generate the final decision. Therefore, in this paper, the obtained image Gi should be merged with its adjacent regions based on similarity calculation at different levels (size = 3, 5, 9). For each layer, the saliency values are calculated from the color discrimination (Equation 2) and the position discrimination (Equation 3).

$$Ci = \sum_{j=1}^{n} \omega(Gj)u(i,j)\sqrt{(ci-cj)^2}, \tag{2}$$

where the ci and cj are the average colors of regions Gi and Gj, $\omega(Gj)$ represents the number of pixels in region Gj, and $u(.)$ is the weight of i and j follow the Gaussian distribution. The color discrimination is used to measure the color difference between the Gi region with others. The higher difference value means more important the region is.

The location discrimination is based on the fact that people tend to be more concentrated on the middle position in one image, so the pixels near the central region are more pronounced than the surrounding ones. As shown in Equation 3, the li is the pixel coordinate in Gi, the lc is the central position coordinate, and α is a threshold specified by the user. The saliency computation S_i can be calculated in Equation 4.

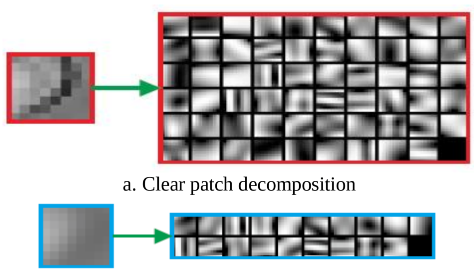
$$Hi = \frac{1}{\omega(\mathrm{Gi})} \sum_{li \in Gi} \exp\{-\alpha \sqrt{(li - lc)^2}\}, \tag{3}$$

$$Si = norm(\mathrm{Ci}) \cdot norm(Hi), \tag{4}$$

The different level size leads to the different S_i, which makes the simple accumulation is not the best choice. In this paper, the saliency values of each layer were fused by the method in reference [16]. The Fig. 2.a is the significant distribution calculated using the GBVS model, and Fig. 2.b is the significance distribution calculated using the proposed approach. It is obvious contours of object are more clear in our proposed approach than the traditional way.

3.2 Blurness Depth Estimation

With the development of high-resolution photography, a large number of high-resolution images appear in our life. The slight blur and motion blur are more and more noticed gradually [17]. Normally, the important objects will be closer to the camera as the foreground part, others will be farther away from the camera as the background. Therefore, the paper proposes a novel way to estimate depth filed according to this theory for meeting people's cognitive habits.



a. Clear patch decomposition

b. Blur patch decomposition

Figure 3. the blur depth descriptor of clear and blur patch

$$\min_{xi} \| yi - Dxi \|_2^2 \quad \| xi \|_0 \le k, \tag{5}$$

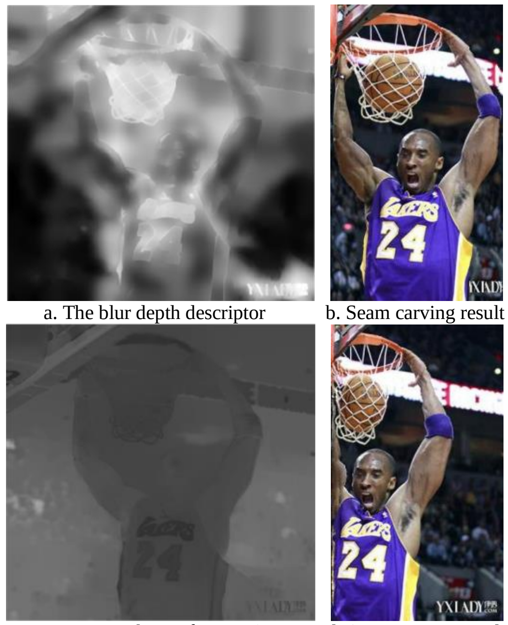
$$\min_{xi} \| xi \|_1 \quad \| Gi - Dxi \|_2 \le k, \tag{6}$$

$$f_{blur} = \| xi \|_0, \tag{7}$$

Recent research shows that through the adaptive method, the depth, saliency and gradient information can be combined together to improve the quality of image retargeting [6]. However, the depth of field information needs to be acquired by the device (such as Kinect), and the slight blurness will cause the image distorted more or less at the edges after retargeting. In order to solve this, the depth of field is estimated by fuzzy theory and blurred edge in this paper.

By image analysis, there are slight blurness existed at the object edge generally which can be the evidence of foreground and background distinction. We propose the blur depth descriptor to depict the spatial distribution of fuzzy information and image depth estimation.

People's visual cognitive systems can easily distinguish vagueness and clarity by means of regional comparisons. We learn from this phenomenon to train a sparse dictionary to represent the fuzzy and clear patches. We first randomly select 10^3 image patches from the high-resolution image dataset. Each image patch is vectorized as yi, xi is the coefficience of yi. The dictionary D can be trained on the image patches based on equation 5-7, in which each patch can be decomposed into a weighted accumulation of basic atoms, shown in Fig. 3. Therefore, the proposed depth estimation algorithm is shown as follow:



a. The blur depth descriptor b. Seam carving result

c. Depth in reference 6 d. Seam carving result

Figure 4. Depth of field calculation and scale effects

Depth of field estimation algorithm:

Input: target image I, blur dictionary D_{blur}.

Output: f_{blur}.

Step1. the target image I is decomposed into $I_0, I_1, I_2, ..., I_n$.

Step2. for I = 0 to n.

Step3. blur decomposition based on equation 6 to generate $x_0, x_1, ..., x_n$.

Step4. calculate $f_0, f_1, ..., f_n$ *by equation 7.*

Step5. end.

We do the comparison between our algorithm with the reference [6]. In Fig. 4.a, our depth estimation obtains a clear edge according to the edge blurness. As a result, the image retargeting preserve the contour completely, shown in Fig. 4.b. The depth estimation in Fig. 4.c does not have clear edge information will lead to the distortion as shown in Fig. 4.d.

3.3 The Proposed Algorithm

Our algorithm is shown as follows:

Input: the target image G, the blur dictionary D_{blur}***, the retargeting ratio r.***

Output: the retargeting result G'.

Step1. watershed(G)$\rightarrow G_{edge}$, $n = \left\| G_{edge} \right\|_0$

Step2. through D_{blur}*, calculate image depth descriptor F.*

Step3. for i = 1 to 3.

Step4. for j = 1 to n.

Step5. calculate the color discrimination degree C_{ij} *by Equation 2.*

Step6. calculate the position discrimination degree H_{ij} *by Equation 3.*

Step7. calculate the saliency S_{ij} *by Equation 4.*

Step8. $S_{ij}^{'} = \lambda \circ S_{ij} + (1 - \lambda) \circ F_{ij}$

Step9. end.

Step10. S_i *is generated by* $S_{ij}^{'}$

Step11. end.

Step12. combine $\{S_i\}$ *to produce (S, r) by Standard Seam Carving algorithm to complete the image scaling G '.*

Where the λ value can be specified by the user, in this case λ = 0.6.

a.The original Image b. Resizing effects c.The minimum energy lines

Figure 5. Distortion of non-saliency field

Applying our algorithm to resize the image in Fig. 5, we find that although the salient object (dolphin) can be preserved, there are some artifacts around the dolphin as Fig. 5. b. The reason is the saliency feature will over-protect the dolphin. There are more energy seams going around the dolphin, as a result, the structure information at this area is destroyed during image retargeting.

a.depth-based salient edge b. Seam carving result c.The minimum energy lines

Figure 6. Improved algorithm to reduce the significant regional deformation

$$S' = \frac{\partial S}{\partial x} + \frac{\partial S}{\partial y}, \tag{8}$$

In order to avoid the distortion in non-significant area, we proposed an improvement to the saliency by calculating the derivative at x-direction and y-direction, shown in equation 8. In this way, the depth-based salient map will keep obvious contour information for every object in the image. In our new algorithm, the depth-based saliency map is shown in Fig. 6.a, and the results after image retargeting is shown in Fig. 6.b. We can observe that the minimum energy lines are distributed more reasonable than before, shown in Fig. 6.c.

The improved algorithm is shown as follow:

Input: the target image G, the blur dictionary D_{blur}, the retargeting ratio r.

Output: the retargeting result G'.

Step1. watershed(G) → G_{edge}, $n = \|G_{edge}\|_0$

Step2. through D_{blur}, calculate image depth descriptor F.

Step3. for i = 1 to 3.

Step4. for j = 1 to n.

Step5. calculate the color discrimination degree C_{ij} by Equation 2.

Step6. calculate the position discrimination degree H_{ij} by Equation 3.

Step7. calculate the saliency S_{ij} by Equation 4.

Step8. Through Equation 8, S→ S '.

Step9. $S^{'}_{ij} = \lambda \circ S'_{ij} + (1-\lambda) \circ F_{ij}$

Step10. end.

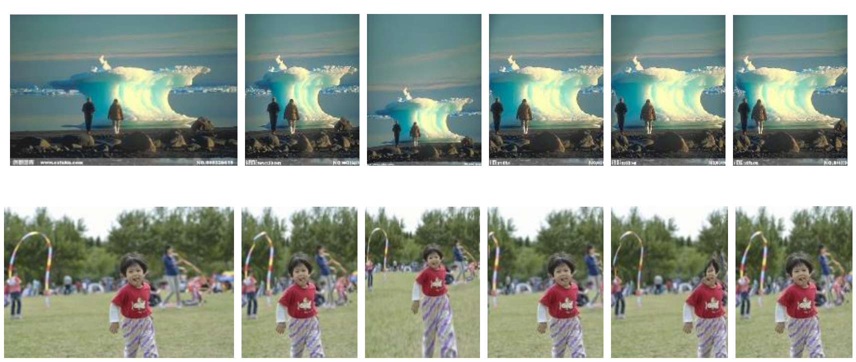
Step11. S_i *is generated by* $S^{'}_{ij}$

Step12. end.

Step13. combine {S_i} to produce (S, r) by Standard Seam Carving algorithm to complete the image scaling G '.

4. EXPERIMENTS AND ANALYSIS

For fairly comparison, we randomly select testing images from Baidu gallery, as shown in Fig. 7. There are four classical algorithms are chosen, such as SC [1], SNS [18], WSM [5] and SA+DE+SC[6]. In Fig. 7, the images are reduce 50% ratio in horizontal way. From the results, we can find out that the SC and SNS algorithms reduce the size of important objects in image. There are slight distortions appeared at background for WSM and SA+DE+SC algorithm. Compared to those ones, ours effect performs well on the salient object edge and background structure preservation, shown in Fig. 7.



(a) (b)

The Original Image SC SNS WSM SA+DE+SC Ours

Figure 7. Image resizing effect comparison

Then we compare our method with SA+DE+SC algorithm for non-salient structure information preservation, shown in Fig. 8. Our approach use the blurness-based depth estimation, and propose contour sensitive saliency computation to resize the image. It will be useful to keep the structure information as well as maintain the salient objects. In Fig. 8.a, from left to right are original high-resolution image, SA+SC algorithm, SA+DE+SC algorithm, our algorithm with derivative on SA, respectively. By analyzing the minimum energy seams, our algorithm with derivative on SA (the last column) is the best one on both salient object keeping and non-salient structure maintaining.


(a) (b)

Figure 8. The non-significant regional structure information comparison

In addition to visual comparison, this paper calculates the average energy values for several major methods. According to the literature [1] higher the average energy indicates the better the algorithm works. This paper compares SC, SNS, WSM, SA + DE + SC, Ours + f '(SA). The experimental image is shown in Fig. 9, the data are shown in Table 1.

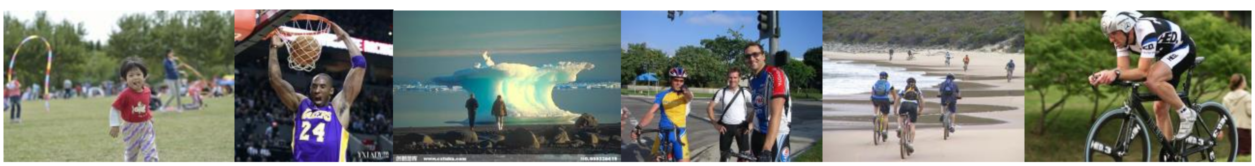


Figure 9. Energy calculation sample design

Table 1. The experimental data

	SC	*SNS*	*WMS(SA+SC)*	*SA + DE +SC*	*Ours+f'(SA)*
test1(50%)	*13.341 4*	12.0211	12.3283	11.6569	*13.9305*
test2(45%)	*19.1714*	17.0730	18.5809	17.2505	*19.1203*
test3(50%)	*9.2229*	5.6317	8.2556	8.5642	*9.4690*
test4(30%)	*24.9025*	17.2835	23.9198	24.3574	*24.7804*
test5(40%)	*15.9920*	11.5781	15.6394	15.8193	*16.0192*
test6(30%)	*18.5992*	16.5535	18.6593	16.4547	*18.5732*

In Table 1, the proposed algorithm in this paper is basically the top two samples of each test in terms of the average energy value after retargeting. Although the standard SC algorithm sometimes obtains a higher value, SC in the visual effect leads to significant regional deformation. therefore, The method proposed in this paper has good performance for on quantitative evaluation and visual effect.

5. CONCLUSION

This paper proposed a novel saliency computation with depth estimation from edge blurness based on seam carving algorithm. It maintains the salient region information, reducing the distortion appeared at the edge areas and preserving the non-salient structure. For current status, the proposed algorithm works well to the single object image. However, for the multi-object images, the results should be improved further.

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