Energy map improvement for Seam Carving

Introduction to Image Processing
Final Project Report

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1. Abstract

Content aware image re-targeting preserves important features of the image while resizing it. The classical algorithm, seam carving, rely on grayscale intensity to define the important features, which results in higher energy at edges of objects. In this project, we take color information into account, which gives the whole important region higher energy but not just the edges. Our approach gives importance ranking automatically and adaptively according to the color distribution of each image, thus eliminate the need of defining protection masks manually.

2. Introduction

Seam carving [1] is an image resizing algorithm which resizes images while preserving the important features. However, the algorithm shows limitations on certain images, such as information-densed images and images with certain energy layouts that prevent seams to bypass important features. This can be corrected by adding higher level cues, either manual or automatic, such as face detection or user given constraints. Our project aims to develop a content-aware image re-targeting algorithm based on seam carving. In our approach, we add higher level cues considering the color information of the given image. By dividing the color space into several divisions according to the frequency distribution of the color histogram, we give importance ranking to each distribution, supposing the distribution with lowest frequency has highest significance. Thus, we obtain the *color map* of the given image. To highlight the structure of the given image, we obtain the *structure map* of the image by detecting the edge of object. We combine the two maps together and achieve the new energy map, presenting better results.

3. Method

3-1. Structure Detection

We detect the edges in the image and consider them the structure of objects. In RGB color space, we use Sobel operator to detect edges in image horizontally and vertically, RGB channel separately, then we add them up to output the *RGB structure energy map*.

Different objects usually have obvious edges due to color difference. Thus, we make use of CIELAB color space's feature, which the Euclidean distance of value represents the color difference perceived by human eye. The Euclidian distance twice, first is between adjacent rows and the second is between adjacent columns, then we combine the two together and produce the *CIELAB structure energy map*.

(a) (b) (c)

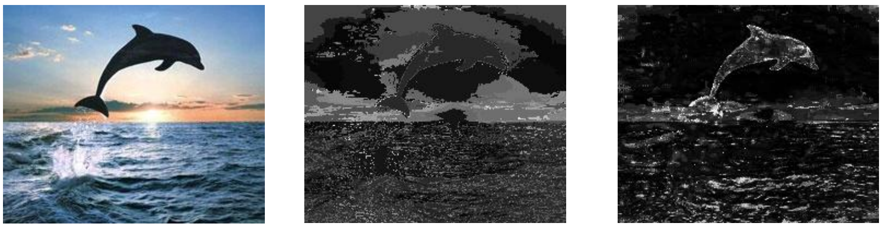
Fig.1. (a) original image. (b) RGB structure energy map. (c) CIELAB structure energy map

3-2. Color ranking

In order to take importance of region into consideration, we analyze color information in the image and assign different importance value to different colors. We divide colors inside an image (value ranges 0 to 255) in to equal-sized continuous divisions, and count the number of occurrences of each division. We consider the less the color appears the more important, so we assign higher values to the ranking to the division. For example, we divide colors into 8 divisions, each of which contain colors from 0~31, 32~63 …, 224~255. Then we assign ranking from 8 to 1 to represent according to occurrence and finally map each division back to 255, 223, …, 31.

In CIELAB color space we do the same operation as in the RGB color space, except for we divide the L* channel (value range 0~100) into only 4 divisions for we want to reduce the influence of lightness.

We call this series of operation 'color ranking' and we obtain the *color energy map*.



(a) (b) (c)

Fig.2. (a) original image. (b) RGB color energy map. (c) CIELAB color energy map

3-3. Combination

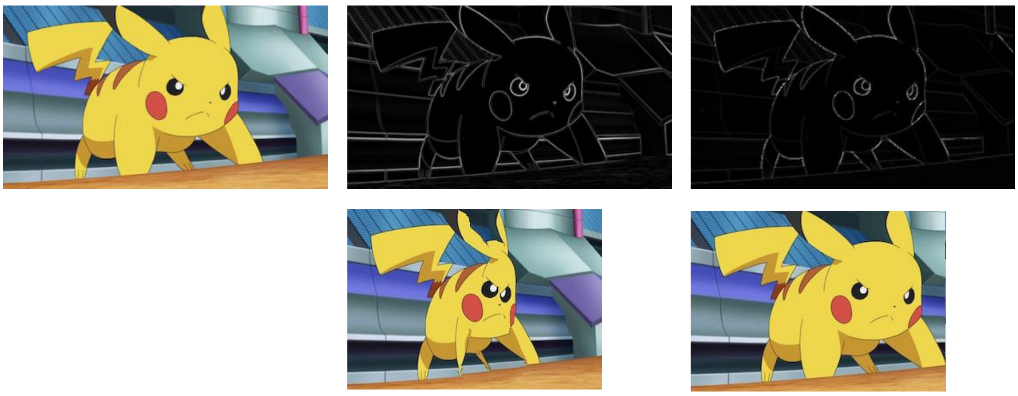
Once we obtain structure energy map and color energy map, the next thing to do is to combine them together to get the combined energy map. To highlight the importance of object structure, we apply Gamma transform, $\gamma = 0.4$, on structure energy map before adding them together.

(a) (b) (c)

Fig.3. (a) original image. (b) RGB combine energy map. (c) CIELAB combine energy map

4. Result

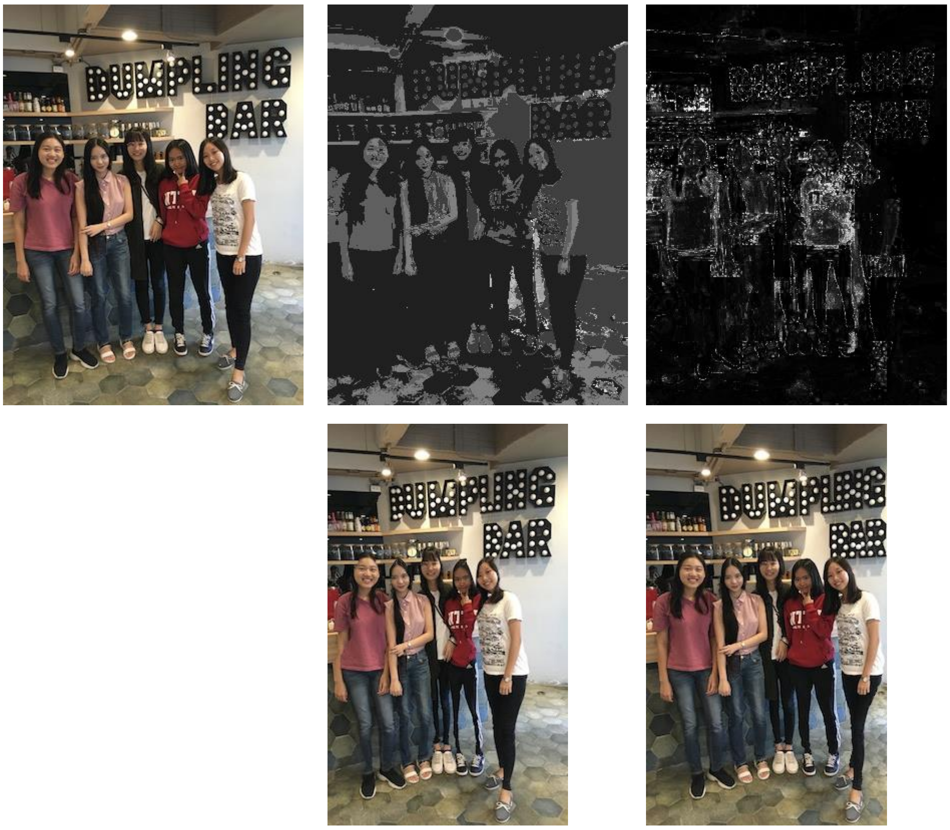
For structure detection, we experiment on two methods: filtering with Sobel operator, and calculating Euclidean distance of neighboring pixels in CIELAB color space. The Sobel operator we defined captures the gradient of intensity. Euclidean distance in CIELAB focus on the difference of colors perceived by human eyes. As we can see, edges exist in background image but are not prominent to human eyes (Fig. 4). Sobel operator highlights those edges, while Euclidean distance in CIELAB ignores those trivial edges.



(A) (B) (C)

Fig.4. *Column (A) shows original image. Column (B) top row is the structure map using Sobel operator, and its corresponding result, re-targeted to 80%. Column (C) top row is the structure map using Euclidean distance of neighboring pixels in CIELAB color space*

For color ranking, we experiment on two color spaces and two divisors: RGB and CIELAB. Our result shows that CIELAB provides better result (Fig.5). We divide the color space by 8 and 125. Our result shows that images with diverse colors gives better result when applying larger divisor; while images with lower color diversity responds better with smaller divisor (Fig.6 and Fig.7).



(A) (B) (C)

Fig.5. *Column (A) shows original image. Column (B) top row is the color map using RGB color space, divided into 8 divisions, and combined with structure map given by Sobel operator. Bottom row shows the corresponding result, re-targeted to 80%. Column (C) top row is the color map using CIELAB color space, with same factors as column (B). Bottom row shows the corresponding result.*

(A) (B) (C)

Fig.6. *Column (A) top row shows original image, and its corresponding result using only structure map given by Sobel operator. Column (B) top row is the color map using 8 as divisor in RGB color space, and combined with structure map given by Sobel operator. Bottom row shows the corresponding result, re-targeted to 80%. Column (C) top row is the color map using 125 as divisor in RGB space, with same factors as column (B). Bottom row shows the corresponding result. Notice that using 125 as divisor gains better result.*

(A) (B) (C)

Fig.7. *Column (A) top row shows original image, and its corresponding result using only structure map given by sobel operator. Column (B) top row is the color map using 8 as divisor in RGB color space, other factors same as Fig.4. Bottom row shows the corresponding result, re-targeted to 80%. Column (C) top row is the color map using 125 as divisor in RGB space, with same factors as column (B). Bottom row shows the corresponding result. Notice that using 8 as divisor gains better result.*

5. Conclusion

Our experiments show that applying color information into energy maps provides better result. CIELAB color space gives information that are closer to human eyes' perceptions. By conducting color map, we can eliminate the need of defining a protection mask manually.

6. References

[1] Avidan, S. and Ariel Shamir. “Seam carving for content-aware image resizing.” SIGGRAPH 2007 (2007).

[2] Rubinstein, Michael et al. “Improved seam carving for video retargeting.” SIGGRAPH 2008 (2008).

[3] Wang, Yu-Shuen et al. “Optimized scale-and-stretch for image resizing.” SIGGRAPH 2008 (2008).

[4] Achanta, R. and S. Süsstrunk. “Saliency detection for content-aware image resizing.” 2009 16th IEEE International Conference on Image Processing (ICIP) (2009): 1005-1008.