Content-aware retargeting based on Information Theoretic Learning

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***Abstract*— In this paper, the problem of content-aware retargeting is approached using the Information Theoretic Learning as a metric of image energy. Comparison with other metrics is performed, presenting the optimal paths selected by Seam Carving using each of the metrics, as well as the results and a performance evaluation by resulting brightness in each image.**

I. Introduction

WITH technological advances in recent decades and the popularity of handhelds, small screens. View large images on small screens generates the discomfort of not displaying all important content at once. The content-aware image retargeting provides the representation of an image by a smaller equivalent, keeping important content and discarding irrelevancies in pictures. We will present a work that uses the algorithm Seam Carving [1] based on Information Theoretic Learning to resize images, providing significant improvements over other metrics used in the comparison.

II. Seam Carving

Image resize is a tool widely used in image manipulation software, resizing uniformly to the target size. Recently, the interest on content-aware image retargeting grew. A common form of such features may be classified by the approaches are *top-down* and *bottom-up*. The approaches *top-down* work seeking known features as a faces detector proposed by [8], so that some regions of interest are preserved. However, the approach *bottom-up* methods depend of visual salience [4] to create a visual saliency image map. Once the saliency map is constructed, cuttings of this map may be used to identify important regions of image. A automatic creator of thumbnails is proposed in [7] requiring as input a saliency map or a face locator. The image is cropped based on the most important image region. Similarly, in [2], was considered the problem of images adaptation for mobile devices.

Was the question asked by Avidan and Shamir [1]: What pixel choose to be removed? Intuitively, our goal is to remove imperceptible pixels to blending with their neighbors and this leads to a simple energy function:

$$e(I) = \left|\frac{\partial}{\partial x} I\right| + \left|\frac{\partial}{\partial y} I\right| \tag{1}$$

Knowing the Equation 1, is possible select an optimal seam passing through the image.

Definition of *vertical seam*:

$$s^x = \{s_i^x\}_{i=1}^n = \{(x(i), i)\}_{i=1}^n, \quad \forall i, |x(i) - x(i-1)| \leq 1 \tag{2}$$

Fig. 1: A seam is a connected path of lowest energy. On the right (top to bottom): energy image, horizontal energy map and vertical energy map [1].

where x is a mapping $x : [1, \ldots, n] \rightarrow [1, \ldots, m]$, which is a vertical seam, in other words, a path of 8-connected pixels from top to bottom, containing only one pixel of each row (look Fig. 1). The same concept is used to *horizontal seam*.

$$s^y = \left\{s_j^y\right\}_{j=1}^n = \{(y(j), j)\}_{j=1}^n, \forall j, |y(j) - y(j-1)| \leq 1 \tag{3}$$

With the energy function e, is defined as the seam cost $E(s) = E(I_s) = \sum_{i=1}^n e(I(s_i))$. Looking up the optimal seam s^* which minimizes the function:

$$s^* = \min_s E(s) = \min_s \sum_{i=1}^n e(I(s_i)) \tag{4}$$

The optimal seam is found by *dynamic programming* [6]. The first step is follow through image of the second row to the last, calculating the minimum accumulated energy M for all possible seams connected to each pair (i, j).

$$\begin{gathered} M(i,j) = e(i,j) + \\ \min(M(i-1,j-1), M(i-1,j), M(i-1,j+1)) \end{gathered} \tag{5}$$

At the end of this process, the lowest value on the last line in M indicate the seam vertically connected with lower energy. The next step is to perform the reverse path always seeking the lowest pair (i, j) connected and with less energy. The Fig. 2 represents the calculation of a horizontal energy map, it was coloured to show the energy accumulation proposed by Equation 5, blue and red respectively represent low energy and high energy. Highlights the seam considered optimal according to Equation 4, for having the lowest accumulated energy of all possibilities.

The Algorithm 1 shows the sequence of steps performed by Seam Carving to reduce the picture width, this same

```
Input: I,w
Output: I
/*
I is the image to be resized
w is the final weight of image
*/
while weight of I < w do
    e = Calculate energy function of image e(I)
    (Equation 1) ;
    M = Calculate energy map based on e(I)
    (Equations 2 e 5) ;
    s* = Find optimal seam based on energy map
    (Equation 4) ;
    Remove pixels in s* and update I ;
end
```

Algorithm 1: Pseudo-algorithm of Seam-Carving for width resize of image

algorithm is easily adapted to reduce the height. It is observed that it was developed to decrease the width of image in a pixel, the reduction of several pixels is nothing more than a repetition of the same sequence of steps.

III. Information Theoretic Learning

The Mean-square Error (MSE) has been the basis for the research of adaptive systems because of the various analytical and computational simplicities in minimizing the energy of the error in processing jobs linear signals [3]. Other metrics now be used to "measure" variations and errors, in information theory some other metrics are available.

ITL (Information Theoretic Learning) as the procedure to adapt the free parameters w of a learning machine $g(., w)$ using an information theoretical criterion. Information theoretic learning seems the natural way to train the parameters of a learning machine because the ultimate goal of learning is to transfer the information contained in the external data (input and or desired response) onto the parametric adaptive system [5].

A. ITL and kernel method

Information Theoretic Learning is a framework to non-parametrically adapt systems based on entropy and divergence [5]. Renyi's α -order entropy of a random variable x is defined by Equation 6:

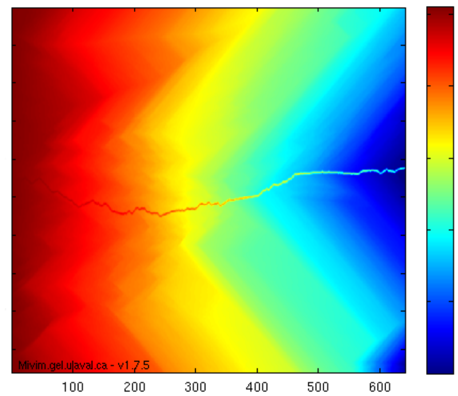
$$H_\alpha = \frac{1}{1-\alpha} log \int f_X^\alpha(x)dx \tag{6}$$

Estimating the PDF (Probability Density Function) with Parzen estimators for the samples $\{x_i, i = 1, 2, ..., N\}$, drawn from the PDF, we obtain the estimator:

$$\hat{f}(x) = \frac{1}{N}\sum_{i=1}^{N} k_\sigma(x - x_i) \tag{7}$$

where $k_\sigma(x)$ é the Gaussian kernel.

(a) Original Image



(b) Horizontal energy map

Fig. 2: Example of dynamic energy map, with optimal seam. (a) Original image e (b) horizontal map with the accumulated energy

$$k_\sigma(x - x_i) = \frac{1}{\sqrt{2\pi\sigma}} \exp(-\frac{(x-x_i)^2}{2\sigma^2}) \tag{8}$$

N is the number of the samples and σ the kernel size. For $\alpha = 2$ (quadratic entropy), we obtain a nonparametric estimator of quadratic entropy as

$$\hat{H}_2(X) = -logIP(x) \tag{9}$$

$$IP(X) = \frac{1}{N^2}\sum_{j=1}^{N}\sum_{i=1}^{N} k_\sigma(x_j - x_i) \tag{10}$$

$IP(X)$ is called information potential (IP). The PDF estimated with Parzen kernels can be thought as defining an information potential field over the space of the samples [3].

IV. Methodology

The experiments aim to analyse the behaviour of Equation 10, as image energy measurement guiding the Seam Carving algorithm, realized a comparative measurement between:

- Gradient: Energy measuring initially proposed in [1], where a mask is applied on 9x9 image, generating its energy based on the gradient method. We will present the results from the Gradient, only by the abbreviation **Grad**;

- Shannon entropy: The Shannon entropy, described by the Equation $-\sum_{x\in X} p(x)\log p(x)$, to determine the local probability, is used the histogram in a 9x9 sub-window. The application of this procedure in the image generates its energy. We will present the results from this equation by the abbreviation **Shannon**;
- Information Potential: Like Shannon entropy, the information potential will evaluate the significance of the information contained in the pixels. We also used a 9x9 sub-window. For the σ parameter, also called *kernel size* of Equation 10, the value used was **10**, obtained empirically by trial and error. We present the results obtained from Information Potential by the abbreviation **IP**.

Each image undergoes a width reduction, storing all paths selected by Seam Carving in each of the metrics.

V. Simulation Results

The results presented here, were conducted to help understand the information potential as a metric of Seam Carving algorithm. The experiment is performed on an image dataset containing various situations, applying a reduction of 200 pixels in width. All images have a fixed width, **800 pixels**, retargeting for the size of **600 pixels**. No changes were made at the height of image.

The Fig. 3 and 4, present seams selected by Seam Carving algorithm, being based on each of the energy measures. The blue lines represent the choice of pixels to be removed so that the image reach the desired size.

To analyse the impact of this image retargeting, was reproduced a measurement of brightness intensity average and the stored values for each experiment. In each of the used pictures, after one pixel removal, was calculated the brightness intensity average image. This procedure was performed for each of the evaluation metrics. Lastly, was applied a arithmetic mean between the results. The Fig. 5 show this result.

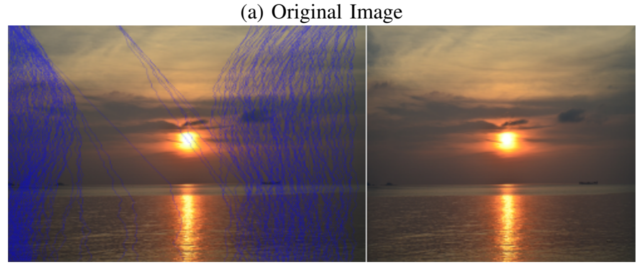
VI. Conclusions

In the results presented by Fig. 3 and 4, was show a sensitivity of information potential to locate, efficiently, edges of objects in images, valorizing these regions.

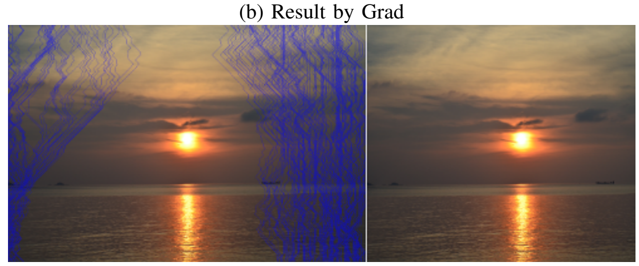
The seams selected by Seam Carving using information potential , more effectively, preserve the existing objects in the image, although this choice, in some cases, does not ensure consistency.

The graph shown in Fig. 5, shows that the information potential better preserves the brightness intensity average of image pixels. Brightness intensity average gives us a sense of how much brightness was preserved in the images. Unfortunately, the absence of a metric to quantize the quality resizing, we are limited in evaluating the performance through a subjective perception of measuring the brightness intensity.

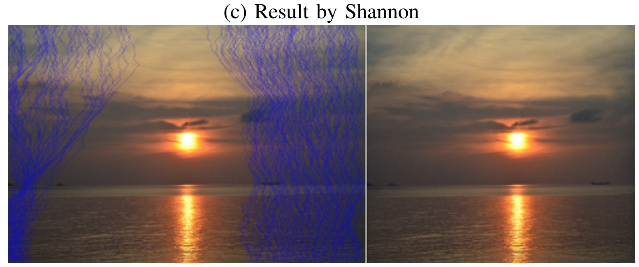
(a) Original Image



(b) Result by Grad



(c) Result by Shannon



(d) Result by IP

Fig. 3: Seams selected by Seam Carving on each of the energy measure.

References

[1] Shai Avidan and Ariel Shamir. Seam carving for content-aware image resizing. *ACM Transactions on Graphics*, 26(3):10, July 2007.

[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. *Multimedia Systems*, 9(4):353–364, 2003.

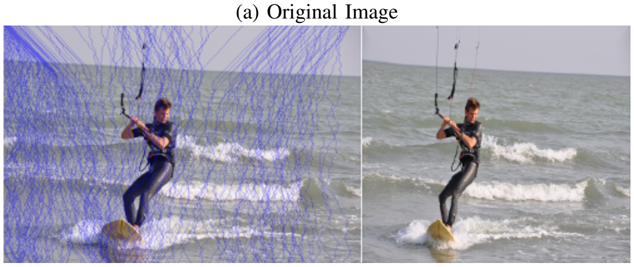
[3] D. Erdogmus and J. C. Principe. Generalized information potential criterion for adaptive system training. *IEEE Transactions on Neural Networks*, 13(5):1035–1044, 2002.

[4] Laurent Itti, Christof Koch, and Ernst Niebur. A model of saliency-based visual attention for rapid scene analysis. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 20(11):1254–1259, 1998.

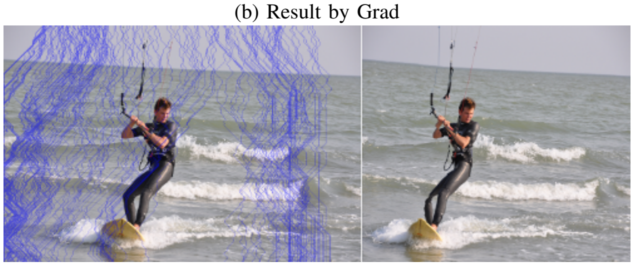
[5] J. C. Principe, Dongxin Xu, and Qun Zhao. Learning from examples with information theoretic criteria. *The Journal of VLSI Signal*, 26(1):61–77, 2000.

[6] Moshe Sniedovich. *Dynamic Programming Foundations and Principles Second Edition*. CRC Press, 2011.

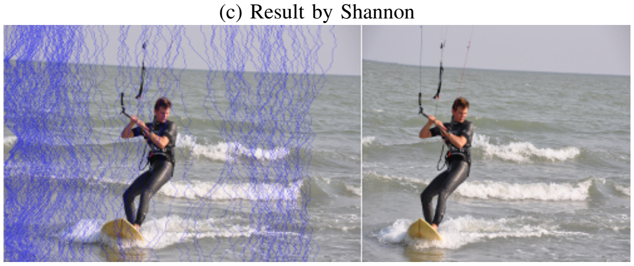
(a) Original Image



(b) Result by Grad



(c) Result by Shannon



(d) Result by IP

Fig. 4: Seams selected by Seam Carving on each of the energy measure.

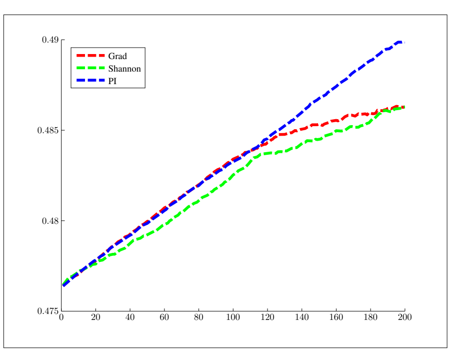


Fig. 5: Comparison between the brightness average of the pixels along the resizing 200 pixels.

[7] Bongwon Suh, Haibin Ling, Benjamin B. Bederson, and David W. Jacobs. Automatic thumbnail cropping and its effectiveness. *Proceedings of the 16th annual ACM symposium on User interface software and technology UIST 03*, 5(2):95–104, 2003.

[8] Paul Viola and Michael Jones. Rapid object detection using a boosted cascade of simple features. In *Proceedings of the 2001 IEEE Computer Society Conference on Computer Vision and Pattern Recognition. CVPR 2001*, volume 1, pages I–511–I–518. IEEE Comput. Soc, 2001.