CONTENT-BASED IMAGE RESIZING ON MOBILE DEVICES

Sebastiano Battiato, Giovanni Maria Farinella, Nicolò Grippaldi and Giovanni Puglisi
Image Processing Laboratory, Department of Mathematics and Computer Science, University of Catania, Catania, Italy

Keywords: Content-aware Image Resizing, Computer Vision on Mobile Devices.

Abstract: Content-aware image resizing are effective algorithms that allow to take into account the visual content of images during the resizing process. Despite the technological advances in the context of mobile devices, content-aware image resizing algorithms are still far to be used on a hand held device due to the computational resources needed during the resizing. In this paper we afford this problem employing a method which has linear complexity with respect to the number of lines (rows/columns) to be reduced/augmented. The method has been tested, both qualitatively and quantitatively, on a mobile platform.

1 INTRODUCTION

The extensive use of different display devices with different resolution increases the demand of image resizing techniques which consider the visual content during the resizing process. Standard resizing techniques, such as scaling, can be used only to change the size of an image of a fixed proportion with respect to the two dimensions. Scaling does not take into account the visual importance of pixels during image resizing (i.e., a resizing with respect to only one of the two dimensions introduces artifacts and distortions). Other standard operations, such as cropping, in which outer parts of an image are removed, could produce images with loss of semantic information. In the last five years, different techniques for content-aware image resizing have been proposed (Avidan and Shamir, 2007; Cho et al., 2008; Rubinstein et al., 2009; Gallea et al., 2010). The main aim of a content-aware image resizing is the preservation of relevant visual information into the resized image. Seam Carving (Avidan and Shamir, 2007) reduces or expands the image by removing or duplicating connected path of pixels (called seams) having low-energy in the energy map corresponding to the image to be resized. Rubinstein et al. (Rubinstein et al., 2009) presented an image resizing algorithm to perform combination of Bi-cubic scaling, cropping and Seam Carving. With this approach better results are obtained in terms of visual quality, but the computational complexity increases due to the use of different resizing operators. Among others, patch-based methods have been also proposed for image retargeting or summarization. Cho et al. (Cho et al., 2008) suggested an algorithm to find an arrangement of patches of the original image that well fit in the resized image. Although the techniques above produce impressive results, the corresponding algorithms have a high computational complexity to be employed in consumer mobile devices. Gallea et al. (Gallea et al., 2010) proposed a fast method for image retargeting based on the solution of a linear system. This model aims to find shift values for each line (row/column) preserving the distance among the relevant ones. The linearity of the considered model allows them to elaborate even large images in reasonable computational time. Building on the technique proposed by Gallea et al. (Gallea et al., 2010), in this paper we propose a method to be employed for content-aware image resizing on mobile devices. The method has linear complexity with respect to the number of lines (rows or columns) to be reduced/augmented. The linear complexity makes the approach attractive for mobile devices environment. In this paper we have performed a set of experiments on Nokia N900 mobile platform (Adams et al., 2010) to evaluate both qualitative and quantitative results of this last method. The paper is organized as follows: Section 2 presents the image resizing method. In Section 3 the experimental phase and the results are detailed. Finally, conclusions are given in Section 4.

2 PROPOSED APPROACH

As already stated in the previous section, although the recent improvement both in terms of memory storage and computational capability of mobile devices,

Battiato S., Farinella G., Grippaldi N. and Puglisi G..
CONTENT-BASED IMAGE RESIZING ON MOBILE DEVICES.
DOI: 10.5220/0003843500870090
In *Proceedings of the International Conference on Computer Vision Theory and Applications* (VISAPP-2012), pages 87-90
ISBN: 978-989-8565-04-4

currently, only fast and simplified strategies can be actually employed on mobile devices. The proposed approach has been hence derived from Gallea et al. (Gallea et al., 2010) through some simplifications and a properly tuning of the involved steps.

The proposed model considers the image as a set of lines $L = [l_1, l_2, \ldots, l_n]$ where l_i represents a single line and n is the dimension of the rows or columns of the original image to be resized. Our approach aims to find a novel set of lines $L' = [l'_1, l'_2, \ldots, l'_{n'}]$, where n' is the desiderate final image dimension, obtained from the original set L by removing (or adding in case of image enlargement) some lines without introducing, if possible, image distortions.

The selection of the lines to be removed is hence a fundamental step of our approach. A careful selection, considering non-informative regions, should preserve the overall quality of the final image. A significance map is then built using a measure based on visual salience (Itti et al., 1998) and gradient information. A weight w_i is associated to each line l_i through the projection along the considered line by using simple operators (i.e., mean, max, min). Note that in our tests (see Section 3) several strategies have been considered and compared to properly find a trade-off between final image quality and complexity of the approach. Starting from the set of weights $W = [w_1, w_2, \ldots w_n]$ two different strategies of line removal (insertion) have been designed. The simplest one removes (or replicates) the $|n' - n|$ lines corresponding to the lowest weights (hence less "significant" in terms of salience and gradient information). The second strategy considers the removal (replication) step as an iterative process. For each iteration it removes (or replicates) the less "significant" line based on its weight value and then updates the whole map of importance of pixels and the set of weights W. Experiments results (see Section 3) show the difference between the above mentioned strategies both in terms of visual quality (artifacts generation) and computational time on a mobile device.

3 EXPERIMENTAL RESULTS

The experiments performed to assess both qualitative and quantitative results are reported in the following subsections. Specifically, the qualitative performances have been tested by employing the proposed algorithms and several energy maps on a PC with a processor Intel Core 2 Duo T5750 2 Ghz and 3 GB RAM. Quantitative performances in terms of computational time have been obtained testing the approaches on a mobile phone Nokia N900. The considered mobile platform has an OMAP Processor with 600 Mhz of clock frequency and 1 GB RAM. The FCam API (Adams et al., 2010) have been used to implement the proposed resizing techniques on the Nokia N900 mobile platform. These API are open source and can be used to develop algorithms and computational photography apps (Battiato et al., 2012) taking into account the new computational cameras paradigm (Adams et al., 2010).

(a) Original Image

(b) Non-Iterative approach

(c) Iterative approach

Figure 1: Results obtained considering both non-iterative (Figure 1(b)) and iterative (Figure 1(c)) approaches. The original image shown in Figure1(a) is reduced of 20%.

3.1 Qualitative Evaluation

The most efficient energy map (in terms of computational costs) we have considered makes use of Sobel filter (only). This energy map is able to take into account discontinuities (e.g., edges). With regards to the algorithm to be used to remove a fixed number of lines (row or columns) once the energy map is computed, we compared two different variants of the original algorithm proposed in (Gallea et al., 2010):

- a non-iterative approach in which the energy map is computed only once and then the k less significant lines, with respect to the computed energy map, are removed (or inserted).
- an iterative approach in which at each step just one line is removed (or inserted) and the energy map in computed on the image obtained from the previous iteration.

Although the non-iterative approach provides a relatively low computational time, it does not obtain satisfactory results. Indeed, the resized images contain artifacts as shown by the red arrows in Figure 1(b). The quality of the resized images increases considering the iterative algorithm, since at each step the saliency map takes into account the changes made by previous iterations (see Figure 1(c)). Of course, a drawback of the last approach is that the computation time grows as the number of iterations. To deal with this problem, rather than computing the energy map at each iteration we compute it locally only on the area which have been changed in the previous iteration (neighborhood of the line removed/added) and retain the other part from the previous energy map. This modification improves the computational performance (time and space) obtaining exactly the same results in terms of visual quality.

Even using algorithm simplifications described above, in the first step of the iterative process the energy map must be calculated on the entire original image and this involves a considerable slowdown in the execution of the algorithm when the image size is very large. To overcome this problem, rather than choosing the line to be removed (added) taking into account the energy map computed on the original image, we proceed with a multiscale approach in which a low resolution version of the image is created with a three levels pyramid of Gaussian and then the choice of the line is propagated locally from the lowest resolution to the highest resolution energy map. In this way, in the highest levels of the pyramid we search only in a neighborhood.

Further tests have been done to improve the quality of the resized image in the neighborhood of the removed/added lines. In particular, we compared two version of removal: i) a brutal removal of the less important line chosen by the algorithm and ii) the one on which the two lines adjacent to the one to be removed are averaged with the removed line in the resized image. A visual comparison between these two approaches is reported in Figure 2. As one can see from the figure, the second approach reduces the number of artifacts in the final resized image.

3.2 Quantitative Evaluation

In order to properly evaluate the portability of the aforementioned alternatives on mobile devices, several quantitative tests to study their impact in terms of computational time have been performed. Figure 3 shows the computational time on a standard PC of the different versions of the resizing algorithm: iterative, iterative considering neighborhood, iterative consid-

(a) Original Image

(b) Brutal removal.

(c) Removal with averaging.

(d) Gallea et al. (Gallea et al., 2010)

Figure 2: Results obtained by reducing the image in (a) at 80% of the original horizontal size. In (b) and (c) the output obtained considering the two versions of proposed method for line removal. In (d) the final image obtained employing the method proposed by Gallea et al. (Gallea et al., 2010).

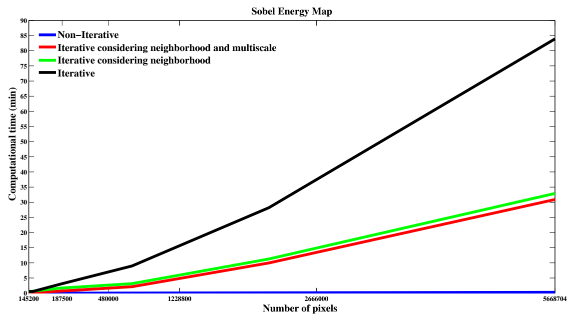

Figure 3: Execution time on a standard PC of the proposed approaches vs. image size. Sobel has been chosen as energy map.

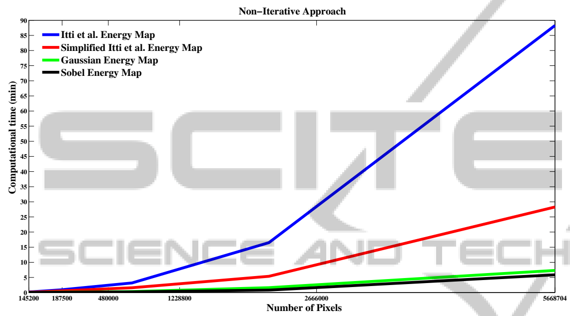

Figure 4: Execution time on a Nokia N900 of the non-iterative approach vs. image size. Each line represents the results obtained with different energy map: Itti et al. (blue), simplified Itti et al. (red), Gaussian (green), Sobel (black).

ering both neighborhood and multiscale, and non-iterative. These tests have been performed considering the Sobel energy map. All the approaches, obviously, increase their computational time at increasing of the image size. Although the non-iterative approach considerably outperforms the others, it shows lower performance in terms of artifact generation as pointed out in previous section. On the contrary, the optimized iterative approaches (considering both neighborhood and multiscale) sensitively reduce the execution time with respect to the original iterative approach without affecting the visual quality of the resized image. From the analysis performed through the quantitative tests on a standard PC, and considering the limitations in terms of CPU clock frequency and memory storage of the mobile devices, only the non-iterative approach has been considered for final implementation on the Nokia N900 platform (Adams et al., 2010; Battiato et al., 2012). Figure 4 shows the execution time of the non-iterative algorithm running on a Nokia N900 at increasing of the image size. Several energy maps have been compared. Considering all the optimizations both in terms of energy map (Sobel) and algorithm (non-iterative), the approach takes about 5 seconds on a Nokia N900 to resize an image of about 5 megapixels.

4 CONCLUSIONS

In this paper we have proposed several strategies to allow content-aware image resizing on mobile devices. All the involved steps have been considered and optimized in order to find a good trade-off between visual quality and computational complexity. Specifically, several energy maps (Itti et al., simplified Itti et al., Gaussian, Sobel) and different versions of the line removal algorithm (iterative, iterative with neighborhood, iterative with neighborhood and multiscale, non-iterative) have been exploited. Moreover, to properly compare the proposed solutions in terms of visual quality and computational load, several tests on a standard PC and on a Nokia N900 mobile phone have been also performed. Future works will be devoted to find additional smart strategies useful to cut down the computational time in order to employ the iterative approaches on mobile devices.

REFERENCES

Adams, A., Talvala, E.-V., Park, S. H., Jacobs, D. E., Ajdin, B., Gelfand, N., Dolson, J., Vaquero, D., Baek, J., Tico, M., Lensch, H. P. A., Matusik, W., Pulli, K., Horowitz, M., and Levoy, M. (2010). The frankencamera: an experimental platform for computational photography. *ACM Trans. Graph.*, 29:29:1–29:12.

Avidan, S. and Shamir, A. (2007). Seam carving for content-aware image resizing. *ACM Transaction on Graphics*, 26(3).

Battiato, S., Farinella, G. M., Messina, E., Puglisi, G., Ravì, D., Capra, A., and Tomaselli, V. (2012). On the performances of computer vision algorithms on mobile platforms. In *SPIE Electronic Imaging - Digital Photography VIII*.

Cho, T., Butman, M., Avidan, S., and Freeman, W. (2008). The patch transform and its applications to image editing. In *IEEE International Conference on Computer Vision and Pattern Recognition (CVPR)*.

Gallea, R., Ardizzone, E., and Pirrone, R. (2010). Real-time content-aware resizing using reduced linear model. In *IEEE International Conference on Image Processing*.

Itti, L., Koch, C., and Niebur, E. (1998). A model of saliency-based visual attention for rapid scene analysis. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 20(11).

Rubinstein, M., Shamir, A., and Avidan, S. (2009). Multi-operator media retargeting. *ACM Transaction on Graphics*, 28(3).