Genetic Seam Carving: A Genetic Algorithm Approach for Content-Aware Image Retargeting

Conference Paper · June 2015

DOI: 10.1007/978-3-319-19390-8_78

Saulo Anderson Freitas de Oliveira
Universidade Federal do Ceará

Ajalmar Rêgo da Rocha Neto
Instituto Federal de Educação, Ciência e Tecnologia do Ceará

Genetic Seam Carving: A Genetic Algorithm Approach for Content-Aware Image Retargeting

Saulo A.F. Oliveira(✉), Francisco N. Bezerra, and Ajalmar R. Rocha Neto

Federal Institute of Ceará, IFCE, Fortaleza, Brazil
{sauloa,nivando,ajalmar}@ifce.edu.br

Abstract. Seam Carving is a method to retarget images by removal of pixels paths with minimal visual impact. The method acts by exhaustive searching of minimal cost paths according to a pixel relevance function. In the present paper, we explore optimal or suboptimal paths obtained by a new Genetic Algorithm method called Genetic Seam Carving. Besides the suboptimal character of this approach, we show in the experiments that, we achieve quality results similar to the original Seam Carving method, and in some cases we even obtain less degradation.

Keywords: Genetic Algorithms · Content-aware retargeting · Seam Carving · SSIM · SIFT

1 Introduction

Image retargeting is a technique that adjusts input images into arbitrary dimensions (rows and columns) and simultaneously preserves regions of interest in the input images. The basic idea of the retargeting process is to find less important regions of interest (ROIs) in the image and then to expand or to reduce surround these regions in order to generate an output image with few noticeable changes. Several content-aware image retargeting methods have been proposed last years, where some of them are focused on the content preservation while other ones on how to obtain these less important ROIs [12]. As an example, we highlight the Seam Carving (SC) method which is a technique to find connected pixels path named seam [1]. For reducing dimensions, Seam Carving method finds and then removes seams located in less important ROIs. A very interesting survey of retargeting and Seam Carving is found in [15].

In a new formulation of retargeting for video [9], the dynamic programming method is replaced by graph cuts that are suitable for 3D volumes. So, instead of removing 1D seams from 2D images, 2D seams are removed from 3D space-time volumes. The usage of streams (wider seams) introduced a new retargeting method based on SC named Stream Carving [5]. The difference between a seam and a stream is the number of pixel width, which in a stream is greater than a conventional seam. This choice is motivated by the usual locations of the seams in an image so that they are usually in easily reproducible areas and may be enlarged without causing any visual distortion. In addition to the presented

R. Paredes et al. (Eds.): IbPRIA 2015, LNCS 9117, pp. 700–707, 2015.
DOI: 10.1007/978-3-319-19390-8_78

works, another improvement is concerned with finding multiple seams simultaneously by extending the seamlet transform [4] in order to carve a few seams at each step of retargeting. These multi-seam carving approaches were explored in [3,4]. Moreover, a merging approach - Seam Merging - with structure preservation was proposed in [8], where the structural distortion is minimized by merging a two-pixel-width seam into a single-pixel-width one.

Besides aforementioned techniques, Computational Intelligence methods have been applied on image processing, in particular Genetic Algorithms (GAs) [6,11]. GAs are optimization methods and therefore they can be used to generate useful solutions to search problems. Due to the underlying features of GAs some optimization problems can be solved without the assumption of linearity, differentiability, continuity or convexity of the objective function. Unfortunately, these desired characteristics are not found in several mathematical methods when applied to the same kind of problems. We have not found, for the best of our knowledge, any work dealing with Genetic Algorithms and Seam Carving for retargeting.

Thus, in this work, we propose a new method called Genetic Seam Carving (GSC) that aims at retargeting images by using Genetic Algorithms. The main idea of our proposal is to use GAs for searching seams by minimizing an energy function was defined as a fitness function. In our proposal, we are also taking into account the area close to the solution to obtain other seams in a multi-seam carving sense. To do so, we analyze these feasible solutions and according to their quality a few seams (related to the optimal or suboptimal one) are selected to be carved. In fact, working with suboptimal seams to be carved, expanded (or so on) leads to similar quality results allowing to propose efficient multi-seam removal as one can see in [3,5]. In our proposal we are able to highlight two different contributions. The first one is a new formulation of the seam search problem in the GAs paradigm and a the second one is a multi-seam carving-driven approach.

The remaining part of this paper is organized as follows. In Sect. 2.1, we recall the Seam Carving method. So, we present our proposal in Sect. 3. After that, We describe the experiments carried out in Sect. 4. Finally, we present some conclusion remarks in Sect. 5.

2 Background

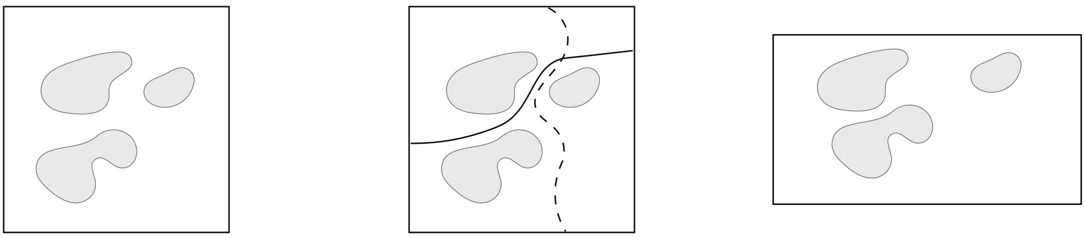
2.1 Seam Carving

Seam Carving [1] searches and evaluates feasible seams and chooses the one with the lowest cost of processing. For sake of simplicity, consider vertical seams in the following description and notation, since a similar description and notation for a horizontal seam can be done straightforward. Moreover, consider the system coordinate as having the first pixel located at the upper left corner. Let I be an image of size $m \times n$, as well as let a vertical seam be defined as $s = \{(i, x(i))\}_{i=1}^{m}$ s.t. $, \forall i, |x(i) - x(i-1)| \leq 1$, where x is a mapping $x : [1, \ldots, m] \rightarrow [1, \ldots, n]$. The seam cost is assigned through an energy function

$e(i, j)$, which gives a pixel certain value indicating the significance of that particularly point in the image. The energy function is based on two terms. The first one penalizes solutions that are inconsistent with the observed data and the second one enforces some kind of spatial coherence [10]. The optimal vertical seam search is computed by an exhaustive algorithm that keeps a cumulative cost for each seam computed. The search starts in the first row (i = 1) and continues to the neighbor pixels in the next row that have the lowest additional cost until the last row (i = m). The cost of a vertical seam that begins at the pixel (i, j) in the image I is computed by the cumulative minimum energy M as

$$M(i, j) = e(i, j) + \min \{M(i+1, j-1), M(i+1, j), M(i+1, j+1)\}, \qquad (1)$$

where $e(i, j)$ is the value obtained by the energy function. The optimal vertical seam is given by $s^* = arg\ min\{M(1, j)\}_{j=1}^{n}$. More details can be found in [1]. Figure 1 illustrates an ideal retargeting process.



(a) Original Image. (b) Illustrative seams. (c) Retargeted image.

Fig. 1. Retargeting process. Vertical and horizontal seams computed from image (a) are shown in (b). Image (c) depicts a retargeted output, where vertical seams were inserted and horizontal ones were carved (removed).

2.2 Genetic Algorithms

Genetic Algorithms (GAs) [14] are a search meta-heuristic method inspired by natural evolution, such as inheritance, mutation, natural selections and crossover. This meta-heuristic can be used to generate useful solutions to optimization problems. Due to the characteristics of GAs methods, it is easier to solve few kind of problems by GAs than other mathematical methods which do have to rely on the assumption of linearity, differentiability, continuity, or convexity of the objective function. In a genetic algorithm, a population of candidate individuals (or solutions) to an optimization problem is evolved toward better solutions by natural selection, i.e., a fitness function. In this population, each individual has a set of genes (gene vector), named chromosome, which can be changed by mutation or combined generation-by-generation with other one to build new individuals by reproduction processes which use crossover. Standard implementation of genetic algorithm for natural selection is the roulette wheel. After the selection process, the selected individuals are used as input to other genetic operators: crossover and mutation. Crossover operator combines two strings of chromosomes, but mutation modifies a few bits in a single chromosome.

3 Genetic Seam Carving

In this section, we present our proposal called Genetic Seam Carving (GSC). The idea behind our proposal is to put Genetic Algorithms and Seam Carving to work together according to an energy function as fitness for guiding our approach into useful solutions. In the following subsections more details are presented.

3.1 Individuals or Chromosomes

Our individual is composed only by a single chromosome and it is defined as $C = [g_1, \ldots, g_{i-1}, g_{i=p}, g_{i+1} \ldots, g_m]$, where m is the image width (also the individual) and p is the pivot position. Each gene has an integer value bounded as follows.

$$g_i \in \begin{cases} [1, m]\,, & \text{if } i = p; \\ [-1, 1]\,, & \text{otherwise.} \end{cases}$$

The pivot indicates the seam construction starting point. The function $f_v(.)$ maps a gene to its corresponding coordinate in the image and is defined as

$$f_v(i) = \begin{cases} g_i, & \text{if } i = p; \\ g_i + f_v(i-1), & \text{if } i > p; \\ g_i + f_v(i+1), & \text{if } i < p. \end{cases} \tag{2}$$

The transformation of an individual into a seam is given by converting its genes into coordinates. The definition of a vertical seam is now $s = \{(i, f_v(i))\}_{i=1}^{m}$. This notation is adopted because it must be guaranteed that an individual maps a 8-connected path, $|f_v(i) - f_v(i+1)| \leq 1, \forall i$ s.t. $1 \geq i \geq m$, so the $f_v(.)$ function complies with this domain restriction. To illustrate the transformation, let $C_1 = [0, -1, 2^*, 0]$ and $C_2 = [3^*, 1, -1, 0]$ be two individuals, where the * indicates the pivot location. The corresponding seams are, $s_1 = \{(1,1), (2,1), (3,2), (4,2)\}$ and $s_2 = \{(1,3), (2,4), (3,3), (4,3)\}$, respectively. We recall that our approach uses a single point crossover operator and an uniform mutation operator. These operators are quite suitable, once our pivot position is fixed at each GAs process.

3.2 Fitness Function

The main idea of our fitness function is to give seams with lower energy higher fitness values. We used edge detection through the Sobel operator as image energy function, as suggested in [1]. Formally, let $e(.)$ be an energy function that yields the importance of a pixel at the coordinate (i, j), the *sobel* function yields the information about the contour, where $0 \leq sobel(i, j) \leq 1$. Now we define the seam cost function E as the sum of its pixels energy

$E(s) = \sum sobel(i,j), \forall (i,j) \in s$. Thus, we define the *fitness*, as the objective function, by

$$fitness(s) = \begin{cases} 0 & \text{, if } s - I = \varnothing; \\ \dfrac{m - E(s)}{m} & \text{, otherwise.} \end{cases} \tag{3}$$

A seam during the crossover or mutation may produce any coordinate out of the image bounds ($s - I = \varnothing$), such as $C_3 = [2^*, -1, -1, 0]$ which produces an invalid seam $s_3 = \{(1,2),(2,1),(3,0),(4,-1)\}$. These kind of seams will be given low fitness value to reduce the probability of mutation and crossover. In fact, their genetic material will be left out of next population.

3.3 Multi-seam Carving

As stated before, we desire to obtain a set of feasible solutions and solutions surround that one with best fitness for improve our proposal in a multi-seam carving way. To do so, we first discard individuals with fitness values under the fitness mean μ_{fit} for non-zero fitness individuals. This set of such individuals is stood for $\mathbb{S}^*$. The idea of Multi-seam carving in our approach is to search in the neighborhood of the individuals that belong to $\mathbb{S}^*$ in order to obtain other seams as good as those ones in $\mathbb{S}^*$. For each $s_i \in \mathbb{S}^*$, we generate k-valid neighbor seams $\{s_\alpha\}_{\alpha=1}^{k}$ by changing the pivot gene value, where $1 \leq |f_v(p_i) - f_v(p_\alpha)| \leq k, \forall \alpha \in [1,k]$. We highlight that changing the pivot also results in changing the other gene values besides pivot for a certain seam.

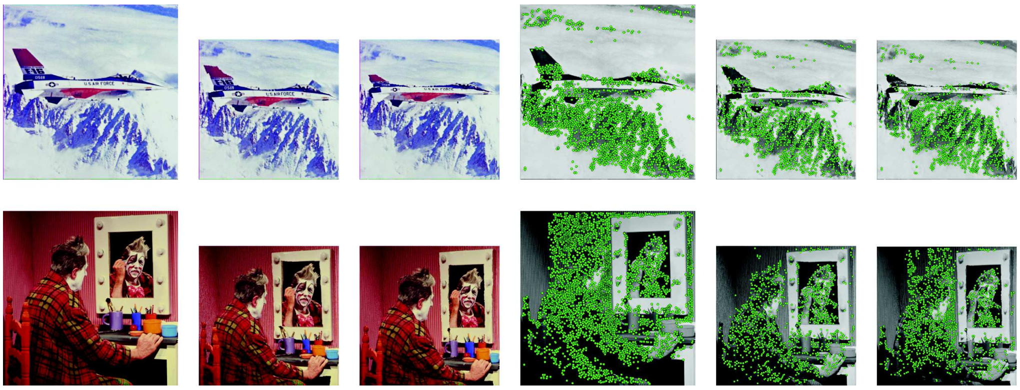
3.4 Algorithm for Genetic Seam Carving

The Algorithm for Genetic Seam Carving is presented below. Take into account that t is the current generation and t_{max} is the max generation number.

while image is not retargeted **do**
    generate randomly the pivot position p;
    generate initial population $P(0)$ with the previously pivot generated;
    for $t = 1$ **to** t_{max};
        select chromosomes from $P(t-1)$ to apply genetic operators;
        apply crossover and mutation on selected chromosomes;
        compute fitness value for each chromosome;
        add 1 to t;
    end for
    remove invalid individuals (with fitness equals zero);
    compute μ_{fit};
    remove individuals under μ_{fit} to get $\mathbb{S}^*$;
    generate k-valid seams $\{s_\alpha\}_{\alpha=1}^{k}$ where $1 \leq |f_v(p_i) - f_v(p_\alpha)| \leq k, \forall \alpha \in [1,k]$
    carve image with the resulting set $\mathbb{S}^* \cup \{s_\alpha\}_{\alpha=1}^{k}$.
end while

4 Experiments and Discussion

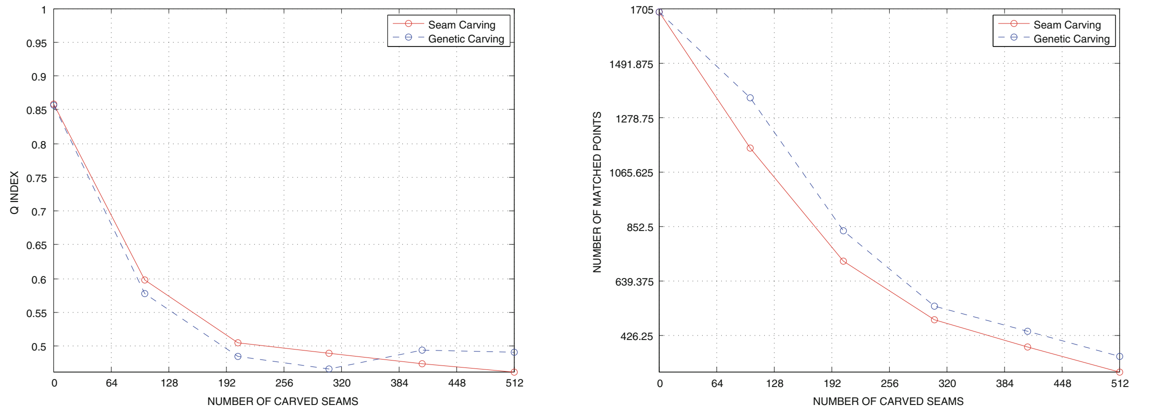
Initially, we adjust some parameters that guide the GA behavior, namely the chromosome size, the population size P_S and the number of generations G_N to evolve. Each of these parameters directly affects memory space or computational time requirements, or both. We choose to keep the population size constant along all generations. We developed an application experiment to assess the GSC performance. For each image in the IVC database [7], we reduced their height and width by 20 %. For the GSC, we carried out this experiment for 10 times because, according to the GA convergence, the results may vary at each experiment. The results can be seen in Fig. 2.



(a) Input. (b) SC. (c) GSC. (d) Input. (b) SC. (c) GSC.

Fig. 2. Worse and best cases of SC and GSC (see Table 1). Columns (a)–(d) show the input images and the interest points found. Columns (b)–(e) show the outputs from SC and the matched points, respectively. The outputs from SC and the matched points are showed in columns (c)–(f).

We express the visual impact caused by carving seams as the result of similarity obtained by the SSIM (Structural SIMilarity) index [13]. Since we have images with different sizes, it is not possible to compute SSIM directly. In this case a technique SIFT-based SSIM [2] is applicable. SIFT (Scale-invariant feature transform) is used to match corresponding interest points between the images before and after carving. Then, for each matched interest point we center a window w, 50×50, and then, compute the SSIM index between both. So now, we define the Q index as the mean of the SSIM index between each matched windows of the original (w) image and the retargeted one (w'), as: $Q_{I'} = \frac{1}{k}\sum_{j=1}^{k} SSIM(w_j, w'_j)$, where k is the number of matched points $\in I'$. As the SSIM index has the maximal bound equals to 1, we assume that a value close to 1 for a given pair of images indicates high similarity. As the carving proceeds removing several seams, high energy pixels are inevitably removed. So, in real case applications, the Q index decreases as more seams are removed, as is illustrated in Fig. 3. Table 1 summarizes the results obtained by the experiments. Q_{SC} and Q_{GSC}: the Q index from the original and the retargeted image



(a) The Q index. (b) Number of matched interest points.

Fig. 3. This metrics are from Lena image, by retargeting 50 % of its width and height. Image (a) shows the quality index Q and image (b) is the number of matched interest points using SC (solid) and GSC (dashed).

by SC and GSC, respectively; $\sigma_{Q_{GSC}}$: the standard deviation for the 10 retargeted images by GSC; $\#P_{SC}$ and $\#P_{GSC}$: the percentages of preserved interest points matched between the original and the retargeted by SC and GSC, respectively. In the case of GSC, we have the average quality index of 10 retargeted images, $Q_{GSC} = \frac{1}{10}\sum_{i=1}^{10} Q(I, I_{GSC_i})$. During our tests, we noted that all 10 carved images generally have similar quality. This observation is confirmed by the very low standard deviation σ_{GSC} shown in the Table 1. Most of Q_{GSC} results showed values close to the Q_{SC}. But, when we consider only the number of matched interest points as a quality metric, GSC outperforms SC in most results. We assume that the optimal and non-optimal seams found helped at the preservation of the interest points during the retargeting.

Table 1. The quality index Q from the images in the IVC database.

Metric	Avion	Barba	Boats	Clown	Fruit	House	Isbabe	Lena	Mandr	Pimen
Q_{SC}(%)	72.91	50.96	65.69	64.98	61.09	56.43	61.93	65.49	52.80	66.04
Q_{GSC}(%)	65.42	**51.67**	**68.55**	**69.45**	**62.69**	52.61	58.18	63.11	47.80	**69.48**
$\sigma_{Q_{GSC}}$	0.0023	0.0002	0.0001	0.0009	0.0002	0.0000	0.0002	0.0000	0.0002	0.0001
$\#P_{SC}$ (%)	61.91	45.22	51.47	38.66	49.71	50.09	37.75	48.86	26.56	55.67
$\#P_{GSC}$ (%)	60.18	**64.38**	50.16	**45.76**	**50.66**	**56.32**	**46.00**	**64.16**	**31.13**	46.81

A present limitation is that GSC not always achieve the optimal seam as in SC, but the seams computed are still valid. At glance we can highlight the fixed population size and number of generations restricting the search. The population size and the number of generations impact directly on the result quality.

5 Conclusion

We proposed a new formulation for the image retargeting problem in the framework of genetic algorithms. Our experiments show that this new formulation can produce image quality similar to the traditional Seam Carving. In some cases, Genetic Seam Carving outperforms Seam Carving according to the number of matched interest points preserved. Our current research seeks out distinct energy functions from which the Genetic Algorithms can benefit. Also, we intend to explore different strategies to choose chromosomes to eliminate at each iteration. In particular, the constant population size and the numbers of generations seems to be very restrictive.

References

1. Avidan, S., Shamir, A.: Seam carving for content-aware image resizing. ACM Trans. Graph. **22**(3), 277–286 (2007)
2. Azuma, D., Tanaka, Y., Hasegawa, M., Kato, S.: Ssim based image quality assessment applicable to resized images. IEICE Technical report (2011)
3. Conger, D.D., Kumar, M., Radha, H.: Multi-seam carving via seamlets. In: IS&T/SPIE Electronic Imaging, p. 78700H. International Society for Optics and Photonics (2011)
4. Conger, D.D., Radha, H., Kumar, M.: Seamlets: content-aware nonlinear wavelet transform. In: 2010 IEEE International Conference on Acoustics Speech and Signal Processing (ICASSP), pp. 1450–1453. IEEE (2010)
5. Domingues, D., Alahi, A., Vandergheynst, P.: Stream carving: an adaptive seam carving algorithm. In: 2010 17th IEEE International Conference on Image Processing (ICIP), pp. 901–904, September 2010
6. Hashemi, S., Kiani, S., Noroozi, N., Moghaddam, M.E.: An image contrast enhancement method based on genetic algorithm. Pattern Recogn. Lett. **31**(13), 1816–1824 (2010). Meta-heuristic Intelligence Based image Processing
7. Le Callet, P., Autrusseau, F.: Subjective quality assessment irccyn/ivc database (2005). http://www.irccyn.ec-nantes.fr/ivcdb/
8. Mishiba, K., Ikehara, M.: Seam merging for image resizing with structure preservation. In: 2011 IEEE International Conference on Acoustics Speech and Signal Processing (ICASSP), pp. 1001–1004. IEEE (2011)
9. Rubinstein, M., Shamir, A., Avidan, S.: Improved seam carving for video retargeting. ACM Trans. Graph. **27**(3), 16:1–16:9 (2008)
10. Szeliski, R., Zabih, R., Scharstein, D., Veksler, O., Kolmogorov, V., Agarwala, A., Tappen, M., Rother, M.: A comparative study of energy minimization methods for markov random fields with smoothness-based priors. IEEE Trans. Pattern Anal. Mach. Intell. **30**(6), 1068–1080 (2008)
11. Tao, W.-B.: Image segmentation by three-level thresholding based on maximum fuzzy entropy and genetic algorithm. Pattern Recogn. Lett. **24**(16), 3069–3078 (2003)
12. Vaquero, D., Turk, M., Pulli, K., Tico, M., Gelfand, N.: A survey of image retargeting techniques. In: SPIE Optical Engineering+ Applications, p. 779814. International Society for Optics and Photonics (2010)
13. Wang, Z., Bovik, A.C., Sheikh, H.R., Simoncelli, E.P.: Image quality assessment: from error visibility to structural similarity. IEEE Trans. Image Process. **13**(4), 600–612 (2004)
14. Whitley, D.: A genetic algorithm tutorial. Stat. Comput. **4**, 65–85 (1994)
15. Yan, Z., Chen, H.: A study of image retargeting based on seam carving. In: 2014 Sixth International Conference on Measuring Technology and Mechatronics Automation (ICMTMA), pp. 60–63. IEEE (2014)