An improved Genetic Algorithms-based Seam Carving method

Conference Paper · October 2015

DOI: 10.1109/LA-CCI.2015.7435947

2 authors:

Saulo Anderson Freitas de Oliveira
Universidade Federal do Ceará

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

An Improved Genetic Algorithms-based Seam Carving Method

Saulo A. F. Oliveira
Department of Teleinformatics
Federal Institute of Ceará, IFCE
Fortaleza, Ceará
Email: saulo.oliveira@ppget.ifce.edu.br

Ajalmar R. Rocha Neto
Department of Teleinformatics
Federal Institute of Ceará, IFCE
Fortaleza, Ceará
Email: ajalmar@ifce.edu.br

***Abstract*—In a previous work, we proposed a new method to retarget images, i.e. to resize an image on both vertical and horizontal orientation, based on Genetic Algorithms called Genetic Seam Carving. The previous work presented a new individual modeling to represent connected pixels paths (seams) that were handled by Genetic Algorithms for image retargeting. This modeling has an important drawback, a fixed base-pixel position, the pivot. This condition is not interesting when the pivot is in a region of interest, such as an object one wants to remain in the image. Thus, our novel proposal presented in this paper aims at solving this issue, which could decrease the retargeting performance so that flexible seams are achieved and evolved. To do so, we also present new genetic operators for out target problem. As expected, our proposal outperforms the Seam Carving and the previous proposal in terms of image quality.**

***Index Terms*—Genetic Algorithms; Image Retargeting; Seam Carving; SIFTFlow**

I. Introduction

In image processing, retargeting is a method which aims at adjusting input images into arbitrary dimensions and also preserving regions of interest (ROIs) from those input images. In other words, the idea is to resize an image while taking its content into consideration to preserve important regions and minimize distortions. For a reduction in size as proposed in this paper, retargeting method finds and remove unimportant pixels from the image causing minimal visual impact. The retargeting problem can be stated as follows. Let $\boldsymbol{I}$ be an input image of size $m \times n$, where m and n are, respectively, the number of rows and columns. Similarly, let $\boldsymbol{I'}$ be an output image of size $m' \times n'$, where $m' < m$ and $n' < n$ for reduction. The objective is then to produce a new image $\boldsymbol{I'}$ which will be a good representative of the original image $\boldsymbol{I}$ [1].

Several content-aware image retargeting methods have been proposed in order to preserve a piece of the input image content or even to obtain these less important ROIs [2]. An interesting survey of retargeting methods is presented in [3]. Seam Carving is an example, which finds connected pixel paths, also called seams [4]. In the image reduction context, Seam Carving (SC) method finds and then removes seams which lies in less important ROIs.

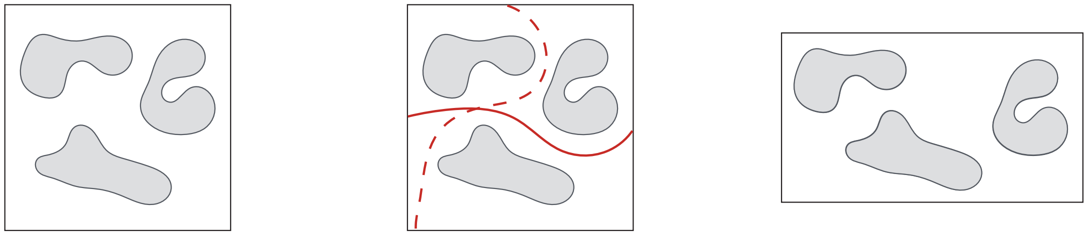
Besides the Seam Carving, several Computational Intelligence methods have been applied in image processing, in particular Genetic Algorithms (GAs) [5], [6]. GAs are optimization tools and therefore they can be used to generate useful solutions to search problems. Due to the underlying features of GAs, 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 classical mathematical methods. We have not found, for the best of our knowledge, any other work than our previous or current proposals dealing with Genetic Algorithms and Seam Carving for retargeting. This paper is all about improving Genetic Seam Carving by having flexible base-pixel instead of fixed ones.

In this paper, we propose an improved Genetic Algorithms-based Seam Carving method by flexible individuals, feature added by flexible pivots. In a nutshell, the method uses GAs for searching seams that minimize a fitness function based in a pixel relevance measure (energy function) and then gets rid of those seams have optimal energy function values. This process is carried out over and over up to reaching the desired number of rows and columns in a multi-seam removal approach (see [7] and [8] for other multi-seam approaches). In our proposal, we highlight two main contributions, a new individual modeling for a seam and new genetic operators.

The remaining part of this paper is organized as follows. In Section II is presented some methods to achieve the retargeting in a Seam Carving sense. In Section III we recall the Seam Carving method and we briefly describe Genetic Algorithms. So, we present our proposal in Section IV. After that, we describe the experiments carried out in Section V. Finally, we present some conclusion remarks in Section VI.

II. Related Work

After the publication of the Seam Carving paper, others proposed improvements to the method. The problem of finding the optimal seam as a graph cut optimization was formulated in [9]. The formulation is then extended to video by finding 2D seams, which are removed from 3D space-time volumes. After that, a new retargeting method called Stream Carving based on SC for streams (wider seams) was introduced [8]. 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



(a) Original Image. (b) Seams arranged. (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).

and may be enlarged without causing any visual distortion. Besides the presented works, another improvement is concerned with finding multiple seams simultaneously by extending the seamlet transform [10] in order to carve a few seams at each retargeting step. These multi-seam carving approaches were explored in [7] and [11]. Furthermore, a merging approach with structure preservation was proposed in [12], in which structural distortion is minimized by merging a two-pixel-width seam into a single-pixel-width one.

III. Background

A. Seam Carving

Seam Carving [4] searches and evaluates feasible seams and chooses the one with the lowest cost of processing. First of all, let (x, y) be the coordinates for the pixel located at row x and column y of an image $\boldsymbol{I}$ and consider the coordinate system with the first pixel $(0, 0)$ located at the upper left corner. Moreover, let a vertical seam be defined as

$$\begin{array}{rcl} \boldsymbol{s^v} & = & \{(x, y) | y = \alpha(x)\}_{x=1}^{m} \\ \text{subject to} & & \forall x, |\alpha(x) - \alpha(x+1)| \leq 1, \end{array} \tag{1}$$

where α is a mapping $\alpha : [1, \ldots, m] \rightarrow [1, \ldots, n]$, and, similarly, for horizontal seam as

$$\begin{array}{rcl} \boldsymbol{s^h} & = & \{(x, y) | x = \beta(y)\}_{y=1}^{n} \\ \text{subject to} & & \forall y, |\beta(y) - \beta(y+1)| \leq 1, \end{array} \tag{2}$$

where β is a mapping $\beta : [1, \ldots, n] \rightarrow [1, \ldots, m]$. Fig. 1 illustrates an ideal retargeting process.

For sake of simplicity, in the following description and notation of Seam Carving, consider vertical seams (the dashed one presented in Fig. 1b) since a similar description and notation for a horizontal seam can be done straightforward. The seam cost is assigned through an energy function $e(x, y)$, 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 [13]. The seam cost function $E(.)$ is now defined by the sum of its pixels energy $E(\boldsymbol{s}) = \sum e(x, y), \forall (x, y) \in \boldsymbol{s}$.

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 $(x = 1)$ and continues to the neighbor pixels in the next row that have the lowest additional cost until the last row $(x = m)$. The cost of a vertical seam that begins at the pixel (x, y) in the image I is computed by the cumulative minimum energy

$$M(x, y) = e(x, y) + \min \left\{ \begin{array}{l} M(x+1, y-1), \\ M(x+1, y), \\ M(x+1, y+1) \end{array} \right\}, \tag{3}$$

where $e(x, y)$ is the value obtained by the energy function. The optimal vertical seam is given by

$$\boldsymbol{s^{v*}} = \arg\min_{y} \{M(1, y)\}_{y=1}^{n} \tag{4}$$

More details can be found in [4].

B. Genetic Algorithms

Genetic Algorithms (GAs) are a class of evolutionary computation algorithms, that use techniques inspired from biology, such as selection, reproduction (crossover) and mutation [14]. GAs are widely used to solve optimization problems and 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 classical mathematical methods. GAs are also used in problems, in which the search space is too large, making it impracticable to be solved by an exhaustive approach. GAs work by holding a set of individuals, a population which is able to evolve. Each individual is a solution for the target problem, in our case an individual indirectly stands for a seam. Crossover and mutation operators are applied to these individuals to diversify the population and thus create new solutions. Each individual receives a grade (fitness), which indicates its quality as a solution for the given problem. Based on this fitness, some individuals are selected to reproduce or even to be discarded from the population as an attempting to simulate the survival for the fittest until a stop criteria is satisfied. More details concerning Genetic Algorithms can be found in [14].

IV. Proposal

In this section, we present our improved Genetic Seam Carving method, called henceforth GSC^2. This method is based on other proposal we have made recently named Genetic Seam Carving (GSC) [15]. The diferences between them are presented throughout this section whenever necessary. For a successful GA modeling, we must define the individual and the fitness function, as well as using standard or customized genetic operators. We present them from this point on.

A. Genetic Representation

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

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

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

$$f(x) = \begin{cases} g_x, & \text{if } x = p; \\ g_x + f(x-1), & \text{if } x > p; \\ g_x + f(x+1), & \text{if } x < p. \end{cases} \quad (5)$$

The transformation of an individual into a seam is given by converting its genes into coordinates. A definition of a vertical seam is given by $\boldsymbol{s^v} = \{(x, f(x))\}_{i=1}^{m}$ and for a horizontal one as $\boldsymbol{s^h} = \{(f(y), y)\}_{i=1}^{n}$. This notation is adopted because an individual must maps a 8-connected. The function $f(.)$ also complies with following domain restriction $|f(x) - f(x+1)| \leq 1$ s.t. $, \forall i, 1 \geq i \geq m$ for a vertical seam. As an example, let $\boldsymbol{c_1}$ be an individual where the symbol $*$ indicates the pivot gene location, $\boldsymbol{c_1} = [0, -1, \mathbf{2^*}, 0]$, so the corresponding seam is $\boldsymbol{s_1^v} = \{(1,1), (2,1), (3,2), (4,2)\}$. Similar idea is used for a horizontal seam.

B. Genetic Operators

As stated, an important drawback of modeling an individual with fixed base pixel in the default GSC is the absence of flexibility to move itself to anywhere on the image during the individual evolution. As the individuals are generated at random, pivots can unfortunately be placed in regions of interest. Due to that, those individuals evolve but not as good as they would do, see Fig. 2. We will see more details below.

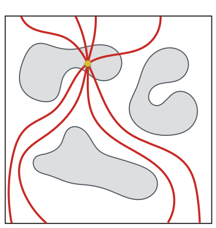


Fig. 2: Fixed pivot for a same individual at distinct generations.

In the default GSC, each individual had the pivot at the same position in order to directly apply the single-point crossover operation. This is the default crossover as we already know except for the pivots, since this happens without changing the pivot values. The pivot values go through individuals but they still being the same. It is straightforward that such way of working is undesired. Anyway, on on hand, this is good in terms of simplicity, but on the other hand, this is also a drawback that comes up with this modeling because if you take a closer look you can realize that all the pivots are at the same image row (for a vertical seam) or column (for a horizontal seam).

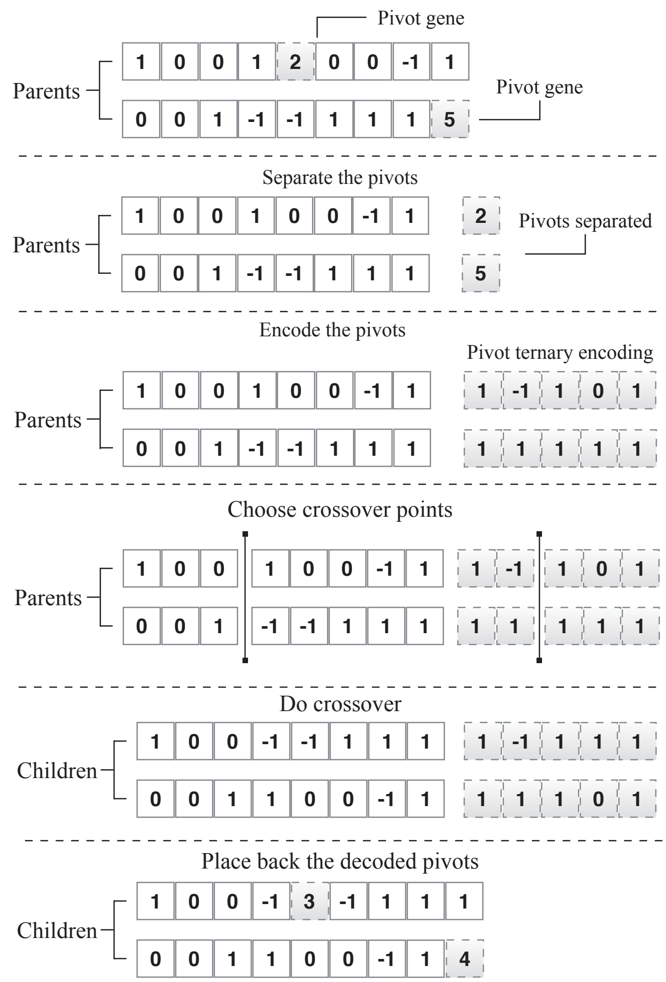


Fig. 3: Crossover operator.

Our proposal for the crossover operator is based on also changing the pivot values by reproducing them. By also changing the pivot values, we mean to generate new values beyond those we got in the beginning. The idea is to encode the integer value into a ternary one, to reproduce them as usual and then to convert these resulting ternary values to integer ones again. These are the new pivots for the individuals which take part in the crossover operation. This process is presented in the Fig. 3.

In the default GSC, k individual positions are selected at random for mutation. Thus, we have the probability $\frac{k}{m}$ or $\frac{k}{n}$ of choosing the pivot, since we have only one pivot from m or n possibilities. However, there is not guarantee the pivot will be chosen. So, our proposal is to choose a random number of genes to suffer mutation as previously; nevertheless, in this case, the pivot is always selected so that we select $k+1$ positions. One of the chosen position is mandatorily the pivot. Therefore, using this customized mutation operator, the pivot gene will have a change in position as shown in Fig. 4.

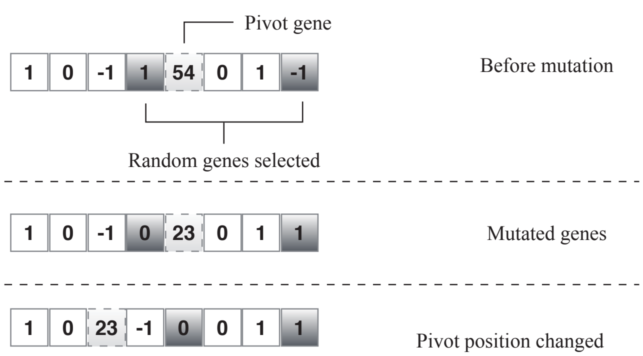


Fig. 4: Mutation operator.

C. Fitness Function

The fitness function for GSC^2 (as well as for the default GSC) gives seams that cause less degradation lower fitness values. In an ideal retargeting scenario, the less object features are changed, the less visual impact is perceived by the observer. Seams that are far from interest regions are preferable, since they minimize the overall distortion. We use edge detection through the Sobel operator as image energy function, as suggested in [4]. Formally, let $e(.)$ be an energy function that yields the importance of a pixel at the coordinate (x, y), the $sobel$ function yields the information about the contour, where $0 \leq sobel(x, y) \leq 1$. Thus, we define the $fitness$, as the objective function, by

$$fitness(\boldsymbol{s}) = \begin{cases} |\boldsymbol{s} - \boldsymbol{I}| & \text{, if } s - I \neq \varnothing; \\ \dfrac{E(\boldsymbol{s})}{n} & \text{, otherwise.} \end{cases} \tag{6}$$

where $|\mathbb{X}|$ stands for the cardinality of set $\mathbb{X}$. A seam during the crossover or mutation may produce any coordinate out of the image bounds ($s - \boldsymbol{I'} \neq \varnothing$), such as $c_2 = [2^*, -1, -1, 0]$ which produces an invalid seam $s_2 = \{(1, 2), (2, 1), (3, 0), (4, -1)\}$. These kind of seams will be given high fitness value to reduce the probability of mutation and crossover. In fact, their genetic material will be left out of next population.

D. Multi-seam Carving

The idea of Multi-seam carving for the default GSC is to search in the population for feasible individuals with fitness values under a certain threshold to process in a row. Our proposal makes it different, we select only those individuals from the evolved population, which have the fitness values equal to the fittest one, since it is common to have more than one seam with the highest fitness value. Therefore, we select fewer seams but with high quality. This set of such individuals is stood for $\mathbb{S}^*$.

E. Algorithm

The Algorithm for Genetic Seam Carving is presented bellow. Let t stand for the current generation and t_{max} stand for the max generation number.

Data: an image $\boldsymbol{I}$ $(m \times n)$ and the ***new size*** $(m' \times n')$.
Result: $\boldsymbol{I}$ retargeted.
while *image is not retargeted* **do**
  generate initial population $P(0)$;
  for $t = 1$ ***to*** t_{max} **do**
    select individuals from $P(t-1)$;
    apply genetic operators on selected individuals;
    compute fitness value for each individual;
  end
  rescue the fittest individuals from $P(t)$ to get $\mathbb{S}^*$;
  foreach $\boldsymbol{s} \in \mathbb{S}^*$ **do**
    carve $\boldsymbol{s}$ from $\boldsymbol{I}$;
    if *image is retargeted* **then**
      break foreach;
    end
  end
end
return $\boldsymbol{I}$;

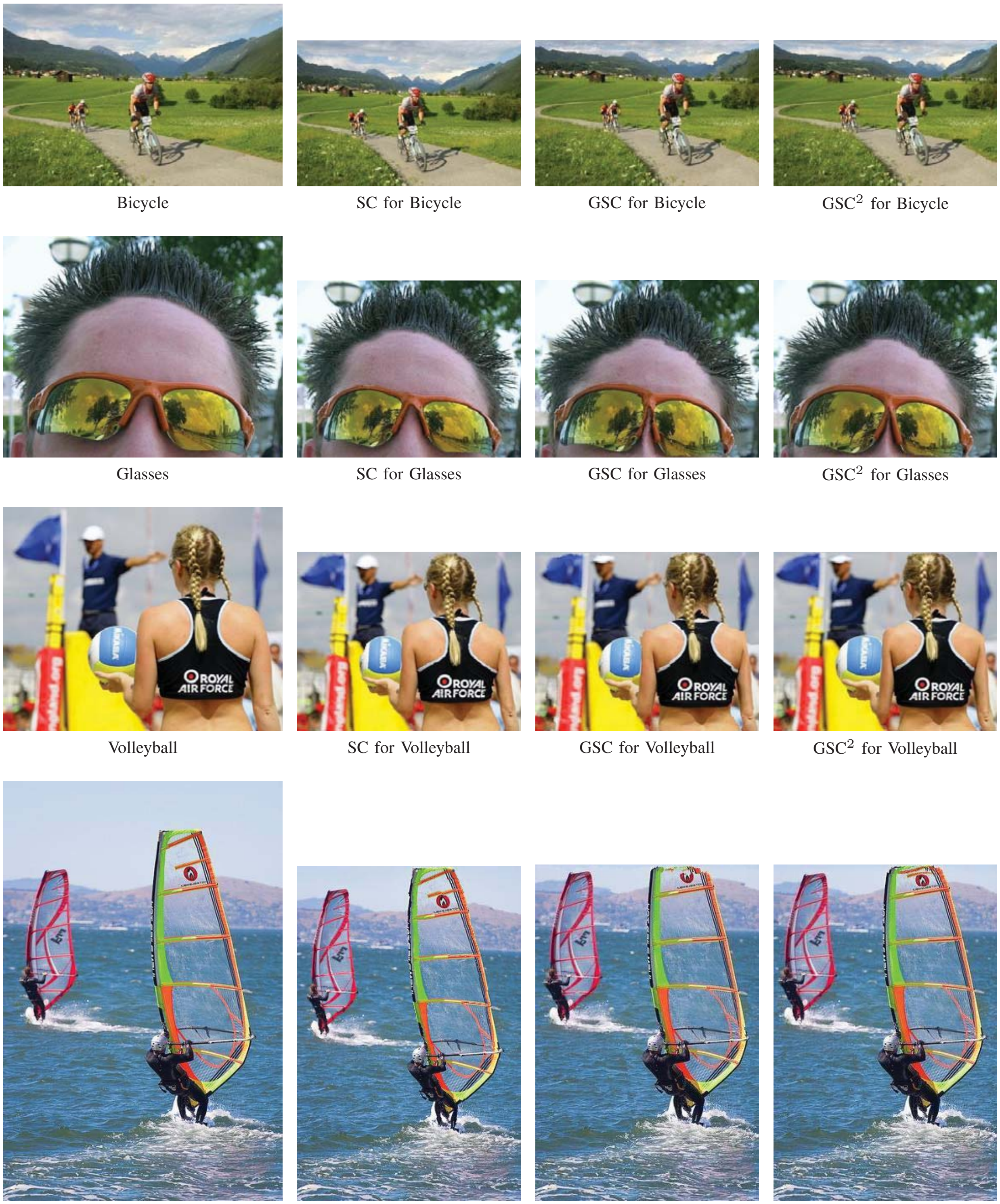
Algorithm 1: The Algorithm for Genetic Seam Carving.

V. Results and Discussion

We carried out some simulations to assess our proposal GSC^2 for image retargeting. We compared GSC^2 to SC and GSC to asses the distortion that naturally comes from losing content in a carving process. In our simulations, we perform a reduction of 20% over a group of 4 images. The magnitude of the gradient through Sobel was used as energy function for both approaches, since it worked quite well [4]. The results for GSC^2, SC and GSC are shown in Fig. 5.

Computational image distance metrics can predict human retargeting perception and have been widely used as image retargeting quality assessment [16]. In such metrics, a cost of transforming the reference image into the retargeting one is represented as a distance. This cost is related to the distortion of the retargeted image. Also, since we have images with different sizes it is not possible to use most of the image quality assessment algorithms, such as signal-to-noise ratio and structure similarity (SSIM) [17].

In this work, we used SIFT flow [18] for image quality assessment. In SIFT flow, a SIFT descriptor [19] is extracted at each pixel to characterize local image structures and encode contextual information. A discrete, discontinuity preserving, flow estimation algorithm is used to match the SIFT descriptors between two images. SIFT flow measures the distortion



Bicycle	SC for Bicycle	GSC for Bicycle	GSC^2 for Bicycle
Glasses	SC for Glasses	GSC for Glasses	GSC^2 for Glasses
Volleyball	SC for Volleyball	GSC for Volleyball	GSC^2 for Volleyball
Surfers (a)	SC for Surfers (b)	GSC for Surfers (c)	GSC^2 for Surfers (d)

Fig. 5: Results from experiment. Column (a) are the original images, column (b) the outputs from SC, column (c) and (d) are the outputs from GSC and GSC^2, respectively.

of the retargeted image by the distance between the reference and retargeted images, which is represented as the energy cost from pixel-matching correspondence between the reference and retargeted images [18]. In short, the lower the energy cost, the less the visual impact. As the SIFT flow score has the minimal value 0, we assume that a value close to 0 for a given pair of images indicates high similarity.

As several seams are removed by retargeting, some regions are inevitably modified and the distance increases as more as the seams are carved. This is depicted in Fig. 6. In the Table I, one can see the obtained results of SIFT flow for each retargeted image from the experiment. Parameters $\sigma = 0.0033$, $\alpha = 2$ and $d = 40$ are fixed in our experiments.

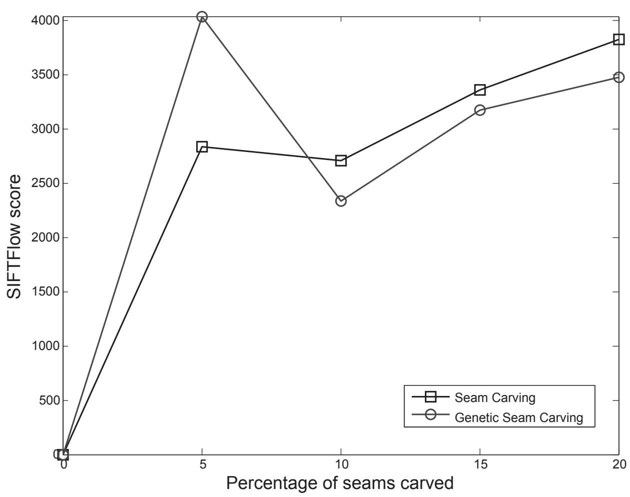


Fig. 6: SIFT flow values for a size reduction of 20% for Surfers.

TABLE I: Comparison of the quality index.

Method	Bicycle	Glasses	Surfers	Volleyball
SC	3389	5383	3827	5032
GSC	3103	5411	3556	4927
GSC^2	**3009**	**5281**	**3479**	**4342**

VI. Conclusion

In this work, a new formulation for the image retargeting problem in the framework of Genetic Algorithms was proposed. As one can see in the results, our proposal GSC^2 outperforms Seam Carving and the previous proposal GSC in terms of image quality. We support that the stochastic character of Genetic Algorithms lead us to feasible seams. Nowadays, we are working to build a new energy function based on the Speed Up Robust Features (SURF) and a multi-objective fitness function that uses information about the amount of energy inserted after carving. We also intend to explore different approaches in order to improve chromosome quality and genetic operators to achieve better and faster results.

Acknowledgment

This work was partially supported through CAPES and Federal Institute of Ceará.

References

[1] A. Shamir and O. Sorkine, "Visual media retargeting," in *ACM SIGGRAPH ASIA 2009 Courses*. ACM, 2009, p. 11.

[2] D. Vaquero, M. Turk, K. Pulli, M. Tico, and N. Gelfand, "A survey of image retargeting techniques," in *SPIE Optical Engineering+ Applications*. International Society for Optics and Photonics, 2010, pp. 779 814–779 814.

[3] Z. Yan and H. Chen, "A study of image retargeting based on seam carving," in *Measuring Technology and Mechatronics Automation (ICMTMA), 2014 Sixth International Conference on*. IEEE, 2014, pp. 60–63.

[4] S. Avidan and A. Shamir, "Seam carving for content-aware image resizing," *ACM Trans. Graph.*, 2007.

[5] S. Hashemi, S. Kiani, N. Noroozi, and M. E. Moghaddam, "An image contrast enhancement method based on genetic algorithm," *Pattern Recognition Letters*, vol. 31, no. 13, pp. 1816 – 1824, 2010, meta-heuristic Intelligence Based Image Processing. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0167865509003365

[6] W.-B. Tao, J.-W. Tian, and J. Liu, "Image segmentation by three-level thresholding based on maximum fuzzy entropy and genetic algorithm," *Pattern Recognition Letters*, vol. 24, no. 16, pp. 3069–3078, 2003.

[7] D. D. Conger, M. Kumar, and H. Radha, "Multi-seam carving via seamlets," in *IS&T/SPIE Electronic Imaging*. International Society for Optics and Photonics, 2011, pp. 78 700H–78 700H.

[8] D. Domingues, A. Alahi, and P. Vandergheynst, "Stream carving: An adaptive seam carving algorithm," in *Image Processing (ICIP), 2010 17th IEEE International Conference on*, Sept 2010, pp. 901–904.

[9] M. Rubinstein, A. Shamir, and S. Avidan, "Improved seam carving for video retargeting," *ACM Trans. Graph.*, pp. 16:1–16:9, Aug. 2008. [Online]. Available: http://doi.acm.org/10.1145/1360612.1360615

[10] D. Conger, H. Radha, and M. Kumar, "Seamlets: Content-aware nonlinear wavelet transform," in *Acoustics Speech and Signal Processing (ICASSP), 2010 IEEE International Conference on*, March 2010, pp. 1450–1453.

[11] D. D. Conger, H. Radha, and M. Kumar, "Seamlets: content-aware nonlinear wavelet transform," in *Acoustics Speech and Signal Processing (ICASSP), 2010 IEEE International Conference on*. IEEE, 2010, pp. 1450–1453.

[12] K. Mishiba and M. Ikehara, "Seam merging for image resizing with structure preservation," in *Acoustics, Speech and Signal Processing (ICASSP), 2011 IEEE International Conference on*. IEEE, 2011, pp. 1001–1004.

[13] R. Szeliski, R. Zabih, D. Scharstein, O. Veksler, V. Kolmogorov, A. Agarwala, M. Tappen, and C. Rother, "A comparative study of energy minimization methods for markov random fields with smoothness-based priors," *Pattern Analysis and Machine Intelligence, IEEE Transactions on*, vol. 30, no. 6, pp. 1068–1080, June 2008.

[14] D. Whitley, "A genetic algorithm tutorial," *Statistics and Computing*, vol. 4, pp. 65–85, 1994.

[15] S. Oliveira, F. Bezerra, and A. Rocha Neto, "Genetic seam carving: A genetic algorithm approach for content-aware image retargeting," in *Pattern Recognition and Image Analysis*, ser. Lecture Notes in Computer Science, R. Paredes, J. S. Cardoso, and X. M. Pardo, Eds., vol. 9117. Springer International Publishing, 2015, pp. 700–707. [Online]. Available: http://dx.doi.org/10.1007/978-3-319-19390-8_78

[16] M. Rubinstein, D. Gutierrez, O. Sorkine, and A. Shamir, "A comparative study of image retargeting," in *ACM transactions on graphics (TOG)*, vol. 29, no. 6. ACM, 2010, p. 160.

[17] Z. Wang, A. C. Bovik, H. R. Sheikh, and E. P. Simoncelli, "Image quality assessment: from error visibility to structural similarity," *Image Processing, IEEE Transactions on*, vol. 13, no. 4, pp. 600–612, 2004.

[18] C. Liu, J. Yuen, A. Torralba, J. Sivic, and W. T. Freeman, "Sift flow: Dense correspondence across different scenes," in *Computer Vision–ECCV 2008*. Springer, 2008, pp. 28–42.

[19] D. G. Lowe, "Distinctive image features from scale-invariant keypoints," *International journal of computer vision*, vol. 60, no. 2, pp. 91–110, 2004.