Abstract
Content-aware image resizing is an effective technique that allows to take into account the visual content of images during the resizing process. The basic idea beyond these algorithms is the resizing of an image by considering vertical and/or horizontal paths of pixels (i.e., seams) which contain low salient information. In this paper we exploit the Gradient Vector Flow (GVF) of the image to establish the paths to be considered during the resizing. The relevance of each path is derived from a saliency map obtained by considering the magnitude of the GVF associated to the image under consideration. The proposed technique has been tested, both qualitatively and quantitatively, by considering a representative set of images labeled with corresponding salient objects (i.e., ground-truth maps). Experimental results demonstrate that our method preserves crucial salient regions better than other state-of-the-art algorithms.

Keywords: Content-Aware Image Resizing, Image Retargeting, Visual Saliency, Gradient Vector Flow

1 Introduction
The extensive use of different display devices with different resolution (e.g., on pc, tablet, smartphone, etc.) increases the demand of image resizing techniques which consider the visual content during the scaling process. Standard resizing techniques considering only geometric constraints, such as scaling, can be used only to change the image size (width and height) of a fixed percentage with respect to the original one. 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 salient information (e.g., objects or part of them).

In the last years, several techniques for content-aware image resizing have been proposed [1, 2, 3, 4, 5, 6]. The main aim of a content-aware image resizing is the preservation of relevant visual information into the resized image. Intuitively, the goal is to remove unnoticeable paths of pixels that blend well with their surroundings, and retain the salient pixels.}

Seam Carving, proposed by Avidan et al. in
[1], is probably the most popular approach to address this problem. Such a technique reduces or expands the image by removing or duplicating connected path of pixels (called seams) having low-energy in the map related to the image to be resized. In [1] different strategies have been compared to compute the energy map (e.g., the entropy energy computed for each pixel taking into account a fixed window, the magnitude of the gradient computed on each pixel, a saliency measure of each pixel computed as in [7], etc.). An interesting and powerful extension of standard resizing operators (i.e., scaling, cropping, etc.) and content-aware based algorithms (i.e., seam carving) can be obtained by their combination, as proposed by Rubinstein et al. in [2]. They propose an algorithm able to search for the optimal sequence of operators to be applied at each step of the resizing to get better results in terms of visual quality of the final reduced image. A drawback of this approach is that the computational complexity increases due to the use of different operators. Among others, patch-based methods have been also proposed for image retargeting or summarization. Cho et al. [3] suggested an algorithm to find an arrangement of patches of the original image that well fit in the resized image, whereas Pritch et al. [4] introduced a method to find the best Shift-Map which defines the pixel displacement useful to produce the output image. Gallea et al. [5] 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 this last technique, in our previous work [6] we have proposed different strategies to be employed for content-aware image resizing on mobile devices.

In this paper we propose a novel algorithm for content aware image resizing. The technique exploits the properties of Gradient Vector Flow (GVF) [8] to properly select the seams to be removed, without introducing artifacts in the resized image. Specifically, GVF is used to produce a vector field useful to preserve salient information. The proposed approach has been tested and compared, both qualitatively and quantitatively, with respect to state-of-the-art approaches. Experimental results confirm the effectiveness of the proposed approach in terms of preservation of salient regions.

The paper is organized as follows: Section 2 presents the proposed image resizing method. In Section 3 the experimental phase and the results are detailed. Finally, conclusions and hints for future works are given in Section 4.

2 PROPOSED METHOD

One of the main issues related to the content aware image resizing is the preservation of the salient information contained in the image under analysis. To this aim, our algorithm makes use of the properties of the Gradient Vector Flow (GVF) [8].

GVF is a dense force field [8] useful to solve the classical problems that affect snakes: sensitivity to initialization and poor convergence to boundary concavity. Starting from the gradient of an image, this field is computed through diffusion equations. Formally, GVF is the field $\mathbf{F}$ of vectors $\mathbf{v} = [u, v]$ that minimizes the following energy function:

$$E = \int \int \mu(u_x^2 + u_y^2 + v_x^2 + v_y^2) + |\nabla f|^2|\mathbf{v} - \nabla f|^2$$

where the subscripts represent partial derivatives along $x$ and $y$ axes respectively, $\mu$ is a regularization parameter, and $|\nabla f|$ is the gradient computed from the intensity of the input image. Due to the above formulation, GVF field values are close to $|\nabla f|$ values where this quantity is large (energy $E$, to be minimized, is dominated by $|\nabla f|^2|\mathbf{v} - \nabla f|^2$), and are slow-varying in ho-
Figure 2: An example of seam generation. Among the three possible directions (in red) the one closest to the GVF norm orientation (in blue) is selected.

Figure 3: Image Resizing Based on GVF

Algorithm 1: Image Resizing Based on GVF

| Input: I, N |
| begin |
| for iteration = 1 to N do |
| \[ F_x, F_y \leftarrow \text{ComputeGVF}(I) \] |
| \( \{s_1, \ldots, s_K\} \leftarrow \text{SeamsComputation}(I, F_x, F_y) \) |
| \( \{c_1, \ldots, c_K\} \leftarrow \text{SeamsCost}(\{s_1, \ldots, s_K\}, [F_x, F_y]) \) |
| \( k = \arg \min_{c_k} \{c_1, \ldots, c_K\} \) |
| \( I \leftarrow \text{RemoveSeam}(I, s_k) \) |
| end |

mogeneous regions (the energy \( E \) is dominated by the sum of the squares of the partial derivatives of GVF field). An example of GVF field is shown in Fig. 1.

GVF is stronger close to the edges of objects within the image. We use this vector field to effectively drive the selection of pixels belonging to a seam. The proposed algorithm works as follows (Fig. 3). Let \( I \) be an image with \( H \) rows and \( W \) columns to be resized with respect to the width. First the GVF and its normalized version \( GVF_{\text{norm}} \) (i.e., each vector with norm one) are computed from the input image \( I \) considering the luminance channel. Several seams \( \{s_1, s_2, \ldots, s_K\} \) are then built (i.e., \text{SeamsComputation}) starting from the top of the image making use of the directions of the already computed \( GVF_{\text{norm}} \). It is worth noting that the directions suggested by \( GVF_{\text{norm}} \) cannot be always followed. Specifically, considering a generic pixel \( p \) of coordinates \((i, j)\) belonging to a seam \( s_k \), the next element of \( s_k \) has to be chosen among \((i + 1, j - 1), (i + 1, j), (i + 1, j + 1)\). These pixels can be related to the following unit vectors \((-\sqrt{2}/2, -\sqrt{2}/2), (0, 1), (\sqrt{2}/2, -\sqrt{2}/2)\). Among the aforementioned unit vectors associated to a specific direction, the one making the smallest angle with \( GVF_{\text{norm}}(i, j) \) is hence selected (see Fig. 3).

To this aim, a simple dot product between \( GVF_{\text{norm}}(i, j) \) and the three considered unit vectors is employed. To sum up a generic seam \( s_k \) is built repeating \( H - 1 \) times the aforementioned direction selection algorithm starting from a pixel \( p \) with coordinates \((1, w)\) at the top of the image \((w = 1, \ldots, W) \) at the first iteration of the resizing. The proposed algorithm works similarly for the resizing with respect to the height.

A cost function is then associated to each computed seam considering the sum of the GVF magnitude \( |GVF| \) related to the pixels belonging to the seam. Specifically the cost \( c_k \) of a seam \( s_k \) is computed as follows (i.e., \text{SeamsCost}):\n
\[
 c_k = \sum_{(i,j) \in s_k} |GVF(i, j)| \tag{2}
\]

For the resizing, the seam with the lower cost \( c_k \) is hence removed from the image at each iteration (i.e., \text{RemoveSeam}). The GVF map is then updated and a new iteration of the seam removal algorithm is performed. It is worth noting that the algorithm described above is repeated for each seam to be removed. Specifically, if \( N \) seams have to be removed, the algorithm is repeated \( N \) times.

3 EXPERIMENTAL RESULTS

The performance of a content-aware image resizing algorithm strongly depends on the adopted energy map which captures the salient regions of an image. As described in previous section, we propose to use GVF to build and select the seams during the resizing. In order to evaluate the results of our approach, we compared it with respect to the classic Seam Carving algorithm proposed by Avidan et al. [1] and with respect to the approach recently proposed by Gallea et al. [5]. The approach in [1] is a local-based approach which takes into account the gradient of the image to select the seams to be removed, whereas the one proposed in [5] is a global-based approach in which an objective function is considered to solve an optimization problem. In [5] the product of the gradient of

![Diagram](image-url)
the image and the saliency map proposed by Itti et al. [9] is taken into account as energy map during the resizing.

To properly assess and compare the different methods, we used 50 images from the image database proposed in [10]\(^1\). The salient object of each image is labeled with 9 bounding boxes marked from nine different users. Hence, for each image a ground-truth map related to the salient object is computed through a voting procedure. Specifically, a pixel in the ground-truth map has a saliency cost equal to \(\frac{n}{9}\) if that pixel belongs to \(n \leq 9\) bounding boxes. So, for each image \(I\) of the dataset the computed ground-truth map \(G_I\) denotes the importance of each pixel of the image. In Fig. 4(a) and Fig. 4(e) are shown respectively an image considered in the experiments and its corresponding ground-truth map (i.e., \(G_I\)). Since the aim of content-aware image resizing is to preserve salient regions, in order to evaluate the performances of a specific algorithm \(A\), the following cost function can be taken into account:

\[
Cost(I, A) = \sum_{p \in \psi_A} G_I(p) \quad (3)
\]

where \(\psi_A\) is the final set of pixels removed by employing the algorithm \(A\) during the resizing of the image \(I\), and \(G_I(p)\) indicates the importance of the removed pixel \(p\). This cost can be used to compare the performances of the different involved algorithms. A lower cost value indicates better performances (i.e., more salient pixels are preserved in the resizing). In Fig. 4 is reported an example of an image resizing at 60% of the width obtained by employing the three considered algorithms. Fig. 4(b), (c), (d) correspond to the maps \(\psi_A\) (i.e., removed seams) obtained with the three different algorithms, whereas Fig. 4(f), (g), (h) depict the values \(G_I(p)\) used to compute the cost function in (3) taking into account of one of the three compared algorithms. In Fig. 5 are reported the results obtained by the different algorithms at varying of the percentage of the resizing with respect to width and height. These results have been obtained by averaging the costs computed as in (3) related to the 50 considered images (given a percentage of resizing and a specific algorithm). The proposed method achieves the best results demonstrating that it more effectively preserves salient areas and hence removes less crucial pixels. In Fig. 6 are shown some visual results obtained by resizing the original images at 60% of the width. A visual comparison reveals that the proposed approach better preserves the main salient regions (i.e., the areas with objects).

4 CONCLUSION AND FUTURE WORKS

In this paper we proposed a content-aware image resizing algorithm which exploits information extracted through Gradient Vector Flow to establish the paths to be considered during the resizing of an image. The proposed approach has been compared with respect to state-of-the-art algorithms achieving at least comparable visual results, and outperforming existent strategies in terms of preservation of salient regions. Future works will be devoted to improve the selection of the paths extracted through Gradient Vector Flow by coupling this information with different energy maps able to better capture the

\(1\)Specifically, we selected 50 images from the Image set B. See [10] for more details.
salient regions of an image (e.g., the one proposed by Itti et al. in [9]). Moreover, a blending method will be considered to obtain better visual results for the joining of paths adjacent to the removed seams.

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References