Saliency-Based Selection of Gradient Vector Flow Paths for Content Aware Image Resizing

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***Abstract*— Content-aware image resizing techniques allow to take into account the visual content of images during the resizing process. The basic idea beyond these algorithms is the removal of vertical and/or horizontal paths of pixels (i.e., seams) containing low salient information. In this paper, we present a method which exploits the gradient vector flow (GVF) of the image to establish the paths to be considered during the resizing. The relevance of each GVF path is straightforward derived from an energy map related to the magnitude of the GVF associated to the image to be resized. To make more relevant, the visual content of the images during the content-aware resizing, we also propose to select the generated GVF paths based on their visual saliency properties. In this way, visually important image regions are better preserved in the final resized image. The proposed technique has been tested, both qualitatively and quantitatively, by considering a representative data set of 1000 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.**

***Index Terms*— Content-aware image resizing, image retargeting, visual saliency, gradient vector flow.**

I. Introduction

THE extensive use of 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 dimension introduces artifacts and distortions). Other standard operations in which outer parts of an image are removed (e.g., cropping), could produce images with loss of salient information (e.g., removal of objects or part of them).

In the last years, several techniques for content-aware image resizing (or content-based visual retargeting) have been proposed [1]–[10]. 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 which are important to generate the needed visual stimuli useful to correctly perceive the visual content. The algorithm should avoid distortion and changes of perspective of the image. Moreover, they should preserve edges, important textured areas belonging to the objects, size of the objects, and relevant details of the scene.

The Seam Carving, proposed by Avidan et al. in [1], is probably the most popular content-aware resizing approach. Such a technique reduces the image by removing connected path of pixels (called seams) having low-energy in the map related to the image to be resized. The authors of [1] compared different strategies to compute the energy map to be considered during the resizing process (e.g., the entropy energy computed for each pixel into a fixed window, the magnitude of the gradient computed on each pixel, a saliency measure of each pixel computed as in [11], 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 a technique 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. On the other hand, 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. In particular, 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. [5] introduced a method to find the best Shift-Map which defines the pixel displacement useful to produce the output image. Wu et al. [9] propose a resizing method exploiting also high level semantic features such as symmetry. Specifically, their approach resizes symmetry regions by summarization and the remaining ones by warping. Another method based on warping is the one proposed in [10]. In this case the resizing method considers non-homogeneous warps to concentrate the resizing distortions in regions with low saliency information. To this aim, the resizing problem is formulated as a quadratic minimization problem and different metrics are considered to measure the image distortion. Gallea et al. [6] 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

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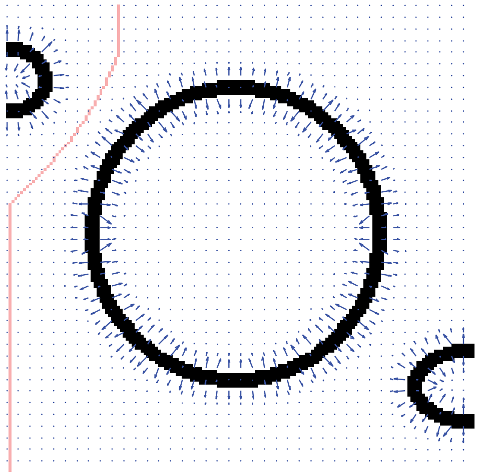

Fig. 1. Input image with its corresponding GVF field overimposed. GVF values are higher in correspondence of the edges information. The seam derived by the proposed resizing approach is shown in red. The gradient vector field forces the seams far from main contours of the objects.

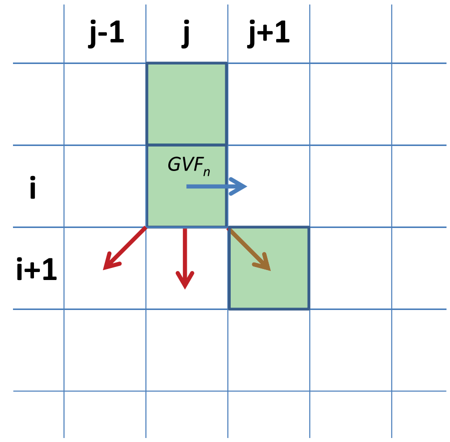

Fig. 2. An example of seam generation. Among the three possible directions (in red) the one with angle closest to the GVF_n orientation (in blue) is chosen.

of the considered model allows them to elaborate even large images in reasonable computational time.

In this paper we introduce a novel algorithm for content aware image resizing. The technique exploits the properties of Gradient Vector Flow (GVF) [12] to properly detect the seams to be removed, without introducing artifacts in the resized image. Specifically, GVF generates a vector field useful to preserve objects by enhancing edges information during the generation of the possible paths to be removed. The vector field produced by GVF is also coupled with a visual saliency map [13] in order to refine the final selection of the paths to be removed. The proposed approach has been tested and compared, both qualitatively and quantitatively, with respect to state-of-the-art approaches on a representative dataset [13], [14]. Experimental results confirm the effectiveness of the proposed approach in terms of preservation of salient regions.

The paper is organized as follows: Section II and Section III describe the proposed image resizing method with and without saliency exploitation. In Section IV the experimental phase and the results are detailed. Section V discusses implementations details useful to speed up the proposed method during the resizing. Finally, conclusions and hints for future works are given in Section VI.

II. Proposed Method

One of the main issues of 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) [12].

GVF is a dense force field [12] 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:

$$E = \int\int \mu(u_x^2 + u_y^2 + v_x^2 + v_y^2) + |\nabla f|^2 |\mathbf{v} - \nabla f|^2 dx dy \quad (1)$$

Algorithm 1 Image Resizing Based on GVF

Input: I, N, K
Output: The resized image $\widehat{I}$
begin
  for $iteration \leftarrow 1$ **to** N **do**
    $[GVF, GVF_n] \leftarrow ComputeGVF(I)$
    $\{s_1, \ldots, s_K\} \leftarrow SeamsComputation(GVF_n, K)$
    $\{c_1, \ldots, c_K\} \leftarrow SeamsCost(\{s_1, \ldots, s_K\}, GVF)$
    $\widehat{k} \leftarrow \mathrm{argmin}_k\{c_1, \ldots, c_K\}$
    $I \leftarrow RemoveSeam(I, s_{\widehat{k}})$
  $\widehat{I} \leftarrow I$
end

where the subscripts represent partial derivatives along x and y axes respectively, μ 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 in those areas 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 homogeneous regions (the energy E is dominated by the sum of the squares of the partial derivatives of GVF field). Hence, GVF is stronger close to the edges of objects within the image. An example of GVF field is shown in Fig. 1. We exploit this vector field to effectively build the set of pixel paths (i.e., the seams) to be considered as candidate in the removal process. The relevance of each GVF path can be straightforward derived from the energy map obtained by the GVF magnitude associated to the image under consideration.

The proposed algorithm works as follows (see Algorithm 1). Let I be an image with H rows and W columns to be resized with respect to the width, and $0 < N < W$ the number of seams to be removed. First the GVF and its normalized version GVF_n (i.e., each vector with norm one) are computed from the input image I considering the luminance channel (i.e., *ComputeGVF*). Several seams $\{s_1, s_2, \ldots, s_K\}$ are then built starting from the top of the image making use of the directions of the already computed GVF_n (i.e., *SeamsComputation*). The algorithm devoted to the generation of the seam has been designed to exploit the properties of the GVF field. Specifically, this field preserves the strong edges

Algorithm 2 Computation of Seams

```
Input: GVF_n, K
Output: {s_1, ..., s_K}
begin
    dir_{-1} = (-√2/2, -√2/2)
    dir_0 = (0, 1)
    dir_{+1} = (√2/2, -√2/2)
    for k ← 1 to K do
        curr_j = floor(W/K) · k
        s_k[1] = (1, curr_j)
        for i ← 1 to H − 1 do
            sim_{-1} = GVF_n(i, curr_j) * dir_{-1}
            sim_0 = GVF_n(i, curr_j) * dir_0
            sim_{+1} = GVF_n(i, curr_j) * dir_{+1}
            sim_max = max(sim_{-1}, sim_0, sim_{+1})
            if sim_max == sim_{-1} then
                curr_j = curr_j − 1
            if sim_max == sim_0 then
                curr_j = curr_j
            if sim_max == sim_{+1} then
                curr_j = curr_j + 1
            s_k[i + 1] = (i + 1, curr_j)
end
```

and propagates the information related to their presence also in the neighboring pixels. Starting then from the top of the image and following the GVF field direction a seam avoiding as much as possible main edges is built (see Algorithm 2). It is worth noting that the directions suggested by GVF_n 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 $GVF_n(i, j)$ is hence considered during the seam generation (see Fig. 2). To this aim, a simple dot product between $GVF_n(i, j)$ 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.

After computing the set of candidate seams $\{s_1, s_2, \ldots, s_K\}$, a cost is associated to each seam by considering the sum of the GVF magnitude $|GVF|$ of the pixels belonging to the seam. Specifically the cost c_k of a seam s_k is computed as follows (i.e., *SeamsCost* in Algorithm 1):

$$c_k = \sum_{(i,j)\in s_k} |GVF(i, j)| \tag{2}$$

The seam with the lower cost c_k is hence removed from the image at each iteration (i.e., *RemoveSeam*). The GVF map is then updated and a new iteration of the seam removal algorithm is performed for each seam to be removed.

It is worth noting that the core of the proposed resizing approach is related to the method adopted to select the seams (i.e., *SeamsComputation*). Indeed, the seam selection method has been designed to exploit the properties of the GVF in order to maintain the strong edges of the images and propagates their contributions also in their neighboring creating then a repulsive field. On the contrary, classic Seam Carving approaches do not propagate the information of a strong edge into the close pixels. Moreover, GVF combines the contribution of several edges in a smooth way. Differently than Seam Carving [1], the proposed approach, due to the repulsive field that propagates the information about the presence of an edge also in its neighboring, can perform a simple seam selection guided by the GVF field without considering all the possible paths. In Fig. 3 all the possible paths generated at iteration t are shown in gray and the best one in red. As can be easily seen, only a limited number of paths are actually considered and, usually, they do not cross the salient region. This property has been also exploited to reduce the computational cost of the overall algorithm (see Section V).

III. Saliency Based Selection of GVF Paths

The visual salience (or visual saliency) refers to the properties of the visual stimuli which are exploited by the human visual system in the tasks of visual attention [15] and rapid scene analysis [16]. The automatic detection of salient regions in images can be used in a broad scope of computer vision applications such as image segmentation [17], content-based image retrieval [18], object detection [19] and recognition [20].

Several saliency estimation methods have been proposed in literature. Some of them, such as the algorithm proposed by Itti et al. [16], originate from the biologically plausible visual architecture proposed by Koch and Ullman [21]. Others methods, such as the one presented by Achanta et al. in [13] and by Hou et al. in [22], are purely computational and do not make any assumption on biological architecture. Finally, techniques based on combining both paradigms, biological and computational, have also been published, as in the work of Harel et al. [23]. All previously mentioned approaches estimate the visual importance of image pixels starting from information extracted in the uncompressed domain. Since most images (e.g., over internet) are stored in the compressed domain of joint photographic expert group (JPEG), Fang et al. [14] have proposed a method to extract saliency directly in the JPEG domain by exploiting information of intensity, color, and texture encoded by the discrete cosine transform (DCT) coefficients on each 8×8 block.

Visual saliency estimation algorithms have straightforward application in content based visual retargeting. Indeed, all the state-of-the-art retargeting algorithms (e.g., [1]) detect the paths to be removed (i.e., the seams) taking into account of an energy map which encodes the importance of each pixel in terms of content. A successful seam carving algorithm should ensure that the most important image regions pointed out by the energy map should not be removed. The algorithm we presented in Section II makes use of the magnitude of the GVF as energy map to drive the selection of the seams to be removed. Despite this information is useful to take care of the saliency of the edges, it does not consider other saliency information.

In Achanta et al. [4] a visual saliency map able to uniformly highlight salient regions with well-defined boundaries [13]

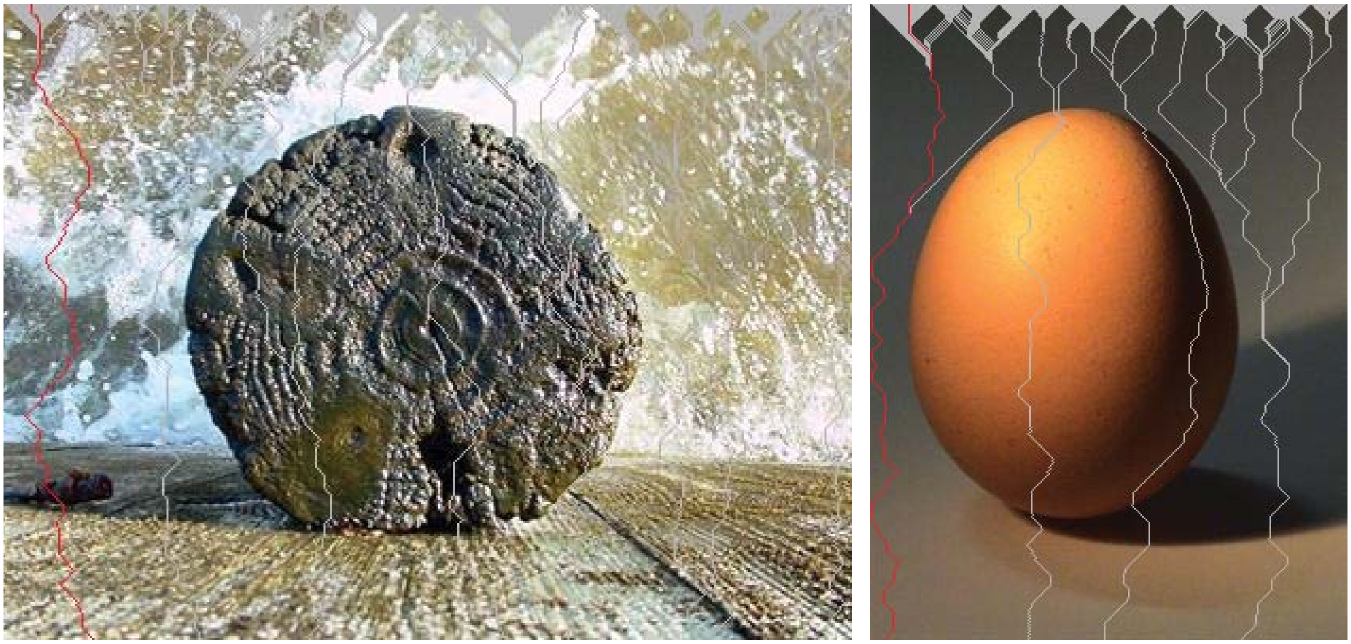

Fig. 3. Seams generated at a generic iteration t by the proposed approach based on GVF field. The seam to be removed, selected considering the related cost, is shown in red.

has been used for content aware image resizing purpose; the classic seam carving algorithm proposed by Avidan et al. [1] has been employed by replacing the energy map computed using the L_1-norm of the image intensity gradient, with the saliency map computed as proposed in [13]. Results presented in [4] and [14] emphasized the fact that by using the visual saliency better performances, with respect to the state-of-the-art methods, are achieved. This strongly motivated us to couple the proposed GVF based approach with saliency information for retargeting purpose.

Differently than [4] and [14] we propose to use visual saliency only for the selection of seams to be removed after that these paths are generated by exploiting the gradient vector flow as detailed in previous section. In this way we are able to combine different kinds of saliency information; the one related to the edges given by the GVF and the one related to the saliency objects within the image encoded by the saliency map. In our experiments we used the saliency map estimator proposed by Achanta et al. [13]. To include visual saliency information, we first generate the seams exploiting the GVF, and then perform the selection based on saliency. Referring to the Algorithm 1 in previous section, we need to replace the function *SeamsCost* defined by the equation (2) with the following one:

$$c_k = \sum_{(i,j)\in s_k} Saliency(i, j) \tag{3}$$

where $Saliency(i, j)$ is the value of visual saliency of the pixel (i, j) computed as described in [13]. The new resizing procedure is summarised in Algorithm 3. Note that in our Algorithm 3 the saliency map related to the image is computed just one time independently from the seams to be removed.

Algorithm 3 Image Resizing Based on Saliency Selection of GVF Paths

Input: I, N
Output: The resized image $\widehat{I}$
begin
$\quad Saliency \leftarrow ComputeSaliency(I)$
$\quad$ **for** $iteration \leftarrow 1$ **to** N **do**
$\quad\quad [GVF, GVF_n] \leftarrow ComputeGVF(I)$
$\quad\quad \{s_1, \ldots, s_K\} \leftarrow SeamsComputation(GVF_n)$
$\quad\quad \{c_1, \ldots, c_K\} \leftarrow SeamsCost(\{s_1, \ldots, s_K\}, Saliency)$
$\quad\quad \widehat{k} \leftarrow \mathrm{argmin}_k\{c_1, \ldots, c_K\}$
$\quad\quad I \leftarrow RemoveSeam(I, s_{\widehat{k}})$
$\quad \widehat{I} \leftarrow I$
end

IV. Experimental Results

As pointed out in [1], [4], and [14], 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 sections, we propose to use GVF to build the seams during the resizing. The selection of the seams to be removed is then driven by GVF magnitude or by the saliency map. As estimation approach to build the visual saliency map we used the one proposed in [13].[1] In order to evaluate the results of our basic approach (i.e., the Algorithm 1 which exploits the equation (2)) and do not consider saliency information, we have compared it with respect to the classic Seam Carving algorithm proposed by Avidan et al. [1], and the approach recently proposed by Gallea et al. [6]. The approach

[1] Note that other visual saliency maps can be used, such as the one proposed in [14] or in [16]. In our experiments we have used the map proposed in [13] since this has obtained good results both, in terms of saliency estimation and computational cost. The original code useful to compute this saliency map is available at the website of the authors.

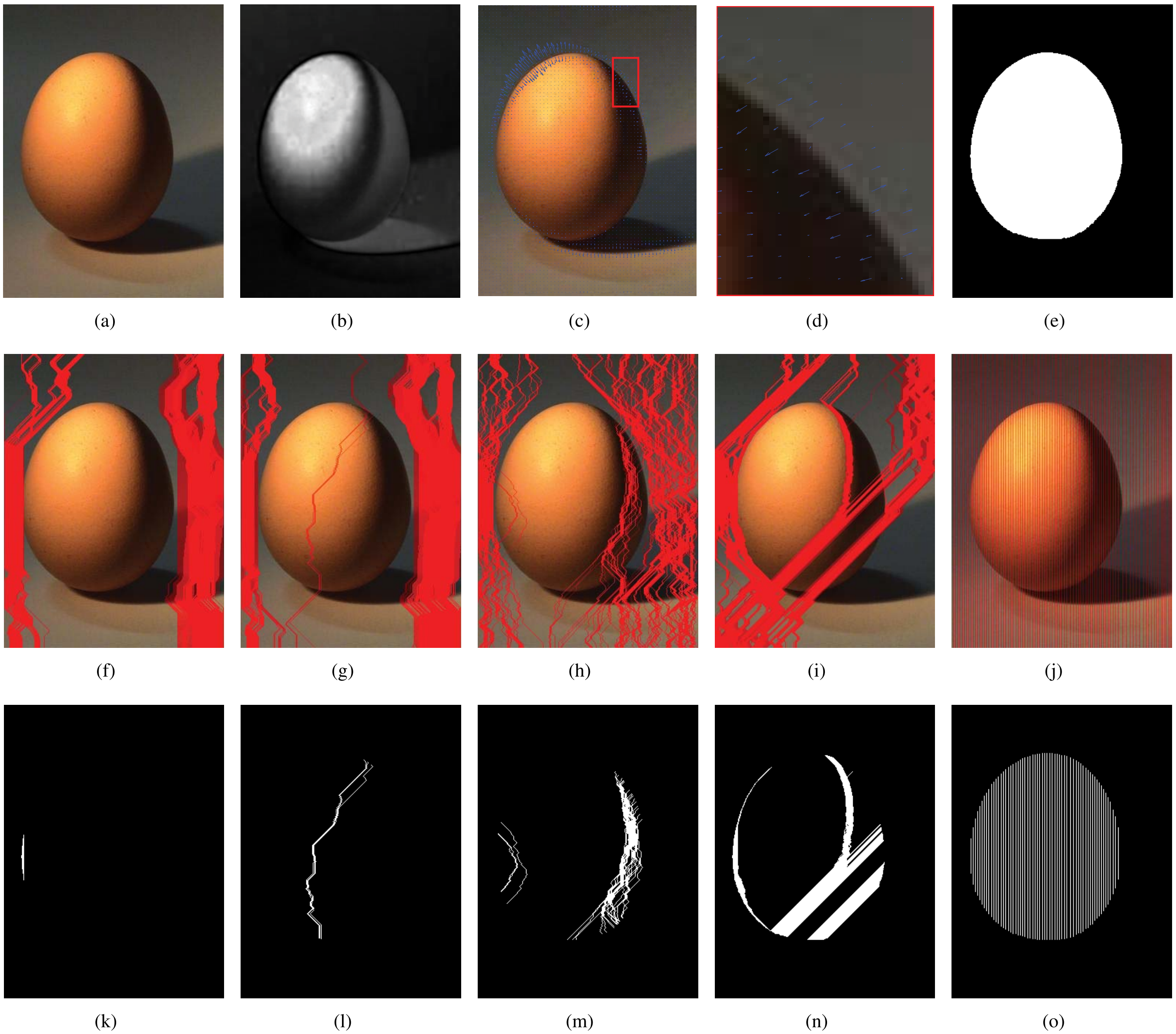

Fig. 4. Visual assessment of the involved algorithms by resizing the input image at 70% of the width. (a) Original image. (b) Saliency map [13] related to the image in (a). (c) Gradient Vector Flow map [12] of the image in (a). (d) Zoomed version of the zone marked with the red bounding box in the image in (c). (e) Ground-truth saliency mask related to the image in (a). (f), (g), (h), (i), (j) show in red the seams removed employing respectively the proposed Algorithm 3, the Algorithm 1, Avidan et al. [1], Achanta et al. [4] and Gallea et al. [6]. In (k), (l), (m), (n), (o) are shown the final maps obtained by combining the ground-truth mask shown in (e) and the maps of the removed seams which are reported in red in (f), (g), (h), (i), (j) respectively. These maps indicate the importance of the removed seams in terms of saliency. The values of these last maps are used to compute the corresponding saliency costs (i.e., the sum of values for each map) and hence employed to compare the different algorithms. As can be assessed by visual inspection of the image in (b), the saliency map alone is not able to capture some information about the edges (e.g., in correspondence of the shadow). On the other hand the GVF gives its contribution around the edges (see image in (c) and (d)). The combination of Saliency and GVF is hence able to exploit information from both sources.

in [1] has been re-implemented, whereas the original code of the method in [6] has been provided by the authors. While [1] proposes a local-based approach which exploits the gradient of the image to select the seams to be removed, the approach in [6] is a global-based approach in which an objective function is considered to solve an optimization problem. In [6] the product of the gradient of the image and the saliency map proposed by Itti et al. [16] is taken into account as energy map during the resizing. Moreover, to underline the contribution of coupling GVF path extraction with saliency based selection (i.e., the Algorithm 3 in which equation (3) is employed and saliency map is computed as in [13]), we have compared the proposed saliency based selection approach with respect to the one proposed in [4]. Similarly to our approach, the one in [4] uses the saliency map proposed in [13] allowing a fair comparison.

In order to objectively assess the performances of the aforementioned methods, we have compared the different approaches on the dataset used in [13] and [14] for saliency detection. This dataset is composed by 1000 images labeled with corresponding accurate object-contour based ground-truth saliency segmentation. The dataset contains enough varieties of scenes and objects which also appear in multiple instances and in different locations (not only centered). For each image I of the dataset, the ground-truth map G_I denotes which pixels of the image are important in term of saliency. In Fig. 4(a) and (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, we used the following cost function in order to objectively evaluate the performances of a specific algorithm A involved in the comparison:

$$Cost(I, A, \lambda, d) = \sum_{p \in \psi_{A,\lambda}(I)} G_I(p) \tag{4}$$

where $\psi_{A,\lambda}(I)$ is the final set of pixels removed by employing the algorithm A during the resizing of the image I of a scale factor $\lambda \in \{95\%, 90\%, 85\%, 80\%, 75\%, 70\%\}$ with respect to the maximum dimension of the image (as defined by equation (5)), and $G_I(p)$ indicates the importance of the removed pixel p in the image I.

$$d = \underset{\widehat{d} \in \{width, height\}}{\arg\max} \; Size(I, \widehat{d}) \tag{5}$$

This cost can be used to fairly compare the performances of the different algorithms at varying of the scale factor. A lower cost value indicates better performances (i.e., more salient pixels are preserved in the resizing). We have measured the performances of the different algorithms on the aforementioned dataset at varying of the scale factor. The final results are obtained by averaging the results of all the executions for a specific scale factor λ.

Fig. 4 reports an example of the seams removed by the different algorithms when resizing the original image at $\lambda = 70\%$ of the width. Red lines in Fig. 4(f)–(j) correspond to the ones in the maps $\psi_{A,\lambda}(I)$ (i.e., the removed seams) obtained with the different algorithms, whereas Fig. 4(k)–(o) depict the values $G_I(p)$ used to compute the cost function in equation (4) taking into account of one of the five compared algorithms. In this simple example containing a single object with non uniform illumination, it is clearly visible that the proposed approaches (Algorithm 1 and 3) are really powerful in preserving edges of objects and their original size. Fig. 4(d) shows a zoomed area related to the GVF of the image in Fig. 4(a) devoted to highlight the information exploited into the seam removal process in order to better preserve edges.

In Fig. 5 are reported the results obtained by the three different algorithms which exploit the magnitude of the image gradient to select seams to be removed during the resizing: our Algorithm 1, the one proposed by Gallea et al. [6], and the original Seam Carving algorithm proposed by Avidan et al. [1]. The results are shown at varying of the percentage of the resizing.

Further experiments to test the robustness of the GVF based approach with respect to noisy input have been performed. Specifically, each image within the considered dataset has been corrupted with Gaussian noise $N(0, \sigma)$ and then the resizing has been performed considering a scale factor $\lambda = 80\%$ with respect to the maximum dimension of the input image.

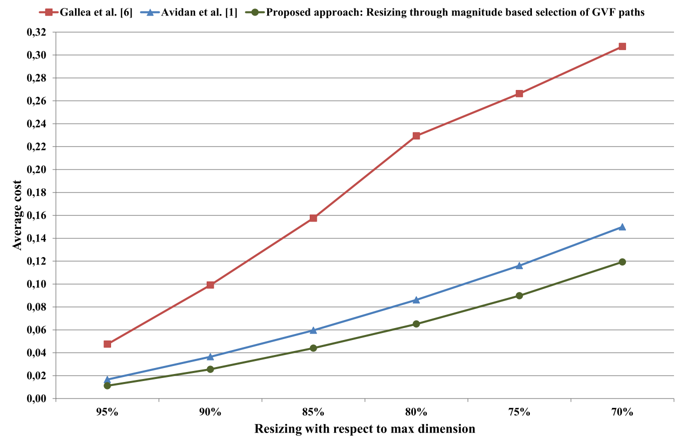

Fig. 5. Average cost computed over 1000 test images at varying of percentage of resizing. A lower value indicates that more salient pixels are preserved (i.e., better performances).

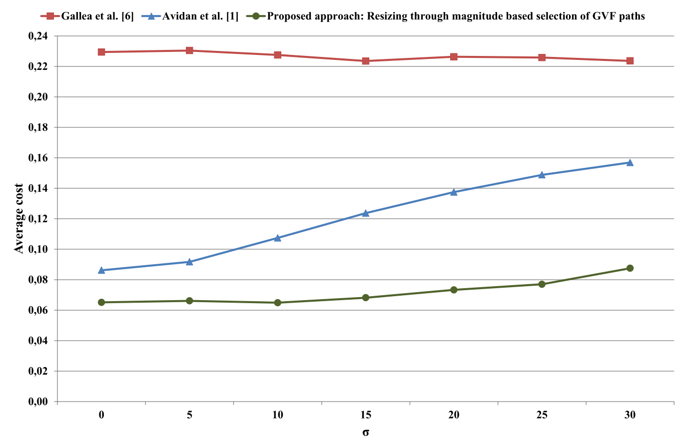

Fig. 6. Average cost computed at varying of noise by considering the 1000 test images resized at 80% of the maximum dimension. A lower value indicates that more salient pixels are preserved (i.e., better performances).

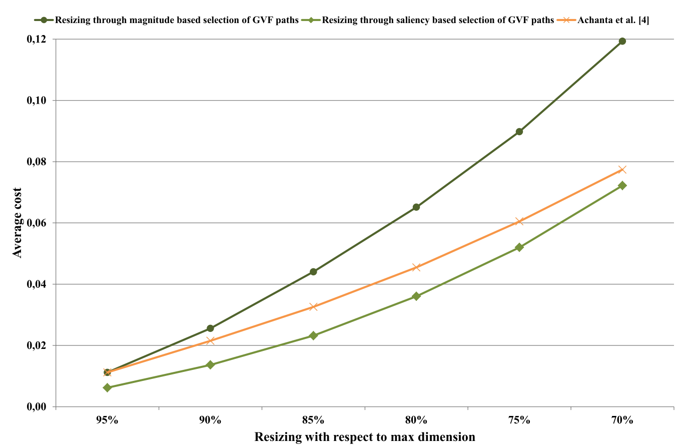

Fig. 7. Average cost computed over 1000 test images at varying of percentage of resizing. A lower value indicates that more salient pixels are preserved (i.e., better performances).

The results obtained by the three different algorithms which exploit the magnitude of the image gradient at varying of $\sigma \in \{0, 5, 10, 15, 20, 25, 30\}$ are reported in Fig. 6. In all

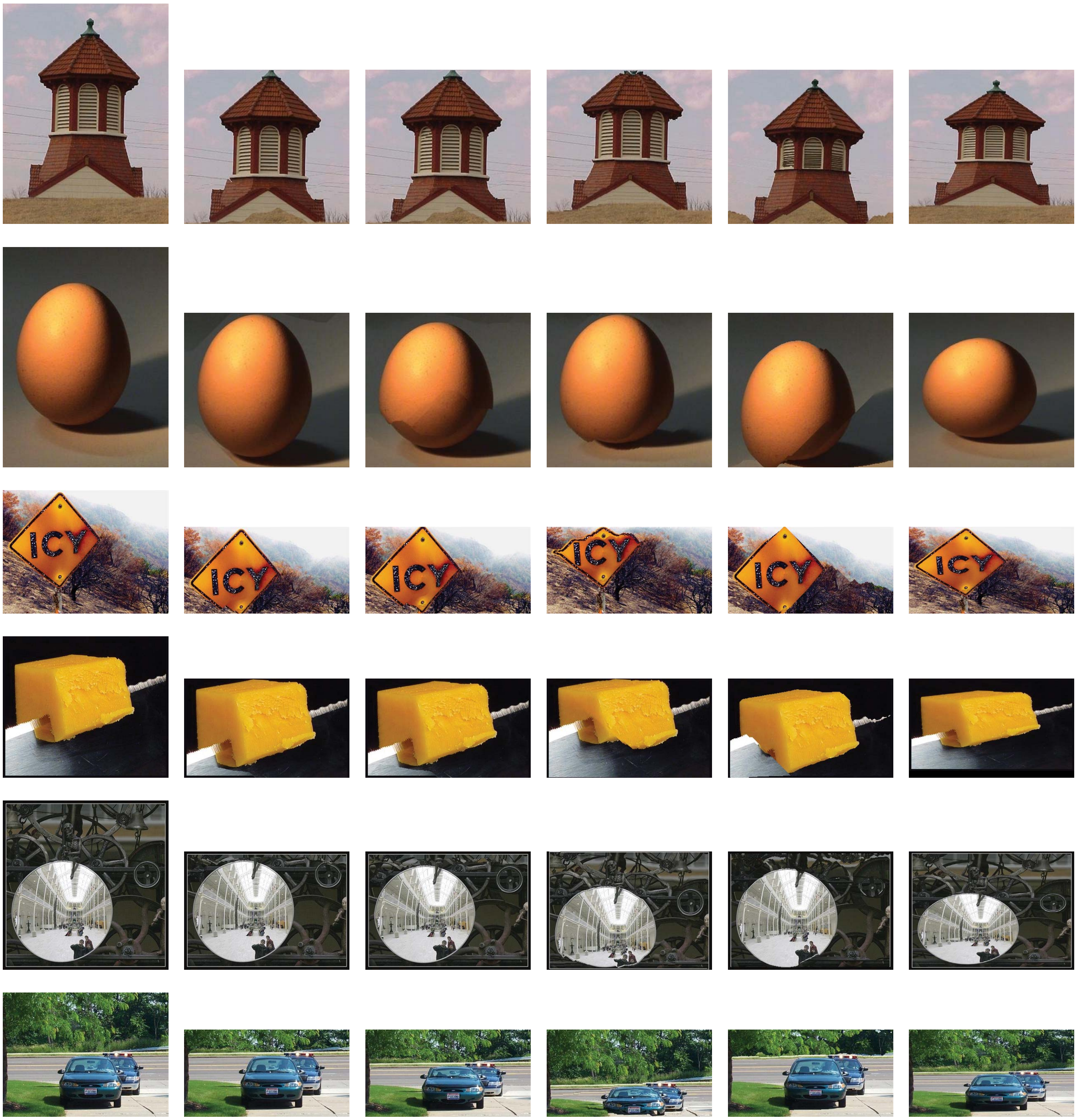

Fig. 8. Examples of content-aware image resizing at 70% of the height. 1^{st} column: original image. 2^{nd} column: our Algorithm 3. 3^{rd} column: our Algorithm 1. 4^{th} column: Avidan et al. [1]. 5^{th} column: Achanta et al. [4]. 6^{th} column: Gallea et al. [6].

cases, the proposed approach outperforms the other content-aware based algorithms.

The proposed method based just on GVF information (i.e., Algorithm 1) achieves the best results demonstrating that the process of building seams by exploiting GVF more effectively preserves salient areas and hence removes less crucial pixels.

By coupling the Algorithm 1 with a saliency estimator (i.e., the one in [4] and [13] in our experiments) the proposed strategy summarized by Algorithm 3 outperforms the approaches from which the solution originates. Fig. 7 shows the results of the proposed approach based on saliency selection (i.e., Algorithm 3) with respect to the approach proposed in [4]. The results obtained by the Algorithm 1 are also reported as baseline. Although both approach based on saliency selection outperform the Algorithms 1, our proposal achieves the best margin in terms of saliency preservation performances.

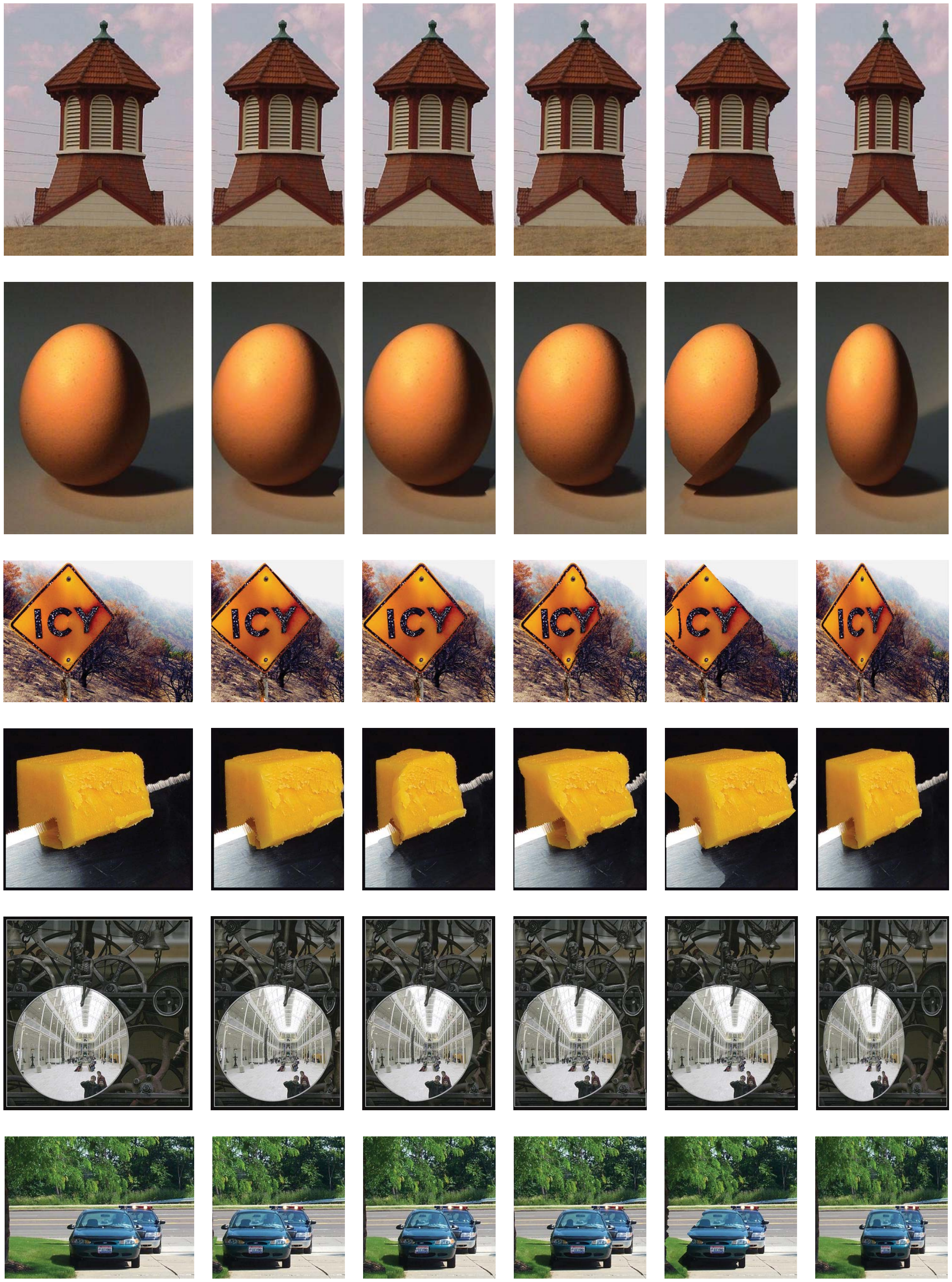

Fig. 9. Examples of content-aware image resizing at 70% of the width. 1^{st} column: original image. 2^{nd} column: our Algorithm 3. 3^{rd} column: our Algorithm 1. 4^{th} column: Avidan et al. [1]. 5^{th} column: Achanta et al. [4]. 6^{th} column: Gallea et al. [6].

To visually assess the results obtained with the five compared algorithms, some visual results obtained by resizing images with a scale factor of 70% with respect to their original dimension (width or height) are shown in Figs. 8 and 9. A visual comparison reveals that the proposed approach with saliency based selection of GVF paths better preserves the main salient regions (i.e., the areas with objects).

In Figs. 10 and 11 some examples of progressive resizing are shown with respect to the different compared algorithms. As can be easy assessed by visual inspection (Fig. 10), already at 5% of the resizing some approaches remove

Fig. 10. Example of progressive resizing with respect to the width. Rows are related to the different algorithms: 1^{st} our Algorithm 3, 2^{nd} our Algorithm 1, 3^{rd} Avidan et al. [1], 4^{th} Achanta et al. [4], 5^{th} Gallea et al. [6]. Columns are related to the resizing factor with respect to the width: 1^{st} original image, 2^{nd} 5%, 3^{rd} 10%, 4^{th} 15%, 5^{th} 20%, 6^{th} 25%, 7^{th} 30%.

information from the object (e.g., see the results at 4^{th} and 5^{th} rows), whereas the proposed Algorithm 3 works well in almost all cases. Comparing the results of 1^{st}, 2^{nd} and 4^{th} rows in Fig. 11 it is straightforward to figure out that the exploitation of both, the GVF for seams generation and visual saliency for seams selection (as done by our Algorithm 3), more information about the salient object is retained.

To better highlight the peculiarities of the proposed approach, more visual examples are shown in Figs. 12 and 13. Specifically, first and second rows show examples of scenes with edges and textures (i.e., the wall) and one saliency object.

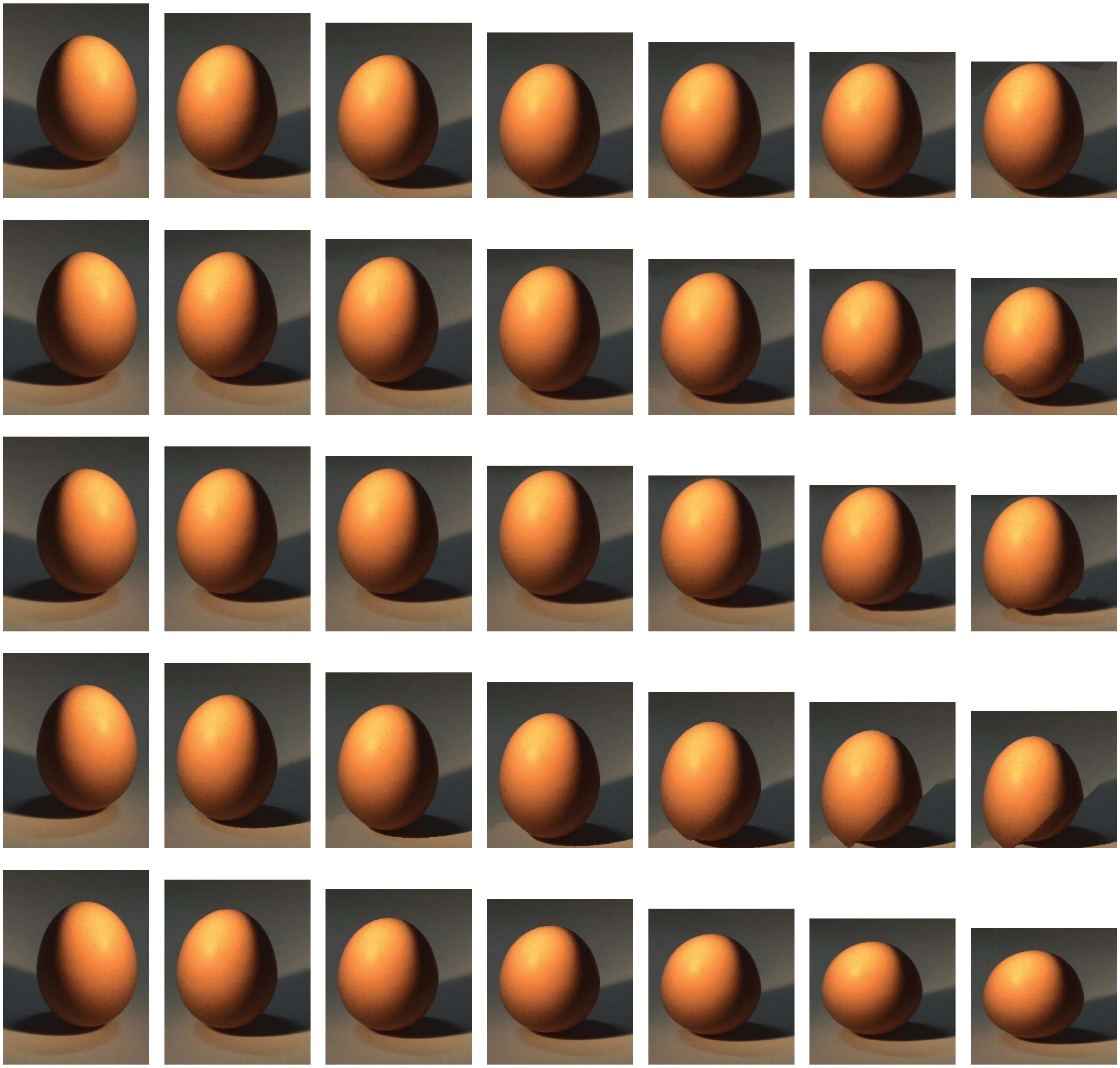

Fig. 11. Example of progressive resizing with respect to the height. Rows are related to the different algorithms: 1^{st} our Algorithm 3, 2^{nd} our Algorithm 1, 3^{rd} Avidan et al. [1], 4^{th} Achanta et al. [4], 5^{th} Gallea et al. [6]. Columns are related to the resizing factor with respect to the height: 1^{st} original image, 2^{nd} 5%, 3^{rd} 10%, 4^{th} 15%, 5^{th} 20%, 6^{th} 25%, 7^{th} 30%.

Our Algorithm 3 clearly preserves the visual content of the scene by maintaining both size of the object and the details related the visual stimuli of textures and edges. In the images in rows three and four, scenes with evident edges are shown. Also in this case the proposed algorithm produces the best results by maintaining the principal salient region (i.e., the plate with text) and the overall context (e.g., the fence and the background information). The example in the fifth row shows the preservation of perspective in the resizing, whereas the other examples are useful to assess the maintenance of size and details of objects as well as the other information which define the context of the scene.

All the aforementioned experiments clearly demonstrate that our proposal based on saliency selection of gradient vector flow paths outperforms both, the proposed basic strategy summarized by Algorithm 1 in which paths are selected just considering the GVF magnitude (i.e., equation (2)), as well as the method presented by Achanta et al. in [4], where the classic seam carving algorithm [1] is modified to consider the visual saliency of images.

V. Implementation Details and Computational Complexity

In almost all approaches for content-based image resizing the computing of a seam consists in building the path of

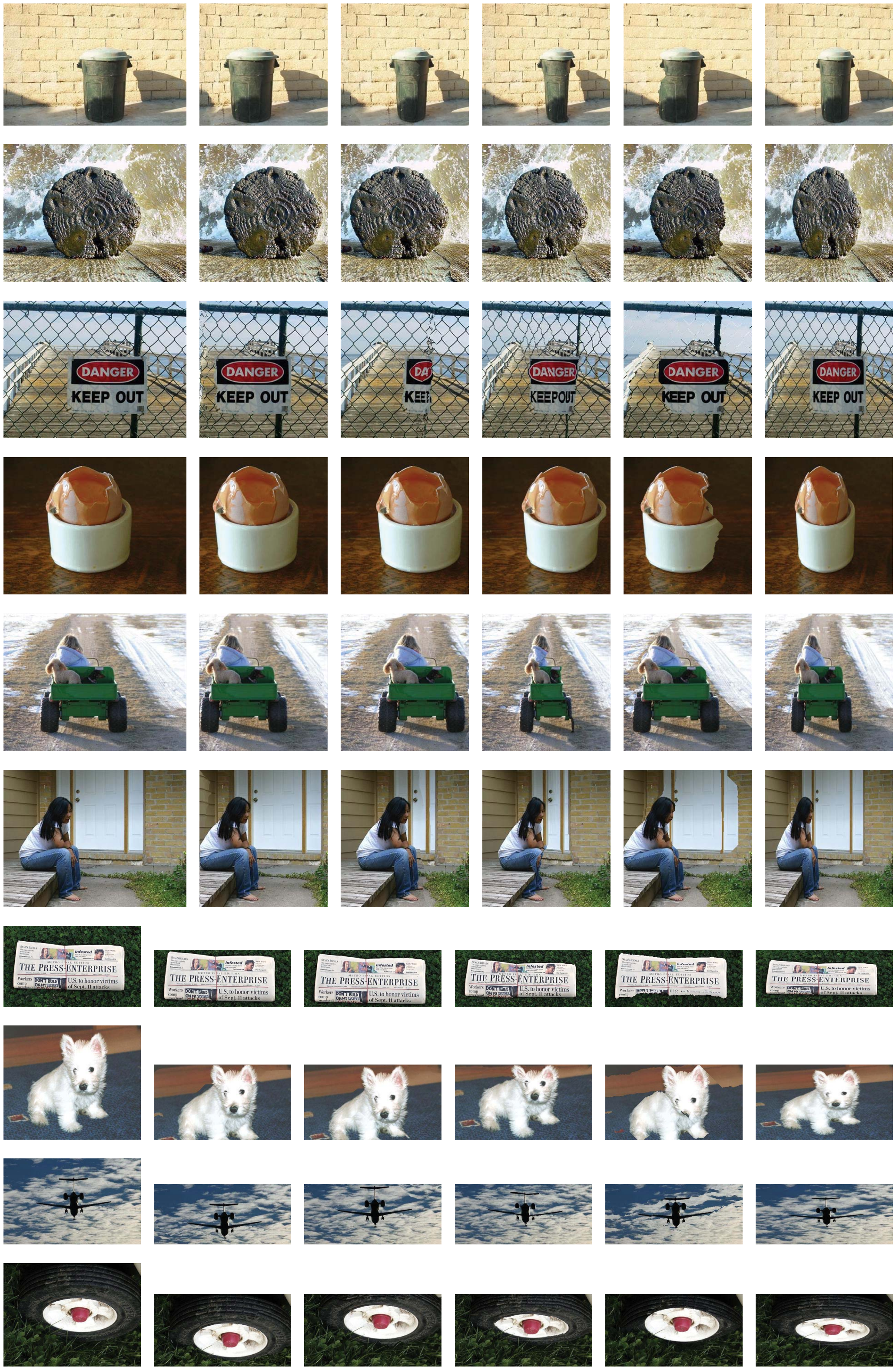

Fig. 12. Examples of content-aware image resizing of scenes containing objects and contexts with edges, textures, and different prospective. Images are resized at 70% of width/height. 1^{st} column: original image. 2^{nd} column: our Algorithm 3. 3^{nd} column: our Algorithm 1. 4^{th} column: Avidan et al. [1]. 5^{th} column: Achanta et al. [4]. 6^{rd} column: Gallea et al. [6].

minimum cost from the top row (left column) of the image to the bottom (right) one. Typically state-of-the-art approaches use dynamic programming to this aim [1], [2], [4], [7], [14]; the algorithms consider all the possible row (column) paths to choose the seam to be removed at each iteration with computational time O(HW) for an image with size $W \times H$.

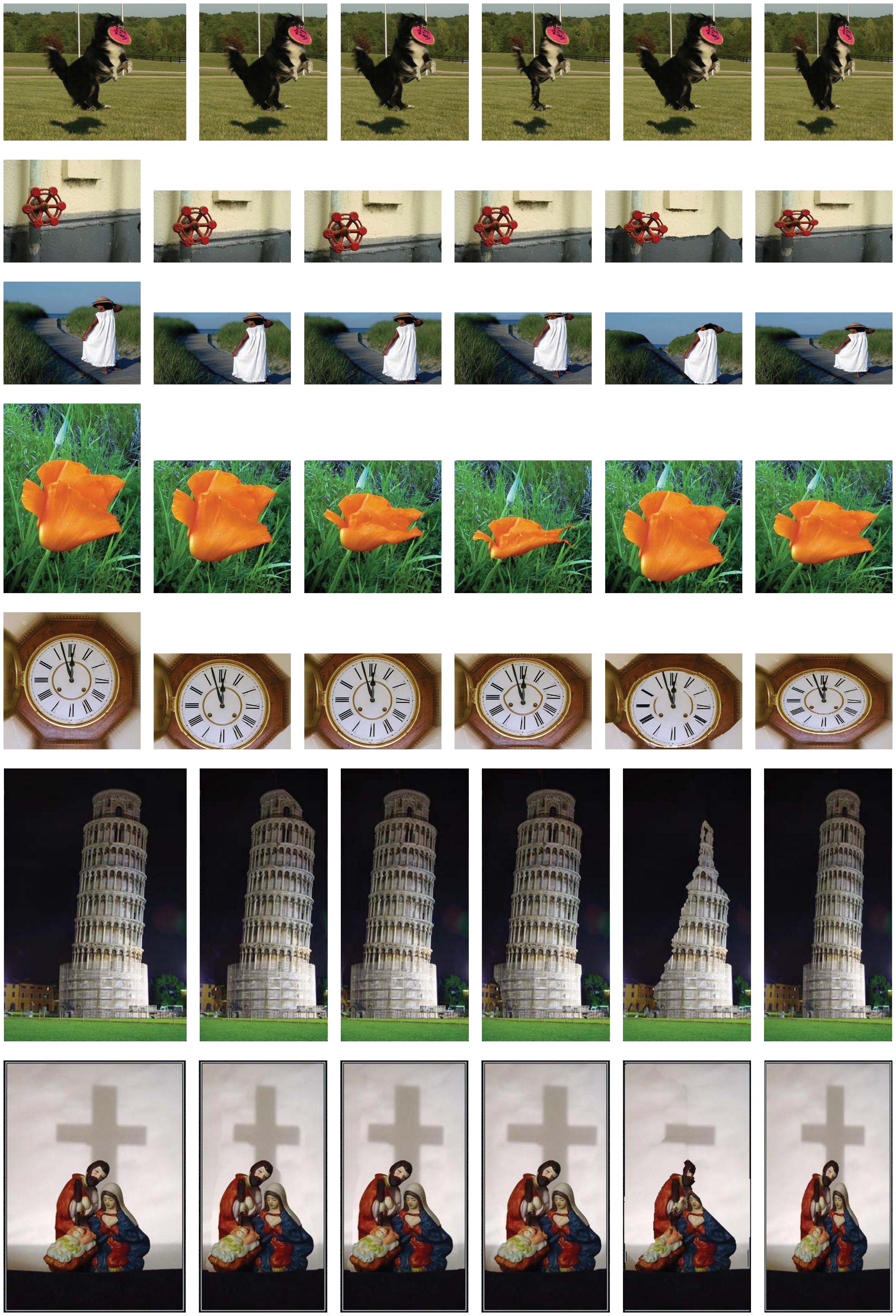

Fig. 13. Examples of content-aware image resizing of scenes containing objects and contexts with edges, textures, and different prospective. Images are resized at 70% of width/height. 1^{st} column: original image. 2^{nd} column: our Algorithm 3. 3^{nd} column: our Algorithm 1. 4^{th} column: Avidan et al. [1]. 5^{th} column: Achanta et al. [4]. 6^{rd} column: Gallea et al. [6].

Although the proposed approach has the same computational cost per iteration, we have exploited the properties of the GVF to reduce the number of paths to be considered. Indeed, the GVF is a vector field which is used by our algorithm to keep away the seams from the edges (see Fig. 1). The rationale to reduce the number of paths to be considered at each iteration is that paths starting from neighbouring pixels (at the first row or column) follow similar GVF flow in building the corresponding seams (see Fig. 3). Hence we have tested the proposed approach considering $\frac{1}{2^n} * W$ (or $\frac{1}{2^n} * H$),

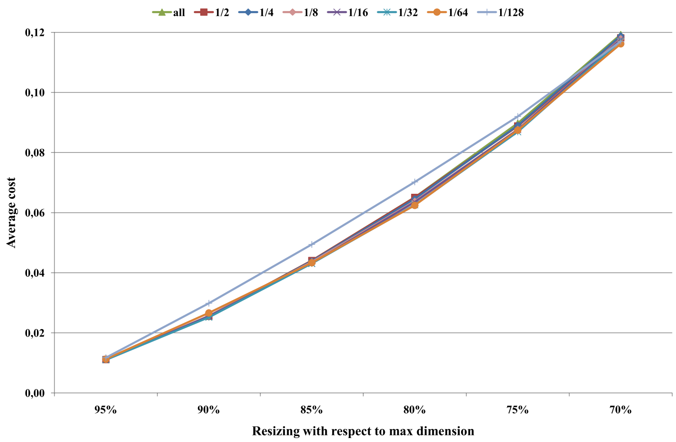

Fig. 14. Average cost of Algorithm 1 computed over 1000 test images at varying of the number of seams considered during the resizing.

TABLE I
AVERAGE TIME IN SECONDS NEEDED TO PERFORM A RESIZING AT 70% OF THE IMAGE DIMENSION

Method	Time
Proposed approach - all seams	92.937
Proposed approach - $\frac{1}{2}$ seams	58.832
Proposed approach - $\frac{1}{4}$ seams	41.909
Proposed approach - $\frac{1}{8}$ seams	33.357
Proposed approach - $\frac{1}{16}$ seams	28.971
Proposed approach - $\frac{1}{32}$ seams	26.858
Proposed approach - $\frac{1}{64}$ seams	25.594
Proposed approach - $\frac{1}{128}$ seams	25.136
Avidan et al. [1]	21.587
Gallea et al. [6]	0.385

$n = 1, 2, \ldots, 7$, equally spaced starting pixels at each iteration during the resizing of the width (or height).

We report the experimental results obtained by reducing the number of seams to be considered on each iteration in order to decrease the computational cost of our algorithm as described above. The experiments have been done on a notebook equipped with a CPU intel core i7-2670QM 2.20GH with 8 Gb of Ram by using a Matlab implementation. To perform the test we have run the proposed algorithm by considering just $\frac{1}{2^n} * W$ (or $\frac{1}{2^n} * H$) equally spaced starting pixels at each iteration during the resizing of the width (or height). In Fig. 14 the average cost indicating the accuracy of the resizing is reported at varying of the number of paths considered at each iteration, whereas in Table I the average computational time in seconds is reported. The experimental results demonstrate the effectiveness of the proposal which reduces the computational cost during the resizing by maintaining almost the same performances in terms of saliency preservation (see also Fig. 15).

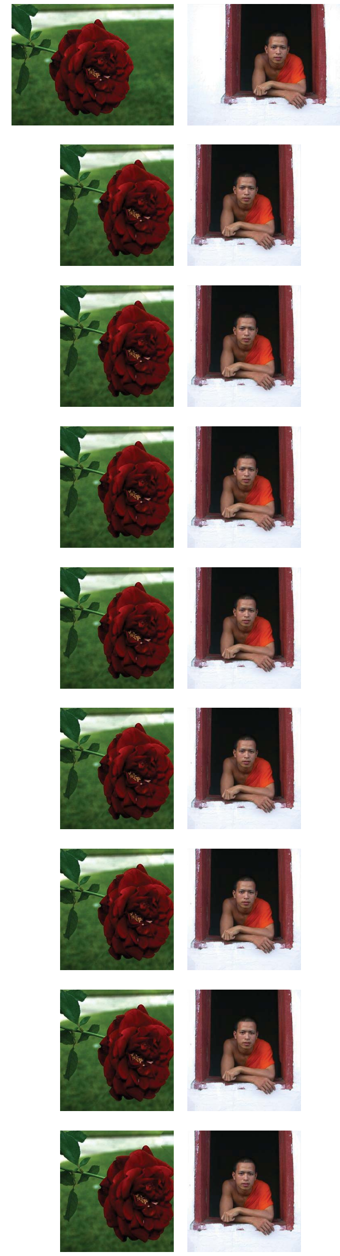

Fig. 15. Resizing images at 30% of the width by considering a reduced number of seams. Top: original images. 1^{st} row: resizing with all seams. From the 2^{nd} to the 9^{th} row are shown the results by considering respectively $\frac{1}{2}$, $\frac{1}{4}$, $\frac{1}{8}$, $\frac{1}{16}$, $\frac{1}{32}$, $\frac{1}{64}$ and $\frac{1}{128}$ of the total seams during the resizing.

VI. CONCLUSION

In this paper we proposed a novel 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 GVF based approach is enriched with saliency information to achieve better results. The proposed solution has been compared with respect to state-of-the-art algorithms on a representative dataset achieving at least comparable visual results, and outperforming with good margins existent strategies in terms of preservation of salient regions. Future works can be devoted to include a blending method in order to obtain better visual results in joining adjacent image regions after seams removal, and to extend it in order to deal with temporal dimension in the application context of video retargeting [24]. Finally, the depth of the scene will be considered to make more visually consistent the resized images [25], [26].

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