

A Hierarchical Scale-and-Stretch Approach for Image Retargeting

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Abstract—Automated image retargeting techniques are becoming important with the proliferation of different display units, such as cell phones, notebooks, televisions etc. Scale-and-stretch techniques have been successfully used for resizing images into different aspect ratios, while also preserving the most prominent visual features. The main idea of scale-and-stretch techniques is to utilize a single grid with predefined resolution, and map onto it the single significance map. The problem of image resizing is subsequently formulated as an optimization problem, which determines the optimal deformation for every local region of the image based on their underlying significance. The use, however, of a single grid with specific distribution is not robust with respect to the size of the significant regions that exist in the image. In this respect, this paper extends the scale-and-stretch techniques with the use of a hierarchical grid that incorporates the significance maps of different grid resolutions in a single grid. The proposed hierarchical approach surpasses current methods and manages to efficiently identify significant regions and achieve better results.

Keywords—Image Retargeting, Hierarchical, Scale-and-Stretch

I. INTRODUCTION

With the proliferation of different display devices, the development of automated image resizing techniques is becoming more and more important. Today, there is a variety of displays that come in different aspect ratios and resolutions. Cropping images to fit the display discards information, while uniformly resizing images to arbitrary aspect ratios produces distortion. In this respect, any resizing algorithm that uses the same deformation operator to every local region, causes distortion of the prominent visual features in the image, and makes it appear squashed or squeezed.

For this reason non-uniform resizing techniques have been proposed in the literature. These resizing methods can be classified into two categories [1]: discrete and continuous. Discrete approaches, such as seam carving [2], remove pixels from the image in order to preserve the most significant content, based on the significance of each pixel. This procedure of removing pixels from the image can result in loss of information and creation of distortion in the objects of the image. Continuous methods [3] [4] [5] have the advantage of not removing image content. They process the image as a continuous domain and perform a continuous geometric deformation, in order to change their size. The deformation process is guided by a significance map, which

identifies which objects should be less deformed. The limitation of the aforementioned approaches is that they utilize significance maps created taking only one grid layer with a specific resolution into account, and thus, they lose important information. The reason for this is that high resolutions lose significant regions of large size, while low resolutions cannot encode significant regions of small size.

Towards the creation of a more efficient image resizing approach, this work proposes a hierarchical scale-and-stretch method for non-linear deformation. The proposed method enhances significant regions of the image based on an underlying hierarchical significance map. This approach takes into account information from multiple layers of different grid resolutions, and is able to efficiently identify both small and large sizes of significant regions. The proposed approach is able to efficiently distribute the distortion of the image to regions of low significance, while significant neighboring regions are more homogeneously resized.

The rest of the paper is organized as follows: Section II presents the related work. Section III presents the details of the proposed approach, while Section IV presents experimental results and comparison with other methods. Finally, the paper concludes in Section V.

II. RELATED WORK

Many content-aware image retargeting approaches have been proposed in the literature. According to Shamir and Sorkine [1], the proposed content-aware image retargeting approaches can be classified into two categories: discrete and continuous. With respect to the discrete approaches, the images are resized by either cropping (e.g. [6] [7]) or seam carving (e.g. [8] [9]). The cropping-based methods select an optimal rectangular area of the image, in order to remove the areas of the image that are outside of the selected rectangle. On the other hand, the seam carving methods remove iteratively multiple seams so as to preserve the most visually salient content. In this context, a seam is a continuous pixel path either from left to right or from top to bottom that has minimum significance. Extending previous discrete-based approaches, Rubinstein et al. [2] proposed a multi-operator algorithm, which combines linear scaling, cropping, and seam carving for content aware discrete image

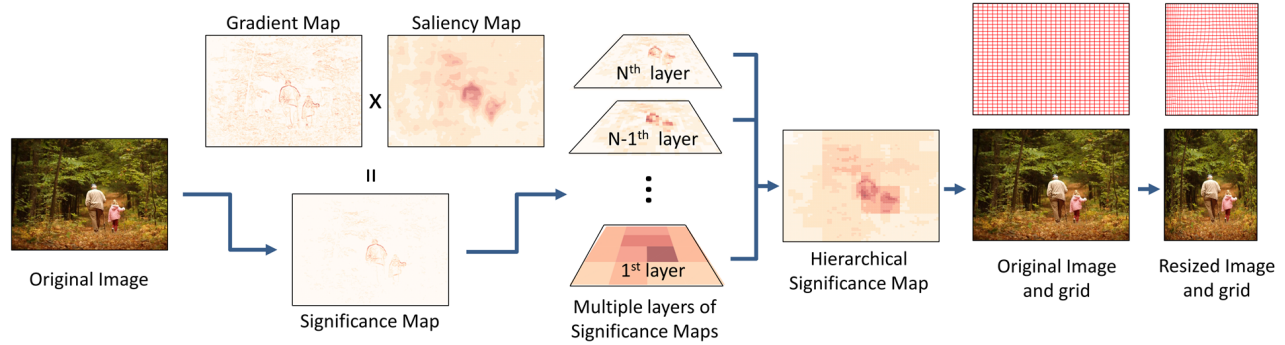


Figure 1. Method overview. The first step is the generation of the significance map of the original image. In the proposed approach the significance map is generated as the product of the saliency and gradient maps. Afterwards, multiple grids of different resolutions are considered in order to represent the significance map. The final hierarchical significance map on the grid is computed as an overlay of all the different grid resolutions. This hierarchical significance map is used for the computation of the quad sized in the target dimensions, by solving an optimization problem.

resizing. Although there are many cases where the discrete-based image resizing approaches produce pleasing results, it should be underlined that there are cases where the seam removal may cause discontinuous artifacts (e.g. a salient objects covers an image from one border to another).

In contrast to discrete methods that remove pixels from the image, the continuous approaches utilize several deformation and smoothness constraints to identify the optimum image warping with respect to the target dimensions. One of the first continuous image resizing approach was proposed by Liu et al. [10], where the authors utilized non-linear warping in order to preserve the important content of the image. The drawback, however, is that the less important image regions may suffer from significant distortions. In order to address this issue, Wolf et al. [11] proposed a warping method that merges less important pixels in order to reduce distortion. The limitation of the proposed method, however, is that the distortion can only be propagated along the resizing direction. Further extending previous approaches, Wang et al. [3] proposed an optimized scale-and-stretch approach that is able to distribute distortion along any direction as necessary. The proposed approach iteratively warps local regions based on their underlining significance, so as to match the optimal scaling factors as close as possible. The proposed approach distributes the distortion in less significant areas, while trying to keep significance areas more homogeneously resized. However, due to the fact that a salient object is covered by many quads that have different significance values (and thus, different scale factors), it may suffer from inconsistent scaling and deformation during resizing. To overcome this issue, multiple methods (e.g. [12] [5] [13] [4]) have been proposed in the literature, which force visually salient objects to undergo homogeneous transformations during image resizing.

All the aforementioned continuous approaches rely on mapping a significance map on a grid, and warping it in order to optimally match the target dimensions. The map,

however, of the significance map onto a single layer grid may generate distortion on the salient objects, since the use of a high resolution grid is able to accurately identify small sized objects, while the low resolution grid is able to identify large sized objects. Inspired by the way human visual perception works [14], this paper proposes the use of a hierarchical significance map, in order to address the aforementioned issue. This approach takes into account information from multiple layers of different grid resolutions, and is able to efficiently identify both small and large sizes of significant regions.

III. HIERARCHICAL SCALE-AND-STRETCH

This section presents the proposed hierarchical Scale-and-Stretch approach for image retargeting. An overview of the proposed approach is presented in Figure 1. The first step is the generation of the significance map of the original image. In the proposed approach the significance map is generated as the product of the saliency and gradient maps, following the approach proposed in [3]. It should be noted however, that the proposed hierarchical approach is not limited on the specific selection of significance map, since it can take into account any type of significance map, as long as it is defined for each pixel of the image.

After the generation of the significance map, multiple grids of different resolutions are considered in order to represent the significance map. The significance of each quad is defined as the average of the significances of the pixels contained in it. The final hierarchical significance map on the grid is computed as an overlay of all the different grid resolutions. The intuition is that low resolution layers can capture large significant objects in the image, while high resolution significance maps can capture small significant objects. Thus, the overlay of different grid resolutions can capture both large and small size objects.

Finally, the image retargeting problem is formulated as an optimization problem, where the goal is the minimization

of the image deformation energy, following the procedure proposed in [3]. This procedure provides more space to quads of high significance at the expense of distributing the distortion of the image to low significance quad.

A. Generation of the hierarchical significance map

The hierarchical significance map takes multiple grid resolutions into account, and is able to efficiently identify significant regions. This hierarchical procedure has been used before in the literature for the generation of saliency maps on images [14] and meshes [15]. The advantage of this hierarchical definition over the single-layer approach, is that it captures both large and small patterns, since low resolution grids might lose small patterns but can capture large patterns, while the opposite stands true for high resolution grids.

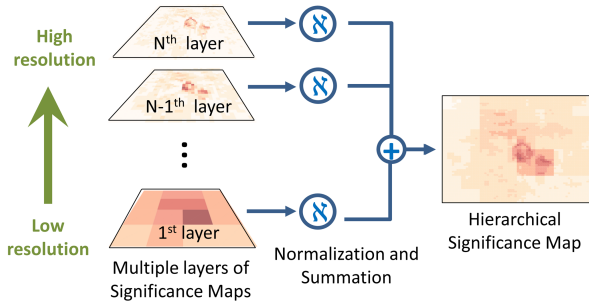


Figure 2. Generation of the hierarchical significance map. The significance map is created for each layer of the grid hierarchy. Afterwards, each layer is normalized, and all the layers are superpositioned for the generation of the final hierarchical significance map.

The procedure of generating the hierarchical significance map is illustrated in Figure 2. A hierarchy of layers is generated, each one covering the original image with different grid resolutions. The significance map is calculated and normalized for each layer separately. Afterwards, the significance maps of each individual layer are superpositioned for the generation of the hierarchical significance map which will be used for the deformation procedure.

For the generation of the hierarchical significance map, the grid of each layer of the hierarchy must be defined. Each grid $G = (V, E, F)$ is comprised of a set of vertices V , a set of edges E and a set of quads F , where $V = [v_0^T, v_1^T, \dots, v_{end}^T]$, and $v_i \in \mathbb{R}^N$ is the vertex position in the N -dimensional space. The vertices and edges partition the input space into a grid comprised of quads of the same size.

Each quad $f_i \in F$ is comprised of a set of edges $E(f_i) \subset E$ and vertices $V(f_i) \subset V$. The total number of quads is $\prod_{i=1}^N n_i$, where n_i is the number of partitions per dimension. Each partition in a dimension is a line segment, equal in size with all the other partitions in the same dimension. An example of a grid is presented in *layer* $l + 1$ of Figure 3, which is comprised of $n_1 * n_2 = 4 * 4 = 16$ rectangular

cells, and 4 partitions per dimension. In the context of this work, we consider that $n_i = n_j = n, \forall i, j$, which allows for the calculation of the hierarchical significance map.

Let $G_l = (V_l, E_l, F_l)$ denote the grid in *layer* l with n_l partitions per dimension. Each grid G_l has $n_l = 2^l$ partitions per dimension, e.g. the grid of *layer* 1, G_1 has $n_1 = 2$ partitions per dimension. The value of l is within $l \in [1, \dots, M]$, where M is the maximum level allowed, and depends on the maximum resolution allowed.

The first step towards the generation of the hierarchical significance map is the definition of a single-layer high resolution significance map in the input data space. There are multiple choices for the selection of the appropriate single-layer significance map. In the context of this work, the experimental results were created and compared using both entropy[16] and saliency maps [17][3]. Afterwards, the calculation of the significance value for each quad is defined as the average significance value of the region covered by it, while the significance map of *layer* l is defined as S_l . The significance value of each quad f_i^l is denoted as $s_i^l \in S_l$. The second step is the normalization of significance maps of each individual layer, for the subsequent superposition of the maps. The operator $\aleph(\cdot)$ defined in [14] is utilized so as to normalize each significance map. For reasons of self-completeness of this document the normalization operator $\aleph(\cdot)$ is presented below:

- 1) Normalize the values of significance each map to $[0, \dots, 1]$, in order to eliminate layer-dependent amplitude differences.
- 2) Find the location of each maps global maximum 1, and compute the average \bar{m} of all its local maxima excluding the global maximum 1.
- 3) Multiply the values of each map by $(1 - \bar{m})^2$.

The same normalization operator $\aleph(\cdot)$ has also been used in other research works (e.g. [15] and [18]), and has as a result the promotion of significance maps, which are comprised of a small number of high significance values, while efficiently suppressing significance maps with a large number of similar values.

The final hierarchical significance map is created for the resolution of the last layer of the grid hierarchy G_M . To achieve this, let us denote as $Q(f_i^l)$, where l is the level of the hierarchy and $f_i^l \in F_l$ is a specific quad belonging to *layer* l , as the set of quads from all the layers of the hierarchy, so that they intersect with the quad f_i^l . Moreover, $A(f_i^l)$ is defined as the set of pixels covered by quad f_i^l . Then two quads f_i^l and f_j^k intersect if and only if $A(f_i^l) \cap A(f_j^k) \neq \emptyset$. Thus the set $Q(f_i^l)$ is defined as follows:

$$Q(f_i^l) = \{f_j^k | \forall j, k \text{ such that } A(f_i^l) \cap A(f_j^k) \neq \emptyset\} \quad (1)$$

In the specific case of this paper that $n_l = 2^l$ partitions per dimension are considered, if two quad intersect, it means

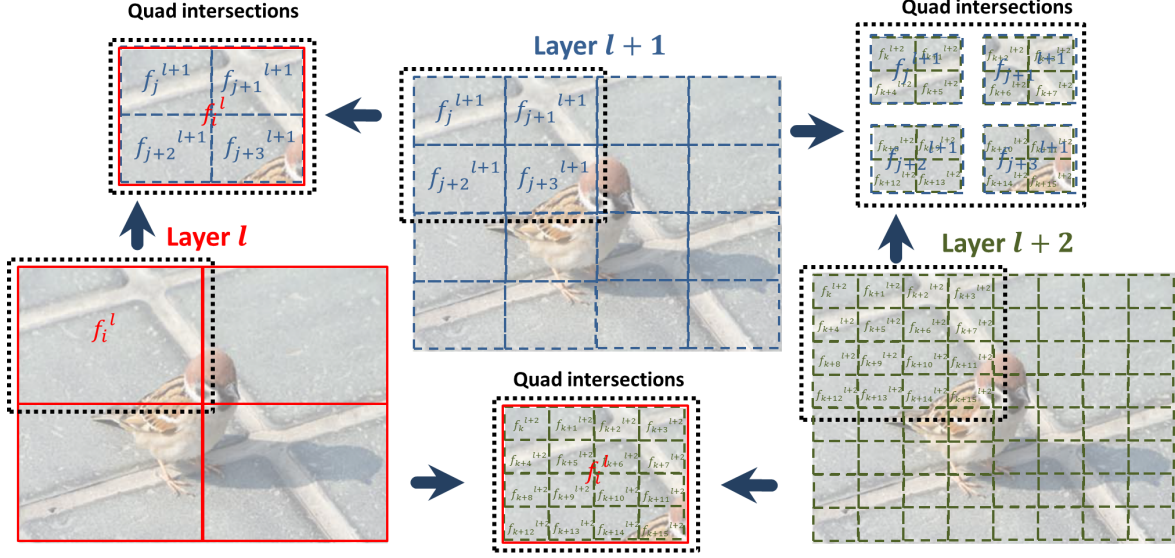


Figure 3. Examples of quad intersections between three layers of the grid hierarchy, namely, layers l , $l+1$, and $l+2$. The quads that intersect are highlighted in the subfigures named “Quad intersections”.

that the largest contains the smaller quad. The same stands true for every $n_l = r^l$ for $r \in \mathbb{N}_{>1}$.

Examples of quad intersections are presented in Figure 3. In this example, three layers of the hierarchy are considered, namely, layers l , $l+1$, and $l+2$. The quads that intersect are highlighted in the subfigures named “Quad intersections”.

In the same notion $Q_s(f_i^l)$ is the set of significance values of all the quads belonging to $Q(f_i^l)$. The superpositioning of the different maps is performed on *layer M* and the final hierarchical significance map, denoted as S^{hier} , is calculated for each quad in *layer M*. Let s_i^h be the final hierarchical significance value of quad $f_i^M \in F_M$. The calculation of s_i^h is described in the equation that follows:

$$s_i^{hier} = \sum_{s_j^l \in Q_s(f_i^M)} \aleph(s_j^l) \quad (2)$$

Finally, the hierarchical significance map is defined as $S^{hier} = \bigcup s_i^{hier}$.

Figure 4 shows the advantage of using a hierarchical significance map when compared to the use of a single layer significance map. Specifically, the hierarchical significance is able to more efficiently identify the significant objects in each image, and thus, preserve to a large degree original size in the retargeting dimensions. A similar result is also illustrated in Figure 5.

B. Grid deformation procedure

This section follows the work presented in [3] and [17], regarding the grid deformation procedure. The deformation procedure presented here has been firstly proposed by [3] for image resizing. The same procedure has afterwards been utilized by [17] for resizing data visualizations. The

deformation procedure is briefly presented here. More details can be found in [3].

The purpose of grid deformation is to enlarge significant regions of the input space, and visualize any patterns that were previously hidden due to high cluttering. The deformation method takes as input a grid $G = (V, E, F)$ and its significance map S , where V the matrix of vertices, E matrix of edges, and F the matrix of quads. These matrices have specific relationships between them, i.e. $F = QV$ and $E = HV$, where Q and H are also matrices which depend on the grid. The result of deformation is a new grid $G' = (V', E', F')$, created by changing the positions of the vertices in V , according to the given significance map.

According to [3], the ideal deformation of each $v_i \in V$ into a new position should be defined as $v'_i = c * v_i$, where c is the scale factor. This equation refers to the uniform scaling case, and requires an extension of the area covered by the data in the input space. In the case that the area covered by the data in the input space is considered static, then the enlargement is not possible. One of the alternatives proposed in the literature (see Section II) is to introduce a non-linear deformation of each quad, so that more space is given to more significant quads [3][17].

The main objective of the utilized grid deformation method is to minimize the total deformation energy, defined as the distance from the uniformly scaled position. Let $f_i \in F$ be a quad defined as $f_i^T = q_i V$, where q_i is a $2^N \times |V|$ matrix (N is the dimension) and its element in the r_{th} row and c_{th} column is defined as:

$$q_{i,rc} = \begin{cases} 1 & , \text{if } v_c \in f_i, \text{ and } f_{i,r} = v_c \\ 0 & , \text{else} \end{cases} \quad (3)$$

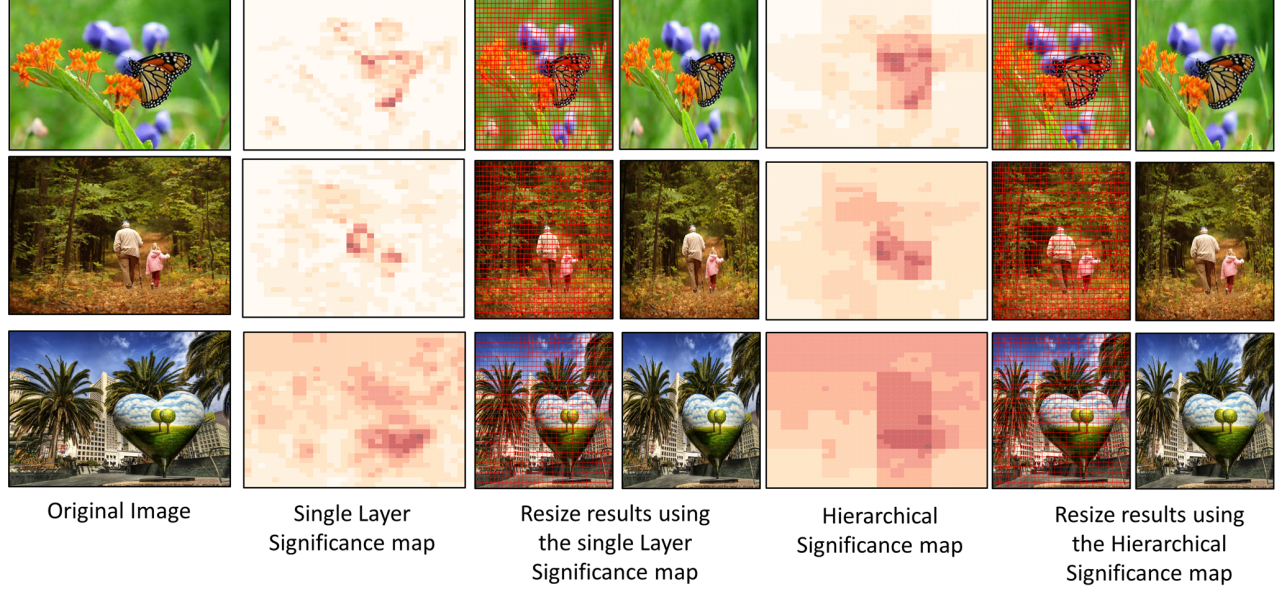


Figure 4. Examples of image retargeting using single layer and hierarchical significance maps. From left to right: Original Image, Single Layer Significance map, Resize results using the single Layer Significance map, Hierarchical Significance map, and Resize results using the Hierarchical Significance map. The results of the hierarchical significance map are able to more efficiently identify the significant objects and preserve their original size.

where f_i, r is the r_{th} vertex in f_i . Given $Q = [q_0^T, q_1^T, \dots, q_{|F|}^T]^T$, the matrix of quads is defined as $F = QV$.

The uniformly scaled quad is defined as $f'_i = c_i f_i$, where c_i is the desired scale matrix for the i_{th} quad. Let $F^T = [f_1, f_2, \dots, f_{|F|}]$ be a matrix of all the quads, and W_F be a $|F| \times |F|$ matrix of the significance of each quad, while its element in the r_{th} row and c_{th} column is defined as:

$$W_{F,rc} = \begin{cases} \sqrt{s_r} & , \text{if } r = c \\ 0 & , \text{else} \end{cases} \quad (4)$$

where s_r is the significance of quad f_r . Furthermore, let C be the desired scale matrix C with:

$$C_{rc} = \begin{cases} c_r & , \text{if } r = c \\ 0 & , \text{else} \end{cases} \quad (5)$$

The total quad deformation energy is defined as follows:

$$\|W_F F' - W_F C F\|^2 \quad (6)$$

or alternatively:

$$\|W_F Q V' - W_F C Q V\|^2 \quad (7)$$

The minimization of the total quad deformation energy allows for the quads with large significance, to have a smaller distance from their uniformly scaled version (which refers to the lack of distortion for all the objects), and thus,

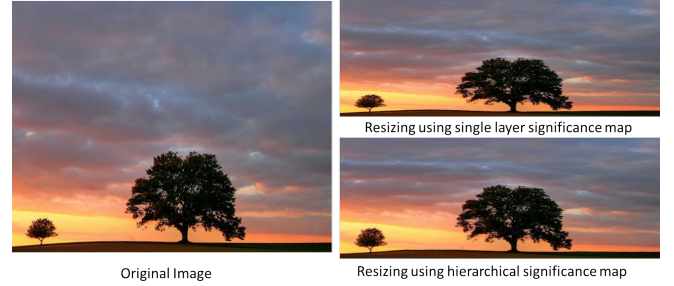


Figure 5. An example of image retargeting using single layer and hierarchical significance maps. The hierarchical significance map is able to more efficiently identify the trees and preserve as much as possible their original size.

under the constraint of static space, significant quads are enlarged more than less significant ones.

An additional energy term that is used for the deformation procedure is the edge bending, as proposed in [3]. This term captures the case in which significant data patterns occupy multiple connected quads, and tries to prevent their distortion [3][17]. Given an edge e_k , its uniformly scaled version is defined as $e'_k = l_k e_k$, where l_k is a 2×2 scale matrix. Let $E^T = [e_1, e_2, \dots, e_{|E|}]$ be a matrix of all the edges, and W_E be a $|E| \times |E|$ matrix of the significance of each edge, while its element in the r_{th} row and c_{th} column is defined as:

$$W_{E,rc} = \begin{cases} \sqrt{s_r} & , \text{if } r = c \\ 0 & , \text{else} \end{cases} \quad (8)$$

where s_r is the average significance factor for all the quads in which edge e_r belongs. Furthermore, let L be the desired scale matrix L with:

$$L_{rc} = \begin{cases} l_r & , \text{if } r = c \\ 0 & , \text{else} \end{cases} \quad (9)$$

The total edge bending energy is defined as follows:

$$\|W_E E' - W_E L E\|^2 \quad (10)$$

or alternatively:

$$\|W_E H V' - W_E L H V\|^2 \quad (11)$$

where H is a matrix such that $E = H V$. The edge bending energy term scales the edge lengths and tries to retain the edge orientations, after the grid deformation.

Finally, the optimal deformed grid is defined as a solution to the following minimization problem:

$$\arg \min_{V'} \|W_F(QV' - CQV)\|^2 + \|W_E(HV' - LHV)\|^2 \quad (12)$$

subject to:

$$\left\{ \begin{array}{l} v'_{i,d} = \min[d] \quad , \text{if } v'_{i,d} \text{ is on the} \\ \quad \quad \quad \text{lower boundary} \\ \quad \quad \quad \text{of dimension } d \\ v'_{i,d} = \max[d] \quad , \text{if } v'_{i,d} \text{ is on the} \\ \quad \quad \quad \text{upper boundary} \\ \quad \quad \quad \text{of dimension } d \end{array} \right\}$$

where $v'_{i,d}$ is the coordinate of vertex $v_i \in V$ in the d_{th} dimension, and $\min[d]$ and $\max[d]$ are the lower and upper boundaries of the d_{th} dimension as defined by the input dataset. After the minimization of the total deformation energy D defined in equation 12, the new grid $G' = (V', E, F)$ is found, where $V' = \bigcup_i v'_i$. The dataset is deformed to this new grid G' , taking the initial grid into account G and utilizing linear interpolation in the one/two/three-dimensional space.

The optimization problem formulated in equation 12 is a quadratic problem with equality constraints. It is efficiently solved as a linear system utilizing matrix factorization. More details for solving the problem can be found in [3].

The scale factors of each quad are also smoothed, as suggested in [17] and [3], in order to allow for neighboring quads to have similar deformations, and thus, lead to perceptually consistent results[17][3]. The smoothing procedure is defined as an optimization problem, by minimizing the following energy term:

$$\sum_{f_i \in F} \sum_{f_j \in N(f_i)} \frac{1}{2} (s_i - s_j) (c'_i - c'_j)^2 + \sum_{f_i \in F} s_i (c'_i - c_j)^2 \quad (13)$$

where c'_i is the new scale factor of quad f_i , and $N(f_i)$ is the set of neighbors of quad f_i . In the case of a regular grid, the set of neighbors of each quad has the same size. On the contrary, in the case of multi-resolution grid, the set of neighbors of a quad might have different size for different quads. This however, is not an issue, since the set of neighbors is well defined in all cases.

IV. EXPERIMENTAL EVALUATION

This section compares the proposed hierarchical approach with other state-of-the-art methods for image re-sizing, and more specifically, with the standard discrete retargeting approach “seam carving” (SC) [19], the standard continuous resizing approach “optimized scale-and-stretch” (OSS) [3], while also with other related approaches that try to preserve shape, namely, “quad-mesh-based” approach (QM) [12] and “Patch-Based Image Warping” (PIW) [4]. These two related approaches try to identify visually salient objects in order to homogeneously resize them, similar to the proposed hierarchical approach.

Figure 6 shows the results of each method in six reference images. In all continuous cases, the same grid resolution has been used for fair comparison. The SC method [19] creates some discontinuous artifacts and distorts the salient objects of the images in most cases. This is specifically true for the bottom three images, where the distortion is the largest, since the significant objects occupy a large region of the image. The OSS approach [3] provides good results in most cases. There are, however, images in which the structure lines are distorted. The reason for this is that the utilized significance map is not able to efficiently identify the significant objects in the image. The QM approach [12] is able to more efficiently preserve the shape of the significant objects and structures in the image. There are, however, cases where distortion is visible, specifically around the borders of salient objects. The PIW approach [4] is a large improvement over the previous methods. The use of patches over the salient objects in order to force homogeneous scaling provides much better results. Distortion is not visible and the shapes and structures in the image are preserved. But the PIW approach does not take advantage of the provided space well, and thus, the size of the significant objects is smaller than it could be, compared to the size of the original image. This is more evident in the three top images, where the bird, the butterfly and the chairs/table are much smaller than they were in the original image. In contrast, our approach can ease this problem, and the size of the salient objects and structures is closer to their original size, while also preserving the shape of salient objects/structures. The reason for this is

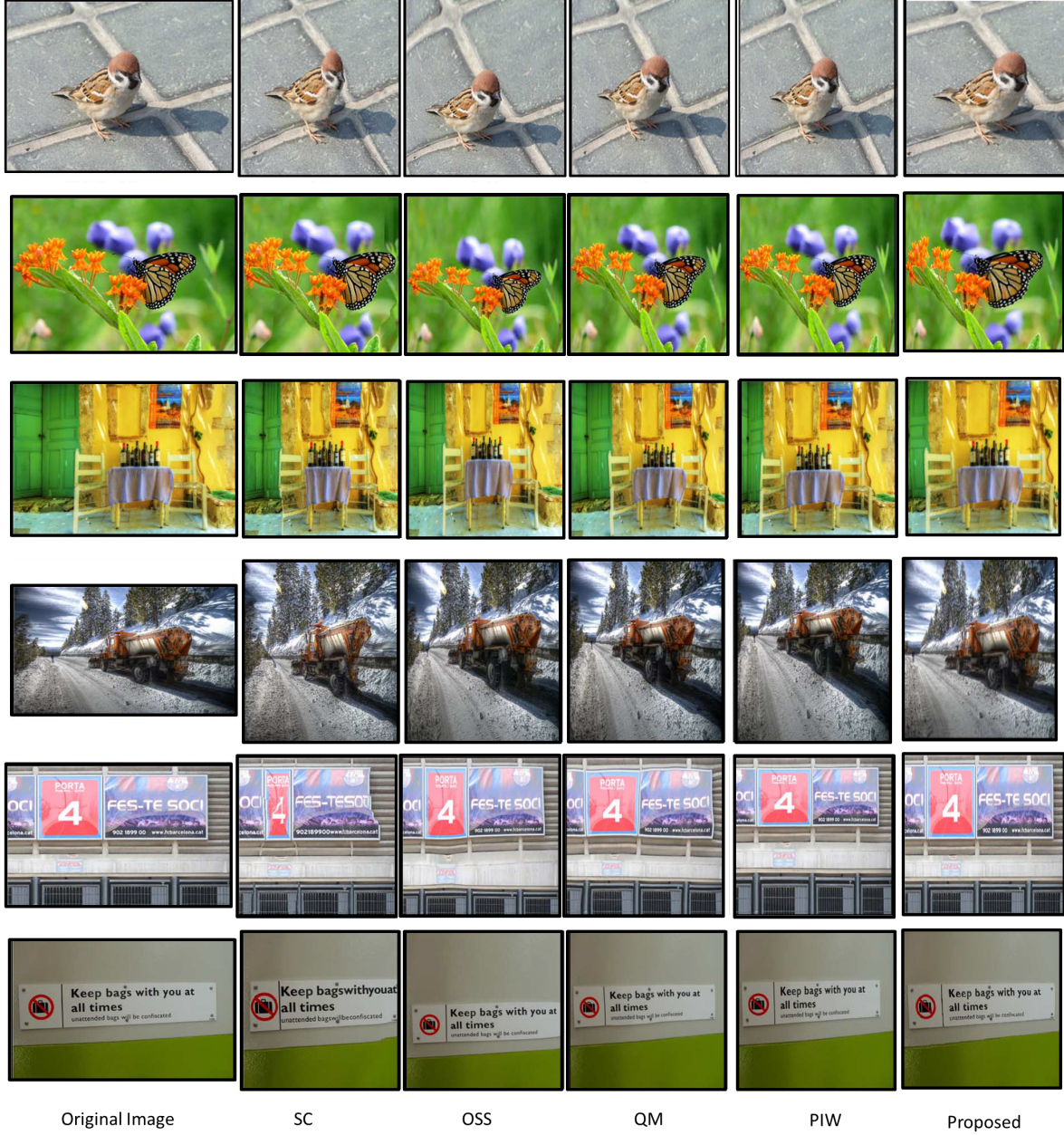


Figure 6. Comparisons with the related approaches including SC [19], OSS [3], SP [12], and PIW [4] using different images. The proposed approach is able to better preserve the shape and size of the salient objects and structures in all images.

that the proposed hierarchical approach is able to efficiently discriminate the salient regions, and thus better preserve them during resizing. This property enables the hierarchical approach to generate better retargeting results with respect to visual quality, when compared with the related approaches.

V. CONCLUSIONS

This work introduced a hierarchical scale-and-stretch approach for image retargeting. The proposed approach utilizes

the information from multiple grids of saliency maps with different resolutions in order to efficiently identify salient objects in the image. The proposed approach identifies both small and large objects/patterns, and scales them with minimum distortion in the magnified space. The efficiency of the proposed approach was demonstrated on multiple images, and the results were found to be superior to previous retargeting methods.

Future work includes the research of additional irregular

grid formations (e.g. non-rectangular grids based on edge detection algorithms), and their effect on the distortion after the retargeting procedure. Alternative significance maps will also be considered, since an important aspect of the future work includes the automatic selection of the most appropriate significance map based on the input image.

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