Topology preserved regular superpixel

Dai Tang[1,2], Huazhu Fu[1], Xiaochun Cao[1]
[1] School of Computer Science and Technology, Tianjin University, Tianjin 300072, China
[2] School of Computer Software, Tianjin University, Tianjin 300072, China
debelletang@hotmail.com {hzfu, xcao}@tju.edu.cn

***Abstract*—Most existing superpixel algorithms ignore the topology and regularities, which results in undesirable sizes and location relationships for subsequent processing. In this paper, we introduce a new method to compute the regular superpixels while preserving the topology. Start from regular seeds, our method relocates them to the pixel with locally maximal edge magnitudes. Then, we find the local optimal path between each relocated seed and its four neighbors using Dijkstra algorithm. Thanks to the local constraints, our method obtains homogeneous superpixels with explicit adjacency in low-texture and uniform regions and, simultaneously, maintains the edge cues in the high contrast and salient contents. Quantitative and qualitative experimental results on Berkeley Segmentation Database Benchmark demonstrate that our proposed algorithm outperforms the existing regular superpixel methods.**

***Keywords*-regular superpixel; topological structure; image segmentation;**

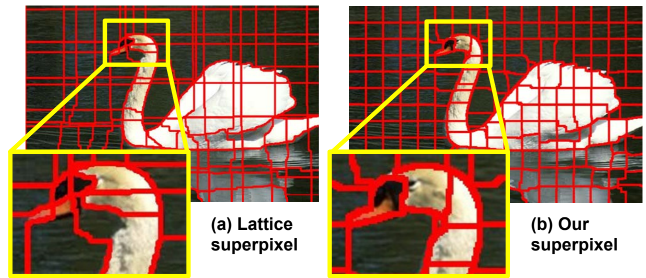

Figure 1. a) The lattice superpixel [13] shows under-segmentation errors, which miss out fractions of pixels across the neck of the swan. b) Our method obeys local optimal constraints, which offers better boundary recall, as compared in the enlarged view. Furthermore, in absence of boundary cues such as the water in the image, our topology superpixels preserve homogeneous shape and size in contrast with the previous superpixel lattice.

I. Introduction

Superpixel is originally defined as a kind of over-segmentation. Many existing superpixel algorithms are widely accepted and employed due to following advantages: superpixel can appropriately respects the boundary of different objects in the image, preserving the region based consistency of pixels; subsequent processes on the superpixel are more efficient than individual pixel, which transform the problem into an analytically tractable model. Therefore, superpixel has become a popular preprocessing for many computer vision applications, such as object recognition [1], image segmentation [2], [3], and image parsing [4], [5].

Traditional over-segmentation algorithms group pixels into superpixel under irregular size and position [6], [7], [8], [9]. Those algorithms performance well in clustering pixels of similar appearance, but neglect the coherence and uniformity of these atomic regions, which inevitably result in the confusion of adjacency and the inconvenience of storage. For example, in some applications, such as image parsing [4], [10], graph-based [11], [12], the spatial relation of each patch acts a important property. However, most superpixel methods ignore this topological constraint. To some degree, it is the specific topology that contribute to the appealing properties of original pixel representation superior to superpixel.

Our work is inspired by [13], [14], where authors provide a method by incrementally adding vertical and horizontal paths. In this case, the greedy superpixel algorithm seeks the optimal path within a predefined strip, while future path costs are modified around previous paths, avoiding multiple crossings. To satisfy this semi-global constraint, the paths are forced to curved, and irregularity of superpixel occurs, which can be clearly observed in low-texture regions. Furthermore, this semi-global constraint easily leads to under-segmentation. Figure I (a) gives an illustration, where the segmentation of water appears irregular and the neck of the swan is an under-segmentation error.

In this paper, we instead emphasize the notion of regular superpixel and summarize the following observations: superpixel is a collection of information over pixel level, preserving equivalent spatially-coherent, and sufficient appearance for a given resolution; topology, homogeneous, and isometric information content, as the typical properties of pixels, should be inherited by the superpixel as much as possible. Based on these consideration, a simple yet effective regular superpixel method is proposed originated from local seeds. Primarily, the superpixel in our method appropriately expresses the contour of physical objects. In particular, the local optimal principle ensures that in the absence of boundary cues, such as low-texture regions, superpixel maintains the homogeneous shape by design. Figure I (b) shows the result of our method, where the local seed constraints bring about overall regular superpixels and the detailed parts of object (e.g. neck of the swan) are precisely segmented.

This paper is organized as follows: Section II introduces

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DOI 10.1109/ICME.2012.184

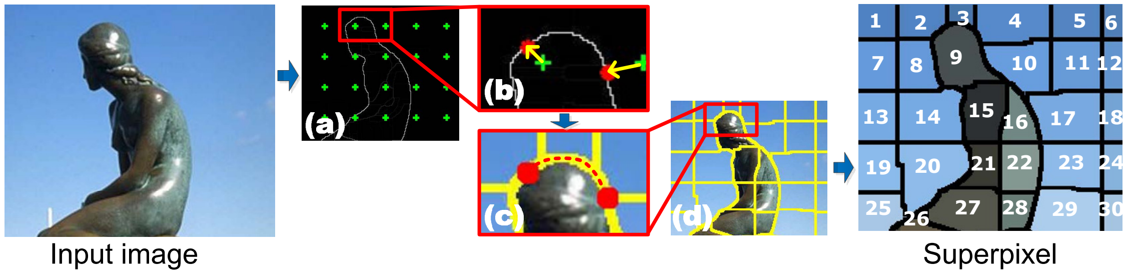

Figure 2. The framework of our method: for an input image (a), we place initial seeds based on regular grid; (b) relocate each seed into appropriate boundary obeying maximal edge magnitude constraints; (c) generate the optimal path between each relocated seed pairs; (d) the connections are proved to be adaptive to object boundaries. Finally, the indexed superpixels responds to our preserved topology.

the detailed implementation of our method, including initialization, relocation and generating paths. Section III shows the experimental results and comparison with previous non-regular algorithms and lattice-like segmentations. Finally, Section IV presents some concluding remarks.

II. Our method

In this section, we give a detailed explanation for our approach. Intuitively, the framework of our method, from initializing seeds to resulting superpixels, is shown in Figure 2. There are three main steps involved: 1) arranging initial seeds under a lattice grid and associating them with proper pixels over the boundary map; 2) for each seed, relocate it to the pixel with locally maximal edge magnitudes, in considerations of both distance term and probability term; 3) generating the local optimal path between vertical and horizontal seed pairs, while the searching area of the path is allocated as self-adaption to control the overall errors.

A. Seed Initialization

The input of our method is a boundary map (see Figure 2 (a)), and we begin with placing original seeds into a regular grid. Actually, this specific layout guarantees the regular topology of the obtained superpixels. Here the density of seeds depends on the number of superpixels, which is a fundamental parameter for subsequence processes. The inter-seed distances M and N are given by:

$$\begin{cases} W/M \approx H/N \\ s = MN \end{cases} \Rightarrow \begin{cases} N \approx \sqrt{sH/W} \\ M = s/N \end{cases}, \qquad (1)$$

where H and W denote the height and width of image, s denotes the resolution. Apparently, these two parameters are tuneable to the resolution s of the objective superpixel map, and co-operate within tacit agreement. As we emphasized on topological properties, homogeneous appearance is one of the necessary requirements for each superpixel. To some extent, equal space sampling is a theoretical support for this calculation formula, which facilitates our regular topology.

B. Seed Relocation

The second step is shown as detailed drawing in Figure 2 (b), where the seeds search for maximal edge magnitudes according to boundary map. Firstly, for each displacement, we set a fixed searching radius r for each seed:

$$r = \gamma \max(W/M, H/N), \qquad (2)$$

where γ is a scale parameter ($\gamma = 0.5$ in our experiments). This searching radius r aims to limit potential collisions of the adjacent seed, and restrict each seed to relocate within a local region R. Note that the overlap of searching region may also bring the wandering arbitrarily of seed and break the topological index. Thanks to the equal space sampling in Eq. (1), the influence of this overlap is restrained.

The question then is to integrate the seeds smoothly into nearby boundaries. The optimal relocated position $\hat{p}$ of seed p in searching region R is defined as:

$$\hat{p} = \arg\max_{p_i \in R} \left[P_b(p_i) \cdot \mathcal{N}\left(\|p_i - p\|_2 \mid 0, \sigma^2 \right) \right], \qquad (3)$$

where $P_b(p_i)$ is the probability of boundary which includes pixel p_i, and $\mathcal{N}$ is Gaussian kernel which plays a penalty term of Euclidean distance between the initial seed and the candidate position p_i. This formula clearly combines two terms: spatial constraint and probability of boundary. In other words, it is considered as the weighting function for the searching process, and leads to maximal edge magnitudes of local region. Under this local constraint, the seeds coincide with proper boundaries respectively.

C. Seed Connection

Followed by the displacement, the third step is to generate the local optimal path connected neighborhood of each relocated seed, vertically and horizontally. Our solution is formulated within the searching algorithm of shortest path. We define an regional undirected graph according to the relative position for each seed pairs. In the undirected graph, the node denotes the pixel, and edge is defined as:

$$E_{ij} = \frac{1}{P_b(\hat{p_i}) + P_b(\hat{p_j})}, \qquad (4)$$

Table I
THE EXPLAINED VARIATION (R^2) RESULTS COMPARING WITH OTHER SUPERPIXEL METHODS [13], [8], [9].

Number	50	100	200	400	800
Our + Canny	0.628	0.681	0.742	0.791	0.827
Our + gPb	0.640	0.678	0.740	0.770	0.807
Lattice [13]	0.520	0.601	0.676	0.750	0.787
Turbo [8]	0.556	0.665	0.727	0.790	0.835
ERS [9]	0.693	0.744	0.790	0.825	0.853

where the weighted edge E_{ij} provides sufficient relevance information, and then optimality path is composed of several selected edges. In our method, Dijkstra algorithm is employed to generate the shortest path, and seed connection has been accomplished. Consequently, the cells of our lattice are built up and each pixel is assigned to only one of them. In Figure 2 (c), the red dotted curve denotes the obtained path between two source seeds, which coincides with the edge of object.

Thus far, we establish high-order relations in terms of topology for superpixels (the rightmost result in Figure 2), which is indexed regularly. Since the constraints of the grid structure and limited radius of the searching area, the obtained superpixels are considerably homogeneous on the whole. In addition, the local optimal principle keeps the independence between regions, which indicates that our algorithm can be extended into a parallel computing resolution.

III. Experiments

We perform our experiments on the Berkeley Segmentation Database Benchmark (BSDB) [15], which contains 300 images with human-labeled ground truth segmentations. Figure 4 shows some examples of our superpixel method with 200 resolutions. It can be seen that the superpixels of our method coincides with most of the edges of the objects. Furthermore, thanks to the local seeds constraints, our method obtains homogeneous superpixels with explicit adjacency in low-texture regions. In Figure 3, we show an example of superpixel with various resolutions ($s = 50, 120, 200, 400$). On one hand, as the resolution increasing, the more details are precisely extracted, such as the weeds and leaves in the background. On the other hand, we see that our method obtains superior results with the lower resolutions and does not lose the saliency object, such as the mushroom in Figure 3.

Superpixel segmentation is different from object segmentation, so the performance metrics are also different. Here the explained variation in [13] is used to evaluate an overall difference between the original pixels and the superpixels as:

$$R^2 = \frac{\sum\limits_{k=1}^{S} k(\mu_k - \mu)^2}{\sum\limits_{i \in I} (x_i - \mu)^2}, \tag{5}$$

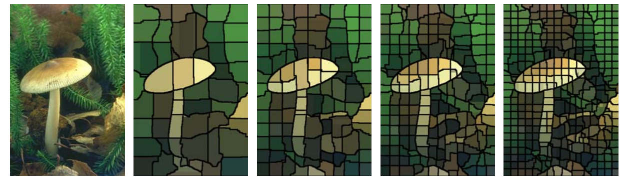

Figure 3. Form left to right: original image, our superpixel with the resolutions $s = 50, 120, 200, 400$. As the resolution increasing, the details of object are partitioned more precisely.

where x_i, μ_i and μ denote the actual pixel value, the mean value of superpixel k and the global pixel mean, respectively. An example of using the superpixel mean can be seen in Figure 3. The explained variation R^2 measures the color distortion level cased by superpixels. Table I shows the the performance of our method with two kinds boundary map: Canny edge [16] and gPb map [17]. Furthermore, we also compare with other three superpixel methods: Lattice superpixel in [13], Turbo pixel in [8] and Entropy rate superpixel (ERS) in [9]. In the light of the experiment, we conclude the following observations: (1) for all the methods, the expected variations achieved higher scores with the increasing number of superpixels. (2) the ERS presents best performance of all methods. It is unsurprising that our method performs worse than ERS, because of the topological restrictions of our method. (3) our method outperforms than Lattice superpixel [13] under all resolutions, since the local seeds connection are more suitable to obtain accurate details. (4) comparison with Turbo pixel [8], our method obtains a better explained variation in low resolution. (5) it is a interesting result that the performance of our method with Canny edge is better than with gPb map under high resolution. One possible reason is that for the high resolution, the Canny edge, which is based on the first derivative of a Gaussian, provides more dense boundary than gPb map and prefers the global boundary in image. For high resolution superpixel, the dense boundary favors to offer a meaningful edge magnitude in low-textured region.

Figure 5 shows some visual comparisons of superpixel results with 200 resolution, from top to bottom: Turbo pixel [8], Lattice superpixel [13], and our method. Our algorithm obtains superpixels that are more regularly shaped and uniform in size than those of other two methods. The prominent advantage of our method is that we maintains obvious topological relation between adjacent patches, as expected.

IV. Conclusion

In this paper, we have presented a comprehensive method to generate regular superpixel. With the local regular seeds, our method obtains topology, homogeneous, and isometric superpixels with explicit adjacency in low-texture and uniform regions, simultaneously, maintains the accuracy in the

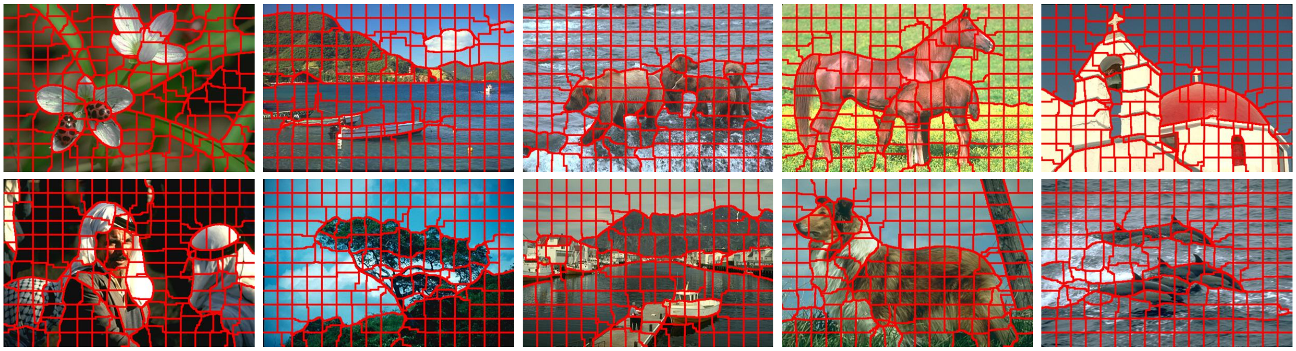

Figure 4. Example results with 200 resolutions on BSDB dataset. Our superpixel obtains the topology and homogenous, simultaneously, maintains high accuracy in the high contrast and salient contents.

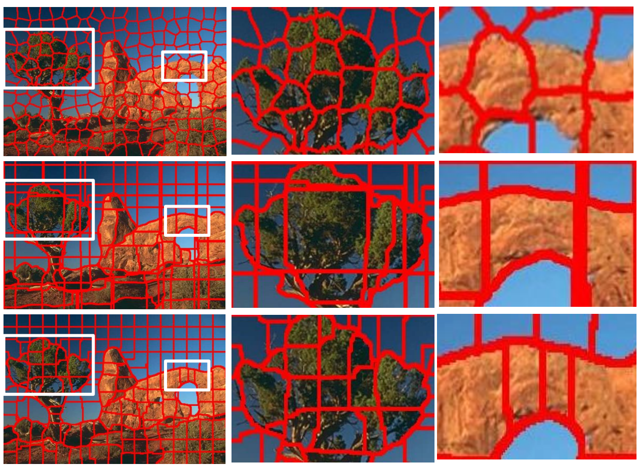

Figure 5. Comparison with other superpixel methods with 200 resolution. Form top to bottom: Turbo pixel [8], Lattice superpixel [13], and our method, with a zoom-in on selected regions in the middle and right columns.

high contrast and salient contents. The experimental results demonstrated the performance of our method sufficiently.

ACKNOWLEDGMENT

This work was supported by National Natural Science Foundation of China (No. 60905019), Tianjin Key Technologies R&D program (No. 11ZCKFGX00800), Tsinghua-Tencent Joint Laboratory for Internet Innovation Technology, and SKL of CG&CAD.

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