



COMPARATIVE ANALYSIS OF SUPERPIXEL SEGMENTATION METHODS

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Abstract:

Superpixel segmentation showed to be a useful preprocessing step in many computer vision applications. Superpixel's purpose is to reduce the redundancy in the image and increase efficiency from the point of view of the next processing task. This led to a variety of algorithms to compute superpixel segmentations, each with individual strengths and weaknesses. Many methods for the computation of superpixels were already presented. A drawback of most of these methods is their high computational complexity and hence high computational time consumption. K mean based SLIC method shows better performance as compare to other while evaluating on the bases of under segmentation error and boundary recall, etc parameters.

Keywords: Image segmentation; Morphological Processing; Superpixel.

Cite This Article: SumitKaur, and Dr. R.K Bansal. (2018). "COMPARATIVE ANALYSIS OF SUPERPIXEL SEGMENTATION METHODS." *International Journal of Engineering Technologies and Management Research*, 5(3), 1-9. DOI: 10.29121/ijetmr.v5.i3.2018.172.

1. Introduction

Image pixels are the base unit in most image processing tasks. However, they are a consequence of the discrete representation of images and not natural entities. In image processing the Image segmentation is a fundamental issue in the field of computer vision. It has been widely studied for the problems of image processing and pattern recognition. Segmentation is usually performed by identifying the differences between interesting and uninteresting objects in an image. As a result, it divides the image into different sets that are composed of homogeneous regions with common properties. As an important preprocessing stage of many applications in the field of computer vision and image processing, superpixels generation has attracted substantial attention during the last decade. The superpixel concept was originally presented by Ren and Malik [1] as the perceptually uniform regions. Superpixels are clusters of pixels which share similar features, thus they can be used as mid-level units to decrease the computational cost in many vision problems, such as image/video segmentation, saliency, tracking, classification, object detection, motion estimation, reconstruction and other vision applications. It has been extensively used in various scenarios of computer vision, such as image segmentation and object recognition. Compared to the traditional pixel representation in image, the superpixel representation greatly reduces the number of image primitives and thus improves the representative efficiency. In one

sentence, superpixels are an over-segmentation of an image - or seen the other way around a perceptual grouping of pixels. Instead of finding the few (e.g one to five) foreground segments that correspond to objects, superpixel segmentation algorithms split the image into typically 25 to 2500 segments. The objective of this over-segmentation is a partitioning of the image such that no superpixel is split by an object boundary, while objects may be divided into multiple superpixels. This way, the object outlines can be recovered from the superpixel boundaries at later processing stages. Such segmentations are sometimes also coined multipurpose image segmentations.

There are many approaches to generate superpixels, each with its own advantages and drawbacks that may be better suited to a particular application. For example, if adherence to image boundaries is of paramount importance, the graph-based method of [2] may be an ideal choice. However, if superpixels are to be used to build a graph, a method that produces a more regular lattice, such as [3], is probably a better choice. While it is difficult to define what constitutes an ideal approach for all applications, we believe the following properties are generally desirable:

- 1) Superpixels should adhere well to image boundaries.
- 2) When used to reduce computational complexity as a preprocessing step, superpixels should be fast to compute, memory efficient, and simple to use.
- 3) When used for segmentation purposes, superpixels should both increase the speed and improve the quality of the results.

Downsides of using superpixel segmentation as preprocessing step are the computational effort for the computation of superpixels and more importantly the risk of losing meaningful image edges by placing them inside a superpixel. Depending on the application and the used superpixel algorithm, subsequent processing steps can struggle with a non-lattice arrangement of the superpixels. Therefore, the careful choice of the superpixel algorithm and its parameters for the particular application are crucial.

2. Applications

2.1. Semantic Segmentation

Semantic segmentation aims at assigning pre-defined class labels to every pixel in an image. One of the most successful frameworks for this task models the problem as an energy minimization of a conditional random field (CRF) [6], [7]. By working directly on the superpixel level instead of the pixel level, the number of nodes in the CRF is significantly reduced (typically from 105 to 102 per image [7]). Therefore, the inference algorithm converges drastically faster [7]. Following [8], we use the method of [9] to evaluate superpixel algorithms on the MSRC-21 database [10]. The original annotations of MSRC-21 are quite imprecise and in order to get reliable results, we use an accurate version provided by [11]. All settings of [9] are kept constant for all superpixel methods.

2.2. Saliency Detection

The goal of saliency detection is to tell whether a pixel belongs to the most salient object. The method of [12] introduces *Cellular Automata* (CA) to intuitively detect the salient object. CA

can be designed in a single-layer (SCA) or multi-layer (MCA) fashion. It's shown in [12] that MCA improves saliency detection accuracy significantly compared to SCA by fusing multiple saliency detection methods. Here we demonstrate that improvement can also be achieved by fusing multi-scale segmentation. SH shows striking advantages for this task as generating the most accurate saliency maps and reducing computational cost significantly.

2.3. Stereo Matching

To demonstrate the usefulness of tree structure provided by SH, we integrate it with the non-local cost aggregation method [13] for stereo matching. Different from traditional local stereo methods, [13] performs cost aggregation over the entire image with a MST in a non-local manner. The method is computationally very efficient, with a complexity comparable to uniform box filtering and also shows edge-preserving and non-local properties. Following [14], we quantitatively evaluate the aggregation accuracy with MST, FH, ERS and our SH on 19 Middlebury data sets. All the methods use the same cost volume and do not employ any post-processing. The subscripts represent relative rank of the methods on each data set. As expected, all segmentation-based structures improve the basic MST. The performance of proposed SH is higher than the other tree structures. It obtains the lowest average error rate and the highest average ranking. SH achieves the most accurate results on 13 (out of 19) datasets.

3. Existing Techniques

A lot of superpixel algorithms have been proposed in the last decade. Therefore, it is difficult to select appropriate approaches for specific applications. In this paper different algorithms available for superpixel segmentation will be reviewed based on their performances. Algorithms for generating superpixels can be broadly categorized as either graph-based or gradient ascent methods.

3.1. Graph Based Algorithms

Normalized Cuts (NC): The normalized cuts algorithm was originally proposed [15] for the task of classical segmentation. The normalized cuts using graph cuts to optimize a global energy function. The Normalized cuts algorithm [16] recursively partitions a graph of all pixels in the image using contour and texture cues, globally minimizing a cost function defined on the edges at the partition boundaries. It produces very regular, visually pleasing superpixels. However, the boundary adherence of NC05 is relatively poor and it is the slowest among the methods (particularly for large images), although attempts to speed up the algorithm exist. For the Normalized Cuts algorithm, the image is represented as a weighted undirected graph $G = (V, E)$. In terms of graph theory image segmentation can be seen as a graph partitioning. The weights of all edges that connect vertices that belong to two different sets sum up to the cut of these two sets. Thus, the edges that belong to the graph cut between two parts of an image graph form the boundary between the associated image segments. There exist efficient algorithms to find minimal cuts in image graphs (e.g. based on the MinFlow - MaxCut theorem). In an earlier approach of graph cut based image segmentation that the minimum cut criteria favors cutting small segments. This is not surprising since larger segments contain more edges in their cut and thus have higher cut values. To avoid this unnatural bias, the Normalized Cut computes the cost

of a partition of V into subsets A and B as a fraction of the total edge connections to all the nodes in the graph:

$$NC(A, B) = \frac{cut(A, B)}{assoc(A, V)} + \frac{cut(A, B)}{assoc(B, V)} \quad (1)$$

Where

$$assoc(A, V) = \sum_{a \in A, v \in V} w(a, v) \quad (2)$$

is the sum of weights from the subset of nodes A to all nodes in the graph. This definition penalizes small sets of vertices since their cut value “almost certainly” becomes a high fraction of their total sum of connection weights.

Felzenszwalb-Huttenlocher Segmentation (FH): an alternative graph-based approach that has been applied to generate superpixels. It performs an agglomerative clustering of pixels as nodes on a graph, such that each superpixel is the minimum spanning tree of the constituent pixels. FH adheres well to image boundaries in practice, but produces superpixels with very irregular sizes and shapes. They define a predicate for measuring the evidence of a boundary between two regions and present an implementation in a greedy algorithm that also satisfies global properties. Its goal is to preserve details in low variability image regions and ignore details in high-variability image regions.

SL: Moore *et al.* propose a method to generate superpixels that conform to a grid by finding optimal paths, or seams, that split the image into smaller vertical or horizontal regions [17]. Optimal paths are found using a graph cuts method similar to *Seam Carving* [18]. While the complexity of SL08 is $O(N^3 \log N)$ according to the authors, this does not account for the pre-computed boundary maps, which strongly influence the quality and speed of the output.

Veksler superpixels (VEK): Veksler et al. [2010] propose another graph cut based approach for superpixel tessellation that focuses on regular partition. They formulate the segmentation problem as an energy minimization problem that explicitly encourages regular superpixels. Superpixels are obtained by stitching together overlapping image patches such that each pixel belongs to only one of the overlapping regions.

3.2. Gradient –Ascent Based

Quickshift (QS): QS can be categorized as gradient ascent method and is a mode-seeking algorithm QuickShift performed well in terms of under segmentation error and boundary recall, ranking 2nd and 3rd overall [19]. However, QS09 showed relatively poor segmentation performance, and other limitations make it a less-than-ideal choice. It has a slow run-time (181s), requires several nonintuitive parameters to be tuned, and does not offer control over the amount or compactness of superpixels. Finally, the source code fails to ensure that superpixels are completely connected components, which can be problematic for subsequent processing. It was originally not intended as superpixel algorithm. After estimating a density $p(x_n)$ each pixel x_n ,

the algorithm follows the gradient of the density to assign each pixel to a mode. The modes represent the final segments.

Marker-Controlled Watershed Segmentation (WS): The watershed approach [21] performs a gradient ascent starting from local minima to produce *watersheds*, lines that separate catchment basins. The resulting superpixels are often highly irregular in size and shape, and do not exhibit good boundary adherence. The approach of [21] is relatively fast ($O(N \log N)$ complexity), but does not offer control over the amount of superpixels or their compactness.

Mean Shift (MS): In [22], mean shift, an iterative mode-seeking procedure for locating local maxima of a density function, is applied to find modes in the color or intensity feature space of an image. Pixels that converge to the same mode define the superpixels. MS02 is an older approach, producing irregularly shaped superpixels of non-uniform size. It is $O(N^2)$ complex, making it relatively slow and does not offer direct control over the amount, size, or compactness of superpixels.

Turbopixel Segmentation (TP): Turbopixels is an algorithm inspired by active contours [20]. After selecting initial superpixel centers, each superpixel is grown by the means of an evolving contour. TP09 produced some of the most compact and consistently sized superpixels, it fared the worst among all methods in both boundary recall and under-segmentation error. TP09 also suffers from a slow running time, and resulted in poor segmentation performance. Next to NC05, it is the slowest superpixel algorithm; it is almost 100 times slower than SLIC for a 2048×1536 image, taking 800s. On the other hand, TP09 has only 1 parameter to tune and offers direct control over the number of superpixels.

4. DBSCAN SLIC

A new method for generating superpixels which is faster than existing methods, more memory efficient, exhibits state-of-the-art boundary adherence, and improves the performance of segmentation algorithms. Simple linear iterative clustering (SLIC) is an adaptation of k-means for superpixel generation, with two important distinctions:

- 1) The number of distance calculations in the optimization is dramatically reduced by limiting the search space to a region proportional to the superpixel size. This reduces the complexity to be linear in the number of pixels N – and independent of the number of superpixels k .
- 2) A weighted distance measure combines color and spatial proximity, while simultaneously providing control over the size and compactness of the superpixels. SLIC is similar to the approach used as a preprocessing step for depth estimation described in [26], which was not fully explored in the context of superpixel generation.

This algorithm simply performs K-means in the 5d space of color information and image location and is therefore closely related to quickshift. As the clustering method is simpler, it is very efficient. It is essential for this algorithm to work in Lab color space to obtain good results. The algorithm quickly gained momentum and is now widely used.

Table 1.1: Shows the algorithm of SLIC

Algorithm: Superpixel by SLIC

```

/* Initialization */
Initialize cluster centers  $C_k = [l_k, a_k, b_k, x_k, y_k]^T$  by sampling pixels at regular grid steps  $S$ .
Move cluster centers to the lowest gradient position in a  $3 \times 3$  neighborhood.
Set label  $l(i) = -1$  for each pixel  $i$ .
Set distance  $d(i) = \infty$  for each pixel  $i$ .
repeat /* Assignment */
  for each cluster center  $C_k$  do
    for each pixel  $i$  in a  $2S \times 2S$  region around  $C_k$  do
      Compute the distance  $D$  between  $C_k$  and  $i$ .
      if  $D < d(i)$  then
        set  $d(i) = D$ 
        set  $l(i) = k$ 
      end if
    end for
  end for
/* Update */
Compute new cluster centers.
Compute residual error  $E$ .
until  $E \leq$  threshold

```

5. Performance Measure

To evaluate the performance of the algorithms for super pixels segmentation there are various performance measures that are being used. Some of them are mentioned below.

5.1. Under-Segmentation Error (UE)

Under-segmentation error (UE) measures the percentage of pixels that leak from the ground truth boundaries [23]. A good superpixel algorithm should try to avoid the undersegmentation areas in the segmentation results. In other words, we need to protect that a superpixel only overlaps with one object. A lower UE indicates that fewer superpixels cross multiple objects

$$UE_G(S) = \frac{\sum_i \sum_{k: S_k \cap G_i \neq \emptyset} |S_k - G_i|}{\sum_i |G_i|} \quad (3)$$

For each ground truth segment G_i we find the overlapping superpixels S_k 's and compute the size of the pixel leaks $|S_k - G_i|$'s. We then sum the pixel leaks over all the segments and normalize it by the image size $P_i |G_i|$.

5.2. Boundary Recall (BR)

Boundary recall [24] is an important metric for measuring the performance of adherence of boundaries in superpixel algorithms. It measures what fraction of the ground truth edges falls

within at least two pixels of a superpixel boundary. A high BR means that very few true boundaries are missed.

$$BR_G(S) = \frac{\sum_{p \in \delta S} \mathbb{I}(\|p - q\| < \epsilon)}{|\delta G|} \tag{4}$$

Which is the ratio of ground truth boundaries that have a nearest superpixel boundary within an ϵ -pixel distance. We use δS and δG to denote the union sets of superpixel boundaries and ground truth boundaries respectively. The indicator function \mathbb{I} checks if the nearest pixel is within distance.

5.3. Achievable Segmentation Accuracy (ASA)

Achievable segmentation accuracy (ASA) computes the highest achievable accuracy of labeling each superpixel with the label of ground truth that has the biggest overlap area. ASA is calculated as the fraction of labeled pixels that are not leaking from the ground truth boundaries. A high ASA means that the superpixels comply well with objects in the image. The ASA of each algorithm is calculated by averaging the values of ASA across all of the images in BSD [25]

$$ASA_G(S) = \frac{\sum_k \max_i |S_k \cap G_i|}{\sum_i |G_i|} \tag{5}$$

6. Comparative Analysis

SLIC is better algorithm the other existing algorithms for Super pixels segmentation of an image.

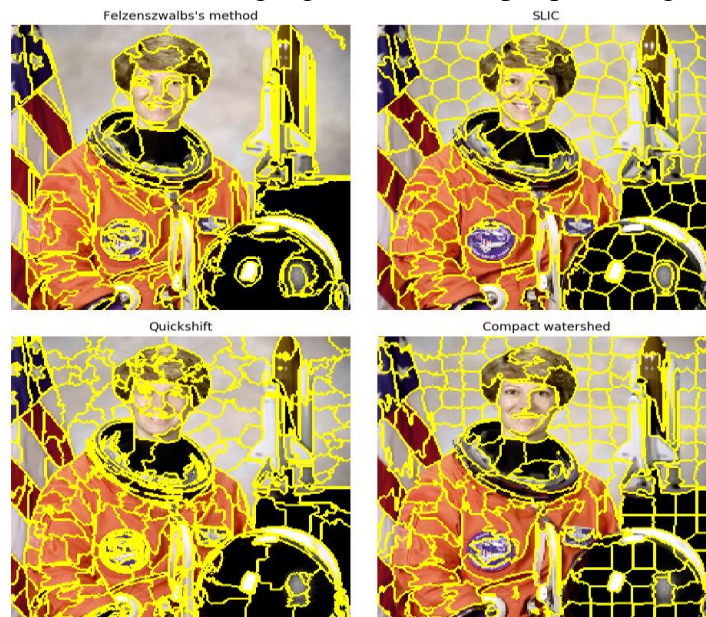


Figure 1.1: Output superpixel images of different algorithms

Table 1.1 shows the comparative summary of the super pixel algorithms based on above mention performance paprameters.

Table 1.1: Comparative analysis of superpixel algorithm with SLIC

	GS	NC	SL	WS	MS	TP	QS	SLIC
<i>Under-segmentation error</i>	0.23	0.22				0.24	0.2	0.19
<i>Boundary recall</i>	0.84	0.68				0.61	0.79	0.82
Segmentation speed								
Segmentation accuracy (using on MSRC)	74.60%	75.90%				62.00%	75.10%	76.9%
Control over amount of superpixels	No	Yes	Yes	No	NO	Yes	No	Yes
Control over superpixel compactness	No	No	No	No	No	No	No	Yes
Supervoxel extension	No	No	No	Yes	No	No	No	Yes
Complexity O(.) Where N is number of Pixels	NlogN	$N^{3/2}$	$N^2 \log N$	NlogN	N^2	N	dN^2	N

7. Conclusion

Superpixels have become an essential tool to the vision community, and in this paper we provide the reader with an indepth performance analysis of modern superpixel techniques. We performed an empirical comparison of five state-of-the-art algorithms, concentrating on their boundary adherence, segmentation speed, and performance. The *k*means clustering, based SLIC, has been shown to outperform existing superpixel methods in nearly every respect. Among the superpixel methods considered here, SLIC is clearly the best overall performer. It is the fastest method, segmenting a 2048×1536 image in 14.94s, and most memory efficient. It boasts excellent boundary adherence, outperforming all other methods in under-segmentation error, and is second only to GS04 in boundary recall by a small margin (by adjusting *m*, it ranks first). When used for segmentation, SLIC showed the best boost in performance on the MSRC and PASCAL datasets. SLIC is simple to use, its sole parameter being the number of desired superpixels, and it is one of the few methods to produce supervoxels. Finally, among existing methods, SLIC is unique in its ability to control the trade-off between superpixel compactness and boundary adherence if desired, through *m*.

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