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# Minimal Interaction Image Segmentation through Adaptive Region Growing

Julie Wan[1]
University of Central Florida, Center for Research in Computer Vision

## Abstract

Interactive image segmentation can ill-perform extraction in spite of human seeing guidance owed to inflexible growing principle. Many semi-automatic segmentation methods invoke further assistance in refining desired segmentation, evincing them as less automatic in practice. I ascertained the efficacy of an adaptive region growing method that models the homogeneity criterion of the to-be-segmented region beforehand. Seeded region growing is performed twice, initially leniently and exploratorily, and then focusedly, pressurized by learned homogeneity parameters. My determination is that semi-automatic segmentation with adaptive region growing is more precocious and less needing of interaction.

## Introduction

Image segmentation commands numerous applications and bottlenecks further recognition, quantification, and analysis. It is the course of partitioning pixels within the spatial domain into significant regions. While humans can effortlessly discern meaningful objects and boundaries, machine vision is attempted through edge and region consciousness, as in through measure of intensity discontinuities and subregion uniformity. Thus, segmentation methodologies vary in apriori desideratum when divulging image contents. Region based segmentation methods cluster or merge pixels of shared or similar quality. Region growing is instrumented through seed selection, growing principle, and terminating condition.

Depending on the degree of user influence, segmentation is characterized as either manual, fully automatic, or semi-automatic. Manual segmentation most aligns with human perception, is obviously the most accurate, but its procedure is onerous, time-consuming, and necessitates user employment. Automatic segmentation, which performs entirely without user engagement, is likely the least aligned with human perception or has costly training exigence. While pixels are each or in tandem analogous to some characteristic, feature, or property, their mosaic totality can overwhelm machine survey and automatic extraction. Automatic segmentation is therefore reserved for larger datasets at some reduction of accuracy. For effective hybridization, semi-automatic methods incorporating user interactions were devised.

Semi-automatic segmentation involves minimal user assistance, primarily endowment of prior knowledge and possible suggestion of growing condition(s). The segmentation is thus initialized

[1] Yes, this was optionally a group project. Yes, I partnered with my cat. I am reachable at juliewan@knights.ucf.edu until UCF IT disowns the account.

with higher fidelity constraints on size, color, location, and objectness which both subdues runtime and calibrates machine sight. User informs through mouse clicks, line drawings, or bounding contours, calling machine attention to desired foreground content(s) and/or background [1]. These motions translate into seed(s)--i.e., incepted region-belonging pixels--from which region segmentation originates.


**Figure 1.** Modalities of user interaction could be boundary seeds (a), region seeds for foreground and background points (b), region seeds in foreground and background scribbles (c), drawn region of interest (d), loose region of interestl (e), tight bounding box (f). The type of interaction dictates whether the approach is seed or region of interest based.

Interactive seeded region growing segmentation is semi-automatic as eventual machine independence is firstly conditioned by human perception. Segmentation effectiveness is therefore assessable with respect to user feedback. User imparted annotations could be under-qualified or sparing however, constrained by human-machine interface and/or user nescience with underlying segmentation mechanics and/or depicted subject matter--e.g., medical diagnosis. Though seeded region growing is highly resultant on seed(s) fidelity and quantity, desired segmentation can be cognized after sufficient user input, or after supplementing the set of informative seeds. This usually entails additional rounds of user involvement or intervention. A more refined segmentation might be abstemious regarding necessary engagement.

The crucible in minimizing contact might be remitted through the homogeneity growing principle. Traditionally, region growing assumes an implicit gray value for image subregions. At each iteration, an adjacent pixel is absorbed into one of its neighboring growing regions contingent on a homogeneity criterion, such as the pixel whose intensity is closest to the running average so as to introduce the least perturbance. The sameness metric is thus iterated, but this can lead to poor segmentation of larger regions and when the homogeneity parameters given are far from actual values. That is, regional criterion of homogeneity is difficult to intuit because textural or intensity variance is imperceptible at a higher level. Thus, this growth strategy, which functions without shape or boundary constraints, is prone to early termination, or incomplete saturation, and to spilling, or overestimation. Spilling occurs when intensities between two adjacent objects are similar or when lineations are blurry, a growing region might violate another region through a narrow spike [2].

## Method

Adaptive region growing, where homogeneity parameters are improved through some preliminary exploration, was proposed in 2002 [3]. To circumvent subsequent user dependence or suggestion, region growing investigates the homogeneity criterion of an appointed area before restarting and actually segmentation using its acquired homogeneity estimate. The median value was assigned as the mean and two separate standard deviations were calculated from gray values greater or lesser than the median. Upper and lower thresholds for delimiting region membership are as follows,

$$T_{upper} = mgv\,(n) + [ud\,(n) \cdot w + c(n)] \quad and \quad T_{lower} = mgv\,(n) - [ld\,(n) \cdot w + c(n)]$$

where n is the number of pixels, weight w is 1.5 to include approximately just 86% of abiding members, assuming values are normally distributed, to obviate spilling. Initial values are obtained from the seed pixel and its 3 x 3 neighborhood, or its 8-connected neighbors. During nascent learning, region membership of adjacent pixels is randomly granted, the homogeneity criterion is weakly applied to prevent early stopping, and a compensating function that expires with learning maturation, $c\,(n) = \frac{20}{\sqrt{n}}$, is added.

The approach holds with the expectations that the user does not select seeds near the region boundary, that the region is compact in proportion, meaning circular rather than elongated, and that the region is capacious enough for reliable estimate formation.

My evaluative algorithm of the adaptive region growing approach is a simplification where the mean is maintained as the definition of mean and just one standard deviation is generated. An input image is preprocessed by way of dimensionality reduction, posterization, and normalization in order to abbreviate complexity. From there, the user commissions seed(s) through mouse clicking on the desired extraction. An exploratory region grows outward from seed pixel(s), indiscriminately permitting membership which forcibly introduces heterogeneity and fits homogeneity parameters for wider region application. The mean, standard deviation, and thresholds are updated at each member intake.

Exploration halts and resets when the area external to the growing region is too heterogeneous for further acceptance. Segmentation then begins with the same seed(s) and its generalized homogeneity principle that is administered with an increased weight of 2.58 in order to receive 99% of members. Random walk is deactivated, only the most qualified active front pixel at each iteration is permitted membership into the region. Adaptive schema is still in effect in order to fine-tune growing parameters for the newly expanded membership size. By way of comparison, non-adaptive region growing is also implemented with thresholds statically set at 1.49 times above and 0.5 times below seed neighborhood mean to simulate 99% region acceptance.

## Results

My chosen input image was of my predominantly white Ragdoll, Marie, whose fur expresses textural and intensity variations at the pixel level. She is surrounded by a darker hand knotted rug which should stave overgrowth. When prompted for interaction, I prodded twice about her belly, conservatively away from the carpet, with the cursor. The seed coordinates were (167, 165) and (196, 172). The non-adaptive and adaptive region growing results are shown beside my cat.

Say “hi,” Marie. Oh, she’s such a gem.

**Figure 2a, 2b.** The input image (left) and non-adaptive seeded region growing segmentation (right).

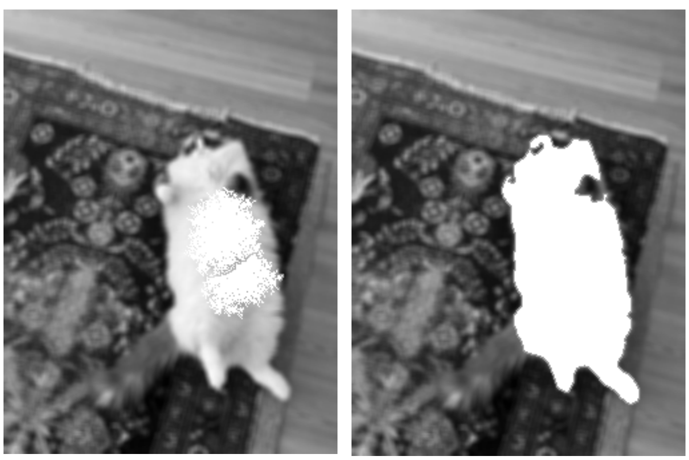

**Figure 3a, 3b.** The exploratory adaptive region growing with random acceptance encompassing 86% of region members (left) and adaptive region growing segmentation with fine-tuned homogeneity parameters and 99% acceptance interval (right).

**Table 1.** Seed coordinates and computed homogeneity parameters for non-adaptive, exploratory, and adaptive growing segmentation. Standard deviation was not pertinent for non-adaptive growing owed to constancy assumption. Other absences arise from when the subsequent seed had already been incorporated into the grow region of the first seed.

| | Seed | Region Mean | Region Std. | Seed | Region Mean | Region Std. |
|---|---|---|---|---|---|---|
| Non-adaptive Growing | (167, 165) | 0.7843 | N/A | (196, 172) | Segmented | N/A |
| Exploratory Growing | (167, 165) | 0.8207 | 0.0794 | (196, 172) | 0.7433 | 0.0672 |
| Adaptive Growing | (167, 165) | 0.7828 | 0.1084 | (196, 172) | Segmented | Segmented |

## Discussion

The non-adaptive region growing demonstration exhibits disappointingly large unsegmented swathes. Similarity constancy assumption results in negligence and early termination, her right side is prematurely contoured and notable artifacts remain where her fur fluctuates in light and shadow (Fig. 2b). The photo was taken in the mid-afternoon when sunlight horizontally, indolently, decanted through our windows, and more fundamentally, her coat palette, though neutral, is not reducible to just "white."

Exploratory growing and random admission necessitates sufficient capaciousness for sampling purity and estimate generalizability as the region proliferates circularly outward (Fig. 3a). Luckily, Marie has become quite rotund upon the reception of an automatic pet feeder. Still, this initial exploration stage should be cleverly constrained such that it can accommodate narrower or diminutive shapes while suppressing overestimation or superfluity.

Adaptive growing, once parameterized with learned homogeneity, more robustly, and almost entirely, saturates Marie's silhouette sans a small portion above her right eye, but this might be due to the lack of a bridge or connection between pixels (Fig. 3b). I almost shed a tear from how satisfying it was to witness 20/20 machine vision.

Interestingly, the final region mean between non-adaptive and adaptive methods are not numerically disparate. And actually, the statically asserted thresholds for non-adaptive growth were more relaxed than the adaptively computed thresholds, 0.3922 through 1.1686, and 0.5031 through 1.0625, respectively. Both procedures were incepted with the same seeds and utilized the same nearest neighbor admission principle. Perhaps early onset of a wide acceptance interval leads the non-adaptive algorithm astray as it admits not the most appropriate candidate situatively, but the most approximate pixel(s) overall. In adaptive region growing, electing the most suited candidate from a narrower pool at each iteration likely results in a more encompassing outcome without islands or gaps. If schedule permits, I will extend the discussion by charting the adaptive algorithm's meteorology over time.

Other routes of scrutiny might be executing seeded growing simultaneously instead of consecutively, as my trial overlooked seeds devoured by preceding growings, possibly followed by some comparative merging of all grown regions for higher fidelity segmentation, especially of larger regions or regions with more variability. Additionally, the median serving as mean with two separate standard deviations computed from values above and below can be implemented as proposed.

## Conclusion

Semi-automatic adaptive seeded region growing segmentation minimizes user interaction by self-learning homogeneity parameters and results in more fulfilling intraregional connectivity and objectness contouring. Further work remains to be done in tailoring the exploration stage to accommodate advanced shapes and boundary and size limitations.

## References

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