Region Growing Segmentation Lab Report

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March 17, 2016

1 Results

In this section we describe the results of the region growing image segmentation algorithm. Effects of changing different parameters are reported and comparisons with another popular image segmentation method are done. For testing purposes the images provided in the lab have been used.

1.1 Threshold parameter

The result of region growing algorithm is strongly dependent on the choice of the threshold parameter that determines whether a new pixel should be added to a region. Choosing a small value of threshold will make the selection process more strict and lead to larger number of regions in the output image, which can result in over-segmentation. The opposite can happen when a large value of threshold is chosen, where the output might have smaller number of regions leading to under-segmentation. The effect is observed in the following figures. For all these casea a A8 connectivity is chosen (details discussed in following section).

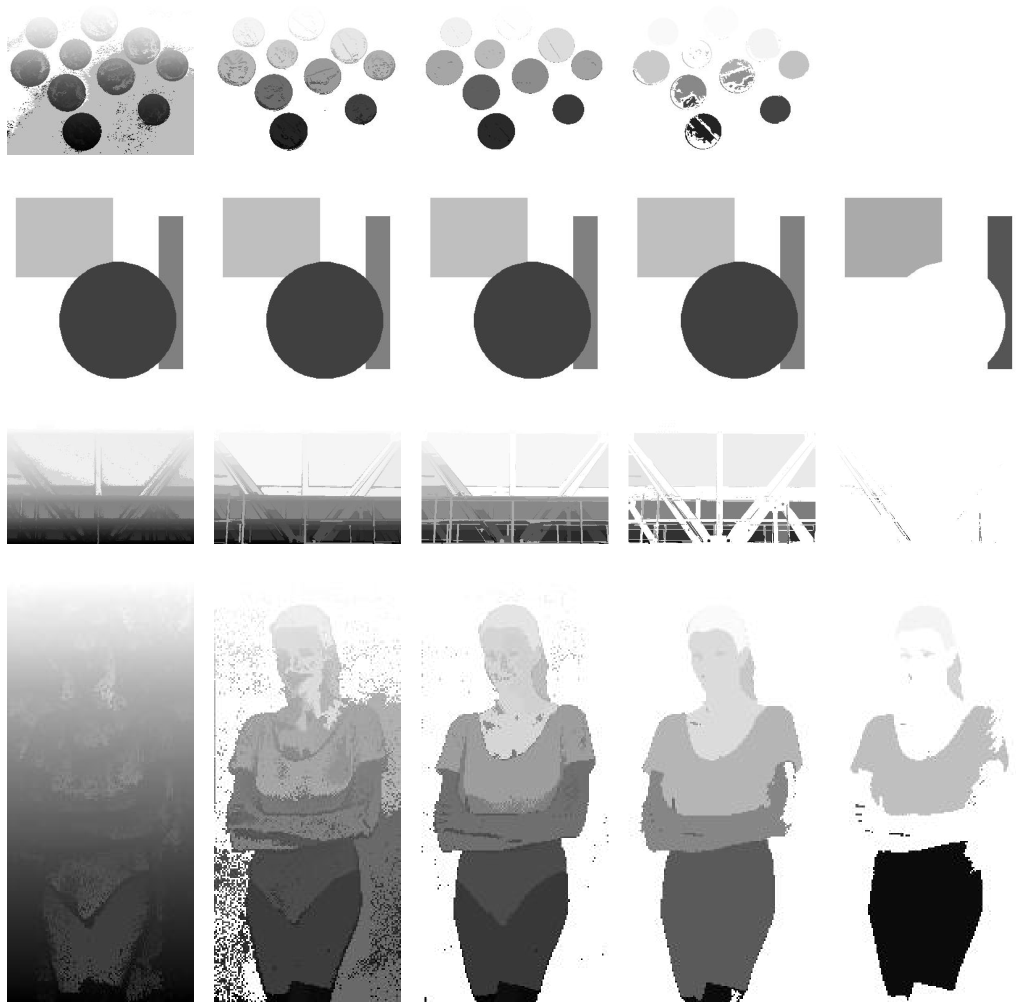

Figure 1: Region Growing Segmentation Output on Test images changing threshold value. From left to right - 5, 25, 50, 100, 200

A small threshold value like 5 produces too many regions in the output image as observed in the leftmost column of Figure 1. As an example, the number of segmented regions for the image of the woman for threshold value 100 is 105 whereas that for threshold value 5 is about 16000. The effect of threshold parameter is not too evident on the second image in the figure where pixels in one image regions have the same color. However when the threshold value is increased such that it is greater than the difference between two such image region color values, the image is under segmented and has only 3 regions.

So an optimal value of threshold is very important for getting good segmentation results with region growing algorithm. This optimal value of threshold depends on the image. For our experiments, the optimal value was around 25-30 for the first 3 images whereas for the image of the woman it was 100.

1.2 Connectivity

Another parameter in the algorithm is the choice of A4 or A8 connectivity during the explore phase. Our regiongrowing MATLAB function accepts the connectivity as an input argument, 4 and 8 being the possible values. Results for both such values are shown in Figure 2.

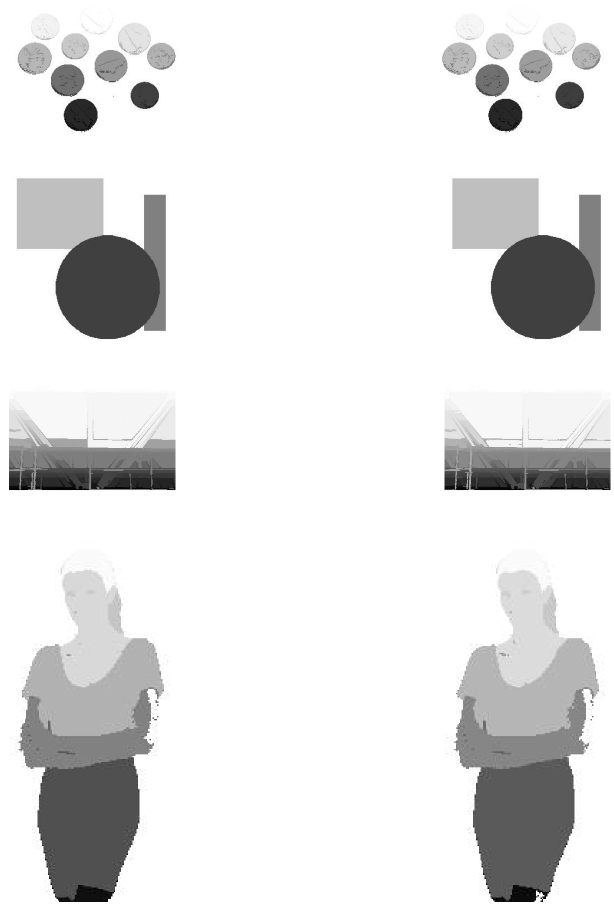

Figure 2: Region Growing Segmentation Output on Test images changing connectivity (left - A4, right A8). From top to bottom threshold value - 30, 25, 25, 100

A table of algorithm run times (without the image display) is provided.

Image	Size	Threshold	A4 Time (seconds)	A8 Time(seconds)
Coins	246x300	30	0.76	1.13
Color	278x275	25	0.78	1.11
Gantrycrane	264x400	25	0.94	1.59
Woman	261x116	100	0.33	0.45

Table 1: Comparison of run times for A4 and A8 connectivity

A8 connectivity is not much better than A4 connectivity from observing the segmented image output. In the image of the woman, A4 is slightly better than A8 in terms of pixels grouped in the same output region but actually not being part of the same image region. This effect can be attributed to the wider reach of A8 connectivity during region exploration.

Considering the lesser run times along with the above mentioned observations, A4 connectivity in the region growing algorithm seems like a suitable first choice.

1.3 Seed Distribution

The output of the algorithm is greatly dependent on the distribution of seeds. How the seed pixels are selected at the start of the algorithm and at each step of starting a new region produces a different segmentation output. We tested four cases with two test images. In one such case, the seed for the first region was pixel at (1,1) and the seed for the following regions were selected row wise from the image. The second case was to go column wise when selecting the seed for the following regions. The third case was to set the seed for the first region at pixel (m,n) in the m by n image and then move back row wise. In the fourth case the seed for the first region was randomly selected in the image. The result for all four cases in two test images are given in the following figure.

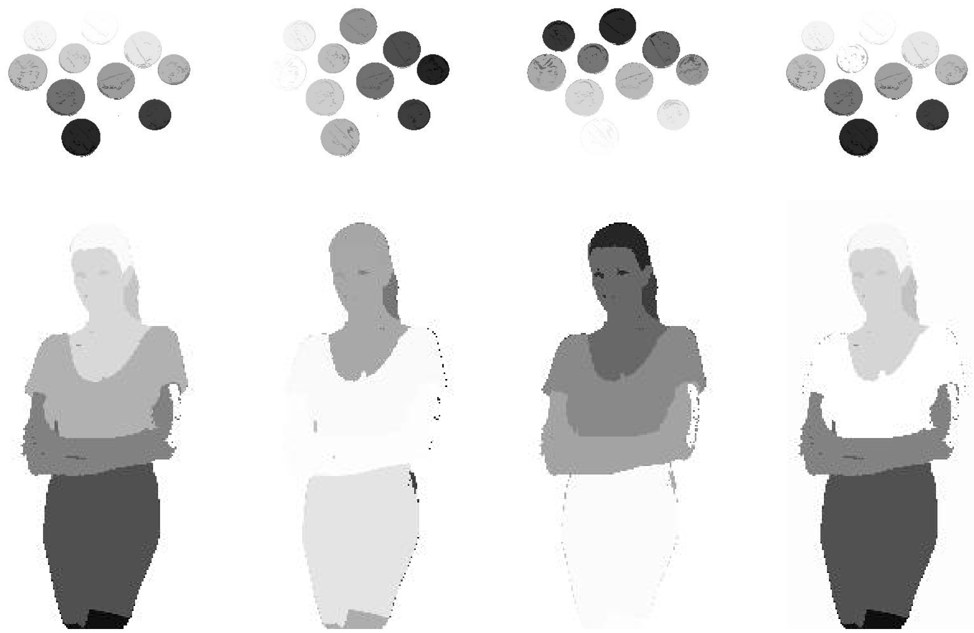

Figure 3: Region Growing Segmentation Output on Test images changing seed distribution. From left to right - initial at (1,1) then row wise, initial at (1,1) then column wise, initial at (m,n) then row wise, random initialization . Top image - A8 with threshold 30. Bottom image - A4 with threshold 100.

Looking at the output, the effect of the seed distribution can be clearly analyzed. For instance, for the second column of second image in Figure 3 the major portion of the image is segmented as the same background region (in white) because column wise selection of new seeds propagated the background region into the actual foreground. In the next case, the selection of the initial seed pixel at the bottom right of the image caused this effect in the bottom half of the image.

So the seed distribution is an important factor in the algorithm performance. As studied in class, there are other better ways of selecting initial seed positions in an image though those were not implemented in this lab.

1.4 Aggregation Criteria

The aggregation criteria used in the algorithm is based on intensity values for grayscale images and RGB values for color images. We also tested with HSV color space for one image. The results of such experiments is given in Figure 4.

Figure 4: Region Growing Segmentation Output on Test images in HSV. From left to right - A4 with threshold 0.1, A4 with threshold 0.5, A8 with threshold 0.5.

The threshold parameters should be in a different scale than for the case of RGB. Though for some cases HSV might be a suitable option, for the images in our test set region growing with RGB was better.

1.5 Implementation

Owing to MATLAB's issue with maximum number of recursive function calls, a sequential version of the algorithm was implemented. A dynamic queue data structure was used to optimize the run time. We also did not use a separate explore function to keep the run time less (otherwise time added from multiple function calls).

1.6 Comparison with other segmentation method

In this section the results of region growing segmentation algorithm have been compared with Fuzzy C-Means (FCM) Clustering segmentation algorithm. For the latter we have used the fcm function in MATLAB. The data is the set of pixel values represented in RGB (3 dimensions) or grayscale (1 dimension). The results of the FCM segmentation depend greatly on the number of clusters paramater. Here we present image by image the visually best results of region growing segmentation compared with some results for FCM segmentation.

Figure 5: Region Growing Segmentation Output vs FCM Clustering Output on Test images. From left to right - Region Growing with A4 Threshold 30, FCM with 2 clusters, FCM with 3 clusters, FCM with 4 clusters, FCM with 11 clusters

In Figure 5 it is observed that FCM with lower number of clusters (for instance 2 or 3) can somewhat separate out the coins from the background successfully, but those are actually different image regions which are better separated out with region growing segmentation. On increasing the number of clusters in FCM to overcome that under segmentation problem, the output is not visually satisfactory, with segmented regions differing from actual regions. The problem of choosing an optimal number of clusters for the FCM algorithm is also evident here.

Figure 6: Region Growing Segmentation Output vs FCM Clustering Output on Test images. From left to right - Region Growing with A4 Threshold 25, FCM with 2 clusters, FCM with 3 clusters

Region growing segmentation is the best choice in segmenting image in Figure 6. FCM with 2 and 3 clusters works producing under segmented results. But the fuzzy c means clustering algorithm in MATLAB fails (with NaN s for the objective function) for cluster number 4 because of the nature of the color regions in the input image. As observed in this case, FCM is very sensitive to the underlying structure of the data whereas region growing method is not, at least not to that extent.

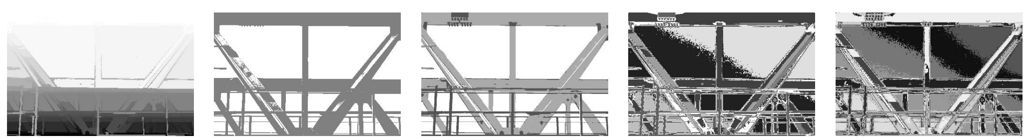

Figure 7: Region Growing Segmentation Output vs FCM Clustering Output on Test images. From left to right - Region Growing with A8 Threshold 25, FCM with 2 clusters, FCM with 3 clusters, FCM with 8 clusters, FCM with 15 clusters

One benefit of clustering based segmentation over region based methods is visible in Figure 7. Two parts of the same sky have been labelled as different regions by region growing segmentation since they are not adjacent. FCM which is based on the similarity of pixels in feature space does not have this problem. But increasing the number of clusters causes over segmentation, and this over segmentation is worse than the over segmentation observed with region growing method in Figure 1.

Figure 8: Region Growing Segmentation Output vs FCM Clustering Output on Test images. From left to right - Region Growing with A4 Threshold 100, FCM with 2 clusters, FCM with 3 clusters, FCM with 5 clusters, FCM with 10 clusters

Similar behavior is observed in the image in Figure 8. The skin on the face and hands has been classified as two different regions with region growing segmentation method. But depending on the application like for instance head tracking of a person, this would be considered as the correct result. Also region growing segmentation output is generally less noisy than FCM output because of the inherent methodology of growing a region in the algorithm.

The following table shows the algorithm run times of region growing segmentation for the test images compared with FCM algorithm run times. The run time for FCM algorithm increases with the number of clusters used so the minimum and maximum in the table are from the set of values used in the above figures. For Region Growing (RG) the parameters (threshold and connectivity) used are also same as the above figures.

Image	RG Run Time (seconds)	Minimum FCM Run Time (seconds)	Maximum FCM Run Time (seconds)
Coins	0.79	0.45	6.27
Color	0.78	1.38	1.03
Gantrycrane	1.44	0.93	21.57
Woman	0.33	0.26	3.5

Table 2: Comparison of run times between Region growing and FCM segmentation

For Region growing segmentation with A4 connectivity we normally get less than a second run times for standard size images like the ones used in testing.