

# CLUSTERING BASED REGION GROWING ALGORITHM FOR COLOR IMAGE SEGMENTATION

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**Abstract:** We propose an image segmentation method based on combining unsupervised clustering in the color space with region growing in the image space. No 'a priori' knowledge is required about the number of regions in the image. The algorithm is useful for marker extraction or complete segmentation of multidimensional, and in particular color, images. The running time depends mostly upon the speed of the unsupervised clustering algorithm that is used.

**Key words:** marker extraction, color image segmentation, clustering, region growing.

## 1. INTRODUCTION

In image segmentation the problem of developing automatic segmentation procedures has always been and still is of great interest. The existing automatic segmentation methods are generally associated with some particular applications where 'a priori' information about the result of the segmentation is known. We aim to develop a general purpose automatic segmentation procedure which does not require any 'a priori' knowledge about the result.

We approach in this paper the problem of automatic segmentation by means of unsupervised classification in the data space, that is the color space for color images. Two extreme alternatives exist: global and local classification. Unlike global classification, the local classification approach which we follow is not limited by the complexity of the image.

It is possible to split the segmentation problem in two parts: marker extraction and marker based segmentation. In this case a robust automatic marker extraction procedure is required. Automatic segmentation starting from a given set of markers has already many solutions. An example of efficient and fast marker based segmentation is the family of Watershed-like Transformations ([1], [2], [3], [4]). To give a correct result, watershed algorithms require a set of initial markers. The number of detected regions is precisely equal to the number of markers.

We propose a segmentation method useful for color images as well as other multidimensional images. By analysing the magnitude of the image gradient and selecting the significant local minima we produce a set of initial seeds having the following characteristics: (a) in general there will be more than one seed for each image object, (b) for small image objects it is possible that there will not be any initial seed to mark them. A set of markers with a one-to-one correspondence with the image objects is then grown starting from the initial seeds. To obtain the final segmentation this set of markers will be further grown using the proposed method until they extend over the whole image.

The method has certain characteristics which make it

useful in different applications: (a) no 'a priori' knowledge is required about the number of regions in the image, (b) the method is suitable for parallel implementations, and (c) there are no restrictions about the dimensionality of the data or image spaces.

## 2. OVERVIEW OF THE METHOD

The segmentation method described here is based on the algorithms in [6] and [7]. This is a combination between Local Classification and Region Growing as depicted in Figure 1.

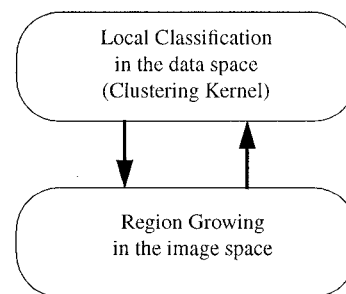


Figure 1. The components of the segmentation

We further extend here the use of this algorithm to a complete segmentation. During the segmentation, a detection of the significant unmarked details, based on the same method, is also accomplished. An unmarked detail in the image is an object which we want to detect, but it is not marked by any initial-seed. The complete segmentation comprises the following stages:

1. Marker extraction stage;
2. The detection of the unmarked details;
3. Finalization of the segmentation.

## 3. THE MARKER EXTRACTION (STAGE 1)

This stage is performed according to the algorithm described in [7]. Starting from the original color image and a set of initial-seeds the algorithm is growing a set of

markers. Initial seeds are generated by analysing the magnitude of the color image gradient. The significant local minima are selected as initial-seeds. The final markers have a one to one correspondence with the image regions that are pointed by at least one initial seed (see Figure 3).

#### 4. THE UNMARKED DETAILS DETECTION (STAGE 2)

The gradient is computed in Stage 1 as a sum of component wise morphological gradients:

$$\text{grad}(p) = |\text{grad}_r(p)| + |\text{grad}_g(p)| + |\text{grad}_b(p)|$$

$$\text{grad}_x(p) = \text{dilation-erosion, where } x=r, g \text{ or } b$$

A flat 3x3 structuring element is used on each component. It is straightforward the fact that for image details with the size smaller than the structuring element used for the computation of the gradient no significant local minima will appear in the gradient magnitude. In order to overcome this problem we use the following classification based algorithm to detect the image objects unmarked by initial seeds. A user-given threshold,  $t_D$ , is required. This specifies the minimum number of points that is acceptable for an unmarked detail.

```
/* Pseudocode 1 */
/* Unmarked detail detection */
```

1. scan the unlabelled areas of the image (denoted as 'NV' in Figure 3). For each position of the classification window:
2. classify points in the clustering window
3. if a resulted class contains a connected (in the image space) group of pixels bigger than a given threshold  $t_D$  than:
4. label them with a new label
5. maximally grow the new detected object (using the algorithm in [6])
6. move the classification window to next position
7. goto Step 2

For this stage we use as input the original color image and the image of labelled markers produced during Stage 1. The result is a corrected image of labelled markers where new labels have been introduced for the unmarked objects that were detected (Figure 5).

The problems that appear here are basically the drawbacks of the algorithm in [6], mainly emerging from the impossibility of using reference points. A new problem appear on smooth edges where the distance between two neighbouring markers can become comparable with the size of the clustering window. The detection of false new regions is also stimulated by the inherent instability of the unsupervised clustering kernel.

To better eliminate the possibility of detecting false regions, a new region must satisfy following conditions:

1. no attempt during its growth to merge with an existent labelled marker. If at least one attempt is made the new region is invalidated.
2. at each classification during the growth process, the points already labelled must be classified in the same

cluster. If not, then the growth is ceased in that particular direction.

The result in Figure 5 was produced using the above mentioned conditions.

#### 5. THE FINALIZATION OF THE SEGMENTATION (STAGE 3)

The goal of this stage is to extend the labels produced at Stages 1 and 2 until they cover the whole image. Because the number of regions in the image is known at this moment we can further use supervised classification.

There are different alternatives representing trade-offs between the precision and the speed that we want to achieve. The pseudocode of the algorithm used to achieve the complete segmentation in Figure 6 is:

```
/* Pseudocode 2 */
/* Finalization of the segmentation */
```

1. scan the unlabelled areas of the image (denoted as 'NV' in Figure 3). For each position of the classification window:
2. compute the number  $N$  of different labels that appear in the clustering window.
3. classify in  $N$  classes the points in the clustering window
4. resolve contentions
5. grow the labels
6. move the classification window to next position
7. goto Step 2

In the clustering window there appear both points labelled during previous classifications and unlabelled points. A 'contention' is the fact that after the classification in step 3 of Pseudocode 2, points already labelled with different labels will get the same label this time.

We have used a simplified, supervised, version of the "least biased fuzzy clustering" (LBFC), the clustering algorithm that was used in the previous stages for unsupervised classification. The 'contentions' are solved by analysing the configuration of the clustering window. If two initial seeds with different labels are found in the same cluster the number of clusters is incremented and the supervised classification is applied again. Isolated points are later labelled based on the color distance to the already labelled neighbours. The permanent label associated to one cluster is the label of the initial seeds in that cluster. If a point (not initial seed) labelled in Stage 1 is found in the same cluster together with a initial seed of a different label the label of the point is deleted before the growth that takes place inside the classification window. In this way it is possible to correct inward the borders of the markers produced in Stage 1.

The 'contentions' can be avoided using a classification algorithm where we specify from the beginning not only the number of classes but also the classification of some of the points (for example NN clustering algorithms). This is a fast solution with the drawback that we can not correct or overcome the errors made during Stage 1. For a better description of the errors that may appear in Stage 1 see [7].

## 6. RESULTS

The results of the above presented method are exemplified on a small crop from an artificial image (Figure 2). The image contains both sharp and smooth edges as well as large and small objects. There are four large regions and a very thin one. The number of initial seeds per region varies from none to 10. The initial seeds are shown as white points in Figure 2.

The result of Stage 1, marker extraction, is presented in Figure 3. The white lines represent the borders of the labelled regions as they were produced by Stage 1. The initial seeds have been correctly merged in four groups labelled 1 to 4. The NV label represents the not visited and thus not labelled areas of the image.

The thin region (labelled 5 in Figure 5) is not marked by any initial seed (Figure 2). There is no initial seed because there is no local minima of the gradient inside region 5. We can notice in Figure 3 that this region has not been labelled, but left as an unvisited area (NV). This allows us to later recover it.

If we are not interested in detecting the regions not pointed by initial seeds we can perform immediately Stage 3 after marker extraction and we get the result in Figure 4.

If following the marker extraction we perform Stage 2 we obtain the result in Figure 5. The thin detail has been detected as a new region (labelled 5). No false regions have been detected on the not visited areas (NV).

In order to obtain a complete segmentation we can perform Stage 3, as described in section 5 and achieve the segmentations presented in Figure 6 and Figure 7.

The result of Stage 2 can be used as starting point for any marker based segmentation. An example is given in Figure 8. We have used here an extension to color images developed by us of a watershed-like algorithm inspired from [1]: SRG (Seeded Region Growing). The SRG algorithm does not use the gradient image like the WSF (Watershed by Flooding), but the original color image. The SRG and WSF algorithms have approximately the same processing time.

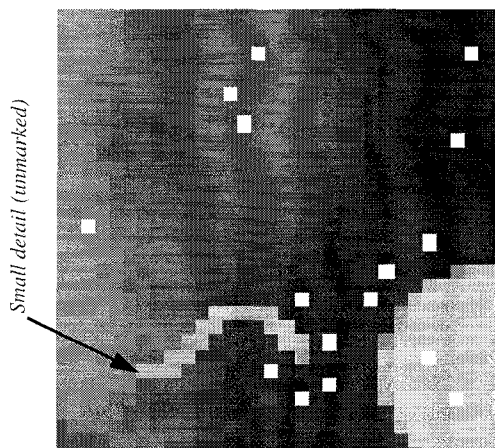


Figure 2. The original color image. Superimposed are the initial seeds (the white points).

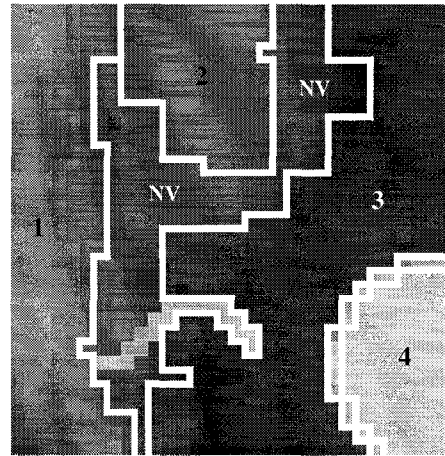


Figure 3. The result of the classification based region growing (Stage 1). Four regions were produced. The small detail has not been destroyed, but left as unvisited region.

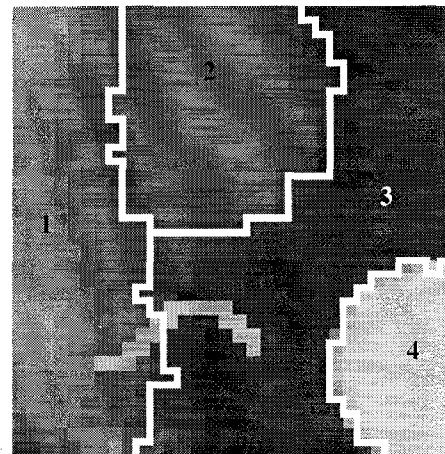


Figure 4. Result of Stage 3. A complete segmentation without performing Stage 2, the detection of unmarked objects.

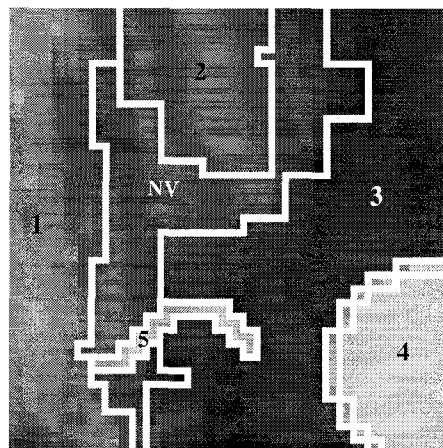


Figure 5. The result of the unmarked objects detection (Stage 2).

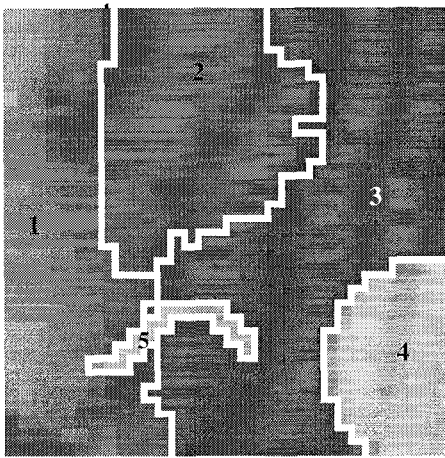


Figure 6. Complete segmentation by the clustering based method. All three stages were performed. Stage 3 uses the simplified LBFC. Small corrections of the Stage 1 and 2 borders are allowed.

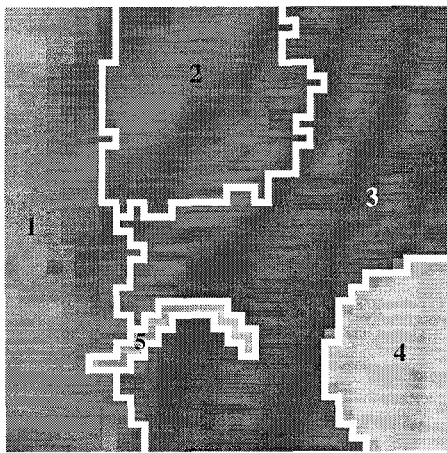


Figure 7. Complete segmentation by the clustering based method. All three stages were performed. Stage 3 uses 1-NN nearest neighbour classification. No correction of Stage 1 or 2 borders is possible.

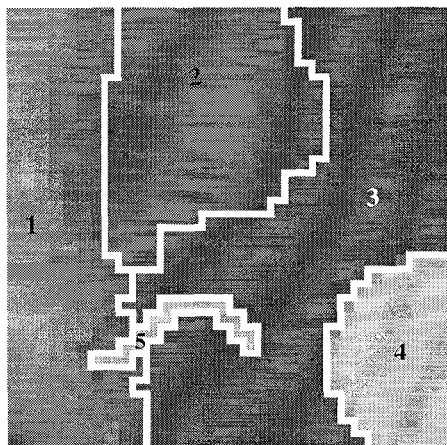


Figure 8. Complete segmentation obtained by growing the labels after Stage 2 with a watershed like algorithm. No correction of Stage 1 or 2 borders is done.

## 7. CONCLUSION

We have proposed in this paper a complete segmentation method useful for unsupervised color image segmentation. Objects in the image not initially marked by any seed can still be recovered. The finalization of segmentation (Stage 3) can be replaced with a fast watershed-like transformation, such as the one described in [1] or any other marker based segmentation algorithm.

Among the possible applications of the proposed method we can enumerate:

1. Automatic marker extraction;
2. Complete automatic segmentation;
3. Interactive segmentation: Starting from a user given point one region can be extracted without processing the whole image. This facility is useful when dealing with very large images.
4. Texture segmentation: The dimensionality of the classification space is increased with new coordinates holding the texture parameters.

The drawback of this method lays in the heavy computation required by the unsupervised clustering kernel.

## 8. REFERENCES

- [1] Rolf Adams, Leanne Bischof: "Seeded region growing", Correspondence in IEEE Transactions on PAMI, vol.16, no. 6, June 1994, pp. 641-647.
- [2] S.Beucher and F.Meyer, "The morphological approach to segmentation: The watershed transformation" in *Mathematical Morphology in Image Processing*, E. R.Dougherty, Editor, Marcel Dekker Inc., New York, 1993, pp.433-481.
- [3] L.Vincent and P. Soille, "Watersheds in digital spaces: An efficient algorithm based on immersion simulations", IEEE Transactions on PAMI, vol.13, no.6, June 1991, pp.583-598.
- [4] B. Cramariuc, A. Moga, M. Gabbouj, "Image segmentation by component labelling", Proceedings of International Conference on Digital Signal Processing, June 1995, Limassol, Cyprus, pp 360-364.
- [5] Gerardo Beni and Xiaomin Liu, "A Least Biased Fuzzy Clustering Method", IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 16, no. 9, Sep. 1994, pp. 954-960.
- [6] B. Cramariuc, M. Gabbouj, "Automatic Marker Extraction for Marker Based Segmentation", Proc. of IEEE Nordic Signal Processing Symposium NORSIG-96, September 24-27, 1996, Espoo, Finland, pp.259-262.
- [7] Bogdan Cramariuc and Moncef Gabbouj, "A robust marker extraction algorithm for color images", submitted to 1997 International conference on Image Processing, October 26-29 1997, Santa Barbara, California, USA.