# AN UNSUPERVISED SEGMENTATION ALGORITHM BASED ON A QUADTREE STRUCTURE*

Adolfo Martínez-Usó Filiberto Pla Pedro García-Sevilla

Departamento de Lenguajes y Sistemas Informáticos, Universidad Jaume I
Campus Riu Sec, 12071 Castellón, Spain
{auso, pla, pgarcia}@lsi.uji.es

**ABTRACT**
Many segmentation techniques are available in the literature and some of them have been widely used in different application problems. Most of these segmentation techniques were motivated by specific application purposes. In this article we present an unsupervised segmentation algorithm through a multiresolution approach which uses both color and edge information. The use of a Quadtree (QT) structure simplifies the combination of a multiresolution approach with the chosen strategy for the segmentation process and speeds up the whole procedure. The algorithm has been tested for segmenting classical images in order to compare our results with the ones provided by other color segmentation methods. It has also been applied to fruit images in order to segment the different zones of the fruit surface. Due to the unsupervised nature of the method, it can adapt to the huge variability of color and shape of the regions in fruit inspection applications.

**KEYWORDS**
Segmentation, Color, Edges, Segmentation Strategy.

## 1 Introduction

There exist many different approaches for image segmentation [1,2], which mainly differ in the criterion used to measure the similarity of two regions and in the strategy applied to guide the segmentation process.

In the image segmentation framework, we can distinguish two main approaches to solve the problem. The first one takes a similarity criterion as the basis for the whole segmentation process and this criterion guides all the algorithm steps. On the other hand, a particular strategy can be established as the basis for the segmentation process. In this case, a more o less general strategy is used to address the problem in a structural way and different criteria can be used to particularize the method for a certain type of segmentation problem. The work we present here can be included in the latter case.

The main motivation of this work was to obtain a method able to segment images of fruits for their classification according to the defects found on their surface.

This approach try to accomplish the following requirements for the image segmentation:

- An unsupervised method would be needed, due to manifold variables and the huge variability of situations which can arise in the images of fruit. Thus, any prior knowledge should be avoided for the segmentation procedure.
- The segmentation method has to be mainly based in color and edge criteria. Edge information must be included in the process, in order to define the segmented region boundaries as accurately as possible [3]. In this sense, not only gray level information should be used in order to segment color regions due to hue/saturation variations.

In order to meet this requirements, a QT structure has been chosen to support the developed method. A QT is commonly used to decompose a given frame into blocks of different sizes since it enables an efficient representation of the resulting decomposition. Furthermore, well-known algorithms are available for searching and neighboring operations over this sort of trees.

It is quite obvious that, from the described requirements, color and edge information would define the particular criterion to be used in the segmentation procedure. Apart from the decision of which is the best color space to represent a given problem, the main point to be fixed is the segmentation strategy to follow. This strategy will be conditioned and orientated by the image representation adopted, that is, by the QT.

The rest of the paper is structured as follows: In section 2, we introduce the QT structure and explain the criterion which has been used to allow the construction of the QT. Section 3 formulate the problem of using color information and propose a method to solve it. Section 4 we present the edge criterion which will be used. Section 5 explain the segmentation strategy and discuss some of the preliminary attempts to solve the problem. Finally, results and some conclusions are drawn in sections 6 and 7 respectively.

* This work has been partly supported by grants CPI2001-2956-C02-02 from Spanish CICYT and IST-2001-37306 from the European Union.

## 2 Generating a Quadtree Image

The QT structure allows to divide an image within a complete tree representation, including neighboring information. This spatial information can be further used by a merging strategy which joins the QT leaves using color and edge information.

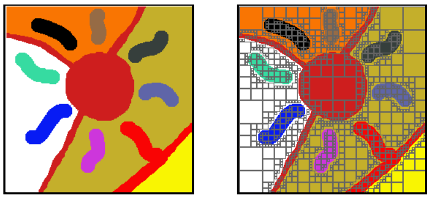


**Fig. 1.** Quadtree structure of a synthetic image using an homogeneity color criterion

To calculate the QT representation of an image, the procedure starts considering the whole image in the root node. If the segmentation criterion is not fulfilled in the region representing the node, then the region is divided into four children regions. The criterion is recursively applied to each subregion until the criterion for a node is accomplished for each leaf (Fig. 1). Obviously, this process will produce subregions of different sizes represented in a tree structure, which may vary from pixel size to the complete image.

This structure has been extensively used in works such as the one by Wilson and Spann [4]. One of the most recent applications of this data structure can be found in [3] where, through a methodology of multiresolution based on a QT, information of borders is combined with a region growing strategy to obtain the image segmentation on gray images.

In this work, we have used a similar strategy but using a different criterion to compare two regions and extending its application to a color environment. Moreover, the algorithms described in Samet [5] have been used in the QT structure for the implementation of the neighborhood operations.

## 3 Use of Color Information

Although many authors use partial information in a particular color space, it is evident that ignoring some color components causes a loss of information that can be very important. Therefore, the presented approach uses the three planes simultaneously in the L*a*b* color space. In this color space the distances between two colors are approximately proportional to the human perceptual difference between them.

In this work, two different color criteria are used to decide whether two regions must be merged or not. The first criterion is used only after the construction of the QT and it merges regions whose color differences are smaller than a given threshold. This first step is used to accelerate the segmentation process when the regions have an homogeneous distribution and it is applied firstly to the leaves of the QT and after that, to regions obtained (clusters of leaves).

Once the first step is completed a second color criterion is used, and it will be applied iteratively until the final segmentation is obtained. In this case, each region (clusters of leaves in the QT) is considered as a set of pixels which follow a Normal distribution. The average value $\mu$ and standard deviation $\sigma$ in the L* plane are calculated for each region. When two regions are compared, the probability density function of each Normal distribution is computed and these distributions are compared according to the absolute value of their differences:

$$| N(\mu_A, \sigma^2_A) - N(\mu_B, \sigma^2_B) |$$

This measure provides a value 0 when the distributions of the values in the two regions are exactly the same, and 2 when they are totally different.

Now, according to some prefixed thresholds, if we decide that the regions are very similar, they are directly merged. On the other hand, if they are very different, the regions are not merged. If none of the previous situations apply, then the planes a*b* are taken into account and the distance between the average values of each region is used to measure the color difference between the two regions. Note that, in our approach, the L* plane has more importance than the a*b* planes and these planes are only taken into account when the L* plane is not sufficiently trustworthy.

## 4 Use of Edge Information

The use of edge information in the segmentation process allows to avoid the merging of regions when the color criterion is satisfied but there exists an edge between the regions. In this sense, gradient information is used to develop a boundary map.

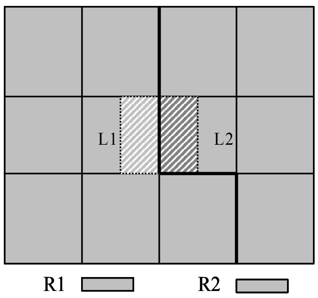



**Fig. 2.** Edge criterion

The gradient information is only checked if the color criterion is fulfilled and it is computed from the first plane of the Principal Component Analysis obtained from the original RGB image.

Let $R_1$ and $R_2$ be two regions with a common boundary. Let $L_1$ and $L_2$ be two leaves of the QT that belong to $R_1$ and $R_2$ respectively, which share a linear segment of the common boundary between the two regions (see Fig. 2). From the leaves $L_1$ and $L_2$ we can compute the values $\sum_{half}\nabla_1$ and $\sum_{half}\nabla_2$ which correspond to sum of half of the values of the gradient magnitude in the corresponding leaf (striped pattern in Fig. 2). For each leaf, the gradient values close to the boundary segment are taken into account. In this way, (1) is computed for each boundary segment.

$$FB = \frac{\left(\sum_{half}\nabla_1 + \sum_{half}\nabla_2\right)}{segment\_size} \qquad (1)$$

Finally, after all boundary segments have been processed, we compute $\left(\sum FB\right)/N$, where N is the number of segments that form the whole boundary between the regions. If the final value obtained does not exceed a prefixed threshold, the two regions are merged into one.

## 5 The Segmentation Process

As it was mentioned in the introduction, the segmentation method proposed is based on a segmentation strategy, supported by a QT data representation of an image, and the use of color and edge information as particular criteria in that strategy.

### 5.1 Segmentation Strategy

The first step of the procedure consists of building an oversegmented representation of the image, that is, the QT is expanded until every square region is homogeneous according to an homogeneity criterion. The simplest homogeneity function is that for which all pixels in the QT leaves have the same color values. This will lead to a significant expansion of the QT. Other homogeneity functions without such strict criteria would lead to a more compact QT, but this would lead to a loss of accuracy in the detected boundaries.

The oversegmented representation is input to the algorithm that starts by recursively merging neighboring leaves based on the first color criterion (see section 3). This criterion establishes a threshold for merging leaves representing smooth regions. This stage is including just to compact the QT in order to increase the efficiency of the whole process.

A further step consists of a merging strategy which looks for leaves in the QT structure that belong to the same region in the image. These regions (clusters) will be represented as sets of leaves in the QT that meet some spatial constraints.

During the fusion process the following premises are respected:

- ✓ Regions are arranged according to their size, giving more importance to the bigger regions and facilitating the merging of small regions with the big ones.
- ✓ Only regions with a common boundary can be merged. This will represent the spatial constraint in the merging process.

The merging strategy, only in its last stage, takes as a color criterion the second one described in section 3. Furthermore, it takes as edge criterion the one described in section 4.

Figure 3 shows the outline of the segmentation strategy used, which is basically an iterative process. In the iterative loop, each cluster is compared to all its neighboring clusters and, when the segmentation criterion is satisfied, the clusters are merged. Candidate merging clusters are searched through a list of clusters ordered by size, beginning with the biggest cluster, favoring initially the merging and formation of bigger regions that will act as seeds to further collect smaller regions.

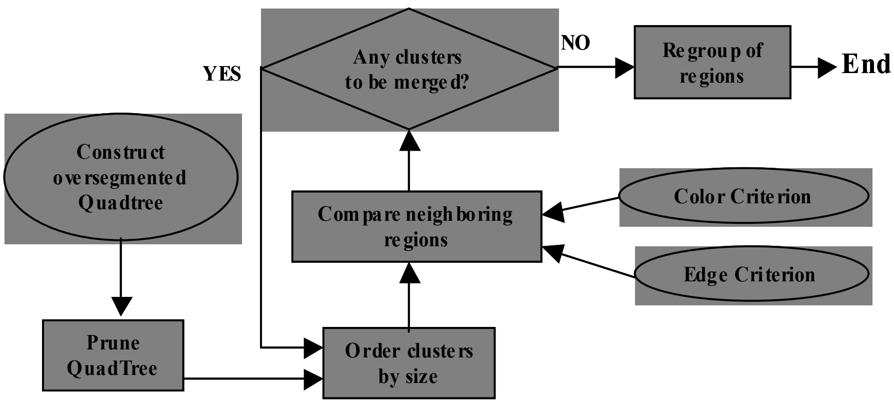



**Fig. 3**. Segmentation process flow chart

This clustering process stops when no other merging can be performed. Finally, the algorithm looks for small regions by means of a threshold that determines which regions are small. Most of these small regions are due to the use of the Gaussian filter and the gradient information. These two stages in the segmentation process produce blurred edges. Therefore, a final step is included to merge these small regions with their similar neighbors, giving more importance to the biggest ones.

### 5.2 Algorithm

The whole segmentation process can be summarized in the following algorithm:

1. Make the Principal Component Analysis of the input image.
2. Construct the gradient image from the first PCA plane.
3. Generate the L*a*b* color image and convolve it with a Gaussian Filter.
4. Construct an oversegmented representation of the L*a*b* image (QT) using a color similarity criterion. The most restrictive one may be that each region has all its pixels with the same color. Create an ordered list according to region sizes.
5. Merge neighboring **leaves** with the same parent node using a color distance threshold. This merging process is not iterative (the aim is to achieve a more compact QT representation to speed-up the rest of the process).
6. Look for the first pair of neighboring **clusters** in the list that can be merged according to the first color merging criterion. The search is done beginning by the biggest cluster (merging bigger regions first is aimed at looking for significant clusters supported by as much pixels as possible that act as seeds that grow by further collecting smaller neighbor clusters).
7. The color criterion is tested for each region and its neighbor regions by means of the second criterion described in section 3. If this criterion is fulfilled, the algorithm looks for border leaves between regions and checks if there are high gradient values (edge criterion in section 4). If both criteria are fulfilled the regions are merged.
8. If any clusters are merged, reorder the list of clusters.
9. Repeat steps 8 and 9 until regions became stable (this part of the process correspond to an iterative sequence that may be seen as a coarse-to-fine segmentation process).
10. Regroup small regions.

Note that each time that the algorithm modifies the QT representation by merging leaves or regions, there is a reorder process according to regions size. At the end of the procedure, every cluster in the list is represented by a set of leaves of the QT, which are labeled as a single resulting region.

## 6 Experiments and Results

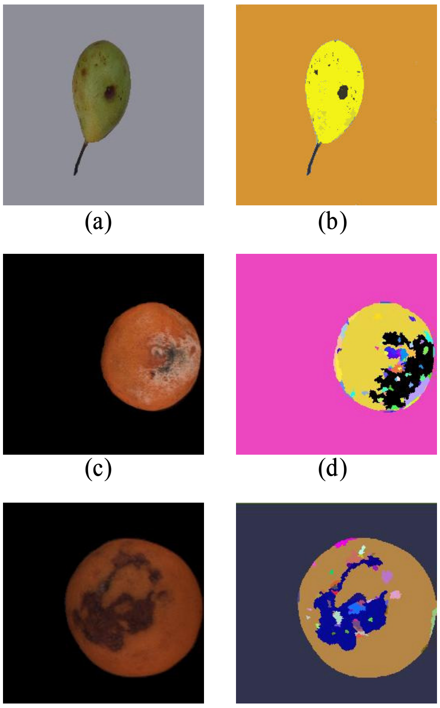
We present some experimental results obtained with classic color images (Fig. 4) as well as with three fruit images (Fig. 5). In addition, in table 1 we present a quantitative evaluation of the image segmentation results by means of the Liu and Yang [6] and Borsotti et al. [7] functions.

**Fig. 4.** Segmentation results using randomly chosen colors for house and peppers images

As it was mentioned in the introduction, the segmentation method presented has been aimed at characterizing images of fruits in visual inspection applications. The segmentations of the fruit images are used as input in a further process to characterize and classify each region in the fruit surface to identify and detect different types of defects and parts of the fruit.

Figure 5 shows some examples of the results of the segmentation on different types of fruits and situations to be characterized. Note how the segmentation process has adapted to the regions of each image due to its unsupervised nature. For instance, in figure 5a there are different type of stains in the fruit surface. Figure 5b show its corresponding segmentation and how the different stains have been quite accurately clustered and separated from the rest of the fruit parts.

Figure 5c and 5e shows examples of fruits with various stains produced by the effect of rot and how the segmentations obtained, figure 5d and 5f, has found the different variations of the stains of the rotten zone. This will allow the extraction of region descriptors for their identification and classification.



(a) (b) (c) (d) (e) (f)

**Fig. 5.** Segmentation results of fruit images using randomly chosen colors

| | Liu Function (F) | Borsotti Function (Q) |
|---|---|---|
| house | 199 | 1860 |
| peppers | 650 | 5518 |
| pear | 26 | 321 |
| orange5c | 128 | 1381 |
| orange5e | 94 | 1191 |

**Table 1.** Quantitative evaluation of image segmentation results

## 7 Conclusions

In this work, some preliminary results of an unsupervised color segmentation algorithm have been presented. The method has been applied to classic images and to fruit images in order to characterize the variety of regions appearing on the fruit surfaces.

The results obtained show how the algorithm can adapt to the different situations and variability of color regions, being able to segment areas and locating the borders quite accurately.

The use of color information combined with a QT representation of the image is the base of an unsupervised segmentation strategy that can locate color regions finding their contours in a satisfactory way.

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