A Quadtree-based Unsupervised Segmentation Algorithm for Fruit Visual Inspection*

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

Abstract. 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 the preliminary results of an unsupervised segmentation algorithm through a multiresolution method using color information for fruit inspection tasks. The use of a Quadtree 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 in fruit images in order to segment the different zones of the fruit surface. Due to the unsupervised nature of the procedure, it can adapt to the huge variability of color and shape of regions in fruit inspection applications.

1 Introduction

Image segmentation has had a large attention since the very beginning in computer vision. There exist many different approaches for image segmentation [5], which mainly differ in the criterion used to measure the similarity of two regions and in the strategy applied to guide the segmentation process. Most of these image segmentation techniques are application oriented and have been developed from specific purposes. There are also different segmentation methods in the literature that try to solve the segmentation problem from a general point of view [1][12]. These segmentation techniques can be applied to a wide range of particular problems. However, each application usually has specific requirements that makes appropriate the development and use of application-oriented approaches, in order to take advantage of the characteristics of each particular application.

In the image segmentation framework, we can distinguish two main approaches to solve the problem. The first one takes a criterion as the basis for the whole segmentation process and this criterion guides all the algorithm steps [4]. 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

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

and different criteria can be used to particularize the method for a certain type of segmentation problem [1]. The work presented here can be included in the later case.

The main motivation of the developed work has been to obtain a method able to segment images of fruits for their classification in visual inspection processes. There exist some approaches in this particular application domain [2][7]. Most of them use supervised techniques to address the problem [6].

Due to the nature of the fruit inspection problem, the following requirements for the image segmentation of fruits should be accomplished:

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

In order to meet the above mentioned requirements, an adequate image data representation should be used that can support those required features. In this case, a Quadtree (QT) structure has been chosen to support the method developed. Quadtree 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 neighbouring operations over these sort of trees.

It is quite obvious that, from the described requirements, color would be the particular criterion to be used in the segmentation procedure. Apart from the decision of which is the color space to best represent a given problem [13], the main point to be fixed is the segmentation strategy to be followed. This strategy will be conditioned and orientated by the image representation adopted, that is, by the QT.

Other unsupervised segmentation algorithms can be found in the literature. Some of them do not use edge information [12]. Other can be computationally expensive for some applications when the process attempts to consider many of the possible image variables [9]. Finally, there are some algorithms that do not use the color information to separate the regions in the image [1].

The rest of the paper is structured as follows. In section 2, we introduce the QT structure and explain what kind of criterion has been used to allow the construction of the QT. In section 3, we explain the segmentation strategy and discuss some of the preliminary attempts to solve the problem. In section 4, we formulate the problem of using color information and propose the method to solve it. In section 5 some results on fruit images for inspection purposes are shown. Finally, some conclusions are described in section 6.

2 Generating an Image Quadtree

The QT data structure is used to successively decompose the image into blocks until fulfilling a certain criterion as shown in Figure 1. It enables an efficient representation of the resulting decomposition. QT has been adopted as the supporting data representation of the segmentation process and, therefore, it is intimately related to our segmentation strategy and must be combined together with the segmentation criteria.

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

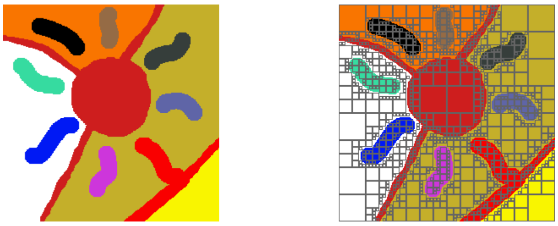

Figure 1. Quadtree structure of a synthetic image using an homogeneity color criterion

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 (children nodes) until the criterion for a node is accomplished (see Figure 1). Obviously, this process will produce subregions of different sizes represented in a tree structure, the subregions 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 in [14]. One of the most recent applications of this data structure can be found in [1] 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 grey images. A similar strategy has been used in this work but using a different criterion to compare two regions and extending its application to a color environment. Moreover, the algorithms described in Samet [10] have been used in the QT structure for the implementation of the neighbourhood operations.

3 The Segmentation Process

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

3.1 Segmentation Strategy

Taking as a starting point the construction of the QT structure, the first step of the procedure consists of building an oversegmented representation of the image, the QT is developed until every square region is homogeneus according to the homogeneity criteria. The simplest homogeneity criteria is that all pixels in the Quatree leaf have the same color. This will lead to a significant expanded QT. Other softer homogeneity criteria would lead to a compacter initial QT without affecting the final segmentation.

The oversegmented representation is input to the algorithm that starts pruning the QT by recursively merging neighbouring leaves based on a color criterion. This criterion establishes a threshold tolerance for merging leaves representing smooth regions. This stage is aimed at compacting the QT in order to increase the accuracy and efficiency of the final process.

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

In this phase of the procedure, edge information is added in the merging criterion in order to find accurate region borders at the same time as looking for consistent image regions.

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.

Figure 2 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 clusters, favoring initially the merging and formation of bigger regions that will act as seeds to further collect smaller regions. This clustering process stops when no other merging can be performed.

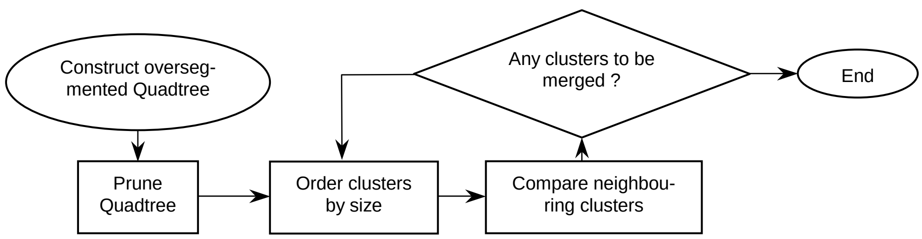

Figure 2. Segmentation process flow chart

3.2 Algorithm

The process described can be summarized in the following algorithm:

1. Generate the L*a*b* color space of the image.
2. Construct an oversegmented representation of the image using a color similarity criterion. The most restrictive one may be that each region has all its pixels with the same color.
3. Prune the QT merging neighboring leaves with the same parent node using a color criterion less restrictive than the one used in the first step. This merging process is not iterative. The aim is to achieve a compacter QT representation to speed-up the rest of the process.
4. Consider each leave from the pruned tree as an initial cluster and create an ordered list according to their size.
5. Look for the first pair of neighbouring clusters in the list that can be merged according to the color merging criterion. The search is done beginning by the biggest cluster in decreasing size order. 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 neighbour clusters.
6. If any clusters are merged, reorder the list of clusters.
7. Repeat steps 5 and 6 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.

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.

4 Use of Color Information

Although many authors in the literature use partial information of a particular color space [8], it is evident that ignoring some color component causes a loss of information that can be very important.

Thus, we have decided to use all color information but taking into account that:

1. There exist problems in the RGB scale. RGB scale has a HW dependency due to the infinite CCD combinations of the cameras. Although this problem can not be avoided in a trivial way, it should be taken into account. Moreover, in RGB space the Euclidean distance between two points is not proportional to the perceptual difference between the two colors represented [11]
2. Pal and Pal [5] considered color like another parameter and showed that it provides important information when the algorithms are selecting the definitive regions that conform the segmentation image.

Therefore, the approach here presented uses the three planes simultaneously in a L*a*b* color space. In this color space the distances between two colors is approximately proportional to the human perceptual difference between those two colors.

We assume that the pixels in each region (clusters of leaves in the QT) follow a Normal distribution. The color average μ and standard deviation σ are calculated. For each region, when the algorithm must decide if two regions are merged, it calculates the Probability Density function of the Normal distribution of both regions and the common area between them is computed. If the difference is lower than a threshold then these two region are merged.

Let us assume that $N_A(\mu_A, \sigma^2_A)$ and $N_B(\mu_B, \sigma^2_B)$ are two normal distributions for neighbouring regions A and B respectively. To calculate the output of the color criterion, the next expression is evaluated in each plane of L*a*b* color space:

$$| N_A(\mu_A, \sigma^2_A) - N_B(\mu_B, \sigma^2_B) | < \text{Threshold}$$

If this difference, in each color component, is below the threshold, the process allows regions A and B to be merged. This is the simpler version of the merging criterion that has been used in the preliminary tests carried out in this work. This criterion can be completed and improved adding some color border information.

5 Experiments and Results

Such as it was mentioned in the introduction, the segmentation method here presented has been aimed at characterizing images of fruits in visual inspection applications. The segmentation of 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.

There exist a great variability of situations and color regions that can arise in fruit images. Thus, the use of an unsupervised color segmentation process like the one presented here is very appealing for such a problem. The proposed algorithm has been tested in different types of fruit images. Images obtained from a RGB color camera were transformed into L*a*b* color space. The results presented here were obtained applying the algorithm over 256x256 images.

Figure 3 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 Figures 3a and 3e there are different type of stains in the fruit surface. Figures 3b and 3f show their corresponding segmentations and how the different stains have been quite accurately clustered and separated from the rest of the fruit parts.

Figure 3c show an example of fruit image where there are many different parts to be identified and separated. Figure 3d shows the result of the proposed algorithm that has been able to satisfactorily segment the different type of regions and parts of the fruit, providing a quite accurate definition of the regions corresponding to the seed and stains of different nature. It is important to note how the regions found by the proposed method fit and adapt to the contour of regions in an accurate way, characterizing the shape of the regions.

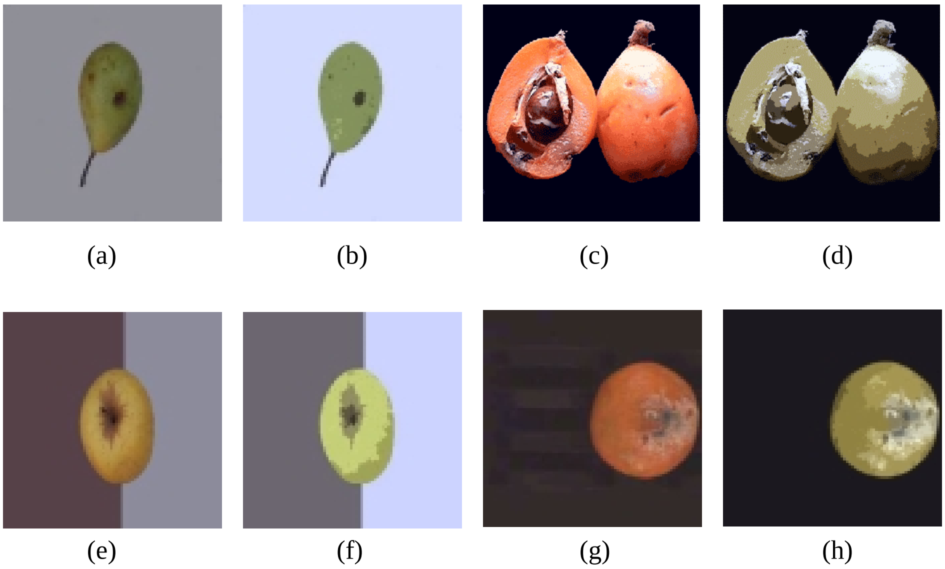

Figure 3. Segmentation results in fruit images.

Figure 3g shows an example of fruit with various stains produced by effect of rot and how the segmentation obtained, Figure 3h, has found the different variations of the stains of the rotten zone. This will allow the extraction of region descriptors in a more appropriate way for their identification and classification.

6 Conclusions and Future Work

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

The results obtained show how the algorithm can adapt to the different situations and variability of color regions, being able to segment areas of the fruit surfaces locating the borders quite accurately, which can facilitate the extraction of region descriptors for further classification purposes.

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.

Future and current work being carried out is directed to add color edge information to the segmentation process. The use of color edge information will allow to obtain even more accurate results in defining the border of the regions obtained in the segmentation.

The method here presented is also being extended to be applied in multispectral images, extending the concept of color borders to multispectral borders and the color criteria to multispectral criteria in the algorithm.

References

1. Bhalerao, A., Wilson, R.: Unsupervised Image Segmentation Combining Region and Boundary Estimation. In Image and Vision Computing. Vol. 19, Num. 6, (2001) 353–386
2. Chen, Y., Mhori, K., Namba, K.: Image Analysis of Bruised Oorin Apples. Proceedings of V Symphosium on Fruit, Nut and Vegetable Production Engineering. Davis, CA, USA (1997)
3. Di Zenzo, S.: A Note on the Gradient of a Multi-Image. Computer Vision, Graphics and Image Processing 33. (1986) 116-128
4. García, P., Pla, F., Gracia, I.: Detecting edges in colour images using dichromatic differences. 7th International Conference on Image Processing and its Applications, IEEE. ISBN: 0-85296-717-9. Manchester (UK). (1999) 363-367
5. Pal, N.R., Pal, K.P.: A Review on Image Segmentation Techniques. Pattern Recognition, 26(9): (1993) 1277–1294
6. Power, W., Clist, R.S.: Comparison of supervised learning techniques applied to colour segmentation of fruit images. SPIE vol. 2904. Boston (1996) 370-381
7. Rigney, M.P., Brusewitz, G.H., Krauzler, G.A.: Asparaus Defect Inspection with Machine Vision. Transactions of the ASAE. vol. 35(6) (1992) 1873-1878
8. Robinson, G.S.: Color edge detection. Optical Engineering, 16(5): (1977) 479-484
9. Saber, E., Murat, A., Bozdagi, G.: Fusion of Color and Edge Information for Improved Segmentation and Edge Linking. IVC, vol.15 (1995) 769-780
10. Samet, H.: Applications of Spatial Data Structures: Computer Graphics, Image Processing and GIS. Addison-Wesley, (1990)
11. Schettini, R.: A segmentation algorithm for color images. Pattern Recognition Letters, vol 14. (1993) 499-506
12. Sharon, E., Brandt, A., Basri, R.: Fast Multiscale Image Segmentation. Computer Vision and Pattern Recognition, 2000. Proceedings. IEEE Conference on. vol.1 (2000) 70–77
13. Singh, M., Markou, M., Singh, S.: Colour Image Texture Analysis: Dependence on Colour Spaces. ICPR. Quebec (2002)
14. Wilson, R.G., Spann, M.: Finite Prolate Spheroidal Sequences and their Applications II: Image Feature Description and Segmentation. IEEE Transactions on Pattern Analysis and Machine Intelligence, 10(2) (1988) 193-203