Color Image Segmentation Using Vector Angle-Based Region Growing

Slawo Wesolkowski and Paul Fieguth
Department of Systems Design
University of Waterloo
Waterloo, Ont. N2L 3G1
Canada
s.wesolkowski@ieee.org
pfieguth@rousseau.uwaterloo.ca

ABSTRACT

A new region growing color image segmentation algorithm is presented in this paper. This algorithm is invariant to highlights and shading. This is accomplished in two steps. First, the average pixel intensity is removed from each RGB coordinate. This transformation mitigates the effects of highlights. Next, region seeds are obtained using the Mixture of Principal Components algorithm. Each region is characterized using two parameters. The first is the distance between the region prototype and the candidate pixel. The second is the distance between the candidate pixel and its nearest neighbor in the region. The inner vector product or vector angle is used as the similarity measure which makes both of these measures shading invariant. Results on a real image illustrate the effectiveness of the method.

Keywords: color image segmentation, region growing, highlight invariance, shading invariance

1. INTRODUCTION

In recent years color constancy - the perception of objects in the real world without illumination effects - has been a major concern in the research community of image science and technology. Humans perceive object surfaces in a scene in spite of shading and highlight effects. This paper proposes an algorithm for color image segmentation which is invariant to shading and highlight effects. The Dichromatic Reflection Model [1] is a useful tool for modeling light reflection, which causes essential illumination effects, and will be used as the theoretical foundation of this paper.

Common approaches for color image segmentation are clustering algorithms such as k-means [2] or Mixture of Principal Components [3], however these algorithms do not take spatial information into account. Furthermore, clustering algorithms require prior information regarding number of clusters, which is a difficult or ambiguous task, requiring the assertion of some criterion on the very nature of the clusters being formed. Some progress has been made on this issue, however much experimentation still needs to be done [5].

An alternative set of algorithms exists which uses color similarity and a region-growing approach to spatial information [7]. Region growing is based on the following principles. The algorithm starts with a seed pixel, examines local pixels around it, determines the most similar one, which is then included in the region if it meets certain criteria. This process is followed until no more pixels can be added. The definition of similarity may be set in any number of different ways.

Region growing algorithms have been used mostly in the analysis of grayscale images; however, some significant work has been completed in the color realm by Tremeau et al. [6]. They discuss the segmentation of RGB color regions which are homogeneous in color (i.e., no illumination effects are considered) thus restricting the application domain. They use a set of thresholds when calculating whether a color pixel is part of a region or not, and the Euclidean distance is used as the measure of similarity between two color vectors. In [10], the authors describe a method where pixels are aggregated together when the distances between the candidate pixel and an adjacent pixel belonging to the region, and between the candidate pixel and the region prototype are both less than some experimentally set thresholds. The region prototype is determined by computing the vector mean of the pixels within the region. The similarity is assessed as in [6] using the Euclidean distance; however, the XYZ space together with normalized *uv* planes is used (for a total of 5 color planes). However, it is well established [8] that the human perception of color similarity is poorly modeled by the Euclidean distance.

This paper is organized as follows. The Dichromatic Reflection Model, as well as justification for highlight and shading invariances are introduced in Section 2. In Section 3, the region growing algorithm used for color image segmentation is explained in detail. Section 4 describes the results while Section 5 concludes the paper.

2. COLOR THEORY

The Dichromatic Reflection Model (DRM) was introduced by Shafer [11,12]. The basic premise behind this model is that light is reflected in two distinct components: specular reflection and diffuse reflection. In this paper, the focus will be on inhomogenous dielectric materials such as plastics. The presentation of the DRM follows closely that given in [5]. Light reflected from an object surface (called the color signal) is described as a function of pixel location x and wavelength λ:

$$\begin{aligned} C^o(\lambda, x) &= body\, reflection + interface\ reflection \\ C^o(\lambda, x) &= \alpha(x) S^o(\lambda) E(\lambda) + \beta(x) E(\lambda) \end{aligned} \tag{1}$$

where $E(\lambda)$ is the spectral power distribution of a light source, $S^o(\lambda)$ is the spectral-surface reflectance of object o, $\alpha(x)$ is the shading factor and $\beta(x)$ is a scalar factor for the specular reflection term. Sensor responses can be represented with

$$\begin{bmatrix} R \\ G \\ B \end{bmatrix} = \int C^o(\lambda, x) \begin{bmatrix} R_R(\lambda) \\ R_G(\lambda) \\ R_B(\lambda) \end{bmatrix} d\lambda \tag{2}$$

where $R_i(\lambda)$ (i=R,G,B) are the camera's spectral sensitivity functions in the visible spectrum. Substituting (1) into (2),

$$\begin{bmatrix} R \\ G \\ B \end{bmatrix} = \alpha(x) \int S^o(\lambda) E(\lambda) \begin{bmatrix} R_R(\lambda) \\ R_G(\lambda) \\ R_B(\lambda) \end{bmatrix} d\lambda + \beta(x) \int E(\lambda) \begin{bmatrix} R_R(\lambda) \\ R_G(\lambda) \\ R_B(\lambda) \end{bmatrix} d\lambda = \alpha(x)\vec{c}_b + \beta(x)\vec{c}_i \tag{3}$$

where $\vec{c}_b$ and $\vec{c}_i$ are the body and the illumination color vectors (are normalized to unit vector length). If the sensor outputs R, G, and B are balanced for a white surface, then the illumination is considered to be white light. This is satisfied as long as the spectral sensitivity functions have the same areas. Otherwise a white balancing procedure needs to be carried out [5,12].

In [5], the authors demonstrate how highlight invariance is obtained by applying the following transformation

$$\begin{aligned} R' &= R - AVG \\ G' &= G - AVG \\ B' &= B - AVG \end{aligned}$$

Since the algorithm described in this paper also uses the vector angle to discriminate between colors, the method is also said to be shading invariant. This has been demonstrated previously [5].

3. REGION GROWING ALGORITHM

A new region growing algorithm is proposed in this paper based on the vector angle color similarity measure and the use of the principal component of the covariance matrix as the "characteristic" color of the region, with the goal of a region-based segmentation which is perceptually-based. The algorithm is presented as follows:

1. Select seed pixels within the image.
2. From each seed pixel grow a region:
   - 2.1. Set the region prototype to be the seed pixel;
   - 2.2. Calculate the similarity between the region prototype and the candidate pixel;
   - 2.3. Calculate the similarity between the candidate and its nearest neighbor in the region;
   - 2.4. Include the candidate pixel if both similarity measures are higher than experimentally-set thresholds;
   - 2.5. Update the region prototype by calculating the new principal component;
   - 2.6. Go to the next pixel to be examined.

This algorithm presents several advantages over other color image segmentation algorithms. First, it is based on the concept of color vector angle. As was shown in the case of MPC [4], the vector angle is a shading-invariant color similarity measure, implying that intensity variations will be discounted in the region growing process, which is clearly not the case when using the Euclidean distance. Secondly, since spatial information is taken into account, regions having a slightly different color, but still spatially distinct, should appear as separate regions due to the region growing process.

Clearly a significant disadvantage of this approach to color image segmentation is the need for seed pixels, and careful consideration needs to be given to the selection of those pixels. In [10], a complex neural network-based approach is used to determine seed pixels. Ikonomakis et al. [9] give an algorithm for selecting such pixels based on the hue values in the HSI space. Alternative approaches include finding those pixels in the color image with the greatest intensity globally, finding points with maximum local intensity or to use the MPC algorithm to select the seeds based on the clustering result. In this paper, the seed points are found by determining the local intensity using the standard second derivative test from calculus.

4. RESULTS

The effectiveness of the color region growing algorithm is demonstrated on a real color scene with different illumination intensities (see Figures 1 and 2). The results of the region growing algorithm are shown in Figures 3 and 4. The seed pixel distribution is shown in Figure 5.

Figure 1: Color scene image with high illumination intensity

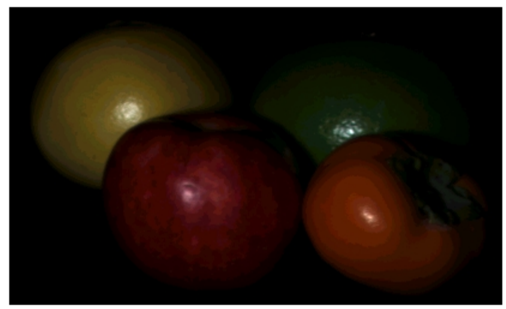

Figure 2: Color scene image with low illumination intensity

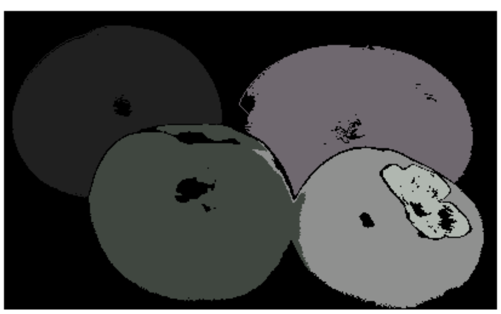

Figure 3: Region growing results for Figure 1

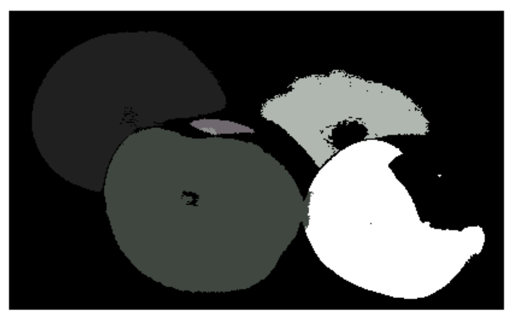

Figure 4: Region growing results for Figure 2

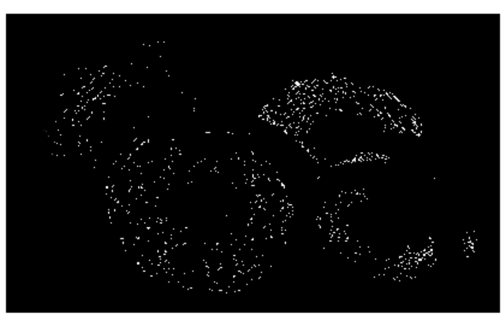

Figure 5: Seed points obtained using the second derivative test

The black area represents that lack of regions since no seed pixels existed there and no regions were able to grow into those areas. 8 regions were found in Figure 1 and 6 regions in Figure 2. The results in Figures 3 and 4 clearly show that most of the highlights have been subsumed into their respective surfaces. However, some highlights still do remain. There is two possible causes for this: (1) the parameters of the algorithm could be further adjusted and (2) the highlight areas are saturated with white light. For the first case, the algorithm was run on both images with an angle tolerance of 1°. Experimentation showed that a higher tolerance would subsume more of the highlights (e.g., the two fruit regions near the bottom of the image merged to a greater extent). Given the results in [5], parameter estimation seems to be the most significant factor contributing to the non-inclusion of parts of the highlight areas into their corresponding regions. In [5], the results were based on the MPC algorithm and did not depend on spatial constraints. Furthermore, the number of classes was fixed and therefore all non-black pixels had to be classified as one of the regions whereas in the region growing approach only pixels satisfying aggregation criteria were included in the final partition. A very low number of the pixels in Figures 1 & 2 is fully saturated, and, therefore, in this case, this does not seem to be a significant factor in the results (even though this is a concern for other images).

5. CONCLUSIONS

A region growing algorithm that is invariant to shading and highlights has been presented. The preliminary results obtained with this algorithm show that a region growing framework is an alternative to global clustering-type algorithms such as MPC. Further work is necessary in setting appropriate parameters and devising regions merging algorithms to handle pixel variations due to highlights. Furthermore, a comprehensive quantitative comparison with other methods is necessary.

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