An Adaptive Color Similarity Function for Color Image Segmentation

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Abstract. In this paper an interactive, semiautomatic image segmentation method is presented which, processes the color information of each pixel as a unit, thus avoiding color information scattering. The process has only two steps: 1) The manual selection of few sample pixels of the color to be segmented in the image; and 2) The automatic generation of the so called *Color Similarity Image* (CSI), which is just a gray level image with all the tonalities of the selected colors. The color information of every pixel is integrated in the segmented image by an adaptive color similarity function designed for direct color comparisons. The color integrating technique is direct, simple, and computationally inexpensive and it has also good performance in gray level and low contrast images.

Keywords: Color image segmentation, Adaptive color similarity function, HSI parameter distances.

1 Introduction

Image segmentation consists of partitioning an entire image into different regions, which are similar in some preestablished manner. Segmentation is an important feature of human visual perception, which manifests itself spontaneously and naturally. It is also one of the most important and difficult tasks in image analysis and processing. All subsequent steps, such as feature extraction and objects recognition depend on the quality of segmentation. Without a good segmentation algorithm, objects of interest in a complex image are difficult (often impossible) to recognize using automated techniques. At present, several segmentation techniques are available for color images, but most of them are just monochromatic methods applied on the individual planes in different color spaces where the results are combined later in different ways [5]. A common problem arises when the color components of a particular pixel are processed separately; the color information is so scattered in its components and most of the color information is lost [2] [5] [7].

In this work, an interactive, semiautomatic image segmentation method is presented which uses the color information for each pixel as a whole, thus avoiding color information scattering. In our method, the three color components (RGB) of every pixel transformed to the HSI color model are integrated in two steps: in the definitions

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of distances in hue, saturation and intensity planes $[\Delta_h, \Delta_s, \Delta_i]$ and in the construction of an adaptive color similarity function that combines these three distances assuming normal probability distributions.

To obtain a consistent color model for direct color comparisons, some simple but important modifications to the classical HSI color space were necessary. These modifications eliminated the discontinuities occurring in the red hue (in 0 and 360 degrees) and all the problems associated with them.

The segmentation method proposed basically relies on the calculation of an adaptive color similarity function for every pixel in a RGB 24-bit true color image. As the results in Section 4 show, the method offers a useful and efficient alternative for the segmentation of objects with different colors in relatively complex color images with good performance in the presence of the unavoidable additive noise. It has also good performance in gray level and low contrast images.

2 Previous Work

There has been a considerable amount of research dedicated to the problem of color image segmentation due to its importance and potential, and because color is an effective and robust visual cue for differentiating between objects in an image. The current available techniques and approaches vary widely from extensions of classical monochromatic techniques to mathematical morphology [2], clustering schemes [4] [10], wavelets [3] and quaternions [9], among others. Until recently, the majority of published approaches were based on monochromatic techniques applied to each color component image in different color spaces, and in different ways to produce a color composite [5].

Some color similarity measures and distances are presented in [8]. All these measures compare color pixels as units. They are all based in three dimensional vector representations of color in which each vector component corresponds to the RGB color channels components.

A technique that combines geometrical and color features for segmentation extending concepts of mathematical morphology (for gray images) is developed in [2] to process color images. The final segmentation is obtained by fusing a hierarchical partition image and a text/graphic finely detailed image. In [7], the authors argue that the common polar color spaces such as HLS, HSV, HSI, and so on are unsuited to image processing and analysis tasks. After presenting three prerequisites for 3D-polar coordinate color spaces well-suited to image processing, they derive a coordinate representation which satisfies their prerequisites that they called Improved HLS (IHLS) space. In the technique presented in [9] the color information for every pixel is represented and analyzed as a unit in the form of quaternions for which every component of the RGB color pixel corresponds to the i , j and k imaginary bases accordingly. This representation of color is shown to be effective only in the context of segmenting color images into regions of similar color texture.

The CIE $L^*a^*b^*$ and the CIE $L^*u^*v^*$ color spaces were developed expressly to represent perceptual uniformity and therefore meet the psychophysical need for a human observer. The difference between two colors can be calculated as the Euclidian

distance between two color points in these spaces, an important characteristic in image segmentation [5] [8].

3 Description of the Method

The method basically relies on the calculation of a color similarity function for every pixel in a RGB 24-bit true color image to form what we call a *Color Similarity Image* (CSI), which is a gray level image. A true color image usually contains millions of colors and many thousands of them represent the same perceived color of a single object due to the presence of additive noise, lack of definition between color borders and regions, shadows in the scene, etc. [1] [6] [8]. The color similarity function allows the clustering of the many thousands colors representing the same perceived color in a single gray output image. The generation of a CSI image only requires calculating Eq. 1 for every pixel in the RGB input image. Thus the complexity is linear with respect to the number of pixels of the source image.

Firstly, we compute the color centroid and color standard deviation of a small sample consisting of few pixels. The computed centroid represents the desired color to be segmented using the technique we designed for that purpose.

Then, our color similarity function uses the color standard deviation calculated from the pixel sample to adapt the level of color scattering in the comparisons [13]. The result of a particular similarity function calculation for every pixel and the color centroid (meaning the similarity measure between the pixel and the color representative value) generates the CSI. The generation of this image is the basis of our method and preserves the information of the color selected from the original color image. This CSI is a digital representation of a continuous function $\in [0 - 1]$ extended to the range of $[0 - 255]$ which can also be viewed as a fuzzy variable of the membership function of every pixel related to a given selected color. In CSI is possible to appreciate not only the color after segmentation but also all the minimal variations in its tonalities when it is multiplied by the original image.

As can be visually observed from the experiments of section 4, the majority of CSI contain some information that is lost during the thresholding step.

The CSI can be thresholded with any non supervised method like Otsu's [11], which was the method used to obtain the results presented in this work.

To generate a CSI we need: (1) a color image in RGB 24-bit true color format and (2) a small set of arbitrarily located pixels forming a sample of the color desired to be segmented. From this sample of pixels we calculate the statistical indicators according to our HSI modified color model [13]. This information is necessary to adapt the color similarity function in order to obtain good results. To obtain the CSI we calculate for every pixel (i, j) in the image the following color similarity function S :

$$S_{i,j} = e^{\left(\frac{-\Delta_h^2}{2\sigma_h^2}\right)} * e^{\left(\frac{-\Delta_s^2}{2\sigma_s^2}\right)} * e^{\left(\frac{-\Delta_i^2}{2\sigma_i^2}\right)} \quad (1)$$

where Δ_h is the hue distance between $hue(i, j)$ and the $average_hue$; Δ_s is the saturation distance between $saturation(i, j)$ and the $average_saturation$; Δ_i is the intensity distance between $intensity(i, j)$ and the $average_intensity$; σ_h is the hue standard deviation of the sample; σ_s is the Saturation standard deviation of the sample; σ_i is the Intensity standard deviation of the sample. In Eq. (1) the color information is integrated giving high importance to perceptual small changes in hue, as well as giving wide or narrow tolerance to the intensity and saturation values depending on the initial sample, which is representative to the desired color to be segmented.

The common disadvantages attributed to the cylindrical color spaces such as the irremovable singularities of hue in very low saturations or in its periodical nature [5] (which is lost in its standard representation as an $angle \in [0^\circ, 360^\circ]$) are overcome in our technique using vector representation in $\mathbb{R}^2$, in the separation of chromatic and achromatic regions, and in the definition of the Δ_h, Δ_s and Δ_i distances.

Among the different options using the same hue and saturation attributes common in the cylindrical spaces like HSI, HSV, HLS, IHLS, etc., we use the intensity value but this choice is of minor importance because the achromatic information is much less important to discriminate colors than the chromatic one (mainly the hue). So the use of all this different spaces should give approximately the same results. The use of Gaussians in the definition of $S_{i,j}$ (Eq. 1) reflects our belief that the color model modifications proposed in this paper takes into account normal distributions of the color attributes in the modified HSI space.

3.1 Pixel Sample Selection

The pixel sample is a representation of the desired color(s) to be segmented from a color image. From this pixel sample we obtain two necessary values to feed our segmentation algorithm: the color centroid and a measure of the dispersion from this centroid, in our case the standard deviation. These two values are represented accordingly to our modified HSI model.

If we take only one pixel, its color would represent the color centroid, and would produce dispersion equal to zero, giving in the calculation of Eq. (1) a Dirac delta. This means that the similarity function would be strictly discriminative to the pixel color. This is not the general intention of segmenting color images where usually a lot of colors are present in the image, many thousands of them representing the same perceived color of a single object or region due to additive noise.

If we additionally take another pixel, we obtain then the centroid from both and the standard deviation of each one of them to feed our algorithm. So when we look for this additional pixel, we should take it from a region which was not (or poorly) segmented when we used only the first pixel.

If we continue adding more and more pixels to the sample we find that the corresponding centroid of the area to be segmented increases in accuracy. Here we may have a relatively minimum representative sample of the color area to segment. Beyond this point, increasing the number of pixels does not affect sensibly the

segmentation quality because adding more pixels to the sample of the same perceived color does not affect the statistical estimators to feed the algorithm.

3.2 The Achromatic Zone G

The achromatic zone G is the region in the HSI color space where no hue is perceived. This means that color is perceived only as a gray level because the color saturation is very low or intensity is either too low or too high.

Given the three-dimensional HSI color space, we define the achromatic zone G as the union of the points inside the cylinder defined by $Saturation < 10\%$ of MAX and the two cones $Intensity < 10\%$ of MAX and $Intensity > 90\%$ of MAX, where MAX is the maximum possible value as presented in [8]. Pixels inside this region are perceived as gray levels.

3.3 Calculating the Average Hue

In order to obtain the average of the hue (H_m) of several pixels from a sample, we take advantage of the vector representation in $\mathfrak{R}^2$. Vectors that represent the hue values of individual pixels are combined using vector addition. From the resulting vector we obtain the average hue corresponding to the angle of this vector with respect to the red axis. Thus H_m is calculated in the following manner:

For every pixel $P(x, y)$ in the sample the following $\mathfrak{R}^3$ to $\mathfrak{R}^2$ transformation is applied:

$$V_1(P) = \begin{bmatrix} 1 & -\cos(\pi/3) & -\cos(\pi/3) \\ 0 & \sin(\pi/3) & -\sin(\pi/3) \end{bmatrix} * \begin{bmatrix} R \\ G \\ B \end{bmatrix} = \begin{bmatrix} x \\ y \end{bmatrix} \quad \text{If } P \notin G \quad (2)$$

and $V(P) = V_1(P) / |V_1(P)|$;

In other case:

$$V(P) = \begin{bmatrix} 0 \\ 0 \end{bmatrix} \quad \text{If } P \in G$$

where $V(P)$ is the normalized projection of the RGB coordinates of the pixel P to the perpendicular plane to the Intensity axis of the RGB cube when the x axis is collinear to the Red axis of the chromatic circle. On the other hand G (see Section 3.2) represents the achromatic zone in the HSI space and $[RGB]^t$ is a vector with the color components of the pixel in the RGB color space.

3.4 Calculating the Hue Distance Δ_h

Using the vector representation of Hue obtained by the $\mathfrak{R}^3$ to $\mathfrak{R}^2$ transformation of RGB space points expressed in Eq. (2), we can calculate the hue distance Δ_h between two colors pixels or color centroids C_1 and C_2 , as follows:

$$\Delta_h(C_1, C_2) = |V_1 - V_2| \quad \text{If } C_1 \text{ and } C_2 \notin G$$

$$= 0 \quad \text{If } C_1 \text{ or } C_2 \in G$$

where G is the achromatic region, and V_1 and V_2 are the vectors in $\mathfrak{R}^2$ calculated with the transformation on C_1 and C_2 given in Eq. (2).

3.5 Saturation Distance and Intensity Distance

We can calculate them by using the standard conversions for saturation and intensity from RGB to HIS space [8], normalized in the range $[0, 1]$:

$$\text{saturation}(P) = 1 - \left[\frac{3}{R + G + B} \min(R, G, B) \right] \quad (3)$$

$$\text{intensity}(P) = \frac{1}{3}(R + G + B)$$

In expression (3), we defined the saturation equal zero in case of the black color.

We use the Euclidean distance to define saturation distance Δ_s and intensity distance Δ_i between two pixels or color centroids.

The CSI is a gray level image, so it can be dealt with any mathematical morphology technique used for gray level images. Filters, operators, thresholds, etc. can be applied directly to the CSI when geometrical characteristics are considered. The common intensity image can be processed too as a complementary information source. The generation of a CSI only requires calculating Eq. 1 for every pixel in the RGB input image. Thus the complexity is linear with respect to the number of pixels of the source image.

4 Results and Discussion

In this section we present the results of our segmentation method applied to three difficult to segment images: a classical complex color image, a gray level infrared image and a low contrast color image. These experiments consisted of segmentation color regions according to the following two steps:

- 1) Selection of the pixel sample. This is the only step to be left up to the user. In order to have a helping direction for this task the following considerations may be useful to select the number of pixels of the sample: If the color of the desired area to segment is solid (without additive noise) it is only necessary to have one pixel sample from the desired area. However, if we want to take in account the color lack of definition happening in the borders, we have to take a sample of the new colors that appear in that area due to the above condition. The pixels of the samples from the original images can be selected arbitrarily, that is, in any order, in any number and physically adjacent or not.

- 2) CSI calculation. This step is automatic; its output is a gray image showing the similarity of each pixel of the RGB true color image to the color centroid formed with the chosen pixel sample taken from the region of interest to be segmented, being white for 100% of similarity and black for 0%.

The user can threshold now the CSI. This step could be necessary to obtain a template for a final segmentation of the desired color from the region of interest; it could be arranged as an automatic step by using, for example, the non-supervised Otsu's thresholding method [11]. This guarantees that the colors segmented be the real ones. During the thresholding of the CSI some information may be lost what could not be convenient. If the CSI itself is used as a template, then we get better segmented areas (without loss of pixels), one for each selected color, but then they are altered in some measure due to the intrinsically gray levels that conform the CSI.

Figure 1 shows an RGB color image (sized 301 x 226 pixels and 27146 different colors) of tissue stained with hemotoxylin and eosin (H&E), which is a very popular staining method in histology and the most widely used stain in medical diagnosis. This staining method helps pathologists to distinguish different tissue types [12].

Fig. 1. Stained tissue

Fig. 2. Sample composed by 4 pixels located in two zones with blue color

In this image we can see three main hues of colors despite the thousands (more than 27,000 colors) of actual RGB values to represent them: blue, pink and white. Different pixel tonalities in the image depend on their particular saturation and on the unavoidable presence of additive noise. The proposed color segmentation method is practically immune to these conditions, although obviously some solutions could be used to improve the quality of the segmented regions, as for example, preprocessing the image for smoothing noises of different types, applying some morphological method to reduce objects with given characteristics, and so on.

In this experiment we took a sample composed by 4 pixels located in two zones with blue color. They are selected from an enlarged 21 x 21 pixels region as shown in Fig. 2.

From this sample we calculated the color centroid and the standard deviation in our modified HSI space; with these two values we use the Eq. 1 to calculate for every pixel the pixel values of the CSI shown in Fig. 3.

Fig. 3. The Color Similarity Image (CSI) of blue

Fig. 4. Zones of the segmented blue color

After applying Otsu’s thresholding method we obtained the color segmentation shown in Fig. 4.

For the pink area we repeated the same process. Figure 5 shows the pixels sample (from 4 pixels), its corresponding CSI is shown in Fig. 6 and the final segmentation of the pink zone is shown in Fig. 7.

Fig. 5. Pixels sample of 4 points for the pink color

Fig. 6. CSI of the pink color

Fig. 7. Zones of the segmented pink color

Repeating the above process in Fig. 8 we show the pixel sample and in Fig. 9 the CSI (left) and the final segmentation of white color areas (right).

In Figure 10 (right) we show a composite image of Fig. 4, Fig. 7, and Fig. 9 (right) using consecutively the logical XOR operation. We use this operation instead of the OR one to guarantee that in the composite image a given pixel appear only in one color segmented zone, as it is expected in all segmentation task. The black pixels

Fig. 8. Pixel sample for the white color

Fig. 9. CSI of the white color (left) and zones of the segmented white color (right)

represent those colors that were not segmented by any of the three color choices or, on the contrary, when the pixel appeared with the same value (1 or 0) in two binary images (they were made black by the consecutive XOR operation). In this example, non-segmented pixels were 4546 pixels from a total of 68026 pixels, which is only 6.6% ($4546/68026$) of the total number of pixels of the original image. It can be observed in Fig 10 (right) that a good amount of the black pixels belongs to borders between regions of different colors where they are clearly undefined.

Fig. 10. Original image (left) and composite image (right)

Comparing both images in Fig. 10 demonstrates the accuracy of the blue, pink and white segmented zones obtained by the method, not only from the point of view of the number of segmented pixels but from the point of view also of the quality of the tonalities of the colors that appear in the original image. These results were obtained with as few as only 12 pixels belonging to only three samples, one associated to each color blue, pink and white. The composite image shown in Fig. 10 (right) was created through the selection of samples with a maximum of 4 pixels for each color considered to be segmented. The size and/or shape of the segmented regions of different colors depend on the number, the distribution and quantity of pixels that makes up each sample, as well as if two or more samples have pixels with the same or very similar color. With samples well selected the method guarantee very good color segmentation.

It is possible with the proposed color segmentation method to divide a region having a particular color (i. e. blue region in Fig. 4) in two or more sub-regions having the same basic color (blue) but having two different saturation (darker nuclei with clearer zones surrounding them). Figure 11 shows the seven pixels sample selected from two different zones belonging to the darker blue nuclei.

Fig. 11. Sample of 7 pixels corresponding to the blue nuclei

Figure 12 shows the CSI of dark blue nuclei, and Fig. 13 shows the final segmented image. Figure 14 shows the well-differentiated nuclei (colored in green) surrounded by clearer blue zones. The possibilities of the method are many, requiring only a few well-selected samples from well-distributed zones and having the suitable number of pixels each.

Fig. 12. CSI of blue nuclei

Fig. 13. Segmented darker blue nuclei

Fig. 14. Well differentiated green nuclei surrounded by clearer blue zones

We will show the good results obtained by our method applied to gray images and low contrast color images in the following two examples. Figure 15 shows a gray level image obtained with an infrared camera; we took a small pixel sample (of 4 pixels) from the face area and obtain its correspondent CSI shown in Figure 16. The segmented face appears in figure 17 after thresholding with Otsu method.

In Figure 18 a fossil inserted in a rock is shown, we took a small pixel sample of the fossil area from which we obtained its corresponding CSI (Fig 19). Figure 20 shows the resulting image after thresholding with Otsu method.

Fig. 15. Infrared image

Fig. 16. CSI of face

Fig. 17. Segmented face

Fig. 18. Leaf fossil in rock

Fig. 19. CSI of fossil

Fig. 20. Threshold by Otsu

5 Conclusions

The results in the previous section demonstrate that the color segmentation method presented in this paper offers a useful and efficient alternative for the segmentation of objects with different colors in relatively complex color images with good performance in the presence of the unavoidable additive noise, in images with low contrast and also in gray level images.

The steps required to obtain a good segmentation of regions with different colors by using the proposed methodology are usually straightforward, simple and repetitive. If color (or a given gray level) is a discriminative characteristic, only the selection of a given threshold to the color similarity function CSI is needed to obtain a good segmentation result. From many experiments we have observed that colors were obtained in a straightforward way only by thresholding the Color Similarity Image.

In our method, the three RGB color components of every pixel transformed to the HSI color model are integrated in two steps: in the definitions of distances $[\Delta_h, \Delta_s, \Delta_i]$ in hue, saturation and intensity planes and in the construction of an adaptive color similarity function that combines these three distances assuming normal probability distributions. Thus the complexity is linear ($O[n]$) with respect to the number of pixels n of the source image. The method discriminates whichever type of different color objects independently on their shapes and tonalities in a very straightforward way.

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