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 [14–10], 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/graphics 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 call improved HLS (IHLSS) 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. [11–6] [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 \( \epsilon \{0 \cdot 1 \} \) extended to the range of \([0 \cdot 255] \) 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 \( S \) :

\[
S_{i,j} = \left( \frac{\Delta_h^2}{2\sigma_h^2} \right) + \left( \frac{\Delta_s^2}{2\sigma_s^2} \right) + \left( \frac{\Delta_i^2}{2\sigma_i^2} \right)
\] (1)
The vector representation of the RGB color space is a vector with the components representing the intensity of red, green, and blue in the color space. This can be written as:

\[
\begin{bmatrix}
R \\
G \\
B
\end{bmatrix}
\]

In order to obtain the average of the RGB color space from a sample of source pixels, we can use the following formula:

\[
\text{Average RGB} = \frac{1}{N} \sum_{i=1}^{N} \begin{bmatrix} R_i \\ G_i \\ B_i \end{bmatrix}
\]

where \( N \) is the number of pixels in the sample.
\[ \Delta_3(C_1, C_2) = |V_1 - V_2| \]

If \( C_1 \) and \( C_2 \) are both in \( G \)

\[ = 0 \]

If \( C_1 \) or \( C_2 \) are in \( G \)

where \( G \) is the achromatic region, and \( V_1 \) and \( V_2 \) are the vectors in \( \mathbb{R}^2 \) 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 \([0, 1]\):

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

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

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

We use the Euclidean distance to define saturation distance \( \Delta_3 \) and intensity distance \( \Delta_2 \) 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 into 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 than the colors segmented be the real ones. During the thresholding of the CSI some information may be lost which 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 hematoxylin 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.
From two different sources, the color of the black pixels in the two different images (Figures 1 and 2) differ. However, when applying the color subtraction method, the black pixels are eliminated, as shown in Figures 3 and 4.

The color subtraction method works by subtracting the color information of the two images. In Figure 3, the original images are shown, and in Figure 4, the color subtraction result is displayed.

The process involves the following steps:
1. **Color Subtraction**: The color information is subtracted from the first image to obtain the second image.
2. **Binary Conversion**: The resulting image is then converted to a binary format.
3. **Comparison**: The binary images are compared to identify the black pixels.
4. **Result**: The black pixels are eliminated, as shown in Figure 4.

This method is useful in scenarios where the color information of the images needs to be compared or analyzed.
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 $\{\Delta_3, \Delta_4, \Delta_5\}$ 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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