

Refined Achromatic Zone Segmentation in Color Images

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Abstract. We present an interactive, semiautomatic image segmentation method that processes the color information of each pixel as a unit, thus avoiding color information scattering. The color information of every pixel is integrated in the segmented image by an adaptive color similarity function designed for direct color comparisons. The border between the achromatic and chromatic zones in the HSI color model has been transformed in order to improve the quality of the pixels segmentation when their colors are very obscure and very clear. The color integrating technique is direct, simple and computationally inexpensive, and it has also good performance in low chromaticity and low contrast images. It is shown that segmentation accuracy is above 95% as average and that the method is fast. These results are significant when compared to other solutions found in the current literature.

Keywords: Color image segmentation; Adaptive color similarity function; Improved HIS color model; Achromatic zone definition.

1 Introduction

Image segmentation consists of partitioning an entire image into different regions, which are similar in some predefined manner. Segmentation is an important feature of human visual perception, which manifests itself spontaneously and naturally. All subsequent steps, such as 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 [1] [2] [3].

At present, several segmentation techniques are available for color images, a good amount of them are monochromatic methods applied on the individual planes in different color spaces where the results are combined later in different ways [3]. A common problem to this approach is that when the color components of a particular pixel are processed separately the color information is so scattered in its components that most of the color information is lost [1] [3] [4].

In this work, an interactive, semiautomatic image segmentation method is presented that uses the color information for each pixel as a whole, thus avoiding color information scattering.

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One weakness in the characterization of the achromatic region as presented in [5], [7] and [10] is its poor performance in the border regions of achromatic and chromatic zones, both in low and high brightness, due to the fact that the commonly used HSI color model does not take into account the human visual response at low and high brightness. Human vision has a nonlinear perceptual response to luminance [11]. This problem was overcome by modifying the saturation value of every pixel by a factor that reflects the human exponential response to brightness. We show this improvement in Section 3 comparing the achromatic zone obtained by both methods.

The results tabulated in Section 3 show that the 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. It has also good performance in gray level and low contrast images [5].

2 Description of the Method

The segmentation method proposed in this paper 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, the spatial resolution of the human vision system, etc. [1] [6] [7]. The color similarity function allows the clustering of the many thousands of colors representing the same perceived color in a single gray output image. The CSI is then automatically thresholded and the output can be used as a segmentation layer, or it can be modified with morphological operators to introduce geometric enhancements if they are needed. The generation of a CSI only requires calculating Eq. 1 (below) for every pixel in the RGB input image. Thus the complexity is linear with respect to the number of pixels of the source image and for that reason inexpensive computationally.

Firstly, we compute the color centroid and color standard deviation of a small sample consisting of few pixels (less than 3-4 pixels per color). 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. The result of a particular similarity function calculation for every pixel and the color centroid (meaning the similarity measure between the pixel and the representative color 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 discrete representation in the range of [0 - 255] of a continuous function whose values are in the normalized range [0 - 1].

The CSI can be thresholded with any automatic thresholding method. To obtain the results presented in this work we used Otsu's method [8] [9].

To generate a CSI we need: 1. A color image in RGB 24-bit true color format and 2. A sample 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 which can be consulted in [5]. 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 empirical color similarity function S (Eq. 1).

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

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 Equation (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 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.

The HSI color model represents colors similarly as humans describe colors in terms of hue, saturation and brightness. Hue is a color attribute that describes pure color whereas saturation gives a measure of the degree to which a pure color is diluted by white light. Brightness is a subjective descriptor that embodies the achromatic notion of intensity [6].

We use the intensity value but we believe that 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 common disadvantages attributed to the HSI color space such as the irremovable singularities of hue in very low saturations or the periodical nature of hue [7], 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. We use the Euclidean distance to define saturation distance Δ_s and intensity distance Δ_i between two pixels or color centroids. We calculate the hue distance Δ_h with vector difference. The statistical values needed in Eq. (1) are calculated from the pixel sample using the common statistics formulae adapted to our model. The details about all this can be consulted in [5] and [10]. Some modifications of the standard HSI color space were necessary in order to create a consistent model to represent colors and color centroids; they can be consulted for reference in [5] and [10].

2.1 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 calculate two values to feed our segmentation algorithm: the color centroid and a measure of the dispersion from this centroid, in our case the standard deviation.

If we take only one pixel, its color would represent the color centroid, and would produce dispersion equal to zero, giving a Dirac delta in the calculation of Eq. (1). This means that the similarity function would be strictly discriminative to the pixel color. This is not the general intention of segmenting color images which usually contain millions of colors, many thousands of which are due to additive noise.

If we additionally take another pixel, we obtain then the centroid from both and the standard deviation 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. That means that in order to obtain good results the pixels for the sample should be taken from the color regions in such a form that they must constitute a good representation of the colors of the region.

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 a given number of well-selected pixels in the sample to increase them does not affect sensibly the segmentation quality because adding more pixels to the sample of approximately the same perceived color does not affect the statistical estimators to feed the algorithm in a sensible manner.

In order to obtain the average of the hue (H_m) of several pixels from a sample, we take advantage of the vector representation of hue in $\mathbb{R}^2$. 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.

2.2 The Achromatic Zone G

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

In order to model better the human visual response in the abrupt corners regions near the union zones of the two cones with the cylinder of the singularity zone G, as presented in [5], [7] and [10], we found heuristically convenient to modify the characterization of the HSI color model for colors belonging to regions with very low or very high brightness. This step will permit us to differentiate the colors in these extreme regions, because the human response to brightness does not have this possibility. In order to adjust the zone G to a better model nearer to the human response to brightness we introduced an exponential function with three parameters to define the improved singularity of zone G: saturation threshold (st), inflection point (ip), and

Slope (Fig 1). Then, the saturation image will be affected now by a factor calculated from the inflection point (ip), and Slope for every pixel (P) as shown in Eq.(2):

$$New_Saturation_ (P) = \left(1 - Slope * (e)^{abs(ip - intensity(P))}\right) * Saturation_ (P) \quad (2)$$

where Slope is a parameter representing the degree of affectation of the exponential factor to the saturation attribute for every pixel; $abs()$ represents the absolute value function and $intensity()$ is defined as an average of the RGB channels in Eq. (6) in [5]. After calculating the New_Saturation values for the source image, it is thresholded with the saturation threshold (st) to obtain the effects of the improved achromatic zone G.

We found good performance with the parameters empirically determined in the following ranges: $st \in [0.07, 0.1]$, $ip \in [0.5, 0.6]$, and $Slope \in [1, 1.5]$.

3 Experiments and Results

In this section we describe the experiments and present the results achieved from our segmentation method applied to two classical color images in RGB 24-bit true color format. These experiments consisted of segmenting color regions according to the following two steps:

Selection of the pixel sample. This is the only step to be left up to the user, and [5] can be consulted as a guide. 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 of the region of interest to be segmented, being white for 100% of similarity and black for 0%.

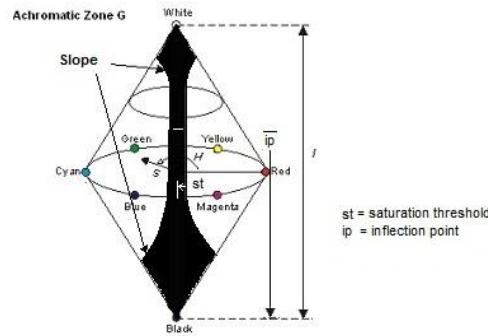


Fig. 1 The new achromatic zone G

The user can now threshold 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 thresholding method [8], [9].

We can also separate the achromatic area to obtain a better segmentation. This achromatic zone can be subdivided later using only intensity as a discriminative characteristic. In Figs. 2, 3 and Table 1 we show the improved results of our new definition of G in Eq. (2) with respect to the former results presented in [5], [7] and [10].

In all the composite images we used the XOR logical function to avoid the possibility that one pixel could belong simultaneously to two different color-segmented zones or regions.

Next, we demonstrate the effectiveness of the proposed color segmentation method in some relatively complex color images.

Figure 2 (left) shows the results of the application of our method to the RGB color image (sized 200 x 200 pixels and with 33 753 different colors) of the popular baboon image. In this image we can see four main hues of colors despite the many thousands of actual RGB values to represent them: The red part of the baboon's nose, the blue part of the nose, the orange eyes and the yellow-orange part of the fur.

In our experiments we do not use any preprocessing at all. We obtained 95.5% of pixels segmented properly (See Table 1). In figure 2 we show the results with the old (center) and new achromatic region G (right) for appreciation. The improvement in quality is significant.

As another example, consider the image of two horses with shadows shown in figure 3 (left). Figure 3 (right) shows the composite image of the different segmented areas. Non-segmented pixels are shown in pseudo red color. We obtained a 97.1% of pixels segmented (See Table 1). Figure 4 shows the segmentation of the achromatic zone with the former (left) and the new definition (right). The improvement in quality is appreciable.

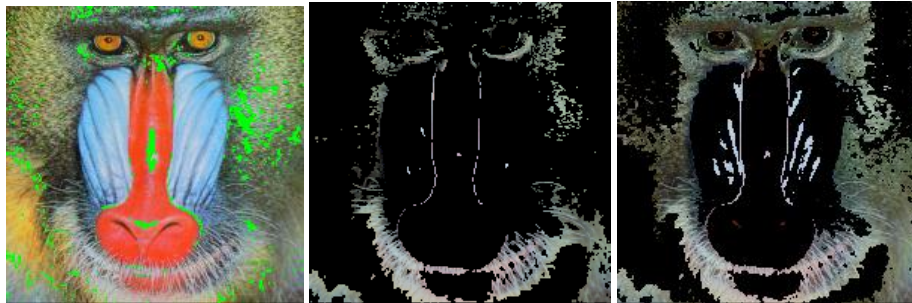


Fig. 2 Composite image of 5 segmented colors (left) and results obtained with the old (center) and the new achromatic zone G (right).

In order to evaluate the efficiency of the color segmentation method and due to the difficulty of obtaining a ground-truth for each complex image to which we applied the method or to compare the results from different methods, the evaluation was based on the number of pixels not segmented with respect to the total number of pixels in the corresponding image. This ratio combines the pixels not belonging to any color cluster and those selected by two or more clusters (obtained by means of the XOR operation) with respect to the total number of pixels in the image. It gives us a measure of the segmentation efficiency. Obviously, the number of different colors in each image

is always less than the total number of pixels in it. The maximum number of selected pixels related to each color sample was always ten or less. In general the number of selected pixels for the samples depends on the complexity of the image (texture of objects), on the diversity of colors and on their spatial distribution in the image.

Table 1 show the results obtained in the segmentation of three images. The last column of Table 1 shows the percent of segmented pixels obtained in these images.. In all cases, the possibility that one pixel could belong to two different colors segmented zones or regions have been avoided by means of the application of the XOR logical function (of two or more partial segmentations). A result with many black pixels indicates that has been coincidence in segmented pixels from two or more partial segmentations considered in the XOR operation.

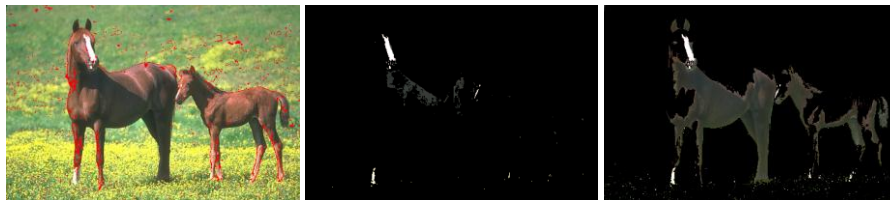


Fig. 3 Composite image of 3 segmented colors (left) and results obtained with the old (center) and the new achromatic zone G (right).

As it can be observed from Table 1, the average accuracy of the color segmentation in both complex images, without an exhaustive selection of colors and a few numbers of pixels (4-5 as average) per color sample, is 96.55%.

In Figure 4 (left) a composite image of 5 segmented colors (with the non-segmented pixels in pseudocolor) of a color fabric is shown; it contains an achromatic region with high saturation but low brightness that is very difficult to separate with the former G zone (Figure 4 center) but easily separated with the new one shown in Fig. 4 (right).. We obtained 95.3% of pixels segmented.

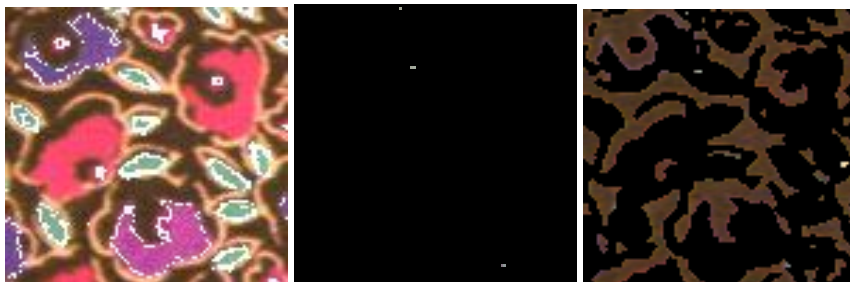


Fig. 4 Composite image of 5 segmented colors (left) and results obtained with the old (center) and the new achromatic zone G (right).

When we compare the new achromatic region G with the former one, the difference is astonishing whereas the new achromatic area seems correctly segmented the former one segmented only a couple of pixels.

Figure 5 (left) shows a composite image of 3 segmented colors of tissue stained with hemotoxylin and eosin (H&E) color image (which is a very popular staining method in histology and the most widely used stain in medical diagnosis) with the non segmented pixels in pseudocolor. The former and the new achromatic areas are shown in Figure 5 (center) and Figure 5 (right) respectively.

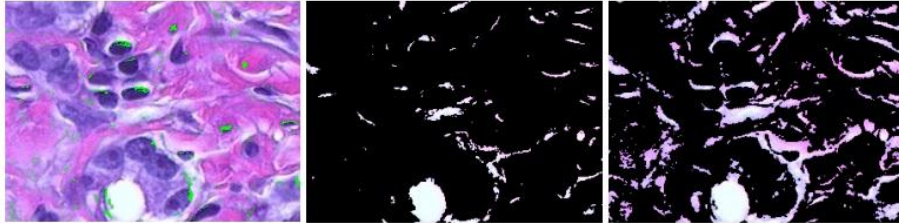


Fig. 5 Composite image of 3 segmented colors (left) and results obtained with the old (center) and the new achromatic zone G (right).

We will show the good results obtained by our method applied to low contrast color images and gray level images in the following three examples: Fig. 6 shows a fossil inserted in a rock, we took a small pixel sample of the fossil area from which we obtained its corresponding CSI (Fig. 6 center). Figure 6 (right) shows the thresholded image after applying the Otsu thresholding method and some morphological processing. Figure 7 shows a gray level image obtained with an infrared camera, we took a small pixel sample from the face area and obtained its correspondent CSI shown in Fig.7 (second left to right). The segmented face appears in Fig.7 (third left to right) after thresholding by Otsu method. Fig.7 (extreme right) shows a composite of the segmented pixels with the non-segmented pixels in green for easier appreciation. Figure 8 shows a gray level image of a person's signature. After taking a four pixels sample from the signature we calculated its CSI shown in Fig. 8 (second left to right). Fig.8 (third left to right) shows the final segmentation after thresholding by Otsu method. Fig.8 (extreme right) shows a composite of the segmented pixels with the non-segmented pixels in green.

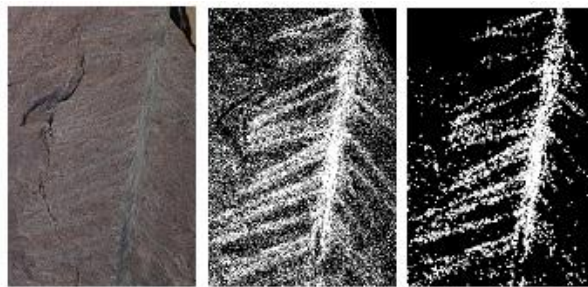


Fig. 6 Fossil embedded in rock. CSI of fossil Thresholded by Otsu and processed



Fig. 7 Low contrast infrared Image CSI of face Segmented face Pixels not segmented in green

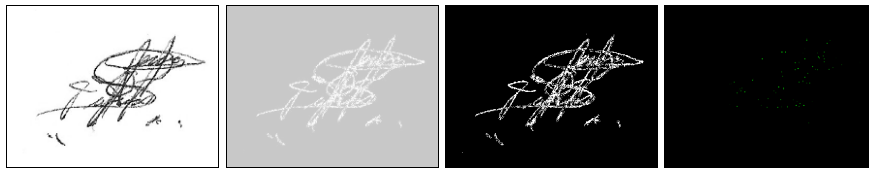


Fig. 8 Signature CSI of signature CSI thresholded by Otsu Pixels not segmented in green

Table 1 Results of the global segmentation per image.

No.	Image	Number of pixels in image	Number of colors (levels)	Number of colors (levels) selected	Total number of pixels used as samples	Number of non-segmented pixels	% of segmented pixels
1	Baboon	40000	33753	5	31	1803	95.5
2	Horses	154401	71727	3	14	4619	97.1
3	Fabric	9900	9349	5	23	465	95.3
4	Stained tissue	68026	27146	3	11	1171	98.3
5	Fossil	121128	40756	7	15	95 262	-
6	Gray level Infrared	81426	255	4	12	347	99.57
7	Signature	98 532	255	2	4	76	99.92

4 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, and in images with low contrast, and with very low chromaticity.

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 is a discriminative characteristic in the layer of interest, only the selection of a given threshold to the color similarity image CSI is needed to obtain a good segmentation result. From many experiments we have observed that a good percentage of colors were segmented in a straightforward way only by thresholding the Color Similarity Image. The method discriminates whichever type of different color objects independently on their shapes and tonalities in a very straightforward way.

The new characterization of the achromatic region improves its performance, compared to that presented in [5], [7] and [10], due to the affectation of saturation by an exponential factor in an effort to better model the human visual response in case of very low or very high brightness. The improvement in quality of its results is significant and can be visually appreciated in examples of Section 3.

One of the inconveniences of the proposed color segmentation method is the degree of human intervention, summarized in the necessity of selecting a pixel sample. This sample has to be carefully chosen in order to obtain the best results. An associated problem of the use of a pixel sample is to obtain the number of data points necessary to capture the color distribution. These related problems will be treated in future developments of the algorithm enforced to obtain a complete automatic version.

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