FUZZY WATERSHED FOR IMAGE SEGMENTATION

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Abstract

The representation of the RGB color space points in spherical coordinates allows to retain the chromatic components of image pixel colors, pulling apart easily the intensity component. This representation allows the definition of a chromatic distance. Using this distance we define a fuzzy gradient with good properties of perceptual color constancy. In this paper we present a watershed based image segmentation method using using this fuzzy gradient. Oversegmentation is corrected applying a region merging strategy based on the chromatic distance defined on the spherical coordinate representation.

Keywords Reflection model, image segmentation, spherical coordinates, chromaticity

1 Introduction

Color images have additional information over grayscale images that may allow the development of robust segmentation processes. There have been works using alternative color spaces with better separation of the chromatic components like HSI, HSL, HSV, Lab [1, 2] to obtain perceptually correct image segmentation. However, chromaticity's illumination can blur and distort color patterns. The segmentation method proposed in this paper has inherent color constancy due to the color representation chosen and the definition of the chromatic distance.

In this paper we use the RGB spherical coordinates representation to achieve image segmentation showing color constancy properties [3–5]. We define a chromatic distance on this representation. The robustness and color constancy of the approach is grounded in the dichromatic reflection model (DRM) [6]. We propose a chromatic gradient operator suitable for the definition of a watershed transformation on color images and a robust region merging for meaningful color image segmentation. The baseline chromatic gradient operator introduced in [3, 7] is very sensitive to noise in the dark areas of the image. We propose in this paper a fuzzy gradient operator overcoming this problem which is useful to build a watershed transformation on color images. To achieve a natural segmentation, we perform region merging on the basis of our proposed chromatic distance over the chromatic characterization of the watershed regions. We give a general schema that combines watershed flooding with region merging in a single process. Finally, we specify our proposal as an instance of the aforementioned general schema.

The paper outline is as follows. Section 2 presents the RGB spherical interpretation, including the definition of the chromatic distance. Section 3 presents the fuzzy watershed image segmentation method. Section 4 shows experimental results comparing our method to other approaches. Finally, Section 5 gives the conclusions of this work.

2 Spherical coordinates in the RGB Color Space

There are several works that use a spherical/cylindrical representation of RGB color space points looking for photometric invariants [8, 9]. We are interested in the correspondence between the angular parameters (θ, ϕ) of the spherical representation of a color point in the RGB space and its chromaticity Ψ.

2.1 Chromaticity interpretation of RGB Spherical Coordinates

An image pixel's color corresponds to a point in the RGB color space $c = \{R_c, G_c, B_b\}$. Chromaticity Ψ_c of a RGB color point c is given by two of its normalized coordinates $r_c = \frac{R_c}{R_c+G_c+B_c}, g_c = \frac{G_c}{R_c+G_c+B_c}, b_c = \frac{B_c}{R_c+G_c+B_c}$, that fulfill the condition $r_c + g_c + b_c = 1$. That is, chromaticity coordinates $\Psi_c = \{r, g, b\}$ correspond to the projection of c on the chromatic plane Π_Ψ, which is defined by the collection of vertices $\{(1, 0, 0), (0, 1, 0), (0, 0, 1)\}$ of the RGB cube which define the Maxwell's chromatic triangle [10], along the chromatic line defined as $L_c = \{y = k \cdot \Psi_c; k \in \mathbb{R}\}$. In other words, all the points in line L_c have the same chromaticity Ψ_c. Chromaticity is a robust color characterization, which is is independent of illumination intensity and preserves the geometry of the objects in the scene.

Denoting a color image in RGB space as $\mathbf{I} = \{\mathbf{I}(x); x \in \mathbb{N}^2\} = \{(R, G, B)_x; x \in \mathbb{N}^2\}$, where x refers to the pixel coordinates in the image grid domain, we denote the corresponding spherical representation as $\mathbf{P} = \{\mathbf{P}(x); x \in \mathbb{N}^2\} = \{(\phi, \theta, l)_x; x \in \mathbb{N}^2\}$, so we will use $(\phi, \theta)_x$ as the chromaticity representation of the pixel's color. Sometimes we use the notation $x = (i, j)$.
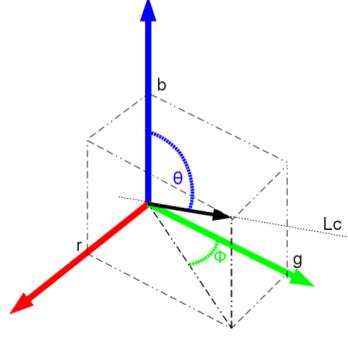
Figure 1: A vector in the RGB space

2.2 The chromatic distance in the RGB space

First, we convert the RGB cartesian coordinates of each pixel to polar coordinates, with the the black color as the RGB space origin. Let us denote the cartesian coordinate image as $I(x) = I_x = (r, g, b)_x; x \in \mathbb{N}^2$ and the spherical coordinate as $P(x) = P_x = (\phi, \theta, l)_x; x \in \mathbb{N}^2$, where p denotes the pixel position. For the remaining of the paper we discard the magnitude l_x because it does not contain chromatic information, therefore $P(x) = P_x = (\phi, \theta)_x; x \in \mathbb{N}^2$. For a pair of image pixels x and y, the color distance between them is defined as:

$$\angle(P_x, P_y) = \sqrt{(\theta_y - \theta_x)^2 + (\phi_y - \phi_x)^2}, \tag{1}$$

that is, the color distance corresponds to the euclidean distance of the Azimuth and Zenith angles of the pixel's RGB color polar representation. This distance does not take into account the intensity component and, thus, will be robust against specular surface reflections. It posses color constancy, because pairs of pixels in the same reflectance surface will have the same distance regardless of their intensity.

2.3 Chromatic gradient operator

We formulate a pair of Prewitt-like gradient pseudo-convolution operations on the basis of the above distance. Note that the $\angle(P_p, P_q)$ distance is always positive. Note also that the process is non linear, so we can not express it by convolution kernels. The row pseudo-convolution is defined as

$$CG_R(P(i,j)) = \sum_{r=-1}^{1} \angle(P(i-r, j+1), P(i-r, j-1)),$$

and the column pseudo-convolution is defined as

$$CG_C(P(i,j)) = \sum_{c=-1}^{1} \angle(P(i+1, j-c), P(i-1, j-c)),$$

so that the color distance between pixels substitutes the intensity subtraction of the Prewitt linear operator. The color gradient image is computed as:

$$CG(x) = CG_R(x) + CG_C(x) \tag{2}$$

2.4 A Fuzzy Color Gradient

Inspired in the human vision, diferent retinal cells need diferent energy for its activation. Cones are vey sensitive to intensity wheras rods need more energy for its activation, whose can detect the cromaticity. Depending of the sourface radiance, these retinal cells can be activated. We follow similar approach in order to define our fuzzy chromatic distance. For pixels with high intensity we are going to use the chromatic gradient defined in equation 2, whereas for pixels with poor illumination are going to use the conventional linear intensity gradient. We use a fuzzy membership function $\alpha(x)$ who gives the membership degree to the "well illuminated pixels class", on the other hand, its standard complement function $\overline{\alpha}(x) = 1 - \alpha(x)$ gives the membership degree to the "poor illuminated pixels class". It is defined as follows

$$\alpha(x) = \begin{cases} 0 & I(x) < a \\ \exp\left(\frac{-(c - \frac{I(x)-a}{b-a})^2}{2\sigma^2}\right) & a \leq I(x) < b \\ 1 & b \leq I(x) \end{cases}, \tag{3}$$

2

where $I(x)$ is the pixel intensity. For intensity values below a threshold a it is an intensity gradient, for values above another threshold b it is a chromatic gradient, and for values between both it is a mixture of the two kinds of gradients whose mixing coefficient is gaussian function of the image intensity. This idea is expressed mathematically as a convex combination of the two gradient operators:

$$FG(x) = \alpha(x) CG(x) + \overline{\alpha}(x) G(x) \tag{4}$$

where x is the pixel location, $G(x)$ is the intensity gradient, calculated using the convolution mask of Eq.2 but using only the intesity parameter l.

This fuzzy gradient does not suffer from noise sensitivity in dark regions of the image, the effect of bright spots is reduced because it is chromatically consistent in bright image regions, and it detects chromatic edges.

3 Fuzzy Watershed Image Segmentation

Watershed transformation is a powerful mathematical morphology technique for image segmentation. It was introduced in image analysis by Beucher and Lantuejoul [11]. The watershed transform considers a bi-dimensional image as a topographic relief map. The value of a pixel is interpreted as its elevation. The watershed lines divide the image into catchment basins, so that each basin is associated with one local minimum in the topographic relief map. The watershed transformation works on the spatial gradient magnitude function of the image. The crest lines in the gradient magnitude image correspond to the edges of image objects. Therefore, the watershed transformation partitions the image into meaningful regions according to the gradient crest lines. We will use the fuzzy gradient as the topographic relief map.

3.1 General Schema

The general schema of the watershed method consists of a flooding process which performs a region growing based on the ordered examination of the level sets of the gradient image. In fact, an ordered succession of thresholds are applied to produce the progression of the flooding. The image is examined iteratively n times, each iteration step the threshold is raised and pixels of the gradient image falling below the new threshold are examined to be labeled with a corresponding region. Initially each region will contain the source of its catchment basin when the flooding level reaches it. Each flooded region is also characterized by a chromaticity value, that corresponds to the source pixel chromaticity. This chromaticity value is used to perform region merging simultaneously with the flooding process. A pixel whose neighboring pixels belong to different regions is a watershed pixel. When a watershed pixel is detected, the adjacent regions may be merged into one if the chromatic distance between the region chromatic values is below a chromatic threshold. The merged region chromatic value is the average of that of the merged regions. The final labeling of the image regions is performed taking into account the equivalences established by the merging process. Watershed pixels whose adjacent regions do not merge into one are labeled as region boundary pixels and retain their chromaticity.

4 Experimental results

The general watershed-merge method is parametrized by:

- The number of iterations n, which determines the resolution of the flooding process going over the gradient magnitude image level sets.

- The gradient operator used to compute the gradient magnitude image, which can be either the intensity gradient $G(x)$ of equation or the fuzzy gradient $FG(x)$ of equation 4.

- The color representation of the image. Assuming the RGB space, it can be either the Cartesian representation $\mathbf{I}(x)$ or the zenithal and azimuthal angles of the spherical representation $\mathbf{P}(x)$. This selection determines the selection of the chromatic distance.

- The chromatic distance, which can be either the Euclidean distance in the RGB Cartesian space, or the chromatic distance of equation 1.

- The chromatic distance threshold δ, which determines the chromatic resolution of the region merging process.

We will use a well known benchmark image [12] to compare our proposed segmentation process with variations of method obtained with other parameter settings. The dark regions are critical to the perceptually correct gradient computation, while the bright spots may induce false edge detection. The method does not compute any specular free image to remove this latter problem.

The operational parameter settings are $n = 100$ and $\delta = 0.1$. In figure2 we show the segmentation results on this image for all combinations of the remaining parameter settings. The column of images labeled "Gradient" has the gradient magnitude images. From top to bottom, figures 2(a), 2(e), 2(i) show, respectively the result of the intensity gradient, the chromatic gradient of equation (2), and the fuzzy gradient of equation (4). The column of images labeled "Watershed" correspond to the image region partition performing only to the flooding process, without any region merging, on the corresponding gradient magnitude images.

Original image

Gradient   Watershed   Segmentation

(a)   (b)   (c)   (d)

(e)   (f)   (g)   (h)
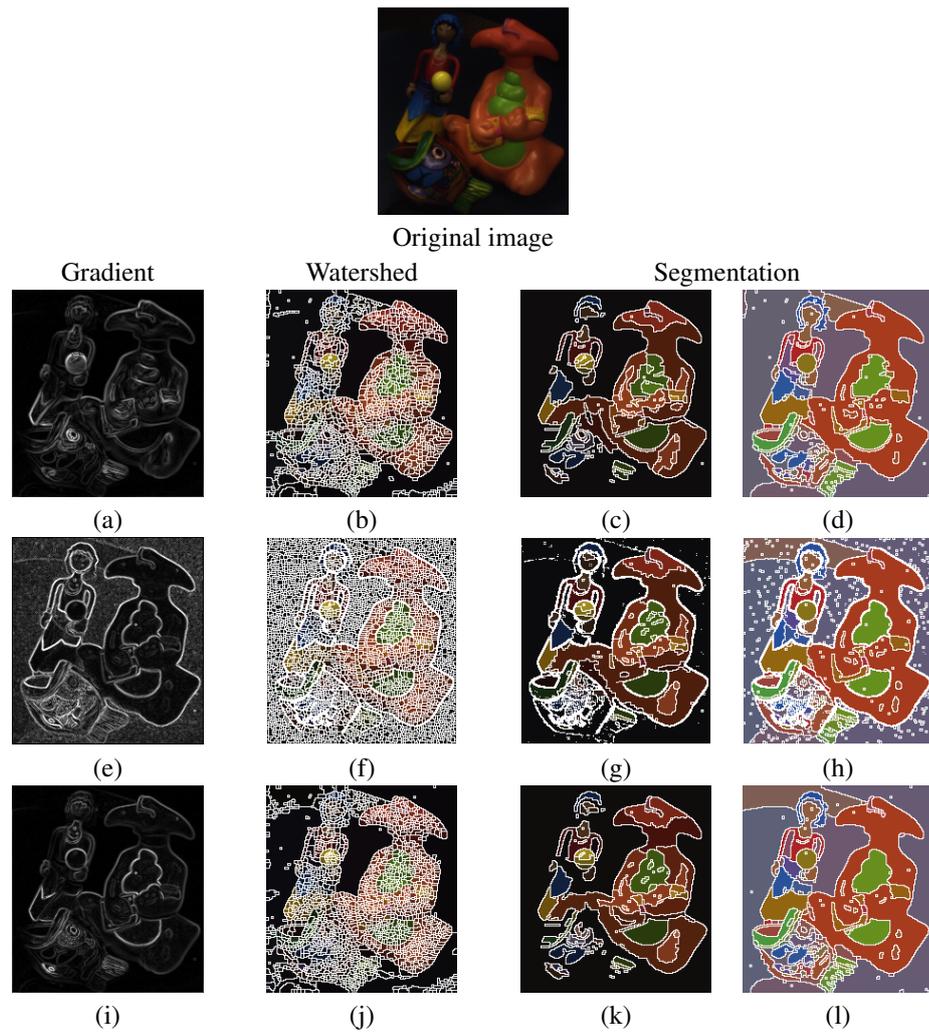
(i)   (j)   (k)   (l)

Figure 2: Image segmentation results with different parametrizations

It can be appreciated that the fuzzy gradient watershed removes most of the dark microregions originated by the chromatic gradient. There are, however, some regions with different colors in this rough dark region which are not fully identified by the intensity gradient watershed of Fig. 2 (b) and are better detected by the fuzzy gradient watershed in Fig. 2(j). The two image columns with the heading "segmentation" show the results of the region merging from the corresponding gradient watershed in the same row. The left column shows the results of using of the Euclidean distance on the RGB Cartesian coordinates. The right segmentation column show the results of the using the chromatic distance of equation (1). If we want to ascertain the effect of the color representation and the chromatic distance we must compare the rightmost columns in Fig. 2. We find that the general effect is that the chromatic distance on polar coordinates is better identifying the subtle color regions in the darkest areas of the image, it detects better the shape of the objects, has better color constancy properties, and it is much less sensitive to bright spots or shining areas. Comparing the gradient operators attending to the final segmentation we observe that the fuzzy gradient is better than the others in removing noise from the dark regions and maintain the object integrity. Overall the best result is obtained with our proposal as shown in Fig. 2(l), where we can easily identify the subtle regions in the upper dark area, the shadow of the lowermost object, and we can clearly identify object with the same color unaffected by shading and bright spots.

5   Conclusions

The paper introduces a fuzzy watershed and region merging segmentation based on the zenithal and azimuthal angles of the spherical representation of colors in the RGB space. These definitions allows the construction of a robust fuzzy chromatic gradient that we use to realize a robust chromatic watershed segmentation. This gradient operator has good color edge detection in lightened areas and does not suffer from the noise in the dark areas. The fuzzy watershed is complemented by a region merging based on the defined chromatic distance. We give a general schema of the algorithm performing both watershed and region merging. Out proposal can be stated by this algorithm fixing the color representation, gradient operator, and region merging distance. We compare our approach with other algorithms obtained with different setting of the general schema, obtaining the best qualitative segmentation.

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