COLOR SPACE SELECTION FOR UNSUPERVISED COLOR IMAGE SEGMENTATION BY HISTOGRAM MULTITHRESHOLDING

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ABSTRACT

In this paper, we propose a new color image segmentation algorithm by unsupervised classification of pixels. This procedure iteratively constructs the classes by histogram multithresholding. For this purpose, the procedure selects different color spaces in which the modes of the 1D-histograms are as well as possible separated, so that each mode corresponds effectively to a region in the image.

1. INTRODUCTION

One of the most important problems in color image analysis is that of segmentation. In this paper, we consider color uniformity for partitioning an image into disjoint regions. The color image segmentation techniques described in the literature can be categorized into two main classes, depending on the distribution of the pixel colors is analyzed either in the image plane or in a color space [1].

The methods which analyze the distribution of the pixel colors in a color space consider that each pixel in the color image is represented by a color point in a color space. The most widely used is the (R,G,B) color space, where a color point is characterized by the color component levels of the corresponding pixel, namely the red (R), the green (G) and the blue (B). Other color spaces can be used and the performance of an image segmentation procedure is known to depend on the choice of the color space [2]. Many authors have tried to determine the color spaces which are the most appropriate for their specific color image segmentation problems [1]. Unfortunately, there does not exist a color space which provides satisfying results for the segmentation of all kinds of images. Vandenbroucke proposes a color image segmentation approach by pixel classification in an hybrid color space which is adapted to the analyzed image [2]. This space, determined by means of a supervised learning scheme, is constituted of several color components which can belong to any of different classical color spaces.

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It is generally assumed that homogeneous regions in the image plane give rise to clusters of color points in the color space, each cluster defining a class of pixels which share similar color properties. The classes can be constructed by means of a cluster analysis procedure which requires the desired number of classes, by the analysis of the color 3D-histogram which requires a large amount of memory [3], or by the analysis of the 1D-histograms of the three color components [4]. When the classes are constructed, the pixels are assigned to one of them by means of a decision rule and are mapped back to the original image plane to produce the segmentation. It is important to underline that a class can represent one or several disjoint regions with the same colors because the spatial arrangement of the pixels is not taken into account.

The analysis of the 1D-histograms of the three color components assumes that the color component levels of the pixels which belong to the regions give rise to modes in each of the three 1D-histograms. The detection of these modes consists in determining the thresholds which delimit them. As a 1D-histogram is the result of the projection of the color 3D-histogram on one single color component, a mode may represent several regions with different colors. The ideal case would be to detect the modes which correspond to regions with the same colors.

As the classes constructed by a classification procedure depend on the used color space, it would be interesting to select the color space which is the most relevant for detecting the modes which correspond to regions. For this purpose, we assume that the higher the number of detected modes by the analysis of the 1D-histogram, the higher the discriminating power of the color component is, the more probably the modes correspond to regions with the same colors. So, among several color spaces, the proposed procedure selects the most relevant, which is the one for which the 1D-histograms contain the highest numbers of detected modes.

In this paper, we propose an original color image seg-

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mentation procedure based on an iterative analysis of the 1D-histograms of the color components. At each iteration step, this procedure constructs one class of pixels. For this purpose, the procedure looks for the most relevant color space among several classical ones. It detects the modes of each of the 1D-histograms of the three color components constituting this most relevant color space. These modes are analyzed to construct one class. The pixels assigned to this class are not taken into account for constructing the classes at the next steps. The iterative procedure stops when there remain only a few pixels which are not assigned to any constructed classes.

The main originality of the proposed unsupervised procedure is the selection of the most relevant color space for constructing each class of pixels at each iteration step.

The second section presents the classical color spaces which are used by the proposed method. The third section describes the proposed color image segmentation algorithm. The fourth section shows the segmentation results obtained by this algorithm.

2. COLOR SPACES

In order to classify color spaces into a few categories with respect to their definitions and their properties, Vandenbroucke proposes to group the classical color spaces into four main families [2]:

- The ***primary spaces***, which are based on the thrichromatic theory, assuming that is possible to match any color by mixing appropriate amounts of the three primary colors. The primary spaces used by the proposed method are (R,G,B), (r,g,b), (X,Y,Z) and (x,y,z).

- The ***luminance-chrominance spaces*** where one component represents the luminance and the two others the chrominance. The luminance-chrominance spaces used by the proposed method are (Y,I,Q), (Y,U,V), (wb,rg,by), (Y,C_1,C_2), (L^*,a^*,b^*) and (L^*,u^*,v^*).

- The ***perceptual spaces*** which try to quantify the subjective human color perception by means of the intensity, the hue and the saturation. The perceptual spaces are not used by the proposed method because of the instability and non-removable singularities of the hue component.

- The ***statistical independent component spaces*** resulting from different statistical methods which provide as less correlated components as possible. The statistical independent component space used by the proposed method is (I_1,I_2,I_3) [5].

When the conditions of the image acquisition are not controlled, the chosen transformations from the (R,G,B) color space to the device-dependent color spaces use default parameters.

3. SEGMENTATION

Each step of our iterative method is shown by figure 1 and is detailed in the next sub-sections.

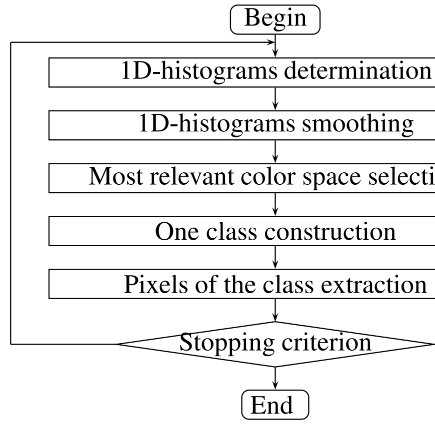


Fig. 1. Color image segmentation flowchart.

3.1. 1D-histograms determination

At each iteration step, the color vectors of the pixels submitted to the analysis are represented into the N_S color spaces ($N_S = 11$) presented in the second section. In the i^{th} color space, we determine each of the three 1D-histograms $h^{i,j}(x)$ of each color component numbered j, $j = 1,2,3$, where x is the color component level.

3.2. 1D-histograms smoothing

It is difficult to detect their modes when the 1D-histograms are corrupted by noise. Hence, we propose to smooth them by means of an adaptive filtering. A smoothed histogram $h^{i,j}_{\sigma}(x)$ is computed by the convolution between the 1D-histogram $h^{i,j}(x)$ and a Gaussian kernel $g_{\sigma}(x)$ where σ is the standard deviation. The effect of the smoothing depends on the value of the standard deviation σ used to define the Gaussian kernel. For each 1D-histogram, σ is adjusted by means of the procedure proposed by Lin [6], so that the smoothed 1D-histogram reveals its modes.

3.3. Most relevant color space selection

3.3.1. Modes detection

The thresholds which delimit the modes of each smoothed histogram $h^{i,j}_{\sigma}(x)$ are determined by the analysis of the zerocrossings of its first derivative function. The number of these so-detected modes is denoted $N_P^{i,j}$.

Three attributes characterize the k^{th} ($k = 1, \dots, N_P^{i,j}$) mode of the 1D-histogram $h_\sigma^{i,j}(x)$:

- the left and right thresholds $T_{left}^{i,j,k}$ and $T_{right}^{i,j,k}$,
- the amplitude $A^{i,j,k} = \max_{l=T_{left}^{i,j,k}}^{l \le T_{right}^{i,j,k}} h_\sigma^{i,j}(l)$.

For each 1D-histogram $h_\sigma^{i,j}(x)$, we denote $K(i,j)$ the rank number of its mode with the highest amplitude.

Furthermore, each 1D-histogram $h_\sigma^{i,j}(x)$ is characterized by the smallest distance $D_P^{i,j}$ between two neighboring modes.

3.3.2. *Within-space most representative 1D-histogram*

Among the three smoothed 1D-histograms of each color space, we determine the *within-space most representative 1D-histogram*. For this purpose, we assume that the higher the number of detected modes in the smoothed 1D-histogram, the more probably a mode corresponds to regions with the same colors in the image. So, the within-space most representative 1D-histogram of the i^{th} color space is the 1D-histogram with the highest number $N_P^{i,j}$ of detected modes.

If several 1D-histograms of the i^{th} color space contain the same highest number $N_P^{i,j}$ of modes, then the within-space most representative 1D-histogram is the 1D-histogram in which the modes are the best separated, i.e. for which $D_P^{i,j}$ is the largest.

We denote $J(i)$ the rank number of the color component which corresponds to the within-space most representative 1D-histogram of the i^{th} color space.

3.3.3. *Color space selection*

In order to select the most relevant color space for the construction of one pixel class, the within-space most representative 1D-histograms of all the color spaces are compared. The most relevant color space is selected so that its within-space most representative 1D-histogram contains the highest number $N_P^{i,J(i)}$ of detected modes.

If several within-space most representative 1D-histograms contain the same highest number of modes, then the most relevant color space is the color space in which the modes of the within-space most representative 1D-histogram are the best separated, i.e. for which $D_P^{i,J(i)}$ is the largest.

We denote I the rank number of the color space which is selected as the most relevant one.

3.4. One class construction

One class of pixels is constructed by analyzing the most relevant color space number I which is determined at each iteration step of the algorithm. This class of pixels is defined by a parallelipedic box in the most relevant color space. This box is delimited by two thresholds defined along each color component of the most relevant color space.

Along the color component number $J(I)$ which corresponds to the within-space most representative 1D-histogram, the two thresholds are those which delimit the mode with the highest amplitude, i.e. $T_{left}^{I,J(I),K(I,J(I))}$ and $T_{right}^{I,J(I),K(I,J(I))}$.

The thresholds selected along the two other color components are chosen among the thresholds $T_{left}^{I,j,k}$ and $T_{right}^{I,j,k}$, $j \neq J(I)$, determined in the mode detection stage. The selected thresholds delimit the box in which fall into the color vectors of pixels with the highest population. The pixels whose color vectors fall into this box constitute the class of pixels constructed at the iteration step.

3.5. Pixels of the class extraction

The pixels which are assigned to the so-constructed class, are extracted from the color image so that they are not taken into account at the next iteration steps of the procedure. The pixels which are assigned to this class and which are connected in the image, constitute one of the reconstructed regions in the segmented image. We assume that each constructed class corresponds to regions with the same colors.

3.6. Stopping criterion

The iterative procedure stops when a percentage p of pixels of the image have not been assigned to any of the previously constructed classes. The parameter p, adjusted by the analyst, allows to tune the desired coarseness of the segmentation.

When the iterative procedure stops, the pixels which have not been assigned to any class, could be assigned to one of the constructed classes by means of a specific decision rule.

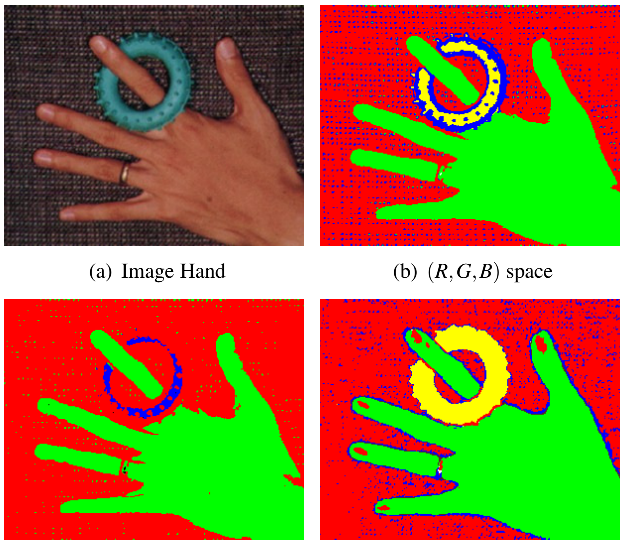
4. RESULTS

In order to show the effectiveness of the proposed method, we compare the segmentation results of the image of figure 2(a). The effectiveness of the selection of the most relevant color space at each iteration step is assessed by analyzing different sets of color spaces. The parameter p is set to 1% for all the segmented images.

The segmented image of figure 2(b) is obtained by the proposed method which only considers the (R,G,B) color space, i.e. the most relevant color space determined at each iteration step is the (R,G,B) color space.

The principle of our approach is similar to the segmentation method proposed by Tominaga, except the modes detection and the selection of the used color space [7]. Tominaga proposes to apply the PCA transform on the image at each iteration step and to analyze the 1D-histogram of the most discriminating component. The segmented image of figure 2(c) is obtained by the proposed method which applies at each iteration step the PCA transform on the image.

The segmented image of figure 2(d) is obtained by our segmentation method which analyzes all the color spaces described in the second section for determining the most relevant color space at each iteration step. During the construction of the classes of pixels of the image of figure 2(a), the most relevant color spaces determined at the iteration steps are (r, g, b), (wb, rg, by) (three times) and (R, G, B).



(a) Image Hand

(b) (R, G, B) space

(c) PCA transform

(d) Proposed method

Fig. 2. Segmentation results

We see two main differences in these segmented images. The pixels which represent the blue ring is divided into two different classes by the method which only analyzes the (R, G, B) space. These pixels are partially merged with the class which represents the background by the method analyzing the PCA transform. All the pixels which represent the blue ring are assigned to one single class by our method. Furthermore, the pixels which represent the finger-nails are not discriminated by the analysis of (R, G, B) space and by the analysis of the PCA transform, whereas our method assigns these pixels to one single class.

These results demonstrate that the selection of the most relevant color space at each iteration step allows to provide relevant segmentation results.

5. CONCLUSION

In this paper, we have proposed a color image segmentation algorithm by unsupervised pixel classification. This iterative method determines at each iteration step one class of pixels. For this purpose, it selects the most relevant color space which discriminates as well as possible the modes of the 1D-histograms.

The criterion used for selecting the most relevant color space is based on the analysis of 1D-histograms. It would be interesting to apply sophisticated criteria which measure the dispersion and compactness of the clusters in the 3D color space.

The histograms neglects the spatial interaction between the pixels. The selection of the most relevant color space is only based on the analysis of color properties of the pixels. We are presently working on the color space selection by means of the analysis of the connectedness properties of the pixels. This procedure simultaneously analyses the color and connectedness properties of the pixels for iteratively constructing the classes of pixels.

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