SEGMENTATION IN COLOR IMAGE ON THE BASIS OF MORPHOLOGICAL CLUSTERING

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Abstract: By using classification in 3-D color space, we represent a method to segment color images. In the ordinary 3-D images, the cluster appears in its histograms do not fit in well-known statistical model. For this reason, we have a classifier that depends on mathematical Morphology, and mostly we use watershed algorithm. By this method we can show the expected color clusters accurately on various images. Lastly, to segment color images into logical regions, we accomplish a Markovian labeling that have the advantages of morphological classification results.

INTRODUCTION: In this review paper, we focus on segment of colour images by using different clustering methods in RGB spatial frequency components. We have several methods that are used parametric classifiers in these components and we assume that the individual cluster follow multivariate normal distributions [1]. Since this supposition can be evaluated in case of natural images, one can introduce non-parametric classifiers to analyze clusters [2]. The morphological classifiers are made up by a family of non-parametric classifiers. This type of classifiers states that by the analyses of histogram morphology, we can identify the clusters. For this purpose, RGB histograms are considered as 3-D images and the processing can be completed by mathematical morphology techniques[3]. In this paper, the watershed algorithm is connected with the original morphological classifier.This paper is organize as: In sect ion 2, 'the states of the art of morphological classifiers'. In section 3,'classifications of watershed algorithm for colour images and their properties'. In section 4, we show the segmentation results and we discuss some results in section 5. Lastly in section 6 we have the conclusion.

STATE OF THE ART OF MORPHOLOGICAL CLASSIFIERS

Every morphological classifier assumed as 3-D digital images with common image operators in order to process them.In[8],Postaire et al. propose a very simple morphological classifier based on binary mathematical morphology. In this the 3-D images firstly changes in binary images in which only cluster cores appear. A morphological classifier is then applied for purpose of regularisation and the clusters are identified by a connected component labelling. Regrettably, the "level-shape" of histogram is the disadvantage of this method. In[9],Zhang and Postaire propose an evolution of the former method. In this method, the 3-D histogram is pre-processed by a morphological filter to increase the separability of clusters, before thresholding. The main problem with this method is that starting compensation between the separations of two clusters may create much contrast.In[10],Park et al. propose to calculate the difference between Gaussians and Histogram and then calculate its threshold . This results a binary images and this binary image of cluster cores is proposed by morphological closing and the

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labelling process is performed. Each cluster is then dilated in the feature space to enlarge its volume. In this method, as well as difference of Gaussians from the histogram and to threshold it. The resulting binary image of cluster cores is processed by a morphological closing and a connected component labelling is performed. Each component, i.e. each cluster, is then dilated to enlarge its volume in the feature space. At this stage of the method, as well as the two methods described above, one cannot give the level to every colour component, some colours of the original image in the colour space do not match to any cluster. Park et al. propose to assign each respective cluster a colour.The watershed algorithm is a morphological algorithm that gives a segmentation of images into basins where one basin is belongs to a local minima of an image and the crest values are the basin boundaries (so-called watersheds). Using this algorithm as a classifier was first suggested by Soille. The watershed algorithm leads due to the presence of local minima in the segmentation of colour space.

CLASSIFICATION WITH THE CONNECTED WATERSHED ALGORITHM

3.1. Method Description

This classification has four steps:Step 1.

The histogram H of the color image is calculated:to magnify the smallest clusters, a log function is applied,and then the reverse process is performed. This results the 3-D image H. Then for any color ‘c’ we have,

$$H^{(1)}(c)=M-\log(1+H(c)),\text{where } M=\max \log(1+H(c)).$$

The projection $H_{RG}^{(1)}$ of $H^{(1)}$ on the red-green plane is shown for three initial color images (HOUSE, LENA, and PEPPERS) in the left column of figure 1. High values in $^{(1)}$ are de-picted by darker pixels. H_{RG}

Step 2. A 3-D Gaussian filter is applied to $H^{(1)}$ in order to smooth the color space data —we have empirically set to 9 the variance which gives us satisfactory results. The resulting 3-D image (of the color space) is $H^{(2)}$.

Step 3. Two operators remove the remaining local minima: first, a morphological closing with the 18-connectivity of structuring elements, then a cutting of very low values. The threshold of the letter operator is set to the median of non-zero values of $H^{(2)}$ and, since a log function has been applied during step 1, one is guaranteed not to suppress a significant cluster.

Step 4. Finally, we apply a connected version of the watershed algorithm [4]; “connected” means that there is no boundary between the basins. The result is a partition of the RGB image: every color c has a label. Let us denote by W the resulting labeling.

The right column of figure 1 depicts for several initial color images the projections of the resulting W on the red-green plane, W_{RG}. Let, l being a label,

$$H(r,g)(l) = \sum_{b,W(r,g,b)=l} H(r,g,b)$$

$$l_m(r,g) = \arg\max h(r,g)(l)$$

$$l'_m(r,g) = \arg \max_{l,\, l\neq lm(r,g)} h(r,g)(l).$$

The projections W_{RG} aim at showing the most represented label for the colors (r, g, ∗) in W according to the original color image contents. This label, $l_m(r, g)$, is depicted by a grey pixel in W_{RG} (or by a color pixel if you have a color version of this paper). Last, a white pixel means that $h(r, g)(l_m(r, g)) < 5$, i.e., that there is about no pixel of the initial image with components (r, g, ∗); and a black pixel means that $l_m(r, g) - l_m^0(r, g) < 5$, i.e., that there is not really a major label.

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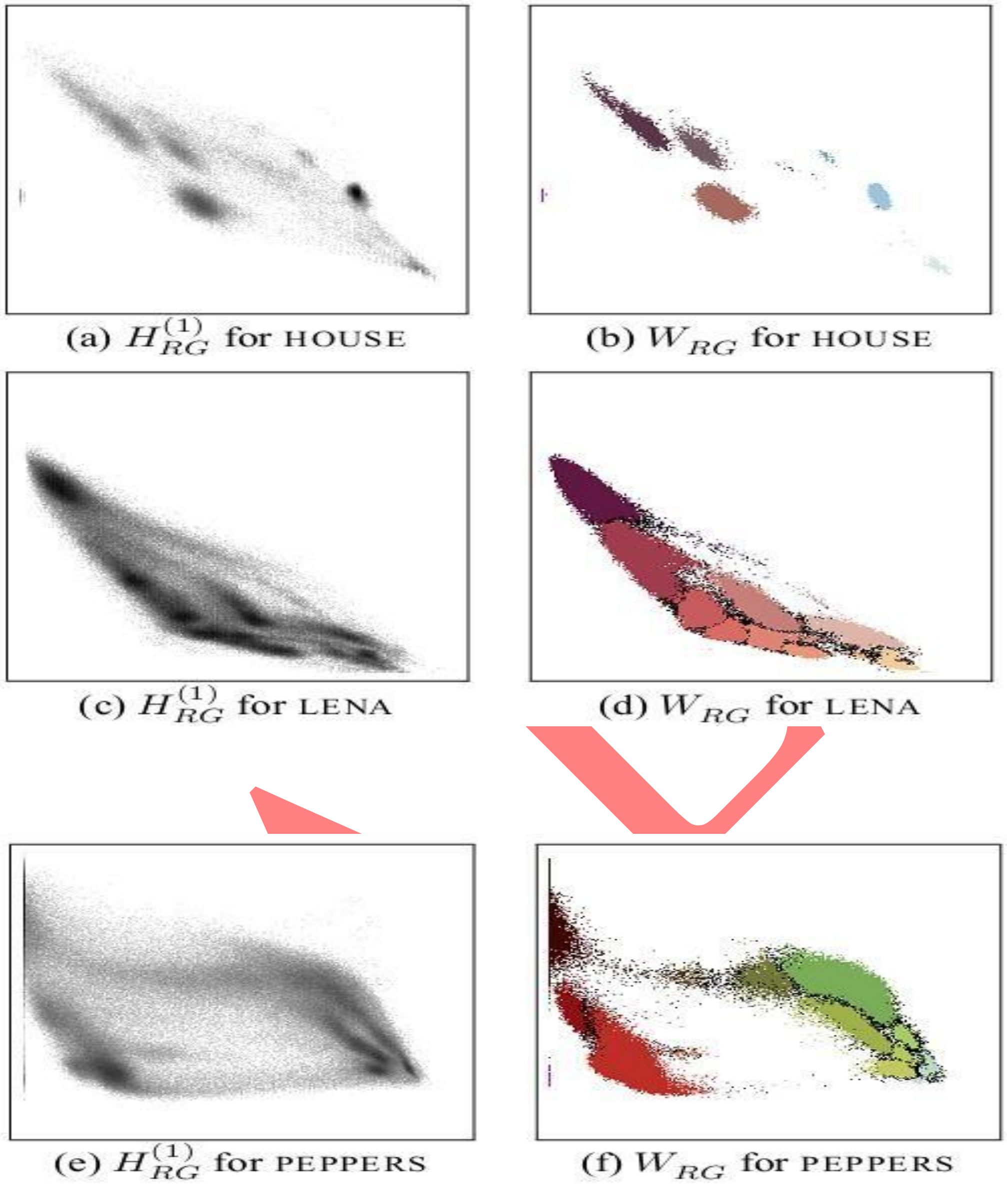

Fig. 1. Projections on the red-green plane of step 1 result (left) and of step 4 results (right).

3.2. Properties

The morphological classification has several strong theoretical properties: its final result is invariant with respect to the following transforms when applied onto H (if we neglect rounding errors).

• Applying an increasing function f:

$H^0(c) = f(H(c)) \Rightarrow W^0(c) = W(c)$.

• Applying a linear transform L to colors:

$H^0(c^0) = H(L c) \Rightarrow W^0(c^0) = W (L c)$.

• Applying a translation T to colors:

$H^0(c^0) = H(T (c)) \Rightarrow W^0(c^0) = W (T (c))$.

• Applying a rotation R to colors:

$H^0(c^0) = H(\,R(c)\,) \Rightarrow W^{\,0}(c^0) = W\,(\,R(c)\,).$

FINAL SEGMENTATION

4.1 Non-contextual labelling

Let W_i , the i[th] basin of W denoted by $\bar{c}_i$, centre of color space in original image

$$\bar{C}_i = \frac{1}{Card_i} \sum_{c \epsilon W_i} H(c)c$$

Where $card_i = \sum_{c \epsilon W_i} H(c)$.

The segmentation S of the color image I for any image pixel(∞) is given as :

$$S(x) = \overline{c_{i(x)}}$$

Where i(x) such that $I(x) \epsilon W_{i(x)}$

(a)Original image (b)Non-Contextual Labelling

4.2. Markovian labeling

To obtain a contextual segmentation, we assume that each basin W_i describes a class ω_i in the RGB space. The *a priori* probability of the class ω_i is estimated by:

$$P(\omega_i) = card_i / \sum_j card_j.$$

The probability $p(x|\omega_i)$ is modeled by a multivariate normal distribution whose parameters are set by analyzing the restriction of the 3-D histogram H to the basin W_i:

$$P(x/w_i) = \exp\left(- \frac{{}^t(I(x)-c_i) \sum_i^{-1+} (I(x)-c_i)}{2\sqrt{\det \sum_i}} \right)$$

Where $\sum_i = 1/card_i - 1 \sum_{c \epsilon W_i} H(c)\ {}^t(c-c_i)(c-c_i)$.

We then perform the Iterated Condition Mode (ICM) al-gorithm [12] with the non-contextual labeling S as initial-ization. We use a simple Potts model to ensure getting regularized regions; with S^M being the labeling of I, N_8 be-ing the neighborhood corresponding to 8-connectivity, and δ being the Kronecker's symbol, we set:

$$U^{potts}(x) = \alpha^X \sum \delta^{SM\ (x0\ )}.$$

$S^M(x)$.

(b)Markovian Segmentation S^M

RESULTS

Figure 2 depicts the results of the non-contextual labelling (sub-figure (b)) and of the Markovian labelling (sub-figure (c)) on the PEPPERS colour image. As one can see, the objects are correctly segmented.We have obtained remarkable results with our method on many images. With the classical HOUSE image, an easy image for the classification in the colour space, the detection of cluster is performed as expected.

CONCLUSION

In this review paper, we have presented an automatic classification method which is based on mathematical morphology with the colour images. In this the watershed algorithm is worked as classifier. This method gives us very good results even in case of coloured images which are difficult to segment. But there is a disadvantage with this method, it is a time consuming and memory consuming.

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