Color Based Image Segmentation

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Abstract

This article addresses color image segmentation in hue-saturation space. A model for circular data is provided by the vM-Gauss distribution, which is a joint distribution of von-Mises and Gaussian distribution. The mixture of vM-Gauss distribution is used to model hue-saturation data. A cluster merging process is applied to separate such identifiable objects in the image. The results are shown on Berkeley segmentation dataset. A cluster association methodology is developed for comparison.

1. Introduction

In this paper, we study the problem of clustering based color image segmentation. The idea behind this approach is to directly cluster the pixels in a certain color space. In this framework, a mixture model based approach is suitable for segmentation. The von-Mises (vM) [1] distribution is defined on an unit circle and analogous to univariate Gaussian distribution in $\Re^2$. Applications of vM and vM-Gauss mixture model can be found in Roy. et al. [3] and the references therein. We consider the hue and saturation components of an HSV image independently. The joint distribution (vM-Gauss) is formulated with a vM and a Gaussian distribution. The parameters of the mixture of vM-Gauss distributions are estimated using expectation maximization (EM) algorithm. A similarity based post processing method is used to merge the clusters in order to retrieve the meaningful objects present in a scene. The Berkeley segmentation dataset [2] is used to observe the performance of the method. A cluster association methodology is used to associate the clusters given by vM-Gauss method to those obtained from the human segmentation results of Berkeley dataset.

2. Mixture of vM-Gauss Distributions

A pair of independent random variables $(\Theta, X), \theta \in [0, 2\pi), x \in (-\infty, \infty)$ is said to follow vM-Gauss distribution if its probability density function is given by

$$f(\Theta, X|\mu, \kappa, \nu, \sigma) = f_1(\Theta|\mu, \kappa).f_2(X|\nu, \sigma), \quad (1)$$

where, f_1 is the von-Mises distribution with mean μ and concentration parameter κ. f_2 is the Gaussian distribution with parameters ν and σ. A mixture of K vM-Gauss distributions is given by:

$$f(\Theta, X|\Xi) = \sum_{h=1}^{K} P(h) f(\Theta, X|h, \Xi_h). \quad (2)$$

where $P(h)$ are the mixing proportions, $f(\Theta, X|h, \Xi_h)$ is a vM-Gauss distribution representing the h^{th} component of the mixture with $\Xi_h = (\mu_h, \kappa_h, \nu_h, \sigma_h)$. $\Xi = (\Xi_1, \ldots, \Xi_K, P(1), \ldots, P(K))$ refers to the entire set of parameters.

3. Color Image Segmentation

We consider the HSV system as a color model. We assume the hue and saturation values of pixels in a color image arise from a finite mixture of vM-Gauss distributions. We apply K-means algorithm to obtain an initial clustering and further apply EM. In order to detect the number of clusters automatically we use *Minimum Mutual Description Length (MMDL)* criteria.

4. Object Detection by Similarity Measures

The Berkeley dataset images contains at least one object that can be identified separately from the background. After clustering, the object may be divided into several clusters. We need to merge individual clusters to

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achieve proper segmentation. For this, we consider both spectral similarity and spatial closeness between clusters as suggested by Roy. et al. [3]. In each iteration we identify the pair of clusters i and j with minimum spectral distance d_{ij} and merge them if $max(s_{ij}, s_{ji}) > T_1$ and $d_{ij} < T_2$ where T_1 and T_2 are threshold values, s_{ij} is the spatial closeness of i and j.

5. Association of clusters

For comparison often we need to associate two sets of k clusters from two different algorithms. We need to determine for each cluster of the first algorithm, the corresponding cluster of the second algorithm, based on some criteria. Let us define a matrix M of dimension $k \times k$ with $m_{ij} = p$, where p pixels belong to cluster i by the first method and to cluster j by the second method. Cluster association is done in such a way that sum of all chosen m_{ij} is maximum. Considering all the local maxima does not guarantee the sum is maximized. We define a reward function $R(i,j)$ as follows.

$$R(i,j) = m_{ij} - \sum_{h=1, h \neq i}^{k} m_{ih} - \sum_{h=1, h \neq j}^{k} m_{hj}. \quad (3)$$

$R(i,j)$ gives a quantity that denotes the gain in total cost if one associates cluster i with cluster j. Each time we find the current maximum m_{ij} of M and compute $R(i,j)$ values for i^{th} row and j^{th} column. After we associate two clusters i and j by taking the maximum reward, we eliminate i^{th} row and j^{th} column from M and repeat the process until we associate all the clusters.

6. Results and Discussions

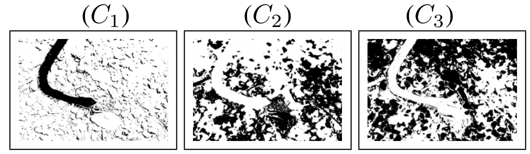
"Snake"

"Pyramid"

Figure 1. Sample images from Berkeley dataset: The original the segmented images are shown side by side.

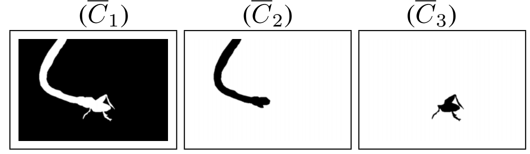
The *Berkeley segmentation dataset* contains several color images along with human segmentation results. From several human segmentations we choose the particular segmentation that preserves the object as a whole and with less number of clusters. We associate the clusters obtained from vM-Gauss method with human segmentation. The cluster merging is performed until we get the same number of clusters as in human segmentation. In Fig. 1 we present results on two sample images taken from the Berkeley dataset. Consider the "Snake" image of Fig. 1. The human segmentation and the merging results are shown in Fig. 2. After associ-

(C_1) (C_2) (C_3)



(a)

$(\overline{C}_1)$ $(\overline{C}_2)$ $(\overline{C}_3)$



(b)

Figure 2. (a) The merging result and (b) the human segmentation results corresponding to the "Snake" image.

ation process the cluster pairs are $(C_3, \overline{C}_1)$, $(C_1, \overline{C}_2)$, $(C_2, \overline{C}_3)$ (see Fig. 2). The sum of chosen m_{ij} is 85840 which is 55.60% of the total data.

7. Conclusions and Future Scope

We study color image segmentation in HS space. The hue values are assumed to follow the vM distribution whereas the saturation values follow the Gaussian distribution independently. Further works should address possible dependency between hue and saturation.

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