Bayesian Framework for image segmentation based on Nonparametric Clustering with Spatial Neighborhood Information

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ABSTRACT
In this paper, we present a Bayesian framework for image segmentation based upon spatial nonparametric clustering. To estimate the density function on a nonparametric form, the proposed model exploits local Gaussian kernels. In addition, we have incorporated the spatial information to the clustering process by adding a spatial function for weighting the posterior probabilities.The main advantages of this model are two. First due to the non parametric structure, it does not require the image regions to have a particular type of density distribution. Second, adding spatial information yields more homogenous and smoothed regions.The experimental results based on real images demonstrate the efficiency of the proposed method and indicate clearly its robustness to noise.

General Terms
Image segmentation, image processing,pattern Recognitioncomputer vision.

Keywords
Image segmentation, nonparametric clustering, spatial Information.

1. INTRODUCTION
Segmentation is a very fundamental problem in image processing which is widely used in a variety of applications on computer vision. It is typically defined as the process of partitioning an image into non-overlapped regions which are homogeneous with respect to some characteristics such as intensity, color, or texture. Many approaches have been proposed to achieve this task [1], [2] among them those based on clustering.In fact image segmentation can be treated as a clustering problem where the features describing each pixel correspond to a pattern, and each image region (i.e. a segment) corresponds to a cluster [3]. Therefore many clustering algorithms have widely been used to solve the segmentation problem. This algorithms can be classified into two categories [4]: *hierarchical clustering* which proceeds successively by either merging smaller clusters into larger ones (agglomerative methods), or by splitting larger clusters (divisive methods), and *partitional clustering* which attempts to directly decompose the data set into a set of disjoint clusters by using a deterministic or a probabilistic measure of similarity.

In deterministic partitional clustering, the measure similarity communally used is the distance and one of the best known deterministic partitional clustering algorithm is K-means [5],[6], where the Euclidian or Mahalanobis distance are often used, this algorithm leads to a “hard” partition of the image; which is a real drawback, especially in case of overlapping between segments. To overcome this shortcoming, many fuzzy extensions of K-means have been proposed for image segmentation such as:the fuzzy c-means algorithm (FCM) [7].

In probabilistic partitional clustering, the clusters are explicitly modeled as distributions where their parameters have to be estimated e.g. Mean and covariance in the Gaussian distribution. In other words the image is considered as a set of regions (segments) where each region is represented by a distribution. Several probabilistic models like Gaussian Mixture Model (GMM) [8] and Latent Dirichlet Allocation [9] have been used in image segmentation; these algorithms have a common point: the parametric modeling of their distribution. The parametric models are effective only when the underlying distribution of the data is either known, or can be closely approximated by the distribution assumed by the model. This is a major disadvantage since it is well known that clusters in real data are not always of the same shape,especially in image segmentation. In this case, the parametric modeling of the probability density function can be difficult due to the complexity of the data (several variables per pixel).This limitation has been overcome by the use of algorithms that exploit nonparametric density estimation methods. These methods do not require any estimation of parameters which is a very advantageous. Several nonparametric clustering algorithms, for instance, Jarvis-Patrick [10], DBSCAN [11] and Mean-shift [12], have been proposed for nonparametric clustering.

Moreover, image segmentation can be viewed as a special type of clustering where the data (the image pixels) have spatial locations associated with them. Thus, except the attributes such as intensity, color or texture, commonly used, the location is an important characteristicin grouping where the prior knowledge that adjacent pixel most likely belong to the same clusters must be considered in image segmentation. To overcome this shortcoming; several approaches address this problem by imposing some form of spatial constraints in the segmentation process, for example Blobworld [13] add the spatial location of each pixel as a characteristic in its feature vector. The DCM-SVFMM [14] algorithm uses the Gauss-Markov random field on its model's parameters to impose spatial constraints. The model discussed in [15], a spatial probability of theneighboring pixels is incorporated in the objective function of FCM.

In this paper, we present a Bayesian framework for image segmentation which combines the spatial information with a nonparametric probabilistic clustering.

To address both clustering and spatial constraints, we use local Gaussian kernels to estimate the nonparametric density function and we incorporate the spatial neighborhood information by weighting the posterior probabilities.

The remainder of this paper is organized as follows: in section 2, the nonparametric approach for estimating the density function is presented. Section 3 is reserved to introducing the spatial information. Experimental results are presented in section 4, and finally, in section 5, we provide conclusions and directions for future research.

2. Nonparametric density estimation

In this section, we describe the Bayesian framework that model the density function in nonparametric form by using Gaussian kernels. The algorithm aims to provide for each pixel the probability of membership to every defined class, and then it makes a decision for classification where each pixel is affected to the class of the highest probability.

Let *M* a mixture density with K distributions (clusters):

$$M(\mathrm{X}) = \sum_{\mathrm{k}=1}^{\mathrm{K}} \pi_{\mathrm{k}}\, M(\mathrm{X}|\theta_{\mathrm{k}}) \qquad (1)$$

where $\forall$ k, $\sum_k \pi_{\mathrm{k}} = 1$are the prior probabilities of each clusters; and $\theta_{\mathrm{k}}$is the set of parameters of the k^{th} conditional distribution $\mathrm{M}(\mathrm{X}|\theta_{\mathrm{k}})$.

In the nonparametric modeling, all distributions are assumed to have the same form. For example in the Gaussian distribution, the set of parameters θ_{k} are the mean and the covariance that we compute from the set of the data (pixels). As we said before, the complex shape ofclusters (regions) in the image makes the choice of an adequate form of distribution difficult. That is why we opt for a nonparametric modeling which is more flexible where it infers the density function from the data itself.

To compute the membership posterior probabilities of each pixel x_n, to each distribution (clusters) we use:

$$\mathrm{P}(\mathrm{k}|\mathrm{x}_{\mathrm{n}}) = \frac{[\pi_{\mathrm{k}} M(\mathrm{x}_{\mathrm{n}}|\mathrm{k})]}{\sum_{\mathrm{i}=1}^{\mathrm{K}}[\pi_{\mathrm{i}} M(\mathrm{x}_{\mathrm{n}}|\mathrm{k})]} \qquad (2)$$

Where *k* is the cluster label of the pixel x_n, n = 1…N, and N is the total number of pixels in the image.

Therefore, to avoid any parametric modeling of the distribution we use local Gaussian kernel $\mathrm{g}_\gamma(\mathrm{x})$with aperture γ for each pixel to compute the density distribution:

$$\mathrm{g}_\gamma(\mathrm{x}_{\mathrm{i}}, \mathrm{x}_{\mathrm{j}}) = \frac{1}{2\pi\gamma^2} e^{-\frac{2\|x_i - x_j\|^2}{\gamma^2}} \qquad (3)$$

To obtain the conditional distribution $M(\mathrm{x}_{\mathrm{n}}|\mathrm{k})$we have to computebefore the joint distribution $M(\mathrm{x}_{\mathrm{n}}, \mathrm{k})$as follows:

$$M(\mathrm{x}_{\mathrm{n}}, \mathrm{k}) = \frac{\sum_{\mathrm{i}=1}^{\mathrm{N}} \mathrm{g}_\gamma(\mathrm{x}_{\mathrm{i}} - \mathrm{x}_{\mathrm{n}})\, \mathrm{c}(\mathrm{i})}{\sum_{\mathrm{i}}^{\mathrm{n}} \sum_{\mathrm{j}}^{\mathrm{n}} \mathrm{g}_\gamma(\mathrm{x}_{\mathrm{i}} - \mathrm{x}_{\mathrm{n}})} \qquad (4)$$

Where C(i) is an indicator function:

$$\mathrm{C}(\mathrm{i}) = \begin{cases} 1, & if\ C(\mathrm{i}) = \mathrm{k} \\ 0, & if\ C(\mathrm{i}) \neq \mathrm{k} \end{cases}$$

This means that C(i) represents cluster label affected to the pixel x_n. More precisely, the kernel will take into account only the pixels of the clusters k.

Since the data treated in our work are pixels, where each one is represented by a feature vector, we propose the use of the Euclidian distance to compute the difference between the x_i and x_n vectors of the i^{th} and n^{th} pixel respectively.

Now, using the Bayesian theorem,we obtainthe conditional distributions $M(\mathrm{x}_{\mathrm{n}}|\mathrm{k})$ and the prior probabilitiesπ_{k} are also computed by marginalization of the joint distribution $M(\mathrm{x}_{\mathrm{n}}, \mathrm{k})$.

Finally, the Maximum a Posteriori criterion (MAP) is adopted:

$$\mathrm{P}(\mathrm{k}|\mathrm{x}_{\mathrm{n}}) = \max_{\mathrm{k}}\{\mathrm{P}(\mathrm{k}|\mathrm{x}_{\mathrm{n}})\} \qquad (5)$$

k =1…K; i.e. each pixel x_n we choose the cluster k which maximizes (4).

3. The spatial information

The model presented above relies upon the assumption of independence of pixels and clusters label. This is inadequate for images where some form of spatial constraints should be introduced. The pixels in an image are highly correlated, i.e. the pixels in the immediate neighborhood possess nearly the same features. Therefore the neighboring pixels should be assigned to the same clusters.

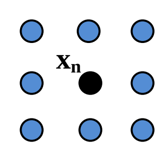


Fig 1:Neighboring pixels of x_n.

To achieve this goal, we introduce a spatial function for weighting the posterior probabilities:

$$S_{x_n k} = \sum_{i \in \delta x_n} \pi_k M(x_i|k) \qquad (6)$$

whereδx_n is square window centered on pixel x_n (Fig 1).

The spatial function is the summation of the posterior probabilities in the neighborhood of each pixel. We propose further modification and the equation (4) is replaced. The posterior probability of the current pixel is now defines as follows:

$$P(k|x_n) = \frac{S_{x_n k}}{\sum_{i=1}^{K} S_{x_n i}} \quad (7)$$

The spatial function of a pixel for a cluster is large if the majority of its neighborhood belongs to the same clusters.

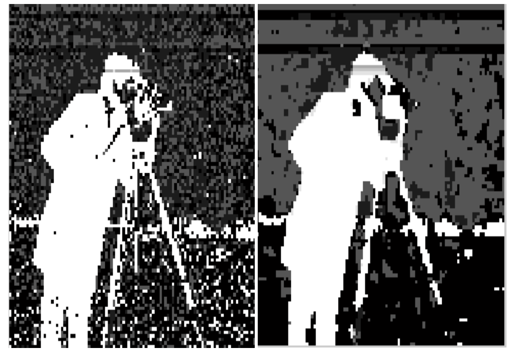
4. Experimental results

The results obtained from the experimentation of the proposed segmentation approach are presented in this section. To show the performance of our approach, we conducted experiments on several examples of image segmentation.

For all cases, pixels are represented by feature vector containing color in RGB space and the parameter γ in (3) was fixed to 0.2.A 3×3 window of image pixels is considered in this paper, thus the spatial influence of the centered pixel is over its 8 neighborhood pixels. All the algorithms presented here were performed using MATLAB 7.8 on a standard PC having a 2.53 GHz core I3 processor with 4 GB RAM.

Experiment 1 is to segment a cameraman image. The cameraman image corrupted by 1% Gaussian noise is shown in Fig 2(b).Fig 2(c) shows the results of the proposed approach without spatial constraint and Fig 2(d) illustrates the results with the spatial information.

(a) **(b)**



(c) **(d)**

Fig 2: Cameramen segmentation results (a) Original image (b) image degraded by Gaussian noise 1% (c) segmented image without spatial information(d)segmented image with spatial information.

The results show that the proposed approach is an effectivemethod. The spatial information makes the method more efficient even in the noise's cases. It greatly reduces the effect of noise and corrects the misclassified pixels.

Experiment 2 is to segment color images from the Berkeley image data base [16].

(a)

(b)

(c)

Fig 3 Segmentation results of color images (a) Original images (b) segmented images without spatial information(c) segmented images with spatial information.

The results of the proposed method without spatial information are shown in Fig3 (b); and those generated by the spatial nonparametric clustering are illustrated in Fig3(c). We can see that the algorithms generate a good segmentation results with meaningful regions; however we can judge that the spatial information incorporated to the clustering process yields better results.

In Fig3 (c), although some of the fine details are blurred (eg. Lips of the women) due to the use of spatial information, we notice that this constraint generates more homogenous regions with smoothed boundaries (eg. pullover's women on the first image, the cross on the top of the second image).

In the light of the above results, we can clearly perceive that spatial information is very important characteristic on the image segmentation process and provides improvement to our results

5. CONCLUSION

In this paper, we have presented a Bayesian framework for image segmentation based on nonparametric clustering. This algorithm is based on the use of local Gaussian kernels as density estimators. Furthermore, the model takes into account the spatial constraints by introducing a spatial function witch weight the posterior probabilities of each pixel to improve the clustering results.

Experimental results show that the spatial information gives good results and makes the segmentation process robust to noise. We judge that the proposed approach give us an interesting research tracks. Important open questions in our algorithm concern the estimation of the segments number, which is a well-known problem in image segmentation. The initialization of the clusters is also a shortcoming, where the result depends strongly on the initialization. These issues constitute the subject of an ongoing research.

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