Image Segmentation by Nonparametric Color Clustering

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Abstract. We present a color image segmentation scheme based on pixel color clustering. The proposed segmentation is based on mean shift clustering method, which is a powerful tool for the analysis of feature space. However, earlier clustering techniques based on mean shift use single scale over the entire feature space and are not feasible to analyze complex multi-modal feature spaces. In this paper, we present an adaptive mean shift method, in which the local scale information is involved. Actual regions in an image can be obtained by segmentation using the proposed clustering technique.

Keywords: image segmentation, clustering, mean shift.

1 Introduction

Image segmentation is a major step in shape feature extraction. Segmentation using clustering involves the search for image points that are similar enough to be grouped together. In the analysis of an image, K-means, ISODATA, and Fuzzy C-means are conventional clustering techniques. Conventional clustering techniques are always based on partitioning of the feature space. A usually used assumption in these methods is that the individual clusters obey multivariate normal distributions, i.e., the feature space can be modeled as a mixture of Gaussians. However, the assumption is not correct in many real data. Nonparametric methods in feature space analysis avoid the use of the normality assumption. Arbitrarily structured feature spaces can be analyzed only by nonparametric methods since these methods do not impose any assumptions. Mean shift (MS) algorithm is a nonparametric technique for feature space analysis. The mean shift theory was proposed in 1975 by Fukunaga and Hostetler [1]. The mean shift method and its applications have been discussed by a series of researchers [2,3,4,5,6]. In the related works, however, the local bandwidth (or local scale) and structure information of neighborhood around individual sample are not considered adequately. In [7], the algorithms only take into account the difference of local bandwidth. The other algorithms do not involve the information of both local bandwidth and the anisotropy of sample's neighborhood in the feature

space. Therefore, these methods are not effective when the real data has complex distribution in the feature space.

This paper introduces a segmentation technique based on the mean shift clustering, a simple nonparametric procedure for estimating density gradients. The clustering technique is improved by considering local scale information to avoid the drawbacks of the abovementioned techniques.

2 The Segmentation Algorithm

The mean shift procedure is a nonparametric analysis technique of feature space. To avoid the drawback of clustering using single scale for the whole feature space, we improve earlier mean shift algorithms by involving the neighborhood information of samples. The neighborhood of a point in feature space can be described using its K -nearest neighbor (KNN). The KNN query is a common type of query in databases. The nature of KNN tells the local density information, while the task of mean shift procedure is to find a local density maximum. Therefore, the combination of KNN and mean shift is an adaptive way to detect the exact local mode based on local density. The partition of the feature space is obtained by means of dividing all data points into groups centered on the modes. The improved method will do mean shift at suitable scales on different locations with various density, so clusters of contrasting sizes and densities could be detected correctly. As far as clusters of arbitrary shapes and structures are concerned, an idea of multi-center is considered, i.e., a cluster is represented by more than one "center" point (mode).

In the feature space, the volume covered by the K -nearest neighbor (KNN) of a point shows the density of its neighborhood. So embedding the KNN information will be a good choice to provide the local density parameter in clustering procedure. The KNN information can be obtained by performing K -nearest neighbor query to the points in the feature space. If the volume that the K -nearest neighbor of a sample holds is small in the feature space, the density around the sample is high because the number of nearest neighbors is fixed. That is to say the points in the neighborhood are close to each other. Therefore the appropriate local scale should be small and computed according to KNN information. On the other hand, if the volume is large, a relative large scale should be used in the mean shift procedure to locate the local mode.

However, clustering by means of the above method cannot be satisfactory in practical applications. The KNN query procedure is quite time consuming, since its computational complexity is $O(Kn^2)$ for a set of n data points and the data set of an image may be very large. So a subset can be randomly selected from the data because the points (pixels) in an image are spatially correlated to a great extent. In our program, a subset of m points ($m \ll n$) is selected from the original data by a random tessellation of the image. The hyper-spheres centered on the m points will cover most of the data points, therefore, the quality of the density gradient estimate is not diminished by the use of sampling, while the computational complexity decreases to $O(Knm)$.

The above algorithm is called adaptive mean shift (AMS) in this paper. Involving the information of K -nearest neighbor in mean shift procedure makes the algorithm

adapt to regions of different density. After the mean shift procedures, m cluster center candidates are defined as the m convergent points. Although a cluster might be anisotropic in the feature space, it can be delineated by more than one point. If some of the m candidates belong to the same cluster, they will be close to each other after adaptive mean shift procedures. Then these close candidate points are assigned to a single cluster. So clusters of arbitrary shapes and structures can be described by several “centers” and the number of clusters is also determined automatically in this way.

3 Experiment and Analysis

In our experiment, a color image is used to test the proposed segmentation method. In both mean shift methods, we transform the RGB color space to the L^*u^*v space, whose coordinates are related to the color values by nonlinear transformation [4]. All feature space computations are performed in the L^*u^*v space measured by Euclidean distances. Note that all small regions less than 10 pixels are removed from the result images for the sake of visual effect.

The experiment uses part of the water lilies image to demonstrate the segmentation based on the adaptive mean shift clustering. Figure 1 shows the original image of water lilies. The main objects in the image are flowers, stems, and leaves. The background is composed of shadow and water.

Fig. 1. The water lilies image

Three methods: region growing, single scale mean shift and adaptive mean shift methods are performed on the experimental image individually. In the adaptive mean shift algorithm, the number of nearest neighbors K and the size of subset m were set to 10 and 1 percent of data size individually. This experiment well demonstrates the superiority of the adaptive mean shift algorithm over the other segmentation techniques. The results of segmentation are shown in figure 2.

As seen from the segmentation results, region-growing technique does not distinguish the image objects well. There are two segmented images by region growing method (figure2 (a) and (b)). The detailed segmentation result (figure2 (a)) cannot show the flowers in the straightforward way. The flowers are over-segmented, while the other objects are properly segmented. And in the coarse one, there are many sub-segmented objects such as the stem. Though the stem and leaves are unsegmented, the flowers are still shown in a complex way. The single scale mean shift also has the problem separating the flowers into many objects, like the region growing

method. Both of them cannot balance the over-segmented and sub-segmented regions in the image. However, the segmentation ability of the adaptive mean shift clustering is excellent. It has a powerful capability distinguishing objects in the image. The flowers are segmented clearly and simply, and the others are also appropriately separated as we can see from figure 2.

Fig. 2. The results of the image segmentation (a) region growing, detailed one, (b) region growing, coarse one, (c) single scale mean shift clustering, (d) the proposed method

4 Conclusions

In this paper, the goal of image segmentation is achieved by mean shift based clustering, a nonparametric clustering technique. Since earlier algorithms use single scale to the entire feature space, they have problems when the structures of clusters in the feature space are very different. The adaptive mean shift method is proposed by involving the local scale information. Clusters with various structures can be found in the procedure. It can be learned by the experiment that the proposed method has the advantage of segmentation quality over earlier methods.

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