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INTEGRAL OBJECTS SEGMENTATION WITH PROXIMITY CONSTRAINTS

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ABSTRACT

Image segmentation is one of the fundamental techniques in image processing and computer vision. General clustering-based methods of image segmentation only consider morphological features such as intensity and/or texture at single pixel level, which usually leads to incomplete segmentation of objects. The case is even worse when some noise emerges. In this paper, features with proximity constraints are proposed for integral segmentation of image objects, which can provide complete and meaningful segmentation results.

Keywords: *Image Segmentation, Proximity Constraints, Clustering Analysis.*

1. INTRODUCTION

With the development of technology, huge amount of data has been and is being created in every past hour. So, it's impossible for human beings to manually process these data in the era of information explosion and thus automatic processing techniques, such as text retrieval and objects recognition, are needed.

Among those carriers of information, images are becoming more and more popular not only because they are cheap and easy to generate in current days, but also because they are meaningful and easy to be understood by human beings. For example, many people love taking photos during their travels. There may be hundreds and even thousands of photos kept at the end of a single trip. Although there is such a software to help them manage these photos, searching for photos subject to certain criteria is still a challenging task due to the lack of effective object recognition techniques. The pre-requisite of objects recognition is segmenting images into meaningful sub-regions, which is a fundamental problem in image processing and computer vision.

A variety of methods have been established for image segmentation, but the major type of image segmentation methods inherits from unsupervised learning methods, i.e., clustering analysis. The most frequently used ones include connectivity based methods, centroid based methods and distribution based methods. Hierarchical clustering falls into the first category which builds clusters based on connectivity defined using a distance in feature space [1]. Centroid-based methods include the well-known K-means algorithm and its variants such as Fuzzy C-means method, competitive learning methods such as RPCL (Rival Penalized Competitive Learning) and DSRPCL (Distance Sensitive Rival Penalized Competitive Learning) [2-7]. In these methods, each cluster is represented by its center. GMM (Gaussian Mixture Model) is a typical mixture distribution based clustering method, which models each cluster by a Gaussian distribution. The famous EM (Expectation-Maximization) algorithm can be used to solve the maximization of likelihood [8]. The BYY (Bayesian Ying-Yang) harmony learning algorithms can also be used to segment images [9-12].

Another type of image segmentation methods is based on curve evolution, being developed from the snake model method [13]. Actually, the utility of

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level set has enabled them to process more complex objects. Their main idea is to represent the object to be segmented with a curve's enclosing region. The curve like the snake function is iteratively evolved under specifically designed rules and can finally attach to the object's boundary [14, 15]. Although these methods can get integral object segmentation, they are very time consuming and also difficult for the segmentation of multiple objects in an image.

As we turn back to the clustering based methods of image segmentation, it can be found out that one major weakness is just that they usually cannot guarantee the integrity of segmentation results. For example, when an object is composed of several components with different morphological feature types, clustering methods tend to divide it into separate parts; Another case is that the segmentation result can be messy due to the existence of noise, which is unavoidable in real world images. The underlying reason for incomplete segmentation is that clustering methods only consider morphological features such as color space features and texture features but neglect the fact that objects in an image are also continuous in spatial space. Although the aforementioned level set methods evolve the curve in spatial space, the evolution is still controlled by morphological features, not to mention its sensitivity to initial selection of level sets and high computational cost.

In this paper, we propose a solution which incorporates spatial constraints into clustering features so that objects integrity can be achieved without much loss of computational efficiency. The paper is organized as follows: In Section 2, we introduce the proximity constraints. In Section 3, we present three clustering methods with the proximity constraints implemented in this paper. In Section 4, the experiment results are demonstrated on both synthetic and real-world images. Finally, discussions and conclusions are made in Section 5.

2. PROXIMITY CONSTRAINTS

In recent years, superpixel analysis is widely used in image segmentation as a pre-processing operation which groups nearby pixels with similar morphological features into superpixels. Inspired by the idea implemented in the SLIC (simple linear iterative clustering) approach by Achanta et al. [16-18], we try to incorporate pixel coordinates into commonly used morphological features as spatial features [16-18]. For example, each pixel in a color image can then be represented by a 5-element vector:

$$F = [R\ G\ B\ \alpha X\ \ \alpha Y],$$

where $[R\ G\ B]$ are the RGB color space features and $[X\ \ Y]$ are row and column coordinates of the pixel in the image. α is used to balance the color space intensity similarity and the spatial compactness. When α is zero, it degenerates to the original feature space. When α becomes large, regular spatial decomposition of the image could be obtained as shown in Figure 2, where the used $[R\ G\ B]$ system could be replaced with LAB system and/or other texture features.

The spatial features actually post the requirement that the segmented object should be an integral region in the image. Thus, proximity constraints are introduced so that nearby pixels are more likely to be in the same cluster.

To demonstrate the performance of the proposed spatial-constrained feature space, we will test it using various clustering methods and conduct certain comparisons of the segmentation results using only RGB features.

3. SELECTED CLUSTERING METHODS

In this section, we present three widely used clustering based segmentation methods, including K-means, RPCL(rival penalized competitive learning) and GMM(Gaussian mixture model) based learning algorithms.

K-means algorithm minimizes the inter-class distances, or equivalently, maximizes the inter-class similarities. Denote each sample as x_j , $j = 1, 2, ..., N$, where N is the number of samples. Each cluster can be represented by $C_i, i = 1, 2, ..., K$, where K is the cluster number. K-means algorithm tries to find the optimum segmentation that minimizes the following cost function:

$$E = \sum_{i=1}^{K} \sum_{j \in C_i} \left\| x_j - \mu_i \right\|^2 ,$$

where μ_i is the mean or center of samples in cluster $C_i, i = 1, 2, ..., K$. Since it is impossible to solve this problem directly, K-means algorithm iteratively updates μ_i given the current segmentation and then updates the segmentation by assigning each sample to its closest cluster. At each step, the cost function is decreased, thus K-means algorithm is guaranteed to converge. Due to its simplicity and efficiency, K-means algorithm has been widely adopted in various problems[6].

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Rival penalized competitive learning (RPCL) algorithm introduces a competition scheme which allows automatic determination of the correct cluster number to give initially that there are more clusters. Unlike K-means method, RPCL algorithm has both learning and de-learning process. The winner center will get further closer to the learned sample while the rival will be forced to get far away from it. The learning scheme for RPCL algorithm is as follows:

1) Randomly select a sample x and find out the winning cluster as well as the rival cluster where the center of the winner cluster has the smallest distance with x and the center of the rival cluster is the second closest one to x. Denote them as C_{winner} and C_{rival}, respectively.

2) Perform the learning and de-learning operation. Specifically, $\mu_{\text{winner}} = \mu_{\text{winner}} + \alpha_w (x - \mu_{\text{winner}})$, and $\mu_{\text{rival}} = \mu_{\text{rival}} + \alpha_c (\mu_{\text{rival}} - x)$, where α_w and α_c are the learning rate and de-learning rate, respectively.

RPCL algorithm is known for its simplicity and its model selection ability[5, 7].

GMM (Gaussian mixture model) is also widely used for clustering analysis, which models each cluster using a Gaussian distribution. In fact, in K-means and RPCL algorithms, only the center is used to represent a cluster. Thus, Gaussian mixture model allows more accurate description of clusters and consequently will lead to more accurate results under certain assumptions. Gaussian mixture model can be formulized as

$$\Phi(x \mid \Theta) = \sum_{i=1}^{K} \pi_i \phi(x \mid \Theta_i) = \sum_{i=1}^{K} \pi_i \phi(x \mid m_i, \Sigma_i),$$

where $\phi(x \mid m_i, \Sigma_i)$ is the Gaussian distribution with mean m_i and variance matrix Σ_i, π_i is the mixing proportion of Gaussian i or cluster C_i, $i = 1, 2, ..., K$. Expectation Maximization (EM) algorithm is used to solve the parameters of GMM. Please note that although Gaussian mixture model is supposed to be more powerful than K-means and RPCL methods, the computational cost is also much higher. Keep this in mind when dealing with specific problems [8].

In the next section, we will show results of applying these clustering methods for image segmentation using the proposed spatial-constrained features.

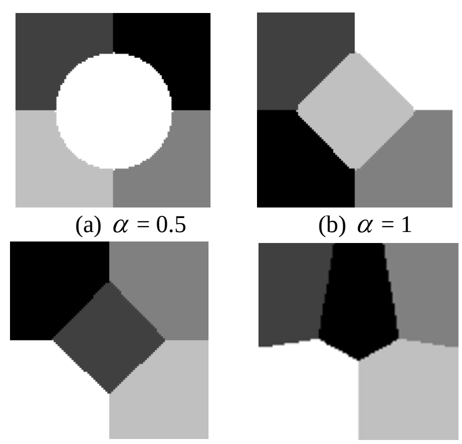
4. EXPERIMENT RESULTS

4.1 On Synthetic Data

To demonstrate the proposed spatial-constrained features, we design a synthetic image which contains intensity 45, 60 and 50 for the outside region, the ring and the small disk inside, respectively, as shown in Figure 1(a). The object of our interest is the large disk composed of the ring and the small disk inside. The small disk is wrongly taken out of the whole disk object when only intensity level is considered, as shown in Figure 1(b).

(a) (b)

Figure 1. (A) Synthetic Image. Intensity Of Region Outside The Large Disk Is Set To 45. Intensity Of The Bright Ring Is Set To 60 And Intensity Of The Small Disk Inside Is Set To 50. Image Contrast Is Adjusted For Visualization Purpose. (B) K-Means Result Using Only Intensity Feature With K Set To 2.



(a) $\alpha = 0.5$ (b) $\alpha = 1$ (c) $\alpha = 2$ (d) $\alpha = 3$

Figure 2. Results Of K-Means Using The Proposed Spatial Constrained Features For Various Values Of α. The Whole Disk Is Fully Recovered When α Is Set To 0.5. K Is Set To 5 In This Case.

We then apply the proposed features $F = [R\ G\ B\ \alpha X\ \alpha Y]$ in K-means algorithm under various settings of α. The large disk is fully recovered when α was set to 0.5 and as α increased, the segmented results tend to be

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controlled more and more by only spatial coordinates, as we mentioned in Section 2.

To investigate the sensitivity of the proposed spatial-constrained features to noise, we test their performances on a polluted version of the synthetic image. Figure 3 shows that segmentation results are more robust to noise in the proposed feature space than in the original feature space.

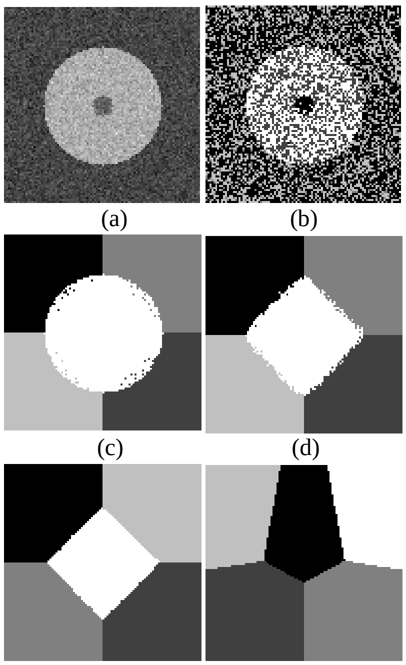

Figure 3. Results Of Applying Spatial-Constrained Features On The Polluted Image (A) Original Image; (B) Segmentation With K-Means Using Only Intensity; (C),(D),(E),(F) Segmentation Results With K-Means Using The Proposed Features; α Was Set To 0.5, 1, 2 And 3, Respectively. K Is Set To 5 For All Segmentations.

4.2 On Real World Images

We also conduct experiments on several real-world images using K-means, RPCL and GMM based learning algorithms. In Figure 4, the object of interest is the region where trees are planted. The result with K-means algorithm using the ordinary RGB features is messy with incomplete segmentation. A lot of regions between trees are taken out of the object. After the proximity constraints are used, all the three methods can obtain integral segmentation of the region. The results demonstrate the ability of proximity constraints to extract integral segmentation of objects of interest.

In Figs 5, 6 and 7, we show how these three approaches perform on real-world images, respectively. The objects of interest are the house, the bird and the bear, respectively. For the house image, K-means algorithm captures the whole house when α is set to 1, while the house is divided to several parts when ordinary RGB features are used. Similarly, for the bird image, RPCL recovers the complete bird when α is set to 2. GMM based method segments the bear image well when α is set to 0.5. In summary, the proposed proximity constraints can effectively improve the performance of various clustering methods in segmenting integral objects.

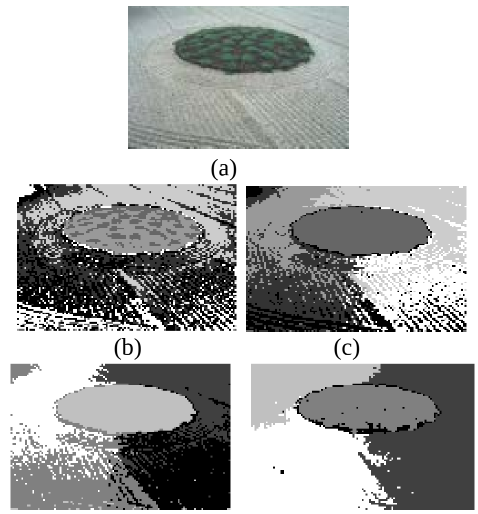

Figure 4. Results Of Applying Spatial Constrained Features On Real-World Images. (A) Original Image; (B) Segmentation With K-Means Using Ordinary RGB Features; (C) Segmentation Results With K-Means Using The Proposed Features; (D) Segmentation Results With RPCL Using The Proposed Features; (E) Segmentation Results With GMM Using The Proposed Features; K Is Set To 5 And α Is Set To 0.5.

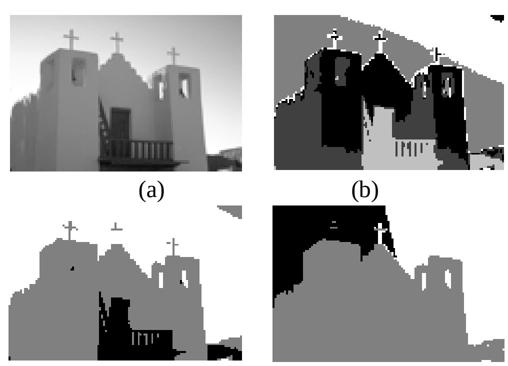

Figure 5. (A) Original Image; (B) Segmentation Result With K-Means Using Ordinary RGB Features; (C),(D) Segmentation Results With K-Means Using The Proposed Features, α Is Set To 0.5 And 1, Respectively. K Is Set To 3 For All Segmentations.

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5. DISCUSSIONS AND CONCLUSIONS

As we mentioned in section 2, parameter α is introduced to balance the intensity similarity and the spatial compactness. We should note that α correlates with scopes of both original feature space and spatial coordinates, which may lead to inconsistency between values of α for images with different types and/or different sizes. One way to remove the inconsistency is to normalize ordinary intensity features and coordinate features to the same scope. In that case, we would have normalized α which can then be compared.

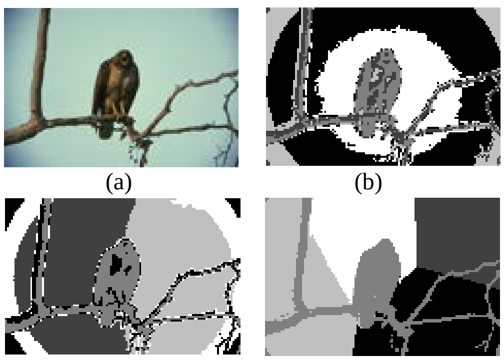
(a) (b) (c) (d)

Figure 6. (A) Original Image; (B) Segmentation Result With RPCL Using Ordinary RGB Features; (C), (D) Segmentation Results With RPCL Using The Proposed Features, α Is Set To 0.5 And 2, Respectively. K Is Set To 5 For All Segmentations.

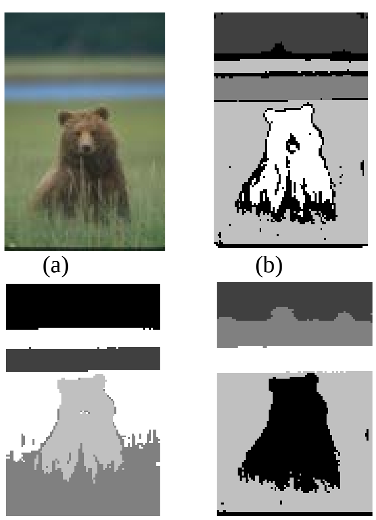
(a) (b) (c) (d)

Figure 7. (A) Original Image; (B) Segmentation Result With GMM Using Ordinary RGB Features; (C),(D) Segmentation Results With GMM Using The Proposed Features; α Is Set To 0.2 And 0.5, Respectively. K Is Set To 5 For All Segmentations.

Due to the diversity of image types and complexity of image contents, α needs to be adjusted for specific images to obtain satisfactory segmentation. This leads to the model selection problem, which is common in image segmentation models and is usually solved by trying out different values and selecting the one with the best result. Fortunately, certain scope of α exists such that the searching domain is greatly reduced. As shown in the aforementioned experiment results on various images, [0 2] should be good enough for most images. Moreover, we expect to design certain information criteria to help choose the best α as those used in determining the number of clusters in the future [19, 20].

In this paper, in order to obtain integral objects, we have introduced the proximity constraints into clustering methods by combining morphological features and spatial coordinate features. Experiment results have demonstrated that the proposed spatial-constrained features can significantly improve the performance of various clustering methods on integral object segmentation.

Spatial constraints introduced here are simple but effective. In the future, we would like to design other spatial constraints which allow more control of the desired shape of objects.

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