Color Image Segmentation Using Rival Penalized Controlled Competitive Learning

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***Abstract*— Color image segmentation has been extensively applied to a lot of applications such as pattern recognition, image compression and matching. In the literature, conventional k-means (MacQueen 1967) is one common algorithm used in pixel-based image segmentation. However, it needs to pre-assign an appropriate cluster number before performing clustering, which is an intractable problem from a practical viewpoint. In contrast, the recently proposed Rival Penalization Controlled Competitive Learning (RPCCL) approach (Cheung 2002) can perform correct clustering without knowing the exact cluster number in analog with the RPCL (Xu et al. 1993). The RPCCL penalizes the rivals with a strength control such that extra seed points are automatically driven far away from the input data set, but without the de-learning rate selecting problem as the RPCL. In this paper, we further investigate the RPCCL on color image segmentation in comparison with the k-means and RPCL algorithms.**

I. Introduction

Color image segmentation has been extensively applied in pattern recognition, image analysis and computer vision such as image retrieval [1], face recognition and image compression [6]. In the literature, one image segmentation approach is pixel-based segmentation, in which the conventional k-means clustering algorithm [3] is commonly used to classify color pixels into k different clusters [5], [7]. The k-means generally requests to pre-assign an appropriate cluster number k. Otherwise, its performance may seriously deteriorate. Unfortunately, such a value selection is an intractable problem from a practical viewpoint.

To circumvent the selection of k, the Rival Penalized Competitive Learning (RPCL) clustering algorithm [8] has been proposed to perform clustering without knowing the cluster number. The basic idea of RPCL is that for each input, not only the winner of the seed points is updated to adapt to the input, but also its nearest rival (i.e., the second winner) is de-learned by a smaller learning rate (also called de-learning rate hereafter). The experiments have shown that the RPCL can automatically select an appropriate cluster number by gradually driving extra seed points far away from the input data set. Actually, the RPCL algorithm has been successfully applied to the vision system in a robot to extract the features objects from the captured image [4]. However, the performance of RPCL is somewhat sensitive to the selection of the de-learning rate. Under the circumstances, we have recently proposed the Rival Penalization Controlled Competitive Learning (RPCCL) clustering algorithm [2], in which the distance between the winner and the rival has been considered in determining the rival-penalized strength as given an input. The basic idea is that, the rival should be more penalized if its distance to the winner is closer than the one between the winner and the input. This idea is also consistent with the social scenario in our daily life. For example, in the president election of a country, the competition between two candidates (we call the final winning person *the winner* and the other one *the rival*) will become more intense if their public opinion polls are closer. Otherwise the winner will be almost sure to win the election with little penalizing the rival during the election campaign. Based on this idea, the RPCCL has embedded a mechanism, in which the rival-penalized strength is dynamically adjusted based on the distance between the winner and the rival relative to the current input. Compared to the RPCL, the RPCCL always fixed the de-learning rate at the same value as the learning rate without requesting further determination. Such a setting however is not allowed as pointed out in [8], which will result in the RPCL not to work completely. The experiments in [2] have shown that the RPCCL outperforms the RPCL. In this paper, we will further investigate the RPCCL on color image segmentation in comparison with the k-means and RPCL. The experiments have shown that the RPCCL utilizes the less seed points, but gives a moderately better image segmentation results.

This paper is organized as follows. In Section II, we briefly introduce the pixel-based image segmentation problem. In Section III, we will graphically elaborate the underlying scheme of the RPCCL, and present its algorithm as well. Section IV experimentally shows the performance of the RPCCL on the color image segmentation in comparison with the k-means and the RPCL. Finally, Section V draws a conclusion.

II. Color Image Segmentation

Image segmentation is the process of segmenting an image into different homogeneous regions, which is a critical step in image analysis and pattern recognition. In the literature, various approaches have been proposed to deal with gray-scale images such as edge-based, region-based and pixel-based approaches. Some of them can also be used in color image. In this paper, we focus on pixel-based segmentation only for color image segmentation. We operate in the well-known Red-Green-Blue (RGB) color space model that represents each pixel in an image by the three-color components. Supposing homogenous objects have similar colors, we can therefore group pixels of similar colors into the same cluster based on a certain distance measure over the three-dimensional

RGB color space. Eventually, color image segmentation based on pixels can be formalized into a three-dimensional data clustering problem using the conventional k-means algorithm as follows:

Given a set of image pixels, denoted as $D = \{\mathbf{x}_i\}_{i=1}^N$, where $\mathbf{x}_i = (x_i^R, x_i^G, x_i^B)^T$ is a 3×1 vector representing a color pixel that x_i^X is a scalar value observed on the X plane and N is the total pixel number of an image,

1) Pre-define the number of clusters k.
2) Initialize the seed points $\{\mathbf{m}_j\}_{j=1}^k$, where $\mathbf{m}_j = (m_j^R, m_j^G, m_j^B)^T$ is a 3×1 vector representing a color pixel that m_j^X is a scalar value observed on the X plane.
3) Pick an input pixel $\mathbf{x}_i$ randomly from the data set D.
4) Calculate the indicator function,
$$I(j|\mathbf{x}_i) = \begin{cases} 1, & \text{if } j = c = \arg\min_r \|\mathbf{x}_i - \mathbf{m}_r\|^2 \\ 0, & \text{otherwise,} \end{cases} \quad (1)$$
which separates the input pixel into k clusters.
5) Update $\mathbf{m}_c$ with $I(c|\mathbf{x}_i) = 1$ only by
$$\mathbf{m}_c^{new} = \mathbf{m}_c^{old} + \alpha_c(\mathbf{x}_i - \mathbf{m}_c^{old}) \quad (2)$$
6) Repeat step 3–step 5 until all $\{\mathbf{m}_j\}_{j=1}^k$ converges.

In the above, the crux of k-means clustering algorithm is to assign an appropriate cluster number k in advance. When k is mis-specified, the performance of k-means algorithms may seriously deteriorate. Moreover, its clustering performance is also greatly affected by the initialized positions of the seed points. Hence, the k-means is not robust in dealing with image segmentation problem.

III. The Rival Penalization Controlled Competitive Learning approach to image segmentation

From a practical viewpoint, the content of images differs from image to image, we are unable to choose an appropriate cluster number for every image in advance. To circumvent this problem, we hereafter utilizes the RPCCL [2], instead of the k-means, to perform color image segmentation. In analog with the RPCL, the basic idea of RPCCL is that for each input, not only the winner seed point is rewarded to adapt to the input, but its nearest rival (i.e. the 2nd winner) is also penalized with the strength dynamically controlled by a scheme, which states that:
The rival should be fully penalized if its distance to the winner is closer than the distance between the winner and the rival increases. Otherwise, the penalizing strength should be decreased as the rival distance to the winner increases.

To implement this scheme, the paper [2] has presented the following function as a measurement of the rival penalization strength:
$$p_r(\mathbf{x}_i) = \frac{\min(\tilde{d}_{cr}, d_{ci})}{\tilde{d}_{cr}}, \quad (3)$$
where $\tilde{d}_{cr}$ and d_{ci} are both a certain distance measuring function. Particulary, we can use Euclidean distance, or more general Mahalanobis distance. That is,

- Euclidean distance
$$\begin{aligned} \tilde{d}_{cr} &= \|\mathbf{m}_r - \mathbf{m}_c\| \\ d_{ci} &= \|\mathbf{x}_i - \mathbf{m}_c\|, \end{aligned} \quad (4)$$

- Mahalanobis distance
$$\begin{aligned} \tilde{d}_{cr} &= \sqrt{(\mathbf{m}_r - \mathbf{m}_c)^T \mathbf{\Sigma}_c^{-1} (\mathbf{m}_r - \mathbf{m}_c)} \\ \tilde{d}_{ci} &= \sqrt{(\mathbf{x}_i - \mathbf{m}_c)^T \mathbf{\Sigma}_c^{-1} (\mathbf{x}_i - \mathbf{m}_c)}, \end{aligned} \quad (5)$$
where $\mathbf{\Sigma}_c$ is the covariance matrix of cluster c.

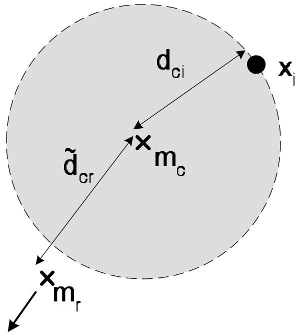
Evidently, $p_r(\mathbf{x}_i)$ must be within the range of $0 < p_r(\mathbf{x}_i) \leq 1$. This rival penalization control scheme can be illustrated in Fig. 1. It can be seen that as $\tilde{d}_{cr} > d_{ci}$, the rival penalization is gradually attenuated as the distance between the rival and the winner increases. On the other hand, when $\tilde{d}_{cr} \leq d_{ci}$, the rival will be fully penalized. i.e., the rival penalization strength $p_r(\mathbf{x}_i)$ reaches its maximum value 1.

In the following, we will give out the RPCCL algorithm with using Euclidean distance only. For more details, interested readers can refer to the paper [2].

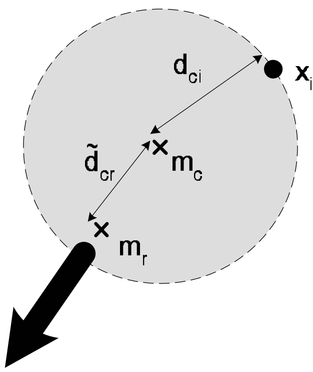
Step 1: Randomly take a sample $\mathbf{x}_i$ from the data set $D = \{\mathbf{x}_i\}_{i=1}^N$, and for $j = 1, 2, \ldots, k$, let
$$I(j|\mathbf{x}_i) = \begin{cases} 1, & \text{if } j = c, \\ -1, & \text{if } j = r, \\ 0, & \text{otherwise,} \end{cases} \quad (6)$$
with
$$\begin{aligned} c &= \arg\min_j \gamma_j \|\mathbf{x}_i - \mathbf{m}_j\|^2, \\ r &= \arg\min_{j \neq c} \gamma_j \|\mathbf{x}_i - \mathbf{m}_j\|^2, \end{aligned} \quad (7)$$
where $\gamma_j = \frac{n_j}{\sum_{r=1}^k n_r}$ is the relative winning frequency of the seed point $\mathbf{m}_j$ in the past, and n_j is the cumulative number of the occurrences of $I(j|\mathbf{x}_t) = 1$ in the past.

Step 2: Update the winner $\mathbf{m}_c$ (i.e., $I(c|\mathbf{x}_i) = 1$) and its rival $\mathbf{m}_r$ (i.e., $I(r|\mathbf{x}_i) = -1$) only by
$$\mathbf{m}_u^{new} = \mathbf{m}_u^{old} + \Delta\mathbf{m}_u, \quad u = c, r \quad (8)$$
with
$$\begin{aligned} \Delta\mathbf{m}_c &= \alpha_c(\mathbf{x}_i - \mathbf{m}_c) & (9) \\ \Delta\mathbf{m}_r &= -\alpha_c p_r(\mathbf{x}_i)(\mathbf{x}_i - \mathbf{m}_r), & (10) \end{aligned}$$
where α_c is the learning rate. These two steps are repeated for each input until $I(j|\mathbf{x}_i)s$ converge.

Actually, the RPCCL is a generalization of the RPCL with including it as a special case. When we always fix $p_r(\mathbf{x}_i)$ at



(a) Gradually Attenuated Rival Penalization



(b) Full Rival Penalization

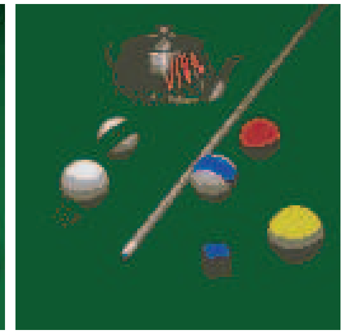
Fig. 1. The graphical representation of rival penalization scheme of the RPCCL algorithm: (a) When $\tilde{d}_{cr} > d_{ci}$, the rival penalization gradually decreases as the distance between the rival and the winner increases. (b) When $\tilde{d}_{cr} \leq d_{ci}$, a full penalization is applied to the rival seed point $\mathbf{m}_r$. i.e., the rival penalization strength $p_r(\mathbf{x}_i)$ reaches its maximum value 1.

a constant, the updating equation of the rival seed point in Eq. 10 is then exactly equal to the one in the RPCL, i.e., the de-learning rate, denoted as α_r in the RPCL, is equal to $\alpha_r = \alpha_c p_r(\mathbf{x}_i)$.

IV. Experimental Results

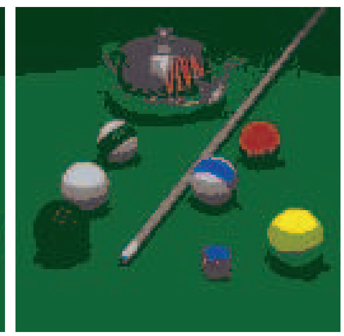
To show the segmentation performance of RPCCL in comparison with the conventional k-means and the RPCL, we conducted three experiments, in each of which we used a 128×128 pixels image. In the all experiments, we arbitrarily let the de-learning rate $\alpha_r = 0.0001$ in the RPCL and the learning rate $\alpha_c = 0.001$ in all RPCL, RPCCL and k-means algorithms.

(a) The Original Pool Image



(b) k-means

(c) RPCL



(d) RPCCL

Fig. 2. Segmentation results of Pool image. (a) The original Pool image. (b) The result by using k-means algorithm where the black ball was missed (c) The result by RPCL with 11 convergent seed points. (d) The result from RPCCL with 10 convergent seed points only.

A. Experiment 1

We used the Pool image with 128×128 pixels as shown in Fig. 2(a). For each algorithm, we used 16 seed points whose positions were randomly assigned in the RGB color space. We then applied k-means, RPCL and RPCCL clustering algorithms to segment the image. After the algorithms' performance converged, a snapshot of their segmentation results at Epoch 35 is shown in Fig. 2(b)–(d), where it can be seen that the black ball was totally missed out after the k-means segmentation process. That is, the segmentation result of k-means is worse than that of the RPCL and RPCCL. In this experiment, the results from RPCL and RPCCL were similar. However, the RPCL drove 5 extra seed points only far away from the input data set, and the remaining 11 seed points were moved to the some cluster centers. In contrast, the RPCCL drove 6 extra seed points far away and the remaining 10 seed points were converged to the proper cluster centers. Further, it showed again that the learning speed of RPCCL is much faster than the RPCL as reported in [2].

B. Experiment 2

We further used another House image with 128×128 pixels to compare the segmentation performance of the three

(a) The original House image

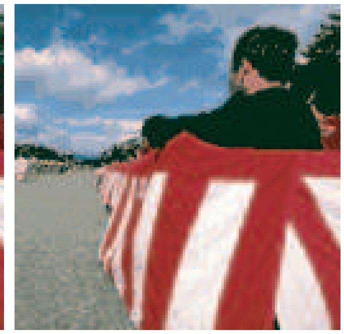
(b) k-means

(c) RPCL

(d) RPCCL

Fig. 3. Segmentation results of the House image. (a) The original House image. (b) Texture is remained on the wall using the k-means segmentation. (c) The results by RPCL with 30 seed points where the texture of the red wall is still remained. (d) The results by RPCCL with 18 seed points only, where a solid wall was segmented.

(a) The original House image



(b) k-means

(c) RPCL

(d) RPCCL

Fig. 4. Segmentation results of the Audience image. (a) The original Audience image. (b) The segmentation result by using k-means algorithm with 30 seed points. (c) The results by RPCL with 29 seed points. (d) The results by RPCCL with 23 seed points only.

clustering algorithms. The original House image is as shown in Fig. 3(a). Here, we let the number of seed points be 30. After the algorithm performance converged, a snapshot of the segmentation results of the three clustering algorithms at Epoch 100 is shown in Fig. 3(b)–(d). In this experiment, the RPCL failed to drive out any seed point from the input data set. In contrast, the RPCCL has drove out 12 extra seed points far away from the input data set. This phenomenon shows again that the RPCL performance is sensitive to the selection of de-learning rate. In this experiment, the results given by the RPCL and k-means were similar, both of which are slightly worse than the RPCCL. It can be seen that the texture of the red wall still remains in both k-means and RPCL segmentation results, while it has been successfully removed by the RPCCL algorithm.

C. Experiment 3

Similar to Experiment 2, we used another Audience image with 128×128 pixels to compare the segmentation performance of the three clustering algorithms. The original Audience image is as shown in Fig. 4(a). Here, we let the number of seed points be 30 again. After the algorithm performance converged, a snapshot of the segmentation results of the three clustering algorithms at Epoch 50 is shown in Fig. 4(b)–(d). In this experiment, the three algorithms all led to the similar results, but the RPCL and RPCCL used a smaller set of seed points. Actually, the RPCL has drove out one seed point from the input data set, whereas the RPCCL drove out 7 extra seed points far away from the input data set. Further, when adjusting the de-learning rate of RPCL up to 0.0002, we found that the RPCL could finally drive out 6 extra seed points away from the input data set. This scenario implies that it could be hard to select an appropriate de-learning rate for RPCL in advance.

V. Conclusion

We have applied RPCCL clustering algorithm to segment the color images in the RGB color space. We have empirically compared the performance results among the k-means, RPCL and RPCCL clustering algorithms. The experimental results have shown that RPCCL outperforms the other two algorithms with the less seed points used in color image segmentation.

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