

# Color Image Segmentation Using Competitive and Cooperative Learning Approach

Yinggan Tang, Xinping Guan

**Abstract**—Color image segmentation can be considered as a cluster procedure in feature space. k-means and its adaptive version, i.e. competitive learning approach are powerful tools for data clustering. But k-means and competitive learning suffer from several drawbacks such as dead-unit problem and need to pre-specify number of cluster. In this paper, we will explore to use competitive and cooperative learning approach to perform color image segmentation. In competitive and cooperative learning approach, seed points not only compete each other, but also the winner will dynamically select several nearest competitors to form a cooperative team to adapt to the input together, finally it can automatically select the correct number of cluster and avoid the dead-units problem. Experimental results show that CCL can obtain better segmentation result.

**Keywords**—Color image segmentation, competitive learning, cluster, k-means algorithm, competitive and cooperative learning.

## I. INTRODUCTION

Image segmentation is a process of grouping an image into homogenous regions with respect to one or more characteristics. It is the first step in image analysis and pattern recognition. In the past decades, many attentions had been paid to monochrome image segmentation and many algorithms had been proposed in literatures [1]. Compared to monochrome image, a color image provides, in addition to intensity, additional information in the image. In fact, human beings intuitively feel that color is an important part of their visual experience and color is useful or even necessary for powerful processing in computer vision. Also the acquisition and processing hardware for color image become more and more available for dealing with the problem of computation complexity caused by the high-dimensional color space. Hence, color image processing becomes increasingly prevalent nowadays.

In this paper, we focus on color image segmentation. In literatures, many methods are available for color image segmentation [2]. Among these methods, one frequently used approach is to use a clustering procedure on feature space

[3]-[5]. k-mean algorithm and its adaptive version, i.e. competitive learning, is a popular method for this purpose. For example, Toshio and Arbib [3] proposed a color image segmentation method using competitive learning based on the least sum of squares criterion. Although k-means and competitive learning algorithm can successfully accomplish data clustering in some situations, it suffers from several drawbacks pointed out in [6]-[7]. First, there is the *dead-unit* problem. That is, if some units are initialized far away from the input data set in comparison with the other units, they then immediately become the dead unit without any winning chance in the forthcoming competitive learning process. Second, it needs to pre-determine the cluster number. When pre-determined cluster number equals to the true cluster number, k-means algorithm can correctly find out the cluster center. Many researchers have done much work to circumvent the above problems. An extension of k-means named Frequency Sensitive Competitive Learning (FSCL) was proposed [8]. In FSCL algorithm, the winning chance of a seed point is penalized along with the increase of past winning frequency, and vice versa. FSCL algorithm can successfully assign one or more seed points to each cluster without dead-unit problem. But its cluster performance decreases when cluster number is incorrectly selected in advance. Another algorithm developed by Xu [7] is Rival Penalized Competitive Learning (RPCL). In RPCL, for each input, not only the winner of the seed points is updated to adapt to the input, but also its rival is de-learned by a smaller constant learning rate called *de-learning rate*. RPCL can select the correct number automatically but its performance is sensitive to the selection of de-learning rate. If de-learning rate is selected too small or too large, cluster result is not so satisfactory. Recently, Cheung [9] proposed a new competitive learning approach, called Competitive and Cooperative Learning approach (CCL). In CCL, seed point not only compete each other for updating to adapt to an input each time, but also the winner will dynamically select several nearest competitors to form a cooperative team to adapt to the input together. As a whole, the seed points locating in the same cluster will have more opportunity to cooperate each other than compete to achieve learning task. Experiment studies have demonstrated the outstanding performance of CCL.

In this paper, we will explore to use CCL approach to perform color image segmentation. The rest of this paper is organized as follows. In Section II, we first briefly overview FSCL and CCL algorithm and then color image segmentation

Manuscript received December 15, 2004. This work was supported by National Nature Foundation of China (No.60174010)

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algorithm is present using CCL. Experimental results is given in Section III. Finally, Section IV draws a conclusion.

## II. COLOR IMAGE SEGMENTATION USING CCL

### A. Brief Overview of CCL

Suppose there are  $N$  data points  $x_1, x_2, \dots, x_N$ , which will be partitioned into  $k$  clusters and seed points are  $w_1, w_2, \dots, w_k$ . To this end, an adaptive version of k-means algorithm, i.e. competitive learning can be used. As mentioned above, competitive learning has the problem of dead-unit. To deal with this problem, Ahalt et al.[8] proposed a frequency sensitive competitive learning (FSCL) approach, in which apart from considering the distance of  $w_i$  to the input, an implicit penalty is also given to those points that have high relative winning frequency in the past competitions. FSCL algorithm consists of the following steps:

Step 1: Pre-specify the number of clusters and initialize the seed points  $\{w_j\}_{j=1}^k$

Step 2: Given an input  $x_i$ , calculate the indicator function  $I(j|x_i)$  by

$$I(j|x_i) = \begin{cases} 1 & \text{if } j = \arg \min_{1 \leq r \leq k} n_r \|x_i - w_r\|^2 \\ 0 & \text{otherwise} \end{cases} \quad (1)$$

where  $n_r$  is the winning times of  $w_r$  in the past.

Step 3: Update the winning seed point  $w_c$ , i.e.  $I(j|x_i) = 1$ , and  $n_c$  by

$$w_c^{\text{new}} = w_c^{\text{old}} + h(x_i - w_c^{\text{old}}) \quad (2)$$

$$n_c^{\text{new}} = n_c^{\text{old}} + 1 \quad (3)$$

respectively. FSCL can overcome the dead-unit problem successfully. However, it needs to pre-assign the number of cluster. If  $k$  is not equal to the true  $k^*$ , FSCL will lead to an incorrect clustering result. RPCL algorithm, proposed by Xu [7], can select the correct number automatically but its performance is sensitive to the selection of de-learning rate. Recently, Cheung [9] proposed a new semi-competitive learning algorithm named Competitive and Cooperative Learning (CCL). The basic idea of CCL is that  $k$  seed points not only compete each other for updating to adapt to an input each time, but also the winner will dynamically select several nearest competitors to form a cooperative team to adapt to the input together. This competitive and cooperative mechanism can automatically merge those extra seed points, meanwhile making the seed points gradually converge to the corresponding cluster centers. Consequently, CCL can perform a robust clustering without prior knowing the exact cluster number so long as the number of seed points is not less than the true one. In the following,  $k^*$  denotes the true number of cluster in input space. CCL can be described as follow:

Step1: Pre-specify the number  $k$  of clusters with  $k \geq k^*$ ,

initialize the seed points  $\{w_j\}_{j=1}^k$ , and set  $n_j = 1$  with  $j = 1, 2, \dots, k$

Step 2: Give an input  $x_i$ , calculates  $I(j|x_i)$  using (1).

Step 3: Let the cooperative set  $C = \{w_c\}$ . We then span  $C$  by

$$C = C \cup \{w_j \mid \|w_c - w_j\| \leq \|w_c - x_i\|\}$$

That is, all of those seed points fallen into the circle centered at  $w_c$  with the radius  $\|w_c - x_i\|$  are the winners as well as  $w_c$ , but the others outside the circle are not.

Step 4: Update all members in  $C$  by

$$w_u^{\text{new}} = w_u^{\text{old}} + h(x_i - w_u^{\text{old}})$$

where  $w_u \in C$ . Furthermore, we here only update  $n_c$  by (4) Repeat Step 2 and Step 4 until all seed points converge. CCL makes each extra seed point finally locate at one of cluster center and we can determine the exact cluster number by counting the number of those points stayed at different positions.

### B. Color Image Segmentation Algorithm Using CCL

Color image segmentation can be considered as a color clustering procedure in a certain feature space. In the past, many color features had been developed, such as RGB color space,  $I_1I_2I_3$  color space developed by Ohta [10], HIS color space, et al. For simplicity, we use RGB color space in this paper.

Let  $I$  be a color image of size  $M_1' \times M_2'$  and let

$N = M_1' \times M_2'$  be the total pixel number of the image. The set of image pixels denotes  $D = \{x_i\}_{i=1}^N$ , where

$x_i = (x_i^R, x_i^G, x_i^B)$  is a  $1' \times 3$  vector representing a color

pixel and  $x_i^X$  is a scalar observed on the  $X$  plane of an image.

Color image segmentation using CCL can be summarized as follows:

Step 1: Input a image and pre-specify the number of cluster  $k$  such that  $k \geq k^*$ , where  $k^*$  is the true number of clusters in the input image.

Step 2: Randomly initialize seed points  $\{m_j\}_{j=1}^k$ , where

$$m_j = (m_j^R, m_j^G, m_j^B) \in D.$$

Step 3: Picks an image pixel  $x_i$  randomly from  $D$  and calculates indicator function  $I(j|x_i)$  using (1).

Step 4: Let the cooperative set  $C = \{m_c\}$ . We then span  $C$  by

$$C = C \cup \{m_j \mid \|m_c - m_j\| \leq \|m_c - x_i\|\}$$

to form a cooperative team.

Step 5: Update all members in  $C$  by

$$m_u^{\text{new}} = m_u^{\text{old}} + h(x_i - m_u^{\text{old}})$$

$$n_c^{\text{new}} = n_c^{\text{old}} + 1$$

where  $m_u \in C$ .

Repeat Step 3 and Step5 until all seed points converge. For each cluster in segmented image, we use converged seed points to represent each cluster. The reason of using CCL to perform color image segmentation is that CCL do not need to specify the precise number of clusters in image in advance and the segmentation result is always satisfactory. In next section, experimental results will be given to verify the performance of CCL in color image segmentation.

### III. EXPERIMENT RESULTS

To demonstrate the segmentation performance of CCL, we do some experiments. The experiment results using CCL are compared with those using FSCL and CL. In all experiments, seeds points are selected randomly in input images and the learning rate is  $h = 0.05$ . The experiments results are shown in Fig.1-Fig.3. In all figures, (a) is original image, (b), (c) and (d) is the segmentation results using CL, FSCL and CCL respectively. In Fig.1, original image is House. For each approach, seed point number is initially set as 10 and the learning epochs are 20. It can be seen from the results that the wall under the lower roof is more homogenous using CCL than using CL and FSCL and the shadow effect can removed to certain extend using CCL than CL and FSCL. Finally, CCL algorithm merged three extra seed points as shown in Table I.

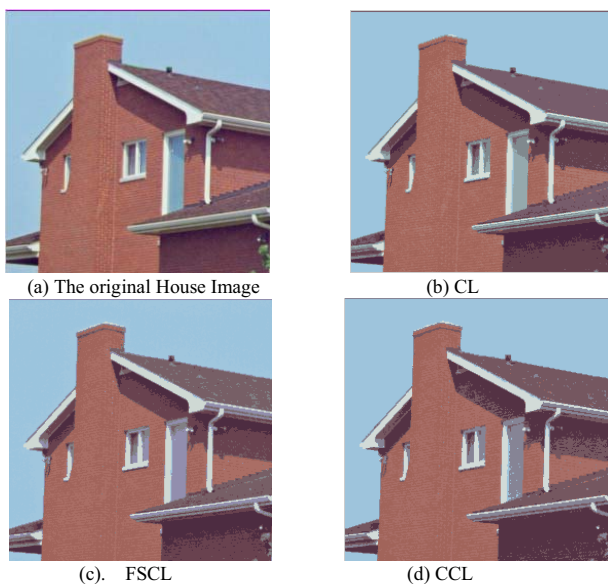


Fig.1. Segmentation results of House image. (a) The original House image.(b) The result using competitive learning (c) The result using frequency sensitive competitive learning (d) The result using competitive and cooperative learning .

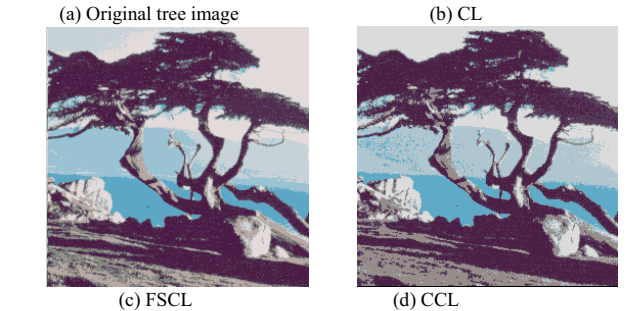


Fig.2. Segmentation results of tree image. (a) The original tree image.(b) The result using competitive learning (c) The result using frequency sensitive competitive learning (d) The result using competitive and cooperative learning .

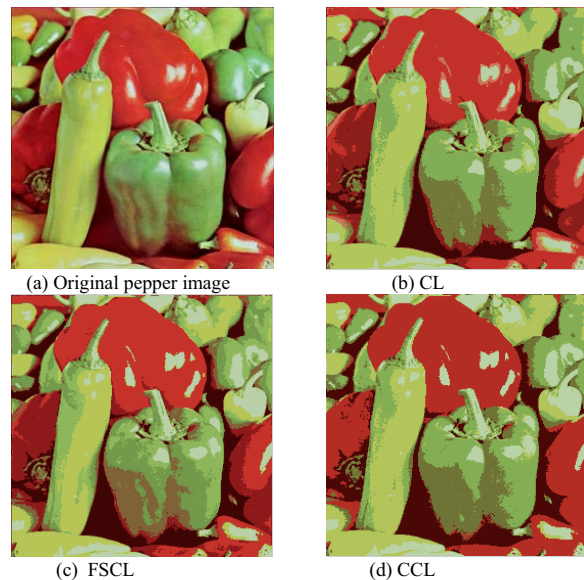


Fig.3. Segmentation results of pepper image. (a) The original Pepper image.(b) The result using competitive learning (c) The result using frequency sensitive competitive learning (d) The result using competitive and cooperative learning .

In Fig.2, original image is tree. In this experiment, seed points are initially set to 10 and learning epochs is 15. From the segmentation result we can see that grass ground is more homogenous using CCL than using than using CL and FSCL. CCL merges two extra seed points and finally select eight seed points. In Fig.3, original image is pepper and seed points are initially set to 8, learning epochs are 15. Due to lights non-uniformity, CL and FSCL algorithm make improper segmentation especially in the regions of strong lights. CCL can remove this effect in a large extend. Finally, all the converged seed points using CCL are shown in Table I. We can see that CCL can merges extra seed point and select correct seed points. Experiment results are better using CCL than using CL and FSCL.

### IV. CONCLUSION

Color image segmentation is considered as a cluster procedure in color space. Competitive and cooperative learning algorithm is used to achieve this end due to it can select correct

number of clusters of images. Compared with segmentation results, one can draw a conclusion that competitive and cooperative algorithm is a more efficient clustering approach for color segmentation than CL and FSCL.

TABLE I  
CONVERGED SEED POINTS OF IMAGE HOUSE, TREE AND PEPPER

House image			Tree image			Pepper image		
R	G	B	R	G	B	R	G	B
158.49	196.96	220.65	85.525	60.545	90.72	131.05	174.34	84.652
117.13	87.639	96.825	175.51	197.73	207.5	185.87	211.24	167.44
158.49	196.96	220.65	150.87	141.84	138.77	180.29	45.39	37.432
210.32	219.95	216.19	2.9703e-53	9.0361e-54	2.6937e-53	180.29	45.39	37.432
84.016	50.258	68.587	76.831	31.048	70.782	73.685	7.0814	6.6097
158.49	196.96	220.65	219.75	219.16	219.43	179.33	196.76	90.989
161.47	100.7	90.549	150.87	141.84	138.77	112.71	115.95	54.983
134.27	132.78	149.98	95.334	171.45	199.95	180.29	45.39	37.432
169.12	110.45	103.58	2.9703e-53	9.0361e-54	2.6937e-53			
158.49	196.96	220.65	2.9703e-53	9.0361e-54	2.6937e-53			

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