A Self-Organizing Map Approach to Segmentation of Color Image

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Abstract: - In this paper, a color segmentation algorithm is presented and the parameters are discussed. This developed algorithm using self-organizing map (SOM) takes account of not only color similarity, but also spatial distance relation. According to the features of color similarity, an image is first segmented to coarse cluster regions. The resulting regions are further found by computing spatial distance between any two cluster regions, and then SOM algorithm and labeling process. The assignment of parameters for SOM algorithm is also discussed experimentally. As a result, the proposed algorithm shows that the segmented object regions are similar to those perceived by human vision.

Key-Words: - color image segmentation, self-organizing map(SOM).

1 Introduction

Image segmentation is the process by which an original image description is partitioned into some meaningful regions. It is usually assumed that the objects are represented by regions that are homogeneous and well-defined in some sense; and many techniques have been developed [1]-[3]. These methods mainly adopt either the local information which considers the neighboring relationship of pixels, or global consideration according to a local analysis of neighborhood pixels of the region. For the visual point of human beings, the global information is of great importance, which can provide the key features for us to analyze and segment an image.

Moreover, the local information can further provide specific features to segment the image effectively. Hence, in this paper, an approach based on self-organizing map [6] is proposed for color image segmentation and the parameters are also discussed. Our approach simultaneously considers both the global color similarity and local spatial distance relation. The main purpose of our approach is to present what human vision perceives when human beings observe an image. In accordance with the global feature, the image is first segmented to many coarse regions. The segmented clusters are further found by computing the local feature.

In addition, the assignment of parameters for SOM algorithm, i.e., the number of output nodes and iterations, is discussed and analyzed experimentally. Its selection will affect the segmentation result. Hence, by the Mean-Square-Error (MSE) measurement computes the difference of color pixel between the resultant image and the original one; and the parameters can be effectively assigned. In section 2, our approach will be discussed in details . Section 3 presents some experimental results. In the final section, we will give a brief conclusion.

2 The proposed approach

The main concept in color image segmentation is to simulate the recognition ability of human vision that utilizes SOM algorithm according to the features of global color similarity and local spatial distance relation. Using global color features in the SOM algorithm, the image can be first segmented into a set of finite color clusters. The distance information is obtained by computing the local spatial distance between any two color clusters. The SOM algorithm and labeling process are then used to classify the color planes into segmented clusters $[f]_{cluster(c)}$. The segmented results present the human attention region for an image.

In our approach, the process is principally constructed by SOM algorithm, labeling process, and spatial distance computation. The system is mentioned as follows. The images are represented as a 2-D color intensity function $f(i,j)$, where i and j denote spatial coordinates. The vector $f(i,j)$ is denoted by triples of numbers representing the strengths of their red(r), green(g), and blue(b) components, and can be denoted by a three-element color vector of $f(i,j) = (r_{i,j}, g_{i,j}, b_{i,j})^T$. Based on pixel classification, the image $[f]$ is segmented into subsets, called color planes $[f]_k$, $k = 1, 2, \ldots, K$, by assignment of the individual color vectors to classes. Each color plane $[f]_k$ contains one set of pixels with approximately the same color vector $(r^{(k)}, g^{(k)}, b^{(k)})^T$ and the other set of pixels with zero vector $(0,0,0)^T$. If the K color vector $[f]$ has been found, the original $[f]$ may be approximately indicated by the linear combination of $[f]_k, k = 1, 2, \ldots, K$;

$$[f] \approx [f]_1 + [f]_2 + \ldots + [f]_k = \sum_{k=1}^{K} [f]_k, \tag{1}$$

where the color plane $[f]_k$ may be approximately expressed as by

$$f_k(i,j) = \begin{cases} (r^{(k)}, g^{(k)}, b^{(k)})^T & \text{if} f(i,j) \approx (r^{(k)}, g^{(k)}, b^{(k)})^T, \\ (0,0,0)^T & \text{otherwise.} \end{cases} \tag{2}$$

That is, color image usually consists of a set of clusters, and each cluster is composed of some color planes. The clustering process can be achieved by computing the spatial distance between any two color planes, $[f]_h$ and $[f]_k$, $(h \neq k)$, to measure their nearness. The small the distance between two color planes, the higher is the possibility of both belonging to the same cluster. Otherwise, it is more possible to belong to different clusters. According to the local spatial distance information, the segmentation of color image is therefore reduced to classify color planes into several clusters. Assume that there are C clusters which appear. The segmented color image can be further denoted as follows.

$$[f] \approx \sum_{c=1}^{C} [f]_{cluster(c)}, \tag{3}$$

where

$$[f]_{cluster(c)} = \sum_{k \in cluster(c)} [f]_k. \tag{4}$$

If $c = 3$, the image is segmented to 3 clusters, such as the left image for Fig.1(a).

The SOM algorithm is first used to classify the pixels of color image $[f]$ into several clusters, and the labeling process is used to generate their respective color planes $([f]_k, k = 1, 2, \ldots, K)$. After the distance information between any two color planes has been obtained, the SOM algorithm and labeling process are then employed to classify the color planes into segmented clusters $([f]_{cluster(c)})$. See [4] for the detailed definition and computations. In [4], an approach based on human vision is proposed to segment the CBP image into pattern and background. However, in our system, we will further verify this algorithm and apply to process the complex image segmentation.

The assignment of parameters for SOM algorithm, that is, the number of output nodes and iterations, is an important item, and its decision usually depends on image data. Generally, these parameters are not critical and usually determined experimentally. In our system, in order to obtain these parameters, the MSE measurement which presents the difference of color pixel value between the resultant image and the original image is effective and easy to operate. If the number of output nodes increases, the MSE value will tend to stable variation in the range of scale. Thus, it is difficult to find out the difference between the resultant image and the original one. Otherwise, the MSE value will decay very sharp, and it becomes easy to find the difference between the resultant image and the original one. The MSE corresponding to the number of iterations is also the same phenomenon. The MSE corresponding to the number of output nodes and iterations is illustrated in Fig.2(a) and (b), respectively. In order to obtain the lower MSE, the higher iteration times may be selected; however, it will take a long time to achieve the convergence state of network, and may affect the result and performance of the system. Hence, the effective selection for these parameters is of great importance.

3 The experimental results

In this section, the results obtained from the proposed system are presented. We have utilized SOM algorithm, labeling process, and spatial distance computation to achieve the segmented clusters. Figures 2 (a)-(b) show the MSE between the resultant image and the original one corresponding to the number of output nodes and iterations of SOM algorithm, respectively. Generally, the assignment of parameters is not critical; rather, it depends on image data. The appropriate selection for the number of output nodes and iterations can only be determined experimentally [6]. From the experiment, the MSE tends to stable and plain variation when the number of output nodes exceeds 70. If the number of output nodes is selected more than this value, the resultant image is close to the original one, such as Fig. 1(b). Thus, the resultant and original images are very close to those obtained by human beings. However, if this parameter is assigned too large, the MSE may slightly change, but human vision will not be affected. It is because that the difference between some of the output nodes represented color is very small, and it is difficult to recognize by human vision. On the other hand, the number of iterations of SOM algorithm also affects the result and convergence time of network. In order to obtain the lower MSE and the faster convergence time, the higher iteration times may be selected; however, it will take a long computing time and may affect the performance of the system. Therefore, according to experimental measurement, the number of output nodes can be set in the range from 70 to 90, and the number of iterations can be assigned in the range from 15 to 30 times. In our experiment, the number of output nodes is set to 80, and the number of iterations is set to 20 times. We obtain 80 output nodes listed in Table 1 by performing SOM algorithm and labeling process for the given an image shown in the left image of Fig. 1 (a). Figure 1(b) shows the resultant image that merges 80 output nodes (color planes) to one picture corresponding to Fig.1(a), respectively. These resultant images are very close to the original ones of human observation. The segmented clusters are obtained by performing the spatial distance computation, the SOM algorithm and labeling process, shown in Figs.1(c)-(e). Each experimental image, as in Fig.1(a), is segmented into three clusters.

For a visual point of view, the global region and special objects, i.e., building, grass, sky, etc., can draw the attention of human eyes. For example, when human beings see the left image of Fig.1(a), the perceiving regions include sky, castle, grass or lake regions, and the segmented results present these regions. However, the experimental results may show some invalid segmented clusters (i.e., irregular edge points), such as the center and right images of Fig.1(d); yet it is acceptable. It is because when human being looks at an image, the global region and special objects are first extracted out, then the local information follows. Therefore, some irregular edge points and rough regions can not be merged together as objects and exist in the segmented results. Consequently, this approach provides a serial of procedures to understand the fundamental process of human vision system in color image segmentation. It also provides some primary information that help us to interpret the object features and meaning for image understanding.

4 Conclusions

We have shown the color image segmentation system based on the viewpoint of human vision. The principal characteristic of this algorithm takes account of both global color similarity and local spatial proximity. The major purpose of our approach is to present the human attention region but not the crisp segmentation region of conventional literature indicated. Thus, the segmented result shows the coarse segmentation but not crisp segmentation. However, this result is acceptable, and provides the primary information which is good for object recognition and image understanding. The experimental results show that the proposed approach is confirmable and feasible. Moreover, this approach can further help us to investigate intuitive human pattern recognition.

References

[1] N.R. Pal and S.K. Pal, A review on image segmentation techniques, *Pattern Recognition*, Vol. 26, No. 9, 1993, pp. 1277-1294.

[2] R. Schettini, A segmentation alforithm for color images, *Pattern Recongintion Letter*, Vol. 14, 1993, pp. 499-506.

[3] A. Tremeau and N. Borel, A region growing and merging algorithm to color segmentation, *Pattern Recognition*, Vol. 30, No. 7, 1997, pp. 1191-1203.

[4] Y.S. Chen and Y.C. Hsu, Computer vision on a colour blindness plate, *Image and Vision Computing*, Vol. 13, No. 6, 1995, pp. 463-478.

[5] W. Pratt, *Digital Image Processing*, 2^{nd} edition, John Wiley & Sons, Inc., 1991.

[6] T. Kohonen, *Self-Organization and Associative Memory*,2^{nd} edition, Springer-Verlag, New York, 1988.

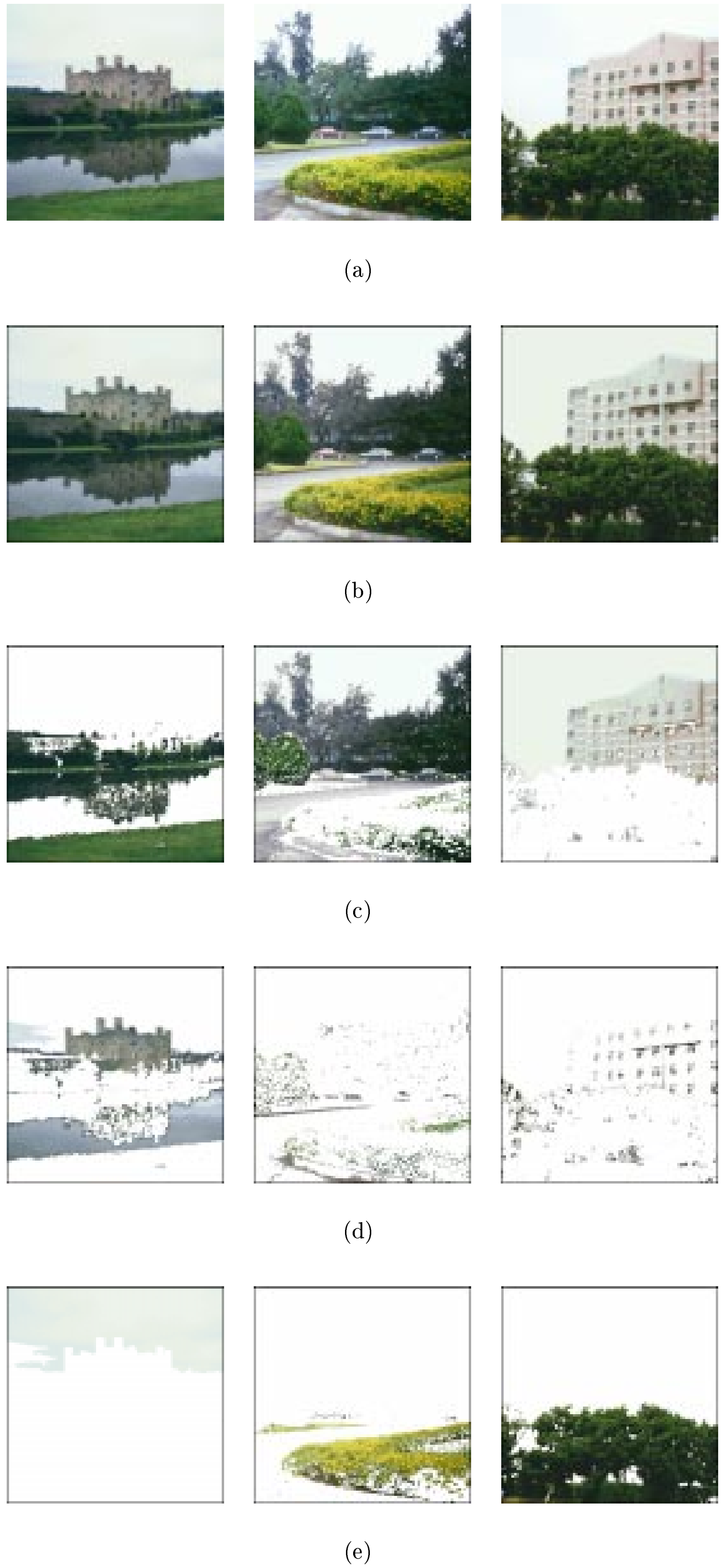
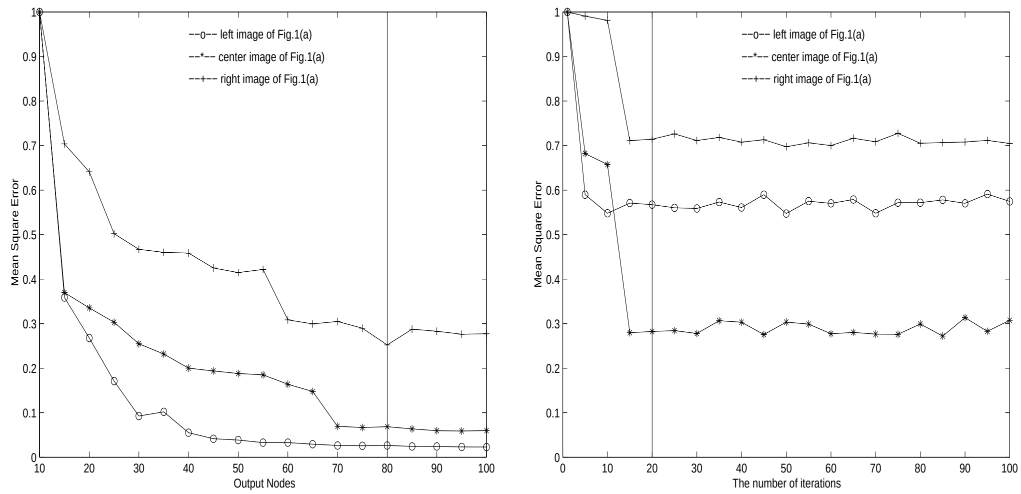


Figure 1: (a) Original images, (b) results of merging 80 output nodes. The segmented clusters are shown in (c)-(e), respectively.



(a) (b)

Figure 2: (a) and (b) illustrate the MSE between the resultant image and the original image corresponding to the number of output nodes, and that corresponding to the number of iterations, respectively.

Table 1: 80 output nodes in which each node is a three-element color vector.

Vector	**Output node**															
Elements	***m*=1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**
$r^{(m)}$	68	60	58	48	34	34	16	25	36	21	54	55	62	67	75	28
$g^{(m)}$	105	69	103	64	57	57	42	51	80	46	97	90	107	90	112	54
$b^{(m)}$	54	54	55	42	53	43	42	46	43	43	52	50	57	55	54	48
	***m*=17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**	**27**	**28**	**29**	**30**	**31**	**32**
$r^{(m)}$	69	74	59	65	55	42	66	128	96	79	79	58	81	69	92	47
$g^{(m)}$	82	89	79	80	72	87	79	147	124	95	96	100	97	113	97	68
$b^{(m)}$	84	81	60	76	66	46	68	157	78	80	61	49	103	60	75	76
	***m*=33**	**34**	**35**	**36**	**37**	**38**	**39**	**40**	**41**	**42**	**43**	**44**	**45**	**46**	**47**	**48**
$r^{(m)}$	47	102	93	80	89	80	143	94	101	163	124	170	140	151	108	153
$g^{(m)}$	92	118	110	118	118	118	156	125	111	166	138	176	139	163	122	148
$b^{(m)}$	49	133	111	65	65	64	167	69	97	157	122	175	113	175	122	125
	***m*=49**	**50**	**51**	**52**	**53**	**54**	**55**	**56**	**57**	**58**	**59**	**60**	**61**	**62**	**63**	**64**
$r^{(m)}$	213	141	160	189	223	237	235	231	233	227	229	145	119	106	154	116
$g^{(m)}$	227	154	174	203	235	243	241	241	240	237	238	159	125	117	154	131
$b^{(m)}$	230	154	189	218	232	235	233	234	230	232	231	171	102	109	137	139
	***m*=65**	**66**	**67**	**68**	**69**	**70**	**71**	**72**	**73**	**74**	**75**	**76**	**77**	**78**	**79**	**80**
$r^{(m)}$	132	136	80	105	158	172	80	40	88	119	105	52	46	46	60	104
$g^{(m)}$	147	152	117	131	157	86	92	61	103	140	130	70	77	66	77	102
$b^{(m)}$	142	165	56	89	147	73	92	58	93	92	76	62	49	62	74	82