EWFCM Algorithm and Region-Based Multi-level Thresholding

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Abstract. Multi-level thresholding is a method that is widely used in image segmentation. However, most of the existing methods are not suited to be directly used in applicable fields, and moreover they are not extended into a step of image segmentation. This paper proposes region-based multi-level thresholding as an image segmentation method. At first, we classify pixels of each color channel to two clusters by using EWFCM algorithm that is an improved FCM algorithm with spatial information between pixels. To obtain better segmentation results, a reduction of clusters is then performed by a region-based reclassification step based on a similarity between regions existing in a cluster and the other clusters. We finally perform a region merging by Bayesian algorithm based on Kullback-Leibler distance between a region and the neighboring regions as a post-processing method, as many regions still exist in image. Experiments show that region-based multi-level thresholding is superior to cluster-, pixel-based multi-level thresholding, and an existing method and much better segmentation results are obtained by the proposed post-processing method.

1 Introduction

Image segmentation plays an important role in understanding and analyzing image. In particular, region segmentation and object detection in image are both essential procedures for practical applications. Methods for image segmentation[1] include texture analysis-based methods, histogram thresholding-based methods, clustering-based methods, and region-based split and merging methods, among which threshold-based image segmentation[1, 2, 6-9] is widely used in many applications, such as document processing and object detection, as it is simple and efficient as regards dividing image into the foreground and background. Histogram thresholding-based methods use various criteria, such as Otsu's method[8], entropy-based method[2, 9], minimum error thresholding[10], and etc. However, none of these histogram thresholding-based methods include spatial information, which can lead to serious errors in the case of image segmentation. Plus, the selection of a threshold is very difficult, as the histograms of most real-images have an ambiguous and indistinguishable distribution. To

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solve the problem, FCM(fuzzy c-mean algorithm)[3-5], as a representative fuzzy clustering algorithm, has become a powerful tool that has been successfully applied to image thresholding to segment image into meaningful regions. However, certain problems like noise still remain, as no spatial information is included. In segmenting image, spatial information is an essential part since a pixel in real-image has a relation with the neighbors. In this paper, we propose EWFCM(entropy-based weighted FCM) algorithm using classification information between a pixel and the neighbors for classifying pixels in each color channel.

Threshold-based methods segment image using thresholds extracted from a brightness distribution of the image and many methods concerning them are being proposed at present. However, most of them focused on selecting the optimal thresholds for segmenting image. In case of segmenting image only using thresholds, they are not suited to be directly used in applicable fields, as image is segmented into very many regions. And most of the existing methods left the extension into image segmentation as a future work, otherwise they were proposed as a pre-processing method to obtain a finally segmented image. Y. Du[6, 7] used a histogram thresholding-based method for each color component in color image, and then multi-level image thresholding is performed by the optimal clusters determined by the within-class and between-class distance of the clusters, which are classified for each color component. Yet, this method is difficult to extend to multi-level thresholding for each color component and a reclassification of cluster-units to detect the optimal clusters leads to incorrect image segmentation. In this paper, we propose region-based multi-level thresholding as an extended method for image segmentation, which is performed to obtain better segmentation results by reducing clusters. Region-based multi-level thresholding is performed by a reclassification step based on similarities between the reclassified regions in a cluster and the other clusters. However, many similar or small regions still exist in image. To remove these regions, we perform a region merging using Bayesian algorithm based on Kullback-Leibler distances between regions.

2 EWFCM Algorithm and Region-Based Multi-level Thresholding

This paper consists of three steps, including EWFCM algorithm for classifying pixels in each color channel, region-based multi-level thresholding for efficiently reducing the clusters, and a region merging by Bayesian algorithm based on Kullback-Leibler distances between regions to obtain better segmentation results.

2.1 EWFCM(Entropy-Based Weighted FCM) algorithm

FCM(fuzzy c-means) algorithm[3-5] is widely used in image segmentation as an unsupervised segmentation algorithm. The objective function $J_m(U,V)$ in FCM algorithm is given by :

$$J_m(U,V)=\sum_{i=1}^{c}\sum_{j=1}^{n}(u_{ij})^m \left\| v_i - x_j \right\|^2 \tag{1}$$

where x_j is the gray-level value of j'th pixel and v_i is the mean value of i'th cluster. A solution of the objective function $J_m(U,V)$ can be obtained via an iterative process, where the degrees of membership and the mean value of cluster are updated via:

$$u_{ij} = \frac{1}{\sum_{k=1}^{c}\left(\| v_i - x_j \| / \| v_k - x_j \| \right)^{2/m-1}} \qquad v_i = \sum_{j=1}^{n}(u_{ij})^m x_j \Big/ \sum_{j=1}^{n}(u_{ij})^m \tag{2}$$

where u_{ij} is the degree of membership between the j'th pixel and i'th cluster, v_i is the mean value of i'th cluster, c is the number of clusters, and m is an arbitrarily chosen FCM weighting exponent that must be greater than one.

FCM algorithm can classify most of noise-free real-images, which have an uncertain and complex data distribution. However, as FCM algorithm does not incorporate spatial information, it may fail to segment image corrupted by noise and other imaging artifacts.

The neighborhood information is incorporated into FCM algorithm to remove any noise. In image, since the center pixel has a relationship with its neighbors, the probability that the center pixel and its neighbors will be classified in the same cluster is high. As such, Y. Yang[5] proposed a spatially weighted FCM algorithm using k-NN(nearest neighbor) algorithm, which is based on a distance between a mean gray-value of a cluster and a gray-value of a current pixel. However, Y. Yang's method may be lead to an incorrect classification if the histogram distributions of clusters are different. And it needs to define a parameter in advance. Therefore, this paper proposes an improved entropy-based weighted FCM(EWFCM) algorithm, where a weight based on entropy that takes into account the spatial relationship between the current pixel and its neighbors is applied to FCM algorithm.

The improved degrees of membership u_{ij}^* and v_i^* are given by:

$$u_{ij}^* = \frac{w_{ij}}{\sum_{k=1}^{c}\left(\| v_i - x_j \| / \| v_k - x_j \| \right)^{2/m-1}} \qquad v_i^* = \sum_{j=1}^{n}(u_{ij}^*)^m x_j \Big/ \sum_{j=1}^{n}(u_{ij}^*)^m \tag{3}$$

For i'th cluster, j'th pixel possessed a high ratio of belonging to i'th cluster when many neighbors of j'th pixel belong to i'th cluster. Then w_{ij} possesses a high weight as regards belonging to i'th cluster, and w_{ij} is calculated as:

$$w_{ij} = 1 - \frac{e_i}{e_i + e_k} = 1 - \frac{p_i \log(p_i)}{p_i \log(p_i) + p_k \log(p_k)} \tag{4}$$

$$p_i = \frac{1 + \#\text{ of } x_{en} \text{ in the set } N_j^i}{1 + \#\text{ of } x_{en} \text{ in the set } N_j} \qquad p_k = \frac{1 + \#\text{ of } x_{en} \text{ in the set } N_j^k}{1 + \#\text{ of } x_{en} \text{ in the set } N_j} \tag{5}$$

where x_{en} is the neighboring pixel of j'th pixel that is the center pixel, N_j is the set of the neighbors nearest to the center pixel, N_j^i is the subset of N_j composed of the pixels belonging to i'th class, N_j^k is the subset of N_j except N_j^i, p_i is the ratio that the neighbors of the j'th pixel belong to the same cluster, and p_k is the ratio that the neighbors of the j'th pixel do not belong to the same cluster. w_{ij} is then obtained by the entropy of Shannon based on those ratios. EWFCM algorithm can correctly classify pixels by only using a classification index between a current pixel and the neighbors and is performed faster than Y. Yang's method. And code image that is based on the cluster number extracted by EWFCM algorithm for each color component is created by $c_j = r_j level^0 + g_j level^1 + b_j level^2$ where, for j'th pixel, c_j is the combined cluster numbers in code image and (r_j, g_j, b_j) is the cluster number extracted by EWFCM algorithm for each color channel. And $level$ is the number of clusters for each color channel. If $level$ is set to 2, code image consists of all 8 clusters, and each cluster is assigned a cluster number from 0 to 7. If $level$ increases, the clusters in the code image abruptly increases. Therefore the clusters need to be reduced in the reclassification step.

2.2 Region-Based Multi-level Thresholding

Based on classification results for each color channel obtained by EWFCM algorithm, a pixel, region, or cluster that exists in code image is used as a reclassification unit. By reducing the clusters in code image by a reclassification step, we can obtain better segmentation results. In this paper, we describe region-based multi-level thresholding and pixel- and cluster-based multi-level thresholding are performed by the same procedure as region-based multi-level thresholding.

Region-based multi-level thresholding is performed by distances between regions segmented from a reclassified cluster and the other clusters. At first, a selection of the reclassified cluster is given by :

$$\max_{k \in all\_cluster} \left(\frac{\mathrm{var}_k}{1.0 + \mathrm{var}_{all}} \times \frac{size_{all} - size_k}{size_{all}} \times \frac{\max\_dis_{all} - \min\_dis_k}{\max\_dis_k} \right) \tag{6}$$

where var_k, var_{all}, $size_k$, and $size_{all}$ are variances and sizes of k'th cluster and image, respectively. And $\max\_dis_k$ and $\min\_dis_k$ are maximum and minimum distances between k'th cluster and the other clusters, respectively. For all clusters($all\_cluster$), a cluster is selected when its variance is large while its size is small and distances between it and the others are short. Regions existing in the reclassified cluster are then reclassified into most similar clusters by :

$$\min_{c \in all\_cluster - k_{index}} \left(\frac{\mathrm{var}_{r,c}}{\mathrm{var}_r + \mathrm{var}_c} \right) \tag{7}$$

where var_r and var_c are variances of r'th region in the reclassified cluster(k_{index}) and c'th cluster among the other clusters ($all\_cluster - k_{index}$), respectively. And $\mathrm{var}_{r,c}$ is variance after r'th region and c'th cluster are merged. A cluster is selected as a most similar cluster when a ratio of a sum of each variance before merging them to variance after merging them is the lowest.

A reclassification step is repeatedly performed until the number of clusters is the same as a pre-defined number. If the number of clusters is not defined, the optimal number of clusters is selected when an average within-class distance for the clusters in process of reclassifying all clusters into 2 clusters is minimal. The optimal number of clusters is selected by:

$$opt_{cluster} = \min_{all\_cluster}\left(\sum_{i=1}^{size_{all\ cluster}} wd_i \Big/ size_{all\_cluster} \right) \qquad all\_clsuter \geq 2 \tag{8}$$

$$wd_i = \frac{\sqrt{\sum_{j=1}^{size_i}\left((r_j - m\_r_i)^2 + (g_j - m\_g_i)^2 + (b_j - m\_b_i)^2\right)}}{size_i} \tag{9}$$

where $opt_{cluster}$ is a minimum average within-class distance for all clusters, $size_{all\_cluster}$ is the number of clusters, wd_i and $size_i$ are a within-class distance and size of i'th cluster, respectively. (r_j, g_j, b_j) is gray-values for red, green, blue color channel of j'th pixel existing in i'th cluster and (m_r_j, m_g_j, m_b_j) is average gray-values for red, green, blue color channel of i'th cluster.

2.3 Region Merging Using Bayesian Algorithm

As a post-processing method that is performed to obtain better segmentation results, regions that size is small are merged into the most similar neighboring regions. And similar regions are merged by Bayesian algorithm based on Kullback-Leibler distances between a merged region and the neighbors. The process for a region merging is as follows:

① A region that has the largest variance among all regions is selected as a merged region by :

$$\max_{r \in all\_region}\left(\mathrm{var}_r \times \frac{size_r}{size_{image}} \right) \tag{10}$$

where var_r and $size_r$ are variance and size of r'th region, respectively, $size_{image}$ is size of image.

② Kullback-Leibler distances between the region selected at ① step and its neighbors are measured by :

$$d(h_c, h_j) = \sum_{g=0}^{255}\left(h_c(g) - h_j(g)\right)\log\frac{h_c(g)}{h_j(g)} \tag{11}$$

where $d(h_c, h_j)$ is a distance between j'th region and c'th region and $h()$ is a function that has probability values obtained from a histogram distribution of the region.

③ After a most similar neighboring region for the region selected at ① step is selected by Bayesian algorithm, the regions are merged if their similarity is larger than a given threshold(0.7).

$$\max_{j \in nr}\left(\frac{P(r_c|r_j)}{\sum_{i=1}^{nr} P(r_c|r_i)}\right) \quad P(r_c|r_j) = \frac{dis_{c\_j}}{\sum_{k=1}^{nr} dis_{c\_k}} \quad dis_{c\_k} = \frac{1.0}{1.0 + d(h_c, h_k)} \tag{12}$$

where, on the assumption that $P(r_j)$ is same, $P(r_c|r_j)$ is a probability value based on a distance(dis_{c_j}) between the region(r_c) selected at ① step and j'th region(r_j) among the neighboring regions(nr) and it is a similarity that takes account of distances of the neighboring regions.
④ ①～③ steps are repeatedly performed until the clusters are not reduced.

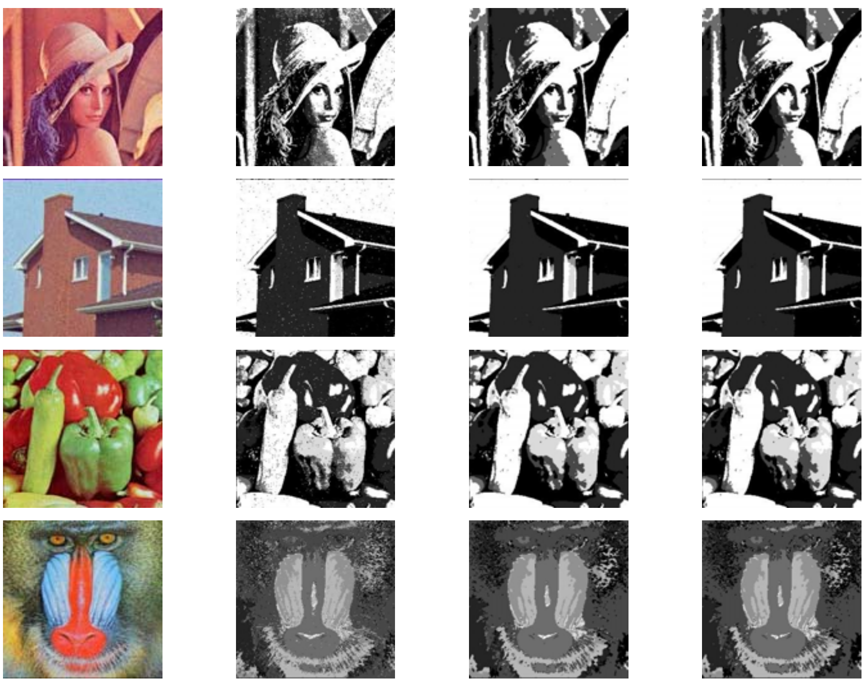
3 Experiment

All the algorithms in this paper were coded using SDK Version 1.4.1 in Window XP. And a function developed by M. Borsotti[11] was used for the performance evaluation.

$$Q(I) = \frac{\sqrt{R}}{10000\,(N \times M)} \times \sum_{i=1}^{R}\left(\frac{e_i^2}{1 + \log(A_i)} + \left(\frac{R(A_i)}{A_i}\right)^2\right) \tag{13}$$

where I is a segmented image, N and M are the width and height of the image, respectively, R is the number of regions in a segmented image, A_i and e_i are the area and average color error for the i'th region, respectively. $R(A_i)$ represents the number of regions with an area equal to A_i. The smaller the value of $Q(I)$, the better the segmentation result.

Fig. 1 shows code images for comparing performances of each method for noise removal. Fig. 1(a) is noisy images with added 5% salt & pepper noise. Figs. 1(b)～(d) are code images that consist of 8 clusters after classifying pixels for each color channel into 2 clusters by FCM algorithm, Y. Yang method, and EWFCM algorithm. Y. Yang method and EWFCM algorithm effectively removed noise while FCM algorithm left noise as it is. And as compared to Y. Yang method, EWFCM algorithm obtained a little better result. Moreover, the computational time of EWFCM algorithm showed approximately 59% from Y. Yang method for Fig. 1(a). After creating code image, a reclassification step is performed to reduce clusters existing in code image. Table 1 shows performance evaluations and the number of regions for the segmented image when a pixel, region, and cluster are used as an unit of the reclassification. Pixel- and cluster-based multi-level thresholding are performed by the same process as region-based multi-level thresholding. Bold and slant letters in table 1 show performance evaluations obtained from the optimal clusters. As be seen in table 1, the optimal number of clusters selected by a minimum average within-class distance doesn't accord with that by M. Borsotti, since a minimum average within-class distance only depends on a difference between average gray-values of a cluster and gray-value of pixels that are classified into the cluster. However, we used a minimum average within-class distance for more quickly selecting the optimal clusters. Region-based multi-level thresholding showed the best performance although the number of regions is smaller. Pixel- and cluster-based multi-level thresholding showed that the number of regions is either same or more although the number of clusters is reduced. This means that a pixel or regions in a cluster are reclassified into the remaining clusters as an independent region and a reclassification of a pixel or a cluster has no effect on more improvement of segmentation results. That is to say, this shows that a region is a more important factor than a pixel and a cluster in segmenting an image. And all methods showed that performance evaluations have a high value if too many clusters are reduced in a reclassification step, since a brightness error in a region is as much larger as reducing the number of regions.



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

Fig. 1. Performance evaluation comparison of the proposed method and the existing methods for removal of noise. (a) Noisy images with added 5% salt & pepper noise. (b) Code images by FCM algorithm. (c) Code images by Y. Yang method. (d) Code images by EWFCM algorithm.

Table 1. Comparison of performance evaluations by region-, cluster-, and pixel-based multi-level thresholding. Row : Number of clusters. Column : Experimental images and reclassification methods, including region-based, cluster-based, and pixel-based reclassification.

		8	7	6	5	4	3	2
Lena	Region	2212.9 (668)	2210.0 (666)	2180.2 (648)	2118.6 (610)	1954.0 (499)	***2578.9 (254)***	5100.7 (61)
	Cluster	2212.9 (668)	2212.9 (668)	2212.9 (668)	2207.9 (665)	2100.1 (600)	***2769.5 (300)***	5821.9 (77)
	Pixel	2212.9 (668)	2212.9 (668)	2240.6 (684)	2099.9 (599)	2383.8 (740)	***3523.6 (507)***	6072.4 (89)
House	Region	313.5 (427)	311.1 (420)	307.9 (411)	306.7 (407)	241.0 (212)	***245.3 (198)***	2307.5 (42)
	Cluster	313.5 (427)	313.1 (426)	307.8 (409)	310.8 (407)	255.8 (230)	263.6 (223)	***1586.2 (18)***
	Pixel	313.5 (427)	313.8 (428)	310.5 (419)	310.2 (417)	311.1 (419)	***267.6 (246)***	1791.4 (24)
Peppers	Region	1218.4 (607)	1204.1 (591)	1153.8 (531)	1124.8 (481)	***1005.7 (286)***	5918.4 (194)	3669.3 (57)
	Cluster	1218.4 (607)	1218.4 (607)	1201.8 (590)	1164.8 (519)	1456.8 (313)	7143.4 (253)	***3464.1 (52)***
	Pixel	1218.4 (607)	1220.4 (607)	1235.1 (618)	1209.1 (557)	1676.1 (443)	5347.6 (254)	***6349.2 (83)***
Baboon	Region	3024.9 (1234)	3022.6 (1232)	2997.9 (1207)	3755.4 (1022)	***3365.5 (749)***	6733.9 (502)	31568.2 (216)
	Cluster	3024.9 (1234)	3024.9 (1234)	3020.0 (1230)	3855.6 (1095)	3479.1 (817)	***6470.0 (440)***	16550.8 (55)
	Pixel	3024.9 (1234)	3037.5 (1244)	3194.7 (1329)	3274.6 (1340)	***3377.9 (1356)***	5435.7 (507)	34327.2 (660)

Fig. 2 shows the segmented images and performance evaluations by the proposed method and Y. Du's method. Y. Du segmented image using the optimal clusters that are selected by a within-class and between-class distances of clusters after creating code image and classifying pixels into 2 clusters for each color channel by Otsu and Kapur methods. In Fig. 2, the proposed method was superior to Y. Du's method despite having less clusters and regions for all experimental images except that Y. Du(Kapur) showed the best performance evaluation for 'lena' image. However, as be seen in Fig. 2, the proposed method showed the best segmentation results in point of visual view. And the optimal number of clusters that is selected by the proposed method was less than that by Y. Du's method. That is to say, this means that the proposed method can display image using less color information than Y. Du's method. Fig. 3 shows the resulting images that are finally segmented by a region merging for

Fig. 2(c). A region merging is performed by Bayesian algorithm based on Kullback-Leibler distances between regions. As compared with the results that are only obtained by region-based multi-level thresholding, better segmentation results were showed although many regions were reduced. Therefore, it shows that the proposed region merging algorithm is valid and effective as a post-processing method for image segmentation.

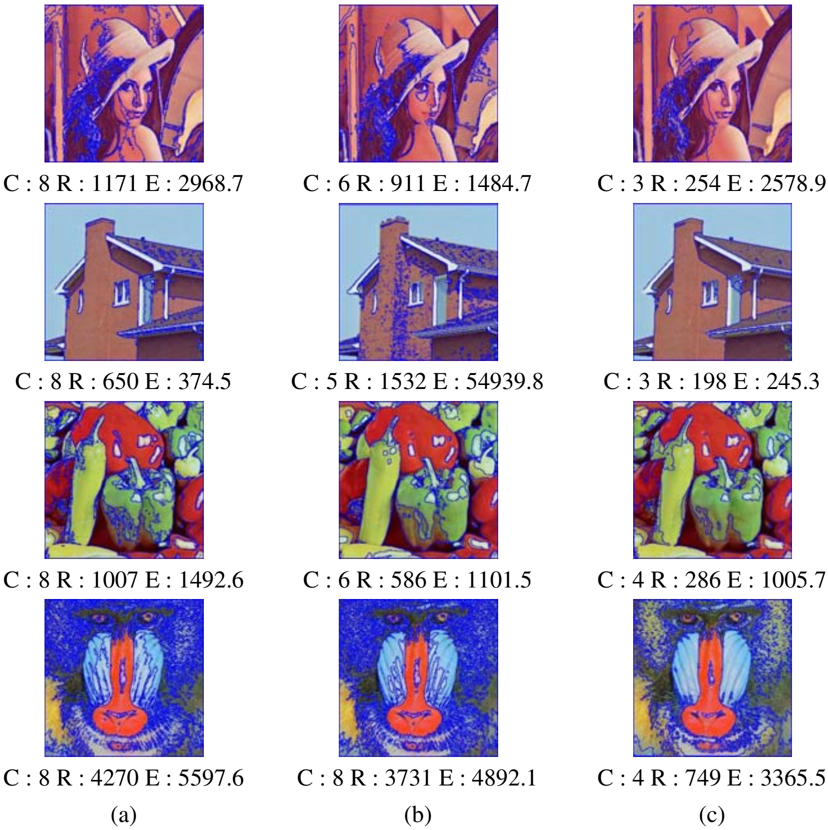


Fig. 2. Segmented images and performance evaluations (a) : by Y. Du(Otsu) (b) : by Y. Du(Kapur) (c) : by the proposed method. C : Number of clusters. R : Number of regions. E : Performance evaluation

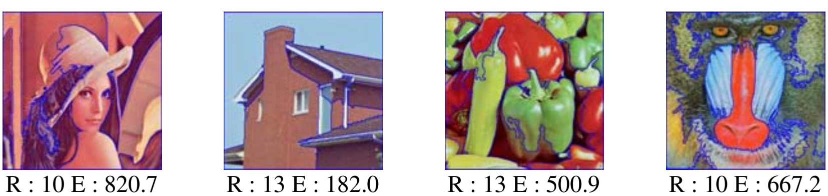


Fig. 3. Finally segmented images and performance evaluations by region merging. R : Number of regions. E : Performance evaluation.

4 Conclusion

This paper proposes region-based multi-level thresholding for color image segmentation. EWFCM algorithm that is used in classifying pixels for each color channel into 2 clusters effectively removed noise and was faster performed than an existing method. And as a multi-level thresholding method that is extended into image segmentation, region-based reclassification showed better segmentation results than a pixel- and a cluster-based reclassification as well as an existing method. In image segmentation, this means that a region is a more important factor than a pixel and a cluster. In addition, by performing a region merging using Bayesian algorithm based on Kullback-Leibler distances between a region and the neighbors, we obtained more accurate segmentation results than those that are obtained by only using region-based multi-level thresholding. The proposed method is possible to be applied into various fields, including extraction of principal color information, object detection, image retrieval, and so on. And an application of the proposed method with reducing the computational time is areas under further study.

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