IJCSE International Journal of Computer Sciences and Engineering Open Access
Research Paper Volume-1, Issue-3 E-ISSN: 2347-2693

Improved Color Image Segmentation using Kindred Thresholding and Region Merging

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www.ijcaonline.org

Received: 02 Nov 2013 Revised: 208 Nov 13 Accepted: 26 Nov 13 Published: 30 Nov 2013

Abstract- In this paper, a color image segmentation approach based on holographic thresholding and region merging is presented. The holographic image considers both the occurrence of the gray levels and the neighboring nearest value amongst pixels. Thus, it employs both the local and global information. Holographic analysis is performed using fuzzy entropy as a tool for finding all major kindred regions at the first stage followed by region merging process which is carried out based on color similarity amongst these regions to avoid over segmentation. The proposed Kindred -based approach (KOB) is compared with the histogram-based approach (HIB). The experimental results demonstrate that the KOB can find similar regions more effectively than HIB does, and thus can solve the problem of discriminating shading in color images to a greater extent.

Keywords: Color Image Segmentation, Fuzzy Logic, Region Merge, Color Space, Thresholding

1. INTRODUCTION

Image segmentation is the first step in image analysis and pattern detection. It is a critical and essential component of an image analysis and/or pattern detection system, and is one of the most difficult tasks in image processing that determines the quality of the final result of analysis.

Color image segmentation is attracting more and more attention. It is a long known fact that the human eye can differentiate thousands of color shades and intensities but only two-dozen shades of gray. This situation often occurs when the objects cannot be extracted using gray scale information but can be extracted using color information. As compared to gray scale, color provides additional information to the intensity. People even realize that color is necessary for pattern recognition and computer vision. Also, the acquisitions as well as 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. Consequently color image processing becomes increasingly prevalent nowadays.

In most of the existing color image segmentation methods, the definition of a region is based on related color. Monochrome image segmentation techniques can be extended to color image, such as clustering, histogram thresholding, edge detection, region growing, fuzzy logic and neural networks by using RGB or their transformations (linear/non-linear) [1].

Monochrome segmentation methods can be directly applied to each component of a color space. Then the results can be combined in some way to obtain the final segmentation results [2]. Generally speaking, monochrome image segmentation approaches are based on either discontinuity and/or similarity of gray level values in a region. This approach based on discontinuity tends to partition an image by detecting isolated points/lines and edges based on abrupt changes in gray levels. The approaches based on similarity include clustering, thresholding, region growing, and region split and merge etc. A mixture of these approaches is often utilized for color image segmentation [3-8]. There are quite a few survey papers on monochrome image segmentation [9–12] which cover major image segmentation techniques available.

Each color representation has its pros and cons. There is still no color representation that can yet dominate the others for all kinds of color images. Nonlinear color transformations such as HSI and normalized color space have essential singularities that can't be removed, and there are spurious modes in the distribution of values resulting from the nonlinear transformations. The main problem of linear color spaces is the high correlation of the three components which makes the three components dependent upon each other and associate strongly with intensity. Therefore, linear spaces are quite inefficient in discriminating shadows, highlights and shading in color images. Using HSI can solve this problem to some extent except that hue is unstable at low saturation [13].

In this paper, a color image segmentation approach based on holographic thresholding and region merging in a color space is presented. The concept of the holographic is used to express the information of homogeneous properties

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among pixels in an image. First, we use holographic analysis to and all major homogeneous regions. Then the region merging process is carried out based on color similarity among these regions to solve the problem of over segmentation.

In the subsequent sections, we describe the proposed method in Section 2. Results are presented in Section 3. Conclusions are presented in Section 4.

2. PROPOSED METHOD

Histogram thresholding is one of the many widely used techniques for monochrome image segmentation but it is based on only gray level and does not take into account the spatial information of pixels with respect to each other. The concept of holographic was defined to express the information of similar properties among pixels in an image. In this paper, we employ the concept of the holographic to extract similar regions in a color image. The proposed method is divided into two stages. In the first stage fuzzy similarity approach is applied to three color components to find thresholds for each color component. In the second stage the segmentation results for the three color components are combined to partition the color space into several clusters. A few of these clusters may only contain too few pixels and should not be considered as proper clusters. There might even be some clusters that are very close to each other and they should be merged. This problem will be solved at the second stage using the region merging approach.

2.1 Holographic Thresholding Approach

2.1.1 Holography

A general concept of the holography is given is as follows. First, fuzzy similarity vector, which sums the degree of similarity occurring between the pixel with gray level t and its neighbors with different angle ϴ, and neighboring distance d, is defined as

$$h(t,\theta,d) = \{\sum \delta_z(|t-r|) | t = g(k,l), t, r \in G, 1 \leq i \leq M, 1 \leq j \leq N, [(i,j),(k,l)] \in (X \times Y) \times (X \times Y) \parallel (i,j)-(k,l)| = d \; along \; the \; \theta \text{ direction}\} \quad (1)$$

where

$\theta \in \{0^0, 45^0, 90^0, 135^0, 180^0, 225^0, 270^0, 315^0\}$

, G is the set of gray levels , and $\delta_z(\,)$ is a Z-function, defined as:

$$\delta_z(x) = Z(x,a,b,c) = \begin{cases} 1 & 0 \leq x \leq a \\ 1 - 2 \times \left(\dfrac{x-a}{c-a}\right)^2 & a \leq x \leq b \\ 2 \times \left(\dfrac{x-c}{c-a}\right)^2 & b \leq x \leq c \\ 0 & c \leq x \leq L \end{cases} \quad (2)$$

where L is the maximum gray level, a=0, b = L/2, and c = L. Z-function is used as the fuzzy membership function to denote the degree of similarity between two pixels with gray levels $g_{,i,j}$ and $g_{,k,l}$ respectively. Then, based on fuzzy similarity vector the holographic threshold of an M, N image is defined as

$$H(t,d) = \frac{1}{4}\left[\frac{h(t,0^2,d)}{(M-1)N} + \frac{h(t,45^2,d)}{(M-1)(N-1)} + \frac{h(t,90^2,d)}{M(N-1)} + \frac{h(t,135^2,d)}{(m-1)(N-1)}\right] \quad (3)$$

In our experiment d = 1 since we want to consider the homogeneity in small regions.

2.1.2 Kindred Threshold

Mode method is one of the widely used techniques for image segmentation. It presumes that images are composed of regions with different gray level ranges. The histogram of an image can be divided into a number of peaks where each corresponds to a region and there exists a threshold at the valley between any two adjacent peaks. Once the kindred of an image is obtained, the mode method can be applied to it in the similar manner. The holographic method considers both the occurrence of the gray levels and the neighboring homogeneity value among pixels, while histogram-based approaches do not take into account any local information. Therefore, kindred thresholding approaches tend to be more effective in finding homogeneous regions than histogram thresholding approaches.

Fuzzy entropy takes into account the fuzziness of the images based on information theory and fuzzy logic and it is used as a criterion to find thresholds automatically. In kindred thresholding method, the kindred is used to find fuzzy region width and thresholds for segmentation. The modified entropy function under fuzzy set is computed based on the fuzzy region width, Shannon's function and the Kindred.

Let $F = \{ f_1, f_2, f_3 \ldots.. f_L \}$ be a set of fuzzy membership values which are obtained by fuzzying all of the gray values in G using the standard S function and a suitable fuzzy region width $f_i = \delta_s(g_i)$ where g_i is a gray in G and δ_s is a membership function represented as:

$$\delta_s = S(g,a,b,c) = \begin{cases} 0 & 0 \leq g \leq a \\ 2 \times \left(\dfrac{g-a}{c-a}\right)^2 & a \leq g \leq b \\ 1 - 2 \times \left(\dfrac{g-c}{c-a}\right)^2 & b \leq g \leq c \\ 1 & c \leq x \leq 1 \end{cases} \quad (4)$$

The degree of the fuzziness in an image I was usually measured by the entropy under fuzzy set F

$$E(F) = \frac{1}{MN \ln 2} \sum_{x=1}^{M} \sum_{y=1}^{N} S_n \left(\delta\big(g(x,y)\big) \right) \quad (5)$$

where $S_n(\delta)$ is the Shannon's entropy function. For simplicity, we use δ to represent $\delta_s(g(x,y))$ and $S_n(\delta)$ can be written as

$$S_n(\delta) = -\delta \ln \delta - (1-\delta) \ln(1-\delta) \quad (6)$$

Fuzzy entropy *E (F)* can also be expressed as:

$$E(F) = \frac{1}{MN \ln 2} \sum_{g=1}^{L} S_n \left(\delta_s(g) \right) f(g) \quad (7)$$

where *f(g)* denotes the number of occurrences of gray '*g*'. It was claimed that the method could sharpen an input histogram by removing the local variations and ambiguities. This principle is not valid for the images where the existent objects cannot be described suitably by the histograms alone where in the spatial dependencies among the pixels have to be considered. Hence, *H(g)* is used in place of *f(g)/MN*, and redefine the *E(F)* as

$$\mathrm{E(F)} = \frac{1}{\ln 2} \sum_{g=1}^{L} S_n \left(\delta_s(g) \right) H(g) \quad (8)$$

where *K(g)* is a kindred denoting the degree of homogeneity of the gray level g. In Eq. 5 $E(F) \in [0, 1]$, indicates the degree of ambiguity of image *I*.

In our experiment, '*a*' is the grey level value corresponding to the leftmost peak of the holographic and '*c*' is the grey level value corresponding to the rightmost peak of the kindred. *(c-a)* is the width of fuzzy region and $b = (c+a)/2$. We apply the fuzzy similarity approach to three components of a color image. Then, the segmented results of three components are combined to get all possible clusters.

Assume the range of gray levels of color component '*i*' $(i = 1, 2, 3)$ is $[Li_0, L_{i1}]$, C_i represents the number of thresholds (including Li_0, L_{i1}) for color component '*i*', then the set of thresholds for color component '*i*', TS_i, is

$$TS_i = \{T_{i,j \mid j=1,2,3,\ldots,C_i}\}, i = 1,2,3 \quad (9)$$

where $T_{i,1}=L_{i0}$ and $T_{i,Ci} = L_{i1}$ and $T_{i,2}$, $T_{i,3}$ … $T_{i,Ci-1}$ are the thresholds obtained by the above approach.

Thus we can partition the color space into several clusters by

$$CLUSTER_{mnl} = \{(x,y) \mid gl_1(x,y) \in [T_{1,m}, T_{1,m+1}], gl_2(x,y) \in [T_{2,n}, T_{2,n+1}] \text{ and } gl_3(x,y) \in [T_{3,l}, T_{3,l+1}] \} \quad (10)$$

where $1 \le m \le C_1$, $1 \le n \le C_2$, $1 \le l \le C_3$, (x,y) is the pixel at row x and column y of a color image, and *gl(1), gl(2) and gl(3)* are the three color component images.
Every cluster is represented by its average color value.

2.1.3 Color Spaces

Color is perceived by human as a combination of tri-stimuli R(red), G(green) and B(blue) which are usually called three primary colors. From RGB, we can calculate different kinds of color representations (spaces) by using either linear or nonlinear transformations. Several color spaces, such as RGB, HIS, CIE $L^*u^*v^*$, etc, are employed for color image segmentation, but none can dominate the others for all kinds of color images. Selecting the best color space still remains one of the difficulties in color image segmentation.

RGB model is the most commonly used model for pictures acquired by digital cameras and television system. Video monitors display color images through modulation of the intensity of the three primary colors (red, blue and green) in each pixel of the image [14]. The major problem of RGB and their linear transformations for color scene segmentation and analysis is the high correlation among the RGB components [15]. High correlation means that if the intensity changes, all the three components will change proportionately.

The HSI (hue-saturation-intensity) system is another commonly used color space in image processing and is more intuitive to the human vision [16, 17]. The HSI system separates color information of an image from its intensity information. Hue and saturation values represent the color information, while intensity that describes the brightness of an image is determined by the amount of the light. HSI color space can be described geometrically as in Fig (2) and is a cylindrical solid.

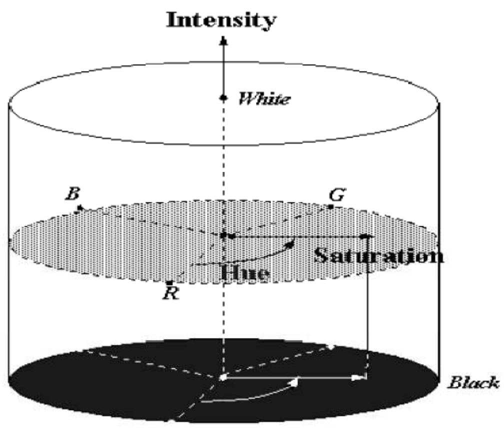

Fig.(1) HSI Color space

The range of the hue is from 0^0 to 360^0 the intensity is the height in the axis direction and the saturation is a radial distance from the cylinder center.

The formulas for hue, saturation and intensity are:

$$Hue = \arctan\left(\frac{\sqrt[2]{3}(G-B)}{(R-G)+(R-B)}\right)$$

$$Int = \frac{(R+G+B)}{3}$$

$$Sat = 1 - \frac{\min(R,G,B)}{Int}$$

The hue is undefined if the saturation is zero, and the saturation is undefined when the intensity is zero. The disadvantage of hue is that it has singularities that cannot be removed near the axis of the color cylinder, where a small variation in *R, G,* and *B* values can cause a large change in the transformed values. The singularities may create discontinuities in the representation of colors [18]. Hue value near its singularities is numerically unbalanced. That is why in many segmentation algorithms pixels having low saturation are left unassigned. In addition, if the intensity of the color lies close to white or black, hue and saturation slightly play a role in distinguishing colors.

Nonlinear color transformations such as HSI and normalized color space have essential singularities which could not be removed, and there were spurious modes in the distribution of values resulting from the nonlinear transformations. It is suggested that linear spaces such as YIQ, be used rather than nonlinear spaces [19]. A major problem of linear color spaces is high correlation of the three components that makes the three components dependent upon each other and associate strongly with intensity. Hence, linear spaces are very difficult to discriminate shadows, highlights and shading in color images. If a linear color space is used, image segmentation has to be performed in a *D* space usually on one component at a time because it is difficult to combine the information innate in these components. However, *nonlinear* color spaces do not have these kinds of problems. Also in HSI space, hue is used for segmentation when the saturation is not low and certain types of highlights, shadows and shading can be discounted.

2.2 The Region Merging Approach

In the first step, finding all major classes is essential to the final segmentation. Therefore, we have to select proper parameters for determining peaks of the holographic and fuzzy entropy of the image. This might lead to over segmentation i.e. homogeneous regions with narrow color transition might be split as separate regions or very small regions might be generated. Hence, the clusters achieved in the first step are not the final segmentation results. Few clusters may contain very few pixels and should not be considered as proper clusters. There might be few clusters that are very close to each other and they may need to be combined. We use the region merging approach to solve this problem.

2.2.1 The Region Merging Criterion

One problem with region merging is how to define merging criteria. Including specific knowledge of psychophysical perception is an ideal way, but this is not practical for application. Generally, region merging is based on both feature space and the spatial relation between pixels simultaneously. In this paper, the definition of a region is based on similar color. For this reason, we only take into account color similarity when deciding if two regions are to be merged.

We select RGB as the color space so as to measure the distance between two clusters C_m and C_n:

$$Dist(C_m, C_n) = \max(|R_m - R_n|, |G_m - G_n|, |B_m - B_n|) \quad (11)$$

where (R_m,G_m,B_m) and (R_n,G_n,B_n) are the average values of color of cluster C_m and cluster C_n.

2.2.2 Region Merging Strategy

Another difficulty with region merging is that the final segmentation is dependent on the order in which regions are examined. The strategy we have used is, firstly each cluster whose number of pixels is less than a predefined threshold is merged into its nearest cluster until no such clusters exist, and then region merging is performed iteratively by combining the two nearest regions each time until the distances of all the pairs of regions are greater than a specified global threshold and the algorithm for the region merging process is described as follows:

```
Begin  /*Region Merging Process*/
/*Merge all those clusters with quite few pixels into their nearest clusters*/
        M := the number of all clusters;
        Set_of_Invalid_Cluster := all those clusters whose
        number of pixels is less than Ns;
while set_of_Invalid_Cluster is NOT EMPTY do
   {
        Find two clusters Cs and Ct satisfying:
        Dist (Cs, Ct) = min {Dist (Ci, Cj)| 1≤ i, j≤ M and at
        least one of Ci and Cj belongs to
        setOfInvalidCluster};
        Merge Cs and Ct into a new cluster Ck;
        M := M-1;
        If the number of pixels of cluster Ck < N0
        then include cluster Ck to set_of_Invalid_Cluster
   }
/* Merge those closest pairs of clusters */
Find two clusters Cs and Ct fulfilling:
        Dist (Cs, Ct) =  min {Dist (Ci, Cj) | 1≤ I, j ≤M};
        While Dist (Cs, Ct) < Ds do {
        Merge Cs and Ct into a new cluster Ck;
        M :=M -1
Find two clusters Cs and Ct satisfying:
        Dist (Cs, Ct) = min {Dist (Ci, Cj) | 1≤ I, j≤ M};
```


}
End /* Region Merging Process */

N_s is the cutoff value for number of pixels in a cluster and Ds is the threshold for the distance between two clusters. According to our experiments on many images, N_s=10 and D_s=20 are more appropriate.

3. EXPERIMENT AND RESULTS

We have done experiments on a variety of images to test the proposed approach. We have also applied the proposed approach to both RGB and HSI color spaces and compared the results with those obtained by using the histogram-based approach.

3.1 Kindred Vs Histogram

Figures (2) and (3) show the experimental results using RGB color space.

Fig.(2a)

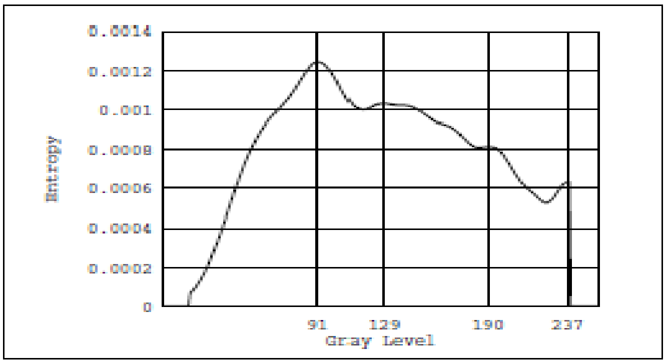

Fig. (2b)

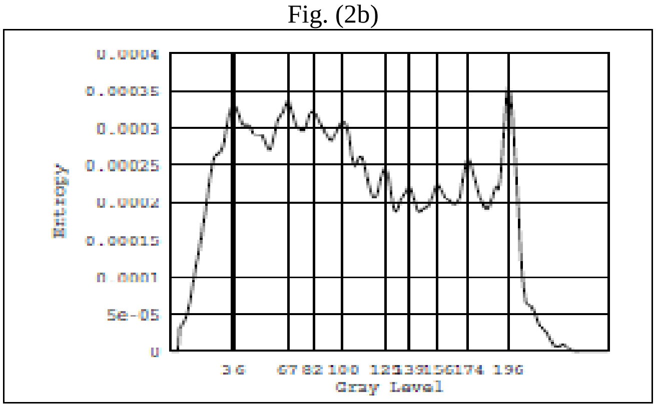

Fig.(2c)

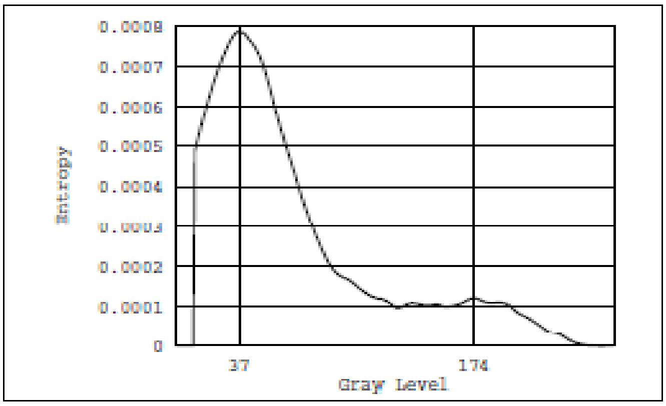

Fig.(2d)

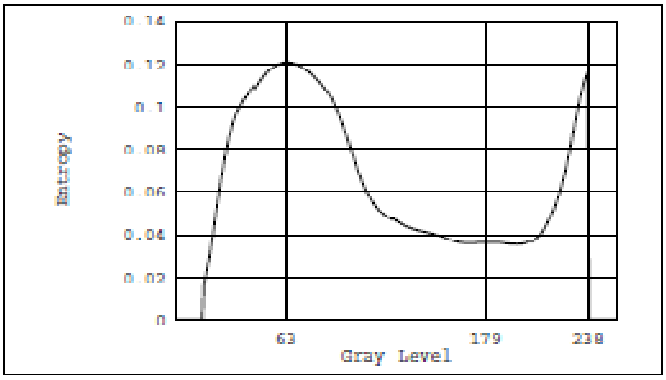

Fig. (2e)

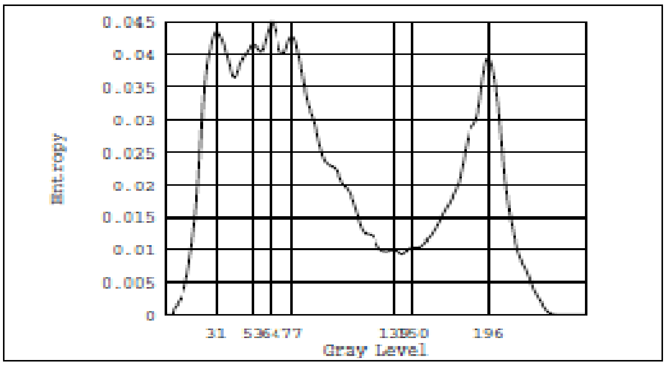

Fig.(2f)

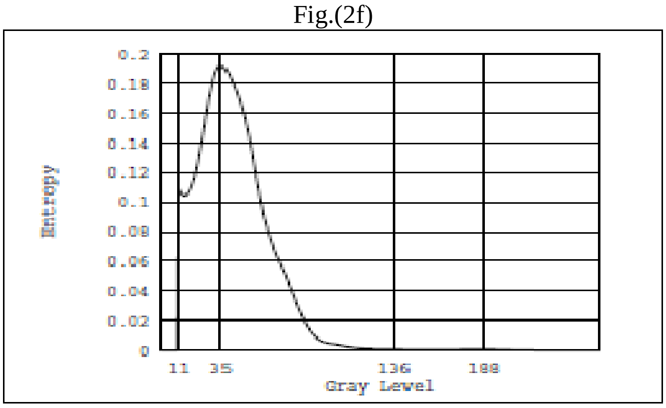

Fig.(2g)

Fig.(2h)

Fig.(2i)

Fig.(2j)

Fig.(2k)

Fig. (2): (a) The original image BUTTERFLY. (b) R's entropy by KOB method. (c) G's entropy by KOB. (d) B's entropy by KOB method. (e) R's entropy by HIB method. (f) G's entropy by HIB method. (g) B's entropy by HIB method. (h) Result after the first stage of the KOB method. (i) Final result of the KOB method. (j) Result after the first stage of HIB method. (k) Final result of the HIB method.

Histogram-based Approach (HIB) is similar to the Kindred-based approach (KOB) except the first one uses histogram for segmenting the image. Tables (1) and (2) list the results of Figures (2) and (3) using the KOB and HIB approaches with RGB representations.

Table 1. Results of the KOB using RGB Color Space

Name of image	No. of segments			No. of clusters	
	R	G	B	Before merging	After merging
Butterfly	5	10	3	74	23
Frog	3	4	5	40	18

Table 2. Results of the HIB using RGB Color Space

Name of image	No. of segments			No. of clusters	
	R	G	B	Before merging	After merging
Butterfly	4	8	5	72	21
Frog	3	3	5	33	12

The original image, BUTTERFLY, is shown in Fig 2(a). The entropies of its RGB components obtained by the KOB are shown in Fig. 2(b), Fig. 2(c), Fig. 2(d) and the entropies of its RGB components obtained by the HIB are shown in Fig. 2(e), Fig. 2(f) and Fig. 2(g) respectively. Fig. 2(h) and 2(i) are the resulting images by KOB, after the first and second steps, and Fig. 2(j) and Fig. 2(k) are the resulting images by the HIB after the first and second step, respectively. In Fig. 2(h) the wings of the butterfly are clearly and homogeneously segmented, while in Fig. 2(j) some areas on the upper left side and below the butterfly are assigned the same color as the wings. The numbers of clusters generated by KOB and HIB are 74 and 72 respectively. Fig. 2(i) is the result after merging operation on Fig. 2(h) and only 23 regions are left, but the effect is still very good because main features are not affected.

Fig.(3) is one more image selected to show the comparison between the two segmentation approaches.

Fig.(3a)

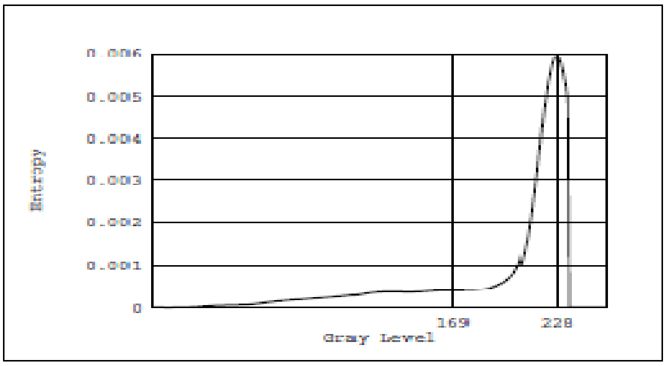

Fig.(3b)

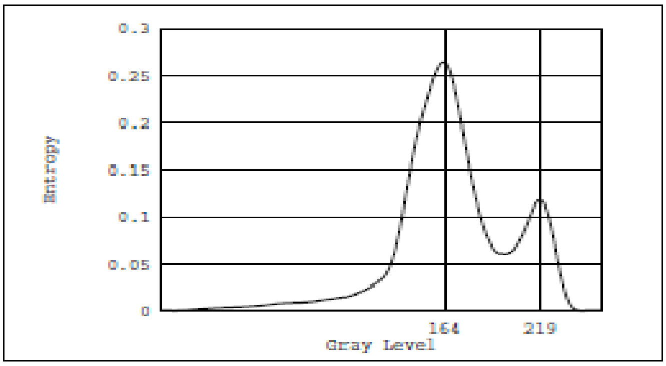

Fig.(3f)

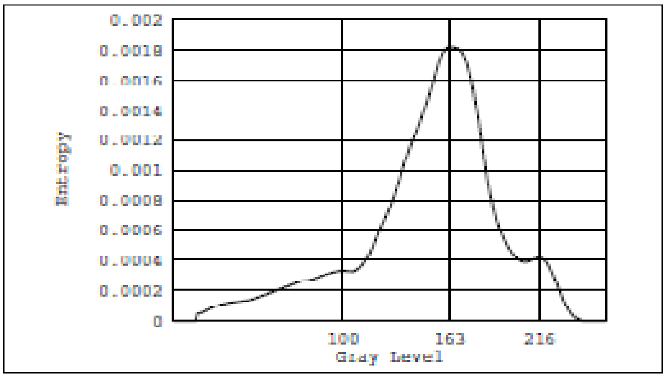

Fig.(3c)

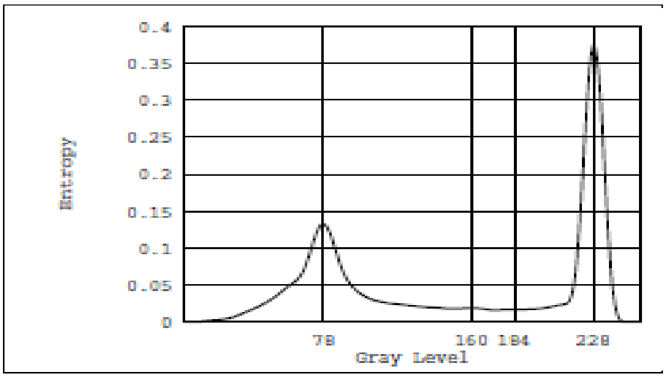

Fig.(3g)

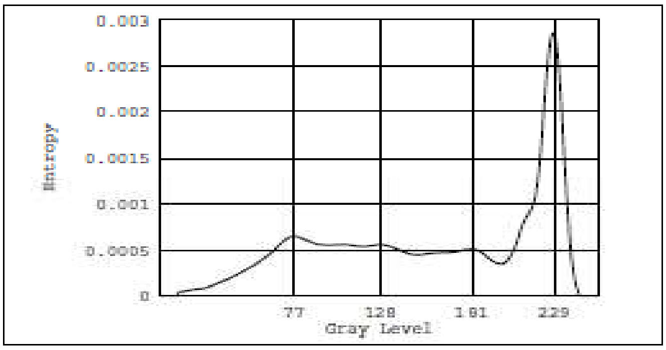

Fig.(3d)

Fig.(3h)

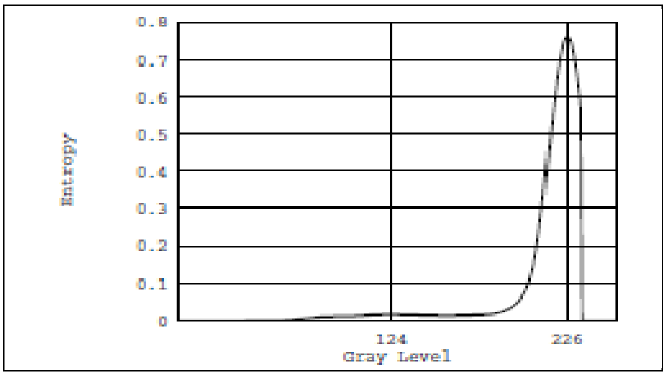

Fig.(3e)

Fig.(3i)

Fig.(3j)

Fig.(3k)

Fig.(3): (a) The original image of Frog. (b) R's entropy by KOB method. (c) G's entropy by KOB method. (d) B's entropy by KOB method. (e) R's entropy by HIB. (f) G's entropy by HIB method. (g) B's entropy by HIB method. (h) Result after the first stage of the KOB method. (i) Final result of the KOB method. (j) Result after the first stage of HIB method. (k) Final result of the HIB method.

In Fig. 3(h) the resulting image by the KOB, good effects are achieved, while in Fig. 3(j) the resulting image by the HIB, we can see that the body of the frog, the lower left corner of the image and the green triangle on the upper right side is not properly segmented. The numbers of clusters generated by KOB and HIB are 40 and 33 respectively. Fig. 3(i) is the image that has resulted after merging operation on Fig. 3(h) with fewer and much more homogeneous segments.

As we can make out from the experimental results, the KOB works better than the HIB. The reason is that while the entropies are computed, the KOB considers both global and local information of an image, while HIB does not consider the spatial dependencies among pixels.

4. CONCLUSIONS

We have presented a color image segmentation approach based on kindred thresholding and region merging. The key point of this approach is that kindred analysis is used to extract all major similar regions at the first stage and the region merging process is performed iteratively based on color similarity among these regions to solve the problem of over- segmentation. The experimental results show that the KOB tends to be more effective to find similar regions and to extract the similar regions with gradual shading in color images than HIB does.

The proposed approach operates in RGB and HSI color spaces for comparison. The Non-removable singularity of hue may create spurious modes in the distribution of values resulting from the nonlinear transformations, which makes the hue value unreliable for segmentation. The RGB color space does not have such a problem. But for a color image with high saturation, segmentation using HSI can produce very good results, even better than that using RGB as the three components R, G and B have high association which makes the three components depend on each other and associate strongly with intensity.

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