Color Image Segmentation and Multi-Level Thresholding by Maximization of Conditional Entropy

R.Sukesh Kumar, Abhisek Verma and Jasprit Singh

***Abstract*—**In this work a novel approach for color image segmentation using higher order entropy as a textural feature for determination of thresholds over a two dimensional image histogram is discussed. A similar approach is applied to achieve multi-level thresholding in both grayscale and color images. The paper discusses two methods of color image segmentation using RGB space as the standard processing space. The threshold for segmentation is decided by the maximization of conditional entropy in the two dimensional histogram of the color image separated into three grayscale images of R, G and B. The features are first developed independently for the three (R, G, B) spaces, and combined to get different color component segmentation. By considering local maxima instead of the maximum of conditional entropy yields multiple thresholds for the same image which forms the basis for multilevel thresholding.

***Keywords*—**conditional entropy, multi-level thresholding, segmentation, two dimensional image histogram

I. INTRODUCTION

THE most critical step in image processing is the segmentation of the image. Basically, segmentation of the image divides the whole image into some unique disjoint regions. The fact that the segmented image should retain maximum useful information and discard unwanted information makes the whole process critical. Various methods of segmentation have been proposed in the literature [1] - [7].

Color images are a very rich source of information, because it provides a better description of a scene as compared to grayscale images. Hence *color segmentation* becomes a very important issue. The two basic models for color images are the RGB color model and the HSI color model.

Color image segmentation in HSI space [1], [8] requires conversion from RGB space to HSI space since maximum digital color images are available in RGB format readily. Also recent studies show that segmentation is one area where RGB space yields better results.

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For segmentation in RGB space two algorithms have been proposed:-

(1) Non-Exclusive R,G,B segmentation.
(2) Exclusive R,G,B segmentation.

In both the above algorithms, the image is considered as three grayscale images of R, G and B and a threshold is achieved for each by the virtue of maximum information contained by maximization of entropy.

In case of non-exclusive R, G, B segmentation the stress is on a particular color's (R, G or B) maximum content only while in the case of exclusive segmentation the stress is on both the maximum content of a particular color and the minimum content of other colors. The above algorithms have been applied on various color images and the implications of the results have been shown.

Further, segmentation of an image into more than two regions would mean that there are multiple thresholds for the image and a region would be defined as a set of points having intensity values between two consecutive thresholds. This concept of *multilevel thresholding* has been implemented as an extension of entropy maximization in which the local maxima of the entropy would yield a set of thresholds instead of the conditional maximum giving a single threshold. The above algorithm has been applied to grayscale and color images and the regions obtained are filled with different shades depending on the thresholds. The number of thresholds is also optimized.

II. THE CONCEPT

A. Two dimensional histogram

The two dimensional histogram [9],[10],[11] of a digital image represents the frequency of occurrence of pixels with gray values m and n separated by a distance $\boldsymbol{\delta}$ at a specified direction θ . In this work we have considered $\theta = 0^0$ and $\delta = 1$. In general, the co-occurrence matrix of an image $\mathbf{I} = [I_{kl}]$ quantized into **L** gray levels is an **L x L** matrix $\boldsymbol{€} = [\mathbf{C_{mn}}]$ with an (m,n)th element

$$C_{mn} = |\{((i,j),(k,l)); I_{ij} = m, I_{kl} = n, \\ d((i,j),(k,l)) = \delta, \angle((k,l),(m,n)) = \theta\}| \quad (1)$$

We assume that texture context information in an image **I** is contained in the overall or "average" spatial relationship, which the gray tones in image **I** have to one another. More specifically, we shall assume that this texture context information is adequately specified by the matrix of relative frequencies. It is appropriate at this point to comment on the computational aspects of obtaining the two dimensional histogram. The number of operations required to process an image using this procedure is directly proportional to the number of resolution cells n present in the image. In comparison, the numbers of operations are of the order of n log n, if one wishes to use Fourier transform to extract texture information. Also, to compute the entries in the two dimensional histogram, one needs to keep only two lines of image data in core at a time. Thus no severe storage constrains are imposed.

B. Textural features

Textural Features are also termed as “descriptors”. The basic idea is to characterize the “content” of the two dimensional histogram via these descriptions.

An image feature is a distinguishing primitive characteristic or attribute of an image field. Many portions of natural scenes are devoid of significant detail over large areas. In these areas the scene can be characterized as exhibiting a repetitive structure analogous of the texture of cloth of the pattern of a tile floor. Several authors [12] - [14] have attempted qualitatively to define texture. Haralick, Shanmugan and Dinstein[11] have proposed a number of textural features based on the two dimensional histogram.

If an image region contains fine texture, the two dimensional histogram will tend to be uniform, and for coarse texture the matrix values will be skewed towards the main diagonal of the matrix.

Various textural features include mean, variance, standard deviation, contrast, ASM and entropy among various others. In this paper we consider the entropy feature as the basis of segmentation [15] - [17]. As entropy is the measure of information content in an image.

C. Entropy

Entropy feature f is defined as

$$f = -\sum_{i}\sum_{j} p(i,j)\log|p(i,j)| \tag{2}$$

where p(i, j) is the (i, j)th entry in the normalized two dimensional histogram.

Many algorithms have been developed to segment the image using this feature including the Pal and Pal paper [15], [18]. In this paper we extend the concept of segmentation using entropy maximization as proposed by Pal and Pal [15], [18] to color images by means of two algorithms. Also the same is extended to multilevel thresholding.

D. Conditional entropy

The two dimensional image histogram obtained from a gray scale image is partitioned into four quadrants namely A, B, C and D as shown in fig [1]. The second order entropy for the normalized submatrices, B and D is defined as :

$$H_B(s) = -\sum_{i=0}^{s}\sum_{j=s+1}^{L-1} P_{ij}^{B}\log_2 P_{ij}^{B} \tag{3}$$

$$H_D(s) = -\sum_{i=s+1}^{L-1}\sum_{j=0}^{s} P_{ij}^{D}\log_2 P_{ij}^{D} \tag{4}$$

The conditional entropy of the image is then defined as :

$$H^C = (H_B(s) + H_D(s))/2 \tag{5}$$

where *s* belongs to *{0, L-1}*.

In order to obtain a threshold to segment an image into two halves (one called the object, the other the background), this conditional entropy H^C is maximized with respect to s as proposed by Pal and Pal [18]. The value of s for which H^C is maximum is taken as the threshold.

III. COLOR IMAGE SEGMENTATION

As seen above the Pal and Pal algorithm can be applied only to gray scale images.

Color provides a wealth of information for the interpretation of an image and the primary objective of image segmentation is to retain maximum useful information and discard unwanted excess information.

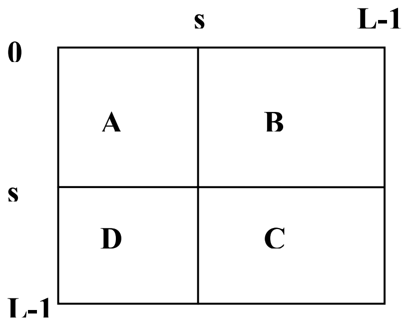

Fig. 1 Two dimensional Histogram

Maximum number of images available is in the form of RGB model. Various color segmentation algorithms require converting from RGB to HSI model. This may lead to loss of information due to rounding off and quantization errors. Hence a novel approach would be segmentation in the RGB space, where the regions of red, green and blue in the image are distinctly separated out. This is required in many applications such as robotic vision, medical applications and remote sensing.

Based on the above arguments the following algorithms for color image segmentation are proposed.

The RGB components of the color images are separated as three grayscale images. The two dimensional histogram of the three grayscale images is obtained. As suggested by Pal and Pal the two dimensional histogram is divided into four parts *A, B, C, D* by a threshold value *s [0,255]* as shown in fig[1]. Second order entropies H_B and H_D are calculated. The conditional entropy H^C is maximized with respect to *s*. The threshold values th_{red}, th_{green}, th_{blue} corresponding to the maximized entropy of the two dimensional histogram of the three grayscale images are calculated. Now two methods of color segmentation are used:

` 1.) Exclusive R, G or B.
2.) Non - exclusive R, G or B.

Consider a color image (RGB model) I defined as

$$I(x, y) = (I_R, I_G, I_B) \tag{6}$$

where I_R, I_G, I_B are the gray level intensities corresponding to red, green and blue grayscale component of the image.

A. *Algorithm 1: Non-exclusive R, G, B*

If the input image is of size *M x N x 3*, then a *mask* of size *M x N x 1* is defined and is filled with all zeros. The color to be segmented from the image is predefined (let us say red). The value of the intensity at any pixel (x,y) in the mask is set to FFH (white) if the intensity value of red (in this case) at position (x,y) in the original image exceeds the calculated threshold for red. In the other case the value of mask at (x,y) is set to 00H (black).

Analytically,

If $\mathbf{I_R} >= \mathbf{th_{red}}$
then **mask (x, y)** = FFH (white)
else **mask (x, y)** = 00H(black)

B. *Algorithm 2: Exclusive R, G, B*

If the input image is of size *M x N x 3*, then a *mask* of size *M x N x 1* is defined and is filled with all zeros. The color to be segmented from the image is predefined (let us say red). The value of the intensity at any pixel (x,y) in the mask is set to FFH (white) if the intensity value of red (in this case) at position (x,y) in the original image exceeds the calculated threshold for red and the intensity values of blue and green at position (x,y) in the original image are less than their respective thresholds. In all other cases the value of mask at (x,y) is set to 00H (black).

If $\mathbf{I_R} >= \mathbf{th_{red}}$ && $\mathbf{I_B} < \mathbf{th_{blue}}$ && $\mathbf{I_G} < \mathbf{th_{green}}$
then **mask (x,y)** = FFH(white)
else **mask (x,y)** = 00H(black).

The mask obtained is now anded with each of the R, G and B layers of the input image to obtain the output segmented image.

Non-exclusive RGB algorithm implies constraints only on the selected color component (here red) i.e. it retrieves all the pixels *I(x,y)* which have I_R qualifying to be red by the entropy maximization and poses no constraints on the green and blue color components(I_G, I_B) thereby all possible red regions are segmented out. While the implications of exclusive RGB algorithm are more stringent i.e. it retrieves all the pixels *I(x,y)* which have I_R qualifying to be red and I_G, I_B not qualifying to be green and blue respectively.

IV. MULTILEVEL THRESHOLDING

Clearly, Pal and Pal approach of entropic thresholding yields only one threshold for an image. This leads to segmentation into two regions, hence is useful for object background classification or object extraction [15].

In real world we require that the image gets segmented into more than two regions, for instance in a medical image we want the cells, bones and tissues to get segmented as three regions. This can be achieved by multiple thresholds**,** T of an image I, where $T = \{t_1, t_2 \ldots\ldots, t_n\}$.

To achieve this the following algorithm is proposed.

A. *Algorithm*

It has been seen that for a gray scale image I when the global entropy H^C is plotted against **s** as shown in fig [16], there are various maxima of the graph rather than a maximum. Obtaining the s corresponding to all the maxima as $\{t_1, t_2 \ldots\ldots, t_n\}$ yields the required multiple thresholds.

The total number of thresholds '*n*' must be optimized to reject redundant regions. This is done as follows. If:

$$abs(H^C(t_i + 1) - H^C(t_i)) < \varepsilon \tag{7}$$

then the threshold corresponding to the smaller of the two entropies is rejected as shown in fig [17]. The number of thresholds left, '*m*' after this approximation is fairly less than *n*. Experimentally it has been seen that the optimum error value $\epsilon = 0.5$ yields good result. Depending on the number of thresholds '*m*' the image should be divided into *m+1* regions. The gray scale intensity value of regions $R = \{r_0, r_1, \ldots\ldots, r_m\}$ is given by :

$$r_i = (255/m) * i \tag{8}$$

The above concept can be extended to color images by defining

$$I'(x, y) = (I_R + I_G + I_B)/3 \tag{9}$$

where I_R, I_G and I_B are red, green and blue color components of the input image I as described earlier. The gray scale I' is now subjected to the same algorithm.

V. RESULTS

A. *Color image segmentation*

Fig [2] is an image of a sea coral. Non-exclusive R,G,B segmentation is applied on it for all the three colors to yield fig[3] (red segmented), fig[4] (blue segmented), fig[5] (green segmented). Similarly exclusive R,G,B segmentation is applied over fig [2] to yield fig[6] (red segmented), fig[7] (blue segmented), the image for green segmentation turned out to be completely black and hence is not included. It is quite clear from the result that the non-exclusive algorithm retains all possible information about the color while the exclusive one, maximizes the information content of one color minimizing the information content of the other two colors. Fig [8] is the image of a fish, similarly the non-exclusive segmentation algorithm results in fig [9], [10] and [11] for R,B,G segmentation respectively and the exclusive segmentation algorithm results in fig [12], [13] and [14] for R,B,G segmentation respectively.

Let us consider fig[3] and fig[6], both are red-segmented. Fig[3] is obtained by non-exclusive segmentation and fig[6] is obtained by exclusive segmentation. It is evident that fig[3] yields all regions where red grayscale value is grater than red threshold value irrespective of the thresholds of green and blue. Fig[6] brings out the regions where information pertaining to red is maximized and the information pertaining to blue and green is minimized. Similar is the case with the fish image.

We can use non exclusive segmentation where only one color dominates because of its simplicity and speed. Exclusive algorithm may be used where the three color are mingled, so that we can distinctly separate the three regions.

B. *Multilevel thresholding*

Fig [15] is a grayscale image of soap bubbles; multi-level thresholding is required on this image to reduce the no. of redundant regions. When conditional entropy of the above image is plotted against 's', and all the local maxima are marked the graph obtained is fig [16], after approximation with $\epsilon = 0.5$, yields the graph as shown in fig [17] where the value of $m=7$, i.e the overall image is divided into seven regions and filled with gray-values obtained from r_i (8). The result so obtained is shown in fig [18].

Clearly the result retains the distinct homogeneous regions while discards the excess details making the further study of such images simpler.

Fig[19] is the image of a tissue. To apply multi-level thresholding on this fig it is converted into grayscale as in fig[20] by using (9) and then the multi-level Thresholding algorithm is applied to obtain fig[21].

Fig[19] is an example of how multi-level thresholding is applied to medical images to study the distinct regions of a tissue cell and also to detect if there is any defect in the tissue. Another example is fig[24] where multi-level thresholding is applied similarly to obtain fig[26]. This shows the finer variations of the clouds in the sky which is not evident with the bare eye.

VI. DISCUSSIONS

A. *Applications*

The above work of color image segmentation and multilevel thresholding can have various applications such as object extraction in color images, marking and classification algorithms which forms the basic image pre-processing steps in the areas of robotic vision, remote sensing and medical imaging.

B. *Future Scope*

Imprecision in images due to noise poses a great challenge in image segmentation and thresholding. Hence the above concept may be extended to deal with noisy images by use of fuzzy tools etc.

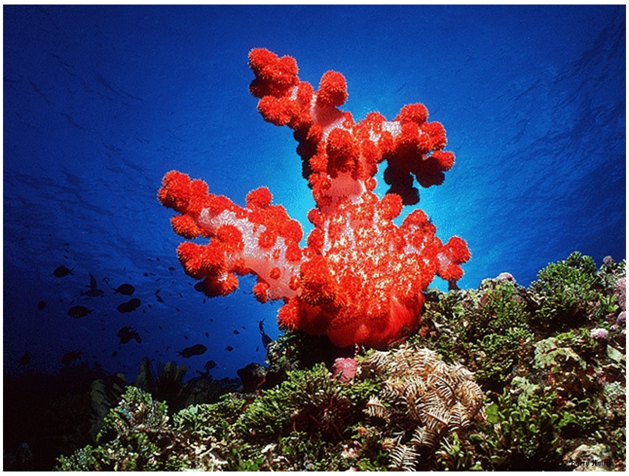

Fig. 2 A sea coral

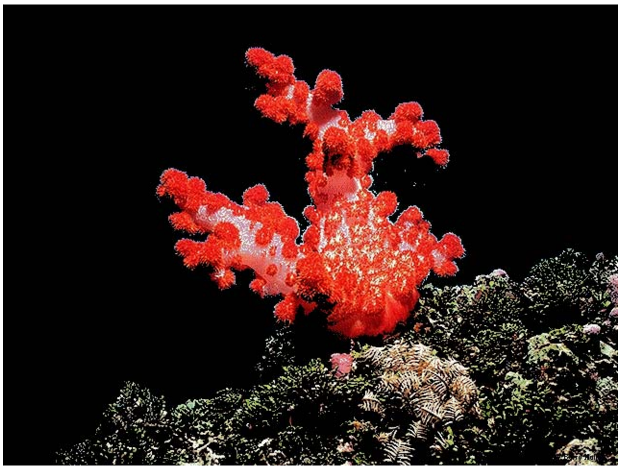

Fig. 3 Non Exclusive Red segmentation of sea coral

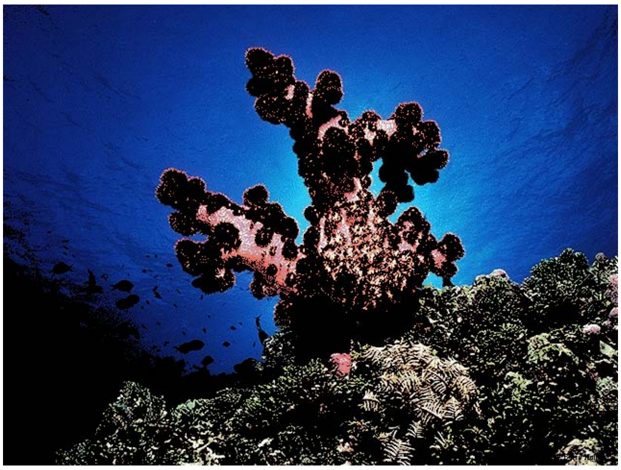

Fig. 4 Non Exclusive Blue segmentation of sea coral

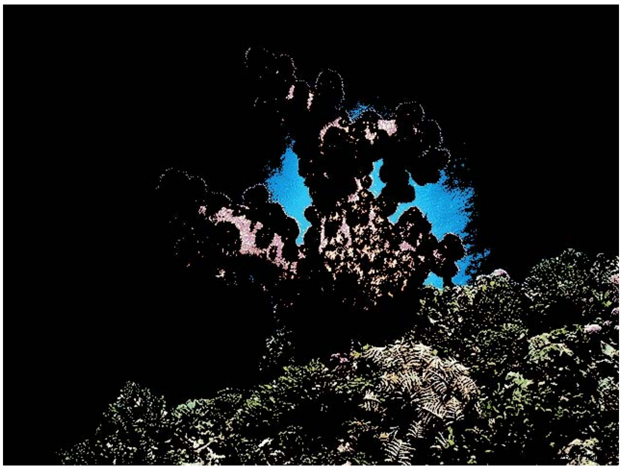

Fig. 5 Non Exclusive Green segmentation of sea coral

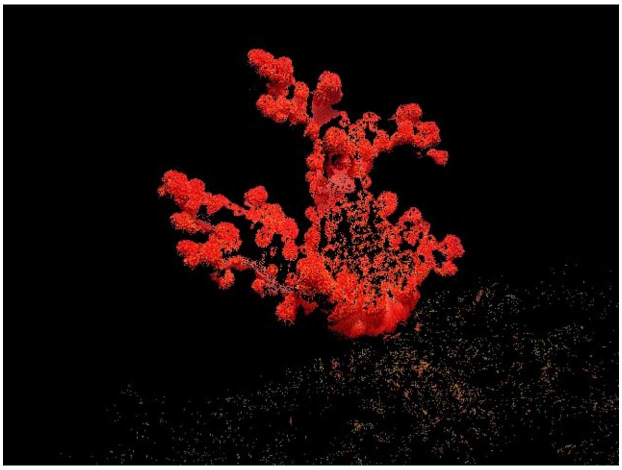

Fig. 6 Exclusive Red segmentation of sea coral

Fig. 7 Exclusive Blue segmentation of sea coral

Fig. 8 A Fish

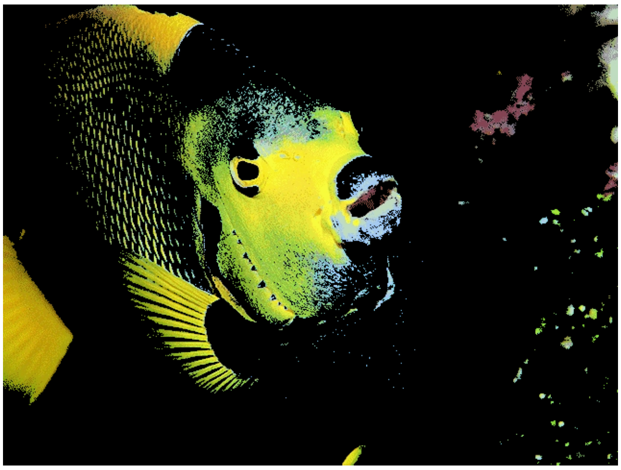

Fig. 9 Non Exclusive Red segmentation of Fish

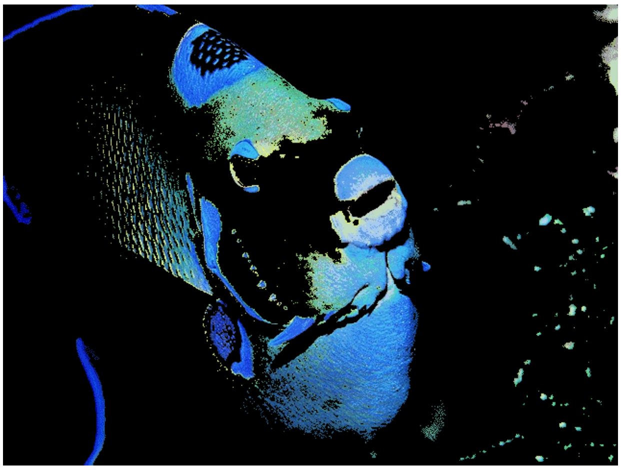

Fig. 10 Non Exclusive Blue segmentation of Fish

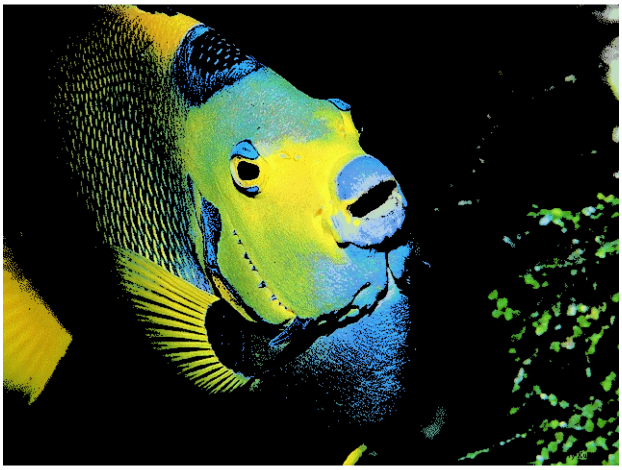

Fig. 11 Non Exclusive Green segmentation of Fish

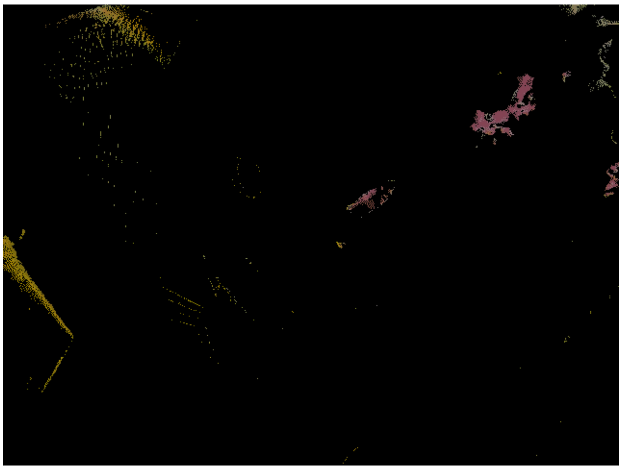

Fig. 12 Exclusive Red segmentation of Fish

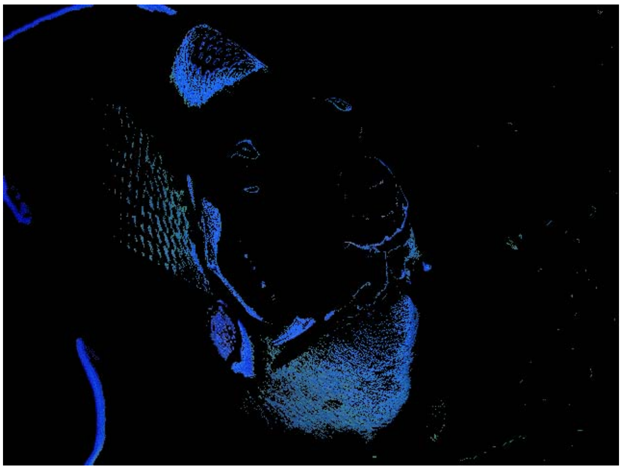

Fig. 13 Exclusive Blue segmentation of Fish

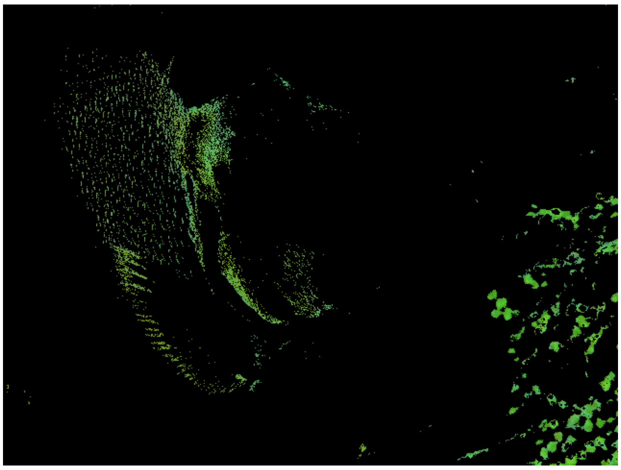

Fig. 14 Exclusive Green segmentation of Fish

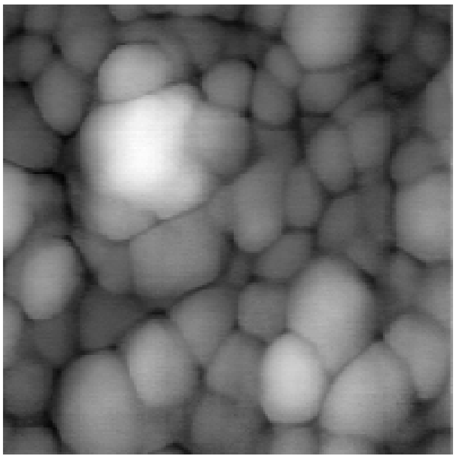

Fig. 15 Soap Bubbles

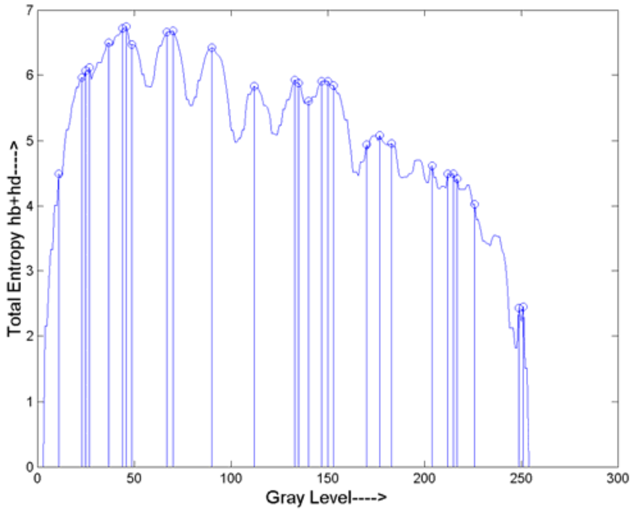

Fig. 16 Plot of $H_B + H_D$ vs. s of Soap Bubbles

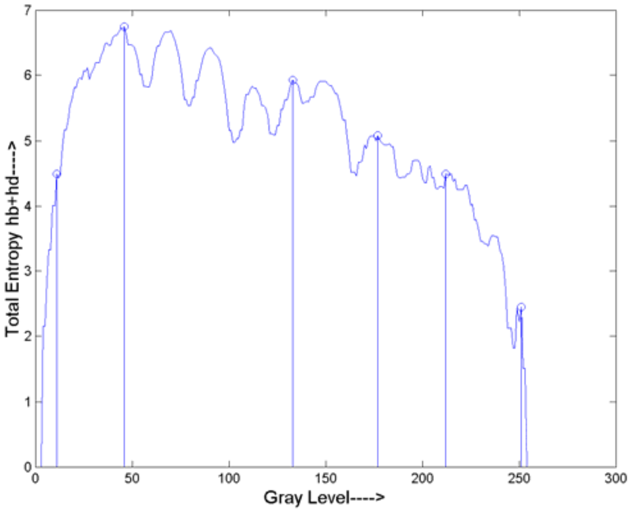

Fig. 17 Plot after optimizing the no. of maxima in fig 16

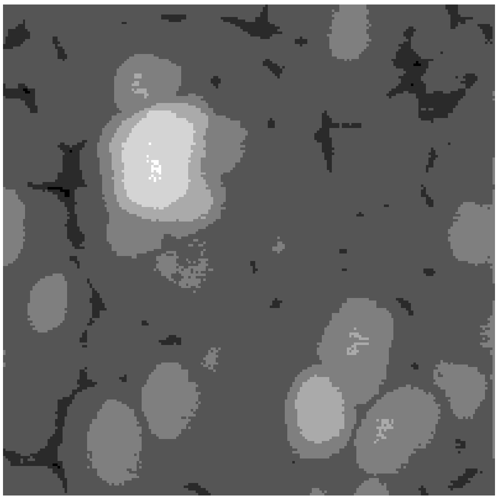

Fig. 18 Multi-level thresholded Soap Bubbles image

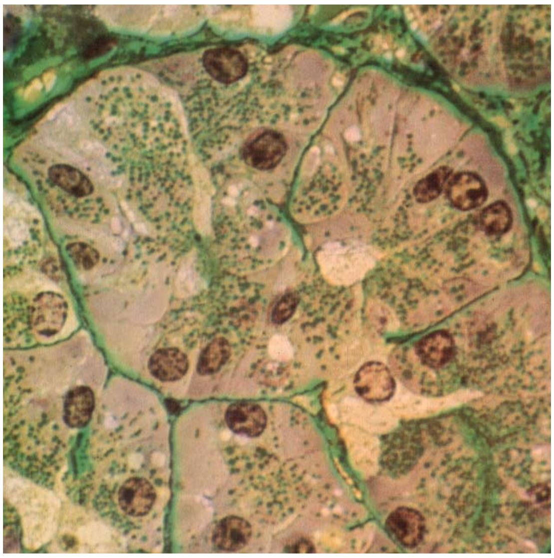

Fig. 19 A Tissue

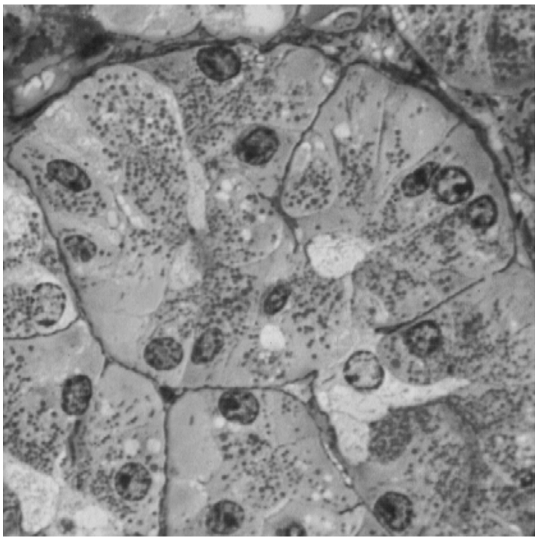

Fig. 20 The grayscale image corresponding to Tissue

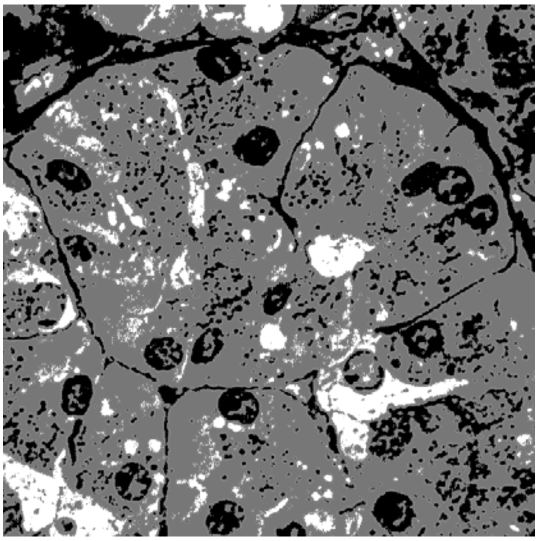

Fig. 21 Multi-level thresholded Tissue image

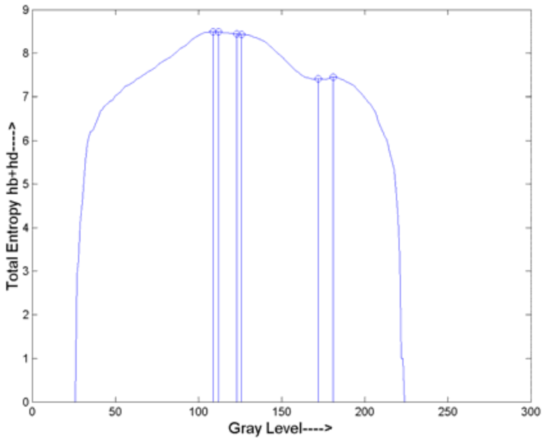

Fig. 22 Plot of $H_B + H_D$ vs. s of Tissue

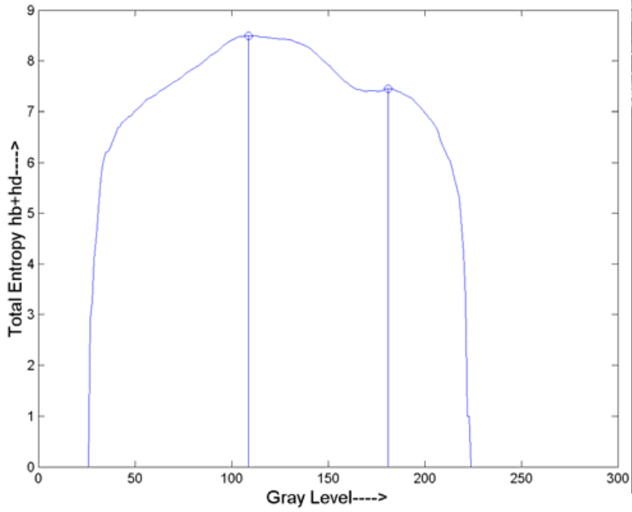

Fig. 23 Plot after optimizing the no. of maxima in fig 22

Fig. 24 Scenery

Fig. 25 The grayscale image corresponding to Scenery

Fig. 26 Multi-level thresholded Scenery image

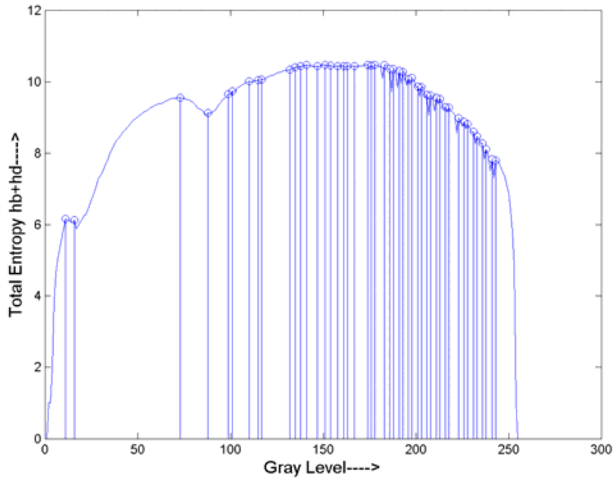

Fig. 27 Plot of $H_B + H_D$ vs. s of Scenery

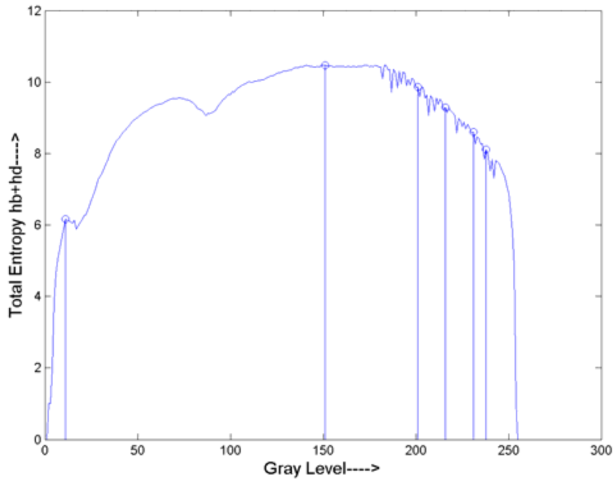

Fig. 28 Plot after optimizing the no. of maxima in fig 27

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