CHAPTER 1

INTRODUCTION TO IMAGE SEGMENTATION

1.1 IMAGE SEGMENTATION

Image segmentation is one of the most important techniques for image processing in computer vision and many computers based automatic application. The goal of image segmentation is to isolate the regions of interest depending on the problem being solved in particular application. Specifically, the segmentation problem is defined as sufficiently segmentation is to make the image more simplified one and that to get more meaningful to analyze for different application. It plays an important role in image analysis. Many applications (e.g., OCR) of image analysis need to obtain the regions of interest before the analysis can start. Therefore, the need of an efficient segmentation method has always been there. Application of image segmentation in detection of masses in digitized mammograms, analyzing medical images from computerized tomography (CT), magnetic resonance imaging (MRI) for computer-aided diagnosis and therapy planning, Object Recognition, Scene understanding and analysis, Automatic pictorial Pattern Recognition, Automatic Traffic control systems, Locating Objects in satellite images like roads, maps etc.(Remote Sensing) .

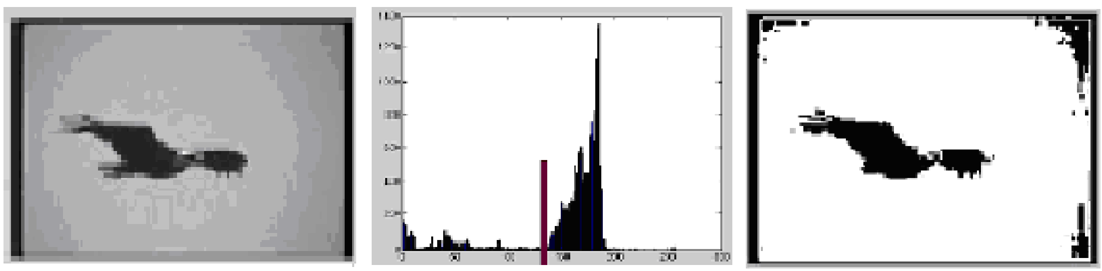
1.2 CONVENTIONAL IMAGE SEGMENTAITION TECHNIQUES:

A. THRESHOLDING BASED:

In its simplest form, thresholding is the process to classify the pixels of a given image into two groups (e.g. foreground and background), One including those pixels with their gray values above the computed threshold, and the other including those with grey values equal to and below that threshold. Thus it is called bi-level thresholding. In multilevel thresholding, more than one threshold use to divide the whole range of gray values in to several sub ground. Image segmentation by thresholding is performed by threshold value T of some image attribute Y(x, y). In the thresholding process if the value of attribute Y(x, y) in the considered pixel is lower than the threshold T; the pixel is labeled as a background. Otherwise it is labeled as foreground. This process generates a binary image given as follows:

$$g(x, y) = \begin{cases} 1 & for \quad Y(x, y) \geq T \\ 0 & for \quad Y(x, y) < T \end{cases}$$ [ref . 1]

Here g(x, y) is the result of the thresholding process with equal sized to original image Y(x, y).



(a) **(b)** **(c)**

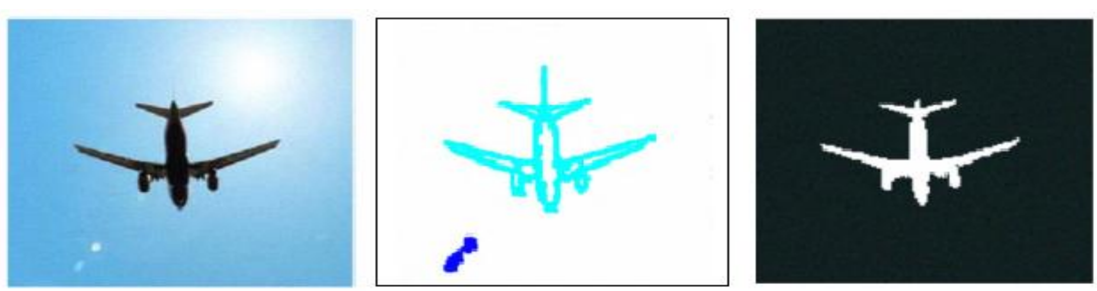
Fig. 1: Threshold based image segmentation example [ref. 1] (a)original image,(b) threshold calculation using histogram,(c) Segmented image

Threshold selection methods:

- Histogram-based methods where threshold is calculated by manipulating separate peaks and valleys in histogram [1].
- Clustering-based methods where the threshold is calculated by clustering algorithms in which whole image divided in cluster of pixel, then threshold is determined by analyzing these clusters to separate foreground and background (i.e. objects) [2].
- Entropy-based methods calculate threshold from the entropy of the foreground and background or from the cross-entropy between the original and binarized image [3].
- Object attribute-based methods which search a measure of similarity (for example shape similarity, edge feature, texture etc.) between the intensities values of pixels and the binarized images [4].

B. EDGE BASED:

Edges in an image represent the boundaries between two dissimilar regions based on intensity values, which may be different surfaces of the object, or perhaps a boundary between light and shadow falling on a single surface. Edge detection is the most common approach using for detecting discontinuities in intensity level between adjacent pixels [5]. First and second order derivatives like gradient and laplacian are used for detection of edges in an image [6]. Edges in an image can be divided into two main categories: intensity edges and texture edges. [7] Intensity edges represent abrupt changes in the intensity values of adjacent pixels in the image. Examples of intensity edges include steps, roofs and ramps. Other type of edges, Texture edges represent boundaries of texture regions that are invariant to lighting conditions. Edge detection methods need additional post processing by using linking procedures to derive closed edge to form meaningful edges. As importance of edge detection techniques, many algorithms are available to derive edges like Sobel (1968) edge detector[8] ,Prewitt(1970) edge detector and Roberts(1965) edge detector calculate edges using their own designed approximations to the derivatives[9], Canny(1986) edge detector [10][11] finds edges by analyzing local maxima of the gradient using derivative of Gaussian filter. Mostly edge based methods are sensitive to image noise. Most edge detection work on the assumption that an edge occurs where there is a discontinuity in the intensity values of adjacent pixels or a very steep intensity gradient in the image. Edge based image segmentation approaches have as a weakest point the contour closure extraction, although most of the edge-based image segmentation approaches succeed in finding of object's edges, most of them fail in computing regions closed boundaries [12].

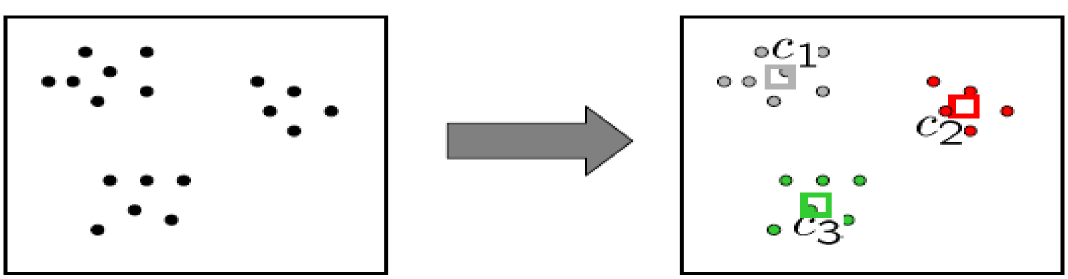


(a) (b) (c)

Fig. 2: Edge based image segmentation example. [ref. 9], (a) Original image, (b) Extracted edges, (c)Segmented image.

C. CLUSTRING BASED

Clustering is an approach in which pixels are classified to a cluster, which is closest among all clusters. Pixels having homogeneous characteristics belong to the same cluster and different with respect to pixels of other clusters. The pixels must follow the homogeneity criteria in the same cluster. Clustering method does not require training samples, so clustering is an unsupervised statistical methods. Due to lack of training sample sets, clustering iteratively perform pixel classification and feature extraction from the image. K-means, fuzzy C-means and expectation maximization methods (EM method) are grouped into this category. The classic clustering and fuzzy clustering methods are sensitive to noise present in image, because it does not take into account spatial information, and it causes form a small isolated spots. Although the clustering method does not require any training, but it needs the initial classification of the image to find out number of final clusters in the result. Spectral clustering has become one of the most popular clustering algorithms, due to its advantages like not stronger assumptions about the shape of the class; just solve the Eigen-value problem. Many variants have been approached to improve the performances of K-means such as two levels k-means clustering algorithm [13] and SMCK-means [14]. However, the drawback resulted from the single prototype in each cluster still exists in these approached. Liu et al. proposed a multi-prototype approach to represent each cluster [15], it can deal with problems of single-prototype clustering, but the clustering result is sensitive to the initialization (number of clusters). Although many clustering algorithms are presented in the literature, there is no universal one to deal with different kinds of clustering problems.

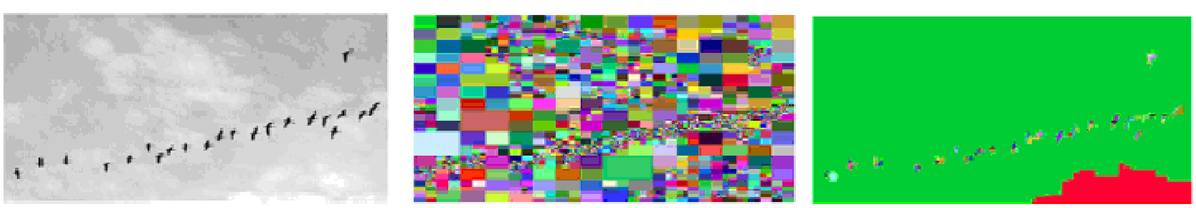


(a) (b)

Fig. 3: clustering based image segmentation example. (a) Initial scattered elements, (b) Clustered elements, [ref. 13].

D. REGION SPLITTING AND MERGING BASED

Region splitting and merging techniques [16, 17, 18] starts with splitting an image into small regions and continued till regions with required degree of homogeneity are formed. Splitting phase impacts the overall segmentation of the image. This phase results in over segmented image which is followed by the merging phase. Thus these techniques of region splitting and merging are complex and time consuming. It has some drawbacks in spite of the fact that it is very time effective. Region splitting and merging methods are incapable of adapting itself to the image features i.e. it resulted in large number of regions at the boundaries rather than the horizontal and vertical ones. These region boundaries are also highly dependent even on simple transformations like translation and scaling. The split-and-merge (SM) algorithm developed by Pavilidis [19], [20] in 1974 is still one of the most popular image segmentation algorithms and is widely used directly or indirectly in image processing. Region stability is measured based on whether all the samples in a sample space (here, pixels in a region) belong to the same sample space (here, the same region) or not. If the regions found unstable, they are further subdivided into several smaller regions or sample spaces. There are many theorems approached to identify region stability such as Ztest. Both the splitting and merging are performed based on manually specified threshold, which might not be the optimum values. So, result of SM segmentation algorithms depend on this threshold. SM segmentation algorithms are not able to segment all types of objects in an image perfectly. For example, images with a small number of objects can be effectively segmented by a SM algorithm while the number of objects increases the same algorithm performs poor.

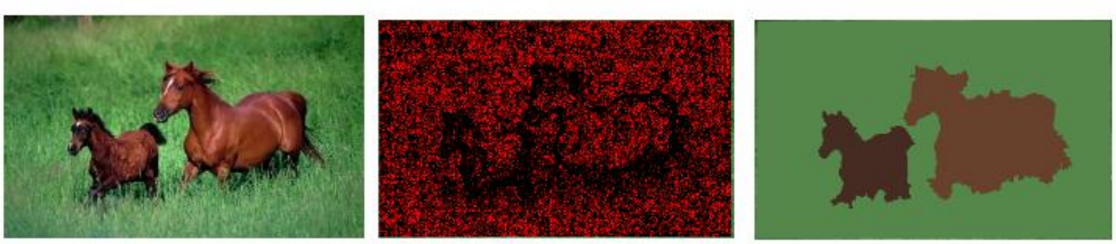


(a) (b) (c)

Fig. 4: Region merging and splitting based image segmentation example. (a) Original image, (b) Splitted regions, (c) Segmented image, [ref. 17].

E. REGION GROWING BASED

The main objective of region growing is to map individual pixels called seeds in input image to a set of pixels called region. It was first introduced by Rolf Adams and Leanne Bischof in 1994 [21]. Region growing method starts with initial seeds and grows with neighboring homogenous elements. Seed may be pixel or region. Due to its efficient results for realistic images, it is used widely in different manners. Wankai Deng et al. [22] used region growing method based on the gradients and variances along and inside of the boundary curve. Chaobing Huang et al. [23] used edge and smoothness factors as criterion to determine initial seed pixels and then seeded region growing method is used to segment images based on seed regions. In the seed based region growing method, selection of initial seed is crucial because it decides the overall segmentation by region growing technique. To select initial seed watershed algorithm by Jun Tang [24] used to first segment image to calculate no overlapped regions and then use centroid of region as initial seeds. Jianping Fan et al [25] find out initial seed by applying edge based segmentation and then use centroid as initial seeds. Weihong Cui et al [26] adopt the Harris corner detector to calculate initial seed. But seed selection affected by particular technique limitation and increases the computation overhead. The general growing procedure starts from some initial points as seed points, compares every pixel with its surrounding neighbors, and if a certain merging criterion is satisfied, the pixel is classified into the same class. Naturally, the choice of a merging criterion is critical to the segmentation's success in this method. Many researchers focus on this important issue to improve the algorithm's effectiveness and accuracy, so most of their algorithms are sensitive to the start position and sequence of the initial seed points.



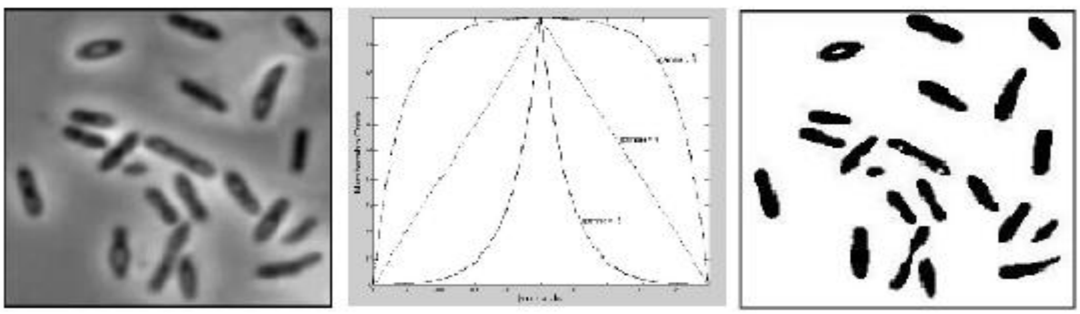
(a) (b) (c)

Fig. 5: Region growing based image segmentation example. (a) Original image,(b) Selected seeds in red, (c) Segmented image. [ref. 23].

F. FUZZY LOGIC BASED

Classical so-called “crisp”, image segmentation techniques while effective when an mage contains well-defined structures, such as edges and regular shapes, do not perform nearly so well in the presence of ill-defined data. In such circumstances, the processing of such images that possess ambiguities produces fuzzy regions. Fuzzy image segmentation Techniques can cope with the imprecise data well and they can be classified into five classes: fuzzy clustering, fuzzy rule based, fuzzy geometry, fuzzy thresholding, and fuzzy integral based image segmentation techniques [27] but among them the most dominant are fuzzy clustering and fuzzy rule based segmentation techniques. The most popular and extensively used fuzzy clustering techniques are: fuzzy c-means (FCM) [28] and possibilistic c-means (PCM) algorithms [29]. These clustering techniques however cannot incorporate human expert knowledge and spatial relation information. Image segmentation without considering the spatial relationships among pixels does not produce good result, as there is a huge amount of overlapping pixel values between different regions. Fuzzy rule based image segmentation techniques can incorporate human expert knowledge, are less computational expensive than fuzzy clustering and able to interpret linguistic as well as numeric variables. But they are very much application dependent and very difficulty to define fuzzy rules that cover all of the pixels.

In most techniques, the structures of the membership functions are predefined and their parameters are either manually or automatically determined [30, 31]. Fuzzy set theory gives a mechanism to represent ambiguity within an image. Each pixel of an image has a degree of belongingness (membership) to a region or a boundary. Kanchan proposed an unsupervised algorithm for color image segmentation [32]. Fuzzy entropy is a function on fuzzy sets that becomes smaller when the sharpness of its argument fuzzy set is improved. The notion of entropy, in the theory of fuzzy sets, was first introduced by Luca and Termini [27]. There have been numerous applications of fuzzy entropies in image segmentation. Based on the idea of Zhao, a new three-level thresholding method for image segmentation proposed in [33]. The image is partitioned into three parts, namely dark, gray and white part, whose member functions of the fuzzy region are Z-function and P-function and S-function respectively. The width and attribute of the fuzzy region can be decided by maximum fuzzy entropy; in turn the thresholds can be decided by the fuzzy parameters, for getting optimal thresholds, and to find the optimal combination of all the fuzzy parameters. One approach in designing such a fuzzy system is an expert to look at training data and try to manually develop a set of fuzzy rules[28]. Two drawbacks with such method are that first it is very cumbersome and time consuming and second there is no guarantee that the produced fuzzy rules are the best possible ones. So, there is need for a method which could produce fuzzy rules and membership functions automatically. Several methods have been proposed in literature for automatic production of fuzzy rules like genetic algorithms and ANFIS [35]. One problem with these methods is that they generate a large number of fuzzy rules which causes slow classification and processing speed [36].



(a) (b) (c)

Fig. 6: Fuzzy rule based image segmentation example. (a) Original image (b) Fuzzy membership function (c) Segmented image, [ref. 28].

G. GRAPH BASED

In Graph based methods, the image being segmented is first modeled as a weighted undirected graph. Each pixel of the image represents a node in the graph, and an edge is formed between every pair of pixels. The weights of edges are measure of the similarity between the pixels in respect to different features. After modeling of undirected graph, image is partitioned into disjoint regions by removing the edges connecting the segments according to particular application. Let G = (V, E) be a graph. Each edge (u, v) has a weight w(u, v) that represents the similarity between u and v. Graph G can be broken into 2 disjoint graphs with node sets A and B by removing edges that connect these sets. Let cut (A, B) = Σ w (u, v). One way to segment G is to find the minimal cut.

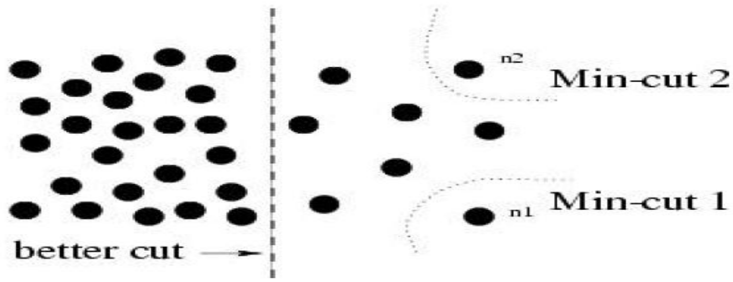


Fig.7 Graph cut representation [ref. 37]

Minimal cut favors cutting off small node groups, so Shi and Malik proposed the normalized cut.The optimal partitioning of the graph is the one that minimizes the weights of the edges that were removed. Shi's [37] proposed an algorithm to minimize the "normalized cut", which represent the ratio of the "cut" to all of the edges in the set. In graph partitioning techniques, Let G = (V,E) be an undirected graph with vertices (V_i , V_j), the set of elements to be segmented, and edges (Vi, Vj) E corresponding to pairs of neighboring vertices. Each edge (Vi, Vj) E has a corresponding weight w((Vi , Vj)), which is a non-negative measure of the similarity between neighboring elements Vi and Vj. In the case of image segmentation, the elements in V are pixels and the weight of an edge is some measure of the dissimilarity between the two pixels connected by that edge. In the graph-based approach, a segmentation S is a partition of V into components such that each component (or region) C S corresponds to a connected component in a graph G = (V ,E) [38]. All the above techniques can be implemented with advanced tools, by using different algorithms or applying different optimizing functions along with methodologies like cost optimization function, Evolutionary algorithms, or using N euro-Fuzzy logics.

CHAPTER 2

REVIEW OF SEED BASED REGION GROWING METHOD

2.1 INTRODUCTION:

Basic function of region growing technique is partition of an image into non overlapped regions. It takes seeds as input, and then merge pixels with similar property and produce a region correspond to each seed. Result of region growing must follow following constraints:

1 $\bigcup_{i=1}^{L} R_i = I$ Here L is total no. of regions.

It means, all regions should form whole image.

2 R_i is connected region, i = 1, 2, 3…n, where n is the number of regions.

3 $R_i \cap R_j = Null$ for all $i \neq j$, mutual exclusion of region.

This method performs segmentation of an image with respect to a set of points known as seeds. The procedure groups pixels or sub regions into larger regions based on predefined criteria for growth. The conventional seed selecting method is an interactive method; it is not automatic. Some researchers use edge-based method to select seeds. The basic approach for segmenting any digital image using SRG is to start with a set of seeds S_1, S_2… S_n. Some times individual sets will consist of single seed point. Given the seeds, SRG then finds a tessellation of images into regions with property that each connected component of region meets exactly one of the Si subjected to this constraint. The regions are chosen to be as homogeneous as possible. To perform region growing we need to address following steps:

1. Selection of initial seeds

Selection of initial seeds plays a prominent role in the process of image segmentation. Seeds should have some similar feature with respect to their neighbors. There should be a seed for every expected region in image. No seeds should be connected to each other. An ideal candidate seed point should have these properties:

i. It should be inside the region and near the center of the region

ii. Assume most of the pixels in the ROI belong to the region (i.e. ROI is not too big compared to the region), the feature of this seed point should be close to the region average

iii. The distances from the seed pixel to its neighbors should be small enough to allow continuous growing

2. Growing formula based on stopping criterion

Given a seed point, the region growing method searches the seed point's neighbors to determine whether they belong to the same region. If they are determined to be so, their neighbors are searched. The process is recursively executed until no more new neighbor can be added to the region. Growing formula decides the homogeneity between seed and neighbors of it based on similarity index. Stopping criteria should be efficient to discriminate neighbor elements in non homogeneous domain.

2.2 LITERATURE SURVEY:

Main objective of region growing is to map individual pixels called seeds in input image to a set of pixels called region. It was first introduced by Rolf Adams and Leanne Bischof in 1994 [21]. Region growing method starts with initial seeds and grows with neighboring homogenous elements. Seed may be pixel or region. Due to its efficient results for realistic images, it is used widely in different manners. In 1994 S. A. Hojjatoleslami and J. Kittler [39] proposed method in which unique feature is that at each step, at most one pixel exhibits the required properties to join the region. The method uses two novel discontinuity measures, average contrast and peripheral contrast, to control the growing process. Wankai Deng et al. [22] proposed region growing method based on the gradients and variances along and inside of the boundary curve and derived good segmentation. Chaobing Huang et al. [23] used edge and smoothness factors as criterion to determine initial seed pixels and then seeded region growing method is used to segment images based on seed regions. In the seed based region growing method, selection of initial seed is crucial because it decides the overall segmentation by region growing technique. To select initial seed watershed algorithm by Jun Tang [24] used to first segment image to calculate no overlapped regions and then use centroid of region as initial seeds. Jianping Fan et al [25] find out initial seed by applying edge based segmentation and then use centroid as initial seeds. Weihong Cui et al [26] adopt the Harris corner detector to calculate initial seed. But seed selection affected by particular technique limitation and increases the computation overhead. Jia-Hong Yang[40] approached a anisotropic diffusion with morphological is used for image smoothing , which can maintain image edges with noises eliminated, as a result, the watershed's over-segmentation is decreased effectively. And then, an automatic seeded region growing algorithm based on the regions similarity of mean hue value and mean saturation value of the watershed segmentation result is developed. Jianhua Xuad [41] proposed a method to segment magnetic resonance (MR) brain image. Starting with a simple region growing algorithm which produces an over segmented image, we apply a sophisticated region merging method which is capable of handling complex image structures. Edge information is then integrated to verify and, where necessary, to correct region boundaries. The results show that this method is reliable and efficient for MR brain image segmentation.

CHAPTER 3

PROPOSED SINGLE SEEDED REGION GROWING METHOD

3.1 MOTIVATION

A common property of these existing image segmentation techniques is that they all make hypotheses about the image and test features, and make decisions by applying the thresholds explicitly or implicitly. Region growing method is introduced by Rolf Adams and Leanne Bischof in 1994 to produce efficient results for realistic images. Regions growing method starts from a usually small number of pixels referred to as seeds. These seeds are grown further on the base of different features in image. The number of regions identified will be equal to the number of seeds specified. The positioning of the seeds is critical to model behavior. Selection of initial seeds plays a prominent role in the process of image segmentation using region growing. Growing formula decides the homogeneity between seed and neighbors of it based on similarity index. Stopping criteria should be efficient to discriminate neighbor elements in non homogeneous domain. So, many researchers have proposed different approaches to derive. In this paper we propose a new algorithm for color image segmentation based on region growing method , start with center pixel of the image as initial seed and growing formula based on intensity values of growing region and intensity values of neighbors of pixel for which decision to be made. The motivation of the presented simple algorithm mainly is to provide results, which can be achieved with very basic means in comparison to highly sophisticated algorithms.

3.2 PROPOSED ALGORITHM

Seed selection is the first step of the region growing technique. Instead of selecting seeds initially proposed algorithm selects center pixel of the image as initial seed. For growing formula it uses intensity values in Red, Green and Blue color space.

In first step of the proposed algorithm image I read in RGB color space. Then center pixel of the image selected as single seed to start the growing phase. (x,y) represent coordinates along x-direction and y-direction respectively. Growing phase start with analyzing intensity values in neighbors of seed pixel in RGB space. $[I_{x,y}]_{R,\ G,\ B}$ represent intensity value at coordinates (x,y) in image I in RGB color space. $MEAN_{RC}$ represent mean intensity values of pixels labeled with RC region. RC is a counter use to label pixel with region which is growing on. Algorithm uses Euclidean distance between intensity values of pixels in RGB space to determine similarity index. In growing formula it first check for similarity of pixel (m, n) to be label with connected pixel (x, y) and with mean value of growing region ($MEAN_{RC}$). If it fulfills criteria then include in growing region and label with RC. Otherwise analyze 8-neigbors of pixel (m, n) to compare closeness to its 8-nieghbors with mean value of region growing. If it is closer to growing region compare to its neighbors then include in growing region, otherwise label this pixel (m, n) as boundary pixel. After completely grown of one region next seed is selected from boundary pixels.

PROPOSED SINGLE SEEDED REGION GROWING ALGORITHM::

STEP 1: Read color image I(R*C).

STEP 2: Initialization

initial seed pixel (x, y) as :

x = R/2; y = C/2;

a counter to track region number which one is growing

RC=1;

STEP3: Assign initial mean value of region RC as:

Label pixel (x,y) with region number RC.

$[MEAN_{RC}]_{R,\ G,\ B} = [I_{x,y}]_{R,\ G,\ B}$.

Where $I_{x,y}$ represent intensity value in image I at coordinates (x, y).

STEP 4: Examine 8-nb of pixel(x, y) in a window I_{MN}(3*3) with center pixel (x, y) labeled with region number RC and pixel (m, n) represent 8-neighbors as:

If pixel (m, n) not labeled with any region number then

calculate distance between center pixel and neighbor pixels for all three R,G and B color space as:

{

$DIST1_{m,n} = DIST\ |\ I_{m,n}-I_{x,y}|$

$DIST2_{m,n} = DIST\ |I_{m,n} - MEAN_{RC}|$ Where

$$DIST(f(x+i,y+j),f(x,y))=\sqrt{(f(x+i,y+j,1)-f(x,y,1))^2}$$

STEP 5: if $DIST1_{m,n}<10$ and $DIST2_{m,n}<50$, then

label pixel (m,n) with RC and update $[MEAN_{RC}]_{R,G,B.}$

Store pixel (m,n) in PG(Pixel to Grow) stack.

Else

Create a set S as:

$S=\{I_{m,n}-I_{m-1,n-1}, I_{m,n}-I_{m-1,n}, I_{m,n}-I_{m-1,n+1}, I_{m,n}-I_{m,n-1}, I_{m,n}-I_{m,n+1}, I_{m,n}-I_{m+1,n-1}, I_{m,n}-I_{m+1,n}, I_{m,n}-I_{m+1,n+1}\}$ and Calculate minima as:

MINIMA= minimum{S}

}

If $[(I_{m,n}-MEAN_{R,C}) < MINIMA]_R$ and $[(I_{m,n}-MEAN_{R,C}) < MINIMA]_G$ And$[(I_{m,n}-MEAN_{R,C}) < MINIMA]_B$ then

label pixel (m,n) with RC and update $[MEAN_{RC}]_{R,G,B}$

Store pixel (m,n) in PG stack.

Else

Label pixel (m,n) as boundary pixel and store in BP(Boundary Pixel) stack.

STEP 6: Repeat step 3-6 until all pixels of PG can be grown.

STEP 7: if BP stack is not empty

Pick a pixel from BP, if it is labeled with some region number remove it form BP otherwise assign it as next seed pixel (x,y).

Update region counter RC as:

RC=RC+1;

Go to step 2 to grow next region RC.

Else if BP is empty

Go to step 8.

STEP 8: Post processing: merge small regions with closest connected region with respect to mean value.

EXIT

CHAPTER 4

FUZZY RULE BASED SINGLE SEEDED REGION GROWING

4.1 MOTIVATION

Classical so-called "crisp", image segmentation techniques while effective when an mage contains well-defined structures, such as edges and regular shapes, do not perform nearly so well in the presence of ill-defined data. In such circumstances, the processing of such images that possess ambiguities produces fuzzy regions. Fuzzy image segmentation Techniques can cope with the imprecise data well.

4.2 PROPOSED ALGORITHM

In Fuzzy rule based seeded region growing algorithm, step 4 and 5 of the non fuzzy algorithm proposed in section 3.2 in which decision is made to label pixel with same region or boundary pixel, solved by fuzzy rule. Basic flow of algorithm is same as non fuzzy algorithm proposed in section 3.2. The fuzzy rule is formulated as follows:

FUZZY RULE: If $I_{x,y}$ and $I_{m,n}$ is VERY SIMILAR AND If $I_{m,n}$ and $MEAN_{RC}$ is SIMILAR OR if $I_{m,n}$ and $MEAN_{RC}$ is RELATIVELY SIMILAR Then

Label pixel (m,n) with same region number (RC)

Else

Label Pixel (m,n) as boundary pixel

Where $I_{x,y}$ represent intensity values at coordinate (x,y) and $I_{m,n}$ represent intensity values of next 8-neighbors of (x,y). $MEAN_{RC}$ is the mean intensity value of region labeled with RC.MINIMA is the lowest difference between pixel (m,n) and its all 8 8-neighbors.

Gaussian distribution function used to determine fuzzy membership values given as follows:

$$\mathrm{FMV}(x, \mu, \sigma) = \exp^{\left(-\frac{(x-\mu)^2}{2\sigma^2}\right)} \qquad \ldots(1)$$

In proposed algorithm fuzzy membership values for all three fuzzy sets SIMILAR, VERY SIMILAR and RELATIVELY SIMILAR calculated as follows:

For VERY SIMILAR ($I_{m,n}$):

$$\mathrm{FMV}(I_{m,n}, I_{x,y}, 10) = \exp^{\left(-\frac{(I_{m,n}-I_{x,y})^2}{2(10)^2}\right)} \qquad \ldots(2)$$

For SIMILAR ($I_{m,n}$):

$$FMV(I_{m,n}, MEAN_{RC}, 50) = \exp^{\left(-\frac{(I_{m,n}-MEAN_{RC})^2}{2(50)^2}\right)} \quad \ldots(3)$$

For RELATIVELY SIMILAR ($I_{m,n}$):

$$FMV(I_{m,n}, MEAN_{RC}, MINIMA) = \exp^{\left(-\frac{(I_{m,n}-MEAN_{RC})^2}{2(MINIMA)^2}\right)} \quad \ldots(4)$$

The standard deviation for all the three Gaussian functions is determined from the algorithm given in section 3.2.

PROPOSED FUZZY SEEDED REGION GROWING ALGORITHM::

The algorithm for fuzzy seeded region growing method is given below and fuzzy rule incorporated in steps 4,5 and 6.

STEP 1: Read color image I(R*C).

STEP 2: Initialization

initial seed pixel(x, y) as :

x = R/2; y = C/2;

a counter to track region number which one is growing

RC=1;

STEP3: Assign initial mean value of region RC as:

Label pixel (x,y) with region number RC.

$[MEAN_{RC}]_{R, G, B} = [I_{x,y}]_{R, G, B}$.

Where $I_{x,y}$ represent intensity value in I at coordinates (x, y) in RGB space$[I_{x,y}, I_{x,y}, I_{x,y}]_{R, G, B}$.

STEP 4: Examine 8-nb of pixel(x, y) in a window I_{MN}(3*3) with center pixel (x, y) and pixel (m, n) represent 8-neighbors.

If pixel (m, n) not labeled with any region number then

calculate fuzzy membership values for pixel (m, n) in the VERY SIMILAR fuzzy set as:

$[M1 = FMV(I_{m,n}, I_{x,y}, 10)]_{R,G,B}$

calculate fuzzy membership values for pixel (m,n) in the SIMILAR fuzzy set as:

$[M2= FMV (I_{m,n}, MEAN_{RC}, 50)]_{R,G,B}$

calculate fuzzy membership values for pixel (m,n) in the RELATIVELY SIMILAR fuzzy set as:

$[M3= FMV(I_{m,n}, MEAN_{RC}, MINIMA)]_{R,G,B}$

STEP: 5 Calculate membership value as:

Solving the AND part of the fuzzy rule as follows:

$[M4 = \min \{M1, M2\}]_{R,G,B}$

And solving OR part of the fuzzy rule as follows:

$[M5 = \max \{M3,M4\}]_{R,G,B}$

STEP : 6 Calculate final membership value from the RGB color space as follows:

$M = \min \{M5_R, M5_G, M5_B\}$

if M is less then 0.6 then

label pixel (m,n) with RC and update $[MEAN_{RC}]_{R,G,B}$,

Store pixel (m,n) in PG(Pixel to Grow) stack.

Else

Label pixel (m,n) as Boundry Pixel and store in BP(Boundary Pixel) stack.

STEP 7: Repeat step 3-6 until pixels of PG can be grown.

STEP 8: if BP stack is not empty

Pick a pixel from BP, if it is labeled with some region number remove it form BP otherwise assign it as next seed pixel (x,y).

Update region counter RC as:

RC=RC+1;

Go to step 2 to grow next region RC.

Else if BP is empty

Go to step 9

STEP 9: Post processing: merge small regions to closest connected region with respect to mean value.

EXIT

CHAPTER 5

RESULTS AND DISCUSSION

5.1 EXPERIMENTAL SETUP

To examine the efficiency of proposed algorithm, it is applied to several color images from the Berkley segmentation database [42] shown in Fig.1 (a). The images are of size 481x321. To implement proposed algorithm, system configured with Intel processor 2.63 GHz and 1 Gigabyte of RAM used and matlab2009 tool used. The results after applying proposed algorithm to these images are shown in Fig.1 (b). These results are obtained by converting the matrix containing labeled regions to an RGB image.

A. Segmentation evaluation index: Liu's F-factor

In order to evaluate segmentation results of real images as well as synthesized ones, and to evaluate results both locally and globally, the global segmentation evaluation index used, Liu's F-factor [43] given by:

$$F(I) = \sqrt{R} \times \sum e_i^2 \Big/ \sqrt{A_i} \qquad \dots (5)$$

where, *I* is the image to be segmented, *R* total number of regions in the segmented image, A_i the area or the number of pixels of the I^{th} region and e_i the color error of regions. e_i is defined as the sum of the Euclidean distance of the color vectors between the original image and the segmented image of each pixel in the region. The term $\sqrt{R}$ □ is a local measure which penalizes small regions or regions with a large color error. e_i indicates whether or not a region is assigned an appropriate feature (color). A large value of e_i means that the feature of the region is not well captured during the SSF process In this paper, *F* is normalized by the size of the image and is scaled down by the factor *1/1000*. The smaller the value of *F*, the better is the segmentation result.

B. Total time taken

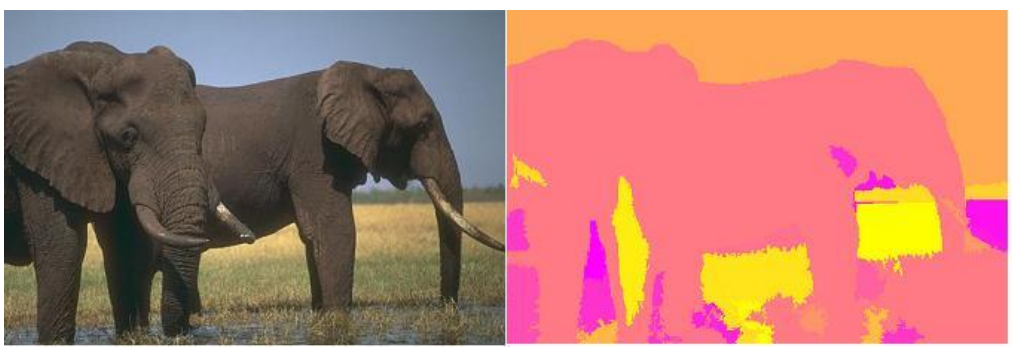
To evaluate the efficiency time consumption by algorithm also calculated Time consumption is a measurement of time complexity of the algorithm. Algorithm should be time efficient to produce segmented results.

C. Total number of region

Total number in segmented images represents the segmented regions by algorithm. Using total number of region segmented, reliability of algorithm can be analyzed by comparing with desired number of regions.

5.2 PROPOSED SINGLE SEEDED REGION GROWING ALGORITHM RESULTS:

1. Rock



2. Elephant

3. Tree and Ox

4. Man on Boat

5. Eagle

6. F1 race Cars

7. Zebra

8. Bridge

9. Fox on ice

10. Boy and Girl

11. Parade

12. Man and Building

13. Airplane

14. Boat and Building

15. Pot

16. Old man

17. Statue

(a) (b)

FIG8. Results of proposed single seed region growing algorithm.(a) Original images (b) Segmented images.

Results are visually acceptable by applying proposed algorithm to Berkley images as shown in Fig.8. After analyzing the results of proposed algorithm, it can be said that results of are good for realistic images. Proposed algorithm does not perform so well for area in images which have very small regions, like in statue image contains base of very small pieces of stones. Also Image like man on boat in which small black regions are present in see (white) affect the over all results of algorithm.

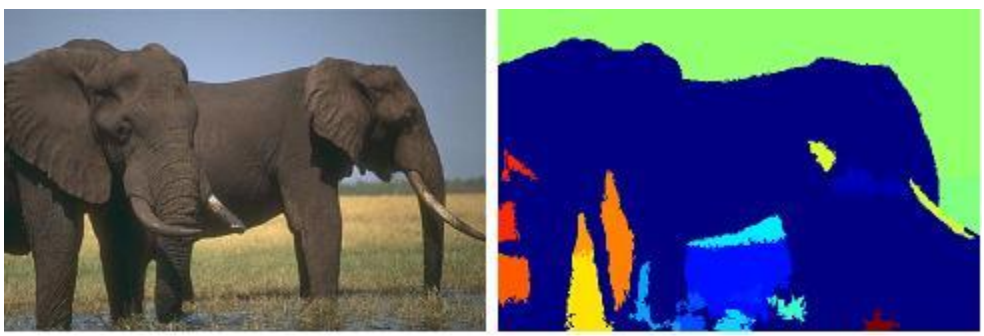
Table 1: Total number of region, Time Taken by algorithm, Liu's f-factor for proposed single seeded region growing algorithm

S. No.	Image	Total number of regions	Time taken (in seconds)	Liu's F-factor values
1	Rock	19	53.32	7.3995e-006
2	Elephant	29	48.00	6.8855e-006
3	Tree and ox	8	46.37	2.3605e-006
4	Man on boat	34	53.42	6.9344e-005
5	Eagle	35	52.74	1.9213e-005
6	F1 race cars	60	87.23	5.3665e-005
7	Zebra	81	56.15	1.4007e-004
8	Bridge	115	65.29	1.4669e-004
9	Fox on ice	7	43.28	4.3446e-006
10	Boy and girl	79	44.32	8.7919e-005
11	Parade	69	48.99	7.1568e-005
12	Man and building	107	58.21	9.9812e-005
13	Airplane	4	23.53	9.2168e-007
14	Boat and building	67	56.98	5.0277e-005
15	Pot	10	33.31	1.9837e-006
16	Old man	24	45.49	5.1674e-006
17	Statue	114	115.23	1.4336e-004

Liu's F-factor (eq^n. 5) has been evaluated all the segmented images by proposed algorithm. It is observed from table (1) that the Liu's F-Factor is low except for some images in which numbers of regions are much. Low values of Liu's f-factor show good segmentation. Number of regions segmented by proposed algorithm is acceptable. It can be seen by the table (1) that number of region is large for the images having high variance areas. Total time taken by proposed algorithm is near about 20 seconds, except images having large number of regions.

5.3 PROPOSED FUZZY SEEDED REGION GROWING ALGORITHM RESULTS

1. Rock



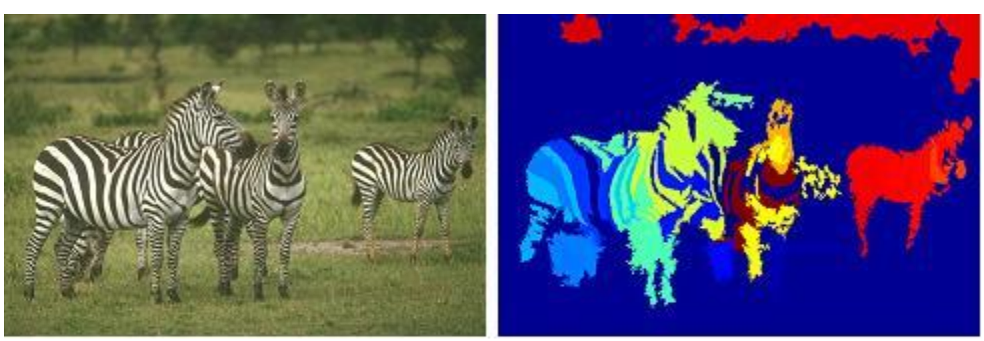
2. Elephant

3. Tree and ox

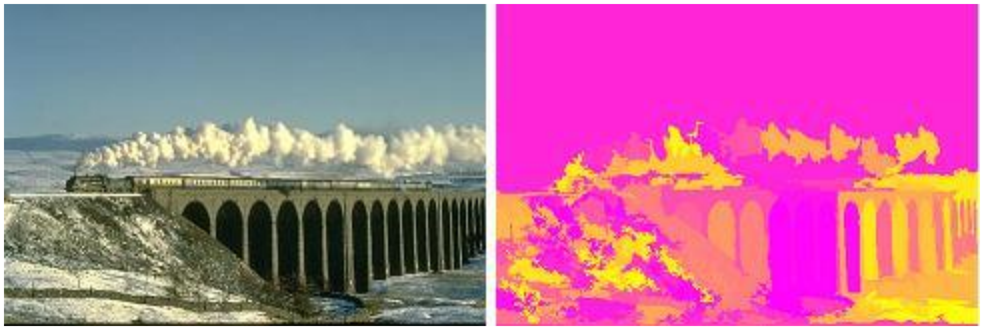
4. Man on boat

5. Eagle

6. F1 race cars



7. Zebra



8. Bridge

9. Fox on ice

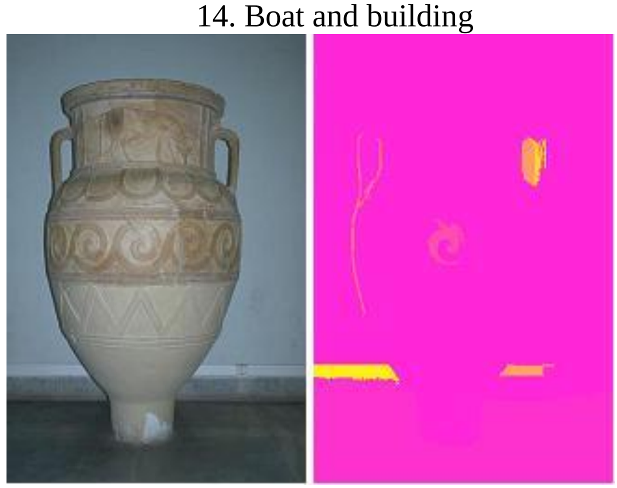
10. Airplane

11. Boy and girl

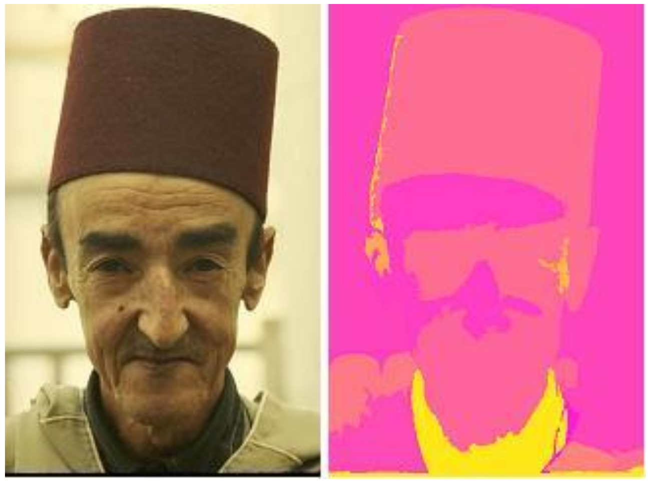
12. Parade

13. Man and building

14. Boat and building



15. Pot



16. Old man

17. Statue

(a) (b)

FIG. 10 Results of proposed fuzzy rule based algorithm. (a) Original images, (b) Segmented images.

After applying proposed fuzzy rule based region growing algorithm it can be see in fig. 2 that results are better with compare to proposed non-fuzzy algorithm (fig. 1). It produces good results for images like tree and fox contain high variance in intensity values correspond to R, G and B color spaces. The result for pot image shows that this algorithm is not efficient for low contrast images.

Table 2: Total number of region, Time Taken by algorithm, Liu's f-factor for proposed fuzzy rule based algorithm:

S.no.	Image	Total number of regions	Time Taken (in seconds)	Liu's factor values
1	Rock	17	75.64	1.5750e-005
2	Elephant	23	73.07	2.3135e-005
3	Tree and ox	7	82.09	8.0481e-006
4	Man on boat	38	81.59	1.6079e-004
5	Eagle	29	73.44	4.1859e-005
6	F1 race cars	54	78.87	9.6163e-005
7	Zebra	73	86.46	7.0045e-005
8	Bridge	93	89.91	1.3949e-004
9	Fox on ice	6	62.31	4.9996e-005
10	Boy and girl	71	86.33	1.6104e-004
11	Parade	48	64.07	1.2373e-004
12	Man and building	89	92.88	2.2110e-004
13	Airplane	4	53.1	2.1707e-006
14	Boat and building	59	78.67	1.1965e-004
15	Pot	8	60.7	2.6396e-006
16	Old man	15	71.74	2.0140e-005
17	Statue	97	119.23	1.8591e-004

Table (2) shows the Liu's f-factor, number of regions and time taken calculated for results by fuzzy rule based region growing algorithm. With compare to non-Fuzzy approach (table 1) values of Liu's f-factor for fuzzy approach are lower for only two images, zebra and bridge. It means fuzzy based approach does not produce better result in the respect of Liu's F-factor but as compare to fig.9 and fig. 10, it can be said that regions are more accurately defined and continuous than the non-fuzzy results. Total number of regions is also lower for this algorithm. Total time taken by algorithm is little higher than non-fuzzy approach, but with acceptable amount.

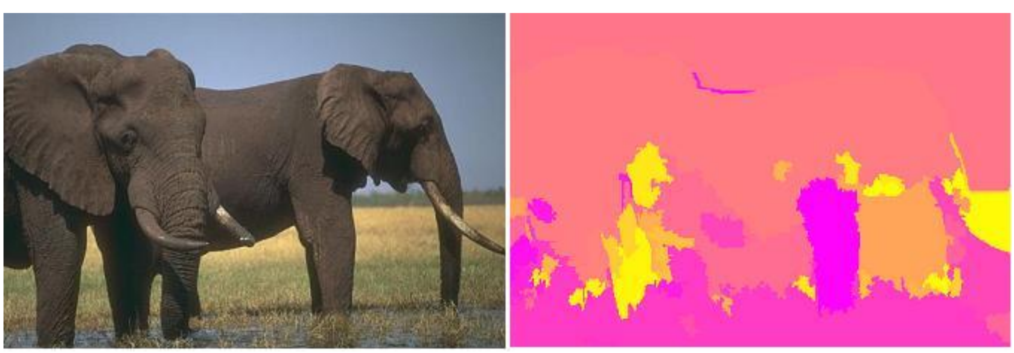
5.4 COMPARISION WITH OTHER TECHNIQUES

Proposed algorithm is also compared with two algorithms, one is proposed by Chaobing Huang (SRGRM) [46] [APPENDIX A] and other one is proposed by Juliana Fernandes Camapum(MRG)[47] [APPENDIX B]. Both proposed methods for image segmentation based on region growing method.

A. RESULTS OF SRGRM ALGORITHM

Chaobing Huang improvises the concept of integration of edge information to select seed regions proposed by them in letter [44]. In this paper, a method of color image segmentation by automatic seed selection and region growing is proposed in HSV color model. The non-edge and smoothness at pixel's neighbor are used as criterion to determine the initial seeds. Seeded region growing and region merging are used to segment color image. According to there results from their segmentation results are more accurate especially in image boundary compare to automatic seeded region growing method proposed by Frank Y Shih[45].

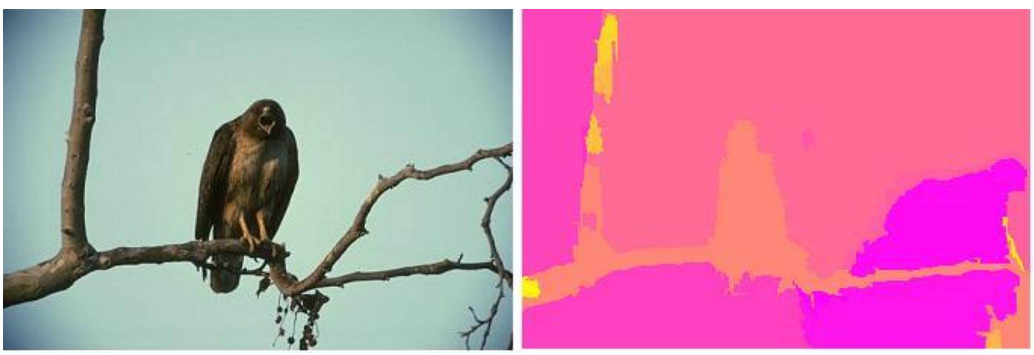
1. Rock



2. Elephant

3. Tree and Ox

4. Man on boat

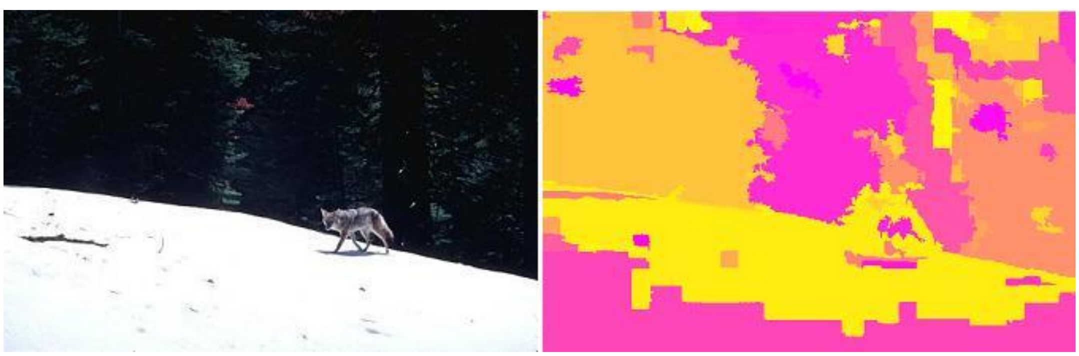


5. Eagle

6. F1 race cars

7. Zebra

8. Bridge



9. Fox on ice

10. Boy and Girl

11. Parade

12. Man and Building

13. Airplane

14. Boat and Building

15. Pot

16. Old man

17. Statue

(a) (b)

FIG. 9 Results of SRGRM algorithm. (a) Original images (b) Segmented images.

Results of SRGRM algorithm shown in fig 9, which are visually poorer compare to proposed algorithm results (fig. 7). This algorithm produces good segmentation for areas having similar intensity values. Problem arises when edges are not connected, because it selects initial seed based on edge and similarity and final result depend on initial selected seeds. When edges are not connected seeds which are connected but different in terms of intensity, are selected and affect the over all result.

Table 3: Total number of region, Time Taken by algorithm, Liu's f-factor for SRGRM algorithm:

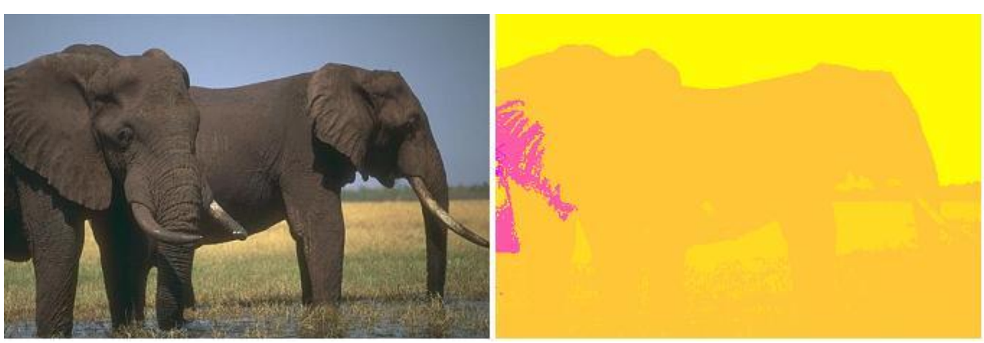
S. No.	Image	Total number of regions	Time taken (in seconds)	Liu's F-factor values
1	Rock	15	48.17	1.8375e-005
2	Elephant	48	52.62	4.6800e-005
3	Tree and ox	69	48.08	7.8902e-006
4	Man on boat	34	54.51	1.4490e-004
5	Eagle	21	61.25	3.5165e-005
6	F1 race cars	87	72.23	1.0616e-004
7	Zebra	28	56.98	1.4311e-005
8	Bridge	31	60.92	6.0620e-005
9	Fox on ice	62	56.39	2.5660e-004
10	Boy and girl	52	53.53	8.2709e-005
11	Parade	39	52.67	9.4216e-005
12	Man and building	89	52.00	1.6505e-004
13	Airplane	182	73.09	4.9870e-006
14	Boat and building	50	57.31	8.9352e-005
15	Pot	50	62.95	1.5363e-005
16	Old man	23	58.65	4.7814e-005
17	Statue	45	52.40	7.4352e-005

Calculated liu's f-factor, number of region and time taken by SRGRM algorithm shown in table (3). Liu's f-factor is greater for this algorithm compare to proposed non-fuzzy approach (table 1) except for zebra, bridge and statue images. And it is greater for some images compare to proposed fuzzy rule based region growing algorithm (table 2). Total numbers of region are acceptable except airplane image. Time taken by this algorithm is greater then proposed non fuzzy approach.

B. RESULTS OF MRG ALGORITHM

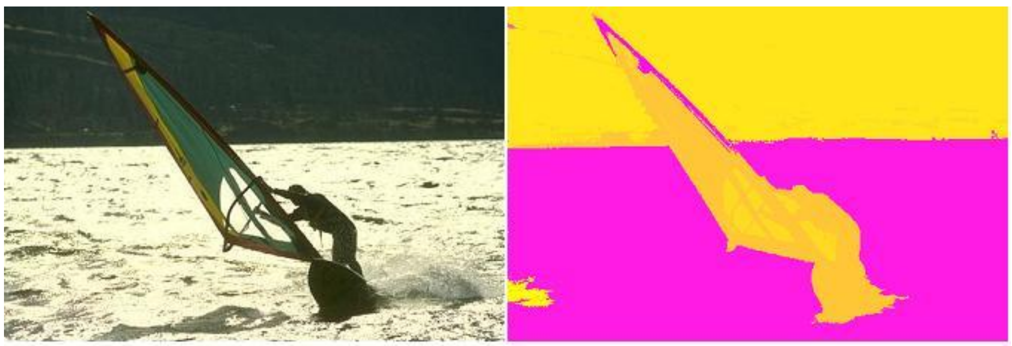
This one proposed by Juliana Fernandes Camapum[47] [APPENDIX B], a new system for automatic segmentation of images of clinical structures. The main contributions are the method of seed pixels selection and predicate of the multi-region growing algorithm. The objective of this work is to help the clinical oncologist in this complex task by providing an accurate and reliable automatic method. Their work follows the one started by Bueno [48]. In order to improve the results, they propose a new method of automatic markers detection through the image histogram. This improvement is very important and resulted in precise segmentation of images with poor contrast and acquired from different CT equipments. The statistic measures showed the high accuracy of segmentation, what make it useful. The multi-region growing algorithm implemented in this work is quite independent of the input images. The seed selection and homogeneity criteria are robust leading to a successful segmentation.

1. Rock



2. Elephant

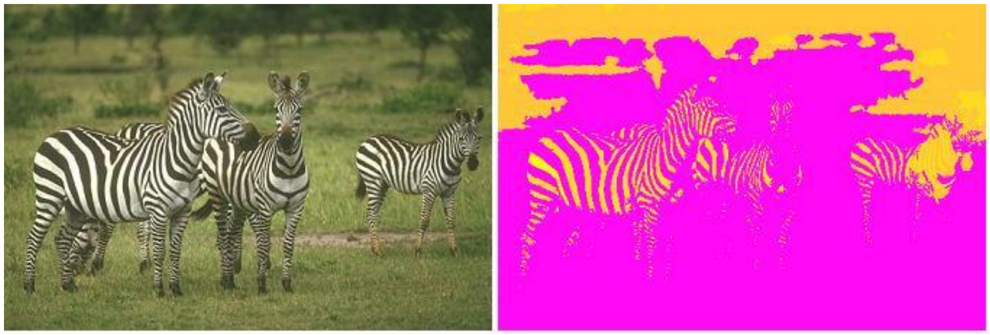
3. Tree and ox



4. Man on boat

5. Eagle

6. F1 race cars



7. Zebra

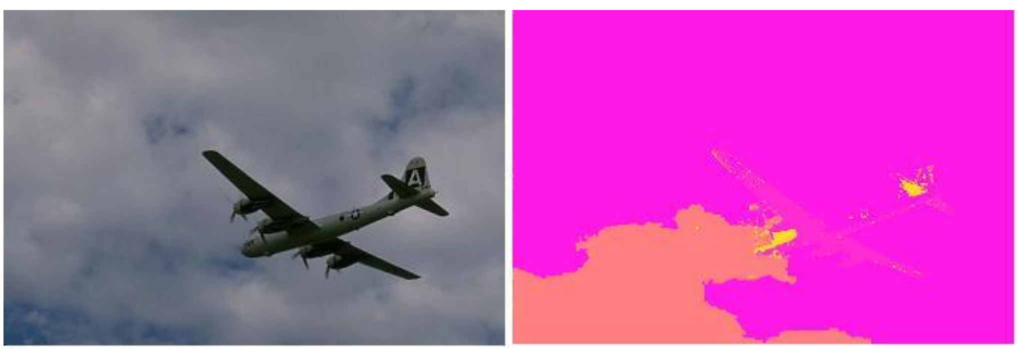
8. Bridge

9. Fox on ice

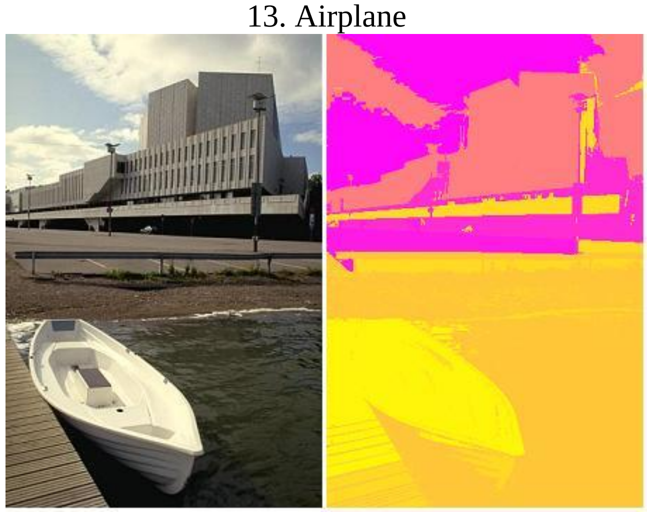
10. Boy and Girl

11. Parade

12. Man and Building



13. Airplane



14. Boat and building

15. Pot

16. Old man

17. Statue

(a) (b)

FIG. 9 Results of MRG algorithm. (a) Original images (b) Segmented images

Results of MRG algorithm shown in fig. 9 are visually good. The main advantage of algorithm is that it doesn’t required post processing. Results of MRG algorithm are better with compare to proposed algorithm in the case of images having very small regions like in statue image. The algorithms perform poorer for the images which have high variance in intensity values.

Table 4: *Total number of region, Time Taken by algorithm, Liu’s f-factor for MRG algorithm:*

S. No.	Image	Total number of regions	Time taken (in seconds)	Liu’s F-factor values
1	Rock	31	32.61	3.5865e-005
2	Elephants	21	30.07	1.5936e-005
3	Tree and Ox	23	28.97	2.3443e-005
4	Man on boat	24	28.39	4.5733e-005
5	Eagle	32	35.05	2.5290e-005
6	F1 race cars	27	28.04	4.1735e-005
7	Zebra	32	38.14	2.5373e-005
8	Bridge	32	35.43	3.4708e-005
9	Fox on ice	24	28.56	1.9009e-005
10	Boy and girl	22	34.17	4.7495e-005
11	Parade	31	38.58	8.2541e-005
12	Man and building	31	24.08	1.1445e-004
13	Airplane	32	29.63	6.1536e-006
14	Boat and building	26	27.89	4.7762e-005
15	Pot	21	32.02	7.1051e-006
16	Old man	33	36.85	4.9913e-005
17	statue	33	37.94	5.4596e-005

MRG algorithm is very time efficient algorithm because it does not required any post processing. Total number of regions is also small because it selects seeds, based on histogram of the image. Liu’s F-factor values are greater compare to proposed non-fuzzy algorithm except for some images.

CHAPTER 6

CONCLUSION AND FUTURE WORK

6.1 CONCLUSION

In this thesis a region growing algorithm for color image segmentation successfully implemented. The proposed method starts with center pixel of the image. Method uses intensity based growing formula in which it first checks for similarity of pixel (to be label) with respect to connected pixel and with mean value of growing region. If it fulfills criteria then it includes the pixel in growing region. Otherwise it analyzes closeness of pixel with respect to its 8-neighbors and the mean value of growing region. If it is closer to growing region compared to its neighbors then it is included in growing region, otherwise it is labeled as boundary pixel. After one region is completely grown, next seed pixel is selected from the boundary pixel stack. The proposed algorithm have been applied to Berkley images with successful results and evaluation of segmented images has been done using Liu's F-factor, total number of regions segmented and time taken by algorithm. Liu's F-factor, total time taken and total number of regions determined for proposed algorithm, are acceptable. A fuzzy rule based modification of the algorithm is also proposed in which decision making steps is solved by fuzzy rule and basic flow of algorithm remain same and the results are compared with that of non-fuzzy algorithm. Limitations of the algorithm have been discussed. The proposed algorithm is also compared with method proposed by Chaobing Huang and another one proposed by Juliana Fernandes Camapum. On the basis of results described in chapter 5, it can be said that the proposed algorithm's results are better compared to both. The proposed method contributes over conventional region growing methods in two aspects, first selection of seeds and another one is growing formula.

6.2 FUTURE WORK

- Instead of intensity values, other features like edge information, texture can be used to improve efficiency of growing formula.
- Efficient region merging approach will support to merge small regions.
- More tuning of fuzzy membership function can produce more efficient result.

APPENDIX

A. "Color Image Segmentation by Seeded Region Growing and Region Merging" (SRGRM)

Chaobing Huang, Quan Liu, Xiaopeng Li proposed an automatic seed selection and region growing method Based on HSV color model. Two factors, the non-edge and smoothness at pixel's neighbor are used as criterion to determine automatically which ones are seed pixels. The seed pixels are merged to form further seed region if they are connected. Then seeded region growing method is used to segment the image based on selected seed regions. Region merging is used to merge similar regions or small regions in the end.

A. Initial seeds selection:

Calculation for no-edge and smoothness factor done by author as follow:

1) No-edge: First it compute the average, maximum and minimum values of hue value over N (i, j), and denote by Avg, Max, Min respectively. Define the following parameters: A π-type fuzzy membership function is then used to compute μ(i, j) for all (i, j) of N(i, j), such that μ(Avg- D)=μ(Avg+D)=0.5 and μ(Avg)=1. Let h(i, j) be the hue value of a pixel at (i, j), the fuzzy membership function is defined as following:

$$\mu(i,j)=1-\frac{1}{2}\left(\frac{h(i,j)-Avg}{D}\right)^2 \quad \ldots (7)$$

The fuzzy entropy is defined as below:

$$e(i,j)=-\mu(i,j)\log(\mu(i,j))-(1-\mu(i,j))\log(1-\mu(i,j)) \quad \ldots (8)$$

For every pixel (i, j), let g(i, j) denote the average of fuzzy entropy over N(i, j), i.e.:

$$g(i,j)=\frac{1}{9}\sum_{(k,l)\in N(i,j)} h(k,l) \quad \ldots (9)$$

where 0≤i<m, 0≤j<n. The G-image of I(i, j) is defined as: G={ g(i,j) | 0≤i<m, 0≤j<n }

The value of g(i, j) over N(i, j) can be viewed as a measure of edge. Calculate the average and the standard deviation of the g-values in the G-image; denote them by t_g and σ_g, respectively. The threshold is defined as following statement:

$$T_g = \begin{cases} t_g - 0.5\sigma_g & (t_g - 0.5\sigma_g) > 0 \\ t_g & otherwise \end{cases} \quad \ldots (10)$$

An initial seed pixel must have the g-value which is less than threshold Tg.

2) Smoothness

For a pixel at location (i, j), the color value at location (i, j) is (h(i. j), s(i. j), v(i. j)). Let denote $(\overline{h(i,j)}, \overline{s(i,j)}, \overline{v(i,j)})$ as the average value of color value over N(i, j). We compute the distance between (h(i. j), s(i. j), v(i. j)) and $(\overline{h(i,j)}, \overline{s(i,j)}, \overline{v(i,j)})$ as following equation.:

$$d(i,j) = \sqrt{(v-\bar{v})^2 + (s\cosh - \bar{s}\cos\bar{h})^2 + (s\sinh - \bar{s}\sin\bar{h})^2} \quad \ldots (11)$$

Where 0≤i<m and 0≤j<n. The D-image of I(i, j) is defined as: D={ d(i,j) | 0≤i<m, 0≤j<n } (7). The value of d(i, j) over N(i, j) can be viewed as a measure of smoothness. Calculate the average and the standard deviation of the d-values in the D-image; denote them by td and σd, respectively. The threshold is defined as following statement:

$$T_d = \begin{cases} t_d - 0.5\sigma_d & (t_d - 0.5\sigma_d) > 0 \\ t_d & otherwise \end{cases} \quad \ldots (12)$$

An initial seed pixel must have the d-value which is less than threshold Td. A pixel is classified as a seed pixel if it satisfies the above two conditions.

B. Form Seed regions

There are many initial seed pixels. If two initial seed pixels are 4-adjacency, they can be merged to a seed region. Classify seed pixels to seed regions according to 4-adjacency. Output of this step are initial seed regions.

C. Seeded region growing

The seeded region growing algorithm is used to further grow the seed regions obtained from previous step. This step produce segmented image with over segmented regions. To overcome the over segmentation problem, authors apply region merging. Two criteria are used: one is the similarity of color and the other is the size of region.

1. Region merging based on color similarity

The distance between two regions k, l is calculated by

$$D(k,l) = \sqrt{(\overline{v_k} - \overline{v_l})^2 + (\overline{s_k}\cos\overline{h_k} - \overline{s_l}\cos\overline{h_l})^2 + (\overline{s_k}\sin\overline{h_k} - \overline{s_l}\sin\overline{h_l})^2} \quad \ldots (13)$$

Where $(\overline{h_k}, \overline{s_k}, \overline{v_k}), (\overline{h_l}, \overline{s_l}, \overline{v_l})$ are mean values of region k, l, respectively. The less the distance between two regions are, the more similar between two regions are. If the distance between two neighboring regions is less than a threshold value, they merge the two regions,

2. Region merging based on size

The size of region means the number of pixels in the region. If the size of a region is smaller than a threshold(1/100), the region is merged into its neighboring region with the smallest color difference. This procedure is repeated until no region has size less than the threshold

B. Segmentation of Clinical Structures from Images of the Human Pelvic Area: (MRG)

Juliana Fernandes Camapum, Alzenir O. Silva, Alan N. Freitas, Hansenclever de F. Bassani, Flávia Mendes O. Freitas proposed a new system for automatic segmentation of images of clinical structures. The algorithm is based on multi-region growing followed by watershed transform. The main contributions of this method are seed pixels selection and predicate of the multi-region growing algorithm.

Multi-Region Growing (MRG)

In this method conventional region growing method extended to the MRG (Multi-Region Growing) where several regions are computed simultaneously. Authors implement a new peak detection algorithm based on image histogram. This algorithm provides the seed pixels and the homogeneity criteria to the MRG. Consequently, they do not need to define any parameter. In this paper seed selection and threshold for growing phase derived from histogram of the whole image. A weight function calculated to select initial seeds and again distance formula used to calculate stopping criteria adaptively for every seed candidate.

Seed Pixels Selection (markers). The markers selection, known as seed pixels, is computed from the image histogram as follows:

For each P calculate g(pi)

$$g(p_i) = freq_i \times dist_i^2 \qquad \dots (14)$$

where pi is the peak i of the histogram, freqi is the height of the peak and

$$dist_i = \begin{cases} 1, \quad if\ p_i\ is\ the\ first\ peak \\ horizontal\ distance\ to\ the\ nearest\ selected\ p_i\ , otherwise \end{cases} \quad \ldots (15)$$

The horizontal distance is calculated by the absolute value of the difference between the gray level of the peak been tested and the nearest peak from the ones which have already been selected. The peak pi, which maximizes the function g (pi), is selected. These pixels will initiate the multi-region growing algorithm.

2.3.2. Homogeneity Criteria. Consider f(x, y) as the gray level of the pixel (x, y). The homogeneity criteria (H_{pi}) is defined as

$$Hp_i(x, y) = \begin{cases} True\ if\ v_i \leq f(x, y) \leq v_{i+1} \\ False\ , otherwise \end{cases} \quad \ldots (16)$$

Where the peak p_i been tested is located between one valley on the left v_i and one valley on the right v_i+1. The computation of the gray level of the valleys is presented in Equation 4. For each peak pi select a gray level I between p_i and p_i+1 that minimize the function h_i(I), as defined in the equation below.

$$v_i = \underset{I}{MIN}(h_i(I))$$
$$h_i(I) - freq_i \times \left[I - \frac{(I_i + I_{i+1})}{2} \right] \quad \ldots (17)$$

where: I is a gray level between the gray levels of two selected peaks pi and pi+1; $freq_i$ is the frequency of I; $\left[\frac{(I_i + I_{i+1})}{2} \right]$ is the middle value between p_i and P_i+1 and $\left[I - \frac{(I_i + I_{i+1})}{2} \right]$ is the distance of I to the middle point between p_i and p_i +1;

The method described above was achieved experimentally and resulted in a very efficient peak detection algorithm.

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