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Image Segmentation using Various Approaches

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***Abstract*—This paper addresses the issue of image segmentation. Image segmentation process is the main basic process or technique used in various image processing problem domains, for example, content based image retrieval; pattern recognition; object recognition; face recognition; medical image processing; fault detection in product industries; etc. Scope of improvement exists in the following areas: Image partitioning; color based feature; texture based feature, searching mechanism for similarity; cluster formation logic; pixel connectivity criterion; intelligent decision making for clustering; processing time; etc. This paper presents the image segmentation mechanism which addresses few of the identified areas where the scope of contribution exists. Presented work basically deals with the development of the mechanism which is divided into three parts first part focuses on the color based image segmentation using k-means clustering methodology. Second part deals with region properties based segmentation. Later, deals with the boundary based segmentation. In all these three approaches, finally the Steiner tree is created to identify the class of the region. For this purpose the Euclidean distance is used. Experimental result justifies the application of the developed mechanism for the image segmentation.**

Keywords-image segmentation, k-means clustering, steiner tree, region growing

I. INTRODUCTION

Image processing is interesting field in this era. Everyone wants to create new inventions in this topic. Image processing is a method to convert an image into digital form and perform some operations on it, in order to get an enhanced image or to extract some useful information from it. Usually Image Processing system includes treating images as two dimensional signals while applying already set signal processing methods to them. It is among rapidly growing technologies today, with its applications in various aspects of a business. Image Processing forms core research area within engineering and computer science disciplines too. There are various types of image processing but our rate of interest is firstly come in the image segmentation. Image segmentation is the process of divides a digital image into multiple set of segments i.e. sets of pixels, superpixels. Image segmentation based on the similarity and dissimilarity of the pixels. Image segmentation also used to identify the region on various types of techniques. Image segmentation is categorized into region-based segmentation, data clustering, and edge-base segmentation.

Clustering is used to partition a set of given observed input data vectors or image pixels into clusters so that members of the same cluster are similar to one another than to members of other clusters where the number, of clusters is usually predefined or set by some validity criterion. Generally, clustering methods can be divided into hierarchical, graph theoretic, decomposing a density function, and minimizing an objective function. Cluster analysis or clustering is the task of grouping a set of objects in such a way that objects in the same group (called a cluster) are more similar (in some sense or another) to each other than to those in other groups (clusters). It is a main task of exploratory data mining, and a common technique for statistical data analysis, used in many fields, including machine learning, pattern recognition, image analysis, information retrieval, and bioinformatics. In centroid-based clustering, clusters are represented by a central vector, which may not necessarily be a member of the data set. When the number of clusters is fixed to k, *k*-means clustering gives a formal definition as an optimization problem: find the *k* cluster centers and assign the objects to the nearest cluster centre, such that the squared distances from the cluster are minimized.

The optimization problem itself is known to be NP-hard, and thus the common approach is to search only for approximate solutions. A particularly well known approximative method is Lloyd's algorithm, often actually referred to as k-means algorithm. k-means has a number of interesting theoretical properties. On the one hand, it partitions the data space into a structure known as a Voronoi diagram. On the other hand, it is conceptually close to nearest neighbour classification, and as such is popular in machine learning. Third, it can be seen as a variation of model based classification, and Lloyd's algorithm as a variation of the Expectation-maximization algorithm. There exist several variants of the k-means algorithm in the literature. Some of them present the guidance on good initial centroids so that the algorithm is more likely to find the optimal result. Another variation of the k-means algorithm is to select a different criterion function altogether. Another variation involves the idea of splitting and merging after completing the k-means algorithm.

Segmentation is the process of partitioning a digital image into set of pixels or regions. The objective of segmentation is to change the depiction of an image into something that is more meaningful and easier to extract information. In other words, in segmentation, a value is assigned to every pixel in an image such that pixel with the same values share certain characteristics, such as color, intensity or texture in a particular region. It is considered as a critical component of an image analysis and/or pattern recognition system and is still recognized as one of the most challenging tasks in the field of image processing. This is due to the fact that image segmentation is inherently ill-posed. Various algorithms have been proposed for segmenting an image but there is no particular standard on which an image should be segmented. So there is still scope for contribution in this area. Image segmentation problems are instinctively related with human perception. It means that the segmented images should form regions that are perceptually important. However, human perception is an ill-defined term and so is image segmentation. One may segment an image on the basis of colors, while other may segment an image on the basis of texture or edges. Thus image segmentation is termed as classical computer vision problem.

This paper presents various approaches for image segmentation. This paper is organized as follows. In section 2, systematic presentation of the literature review is done; which involves the gist of the related approaches along with the summary of the related work that is more relevant to developed approach. Section 3 focuses on the formulation of the identified problem. Section 4 is dedicated to the proposed approach; where the three basic approaches are discussed to form the segmentation mechanism. Section 5 emphasize on the experimental results followed by the discussion. Section 6 addresses the conclusions along with the future directions followed by the references.

II. Related Work

This section presents the critical analysis of existing literature which is relevant to image segmentation and the mechanisms associated with Steiner tree. Though, the literature consists of a lot many research contributions, but, here, we have analyzed few of them. The claims by the concerned contributors are highlighted. Finally, the findings are summarized related to the studied and analyzed research papers.

A. *Steiner Tree Related Work*

Garey et al. [1] evaluated the complexity of computing Steiner Minimal Trees. Garey and Johnson [2], proved the Rectilinear Steiner Tree Problem is NP-complete. Rayward-smith and Clare [3], discussed a mechanism to find Steiner vertices. Diane and Plesnik [4], discussed the heuristics approaches. Laarhoven and William [5] proposed exact and heuristic algorithms for the Euclidean Steiner Tree Problem in their PhD thesis. Kapsalis et al. [6]; Ding and Ishii [7] and Esbensen [8], discussed the Genetic Algorithm based approach for Steiner Tree Problem. Hougardy and Promel [9], discussed an approximation algorithm for the Steiner Problem in graphs. Robins and Zelikovski [10] proposed an approximation algorithm for Steiner Tree in graphs. Jain [11], proposed an approximation algorithm for the Generalized Steiner Tree Network Problem. Shen and Guo [12], proposed 2-approximation algorithms for computing 2-connected Steiner Minimal Networks. Zhan and Zhang [13], explored the discrete particle swarm optimization for multiple destination routing problems. Ma and Liu [14] discussed an approach based on a particle swarm optimization for Steiner Tree Problem. Hu et al. [15], proposed a rectilinear Steiner Minimum Tree algorithm Based on ant colony optimization. Tashakori et al. [16], solved Dynamic Steiner Tree Problem by using ant colony system. Li et al. [17], discussed an ant based Distributed Constrained Steiner Tree algorithm for Jointly Conserving Energy and Bounding Delay in ad hoc multicast routing. Noferesti and Rajayi [18], solved Steiner Tree Problem by using learning automata. Wang and Jan [19], proposed a factoring approach for the Steiner tree problem in undirected networks. Noferesti and Shah-Hosseini [20], proposed a hybrid algorithm for solving Steiner Tree Problem. In 2011, Noferesti and Rajaei [21], discussed a hybrid algorithm based on ant colony system and learning automata for solving Steiner Tree Problem. Hu et al. [22], discussed the Multicast Routing problem which later solved by an ant colony optimization approach where the concept of Steiner tree is explored.

B. *Other Work*

In the year 2011, Bo Peng, Lei Zhang, David Zhang and Jian Yang introduced an iterated region merging-based graph cuts algorithm [23]. They used the performance evaluation parameters of true-positive fraction (TPF), false-positive fraction (FPF), true-negative fraction (TNF) and false-negative fraction (FNF) for comparison. They carried out experimentations on 50 benchmark test images selected from online resources. The mentioned approach reduces the interference of unknown background regions segmenting the objects from complex background. However, the approach requires a lot of user interaction and computational complexity of the algorithm seems to be more as time estimation is not presented. Wenbing Tao, Feng Chang, Liman Liu, Hai Jin and Tianjiang Wang, in 2010, worked on interactively multiphase image segmentation based on variational formulation and graph cuts [24] and show that their algorithm can segment complex natural color images. However, the visual quality of segmentation is not maintained. Jong-Sung Kim and Ki-Sang Hong, in the year 2009, show that color–texture segmentation of an image is done by regarding it as a minimum cut problem in a weighted graph. They developed a texture descriptor based on the texton theory which is used to efficiently represent the texture attributes of the given image [25]. They used F-measure, precision, recall as performance evaluation parameter and carry out experimentations on MIT VisTex datasets and Berkeley datasets. However, the mentioned approach does not evenly treat color and texture at the initial segmentation of color textured images.

In [26], Hailing Zhou, Jianmin Zheng, Lei Wei, in 2013, proposed that combining both color and texture information for graph cut and including structure tensors, incorporating active contours into the segmentation process, and using a ‘‘softbrush’’ tool to impose soft constraints overcomes the difficulties of previous segmentation algorithms. The performance evaluation parameter used by them is error rate (%). They carried out their experimentations on Brodatz, Berkeley and MSRC data sets. However, equally fusing color and texture, or only using color or texture may not generate good segmentation results. In year 2010, Lei Zhang and Qiang Ji proposed that the Conditional Random Field (CRF) model and the Bayesian Network (BN) model when combined through the theories of Factor Graph form a unified probabilistic graphical model [27]. They used the parameters like segmentation consistency and overall accuracy for performance evaluation. They claim that as compared to CRF model and BN model alone the proposed approach produces better results. However, complexity is more and time required for the algorithm to execute seems to be more as compared to CRF model or BN model alone. In 2011, F. Malmberg, J. Lindblad, N. Sladoje, I. Nyström, presented a framework for object representation based on fuzzy segmented graphs [28]. They claim that the unavoidable loss of information when representing continuous structures by finite sets is reduced enabling feature estimates with sub-pixel precision. They evaluated their results using the performance evaluation parameters Area error% and Maximal area error%. However, the algorithm primarily focuses on fuzzy segmentation and also the computational complexity seems to be higher as time evaluation is not presented. In 2011, Akif Burak Tosun et al used graph run-length matrices for histopathological image segmentation [29]. They claim that the proposed work lead to high segmentation accuracy, providing a reasonable number of segmented regions. They used performance evaluation parameters like accuracy, sensitivity, specificity, threshold and computational time and carried out experimentations on database of Pathology Department archives of Hacettepe School of Medicine. However in the algorithm, region growing is achieved on the primitives, not on the pixels. The primitives do not cover all of the pixels.

In the year 2010, Yin Yin et al proposed Layered Optimal Graph Image Segmentation of Multiple Objects and Surfaces (LOGISMOS) Cartilage Segmentation in the Knee Joint [30]. They used Dice Similarity Coefficients (DSC) as performance evaluation parameter and carry out their experimentations on 3-D MR image datasets from the Osteoarthritis Initiative Database. They claim that the developed framework can be applied to a broad range of complex and multisurface segmentation problems. However osteophytes which can cause difficulties in the preliminary segmentation steps are not dealt with. In the year 2013, Costas Panagiotakis et al introduced a Markov Random Field (MRF) model which is used to get the image segmentation by minimizing a min–max Bayesian criterion [31]. They used the parameters like region precision (RP) and boundary precision (BP) to compare with other existing algorithms. They carry out experimentations and found that the approach reduces the problem of graph clustering to the simpler problem of point clustering. However, as the size of image increases, the time required to covert the problem of graph clustering to point clustering seems to increase. T.N. Janakiraman and P.V.S.S.R. Chandra Mouli, in the year 2010, claimed that by treating image as an undirected weighted non-planar finite graph (G), image segmentation is handled as graph partitioning problem [32]. The proposed approach locates region boundaries or clusters and runs in polynomial time. They carry out their experimentations on Berkeley Image database and used the performance evaluation parameter of F-measure. They observed that those images having uniform background or average intensity range obtained best results. However, the proposed approach could not segment the images having high overlapping of objects or very dark images.

Deepthi Narayan, Srikanta Murthy K. and G. Hemantha Kumar in the year 2008 used a Weighted Euclidean distance to calculate the edge weight and a slight modification is done in the existing graph based image segmentation algorithm [33]. They carried out their experimentations on Vision Texture database and Berkeley Segmentation Dataset. They claim that the experimental results show the improvement in the segmentation quality as compared to the approaches that already exist. However, efficiency is less and the performance evaluation parameter is not present so as to support the concerned author's claim as how the segmented image obtained from the mentioned algorithm is improved. In 2013 Yong Yang, Shoudong Han, Tianjiang Wan, Wenbing Tao and Xue-Cheng Tai proposed Multilayer graphcuts based unsupervised color–texture image segmentation using multivariate mixed student's t-distribution and regional credibility merging [34]. They carried out their experimentations on MIT VisTex, Berkeley segmentation database and saliency object database and used the performance evaluation parameter PRI and NPR. Their proposed approach provides effective over/error-segmentation reduction, high segmentation accuracy, and outperforming visual entirety/consistency. However, the scale of MSST is not adaptively determined. Also the computation complexity is more as both the color and texture segmentation is done. Xiaohua Zhang, Jiawei Chen, and Hongyun Meng in the year 2013 proposed SAR Image Change Detection Based on Graph-Cut and Generalized Gaussian Model [35]. They claim that PPB difference image can suppress the effect of speckle and increase the discrimination of the changed and the unchanged regions. In addition, the graph-cut initialization can extract the spatial structure of the difference image, which provides the important spatial prior information for the initialization of the change mask, and lead the EM algorithm to converge fast indirectly. They used the performance evaluation parameters like False alarm (FA), missed error (ME), overall error (OE), and the Kappa coefficient. They carried out their experimentations on Bern data set, Ottawa data set and Yellow River data set. However, the sparsity of the change map is not exploited and other properties of the multitemporal image are not focused, such as low rank and compressibility. Also GCD does not work on changed map. In 2011, Shifeng Li and Huchuan Lu, introduced a super-pixel based graph cuts algorithm for human body segmentation from images is used [36]. They claim that the approach can segment the object more accurately than the geodesic star convexity graph cuts, Grabcut and also standard graph cuts with a few user-provided seeds and is robust to the parameters changes. The parameters used by the concerned authors are Smoothness and Balance for comparison. However, the computational complexity seems to be more as time evaluation is not presented. Above literature is summarized in the Table 1.

C. *Our Findings*

Image segmentation is supervised or unsupervised clustering problem: Supervised clustering includes hierarchical approaches and unsupervised clustering includes density based approaches. Image segmentation is multi-objective optimization problem: Image segmentation is the region growing or region splitting process which includes variety number of parameters for decision making. Region formation or splitting is the clustering process and it may have multiple objectives, i.e., minimize overall deviation of intra-cluster spread of data, maximize the inter-cluster connectivity, minimize the number of features or minimize the error rate of the classifier etc. Image segmentation ingredients: Most of the approaches are driven by the basic key values which act as the input to the algorithm or method. Some of them are- pixel intensity; color; texture; histogram; pixel connectivity, threshold value; etc.

TABLE I. TABLE TYPE STYLES

Sr. No.	Ref. No. Author, Year	Claims by Concerned Author(s)	Our findings
1	[23] Bo Peng et al., 2011	The approach can reduce the interference of unknown background regions segmenting the objects from complex background.	Requires a lot of user interaction computational complexity of the algorithm seems to be more as time estimation is not presented.
2	[24] Wenbing et al., 2010	Can segment complex real world color natural images.	Visual quality is not maintained.
3	[25] Kim and Sang, 2009	This approach can efficiently segment images based on texture as well as color	The approach cannot be evenly treat texture and color.
4	[26] Zhou et al., 2013	The approach overcomes the problems of previous algorithms in handling images containing textures or low contrast boundaries and producing a smooth and accurate segmentation boundary.	Equally fusing color and texture, or only using color or texture may not generate good segmentation.
5	[27] Zhang and Qiang, 2010	As compared to CRF model and BN model alone the proposed approach produces better results.	Complexity is more and time required for the algorithm to execute seems to be more as compared to CRF model or BN model alone.
6	[28] Malmberg et al., 2011	The unavoidable loss of information when representing continuous structures by finite sets is reduced enabling feature estimates with sub-pixel precision.	The algorithm primarily focuses on fuzzy segmentation and also the computational complexity seems to be higher as time evaluation is not presented.
7	[29] Gunduz-Demir et al., 2011	The proposed work provides a appropriate number of segmented components and it also leads to high segmentation accuracy.	Region growing is achieved on the primitives by the algorithm and not on the pixels. The primitives do not cover all of the pixels.
8	[30] Zhang et al., 2010.	The developed framework can be applied to a wide range of multiobject and multisurface segmentation problems.	Osteophytesis not particularly dealt with in this approach. It is found that it can cause difficulties in the preliminary segmentation steps.
9	[31] Fragopoulou et al., 2013	The approach reduces the problem of graph clustering to the simpler problem of point clustering.	As the size of image increases, the time required to covert the problem of graph clustering to point clustering seems to increase.
10	[32] Janakiraman and Mouli, 2010.	The authors observed that the images having uniform background or average intensity range obtained best results.	The proposed approach could not segment the images having high overlapping of objects or very dark images.
11	[33] Narayan et al., 2008	The author claims that the segmentation quality of their work is improved as compared to the approaches that already exist.	Efficiency is less and the performance evaluation parameter is not present so as to support the author's claim as how their segmentations results are improved.
12	[34] Yang et al., 2013	The proposed approach provides effective over/error-segmentation reduction, high segmentation accuracy, and out-performing visual entirety or consistency.	The scale of MSST is not adaptively determined. Also the computation complexity is more as both the color and texture segmentation is done.
13	[35] Zhang et al., 2013	The PPB difference image can suppress the effect of speckle and increase the discrimination of the changed and the unchanged regions. In addition, the graph-cut initialization can extract the spatial structure.	The sparsity of the change map is not exploited and other properties of the multi-temporal image are not focused, such as low rank and compressibility. Also GCD does not work on changed map.
14	[36] Li and Lu, 2011	The approach can segment the object more accurately with a few user provided seeds and is robust to the parameters changes.	Complexity of algorithm seems to be more and thus it may require more computational time as time evaluation is not presented

III. PROBLEM FORMULATION

This section presents the formulation of the identified problem. Presented approach is developed based on the Steiner tree. This section, firstly, discusses the basic Steiner tree problem and later it presents the discussion on the formulated problem. The problem of Steiner tree can be formulated as below:

- The image is initially mapped on a graph G = (V, E), where, V= $\{v_1, v_2, \ldots, v_n\}$ is a set of vertices corresponding to the image elements, which might represent pixels or regions. E is a set of edges connecting certain pairs of neighboring vertices.
- The Steiner tree problem in graphs is formally defined as follows: Given an edge-weighted graph G = (V, E), and a

subset of vertices called terminals, the goal is to find a minimum-weight connected sub-graph of G that includes all terminals. It has been proven that the resulting sub-graph is always a tree and it is known as the Steiner tree. The cost of a Steiner tree is defined as the total cost of all links included in the tree.

- Other variants of Steiner tree problem includes: Vertex-Weighted Steiner Tree problem, Steiner Forest Problem, Dynamic Steiner Tree Problem.
- Two famous special cases of the Steiner tree problem are- Euclidean Steiner Tree (Euclidean Distance (L2 Metric) and Rectilinear Steiner Tree (Absolute Distance (L1 Metric))
- Steiner tree problems arising in practical applications usually involve cost functions that do not satisfy the L1 or L2 metric.
- This motivates the study of the Steiner tree Problem in graphs and images.
- Since in the Steiner tree in graphs we do not have any restrictions on the length function for the edges in the graph.
- We can model any Steiner tree problem in any metric by a Steiner tree problem in Images.

Presented work basically deals with the development of an image segmentation approach based on the Steiner tree. Firstly, the given image is segmented and later, based on the formed regions, the numbers of Steiner nodes in the image are identified. For every region the different properties are evaluated. Based on these properties the Steiner tree is formed to reach the Steiner nodes. Formulation of problem is summarized below:

- If k number of regions is there, then the number of Steiner nodes is k. All these k number of nodes will be at the last level of the directed graph. Root node is the node for image itself.
- For every property, each level of the directed graph is dedicated.
- Various nodes are there for every level depends on the values of the concerned property. These nodes are formed for the minimum and maximum value of the property and apart from these; some other nodes are also formed.
- Based on the value of the property, if it is not equals to the nodes in the directed graph, then the Steiner nodes are created for each property level.
- Finally, tree is generated which is nothing but the Steiner tree to represent the particular region class.

IV. Proposed Approach

This section gives the description about the mechanism that we have proposed. This section consists of the flow of our mechanism. Initially, it discusses about the block schematic of the proposed mechanism. Later, all the three parts of the proposed mechanism are discussed. Pseudocode for every approach involve in the proposed mechanism is summarized in this section.

A. Proposed Mechanism

The presented work is divided into three parts, namely,

- Color-Based Segmentation Using K-Means Clustering
- Region properties based image segmentation
- Region boundary based image segmentation

In every part, finally, Steiner trees are formed to locate and identify the segmented regions of the given image. Block schematic of the proposed mechanism is depicted in the Figure 1.

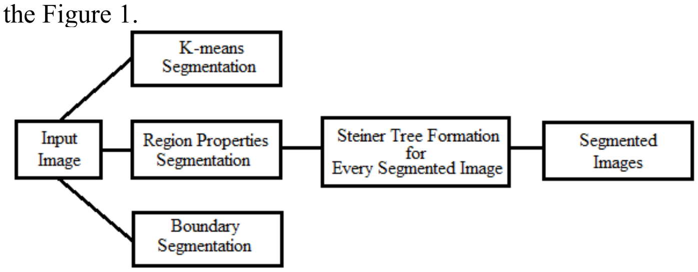


Figure 1: Block Schematic of Proposed Mechanism

B. *Color-Based Segmentation Using K-Means Clustering*

In this section, the Color-based segmentation using K-means clustering is discussed. Here, our goal is to segment colors in an automated fashion using the L*a*b* color space and K-means clustering. Flow of the approach is defined as follows:

- Read image
- Convert image from RGB color space to L*a*b* color space
- Classify the colors in 'a*b*' space using K-means clustering
- Label every pixel in the image using the results from K-means
- Create images that segment the input image by color.

If we ignore the variations in brightness, there are three colors: white, blue, and pink which are visible to necked eye. How easily we can visually distinguish these colors from one another. The L*a*b* color space (also known as CIELAB or CIE L*a*b*) enables us to quantify these visual differences. The L*a*b* color space is derived from the CIE XYZ tristimulus values. The L*a*b* space consists of a luminosity layer 'L*', chromaticity-layer 'a*' indicating where color falls along the red-green axis, and chromaticity-layer 'b*' indicating where the color falls along the blue-yellow axis. All of the color information is in the 'a*' and 'b*' layers. We can measure the difference between two colors using the Euclidean distance metric. Convert the image to L*a*b* color space using makecform and applycform. Clustering is a way to separate groups of objects. K-means clustering treats each object as having a location in space. It finds partitions such that objects within each cluster are as close to each other as possible, and as far from objects in other clusters as possible. K-means clustering requires that we specify the number of clusters to be partitioned and a distance metric to quantify how close two objects are to each other. Since the color information exists in the 'a*b*' space, our objects are pixels with 'a*' and 'b*' values. We have used kmeans to cluster the objects into six clusters using the Euclidean distance metric. For every object in our input, kmeans returns an index corresponding to a cluster. The cluster_center output from kmeans is used later in the implementation. We have labeled every pixel in the image with its cluster_index. Using pixel_labels, we can separate objects in input image by color, which will result in six images.

C. *Region Properties Based Image Segmentation*

In this section, the region properties based segmentation is discussed. Here, our goal is to segment the image and identify the properties of the concerned segments. Flow of the approach is defined as follows:

- Read image
- Create a binary image
- Calculate region properties using pixel values of grayscale image
- Calculate custom pixel value-based properties

D. *Region Boundary Based Image Segmentation*

In this section, the region boundary based segmentation is discussed. Here, our goal is to segment the image based on the identified boundaries and identify the properties of the concerned segments. Flow of the approach is defined as follows:

- Read image
- Evaluate the threshold value
- Create the binary image
- Trace the exterior boundaries of the regions, as well as boundaries of holes inside these regions, in the binary image.

E. *Steiner Tree Formation*

In this section, the discussion about the Steiner tree formation is carried out. Figure 2 shows an overview of how this process is carried out and how the concept of Steiner tree comes into play.

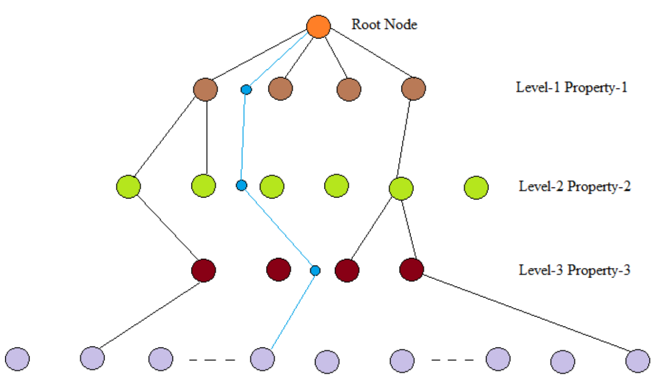


Figure 2: Tree for Region Identification

Figure 2 comprises of four different levels, each corresponding to a specific property. The sole aim of this phase is to get the region class that has been detected in the input image. For each level (1, 2, and 3), the property values are evaluated. For minimum value and maximum value, two extreme nodes are identified. Middle nodes are identified with some constant interval. If any different value occurs i.e. other than the marked values for the identified nodes, then the Steiner nodes are formed at each level. To reach to the identified Steiner nodes of the regions, a path is detected through intermediate Steiner nodes at each level. Here, total number of Steiner nodes at last level depends on the identified regions through the implementation of previously discussed three approaches. In the Figure 2, the colored nodes at the bottom level represent the Steiner nodes that would connect the different levels in the tree structure in order to reach the class of the region. We have used the nearest neighbor evaluation to get the value of edge between the newly generated Steiner node and the Min & Max node of the value of each property, like centroid, area, etc. on the same level of the graph. Figure 4.3 explains the working of the Steiner node.

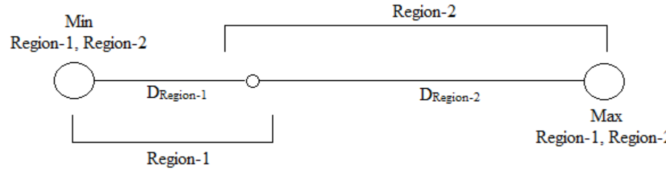


Figure 3: Working of Intermediate Steiner Node

It can be seen from Figure 3, the range of regions is known a priori, but as can be seen there exists an overlapping region and if the value of the property fall in the overlapping region then in that case the Steiner node evaluates on shortest path to the nearest node and decides the class of the region. And if the value of the property does not fall in the overlapping region then the decision about the class of the region is done directly as the ranges are known. Based on the edge value, the decision of the region class is drawn. If the edge value between the Steiner node and the Min node is less than the edge value of Steiner node and the Max node, then the concerned class of the area value which is Region-1.

In the above case, the two distances $D_{Region-1}$ and $D_{Region-2}$ are evaluated and the distance which is less will be the region class. This procedure is performed at each level for the different properties. And hence as the value of $D_{Region-1}$ is less, the class of the region is decided as 'Region-1' and vice-versa.

F. *Pseudocode*

This section presents the pseudocodes for the proposed mechanism. Pseudocode for the color-based segmentation using K-means clustering is given in Figure 4. Pseudocode for the region properties based segmentation is given in Figure 5. Pseudocode for the boundary based segmentation is given in Figure 6.

```
Read image from the console in some variable
For every image { Convert Image from RGB Color Space to L*a*b* Color Space using makecform and applycform;
Classify the Colors in 'a*b*' Space Using K-Means Clustering;
Provide the number of classes of region is equal to 6;
Perform k-means clustering;
Label every pixel in the image using the results from Kmeans;
Create images that segment the input image by color;
Record the data for Steiner tree;
{ Procedure is based on the recording of the total number of regions identified for particular image }
Create the directed graph; {Procedure is based on the region properties}
Find the Steiner tree based on the distance;
{ Procedure is based on the Euclidean distance evaluation }
Display the segmented images; }
```

Figure 4: Pseudocode for the color-based segmentation using K-means clustering.

Read image from the console in some variable;
For every image
{ Create binary image; Calculate region properties using pixel values; Calculate custom pixel value-based properties; Identify the number of regions;
Record the data for Steiner tree;
{ Procedure is based on the recording of the total number of regions identified for particular image; }
Create the directed graph;
{ Procedure is based on the region properties; }
Find the Steiner tree based on the distance;
{ Procedure is based on the Euclidean distance evaluation; }
Display the segmented images; }

Figure 5: Pseudocode for the region properties based segmentation.

Read image from the console in some variable;
For every image
{ Evaluation of the threshold value;
{ Procedure is based on adaptive or global thresholding; }
Create binary image; Trace the exterior boundaries of the regions, as well as boundaries of holes inside these regions, in the binary image. Calculate region properties using pixel values; Identify the number of regions;
Record the data for Steiner tree;
{ Procedure is based on the recording of the total number of regions identified for particular image; }
Create the directed graph;
{ Procedure is based on the region properties; }
Find the Steiner tree based on the distance;
{ Procedure is based on the Euclidean distance evaluation; }
Display the segmented images; }

Figure 6: Pseudocode for the boundary based segmentation.

V. EXPERIMENTAL RESULTS AND DISCUSSIONS

This section presents the discussion the experimental setup and the results. Further the section is extended to have the discussion on the obtained results. Various experimentations are carried out on the different images using the approaches discussed in previous section.

A. *Experimental Setup*

The approach is implemented using Matlab. The experimentations are carried out on Intel(R) Core(TM) i3-2350M CPU @ 2.30GHz, 2300 Mhz, 2 Core(s), 4 Logical Processor(s). The RAM of the system used is 4GB. The experimentations are carried out on natural color and grayscale images taken from Berkeley Image Database [37].

B. *Results of the Proposed Mechanism*

Various experimentations are carried out using 296059.jpg and 296007.jpg images. Results of the color-based segmentation using K-means clustering is shown in Figure 10 for 296007.jpg. Results of region properties based segmentation is shown in Figure 11 through Figure 13 for 296059.jpg and in Figure 14 through Figure 16 for 296007.jpg. Figure 17 shows the results of boundary based segmentation for 296059.jpg. Figure 18 shows the results of boundary based segmentation for 296007.jpg. Table 2 shows the cluster centers found in K-means clustering. Table 3 shows the properties found in region properties based segmentation. Properties found in boundary based segmentation are shown in Table 4.

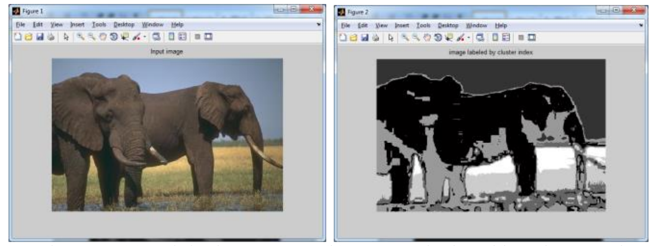
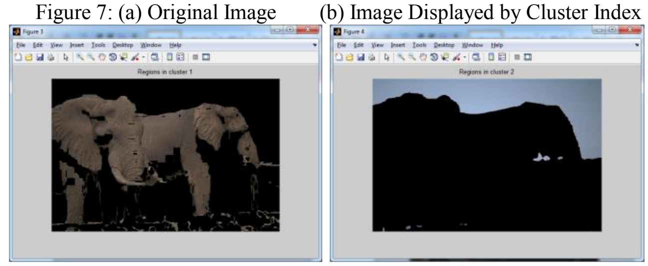
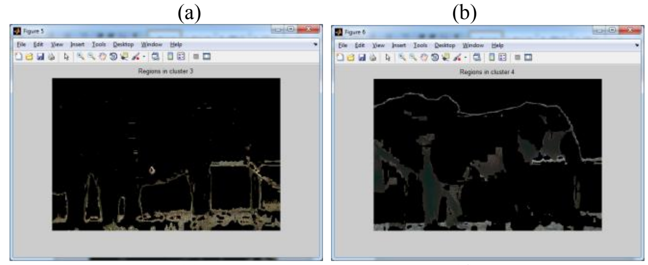


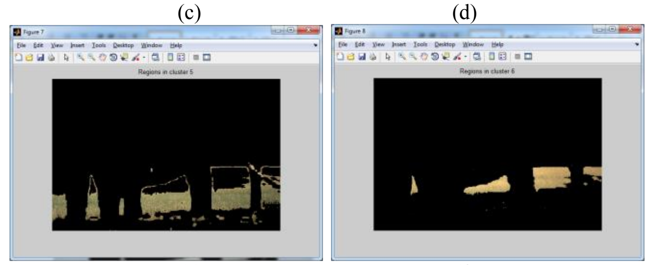
Figure 7: (a) Original Image (b) Image Displayed by Cluster Index



(a) (b)



(c) (d)



(e) (f)

Figure 8: Regions in (a) Cluster 1 (b) Cluster 2 (c) Cluster 3 (d) Cluster 4 (e) Cluster 5 (f) Cluster 6.

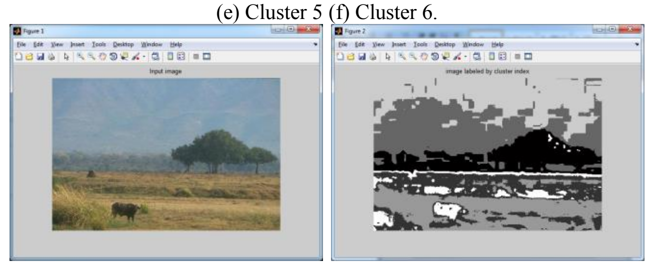
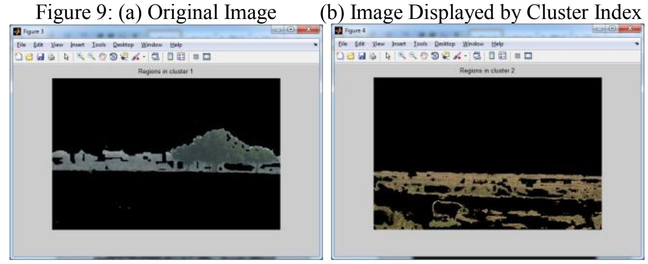
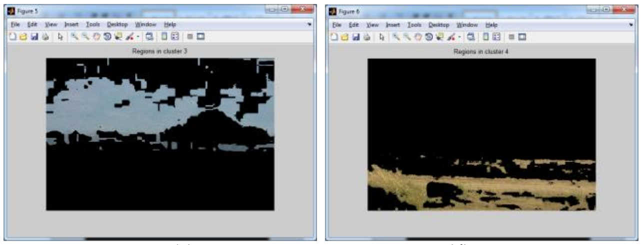


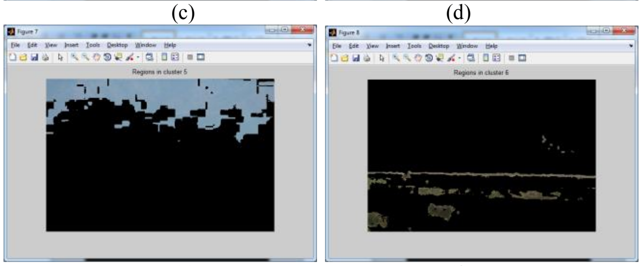
Figure 9: (a) Original Image (b) Image Displayed by Cluster Index



(a) (b)



(c) (d)



(e) (f)

Figure 10: Regions in (a) Cluster 1 (b) Cluster 2 (c) Cluster 3 (d) Cluster 4 (e) Cluster 5 (f) Cluster 6.

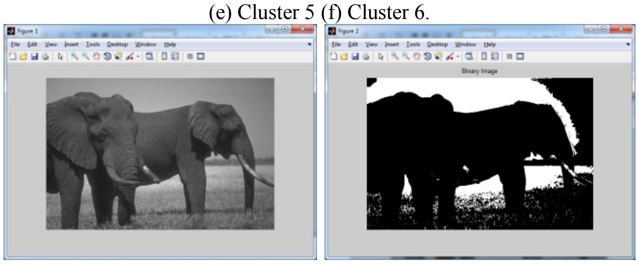


Figure 11: (a) Original Graylevel Image (b) Converted Binary Image

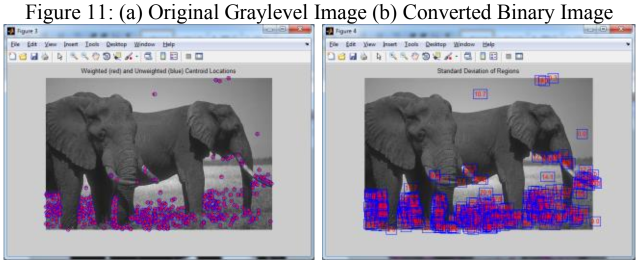


Figure 12: (a) Weighted and Unweighted Centroid Locations (b) Standard Deviation of Regions

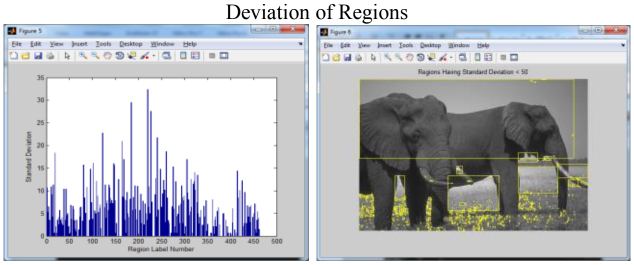


Figure 13: (a) Standard Deviation of Different Regions (b) Regions having Standard Deviation Less Than 50

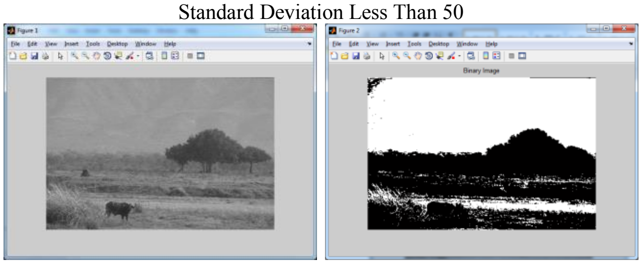


Figure 14: (a) Original Graylevel Image (b) Converted Binary Image

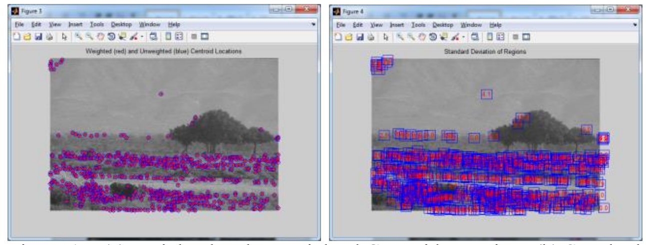


Figure 15: (a) Weighted and Unweighted Centroid Locations (b) Standard Deviation of Regions

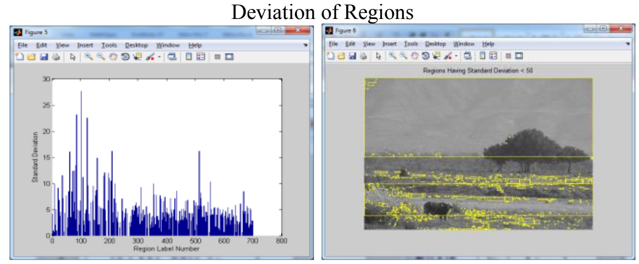


Figure 16: (a) Standard Deviation of Different Regions (b) Regions having Standard Deviation Less Than 50

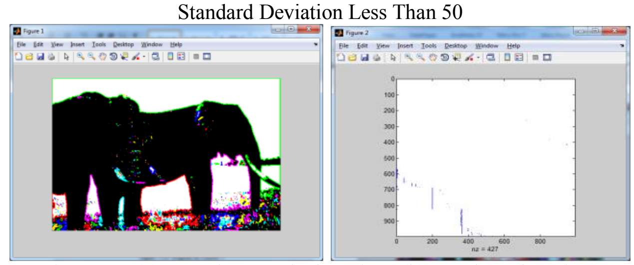


Figure 17: (a) Boundary Marked Regions (b) Number of Regions

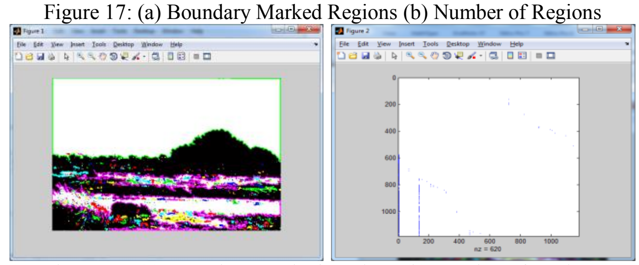


Figure 18: (a) Boundary Marked Regions (b) Number of Regions

C. Discussion

Based on the obtained results, it is found that the six clusters are formed in the first part of the approach. In second part, various properties of the identified regions are evaluated. 571 and 573 regions are identified in the boundary based segmentation.

TABLE II. CLUSTER CENTER FOUND IN K-MEANS CLUSTERING

Cluster Numbers	296059.jpg		296007.jpg	
Cluster 1	125.3128	129.4496	131.3894	155.8577
Cluster 2	129.8114	134.44	129.1715	148.3326
Cluster 3	133.0039	161.5814	122.3133	113.3575
Cluster 4	127.2037	149.6993	122.586	117.9691
Cluster 5	125.6536	112.6874	124.9604	136.1273
Cluster 6	132.223	137.7354	122.9566	125.3039

TABLE III. PROPERTIES FOUND IN REGION PROPERTIES BASED SEGMENTATION

Image Name	No. of Regions	Properties for First Region				
		Area	Convex Area	Filled Area	Solidity	Euler Number
296059.jpg	464	21433	46409	21488	0.4618	-34
296007.jpg	701	69891	79845	69985	0.8753	-35

TABLE IV. PROPERTIES FOUND IN BOUNDARY BASED SEGMENTATION

Image Name	Threshold	Connectivity	No. of Regions
296059.jpg	0.4196	8	571
296007.jpg	0.4824	8	573

VI. CONCLUSION AND FUTURE SCOPE

A. *Conclusion*

Presented mechanism is divided into three parts. Experimental results are obtained for the Berkley image database. Based on the study of image segmentation and obtained results following conclusions are drawn:

- For the first part, given RGB color image firstly, converted t the L*a*b* color space. Later, six numbers of clusters are formed using the k-means clustering methodology.
- As human perception involves in the segmentation results, it is observed from the obtained results that the formed clusters are representing the proper regions.
- Second part of the mechanism where the different properties of the regions are evaluated. Input image to this approach is the graylevel image and based on the obtained results, it is found that the given images, namely, 296059.jpg and 269007.jpg, are divided into the 464 and 701 regions. The presented approach captures perceptually important regions. This can be justified from the output images shown and discussed in section 5.
- Third part of the mechanism is the development of the approach based on the boundaries. Here, in this approach, once again the input image is the graylevel image. This graylevel image is converted to the binary image. This conversion took place on the basis of the threshold. Threshold value is evaluated for two images namely, 296059.jpg and 269007.jpg. Later the regions are identified.
- But main difference in the second part and third part is that- for the image 296059.jpg , evaluated and identified regions are 571 in comparison with the 464 identified by the second approach and for the image 269007.jpg evaluated and identified regions are 573 in comparison with the 701 identified by the second approach.

B. *Future Scope*

Possible direction for the extension of the presented work is summarized below:

- To use k-means, we have initialized the cluster number value to six; one can do the different experimentations to identify the correct value of k by conducting different number of experimentations.
- Another scope is there to develop certain mechanism or approach to identify the k value automatically.
- Steiner tree based identification of the different regions can be extended as the optimization problem and there is a scope to use the classical optimization algorithms to get the solution.
- As this problem is the optimization problem, there is a scope to use the non-classical optimization techniques such as the ant colony optimization, bio-inspired optimization, particle swarm optimization, etc.

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