International journal of Engineering Research-Online
A Peer Reviewed International Journal
Articles available online http://www.ijoer.in

Vol.1., Issue.4., 2013

RESEARCH ARTICLE

ISSN:2321-7758

CRITICAL ANALYSIS OF IMAGE SEGMENTATION ALGORITHMS

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Article Received: 23/12/2013 | Article Revised on:09/01/2014 | Article Accepted on:12/01/2014

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ABSTRACT

A major concern, in digital processing of images as well as computer vision, is the image segmentation. Computer vision or image recognition deals with decrypt into pats of an image. Among the different aspects of computer vision unlike a few like tracking detection, recognition etc which are well defined, image segmentation has not been clearly defined. Different fundamental algorithms of image segmentation are implemented like Hough Transform Algorithm (Edge Linking & Boundary Detection), Region Growing (Similarity Based Segmentation), Iterative Thresholding Method. A number of image segmentation techniques are available, but there is no one single technique that is suitable to all the applications. Hence researchers select the techniques as per the application or combine more than one technique as per the requirement of the application. This paper focuses on the experimental results of various image segmentation techniques. This paper deals with two aspects in analysing the results of various techniques of image segmentation. First, the various image segmentation techniques are presented. Second, the various image segmentation techniques are implemented. The techniques involved in this paper are color image segmentation, a fast image segmentation using Delaunay triangulation, Grow cut image segmentation, image segmentation via topological derivative, Defocus image segmentation, TVREG variational image segmentation and Efficient graph based image segmentation.

Keywords— Image Segmentation.

INTRODUCTION

Considering the aspects of image analysis and pattern recognition, it starts with image segmentation, splitting an image into separate zone. Each zone consisting of a group of pixels homogeneous with respect to colour, texture, motion, grey levels etc. A region is defined as a homogeneous group of connected pixels with respect to a chosen property. The image segmentation problem is basically one of the psychophysical perception and therefore not susceptible to a purely analytical solution.

Images normally contain textured and un textured regions enabling capitalizing on the difference between the cues of contour and texture simultaneously by treating the interposition of contour and analysing the texture using textons. Allocation of grey scale images into discrete areas of coherent brightness and texture are carried out by an algorithm [1].

Each of these cues had a domain of applicability, so to facilitate cue combination, they introduced a gating operator based on the texturedness of the neighbourhood at a pixel. To obtain a local measure of how two nearby pixels were belonged to the same region, they used the spectral graph theoretic framework of normalized cuts to find partitions of the different zones of the image with coherent texture and brightness.

Segmentation is an essential process in image processing because of its wild application such as image analysis, medical image analysis and pattern recognition. For any image colour and texture are the most significant and basic features. Normally, colour textured image segmentation consisted of two steps: (i) extracting the feature and (ii) clustering the feature vector. Haralick features may be extracted from the integrated colour and intensity co-occurrence matrix by a hybrid approach [2] and using an Extended interval Type – 2 Fuzzy C mean clustering algorithm. The future vectors are clustered into several categories in regard to different areas of the textured images.

Generally, segmentation algorithm operates under either on specification of the boundary of the discard image or an adjacent boundary defining the desired boundary or specifying a small set of pixels of the desired image and if possible a set of pixels of the background. We also note that any of the automatic segmentation algorithms might be considered supervised by subsequent user selection of the desired segment. However, if the desired object is not a complete segment, a secondary clustering/segmentation algorithm must be employed to split or merge the automatic segments.

The intelligent scissors algorithm [3] treats the image as a graph where each pixel is associated with a node and a connectivity structure is imposed. In this process, there is a need place points on the boundary of the image. Dijkstra's algorithm is then used to compute the shortest path between the user-defined points and this path is treated as the object boundary. The algorithm is simple to implement, very fast and may be used to obtain an arbitrary boundary with enough points. If the boundary is noisy or of low contrast large number of points here to be specified and not applicable for 3D boundaries.

The graph cuts [4], [5] technique has been developed as a method for interactive, seeded, segmentation. As with intelligent scissors, graph cuts views the image as a graph, weighted to reflect intensity changes. In order to arrive at a minimum-weight at between the source and the sink, some modes are marked as foreground and others as background to enable the algorithm to perform a maximum flow/minimum cut analysis. A feature of this algorithm is that an arbitrary segmentation may be obtained with enough user interaction and it generalizes easily to 3D and beyond. The algorithms performs well in many cases but still poses a few problems. For example, since the algorithm returns the smallest cut separating the seeds, the algorithm will often return the cut that minimally separates the seeds from the rest of the image, if a small number of seeds are used. Hence, it may be necessary to place seeds continuously so as to avoid the "small cut" problem.

Additionally, the K-way graph cuts problem is NP-Hard, requiring use of a heuristic to obtain a solution. Although one may find a solution within a bound of the optimal multi way cut [6], the problem becomes more difficult and one cannot be sure that the optimal cut is achieved. Finally, multiple "smallest cuts" may exist in the image that are quite different from each other. Therefore, a small amount of noise (adjusting even a single pixel) could cause the contour returned by the algorithm to change drastically. Mathematically, we note that the present algorithm may be considered as a relaxation of the binary values of the potential function in graph cuts. Although this may appear to constitute a minor modification of graph cuts, in fact the motivation, theoretical properties, practical behaviour and method of solution are all quite different. The graph cuts approach of [4] differs from the present work by including a priors term on the intensity of the foreground and background (with a consequent additional parameter). Although they will not further discuss it here, such a modification to the random walker algorithm may also be achieved [7].

By extending the graph cuts segmentation algorithm in two different directions the issues of speed colour images and the user interaction may be solved. The first type of extension to the graph cuts algorithm has focused on speed increases by coarsening the graph before applying the graph cuts algorithm. This coarsening has been accomplished in two manners: 1) By applying a standard multilevel approach and solving subsequent, smaller graph cuts problems in a fixed band to produce the final, full-resolution segmentation [8], 2) By applying a watershed algorithm to the image and treating each watershed basin as a "supernode" in a coarse graph to which graph cuts in applied [9]. They note that the Lazy Snapping approach of [9] additionally proposes interactive tools for dividing watershed basins that may have incorrectly merged the foreground and background regions. The primary goal of these two approaches is to increase the computational speed of graph cuts by intelligently reducing the number of nodes in the graph. As stated in [8], the objective is to produce the same segmentation result as regular graph cuts by introducing a heuristic that greatly speeds the computation. Therefore, the benefits and difficulties of the graph cuts algorithm listed above also apply to these approaches, with an added uncertainty about the role of the coarsening operator in the final result (i.e., the final segmentation is no longer guaranteed to be the minimum cut). Additionally, both approaches to increasing the computational speed of graph cuts could equally be applied to the present algorithm with similar computational gains.

Using an algorithm for general image segmentation based on a minuscule set of pre labelled pixels either interactively or automatically general for a specific purpose. Each un seeded pixels is assigned to the label of the seed point. Any signal from the pixel, not biased to cross the object boundaries (ix) intensity gradient may reach first. The segmentation are produced based on the separation of quantities defined at the nodes ((x) potentials) and the resulting graph may represent any dimension or topology.

This paper [11] introduces a new supervised segmentation algorithm for remotely sensed hyper spectral image data which integrates the spectral and spatial information in a Bayesian framework. A subspace projection technique is used to improve noise and mixed pixels and from such spectral information the posterior probability distribution is abstained using a Multinomial Logistic Regression. MLR – algorithm. Then, contextual information is included using a multilevel logistic Markov–Gibbs Markov random field prior. Finally, a maximum a posterior segmentation is efficiently computed by the a-Expansion mincut-based integer optimization algorithm. The proposed segmentation approach is experimentally evaluated using both simulated and real hyper spectral data sets, exhibiting state-of-the-art performance

when compared with recently introduced hyper spectral image classification methods. The integration of subspace projection methods with the MLR algorithm, combined with the use of spatial–contextual information, represents an innovative contribution in the literature. This approach is shown to provide accurate characterization of hyper spectral imagery in both the spectral and the spatial domain.

Subspace projection methods can provide competitive advantages by separating classes which are very similar in spectral sense, thus addressing the limitations in the classification process due to the presence of highly mixed pixels. The idea of applying subspace projection methods to improve classification relies on the basic assumption that the samples within each class can approximately lie in a lower dimensional subspace. Thus, each class may be represented by a subspace spanned by a set of basis vectors, while the classification criterion for a new input sample would be the distance from the class subspace [12]–[14].

MR images are normally reconstructed by taking the modulus of complex images. Normally distributed complex values are not normally distributed when the magnitude is taken. Instead, they obey a Rician distribution. This means that any clusters representing the background are not well modelled by a single Gaussian, but it makes very little difference for most of the other clusters. By knowing the prior spatial probability of each voxel being grey matter, white matter or cerebro-spinal fluid, it is possible to obtain a more robust classification. In addition, a step for correcting intensity non-uniformity is also included, which makes the method more applicable to images corrupted by smooth intensity variations. It should be noted that no pre-processing to remove scalp or other non-brain tissue was performed on the image. The tissue classification method should produce slightly better results if this non-brain tissue is excluded from the computations. As the algorithm stands, a small amount of non-brain tissue remains in the grey matter partition, which has arisen from voxels that lie close to grey matter and have similar intensities.

Combining the active appearance Model (AAM) Live Wire (LW) and Graph Cuts (GCs) procedure was suggested for abdominal 3-D organ segmentation [15]. In the recognition part, a novel algorithm is proposed for improving the conventional AAM matching method, which effectively combines the AAM and LW methods, resulting in the oriented AAM (OAAM).

IMAGE SEGMENTATION AND EXTRACTION

Segmentation involves partitioning an image into a set of homogeneous and meaningful regions, such that the pixels in each partitioned region possess an identical set of properties. Image segmentation is one of the most challenging tasks in image processing and is a very important pre-processing step in the problems in the area of image analysis, computer vision, and pattern recognition. In many applications, the quality of final object classification and scene interpretation depends largely on the quality of the segmented output. In segmentation, an image is partitioned into different non-overlapping homogeneous regions, where the homogeneity of a region may be composed based on different criteria such as gray level, color or texture. Techniques like histogram based, edge based region based clustering and combination of these techniques have been developed in the area of image segmentation. Even though many algorithm were available, a single algorithm appropriate for all images is not yet available.

COLOUR IMAGE SEGMENTATION

Color images can provide more information than gray level images. color image segmentation is useful in many applications. From the segmentation results, it is possible to identify regions of interest and objects in the scene, which is very beneficial to the subsequent image analysis or annotation. Recent work includes a variety of techniques: for example, stochastic model based approaches ,morphological watershed based region growing, energy diffusion, and graph partitioning. Quantitative evaluation methods have also been suggested. Since the problem is of very complex nature, algorithm that can work on large types of date are few. Segmentation becomes different due to the texture of the image. Images containing homogeneous colour regions. Clustering methods in colour space will be sufficient. However natural scene are rich in colour and texture. It is difficult to identify image regions containing color-texture patterns.

A FAST IMAGE SEGMENTATION USING DELAUNAY TRIANGULATION

A Delaunay triangulation for a set P of points in a plane is a triangulation DT(P) such that no point in P is inside the circumcircle of any triangle in DT(P). Delaunay triangulations maximize the minimum angle of all the angles of the triangles in the triangulation; they tend to avoid skinny triangles. Delaunay triangulations can be used to determine the density or intensity of points samplings by means of the DTFE.

Delaunay triangulations are often used to build meshes for space-discretised solvers such as the finite element method and the finite volume method of physics simulation, because of the angle guarantee and because fast triangulation algorithms have been developed. Using a typical algorithm-Ruppperts'- the coarse and complex domain to be meshed is refined for making the mesh to be numerically stable.

GROW CUT IMAGE SEGMENTATION

Image cutout is the process of removing or isolating an object in a picture. GrowCut is an interactive segmentation algorithm matting tool designed to extract solid or opaque objects as well as objects having smooth or fuzzy edges.. It uses Cellular Automaton as an image model. Automata evolution models segmentation process. Each cell of the automata has some label. During automata evolution some cells capture their neighbors, replacing their labels. In GrowCut, a user vaguely draws some strokes inside the object of interest with an object brush, and outside the object with a background brush.A cellular automaton is generally an algorithm discrete in both space and time, that operates on a lattice of sites..A (bi-directional, deterministic) cellular automaton is a triplet $A = (S,N,X)$, where S is an non-empty *state set*, N is the *neighborhood system*, and X : S^N ->S is the local transition function (rule). This function defines the rule of calculating the cell's state at t +1 time step, given the states of the neighborhood cells at previous time step t. Commonly used neighborhood systems N are the von Neumann and Moore neighborhoods.

IMAGE SEGMENTATION VIA TOPOLOGICAL DERIVATIVE

Segmentates an image using both the Continuous and Discrete Topological Derivative algorithms. The main idea behind this algorithms is to compute the topological derivative for an appropriate functional and a perturbation given by changing the class that a particular pixel is segmented in from one class to another in the set class. This derivative is used as an indicator function to find the best class that each pixels should be classified Topological derivatives approach is used for image segmentation after best suited restoration process.

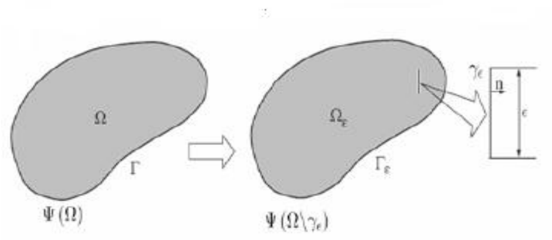

Fig. 1 Concept of Topological Derivative

DEFOCUS BASED IMAGE SEGMENTATION

Defocus-based segmentation is desirable because defocus techniques are computationally simple. Image defocus is a measure of image sharpness. Typically, the foreground contains important information; whereas the background does not. Image defocus is easily measured from high frequency components, such as image edges. Defocus is measured from edge strength. The defocus d is

$$d = \frac{\sum_x \sum_y |S(x,y)|^2}{\omega}$$

Where S(x,y) is the magnitude of Sobel edge detection on image g(x,y) and w is the edge width in g(x,y).

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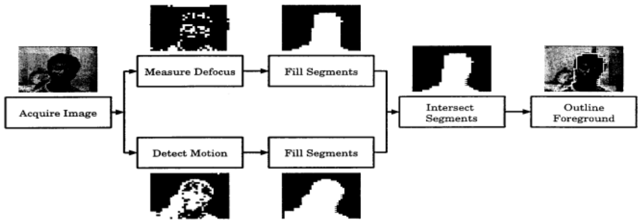

Fig. 2 Foreground and Background Segmentation method

TVREG VARIATIONAL IMAGE SEGMENTATION

The tvreg package applies total variation (TV) regularization to perform image denoising, deconvolution, and inpainting. Three different noise models are supported: Gaussian (L^2), Laplace (L^1), and Poisson. The general TV restoration problem is solved by implementing the TVREG package which applies Total Variation (TV) regularization to accomplish image denoising, deconvolution and inpainting, This is supported by the three noise models such as Gaussian (L^2), (L^1) and Poisson. The problem is stated as:

$$\min_{u \in BV(\Omega)} \int_{\Omega} |\nabla u(x)| dx + \int_{\Omega} \lambda(x) F(Ku(x), f(x)) dx$$

This is solved by the Bregman method, and Chan-Vase two-phase segmentation method, supporting gray scale, colour and arbitrary multi channel images.

EFFICIENT GRAPH BASED IMAGE SEGMENTATION

Graph based image-segmentation is a fast and efficient method of generating a set of segments from an image. Graph-based image segmentation techniques generally represent the problem in terms of a graph G = (V;E) where each node vi 2 V corresponds to a pixel in the image, and the edges in E connect certain pairs of neighboring pixels. Each edge based on the properties if pixels it connects, pixel image intensities specifies a weight. Based on the pair of ventures may or may not be connected by an edge in computing a segmentation, fixed thresholds and local measures are used in the graph based method. The algorithm nuns in time nearly linear to the number of graph edges, is fast and capable of preserving details in images of low variability and avoiding them in high variability regions to preserve detail in low-variability image regions while ignoring detail in high-variability regions.

Let G = (V;E) be an undirected graph with vertices vi 2 V , the set of elements to be segmented, and edges (vi; vj) 2 E corresponding to pairs of neighboring vertices. Each edge (vi; vj) 2 E has a corresponding weight w((vi; vj)), which is a non-negative measure of the dissimilarity 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 (e.g., the difference in intensity, color, motion, location or some other local attribute). In the graph-based approach, a segmentation S is a partition of V into components such that each component (or region) C 2 S corresponds to a connected component in a graph G0 = (V;E0), where E0 µ E.

a) Executing the algorithm – steps.

(i) Define the input.
The input is a graph defined as G = (V,E)
V denotes the verities number ‘n’
E denotes the edges number ‘m’

Each edge is assigned with a weight giving the magnitude of dissimilarity between adjacent pixels.

(ii) Make the Segmentation so as to make each component C 2 S corresponds to a connected component in a graph G' = (V;E') where E': E.

(iii) Compare the weights of the edge connecting two verities in adjacent components with the internal differences of both components. If the difference is small the two components may be merged otherwise retain the status.

(iv) Repeat the step (iii) above for E = 1,2…….m

(v) Return S m components after the find iteration.

ACTIVE VOLUME MODEL FOR MEDICAL IMAGE SEGMENTATION

The different components of the model are

i Region of interest ROI and Prediction ROI
ii Segmentation based on shape
iii Active volume model
iv Multiple Surface Active Volume Model
v Classification of features
vi Identification of tumor and its status.
vii Analysis of the data.

i) ROI and Prediction ROI

This module involves the generation a binary mask for the luminance image. ROI is used for deforming the image. This approach is used to achieve the repeated model until satisfy the object boundary. A region of interest (ROI) is a portion of an image that you want to filter or perform some other operation on. ROI is defined by creating a binary mask, which is a binary image that is the same size as the image you want to process with pixels that define the ROI set to 1 and all other pixels set to 0. The regions can be geographic in nature, such as polygons that encompass contiguous pixels, or they can be defined by a range of intensities. In the latter case, the pixels are not necessarily contiguous. After the image is binary mask, the prediction ROI is used to monitor the image and remove the noise which is presented in the ROI area.

ii) Shape based Segmentation

This module involves shape based segmentation for the prediction ROI by setting the tumor threshold value to segment the area from the background of the image and the boundary is achieved by the binary edge map.

iii) Active Volume Model

This module involves convergence is fast, typically taking no more than 20 iterations. Several factors contribute to this efficiency: AVM Focuses on an accurate representation of the foreground object attribute but not explicit representation of background, the model's deformations can be solved in a linear system, and multiple external constraints are directly from the predicted object region boundary. The model boundary parametrically v(s)=(x(s),y(s)), the Explicit Shape Representation of AVM is defined :

$$E_{\text{int}} = \int_0^1 \left(\alpha \left| v_s(s) \right|^2 + \beta \left| v_{ss}(s) \right|^2 \right) ds$$

The internal energy function can be written compactly as :

$$E_{\text{int}} = \frac{1}{2} \int_{\Lambda} (Bv)^T D(Bv)\, d\Lambda$$

where B is the differential operator for the model vertices v on the mesh and D is the stress matrix, the implicit shape representation is considered

$$\phi_{\Lambda}(x) = \begin{cases} 0, & x \in \Lambda \\ +ED(x,\Lambda) > 0, & x \in R_{\Lambda} \\ -ED(x,\Lambda) < 0, & x \in \Omega - R_{\Lambda} \end{cases}$$

where ED(x,Λ) refers to the minimum Euclidean distance between the image pixel/voxel location x and the model surface Λ.

iv) Multiple Surface Active Volume Model

This module involves the Multiple-Surface AVMs to segment coupled medical objects simultaneously. MSAVM are more robust to initial positions and yield more accurate segmentation results. It has flexible initialization and fast convergence. MSAVM can avoid such leakage and overcome the local minima to and the desired object boundary, the energy function for the surface of MSAVM is defined as

$$E=E_{int}+E_R+E_{dist}$$

where E_{int} is the same as the internal energy. E_R is the external energy term derived from the predicted object ROI.

v) Feature classification

This module involves the feature classification from the AVM and MSAVM model. Feature classification involves the following features, Such as Coarseness, Skewness, Contrast, Busyness and Standard deviation. This show the table with the features values to find the status and identification.

a) Coarseness

The variance is a well-known metric to indicate the amount of coarseness in the pixel values. Variance of the image is used as a feature to help to identify status.

b) Skewness

The skewness measures the degree of asymmetry of a distribution around its mean. It is zero when the distribution is symmetric, positive if the distribution shape is more spread to the right and negative if it is more spread to the left.

c) Contrast

Contrast (CON) also known as inertia: is the measurement of intensity contrast or local variations between the image pixels, giving lower values for uniform texture.

d) Busyness

Successive still images appearing in sequence as a shimmering blur of dots around edges, resembling mosquitoes swarming around the object results in edge busyness and spurious dots.

(e) Standard Deviation

As a measure of spread or variability, standard deviation the Root Mean Square (RMS) of the difference if the values from the arithmetic mean, helps in measuring how far away each number is located in a set of data from their mean.

Tumor Identification and Status

This module involves to identifying the tumour and the status of the brain tumour by the above feature classification. If the value of the coarseness range from greater than 0.1 to less than 0.7 or busyness range from greater than 0.02 to less than 0.14 or Contrast range from 0.1 to less than 0.9 or Standard deviation greater than 1.3 to less than 2.3.2 the tumor is found and the status of the tumor is shown. Otherwise tumor not found and the status is not mention.

Table 1: Feature Classification to identify Tumor status

Coarseness	Busyness	Contrast	Std	Skewness	Status
0.1450	6.4552	0.0073	6.4552	3.3511	Found
0	4.9987	0	4.9987	Nil	Not Found
0.1983	7.3635	0.0069	7.3635	4.8483	Found

vii) Analysis

This module involves analyzing the input image vs. segmentation and average of the segmented output. After the feature classification the process is used to show the chart for the output.

XI. Experimental Results

A. Images used in the Experiments

The images Car, Fruits, Bear, Test, Lotus, Blockset, Peppers, Tiger food, Men, Wrench, Light house and Tree are used for the experiments. The original image is shown in Fig. 3.

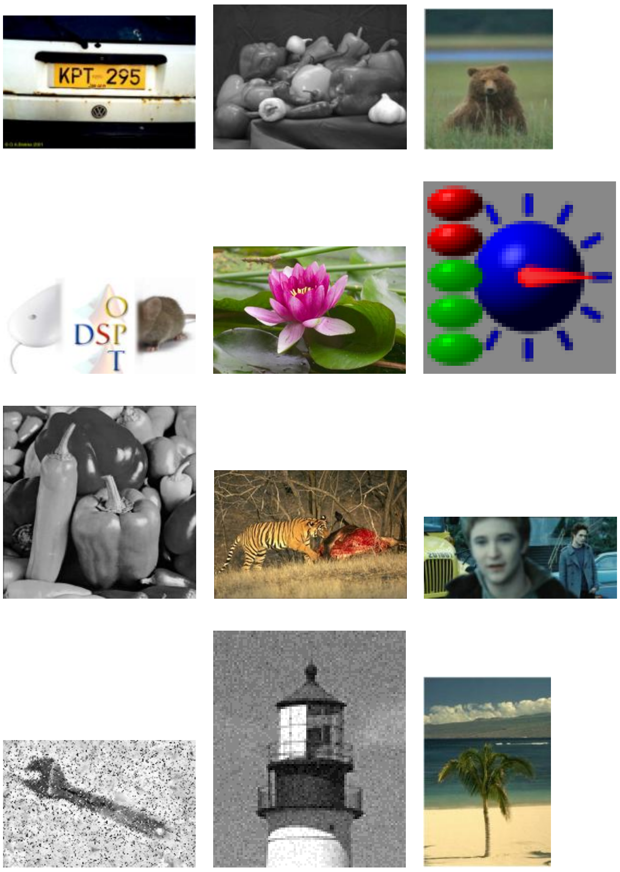

Fig. 3 Input Images: Car, Fruits, Bear, Test, Lotus, Blockset, Peppers, Tiger food, Men, Wrench, Light house and Tree

B. Performance of Image Segmentation and Extraction

The result of this technique is shown in Fig. 4.

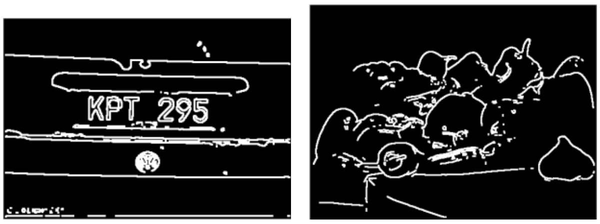

Fig. 4 Image Segmentation and Extraction

C. Performance of Color Image Segmentation

The result of this technique is shown in Fig. 5.


Fig. 5 Color Image Segmentation

D. Performance of a fast Image Segmentation using Delaunay Triangulation

The result of this technique is shown in Fig. 6.


Fig. 6 A Fast Image Segmentation and Extraction using Delaunay Triangulation

E. Performance of Grow Cut Image Segmentation

The result of this technique is shown in Fig. 7.

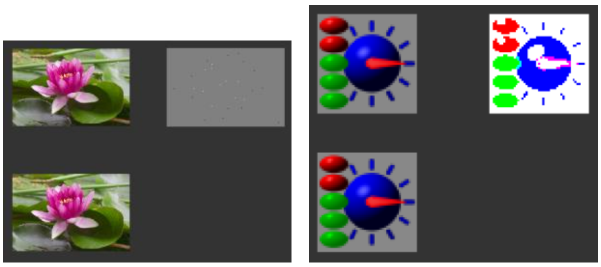
Fig. 7 Grow Cut Image Segmentation

F. Performance of Image Segmentation via Topological Derivative

The main features of this image segmentation via Topological Derivative are . The result of this technique is shown in Fig. 6.

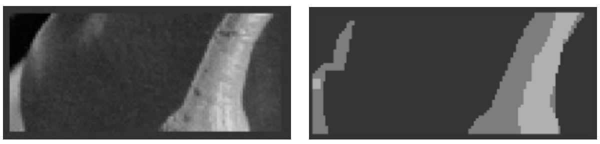

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Fig. 6 Image Segmentation via Topological Derivative

G. Performance of Defocus based Image Segmentation

The main features of this Defocus based image segmentation are . The result of this technique is shown in Fig. 7.

Fig. 7 Defocus based Image Segmentation

H. Performance of TVREG Variational Image Segmentation

The main features of this TVREG Variational image segmentation are . The result of this technique is shown in Fig. 8.

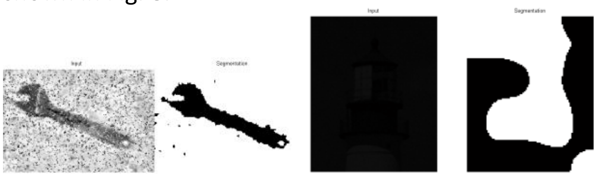


Fig. 8 TVREG Variational Image Segmentation

I. Performance of Efficient Graph based Image Segmentation

The main features of this Efficient graph based image segmentation are . The result of this technique is shown in Fig. 9.

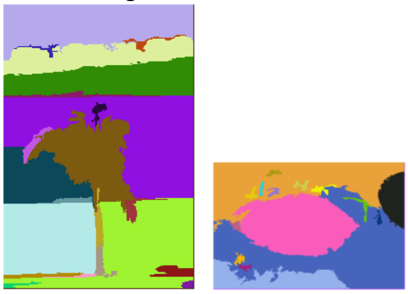


Fig. 9 Efficient Graph based Image Segmentation

J. Performance of Active Volume Model

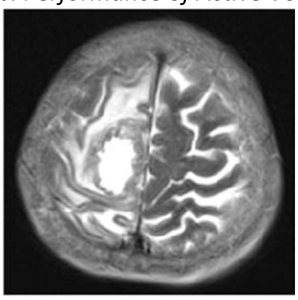
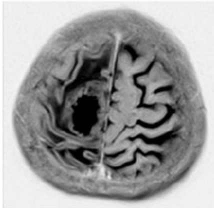
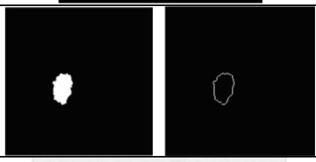
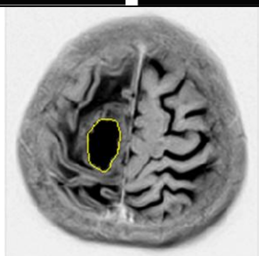
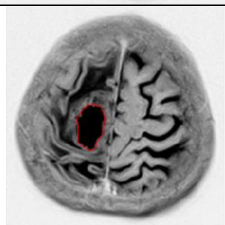
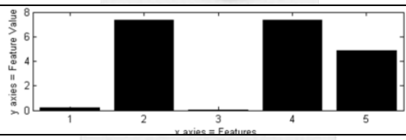
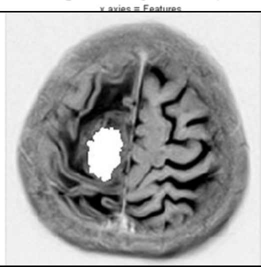
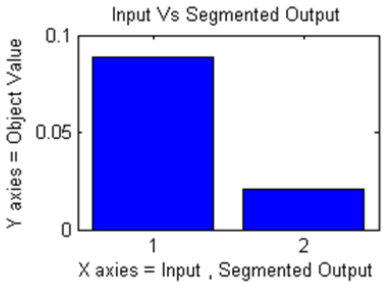


Fig. 10 Input Images for AVM

Modules in AVM	Output Image
Luminance Image	
ROI Area and Prediction	 
Shape Based Segmentation	
Active Volume Model	
Multiple Surface Active Volume Model	
Feature Classification	
Tumour Identification	

Analysis	

CONCLUSION AND SCOPE FOR FUTURE WORK

In this paper different ways to integrate prior knowledge into image segmentation methods are explored. Several techniques have been put forth with in literature to accomplish segmentation.

The present paper is an attempt to explore different means to integrate prior knowledge with image segmentation methods. Several techniques are suggested to accomplish segmentation. The comprehensive experimental results show considerable scope for improving the accuracy of the techniques, particularly for images with textured backgrounds.

There is further need to simplify the time complexity if the various segmentation algorithms. Also, implementing this algorithm on a parallel or distributed platform may also be undertaken.

In future, Hybridization of two or more approaches to take advantages of their best properties will be attempted.

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