

SEGMENTATION OF BIOMEDICAL IMAGES USING ACTIVE CONTOUR MODEL

¹Bhatt Shital Dineshchandra, ²Domadia Sunayana, ³Tandel Tejal

¹Assistant Professor, ²Assistant Professor, ³Assistant Professor
Electronics and Communication
MBICT, New V.V.Nagar, India

Abstract : The concept of active contours models was first introduced in 1987 and has later been developed by different researchers. An active contour is an energy minimizing spline that detects specified features within an image. It is a flexible curve (or surface) which can be dynamically adapted to required edges or objects in the image (it can be used to automatic objects segmentation). It consists of a set of control points connected by straight lines. The active contour is defined by the number of control points as well as sequence of each other. Fitting active contours to shapes in images is an interactive process. The user must suggest an initial contour, which is quite close to the intended shape. The contour will then be attracted to features in the image extracted by internal energy creating an attractor image.

IndexTerms - active contours, segmentation

I. Introduction

Segmentation is the process of partitioning a digital image into multiple regions and extracting a meaningful region. Image segmentation refers to the decomposition of a scene into different components (thus to facilitate the task at higher levels such as object detection and recognition)

There are three basic types of gray-level discontinuities in a digital image: points, lines, and edges. The most common way to look for discontinuities is to run a mask through the image. Image segmentation is a fundamental task in image analysis responsible for partitioning an image into multiple sub-regions based on a desired feature [1]. Image segmentation is a basic task, responsible for the separating process. The function of segmentation is to dividing an image into its basic and disjoint sub-regions, which are identical according to their property, e.g. intensity, color, and quality.

II. Region-based Segmentation Methods

A region is composed of some pixels which two by two are neighbours and the boundary is made from differences between two regions. Most of the image segmentation methods are based on region and boundary properties. Here we explain two most popular regionbased approaches: thresholding and region growing [2].

2.1 Thresholding

Thresholding is one of the simplest and fastest segmentation methods based on the assumption that images are formed from regions with different grey levels. The histogram of images has different peaks and valleys which can divide images into different parts. Threshold is a value in a histogram that divides intensities into two parts: the first part is the “foreground” having pixels with intensities greater than or equal to the threshold and the second part is the “background” having pixels with intensities less than the threshold.

Thresholding segmentation usually does not take into account the spatial information of images which leads to sensitivity to noise and intensity in homogeneities. Global thresholding works on the idea that an image has a bimodal histogram and the object can be separated from the background using a threshold value.

Local Thresholding

Global thresholding does not provide satisfactory results for some type of images such as images which do not have a constant background and have diversity across the object. The local thresholding method divides images into subimages and then calculates the threshold value for each part.

Different statistical methods are used to select the threshold value for each subimage, for example, mean, standard deviation, mean and standard deviation together, and mean of maximum and minimum. Local thresholding needs more time to segment an image compared to global thresholding.

Otsu's Thresholding

Threshold value is usually selected visually which leads to problems and may even lead to poor results. The goal of Otsu's thresholding is to find an optimal value for global thresholding. In this method, it is assumed that an image has two pixel classes

or has a bimodal histogram. It chooses the threshold to minimize the intra-class variance (the variance within the class) of black and white cluster pixels.

Region Growing

Region growing is an interactive segmentation method which requires some seed points to be initialized and start the process. This technique separates a region of images based on some predefined law according to intensity information.

The disadvantage of region growing is that the result of this technique significantly depends on the seed point selection. Selecting a seed point depends on human ability; thus, the extracted shape considerably depends on the user. Although noise sensitivity in this method is less than thresholding, but it can make a hole in the extracted shape or produce a disconnected area.

III. Applications of Image Segmentation in Medical

Medical images have become essential in medical diagnosis and treatment. These images play a substantial role in medical applications because doctors exhibit interest in exploring the internal anatomy. Many techniques have been developed based on X-ray and cross-sectional images like Computed Tomography (CT) or Magnetic Resonance Imaging (MRI), or other tomographic modalities (SPECT, PET, or ultrasound) [2].

Over the years, medical image processing has contributed a lot in medical applications; for example, the use of image segmentation, image registration, and image guided surgery is so common in medical surgery.

The most important part of medical image processing is image segmentation. Image segmentation is a procedure for extracting the region of interest (ROI) through an automatic or semi-automatic process. Many image segmentation methods have been used in medical applications to segment tissues and body organs. Some of the applications consist of border detection in angiograms of coronary, surgical planning, simulation of surgeries, tumor detection and segmentation, brain development study, functional mapping, blood cells automated classification, mass detection in mammograms, image registration, heart segmentation and analysis of cardiac images.

Segmentation and boundary detection is one of the most important task in image processing. In segmentation, an image is partitioned into a set of distinct regions. This is an intermediate step in various image processing applications like content based image and video retrieval, object recognition and tracking, and biomedical engineering etc. In this paper, we implemented a geometric active contour model which uses level set methods and an energy function, by minimizing it we can solve the boundary of an object. This algorithm does not depend on the gradient of the image, so its performance is good for noisy images also. It can be used to detect lesion or tumor in an MRI image.

Boundary detection and segmentation of objects has many applications in object tracking and object recognition, robotics, and biomedical engineering. The detection of object boundaries through active contours is an emerging new research topic in computer vision and pattern recognition. In general, most of the active contour models converge towards some desired contour by minimizing a sum of internal and external energy terms. For such type of active contours we define a contour as an initial segmentation in the image plane and then we solve this contour using mathematical equations. The goal is to stop the evolution of contour on the exact boundary of the object. The evolution equation can be defined in different ways such as the contour may move with a velocity that depends on the local curvature or the gradient of the image at the given point.

IV. Active Contours Models

The concept of active contours models was first introduced in 1987 and has later been developed by different researchers. An active contour is an energy minimizing spline that detects specified features within an image. It is a flexible curve (or surface) which can be dynamically adapted to required edges or objects in the image (it can be used to automatic objects segmentation). It consists of a set of control points connected by straight lines. The active contour is defined by the number of control points as well as sequence of each other. Fitting active contours to shapes in images is an interactive process. The user must suggest an initial contour, which is quite close to the intended shape. The contour will then be attracted to features in the image extracted by internal energy creating an attractor image.

Active contours have been widely used as attractive image segmentation methods because they always produce sub-regions with continuous boundaries, while the kernel-based edge detection methods, e.g. Sobel edge detectors, often produce discontinuous boundaries. The use of level set theory has provided more flexibility and convenience in the implementation of active contours [3]. However, traditional edge-based active contour models have been applicable to only relatively simple images whose sub-regions are uniform without internal edges.

Active contours are connectivity-preserving relaxation methods, valid to the image segmentation problems. Active contours have been used for image segmentation and boundary tracking since the first introduction of snakes by Kass et al. The fundamental idea is to start with first boundary shapes represented in a type of closed curves, i.e. contours, and iteratively change them by applying shrink/expansion operations according to the constraints of images. Those shrink/expansion operations, called contour evolution, are done by the minimization of an energy function like fixed regionbased segmentation methods or by the simulation of a geometric fractional differential equation (PDE).

A benefit of dynamic contours as image segmentation methods is that they dividing an image into sub-regions with continuous boundaries, while the border detectors based on threshold or local filtering, e.g. Canny or Sobel operator, regularly result in irregular boundaries. Apply of level set theory has provided more flexibility and convenience in the completion of active contours.

4.1 Basic Types of Deformable Models

There are 2 basic types of deformable models: parametric and geometric [4].

4.1.1 The parametric deformable models

It represent curves and surfaces during deforming explicitly in parametric form. The parametric models can be described with help of some of the following formulations, and so by formulation of energy minimizing or formulation of dynamic force.

4.1.2 The formulation of minimizing energy

The base of deformable models on the basis of energy minimization is searching of parametric curve that minimizes weighted sum of internal energy and potential energy. Internal energy specifies tension or smoothness of contour. The potential energy is defined in the image domain and it usually has minimal value at the point where it is high intensity gradient in the image what is shown on the object edge. Total energy minimization occurs when internal and external energies are equal.

4.1.3 The formulation of dynamic force

It is used in those cases in which it is more comfortable to form deformable model straight from dynamic problem with help of force formulation. These formulations facilitate the use of common external forces, even those which are not potential, e.g. forces which can not be described as a negative gradient of potential energy function.

4.2 The geometric deformable models

It offer elegant solution of the most important limits of parametric deformable models. These models are based on the evolution curve theory and the level set method. At curves and surfaces evolution only geometric criteria are used that leads to the evolution independent from parametrization. As well as at the parametric deformable models, the evolution is connected to image data at objects edge finding. Forasmuch as the evolution is independent from parametrization, the curves and surfaces generating can be represented as the 'level set' of a multidimensional function. The result of this is that topological changes are easy to control. The active contour can be either closed or open curve.

4.3 Image Segmentation using Active contours: the Taxonomy

There are two major approaches in image segmentation: edge- and region- based. Edge based segmentation partitions an image based on discontinuities with sub-regions, while region-based segmentation does the similar function based on the uniformity of a desired property within a sub-region [5].

Edge-based Segmentation

Edge-based segmentation looks for discontinuities in the intensity of an image. It is more likely edge detection or boundary detection rather than the exact meaning of image segmentation. An edge can be defined as the border between two regions with relatively separate properties. The assumption of edge based segmentation is that every sub-region in an image is sufficiently uniform so that the transition between two sub-regions can be determined on the basis of discontinuities alone.

Edge detection by gradient operations usually works well only in the images with sharp intensity transitions and relatively low noise. Due to its sensitivity to noise, various smoothing operation is usually essential as preprocessing, and the smoothing effect consequently blurs the edge information. However, the computational cost is comparatively lower than other segmentation methods because the computation can be complete by a local filtering operation, i.e. convolution of an image with a kernel.

Region-based Segmentation

Region-based segmentation looks for equality inside a sub-region, based on a desired property, e.g. intensity, color, and texture. Region rising is a technique that merges pixels or small sub-regions into a bigger sub region. The simplest implementation of this approach is pixel aggregation, which starts with a set of seed points and grows regions from these seeds by appending nearby pixels if they satisfy the given criteria. Despite the simple character of the algorithm, there are basic problems in region rising: the selection of initial seeds and suitable properties to grow the regions. Selecting initial seeds can be frequently based on the character of applications or images.

Additional criteria that use properties to raise the regions lead area growing into more sophisticated methods, e.g. region competition. Region competition merges neighboring sub-regions under criteria involving the equality of regions or sharpness of boundaries. Strong criteria tend to generate oversegmented results, while weak criteria lean to produce poor segmentation outcome by over-merging the subregions with blurry boundaries.

An alternative of region rising is split-and-merge, which partitions an image firstly into a set of arbitrary, disjointed sub-regions, and then combine and/or split the sub-regions in an attempt to satisfy the segmentation criteria.

Active Contours

The method of active contours has become quite popular for a range of applications, mainly image segmentation and motion tracking, through the last decade. This methodology is based upon the use of deformable contours which match to various object shapes and motions.

There are two main approaches in active contours based on the mathematic implementation: snakes and level sets. Snakes explicitly shift predefined snake points based on an energy minimization method, while level set approaches move contours completely as a particular level of a function.

As image segmentation methods, there are two kinds of active contour models according to the force evolving the contours: edge- and region-based. Edge-based active contours apply an edge detector, typically based on the image gradient, to locate the boundaries of sub-regions and to draw the contours to the detected boundaries. Edge-based approaches are closely connected to the edge-based segmentation. Region based active contours apply the statistical information of image intensity inside each subset instead of searching geometrical boundaries. Region-based approaches are also closely connected to the region-based segmentation.

Snakes

A set of snake points residing on the image plane are defined in the first stage and then the next location of those snake points are determined by the local minimum E . The associated form of those snake points is considered as the contour. The snakes points are firstly placed at more distance from the boundary of the object, i.e. the moth. Then, every point moves towards the optimum coordinates, where the energy utility converges to the minimum. The snakes points ultimately stop on the boundary of the object. The classic snakes give an perfect location of the edges only if the first contour is given sufficiently near the edges because they make use of only the local information along the contour. Estimating a correct position of first contours without prior knowledge is a complex problem. Also, classic snakes cannot detect more than one boundary concurrently because the snakes maintain the equal topology throughout the evolution stage. That is, snakes cannot divide to several boundaries or combine from multiple first contours.

Level Set Methods

Level set theory is a formulation to apply active contours, was proposed by Osher and Sethian. They represented a contour implicitly via a two dimensional Lipschitz - continuous – function $\varphi(x, y) : \Omega \rightarrow \mathfrak{R}$ defined on the image plane. The function $\varphi(x, y)$ is called level set function, and a particular level, generally the zero level, of $\varphi(x, y)$ is defined as the contour.

Edge-based Active Contours

Edge-based active contours are strongly connected to the edge-based segmentation. Most edge based active contour models consist of two parts: the regularity part, which determines the form of contours, and the edge recognition part, which attracts the contour towards the boundaries. Edge-based active contour models have a little disadvantages compared to the region-based active contour models, discussed in the next section. Because of the constant term, edge based active contour models evolve the contour towards only one way, each inside or outside. Therefore, an primary contour must be placed completely inside or outside of ROI, and some level of a previous knowledge is still necessary. Also, edge-based active contours inherit a few disadvantages of the edge-based segmentation methods due to the parallel method used. Edge-based active contours rely on the image gradient process, edge-based active contours may omit the blurry boundaries, and they are sensitive to local minima or noise as edge-based segmentation does. Gradient vector flow quick geodesic dynamic contours proposed by Paragios replaced the border detection (boundary attraction) word with gradient vector field that refers to a spatial diffusion of the boundary information and guides the propagation to the object boundaries from equally sides, to give extra freedom from the restriction of first contour position.

Region-based Active Contours

Most region-based active contour models consist of two parts: the regularity part, which determines the smooth form of contours, and the energy minimization part, which searches for equality of a preferred feature within a subset. A good characteristic of region-based active contours is that the first contours can be situated anyplace in the image as region-based segmentation relies on the global energy minimization rather than local energy minimization. Therefore, less previous knowledge is required than edge-based active contours

Although usual region-based active contours partition an image into several sub regions, those several regions belong to only two subsets: both the inside or the outside of contours. Chan and Vese proposed multi-phase active contour model, which increases the amount of subsets that active contours can locate simultaneously. Multiple active contours evolve independently based on the piecewise-constant model or the piecewise-smooth model, and multiple subsets are defined by a set of disjoint combination of the level set functions.

Due to the global energy minimization; region based active contours usually do not have any restriction on the placement of first contours. That is, region-based active contour can detect interior boundaries regardless of the position of initial contour. That is,

region-based active contour can detect inner boundaries regardless of the position of initial contours. The use of pre-defined initial contours provides a method of independent segmentation. Also, they are less responsive to local minima or noise than edge-based active contours. However, due to the supposition of uniform image intensity, most methods are relevant only to images where each subset is stand for able by a simple expression, e.g. single Gaussian distribution or a constant. If a subset, i.e. class, consists of multiple distinguishing sub-classes, these methods would produce over-segmented or under-segmented results. We propose novel region-based active contour models which produce better results using multivariate mixture density functions.

Active Contours integrating Edge- and Region based Segmentation

In order to develop the segmentation performance, the integration of edge- and region based information sources using active contours has been proposed by a few authors. Geodesic active region is a supervised active contour model, proposed by Paragios, integrating edge- and region-based segmentation module in an energy function. A statistical analysis based on the Minimum Description Length (MDL) measure and the Maximum Likelihood (ML) principle for the observed density function, i.e. an image histogram, indicates the number of sub-regions and the statistical PDF within those sub-regions using a mixture of Gaussian elements. Regional probability is estimated from the statistical PDF based on previous knowledge, i.e. training samples. Then, the margin information is resolute by a probabilistic edge detector, expected from the regional probabilities of neighborhood. For example, an image pixel is more likely an edge pixel if the neighborhood pixels, located on the opposed sides, have high regional probabilities for a different class. The geodesic active region model is later useful to a medical imaging problem with a gradient vector flow-based boundary factor. The approach was based on a joined propagation of two active contours, and integrates visual information with anatomical constraints.

V. Segmentation of biomedical images using active contour model

The image energy of the proposed model is derived from a robust image gradient feature which gives the active contour a global representation of the geometric configuration, making it more robust in dealing with image noise, weak edges, and initial configurations.

Shape segmentation is an important area in biomedical image analysis and has a wide range of uses such as tissue classification, virtual endoscopy, image-guided surgery, diagnosis, biomedical simulation, and image-based modeling [6]. Geometric reconstruction from biomedical image volumes by manual labeling can be very tedious due to the sheer size of the image datasets, and the complexity and variability of the anatomic object shapes. Also, inter and intra variability of the geometries extracted manually by different users, and geometries extracted by the same user at different times, can be considerably large. It is therefore useful to design a robust algorithm for the automatic delineation of anatomic structures from images acquired from different imaging modalities such as magnetic resonance imaging, computed tomography imaging, and ultrasound imaging. Some of the main challenges include the extraction of object boundaries or regions from images with noise and intensity inhomogeneity, which often exist in biomedical images due to factors such as sampling artifacts and bias field. Other factors such as weak object edges, low resolution, and spatial aliasing can also affect the accuracy and efficiency of the shape extraction process.

Active contours or deformable models provide an effective framework for object segmentation and has been widely used in biomedical image segmentation, as they can easily adapt to shape variations. Various types of useful information can also be incorporated to regularize the smoothness and shape of the contour.

However, it is still a great challenge for active contour models to achieve strong invariance to initialization and robust convergence. This is particularly true when the active contour is applied on real image datasets consisting of intensity inhomogeneity and complex geometries. In the presence of artifacts, occlusions or large amount of noise, it is difficult for purely image-based models to extract image objects accurately. In such cases, prior knowledge of shape information can be very useful as it provides a constraint to the deformation of the contour such that the model favors similar shapes represented in the training set.

A variational level set model for shape segmentation using Bayesian inference. The proposed model uses an image-based energy and shape-based energy to attract the active contour toward the object shape. Image intensity and color or their local distributions has been commonly used to derive the image energy. Image intensity gradient is sensitive to image noise and weak edges as it uses local image information, and region-based models are often affected by intensity variations. In the present work, the image-based energy is therefore derived from the global interaction of image intensity gradient vectors. This gradient vector interaction field is also known as the geometric potential field and that its vector form can increase the robustness and efficiency of the active contours in handling image noise, challenging initialization, weak edge, and even broken object boundaries.

Its characteristics are fundamentally different from image intensity or image intensity gradient, as it exhibits a coherent and global geometric configuration of the image objects. The shape-based energy is incorporated into the segmentation model using nonparametric shape distribution. The use of the nonparametric technique of KDE allows the shape prior to model arbitrary shape distributions and can therefore handle large shape variations in the training set. The image-based and shape-based energy, allows the active contour to efficiently handle feature inhomogeneity, occlusion, image noise, and weak object edges.

This model consists of an image attraction force, which propagates contours toward object boundaries, and a global shape force, which deforms the model according to the shape distribution learned from a training set. The image attraction force is derived

from the interaction of gradient vectors. It differs from conventional image intensity gradient-based methods, as it utilizes pixel interactions across the whole image domain. A shape distance is defined to measure the dissimilarity between shapes.

5.1 Bayesian formulation of segmentation model

The segmentation model is formulated using Bayesian inference, where the segmentation of an image represented by the image intensity I can be considered as maximizing the conditional probability.

Maximizing the posterior probability is equivalent to minimizing the negative log-likelihood, which is given as a sum of the image energy and shape energy. The minimization of the energy functional can therefore be interpreted as a segmentation model that simultaneously maximizes the accuracy of the object boundaries located by the evolving shape, and the similarity of the evolving shape with respect to the shapes represented in the training set.

5.2 Image-based energy

The image-based term is used to propagate the model toward the feature of interest in the image and can be image intensity gradient-based or region-based. Image object edge-based approaches represent object boundaries using image intensity gradient, while region-based approaches use characteristics such as color and texture to define the region within an object. Image gradient-based methods can be very effective when object boundaries are well defined. Region-based methods make use of regional statistics such as means and variances to derive the external energies or forces and are thus more robust to noise interference. However, as region-based models are often based on the assumption that image objects consist of distinct regional statistics, they cannot deal with intensity inhomogeneity in images.

5.3 Shape-based energy

A nonparametric technique is used to generate a statistical shape distance measure for level set-based shape representations. The signed distance function, which can be conveniently derived from the level set function, is used to represent a shape. The nonparametric technique of KDE can then be used to model the statistical shape distribution. Here, the shape energy functional is defined on the basis of a probability density on the space of signed distance functions by integrating the shape distance.

5.4 Variational level set segmentation model with global shape prior

The minimization of the energy functional generates a segmentation model, which attracts the active contour toward image object boundaries and similar shapes in the training set. The variational segmentation model therefore maximizes the alignment between the active contour and the image object boundaries, and the similarity of the evolving shape with respect to the shapes represented using the statistical shape distribution. The training set is generated or extracted manually in the form of binary images, and the signed distance functions, which represent the shapes, are computed using an efficient distance transform algorithm. The image-based energy derived from the global interaction of gradient vectors provides a more coherent and global representation of the geometric configuration. The active contour model is thus more robust to image noise and weak edges, and has a strong invariance to initializations. By using kernel density estimation, the incorporated shape prior can model arbitrary shape distributions. The proposed model can thus segment complex shapes from occluded and noisy images effectively. Several examples are provided using various object shapes from synthetic and real images. It is shown that the proposed model with gradient vector interaction-based and shape-based energies can be used to segment various object shapes from biomedical images efficiently.

VI. Automatic Segmentation and Classification of Mitotic Cell Nuclei

Segmentation accuracy determines the success or failure of computerized analysis procedure in biomedical applications. The process involves detection and classification of cell nuclei based on computed features. The proposed method uses Active Contour Model for segmentation of cell nuclei and two versatile classifiers such as Support Vector Machine (SVM) and Random Forest (RF) for classification stage [7]. Analysis results showed good detection accuracy for RF classifier compared to SVM. Different stages of analysis include detection, segmentation, feature computation and classification.

In biologic samples homogeneity is rare within a population of cells. In order to identify a cell as normal or malignant, shape and texture of its chromatin has to be considered. Simple thresholding operations give very poor detection since there is difficulty in finding a reliable threshold due to diffusion of nuclei and background regions. Watershed transforms leads to over segmentation and consequently results in sub optimal detection. Cosatto et al. proposed a method which combines Active Contour Model (ACM) with Hough transform and Difference of Gaussian (DoG) filter to detect cell nuclei. But it suits only for circular nuclei and require excessive computation. A gamma-gaussian mixture model was proposed for detection of mitotic nuclei by isolating tumor region from non-tumor areas. But it requires a context aware post processing step in the classification stage.

The features computed from the segmented nuclei are used by the classifiers to separate the nuclei into different classes. Recently, in addition to morphological and intensity features, Run-Length and co-occurrence features are explored from different color channels for mitosis detection in breast cancer images. It results in poor classification performance and need to find subset of features to improve the performance. This paper focuses a hybrid approach in analysis that starts with an initial binarisation by

thresholding and morphological processing, and subsequent refinement with active contour modeling to segment the nuclei. Further, it requires a single color channel and limited set of nuclei features to classify mitotic nuclei.

This has mainly three stages, viz, (i) Detection of nuclei locations (ii) Segmentation of detected nuclei and (iii) Feature computation and classification of segmented nuclei. The first and the foremost important stage is the detection of nuclear regions in the Haematoxylin and Eosin (H & E) stained images. It is a crucial step since the error resulting from this is transferred to later stages and causes incorrect results in analysis. In the second stage accurate segmentation of detected nuclei regions by morphological reconstruction and active contour modeling are done. Third stage consists of two phases; (a) The training phase in which a feature set is compiled from computed features of ground truth nuclei with which classifiers are trained and (b) the classification phase where the test set of images are verified for normal and mitosis nuclei and classify accordingly.

REFERENCES

- [1]. A. Chopra and B.R. Dandu, "Image Segmentation Using Active Contour Model", International Journal of Computational Engineering Research, Vol. 2, issue 3, pp. 819-822, June-2012.
- [2]. A. Norouzi, M.S.M. Rahim, A. Altameem, T. Saba, A.E. Rad, A. Rehman and M. Uddin, "Medical Image Segmentation Methods, Algorithms and Applications", IETE Technical Review, Vol.31, No. 3, pp. 199-209, June-2014.
- [3]. D.R. Byreddy and MV Raghunadh, "An Application of Geometric Active Contour in Bio-medical Engineering", International Conference on Circuits, Systems, Communication and Information Technology Applications, pp. 322-326, 2014.
- [4]. M. Bakos, "Active Contour and their Utilization at Image Segmentation", 5th Slovakian-Hungarian Joint Symposium on Applied Machine Intelligence and Informatics, pp. 313-317, January 2007.
- [5]. D. Baswaraj, A. Govardhan and P. Premchand, "Active Contours and Image Segmentation: The Current State of the art", Global Journal of Computer Science and Technology Graphis & Vision, Vol. 12, No. 11, pp.

