Medical Images Segmentation Using Contouring Techniques

A
thesis
submitted towards the partial fulfillment of
the requirements of the degree of

Master of Engineering
In
Electronic Instrumentation and Control Engineering

Submitted By

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Declaration I

*This is to certify that my work presented in this thesis entitled **"Medical Images Segmentation Using Contouring Techniques"** submitted in partial fulfillment of the requirement for the award of the degree of **Master of Engineering in Electronic Instrumentation and Control Engineering** at **Thapar University, Patiala**, is an original record under supervision and guidance of **Ms. Gagandeep Kaur, Lecturer (SG).** The matter embodied in this report has not been submitted anywhere for the award of any degree.*

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Abstract III

The underlying application domain for this work is medical imaging. Medical imaging allows scientists to observe anatomic structures inside the human body in a non-invasive way. The technological advances within medical imaging and medical image analysis have had a great impact on the medicine, both within clinical and research applications. It has expanded beyond simple visualization of anatomic structures and become a tool in surgical planning and simulation, intra-operative navigation, diagnosis, tracking the progress of a disease etc. As a tool in the medical research, medical imaging has for example become an irreplaceable aid in brain research applications such as cognitive psychology and morphological analysis of brain structures.

As it is mentioned in the introductory part of this chapter, the problem of extracting information form images is the most important and challenging problem in the image analysis. Modern medical imaging devices such as CT and especially MRI, provide visually satisfactory images of the internal human organs. Problems arise when we want to utilize computers in order to automate the extraction of information from an image set.i have studied the characteristics of a brain image from an image processing point of view basically to detect tumor. The preprocessing of image is done to reduce the effect of speckles and preserve the tumor edges and thereby provide the foundation for a successful segmentation.

The segmentation method we chose to implement were *level set method*- for it,s strength in segmenting volumes and *the snake*- which manages to conserve weak edges. These methods were implemented with Matlab from mathsworks. It was chosen for it,s wide range of medical image processing functions.

As it is shown throughout this work, many active contour models give satisfactory results in some specific situations but fail to meet the various requirements e.g. they may be designed for a specific problem and can not be used on a variety of shapes, or the contour may be to rigid and therefore unable to capture complexity of anatomic structure. Another problem which arises in some models is a time consuming preprocessing of the images required to create a model capable of detecting a specific structure. Even though, these models give satisfactory results in some applications, they are not well suited for large scale automated processing of images in clinical applications.

In this work we observe representatives of different classes of active contour models, studied them theoretically, then choose two methods for implementation. What we have tried is to determine is how “good” different active contour models are for medical image segmentation. The actual analysis in the medical imaging causes corrective action by taking proper medication whose decision is based on the contour analysis. Another original contribution of this work is the Fourier spectral algorithm for iterating the evolution equation, which has not been used in the literature.

The results show that bath methods may successfully segment a tumor provided the parameters are set properly. Both methods required an initialization inside the tumor. Future work can be aimed at an algorithm to automatically estimate parameters, we believe automatic segmentation can be used to support the therapy and there by increase the quality of the treatment.

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CAD	**Computer Aided Diagnosis**
CAT	**Computer Axial Tomography**
CT	**Computer Tomography**
DWT	**Discrete Wavelet Transform**
FT	**Fourier Transform**
GUI	**Graphic User Interface**
I/O	**Input/Output**
MDL	**Minimum Description Length**
ML	**Maximum Likelihood**
MRI	**Magnetic Resonance Image**
PDE	**Partial differential equation**
PET	**Positron emission tomography**
ROI	**Region of Interest**

CHAPTER 1

Overview of Image Processing Basics

1.1 DEFINATION & TERMINOLOGY

1.1 .1 Image Processing

Image Processing is any form of information processing for which both the input and output are images, such as photographs or frames of video. In general, information processing can be the changing (processing) of information in any manner detectable by an observer. So, image processing can more specifically be defined in terms as the conversion of latent information into manifest information. Most image processing techniques involve treating the image as a two-dimensional signal and applying standard signal processing techniques to it.

Image processing operations can be roughly divided into three major categories,

- Image Compression
- Image Segmentation
- Image Enhancement and Restoration.

1.1.2 Digital Image Processing

An image may be defined as two dimensional function f(x, y) where x and y are spatial coordinates and amplitude of f at any points of coordinates (x, y) is called the intensity of the grey scale of the image at that point. When (x, y) and the amplitude values of ‘f’ are all finite, discrete quantities we call the image a digital image. The field of digital image processing refers to processing digital images by means of digital computer.

Digital image processing is the use of computer algorithms to perform image processing on digital images. Digital image processing has the same advantages over analog image processing as digital signal processing has over analog signal processing — it allows a much wider range of algorithms to be applied to the input data, and can avoid problems such as the build-up of noise and signal distortion during processing. The most common kind of digital image processing is digital image editing.

In particular, digital image processing is the only practical technology for-

- Classification
- Feature extraction
- Pattern recognition
- Projection
- Multi-scale signal analysis

Many of the techniques of digital image processing, or digital picture processing as it was often called, were developed in the 1960s at the Jet Propulsion Laboratory, MIT with application to satellite imagery, wire photo standards conversion, medical imaging and photo enhancement. But the cost of processing was fairly high with the computing equipment of that era. In the 1970s, digital image processing proliferated, when cheaper computers and dedicated hardware became available. Images could then be processed in real time, for some dedicated problems such as television standards conversion. As general-purpose computers became faster, they started to take over the role of dedicated hardware for all but the most specialized and compute-intensive operations.

With the fast computers and signal processors available in the 2000s, digital image processing has become the most common form of image processing, and is generally used because it is not only the most versatile method, but also the cheapest. Most images IN MATLAB are stored as two-dimensional arrays (i.e., matrices), in which each element of the matrix corresponds to a single pixel in the displayed image. (Pixel is derived from picture element and usually denotes a single dot on a computer display.)

1.1.3 Image Segmentation

Segmentation refers to the process of partitioning a digital image into multiple regions (sets of pixels). The goal of segmentation is to simplify and/or change the representation of an image into something that is more meaningful and easier to analyze. Image segmentation is typically used to locate objects and boundaries (lines, curves, etc.) in images. Image segmentation, an image processing technique to separate objects from the background in an image, is an important step in image processing with many applications such as machine vision, face recognition, and medical image analysis.

The result of image segmentation is a set of regions that collectively cover the entire image, or a set of contours extracted from the image (see edge detection). Each of the pixels in a region is similar with respect to some characteristic or computed property, such as color, intensity, or texture. Adjacent regions are significantly different with respect to the same characteristic.

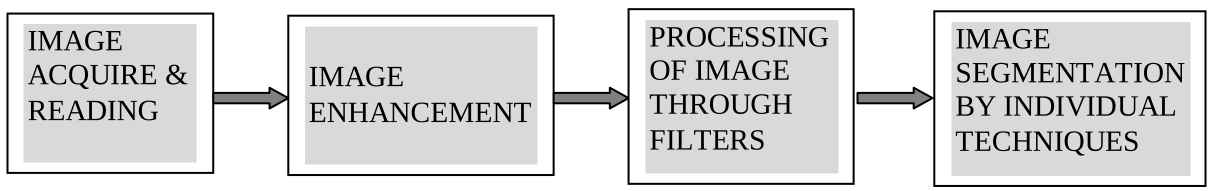


Fig 1.1 Block diagram of general Image Segmentation System

1.1.4 Applications of Image Segmentation

Some of the practical applications of image segmentation are:

1. **Medical Imaging**

    i. Locate tumors and other pathologies

    ii. Measure tissue volumes

    iii. Computer-guided surgery

    iv. Diagnosis

    v. Treatment planning

    vi. Study of anatomical structure

As health care systems and hospitals become more digitalized, medical image processing plays a more important role. As an intermediate step, image segmentation is crucial in image registration and classification problems. Furthermore, medical image segmentation offers help in diagnosis and treatment in many situations. First of all, through 2-dimensional segmentation, a 3-dimensional model can be reconstructed, which helps with visualization for diagnosis and aid in surgery. Also, doctors can estimate dimension (volume, area, length) of the object of interest such as a tumor such that radiation therapy can be automated. With the trend of the digitization of medical data, segmentation also helps form a digital atlas of the patient's anatomy, thus eliminating the need for patient specific tools.

2. Locate objects in satellite images (roads, forests, etc.)

3. **Face recognition:** These days, as terrorist threats loom and security systems become more in demand, face recognition is an important area of research as computers help matches people to database profiles through identifying face features. To be able to isolate face features such as eyes, mouth and eye brows are difficult widely researched problems.

4. **Automatic traffic controlling systems:** Highway toll systems use cameras to extract car license plates, and in manufacturing, images help discover possible defects in products such as cracks or breakages.

5. **Machine vision:** In machine vision, robots can rely on cameras to give information about the surroundings, such as identifying proper route or possible obstacles.

1.1.5. Function of Segmentation

The function of segmentation is simply to partition an image into multiple sub-regions, while the function of pattern classification is to identify the partitioned sub-regions. Thus, segmentation and pattern classification usually function as separate and sequential processes as shown in *Table 1.1*. However, they might function as an integrated process as shown in *Table 1.2* depending on the image analysis problem and the performance of the segmentation method. In either way, segmentation critically affects the results of pattern classification, and often determines the eventual success or failure of the image analysis.

Figure 1.2: X-Ray image of a Hand

Table 1.1: *Medical imaging scenario 1: an X-ray image of a hand. Segmentation and pattern classification as sequential and separate procedures*.

Input data: an X-ray image of a hand as shown in figure 1.2 1. **Segmentation:** separate bones from the X-ray image. • Supervised method: trained features or sample data of bones are provided. • Unsupervised method: separate bright regions from the background. • **Result:** bones are extracted, but we do not know what kinds of bones they are. 2. **Shape description:** describe the extracted bones in a form of numerical features 3. **Pattern classification:** identify each bone based on the features **Output data:** the identity of bones, e.g. thumb, index finger, ring finger, etc.

Table 1.2: Medical imaging scenario 2: an MR image of a brain. Segmentation and pattern classification as an integrated procedure.

Input data: an MR image of a Brain (as shown in fig 1.4) 1. **Segmentation & pattern classification:** partition white and gray matters in the MR image. • Supervised: trained features or sample data of white and gray matters are provided. • Unsupervised: partition the brightest regions and brighter regions from the background. **Output data:** extracted white and gray matter.

Since segmentation is an important task in image analysis, it is involved in most image analysis applications, particularly those related to pattern classification, e.g. medical imaging, remote sensing, security surveillance, military target detection. The level to which segmentation is carried depends on the problem being solved. That is, segmentation should stop when the region of interest (ROI) in the application have been isolated. Due to this property of problem dependence, autonomous segmentation is one of the most difficult tasks in image analysis. Noise and mixed pixels caused by the poor resolution of sensor images make the segmentation problem even more difficult. In this document, we propose novel segmentation methods using a variation framework, called active contours. Active contours are connectivity-preserving relaxation [2] methods, applicable to the image segmentation problems.

The basic idea is to start with initial boundary shapes represented in a form of closed curves, i.e. contours, and iteratively modify them by applying shrink/expansion operations according to the constraints of the image. Those shrink/expansion operations, called contour evolution, are performed by the minimization of an energy function like traditional region-based segmentation methods or by the simulation of a geometric partial differential equation (PDE)

An advantage of active contours as image segmentation methods is that they partition an image into sub-regions with continuous boundaries, while the edge detectors based on threshold or local filtering, e.g. Canny [5] or Sobel operator, often result in discontinuous boundaries. The use of level set theory has provided more flexibility and convenience in the implementation of active contours. Depending on the implementation scheme, active contours can use various properties used for other segmentation methods such as edges, statistics, and texture. In this document, the proposed active contour models using the statistical information of image intensity within a sub-region.

1.1.6. Medical Imaging

Medical imaging is the process by which physicians evaluate an area of the subject's body that is not externally visible. Medical imaging may be clinically motivated, seeking to diagnose and examine disease in specific human patients. Alternatively, it may be used by researchers in order to understand processes in living organisms. Many of the techniques developed for medical imaging also have scientific and industrial applications.

Medical imaging often involves the solution of mathematical inverse problems. This means that cause (the properties of living tissue) is inferred from effect (the observed signal). In the case of ultrasonography the probe consists of ultrasonic pressure waves and echoes inside the tissue, show the internal structure. In the case of radiography, the probe is x-ray radiation which is absorbed at different rates by different types of tissue such as bone, muscle and fat. Medical imaging evolved from the discovery of X-rays to the newest magnetic resonance image (MRI). Commonly used techniques currently include x-ray, computer tomography

(CT), ultra- sound, MRI, and positron emission tomography (PET). This section will briefly discuss the nature of some of these images and the technology behind them.

1.1.6.1 X-ray

X-ray is the first and oldest medical imaging technique available to doctors for the visualization of the body without surgery. It is generally noninvasive, except when used in methods such as angiography where a radiopaque substance is injected into the bloodstream to highlight the circulation in any part of the body [20].

However, X-rays have ionizing effects on the body and therefore should not be repeatedly used. X-rays were first discovered by Wilhelm Raontgen in 1895. The technique involves having a film or screen containing a radiation-sensitive material exposed to the X-rays transmitted through a region of the body. The developed film or excited phosphorous screen exhibits a geometric pattern produced by the structures in the beam path [20]. X-ray imaging is limited as the signal can be reduced due to the scattering of a large percentage of radiation from the body, and much detail is lost in the radiographic process with the superposition of 3D structural information onto a 2D surface. Therefore the 3D nature of bones, muscles, ligaments and vessels are all hard to capture on X-ray. The use of X-rays is usually limited to scanning bone. Fig. 1.1 shows an angiography of the left ventricle.

Figure 1.3: A left ventricle angiography

1.1.6.2 Ultrasound Image

An ultrasound image is based on using a propagating ultrasonic wave that partially reflects at the interface between different tissues [23]. The reflections are measured as a function of time, and the position of the tissue can thus be obtained if the velocity of the wave in the medium is known. As the wave propagates through the body, diffraction, refraction, dispersion, and scattering occurs and can affect the image quality. Speckle noise patterns due to scatter are common, but are important to help the user distinguish between different tissues. There are also possible artifacts due to reverberations when waves are reflected back and forth between the transducer and the tissue. Ultrasound is commonly used for soft tissues, fluids, and small calcifications that are preferably close to the patient's body surface and not hidden by bony structures.

Medical ultrasonography uses high frequency sound waves of between *2.0 to 10.0 megahertz* that are reflected by tissue to varying degrees to produce a 2D image, traditionally on a TV monitor. This is often used to visualize the fetus in pregnant women. Other important uses include, imaging the abdominal organs, heart, and the veins of the leg.

While US may provide less anatomical information than other techniques such as CT or MRI, it has several advantages which make it ideal as a first line test in numerous situations, in particular that it studies the function of moving structures in real-time. It is also very safe to use, as the patient is not exposed to radiation and the ultrasound does not appear to cause any adverse effects. It is also relatively cheap and quick to perform. The real time moving image obtained can be used to guide drainage and biopsy procedures.

1.1.6.3 Magnetic Resonance Image

Magnetic resonance imaging was developed in the early 1970s and has become a versatile and clinically useful diagnostic imaging modality [20]. In contrast to X-ray and CT, MRI is a noninvasive imaging technology that does not use ionizing radiation. It is based on perturbing magnetic fields with radio waves. In MRI, hydrogen nuclei (protons) are imaged due to their strong magnetic moment and prevalence in the soft tissues of the body (water molecules). The signal being measured can be controlled through modulation of the magnetic field and radiofrequency pulse sequences used to alter the spins of protons in the structure being imaged. MRI best captures human soft tissue anatomy, as it is able to provide high contrast between soft tissues. In addition, its signal is not disturbed by bone. It is therefore used often to find pathological changes such as tumors, hemorrhages and inflammations, and the central nervous system where there are many bones [12]. Unlike many other medical imaging modalities, the contrast in an MR image depends strongly upon the way the image is acquired.

By altering RF and gradient pulses, and choosing relaxation timings, it is possible to highlight different components in the object being imaged and produce high contrast images. These two features facilitate segmentation.Moreover, MR images are not always high-contrast. Many T2- weighted and proton density images have low contrast between gray matter and white matter .Fig. 1.4 shows an MRI of the brain. An MRI uses powerful magnets to excite hydrogen nuclei in water molecules in human tissue, producing a detectable signal. Like a CT scan, an MRI traditionally creates a 2D image of a thin slice of the body. The difference between a CT image and an MRI image is in the details. In CT scan, X-rays must be blocked by some form of dense tissue to create an image, therefore the image quality when looking at soft tissues will be poor. An MRI cans only see hydrogen based objects, so bone, which is calcium based, will be a void in the image, and will not affect soft tissue views. This makes it excellent for peering into joints. As an MRI does not use ionizing radiation, it is the preferred imaging method for children and pregnant women

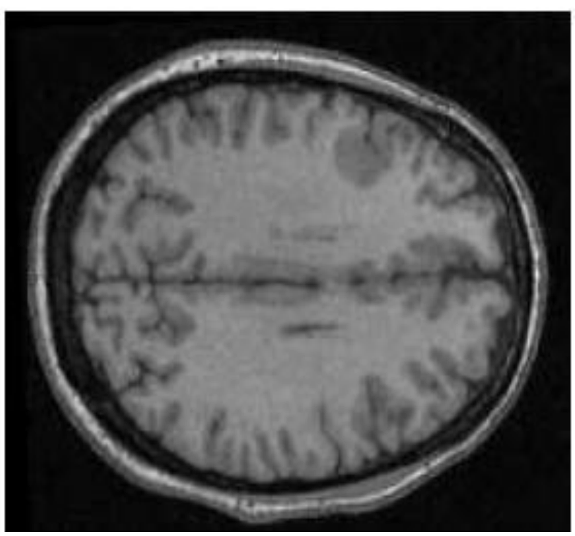


Figure 1.4: A brain MRI (courtesy of Merge Efilm)

1.1.6.4 Tomography

Tomography is the method of showing a single plane, or slice, of an object. There are several forms of tomography-

- Linear Tomography
- Poly Tomography
- Computed Tomography (CAT or CT)

A CT scan, also known as a CAT scan (computed axial tomography scan), is a helical tomography, which traditionally produces a 2D image of the structures in a thin section of the body. It uses x-ray, which is ionizing radiation.

1.1.6.5Radiography

Radiographs, more commonly known as x-rays, are often used to determine the type and extent of a fracture as well as for detecting pathological changes in the lungs. With the use of radio-opaque contrast media, such as barium, they can also be used to visualize the structure of the stomach and intestines - this can help diagnose ulcers or certain types of colon cancer.

1.1.6.6. Fluoroscopy

Fluoroscopy produces real-time images of internal structures of the body in a similar fashion to radiography, but employs a constant input of x rays. Contrast media, such as barium, iodine, and air are used to visualize internal organs as they work. Fluoroscopy is also used in image-guided procedures, where constant feedback during a procedure is required.

CHAPTER 2

Image Segmentation: Techniques

There are two main approaches in image segmentation: edge- and region- based. Edge based segmentation partitions an image based on discontinuities among sub-regions, while region-based segmentation does the same function based on the uniformity of a desired property within a sub-region. In this chapter, we briefly discuss existing image segmentation technologies as background.

2.1Techniques of Image Segmentation

Several general-purpose algorithms and techniques have been developed for image segmentation.

2.1.1 Clustering Methods

2.1.2 Edge Detection Methods

2.1.3 Region Growing Methods

2.1.4 Thresholding

2.1.5 Histogram-Based Methods

2.1.6 Level Set Methods

2.1.7 Graph Partitioning Methods

2.1.8 Model based Segmentation

2.1.9 Multi-scale Segmentation

2.1.10 Neural Networks Segmentation

2.1.1 Clustering Methods:

The K-means algorithm is an iterative technique that is used to partition an image into *K* clusters. The basic algorithm is:

1. Pick *K* cluster centers, either randomly or based on some heuristic
2. Assign each pixel in the image to the cluster that minimizes the variance between the pixel and the cluster center
3. Re-compute the cluster centers by averaging all of the pixels in the cluster
4. Repeat steps 2 and 3 until convergence is attained (e.g. no pixels change clusters)

In this case, variance is the squared or absolute difference between a pixel and a cluster center. The difference is typically based on pixel color, intensity, texture, and location, or a weighted combination of these factors. *K* can be selected manually, randomly, or by a heuristic.

This algorithm is guaranteed to converge, but it may not return the optimal solution. The quality of the solution depends on the initial set of clusters and the value of K

2.1.1.1Advantages of K-means Clustering

- May be able to detect small variations in intensity value
- Combinations of any grouping criteria can be used
- Simple algorithm to understand and implement

2.1.1.2 Disadvantages of K-means Clustering

- Noise could be interpreted as new segments
- Incorporating spatial information makes it less general
- The number of clusters, k, must be specified by the user

2.1.2 Edge-Based Segmentation

Edge detection is a well-developed field on its own within image processing. Region boundaries and edges are closely related, since there is often a sharp adjustment in intensity at the region boundaries. Edge detection techniques have therefore been used to as the base of another segmentation technique. The edges identified by edge detection are often disconnected. To segment an object from an image however, one needs closed region boundaries. Discontinuities are bridged if the distance between the two edges is within some predetermined threshold.

- Edge-based segmentation represents a large group of methods based on information about edges in the image; it is one of the earliest segmentation approaches and still remains very important.

- Edge-based segmentations rely on edges found in an image by edge detecting operators -- these edges mark image locations of discontinuities in gray level, color, texture, etc.

- The final aim is to reach at least a partial segmentation -- that is, to group local edges into an image where only edge chains with a correspondence to existing objects or image parts are present.

- The most common problems of edge-based segmentation, caused by image noise or unsuitable information in an image, are an edge presence in locations where there is no border, and no edge presence where a real border exists.

Edge-based segmentation looks for discontinuities in the intensity of an image. It is more likely edge detection or boundary detection rather than the literal meaning of image segmentation. An edge can be defined as the boundary between two regions with relatively distinct 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. The gradient vector of an image I(x, y), given by

$$\nabla I = \begin{bmatrix} \partial I/\partial x \\ \partial I/\partial y \end{bmatrix} : \Omega \rightarrow R^2 \qquad 2.1$$

and is obtained by the partial derivatives $\partial I/\partial x$ and $\partial I/\partial y$ at every pixel location. The local derivative operation can be done by convolving an image with kernels shown in figure 2.1.

-1
0
1

-1	0	1

Figure 2.1: Examples of gradient kernels along: (a) vertical direction, (b) horizontal direction magnitude of the first derivative

$$|\nabla I| = \sqrt{\frac{\partial^2 I}{\partial x^2} + \frac{\partial^2 I}{\partial y^2}} \quad : \Omega \rightarrow R \qquad 2.2$$

The Laplacian of an image function I(x, y) is the sum of the second-order derivatives, defined as

$$\nabla^2 I = \frac{\partial^2 I}{\partial x^2} + \frac{\partial^2 I}{\partial y^2} \; : \Omega \rightarrow R \qquad 2.4$$

The general use of the Laplacian is in finding the location of edges using its zero-crossings [12]. A critical disadvantage of the gradient operation is that the derivative enhances noise. As a second-order derivative, the Laplacian is even more sensitive to noise.

Sobel operation is performed by convolving an image with kernels shown in figure 2.2. Sobel operators have the advantage of providing both a derivative and a smoothing effect [12, 15]. The smoothing effect is a particularly attractive feature of the Sobel operators compared to the gradient kernels shown in figure 2.1 because the derivative enhances noise.

-1	-2	-1
0	0	0
1	2	1

-1	0	1
-2	0	2
-1	0	1

Figure 2.2: Sobel operators along: (a) vertical direction, (b) horizontal direction

Canny edge detector [16, 5] is based on the extreme of the first derivative of the Gaussian operator applied to an image. The operator first smoothes the image to eliminate noise, and then finds high gradient regions. After non-maximum suppression, the edges are finally determined by two thresholds, i.e. $\tau_{\min}$ and $\tau_{\max}$ as shown in table 2.1.

The Canny edge detector is known as an optimal edge detector because it satisfies the criteria of low error rate, good localization of edge points, and a single response to a single edge pixel [17]

Table 2.1: Path searching in Canny edge detector

• If $\lvert\nabla I(x, y)\rvert > \tau_{max}$, then I(x, y) is an edge pixel.
• If $\tau_{min} < \lvert\nabla I(x, y)\rvert < \tau_{max}$
– If there is a path from (x, y) to neighbor (φ) and $\lvert\nabla I(\varphi)\rvert > \tau_{min}$, then I(x, y) is an edge pixel.
– Otherwise, I(x, y) is a non-edge pixel.
• If $\lvert\nabla I(x, y)\rvert < \tau_{min}$,then I(x, y) is a non-edge pixel.

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

2.1.3 Region-based Segmentation

Region-based segmentation looks for uniformity within a sub-region, based on a desired property, e.g. intensity, color, and texture. Clustering techniques encountered in pattern classification literature have similar objectives and can be applied for image segmentation [18]. Region growing [19] is a technique that merges pixels or small sub-regions into a larger sub region. The simplest implementation of this approach is pixel aggregation [12], which starts with a set of seed points and grows regions from these seeds by appending neighboring pixels if they satisfy the given criteria. The first region growing method was the seeded region growing method. This method takes a set of seeds as input along with the image. The seeds mark each of the objects to be segmented. The regions are iteratively grown by comparing all unallocated neighboring pixels to the regions. The difference between a pixel's intensity value and the region's mean, δ, is used as a measure of similarity. The pixel with the smallest difference measured this way is allocated to the respective region. This process continues until all pixels are allocated to a region.

Seeded region growing requires seeds as additional input. The segmentation results are dependent on the choice of seeds. Noise in the image can cause the seeds to be poorly placed. Unseeded region growing is a modified algorithm that doesn't require explicit seeds. It starts off with a single region A_1 – the pixel chosen here does not significantly influence final segmentation. At each iteration it considers the neighboring pixels in the same way as seeded region growing. It differs from seeded region growing in that if the minimum δ is less than a then a predefined threshold T then it is added to the respective region A_j. If not, then the pixel is considered significantly different from all current regions A_i and a new region A_n is created with this pixel.

2	2	9
2	2	9
2	9	9

2	4	8
3	5	9
4	6	7

Figure 2.3: Pixel aggregation: (a) original image with seeds underlined; (b) segmentation result with τ = 4

Segmentation starts with two initial seeds, and then the regions grow if they satisfy a criterion such as

$$|\mathrm{I}(\mathrm{x},\mathrm{y}) - \mathrm{I}(\mathrm{seed}) < \tau| \qquad 2.4$$

Despite the simple nature of the algorithm, there are fundamental problems in region growing: the selection of initial seeds and suitable properties to grow the regions. Selecting initial seeds can be often based on the nature of applications or images. For example, the ROI is generally brighter than the background in IR images. In this case, choosing bright pixels as initial seeds would be a proper choice.

Additional criteria that utilize properties to grow the regions lead region growing into more sophisticated methods, e.g. region competition. Region competition [20, 21] merges adjacent sub-regions under criteria involving the uniformity of regions or sharpness of boundaries. Strong criteria tend to produce over-segmented results, while weak criteria tend to produce poor segmentation results by over-merging the sub-regions with blurry boundaries. An alternative of region growing is split-and-merge [22], which partitions an image initially into a set of arbitrary, disjointed sub-regions, and then merges and/or split the sub-regions in an attempt to satisfy the segmentation criteria.

Another common approach in region-based segmentation is characterizing statistical uniformity of sub-regions using parametric models, so called statistical estimation. With this approach, two sub-regions are considered to be uniform, and consequently merged, if they can be represented by a single instance of the model, i.e. if they have common parameter values within a threshold. In practice, the parameters of a sub-region cannot be observed directly but can only be inferred from the observed data and the knowledge of the imaging process. In statistical approaches, this inference is often made using Bayes's rule [23] and the conditional PDF p(I(x, y)|θm), which presents the conditional probability that certain data I(x, y) (or statistics derived from the data) will be observed, given that sub-region m has the parameter values of θ_m. In typical statistical region merging algorithms [24], stochastic estimates in the parameter space are obtained for different sub-regions, and merging decisions are based on the similarity of these parameters. A limitation of most estimation-based segmentation methods is that they do not explicitly represent the uncertainty in the estimated parameter values and, therefore, are prone to error when parameter estimates are poor.

Region-based approaches are generally less sensitive to noise, and usually produce more reasonable segmentation results as they rely on global properties rather than local properties, but their implementation complexity and computational cost can be often quite large.

Statistical segmentation methods, both estimation-based and Bayesian-based, have been extended to many active contour models including the proposed models.

The objective of segmentation is to partition an image into regions. Let R represent the entire image region. Segmentation as a process that partitions R into n sub regions, R_1, R_2…R_n. Region growing is a region based segmentation that groups pixels or sub regions into larger regions based on predefined criteria for growth. The basic approach is to start with a set of seed points and from these grow regions by appending to each seed those neighboring pixels that have predefined properties similar to the seed. Selecting a set of one or more starting points often can be based on the nature of the problem. When a priori information is not available, one procedure is to compute at every pixel the same set of properties that ultimately will be used to assign pixels to regions during the growing process. If the result of these computations shows clusters of values, the pixels whose properties place them near the centroid of these clusters can be used as seeds. The selection of similarity criteria depends not only on the problem under consideration, but also on the type of image data available. There are some problems with region based segmentation.

1.) When the images are monochrome, region analysis must be carried out with a set of descriptors based on intensity levels and spatial properties. Descriptors alone can yield misleading results if connectivity information is not used in the region-growing process.

2.) Another problem in region growing is the formulation of a stopping rule. Basically, growing a region should when no more pixels satisfy the criteria for inclusion in that region. Criteria such as intensity values, texture and color, are local in nature and do not take into account the history of region growth. Additional criteria that increase the power of a region-growing algorithm utilize the concept of size, likeness between a candidate pixel and the pixels grown so far and the shape of the region being grown.

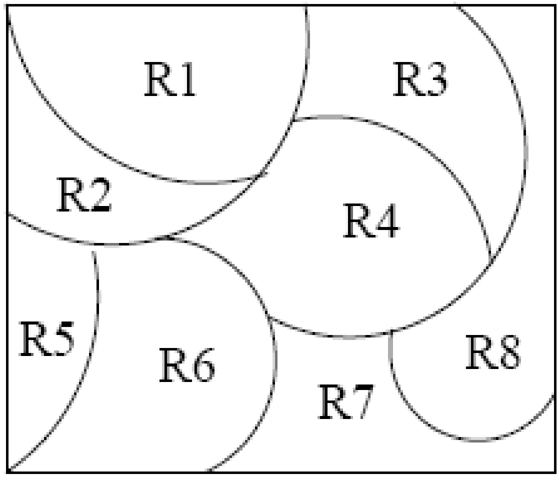
- It is easy to construct regions from their borders, and it is easy to detect borders of existing regions.

- However, segmentations resulting from edge-based methods and region-growing methods are not usually exactly the same, and a combination of results may often be a good idea.

- Region growing techniques are generally better in noisy images, where borders are extremely difficult to detect

- Homogeneity is an important property of regions and is used as the main segmentation criterion in region growing, whose basic idea is to divide an image into zones of maximum homogeneity. The criteria for homogeneity can be based on gray-level, color, texture, shape, model (using semantic information), etc.The simplest homogeneity criterion uses an average gray-level of the region, its color properties, simple texture properties, or an m-dimensional vector of average gray values for multi-spectral images.

- Properties chosen to describe regions influence the form, complexity, and amount of prior information in the specific region-growing segmentation method.
- A complete segmentation of an image R is a finite set of regions shown in fig 2.4



$$\mathbf{R_1, \dots \dots, R_s}$$

$$\mathbf{R} = \bigcup_{\mathbf{i=1}}^{\mathbf{s}} \mathbf{R_i}$$

$$\boldsymbol{R_1 \cap R_j} = \emptyset \qquad 2.5$$

where $i \neq j$ and S is the total number of regions in the image. Further assumptions needed in this section are that regions must satisfy the following conditions:

$H(R_i) = \mathrm{TRUE}$ for i=1,….s

$$H(R_i \cup R_j) = FALSE \qquad for\ i \neq j\ and\ R_i\ is\ adjacent\ to\ R_j \qquad 2.6$$

Resulting regions of the segmented image must be both homogeneous and maximal, where by 'maximal' we mean that the homogeneity criterion would not be true after merging a region with any adjacent region.

2.1.3.1Region Splitting

The basic idea of region splitting is to break the image into a set of disjoint regions, which are coherent within themselves:

•Initially take the image as a whole to be the area of interest.

•Look at the area of interest and decide if all pixels contained in the region satisfy some *similarity constraint.*

•If TRUE then the area of interest corresponds to a region in the image.

•If FALSE split the area of interest (usually into four equal sub-areas) and consider each of the sub-areas as the area of interest in turn.

•This process continues until no further splitting occurs.

2.1.3.2 Region Merging

The result of region merging usually depends on the order in which region are merged. The simplest methods begin merging by starting the segmentation using regions of 2x2, 4x4 or 8x8 pixels. Region descriptions are then based on their statistical gray level properties. A region description is compared with the description of an adjacent region; if the match, they are merged into a larger region and a new region description is computed. Otherwise regions are marked as non-matching.

Merging of adjacent regions continues between all neighbors, including newly formed ones. If a region cannot be merged with any of its neighbors, it is marked `final' and the merging process stops when all image regions are so marked.

Merging heuristics:

- Two adjacent regions are merged if a significant part of their common boundary consists of weak edges

- Two adjacent regions are also merged if a significant part of their common boundary consists of weak edges, but in this case not considering the total length of the region borders.

Of the two given heuristics, the first is more general and the second cannot be used alone because it does not consider the influence of different region sizes.

Region merging process could start by considering

•small segments (2*2,…,8*8) selected a priori from the image

•segments generated by thresholding

•regions generated by a region splitting module

The last case is called as "Split and Merge" method. Region merging methods generally use similar criteria of homogeneity as region splitting methods, and only differ in the direction of their application.

2.1.3.3. SPLIT & MERGE

To illustrate the basic principle of split and merge methods, let us consider an imaginary image.

•Let A denote the whole image shown in *Fig.2.5 (a)* below.

•Not all the pixels in *Fig 2.5(a)* are similar. So the region is split as in *Fig.2.5 (b)*.

•Assume that all pixels within each of the regions A1, A2and A3 are similar, but those in A4are not.

•Therefore A4 is split next, as shown in *Fig.2.5 (c)*.

•Now assume that all pixels within each region are similar with respect to that region, and that after comparing the split regions, regions A43and A44are found to be identical.

•These pair of regions is thus merged together, as in shown in Fig.2.5 (d).

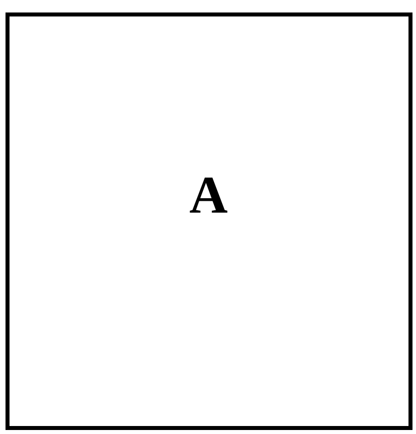


Figure 2.5 (a) Whole Image

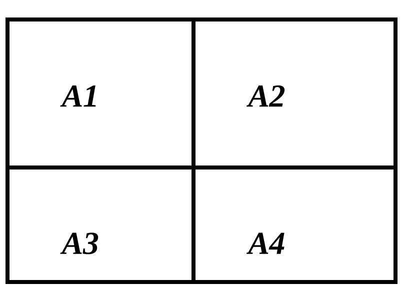


Figure2.5 (b)first Split

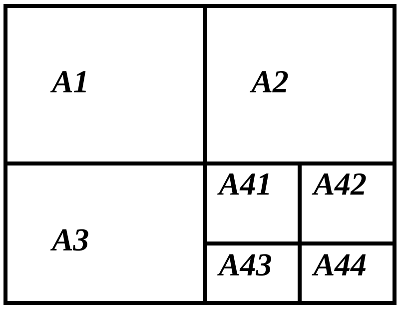


Figure 2.5 (c) Second Split

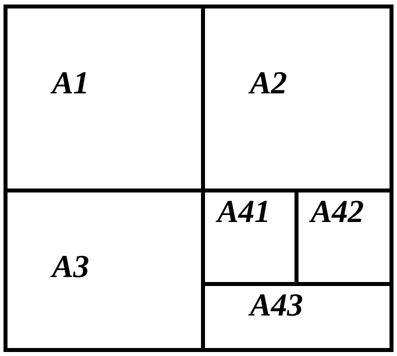


Figure 2.5 (d) Merge

A combination of splitting and merging may result in a method with the advantages of both the approaches. Split-and-merge approaches work using pyramid image representations. Regions are square-shaped and correspond to elements of the appropriate pyramid level. If any region in any pyramid level is not homogeneous (excluding the lowest level), it is split into four sub-regions --these are elements of higher resolution at the level below. If four regions exist at any pyramid level with approximately the same value of homogeneity measure, they are merged into a single region in an upper pyramid level. We can also describe the splitting of the image using a tree structure, using a modified quad tree. Each non-terminal node in the tree has at most four descendants, although it may have less due to merging.

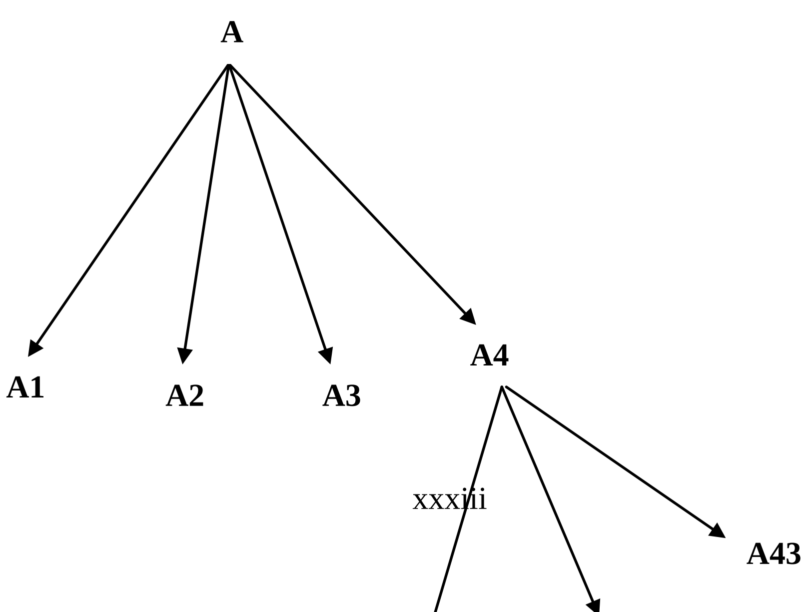
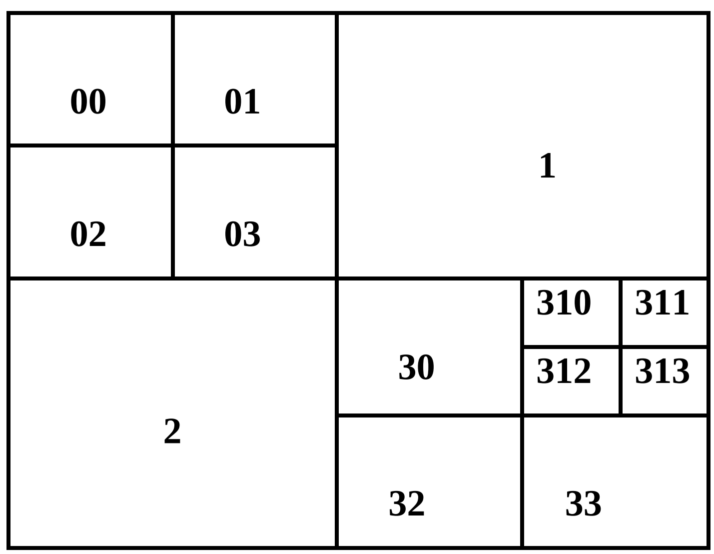


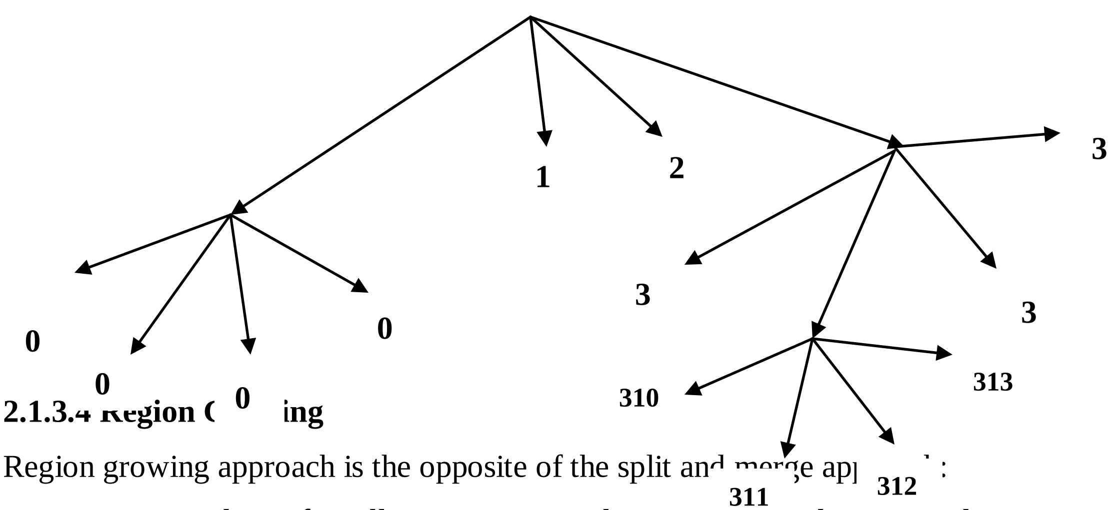
Figure 2.6 : Quad tree

Quadtree decomposition is an operation that subdivides an image into blocks that contain "similar" pixels. Usually the blocks are square, although sometimes they may be rectangular. For the purpose of this demo, pixels in a block are said to be "similar" if the range of pixel values in the block are not greater than some threshold. Quadtree decomposition is used in variety of image analysis and compression applications.

An unpleasant drawback of segmentation quad trees is the square region shape assumption. It is not possible to merge regions which are not part of the same branch of the segmentation tree. Because both split-and-merge processing options are available, the starting segmentation does not have to satisfy any of the homogeneity conditions.

The segmentation process can be understood as the construction of a segmentation quadtree where each leaf node represents a homogeneous region. Splitting and merging corresponds to removing or building parts of the segmentation quadtree.





2.1.3.4 Region Growing

Region growing approach is the opposite of the split and merge approach :

•An initial set of small areas is iteratively merged according to similarity constraints.

•Start by choosing an arbitrary *seed pixel* and compare it with neighboring pixels (as shown in Fig 2.7 (a)and fig 2.7 (b)).

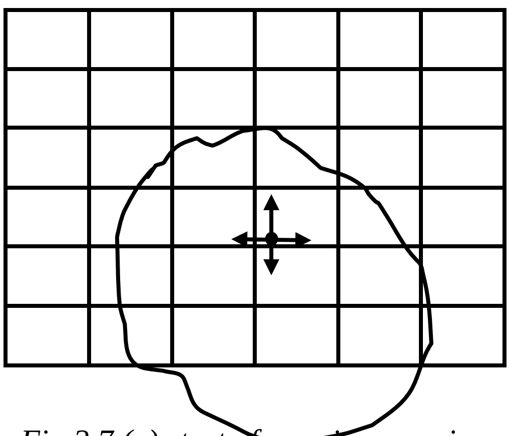
•Region is *grown* from the seed pixel by adding in neighboring pixels that are similar, increasing the size of the region.

•When the growth of one region stops we simply choose another seed pixel which does not yet belong to any region and start again.

•This whole process is continued until all pixels belong to some region.

•A bottom up method.

Region growing methods often give very good segmentations that correspond well to the observed edges.



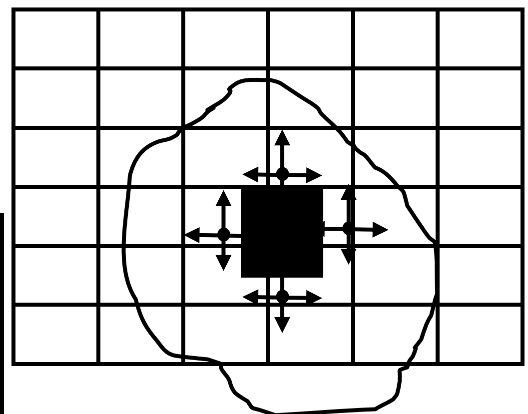


Fig 2.7 (a) start of growing a region   *Figure 2.7 (b)Growing process after few Iteration*

Here *Direction of growth*   *Seed Pixel*   *Grown Pixel*

However starting with a particular seed pixel and letting this region grow completely before trying other seeds biases the segmentation in favour of the regions which are segmented first. This can have several undesirable effects:

•Current region dominates the growth process ambiguities around edges of adjacent regions may not be resolved correctly.

•Different choices of seeds may give different segmentation results.

•Problems can occur if the (arbitrarily chosen) seed point lies on an edge.

To counter the above problems, simultaneous region growing techniques have been developed.

•Similarities of neighboring regions are taken into account in the growing process.

•No single region is allowed to completely dominate the proceedings.

•A number of regions are allowed to grow at the same time.

•Similar regions will gradually coalesce into expanding regions.

Figure 2.8(a)original Image

Figure 2.8(b)image after segmentation

2.1.4 THRESHOLDING:

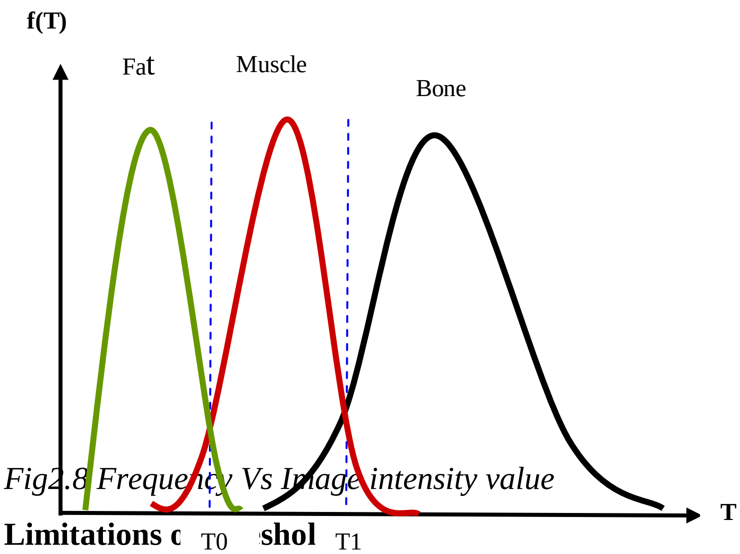
Because of its intuitive properties and simplicity of implementation image thresholding enjoys a central position in applications of image segmentation. One obvious way to extract the objects from the background is to select a threshold T that separates these modes. Then any point (x, y) for which f(x, y) $\geq$ T is called an object point; otherwise, the point is called a background point. In other words, the threshold image g(x, y) is defined as

g(x, y) = 1 if f(x, y) $\geq$ T or

$$g(x, y) = 0 \text{ if } \quad f(x, y) < T. \qquad (2.7)$$

Pixels labeled 1 correspond to objects, whereas pixels labeled 0 correspond to the background. When T is a constant, this approach is called global thresholding and when 'T' is a function of f(x, y), this approach is called local thresholding. Global thresholding methods can fail when the background illumination is uneven.

Thresholding is the simplest way to perform segmentation, and it is used extensively in many image processing applications. The assumption is that different regions in an image will have a distinct frequency distribution and can be discriminated on the basis of the mean and standard deviationof each distribution (see Figure). For example, given the histogram of a two-dimensional medical image I(x,y) , we can define a simple threshold rule to classify bony and fat tissues or a compound threshold rule to classify muscle tissue:



If, I(x,y) > T1 => Bony

If, I(x,y) < T0 => Fat

If, T0 < I(x,y) < T1 => Muscle

Fig2.8 Frequency Vs Image intensity value

Limitations of Thresholding

- The major drawback to threshold-based approaches is that they often lack the sensitivity and specificity needed for accurate classification.

- The problem gets severe in case of multi-modal histograms with no sharp or well-defined boundaries.

- It is often difficult to define functional and statistical measures only on the basis of gray level value (histogram).

2.1.5 Histogram-Based Methods:

Histogram-based methods are very efficient when compared to other image segmentation methods because they typically require only one pass through the pixels. In this technique, a histogram is computed from all of the pixels in the image, and the peaks and valleys in the histogram are used to locate the clusters in the image. Color or intensity can be used as the measure.

A refinement of this technique is to recursively apply the histogram-seeking method to clusters in the image in order to divide them into smaller clusters. This is repeated with smaller and smaller clusters until no more clusters are formed.

One disadvantage of the histogram-seeking method is that it may be difficult to identify significant peaks and valleys in the image. This may affect the quality and usefulness of the final solution.

2.1.6 Level Set Methods

Curve propagation is a popular technique in image analysis for object extraction, object tracking, stereo reconstruction, etc. The central idea behind such an approach is to evolve a curve towards the lowest potential of a cost function, where its definition reflects the task to be addressed and imposes certain smoothness constraints. Langragian techniques are based on parameter zing the contour according to some sampling strategy and then evolve each element according to image and internal terms. While such a technique can be very efficient, it suffers from various limitations like deciding on the sampling strategy, estimating the internal geometric properties of the curve, changing its topology, addressing problems in higher dimensions, etc.

The central idea is represent the evolving contour using a signed function, where its zero level corresponds to the actual contour. Then, according to the motion equation of the contour, one can easily derive a similar flow for the implicit surface that when applied to the zero-level will reflect the propagation of the contour. The level set method encodes numerous advantages: it is implicit, parameter free, provides a direct way to estimate the geometric properties of the evolving structure, can change the topology and is intrinsic.

2.1.7 Graph Partitioning Methods

In this method, the image being segmented is modeled as a weighted undirected graph. Each pixel is a node in the graph, and an edge is formed between every pair of pixels. The weight of an edge is a measure of the similarity between the pixels. The image is partitioned into disjoint sets (segments) by removing the edges connecting the segments. The optimal partitioning of the graph is the one that minimizes the weights of the edges that were removed (the “cut”).

2.1.8 Model based Segmentation

The central assumption of such an approach is that structures of interest/organs have a repetitive form of geometry. Therefore, one can seek for a probabilistic model towards explaining the variation of the shape of the organ and then when segmenting an image impose constraints using this model as prior. Such a task involves

(i) registration of the training examples to a common pose,

(ii) probabilistic representation of the variation of the registered samples, and

(iii)statistical inference between the model and the image.

2.1.9 Multi-scale Segmentation

Image segmentations are computed at multiple scales in scale-space and sometimes propagated from coarse to fine scales; see scale-space segmentation. Segmentation criteria can be arbitrarily complex and may take into account global as well as local criteria. A common requirement is that each region must be connected in some sense.

2.1.10 Neural Networks Segmentation

That kind of segmentation relays on processing small areas of an image by the neural network or a set of neural networks. After such processing the decision-taking mechanism marks the areas of an image accordingly to the category recognized by the neural network.

2.2 OTHERS METHOD

The watershed algorithm [47, 48] is a morphology-based segmentation method [49, 50, 51]. It is based on the assumption that any gray-tone image can be considered as a topographic surface [52]. If we flood this surface from its minima preventing the merge of the waters coming from different sources, the surface is eventually separated as two different sets: the catchment basins and the watershed lines. If we apply this transformation to the magnitude of image gradient $|\partial I|$, the catchment basins correspond to the uniform sub-regions in the image and the watershed lines correspond to the edges.

Texture is another feature that we can use to determine the segmentation criteria. Images can be considered as either a collection of pixels in the spatial domain or the sum of sinusoids of infinite extent in the spatial-frequency domain. In a joint space/spatial-frequency representations for images, frequency is considered as a local phenomenon that can vary with position throughout the image. The human visual system is performing a form of local spatial-frequency analysis on the retinal image, and the analysis is done by a bank of band pass filters.

The same approach can be used to partition textured images in image analysis. Perceptually significant texture differences presumably correspond to differences in the local spatial frequency content using the space/spatial-frequency paradigm. Texture segmentation is done by two steps: decomposing an image into a joint space/spatial-frequency representation with a bank of band pass filters and using this information to locate the regions of similar local spatial frequency content.

CHAPTER 3

Literature Study

MICHAEL KASS, ANDREW WITKIN, AND DEMETRI TERZOPOULOS [1], "SNAKES: ACITVE CONTOUR MODELS" (1988):

Active contour model was first proposed by Kass, Witkin, and Terzopoulos. They used the concept of Snakes which provide a unified account of number of visual problems for the detection of edges, lines, subjective contours, motion tracking and stereo matching. Snake is an energy-minimizing spline guide by external constraint forces and influenced by image forces that pull it toward features such as lines and edges. In this technique initially, the user places a snake near an image structure of some sort. The constraint forces that act on a snake then push the user defined snake towards features of interest. The energy of a snake depends on where the snake is placed and how its shape changes locally in space. The idea is to lock the snake according to the features of an image by minimizing an integral which represents the snake's total energy.

The basic equation on which this active contour model depends is given below

$$E^{*}_{snake} = \int E_{int}(V(S)) + E_{image}(V(S)) + E_{con}(V(S))$$

E_{int} – Internal Constraints (internal energy due to bending. Serves to impose piecewise smoothness constraint.)

E_{image}– Image Constraints (image forces pushing the snake toward image.)

E_{con} – External Constraints (external constraints are responsible for putting the snake near the desired local minimum.)

AMIR A. AMINI, SAEID TEHRANI, TERRY E. WEYMOUTH [2], "USING DYNAMIC PROGRAMMING FOR MINIMIZING THE ENERGY OF ACTIVE CONTOUR IN THE PRESENCE OF HARD CONSTRAINTS" (1988):

There are number of problem in model of active contour proposed by Kass. In a given moderate noisy force field, snake clusters into a dense structure at certain places and even some points move on top of one another. This is because there is no constraint for the interdistance of the points on the contour. To remove such problems a new algorithm for minimizing the energy of active contour in the presence of hard constraints has been proposed. In this technique the local geometry of the active contour models are constrained effectively by using hard constraints.

MARIJIN E. BRUMMER AND RUSSELL M. MERSEREAU [3], "AUTOMATIC DETECTION OF BRAIN CONTOURS IN MRI DATA SETS" (1993):

A software procedure is presented for fully automated detection of brain contours from single-echo 3-D MRI data. The procedure detects structures in a head data volume in a hierarchical fashion. Automatic detection starts with a histogram based threshold step, whenever necessary proceeded by an image intensity correction procedure. This step is followed by a morphological procedure which refines the binary threshold mask images. A final step of the procedure performs overlap tests on candidate brain regions of interest in neighboring slice images to propagate coherent 2-D brain masks through the third dimension.

C.DAVATZIKOS AND J L PRINCE [4], "ADAPTIVE ACTIVE CONTOUR ALGORITHMS FOR EXTRACING AND MAPPING THICK" (1993):

Thick curves arise naturally in certain applications such as magnetic resonance imaging of the brain and can also arise in computer vision problems through morphological dilation of boundaries of objects. This technique describes two new adaptive active contour algorithms for the extraction and mapping of the skeleton of a thick curve. Both algorithms modify the regularization constant KO in attempt to maintain convexity of the energy function while simultaneously improving the fidelity of the result. The first algorithm changes KO over time while the second adapts KO spatially. Both algorithms

demonstrate an improved performance compared to a fixed-parameter active contour algorithm. The time adaptive algorithm improves the performance of the active contour model at the expense of increased computational requirements. The spatially adaptive algorithm is a good compromise between the non-adaptive and the time-adaptive algorithms. Although the way that the regularization parameter *KO* is varied in these two formulations is somewhat heuristic, the results are promising.

AMIT CHAKRABORTY, LAWRENCE H.STAIB AND JAMES S. DUNCAN [5], "AN INTEGRATED APPROACH TO BOUNDARY FINDING IN MEDICAL IMAGES" (1994):

A key issue in biomedical image analysis is to accurately segment and quantify structures. Gradient based boundary finding and region based segmentation, the two conventional methods of image segmentation often suffer from a variety of limitations. The method proposed in this paper endeavors to integrate the two approaches in an effort to form a unified approach that is robust to noise and poor initialization. This technique uses Green's theorem to derive the boundary of a homogeneous region-classified area in the image and integrates this with a grey-level gradient- based boundary finder.

STEVEN LOBREGT AND MAX A. VIERGEVER [6], "A DISCRETE DYNAMIC CONTOUR MODEL" (1995):

A discrete contour model has been developed that combine's conceptual and computational simplicity with variable resolution and adjustable behavior. It is based on a simple structure and its deformation is controlled by basic physical rules. It incorporates elegant and efficient solutions to the shrinking and clustering problems from which active model approaches suffer. The method is easy to use because of the small number of parameters that control the deformation process. The discrete contour model has potential in the area of contour definition for a large variety of clinical applications. As compared with conventional contour extraction methods, the strong argument in favor of the method presented here is that it handles and processes a contour as one topologically consistent object, yet the deformation process which controls the shape of the model is based on local operations on the vertices of the model. As compared with manual contour definition methods, the advantage of the present approach is the minimum of user interaction which is required, and the reproducibility of the result.

A sensitive point of the method is the dependency of the final result on the image features that are used to drive the contour deformation. The method relies on the assumption that some process exists for the extraction of adequate image features in a particular application context. Extraction of useful image features is therefore an important subject for further investigation. Its importance for the success of the contour model, that the model should not be overestimated, because simple image features like gray value and gray value gradient were found to be quite inappropriate in a variety of situations. Future research will go in the direction of selection of appropriate image features for specific applications, adaptivity of the model to local image context, and extension of the method to 3-D images.

VICENT CASELLES [7], "GEOMETRIC MODELS FOR ACTIVE CONTOURS"

(1995):

This technique is based on active contours evolving in time according to intrinsic geometric measures of the image. The evolving contours naturally split and merge, allowing the simultaneous detection of several objects and both interior and exterior boundaries. The proposed approach is based on the relation between active contours and the computation of minimal distance curves or minimal surfaces in a Riemannian space that's metric is derived from the image. Previous models of geometric active contours are improved, allowing stable boundary detection when their gradients suffer from large variations, including gaps.

CHRIS A. DAVATZIKOS AND J.L.PRINCE [8], "AN ACTIVE CONTOUR MODEL FOR MAPPING THE CORTEX" (1995):

A new active contour model for finding and mapping the outer cortex in brain images is developed. A cross-section of the brain cortex is modeled as a ribbon, and a constant speed mapping of its spine is sought. A variation formulation, an associated force balance condition, and a numerical approach are proposed to achieve this goal. The primary difference between this formulation and that of snakes is in the specification of the external force acting on the active contour. A study of the uniqueness and fidelity of the solutions is made through convexity and frequency domain analyses, and a criterion for selection of the regularization coefficient is developed.

MUSTAFA KARAMAN, M. ALPER KUTAY AND GOZDE BOZDAGI [9], "AN ADAPTIVE SPECKLE SUPPRESSION FILTER FOR MEDICAL ULTRASONIC IMAGING" (1995):

An adaptive smoothing technique for speckle suppression in medical B-scan ultrasonic imaging is presented in this paper. The technique is based on filtering with appropriately shaped and sized local kernels. For each image pixel, a filtering kernel, which fits to the local homogeneous region containing the processed pixel, is obtained through a local statistics based region growing technique. Performance of the proposed filter has been tested on the phantom and tissue images. The filter effectively reduces the speckle while preserving the resolvable details.

V.L.NARAYANA MURTHY AND A.MAKUR [10], "DESIGN OF SOME 2-D FILTER THROUGH THE TRANSFORMATION TECHNIQUE" (1996):

The transformation technique is a powerful tool for designing 2-D FIR filters. However, it is not useful for the design of specially shaped filters with pass band, stop band regions not centered around the origin. The authors extend this technique to design two types of filters. A notch filter has a stop band centered about a small region in the 2-D frequency plane and a directional filter has a pass band extending fully along a straight line passing through the origin.

CHRISTOS DAVATZIKOS AND J L PRINCE [11], "CONVEXITY ANALYSIS OF ACTIVE CONTOUR PROBLEMS" (1996):

This technique reveals important characteristics of the convexity of active contour problem, and suggests that external potentials involving center of mass computations may be better behaved than the usual potentials based on image gradients. Most importantly it provides an explanation for the poor convergence behavior at concave boundaries and suggests an alternate algorithm for approaching these types of boundaries. This paper studied a general active contour formulation (VP), and derived conditions for the convexity of its energy function. The derived condition quantitatively expressed the relation between the convexity of the energy function and the selection of the regularization parameters. The results were then applied to four special cases of VP designed to find parameterizations of boundaries, which are modeled as ribbons. The first main conclusion drawn from this analysis is that in order for the energy function of VP to be convex, *KO* and *K1* should be selected from a specific domain in the *Ko-Kl* plane. This region is determined by the potential *P* of the active contour formulation. Specifically, it was shown that, under certain assumptions, there exists a connected domain where the energy function is convex for any pair of positive regularization constants, for all four potentials for boundary parameterization. This implies that an active contour algorithm can avoid local minima by searching for a solution within the domain of convexity. The development of such domain adaptive active contour algorithms is a direction of further research originating from the convexity analysis presented in this paper.

YING LUN FOK, JOSEPH C.K CHAN AND ROLAND T.CHIN [12] "AUTOMATED ANALYSIS OF NERVE CELL IMAGES USING CONTOUR" (1996):

The number of axons in a nerve is typically in the order of tens of thousands and a study of a particular aspect of the nerve often involves many nerves. A method that automates the analysis of axons from electron micrographic images is presented. It begins with a rough identification of all the axon centers by use of an elliptical Hough transform procedure. Boundaries of each axon are then extracted based on *active contour model,* or *snakes.* However, false axon detection is still common due to poor image quality and the presence of other irrelevant cell features, thus a conflict resolution scheme is developed to eliminate false axons to further improve the performance of detection. The developed method has been tested on a number of nerve images and its results are presented.

ANTHONY YEZZI, SATYANAD KICHENASSAMY, ARUN KUMAR, PETER OLVER AND ALLEN TANNENBAUM [13], "A GEOMETRIC SNAKE MODEL FOR SEGMENTATION OF MEDICAL IMAGERY" (1997):

The method is based on defining feature-based metrics on a given image which in turn leads to a novel snake paradigm in which the feature of interest may be considered to lie at the bottom of a potential well. Thus, the snake is attracted very quickly and efficiently to the desired feature. Since the geometric curve evolution equations can in fact treat merging and splitting of contours, the model gives the user the capability of automatically handling topological changes within the gradient flow energy framework. Moreover, the model has an important advantage over the geometric snakes as well.

VICENT CASELLES, RON KIMMEL AND GUILLERMO SAPIRO [14], "GEODESIC ACTIVE CONTOURS" (1997):

The technique is based on active contours evolving in time according to intrinsic geometric measures of the image. The evolving contours naturally split and merge, allowing the simultaneous detection of several objects, both interior and exterior boundaries. The proposed approach is based on the relation between active contours and the computation of geodesics or minimal distance curves. The minimal distance curve lays in a Riemannian space whose metric is defined by the image content. This geodesic approach for object segmentation allows to connect classical "snakes" based on energy minimization and geometric active contours based on the theory of curve evolution. This approach also gives possible connections between classical energy based deformable contours and geometric curve evolution ones. The geodesic formulation introduced a new term to the curve evolution models that further attract the deforming curve to the boundary, improving the detection of boundaries with large differences in their gradient.

STEVE R. GUNN AND MARK S. NIXON [15], "A ROBUST SNAKE IMPLEMENTATION; A DUAL ACTIVE CONTOUR", (1997):

A conventional active contour formulation suffers difficulty in appropriate choice of an initial contour and values of parameters. Recent approaches have aimed to resolve these problems but have to compromise on other performance aspects. To relieve the problem in initialization, a dual active contour is used, which is combined with a local shape model to improve the parameterization. One contour expands from inside the target feature, the other contracts from the outside. The two contours are interlinked to provide a balanced technique with an ability to reject “weak local energy minima. A comprehensive dual contour technique that overcomes the primary problems of sensitivity to initialization and parameters associated with the original techniques has been developed. The original technique used the internal forces to provide a contraction of the contour, to move it towards features. This increased the sensitivity to the parameters and therefore this removed the contraction force from the internal constraints. The contraction force is replaced with a new adaptive driving force which allows the contour to find minima, and to escape from them if a better solution has been found by the other contour. Furthermore if shape information and orientation are available, the technique is able to exploit this by integration within the internal energy function..

C.XU AND J.L.PRINCE [16], “SNAKES, SHAPES, AND GRADIENT VECTOR FLOW” (1998):

Problems associated with initialization and poor convergence to boundary concavities, however, has limited utility of traditional snake. This paper presents a new external force for active contours and deformable surfaces, which we called the gradient vector flow (GVF) field. It is shown that it allows for flexible initialization of the snake or deformable surface and encourages convergence to boundary concavities, largely solving both problems. This external force, which we call gradient vector flow (GVF), is computed as a diffusion of the gradient vectors of a gray-level or binary edge map derived from the image.

M. STELLA ATKINS AND BLAIR T MACKIEWICH [17], “FULLY AUTOMATIC SEGMENTATION OF THE BRAIN IN MRI” (1998):

The method proposed in this paper uses an integrated approach which employs image processing techniques based on anisotropic filters and “snakes” contouring techniques. The algorithm consists of three incremental steps. The first step uses histogram analysis to localize the head, providing a region which must completely surround the brain. The second step uses nonlinear anisotropic diffusion and automatic thresholding to create a mask that isolates the brain within the detected head region. Using this mask as a seed, the final step employs an active contour model algorithm to detect the intracranial boundary.

HAIYING TANG AND TIANGE ZHUANG [18], "AN IMPROVED ADAPTIVE B-SPLINE ACTIVE CONTOUR MODEL" (1998):

This paper presents an adaptive B-spline active contour algorithm based on the active contour model, which makes the active contour approach the real image edge as close as possible. Combining the principles of the optimal edge detection filter, the active B-Spline contour model improves the energy function, which speeds up the search procedure of the edge in an image and widens the automatic search scope. In Optimal edge detector the convergence speed is much faster and the search scope is much wider.

B.SOLAIMAN, R.DEBON, F.PIPELIER, J.M CAUVIN AND C.ROUX [19], "INFORMATION FUSION: APPLICATION TO DATA AND MODEL FUSION FOR ULTRASOUND IMAGE SEGMENTATION" (1999):

This technique detects the esophagus inner wall from ultrasound medical images. The system architecture including both model and data fusion. The data fusion is accomplished using fuzzy modeling, which can be seen as a monosensor /multiple sources data fusion system. The model fusion is performed using a full-adapted snake theory, which projects the fuzzy decision into the binary decision space. This approach constitutes a robust solution to the problem of esophagus inner wall detection even in the difficult case of tumoral regions study. Sometimes inner wall position differs from one or two pixels which can be noticed near harmonics areas, but the method is very successful in nonpathologic cases. The shape of the inner wall is globally respected. These encouraging results are explained by a complete adaptation of models (fusion and dynamic contours) to the particular case of convex and closed contour defined by wall esophagus. Finally, even if the proposed algorithm is iterative, this method is not computational time expensive and is noise independent.

RICHARD N. CZERWINSKI, DOUGLAS L. JONES AND WILLIAM D. O'BRIEN [20] "DETECTION OF LINES AND BOUNDARIES IN SPECKLE IMAGES-APPLICATION TO MEDICAL ULTRASOUND" (1999):

This paper describes an approach to boundary detection in ultrasound speckle based on an image enhancement technique. This paper has discussed the use of the Sticks algorithm to enhance images for boundary detection. The technique operates by applying a set of templates as a filter bank, and retaining the largest filter output at each point as a test statistic. It has been shown that by modifying the length and thickness of the templates, the technique can be made more sensitive to thicker lines, or achieve a different trade off between speckle suppression and the ability to follow tightly curving boundaries.

CHUNG-HUI AND AHMED H. TEWFIK [21] "MULTISCALE SIGMA FILTER AND ACTIVE CONTOUR FOR IMAGE SEGMENTATION" (1999):

Image segmentation is essential for image recognition. To achieve image segmentation, it is often desirable to process the image into piecewise smooth regions while preserving or even enhancing important edges. The proposed multistage active contour method can be summarized as follows:

1. Apply the active contour method at the coarsest level to capture the boundary of an object.
2. Generate a second outer contour that encompasses the object and move it inwards.
3. Find the connected shortest path lying between these two contours.
4. Interpolate the level set to the next higher level and construct inner and outer contours.
5. Move these two contours towards each other.
6. Estimate the best-connected path with the same refinement procedure.

JOSE SILVESTRE SILVAI, AUGUSTO SILVA AND BEATRIZ SOUSA SANTOS [22] "A FAST APPROACH TO LUNG SEGMENTATION IN XRAY CT IMAGES" (2000):

This paper describes a method for the segmentation of pulmonary regions on thoracic cross sectional images obtained by X-ray computer tomography. Relying on priori information about the general location and morphology of the lungs, the method is based on the interpretation of the histogram, mapping each peak to a group of anatomical structures. Morphologic filtering is applied to bypass misleading effects of pulmonary blood vessels.

CHAO HAN, THOMAS S HATSUKAMI, JENQ NENG HWANG AND CHUN YUAN [23] "A FAST MINIMAL PATH ACTIVE CONTOUR MODEL" (2001):

A new minimal path active contour model for boundary extraction is presented. Implementing the new approach requires four steps

1) Users place some initial end points on or near the desired boundary through an interactive interface.

2) Potential searching window is defined between two end points.

3) Graph search method based on conic curves is used to search the boundary;

4) “Wriggling” procedure is used to calibrate the contour and reduce sensitivity of the search results.

OLIVIER GERMAIN AND PHILIPPE REFREGIER [24] “EDGE LOCATION IN SAR IMAGES: PERFORMANCE OF THE LIKELIHOOD RATIO FILTER AND ACCURACY” (2001):

The likelihood ratio edge detector is an efficient filter for the segmentation of synthetic aperture radar (SAR) images. This filter provides biased location of the edge, when the window does not have the same orientation as the edge. A phenomenological model is proposed to characterize this bias and introduction of an efficient technique to refine edge location is made. The combination of these two methods permits to achieve accurate and regularized edge location.

SAMUEL D. FENSTER AND JOHN R KENDER [25] “SECTORED SNAKES: EVALUATING LEARNED ENERGY SEGMENTATION” (2001):

This paper describe how to teach deformable models to maximize image segmentation correctness based on user-specified criteria, and present a method for evaluating which criteria work best. A traditional deformable model (snake in 2D) fails to find an object's boundary when the strongest nearby image edges are not the ones sought. But models can be trained to respond to other image features instead, by learning their probability distributions. The implementer must then decide on which of many image qualities to teach the model.

TONY F.CHAN AND LUMINITA A. VESE [26] “ACTIVE CONTOURS WITHOUT EDGES” (2001):

In this paper, a new model for active contours to detect objects in a given image, based on techniques of curve evolution is proposed. This model can detect objects whose boundaries are not necessarily defined by gradient. It minimizes the energy which can be seen as a particular case of the minimal partition problem. In the level set formulation, the problem becomes a “mean-curvature flow”-like evolving the active contour, which will stop on the desired boundary. However, the stopping term does not depend on the gradient of the image, as in the classical active contour models, but instead related to a particular segmentation of the image. The model is not based on an edge-function to stop the evolving curve on the desired boundary. Also, there is no need to smooth the initial image, even if it is very noisy and in this way, the locations of boundaries are very well detected and preserved. By the model, objects whose boundaries are not necessarily defined by gradient or with very smooth boundaries can be detected, for which the classical active contour models are not applicable.

R.KIMMEL, A.M. BRUCKSTEIN [27] "ON EDGE DETECTION, EDGE INTEGRATION AND GEOMETRIC ACTIVE CONTOURS" (2002):

This paper explains the robustness of the Haralick operator compared to the Marr-Hildreth edge detector. Most importantly, it enables to design new and better edge detectors and active contours for images. It shows the way to use similar variational principles to design new edge detectors in which homogeneity can be defined differently. Specifically, it is shown how to use the Haralick-like term as part of a geometric active contour model that improves the performances of the classical geodesic active contour in cases where the homogeneity, defined by the variational principle is significant. The analysis also shows the direct link between edge detection and edge integration processes that incorporate uniformity as part of their measure.

NILANJAN RAY AND SCOTT T. ACTON [28] "ACTIVE CONTOURS FOR CELL TRACKING" (2002):

This paper introduces an active contour or snake based method for tracking cells within a video sequence. Specifically, cell tracking techniques is applied to rolling leukocytes observed in vivo (in living animal) from video microscopy. The principal contribution of this work lies in introducing the shape and size constraint as a geometric primitive in the parametric snake energy model. The energy functional is then minimized through the basic principles of the calculus of variations to obtain the Euler equations used in contour updating. A partial differential equation (PDE) based generalized gradient vector flow (GVF) that accommodates for contrast changes and weak cell edges. Whereas previous GVF models are sensitive to initial contour placement, the modified GVF construction with Dirichlet type boundary condition (BC) allows a snake tracker to be robust for a wide range of initial positions. Another contribution in this work is to incorporate an energy term in the snake model that eliminates the need for explicitly resembling the snake contour intermittently as performed in traditional snake evolution.

JADWIGA ROGOWSKAL AND MARK E BREZINSKI [29] "IMAGE PROCESSING TECHNIQUES FOR NOISE REMOVAL, ENHANCEMENT AND SEGMENTATION OF CARTILAGE OCT IMAGES" (2002):

Detection of the bone cartilage interface is critical for the assessment of cartilage width. At present, the quantitative evaluations of cartilage thickness are being done using manual tracing of cartilage–bone borders. Since data is being obtained near video rate with OCT, automated identification of the bone–cartilage interface is critical. In order to automate the process of boundary detection on OCT images, there is a need for developing new image processing techniques. In this paper the image processing techniques for speckle removal, image enhancement and segmentation of cartilage OCT images has been described. In particular, this paper focuses on rabbit cartilage since this is an important animal model for testing both condor protective agents and cartilage repair techniques. In this study, a variety of techniques were examined. Ultimately, by combining an adaptive filtering technique with edge detection (vertical gradient, Sobel edge detection), cartilage edges can be detected. Once the cartilage edges are outlined, the cartilage thickness can be measured.

FAN SHAO, KECK VOON LING, WAN SINGNG, RUO YUN WU [30] "PROSTRATE BOUNDARY DETECTION FROM ULTRASOUND IMAGES" (2003):

Because of the poor quality of ultrasonographic images, prostate boundary detection still remains a challenging task. Currently, this task is performed manually, which is arduous and heavily user dependent. To improve the efficiency by automating the boundary detection process, numerous methods have been proposed. A review of these methods, aiming to find a good solution that could efficiently detect the prostate boundary ultrasound images has been presented. It is unlikely that automatic prostate boundary detection methods will ever replace physicians, but they will likely become crucial elements in prostate disease diagnosis and treatment, particularly in computer-assisted surgery.

LIJUN YIN, SANDEEP DESHPANDE, JA KWEI CHANG [31] "AUTOMATIC LESION/TUMOR DETECTION USING INTELLIGENT MESH-BASED ACTIVE CONTOUR" (2003):

Automatic detection of the lesion/tumor region is always of interest in medical imaging system. The issue in this paper is to improve the accuracy and robustness as compared to the conventional methods. Active contour has been commonly used for the detection of irregular shape of region, however, it suffers the problem of the false attraction given the noisy image, and requires the correct estimation of the initial location of the object to be detected.

SUBHASH KULKARNI, VALLABH KUMAR, B.N.CHATTERJI [32] "EDGELESS ACTIVE CONTOURING FOR VECTOR VALUED NATURAL IMAGE SEGMENTATION" (2003).

This paper present an efficient geometric active contouring method based on level set approach for extracting objects from natural images described in vector valued form. Natural images are characterized by absence of global minima for mean squared error and energy minimization formulation based on the principles of calculus of variations that helps in effective segmentation based on boundary information. The approach adopted is to treat this segmentation as minimum partition, approximation problem, using additional regularization terms. The constraints for stopping the evolving curve are derived by coupling information from each of the vectors of the vector described image. The coupling effect from each vector increases the segmentation accuracy.

RAQUEL VALDES CRISTERNA, VERONICA MEDINA BANUELOS, YANEZ SUAREZ [33] "COUPLING OF RADIAL-BASIS NETWORK AND ACTIVE CONTOUR MODEL FOR MULTISPECTAL BRAIN MRI SEGMENTATION" (2004):

Magnetic resonance (MR) has been accepted as the reference image study in the clinical environment. The development of new sequences has allowed obtaining diverse images with high clinical importance and whose interpretation requires their joint analysis (multispectral MRI). Recent approaches to segment MRI point toward the definition of hybrid models, where the advantages of region and contour-based methods can be exploited to look for the integration or fusion of information, thus enhancing the performance of the individual approaches. Following this perspective, a hybrid model for multispectral brain MRI segmentation is presented. The model couples a segmenter, based on a radial basis network (RBFNNcc), and an active contour model, based on a cubic spline active contour (CSAC) interpolation. The RBFNNcc stage providing a good initial contour to the CSAC. Multispectral information as well as a restriction term are included into the CSAC energy equation. The latter depends on the MAP probability estimates and limits the CSAC solution space. In order to refine the restriction term and to adjust to new image characteristics, the contour obtained after each iteration of the CSAC is fed back to the RBFNNcc to improve its parameters.

FOUED DERRAZ, MOHAMED BELADGHAM AND MOHAMED KHELIF [34] "APPLICATION OF ACTIVE CONTOUR MODELS IN MEDICAL IMAGE SEGMENTATION" (2004):

The main conclusion from this work is that there is no ideal segmentation method. Both parametric and geometric active contours are driven by forces extracted from the image itself, what makes them extremely dependent on the image quality, that is, lowly noised, fair definition of the structures' edges and absence of local minima. Even if one is able to overcome these problems, there are still further difficulties, like the initialization problem for example, which has a strong impact on the correct contour's convergence. This kind of problem may cause the procedure to be repeated until the result obtained is good enough for the user. Finally, it is important to observe that an efficient, precise medical image segmentation system should necessarily add to the model some level of intrinsic knowledge about the problem. Variables like the kind, shape and relative location of the common structures or pathology, and their size compared to some reference system such as an anatomy atlas would improve enormously the model's robustness and autonomy.

WANGMENG ZUO, KUANQUAN WANG, DAVID ZHANG, AND HONGZHI ZHANG [35] "COMBINATION OF POLAR EDGE DETECTION AND ACTIVE CONTOUR MODEL FOR AUTOMATED TONGUE SEGMENTATION" (2004):

Automated tongue segmentation is difficult due to the complexity of pathological tongue, variance of tongue shape and interference of the lips. This paper presents a novel method for automated tongue segmentation by combining polar edge detector and active contour model. First a novel polar edge detector is proposed to effectively extract the edge of the tongue body. Then a method to filter out the edge that is useless for tongue segmentation is introduced. A local adaptive edge bi-thresholding technique is also proposed. Finally an initialization and active contour model are proposed to segment the tongue body from the image.

SONG GAO AND TIEN D BUI [37] "IMAGE SEGMENTATION AND SELECTIVE SMOOTHING BY USING MUMFORD-SHAH MODEL" (2005):

In this paper, a new hierarchical method has been developed which has many advantages compared to the Chan and Vese multiphase active contour models. First, unlike previous works, the curve evolution partial differential equations (PDEs) for different level-set functions are decoupled. Each curve evolution PDE is the equation of motion of just one level-set function, and different level-set equations of motion are solved in a hierarchy. This decoupling of the motion equations of the level-set functions speeds up the segmentation process significantly. Secondly because of the coupling of the curve evolution equations associated with different level-set functions, the initialization of the level sets in Chan and Vese's method is difficult to handle. In fact, different initial conditions may produce completely different results. The hierarchical method proposed in this paper can avoid the problem due to the choice of initial conditions. Third, in this paper, the diffusion equation for denoising has been used. This method, therefore, can deal with very noisy images.

WANG WENVUAN [38] "AN ACTIVE CONTOUR MODEL FOR SELECTIVE SEGMENTATION" (2005):

In this paper, a new active contour model for image selective segmentation has been developed. The model adopts cascade anisotropic diffusion preprocessing and a selective term in level set function. Cascade anisotropic diffusion filtering is powerful and flexible to enhance image for various segmentation tasks. The selective term in level set function can evolve a single curve to capture a selective segmentation region which is interested in. Although some models utilized the color or intensity information within the contour, they did not provide an explicit model for these priors. Another drawback of above models is the algorithm efficiency. To overcome these drawbacks image features like color and intensity has been used.

BARIS SUMENGEN AND B.S. MANJUNATH [40] "GRAPH PARTITIONING ACTIVE CONTOURS (GPAC) FOR IMAGE SEGMENTATION" (2006):

In this paper a new curve evolution framework, the graph partitioning active contours (GPAC) is introduced. Using global features, the curve evolution is able to produce results close to the ideal minimization. The proposed method, GPAC, is based on pairwise dissimilarities between pixels. The method is quite flexible since the dissimilarity metric can be adapted to the application at hand or to the domain knowledge.

CHEN SAGIV, NIR A SOCHEN, AND YEHOSHUA Y ZEEVI [41] "INTEGRATED ACTIVE CONTOURS FOR TEXTURE SEGMENTATION" (2006):

This paper addresses the issue of textured image segmentation in the context of the Gabor feature space of images. Gabor filters tuned to a set of orientations, scales and frequencies are applied to the images to create the Gabor feature space. A two-dimensional Riemannian manifold of local features is extracted via the Beltrami framework. The metric of this surface provides a good indicator of texture changes. Moreover, an integrated approach, extending the geodesic and edgeless active contours approaches to texture segmentation, is presented. It is shown that combining boundary and region information yields more robust and accurate texture segmentation results.

M. CECCARELLI, N.DE LUCA, A. MORGANELLA [43] "AN ACTIVE CONTOUR APPROACH TO AUTOMATIC DETECTION OF THE INTIMA-MEDIA THICKNESS" (2006):

In this paper, a snake-based approach for the automatic detection of the intima-media thickness (IMT) of the far wall of the common carotid artery has been proposed. The detection of the intima layer plays a fundamental role as it represents the initial contour from where the method should start. An automatic segmentation approach which makes use of a first non linear filtering based on anisotropic diffusion followed by an iterative relaxation procedure has been proposed. Once the intima layer has been detected our method tries to locate an optimal initial contour to detect the wall of the artery by minimizing of a modified energy functional.

WEI SHANG GUAN, YAN LING HAO, ZHI ZHONG LU AND WEI WANG [44] "THE RESEARCH OF ROI ACQUIRES AIRTHMETIC BASE ON MEDICAL ULTRASOUND IMAGE" (2006):

In practical diagnose and therapy, medical ultrasound image has great application value, but as the image theory, the image has serious noise. In this paper, the noise of medical ultrasonic image is analyzed. Sobel edge detection arithmetic, canny optimization edge detection arithmetic, amendatory region grows arithmetic and Auto-snake arithmetic is used.

AHMED M. BADAWI AND MUHAMMAD A. RUSHDI [45] "SPECKLE REDUCTION IN MEDICAL ULTRASOUND: A NOVEL SCATTERER DENSITY

WEIGHTED NONLINEAR DIFFUSION ALGORITHM IMPLEMENTED AS A NEURAL NETWORK FILTER" (2006):

This paper proposes a novel algorithm for speckle reduction in medical ultrasound imaging while preserving the edges with the added advantages of adaptive noise filtering and speed.

CHAPTER 4

Active Contours: Background

4.1 Introduction

The technique of active contours has become quite popular for a variety of applications, particularly image segmentation and motion tracking, during the last decade. This methodology is based upon the utilization of deformable contours which conform to various object shapes and motions. This chapter provides a theoretical background of active contours and an overview of existing active contour methods.

There are two main approaches in active contours based on the mathematic implementation: snakes and level sets. Snakes explicitly move predefined snake points based on an energy minimization scheme, while level set approaches move contours implicitly 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 use an edge detector, usually based on the image gradient, to find the boundaries of sub-regions and to attract the contours to the detected boundaries.. Region-based active contours use the statistical information of image intensity within each subset instead of searching geometrical boundaries.

Active Contour or snake are define as energy-minimizing spline guide by external constraint forces and influenced by image forces that pull it toward features such as lines and edges. Snakes provide a unified account of a number of visual problems including detection of edges, lines, and subjective contours, motion tracking and stereo matching. Three parts characterize an active contour algorithm:

1) A model of the internal forces, e.g., elasticity and bending moments [27], which describes the active contour as a physical object

2) A model of the external forces which describes how the active contour is attracted to the data.

3) An iterative procedure which attempts to find the configuration that best matches both the internal and external forces.

4.2 Advantages of using Active Contour

Active contour methods offer several advantages.

1. An active contour is modeled directly as a curve and is maintained as a curve throughout the iterative process that deforms it toward the final solution [13]. Thus, characteristics of the desired curve such as its length, curvature, and conformation to the data can be evaluated or imposed as an explicit part of the algorithm.
2. An optimality criterion involving both intrinsic properties of the curve and the curve's relationship to the data is specified, and an optimal solution is sought [20].
3. An explicit map between the curve and the unit interval is the active contour as a physical object. Active contour models are widely used in the diagnosis and analysis of biomedical images such as X-ray, MRI etc [21].

4.3 Types of Active Contour

Active contour models can be classified according to several different criteria. One of the classifications is based on the "flexibility" of the active contour in was proposed in a slightly modified version by Jain [17]. The active contour models proposed in the literature can be accordingly partitioned in two classes

- Free form active contour models
- Limited form active contour models

In the free form active contour models, there is no global structure of the contour; it is constrained only by local continuity and smoothness constraints. The snakes are free form active contours . These models do not use a priori information about the shape in a direct manner. This information is on the other hand used in adjusting the model parameters so that the contour possesses properties (elasticity, rigidness, etc.) that enable it to embrace the object of interest.

The limited form active contour models use a priori information about the geometrical shape directly. This information is available in the form of a sketch or a parameter vector that encodes the shape of interest. The geometric shape of the contour is adjusted by varying the parameters. Deformable templates from the introduction are limited form active contour models. The reason that we call these models limited is the fact that they can not take any arbitrary shape. The variability of the shape is limited by the prototype template. parameterization and the way we generate deformed templates.

Another criteria for classification can be the way the image information is utilized to align the active contour with the object of interest. The models can be accordingly classified into

- Region-based models
- Boundary-based models

Region based models derive a contour representation from the segmentation of the image into well defined regions. The image is examined point-wise in order to decide if a pixel belongs inside an object, outside all objects or at the object boundary. A pixel belongs to the boundary if it is in the object region and has neighbors in the background. This segmentation is then used to produce an image force field which aligns the active contour with object of interest.Edge-based methods use a continuous approximation of the original image intensity function so that the boundary can be characterized by a differential property. By point-wise examination of the image, a pixel is said to belong to the boundary if it is a local maximum of the image gradient. In this boundary detection process, the fact that these boundary points constitute a closed geometric contour is not taken into account.

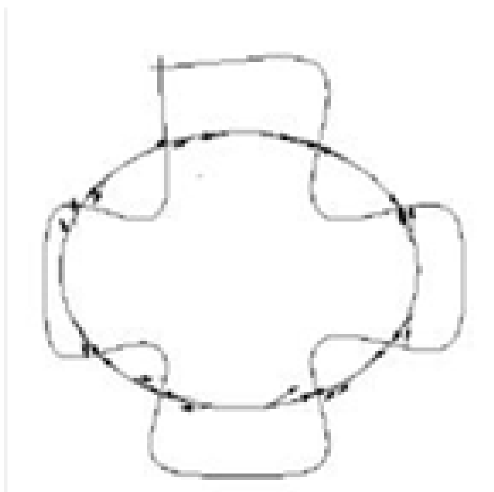


Figure 4.1 : Edge-based external forces acting on the contour

Figure 4.2 Region-based external forces acting on the contour

Image force field is easily computed for the edge based methods from a potential energy function. In region-based models, it is more complicated. One can not use the potential function since it only defines boundaries and is therefore not a function in the image plane which is required for the image segmentation. Because of the limited scope of this work, we will only study edge-based models.

4.3.1 Edge-Based Active Contours

Edge-based active contours are closely related to the edge-based segmentation. Most edge based active contour models consist of two parts: the regularity part, which determines the shape of contours, and the edge detection part, which attracts the contour towards the edges. Geometric active contour model was proposed by Caselles et al. [81] adding an additional term, called stopping function, to the speed function. It was the first level set implemented active contour model for the image segmentation problem. Malladi et al. [82, 78] proposed a similar model given by

$$\frac{\partial \varphi(x,y)}{\partial t} = g\left[I(x,y)k\big(\varphi(x,y)\big) + \gamma\right]|\Delta\varphi(x,y)| \qquad 4.1$$

where $g(\cdot)$: $\Omega \rightarrow R$ denotes the stopping function, i.e. a positive and decreasing function of the image gradient.

The edge-based active contour models have a few disadvantages compared to the region-based active contour models, discussed in the next section. Because of the constant term γ, edge-based active contour models evolve the contour towards only one direction, either inside or outside. Therefore, an initial contour should be placed completely inside or outside of ROI, and some level of a prior knowledge is still required. Also, edge-based active contours inherit some disadvantages of the edge-based segmentation methods due to the similar technique used. Since both edge-based segmentation and edge-based active contours rely on the image gradient operation, edge-based active contours may skip the blurry boundaries, and they are sensitive to local minima or noise as edge-based segmentation does

4.3.2Region-based Active Contours

Most region-based active contour models consist of two parts: the regularity part, which determines the smooth shape of contours, and the energy minimization part, which searches for uniformity of a desired feature within a subset. A nice characteristic of region-based active contours is that the initial contours can be located anywhere in the image as region-based segmentation relies on the global energy minimization rather than local energy minimization. Therefore, less prior knowledge is required than edge-based active contours. Region-based segmentation looks for uniformity within a sub-region based on a desired feature, e.g. intensity, color, and texture. Region-based active contour models have shown attractive characteristics, such as the unrestricted position of initial contours, the automatic detection of interior boundaries, and reasonable segmentation due to global energy minimization though the segmentation results are still case dependent. Region-based active contours evolve deformable shapes based on two forces: energy minimization based on the statistical properties, which pursues the uniformity within each subset, and curvature motion motivated by level set function, which keeps the regularity of active contours.

4.3.3 Image, Subset, and Sub-region

Let us redefine the notation of terms used in our segmentation model. As introduced in chapter 1, an image I(x, y) is the native input data of the image analysis, a function defined on a two-dimensional spatial domain. We define a multispectral image as a general form of images and a scalar image as a particular case of multispectral images. A multispectral image I(x, y) can be defined as a set of vectors given by

$$[I_1(x,y), I_2(x,y) \ldots \ldots I_b(x,y) \ldots \ldots I_B(x,y)]^T \quad \Omega \rightarrow R^B \qquad 4.2$$

where $I_b(x,y)$ denotes a scalar image measured at band b. Let the vector-valued image intensity of I(x, y) be a multi-dimensional random variable $I_B(x,y)$ where B denotes the dimension of I and is equivalent to the number of optical bands measured.

Let ψ represent the entire region of an image I(x, y). Image segmentation is a task to partition the entire region ψ into n sub-regions, $\{\psi_1, \psi_2 \ldots\ldots \psi_i, \ldots\ldots \psi_n\}$ with the criteria shown in table 4.1. Ci denotes the boundary wrapping sub-region ψ_i.

Table 4.1: The criteria of general image segmentation

1. $C = \cup_{i=1}^{n} C_i$
2. $C_i \cap C_j \neq \emptyset \; if \; \psi_i$ and $\psi_j \; are \; neighbors$
3. $\psi = (\cup_{i=1}^{n} \psi_i) \cup C$
4. I(x,y) are connected , $\forall (x,y) \in \psi_i,$
5. $\psi_i \cap \psi_j = \theta, \forall_{i,j}, if \; i \neq j$

The first and second conditions indicate the property of boundaries wrapping sub-regions $\{\psi_i\}$. As each sub-region has a boundary, the boundaries of two neighbor sub-regions are overlapped. C denotes the entire set of boundaries. The third condition indicates that the segmentation must be complete; that is, every image pixel should be an element of a sub-region ψ_i or boundaries C. The forth condition requires that all image pixels in a sub-region must be connected in a predefined sense; that is, they should be located at the inside of a boundary. The fifth condition indicates that the sub-regions must be disjoint each other, so an image pixel should be an element of only one sub-region. Here, we can notice the difference between the image segmentation problem and the pattern classification problem. A data sample can be a member of multiple classes in pattern classification

Table 4.2: The criteria of region-based image segmentation

1. $C = \bigcup_{i=1}^{n} C_i$
2. $C_i \bigcap C_j \neq \emptyset \; if \; \Omega_i and \; \Omega_j \; are \; neighbor$
3. $\Omega = (\bigcup_{i=1}^{m} \Omega_i) \;\; \cup C$
4. $\Omega_i \; \cap \Omega_j \; = \emptyset \; for \; \forall_{i,j}$ if i≠j
1. $C_i \cap C_j \;\; \neq \emptyset \; if \; \psi_i$ and ψ_j $are \; neighbors$
2. $\psi = (\bigcup_{i=1}^{n} \psi_i) \cup C$
3. I(x,y) are connected , $\forall(x, y) \in \psi_{i,}$

Table 4.1 lists the criteria of general image segmentation, and we here introduce slightly different criteria for region-based segmentation. Let a set Ω, instead of a region ψ, represent the entire domain of an image I(x, y). The region-based image segmentation is a task to partition the entire set of an image into m subsets, $\{\Omega_1, \Omega_2, \ldots, \Omega_i, \ldots, \Omega_m\}$, with the criteria shown in *table 4.2.* The only difference between a subsetΩ_i and a sub-region ψ_j is that a subset Ω_i does not necessarily form a spatial unit. That is, Ω_i may contain multiple sub-regions ψ_j residing in different spatial locations on the entire set of an image. Following expression shows the relation between n subsets and m sub-regions:

$$(\Omega = \psi) \supseteq \; \Omega_i \supseteq \psi_j \supseteq (x, y)$$

where i = 1, 2, . . . ,m and j = 1, 2, . . . , n.3 (Ω= ψ) denotes the entire set of an image as the largest possible spatial unit, while (x, y) denotes an image pixel as the smallest possible spatial unit. Figure 4.1 shows an example that sub-regions and subsets are not identical. The entire set of the image (Ω= ψ) consists of two subsets $\{\Omega_0, \Omega_1\}$ and three sub-regions $\{\psi_0, \psi_1, \psi_2\}$ A subset $\Omega_1$exists at two different spatial locations, where each of them is independently marked as ψ_1 and ψ_2. Therefore, two main approaches of segmentation, i.e. edge- and region-based, can be reintroduced such that edge-based segmentation partitions an image I(x, y) into multiple sub-regions ψ_j searching for discontinuities among sub-regions, while region-based segmentation partitions an image I(x, y) into multiple subsets Ω_i searching for uniformity within a subset Ω_i.

4.4 Active Contours Integrating Edge- based and Region-based Segmentation

In order to improve 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) criterion 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 prior knowledge, i.e. training samples. Then, the boundary information is determined by a probabilistic edge detector, estimated from the regional probabilities of neighborhood.

Jehan-Besson et al. also proposed an active contour model minimizing an energy criterion involving both region and boundary functional. These functional are derived through a shape derivative approach instead of classical calculus of variation. They focus on statistical property, i.e. the PDF of the color histogram of a sub-region. Active contours are propagated minimizing the distance between two histograms for matching or tracking purposes.

4.5 SNAKE

Snake is a parametric curve defined within domain of an image. All snake properties and its behavior is specified through a function called energy functional by analogy with physical systems. A partial differential equation controlling the snake causes it to evolve so as to reduce its energy. The physical analogy can be extended, and the motion of the snake can be viewed as being due to simulated forces acting upon it. In order to gain an intuitive understanding of the snake model, it is therefore suitable to compare it with a real physical model.

Let us view the edge map of the image as a landscape on which the parametric curve can slither. A force is acting upon the curve and it is moving across the landscape trying to reach the energy equilibrium. The model driving it across the landscape has two components: one telling the snake how to behave (to preserve the original shape, to develop a corner etc.), another one instructing it where to go. We want the curve to cling to the boundary of a specific object in the scene. The boundary can be recognized as low values of the negative edge map, so the equilibrium equation should be set up in such a way that the curve tends to minimize the term involving the negative edge map, or as we will denote it - the potential energy of the dynamic system. Since we know the general shape of the object in question, we may design the evolution equation in such a way that the snake easily can embrace the object; it may have to be elastic, stiff, be able to develop a corner or similar.

Now, as we understand the idea, we have to design the system mathematically in order to be able to implement it. The first snake model was proposed by Kass [22] in 1987. The energy functional which the snake was to minimize in order to achieve equilibrium was defined as following

$$E_{snake} = \int_0^1 \{E_{int}\left(V(s)\right) + E_{image}\left(V(s)\right)\}d(s) \qquad 4.3$$

where the position of the snake on the image is represented parametrically by a planar curve v(s)=(x(s),y(s)) , E_{int} represents the internal energy of the curve due to the bending and the E_{image} represents the image forces pushing the snake toward the desired object. The proposed internal energy model was defined as

$$E_{int} = \left\{\alpha(s)|V_s(s)|^2 + \beta(s)|V_{ss}(s)|^2\right\}/2 \qquad s\epsilon[0,1] \qquad 4.4$$

where $V_s(s)$ is the first derivative and $V_{ss}(s)$ the second derivative of V(s) with respect to s. Note that we assume continuous image and curve coordinates. In applications, we work with digital images and a discretization must be formulated. Since the object in interest should be recognized by the snake as a set of low values on the negative edge map, i.e. spatial gradient magnitude, the model for the image energy was defined as

$$E_{ext} = -|\nabla I(x,y)|^2 \qquad 4.5$$

if the object was homogeneous inside (both the boundary and the area inside the boundary have approximately the same grey level) or

$$E_{ext} = -I(x,y) \quad 4.6$$

if the image is a line drawing (black on white). The term I(x,y) represents the grey level values of the image.

Lets now try to analyze it by viewing it in terms of our intuitive landscape model. The first derivative of v(s) with respect to gives us the rate of change of length of the curve, which means the longitudinal contraction of the curve. The coefficient α(s) allows the curve to have smaller or larger degree of contraction and therefore makes the snake act like an elastic string. Large values of α(s) mean large contraction of the snake in the direction of the force. Therefore is α(s) denoted as the elasticity coefficient.

The second derivative gives us the rate of convexity or the curvature. The coefficient β(s) regulates than the rate of the change of the curve in the direction normal to its boundary. This term makes the snake act like a rigid string. That means that the curve preserves the smoothness, the straight -line shape but does not contract. If the value of β(s) is high the curve is hard and resists bending, while small values of β(s) is small allow the curve to develop a corner. By adjusting these two coefficients, the curve gets an appropriate elasticity and is able to embrace the object of interest.

The second energy term is easy to interpret. We can regard the image intensity function as a landscape and the snake is rolling down to a valley driven by a gravity alike force . If we think of the low values of the negative edge map as the valley, calculate the edge map over the image and make the snake go in the direction of the minima on the edge map, it will roll to the valley and stay there. Having defined the various energy terms that derive the snake, the initial position must be interactively specified by the user. Those are the principles behind the snake. It will be shown later that this model may be improved in many ways to be able to estimate a variety of complex object.

The classic snakes provide an accurate location of the edges only if the initial contour is given sufficiently near the edges because they make use of only the local information along the contour. Estimating a proper position of initial contours without prior knowledge is a difficult problem. Also, classic snakes cannot detect more than one boundary simultaneously because the snakes maintain the same topology during the evolution stage. That is, snakes cannot split to multiple boundaries or merge from multiple initial contours. Level set theory has given a solution for this problem.

4.5.1 **SNAKE Energy**

General model of an active contour model in the image plane (x,y)is given by

$$v(s)= (x(s), y(s)) \quad 4.7$$

where x and y are the coordinate functions and s $\in$ [0,1] is the parametric domain

Active contours work by minimizing contour energy:

$$\mathbf{E^{*}_{snake} = \int E_{snake} (v (s)) ds} \quad 4.8$$

Snake Energy Function

$$\mathbf{E^{*}_{snake}= \int E_{int} (v(s)) +E_{image} (v (s)) + E_{con} (v (s))} \quad 4.9$$

$\mathbf{E_{int}}$ – Internal Constraints (internal energy due to bending serves to impose piecewise smoothness constraint.)

$\mathbf{E_{image}}$ – Image Constraints (image forces pushing the snake toward image.)

$\mathbf{E_{con}}$ – External Constraints (external constraints are responsible for putting the snake near the desired local minimum.)

4.5.2 Internal Energy

The snake is a controlled continuity spline [18]. A traditional snake that moves through the spatial domain of an image to minimize the internal energy functional is given below.

$$\mathbf{E_{int} = [\alpha(s) * ([f'(s)]^{2}) + \beta(s) * ([f''(s)]^{2})] / 2} \quad 4.10$$

The first order derivative **f'(s)** makes the spline act like a membrane and the second order derivative **f''(s)** makes it act like a thin plate

α(s) and **β(s)** controls the relative importance of membrane and thin plate terms [25].

Setting β(s) =0 for a point allows the snake to become second order discontinuous and develop a corner.

4.5.3 Image Forces

Image forces attract the snake towards image features. The equation below shows the various factors on which the movement of the snake on a particular image depends.

$$\mathbf{E0 = W1\ E1 + W2\ E2 + W3\ E3} \quad 4.11$$

Where **E1** is the image intensity function

and E2 is the large intensity gradient.

In accordance to the theory of calculations of variations we have Eulaer-Lagrange equation by which the shape of the contour subject to an image I (x,y) is dictated as

$$\epsilon(v) = S(v) + P(v) \qquad 4.12$$

The functional can be seen as energy representation and the final shape of the contour corresponding to the minimum of this energy. The mathematical equation may also be written as

$$S(v) = \int_0^1 w_1 (s) \left|\frac{\partial v}{\partial s}\right|^2 + w_2 (s) \left|\frac{\partial^2 v}{\partial s^2}\right|^2 d(s) \qquad 4.13$$

The above model has two parameters one w_1 (s) controls the tension and w_2 (s) controls the rigidity. In general

$$P(v) = \int_0^1 p(v(s))ds \qquad 4.14$$

Where p(x,y) denotes a scalar potential function defined on image plane. To apply snakes to images external potentials are designed whose local minima coincide with the intensity extreme edges and other images feature of interest.

The Euler equation is given by

$$\epsilon(v) = S(v) + P(v) \qquad 4.15$$

$$\epsilon(v) = \int_0^1 w_1(s) \left|\frac{\partial v}{\partial s}\right|^2 + w_2 (s) \left|\frac{\partial^2 v}{\partial s^2}\right|^2 d(s) + \int_0^1 p(v(s))ds$$

Hence $\frac{\partial}{\partial s} w_2 (s) \left|\frac{\partial v}{\partial s}\right|^2 + \frac{\partial^2}{\partial s^2} w_2 (s) \left|\frac{\partial^2 v}{\partial s^2}\right|^2 + \nabla p(v(s,t)) = 0$

This vector differential equation gives the condition for balance of vector forces under equilibrium. The first two terms represents the internal stretching and bending foresees where as the third term represents the external forces that couple the snake to the image.

4.5.4 Methodology for Medical image analysis with contour models

The image that are of CT images, X-ray images and MRI images. The results obtained after segmentation and contour detection are as shown . the following are the steps employed for using the snake model software

1. Read the Image
2. Perform preprocessing (filtering / enhancement)
3. Apply segmentation process
4. Identify the region of interest (ROI)
5. Apply different contouring techniques
6. Get the detailed information about the geometry of the image

7. Repeat the above procedure in case of multiple contour analysis (once for each of region of interest)

8. Selection of various parameters depends on the accuracy required

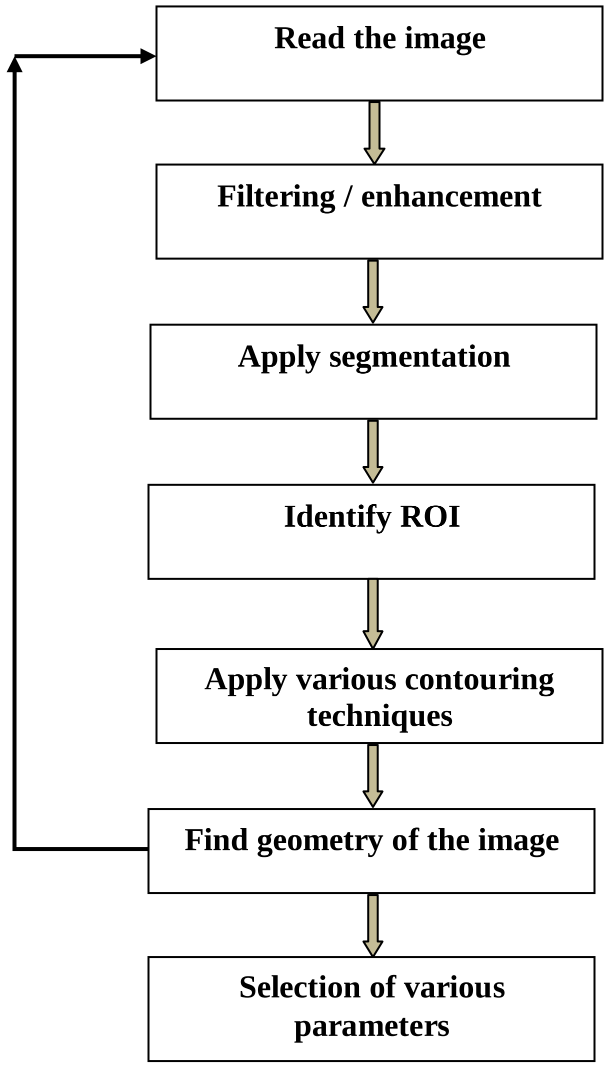


Fig 4.3 Methodology for Medical image analysis with contour models

4.6 Problem in Traditional Snakes

There are number of problems in model of active contour proposed by Kass [2]. Given a moderate noisy force field, it is not surprising to see points on a snake clustering into a dense structure at certain places [11] [26]. It is even possible for points to move on top of one another. There are two key difficulties with parametric active contour algorithms. First, the initial contour must, in general, be close to the true boundary or else it will likely converge to the wrong result [6] [14]. The second problem is that active contours have difficulties progressing into boundary concavities [7] [15].

In short traditional snake has two major problems:

1. Poor Convergence and Limited Capture range

2. Initialization of Snake

4.6.1 Problem Formulation

It was observed that when Xu and Prince Algorithm was applied on images for segmentation the desired area chosen for segmentation was not completely segmented. The algorithm was modified to achieve the following objectives.

- To increase the area of segmentation.
- To obtain the type of images on which M Kass algorithm works properly.

4.7 What is a Deformable Template?

Deformable templates constitute another important approach to object estimation. The mathematical background of the deformable templates can be traced back to the shape class description based on pattern theory .This approach employs prior knowledge about the shape of the object in a direct manner. This prior shape information is specified as a sketch, binary template or a parametric prototype. The a priori information is than encoded either in the form of edge information from a binary template or the parameter vector. That information does not need to be exact in the sense that it matches the boundaries of the image exactly.

We may say that the difference between snakes and deformable templates is that snakes are form-free energy minimizing functions. In snakes model, there is no global structure of the curve except for some general regularization constraints such as continuity and smoothness of the boundary. On the other hand, parametric deformable templates control deformations using a set of parameters which are capable of encoding a specific shape. This type of model is used when more specific shape information is available, which can be described either by a binary temple or a set of parameters. The prototype template describes one and the most likely instance of the object shape. We apply a parametric transformation to the prototype and deform its boundaries varying the deformation parameters in order to capture a large variety of possible instances. If the object in interest is of biological nature, the form will resemble, but still vary from individual to individual. Those small variations may be captured by the random deformations of the prototype, so that a deformed template may match the object in interest better then the original template. Objects may also be noise corrupted or degraded in some way so that the original shape is lost. In that case too a deformed template may match the object better than the original one. Using an appropriate edge detector ,we extract boundaries of the objects in the image. Then, we match all found objects with our template base and check for similar objects by aligning the templates in the data base with the image in question using some potential energy function. Since not all transformations result in templates that visually resemble the prototype template, and all the prior shape information is represented in the prototype template, it is natural to assume that the prototype template is the most likely a priori shape of the object.

Further, small deformations that leave the template similar to its original shape are more likely than larger displacements. Therefore, we impose a probability distribution on the images in data base to bias the possible deformed templates. Varying parameters of the distribution, we adjust the confidence about our prototype template. Having understood the idea behind deformable templates, the distinction between low- and high-level methods becomes clear and we see how did they get their respective names. In order to project a shape found in an image onto the shape base, we have to extract that shape from the image. For this purpose are low-level methods suitable. We might say that they operate on a lower level doing the rough part of the work - extracting objects - while the high-level methods are analyzing the results and making a decision. It will be shown that there are many ways to generate a prototype template, deform it and make a decision as to which template resembles the object most.

4.8 What is a Dynamic Contour?

Dynamic contours will not be discussed in this work but a short description will be given. It is also important to mention that both snakes and deformable templates may be labeled as dynamic contours because they show dynamic behavior. In this work we will, however, reserve this label for a specific group of active contours. Active contours can be applied statically, to single images, or dynamically to image sequences. In dynamical applications, some additional moments may be incorporated in the model to convey any prior knowledge about object motions and deformation. As opposed to snake where only the active contour is varying, in dynamic contours the edge map is varying too and the snake is applied on a sequence of images. The equation of motion for such a system extends from the snake model to a new model with additional terms governing inertia and viscosity. This group of active contours find their applications in motion tracking, traffic monitoring, visual speech recognition and so on.

The first model of active contour was proposed by Kass et al. [3] and named snakes due to the appearance of contour1 evolution. Let us define a contour parameterized by arc length s as

$$C(s) = \{(x(s), y(s)) : 0 \leq s \leq L : R \rightarrow \Omega \qquad 4.16$$

where L denotes the length of the contour C, and denotes the entire domain of an image I(x, y). The corresponding expression in a discrete domain approximates the continuous expression as

$$C(s) \approx C(n) = \{(x(n), y(n)) : 0 \leq n \leq N, s = 0 + n\Delta s\} \qquad 4.17$$

where L = NΔs. An energy function E(C) can be defined on the contour such as

$$E(C) = E_{int} + E_{ext} \qquad 4.18$$

where E_{int} and E_{ext} respectively denote the internal energy and external energy functions. The internal energy function determines the regularity, i.e. smooth shape, of the contour.

Figure *4.4 : example of classic snake*

Figure 4.4 shows an example of classic snakes. There are about 70 snake's points in the image, and the snake points form a contour around the moth. The snake's points are initially placed at further distance from the boundary of the object, i.e. the moth. Then, each point moves towards the optimum coordinates, where the energy function converges to the minimum. The snakes points eventually stop on the boundary of the object.

CHAPTER 5

Active Contours- Classifications

5.1 Introduction

Yet another classification partitions the active contours into

- Parametric active contours
- Non-parametric (geometric)active contours

5.1.1 Parametric Active Contour

A parametric active contour is a contour that is represented by a small number of parameters that capture the shape of the object. If the parameterization is achieved by expressing the curve in terms of a basis, where the discrete function representing the curve is expressed as a weighted sum of a set of known functions, distinction between parametric and non-parametric contours is clear. First, there is a parameter space different from the physical space where the curve is initially defined. Second, different bases give parameter spaces with different properties and third, some of the operations that are performed on the contour are can be defined in the parameter space. Examples of such parameterizations are Fourier, B-spline and Wavelet representation.

In particular, parametric active contours are represented explicitly as parameterized curves [1, 8] in a Lagrangian formulation. Parametric active contours are the older of the two formulations and have been used extensively in many applications over the last decade. A rich variety of modifications based on physical and non-physical concepts have been implemented to solve different shape estimation problems.

The classical parametric active contours, proposed by Kass *et al.* [1], are formulated by minimizing an energy functional that takes a minimum when contours are smooth and reside on object boundaries. Solving the energy minimization problem leads to a dynamic equation that has both internal and external forces. The external forces resulting from this formulation are conservative forces in that they can be written as gradients of scalar potential functions. Active contours using non-conservative forces, however, have been shown to have improved performance over traditional energy-minimizing active contours [16, 24]. Therefore, we now formulate parametric active contours directly from Newton's law, which permits use of the most general external forces.

Mathematically, a parametric active contour is a time varying curve

$$\tau X_t = F_{int} + F_{ext} \qquad 5.1$$

X_tt is the partial derivative of X with respect to t and τX_t is Damping force with τ being an arbitrary non negative constant , F_{int} and F_{ext} internal & external forces respectively. The contour comes to a rest when the net effect of the damping, internal, and external forces reaches zero. The external force is designed to pull an active contour towards object boundaries or other features of interest. Many types of external forces have been developed in the past (see [41] for a comprehensive list of external forces), including the well-known pressure force [3] and the Gaussian potential force [1]. The internal force is the sum of elastic and rigid forces defined as follows

$$F_{elastic} = [\alpha\ (s,t) X_s\ (s,t)]s \qquad 5.2$$

$$F_{rigid} = -\ [\beta\ (s,t) X_{ss}\ (s,t)]ss \qquad 5.3$$

where the coefficients α $(s,t)$and β (s,t)can be used to control the strength of the contour's elasticity and rigidity, respectively. In this general formulation, these coefficients are allowed to vary both along the length of the curve and over time. In practice, however, α is usually a positive constant and β is usually zero. It is important to maintain the most general formulation, however, in order to understand the precise relationship between parametric and geometric active contours.

5.1.2 Geometric Active Contour

Geometric active contours are based on the theory of curve evolution and the level set method. In this framework, curves evolve using only geometric measures, resulting in a contour evolution that is independent of the curve's parameterization. This avoids the need to repeatedly reparameterize the curve or to explicitly handle topological changes. The parametric representations of the curves themselves are computed only after the evolution of the level set function is complete.

Let φ(x, t) be a 2-D scalar function whose zero level set defines the geometric active contour. The original geometric active contour formulation evolves φ according to

$$\emptyset_t = c\ (k + V_0)\ |\nabla \emptyset| \qquad 5.4$$

where k is the curvature, V_0 is a constant, and

$$c = c(x) = \frac{1}{1+|\nabla(G_\sigma\ (x) * I(x))|} \qquad 5.5$$

is an edge potential derived from the image. In equation (5.4), the product c (k+V_0) determines the overall evolution speed of level sets of ø(x, t) along their normal direction. The use of curvature k has the effect of smoothing the contour, while the use of V_0 has the effect of shrinking or expanding contour at a constant speed. The speed of contour evolution is coupled with the image data through a multiplicative stopping term c. This scheme works well for objects that have good contrast. When the object boundary is indistinct or has gaps, however, this contour tends to leak through the boundary.

Geometric active contours were introduced more recently and were hailed as the solution to the problem of required topological changes during curve evolution [4, 5]. Geometric active contours are represented implicitly as level sets of two dimensional distance functions [9–11] which evolve according to an Eulerian formulation. They are based on the theory of curve evolution implemented via level set techniques

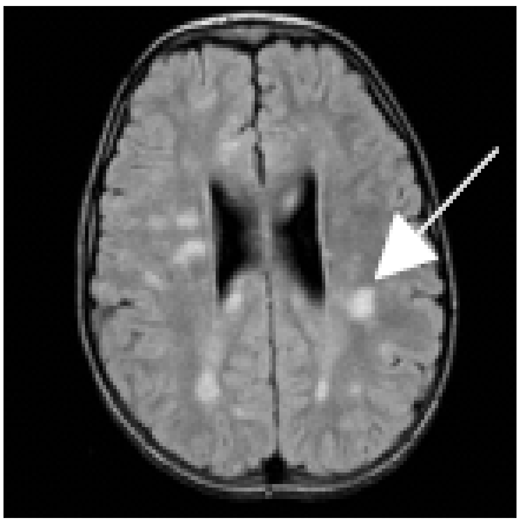
Modifications and enhancements have been added to change their behavior or improve their performance in a variety of applications [6, 7, 17–19], including a number of more global region based models which have appeared recently in the literature .While similarities between the two active contour formulations have always been apparent, only recently have the precise relationships begun to emerge in the literature. Caselles *et al.* [17] showed that their geometric active contours are equivalent to a special class of classical parametric active contours. Aubert and Blanc-F´eraud [20] revisited this equivalence and extended it to the 3-D (active surface) case. The equivalence derived in these two cases is limited in two respects, however. First, it applies only to those active contours derived from energy minimization principles. Therefore, the question of whether a geometric formulation can be found for more general active contours is not addressed. Second, the equivalence only applies to active contours with elastic forces; rigid forces are neglected.

For example, it is not clear how one would incorporate non-conservative external forces, such as the forces defined in [16]. Also, it is not clear how to incorporate regional pressure forces, such as those used in [22, 23]. It has been well known that the use of elastic internal forces may cause undesirable shrinking effect, whereas the use of rigid internal forces can smooth the contour without this adverse effect. However, the use of rigid internal forces have been largely lacking in geometric active contour formulations so far. Since these are commonly used features in parametric active contours, there is a clear need to establish an equivalent model in geometric active contours so that the computational and topological advantages of geometric active contours can be simultaneously exploited.

CHAPTER 6
Results & Conclusions

6.1 INTRODUCTION

In this section we show how the previous active contour models, both parametric and geometric, can be applied to medical image segmentation. In order to shows the interests of the segmentation by active contour models. We select an MR image of 256x256 pixels. This image is selected from image database set [24]. The image represents slice brain attained of tumors pathology. Partitioning a region or regions of interest in images of the brain such that each region corresponds to one or more anatomic structures



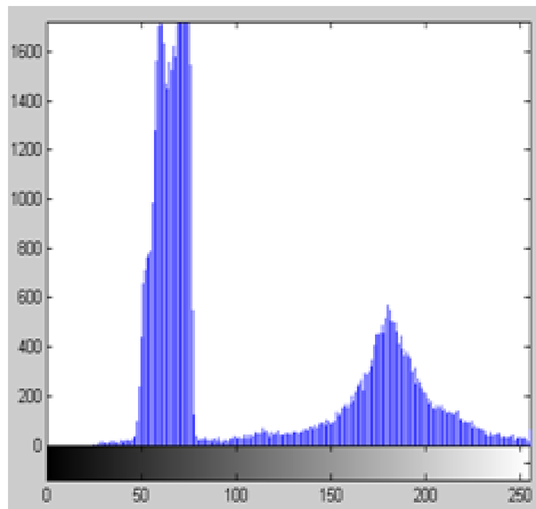


Figure6.1 (a) original Image *figure 6.1(b)histogram of original image*

Figure 6.1 Trans-axial slice brain image corresponding to child of the 8 year old with tumors depicted.

The figure 6.1 (a) shows the original image of brain where image segmentation is performed using two different contouring techniques , one is segmentation of original image using Parametric Active contour method and second is segmentation of image using Geometric Active contour methods as shown in figure 6.2 and figure 6.3 respectively. In the original image, the edge map shows higher values where the image gradient is larger, and low values over homogeneous regions.

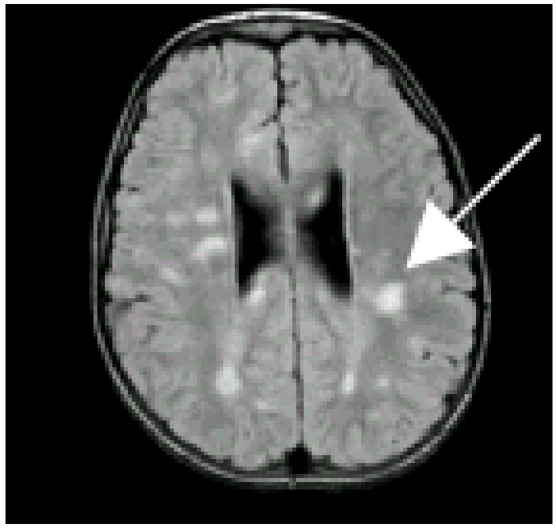


Figure 6.1 (c) Original image after edge blurring using Gaussian Filters

The Gaussian filter blurs the edges as shown in figure 6.1(c), thus increasing the snake's capture range as it spreads the force vectors along the potential field. Using a traditional snake model and a fair initial position, we can see that it correctly evolves towards the desired contour.

6.2 Segmentation using Parametric Active Contour method

The figure 6.2(a) shows the Segmentation of a tumor in an MRI brain data by using Parametric active contour model (GVF). A parameter-varying snake model is introduced incorporating prior knowledge on the contours' shape and shape similarity metric. In practice, parameters of snakes affect the segmentation results to a great extent. Intuitively, the external energy should govern the minimization procedure when the segmentation is started, in order to force the initial contour to evolve close to boundaries. For the later stages, the shape prior becomes a more important feature for segmentation. For several experiments, we have fixed set of pairs (α, β). The experiments where done for α=1, and β=0.03. This pair of (α, β) has drawn agree results, and isolate correctly the tumors. On the other terms, if some parts of the snake where initialized over homogeneous regions of the image, the contour wouldn't evolve correctly stalling where the force field vectors have lower magnitude

Tumor

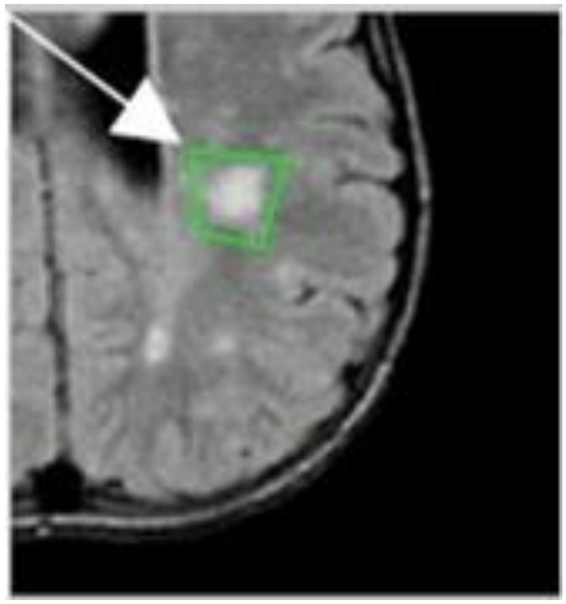


Figure 6.2 (a) initial contour

Figure 6.2 (b)final contour

Figure 6.2(a) and 6.2 (b) ***)*** *Segmentation of a tumor in an MRI brain data by the parametric active contour model (GVF model)*

In adding the balloon model, it makes the snake less dependent on its initialization, by the use of pressure forces. The GVF model also improves the problems related to bad initial position without using pressure forces. Be-sides, this model doesn't need a previous knowledge about whether the snake will grow or shrink, as does the Balloon model. However, it's important not to overestimate the GVF snake initialization capability. If it is done way too distant of the desired contour, the snake may take a very long time to converge or even stall over homogeneous regions. The GVF model has shown better performance and more accurate results than the traditional, Balloon or Distance Vector models. But, it's also hard for fixing a good choice of parameter that leads to locate the tumors area in the brain slice.

6.3. Segmentation using Geometric Active Contour method

The second method of segmentation of tumors in MRI of brain is by using Geometric Active Contour technique. In this method the pathology is segmented by fixing of the speed function equal to several values between F= 1 and F=2.

We observe that for F=1, the tumors area segmented is mores less then in the case of the parametric contour.

Figure 6.3 (a)Initial Contour

Figure 6.3 (b)final contour

Figure 6.3(a) and 6.3(b) Segmentation of a tumor in an MRI brain data by the geometric active contour model (Level-Set method)

To compare the results drawn both by the parametric and geometric model, the key difficulty when working with active contour models is the correct definition of both the external energy term and speed function. Since both are based on the image gradient, one might expect similar behavior to both models. Problems related to bad initialization, local minima, and incorrect convergence may happen when working with either model, unless proper care is taken. Parametric model was been a more simple way than the geometric, regarding both the contour representation and implementation complexity. The explicit formulation of an evolving closed contour searching for an energy function minimization is far more intuitive. One may question about the Snake's lack of robustness when dealing with sharp corners, topological changes and initialization problems, but as we have shown, there is no ideal method, only specific procedures to ensure the correct result obtained from specific image sets. On the other terms, the mathematical formulation of geometric models is more robust. Issues like topological changes and sharp corners are dealt with naturally.

6.4 . CONCLUSIONS

The main conclusion from this work is that there is no ideal segmentation method. Both parametric and geometric active contours are driven by forces extracted from the image itself, what makes them extremely dependent on the image quality, that is, lowly noised, fair definition of the structures' edges and absence of local minima. Even if one is able to overcome these problems, there are still further difficulties, like the initialization problem for example, which has a strong impact on the correct contour's convergence. This kind of problem may cause the procedure to be repeated until the result obtained is good enough for the user.

Finally, it is important to observe that an efficient, precise medical image segmentation system should necessarily add to the model some level of intrinsic knowledge about the problem. Variables like the kind, shape and relative location of the common structures or pathology, and their size compared to some reference system such as an anatomy atlas [20], would improve enormously the model's robustness and autonomy.

Appendix-A (Image Data Source)

Resources	Description
Database	**1. http://www.cs.uwaterloo.ca/~jorchard** **2. http://www.billingsmricenter.com** 3. Related IEEE/IEE publications
Text Books	1. Digital Image Processing - by Keenneth R Castleman 2. Digital Image Processing - by Rafact Gonzalez and Richard E. Woods,

Appendix-B (Publication from related work)

1. **Kaur Harneel Pal, Dhingra Shalini, " Medical Image Segmentation using Active Contour Models", 2nd National Conference on Information & Emerging Technologies, IET Bhaddal, Ropar proceedings pp 207-211, 7th -8th September,2007**

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