Comparative Studies of Contouring Algorithms for Cardiac Image Segmentation

A Thesis

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By

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Abstract

In the past few decades, cardiac image analysis especially segmentation has been a subject of several studies. In its basic form, cardiac image segmentation involves identifying heart or any of its anatomically or physiologically relevant features from 2D or 3D images. Methods for cardiac image segmentation can be divided into two major categories, namely, low and medium level cardiac segmentation techniques and high level cardiac segmentation techniques also called model based pattern recognition methods.

The low and medium level cardiac image segmentation techniques can be further divided into three categories: (a) histogramming and thresholding based cardiac image segmentation techniques, (b) edge based cardiac image segmentation techniques and (c) mathematical morphological approaches for cardiac image segmentation. These approaches suffer from several drawbacks. For example, majority of these techniques are based on thresholding or histogramming and therefore disregard all local features in the image. Prior distribution is not utilized in these approaches. Moreover, these approaches do not include hand-drawn techniques of cardiac segmentation and hence, the concept of fitting mathematical equations to justify the approach does not exist.

Model based pattern recognition methods include learning-based techniques and methods involving energy minimization. These methods can overcome the shortcomings
encountered in low and medium level segmentation techniques. These approaches do not require thresholding and priors can be estimated from the measured images.

The aim of this thesis is to not only review the previous work related to cardiac image segmentation but also implement and compare results from several state-of-the-art segmentation techniques, namely, cardiac contour initialization using morphological operators, cardiac segmentation using snakes (active contour) and its extensions, and STACS (stochastic active contour scheme). These approaches are described in more detail in Chapter 3.

In conclusion, cardiac image segmentation remains an active area of research. Further developments, especially to improve robustness, are required to broaden the applicability of these techniques for medical imaging data. Further exploration of model based pattern recognition methods may provide more consistent and accurate results.
Dedication

Dedicated to four extraordinary human beings who have given meaning to my life…

my mom, my dad, my advisor Dr. Raghu Machiraju and my friend Dr. Rizwan Ahmad
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obtained using snake model, snake model with ellipse, snake model with stages and snake model with ellipse and stages in Figure 24-27.
Chapter 1: Introduction

1.1 Description of the problem

The basic aim of segmentation is to partition a domain $\Omega$ of the given image into two or more regions. An example of two-region cardiac image segmentation is shown in Figure 1. The region $\Omega_1$ corresponds to the object of interest, heart in this case, and region $\Omega_2$ corresponds to background. The contour $C$ separates the two regions. The problem of separating $\Omega_1$ from $\Omega_2$ can equivalently be posed as a problem to find the contour $C$. In this work, I am interested in cardiac image segmentation problem where I identify the heart from its background. In other words, my aim is to identify two groups of pixels $u_1$ and $u_2$ defined as follows:

\[ u_1 = \{u_{ij}; \forall (i,j) \in \Omega_1\} \quad (1) \]

\[ u_2 = \{u_{ij}; \forall (i,j) \in \Omega_2\} \quad (2) \]
Figure 1. Labeled MRI Image of a rat. Cardiac boundary represented by contour $C$ is separating heart and background of the image. Region inside the contour $C$ is named as $\Omega_1$ and region outside the contour $C$ is named as $\Omega_2$.

1.2 Challenges

Cardiac image segmentation is a challenging problem. Some of the major technical problems encountered in cardiac image segmentation are listed below.

- Variability in heart rates, sizes, positions and orientations, as well as variations in image contrast and resolution may challenge the consistency and accuracy of any single segmentation technique [15].

- The reconstructed image may contain noise and artifacts that may arise due to one or more following reasons.
  
  o Thermal noise (see Appendix for definition).
  o Cardiac and breathing motion.
  o Image reconstruction from limited data.
• Edge based techniques are particularly sensitive to noise, which may translate to the generation of spurious edges and hence affects the accuracy of the method.

• Quantization errors may occur when a continuous cardiac boundary is approximated by a digital curve.

• The shape of the heart is very irregular. Therefore, it is not be accurately approximated by regular shapes like ellipse. More complex models may be required to accurately represent the cardiac boundary.

• Tissues belonging to the heart may have same gray-scale intensity as the tissues in the background, making intensity and edge based methods prone to error arising from this ambiguity.

**1.3 Contributions**

The major contributions of this thesis are not only to provide a brief survey of cardiac image segmentation algorithms but also to implement and apply several cardiac image segmentation approaches to MRI images of mouse heart. The thesis document contains the implementation results of the following cardiac segmentation techniques:

• Snake model

• Snake model with ellipse

• Snake model with ellipse and stages

• STACS
The techniques are compared in terms of subjective quality and objective measures. These objective measures include area inside the contour, area similarity measure (ASM) and shape similarity measure (SSM).

The concept of introducing ellipse in snake model is based on the assumption of similarity of shape of cardiac boundary to an ellipse. The intuition behind the concept of stages comes from rhythmic contraction and expansion of heart during systolic and diastolic phases, respectively. In systolic phase, it is assumed that the cardiac boundary would contract. Similarly, in diastolic phase, it is assumed that the cardiac boundary would expand. This apriori information can be added to the snake model to improve robustness of segmentation.

This document not only describes different approaches including snake model, snake model with ellipse, snake model with stages, snake model with ellipse and stages and STACS but also provides a comparison of their implementation results.

1.4 Organization

The rest of the thesis is organized as follows: in Chapter 2 we discuss the background of the work including description and importance of MRI, low and medium level segmentation techniques and model based pattern recognition methods. Chapter 3 describe in detail about the cardiac MRI data and different cardiac MR image segmentation approaches. Chapter 4 provides a comparison of these approaches for a single MRI dataset. The comparison is made using objective measures including area
inside the contour in terms of number of pixels, ASM and SSM values. Finally, Chapter 5 narrates the conclusion and future work.
Chapter 2: Background

The basic aim of this chapter is to provide literature survey related to cardiac image segmentation using magnetic resonance imaging (MRI). Section 2.1 provides a description of the MRI, sketches the importance of MRI and cardiac image segmentation using MRI. It also enumerates the experimental parameters used to collect MRI data. Besides, the classification of cardiac image segmentation techniques into low-level, mid-level and high-level techniques (model based pattern recognition methods) is also described in this section. This classification scheme is shown in Figure 2. Furthermore, the model based pattern recognition methods are further divided into training based and energy minimization approaches. Quantitative tools are used to assess the accuracy of cardiac image boundary. These tools include objective measures like ASM and SSM. Section 2.2 gives a description of low and medium level cardiac techniques. Besides, this section also provides the disadvantages of low and medium level cardiac techniques. Section 2.3 gives a description of model based pattern recognition methods. This section also explains the features of model based pattern recognition methods that provide the solution to the shortcomings of low and medium level segmentation techniques. As different cardiac imaging modalities (CT, MRI, ultrasound and X-rays) are inter-related, when it comes to different techniques [15], that is why, the images from different modalities could be common candidates for given cardiac segmentation algorithm.
Figure 2. The cardiac image segmentation techniques can be divided into low, medium or high level techniques. High level cardiac segmentation techniques can be sub-divided into training based approaches and energy minimization cardiac segmentation techniques [15].

2.1 Magnetic Resonance Imaging (MRI)

Magnetic resonance imaging (MRI) is a technique used in radiology to visualize detailed internal structures [5]. Using magnetic field (see Appendix A), MRI scanner aligns the magnetization of nuclei with non-zero spin quantum numbers. Application of radio frequency fields systematically alters the alignment of this magnetization, which causes the nuclei to produce a rotating magnetic field that is detectable by the scanner. This information is recorded to construct an image of the scanned area of the body. Due to magnetic field gradients (see Appendix A), nuclei at different location rotates at different
speeds. Hence, 3-D spatial encoding is performed by applying combinations of magnetic field gradient [5].

In the 1950s, Herman Carr created a one-dimensional MR image and later Paul Lauterbur generated the first 2D and 3D MRI images using gradient fields [5]. Later Lauterbur published the first nuclear magnetic resonance image in 1973.

2.1.1 The Larmor Equation

The Eq.3 identifies the frequency of precession [50]. It is a fundamental equation for MRI that is written as follows:

\[ f = \gamma \beta_0 \]  

where \( f \) is the frequency of precession, \( \gamma \) is the gyromagnetic ratio and \( \beta_0 \) is the magnetic field.

The Larmor equation gives the relationship between \( \beta_0 \), the strength of static magnetic field, to the precessional frequency \((f)\) through the gyromagnetic ratio \((\gamma)\), which has a precise value characteristics of each nuclear species.

The units of gyromagnetic ratio has megahertz per tesla (MHz/T). For example, hydrogen has a gyromagnetic ratio of 42 MHz/T. If \( \beta_0 \) is 1T then the precessional frequency is measured at 42 MHz. The precessional frequency is also called the Larmor frequency.

2.1.2 How MRI Works?

Due to high water composition in the body, tissues contain many hydrogen nuclei or protons since each water molecule contains two hydrogen atoms [5]. There are two spins of hydrogen dipole, a high-spin and a low-spin. Both the dipole and the magnetic field
are parallel to each other at low-spin. At high-spin, both the dipole and magnetic field are in anti-parallel directions. The magnetic moments (see Appendix A) of some of these protons become aligned with the direction of the field, when an object is subjected to powerful magnetic field of the scanner. A further varying magnetic field is created when the radio frequency (see Appendix A) transmitter is briefly turned on. The energy absorbed at the resonance frequency (see Appendix A) is a manifestation of photons of this field being absorbed and flipping the spins of the aligned protons in the tissue. The strength of the applied magnetic field determines the resonance frequency. These protons which absorb energy revert back to the original state. A transition from high-spin to low-spin is released as photons. That released energy is detected by the scanner and converted to an electric signal.

An image is constructed by noting the difference when different protons in different tissues return to their equilibrium state at different rates and that difference can be detected. The five tissue parameters that can be studied using MRI are as follows:

1) Spin density
2) T₁ relaxation time
3) T₂ relaxation time
4) Flow shift
5) Spectral shift

MR images reflect the distribution of one of the above mentioned parameters. Deliberate changes in MRI scanner settings can be used to create contrast between different tissues or different tissues properties. Spin density, T₁ and T₂ weighted images are used to study
anatomical features while flow or spectral shift properties are used to create functional images. The original 3D locations of the released photons can be recovered from the resulting signal by use of inverse Fourier transform.

Using MRI, we can possibly image every part of the body. Tissues with many hydrogen nuclei and little density contrast, such as the brain, muscle, connective tissue and most tumors are ideal candidates for MRI.

2.1.3 Basic MRI scans

2.1.3.1 T₁-weighted MRI

T₁ is a measure of the longitudinal relaxation time. The time it takes for hydrogen nuclei to recover back to 67% of original magnetization is called the T₁ value. Hydrogen nuclei in fatty tissue relax back to longitudinal B_0 axis at a different rate than hydrogen nuclei of the other tissue. T₁-weighted MR images represent the T₁ distribution across a field-of-view (FOV).

In T₁-weighted scans, fat is differentiated from water by making fat brighter and water darker. It uses gradient echo (GRE) sequence with short T_E and short T_R. An Inversion pulse can be used to increase the T₁ weighting as in an MP RAGE (magnetization-prepared rapid acquisition with gradient echo) sequence. Since T₁ weighting scans have short repetition time (T_R), data acquisition takes less time allowing the acquisition of high resolution 3D datasets.
In T₁ weighted images, one minimizes T₂ differences while maximizing T₁ differences in the tissue. Hydrogen in different tissues have different proton density as well as T₁ and T₂.

2.1.3.2 T₂-weighted MRI

T₂, also called transverse relaxation time is a measure of how long transverse magnetization would last in a perfectly uniform external magnetic field [52]. In other words, it is a measure of how long the resonating protons remain coherent or precess (rotate) in phase following a 90° RF pulse. It is a biological parameter used in MRIs to distinguish between tissue types. It is a tissue-specific time constant and is dependent on the exchange of energy between nearby nuclei [48].

T₂-weighted images are used to indicate where most of the contrast between tissues or tissue states manifests due to differences in T₂ measurement created typically by using longer Tₑ and Tᵣ times [49]. In T₂-weighted scans, fat is differentiated from water by making fat darker and water lighter. T₂*-weighted MRI scans use a GRE sequence, with long Tₑ and long Tᵣ. More details are found in [5].

2.1.3.3 Spin density weighted MRI

It uses spin echo or sometimes a GRE sequence, with short Tₑ and long Tᵣ. These show no contrast from either T₂ or T₁ decay. The only signal change comes from differences in the amount of available spins (hydrogen nuclei). Figure 3 describes the T₁, T₂ and proton density (spin density) weighted MR images of human brain.
2.1.4 Why Magnetic Resonance Imaging?

Magnetic resonance imaging (MRI) has gained a lot of popularity within last few decades [14]. In the near future, it is expected that MRI would gain more popularity with the implementation of new imaging techniques and sequences. Contrast resolution (see Appendix A for definition) is the principal advantage of MRI that enables it to visualize soft tissues of the body [50]. Hence, MRI is useful in imaging heart, brain, muscles and cancers as compared to other imaging modalities such as computed tomography (CT) or X-rays [5].

Spatial resolution (see Appendix A for definition) of MRI was not better than CT in the early years [14], but with rapid development of MRI technology, higher resolution such as 256x256 and even 512x512 became available for routine clinical work. MRI provides significantly better soft-tissue contrast than CT. Therefore, MRI is more suitable to separate abnormal soft tissues from normal tissues than other imaging modalities.
MRI has excellent sensitivity. However, the specificity (see Appendix A for definition) of this imaging modality may be inferior when compared to other imaging modalities [14]. Multiplanar imaging is a feature of MRI [14] that enables cross-sectional images on any plane without repositioning the patient. MRI allows to obtain images on any imaging plane without moving the patient on the MRI table. However, in other imaging modalities particularly CT, the imaging plane can be sagittal or oblique, and coronal images can be obtained only in some body parts. Hence in case of MRI, the tissue can be viewed from various angles [14].

MRI does not have potential harmful effects of ionizing radiation because MRI uses RF electromagnetic radiation and magnetic fields, which do not cause ionization [50]. MRI allows MR angiography (MRA). MRA (see Appendix A) allows to obtain vascular images without using any vascular contrast agent or any invasive procedure. Another advantage to MRI is the possibility of doing in vivo spectroscopy that allows one to analyze the biochemical properties and metabolic activities of the tissues. Similarly, many organs (e.g., posterior possa, spine) that cannot be studied with other techniques can easily be imaged with MRI. Also, MRI is considered a first line imaging modality in the head and spine.

2.1.5 Importance of Cardiac Image Segmentation using MRI

Cardiovascular research has gained importance to such an extent that the earmarked budget in United States alone for cardiovascular research was $2542 million in 2010 [38]. The estimate for cardiovascular research is similar in amount for the years 2011 and
2012, respectively. Though cardiac imaging can be accomplished by using several modalities, the most important modality among is cardiac MRI [15].

Cardiac MRI, cardiac CT, cardiac nuclear and cardiac ultrasound are the most popular among the several cardiac imaging modalities. No matter what cardiac imaging modality one uses, the clinical importance of cardiac boundary estimation has been highest [15]. The cardiac anatomy and performance analysis depend on accurate boundary estimation (see Appendix A). Cardiac boundary estimation also enables the cardiologists in their studies of cardiomyopathy (see Appendix for definition). The cardiac boundaries can be used to calculate the cardiac volume which in turn helps in calculating ejection fraction (EF). These boundaries are traced from frame to frame of cardiac cycle, and are used to study the behavior of the heart in relation to coronary heart disease. Cardiac boundary estimation can be done manually. However, this approach is not practical for large datasets. Hence, it is desirable to have automated and accurate boundary estimation.

### 2.2 Low and Medium Level Segmentation Techniques

As mentioned in [15], this section is mainly divided into three parts that are as follows:

1) Segmentation based on histogramming and thresholding
2) Cardiac edge detection
3) Mathematical morphological approaches for cardiac segmentation

#### 2.2.1 Thresholding Based Techniques

For thresholding based techniques, smoothing is the first step performed [15]. The drawback of smoothing, however, is that edge information can be lost. Hence edge-
preserving filters and region sharpening techniques are required. Nagao et al. in [17] presented a smoothing algorithm that sought the most homogeneous neighbourhood area around each point in an image and then assigned each point the average gray level of selected neighborhood. The advantage of this algorithm was that it not only removed noise in a flat region but preserved sharp edges at the same time. Besides, it also sharpened the blurred edges. Vonesh et al. in [18] examined digital subtraction (DS) techniques to reduce image noise from intravascular ultrasound data (IWD). They digitized and subtracted images using simple "mask-mode algorithm". Statistical comparison of the image sets showed that difference image data had significantly lower noise content than in the initial image sets. Lamberti et al. in [19] were the first to implement morphology-based smoothing. In [20], gray scale morphological smoothing was achieved by gray scale opening followed by grey scale closing.

Thresholding was generally conducted after smoothing. All the pixels having grey scale intensities above the threshold were classified as heart and rest of the pixels were classified as background [15]. Wollschleger et al. in [21] developed a frame-by-frame left ventricular contour detection algorithm. This algorithm was based on low pass filtering and interactive thresholding.

Revanakar et al. in [22-24] described several interactive thresholding schemes that were applied to echocardiograms. They described a collaborative method to extract the myocardium from a sequence of 2D echocardiograms. Morphologically adaptive thresholding scheme generated a rough estimate of the myocardium's contour. Later this estimate was refined collaboratively with the corrections specified by the user input via a
graphical user interface. The markings were mapped to an image processing scheme that provided further refinement.

Chow et al. in [25] introduced the concept of dynamic thresholding for cardiac images. They developed the cardiac boundary detection algorithm for cardio angiograms using dynamic thresholding. Chow's algorithm consists of the following steps.

- Divide the image into smaller regions. Then calculate histogram of each region.
- Choose histograms that exhibit large distributional variance and show that the variance of the region is a function of variance of the contrast agent, mean value of the contrast agent and the fraction of the area of the region occupied by the object.
- Distributed parameters namely the mean, variance and fraction of area of the object and background for the selected histograms underwent the bimodality histogram test.
- The quadratic equation is solved using the maximum likelihood formulation.

Chow's algorithm, however, was not robust enough to handle the grey scale distribution of X-ray cardiac dataset. Otsu in [26], described a nonparametric and unsupervised method to select a threshold automatically for image segmentation. The salient features of Otsu method are as follows:

- It uses discriminant analysis for selecting an optimal threshold.
- It is a simple procedure that requires the zeroth- and first-order cumulative moments of the gray-level histogram.
- It can be extended to multi-threshold problems.
2.2.2 Edge Based Techniques

Fu et al. in [27] surveyed various approaches to image segmentation. He reported that the existing image segmentation techniques were strongly application dependent. For example, the edge detection techniques were mostly used in chest X-ray image segmentation, while thresholding and clustering techniques were widely applied in all image segmentations. Both semantic and a priori information were critical to the solution of segmentation problem. Therefore, Fu et al. suggested combining spatial and semantic information with edge detection and thresholding or clustering techniques to perform image segmentation [27].

Grattoni et al. in [28] suggested an algorithm to outline the cardiac cavity from end-diastolic angiographic images in the right anterior oblique projection in human subjects. Grattoni et al. called the LV processing 'sui-generis', which meant they were subject to large variations from case to case. Grattoni's algorithm consists of four major steps:

- Low pass filtering is used to smooth the left ventricular images.
- The gradient directions are computed by a Sobel operator.
- Gradient image should be thresholded by keeping certain parts of the edges, which is done by computing the maximum of the gradient magnitude in the direction of its maximum rate of change of gradient.
- Connect the edge based information using a heuristic boundary follower.

Apicella et al. presented an approach for the measurement of ventricle volumes [2]. They defined a three step process. In the first step, the edges of ventricle are determined by using at least two images of heart. The first image is at a selected location of cardiac
cycle and the second image is a time delayed version of the first. These two images are subtracted leaving behind the boundary of ventricle. In the second step, portions of the image outside of the identified edges are classified as tissue and a selected portion of the data within boundary edges is classified as blood. The distribution of blood and tissue image intensities is fit to a pair of smooth curves which indicate the probability that a voxel of a given intensity is blood or tissue. In the step 3, contiguous voxels containing blood are counted or summed. The number of voxels along with voxel size are used to estimate the volume of the ventricle or other region of interest.

**2.2.3 Mathematical Morphology-based Techniques**

The watershed segmentation could not identify the correct edges in case of cardiac segmentation [15]. The watershed lines were very likely to dislocate the position of an edge. The approach taken by Suri [33] was also analogous to the watershed approach. He used elliptical bands to find the shoulder edges. Elliptical bands are generated from the classifier boundaries [83]. Besides, Suri used the knowledge of changing gradient angles along the curvature of the walls.

**2.2.4 Drawbacks**

Suri in [15] pointed out many drawbacks of low and medium-level segmentation techniques that are as follows:

- A major drawback of thresholding and histogramming is that images generated from these methods exhibit significant variability from dataset to dataset and may require user intervention.
• They are insensitive to local characteristics of the spatial distribution of intensities.

• Modeling of spatial neighborhood interdependence and temporal coherence are not exploited.

• They do not use prior distribution.

• The low-level techniques emerged as a sequence of steps, and the idea of involving hand-drawn techniques was not used extensively. Hence, the concept of fitting mathematical equations to justify the approach does not exist.

• As these approaches have many drawbacks, a better technique can be to use these approaches in conjunction with high-level techniques.

### 2.3 Model Based Pattern Recognition Methods

Model-based cardiac computer vision and pattern recognition methods use mathematical models to describe shape and other features. The premise behind these model-based techniques is finding a mathematical model that matches the cardiac shape, and then tailoring that mathematical model to fit the data. This fitting process involves estimating the fitting parameters using part of cardiac image data. These off-line parameters are then used in modeling the new cardiac data. The major contribution of model-based cardiac segmentation techniques is the automatic adjustment to the data size by changing the dimensions of the mathematical equations. Some of the features of model-based pattern recognition techniques are as follows [15]:

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Dynamic updates of model based techniques during the fitting process is one of the major advantages.

Model-based techniques have the ability to learn the shape or any other feature from a group of local pixels.

An important feature of these model-based techniques is to incorporate low-level features in their mathematical models. That adds robustness to the estimation system.

Model-based approaches are faster, accurate, reliable, robust and noise insensitive.

They require no thresholding.

They originate from mathematical formulations characterizing cardiac shape.

These models can be easily framed in a Bayesian framework where the priors can be estimated from a database of hand-drawn images.

These models can be optimized using energy minimization techniques.

Their computing power is tremendous as the models can be easily brought into matrix domain. Hence, due to high computing power, these models can handle a huge database of patient studies.

These models have a great learning capability and can be easily adapted to neural network and other machine learning methods.

Gupta et al. provided a semi-automatic approach in which the user initialized the approximate cardiac boundary [3]. After the initialization of the cardiac boundary, the algorithm generated contours for inner and outer walls, and automatically propagated
them to other slices in the End Diastolic (ED) phase (spatial propagation) and to slices in all phases (temporal propagation) of the cardiac study.

We can write 2D shape as follows:

\[ \nu(s) = (x(s), y(s)) \]  

(4)

where \( s = 1, 2, 3, \ldots n \) and

\( n \) is the total number of points on the contour \( C \).

The energy associated with the 2D shape can be written as follows:

\[ E = E_{geo} + E_{int} + E_{ext} \]  

(5)

where \( E_{geo} \) provides the geometric model for the object to be detected,

\( E_{int} \) is the internal energy in the contour and

\( E_{ext} \) is the external energy that drives the shape to the desired object and is derived from the image data.

To minimize energy, Gupta et al. used steep descent (SD) method and dynamic programming. Guttman et al. in 1997 developed an interactive beating heart model upon which these parameters including strain tensor, eigen values and eigen vectors of strain tensor, displacements and temporal derivatives can be displayed [29]. Their work yielded continual improvement in image acquisition, new experiments to obtain more detailed information about tissue viability, development of faster analysis tools and new ways to visualize the functional data.

George et al. in 2002 presented an integrated model-based processing scheme for cardiac MRI [30]. The model used different parameters including wall motion, myocardial
thickening and myocardial mass measurements. The sensitive task of discriminating the tissue type was handled by a trained neural network based classifier.

Pednekar et al. in 2002, presented an algorithm for automatic computation of EF that was based on cardiac segmentation by combining the fuzzy connectedness and deformable model frameworks [31].

Pluempitiwiriyawej et al. in April 2004, implemented STACS [1]. In this approach, the weighted combination of four models were used. These four models were translated into an objective functional with four different terms and the aim was to minimize this objective functional to facilitate the cardiac boundary classification [4]. The algorithm overcomes unique challenges by minimizing energy functional with four terms. The results are compared by using two similarity measures, ASM and SSM. The three different attractive features of STACS are as follows:

- It has an ability to segment images with low texture contrast by modeling stochastically the image textures.
- It is robust to initial contour and noise because of the utilization of both edge and region-based information.
- It has an ability to segment the heart from the chest wall and the undesired papillary muscles due to inclusion of heart shape priors.

A new segmentation algorithm was proposed in 2004 that automatically segmented the endocardium, epicardium and papillary muscles of left ventricle from short axis cardiac MRI data sets [34]. The algorithm was based on image intensity gradient analysis using
higher order derivatives and local parameterization to obtain reliable segmentation results.

Chenoune et al. in 2005 proposed an approach [35]. In that approach, first a segmentation process, based on level set method was directly applied on 2D+t dataset to detect endocardial contours. Secondly, the successive segmented contours were matched using a procedure of global alignment, followed by a morphing process based on level set approach.

Blok et al. proposed an approach that used long axis cardiac MRI images. This approach detects the contour by using adaptive virtual exploring robot [36]. Yushkevich et al. in [37] described a method to perform segmentation of anatomical structures using user guided level sets.

Shang et al. produced a novel method for segmentation of 4D cardiac images [39]. The proposed method improved the traditional active shape model method by adopting a 3D spatially hierarchical expression of shape model, which was used as an internal regulation force during segmentation process.

Zhu et al. proposed a new algorithm that is motivated by approximate incompressibility of myocardium during a cardiac cycle and takes it as an important constraint [40]. They designed a probabilistic framework that includes a deformable model which evolves according to regional intensity distribution while maintaining volume of myocardium.

Depa et al. in 2010, demonstrated an automatic method for left atrium segmentation using weighted voting label fusion and a variant of demons registration algorithm adapted to handle images with different intensity distributions [42].
Model based pattern recognition techniques are divided into two categories

- Training based cardiac fitting.
- Cardiac active contour models in spatial and temporal domains (energy minimization).

2.3.1 Training Based Cardiac Fitting (or Learning Based Cardiac Fitting)

Training based cardiac fitting includes boundary fusion models, cardiac apex model, cardiac neural network models and general purpose training-based validation model for the validation of cardiac segmentation. It also includes fusion of low level features in cardiac models.

2.3.2 Cardiac Active Contour Models in Spatial and Temporal Domains (Energy Minimization)

Cardiac active contour based models utilizes energy functions. Methods such as cardiac super quadratic fitting, snake fitting in temporal and spatial domain, STACS etc., belong to this category. Cardiac ballooning is another interesting approach. In this approach, a polygon is approximated to a sphere and the geometrically deformed balloon model is evolved until the balloon surface conformed to the objects' surface in 3D data. Many of the techniques described in this section have been developed for LV segmentation, but can be extended for other cardiac segmentation applications.
Chapter 3: Comparison of Different Cardiac Image Segmentation Algorithms

The basic aim of this chapter is to describe and compare the approaches that I have implemented. Section 3.1 describes the MRI input data used in the implementation of cardiac segmentation algorithms. Section 3.2 of this chapter discusses the cardiac image segmentation using morphological operator. The cardiac boundary obtained by applying morphological operators can be used as a contour initialization for the model based pattern recognition approaches including snake model, snake model with ellipse, snake model with stages, snake model with ellipse and stages and STACS. Hence, enabling the fully automatic cardiac image segmentation. Section 3.3 describes the snake model in detail. Two innovative ideas have been incorporated in the snake model that produced better results. The first idea is to incorporate a shape prior i.e., ellipse in the snake model. Secondly, the concept of stages should be introduced in the snake model. These two ideas formed the basis of two new approaches i.e., snake model with ellipse and snake model with ellipse and stages, that are described in Section 3.4 and Section 3.5 of this chapter. Section 3.6 describes the STACS in detail.
3.1 Description of MRI Data

2D cardiac MRI data for rat and mouse have been used in the implementation of cardiac segmentation algorithms. The data comprises of 2D frames corresponding to a full cardiac cycle. The acquisition parameters including T₁ weighted images, matrix size, repetition time, echo time, the number of averages, field of view, resolution and flip angle are defined in Appendix A, and their values are as follows:

- T₁ weighted images are used. All MRI image frames were taken along the short axis.
- Matrix size for MRI image is 256x192 pixels.
- Repetition time for input data is taken to be 8 ms for rat or 16 ms for mice.
- Echo time for input data was taken to be 1.6 ms.
- The number of averages for the data was taken to be 8.
- Field of view was taken to be 5.1 cm² for rat and 3 cm² for mice.
- The resolution was 2 mm in one direction and 2.6 cm in other direction for rat.
  The resolution was 1.2 mm in one direction and 1.6 mm in other direction for mice.
- Flip angle for the input data was taken to be either 10° or 15°.

3.2 Cardiac Image Segmentation using Morphological Operators

In this approach, different morphological operators and image processing techniques including image dilation and erosion were applied to get the cardiac image boundary. The approach worked well especially for initializing the contours and hence can be used in
combination with model-based cardiac image segmentation techniques. The weakness of this approach was revealed by the fact that it required thresholding; intelligent thresholding can be used to overcome this shortcoming.

In Figure 4 (a), the original image is shown. The image was then converted to its binary form (shown in Figure 4 (b)). The binary image contained noise in the form of small openings or holes. To remove those small unwanted features, image dilation was used.

After applying the dilation operation on the image in Figure 4 (b), we obtained the image shown in Figure 4 (c). The drawback of the dilation operation can be seen in part (c), as containing a lot of noise in the form of small white dots. In order to get rid of this noise, erosion is applied two times to the image in part (c). After applying the erosion operator for the very first time, the noise was reduced as shown in Figure 4 (d). However, the unwanted noise still existed, that motivated me to apply erosion again to remove that unwanted noise. After applying erosion operation the second time, the resulting image is shown in Figure 4 (e). As estimating the cardiac boundary was the main goal of this task, difference operator can be used to find the edges of the binary image shown in Figure 4 (e). Images in Figure 4 (f) and (g) are obtained by applying difference operator in horizontal and vertical direction respectively. The addition of these images creates a sharper image as shown in Figure 4 (h). But if the image in Figure 4 (h) is closely analyzed, it can easily be predicted that the largest component (or an edge) in the whole image was itself a cardiac boundary. Hence, an algorithm that finds the largest connected component was applied to an image of Figure 4 (h). The resultant image containing only the sharp cardiac segmentation boundary is obtained in Figure 4 (i).
Figure 4. Shows the result of application of different morphological operators to find the cardiac boundary. (a) Original contour, (b) Binary image, (c) Image obtained after applying image dilation, (d) Image obtained after applying erosion, (e) Image obtained after applying erosion again, (f) Image obtained after applying difference operator horizontal to the image of part e, (g) Image obtained after applying difference operator vertically to image of part e, (h) Image obtained after adding images of part f and g, and (i) Largest connected component used to initialize cardiac segmentation.
3.3 Snake Model

Kass et al. in 1998 presented an energy-minimizing spline guided by energy functionals that pulled the spline towards features such as lines and edges in the image [44]. These energy minimizing splines were called snake because the spline made the contour slither while minimized the energy at the same time. Snakes can be considered as a member of more general class of techniques that matched a deformable model to an image by means of energy minimization. The contour was initialized by the user, and then snake deformed itself into conformity with the nearest salient contour. The snake based method differed from other traditional approaches of detecting edges and then linking them. The active contour model of the snake is based on a variational approach.

In order to make snakes useful for methods of early computer vision, energy functionals were required that attract them to salient features in images. In this thesis, three different energy functionals are implemented [44]. They attract a snake to lines, edges and terminations. These three energy functionals are written below:

- Line functional \( E_{line} \)
- Edge functional \( E_{edge} \)
- Termination functional \( E_{term} \)

The total image energy can be expressed as a weighted combination of these three energy functionals [44] as written below in Eq. 6:

\[
E_{image} = w_{line}E_{line} + w_{edge}E_{edge} + w_{term}E_{term}
\]  

(6)

A wide range of snake behavior can be created by adjusting the weights.
Line functional is the simplest and the most useful image functional. It is the image intensity itself and can be written in Eq. 7 as follows:

$$E_{\text{line}} = I(x, y) \quad \text{where \quad} I(x, y) \text{ is an image}$$

(7)

The snake will be attracted to either light or dark lines depending on the sign of weight associated with $E_{\text{line}}$. The snake movement continues until it aligns itself with the lightest or darkest nearby contour. In other words, it can be implied that the snake moves rapidly to the positions of peak intensity.

Edge energy is based on the gradients of an image. In this implementation, $E_{\text{edge}}$ is equal to the negative of square of gradient value for each pixel. It is expressed by the Eq. 8 as follows [44]:

$$E_{\text{edge}} = -|\nabla I(x, y)|^2$$

(8)

where $\nabla$ is the discrete gradient operator.

$E_{\text{edge}}$ forces snake to move towards the direction of large image gradients. This phenomena is explained in Figure 5. In the upper left portion of the figure, the user has pulled the part of snake off the pear. The remaining images (upper right, lower left and lower right images) in the illustration show the snake snapping the contour back rapidly to the boundary of the pear. Termination functional is the another energy functional. Curvature of level lines in a slightly smoothed image is used to find the terminations of line segments and contours. This curvature of level lines is denoted as $E_{\text{term}}$. The image is convolved with the Gaussian to get a slightly smoothed version denoted as $C(x, y)$ that is shown in the Eq. 9 as follows:

$$C(x, y) = G_{\alpha}(x, y) * I(x, y)$$

(9)
Figure 5. In the upper left of the figure, the user has pulled a snake away from the edge of the pear. The snake snaps back to the edge of pear as shown in upper right, lower left and lower right portions of the figure [44].

Let \[ \theta = \tan^{-1}(C_y / C_x) \] be the gradient angle,

\[ n = (\cos \theta, \sin \theta) \] be a unit vector along the gradient direction

\[ n_\perp = (-\sin \theta, \cos \theta) \] be a unit vector perpendicular to gradient direction

Then \[ E_{\text{term}} \] is written in Eq. 10 as follows:

\[
E_{\text{term}} = \frac{\partial \theta}{\partial n_\perp}
\]

\[
= \frac{\partial^2 c / \partial n_\perp^2}{\partial c / \partial n}
\]

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By combining the $E_{edge}$ and $E_{term}$ of the Eqs. [10] and [11], a snake can be created that is attracted to edges or terminations.

Figure 6 shows the subjective quality of images obtained after applying the snake model. Figure 6 (left) shows the contour obtained after initialization. Initialization can be conducted using either the manual or automatic methods. In this thesis, I implemented manual initialization as well as automatic initialization for the snake model. The automatic initialization was performed using the morphological operators as defined in Section 3.1. In Figure 6, the left image contains the manually initialized contour. Then snake model is applied on it and the final image is obtained that is shown in the right image of same figure. While minimizing the energy, the snake model also makes the contour slither around the cardiac boundary, as can easily be observed in the right image of this figure.

Figure 6. On the left is initialized snake contour while on the right is the final snake contour.
The MRI image data used in the thesis contained a cardiac cycle consisting of 12 frames. That cardiac cycle can be divided into systolic phase and diastolic phase (defined in the Appendix A). The snake model is applied to cardiac MRI image frames during both systolic and diastolic phases. The subjective quality of the results obtained after applying the snake model during the systolic phase is shown in Figure 7. Figure 7 (left) contains the contour obtained after applying the snake model to the previous frame which provides a good initialization for the current frame. In this way, the temporal information is also used for cardiac contour initialization. The Figure 7 (right) contains the resultant image obtained after applying the snake model to the image of Figure 7 (left). After seeing right image contour, it can easily be inferred that the left image contour underwent a contraction after the application of the snake model, which is an expected behavior for snake model in the systolic phase (see Appendix A).

![Figure 7. Systolic phase. The image on the left is the snake contour initialized from previous frame. The image on the right is the final snake contour.](image)

The subjective quality of the results obtained after applying the snake model during the diastolic phase is shown in Figure 8. Figure 8 (left) uses the contour of previous frame as
a contour initialization for the current frame. By using temporal information in the previous frame, the contour of current frame is initialized. Figure 8 (right) contains the resultant image obtained after applying snake model to the left image. It can be easily inferred that left image underwent a contour expansion after application of snake model.

![Figure 8. Contouring in diastolic phase. On the left is the snake contour initialized from previous frame. On the right is the final snake contour.](image)

### 3.3.1 Drawbacks

The drawbacks associated with snake model are as follows:

- If the snake is initialized “too far” from the object boundary, it is possible that the contour may not be able to converge to the correct boundary.
- If the energy scaling factor is “too big” for a given image, snake can still converge onto image boundary but keeps on wiggling along the object boundary.
- For images with high gradient values, the results are extremely sensitive to $E_{edge}$ value.
3.4 Snake Model with Ellipse

The snake model does not exploit the cardiac shape, which resembles an ellipse. An inclusion of a shape prior can potentially improve the performance of the snake method. Finally, an elliptical prior was used to approximate the heart shape during both the systolic and diastolic phases of cardiac cycle. To incorporate the concept of ellipse in the snake model, we modify the image energy functional in Eq. 6 to add a fourth term, yielding the Eq. 12 as follows:

$$E_{image} = W_{line}E_{line} + W_{edge}E_{edge} + W_{term}E_{term} + W_{shap}E_{shap}$$  \hspace{1cm} (12)

Energy of the cardiac shape was calculated using the principal component analysis (PCA). The PCA computes two matrix eigen-vectors and eigen-values of the snake contour from the previous frame and uses them to generate an ellipse as shown in Figure 9.

Figure 9. Snake model with ellipse shape control energy.

However, there was a problem using the $E_{shap}$ in the image energy. The current contour matrix is based on the previous frame snake result, and thus influences the computation
of future frames. Hence, if the snake contour moves in the incorrect direction in a particular frame, the subsequent frame will also be wrong as shown in Figure 10. It is due to the fact, that our snake implementation uses temporal information of cardiac frames i.e., current frame computation depends on the snake results of previous frame.

Figure 10. A limitation using shape prior from the previous frame. The ellipse axis computed from the previous frame are not accurate for the current frame shown in the figure.

3.5 Snake Model with Ellipse and Stages

A cardiac cycle consists of systolic or diastolic phases. In the systolic phase, the cardiac boundary contracts. Similarly, cardiac boundary expands in diastolic phase. The cardiac movement is depicted in the Figure 11.

Figure 11. Cardiac boundary movement. Frame numbers are represented along x-axis and number of pixels (enclosed in the cardiac boundary) are represented along y-axis.
Time, or frame number, is used as x-coordinate whereas cardiac area (in terms of number of pixels) enclosed by the contour is used as y-coordinate in the Figure 11. The intuition in Figure 11 can be used to further improve the snake model. For example, from figure 11, it is easy to deduce that frame 9 belongs to diastolic stage. Similarly, if frame number 41 is given, then it can be implied from the figure that it belongs to systolic stage. The distance between the point on cardiac contour and the cardiac center can be used to predict contour movement from frame to frame.

If it is systolic phase, then the distance of each point \((x, y)\) on the cardiac contour from the cardiac center is only allowed to decrease. In other words, if the new computed point \( (x_n, y_n) \) on the cardiac contour increases the distance \((dist = ||\text{snake}(x_n, y_n) - \text{center}||)\) then the snake contour would keep the previous point \((x_p, y_p)\) and will not update the contour with the new computed point \((x_n, y_n)\). However, if the new computed point \((x_n, y_n)\) on the cardiac contour decreases the distance \((dist = ||\text{snake}(x_n, y_n) - \text{center}||)\) then the snake contour would update the previous point \((x_p, y_p)\) with the new computed point \((x_n, y_n)\).

In diastolic phase, distance of each point \((x, y)\) on the cardiac contour from the cardiac center is only allowed to increase. In other words, if the new computed point \((x_n, y_n)\) on the cardiac contour decreases the distance \((dist = ||\text{snake}(x, y) - \text{center}||)\) then the snake contour would keep the previous point \((x_p, y_p)\) and will not update the contour with the new computed point \((x_n, y_n)\). However, if the new computed point \((x_n, y_n)\) on the cardiac contour increases the distance \((dist = ||\text{snake}(x, y) - \text{center}||)\) then the
snake contour would update the previous point \((x_p, y_p)\) with the new computed point \((x_n, y_n)\).

By introducing the concept of stages, the problem mentioned in the previous section (Section 3.3) can be solved as shown in Figure 12.

![Snake model segmentation with ellipse-shape control energy and stages.](image)

Figure 12. Snake model segmentation with ellipse-shape control energy and stages.

### 3.6 STACS: Stochastic Active Contour Scheme for Cardiac MR Image

**Segmentation**

STACS is a novel approach for automatic cardiac image segmentation [4]. STACS can be placed in model based pattern recognition techniques, more specifically active contour models (energy minimization techniques) as defined in Section 2. STACS minimizes an energy functional that combines stochastic region-based and edge-based information with cardiac shape priors and local properties of the contour. STACS includes an annealing schedule that dynamically balances the weight of different terms in the energy functional. The application of STACS to a set of 12 cardiac MR frames shows that it can successfully segment the heart from its surroundings. STACS automatically generated
contours are compared with manually-traced contours using three different parameters including area of contour, ASM and SSM. The assessment demonstrates very good and consistent segmentation performance of STACS.

Broadly speaking, the main goal of STACS is to develop a method that automatically locates a contour $C$ that separates the pixels belonging to the heart from the pixels belonging to the background. To achieve this goal, the STACS uses four energy functionals named as model matching ($J_1$), edge information ($J_2$), shape priors ($J_3$) and contour smoothness ($J_4$). These four energy functionals can be combined into an objective functional in Eq. 13 as follows:

$$J(C) = \lambda_1 J_1(C) + \lambda_2 J_2(C) + \lambda_3 J_3(C) + \lambda_4 J_4(C), \quad (13)$$

where $\lambda_1$, $\lambda_2$, $\lambda_3$ and $\lambda_4$ are the parameters that control the relative strength of each of the terms $J_1$, $J_2$, $J_3$ and $J_4$ respectively.

With the contour $C$ embedded as the zero of the level set function $\Phi(x, y)$ i.e.,

$$C = \{(x, y) \in \Omega : \Phi(x, y) = 0\}, \quad (14)$$

The energy function $J(C)$ becomes

$$J(\Phi) = \lambda_1 J_1(\Phi) + \lambda_2 J_2(\Phi) + \lambda_3 J_3(\Phi) + \lambda_4 J_4(\Phi). \quad (15)$$

### 3.6.1 Region based term: Model Matching ($J_1(\Phi)$)

In the region based term, it is assumed that pixels inside and outside the heart follow different stochastic models. The intensities of the pixels that belong to heart are modeled by a stochastic model, named as $M_1$. Similarly, intensities of the pixels that belong to background are described by another stochastic model $M_2$. The segmentation task partitions the image pixels $\{(i, j) \in \Omega \}$ into two regions, separated by a contour $C$. The
region inside the contour \(C, \Omega_1\), represents an object and intensity values of the pixels in this region are shown in Eq. 16 as follows:

\[
\mathbf{u}_1 = \{u_{ij}; (i,j) \in \Omega_1\} \tag{16}
\]

The region outside the contour \(C, \Omega_2\), represents the background and the corresponding intensity values of the pixels in this region are shown in Eq. 17 as follows:

\[
\mathbf{u}_2 = \{u_{ij}; (i,j) \in \Omega_2\} \tag{17}
\]

When the contour \(C\) is embedded as zero level of the level set function \(\phi\), the final Eq. [18] is given as follows:

\[
J_1(\phi) = \int (-\ln[p_1(u(x,y))]H(\phi(x,y)) - \ln[p_2(u(x,y))][1 - H(\phi)]) \, dx \, dy
\]

\[
(18)
\]

where \(H(\phi) = \left(\frac{1}{2}\right) \left[1 + \left(\frac{\phi}{\pi}\right) \tan^{-1}(\phi/\varepsilon)\right]\) is the regularized heaviside function,

\[
H(\phi) = \begin{cases} 
1 & \text{if } \phi > 0 \text{ i.e., pixels are inside the contour} \\
1/2 & \text{if } \phi = 0 \text{ i.e., pixels are on the contour} \\
0 & \text{if } \phi > 0 \text{ i.e., pixels are outside the contour}
\end{cases}
\]

\(p_1\) is the probability density function (pdf) associated with the model \(M_1\),

\(p_2\) is the probability density function (pdf) associated with the model \(M_2\) and

\(\Phi\) is a level set function.

It can easily be observed that regularized Heaviside function \((H(\phi))\) indicates the pixels within the contour (as can be seen above that \(H(\phi)=1\) when pixels are inside the
contour). Similarly, \(1 - H(\Phi)\) represents the pixels outside the contour (as \(H(\Phi) = 0\), so \(1 - H(\Phi) = 1\) when pixels are outside the contour).

The probability density functions \((p_1\) and \(p_2\)) corresponding to the two regions \(\Omega_1\) and \(\Omega_2\) are shown in Figure 13 as histograms:

![Figure 13. Histograms \((p_1\) and \(p_2\)) of two regions \(\Omega_1\) and \(\Omega_2\)](image)

When only \(J_1\) (region based term) applied to image with an initialized contour, the contour starts converging to the cardiac boundary as shown in Figure 14 as follows. Figure 14 (a) shows the initialized cardiac contour. Then the \(J_1\) shown in above equation was applied to it and contour moved towards the cardiac boundary as shown in part (b). After applying few more iterations, the contour moved more closely to the cardiac boundary but still gaps are left behind as shown part (c). After few more iterations, the final image is shown.
in part (d). In that image, the contour is more close to the original cardiac boundary and there is no gap between contour and cardiac boundary. However, the contour is bit jagged. To reduce this jaggedness, STACS implements contour smoothing term \( J_4 \).

![Figure 14](image)

Figure 14. Showing the result of applying model \( J_1 \). (a) The original contour, (b) Intermediate iteration: contour moves closely to cardiac boundary but still there are few gaps, (c) Intermediate iteration: contour is more closed to the cardiac boundary. But still there are some gaps in right and lower right regions of cardiac boundary and (d) Final iteration: contour has moved accurately to the cardiac boundary. There are not much gaps left. But still cardiac boundary is bit jagged. To overcome this jaggedness, contour smoothing term \( J_4 \) is introduced.
3.6.2 Edge-Based Term ($J_2(\Phi)$)

The basic principle of the edge based term is that contour should be attracted to clues given by prominent edges in the edge map of image [4]. To make the contour attracted to prominent edges, the edge map ($Y(x, y)$) that is derived from the original image $u(x, y)$, needs to be minimized.

When the contour $C$ is embedded as the zero level set of $\Phi$, we get the Eq. 19 as follows:

$$J_2(\Phi) = \int_{\Omega} Y(x, y)|\nabla H(\Phi(x, y))| \, dx \, dy \tag{19}$$

$$J_2(\Phi) = \int_{\Omega} Y(x, y) \delta_e(\Phi(x, y)) |\nabla \Phi(x, y)| \, dx \, dy \tag{20}$$

where $Y(x, y) = -|\nabla G_\theta * u(x, y)|$ and

\[
\begin{cases}
G_\theta \text{ is the 2-D Gaussian kernel with variance } \theta_2 \\
\nabla \text{ is the gradient operator} \\
* \text{ is the 2D convolution operator} \\
The 2-D Gaussian Kernel is used to smooth out the noise, thus helping to eliminate spurious edges that may occur after applying gradient
\end{cases}
\]

$$\nabla H(\Phi(x, y)) = \frac{d(H(\Phi))}{d\Phi} |\nabla \Phi(x, y)|$$

$$= \delta_e(\Phi(x, y)) |\nabla \Phi(x, y)|$$

\[
\begin{cases}
\delta_e(\Phi(x, y)) = \frac{d(H(\Phi))}{d\Phi} \text{ defines} \\
\text{the pixels that are on the contour}
\end{cases}
\]

To examine the results exclusively for the term $J_2$, only operators from this term is applied to the Figure 15 (a). The Figure 15 (a) contains the original image with initialized contour. Figure 15 (b) shows the image obtained after intermediate iteration. In this image, the contour moves towards the cardiac boundary but still gaps are present between the contour and the cardiac boundary. As it is mentioned that the basic principle of the
An edge based term is that the contour should be attracted to clues given by prominent edges in the edge map of image. That is why, the edge map that is derived from the original image $u(x, y)$ need to be minimized. In Figure 15 (c), it can be observed that the contour moves closely to the prominent edges i.e., cardiac boundary of the image. There are small gaps still left in the upper left and lower right regions of part c. These gaps are mostly filled in the Figure 15 (d).

Figure 15. Showing the result of applying model $J_2$. (a) The original contour, (b) Intermediate iteration: contour moves closely to cardiac boundary but still there are few gaps, (c) Intermediate iteration: contour is very close to cardiac boundary. Upper left and lower right regions still have some gaps and (d) Contour is almost moved to prominent edges i.e., cardiac boundary.
3.6.3 Shape Prior Term ($J_3(\Phi)$)

Due to low contrast and similar texture between the tissues to be segmented, region based terms ($J_1$) and edge based terms ($J_2$) cannot themselves segment the heart and its chambers successfully [4]. Reasonable knowledge exists about the shape of the heart. Incorporating wide range of shapes into our model seems to yield promising results. Hence, incorporating a parametrically described shape prior, including an ellipse into this active contour scheme produced better results.

Primarily, we need to minimize the following Eq. 21:

$$J_3(C) = \int_{\Omega} D^2(x,y) \, ds$$

(21)

where $D(x,y)$ is the ellipse distance function defined as

$$D(x,y) = \tilde{a}x^2 + \tilde{b}xy + \tilde{c}y^2 + \tilde{d}x + \tilde{e}y + \tilde{f}$$

(22)

Embedding $C$ as the zero level set function $\phi(x, y)$, $J_3$ can be written in Eq. 23 as follows:

$$J_3(\Phi) = \int_{\Omega} D^2(x,y) \delta_e(\phi(x,y)) |\nabla \phi(x,y)| \, dx \, dy$$

(23)

where $D(x,y)$ is another level set function, representing the distance to the ellipse contour,

$\delta_e(\phi(x,y))$ is the regularized delta function that selectively masks out only the pixels on the contour $C$ and

$|\nabla \phi(x,y)|$ is the magnitude of gradient $\phi(x,y)$.

To see the results exclusively for model $J_3$, this model is applied in Figure 16 (a). This figure contains the original image with initialized contour shown in blue color and ellipse boundary shown in red color. Ellipse boundary is estimated using the boundary of
initialized contour. Figure 16 (b) shows the intermediate iteration. The main aim is to minimize the distance $D(x, y)$ i.e., minimizing the distance of active contour from the ellipse boundary. It is done by moving the contour towards the ellipse boundary. The contour now moves towards the ellipse boundary but still gaps are present between the contour boundary and the ellipse boundary. In Figure 16 (c), it can be observed that the contour moves closely to the ellipse contour. There are small gaps still left in the upper left and lower right regions of part c. In Figure 16 (d), the distance of the ellipse from the active contour is reduced. It can be safely said that distance of active contour from the ellipse boundary is almost equal to zero and that is the basic objective of this model.

In Figure 17 (a), I selected an initial contour that is not smooth at all. In fact, the boundary of that contour is made very random in shape to study the behavior of the model $J_3$. In Figure 17 (b), the active contour moves close to ellipse boundary and at the same time, it become more smooth as compared to its shape in part a. In Figure 17 (c), the shape of active contour is smooth and it is very close to the elliptical shape. However, still there are gaps in upper left, upper right and lower right region. In part d, the active contour is almost on the ellipse boundary and distance $D(x, y)$ is almost zero.

In Figure 18 (a), the active contour boundary is initialized as a highly distorted curve to exploit the behavior of this model for the worse case. In order to study the behavior of this model independently over the diverse input, the different contour boundary initializations were made. The blue color boundary is shown as the initialization of the contour and the red color boundary is the boundary of the ellipse. In Figure 18 (b), the active contour becomes smoother as compared to the initialized contour in part a.
However, still more smoothness is required. As already mentioned, the main aim of this model is to reduce $D(x,y)$ i.e., the distance between the cardiac boundary and ellipse boundary. Figure 18 (c) shows the active contour boundary after few more iterations. The active contour boundary in part c is much smoother than the cardiac boundary in Figure 18 (a) and (b). At the same time, the distance $D(x,y)$ is also minimized in part c as compared to Figure 18 (a) and (b). In Figure 18 (d), the contour is almost as smooth as the ellipse boundary and the distance ($D(x,y)$) between the active contour and ellipse boundary is almost zero. Hence, it can easily be observed from Figures 16-18, that the shape prior model $J_3$, minimizes the distance ($D(x,y)$) between the ellipse contour and active contour as well as contributes towards smoothing the active contour. Different shapes other than ellipse can be exploited in order to yield better results.
Figure 16. Showing the result of applying model $J_3$. (a) The original contour, (b) Intermediate iteration: contour moves closely to ellipse boundary but still there are few gaps, (c) Intermediate iteration: contour is very close to ellipse boundary. Upper left region has more gaps and (d) Final iteration: contour is almost on the ellipse boundary.
Figure 17. Application of $J_3$. (a) Original contour, (b) Intermediate iteration: contour moves closely to ellipse boundary but still there are few gaps, (c) Intermediate iteration: contour is very close to ellipse boundary. Still there are few gaps in the upper left, upper right and lower right region and (d) Final Iteration: contour is almost on the ellipse boundary. There are very small gaps in the upper left region of the image.
Figure 18. Application of $J_3$. (a) The original contour, (b) Intermediate iteration: contour moves closely to ellipse boundary but still there are few gaps, (c) Intermediate iteration: contour is very close to ellipse boundary. Still there are gaps between active contour and ellipse boundary and (d) Active contour is almost on the ellipse boundary, hence the distance $D(x, y)$ between active contour and ellipse boundary is almost zero.
3.6.4 Contour Smoothing Term \((J_4(\Phi))\)

Contour smoothness is the last term used for cardiac segmentation. Smoothness is achieved by minimizing the total Euclidean arc length of the contour \(C\) [4]. In other words, we minimize the following functional written in Eq. 24:

\[
J_4 = \int_C ds
\]  

(24)

where \(ds\) is the total Euclidean arc length of the contour \(C\)

The Eq. 24 can be re-written in terms of levels set function \(\Phi(x, y)\) in Eq. 25 as follows:

\[
J_4(\Phi) = \int_{\Omega} \delta_e(\Phi(x, y)) |\nabla \Phi(x, y)| \, dx \, dy
\]  

(25)

where \(\delta_e(\Phi(x, y))\) is the regularized delta function and

\(|\nabla \Phi(x, y)|\) is the gradient of \(\Phi(x, y)\).

If this contour smoothing model \((J_4)\) is minimized alone, then the contour will evolve to become a circle as can be seen in Figure 19. The effects of applying the model \(J_4\) alone is shown in detail in Figure 19. The part a shows the manually initialized contour. While initializing the contour, I distorted it to see the behavior of the model \(J_4\) on this input. Figure 19 (b) shows the contour gets more smooth and ultimately in Figure 19 (c), the contour becomes very smooth. In the last iteration, the contour can be compared with the shape of the circle. If continued while applying the model \(J_4\) alone the contour shrinks in the form of a circle, withers away and completely disappears. However, if we use this model with other three models \((J_1, J_2\) and \(J_3\)), the conjugate effect of \(J_4\) prevents this, and the effect of the \(J_4\) term is only to force the contour smoothness.
Figure 19. Showing the result of applying model Application of \( J_4 \). (a) Original contour manually initialized with more distortion, (b) Intermediate iteration: contour starts getting more smooth and at the same time contour moves towards the cardiac boundary, (c) Intermediate iteration: contour become more smooth and (d) Final iteration: contour become very smooth approximating a circle.
3.6.5 STACS using Region-based term ($J_1$), Edge-based term ($J_2$), Shape Prior term ($J_3$) and Contour Smoothing Term ($J_4$)

In this section, the weighted combination of all the four models shown in Eq. 17 is applied to the initialized contour of the part (a) of Figure 20. The values of the weighting parameters ($\lambda_1$, $\lambda_2$, $\lambda_3$ and $\lambda_4$) are chosen empirically based on my cumulative experience developed after testing the minimization algorithm with many different data.

The weighted combination of these four models is applied to the image in Figure 20 (a). The part b, shows that contour start moving closely towards the cardiac boundary. In the initial iterations i.e., Figure 20 (a) and (b), the region and edge-based terms, $J_1$ and $J_2$ are the main drivers of the minimization process forcing the initial contour to evolve closely to the relevant boundaries. In later iterations, the shape prior becomes an important feature, since, the contour should resemble the assumed shape prior i.e., ellipse as shown in Figure 20 (c) and (d). Hence, the weights ($\lambda_i$) should adapt and evolve as the segmentation proceeds. I assign more weight to $\lambda_1$ and $\lambda_2$ in the initial iterations as the region-based terms and edge-based terms are more important. In later iterations, I gave more weight to $\lambda_3$ as shown in Figure 20 (c) and (d), because eventually the shape of the contour is required to resemble with ellipse.
Figure 20. Showing the result of applying the weighted combination of four models. (a) Original manually initialized contour, (b) Intermediate iteration: contour starts moving towards the cardiac boundary, (c) Intermediate iteration: contour become more closed to the cardiac boundary but still there are gaps in the upper left and lower right regions and (d) Final Iteration: Contour becomes very close to cardiac boundary such that the distance between the contour and the cardiac boundary is minimum.
Rendering algorithm has been developed on the basis of 8-neighbours. For each pixel and its 8 neighbors, the energy (obtained by the weighted combination of four models of STACS) is calculated. Out of those nine choices (of pixel), one is chosen having the least energy. An effective rendering algorithm was developed to overcome few challenges including branching and clustering. Branching and clustering have been reduced by using the following approaches:

(i) Centroidal based averaging

(ii) Simple averaging

In centroidal based averaging, first we calculate the centroid of the contour. Centroid is calculated as follows:

\[
x_c = \frac{\sum (x - \text{coordinates of the points on the contour})}{\text{total no. of points}}
\]

\[
y_c = \frac{\sum (y - \text{coordinates of the points on the contour})}{\text{total no. of points}}
\]

Then we calculate the Euclidean distance of each point on the contour from the centroid \((x_c, y_c)\). Then for each point \((x, y)\), we define the window of five points. We take the centroidal distance of two points before point \((x, y)\) and centroidal distance of two points after point \((x, y)\). If the centroidal distance of current point \((x, y)\) is in the middle of centroidal distance of these four points then the point is at right place. Otherwise, centroidal distance of current point \((x, y)\) is re-calculated by taking the average of centroidal distance of these four points and assign it to current point.

Simple averaging is also done using the window size of 5 points. For each point \((x, y)\) on the contour, two points were taken before that point \((x, y)\) and two points were taken
after the point \((x, y)\). Then simple average value of all these five were assigned to that point \((x, y)\).

In the case of STACS implementation, another smoothing term is added to make the cardiac boundary more smooth.
Chapter 4: Statistical Results

This section describes the statistical results of the implemented approaches of Chapter 3. The statistical results are based on objective measures including area of region inside a contour $c$, ASM and SSM. These objective measures enable us to present good comparison between the implemented approaches including snake model, snake model with ellipse, snake model with stages, snake model with ellipse and stages and STACS. The subjective measure for these implemented approaches is given in Appendix B. The data for the implementation of these approaches is the cardiac cycle consisting of 12 MRI image frames of systolic and diastolic stages. Section 4.1 deals with the area of region inside the contour. This section presents the results containing the area of region inside the contour for all the considered methods in the form of Table 1 and corresponding graph shown in Figure 21. Section 4.2 presents the results of ASM in Table 2 and corresponding graph show in Figure 22. Section 4.3 presents the results of SSM in Table 3 and Figure 23.

4.1 Area of region inside contour

Table 1 shows the area of region inside the contour (in terms of number of pixels) using 12 MRI frames of a cardiac cycle consisting of systolic and diastolic stages. The first column shows the frame numbers. Areas shown in column 2 are obtained using the
manually segmented cardiac frames. Areas of the contour calculated manually are taken as reference. Areas calculated using snake model, snake model with ellipse, snake model with stages, snake model with ellipse and stages and STACS are shown in the column 3 to column 7 respectively. The data of Table 1 is presented in the Figure 21 as well to give graphical view of the same data.

<table>
<thead>
<tr>
<th>Frame</th>
<th>Manually</th>
<th>Snake Model</th>
<th>Snake w. Ellipse</th>
<th>Snake w. Stages</th>
<th>Snake w. Ellipse and Stages</th>
<th>STACS</th>
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| Table 1. Comparison of areas of the contour calculated manually, using snake model, using snake model with ellipse, using snake model with stages, using snake model with ellipse and stages and STACS. |

It can be observed in the Table 1 or by seeing the Figure 21, that areas calculated using STACS are more close to the reference (i.e., values calculated manually) except for fourth and eighth frames. Hence, it can be stated that STACS outperforms all the other approaches. Snake model with stages shows good results for the initial seven frames but its accuracy decreases over later iterations. Snake model with ellipse and stages shows
good results (results close to reference) for the first, third, fourth, sixth and eighth frames. However, snake model and snake model with ellipse exhibit similar results.

![Graph showing comparison of areas of the contour](image)

Figure 21. Comparison of areas of the contour calculated manually, using snake model, using snake model with ellipse, using snake model with stages, using snake model with ellipse and stages and STACS.

### 4.2 Area Similarity Measure (ASM)

This section presents the comparison of different approaches including snake model, snake model with ellipse, snake model with stages, snake model with ellipse and stages and STACS using ASM. ASM is one of the commonly used methods for assessing the validation of functional MR image segmentation [4]. It provides a good measure of how much similarity exists with respect to the sizes (areas) and the relative locations between the automatically and reference (manually generated) contours.
Let $C_a$ be a set of points on an automatically generated contour and $C_r$ be a set of points on a reference contour [1]. One of the methods to compare the areas within $C_a$ and $C_r$ are as follows:

$S_{area} = 2 \frac{n(A_a \cap A_r)}{n(A_a) + n(A_r)}$  \hfill (28)

where $A_a$ be the set of pixels representing the areas within contour $C_a$,

$A_r$ be the set of pixels representing the areas within contour $C_r$,

$n(A_a)$ be the number of pixels that are present inside the automatically generated contour ($C_a$),

$n(A_r)$ be the number of pixels that are present inside the manually generated contour ($C_r$),

$n (A_a \cap A_r)$ be the number of pixels that are present inside the contour $C_a$ and contour $C_r$ simultaneously and

$\cap$ is the element-wise "and" operator.

According to [47], $S_{area} > 0.7$ indicates an excellent agreement between the two comparing regions. In Table 2, the ASM values are shown. The first column contains the frame numbers and the column 2 to column 6 contains the ASM values for the snake model, snake model with ellipse, snake model with stages, snake model with ellipse and stages and STACS respectively.
The values in Table 2 are also presented in graphical form in Figure 22. The values clearly show that STACS shows significantly better results as compared to snake model except for the third, sixth, eighth and ninth frame. Snake with ellipse show good results and outperforms STACS for third, sixth, seventh, eighth and ninth frames of the data.

<table>
<thead>
<tr>
<th>Frame</th>
<th>Snake Model</th>
<th>Snake w. Ellipse</th>
<th>Snake w. Stages</th>
<th>Snake w. Ellipse and Stages</th>
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</table>

Table 2. Comparison of ASM values for different approaches including snake model, snake model with ellipse, snake model with stages, snake model with ellipse and stages and STACS.

Figure 22. Comparison of ASM values for snake model, snake model with ellipse, snake model with stages, snake model with ellipse and stages and STACS.
4.3 *Shape Similarity Measure (SSM)*

This section presents the comparison of the different approaches based on SSM. ASM may be less informative with respect to details on the shapes of the two contours. Two different shape contours may result in the same ASM if both the contours have identical shape, as well as, their intersecting regions and the sums of their individual areas (inside the contour) are same [1]. In order to overcome this problem, another approach named SSM is presented that measures the similarity in shape of the two given contours. The basic aim of this approach is to quantitatively assess the similarity between the shape of the two contours and the range of values of this measure is in the unit interval. The details of SSM values and their calculations are given in [1] for our data.

In Table 3, the SSM values are shown below. The first column contains the frame numbers and column 2 to 6 contains the SSM values for snake model, snake model with ellipse, snake model with stages, snake model with ellipse and stages and STACS respectively.

The values of Table 3 are also presented in a graphical form in Figure 23. The frame numbers are written on x-axis and the SSM values are written on y-axis. It can be observed that the STACS outperforms snake model for all the frames. STACS exhibits better results as compared to snake model with ellipse and stages, snake model with ellipse and snake model with stages for all the frames except tenth, eleventh and twelfth frames. Snake model with stages outperform snake model with ellipse and stages, snake model and snake model with ellipse for all the frames except first, fifth and seventh frames.
<table>
<thead>
<tr>
<th>Frame</th>
<th>Snake Model</th>
<th>Snake w. Ellipse</th>
<th>Snake w. Stages</th>
<th>Snake w. Ellipse and Stages</th>
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<td>0.65664</td>
<td>0.85499</td>
</tr>
<tr>
<td>Frame 6</td>
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<td>0.67679</td>
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</tr>
<tr>
<td>Frame 7</td>
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<td>0.71392</td>
<td>0.69425</td>
<td>0.63481</td>
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</tr>
<tr>
<td>Frame 8</td>
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<td>0.64626</td>
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</tr>
<tr>
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<td>0.56097</td>
<td>0.71025</td>
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<tr>
<td>Frame 10</td>
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<tr>
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<td>0.50507</td>
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<tr>
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<td>0.51015</td>
<td>0.78603</td>
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</table>

Table 3. Comparison of SSM values for different approaches including snake model, snake model with ellipse, snake model with stages, snake model with ellipse and stages and STACS.

Figure 23. Comparison of SSM values for different approaches
Chapter 5: Conclusion and Future Work

In this thesis document, I have described past and current cardiac segmentation approaches along with the implementation, presenting subjective quality and showing statistical results of few approaches. More emphasis is given to the state-of-the-art cardiac imaging algorithms based on model based techniques that have dominated for the last 25 years. The thesis also presents the low and medium level segmentation techniques along with their shortcomings, that are being fulfilled by high level segmentation techniques. In the thesis document, the low and medium level techniques are used in combination with high level techniques. There are two methods presented to perform contour initialization. One being the manual initialization using hand-drawn cardiac boundaries and the other method is application of low and medium level techniques to provide initial contour estimation. The later method eliminates the need for manual intervention to provide hand-drawn boundaries, hence, allowing fully automatic cardiac segmentation approach. The active contour-based and learning based (training-based) models played a major role in segmentation of the heart. It might be a thought provoking idea to extract certain features from the low and medium level techniques and then combining those with global shape models to build a robust cardiac analysis system. In future, learning-based approaches should be explored more for cardiac image segmentation using MRI data. At the end, the future challenge of cardiac image
segmentation would be to develop a robust, fast and computationally inexpensive system in two, three or four dimensions.
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Appendix A: Glossary of Terms

1. **Repetition time** $T_R$: As written in [7], “The amount of time that exists between successive pulse sequences applied to the same slice.”

2. **Echo Time** $T_E$: As [8] says, “The echo time represents the time in milliseconds between the application of the $90^\circ$ pulse and the peak of the echo signal in spin echo and inversion recovery pulse sequences.”

3. **Number of Signal Averages**: As defined in [11], “The NSA determines each distinct position-encoded signal to be used in image reconstruction.”

4. **Matrix Size**: As [13] says, that matrix size is the number of data points collected in one, two or all three directions. It is normally used for the 2D in plane sampling.

5. **Field of View**: As written in [12], the field of view (FOV) is defined as the square image area that contains the object of interest to be measured. Hence, smaller field of view implies higher resolution and smaller voxel size.

6. **Resolution**: As written in [10], the resolution in the plane is defined as a function of FOV (field of view) divided by the matrix size.

7. **Flip Angle**: Flip angle is defined in [9] as the angle at which longitudinal magnetization is tipped towards the transverse plane.
8. **Cardiomyopathy:** As written in [16], Cardiomyopathy means the deterioration of function of myocardium. People having this 'heart muscle disease' are often at risk of arrhythmia or sudden cardiac death or both.

9. **Ejection Fraction (E_f):** As stated in [17], "Ejection fraction is the fraction of blood pumped out of right and left ventricles with each heart beat".

10. **Thermal noise:** Thermal noise can be defined as electrical noise that is caused by thermal agitation of conducting electrons [43].

11. **Cardiac cycle:** The cardiac cycle refers to all or any of the events related to the flow or blood pressure that occurs from the beginning of one heartbeat to the beginning of the next [45].

12. **Systolic phase:** The heart contracts and pumps blood out during the systolic phase [46].

13. **Diastolic phase:** The heart relaxes and blood is filled in the ventricles during diastolic phase [46].

14. **Contrast Resolution:** Contrast resolution is the ability to distinguish between differences in intensity in an image [51].

15. **Spatial Resolution:** Spatial resolution can be defined as the ability to identify an object, usually a small, dense object like a metal fragment or microcalcification, as separate and distinct from another object [50].

16. **Sensitivity:** Sensitivity describes how well an imaging system can detect subtle differences.
17. **Specificity**: Specificity refers to the ability to precisely identify the nature of subtle differences in anatomy [50].

18. **Cardiac boundary estimation**: Cardiac boundary estimation means to find the contour $C$ that separate the heart from the background.

19. **Magnetic field (H)**: A magnetic field produces a magnetizing force on a body within it. This is the area of potential concern for safety limits because the dangers of large magnetic fields are largely hypothetical. The forces, experienced by moving charged particles, current carrying wires and small magnets in the vicinity of magnet are due to magnetic induction ($B$), which includes the effect of magnetization, while the magnetic field ($H$) is defined so as not to include magnetization. However, both $B$ and $H$ are often loosely used to denote magnetic fields. The direction of the magnetic field is defined as the direction that the north pole of the small magnet points when in equilibrium [53].

20. **Magnetic Field Gradient**: It is a magnetic field which changes in strength in a certain given direction. Its units are teslas per meter. Such fields are used in MR imaging with selective excitation to select a region for imaging and also to encode the location of MR signals received from the object being imaged [53].

21. **Magnetic moment**: Magnetic moment is a measure of the net magnetic properties of an object or particle. A nucleus with an intrinsic spin will have an associated magnetic dipole moment, so that it will interact with a magnetic field (as if it were a tiny bar magnet) [53].

22. **Angiography**: Angiography is the application of MRI to produce images of blood vessels, for example with flow effect or relaxation time differences [53].
23. **Magnetic resonance angiography (MRA):** Angiography using MRI is called Magnetic resonance angiography [53].

24. **Resonance frequency:** It is a frequency at which resonance phenomenon occurs; given by the Larmor equation for NMR; determined by inductance and capacitance for RF circuits [53].

26. **Radiofrequency (RF):** It is a wave frequency intermediate between auditory and infrared. The RF used in MR studies is commonly in the megahertz (MHz) range. The RF used in ESR studies is commonly in the gigahertz (GHz) range [53].
Appendix B: Results of Perceptual Quality using different approaches

The perceptual quality obtained as a result of applying the snake model, snake model with ellipse, snake model with stages, snake model with ellipse and stages and STACS is shown in Figure 24-28 respectively. It should be noted that perceptual quality is a subjective measure and it depends on user opinion and preferences. There are 12 frames for each slice and the parts a-l in Figure 24-28 shows the frames 1-12. The cardiac boundary in red color shown in the Figure 24-28 is a contour $C$ obtained as a result of application of snake model, snake model with ellipse, snake model with stages, snake model with ellipse and stages and STACS respectively. The contour $C$ segments the given image into object of interest, heart in this case and the background.
Figure 24. Parts a-l shows the perceptual quality for the frames 1-12, obtained after applying the snake model. The contour in part a is initialized using morphological operators and then the snake model was applied to further refine the contour. Hence, it is a fully automatic approach in which no manual intervention was required during initialization and in applying the snake model. The contour obtained in frame 1 after applying the snake model is used as an initialization contour for the frame 2. Similarly, the contour obtained after application of snake model in frame 2, is used to initialize the contour in frame 3 and so on. Hence, temporal information is used to initialize the contours for frames 2-12. Although the cardiac boundary obtained by applying snake model has segmented the heart from the background, still there are some gaps left between the heart and the cardiac boundary that are addressed in the other approaches.
Figure 25. Part a-l shows the perceptual quality for the frames 1-12, obtained as a result of applying snake model with ellipse. The contour in part a is initialized using morphological operators and then the snake model with ellipse was applied to further refine the contour. Hence, it is a fully automatic approach in which no manual intervention was required during initialization and in applying the snake model with ellipse. The contour obtained in frame 1 after applying the snake model with ellipse is used as an initialization contour for the frame 2. Similarly, the contour obtained after application of snake model with ellipse in frame 2, is used to initialize the contour in frame 3 and so on. Hence, temporal information is used to initialize the contours for the frames 2-12. The gaps between the heart and cardiac boundary in images shown in the part i-l are reduced using snake model with ellipse approach as compared to corresponding images obtained using snake model in Figure 24.
Figure 26. Part a-l shows the perceptual quality for the frames 1-12, obtained as a result of applying snake model with stages. The contour in part a is initialized using morphological operators and then the snake model with stages was applied to further refine the contour. Hence, it is a fully automatic approach in which no manual intervention was required during initialization and in applying the snake model with stages. The contour obtained in frame 1 after applying the snake model with stages is used as an initialization contour for the frame 2. Similarly, the contour obtained after application of snake model with stages in frame 2, is used to initialize the contour in frame 3 and so on.
Figure 27. Part a-l shows the perceptual quality for the frames 1-12, obtained as a result of applying snake model with ellipse and stages. The contour in part a is initialized using morphological operators and then the snake model was applied to further refine the contour. Hence, it is a fully automatic approach in which no manual intervention was required during initialization and in applying the snake model. The contour obtained in frame 1 after applying the snake model with ellipse and stages is used as an initialization contour for the frame 2. Similarly, the contour obtained after application of snake model with ellipse and stages in frame 2, is used to initialize the contour in frame 3 and so on.
Figure 28. Part a-l shows the perceptual quality for the frames 1-12, obtained as a result of applying STACS. The contour in parts a-l are initialized using morphological operators and then the STACS was applied to further refine the contour. Hence, it is a fully automatic approach in which no manual intervention was required during initialization and in applying the STACS. The contour obtained in frame 1 after applying the STACS is used as an initialization contour for the frame 2. Similarly, the contour obtained after application of STACS in frame 2, is used to initialize the contour in frame 3 and so on. The gaps between the heart and cardiac boundary in images shown in the parts a-d and parts i-l are reduced using STACS as compared to corresponding images obtained using snake model, snake model with ellipse, snake model with stages and snake model with ellipse and stages in Figure 24-27.