Automatic cardiac ventricular boundary detection

Cheng, Jierong

2007

Cheng, J. (2012). Automatic cardiac ventricular boundary detection. Doctoral thesis,
Nanyang Technological University, Singapore.

<https://hdl.handle.net/10356/3474>

<https://doi.org/10.32657/10356/3474>

Nanyang Technological University

Downloaded on 26 Apr 2023 18:03:53 SGT

Automatic Cardiac Ventricular Boundary Detection

CHENG JIERONG

School of Electrical and Electronic Engineering

A thesis submitted to the Nanyang Technological University
in fulfillment of the requirement for the degree of
Doctor of Philosophy

2007

Acknowledgement

Firstly, I would like to thank my supervisor, A/P Foo Say Wei, for his constant support and critical guidance throughout my graduate study years.

And I also own a special thank to following people:

Thanks to A/P Shankar M. Krishnan for giving me visionary insights in echocardiography, valuable comments and challenges.

Thanks to Zhang Han, also student of Prof. Foo, for giving me advice and suggestions on image processing.

Thanks to all the members of the Biomedical Engineering Research Center and my good friend Zhang Fan.

Table of Contents

Summary	vii
List of Figures	ix
List of Tables	xix
List of Abbreviations	xxi
1 Introduction	1
1.1 Motivation	1
1.1.1 Heart Disease and Echocardiography	1
1.1.2 Cardiac Ultrasound Imaging	3
1.1.3 Difficulties Associated with 2D Echocardiography	6
1.2 Objectives	8
1.3 Major Contributions	9
1.4 Organization of the Thesis	10
2 Background	13
2.1 Cardiac Function Parameters	13
2.1.1 Global Functional Analysis	13

2.1.2	Motion and Deformation Analysis	15
2.2	Manual Segmentation	15
2.3	Semi-automatic Segmentation	16
2.3.1	A Classical Method of Boundary Detection	17
2.3.2	Segmentation Methods	18
2.3.3	Boundary Identification Methods	25
3	Detection of Region of Interest	31
3.1	Introduction	31
3.2	Algorithm Design	32
3.2.1	Preprocessing	32
3.2.2	Binary Image Processing	33
3.2.3	Watershed Segmentation	34
3.2.4	Post-processing	35
3.3	Application on LV Boundary Detection	37
3.3.1	Snake	37
3.3.2	Edge Map Calculation	39
3.3.3	Snake Deformation	42
3.4	Results and Discussion	42
3.5	Summary	43
4	Long-axis Echocardiographic Image Segmentation Using Marko-	
	vian Level Set Method	47
4.1	Introduction	47
4.2	Hierarchical MRF Based Segmentation Model	49

4.2.1	MRF Based Segmentation Model	49
4.2.2	Hierarchical MRF Basics	53
4.2.3	Parameter estimation	56
4.3	Level Set	58
4.3.1	Curve Propagation Theory	59
4.3.2	Geodesic Active Contours	60
4.3.3	Level Set Method	61
4.4	Markovian Level Set	62
4.4.1	2D polar coordinate system	62
4.4.2	MRF Model	64
4.4.3	Deformation Smoothness	67
4.4.4	Segmentation Procedure	69
4.5	Results and Discussion	72
4.5.1	Parameters	72
4.5.2	Quantitative Measures	73
4.5.3	Results	74
4.6	Summary	87
5	Short-axis Echocardiographic Image Segmentation Using Dy-	
	namic Directional Gradient Vector Flow	89
5.1	Introduction	90
5.2	Background	92
5.2.1	Traditional Snakes	92
5.2.2	GVF Snakes	93
5.3	Dynamic Directional GVF	96

5.3.1	Directional Edge Map	96
5.3.2	Dynamic Directional GVF Field	100
5.3.3	Snake Deformation	101
5.4	Comparison with DGVF	102
5.5	Performance of The Method	104
5.5.1	Synthetic Images	104
5.5.2	Photographic Images	111
5.5.3	Echocardiographic Images	119
5.6	Summary	125
6	Conclusion and Recommendations	127
6.1	Conclusion	127
6.2	Recommendations for Further Research	130
6.2.1	Temporal Analysis	131
6.2.2	Shape Analysis	132
6.2.3	Extension to 3D Domain	133
A	The Distraction Phenomenon	135
	Author's Publications	141
	Bibliography	145

SUMMARY

Echocardiography is a common diagnostic imaging modality for patients with heart diseases. One essential goal in the analysis of echocardiographic images is to identify the locations of the endocardial boundary. This is necessary in order to visualize the structure of the patient's heart, and to derive quantitative parameters from the images. However, manual identification of endocardial boundary is time-consuming, inconvenient, and dependant on the competence of the clinician.

In this thesis, three new algorithms are developed for boundary detection in two dimensional (2D) echocardiographic images.

For long-axis echocardiographic images, a pre-segmentation algorithm is developed to locate the left ventricular (LV) region without user intervention. It incorporates morphological operations and the watershed transform, together with prior anatomical knowledge. The resulting LV center and region of interest (ROI) provide an initial condition thus expediting and facilitating the next phase of boundary detection.

The final segmentation to find the actual LV boundary in long-axis echocardiographic images is carried out using a Markovian level set method. A 2D Markov random field (MRF) is implemented in polar coordinates, and the

local smoothness and the image data are imposed by a Bayesian framework. By conversion between a label field and a level set function, the segmentation process is carried out by updating the level set function iteratively. Experimental results demonstrate that the computer-generated boundaries are highly correlated with those manually drawn.

A new external force for snakes is proposed as dynamic directional gradient vector flow (DDGVF) for LV boundary detection in short-axis echocardiographic images. Experimental results show that DDGVF successfully distinguishes positive and negative boundaries while preserving a large capture range and the ability to move into boundary cavities.

The techniques developed in this thesis have the potential to be integrated into an accurate and automatic system that could be used in routine clinical practice.

List of Figures

1.1	(a) A typical long-axis echocardiographic image; (b) A typical short-axis echocardiographic image.	3
2.1	A classical boundary detection scheme	17
3.1	Binary image processing. (a) The composite image and (b) after preprocessing.	33
3.2	Binary image processing. (a) The binary image before morphological close and (b) after morphological close.	34
3.3	(a) The Euclidean distance map; (b) watershed segmentation.	36
3.4	(a) The masked binary image; (b) The ROI of the composite image (enclosed by dashed line) and the LVCP (white point). .	36
3.5	Illustration of transition from M_g to M_d	40
3.6	(a) The directional gradient at the first scale; (b) the directional gradient at the second scale; (c) the directional gradient at the third scale; (d) the multiscale directional edge map of the left ventricle.	41

3.7	Results of Dataset I (containing 38 images of 200×200 pixels): (a) ROI segmentation in composite image and (b)-(c) LV boundary detected in end-diastole frame and end-systole frame respectively.	43
3.8	Results of Dataset II (containing 16 images of 136×121 pixels): (a) ROI segmentation in composite image and (b)-(c) LV boundary detected in end-diastole frame and end-systole frame respectively.	43
3.9	Results of Dataset III (containing 13 images of 136×121 pixels): (a) ROI segmentation in composite image and (b)-(c) LV boundary detected in end-diastole frame and end-systole frame respectively.	44
3.10	Results of Dataset IV (containing 22 images of 197×171 pixels): (a) ROI segmentation in composite image and (b)-(c) LV boundary detected in end-diastole frame and end-systole frame respectively.	44
3.11	Results of Dataset V (containing 15 images of 210×221 pixels): (a) ROI segmentation in composite image and (b)-(c) LV boundary detected in end-diastole frame and end-systole frame respectively.	44
4.1	The 2D polar coordinate system.	63
4.2	Radial lines with (a) $b/a = 1$ and (b) $b/a = 3/2$	64

4.3	The second-order neighborhood system in (a) Cartesian coordinates and (b) polar coordinates; (c) all doubleton (double-pixel) cliques.	65
4.4	The overall segmentation procedure.	69
4.5	(a) Initial boundary points generated by K-means clustering algorithm in the third scale. (b)-(d) Boundary point generated by Markovian level set in the third, the second and the first scales respectively. (e) Final label field (the white points denote pixels labeled as myocardium). (b) Final boundary point after smoothing.	70
4.6	(a) Original clean image simulating a long-axis echocardiographic image with dropout. Boundary points detected from synthetic images with the first noise model using (b) P-MRF , (c) C-MRF and (d) MLS.	76
4.7	Boundary points detected from synthetic images with the second noise model using P-MRF (first column), C-MRF (second column) and MLS (third column). The standard deviations of Gaussian white noise are: 2, 4, 6, 8, from top to bottom. . . .	77

4.8	Intermediate results obtained from the three method: (a)-(b) P-MRF, (c)-(d) C-MRF, and (e)-(f) MLS ($c=0$) on the same image. First column: segmented myocardium-labeled fields. Second column: boundary points detected from the label fields. The points indicated in (a) and (e) are the pixels labeled as myocardium. The region enclosed by highlighted pixels in (c) is the region labeled as myocardium. The arrows indicate incorrect (b) or missing (d) boundary points.	79
4.9	Dataset I: comparison of final LV boundary obtained using (a)-(b) P-MRF, (c)-(d) C-MRF, and (e)-(f) MLS methods. . . .	80
4.10	Dataset II: comparison of final LV boundary obtained using (a)-(b) P-MRF, (c)-(d) C-MRF, and (e)-(f) MLS methods.	81
4.11	Dataset III: comparison of final LV boundary obtained using (a)-(b) P-MRF, (c)-(d) C-MRF, and (e)-(f) MLS methods. . .	82
4.12	Dataset IV: comparison of final LV boundary obtained using (a)-(b) P-MRF, (c)-(d) C-MRF, and (e)-(f) MLS methods. . .	83
4.13	Dataset V: comparison of final LV boundary obtained using (a)-(b) P-MRF, (c)-(d) C-MRF, and (e)-(f) MLS methods.	84
5.1	(a) 100×100 -pixel binary image of step edges; (b) edge map of GVF: gradient magnitude; (c), (d) GVF field in the x and y direction respectively (before normalized with respect to their magnitudes).	95
5.2	Detection of positive and negative step edges.	97

5.3	The DDGVF field in the (a) x , (b) $-x$, (c) y and (d) $-y$ directions for positive step edges.	99
5.4	The difference between (a) DDGVF snake and (b) DGVF snake. The arrows indicate the directions of edge in which snakes seek the boundary. The reference point is marked by 'R' in (b). . .	103
5.5	The edge maps of DGVF obtained from Fig. 5.1(a) for (a) positive boundary and (b) negative boundary.	103
5.6	Performance of GVF, DGVF and DDGVF snakes on step edge image. The dashed line circles are initial snake positions and the solid line contours are final contours of the snakes. Three initial circles of different sizes are used as depicted in the three rows. (a) results of boundary detection using the GVF snake; (b)-(c) results of the DDGVF positive and negative boundary-searching snake respectively; (d)-(e) results of the DGVF positive and negative boundary-searching snake respectively.	106
5.7	Performance of GVF, DGVF and DDGVF snakes on step edge image. The dashed line circles are initial snake positions and the solid line contours are final contours of the snakes. Three initial circles of different sizes are used as depicted in the three rows. (a) results of boundary detection using the GVF snake; (b)-(c) results of the DDGVF positive and negative boundary-searching snake respectively; (d)-(e) results of the DGVF positive and negative boundary-searching snake respectively.	107

- 5.8 Performance of GVF, DGVF and DDGVF snakes on step edge image. The dashed line circles are initial snake positions and the solid line contours are final contours of the snakes. Three initial circles of different sizes are used as depicted in the three rows. (a) results of boundary detection using the GVF snake; (b)-(c) results of the DDGVF positive and negative boundary-searching snake respectively; (d)-(e) results of the DGVF positive and negative boundary-searching snake respectively. 108
- 5.9 Performance of DGVF and DDGVF snakes on 176×176 -pixel step edge image. (a) The original step edge image with the initial snake position (dashed line circles) and the reference point (cross) indicated ; (b) the edge map of DGVF; (c) results of boundary detection using the positive boundary-searching DGVF snake; (d) results of boundary detection using the positive boundary-searching DDGVF snake. 108
- 5.10 Performance of GVF and DDGVF snakes on 176×176 -pixel line-drawing image. (a) The original image of line-drawing with the initial snake position indicated (dashed line circles); (b) results of boundary detection using the GVF snake; (c) results of boundary detection using the line-searching DDGVF snake. 110

-
- 5.11 Performance of GVF and DDGVF snakes on 176×176 -pixel line-drawing image. (a) The original image of line-drawing with the initial snake position indicated (dashed line circles); (b) results of boundary detection using the GVF snake; (c) results of boundary detection using the line-searching DDGVF snake. 110
- 5.12 (a) Original clean image simulating a short-axis echocardiographic image. Boundary points detected from synthetic images with the first noise model using (b) GVF, (c) DGVF and (d) DDGVF. 112
- 5.13 Boundary points detected from synthetic images with the second noise model using GVF (first column), DGVF (second column) and DDGVF (third column). The standard deviations of Gaussian white noise are: 2, 4, 6, 8, from top to bottom. . . . 113
- 5.14 Performance of GVF, DGVF and DDGVF snakes on photographic images. (a) Image of ‘peppers’ (256×256 -pixel); (e) image of ‘APC’ (192×192 -pixel); (i) image of ‘Garbo’ (128×128 -pixel). (a) The original images with the initial snake position indicated (dashed line circles); (b) results of boundary detection using the GVF snake; (c) results of boundary detection using the DGVF snake; (d) results of boundary detection using the DDGVF snake. 115

5.15	Performance of GVF, DGVF and DDGVF snakes on photographic image ‘APC’(192 × 192-pixel). (a) The original images with the initial snake position indicated (dashed line circles); (b) results of boundary detection using the GVF snake; (c) results of boundary detection using the DGVF snake; (d) results of boundary detection using the DDGVF snake.	116
5.16	Performance of GVF, DGVF and DDGVF snakes on photographic image ‘Garbo’ (128 × 128-pixel). (a) The original images with the initial snake position indicated (dashed line circles); (b) results of boundary detection using the GVF snake; (c) results of boundary detection using the DGVF snake; (d) results of boundary detection using the DDGVF snake.	117
5.17	(a) Ground truth points for the chin boundary. (b) Ground truth points for the whole boundary. (c) Mean boundary errors between the computer-detected boundaries and the ground truth boundaries.	118
5.18	Performance of DDGVF snakes on the ‘Garbo’ image with reduced iteration for the calculation of DDGVF field.	119
5.19	Performance of GVF, DGVF and DDGVF snakes on 220 × 220-pixel echocardiographic images. (a) The original echocardiographic images with the initial snake position indicated (dashed line circles); (b) results of boundary detection using the GVF snake; (c) results of boundary detection using the DGVF snake; (d) results of boundary detection using the DDGVF snake. . .	121

5.20	Performance of GVF, DGVF and DDGVF snakes on 220×220 -pixel echocardiographic images. (a) The original echocardiographic images with the initial snake position indicated (dashed line circles); (b) results of boundary detection using the GVF snake; (c) results of boundary detection using the DGVF snake; (d) results of boundary detection using the DDGVF snake.	122
5.21	Performance of GVF, DGVF and DDGVF snakes on 220×220 -pixel echocardiographic images. (a) The original echocardiographic images with the initial snake position indicated (dashed line circles); (b) results of boundary detection using the GVF snake; (c) results of boundary detection using the DGVF snake; (d) results of boundary detection using the DDGVF snake.	123
5.22	Results of DDGVF applied on long-axis images.	125
A.1	Original images with of 100×100 with (a) $R = 1.5$, (b) $R = 2$, and (c) $R = 4$. The maximum intensity value is 1. The intensity of the background is 0.8. R is the ratio of the intensity difference $R = (1 - U)/(1 - 0.8)$, where U is the intensity of the rectangular. (d) Original image with $R = 2$, $H = 6$, and $L = 20$. (e) Boundaries obtained from DDGVF after 25 iterations; (f) Boundaries obtained from DDGVF after 25 iterations where distraction happens.	137
A.2	Threshold of distraction corresponding to R , L , and H when $Iter = 100$. In the areas above the red dashed lines, distraction happens.	138

A.3	Threshold of distraction corresponding to $Iter$, L , and H when $R = 1.5$. In the areas above the red dashed lines, distraction happens.	138
A.4	Threshold of distraction corresponding to $Iter$, L , and H when $R = 2$. In the areas above the red dashed lines, distraction happens.	139
A.5	Threshold of distraction corresponding to $Iter$, L , and H when $R = 4$. In the areas above the red dashed lines, distraction happens.	139

List of Tables

4.1	Errors and area correlation measured from 30 noisy synthetic images with Rayleigh speckle noise ($b = 0.7979$).	76
4.2	Boundary error metrics measured in Dataset I (containing 20 images of 200×200 pixels).	84
4.3	Boundary error metrics measured in Dataset II (containing 16 images of 136×121 pixels).	85
4.4	Boundary error metrics measured in Dataset III (containing 13 images of 136×121 pixels).	85
4.5	Boundary error metrics measured in Dataset IV (containing 22 images of 197×171 pixels).	85
4.6	Boundary error metrics measured in Dataset V (containing 15 images of 210×221 pixels).	85
4.7	Area correlation of Datasets I-V.	86
4.8	Normalized boundary distances and area correlation across Datasets I-V.	86
5.1	Errors and area correlation measured from 30 noisy synthetic images with Rayleigh speckle noise ($b = 0.7979$).	112

5.2	Boundary errors in pixels and area correlation.	120
-----	---	-----

List of Abbreviations

1D	One Dimensional
2D	Two Dimensional
3D	Three Dimensional
AAM	Active Appearance Models
AAMM	Active Appearance Motion Models
ANN	Artificial Neural Network
ASM	Active Shape Models
C-MRF	2D MRF in Cartesian Coordinates
CO	Cardiac Output
CT	Computerized Tomography
DCP	Distance to the Closest Point
DDGVF	Dynamic Directional Gradient Vector Flow
DGVF	Directional Gradient Vector Flow
EF	Ejection Fraction
EM	Expectation-Maximization
FMED	Fuzzy Multiscale Edge Detection

GGVF	Generalized Gradient Vector Flow
GVF	Gradient Vector Flow
HD	Hausdorff Distance
ICM	Iterated Conditional Modes
LV	Left Ventricle
LVCP	Left Ventricular Center Point
LVV	Left Ventricular Volume
LVM	Left Ventricular Mass
MAP	Maximum A Posteriori
MDL	Minimum Description Length
MD	Mean Distance
ML	Maximum Likelihood
MLS	Markovian Level Set
MRF	Markovian Random Field
MRI	Magnetic Resonance Imaging
PCA	Principal Component Analysis
P-MRF	2D MRF in Polar Coordinates
ROI	Region of Interest
SA	Simulated Annealing
SV	Stroke Volume
WT	Wall Thickening

Chapter 1

Introduction

1.1 Motivation

1.1.1 Heart Disease and Echocardiography

Heart disease is one of the leading causes of death. In Singapore since 1998, ischemia and other heart diseases (including heart diseases such as heart failure from a variety of cases, hypertension, etc.) have been the second principal cause of death. In the year 2000, 3200 patients in Singapore died of ischemic heart diseases and related causes.

Among the various cardiac imaging modalities, echocardiography is particularly attractive for the advantages of being noninvasive, causing minimal discomfort, absence of ionizing radiation, real-time processing, and relatively low cost.

Echocardiography is a test used to diagnose heart diseases. From the images, it is possible to assess the size, shape, and function of the heart chambers; the amount of blood pumped by the heart; the shape and movement of the

heart valves. Tracing of the endocardial boundaries of the left ventricle on a series of images covering the entire cardiac cycle allows quantitative interpretation of LV contraction dynamics. However, manual tracing of these boundaries is a time consuming and tedious task. Moreover, the resulting outlines vary between different observers and may have a subjective bias. Hence, there is a need for automatic detection of these boundaries.

Echocardiography refers to cardiac ultrasonography which depicts the heart and surrounding structures. The echocardiographic images are obtained using ultrasound machines. Three types of echocardiography are used clinically: M-mode (one dimensional (1D)), B-mode (2D), and Doppler [1]. In this study, the focus is on 2D echocardiography.

For two-dimensional (2D) echocardiography, it is possible to obtain an almost infinite variety of cross-sectional images of the heart. It is therefore desirable to standardize on a limited number of views that cover the majority of applications and that can be described readily in terms of transducer orientation and anatomical features. To this end, it has been agreed that 2D echocardiographic images should be based on three orthogonal planes. Adoption of these standards should facilitate consistent performance, recording, teaching, and communicating results of studies obtained by 2D echocardiography. In the thesis, the *long-axis* images are images obtained from the four-chamber plane with the apical transducer position (Fig. 1.1(a)) and the *short-axis* images are for images obtained from the short-axis plane with the parasternal transducer position (Fig. 1.1(b)). These terms are commonly used in the description of echocardiographic images.

Figure 1.1: (a) A typical long-axis echocardiographic image; (b) A typical short-axis echocardiographic image.

1.1.2 Cardiac Ultrasound Imaging

In ultrasound imaging systems, pulsed and high frequency sound waves are reflected back from body tissues and processed by the ultrasound machine to create characteristic images. Defined bursts of ultrasound waves are emitted from the transducer, which also acts as a receiver. Ultrasound can be directed in a specific direction. It obeys the laws of geometric optics with regard to reflection, transmission and refraction. The ultrasound wave is reflected, refracted and absorbed at those interfaces of differing echogenicity. The transducer senses and processes only reflected sound waves (echoes) and acts as a receiver over 99% of the time. Echocardiographic images are displayed on an oscilloscope screen in real-time and can be recorded digitally on videotape, paper, radiographic film, etc. The intensity of the reflected sound wave depends mainly on the following factors: the distance of the imaged object away from the transducer, the difference in acoustic impedance between adjacent

structures, and the frequency of the ultrasound wave used.

Air-filled structures such as the lung and bone are excellent reflectors of ultrasound and prevent transmission of the ultrasound beam to the deeper structures. Therefore, the intercostal spaces in the axillary region at the cardiac notch are used as the cardiac windows. Air-free contact between the transducer and body wall is necessary and is achieved by the use of ultrasound coupling gel and clipping the hair of the patient in this region if the hair coat is dense. The ultrasound transducer must be positioned so that the ultrasound beam is perpendicular to the intracardiac structures for optimal image quality while the ultrasound beam must be as parallel as possible to flow disturbances to accurately quantify the flow abnormality with Doppler echocardiography. Correct placement of the ultrasound cursor within the particular view is essential for obtaining accurate and reproducible measurements. The equipment settings also affect the quality of images obtained.

Many materials, such as myocardial tissues and other muscle tissues, exhibit structures which are organized into aligned fibers. The presence of these fibers give rise to angular dependencies, or anisotropy, in the ultrasonic properties of these media, a fact which can be exploited to obtain additional information on the internal structure of the material [2]. The effects of tissue anisotropy in echocardiography are studied in [3, 4].

As a result, echocardiographic image information is highly anisotropic and position dependent, since reflection intensity, spatial resolution, and signal-to-noise ratio (SNR) depend on the depth and angle of incidence of the ultrasound beam, as well as user-controlled depth gain settings.

The 2D echocardiography allows the anatomy and movements of intracardiac structures to be studied noninvasively. A variety of planes through the heart can be imaged from several locations on the chest wall. The application of pulsed and continuous-wave Doppler principles to 2D echocardiography permits blood flow direction and magnitude be derived and mapped onto a small region of interest of the image. One of the limiting factors of 2D echocardiography is the ultrasound window (presence of attenuating tissues in the interface between the transducer and the organ of interest). To overcome this problem transesophageal echocardiography can be used, which allows for high-quality color flow images at the expense of being invasive.

Three dimensional (3D) echocardiography [5] is a relatively new development in ultrasound imaging that allows 3D quantization of organ geometry since the complete organ structure can be imaged. This technique has been used to compute LV volume and mass and to perform wall motion analysis. In different types of 3D ultrasound imaging systems, images are acquired by free-hand acquisitions, mechanical localizers or 3D probes [6]. In mechanical 3D probe assemblies, the third dimension is obtained by mechanical movement of the transducer in a precise and predefined manner with three types of motions: linear, fan and rotation scanning. However, the ultimate approach for most 3D ultrasound image acquisition is the use of a 2D transducer array, where the third dimension is achieved by replacing physical movement of the transducer by electronic scanning.

1.1.3 Difficulties Associated with 2D Echocardiography

Feature extraction from echocardiographic images is of major importance for quantitative analysis of the heart function. An echocardiographic expert is able to identify and retrieve information from video images. This is because of the ability of the human eye to integrate information and the inherent 3D acquisition and real-time characteristic of echocardiography. In comparison, automatic processing of echocardiographic images by computers is hampered by the poor quality of the images. The main degradation mechanisms include [7]:

1) *Dropouts*: Echocardiographic images often contain regions where the signal has *dropped out*. Dropouts create holes in image boundaries which have to be bridged by algorithms. Shape prior have been used to deal with data dropouts [8], but shape priors can fail for large gaps if they are illy represented.

2) *Poor contrast*: The acoustic characteristics of blood and myocardium are similar, thus there is little contrast between them. Some parts of the pericardium have no contrast at all. This makes the determination of the endocardial boundary difficult. In recent years contrast agents such as micro-bubbles are developed to improve the image quality by increasing the backscattered echoes from the desired regions.

3) *Artifacts*: Artifacts like papillary muscles, valves, and chordae often interfere with computer-based processing. It is hard to

exclude these artifacts from the boundary of myocardium. The shading artifacts, which cause intensity non-uniformity, may need intensity inhomogeneity correction [9,10] in severe cases to improve image analysis results.

4) *Speckle noise*: Another difficulty with echocardiographic image processing is speckle noise, which is a granular pattern formed due to constructive and destructive interferences of backscattered echoes from the scatterers that are typically much smaller than the spatial resolution in medical ultrasound systems. Speckle noise obscures subtle features in an ultrasound image, and degrades the performance of many ultrasound image processing tasks such as segmentation and boundary detection. In the last two decades, various speckle reduction techniques have been reported, including compounding [11,12], nonlinear spatial filters [13–17], and wavelet-based techniques [18–20].

5) *Blur*: The received wave is focused by dynamic focusing techniques. However, the transmitted pulse can only be focused at a fixed point (typically half of maximum range). Blur is generated in the image when the focus cannot be maintained. For this reason, blur near the transducer and near the maximum range are stronger than blur at the middle range.

6) *Acquisition in polar coordinates*: Since the data are acquired in polar coordinates, the inter-sampling space is nonuniform. Some

kind of interpolation is necessary for large ranges, due to the sparseness of samples. This leads to the nonhomogeneous characteristics of the echocardiographic image.

7) Sidelobes and grating lobes: Since the dynamic range of detected echoes is huge (about 115 dB), a low sidelobe level is crucial. Although acoustic phased-array transducers have been greatly improved since their first days, some weak echoes can still be masked by stronger echoes not coming from the point being imaged.

1.2 Objectives

LV boundary detection is an essential task for quantitative evaluation of heart function. Many sophisticated techniques have been proposed for boundary detection from echocardiographic or other ultrasound images in the literature. These include watershed transform [21, 22], wavelet transform [23, 24], active contour model [22, 25, 26], intensity inhomogeneity correction [9], Bayesian segmentation [27], active shape model [28], active appearance motion model [29] and artificial neural network [30]. However, these computer-based approaches have certain limitations. Most of the cited methods require intervention from a human operator, such as requiring clinicians to provide values of parameters, initial seed point, initial curve for the LV boundary, etc. The speckle noise and artifacts also reduce the effectiveness and accuracy of the methods: very often not all the edges detected are on the true boundary.

The work reported in this thesis is a contribution to the field of automatic

boundary detection methods for 2D echocardiographic images. Attempts are made to overcome the difficulties associated with echocardiography stated in Section 1.1.3. This work is done with the following objectives:

- To reduce the number of inputs from the human operator, either in the form of values of different algorithm parameters, an initial seed point, or an initial curve. In this work, human interaction is reduced as much as possible to increase the efficiency of the system.
- To increase the accuracy of segmentation algorithms for LV boundary detection, while reducing the influence of speckle noise, low contrast and artifacts. To test the performance of segmentation algorithms, computer-detected boundaries are compared with expert-drawn boundaries.
- To evaluate proposed methods on several clinical datasets. Many researchers have evaluated their algorithms on images of phantoms, *in vitro* hearts, live animals under nearly ideal laboratory conditions, or highly selected sets of good quality clinical data. The algorithms in this thesis are tested on images of *in vivo* human heart to ensure good clinical applicability.

1.3 Major Contributions

The major contributions of this thesis are summarized as follows:

- The development of a pre-segmentation algorithm which detects the LV center point and ROI to expedite and facilitate subsequent LV boundary detection.

- The development of a Markovian level set method for LV boundary detection in long-axis echocardiographic images. It combines a MRF model which makes use of local statistics with a level set method which handles topological changes, to detect a continuous and smooth LV boundary.
- The development of a new dynamic external force for snake method, which is effective for LV boundary detection in short-axis echocardiographic images. The external force model based on gradient vector flow endows the snake with a large capture range and the ability to move into boundary cavities. By incorporating directional gradient information, the snake is enabled to discern positive and negative boundaries.

The work presented in this thesis has resulted in three journal papers and nine international conference papers, as listed in Publications by the Author.

1.4 Organization of the Thesis

The rest of the thesis is organized as follows:

In Chapter 2, the background of cardiac functional evaluation and left ventricular segmentation are given. A brief literature review on computer-based LV boundary detection methods is presented.

In Chapter 3, a new pre-segmentation algorithm for LV center point and ROI detection is described. This algorithm incorporates morphological operation and watershed transform to locate the LV region. Based on the resulting ROI and LV center, applications on boundary detection by the snake model with a multiscale directional edge map are also presented.

In Chapter 4, a novel Markovian level set (MLS) method is developed for LV boundary detection in long-axis echocardiographic images. The determination of ROI and LV center as described in Chapter 3 is utilized. The MLS method uses a 2D MRF in polar coordinates, where the local smoothness and the image data are imposed by a Bayesian framework. By conversion between a label field and a level set function, the segmentation process is carried out by updating the level set function iteratively. Both qualitative and quantitative results are provided to compare the MLS method with two related MRF-based methods.

In Chapter 5, a novel dynamic directional gradient vector flow (DDGVF) method for snakes is developed for LV boundary detection in short-axis echocardiographic images. By incorporating directional gradient information, the snake is able to discern edges of different orientations. Experimental results comparing DDGVF with the recently proposed directional gradient vector flow (DGVF) [31] are given.

Finally, the summary of this research along with discussions of some future research directions is given in Chapter 6.

Chapter 2

Background

The study of the changes in the shape, size, and movements of the heart during the beat contains important diagnostic information regarding the cardiac pumping function. Normally for a cardiologist, echocardiographic images are viewed in a qualitative fashion by visually considering some particular alterations of cardiac shape, size, and motion to identify specific abnormalities of cardiac structure and function.

2.1 Cardiac Function Parameters

Classical functional analysis can be divided into global functional analysis and motion/deformation analysis, from which the most clinically relevant parameters can be obtained [32].

2.1.1 Global Functional Analysis

Weber and Hawthorne [33] proposed a classification of cardiac indexes according to their intrinsic dimensionality: linear, surface and volumetric descriptors.

Linear parameters have been used intensively in the past since they can easily be derived from 2D imaging techniques like 2D Echocardiography and X-ray angiocardiography. However, they assume an ‘idealized’ geometry of the left ventricle and the performance of their proposed method is strongly depend on external or internal reference and coordinate systems. Besides total ventricular wall area, other surface indexes based on curvature and derived parameters have been investigated from 2D studies. More recently, many image processing approaches to LV modeling have suggested true 3D global and local shape indexes based on surface properties. In practice, assessment of cardiac function still relies on simple global volumetric measures like LV volume and mass, and ejection fraction (EF). These and other basic parameters will be presented in the following paragraphs.

Left Ventricular Volume (LVV): LVV is a basic parameter required to derive other LV indexes like, e.g., EF. Angiocardiography and echocardiography have been traditionally used to assess this quantity.

Left Ventricular Mass (LVM): LV hypertrophy, as defined by echocardiography, is a predictor of cardiovascular risk and higher mortality.

Stroke Volume (SV): SV is defined as the volume ejected between the end of diastole and the end of systole.

Ejection Fraction (EF): EF is a global index of LV fiber shortening [34] and is generally considered as one of the most meaningful measures of the LV pump function. It is defined as the ratio of the SV to the end-diastolic volume (EDV).

Cardiac Output (CO): The role of the heart is to deliver an adequate

quantity of oxygenated blood to the body. This blood flow is known as the cardiac output and is expressed in liters per minute.

2.1.2 Motion and Deformation Analysis

Motion analysis: A number of techniques have been used in order to describe and quantify the motion of the heart. They can be divided into three main categories [35]: i) detecting endocardial motion by observing image intensity changes, ii) determining the boundary wall of the ventricle, and subsequently tracking it, and iii) attempting to track anatomical, implanted or induced myocardial landmarks.

Wall Thickening (WT): The most widely employed method for WT computation is the centerline method [36]. Starting with the endocardial and epicardial contours at each slice, the centerline method, in its original formulation, measures WT in chords drawn perpendicular to a line that is equidistant to both contours (the centerline).

Strain Analysis (SA): SA is a method to describe the internal deformation of a continuum body. It is an appealing tool to study and quantify myocardial deformation. A comprehensive exposition of this theory can be found in [37].

2.2 Manual Segmentation

Most of the quantification methods mentioned above are based upon the identification of the boundaries of the LV cavity (especially endocardial boundary). Traditionally these boundaries are determined manually by expert clinicians

viewing a sequence of echocardiographic images in real-time, slow motion, and stop frame modes. Manual segmentation is performed by human operators with a computer, an input device (usually a mouse), and a display device to trace the endocardial and epicardial boundaries in echocardiographic images. Because human operators can use knowledge of the anatomical structure of the heart, the results of manual segmentation are usually more reliable than those of automatic and semi-automatic segmentation. Therefore, it is often considered the ‘gold standard’ and is widely used in routine clinical practice.

Nevertheless, manual tracing of image borders is tedious and significant intraobserver and interobserver variability may exist in measurements [38]. These problems encourage many computer vision and medical image processing researchers to investigate automatic or semi-automatic techniques for LV boundary detection in the standard 2D echocardiographic images [23].

2.3 Semi-automatic Segmentation

Recently, computer-based processing techniques facilitate the quantification of cardiac function using 2D echocardiographic images, including noninvasive determination of left ventricular volume, ejection fraction and regional wall motion. However, automatic extraction of the endocardial boundary from echocardiographic images is a particularly challenging problem. Image analysis is greatly complicated by the inherent characteristics of these images [39].

Figure 2.1: A classical boundary detection scheme

2.3.1 A Classical Method of Boundary Detection

A classical approach to this problem consists of several distinct phases of analysis, as shown in Fig. 2.1:

Following acquisition of image data in digital form, images first undergo some form of pre-processing operation. The main purpose of the pre-processing operation is to suppress speckle and improve contrast [18]. The pre-processed images are then subjected to a segmentation operation, such as thresholding or edge detection. Next, a boundary identification algorithm extracts the LV boundary from the segmented images. Finally, the boundary identified may be subjected to various post-processing operations, such as removal of spurious boundary points, interpolation, smoothing, etc. Among these phases of analysis, segmentation and boundary identification are very important operations. They are combined into one algorithm in some approaches. However, the application of the conventional object border detection techniques are not appropriate in echocardiographic images [23]. Studies show that more sophisticated techniques are required for LV boundary identification in 2D echocardiographic images. This requires *a priori* assumptions and domain knowledge about the

standard ultrasound images, (e.g., heart anatomy and morphology, intensity, spatial and temporal information, and even noise characteristics) to be incorporated into the system. Various complex algorithms have been proposed for 2D echocardiographic image analysis based on these *a priori* assumptions.

2.3.2 Segmentation Methods

The basic segmentation goal is to distinguish the region of myocardium from background (blood). The algorithms which have been used for this purpose fall into two major classes: edge detection methods, and regional segmentation methods. In the case of edge detection algorithms, edge points are identified directly.

1. Edge-based segmentation

Edges are points of sharp variations of intensity in an image. There are many different types of sharp variation points in images, e.g., sharp variation created by occlusions, shadows, highlights, roofs, textures, etc. Generally they are located at the boundaries of important image structures. Hence, edges are often among the most important features for analyzing the properties of images.

Edge detection is most frequently achieved by some forms of spatial difference operator. Some types of spatial gradient operator is applied to the image, then a search is made for the high derivative values which occur at the endocardial boundary. A basic disadvantage of the derivative methods is that they do not perform well in the presence of noise. This problem is particularly acute in the case of ultrasound images, with

their high speckle noise content. A limitation of derivative based operators, therefore, is that they generate a relatively low ratio of true to false edges. However, they are extremely easy to implement in software, and are very commonly adopted for this reason. A variety of derivative algorithms have been implemented, including both first- and second-derivative operators, and both 1D and 2D implementations.

- **2D differencing operators**

In the case of 2D derivative operators, the entire image is convolved with a linear difference operator. Second-derivative (Laplacian) operator generates a scalar edge magnitude. Although first-derivative (gradient) operator requires application of two operators followed by a magnitude operation to generate the scalar edge value, it has the advantage of producing a vector edge value, which can be very useful in the subsequent boundary identification process. Derivatives are uniquely defined in continuous domain. However, several different gradient and Laplacian operators can be defined in the discrete world of digitalized images. As a result, a variety of derivative formulations have been proposed, e.g. difference of Gaussians (DoG) operator and Marr-Hildreth operator [40], most of which include some noise reducing component.

- **1D differencing operators**

In the case of 1D derivative operators, derivative values are calculated along a family of lines within the image. A limitation of 1D

operators is that they produce only the scalar component of gradient in the derivative direction. Since this is greatest when the derivative direction is perpendicular to the edge, 1D derivative operators are usually implemented radially, i.e. along a family of lines originating from the LV center point. As in the 2D case, radial difference operators have been implemented in a variety of first and second derivative formulations.

- **Matched filtering**

Edge detection has also been effected by various other methods. Matched filtering, or template matching, is a powerful means for locating a specific feature within a noisy dataset. An ideal version, or template, of the feature to be detected is defined, then the cross-correlation of the template with the data is calculated. The maxima in the cross-correlation are the locations where the template is matched most closely.

- **Artificial neural networks**

Hunter *et al.* [30] use an artificial neural network (ANN) to detect edge candidates. First, an intermediate vector is derived from the 7×7 region around each pixel in the raw image data, which is then fed to the neural net. The vector includes several intensity and gradient terms, and the radial angle. After training, ANNs are able to approximate a mapping function to classify the pixel as either an endocardial edge, an epicardial edge, or a non-edge. A major

disadvantage of this method is the inevitable requirement of training set, which is a tedious and time-consuming work. The trained network is used to classify the points in other images from the same sequence. However, in the case of images from another sequence, the results may not be so satisfying, because the characters of those features like gradients and pixel intensity are different between sequences of echocardiographic images. For example, large contrast changes and changes in orientation of the boundary can happen in sequences taken at different times or for different patients, (actually possible even in images from same sequence). In such situations, manual definition of a new training set is demanded, unless a more robust network is designed.

- **Wavelet transform**

With the development of the wavelet transform techniques, several methods based on multiscale edge detection have been proposed for boundary detection in echocardiographic images [24, 41–43]. Wavelet-based detection in ultrasound images are reported in [44], where the signal information at various resolution is provided using wavelet transform [44]. Normally in fine scales the SNR of the image is poor whereas in coarse scales the localization ability is reduced. Hence there is an ambiguity in edge detection and localization, which makes the decision on the operator size very important. However, the multiscale analysis technique has made an appropriate tradeoff between this ambiguity by combining the

information of an image at different scales. A fuzzy multiscale edge detection (FMED) method was investigated by Setarehdan and Soraghan [23]. In addition to wavelet transform, Gaussian pyramid can also be used for multiscale analysis [45].

Conventional edge detection techniques include both spatial and frequency filters, such as the Canny method, gradient or derivative methods such as the Sobel operator, the ‘stick’ operator. The detected edges can be linked by the Hough transform and graph-theoretic techniques. The conventional techniques, being developed for clean images, are not appropriate for ultrasound images because of the poor quality of images aforementioned in Section 1.1.3. The standard sequence of edge detection used in image processing, consisting of smoothing, edge operation, and applying a threshold, is less suitable to ultrasound images than to standard density images.

Recently, more complex algorithms have been introduced for edge detection. Nevertheless, it is difficult to compare different edge detection methods because most of these methods depend on threshold values and, hence, the result of comparison might depend on the specific values used. Furthermore, edge detection in ultrasound images is made difficult due to the presence of the different kinds of noise.

2. Region-based segmentation

Boundary-based methods are based on the assumption that the pixel values change rapidly at the boundary between regions. Region-based

approaches are based on the assumption that the feature vectors of the pixels within the same region are similar to each other, while those among different regions are not. In the case of region-based segmentation methods, the image is segmented into dissimilar regions, such as blood and myocardium, edge points are then defined by the region boundaries.

- **Thresholding**

Like spatial differencing, thresholding is based on the widely differing backscatter levels of blood and myocardium. A gray level threshold, falling somewhere between the average values expected for blood and myocardium, is chosen. Image pixels falling below this value are then considered to be myocardium. In this way the image is partitioned into disjoint regions of blood and myocardium, and those pixels falling at the region boundaries are considered to be boundary points. Thresholding is extremely easy to implement in software, and is the most commonly used regional segmentation method. The basic requirement in all thresholding methods is the determination of threshold value. One approach is to do it interactively. In addition to requiring manual input, one disadvantage of this method is that it requires the operator to make a subjective judgement of the resulting edge map. Another approach is to derive a threshold automatically from the image histogram or the temporal information contained in a sequence of images. Thresholding is applied globally in most cases. However, regional thresholding can be implemented to divide the image into a number of disjoint regions,

and for each region an independent local threshold is determined.

- **Region growing**

One of region-based algorithms is known as region growing [46,47].

The general procedure is to compare each pixel with its neighbors and if some criteria of homogeneity are satisfied then the pixel is labeled the same class as its neighbors. As the choice of homogeneity criterion is critical, the resultant segmentation is subject to noise and may generate irregular boundaries and small holes.

- **Texture analysis**

The microscopic structure of different tissues gives rise to different image textures. There are numerous possible measures of texture analysis, such as gray level run-length statistics, grey level difference statistics, and various others. Texture has been used in ultrasound and other imaging modalities to distinguish between different types of tissues [48]. A review of methods for myocardial texture analysis from echocardiographic images is presented in [49]. The general approach is to experimentally identify a vector of textual parameters which vary widely between the two types of tissue, and use this vector to discriminate one type of tissue from the other. The potentials of co-occurrence matrix analysis for ultrasound image texture can be found in [50]. Recently, texture characterization based on the discrete wavelet transform which integrates the multichannel filtering theory and statistical modeling, has attracted much attention

and was found useful for a variety of texture applications [51–53].

- **Global optimization**

Global optimization approaches are based on global criteria such as Bayesian [54–58], and minimum description length (MDL) criteria [59]. Determination of the globally optimal solution is found to be computationally costly. Furthermore, due to the poor quality of ultrasound images, segmentation algorithms based only on global information (such as thresholding techniques, global clustering approaches and intensity-dependent edge detection) are not suitable and give poor results. Several solutions are proposed to avoid the intensity inhomogeneity problem or take into account the non-uniformity of tissue classes [50, 56, 60, 61].

2.3.3 Boundary Identification Methods

After carrying out some form of image segmentation, the next step is to extract the endocardial boundary from the segmented image.

1. Radial search methods

A very commonly used method of boundary identification is radial search procedure, in which the segmented image is searched along (or the segmentation operation proceeds along) a family of radial lines originating from the LV center point. Various methods have been proposed to identify the location of the endocardial boundary along each radius. In many cases the boundary location is identified as the first edge point, or largest

magnitude edge point, along the radius. A limitation of radial search methods is that they are based on the assumption that the endocardial boundary is a single-valued function in polar coordinates, i.e. each radial line intersects the boundary only once (when a center point is properly chosen). This is the case for most short-axis views, but in other echocardiographic views the boundary is typically not single valued. The radial search method is therefore largely restricted to the short-axis view only.

2. Cost function methods

Another commonly used method of boundary extraction is the method that minimizes a cost, or energy, function. The cost function is a quantification of how well a particular boundary fits the edge map and satisfies other *a priori* boundary criteria. The target border is then the one with minimum cost function value. A major advantage of cost function methods is that they are not restricted to single-valued borders in polar coordinates. A further advantage is that the cost function can be formulated to include multiple boundary criteria such as intensity and texture difference, temporal and shape constraints.

- **Cost function minimization**

Computationally efficient, but sub-optimal, search method in practical terms must be used to determine an approximate minimum cost contour. This is usually accomplished by some forms of dynamic programming procedure. Friedland and Adam [62] solve the minimization problem by simulated annealing, an algorithm for

highly parallel iterative stochastic relaxation optimization. Both dynamic programming and simulated annealing require that the search domain be restricted to a region which is known *a priori* to contain the target boundary. The need of manual specification of a search region is a major disadvantage of cost function minimization methods.

- **Active contour models**

The snake energy function [63–65], or active contour model, is similar to the cost function approach, except that the LV contour is initially modeled as a deformable curve, or snake, and the edge map is modeled as a set of forces which act upon the snake. The total energy of this model includes the bending and stretching energy of the snake, and the potential energy associated with the edge point forces. The target contour is then the minimum energy configuration of this model. Chalana *et al.* [26] proposed a multiple active model for cardiac boundary detection on echocardiographic sequences, which is an extension of the original active contour model to 3D (2D+T). Other extensions of the snake model include multiscale optimization [25], deformable templates and Markov Random Field [66], and early vision-based snake models [67]. Recently, several alternative region-based snake methods [68–72] have been proposed where the statistical distribution of the grey levels inside and outside the snake is exploited. A disadvantage of snake is the need to specify an initial snake configuration, and the minimum

energy configuration can be very sensitive to the initial condition.

An approximate solution to the minimization problem has to be determined by some form of computationally efficient algorithm, in common with the cost function method. The snake model can be extended to the temporal domain [26] and three spatial dimensions which is named active surface models [73].

- **Active shape models**

Parker *et al.* [28] carried out LV boundary identification using active shape models, or ASMs. An ASM is similar to a snake, except that the ASM's shape deformation is constrained to conform to a statistical model of the target object. The statistical model is created from a set of training objects. The model consists of the average object shape, together with a set of eigenvectors representing the main modes of shape variation. This defines a subspace of allowable configurations for the ASM. The ASM is then constrained to the statistical model by least squares approximation. Jacob *et al.* [74] described a statistical shape model trained from example LV contours by Principal Component Analysis (PCA), combined with a Kalman filter for prediction of dynamic shape changes and feature detection of left ventricle. This method relies on the assumption that the shape and motion models can well represent the deformations not only in the dataset of interest, but also in the case of abnormal motion of a diseased heart. The extension of ASM includes active appearance models (AAM) and active appearance

motion models (AAMM) [29]. However, AAMM suffers the same kind of limitation as shape-model based methods, since its reliability depends on the range of variabilities covered in the training set. In the case of images from different types of devices, the accuracy of the model may vary significantly and may require further training of the new dataset.

3. Use of anatomical models

A disadvantage of both radial search methods and cost function methods is that they are not able to reliably distinguish the LV boundary from other boundary structures which may be present in the image, such as the right ventricle, mitral valve, or epicardial boundary. Several attempts have been made to deal with this by implementing boundary identification schemes which incorporate the use of *a priori* anatomical information [75]. Some use anatomical models to generate initial boundary approximations for cost function methods, and others use matched filters to identify a set of specific anatomical features, followed by a set of heuristic anatomical rules to locate the endocardial boundary.

4. Other boundary identification methods

The intractability of echocardiographic images to conventional analysis has led several investigators to implement methods which mimic human cognitive processes. These include the use of anatomical models and the use of artificial neural network, previously discussed as an edge detection method. Another method which is intended to mimic human information

processing is the use of fuzzy logic techniques [76]. The logical integration of knowledge is represented by operations on fuzzy relations in this method.

Boundary identification schemes based on morphological operations are reported in [77]. By suitable application of operations in succession, such as growing and shrinking, the merging or splitting of regions, and smoothing region boundaries, it is possible to segment the image into a set of homogeneous connected regions.

Chapter 3

Detection of Region of Interest

3.1 Introduction

Automatic boundary detection of left ventricle in echocardiographic images is an essential task for reliable and objective assessment of the heart function. The first step of many existing methods is the localization of the left ventricular center point (LVCP) or determination of an initial contour. For example, the active contour model method [26] requires a good initialization at the beginning of deformation, since the snake is often very sensitive to the initial position of the contour. Most of the present methods require initial intervention by human beings, e.g., outlining a rough boundary curve, selecting a seed point or LV center. These human interventions reduce the independence of the algorithms.

An automatic fuzzy-based method for estimating the location of the LVCP in a single echocardiographic image was proposed in [78]. The system uses descriptive features of the LVCP in the extraction process. The rationale

behind this fuzzy based approach are: (1) LVCP usually appears as a *dark* hole surrounded by bright pixels in the image, and (2) it is located approximated in the *central* part of the image. However, the two assumptions may not be valid in all situations. For example, the templates for dark neighborhood of LVCP are not able to work for echocardiographic images with low resolution, and there are situations where LVCP is not in the central part of the image.

A new approach to locate the LV region automatically has been developed in this chapter to do away with the limitations mentioned above. The method makes use of watershed transform and morphological operation to locate the region containing the left ventricle. The details of the proposed algorithm and its application are described in the following sections. The identification of ROI, a region containing the whole endocardial boundary, is the first phase in the automatic detection of the LV boundary. The ROI provides an initial condition, thus expediting and facilitating the second phase of boundary detection.

3.2 Algorithm Design

3.2.1 Preprocessing

From a four-chamber-view gray-scale echocardiographic image, it can be observed that the interior of the four chambers of the heart are darker than the myocardial walls. This characteristic feature is utilized in the LV boundary detection.

First, a composite image (Fig. 3.1(a)) is generated where the pixel inten-

Figure 3.1: Binary image processing. (a) The composite image and (b) after preprocessing.

sities are the maximum values from the corresponding pixels in a sequence of images. The composite image is smoothed by the adaptive neighborhood smoothing method [21] to reduce the influence of speckle noise. Suppose that the interior region of the ventricle has intensities consistently below a threshold gray level τ , a large smoothing kernel is used for pixels less than the threshold τ and a small smoothing kernel is used for pixels above τ . For an image of $m \times n$ pixels, the sizes of the large kernel and the small kernel are $K_l \times \sqrt{m \times n}$ and $K_s \times \sqrt{m \times n}$ respectively (the selection of the values of K_l and K_s are given in Section 3.4). The smoothing step is repeated twice to ensure that the low-intensity regions are smoothed more thoroughly than the high-intensity regions. The resulting image is shown in Fig. 3.1(b).

3.2.2 Binary Image Processing

The resulting image is then converted to a binary image by setting the threshold τ for the gray level pixel values.

Figure 3.2: Binary image processing. (a) The binary image before morphological close and (b) after morphological close.

There may be some extraneous objects in the resulting binary image, and the heart chambers may connect with each other. The holes in the binary image are filled by morphological operations to remove the extraneous objects generated by speckle noise or artifacts. The binary image (Fig. 3.2(a)) is subjected to a morphological *close* with structuring element of size $C \times \sqrt{m \times n}$ to separate the overlapping chambers, where C is a constant. The morphological *close* makes the objects in the image which are mainly the cardiac chambers shrink according to the size and shape of the structuring element. After this step, four different regions corresponding to the four cardiac chambers are separated as shown in Fig. 3.2(b).

3.2.3 Watershed Segmentation

The Euclidean distance transform of the resulting image is computed and the obtained Euclidean distance map is shown in Fig. 3.3(a). The intensity of each pixel in the image is a function of the distance between the pixel

and the nearest nonzero pixel of the binary image. Watershed immersion algorithm [79] is applied to the Euclidean distance map to accomplish binary image segmentation.

For an image f defined on a digital grid: $\mathcal{X} \subset \mathbb{Z}$, the catchment basin CB_i of a regional minimum $\mathcal{M}_i$ ($i = 1, \dots, K$) is defined by:

$$CB_i = \{x \in \mathcal{X} \mid \forall j \neq i, 1 \leq j \leq K : \alpha_i + L_i(x) < \alpha_j + L_j(x)\}. \quad (3.2.1)$$

where α_i is the level of f on $\mathcal{M}_i$, and $L_i(x)$ is the corresponding topographical distance transform [80]. $WS(f)$, the watershed line of the image f , is the set of points not belonging to any catchment basin $CB(\mathcal{M}_i)$:

$$WS(f) = \mathcal{X} \setminus \bigcup_i CB(\mathcal{M}_i). \quad (3.2.2)$$

At the location of overlap in the binary image, there is a ridge in the corresponding map where the two catchment basins of each overlapping object meet. Each of the two catchment basins is labeled uniquely and the lines separating them are labeled as a chamber watershed (Fig. 3.3(b)).

3.2.4 Post-processing

The binary image is then masked by multiplication with the label image. Every object in the masked binary image (Fig. 3.4(a)) is labeled with different integer value for distinct identification. Objects connected to the image border (ultrasound fan area) are removed from the image. Only the four objects

Figure 3.3: (a) The Euclidean distance map; (b) watershed segmentation.

Figure 3.4: (a) The masked binary image; (b) The ROI of the composite image (enclosed by dashed line) and the LVCP (white point).

corresponding to the heart chambers are retained. Based on anatomical knowledge, left ventricle is the object on the top-right of the image in this particular case. In the watershed label map, the catchment basin to which this object belongs is considered as the region corresponding to the left ventricle. This region defines the ROI and its center of gravity (i.e. the average location of the pixels within the region) is defined as the LVCP (Fig. 3.4(b)).

3.3 Application on LV Boundary Detection

The LV endocardial (interior) boundary can be detected based on the identified ROI and LVCP.

3.3.1 Snake

The left ventricle is determined within the ROI using a snake. In the snake (or active contour model) originally introduced by Kass *et al.* [63], the problem of boundary detection is formulated as an energy function minimization problem.

A snake is an active contour defined by

$$\Gamma(s) = (x(s), y(s)) \quad (3.3.3)$$

where s is a parametrization of the contour. $\Gamma(s)$ is the closed boundary of a region R (i.e., $\Gamma(s) = \partial R$).

The energy of the snake is defined as

$$E_{snake} = \oint_{\Gamma(s)} \left[\alpha |\Gamma_s|^2 + \beta |\Gamma_{ss}|^2 + E_{ext}(\Gamma(s)) \right] ds. \quad (3.3.4)$$

where Γ_s and Γ_{ss} are the first and second derivatives with respect to s . Elastic energy $|\Gamma_s|^2$ is responsible for the shrinking of the contour and bending energy $|\Gamma_{ss}|^2$ is minimum for a circle. α and β are coefficients associated with $|\Gamma_s|^2$ and $|\Gamma_{ss}|^2$ respectively.

The external energy E_{ext} is derived from the image and assumed to have smaller values for the features of interest. The choice of a proper external

energy E_{ext} is one of the most difficult problems in snake-based segmentation methods [81]. The conventional snake is contour-based as its external energy is defined to move the contour to the areas of high gradients:

$$E_{ext}(x, y) = -\lambda \left| \nabla [G_\sigma * I(x, y)] \right|^2. \quad (3.3.5)$$

where G_σ is a 2D Gaussian function with standard deviation σ and λ is a weighting coefficient.

The snake model has been adopted in detecting the boundaries of the objects in ultrasound images. One of the desirable features of snake-based methods is that a closed boundary is always obtained, even in the presence of weak edge definitions in ultrasound images. Another advantage is that the snake can incorporate both the edge and region information in its energy function definition, which is a crucial guide in the deformation process. Despite the advantages, this model suffers from a number of limitations. First, the snake requires an initial contour which cannot be too far away from the target boundary [26]. Second, the snake cannot capture objects with concave parts or high curvature contours. For the first limitation, a good initial estimate of the LV boundary can be obtained using the proposed algorithm in Section 3.2 to supply a gap. As for the second limitation, it may not be obvious since the endocardial boundary of left ventricle is generally smooth and regular.

3.3.2 Edge Map Calculation

For echocardiographic images with speckle noise and artifacts which are inherent to acoustic images, the approach expressed by Eqn. (3.3.5) is not suitable. In this section, a new method to estimate the external energy in the snake model is described.

Using 2D discrete dyadic wavelet transform, the horizontal derivative G_x and the vertical derivative G_y of the echocardiographic image, for the scales j ($j = 1, 2, \dots, J$), are determined by applying the wavelet transform on the preprocessed image (Fig. 3.1(b)). Subsequently, the directional gradient is computed. The magnitude M_g and direction θ_g of the gradient are obtained from G_x, G_y as follows:

$$M_g^j(x, y) = \sqrt{\left[G_x^j(x, y)\right]^2 + \left[G_y^j(x, y)\right]^2}, \quad (3.3.6)$$

$$\theta_g^j(x, y) = \text{angle}(G_x^j(x, y) - i * G_y^j(x, y)). \quad (3.3.7)$$

where $i = \sqrt{-1}$.

The LVCP is defined as the center of the ROI. Let θ_p be the angle of any point P in the image with reference to LVCP, then the directional gradient M_d is determined by the following equation as shown in Fig. 3.5.

$$M_d^j(x, y) = M_g^j(x, y) * \cos(\theta_g^j(x, y) - \theta_p^j(x, y)). \quad (3.3.8)$$

For endocardial boundary, only positive intensity changes are to be identified along the radial lines from the LVCP. Hence, for the detection of endo-

Figure 3.5: Illustration of transition from M_g to M_d .

cardial boundary, only positive directional gradients are of interest. The first three scales are used to compute the edge map:

$$M_{endo}^j(x, y) = \begin{cases} M_d^j(x, y) & \text{if } M_d^j(x, y) > 0 \\ 0 & \text{otherwise,} \end{cases} \quad (3.3.9)$$

for $j = 1, 2, 3$.

The necessary number of scales is dependent on the size of the image to be processed. For the echocardiographic images used in the thesis, the experiments show that three scales are appropriate.

$$F = M_{endo}^1 + M_{endo}^2 + M_{endo}^3. \quad (3.3.10)$$

The directional gradients from the three scales are added in Eqn. (3.3.10) to combine the multiscale information. Strong edges are emphasized and weak edges of higher scales are also preserved (Fig. 3.6(d)) in the resultant multiscale directional edge map F . The new external energy is obtained as follows:

$$E_{ext}(x, y) = -\lambda F(x, y)^2. \quad (3.3.11)$$

Figure 3.6: (a) The directional gradient at the first scale; (b) the directional gradient at the second scale; (c) the directional gradient at the third scale; (d) the multiscale directional edge map of the left ventricle.

3.3.3 Snake Deformation

After obtaining the external energy using Eqn. (3.3.11), the snake is deformed to determine the LV boundary. To track the LV boundary in a sequence of echocardiographic images, such as from a cardiac cycle, the detected boundary from one frame can be used as the initial curve for the next frame.

3.4 Results and Discussion

There are six parameters involved in the proposed method: the threshold τ , K_l and K_s for smoothing kernel sizes, C for structuring element size, and the energy weights α and β . The value of τ is obtained by Otsu's method [82]. The other five parameters of the method are set as $K_l=0.025$, $K_s=0.0125$, $C=0.04$, $\alpha=0.1$, and $\beta=0.1$ for all the experiments. The values of these parameters are determined by trial-and-error to obtain optimal results.

The following guidelines are used for adjusting the values of these parameters for other images. As indicated in Section 3.2.1, the smoothing kernel sizes and structuring element size are set to be proportional to the size of the image by K_l , K_s and C . Their optimal values are decided by the size of the object (left ventricle) in the image. K_l , K_s and C are constant for normal echocardiographic images. Larger/smaller values are required for the three parameters, when the ratio of the object (left ventricle) size to the whole image size is larger/smaller than the normal ratio.

The results of LV center point and boundary detection in Datasets I-V are given in Figs. 3.7-3.11. The computation time for LV ROI and center

Figure 3.7: Results of Dataset I (containing 38 images of 200×200 pixels): (a) ROI segmentation in composite image and (b)-(c) LV boundary detected in end-diastole frame and end-systole frame respectively.

Figure 3.8: Results of Dataset II (containing 16 images of 136×121 pixels): (a) ROI segmentation in composite image and (b)-(c) LV boundary detected in end-diastole frame and end-systole frame respectively.

detection (implemented in Matlab) is 1-2 seconds on a Pentium IV 2.6 GHz PC.

3.5 Summary

A novel method using morphological operations and watershed segmentation is proposed to automatically detect the center of the left ventricle from echocardiographic images. The proposed method does not require human intervention. The location of the LVCP is tracked automatically and the parameters are adjusted adaptively. The proposed method of localization of ROI limits the

Figure 3.9: Results of Dataset III (containing 13 images of 136×121 pixels): (a) ROI segmentation in composite image and (b)-(c) LV boundary detected in end-diastole frame and end-systole frame respectively.

Figure 3.10: Results of Dataset IV (containing 22 images of 197×171 pixels): (a) ROI segmentation in composite image and (b)-(c) LV boundary detected in end-diastole frame and end-systole frame respectively.

Figure 3.11: Results of Dataset V (containing 15 images of 210×221 pixels): (a) ROI segmentation in composite image and (b)-(c) LV boundary detected in end-diastole frame and end-systole frame respectively.

interference from artifacts and also provides an initial contour for LV boundary detection. In addition, this approximative segmentation greatly reduces the computation time needed for the final segmentation, the detection of the actual LV boundary.

The LV center in short-axis echocardiographic images may also be detected automatically, but not by the proposed watershed pre-segmentation method which is designed for the long-axis image. A possible solution is to make use of the characteristics of short-axis images as a prior knowledge or assumptions, e.g. the LV center locates approximately in the central part of the images and it appears darker than the surrounding region (the larger the depth of blood, the low the level of echo return).

Chapter 4

Long-axis Echocardiographic Image Segmentation Using Markovian Level Set Method

In Chapter 3, a new pre-segmentation algorithm for the LV center point and ROI detection is described, and its applications to boundary detection by the snake model with a multiscale directional edge map is also presented. In this chapter, a more sophisticated method is proposed for long-axis echocardiographic image segmentation with improved performance.

4.1 Introduction

As pointed out in Chapter 1, the inherent characteristics of B-mode ultrasound images, including low contrast, speckle noise, dropouts, and ill-defined edges, greatly complicate automatic LV boundary detection and volume visualization.

The papillary muscles and heart valves also produce undesirable artifacts in echocardiographic images, which can impose problems in boundary detection using a simple approach.

Markov Random Field (MRF) and Bayesian based methods have been investigated by several researchers to segment ultrasound images [7, 27, 54]. A MRF is a probabilistic model of the elements of a multidimensional random variable where the components have only local interactions [83]. According to MRF theory, an energy function of the field can be derived from neighbors and cliques. The *Gibbs Sampler* algorithm proposed by S. Geman and D. Geman [84] gives a constructive iterative procedure to realize the field in practical applications. Additionally, the Simulated Annealing (SA) algorithm [84] was proposed to find the maximum a posteriori (MAP) estimation of the field.

Some researchers make use of both snakes and MRF for segmentation. A work using a Markovian snake model in polar coordinates was developed by Friedland and Adam [62] for fast detection of LV boundaries from 2D echocardiograms. In the elliptical ROI defined by means of a Hough transform, *rays* radiate from the center. The allowed contour positions on every ray are discretized, and a 1D (in angular coordinates) MRF is defined so as to impose smoothness in the solution contour. In this method, the SA algorithm is performed upon the MRF for optimization, and no Bayesian philosophy is used. Figueiredo and Leito [85] proposed a similar model but using Bayesian philosophy. The joint optimization of both the contour and the parameters of the model is achieved by means of an adaptive version of the Iterated Conditional Modes (ICM) algorithm [86]. The first approach where ultrasound statis-

tics was considered was proposed in [7]. The same polar representation of a first-order MRF is adopted while the optimum is obtained using dynamic programming. Haas *et al.* [87] extended the Markovian snake model to 3D where the temporal coordinate is replaced with the depth coordinate. An alternative approach is to realize the Markovian snake model in Cartesian coordinates, where the number of snaxels (snake elements) is allowed to change [88]. The image energy in snake model can also be defined from region statistics [89,90] instead of image edges. Mignotte *et al.* [90] combined MRF with deformable templates under a Bayesian approach.

In this chapter, an algorithm named *Markovian level set* is proposed for boundary detection of the LV in long-axis echocardiographic images. The proposed method differs from other MRF-based methods in that it combines the MRF and the level set method to alleviate some of the aforementioned problems.

4.2 Hierarchical MRF Based Segmentation Model

4.2.1 MRF Based Segmentation Model

A common MRF based segmentation model is in the Bayesian framework. Consider two random fields $Z = (X, Y)$, where $Y = \{Y_s, s \in S\}$ is the field of observations located on a lattice S of N sites s , and $X = \{X_s, s \in S\}$ is the label field. Each of the Y_s takes its value in $\{0, \dots, 255\}$ and each X is in $\{e_0 = \text{blood}, e_1 = \text{myocardium}\}$. The discrete probability $P(X = x)$ is written as $P(x)$ to simplify notations. The distribution of (X, Y) is defined firstly by

prior distribution $P(x)$ and secondly by site-wise likelihoods $P(y_s/x_s)$. The joint and posterior distributions are expressed in the following forms:

$$P(x, y) = P(x)p(y|x) \quad (4.2.1)$$

$$P(x|y) = \frac{P(x, y)}{P(y)} \propto P(x)p(y|x) \quad (4.2.2)$$

The prior distribution $P(x)$ depends on a parameter vector Φ_x while data likelihood $p(y_s/x_s)$ depends on another parameter vector Φ_y . Thus the joint and posterior distributions depend on $\Phi \triangleq (\Phi_x, \Phi_y)$.

The segmentation label map $\hat{x}$ is determined by

$$\begin{aligned} \hat{x} &= \arg \max_x P(x|y) \\ &= \arg \max_x \left\{ p(y|x)P(x) \right\}. \end{aligned} \quad (4.2.3)$$

Prior distribution

The prior distribution $P(x)$ is supposed to be stationary and Markovian. The random field X is an MRF with respect to neighborhood system $\mathcal{N}(s)$ if $P(x_s) > 0$ for all w and

$$P(x_s|x_r, r \neq s) = P(x_s|x_r, r \in \mathcal{N}(s)). \quad (4.2.4)$$

It means that the conditional probability of a particular site depends only on its immediate neighbors as defined by $\mathcal{N}(s)$. Since a MRF is completely described by a Gibbs distribution, the Gibbs random field form of $P(x_s)$ is

then expressed:

$$P(x_s) = \frac{1}{Z_X} \exp[-U(x_s)] \quad (4.2.5)$$

where $U(x_s)$ is the Gibbs potential, given by the summation of the clique energy $V(x_C)$ over all cliques C :

$$U(x_s) = \sum_C V(x_C) \quad (4.2.6)$$

and Z_X is a normalizing constant called the partition function, given by

$$Z_X = \sum_s \exp[-U(x_s)]. \quad (4.2.7)$$

To model the hidden region label process, the multi-level logistic MRF (LMRF) with the second-order neighborhood system is used for segmentation. In this model, all clique energies are assumed to be zero except for the doubleton clique energies which are given by

$$V(x_s, x_r) = \begin{cases} -\beta & \text{if } x_s = x_r \\ \beta & \text{otherwise} \end{cases}$$

where $r \in \mathcal{N}(s)$. β is the Gibbsian parameter, which has to be positive since two neighboring pixels are more likely to belong to the same class than to different classes, hence the region labeling component imposes a homogeneity constraint on the image segmentation process. Increasing the value of β increases the region size and leads to excessive smoothing of boundaries.

To maximize $P(x_s)$ is equivalent to minimize $U(x_s)$. Thus the latter can

be considered as an energy regarding image regions:

$$E_R(x_s) = U(x_s) = \beta \sum_{r \in \mathcal{N}(s)} \delta(x_s, x_r). \quad (4.2.8)$$

where

$$\delta(x_s, x_r) = \begin{cases} -1 & \text{if } x_s = x_r \\ +1 & \text{otherwise.} \end{cases}$$

Data likelihood

The extracted image features often vary due to the existence of noise in the image. Three main models have been identified by investigations on the statistics of ultrasound echo envelope [91]. The first is for fully developed speckle induced by a large number of randomly located scatterers, which is well modeled by a *Rayleigh distribution*. The second is for the presence of a regular structure of scatterers within the tissue, the B-mode brightness statistics are approximated by a *Rician distribution*. The third is for partially developed speckles induced by a low effective number of scatterers which can be modeled by a *K-distribution*. After low-pass filtering and decimation, the statistics of the images are greatly changed and become difficult to model.

In [54] the difficulty is avoided by taking advantages of the Central Limit Theorem. According to the theorem, the average of a large number of random variables must tend toward a Gaussian distribution around their collective mean. It is reasonable to assume that the pixel values within a given region follow a Gaussian distribution with a slowly-varying mean μ , and with variance σ_x^2 . In this study, the distributions of all feature data are assumed to be

Gaussian with different means and standard deviations. Given the region labeled x_s in the k th feature component, the parameters are estimated from the region inside the window of width W centered at s . The data likelihood is given by

$$p(y_s^k|x_s) = \frac{1}{\sqrt{2\pi\sigma_{x_s}^k{}^2}} \exp \left[-\frac{(y_s^k - \mu_{x_s}^k)^2}{2\sigma_{x_s}^k{}^2} \right]. \quad (4.2.9)$$

An energy regarding the feature data is then derived:

$$\begin{aligned} E_F(y_s|x_s) &= -\log p(y_s|x_s) \\ &= \sum_{k=1}^K \left[\frac{(y_s^k - \mu_{x_s}^k)^2}{2\sigma_{x_s}^k{}^2} + \log(\sqrt{2\pi}\sigma_{x_s}^k) \right]. \end{aligned} \quad (4.2.10)$$

This feature modeling component constrains the regional intensity to be close to the feature data.

The MAP estimation of X is then given by

$$\begin{aligned} \hat{x} &= \arg \max_x \left\{ p(y|x)P(x) \right\} \\ &= \arg \min_x \left\{ E_R(x) + E_F(y|x) \right\}. \end{aligned} \quad (4.2.11)$$

4.2.2 Hierarchical MRF Basics

The hierarchical MRF has a pyramid structure. At each scale n , the labeling is denoted by the random field X^n and the set of lattice points is denoted by S^n . X^0 is the finest scale random field with each point corresponding to a single image pixel. Each label at a scale X^n ($n > 0$) corresponds to a group of four points in the next finer scale X^{n-1} .

In the Hierarchical Markovian model, a number of conditional independence properties are assumed. The fundamental assumption is that the sequence of random fields from coarse to fine scales form a Markov chain, i.e.

$$P(x^n|x^l, l > n) = P(x^n|x^{n+1}) = p(x^n|x^{n+1}). \quad (4.2.12)$$

Therefore, the distribution of X^n given all coarser scale fields depends only on X^{n+1} . This is reasonable since X^{n+1} should contain all the relevant information from previous coarser scales.

The second assumption is that the probabilities of inter-scale transitions can be factorized in the following way:

$$P(x^n|x^{n+1}) = \prod_{s \in S^n} P(x_s|x_{s^-}) \quad (4.2.13)$$

where s^- designates the single father (the corresponding site in the next coarser scale) of a site s . Correspondingly, Y is exclusively dependent on X^0 :

$$P(y|x^n, n > 0) = P(y|x^0). \quad (4.2.14)$$

The joint distribution $P(x, y)$ may be expressed as the product of the above distributions

$$P(x, y) = p(y|x^0) \left\{ \prod_{n=0}^{L-1} p(x^n|x^{n+1}) \right\} p(x^L) \quad (4.2.15)$$

for the coarsest scale:

$$\begin{aligned}\hat{x}^L &= \arg \max_{x^L} \log p(x^L|y) \\ &= \arg \max_{x^L} \log p(y|x^L).\end{aligned}\tag{4.2.16}$$

for finer scales ($0 \leq n < L$)

$$\begin{aligned}\hat{x}^n &= \arg \max_{x^n} \log p(x^n|\hat{x}^{n+1}, y) \\ &= \arg \max_{x^n} \left\{ \log p(y|x^n) + \log p(x^n|\hat{x}^{n+1}) \right\}.\end{aligned}\tag{4.2.17}$$

Compared with simple MRF based segmentation model, the hierarchical Markovian model replaces the purely spatial priors with hierarchical priors, where the interactions between variables are not only supported by the grid over the image pixels but also defined from scale to scale. A multi-level MRF with interscale neighborhood as well as intrascale neighborhood is adopted. The chosen intrascale neighborhood is second-order (same as in simple MRF models):

$$V(x_s^n, x_r^n) = \begin{cases} -\beta_n & \text{if } x_s^n = x_r^n \\ \beta_n & \text{otherwise} \end{cases}$$

at the n th scale. The interscale neighborhood is one parent from the last coarser scale:

$$V(x_s^n, x_{s_p}^{n+1}) = \begin{cases} -\beta_{n,n+1} & \text{if } x_s^n = x_{s_p}^{n+1} \\ \beta_{n,n+1} & \text{otherwise} \end{cases}$$

where $s_p = (s + 1)/2$.

The resulting region energy is

$$E_R^L(x_s) = \beta_L \sum_{r \in \mathcal{N}(s)} \delta(x_s, x_r). \quad (4.2.18)$$

$$E_R^n(x_s) = \beta_n \sum_{r \in \mathcal{N}(s)} \delta(x_s, x_r) + \beta_{n,n+1} \delta(x_s^n, x_{s_p}^{n+1}). \quad (4.2.19)$$

The first term in Eqn. (4.2.19) denotes the spatial region energy, and the second term denotes the hierarchical region energy.

4.2.3 Parameter estimation

The two-step expectation-maximization (EM) algorithm [92] is applied to perform the maximum likelihood (ML) estimation with incompletely observed data. The observed image Y (L -level wavelet transformed image) is called incomplete data. The observed image Y and the unobservable region label image X constitute a set (X, Y) , which is complete data. The E-step and M-step run iteratively.

- E-step: In this step, the conditional expectation $\mathcal{Q}$ over the unobservable tissue labels x_s is calculated, given the observed data y_s and the current parameter estimation $\Phi^{(p)}$, and then the labels is substituted with the expectations. In other words, the image sites are statistically classified based on the current parameter estimation.

$$\mathcal{Q}(\Phi|\Phi^{(p)}) = \sum_{x_s} p(x_s|y_s; \Phi^{(p)}) \log p(x_s, y_s; \Phi) \quad (4.2.20)$$

- M-step: In this step, the ML estimation of the parameters is performed as if there were no missing data, i.e. as it had been filled in by expectations. In other words, the parameters are re-estimated based on the current classification.

$$\Phi^{(p+1)} = \arg \max_{\Phi} \mathcal{Q}(\Phi | \Phi^{(p)}). \quad (4.2.21)$$

where $\Phi \triangleq (\Phi_x, \Phi_y)$ represents the set of all parameters to be estimated.

For the models used in Sec. 4.2.1, Φ_x refers to β and Φ_y refers to (μ, σ) .

By the simultaneous classification and parameter estimation, likelihood is increased at each iteration. EM is shown to converge to the ML estimates at least locally under some moderate conditions [93].

Noise model parameters

Rewriting Eqn. (4.2.9) for *blood* regions (class $x_s = e_0$) with noise model parameters (Φ_y) added, we have

$$p(y_s | e_0, \Phi_y) = \frac{1}{\sqrt{2\pi\sigma_{x_s}^2}} \exp \left[-\frac{(y_s - \mu_{x_s})^2}{2\sigma_{x_s}^2} \right]. \quad (4.2.22)$$

The empirical mean and empirical variance of the corresponding ML estimator are given by

$$\hat{\mu} = \frac{1}{N_0} \sum_{s \in S: x_s = e_0} y_s \quad (4.2.23)$$

$$\hat{\sigma}^2 = \frac{1}{N_0 - 1} \sum_{s \in S: x_s = e_0} (y_s - \hat{\mu})^2 \quad (4.2.24)$$

where $N_0 \triangleq \#\{s \in S : x_s = e_0\}$ is the number of pixels located in the blood region.

Similar set of equations can be derived for *myocardium* regions (class $x_s = e_1$).

A prior model parameters

The standard prior model is a second-order anisotropic Ising model ruled by four parameters $\Phi_x = (\beta_1, \beta_2, \beta_3, \beta_4)^T$. $\beta_1 - \beta_4$ correspond to the horizontal, vertical, right and left diagonal cliques respectively. A simple isotropic model is used where $\beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta$. The variation of β is set as a function of the decomposition level in hierarchical MRF model. As indicated above, the parameter β controls the influence of the spatial constraint energy function (Eqn. (4.4.33)). A low β value is used for low scale images which are already smooth. β is increased by $\Delta\beta$ for finer scale, when details are added. A large β is obtained at the finest scale to smooth the boundary at the expense of some contour details.

4.3 Level Set

MRF theory is popularly used in image segmentation as it provides a convenient way to model the contextual information in an image, which is crucial for interpretation of the image content. By the MRF-MAP classification, the prior distribution and the noise likelihood distribution are combined for the estimation of class labeling. For noisy echocardiographic images, MRF is good at the detection of edges at regions of low contrast, by using the local statistic information. However, the MRF-based segmentation is essentially a regional method, which makes it hard to regulate the shape of boundary during the

segmentation process. On the other hand, the level set method is a curve evolution method where the curvatures and normals may be easily evaluated in this setting. MRF and level set are combined to detect a continuous and smooth boundary.

4.3.1 Curve Propagation Theory

In the curve propagation theory, the deformation of curves is studied using only measures such as the unit normal and curvature as opposed to the quantities that depend on parameters such as the derivatives of an arbitrary parameterized curve. Let $C(p, t)$ be a moving curve in a Euclidean plane, which is generated by the movement of an initial curve $C_0(p)$ in the direction of its inward Euclidean normal vector $\mathcal{N}$:

$$\begin{cases} C_t = F(\mathcal{K})\mathcal{N} \\ C(p, 0) = C_0(p), \end{cases} \quad (4.3.25)$$

where F is the speed of the curve movement and $\mathcal{K}$ is the curvature. According to the above equation, the curve evolves by a Lagrangian approach, where the positions are updated using a difference approximation scheme. A main drawback of this approach is that the evolving model is not able to deal with topological changes of the moving front.

Osher and Sethian [94] introduced the *Level Set* method for implementing curve propagation. It is used to account for automatic topology adaption and also provide the basis for a numerical scheme that is used by geometric deformable models [95]. The curve is implicitly represented as a level set of

a 2D scalar function $\phi(x, y, t)$ in level set method. Corresponding to Eqn. (4.3.25), the motion function of surface ϕ is derived by

$$\begin{cases} \phi_t = -F(\mathcal{K})|\nabla\phi| \\ \phi(C_0(p), 0) = 0, \end{cases} \quad (4.3.26)$$

where $|\cdot|$ denotes the gradient norm. The zero level set values of the function ϕ always yields to the moving front $C(p, t)$. This propagation framework has the following advantages [96]. Firstly, ϕ remains a function during its evolution, and the curve $C(p)$ may change topology as the function ϕ evolves. Secondly, the numerical simulations may be developed easily by an explicit finite difference approach. Finally, intrinsic geometric properties of the curve can be estimated directly from the level set function e.g. normal and curvature, and the method can be easily extended to deal with problems in higher dimensions.

4.3.2 Geodesic Active Contours

The geodesic active contours model [97, 98] was introduced as a geometric alternative for snakes [63]. Let $I : [0, a] \times [0, b] \rightarrow \mathcal{R}^+$ be a given input image plane, the curve $C(p)$ evolves to minimize the following energy:

$$E[C(p)] = \int_0^1 g(|\nabla I(C(p))|) |\dot{C}(p)| \, dp, \quad (4.3.27)$$

where $\dot{C}(p)$ is the partial derivative of curve with respect to its parameter p , and $g(\cdot)$ is a monotonically decreasing function such that $g(r) \rightarrow 0$ as $r \rightarrow \infty$, and $g(0) = 1$. The objective function can be minimized by solving

the associated Euler-Lagrange equation. The flow that deforms the initial curve $C(p, 0) = C_0(p)$ toward the minima of Eqn. (4.3.27) is given by a steady state solution of:

$$C_t = \left[g(|\nabla I|) \mathcal{K} - \nabla g(|\nabla I|) \cdot \mathcal{N} \right] \mathcal{N}, \quad (4.3.28)$$

where t denotes the time as the contour evolves.

4.3.3 Level Set Method

By introducing the level set formulation, the curve $C(p, t)$ can be considered as the zero level set of a time-varying function $\phi(x, y, t) : [0, a] \times [0, b] \rightarrow \mathcal{R}$. Usually, $\phi(x, y, t)$ is defined as a distance function of point (x,y) to the zero level set with negative in the interior and positive at the exterior of the zero level set or vice versa.

This model is parameter-free and topology-free. Based on Eqn. (4.3.25) and (4.3.26), a steady state solution of this geodesic problem can be derived:

$$\phi_t = g(|\nabla I|) \mathcal{K} |\nabla \phi| + \nabla g(|\nabla I|) \cdot \nabla \phi, \quad (4.3.29)$$

where $\phi(x, y, 0) = \phi_0(x, y)$. The normal $\mathcal{N}$ and curvature $\mathcal{K}$ can be estimated directly from the level set function ϕ :

$$\left[\mathcal{N} = -\frac{\nabla \phi}{|\nabla \phi|}, \mathcal{K} = \operatorname{div} \left(\frac{\nabla \phi}{|\nabla \phi|} \right) \right].$$

Compared with the classical snake which is essentially a parametric active

contour model, the geodesic active contour model does not depend on the curve parameterization. Furthermore, it handles topological changes naturally, which allows detection of all the objects in the image without knowing their exact number.

A direct implementation of Eqn. (4.3.29) is computationally expensive due to numerous redundant calculations that are performed for pixels which are of no interest during the front propagation. Several methods have been proposed to overcome this drawback: the Narrow Band [99], the Fast Marching [100], and the Hermes algorithm [96].

4.4 Markovian Level Set

4.4.1 2D polar coordinate system

In Chapter 3, a novel method for automatic ROI segmentation and LV center detection is presented. For boundary detection in long-axis echocardiographic images, the method is used as a preprocessing process to get the locations of ROI and LV center. The 2D polar coordinate system adopted is schematized in Fig. 4.1. As shown in Fig. 4.1, a circular region from the center is excluded from the ROI (gray zone). Let $\mathbf{r} = \{r^1, r^2, \dots, r^M\}$ represent the scan lines radiated from the center, where M is the total number of radii. On each scan line r^i , there are N_i neighboring radial positions within the ROI. Therefore, a site in this system is denoted by s_j^i , where $i \in \{1, 2, \dots, M\}$ and $j \in \{1, 2, \dots, N_i\}$. Since the scan lines are distributed radially instead of in parallel, not all the pixels within the ROI are included as a site.

Figure 4.1: The 2D polar coordinate system.

As the LV cavity has an elliptic shape whose long-axis is vertical. Therefore, we choose to distribute the radial lines more densely near the y -axis than near the x -axis, so that the distances between the sampled sites in the direction along the circumference would be more even. This can be achieved by choosing the angle of the i th radial line according to the expression below

$$\theta_i = \arg \tan \left(\sqrt{\frac{b}{a}} \tan \left(\frac{2\pi(i-1)}{M} \right) \right), \quad (4.4.30)$$

where a and b are the minor and major radii of the ellipse respectively. In Eqn.(4.4.30), the denseness of the radial lines is adjusted according to b/a . Considering the LV cavity, the ratio of long-axis to short-axis is approximately $3/2$, thus b/a is set to $3/2$. The effect of the distribution of the radial lines is illustrated in Fig. 4.2.

Figure 4.2: Radial lines with (a) $b/a = 1$ and (b) $b/a = 3/2$.

4.4.2 MRF Model

On a finite grid S (the gray zone in Fig. 4.1), the sites $s \in S$ correspond to each component of the random variable. A MRF is defined in terms of a neighborhood. Given a neighborhood, a clique is a subset of it where all the components of the clique are neighbors of each other. Similar to 2D MRF models in Cartesian coordinates, the second-order neighborhood system is used for each site s_j^i :

$$\mathcal{N}(s) = \{s_{j+1}^i, s_{j-1}^i, s_j^{i+1}, s_j^{i-1}, s_{j+1}^{i+1}, s_{j-1}^{i-1}, s_{j+1}^{i-1}, s_{j-1}^{i+1}\}. \quad (4.4.31)$$

It is noted that for a radial system vs. a Cartesian system, the neighborhood is fan-shaped instead of a square (Fig. 4.3).

From neighbors and cliques, energy functions of the field are defined. As mentioned in Section 4.2.1, the feature energy resulting from data-likelihood

Figure 4.3: The second-order neighborhood system in (a) Cartesian coordinates and (b) polar coordinates; (c) all doubleton (double-pixel) cliques.

function is:

$$\begin{aligned}
 E_F(y_s|x_s) &= -\log p(y_s|x_s) \\
 &= \sum_{k=1}^K \left[\frac{(y_s^k - \mu_{x_s}^k)^2}{2\sigma_{x_s}^k{}^2} + \log(\sqrt{2\pi}\sigma_{x_s}^k) \right]. \quad (4.4.32)
 \end{aligned}$$

and the region energy resulting from a *prior* distribution function is:

$$E_R(x_s) = -\log p(x_s) = \beta \sum_{r \in \mathcal{N}(s)} \delta(x_s, x_r). \quad (4.4.33)$$

In the original MRF model, the segmentation is performed by maximizing the *a posteriori* segmentation probability, i.e. minimizing the energy function of the given input image. In the proposed Markovian level set model, the labeling field is regarded as a level set function ϕ . Sites with different class labels have function values with opposite signs. Therefore, boundary between

different tissue classes corresponds to the zero level set. Minimizing the energy function can be achieved by updating the level set function ϕ , which is described as follows.

Given an initial label field $X = \{X_s, s \in S\}$, $X \in \{e_0 = \text{blood}, e_1 = \text{myocardium}\}$, its edge set C is regarded as a zero level set and the initial level set function is set as follows

$$\phi(s, t = 0) = \begin{cases} d, & \text{if } x_s = e_1 \\ -d, & \text{if } x_s = e_0. \end{cases} \quad (4.4.34)$$

where d is the distance from x_s to C . The level set function is evolved by comparing the two energy functions

$$E_0 = E(x_s = e_0 | y_s)$$

$$E_1 = E(x_s = e_1 | y_s)$$

where

$$E(x_s | y_s) = E_F(y_s | x_s) + E_R(x_s).$$

For each site s , it is aimed at shrinking the curve if the true state for s is $x_s = e_1$:

$$E_0 > E_1 \Rightarrow P(x_s = e_1 | y_s) > P(x_s = e_0 | y_s) \Rightarrow \phi_t > 0$$

and expanding it when the true state is $x_s = e_0$:

$$E_0 < E_1 \Rightarrow P(x_s = e_0 | y_s) > P(x_s = e_1 | y_s) \Rightarrow \phi_t < 0.$$

Therefore the evolving equation for ϕ is given by

$$\phi_t = E_0 - E_1. \quad (4.4.35)$$

The zero level set of the evolving function $\phi(s, t) = 0$ always matches the propagating front. Along each radial line, the desired LV endocardial boundary corresponds to the *first positive* zero-crossing.

On the other hand, a label field can be derived from a level set function using

$$x_s = \begin{cases} e_1, & \text{if } \phi(s, t) > 0 \\ e_0, & \text{if } \phi(s, t) < 0. \end{cases} \quad (4.4.36)$$

4.4.3 Deformation Smoothness

The deformation smoothness is regulated in terms of first and second derivatives in snake models. In Markovian snake model, the derivatives are carried out in polar coordinates instead of Cartesian to avoid the trend of snake to vanish to a point if there is no image force. Traditionally the derivatives are approximated by finite differences of the contour vectors:

$$\frac{d\rho}{ds} = (\rho_{s+1} - \rho_{s-1})/2 \quad (4.4.37)$$

$$\frac{d^2\rho}{ds^2} = \rho_{s+1} - 2\rho_s + \rho_{s-1}, \quad (4.4.38)$$

where ρ_s is the contour vector at site s .

In the case of level set method where the propagating curve is implicitly represented by the zero level set function, the curvature $\mathcal{K}$ can be estimated

directly from the level set function $\phi(x, y)$:

$$\mathcal{K} = \frac{\phi_{xx}\phi_y^2 - 2\phi_{xy}\phi_x\phi_y + \phi_{yy}\phi_x^2}{(\phi_x^2 + \phi_y^2)^{3/2}}. \quad (4.4.39)$$

The above equation is used for square neighborhood system in Cartesian coordinate. However, for fan-shape neighborhood system in polar coordinate, Eqn. (4.4.39) is not applicable.

A *boundary point* $b^i(x, y)$ is defined as the first positive zero-crossing of the level set function, along each radial line r^i . The curvature is derived by

$$\mathcal{K} = \frac{\dot{x}\ddot{y} - \dot{y}\ddot{x}}{(\dot{x}^2 + \dot{y}^2)^{3/2}}, \quad (4.4.40)$$

where the first $(\dot{x}, \dot{y})$ and second $(\ddot{x}, \ddot{y})$ derivatives are calculated from the coordinates of b^i and its neighbors b^{i-1} and b^{i+1} . For non-boundary point, the curvature at this site is set to be zero.

In Eqn. (4.4.40), the (x, y) coordinates have to be translated to have $(x = 0, y = 0)$ at the LV center. Therefore, the boundary curvature is measured in the polar system. The boundary smoothness is more easily and explicitly achieved in the polar coordinate system. Unlike in Eqn. (4.3.29), the norm of the gradient $(|\nabla\phi|)$ is not considered here since the *tangential* smoothness is directly regulated by $\mathcal{K}$. The updating of the level set function becomes

$$\phi_t = E_0 - E_1 + c\mathcal{K}. \quad (4.4.41)$$

where c is the weight of smoothness.

Figure 4.4: The overall segmentation procedure.

4.4.4 Segmentation Procedure

A hierarchical structure is adopted in the overall segmentation procedure as shown in Fig. 4.4. A demonstration of intermediate results is displayed in Fig. 4.5.

- Starting from the original (highest scale) input image, a multiscale pyramid is built using the discrete wavelet transform [44]. From the image in each scale and the corresponding ROI and LV center, a 2D polar system is built. The intensity and location of each site on each radial line is recorded. During the segmentation procedure, these sites will be

Figure 4.5: (a) Initial boundary points generated by K-means clustering algorithm in the third scale. (b)-(d) Boundary point generated by Markovian level set in the third, the second and the first scales respectively. (e) Final label field (the white points denote pixels labeled as myocardium). (b) Final boundary point after smoothing.

classified as pixels of blood or myocardium.

- An initial classification is carried out at the coarsest scale using K-means clustering algorithm. It is observed that the myocardium appears to be brighter pixels than the blood. From the resulting two classes of pixels, the one with higher average intensity is labeled as $\{e_1 = \textit{myocardium}\}$ and the one with lower average intensity is labeled as $\{e_0 = \textit{blood}\}$.
- Starting from the initial classification, the algorithm alternates between updating the level set function and the estimation of model parameters, until there is no further changes in the labels occurring. Given the region labels $x \in \{e_0, e_1\}$ within a window centered at s , the local class means $\mu_s^{e_k}$ and variances $\sigma_s^{e_k}$ for both classes ($k = 0, 1$) are estimated.
- Initially, for robust estimation of the model parameters, a large window size W is used for the coarsest scale. As the algorithm progresses to finer scales, smaller windows are used to give more reliable and accurate estimations of the local characteristics.
- Before and after updating the level set function, there are conversions between the label field X and the level set function ϕ . A level set function can be derived from a label field X using Eqn. (4.4.34), and Eqn.(4.4.36) vice versa.

4.5 Results and Discussion

4.5.1 Parameters

There are five parameters involved in the proposed method:

Gibbsian parameter $\beta = 0.1$ ($\Delta\beta = 0.04$),

number of radii $M = 60$,

tangential smoothness weight $c = 1$,

window size $W = 1/4$ of the whole image size,

number of scale levels $L = 4$.

From the coarsest scale, β is increased by $\Delta\beta$ at each increase of scale level, and W is reduced by a factor of four. The values of these parameters are determined by trial-and-error to obtain optimal results. The same set of parameters are used in all of the experiments.

As indicated in Section 4.2.1, the parameter β allows one to control the influence of the spatial constraint term in the energy function. When β is too small, the spatial continuity of classes is weak and the boundaries between classes are irregular. On the other hand, taking β to be higher accentuates the intra-class smoothness, but details on the inter-class contours are erased. The tangential smoothness weight c gives similar regulation except that it emphasizes on the smoothness of the boundary along tangential direction.

Using the multiscale approach, the segmentation process easily converges to optimal status with accelerated segmentation speed. The optimal value of L depends on the resolution of the objects in the original image. If L is set too small, the algorithm may converge to an unreliable solution because of the

speckle noise in the fine scales which disturbs the initial K-means segmentation.

4.5.2 Quantitative Measures

Boundary Error Metrics

To compare the boundaries generated independently by computer and expert, two boundary error metrics are calculated : Hausdorff distance and the mean absolute distance [38]. The two curves are represented as sets of points $\mathcal{A} = \{a_1, a_2, \dots, a_m\}$ and $\mathcal{B} = \{b_1, b_2, \dots, b_n\}$. For the evaluation presented here, $\mathcal{A}$ is the boundary determined by the computer-based methods and $\mathcal{B}$ is the boundary drawn by experienced clinicians. The distance to the closest point (DCP) for a_i to the curve $\mathcal{B}$ is defined as

$$d(a_i, \mathcal{B}) = \min_j \| b_j - a_i \| \quad (4.5.42)$$

where $\| \cdot \|$ is the 2D Euclidean distance between any two points. The Hausdorff distance between the two curves is defined as the maximum $d(a_i, \mathcal{B})$ over all i . The mean absolute distance is the average of $d(a_i, \mathcal{B})$ over all i . The Hausdorff distance is a measure of the largest disagreement between the two curves, while the mean absolute distance estimates the averaged disagreement between the two curves. The corresponding normalized distances are computed by dividing the absolute distance by the boundary length as determined in the expert-drawn boundaries.

Area Correlation Metric

Another standard measure is the Jaccard similarity coefficient (Intersection/Union) [101], which compares the areas enclosed by the boundary detected by the computer-aided methods and the boundary drawn by the expert. The value ranges from 0 (no overlap) to 1 (total overlap), thus the higher value the better correlation.

4.5.3 Results

The results of boundary detection by simple 2D MRF in polar coordinates (P-MRF) and 2D MRF in Cartesian coordinates (C-MRF) are presented to validate the effectiveness of the proposed Markovian level set (MLS) method. The P-MRF method is defined in the same polar coordinates system as described in Section 4.4.1. The labeling field is optimized using the traditional Bayesian philosophy, instead of updating a level set function as in MLS. The C-MRF method uses hierarchical MRF in Cartesian coordinates and three ultrasound texture features [102] are used in addition to image intensity: angular second moment, correlation, and homogeneity.

Synthetic Images

Experiments using controlled shape and noise level are carried out to assess the capability of the MLS method to cope with noise. In the simulation using concentric circles to represent the left ventricle, the following two speckle noise models [103] are used

1. Rayleigh noise model $y = x * n_1$ is used to simulate envelope images

in ultrasound systems. The speckle polluted images are obtained by multiplying the ground truth image x with n_1 which follows Rayleigh distribution with parameter b . In this noise model, we fix b to 0.7979 (so that the mean is 1 and the variance is 0.2732) and run the simulation for 30 times to generate 30 random images.

2. $y = x + \sqrt{x} * n_2$ is used to simulate displayed ultrasound images. n_2 is Gaussian noise and we fix the mean in 0 and vary the standard deviation from 2 to 8.

The average normalized boundary distances and area correlation for 30 images are listed in Table 4.1.

In the MLS method, the spatial smoothness constraints are incorporated in the algorithm by using the MRF prior distribution. In addition, the smoothness along the tangent of the contour can be regulated by the curvature term K . From Figs. 4.6 and 4.7, it can be observed that the proposed MLS performs better than P-MRF and C-MRF in the presence of noise.

In the regions with dropouts or low contrast, the pixels on some radial lines will all be classified as ‘blood’ initially. In such case, no boundary point can be detected (or boundary points are very far away), which results in very large curvature. The curvature smoothing term K in the updating function (Eqn. 4.4.41) is very useful here in that it adds a large positive value in the level set function. Hence, the open region is morphologically closed to form a continuous boundary. In Fig. 4.7, the proposed MLS performs better than C-MRF and P-MRF in the presence of dropouts.

Figure 4.6: (a) Original clean image simulating a long-axis echocardiographic image with dropout. Boundary points detected from synthetic images with the first noise model using (b) P-MRF, (c) C-MRF and (d) MLS.

Table 4.1: Errors and area correlation measured from 30 noisy synthetic images with Rayleigh speckle noise ($b = 0.7979$).

Measures	P-MRF	C-MRF	MLS
Norm. HD	15.12 ± 14.26 %	17.31 ± 12.52 %	10.80 ± 5.52 %
Norm. MD	2.79 ± 0.58 %	2.30 ± 0.44 %	2.67 ± 0.59 %
Intersection/Union	0.920 ± 0.020	0.879 ± 0.226	0.924 ± 0.023

Figure 4.7: Boundary points detected from synthetic images with the second noise model using P-MRF (first column), C-MRF (second column) and MLS (third column). The standard deviations of Gaussian white noise are: 2, 4, 6, 8, from top to bottom.

Echocardiographic Images

The proposed automated method is applied to five sequences of long axis echocardiographic images denoted by Datasets I-V.

The label fields and the resulting boundary points obtained using the three methods are displayed in Fig. 4.8 for comparison. In this figure, the results of the MLS method are obtained without control of deformation smoothness as well as the two other methods, i.e. $c=0$, to give a fairer comparison. It is noticed that MLS generates less false boundary points than P-MRF (Fig. 4.8(b)), and does not miss true boundary points like C-MRF (Fig. 4.8(d)) at regions of low contrast.

The results of LV boundary detection for Datasets I-V are given in Figs. 4.9-4.13 respectively. In each figure, column one and two are two different frames from the same dataset. The desired boundaries should lie on positive intensity edges and be smooth and regular (no sharp spines or cavities) in the same time. For example, in Fig. 4.11(c), the boundary detected by the C-MRF method has a sharp spine on the bottom-left, and misses the boundary on the top of the left ventricle because of the low contrast. In comparison, the boundary detected by the proposed MLS method (Fig. 4.11(e)) is smoother and able to reach the top of left ventricle.

The average HD and MD from each image sequence are listed in Tables 4.2-4.6. The small distances (errors) of the proposed method indicate good correlation between the boundaries detected the proposed method and those drawn by the expert.

The average normalized boundary distances and area correlation for all the

Figure 4.8: Intermediate results obtained from the three method: (a)-(b) P-MRF, (c)-(d) C-MRF, and (e)-(f) MLS ($c=0$) on the same image. First column: segmented myocardium-labeled fields. Second column: boundary points detected from the label fields. The points indicated in (a) and (e) are the pixels labeled as myocardium. The region enclosed by highlighted pixels in (c) is the region labeled as myocardium. The arrows indicate incorrect (b) or missing (d) boundary points.

Figure 4.9: Dataset I: comparison of final LV boundary obtained using (a)-(b) P-MRF, (c)-(d) C-MRF, and (e)-(f) MLS methods.

Figure 4.10: Dataset II: comparison of final LV boundary obtained using (a)-(b) P-MRF, (c)-(d) C-MRF, and (e)-(f) MLS methods.

Figure 4.11: Dataset III: comparison of final LV boundary obtained using (a)-(b) P-MRF, (c)-(d) C-MRF, and (e)-(f) MLS methods.

Figure 4.12: Dataset IV: comparison of final LV boundary obtained using (a)-(b) P-MRF, (c)-(d) C-MRF, and (e)-(f) MLS methods.

Figure 4.13: Dataset V: comparison of final LV boundary obtained using (a)-(b) P-MRF, (c)-(d) C-MRF, and (e)-(f) MLS methods.

Table 4.2: Boundary error metrics measured in Dataset I (containing 20 images of 200×200 pixels).

Error Measures	P-MRF	C-MRF	MLS
HD (pixels)	17.88 ± 3.35	15.76 ± 3.87	15.18 ± 3.31
MD (pixels)	4.44 ± 0.75	4.63 ± 1.20	4.54 ± 1.01
Norm. HD	8.19 ± 1.69 %	7.19 ± 1.74 %	6.93 ± 1.52 %
Norm. MD	2.02 ± 0.31 %	2.12 ± 0.55 %	2.06 ± 0.38 %

Table 4.3: Boundary error metrics measured in Dataset II (containing 16 images of 136×121 pixels).

Error Measures	P-MRF	C-MRF	MLS
HD (pixels)	14.12 ± 4.85	15.24 ± 2.26	11.92 ± 3.44
MD (pixels)	3.63 ± 0.64	5.29 ± 1.12	3.75 ± 0.65
Norm. HD	7.85 ± 3.12 %	8.36 ± 1.40 %	6.61 ± 2.30 %
Norm. MD	2.00 ± 0.41 %	2.88 ± 0.54 %	2.05 ± 0.33 %

Table 4.4: Boundary error metrics measured in Dataset III (containing 13 images of 136×121 pixels).

Error Measures	P-MRF	C-MRF	MLS
HD (pixels)	11.99 ± 3.26	13.11 ± 1.04	11.27 ± 3.76
MD (pixels)	3.21 ± 0.67	4.80 ± 0.34	3.24 ± 0.70
Norm. HD	6.70 ± 1.73 %	7.34 ± 0.57 %	6.31 ± 2.06 %
Norm. MD	1.80 ± 0.36 %	2.69 ± 0.21 %	1.81 ± 0.36 %

Table 4.5: Boundary error metrics measured in Dataset IV (containing 22 images of 197×171 pixels).

Error Measures	P-MRF	C-MRF	MLS
HD (pixels)	18.64 ± 5.65	17.15 ± 6.21	13.54 ± 5.52
MD (pixels)	4.83 ± 1.37	4.66 ± 1.21	4.50 ± 0.97
Norm. HD	6.14 ± 1.86 %	5.68 ± 2.12 %	4.47 ± 1.83 %
Norm. MD	1.59 ± 0.46 %	1.54 ± 0.42 %	1.49 ± 0.32 %

Table 4.6: Boundary error metrics measured in Dataset V (containing 15 images of 210×221 pixels).

Error Measures	P-MRF	C-MRF	MLS
HD (pixels)	21.50 ± 7.34	14.53 ± 8.01	16.89 ± 5.67
MD (pixels)	5.26 ± 0.75	4.42 ± 0.62	5.02 ± 0.68
Norm. HD	8.90 ± 3.09 %	6.05 ± 3.42 %	7.18 ± 3.13 %
Norm. MD	2.20 ± 0.43 %	1.85 ± 0.36 %	2.10 ± 0.41 %

Table 4.7: Area correlation of Datasets I-V.

Intersection/Union	P-MRF	C-MRF	MLS
Dataset I	0.722±0.177	0.720±0.167	0.772±0.060
Dataset II	0.796±0.058	0.650±0.058	0.767±0.041
Dataset III	0.805±0.053	0.670±0.061	0.792±0.045
Dataset IV	0.787±0.178	0.790±0.178	0.833±0.037
Dataset V	0.808±0.041	0.774±0.058	0.812±0.031

Table 4.8: Normalized boundary distances and area correlation across Datasets I-V.

Error Measures	P-MRF	C-MRF	MLS
Norm. HD	7.50±2.50 %	6.85±2.25 %	6.19±2.37 %
Norm. MD	1.90±0.45 %	2.15±0.67 %	1.88±0.43 %
Intersection/Union	0.800±0.098	0.727±0.137	0.797±0.051

86 images are listed in Table 4.8.

To further validate the superiority of the proposed MLS method, the two-tailed paired t-test is conducted under the null hypothesis that there is no statistically significant difference between the distance values achieved by the MLS and two other MRF method. The total normalized error metrics measured from all the 86 images are used for the t-test.

In terms of the normalized Hausdorff distance, the hypothesis is rejected by $p < 6 \times 10^{-4}$ for the P-MRF method, and accepted for the C-MRF method. In terms of the normalized mean absolute distance, the hypothesis is accepted for the P-MRF method and rejected by $p < 2 \times 10^{-3}$ for the C-MRF method. In terms of the Jaccard similarity coefficient (Intersection/Union), the hypothesis is accepted for the P-MRF method and rejected by $p < 2 \times 10^{-5}$ for the C-MRF method.

In other words, the MLS method generates significantly small normalized

Hausdorff distance compared with the P-MRF method. Compared with the C-MRF method, the MLS method generates significantly small normalized mean absolute distance and significantly higher area correlation.

4.6 Summary

A novel method combining MRF and level set is proposed to detect the boundary of the left ventricle from echocardiographic images automatically. A 2D MRF in polar coordinates is used, where the local smoothness and the image data are imposed by a Bayesian framework. By conversion between the label field and the level set function, the segmentation process is carried out by updating the level set function iteratively. The proposed method is tested using five image datasets from different patients. Experimental results show that the computer-detected boundaries are highly correlated with expert-drawn boundaries. The proposed Markovian Level Set method is compared with the methods with simple 2D MRF in polar coordinates and Cartesian coordinates. T-test on the quantitative results measured shows that the proposed method outperforms the other two methods.

The originality of the method resides in regarding the label field as a level set function, and performing the labeling process by updating the level set function. The combination of the Markovian labelling field and the level set function, is able to handle the problem of speckle noise, low contrast and artifacts in echocardiographic images. The advantages of the proposed method compared with other related methods are listed below:

- The LV boundary is a single-value function in polar coordinates whose origin point is the center of the left ventricle, in long-axis echocardiographic images. Since this assumption is valid in most cases, the radial-based strategy can be used. Compared with Cartesian coordinates, 2D MRF in polar system is able to cope with the boundary smoothness more explicitly and easily. In addition, not all the pixels within ROI need to be processed, thus the computational time is reduced.
- The intensity contrast varies along the LV boundary and there are dropouts with hardly any contrast in long-axis echocardiographic images. With the inherent ability to make use of local statistics, the Markovian level set method is superior to the original level set method in the detection of a continuous LV boundary.
- Compared with the Markovian snake model, the proposed Markovian level set model is able to handle topological changes naturally, which is useful when multiple object boundaries are desired during the segmentation. Only the endocardial boundary is desired in this study. However, the proposed method can also detect the epicardial boundary at the same time.
- One disadvantage of the level set method is that it may generate undesired changes in the presence of noise. This is not a problem using the proposed method by imposing the regional continuity and the contour smoothness.

Chapter 5

Short-axis Echocardiographic Image Segmentation Using Dynamic Directional Gradient Vector Flow

In Chapter 4, the Markovian level set (MLS) method is developed for LV boundary detection in long-axis echocardiographic images. It is assumed that the LV boundary is a single-value function in polar coordinates whose origin point is the LV center. However, this assumption is not likely to be valid for short-axis echocardiographic images, thus the radial-based strategy may not work well in this case. A snake-based method is proposed and presented in this chapter for short-axis echocardiographic image segmentation.

5.1 Introduction

Snakes, or *active contour models*, was first proposed by Kass *et al.* [63] in 1987. Since its publication, deformable models have become one of the most active and successful research areas in image segmentation [95].

Deformable models are curves or surfaces defined within an image domain that move under the influence of internal forces and external forces. Internal forces, which are defined within the curve or surface itself, are designed to smooth the model during deformation. External forces, which are computed from the image data, are defined to move the model toward desired features in the image. Hence deformable models are able to incorporate different information about the object shape, according to different applications.

There are basically two types of deformable models: parametric deformable models [63, 104, 105] and geometric deformable models [97, 106]. Parametric deformable models represent curves and surfaces explicitly in their parametric forms while geometric deformable models represent curves and surfaces implicitly as a level set of higher-dimensional scalar function [94, 99]. Compared with parametric deformable models, geometric deformable models are able to handle topological changes naturally. However, more attention has been paid to the former, as topological adaption is not always required, for example, when applied to medical images with noise.

For parametric deformable models, snakes are widely applied in boundary detection, shape modeling, and motion tracking etc. Various improvement of snakes has been proposed for different applications. Some are proposed to change the topology of snakes [107], and others are to extend the model to

higher dimension data [108] and color images [109]. However, most of the methods are concerned with the external energy in the snake model, such as balloons [104], distance potential force [110], diffusion snakes [111], dual snakes [112], gradient vector flow (GVF) [113], its generalization (GGVF) [114] and improvement [31, 115, 116].

The value of the gradient is an important information for image processing and analysis. On the problem of the direction of gradient, Park *et al.* [64] proposed a method to improve the active contour model by including the gradient direction in the external image force. The angle between the gradient direction and the contour's normal direction at each snaxel (snake element) is calculated, in order to consider the directional information of the gradient. If the absolute angle is larger than $\pi/2$, the external force at the corresponding snaxel is set to zero. In this case, the directional snake does not get attracted to the edges with an opposite direction to the gradient direction. Thus, only the edges with a desired gradient direction participate in the snake deformation. However, this new definition of the external force highly depends on the initial location of the snake in the image. In the energies and algorithms for parametric snakes [117], the gradient direction is taken into account by the new edge-based energy, which uses the gradient vector field in the energy integral directly instead of a scalar field derived from the magnitude of the gradient vector field. This method also requires that the snake be initialized very close to the desired boundary.

In this chapter, a new type of dynamic external force for snakes is proposed. Based on gradient vector flow [113], the external force model endows

the snake with a large capture range and the ability to move into boundary cavities. By incorporating directional gradient information, the snake is able to discern edges of different orientations. This is particularly useful for boundary detection in echocardiographic images with complex boundary.

5.2 Background

5.2.1 Traditional Snakes

A snake is a curve $\mathbf{x}(s) = [x(s), y(s)]$, $s \in [0,1]$, which moves through the spatial domain of an image to minimize the following energy function:

$$E(\mathbf{x}) = \int_0^1 [\frac{1}{2}(\alpha|\frac{\partial \mathbf{x}}{\partial s}|^2 + \beta|\frac{\partial^2 \mathbf{x}}{\partial s^2}|^2) + E_{ext}(\mathbf{x})]ds \quad (5.2.1)$$

where α and β are the weights controlling the snake's tension and rigidity respectively. The first-order derivative $\partial \mathbf{x} / \partial s$ controls stretching and the second-order derivative $\partial^2 \mathbf{x} / \partial s^2$ controls bending. The first two terms comprise the internal energy of the snake. The external energy E_{ext} is derived from the image and set to small values at the features of interest. As the gradients at the object boundaries in the image are usually high, external energy of the form $-|\nabla(G_\sigma(x, y) * I(x, y))|^2$ is used for step edges [63] and $\pm G_\sigma(x, y) * I(x, y)$ for line-drawings, where G_σ is a 2D Gaussian function with standard deviation σ .

To minimize $E(x)$, the deformable contour has to evolve dynamically as a

function of time t given by:

$$\gamma \frac{\partial \mathbf{x}}{\partial t} = \frac{\partial}{\partial s} \left(\alpha \frac{\partial \mathbf{x}}{\partial s} \right) - \frac{\partial^2}{\partial s^2} \left(\beta \frac{\partial^2 \mathbf{x}}{\partial s^2} \right) + F_{ext}(\mathbf{x}). \quad (5.2.2)$$

On the right side of the equation, the first two terms are the internal force shrinking and smoothing the contour while the external force $F_{ext}(\mathbf{x}) = -\nabla E_{ext}(\mathbf{x})$ pulls the contour to the desired features in the image, e.g. object boundaries.

There are two key drawbacks associated with snakes introduced by Kass *et al.* [63]. First, the initial position of the snake must be close enough to the desired contour in the image. Otherwise the snake may be trapped in local minima instead of evolving correctly toward the desired contour. Second, poor convergence may result as the snake has difficulty evolving to concavities or sharp corners.

5.2.2 GVF Snakes

Xu and Prince [113, 118] proposed *gradient vector flow* (GVF) as a new external force for snakes to solve the problem of limited capture range and poor convergence. Starting from Eqn. (5.2.2), the external force $-\nabla E_{ext}(\mathbf{x})$ is replaced with a GVF field $\mathbf{v}(x, y) = [u(x, y), v(x, y)]$ defined as the equilibrium solution of the following system of partial differential equations:

$$\mathbf{v}_t = \mu \nabla^2 \mathbf{v} - (\mathbf{v} - \nabla f) |\nabla f|^2, \quad \mathbf{v}_0 = \nabla f \quad (5.2.3)$$

where $\mathbf{v}_t$ denotes the partial derivative of $\mathbf{v}$ with respect to t , and $\nabla^2 = \partial^2/\partial x^2 + \partial^2/\partial y^2$ is the Laplacian operator. f is an edge map derived from the

image and defined to have larger values at the features of interest. A typical choice is given as follows:

$$f(x, y) = -E_{ext}(x, y) = |\nabla(G_\sigma(x, y) * I(x, y))|^2 \quad (5.2.4)$$

for step edges or

$$f(x, y) = -E_{ext}(x, y) = -G_\sigma(x, y) * I(x, y) \quad (5.2.5)$$

for line-drawings (black on white). An example of GVF edge map and field is shown in Fig. 5.1.

When $|\nabla f|$ is small, the solution of Eqn. (5.2.3) is dominated by $\mathbf{v}_t = \mu \nabla^2 \mathbf{v}$, which implies homogeneous linear diffusion yielding a slowly varying field of $\mathbf{v}$. Whereas when $|\nabla f|$ is large, the second term in Eqn. (5.2.3) is dominant and produces the effect of keeping $\mathbf{v}$ nearly equal to ∇f . The parameter μ regulates the tradeoff between the first term and the second term in the equation and should be set according to the amount of noise present in the image (larger μ for higher level of noise).

As the GVF field is calculated as a diffusion of the gradient vectors of a gray-level or binary edge map derived from the image, it greatly increases the capture range of the snake and its capability to move into boundary concavities.

Figure 5.1: (a) 100×100 -pixel binary image of step edges; (b) edge map of GVF: gradient magnitude; (c), (d) GVF field in the x and y direction respectively (before normalized with respect to their magnitudes).

5.3 Dynamic Directional GVF

The role of external force in snakes is to attract the deformable contour to the features of interest in the image. Both traditional snakes and GVF snakes define the external energy to be a function of $|\nabla I|$, the gradient magnitude of the image, which is a conventional step edge detector. As the magnitude operator discards the signs of gradient, the snake is unable to distinguish between positive and negative step edges. The dynamic directional gradient vector flow (DDGVF) is proposed to distinguish between positive boundaries and negative boundaries. For gray-level images, a boundary is defined to be positive if there are positive step edges along its outward normals, i.e. the intensity gradients along the boundary are pointing inward. Contrarily, a boundary is defined to be negative if there are negative step edges along its outward normals.

5.3.1 Directional Edge Map

As presented above, the solution of GVF field is based on the edge map f in Eqn. (5.2.4). A new edge map is used to preserve the gradient directional information.

$$\mathbf{g}(x, y) = \nabla(G_\sigma(x, y) * I(x, y)) = (g_x(x, y), g_y(x, y)) \quad (5.3.6)$$

where g_x and g_y are the horizontal and vertical gradients of the image I after it is smoothed by a 2D Gaussian function G_σ . Subsequently the DDGVF field is solved in the horizontal and vertical directions separately.

Figure 5.2: Detection of positive and negative step edges.

Consider a 1D signal s depicted in Fig. 5.2, there are two opposite directions to look through it: x and $-x$. In the x direction, d_1 is a positive step edge and d_2 is a negative step edge. While in the $-x$ direction the situation is reversed: d_2 is a positive step edge and d_1 is negative. Thus, if only positive (or negative) edges are to be detected, the result will depend on the direction of approach. The function $\max\{s_x, 0\}$ keeps the positive step edges in the x direction and $-\min\{s_x, 0\}$ keeps the positive step edges in the $-x$ direction, where $s_x = \frac{ds}{dx}$. As for negative step edges, $-\min\{s_x, 0\}$ is for the x direction and $\max\{s_x, 0\}$ for the $-x$ direction.

Similarly in the 2D case, detection of a positive (or negative) boundary is dependent on the direction of approach that associates with the deformable contour's normal direction at each snaxel. Since the location of snake is unknown before initialization, image gradients from all directions are considered.

For a positive boundary:

$$f_x^+(x, y) = \max\{g_x(x, y), 0\} \quad (5.3.7a)$$

$$f_x^-(x, y) = -\min\{g_x(x, y), 0\} \quad (5.3.7b)$$

$$f_y^+(x, y) = \max\{g_y(x, y), 0\} \quad (5.3.7c)$$

$$f_y^-(x, y) = -\min\{g_y(x, y), 0\} \quad (5.3.7d)$$

and for a negative boundary:

$$f_x^+(x, y) = -\min\{g_x(x, y), 0\} \quad (5.3.8a)$$

$$f_x^-(x, y) = \max\{g_x(x, y), 0\} \quad (5.3.8b)$$

$$f_y^+(x, y) = -\min\{g_y(x, y), 0\} \quad (5.3.8c)$$

$$f_y^-(x, y) = \max\{g_y(x, y), 0\} \quad (5.3.8d)$$

where f_x^+ , f_x^- , f_y^+ and f_y^- are the gradients of positive step edges in x , $-x$, y and $-y$ directions. They compose the directional edge map $\mathbf{f}(x, y) = [f_x^+(x, y), f_x^-(x, y), f_y^+(x, y), f_y^-(x, y)]$.

For line-drawings, the directional edge map can be computed using Eqn. (5.2.5):

$$\begin{aligned} f_x^+(x, y) &= f_x^-(x, y) = f_y^+(x, y) = f_y^-(x, y) \\ &= -G_\sigma(x, y) * I(x, y). \end{aligned} \quad (5.3.9)$$

Figure 5.3: The DDGVF field in the (a) x , (b) $-x$, (c) y and (d) $-y$ directions for positive step edges.

5.3.2 Dynamic Directional GVF Field

The DDGVF field has four components: $\mathbf{v}(x, y) = [u^+(x, y), u^-(x, y), v^+(x, y), v^-(x, y)]$ for four directions. These components are found by solving the following partial differential equations:

$$\mathbf{v}_t = \mu \nabla^2 \mathbf{v} - (\mathbf{v} - \mathbf{df}) \mathbf{df}^2, \quad \mathbf{v}_0 = \mathbf{df} \quad (5.3.10)$$

where $\mathbf{df} = [df_x^+, df_x^-, df_y^+, df_y^-]$, and

$$df_x^+ = \frac{\partial}{\partial x} f_x^+ \quad (5.3.11a)$$

$$df_x^- = \frac{\partial}{\partial x} f_x^- \quad (5.3.11b)$$

$$df_y^+ = \frac{\partial}{\partial y} f_y^+ \quad (5.3.11c)$$

$$df_y^- = \frac{\partial}{\partial y} f_y^-. \quad (5.3.11d)$$

Eqn. (5.3.10) can be rewritten as

$$u_t^+ = \mu \nabla^2 u^+ - (u^+ - df_x^+)(df_x^+)^2, \quad u_0^+ = df_x^+ \quad (5.3.12a)$$

$$u_t^- = \mu \nabla^2 u^- - (u^- - df_x^-)(df_x^-)^2, \quad u_0^- = df_x^- \quad (5.3.12b)$$

$$v_t^+ = \mu \nabla^2 v^+ - (v^+ - df_y^+)(df_y^+)^2, \quad v_0^+ = df_y^+ \quad (5.3.12c)$$

$$v_t^- = \mu \nabla^2 v^- - (v^- - df_y^-)(df_y^-)^2, \quad v_0^- = df_y^-. \quad (5.3.12d)$$

These four equations in Eqn. (5.3.12) are decoupled, and therefore can be solved as separate scalar partial differential equations in u^+, u^-, v^+ and v^- . Compared with Eqn. (5.2.3), Eqn. (5.3.10) uses $\mathbf{df}^2$ instead of $|\nabla f|^2$, en-

ensuring that u^+, u^-, v^+ and v^- are decoupled from each other. As the snake's orientation has yet to be determined, all the four directions have to be assessed. The DDGVF field of Fig. 5.1(a) is shown in Fig. 5.3.

5.3.3 Snake Deformation

The external forces of snakes can be classified as static or dynamic forces [113]. Static forces are computed from the image data and do not change as the snake deforms. Dynamic forces are associated with the snake and therefore change as the snake deforms. The traditional external forces and GVF are both static external forces. An example of dynamic external force is the pressure inside a balloon [104], which causes the snake to inflate or deflate by a constant force along the normal direction of the contour.

The DDGVF field $\mathbf{v}$ is derived from the image as well as GVF field, however, it cannot be directly applied to the snake as a static external force. For each snaxel in deformation, the external force it is subjected to is dependent on the snaxel's location in the image and the shape of the snake (Fig. 5.4(a)). Hence the DDGVF field is essentially a dynamic external force.

Let θ be the contour's normal direction at a certain snaxel, then $\cos(\theta)$ is the normal vector's component in the x direction, and $\sin(\theta)$ is the normal vector's component in the y direction. If $\cos(\theta)$ is more/less than zero, u^+/u^- should be used as the horizontal external force F_x at that snaxel. Similarly, If $\sin(\theta)$ is more/less than zero, v^+/v^- should be used as the vertical external

force F_y at that snaxel.

$$F_x = u^+ * \max\{\cos(\theta), 0\} - u^- * \min\{\cos(\theta), 0\} \quad (5.3.13a)$$

$$F_y = v^+ * \max\{\sin(\theta), 0\} - v^- * \min\{\sin(\theta), 0\}. \quad (5.3.13b)$$

Hence the snake is deformed as in Eqn. (5.2.2) under the external force

$$F_{ext} = [F_x, F_y].$$

5.4 Comparison with DGVF

Tang *et al.* [31] proposed a directional gradient vector flow (DGVF) for snakes, which uses directional gradient to help the snake converge at the correct surface. The edge map function in DGVF is computed by $D_n(I) = \nabla I \cdot \mathbf{n}$, where ∇I is the gradient and $\mathbf{n}$ is the direction of the edge specified by the user. More specifically, $\mathbf{n}$ is the radial direction of each pixel with reference to a point within the object boundary (Fig. 5.4(b)). This ‘radial-search based’ strategy has a hidden assumption that the object boundary is a single-valued function in polar coordinates. For some objects of complex shape, the user may not be able to find such a reference point to satisfy the assumption. An example of the edge maps in the DGVF method is shown in Fig. 5.5.

The major difference between DDGVF and DGVF is that DDGVF is a dynamic external force while DGVF is a static external force. As shown in Fig. 5.4, the edge direction in which DGVF snake seeks the boundary is fixed without considering the shape of the deforming snake while this is not the case for DDGVF snake. The advantage of DDGVF over DGVF is that it makes use

Figure 5.4: The difference between (a) DDGVF snake and (b) DGVF snake. The arrows indicate the directions of edge in which snakes seek the boundary. The reference point is marked by 'R' in (b).

Figure 5.5: The edge maps of DGVF obtained from Fig. 5.1(a) for (a) positive boundary and (b) negative boundary.

of the directional gradient information dynamically in the snake deformation and thus achieves better boundary detection results for objects of complex shape. On the other hand, DGVF can have the same good results as DDGVF for objects of simple shape while requires less computational time.

The location of LV center does not matter in DDGVF method. What matters is the contour itself. Although the initial contour is usually a circle whose center is manually defined, the edges are searched from the normal directions of the deforming contour instead of from the center. The radial search from LV center is abandoned as it does not work for concave boundary.

5.5 Performance of The Method

The performance of the GVF snake, the DGVF snake and the DDGVF snake are compared in this section. The snakes are dynamically reparameterized during deformation and the distances between neighboring snaxels are maintained within 0.5-1.5 pixels. The same initial contour and parameter values are employed for each test image. All the edge maps used in snake are normalized to the range $[0, 1]$. The regularization parameter μ is set to 0.2, and the standard deviation of Gaussian function σ is set to 1.

5.5.1 Synthetic Images

In computation of the GVF and DDGVF fields, the number of iteration required to solve the partial differential equations (Eqn. (5.2.3) and Eqn. (5.3.10)) for an image of $m \times n$ pixels is $\sqrt{m \times n}$. During snake deformation, the parameters for snake shape regularization are set as follows: $\alpha = 1$, $\beta = 0$ and $\gamma = 0.6$. The values of these parameters are determined by trial-and-error to obtain optimal results.

Step Edge Images

The original image is a binary image of an irregular white loop in a black background (Fig. 5.1(a)). This image can be considered as a simulation of echocardiographic images: the white loop denotes the myocardium and the background denotes blood. It is noted that in the edge map of GVF (Fig. 5.1(b)), the inner boundary and the outer boundary of the loop are both of high intensity because of the magnitude operator. Therefore these two

boundaries are indistinguishable in the GVF edge map and the resultant GVF field.

The effect of the initial position of snakes on the performance of the GVF and DDGVF fields in Fig. 5.1(a) is illustrated in Fig. 5.6-5.8. When the initial contour is not far away from the positive and negative boundaries, it is found that the GVF snake is confused at those regions where the width of the loop is narrow. For two boundaries both of high gradient, the snake is attracted to the boundary which is nearer to the initial boundary (Fig. 5.7(a)). When the initial contour is far away from the desired boundaries, the GVF snake is able to converge to the nearer boundary. However at the regions where the two boundaries are very close, the snake is also affected by the GVF field which pulls it to the farther boundary. As a result, the snake stays in the middle of the two boundaries (Figs. 5.6(a) and 5.8(a)). On the other hand, the DDGVF snake is able to detect definitely the positive boundary (Figs. 5.6(b), 5.7(b) and 5.8(b)) or negative boundary (Figs. 5.6(c), 5.7(c) and 5.8(c)) independent of the initial contour.

One major advantage of GVF over the traditional potential forces is that it has a much larger capture range. From Fig. 5.6 to 5.8 it is found that the DDGVF possesses the same large capture range as GVF.

As for the DGVF method, the object boundary in this case is regular and the reference center can be easily set as the center of the image. The positive and negative boundaries are discerned completely in Fig. 5.5. From the corresponding edge maps, the DGVF snake as well as the DDGVF snake detects the positive and negative boundaries correctly (Fig. 5.6-5.8). However,

Figure 5.6: Performance of GVF, DGVF and DDGVF snakes on step edge image. The dashed line circles are initial snake positions and the solid line contours are final contours of the snakes. Three initial circles of different sizes are used as depicted in the three rows. (a) results of boundary detection using the GVF snake; (b)-(c) results of the DDGVF positive and negative boundary-searching snake respectively; (d)-(e) results of the DGVF positive and negative boundary-searching snake respectively.

Figure 5.7: Performance of GVF, DGVF and DDGVF snakes on step edge image. The dashed line circles are initial snake positions and the solid line contours are final contours of the snakes. Three initial circles of different sizes are used as depicted in the three rows. (a) results of boundary detection using the GVF snake; (b)-(c) results of the DDGVF positive and negative boundary-searching snake respectively; (d)-(e) results of the DGVF positive and negative boundary-searching snake respectively.

Figure 5.8: Performance of GVF, DGVF and DDGVF snakes on step edge image. The dashed line circles are initial snake positions and the solid line contours are final contours of the snakes. Three initial circles of different sizes are used as depicted in the three rows. (a) results of boundary detection using the GVF snake; (b)-(c) results of the DDGVF positive and negative boundary-searching snake respectively; (d)-(e) results of the DGVF positive and negative boundary-searching snake respectively.

Figure 5.9: Performance of DGVF and DDGVF snakes on 176×176 -pixel step edge image. (a) The original step edge image with the initial snake position (dashed line circles) and the reference point (cross) indicated ; (b) the edge map of DGVF; (c) results of boundary detection using the positive boundary-searching DGVF snake; (d) results of boundary detection using the positive boundary-searching DDGVF snake.

It does not work for the U-shape object in Fig. 5.9(a). Because of the concavity in the object boundary, the positive boundary found by the radial search from the reference point is incomplete in the edge map (Fig. 5.9(b)). Consequently, the DGVF snake is not able to detect the full object boundary but only the fan-shaped contour in Fig. 5.9(c). As shown in Fig. 5.9(d), the contour detected by the DDGVF snake is correct.

Line-Drawing Images

In line-drawing images, the positive and negative boundaries are merged into a single line and thus it is unable and unnecessary to distinguish them. If the image is a line-drawing (black on white), the edge map of GVF can be computed with Eqn. (5.2.4). The GVF converges at the middle of the line-drawing. In this case, since DDGVF uses the same edge map as GVF (Eqn. (5.3.9)), the DDGVF snake achieves similarly good result as GVF.

Another major advantage of GVF field is that it is able to move snakes into boundary cavities. This capability is demonstrated in [113] by an image of a U-shaped object (Fig. 5.10(b)). The DDGVF snake moves downward into the cavity and detect the boundary of the U-shaped object precisely in Fig. 5.10(c). Thus the DDGVF demonstrates the same ability of converging the snake to the boundary concavity as GVF.

The DDGVF is also able to converge to a boundary confined by a group of separated points, when applied to a point-drawing image (Fig. 5.11(a)).

Figure 5.10: Performance of GVF and DDGVF snakes on 176×176 -pixel line-drawing image. (a) The original image of line-drawing with the initial snake position indicated (dashed line circles); (b) results of boundary detection using the GVF snake; (c) results of boundary detection using the line-searching DDGVF snake.

Figure 5.11: Performance of GVF and DDGVF snakes on 176×176 -pixel line-drawing image. (a) The original image of line-drawing with the initial snake position indicated (dashed line circles); (b) results of boundary detection using the GVF snake; (c) results of boundary detection using the line-searching DDGVF snake.

Noisy Images

Experiments using controlled shape and noise level are carried out to assess the capability of the DDGVF method in coping with noise. In the simulation, the following two speckle noise models are used:

1. Rayleigh noise model $y = x * n_1$ is used to simulate envelope images in ultrasound systems. The speckle polluted images are obtained by multiplying the ground truth image x with n_1 which follows Rayleigh distribution with parameter b . In this noise model, we fix b to 0.7979 (so that the mean is 1 and the variance is 0.2732) and run the simulation for 30 times to generate 30 random images.
2. $y = x + \sqrt{x} * n_2$ is used to simulate displayed ultrasound images. n_2 is Gaussian noise and we fix the mean in 0 and vary the standard deviation from 2 to 8.

The average normalized boundary distances and area correlation for 30 images are listed in Table 5.1.

From Figs. 5.12 and 5.13, it can be observed that the proposed DDGVF snake performs well in the presence of noise. In comparison, the GVF snake tends to be attracted by the exterior boundary and the DGVF snake fails to detect the shape with concavity.

5.5.2 Photographic Images

Experiments are performed on images to demonstrate the superior robustness of DDGVF over the traditional GVF and DGVF methods. Three images:

Figure 5.12: (a) Original clean image simulating a short-axis echocardiographic image. Boundary points detected from synthetic images with the first noise model using (b) GVF, (c) DGVF and (d) DDGVF.

Table 5.1: Errors and area correlation measured from 30 noisy synthetic images with Rayleigh speckle noise ($b = 0.7979$).

Measures	GVFF	DGVF	DDGVF
Norm. HD	10.45 ± 2.49 %	11.13 ± 3.40 %	6.85 ± 1.97 %
Norm. MD	3.25 ± 0.73 %	2.52 ± 0.54 %	1.88 ± 0.20 %
Intersection/Union	0.833 ± 0.048	0.827 ± 0.071	0.928 ± 0.033

Figure 5.13: Boundary points detected from synthetic images with the second noise model using GVF (first column), DGVF (second column) and DDGVF (third column). The standard deviations of Gaussian white noise are: 2, 4, 6, 8, from top to bottom.

‘peppers’, ‘APC (armored personnel carrier)’ and ‘Garbo’ are used. Since the ROI is relatively small in the images, the GVF, DGVF and DDGVF fields are computed using $0.5 * \sqrt{m \times n}$ iterations for an image of $m \times n$ pixels. The parameters for snake shape regularization are set as follows: $\alpha = 1$, $\beta = 0$ and $\gamma = 0.6$. The reference point in the DGVF edge map is set at the center of the initial contour.

For the first image, the goal is to segment the pepper which lies in the middle. In Fig. 5.14(b), the bottom-left part of the DGVF snake is attracted by the boundary of the pepper on the left. By contrast, the DGVF and DDGVF snakes handle the disturbance easily because the desired boundary can be distinguished as a negative boundary. In Fig. 5.14(c), the DGVF snake fails at the top of the boundary where the stem of the pepper forms a sharp convex. The desired boundary in the second image is the outline of the APC including its shadow. The GVF snake shown in Fig. 5.15(b) achieves almost the same good result as the DDGVF snake except the indentation at the wheels. In Fig. 5.15(c), the DGVF snake is unable to include the shadow on the left. The shadow has a vertical line which is nearly on the same line as the reference point, so the DGVF edge map is not able to recognize the shadow’s edge by ‘radial-search’. For the ‘Garbo’ image, the face contour is to be detected. The GVF snake is largely distracted by the strong edges around the eyes and lips (Fig. 5.16(b)). The performance of the DGVF snake is not satisfactory in the eye region as can be observed in Fig. 5.16(c).

The proposed DDGVF field is actually more effective in object/background separation in comparison to the above results.

Figure 5.14: Performance of GVF, DGVF and DDGVF snakes on photographic images. (a) Image of ‘peppers’ (256×256 -pixel); (e) image of ‘APC’ (192×192 -pixel); (i) image of ‘Garbo’ (128×128 -pixel). (a) The original images with the initial snake position indicated (dashed line circles); (b) results of boundary detection using the GVF snake; (c) results of boundary detection using the DGVF snake; (d) results of boundary detection using the DDGVF snake.

Figure 5.15: Performance of GVF, DGVF and DDGVF snakes on photographic image 'APC' (192×192 -pixel). (a) The original images with the initial snake position indicated (dashed line circles); (b) results of boundary detection using the GVF snake; (c) results of boundary detection using the DGVF snake; (d) results of boundary detection using the DDGVF snake.

Figure 5.16: Performance of GVF, DGVF and DDGVF snakes on photographic image 'Garbo' (128×128 -pixel). (a) The original images with the initial snake position indicated (dashed line circles); (b) results of boundary detection using the GVF snake; (c) results of boundary detection using the DGVF snake; (d) results of boundary detection using the DDGVF snake.

Figure 5.17: (a) Ground truth points for the chin boundary. (b) Ground truth points for the whole boundary. (c) Mean boundary errors between the computer-detected boundaries and the ground truth boundaries.

In the 'Garbo' image, her upper lip is a stronger negative edge than her left chin. Because of the large capture range, the contour is attracted by the upper lip. We call it the 'distraction' phenomenon and a study on it is carried out in Appendix A. According to Fig. 5.17, the optimal iteration time is 40 where the whole boundary error reaches minimum. When the iteration time is reduced to 40, the influence from the upper lip is reduced and the detected boundary stays on the chin (Fig. 5.18).

Figure 5.18: Performance of DDGVF snakes on the ‘Garbo’ image with reduced iteration for the calculation of DDGVF field.

5.5.3 Echocardiographic Images

The GVF, DGVF and DDGVF are then applied to short-axis echocardiographic images to test their sensitivity to noise. The desired contour is the endocardial boundary of left ventricle. Echocardiographic image segmentation has been proven to be intractable to the classic techniques, due to the inherent noisy nature.

The interior of the left ventricle appears darker than the myocardium around in echocardiographic images, thus the endocardial boundary is roughly a positive boundary. The GVF, DGVF and DDGVF fields are computed using $0.5 * \sqrt{m \times n}$ iterations for an image of $m \times n$ pixels. Because of the presence of noise, larger α and β ($\alpha = 2$, $\beta = 1$ and $\gamma = 0.6$) are used to confine and regularize the shape of snake.

The performance of the GVF, DGVF and DDGVF snakes is shown in Fig. 5.22. As shown in Figs. 5.19(b), 5.20(b) and 5.21(b), the GVF snake fails to detect the real boundaries, at the regions where the potential force propagating from the desired boundary is smaller than that of local noise. Being attracted

Table 5.2: Boundary errors in pixels and area correlation.

Error Measures	GVF	DGVF	DDGVF
Hausdorff distance	7.90 ± 3.82 %	7.21 ± 3.82 %	5.58 ± 2.79 %
Mean distance	2.51 ± 0.86 %	2.23 ± 0.64 %	1.91 ± 0.44 %
Intersection/Union	0.764 ± 0.116	0.755 ± 0.186	0.848 ± 0.066

by not only the positive edges, the GVF snake tends to move to the exterior of the endocardium. The DGVF snake, being able to discern positive boundary from negative boundary, works better than the GVF snake. However, due to the deficiency of edge map mentioned above, the DGVF snake is not able to reach sharp convex in the contour, e.g. the left corner in Fig. 5.19(c) and the top-right corner in Fig. 5.20(c).

In comparison, the DDGVF snake is only attracted to the positive boundaries and is capable of distinguishing the desired edges from the false edges. Thus the proposed DDGVF snake model is superior to the GVF and DGVF snake models for the segmentation of echocardiographic images.

On a dataset consisting of 40 images of 116×116 pixels, the GVF, DGVF and DDGVF methods are applied and the computer-detected boundaries are compared with the expert-drawn boundaries. The computation time of the DDGVF method (implemented in C) for one image is around 0.2 seconds on a Pentium IV 2.6 GHz PC. The Hausdorff distance, mean absolute distance measured between the boundaries and Jaccard similarity coefficient (Intersection/Union) of the area enclosed are listed in Table 5.2.

To further validate the superiority of the proposed DDGVF method, the two-tailed paired t-test is conducted under the null hypothesis that there is no statistically significant difference between the three quantitative values

Figure 5.19: Performance of GVF, DGVF and DDGVF snakes on 220×220 -pixel echocardiographic images. (a) The original echocardiographic images with the initial snake position indicated (dashed line circles); (b) results of boundary detection using the GVF snake; (c) results of boundary detection using the DGVF snake; (d) results of boundary detection using the DDGVF snake.

Figure 5.20: Performance of GVF, DGVF and DDGVF snakes on 220×220 -pixel echocardiographic images. (a) The original echocardiographic images with the initial snake position indicated (dashed line circles); (b) results of boundary detection using the GVF snake; (c) results of boundary detection using the DGVF snake; (d) results of boundary detection using the DDGVF snake.

Figure 5.21: Performance of GVF, DGVF and DDGVF snakes on 220×220 -pixel echocardiographic images. (a) The original echocardiographic images with the initial snake position indicated (dashed line circles); (b) results of boundary detection using the GVF snake; (c) results of boundary detection using the DGVF snake; (d) results of boundary detection using the DDGVF snake.

achieved by the DDGVF and two other methods. The values measured from all the 40 images are used for the t-test.

In terms of the Hausdorff distance, the hypothesis is rejected by $p < 2 \times 10^{-3}$ for the GVF method, and rejected by $p < 4 \times 10^{-2}$ for the DGVF method. In terms of the mean absolute distance, the hypothesis is rejected by $p < 2 \times 10^{-4}$ for the GVF method and rejected by $p < 2 \times 10^{-2}$ for the DGVF method. In terms of the Jaccard similarity coefficient (Intersection/Union), the hypothesis is rejected by $p < 2 \times 10^{-4}$ for the GVF method and rejected by $p < 4 \times 10^{-3}$ for the DGVF method.

In other words, the DDGVF method generates significantly small Hausdorff distance and mean absolute distance than both the GVF and DGVF method. The DDGVF method also achieves significantly higher area correlation than both the GVF and DGVF method.

Long-axis Images

As aforementioned at the beginning of this chapter, the MLS method does not work for short-axis images. The MLS method is based on a radial search strategy which works well for circle-like or ellipse-like boundaries. But the LV boundary in short-axis images is concave, thus it may not be a single-value function with respect to the radial lines.

The DDGVF method has difficulties with long-axis images, where dropouts and artifacts are present. The snake needs strong attracting force from strong edges to move, i.e. it is not good at detecting edges of low contrast. At the regions of low contrast, the edges are hard to be detected especially after the

Figure 5.22: Results of DDGVF applied on long-axis images.

diffusion during solving the DDGVF field. It is common in long-axis images that there is a large part of boundary of hardly any contrast. In such case, the DDGVF snake will not be able to move to the correct boundary. In Fig. 5.22(a), the snake is easily disturbed at the weak edges and the top of the contour stops moving because there is no enough attraction from the top of LV. Similarly when the mitral valve is open (Fig. 5.22(b)), the snake also fails at the bottom part.

In summary, the two proposed methods have complementary advantages, so the MLS method is suitable for long-axis images whereas the DDGVF method is suitable for short-axis images.

5.6 Summary

A new type of dynamic external force for snakes called dynamic directional gradient vector flow (DDGVF) is proposed. The method generates the external force field in the horizontal and vertical directions separately to preserve the

directional gradient information. Since the DDGVF field is utilized dynamically according to the orientation of snake in deformation, the DDGVF snake is attracted to the positive or negative step edges exclusively, regardless of the proximity of the two types of edges. The originality of the DDGVF method is to use a directional edge map with two gradient components. Unlike the traditional methods which use only the gradient magnitude, the DDGVF field has four components and thus preserves the directional information which helps to distinguish edges of different directions. The DDGVF snake also demonstrates good convergence and large capture range. This algorithm is particularly useful for segmentation of echocardiographic images with complex boundary.

The proposed DDGVF method is compared with the gradient vector flow (GVF) and directional gradient vector flow (DGVF) methods. Quantitative results measured from the detected boundaries show that the proposed method outperforms the other two methods significantly.

Chapter 6

Conclusion and Recommendations

6.1 Conclusion

2D echocardiography is a highly effective tool for the diagnosis of heart diseases. The automated determination of the geometry of left ventricle would be a great asset to physicians for diagnosis and treatment. The key contribution of this thesis lies in the development of two novel methods designed for two kinds of echocardiographic images with different characteristics. MRF, level set, and snake methods are extensively studied and widely used in medical image segmentation. The methods developed in the thesis can significantly improve their performance of boundary detection in echocardiographic images.

A method to locate of LV region and center point without user interaction for long-axis echocardiographic images is proposed. A pre-segmentation algorithm is developed for this purpose. It incorporates morphological op-

eration and watershed transform, together with prior anatomical knowledge. The resulting LV center and ROI provide an initial condition thus expediting and facilitating the next phase of boundary detection. This approximate segmentation not only reduces the computation time, but also reduces the interobserver and intraobserver variability which may exist in ROI definition. Among the numerous methods proposed for computer-based boundary detection in the literature, many require an interactive input of a ROI or center point. The method proposed in Chapter 3 of this thesis is a novel approach which automatically generates the ROI and LV center.

The final segmentation to find the actual LV boundary in long-axis echocardiographic images is carried out using a Markovian level set (MLS) method. We are the first in literature which put the Markov random field (MRF) in a radial neighborhood and also the first to combine MRF with level set method. The originality resides in regarding the label field as a level set function, and thus enabling the regularization of boundary during the segmentation process. The method is a novel way to combine the edge and region information for the segmentation of echocardiographic images. When compared with the Bayesian segmentation method [27] which is a popular method for medical image segmentation, the experimental results show that the proposed method is more robust and effective in the boundary detection in long-axis images with dropouts, noise and low contrast.

A new external force for snakes was proposed as dynamic directional gradient vector flow (DDGVF) for boundary detection in short-axis echocardiographic images. This is the first approach in the literature which enables

the snake model to distinguish between positive and negative boundaries for concave shape, by introducing a new dynamic external force. The originality resides in the use of directional edge map with two gradient components, unlike the traditional methods which use only the gradient magnitude. The method is compared with the gradient vector flow [113] and directional gradient vector flow [31] methods which are recent proposed snake-based methods. The experimental results show that the proposed method is more robust and effective in the boundary detection in short-axis images, with the presence of noise and concave shape.

Although the focus of this work is to develop segmentation methods to detect the LV boundary, the algorithms may be applied to detect the boundary of other cardiac chambers, the artery, the aorta and images obtained by other imaging modalities such as computerized tomography (CT) and magnetic resonance imaging (MRI).

Feature extraction from echocardiographic images is of major importance for quantitative analysis of the heart function. Ventricular boundary is an essential feature from which many other features can be derived, e.g. ventricular volume, ejection fraction, thickness of myocardium, ventricular mass, and 3D reconstruction/modeling throughout the cardiac cycle. Although manual tracing is still considered the most accurate and reliable method, the automated methods can reduce the time necessary for manual tracing when numerous images are to be processed. Automation of the boundary detection task, leading to reliable, objective, and reproducible analysis, is strongly desirable.

For long-axis echocardiographic images, the methods presented in Chapter

3 and 4 can be integrated into a system which automatically detects the ROI, center point, and the LV boundary in succession. Tracing the boundaries on a sequence of images covering the entire cardiac cycle allows quantitative interpretation of LV contraction dynamics.

For short-axis echocardiographic images, the method developed in Chapter 5 can be the first process of an automated system for recovering the left ventricle surface from a set of 2D echocardiographic images. The strategy involves three main processes: 1) the detection of the LV boundary in a set of echocardiographic images, 2) the reconstruction of the LV surface from the extracted boundaries, and 3) the 3D interactive display (using a rendering module) and computation of functional descriptors (using an analysis module) such as the ventricle volume and the related parameters.

6.2 Recommendations for Further Research

As cardiac disease treatment is moving into the intraoperative environment, both the cost and time pressures to the hospitals and clinics are increasing. Hence, faster processing is needed, and more accuracy and more automation to minimize physicians' input are the keys to future acceptance of these tools.

Although full automation is a desirable end goal, its difficulty has been acknowledged many times in the literature. There is a growing consensus that user interaction is, to some extent, unavoidable, and that it has to be considered as an integrated part of the segmentation procedure. Therefore, development of efficient tools for interaction will play an important role in the

near future. ‘Efficient’ entails that with minimal and intuitive user interaction the operator keeps control over the segmentation process to correct or overrule its results where it has failed, and to guide the algorithm in abnormal situations (e.g., in front of a pathological case). Of course, the issue of reproducibility in case of human intervention needs attention. Where well-defined repetitive tasks are recognized, or where a local user interaction can be extrapolated to a broader area, the process should be automated, thus improving segmentation throughput and repeatability.

The parameters employed in the proposed pre-segmentation algorithms are selected by trial-and-error. The relation between the parameters and the performance of the algorithm can be further studied, so that the parameters can be adaptively derived from the characteristics of the input echocardiographic images.

In this study, the segmentation methods use only edge or gradient information from the image. Ultrasound images are also rich in texture information and this may be exploited. One approach is to analyze the statistical characteristics of echocardiographic images and integrate texture, edge, time, shape and pathology information in a unified framework to optimize the information available for segmentation.

6.2.1 Temporal Analysis

The proposed methods are tested on static 2D echocardiographic images. A human expert observer often uses temporal image sequences as another important a priori source of information. If neighboring frames are also considered

when tracking the LV borders, information can be obtained on the boundary pieces in the regions of very poor contrast. Many systemic and subjective factors, including time gain compensation, the thickness of the patient chest, etc., affect the gray-level intensity of features in the image. In this sense, the motion data over the cycle provides a very useful source of information for deciding the location of boundaries in a series of echocardiographic images. This observation motivates improvement of the algorithms by using the temporal information of a moving noisy boundary. The possible directions are

- Introducing temporal information into tracking process using deformable templates. It combines a shape-space model with a second model describing the motion of the object in a Kalman-filter framework. Parameters of the model can be learned from a training set. The shape and motion models should well represent the deformations in the dataset of interest and in the case of abnormal motion (such as a diseased heart).
- Optical flow-based methods which provide an image-driven approach to estimating temporal information from image sequences. The best features of the snake model and optical flow can be combined in a tracking framework where the position of the detected edges in the next frame is predicted by optical flow correlation. How to reduce the noise-sensitivity of optical flow methods would be important.

6.2.2 Shape Analysis

The methods presented do not include information about the allowable range of shape and appearance variations of the target, i.e. the left ventricle. Ultra-

sonic image information is often ill-defined or incomplete. Therefore, extensive model knowledge about the characteristics of organ shape and appearance, anatomical and pathological shape variations and spatial organ embedding should form an integral part of a robust boundary detection approach. Since ultrasound images are generally acquired in standardized cross sections, images obtained in the same part of the anatomy have similar characteristics. Suppose normal LV boundaries are detected from a standard sequence of echocardiographic images, the characteristics of LV shape and appearance can be extracted from these present results, and used as an initial or guiding situation in other sequences of images to be processed. This *a priori* knowledge will be very effective in coping with problems posed by the existence of the papillary muscles, trabeculation, and the mitral valve in the left ventricle.

6.2.3 Extension to 3D Domain

3D medical ultrasound imaging has attracted attention in recent years. Conventional 2D ultrasound imaging systems have limitations in quantifying the volume of structures of interests in human body. The 3D ultrasound imaging systems can tackle this problem. A simple way to perform segmentation on 3D images is to detect the ventricular boundary on each 2D slice in the 3D images. The main drawback of the slice-by-slice approach is that no interaction is permitted between neighboring slices. A more efficient approach is to develop a 3D segmentation method which works directly on volume data instead of slices. In this way, information between adjacent slices can be explored to reduce artifacts and reconstruct missing edges.

As aforementioned in Section 2.3.3, the active contour model (snakes) for 2D images can be extended to 3D volume data. In [110] and [105], finite element and physics-based methods are used to implement a 3D elastically deformable surface (cylinder and sphere, respectively) which evolves in 3D images, for segmentation and tracking in 3D/4D(3D+T) cardiac images. The 2D snake-based methods introduced in this thesis can be extended to 3D domain based on the active surface model frameworks mentioned above.

Since the shape of the cardiac ventricles is approximately known, it seems natural to incorporate prior shape knowledge into the 3D segmentation process. Such model-driven techniques have received ample attention in medical analysis in the last decade. Similar to the 2D case, model-based 3D cardiac segmentation has not reached the status of being effectively automated since current techniques either require substantial expert guidance, ad hoc parameter fine-tuning or nontrivial preprocessing. How to devise an efficient and intuitive mechanisms for 3D manipulation of models and volumetric data, and how to integrate them into the deformation of the models remain topics of future research.

Appendix A

The Distraction Phenomenon

In this appendix, the distraction phenomenon is studied.

As the GVF field is calculated as a diffusion of the gradient vectors of an edge map derived from the image, it greatly increases the capture range of the snake and its capability to move into boundary concavities. The diffusion process is somehow similar to smooth filtering: the larger the iteration times (equivalent to larger size of the smoothing kernel), the wider the range of pixels involved.

An experiment is carried out to illustrate this phenomenon where the desired square boundary is attracted by a stronger negative edge above when iteration time is increased. Four parameters are considered: R (ratio of intensity difference), L (length), H (distance) and $Iter$ (iteration time). The meaning of R , L , and H are explained in Fig. A.1. In Figs. A.2-A.5, the threshold of distraction corresponding to different R , L , H , and $Iter$ are displayed. From the experimental results, it is found that the distraction happens only when a nearby edge is stronger than the desired boundary (large R), near

enough (small H), and long enough (large L). When all the three conditions are satisfied, a proper iteration time should be selected to prevent the distraction. When H increases to some extent (the red dashed line becomes vertical), the square boundary will not be distracted no matter how large is the iteration time.

In the ‘Garbo’ image, $H \approx 13$, $L \approx 18$. Thus distraction happens when iteration time is larger than 75 according to Fig. A.5.

In GVF-based methods, the iterations time for the calculation of GVF force are usually set to be proportional to the size of images. Actually the optimal iteration time or optimal capture range should be large enough to attract the snake without interference from undesired objects nearby. Therefore, the optimal iteration time is hard to obtain as the positions of the snake and other objects nearby vary case by case. This is a shortcoming of GVF-based methods, which depend on an iteration-based calculation. When there are multiple strong edges available in the image, as in the ‘Garbo’ case, it is recommended not to overdo the number of iterations. Another solution is to exclude the boundaries of undesired object first, by imposing more restrictions in the search of object boundary.

Figure A.1: Original images with of 100×100 with (a) $R = 1.5$, (b) $R = 2$, and (c) $R = 4$. The maximum intensity value is 1. The intensity of the background is 0.8. R is the ratio of the intensity difference $R = (1 - U)/(1 - 0.8)$, where U is the intensity of the rectangular. (d) Original image with $R = 2$, $H = 6$, and $L = 20$. (e) Boundaries obtained from DDGVF after 25 iterations; (f) Boundaries obtained from DDGVF after 25 iterations where distraction happens.

Figure A.2: Threshold of distraction corresponding to R , L , and H when $Iter = 100$. In the areas above the red dashed lines, distraction happens.

Figure A.3: Threshold of distraction corresponding to $Iter$, L , and H when $R = 1.5$. In the areas above the red dashed lines, distraction happens.

Figure A.4: Threshold of distraction corresponding to $Iter$, L , and H when $R = 2$. In the areas above the red dashed lines, distraction happens.

Figure A.5: Threshold of distraction corresponding to $Iter$, L , and H when $R = 4$. In the areas above the red dashed lines, distraction happens.

Author's Publications

Journal Papers

1. **Jierong Cheng**, Say Wei Foo and Shankar M. Krishnan, "Watershed presegmented Snake for Boundary Detection and Tracking of Left Ventricle in Echocardiographic Images", *IEEE Transactions on Information Technology in BioMedicine*, vol. 10, no. 2, pp. 414-416, 2006.
2. **Jierong Cheng** and Say Wei Foo, "Dynamic Directional Gradient Vector Flow for Snakes", *IEEE Transactions on Image Processing*, vol. 15, no. 6, pp. 1563-1571, 2006.
3. **Jierong Cheng** and Say Wei Foo, "Boundary Detection in Echocardiographic Images using Markovian Level Set Method", to be published in *IEICE Transactions on Information and Systems*.

Conference Papers

1. **Jierong Cheng**, Say Wei Foo and Shankar M. Krishnan, "Automatic Left Ventricular Boundary Detection from Echocardiographic Images Using Multiscale Analysis", in *Proc. The 2003 International Conference*

- on Mathematics and Engineering Techniques in Medicine and Biological Sciences*, (Las Vegas, USA), pp. 399-405, June 2003.
2. **Jierong Cheng**, Say Wei Foo and Shankar M. Krishnan, “Automatic Detection of Left Ventricular Endocardial and Epicardial Boundary from Echocardiographic Images”, in *Proc. World Congress on Medical Physics and Biomedical Engineering*, (Sydney, Australia), August 2003.
 3. **Jierong Cheng**, Say Wei Foo and Shankar M. Krishnan, “A Novel Approach to Automatic Left Ventricular Contour Tracking”, in *Proc. The 11th International BioEngineering Conference*, (Singapore), September 2004.
 4. **Jierong Cheng**, Say Wei Foo and Shankar M. Krishnan, “Echocardiographic Image Sequence Segmentation by Multiscale Directional Snake”, in *Proc. The 4th IEEE International Symposium on Signal Processing and Information Technology*, (Rome, Italy), pp. 318-321, December 2004.
 5. **Jierong Cheng**, Say Wei Foo and Shankar M. Krishnan, “Directional Gradient Vector Flow for Snakes”, in *Proc. The 4th IEEE International Symposium on Signal Processing and Information Technology*, (Rome, Italy), pp. 26-29, December 2004.
 6. **Jierong Cheng**, Say Wei Foo and Shankar M. Krishnan, “Boundary Detection in Echocardiographic Images by Directional Gradient Vector Flow”, in *Proc. IEEE International Workshop on BioMedical Circuits and Systems*, (Singapore), December 2004.

7. **Jierong Cheng**, Say Wei Foo and Shankar M. Krishnan, “Automatic Detection of Region of Interest and Center Point of Left Ventricle Using Watershed Segmentation”, in *Proc. IEEE International Symposium on Circuits and Systems*, (Kobe, Japan), vol. 1, pp. 149-151, May 2005.
8. **Jierong Cheng** and Say Wei Foo, “Markovian Level Set: A New Method for Boundary Detection from Echocardiographic Images”, in *Proc. International Conference on Acoustics, Speech, and Signal Processing*, (Toulouse, France), vol. 2, pp. II/1132-II/1135, May 2006.
9. **Jierong Cheng** and Say Wei Foo, “Markovian Level Set for Echocardiographic Image Segmentation”, in *Proc. IEEE International Symposium on Circuits and Systems*, (Island of Kos, Greece), pp. 5567-5570, May 2006.

Bibliography

- [1] J. U. Quistgaard, “Signal acquisition and processing in medical diagnostic ultrasound,” *IEEE Signal Processing Magazine*, vol. 14, no. 1, pp. 67–74, 1997.
- [2] J. G. Mottley and J. G. Miller, “Anisotropy of the ultrasonic backscatter of myocardial tissue: I theory and measurements in vivo,” *J. Acoust. Soc. Am*, vol. 83, pp. 755–761, 1988.
- [3] M. R. Holland, U. M. Wilkenshoff, A. E. Finch-Johnston, S. M. Handley, J. E. Perez, and J. G. Miller, “Effects of myocardial fiber orientation in echocardiography: quantitative measurements and computer simulation of the regional dependence of backscattered ultrasound in the parasternal short-axis view,” *J Am Soc Echocardiogr.*, vol. 11, no. 10, pp. 929–937, 1998.
- [4] M. R. Holland, A. E. Finch-Johnston, K. D. Wallace, S. M. Handley, U. M. Wilkenshoff, J. E. Perez, and J. G. Miller, “Effects of tissue anisotropy and contrast acoustic properties on myocardial scattering in contrast echocardiography,” *J Am Soc Echocardiogr.*, vol. 12, no. 7, pp. 564–573, 1999.

- [5] T. R. Nelson, D. B. Downey, D. H. Pretorius, and A. Fenster, *Three-Dimensional ultrasound*. Philadelphia, PA: Lippincott Williams & Wilkins, 1999.
- [6] A. Fenster and D. B. Downey, "3-d ultrasound imaging: a review," *IEEE Engineering in Medicine and Biology Magazine*, vol. 15, no. 6, pp. 41–51, 1996.
- [7] J. M. B. Dias and J. M. N. Leitaó, "Wall position and thickness estimation from sequences of echocardiographic images," *IEEE Trans. Med. Imag.*, vol. 15, no. 1, pp. 25–38, 1996.
- [8] Y. Chen, H. Tagare, S. Thiruvankadam, F. Huang, D. Wilson, K. S. Gopinath, R. W. Briggs, and E. A. Geiser, "Using prior shapes in geometric active contours in a variational framework," *International journal of computer vision*, vol. 50, no. 3, pp. 315–328, 2002.
- [9] G. Xiao, M. Brady, and J. A. Noble, "Segmentation of ultrasound b-mode images with intensity inhomogeneity correction," *IEEE Trans. Med. Imag.*, vol. 21, no. 1, pp. 48–57, 2002.
- [10] D. Boukerroui, J. A. Noble, M. C. Robini, and M. Brady, "Enhancement of contrast regions in suboptimal ultrasound images with application to echocardiography," *Ultrasound Med. Biol.*, vol. 27, no. 12, pp. 1583–1594, 2001.

-
- [11] M. O'Donnell and S. D. Silverstein, "Optimum displacement for compound image generation in medical ultrasound," *IEEE Trans. Ultrason. Ferroelect. Freq. Constr.*, vol. 35, no. 4, pp. 470–476, 1988.
- [12] G. E. Trahey, J. W. Allison, S. W. Smith, and O. T. von Ramm, "A quantitative approach to speckle reduction via frequency compounding," *Ultrason. Imaging*, vol. 8, no. 3, pp. 151–164, 1986.
- [13] T. Loupas, W. N. McDicken, and P. L. Allan, "An adaptive weighted median filter for speckle suppression in medical ultrasonic images," *IEEE Trans. Circuits and Systems*, vol. 36, no. 1, pp. 129–135, 1989.
- [14] R. N. Czerwinski, D. L. Jones, and W. D. O'Brien, "Detection of lines and boundaries in speckle images - application to medical ultrasound," *IEEE Trans. Med. Imaging*, vol. 18, no. 2, pp. 126–136, 1999.
- [15] Y. Chen, R. M. Yin, P. Flynn, and S. Broschat, "Aggressive region growing for speckle reduction in ultrasound images," *Pattern Recognition Letters*, vol. 24, no. 4, 2003.
- [16] Y. J. Yu and S. T. Acton, "Speckle reducing anisotropic diffusion," *IEEE Trans. Image Processing*, vol. 11, no. 11, pp. 1260–1270, 2002.
- [17] K. Z. Abd-Elmoniem, A. M. Youssef, and Y. M. Kadah, "Real-time speckle reduction and coherence enhancement in ultrasound imaging via nonlinear anisotropic diffusion," *IEEE Trans. Biomed. Engr.*, vol. 49, no. 9, pp. 997–1014, 2002.

- [18] X. Zong, A. F. Laine, and E. A. Geiser, "Speckle reduction and contrast enhancement of echocardiograms via multiscale nonlinear processing," *IEEE Trans. Med. Imaging*, vol. 17, no. 4, pp. 532–540, 1998.
- [19] X. Hao, S. Gao, and X. Gao, "A novel multiscale nonlinear thresholding method for ultrasonic speckle suppressing," *IEEE Trans. Med. Imaging*, vol. 18, no. 9, pp. 787–794, 1999.
- [20] A. B. A. Achim and P. Tsakalides, "Novel bayesian multiscale method for speckle removal in medical ultrasound images," *IEEE Trans. Med. Imaging*, vol. 20, no. 8, pp. 772–783, 2001.
- [21] A. Krivanek and M. Sonka, "Ovarian ultrasound image analysis: follicle segmentation," *IEEE Trans. Med. Imag.*, vol. 17, no. 6, pp. 935–944, 1998.
- [22] C. Chen, H. Lu, and Y. Huang, "Cell-based dual snake model: a new approach to extracting highly winding boundaries in the ultrasound images," *Ultrasound Med. Biol.*, vol. 28, no. 8, pp. 1061–1073, 2002.
- [23] S. K. Setarehdan and J. J. Soraghan, "Automatic cardiac left ventricular boundary detection and tracking using hybrid fuzzy temporal and fuzzy multiscale edge detection," *IEEE Trans. Biomed. Eng.*, vol. 46, no. 11, pp. 1364–1378, 1999.
- [24] J. H. Kaspersen, T. Lango, and F. Lindseth, "Wavelet-based edge detection in ultrasound images," *Ultrasound Med. Biol.*, vol. 27, no. 1, pp. 89–99, 2001.

-
- [25] M. Mignotte and J. Meunier, "A multiscale optimization approach for the dynamic contour-based boundary detection issue," *Computerized Medical Imaging and Graphics*, vol. 25, no. 3, pp. 265–275, 2001.
- [26] V. Chalana, D. T. Linker, D. R. Haynor, and Y. Kim, "A multiple active contour model for cardiac boundary detection on echocardiographic sequences," *IEEE Trans. Med. Imag.*, vol. 15, no. 3, pp. 290–298, 1996.
- [27] D. Boukerroui, A. Baskurt, J. A. Nobel, and O. Basset, "Segmentation of ultrasound images-multiresolution 2d and 3d algorithm based on global and local statistics," *Pattern Recognition Letters*, vol. 24, no. 4, 2003.
- [28] A. D. Parker, A. Hill, C. J. Taylor, T. F. Cootes, X. Y. Jin, and D. G. Gibson, "Application of point distribution models to the automated analysis of echocardiograms," in *Proc. Computers in Cardiology*, (Bethesda, MD), pp. 25–28, 1994.
- [29] J. G. Bosch, S. C. Mitchell, B. P. F. Lelieveldt, F. Nijland, O. Kamp, M. Sonka, and J. H. C. Reiber, "Automatic segmentation of echocardiographic sequences by active appearance motion models," *IEEE Trans. Med. Imag.*, vol. 21, no. 11, pp. 1374–1383, 2002.
- [30] I. A. Hunter, J. J. Soraghan, and T. McDonagh, "Fully automatic left ventricular boundary extraction in echocardiographic images," *Computers in Cardiology*, vol. 22, pp. 741–744, 1995.
- [31] J. Tang, S. Millington, S. T. Acton, J. Crandall, and S. Hurwitz, "Ankle cartilage surface segmentation using directional gradient vector flow

-
- snake,” in *Pro. Int’l Conf. on Image Processing*, vol. 4, pp. 2745–2748, 2004.
- [32] A. F. Frangi, W. J. Niessen, and M. A. Viergever, “Three-dimensional modeling for functional analysis of cardiac images: A review,” *IEEE Trans. Med. Imag.*, vol. 20, no. 1, pp. 2–25, 2001.
- [33] K. T. Weber and E. W. Hawthorne, “Descriptors and determinants of cardiac shape: An overview,” *Fed. Proc.*, vol. 40, no. 7, pp. 2005–2010, 1981.
- [34] P. Hernandez-Lattuf, “Ejection phase indices of left ventricular contractility,” *Cardiovascular Diseases*, vol. 2, no. 4, pp. 384–390, 1975.
- [35] J. C. McEachen, A. Neohorai, and J. S. Duncan, “A recursive filter for temporal analysis of cardiac motion,” in *Proc. IEEE Workshop on Biomedical Image Analysis*, (Seattle, WA), pp. 124–133, 1994.
- [36] F. H. Sheehan, E. L. Bolson, H. T. Dodge, D. G. Mathey, J. Schofer, and H. K. Woo, “Advantages and applications of the centerline method for characterizing regional ventricular function,” *Circulation*, vol. 74, no. 2, pp. 293–305, 1986.
- [37] Y. C. Fung, *Biomechanics: motion, flow, stress and growth*. New York: Springer Verlag, 1990.
- [38] V. Chalana and Y. Kim, “A methodology for evaluation of boundary detection algorithms on medical images,” *IEEE Trans. Med. Imag.*, vol. 16, no. 5, pp. 642–652, 1997.

-
- [39] A. Hammoude, “Endocardial border identification in two-dimensional echocardiographic images: review of methods,” *Computerized Medical Imaging and Graphics*, vol. 22, no. 3, pp. 181–193, 1998.
- [40] D. Marr and E. Hildreth, “Theory of edge detection,” *Proceedings of the Royal Society London*, vol. 207, pp. 187–217, 1980.
- [41] R. G. Aarnink, J. J. M. C. H. Rosette, W. F. J. Feiz, F. M. J. Debruyne, and H. Wijkstra, “A preprocessing algorithm for edge detection with multiple scales of resolution,” *Europe Journal of Ultrasound*, vol. 5, no. 2, pp. 113–126, 1997.
- [42] R. Krips and D. R. Adam, “Left ventricular wall segmentation in ultrasound cross-sectional images,” *Computers in Cardiology*, vol. 26, pp. 141–144, 1999.
- [43] I. Koren, A. F. Laine, J. Fan, and F. J. Taylor, “Edge detection in echocardiographic image sequences by 3d multiscale analysis,” in *Proc. IEEE Int. Conf. on Image Processing*, vol. 1, pp. 288–292, 1994.
- [44] S. G. Mallat, “A theory for multiresolution signal decomposition: the wavelet transform,” *IEEE Trans. Pattern Anal. Machine Intell.*, vol. 11, no. 7, pp. 674–693, 1989.
- [45] N. Lin, W. Yu, and J. S. Duncan, “Combinative multi-scale level set framework for echocardiographic image segmentation,” *Medical Image Analysis*, vol. 7, pp. 529–537, 2003.

- [46] R. Adams and L. Bischof, "Seeded region growing," *IEEE Trans. Pattern Anal. Machine Intell.*, vol. 16, pp. 641–647, 1994.
- [47] X. Hao, C. Bruce, C. Pislaru, C. Greenleaf, and J. F. M. Foundation, "A novel region growing method for segmentating ultrasound images," *Proc. IEEE Ultrasonics Symposium*, vol. 2, pp. 1717–1720, 2000.
- [48] R. Muzzolini, Y. Yang, and R. Pierson, "Multiresolution texture segmentation with application to diagnostic ultrasound images," *IEEE Trans. Med. Imag.*, vol. 12, no. 1, pp. 108–123, 1993.
- [49] E. K. Kerut, M. Given, and T. D. Giles, "Review of methods for texture analysis of myocardium from echocardiographic images: a mean of tissue characterization," *Echocardiography*, vol. 20, no. 8, pp. 727–736, 2003.
- [50] F. M. J. Valckx and J. M. Thijssen, "Characterization of echographic image texture by cooccurrence matrix parameters," *Ultrasound Med. Biol.*, vol. 23, no. 4, pp. 557–571, 1997.
- [51] G. V. de Wouwer, P. Scheunders, and D. V. Dyck, "Statistical texture characterization from discrete wavelet representation," *IEEE Trans. Image Processing*, vol. 8, no. 4, pp. 592–598, 1999.
- [52] G. Fan and X. Xia, "Wavelet-based texture analysis and synthesis using hidden markov models," *IEEE Trans. Circuits and Systems-I*, vol. 50, no. 1, pp. 106–120, 2003.

-
- [53] J. Aujol, G. Aubert, and L. Blanc-Féraud, "Wavelet-based level set evolution for classification of textured images," *IEEE Trans. Image Processing*, vol. 12, no. 12, pp. 1634–1641, 2003.
- [54] E. A. Ashton and K. J. Parker, "Multiple resolution bayesian segmentation of ultrasound images," *Ultrasonic imaging*, vol. 17, pp. 291–304, 1995.
- [55] T. N. Pappas, "An adaptive clustering algorithm for image segmentation," *IEEE Tran. Signal Proc.*, vol. 40, no. 4, pp. 901–914, 1992.
- [56] D. Boukerroui, O. Basset, N. Guerin, and A. Baskurt, "Multiresolution texture based adaptive clustering algorithm for breast lesion segmentation," *Eur. J. Ultrasound*, vol. 8, no. 2, pp. 135–144, 1998.
- [57] D. Boukerroui, O. Basset, A. Baskurt, and G. Gimenez, "A multiparametric and multiresolution segmentation algorithm of 3-d ultrasonic data," *IEEE Tran. Ultrason., Ferroelect., Freq. Contr.*, vol. 48, no. 1, pp. 64–77, 2001.
- [58] D. Boukerroui, A. Baskurt, J. A. Nobel, and O. Basset, "Segmentation of ultrasound images-multiresolution 2d and 3d algorithm based on global and local statistics," *Pattern Recognition Letters*, vol. 24, pp. 779–790, 2003.
- [59] R. H. Davies, C. J. Twining, T. F. Cootes, J. C. Waterton, and C. J. Taylor, "A minimum description length approach to statistical shape modelling," *IEEE Trans. Med. Imag.*, vol. 21, no. 5, pp. 525–537, 2002.

- [60] G. Xiao, M. Brady, J. A. Noble, and Y. Zhang, "Segmentation of ultrasound b-mode images with intensity inhomogeneity correction," *IEEE Trans. Med. Imag.*, vol. 21, no. 1, pp. 48–57, 2002.
- [61] M. Mulet-Parada and J. A. Noble, "2d+t acoustic boundary detection in echocardiography," *Medical Image Analysis*, vol. 4, no. 1, pp. 21–30, 2000.
- [62] N. Friedland and D. R. Adam, "Automatic ventricular cavity boundary detection from sequential ultrasound images using simulated annealing," *IEEE Trans. Med. Imag.*, vol. 8, no. 4, pp. 344–353, 1989.
- [63] M. Kass, A. Witkin, and D. Terzopoulos, "Snakes: active contour models," *International Journal of Computer Vision*, vol. 1, no. 4, pp. 321–331, 1987.
- [64] H. Park, T. Schoepflin, and Y. Kim, "Active contour model with gradient directional information: directional snake," *IEEE Trans. Circuits Syst. Video Technol.*, vol. 11, no. 2, pp. 252–256, 2001.
- [65] P. C. Yuen, G. C. Feng, and J. P. Zhou, "A contour detection method: initialization and contour model," *Pattern Recognition Letters*, vol. 20, no. 2, pp. 141–148, 1999.
- [66] M. Mignotte, J. Meunier, and J. Tardif, "Endocardial boundary estimation and tracking in echocardiographic images using deformable templates and markov random fields," *Pattern Analysis & Application*, vol. 4, pp. 256–271, 2001.

-
- [67] C. Chen, H. Lu, and Y. Lin, "An early vision-based snake model for ultrasound image segmentation," *Ultrasound Med. Biol.*, vol. 26, no. 2, pp. 273–285, 2000.
- [68] C. Chesnaud, P. Refregier, and V. Boulet, "Statistical region snake-based segmentation adapted to different physical noise models," *IEEE Trans. Pattern Anal. Machine Intell.*, vol. 21, no. 11, pp. 1145–1157, 1999.
- [69] A. Yezzi, A. Tsai, and A. Willsky, "A statistical approach to snakes for bimodal and trimodal imagery," in *Pro. IEEE Int'l Conf. Computer Vision*, vol. 2, pp. 898–903, 1999.
- [70] H. Nguyen, M. Worring, and R. Boomgaard, "Watersnakes: energy-driven watershed segmentation," *IEEE Trans. Pattern Anal. Machine Intell.*, vol. 25, no. 3, pp. 330–342, 2003.
- [71] R. Radeva and J. Vitria, "Region-based approach for discriminant snakes," in *Proc. IEEE Int. Conf. on Image Processing*, vol. 2, pp. 801–804, 2001.
- [72] M. Mignotte and J. Meunier, "A multiscale optimization approach for the dynamic contour-based boundary detection issue," *Computerized Medical Imaging and Graphics*, vol. 25, no. 3, pp. 265–275, 2001.
- [73] Z. Zhang and M. Braun, "Fully 3d active surface models with self-inflation and self-deflation forces," *IEEE Proc. Conf. on Comput. Vis. and Patt. Recog.*, pp. 85–90, 1997.

- [74] G. Jacob, J. A. Noble, C. Behrenbruch, A. D. Kelion, and A. P. Banning, "A shape-space-based approach to tracking myocardial border and quantifying regional left-ventricular function applied in echocardiography," *IEEE Trans. Med. Imag.*, vol. 21, no. 3, pp. 226–238, 2002.
- [75] C. Y. Han, K. N. Lin, W. G. Wee, R. M. Mintz, and D. T. Porembka, "Knowledge-based image analysis for automated boundary extraction of transesophageal echocardiographic left-ventricular images," *IEEE Trans. Med. Imag.*, vol. 10, no. 4, pp. 602–610, 1991.
- [76] J. Feng, W. Lin, and C. Chen, "Epicardial boundary detection using fuzzy reasoning," *IEEE Trans. Med. Imag.*, vol. 10, no. 2, pp. 187–199, 1991.
- [77] J. W. Klinger, C. L. Vaughan, T. D. Fraker, and L. T. Andrews, "Segmentation of echocardiographic images using mathematical morphology," *IEEE Trans. Biomed. Eng.*, vol. 35, no. 11, pp. 925–934, 1988.
- [78] S. K. Setarehdan and J. J. Soraghan, "Automatic left ventricular center point extraction in echocardiographic images," *Journal of Signal Processing*, vol. 61, no. 3, pp. 275–288, 1997.
- [79] L. Vincent and P. Soille, "Watersheds in digital spaces: An efficient algorithm based on immersion simulations," *IEEE Trans. Pattern Anal. Machine Intell.*, vol. 13, no. 6, pp. 583–598, 1991.

-
- [80] M. W. H. T. Nguyen and R. Boomgaard, "Watersnakes: Energy-driven watershed segmentation," *IEEE Trans. Pattern Anal. Machine Intell.*, vol. 25, no. 3, pp. 330–342, 2003.
- [81] C. Chesnaud, P. Refregier, and V. Boulet, "Statistical region snake-based segmentation adapted to different physical noise models," *IEEE Trans. Pattern Anal. Machine Intell.*, vol. 21, no. 11, pp. 1145–1157, 1999.
- [82] N. Otsu, "A threshold selection method from gray-level histograms," *IEEE Transactions on Systems, Man, and Cybernetics*, vol. 9, pp. 62–66, 1979.
- [83] G. Winkler, *Image Analysis, Random Fields, and Dynamic Monte Carlo Methods: A Mathematical Introduction*. Heidelberg, Germany: Springer Verlag, 1995.
- [84] S. Geman and D. Geman, "Stochastic relaxation, Gibbs distributions, and the Bayesian restoration of images," *IEEE Trans. Pattern Anal. Machine Intell.*, vol. 6, no. 6, pp. 732–741, 1984.
- [85] M. T. de Figueiredo and J. M. N. Leitao, "Bayesian estimation of ventricular contours in angiographic images," *IEEE Trans. Med. Imag.*, vol. 11, no. 3, pp. 416–429, 1992.
- [86] J. E. Besag, "On the statistical analysis of dirty pictures," *J. Roy. Stat. Soc. Ser. B*, vol. 48, no. 3, pp. 259–302, 1986.

- [87] C. Haas, H. Ermert, S. Holt, P. Grewe, A. Machraoui, and J. Barmeyer, "Segmentation of 3d intravascular ultrasonic images based on a random field model," *Ultrasound Med. Biol.*, vol. 26, no. 2, pp. 297–306, 2000.
- [88] G. Storvik, "A bayesian approach to dynamic contours through stochastic sampling and simulated annealing," *IEEE Trans. Pattern Anal. Machine Intell.*, vol. 16, no. 10, pp. 976–986, 1994.
- [89] C. Chesnaud, P. Refregier, and V. Boulet, "Statistical region snake-based segmentation adapted to different physical noise models," *IEEE Trans. Pattern Anal. Machine Intell.*, vol. 21, no. 11, pp. 1145–1157, 1999.
- [90] M. Mignotte, J. Meunier, and J. Tardif, "Endocardial boundary estimation and tracking in echocardiographic images using deformable templates and markov random fields," *Pattern Analysis and Application*, vol. 4, no. 4, pp. 256–271, 2001.
- [91] E. Brusseau, C. L. de Korte, F. Mastik, J. Schaar, and A. F. W. van der Steen, "Fully automatic luminal contour segmentation in intracoronary ultrasound imaging - a statistical approach," *IEEE Trans. Med. Imag.*, vol. 23, no. 5, pp. 554–566, 2004.
- [92] A. Dempster, N. Laird, and D. Rubin, "Maximum likelihood from incomplete data via the em algorithm," *J. Roy. Stat. Soc. Ser. B*, vol. 39, no. 1, pp. 1–38, 1977.
- [93] C. F. J. Wu, "On the convergence properties of the em algorithm," *The Annals of Statistics*, vol. 11, no. 1, pp. 95–103, 1983.

-
- [94] S. Osher and J. A. Sethian, "Fronts propagating with curvature-dependent speed: algorithms based on Hamilton-Jacobi formulations," *J. Computational Physics*, vol. 79, pp. 12–49, 1988.
 - [95] C. Xu, D. L. Pham, and J. L. Prince, "Image segmentation using deformable models," in *Handbook of Medical Imaging: Volume 2. Medical Image Processing and Analysis* (M. Sonka and J. M. Fitzpatrick, eds.), ch. 3, pp. 129–174, SPIE Press, 2000.
 - [96] N. Paragios and R. Deriche, "Geodesic active contours and level sets for the detection and tracking of moving objects," *IEEE Trans. Pattern Anal. Machine Intell.*, vol. 22, no. 3, pp. 266–280, 2000.
 - [97] V. Caselles, R. Kimmel, and G. Sapiro, "Geodesic active contours," *International journal of computer vision*, vol. 22, no. 1, pp. 61–79, 1997.
 - [98] S. Kichenassamy, A. Kummar, P. Olver, A. Tannenbaum, and A. Yezzi, "Gradient flows and geometric active contours," in *Pro. IEEE Int'l Conf. Computer Vision*, pp. 810–815, 1995.
 - [99] D. Adalsteinsson and J. A. Sethian, "A fast level set method for propagating interfaces," *J. Computational Physics*, vol. 118, no. 2, pp. 269–277, 1995.
 - [100] J. Sethian, *Level Set Methods*. Cambridge Univ. Press, 1996.
 - [101] D. A. Jackson, K. M. Somers, and H. H. Harvey, "Similarity coefficients: measures for co-occurrence and association or simply measures of occurrence?," *American Naturalist*, vol. 133, no. 3, pp. 436–453, 1989.

- [102] R. M. Haralick, K. Shanmugan, and I. Dinstein, "Textural features for image classification," *IEEE Trans. System Management and Cybernetics*, no. 6, pp. 610–621, 1973.
- [103] C. Kotropoulos, X. Magnisalis, I. Pitas, and M. G. Strintzis, "Non-linear ultrasonic image processing based on signal-adaptive filters and self-organizing neural networks," *IEEE Trans. Image Processing*, vol. 3, no. 1, pp. 65–77, 1994.
- [104] L. D. Cohen, "On active contour models and balloons," *Computer Vision, Graphics, and Image Processing: Image Understanding*, vol. 53, no. 2, pp. 211–218, 1991.
- [105] T. McInerney and D. Terzopoulos, "A dynamic finite element surface model for segmentation and tracking in multidimensional medical images with application to cardiac 4D image analysis," *Computerized Medical Imaging and Graphics*, vol. 19, no. 1, pp. 69–83, 1995.
- [106] R. Malladi, J. A. Sethian, and B. C. Vemuri, "Shape modeling with front propagation: a level set approach," *IEEE Trans. Pattern Anal. Machine Intell.*, vol. 17, no. 2, pp. 158–175, 1995.
- [107] T. McInerney and D. Terzopoulos, "Topologically adaptive snakes," in *Pro. IEEE Int'l Conf. Computer Vision*, pp. 840–845, 1995.
- [108] J. Bredno, T. M. Lehmann, and K. Spitzer, "A general discrete contour model in two, three, and four dimensions for topology-adaptive mul-

-
- tichannel segmentation,” *IEEE Trans. Pattern Anal. Machine Intell.*, vol. 25, no. 5, pp. 550–563, 2003.
- [109] A. Dumitras and A. N. Venetsanopoulos, “Angular map-driven snakes with application to object shape description in color images,” *IEEE Trans. Image Processing*, vol. 10, no. 12, pp. 1851–1859, 2001.
- [110] L. D. Cohen and I. Cohen, “Finite-element methods for active contour models and balloons for 2-D and 3-D images,” *IEEE Trans. Pattern Anal. Machine Intell.*, vol. 15, no. 11, pp. 1131–1147, 1993.
- [111] D. Cremers, F. Tischhäuser, J. Weickert, and C. Schnörr, “Diffusion snakes: introducing statistical shape knowledge into the Mumford-Shah functional,” *International journal of computer vision*, vol. 50, no. 3, pp. 295–313, 2002.
- [112] S. R. Gunn and M. S. Nixon, “A robust snake implementation; a dual active contour,” *IEEE Trans. Pattern Anal. Machine Intell.*, vol. 19, no. 1, pp. 63–68, 1997.
- [113] C. Xu and J. L. Prince, “Snakes, shapes, and gradient vector flow,” *IEEE Trans. Image Processing*, vol. 7, no. 3, pp. 359–369, 1998.
- [114] C. Xu and J. L. Prince, “Generalized gradient vector flow external forces for active contours,” *Signal Processing*, vol. 71, pp. 131–139, 1998.
- [115] M. Wei, Y. Zhou, and M. Wan, “A fast snake model based on non-linear diffusion for medical image segmentation,” *Computerized Medical Imaging and Graphics*, vol. 28, no. 3, pp. 109–117, 2004.

- [116] N. Paragios, O. Mellina-Gottardo, and V. Ramesh, “Gradient vector flow fast geometric active contours,” *IEEE Trans. Pattern Anal. Machine Intell.*, vol. 26, no. 3, pp. 402–407, 2004.
- [117] M. Jacob, T. Blu, and M. Unser, “Efficient energies and algorithms for parametric snakes,” *IEEE Trans. Image Processing*, vol. 13, no. 9, pp. 1231–1244, 2004.
- [118] C. Xu and J. L. Prince, “Gradient vector flow: A new external force for snakes,” *IEEE Proc. Conf. on Comput. Vis. and Patt. Recog.*, pp. 66–71, 1997.