



**UNIVERSITI PUTRA MALAYSIA**

**TUMOR EXTRACTION FOR BRAIN MAGNETIC RESONANCE  
IMAGING USING MODIFIED GAUSSIAN DISTRIBUTION**

**QUSSAY ABBAS SALIH AL-BADRI.**

**Fk 2006 19**



**TUMOR EXTRACTION FOR BRAIN MAGNETIC RESONANCE IMAGING  
USING MODIFIED GAUSSIAN DISTRIBUTION**

**By**

**QUSSAY ABBAS SALIH AL-BADRI**

**Thesis Submitted to the School of Graduate Studies, Universiti Putra Malaysia, in  
Fulfilment of the Requirement for the Degree of Doctor of Philosophy**

**January 2006**



## **DEDICATION**

**In the name of God, Most Gracious, Most Merciful**

### **Dedication to**

*This thesis is dedicated to my parents, and my brothers who have always been with me all the time, for all the sacrifices they made to help me reach this point.*

**My Parents,**

**Professor Dr. Abbas Salih Al-Badri**

**Professor Dr. Layla Abd Al-Wahab**

**My Brothers,**

**Oday, Ghaith, Meis, and the rest of my family**



Abstract of thesis presented to the Senate of Universiti Putra Malaysia in fulfilment  
of the requirements for the degree of Doctor of Philosophy

**TUMOR EXTRACTION FOR BRAIN MAGNETIC RESONANCE  
IMAGING USING MODIFIED GAUSSIAN DISTRIBUTION**

By

**QUSSAY ABBAS SALIH AL-BADRI**

**January 2006**

**Chairman: Associate Professor Abdul Rahman Ramli, PhD**

**Faculty : Engineering**

Magnetic Resonance Imaging (MRI) is extensively used in the study of brain. Segmentation of MR brain images is necessary for a number of clinical investigations of various complexity, change detection, cortical labeling, and visualization in surgical planning. The volume of enhancing lesions, following the administration of paramagnetic contrast agent is an important indicator of pathology in multiple sclerosis (MS). Manual estimation of enhancing lesion volumes introduces significant errors, and operator bias, besides being time consuming and subjective. Therefore, there is a need for automatic identification and estimation of volumes of the present MS lesions specially by dealing with a large number of images that are typically acquired in multi-center clinical trials.

In the developed techniques, 150 T1- and T2-weighted spin echo images were taken from the routine scans of Kuala Lumpur General Hospital.



Multiple sclerosis lesions visualized by morphological MRI are classified through a feature map technique on T1 weighted MRI tissue. Gray level morphology methods are used to make tissue types in the images more homogenous and minimize difficulties with connections to outside tissue. A method for fuzzy connectedness and combinations of the different segmentation techniques were experimented. A gain-based correction method; probability density function model are used to cluster white and gray matters, cerebrospinal fluid, and meninges. Results of segmentation have been validated by a group of neuro-radiologists.

3D visualization has been implemented for the segmented regions as well as brain lesion. The visualization of the segmented structures uses a combination of volume rendering and surface rendering.

The mutual information algorithms used in this work has been developed and experimented in the system and has proven to yield more accurate and stable results than other algorithms.

Currently testing the validation of the proposed segmentation in a validation study that compares resulting MS lesion as well as gray and white matter tissue structures with Neural Network expert segmentation system. The proposed method versus Neural Network rater validation showed an average validation score of overlap ratio of >85% for gray and white matters tissue segmentation and for MS lesion the rater validation showed an average overlap ratio of > 87%.



Abstrak tesis yang dikemukakan Senat Universiti Putra Malaysia sebagai  
memenuhi keperluan untuk ijazah Doktor of Falsafah

**PENYARIAN TUMUR UNTUK RESONANS MAGNETIK PENGIMEJAN  
OTAK PENGUBAHSUAIAN DENGAN TABURAN GAUSSIAN**

Oleh

**QUSSAY ABBAS SALIH AL-BADRI**

**Januari 2006**

**Pengerusi: Profesor Madya Abdul Rahman Ramli, PhD**

**Fakulti : Kejuruteraan**

Kaedah Pengimejan Resonans Magnetik atau (MRI) digunakan secara meluas di dalam bidang kajian otak. Segmentasi imej otak MR diperlukan untuk siasatan klinikal bagi pelbagai kerumitan, dan pengesanan pertukaran, pelabelan kortikal, dan visualisasi perancangan pembedahan. Jumlah pertambahan *lesion*, berikutan pentadbiran ejen kontras paramagnetic merupakan petunjuk penting bagi patologi berbilang sklerosis (MS). Jumlah *lesion* yang bertambah yang dianggarkan secara manual memperlihatkan ralat yang ketara, kecenderungan operator, mengambil masa serta subjektif. Oleh itu, identifikasi secara automatik dan anggaran jumlah pertambahan *lesion* dalam MS adalah perlu terutamanya apabila menguruskan sejumlah besar imej yang lazimnya diambil dalam percubaan klinikal di pelbagai tempat.

Dalam teknik yang dibangunkan ini, lebih daripada 150 imej *T1-and-T2-weighted spin echo* diambil dari imbas rutin di Hospital Besar Kuala Lumpur.

Penambahan bukan-*lesion* menerusi pemetaan kebarangkalian fungsi ketumpatan yang digambarkan oleh morfologikal MRI, diklasifikasikan menerusi teknik pemetaan sifat, dan ke atas tisu berpemberat *T1* MRI. Kaedah morfologi tahap kelabu digunakan supaya jenis tisu lebih seragam, selain mengurangkan kesulitan dengan tisu luar. Kombinasi kaedah penambahan tersebut dengan teknik segmentasi berbeza dieksperimentasi. Kaedah perolehan berdasarkan pembetulan dipilih; model fungsi kebarangkalian ketumpatan digunakan untuk mengelompok bahan-bahan putih dan kelabu, cecair *cerebrospinal* dan *meninges*. Keputusan segmentasi disahkan oleh ahli neuro-radiologi.

Visualisasi 3D dilaksanakan untuk segmentasi bahagian dan *lesion* otak. visualisasi struktur segmen tersebut menggunakan kombinasi terjemahan jumlah dan terjemahan permukaan.

Algoritma informasi bersama yang digunakan dalam kerja ini telah dibangunkan dan dieksperimen di dalam sistem ini dan terbukti kesahihan dan ketepatannya berbanding dengan algoritma yang lain.

Kesahihan ketepatan segmentasi yang dicadangkan dalam perbandingan *MS lesion* terutamanya dalam tahap kelabu dan putih tisu struktur menggunakan rangkaian neural sistem segmentasi. Kaedah yang dicadangkan dibandingkan antara rangkaian neural menunjukkan purata kebolehpercayaan dalam nisbah  $> 85\%$  untuk tahap kelabu dan putih tisu struktur serta *MS lesion* menunjukkan purata nisbah  $> 87\%$ .

## ACKNOWLEDGEMENTS

First of all, I would like to express my utmost thanks and gratitude to Almighty Allah S.W.T for giving me the ability to finish this thesis successfully.

The author gratefully wish to express his profound appreciation and gratitude to his supervisor, Associate Professor Dr. Abdul Rahman Ramli, for his supervision, guidance, supporting, and constructive suggestion and comments throughout the duration of the project until it turns to real success.

The author also indebted to the members of his supervisory committee, Associate Professor Dr. Rozi Mahmud and Dr. Rahmita Wirza, for their affectionate guidance, prompt decision and valuable assistance during this period.

Appreciation also to the assistance rendered by the respective lecturers, staffs, technicians of the faculty of engineering for providing the facilities required for undertaking this project.

The author would like to thank his family for the encouragement and support without which is impossible for the success of this project, specially my lovely wife Suzan A. Tahir which she stand supporting me all the way until the end of my study and my friends, for offering helps and supports all the time.



## TABLE OF CONTENTS

	<b>Page</b>
<b>DEDICATION</b>	ii
<b>ABSTRACT</b>	iii
<b>ABSTRAK</b>	v
<b>ACKNOWLEDGEMENTS</b>	vii
<b>APPROVAL</b>	viii
<b>DECLARATION</b>	x
<b>LIST OF TABLES</b>	xiii
<b>LIST OF FIGURES</b>	xiv
<b>LIST OF ABBREVIATIONS</b>	xix
 <b>CHAPTER</b>	
<b>1 INTRODUCTION</b>	<b>1</b>
1.1 The Brain Segmentation Problem	2
1.2 Problem Statement	5
1.3 Motivation	7
1.4 Scope of the Thesis	8
1.5 Objective of Thesis	9
1.6 Thesis Organization	10
 <b>2 LITERATURE REVIEW</b>	 <b>12</b>
2.1 MRI Segmentation Challenge	13
2.2 Image Formation in MRI	15
2.3 MRI Enhancement of Collected Data	16
2.3.1 Partial Volume Effect	21
2.3.2 Radio Frequency and Magnetic Field Inhomogeneities	22
2.3.3 Imaging Sequence Effects	23
2.3.4 Constructing a Model for the Brain	24
2.3.5 MR Imaging of Brain Tumors	25
2.4 Manual Labeling of MRI	28
2.5 MRI Segmentation Background	29
2.6 Region MRI Segmentation Definitions	30
2.7 Multi-Spectral Segmentation	31
2.8 Snakes	33
2.9 Balloons	34
2.10 Iterative Optimization	34
2.11 Hierarchical Clustering	34
2.12 Nonparametric Clustering	35
2.13 The Sum-of-Squared-Error Criterion	36
2.14 The Scatter Matrices	36
2.15 EM (Expectation-Maximization) Segmentation	37
2.16 Mathematic Morphology	40
2.17 Artificial Neural Networks	42



2.17.1	Match-Based Learning, Error-Based Learning, and Stable Fast Learning	44
2.17.2	Model of Fuzzy C-mean Method (FCM)	46
2.17.3	Modified FCM Algorithm (M-FCM)	46
2.17.4	Neural Classification of Multiple Sclerosis Lesions	47
2.18	Validation of MRI Segmentation	49
2.19	Visualization Techniques	53
2.19.1	Volume Visualization	53
2.19.2	Viewing Algorithms	55
2.19.3	Surface Rendering	55
2.19.4	Volume Rendering	58
2.20	Conclusion	59
<b>3</b>	<b>METHODOLOGY</b>	<b>61</b>
3.1	Description of Input Data	63
3.2	Segmenting the Brain Tissue	64
3.2.1	Removal of Thin Connectors Using Morphological Operations	65
3.2.2	Gain Correction	69
3.3	Fuzzy Connected Techniques	80
3.4	3D Object Based Visualization Techniques	96
3.4.1	Surface Rendering	100
3.4.1.1	Ray Casting	101
3.4.2	Volume Rendering	106
3.5	Implementation	108
3.6	Conclusion	113
<b>4</b>	<b>RESULTS AND DISCUSSION</b>	<b>116</b>
4.1	Removal of Thin Connector Using Morphological Operation	118
4.2	Gain Correction with Morphological Filter Delineation	125
4.3	Fuzzy Connected Techniques for Tumor and Tissue Extraction	135
4.4	Intensity Evaluation of ROI of T1 and T2 Weighted MRI	137
4.5	Intensity Evaluation Difficulties of T1 Weighted MRI	145
4.6	Validation of Lesion Identification	152
4.7	Visualization Brain Views	161
4.8	Discussion	164
<b>5</b>	<b>CONCLUSION</b>	<b>171</b>
5.1	Suggestion for Future Work	174
	<b>REFERENCES</b>	<b>177</b>
	<b>APPENDICES</b>	<b>196</b>
	<b>BIODATA OF THE AUTHOR</b>	<b>224</b>
	<b>LIST OF PUBLICATIONS FROM THIS THESIS</b>	<b>226</b>



## LIST OF TABLES

<b>Table</b>		<b>Page</b>
2.1	Factors influencing the contrast of a MRI	19
2.2	Signal intensity of different components on the gray scale.	20
3.1	Mean Opinion Score (MOS) method used for subjective evaluation.	113
4.1	T1 weighted MRI, intensity values versus number of sliced.	145
4.2	T2 weighted MRI, intensity values versus number of slice	145
4.3	Results of the average score for all readers for T1 MR Gray matter images.	150
4.4	Results of the average score for all readers for T1 MR white matter images.	151
4.5	Results of the average score for all the radiologist readers.	156
4.6	Results of the average score for all readers for T1 MS lesion tissue	159



## LIST OF FIGURES

Figure		Page
2.1	Samples of MRI used in the study and their histograms, (a) T1- weighted image, (b) histogram of T1 weighted image intensity distributions, (c) T2-weighted image, (d) histogram of T1 weighted image intensity distributions.	18
2.2	Distribution of different components of brain on T1 and T2 weighted scale from (left to right)	21
2.3	An annotated gradient echo MRI axial slice (air, CSF and cranium are dark in this images)	24
2.4	(Left) T1-weighted axial view of brain with metastatic disease appears as small, white nodules. (Right) Coronal T1-weighted view of same brain.	26
2.5	T1 weighted images before and after contrast agent injection and a T2 weighted image showing a large glioblastoma that has developed in the left occipital lobe.	27
2.6	T2 weighted MRI show early stage MS (Left) axial view, (Right) Coronal view	28
2.7	Entropy calculation	31
2.8	Valley seeking algorithms	35
2.9	Intensity distributions for the head and brain in MRI	37
2.10	Illustrate from top to bottom a binarized MR coronal cross section, erosion of the MRI with a circular structuring element of radius 3, dilation of the largest connected component in the eroded image with a circular structuring element of radius 4.	42
3.1	Sample of axial slice T1 weighted brain MRI illustrate the intensity inhomogeneity difficulties.	62
3.2	Proposed image segmentation and 3D reconstruction techniques	63
3.3	Sample of three sagittal, axial and coronal slice (from left to right) slice positions for MR brain images	64
3.4	Morphological operation using erosion and dilation on grayscale brain image for extracting the central largest component (brain).	67
3.5	Translation operations on Euclidean (left) and digital (right) setting	69

3.6	Erosion on Euclidean (left) and digital (right) setting	71
3.7	Dilation on Euclidean (left) and digital (right) setting	72
3.8	Grayscale Dilation based on Umbra transform and Surface in digital setting Theoretically, given two signals $f$ and $g$ , dilation of $f$ by $g$ can be computed as $S[U[f] \oplus U[g]]$ where $\oplus$ is the binary dilation operator.	74
3.9	Grayscale opening operation shows how it can eliminate the peak of the signal.	76
3.10	Grayscale closing shows how it can fill the hole of the signal.	77
3.11	Novel grayscale morphological operation, $[\text{original} + (\text{Opening}) - (\text{Closing})]$	79
3.12	Voxel intensity for pure tissue classes is represented as an $M$ -element column vector, and the fraction of pure tissue class $k$ as the possible tissue type of a linear intensity distribution.	84
3.13	Pure and non-pure tissue based on pixel intensity distribution and probability density function.	87
3.14	Scattered pure and no-pure tissue	87
3.15	Topological coupling between neighboring clusters.	88
3.16	Two Gaussian distribution and linear combination of the Gaussian classes	89
3.17	The generalized combined Gaussian distribution mixture classes (pure and non-pure).	90
3.18	Scatter voxel representation for pure and non-pure classes of multiple Gaussian models (a) before the multiple Gaussian distribution, (b) after applying multiple Gaussian.	91
3.19	Two possible partitions of 12 data points into two clusters	93
3.20	Figure 3.20: Fuzzy connected segmentation. Sections for MR imaging scene with T2 weighted (a). Sections created with fuzzy connected segmentation demonstrate the union of white matter and gray matter tissue (b), the cerebrospinal fluid (c), and the union of multiple sclerosis lesions (d).	99
3.21	Illustrates the principle of the ray casting method used in render surfaces.	102
3.22	Tri-linear interpolations between voxel centers	103

3.23	The implemented techniques steps by step from MRI data input to display 2D MR imaginary segmentation and 3D visualization.	111
4.1	Axial view of brain surface and tissues surface for (a) healthy (b) and (c) non-healthy patients that show a tumor suspected patient.	119
4.2	MRI T1 weighted brain image (a) Original axial view, (b) connected regions, (c) morphological operations added with feature extraction performed by using 3×3 blocks, (d) Converting the entropy values to the labeled values by creating binary mask.	120
4.3	MRI brain extraction of coronal cross section sample 1	121
4.4	MRI brain extraction of coronal cross section sample 2	122
4.5	MRI brain extraction of axial cross section sample	122
4.6	MRI T1 weighted brain image (e) extracting the maximum labeled area scalar, (f) Retrieves the morphological operation data.	123
4.7	Clustering variance of region size $N/5$ , for MRI T1 weighted brain image.	124
4.8	T1 weighted MRI axial slice, (a) original brain image (b) brain image segment	127
4.9	Morphological operations of the blocks of feature set	127
4.10	Figure 4.10 Histogram of the original image segment listed in (a), and enhanced image segment in (b).	128
4.11	Misclassified clustering output of MRI as (fat, muscle, nervs, and gray and white matters).	130
4.12	(a) Input test image, (b) output of clustering algorithm	130
4.13	Brain clustering algorithm involved in brain segmentation (a) original image, (b) histogram normalization on original image, (c) morphological operation filters (erosion and dilation) effects, (d) histogram normalization after erosion and dilation enhancement effects, (e) binary mask, (f) retrieves the final brain mask images.	131
4.14	Output of brain clustering algorithm	131
4.15	Grayscale morphological operations followed by contour image intensity: (a) original image, (b) grayscale morphological erosion and conditional delineation, (c) original image 3D surface, (d) 3D surface of grayscale erosion and conditional dilation.	133

4.16	Bias field correction using novel proposed PDF algorithm for T1-weighted MRI.	134
4.17	Combination of grayscale morphological operation, gain correction, and enhancement of eroding and delineation, (a) brain image axial slice, (b) gray matter tissue extraction, (c) white matter tissue extraction.	136
4.18	Original and segmented MRI (c) 5.5 years, slice 50	136
4.19	T1 weighted MRI, (a) Original image, (b) meneinges segment, (c) cerebrospinal segment, (d) white matter segment and (e) gray matter segment.	137
4.20	T2 weighted MRI, (a) Original image, (b) meneinges segment, (c) cerebrospinal segment, (d) white matter segment and (e) gray matter segment.	140
4.21	T1 weighted MRI intensity area values groups versus slice numbers	141
4.22	T2 weighted MRI intensity area values groups versus slice numbers	142
4.23	T1 and T2 weighted MRI intensity area values groups versus slice numbers comparison.	143
4.24	Histograms for Tumor and the Intra-Cranial Region. Solid black lines indicate thresholds in T1 and PD-weighted space.	146
4.25	Output of clustering algorithms of white and gray matters for T1 weighted MRI regions tissue (a) direct clustering method (b) original images (c) The proposed clustering method.	149
4.26	Subjective score comparison between proposed method and direct method, for gray matter T1 weighted MRI.	158
4.27	Subjective score comparison between proposed and direct method, for white matter T1 weighted MRI.	150
4.28	Figure 4.28 Comparison of segmentation results between Neural Network and the proposed method, when applied on two groups of T1 weighted MR (a) phantom and (b) real image corrupted with inhomogeneity and noise.	151
4.29	Comparison of MS lesion detection between the proposed method and Neural Network method.	153
4.30	Comparison of gray and white matters between the proposed method and Neural Network method segmentation.	154



- 4.31 Four separate runs contour clustering for T1 weighted MRI having MS, (a) original image, (b) morphological operation, (c) gain correction using probability density function, (d) enhanced with delineation. 155
- 4.32 Delineation of gain enhanced MS lesions on two contiguous slices. Same lesions superimposed on the T1-weighted images are shown the last two images in row respectively where lesion highlighted in white color. 158
- 4.33 3D visualization for (a) Full brain structure, (b) selected slices 3D view, (c) Z-axis, (d) brain tissue without skin as well as bone, and lastly (e) white matter tumor detection over second MRI slice. 160
- 4.34 3D MRI brain tumor reconstruction and detection GUI interface using the proposed clustering model. 162



## LIST OF ABBREVIATIONS

MRI	Magnetic Resonance Imaging
NMR	Nuclear Magnetic Resonance
CT	Computerized Tomography
PET	Positron Emission Tomography
FMRI	functional Magnetic Resonance Imaging
SPECT	Single Photon Emission Computed Tomography
RF	Radio Frequency
CSF	Cerebrospinal Fluid
MPT	Moment Preserving Thresholding
ML	Maximum Likelihood
KNN	Nearest Neighborhood ( $kNN$ )
EM	Expectation Maximization
MAP	Maximum-A-Posterior
SE	Spin Echo
TSE	Turbo Spin Echo)
FOV	Field of View
PDF	Probability Density Function
PCMR	Phase Contrast MR
PV	Partial Volume
MLE	Maximum Likelihood Estimation
ROI	Regions-of-Interests



UPMMC                      University Putra Malaysia Medical Center

MOS                        Mean Opinion Score



## CHAPTER I

### INTRODUCTION

Recently radiologists can review images of several cross sections of a brain and abdomen. Some times, they required to make 3D reconstruction in order to make a clinical diagnosis or to evaluate the results of a therapy on a patient. In recent years, the interdisciplinary field of medical image processing has produced several automatic and semi-automatic tools to assist medical practitioners and researchers. For instance, tools for 3D visualization of anatomy (i.e. reconstruction and rendering) used in surgical planning as well as educational purposes, are available in several hospitals and research laboratories.

The validations of automatically anatomical structures models are frequently non-rigid and exhibit substantial morphological variation from subject to subject. Hence the task of segmenting these structures from medical images is one of the difficulties to identify a region in an image with only approximate knowledge of its shape, size, gray level appearance, and spatial location. Different segmentation applications are available to add some knowledge in each of these categories, and the challenge is to combine them to overcome lack of information in one category is offset by the information in the others. In this thesis, methodology for segmentation of brain tissue of MRI and MS lesion will be studied. By applying a series of



combined techniques that exploit gray level, topological and spatial information in the brain images will be discussed.

The specific techniques used are probability of density function segmentation for an intensity based correction and classification of the data. Where it combined with a binary and grayscale morphology and connectivity for incorporation of relative topological information. Four steps have been implemented where the segmentation of the brain divided base on the brain structure intensity and statistical distribution of the tissues.

The goals of medical image processing include increased automation of the existing tools that have proven useful to the medical community yet still require assistance from experts.

### **1.1 The Brain Segmentation Problem**

Segmentation is an important step in most medical image analysis. In many classification processes, segmentation forms the first step. The applications of segmentation include diagnosis, evaluation and treatment of the disease. Since manual segmentation is tedious, time consuming and subjective, attempts have been made to automatically classify and quantify tissues, organs, and disease states from images obtained by various medical imaging modalities.

Segmentation of medical images is a challenging task due to the complexity of the images and the absence of models of anatomy that fully capture the possible

deformities in each structure. Due to the relative low signal to noise ratios and inherent artifacts generally present in medical images, their segmentation is particularly difficult. Because of these problems, even though many algorithms have been reported, most of them have inconsistent results and limited applications. Thus, only a few algorithms are being used in practice.

No other imaging modality has witnessed the explosive growth and development that Magnetic Resonance Imaging (MRI) has over the past 10 years. Once labeled NMR, for Nuclear Magnetic Resonance imaging, the nuclear term has been removed due to its negative connotations among the general public. Using a combination of the inherent magnetic resonance properties of tissue and application of radio frequency pulses, MRI obtains images by measuring various tissue characteristics. The result of frequency information is converted, using Fourier Transform techniques, to spatial intensity information of slices through the body. These slices can be integrated using advanced computer graphics techniques to produce 3D views of the imaged tissues.

MRI is extensively used in brain studies, that it is an advanced medical imaging technique providing rich information about the anatomy of human soft tissue.

Brain tissue is a particularly complex structure, and its segmentation is an important step for derivation of computerized anatomical atlases, as well as pre-and intra-operative guidance for therapeutic intervention.



MRI segmentation has been proposed for a number of clinical investigations of varying complexity. Measurements of tumor volume and its response to therapy have used image grayscale methods as applied to X-Ray Computerized Tomography (CT) or simple MRI datasets (Cline et al, 1987). However, the differentiation of tissues within tumors that have similar MRI characteristics such as edema, necrotic or scar tissue have proven to be important in the evaluation of response to therapy. Hence, multi-spectral methods have been proposed (Vannier et al, 1991; Clarke, et al, 1993). Recently, multi-modality approaches, such as Positron Emission Tomography (PET) and functional Magnetic Resonance Imaging (fMRI) studies using radiotracers (Tjuvajev et al, 1994), or contrast materials (Tjuvajev et al, 1994; Buchbinder et al, 1991) have been suggested to provide superior tumor tissue specification and to identify active tumor tissue. Hence, segmentation methods need to include these additional image data sets. In the same context, a similar progression of segmentation methods is evolving for the planning of surgical procedures primarily in neurological investigations (Hill et al, 1993; Zhang, 1990; Cline et al, 1987), surgery simulations (Hu et al, 1990; Kamada et al, 1993) or the actual implementation of surgery in the operating suite where both normal tissues and the localization of the lesion or mass needs to be accurately identified.

The methods proposed include grayscale image segmentation and multi-spectral segmentation for anatomical images with additional recent efforts directed toward the mapping of functional metrics fMRI to provide locations of important functional regions of the brain as required for optimal surgical planning.