



# Registration of mass-like objects in sequential mammograms using graph matching

by

Fei Ma, *M.Sc.*

School of Computer Science, Engineering and Mathematics,  
Faculty of Science and Engineering

October 10, 2008

A thesis presented to the  
Flinders University  
in total fulfillment of the requirements for the degree of  
Doctor of Philosophy

Adelaide, South Australia, 2009

© (Fei Ma, 2009)

# Contents

<b>Summary</b>	<b>x</b>
<b>Publications</b>	<b>xii</b>
<b>Certification</b>	<b>xiv</b>
<b>Acknowledgements</b>	<b>xv</b>
<b>1 Introduction</b>	<b>1</b>
1.1 Incidence of Breast Cancer . . . . .	1
1.2 Breast Cancer Screening . . . . .	2
1.3 Sensitivity and Specificity of Mammography . . . . .	4
1.4 Computer-Aided Detection Program . . . . .	4
1.5 Motivation and Approach . . . . .	6
1.6 Overview of the Thesis . . . . .	9
<b>2 Technical Background and Literature Review</b>	<b>10</b>
2.1 Temporal Mammogram Registration . . . . .	10
2.2 Graph Matching . . . . .	14
2.3 Pyramid Based Image Segmentation . . . . .	17
<b>3 Mammogram Segmentation using Adaptive Pyramid Algorithm</b>	<b>22</b>
3.1 Basic Notation and Terminology . . . . .	23
3.2 Segmentation by AP . . . . .	24
3.3 Merging Segmented Components . . . . .	28
3.4 Robustness of AP . . . . .	30
3.4.1 Methods . . . . .	31
3.4.2 Results . . . . .	33
3.4.3 Discussion and Conclusion . . . . .	34

<b>4</b>	<b>Automatic Pectoral Muscle Extraction on MLO View Mammograms</b>	<b>39</b>
4.1	Identification of Pectoral Muscle Components . . . . .	40
4.2	Adaptive Deformable Contour Model . . . . .	41
4.3	Database . . . . .	44
4.4	Results . . . . .	44
4.4.1	Area Normalized Error . . . . .	45
4.4.2	Row Normalized Error . . . . .	49
4.5	Discussion and Conclusion . . . . .	51
<b>5</b>	<b>Automatic Breast Boundary Segmentation</b>	<b>55</b>
5.1	Breast Boundary Extraction Based on AP Segmentation . . . . .	56
5.2	Breast Boundary Extraction Based on ROW Filters and MRF Smoothing . . . . .	58
5.2.1	Pre-filtering with ROW Filters . . . . .	58
5.2.2	Breast Boundary Modelling and Smoothing via 1-D MRF and ICM . . . . .	62
5.3	Performance Analysis . . . . .	63
5.4	Discussion and Conclusion . . . . .	67
<b>6</b>	<b>Mass Features</b>	<b>69</b>
6.1	Shape Based Features . . . . .	70
6.2	Texture Based Features . . . . .	72
6.3	Location Based Feature . . . . .	72
6.4	Feature Filter . . . . .	74
6.5	Mass-like Score . . . . .	74
<b>7</b>	<b>Graph Matching</b>	<b>77</b>
7.1	Fuzzy Spatial Relation Representation . . . . .	77
7.2	Graph Matching . . . . .	79
7.2.1	Complete Graph Representation . . . . .	80
7.2.2	Match Cost Function . . . . .	80
7.2.3	Identification of the Best Solution . . . . .	82
7.2.4	Graph Matching Algorithm . . . . .	83
7.2.5	Final Result Filtering . . . . .	85

<b>8 Experiments and Results</b>	<b>87</b>
8.1 Experiments with Constructed Mammogram Pairs . . . . .	87
8.1.1 Database and Methods . . . . .	88
8.1.2 Relabelled Images . . . . .	90
8.1.3 Relabelled and Shifted Images . . . . .	91
8.1.4 Relabelled and Warped Images . . . . .	94
8.2 Experiments with Real Temporal Mammograms . . . . .	97
8.2.1 Dataset . . . . .	97
8.2.2 Feature Filter and Mass-like Score . . . . .	98
8.2.3 Evaluation Based on Visual Perception . . . . .	100
8.2.4 Evaluation Based on False Positive Detection Reduction .	102
8.3 Discussion . . . . .	104
<b>9 Final Remarks and Conclusion</b>	<b>108</b>
9.1 Final Remarks . . . . .	108
9.2 Conclusion . . . . .	110
<b>Bibliography</b>	<b>112</b>

# List of Figures

1.1	Example of temporal mammograms . . . . .	3
2.1	Regular and irregular pyramids . . . . .	19
3.1	Examples of components after initial segmentation by AP . . . . .	26
3.2	Examples of mass segmentation: mini-MIAS images . . . . .	27
3.3	Examples of mass segmentation: local images . . . . .	28
3.4	Examples of merged components . . . . .	29
3.5	Examples of surrounded components . . . . .	30
3.6	Control points for image warping . . . . .	32
3.7	Matched and unmatched component pairs . . . . .	33
3.8	Examples of robust and non-robust segmentation . . . . .	36
3.9	Examples of segmentation of salient components . . . . .	37
3.10	Examples of segmentation of non-salient components . . . . .	38
4.1	Example of asymmetric neighborhood used in adaptive deformable contour model . . . . .	43
4.2	False positive and false negative . . . . .	45
4.3	Two images with pectoral muscle absence . . . . .	47
4.4	False source of error . . . . .	48
4.5	Area normalized error affected by different breast positionings . . . . .	49
4.6	Histogram of $RNE$ of AP and MST segmentation . . . . .	50
4.7	Pectoral muscle boundary extraction for mdb033 . . . . .	52
4.8	Pectoral muscle boundary extraction for mdb110 . . . . .	52
4.9	Example of pectoral muscle boundary extraction with bad initial boundary . . . . .	53
4.10	Example of poor pectoral muscle boundary extraction . . . . .	54

5.1	Coordinate system defined for the mammogram . . . . .	57
5.2	Real rational orthogonal wavelets with $q = 1, 2$ and $3$ . . . . .	60
5.3	Example of ROW filtering and the Canny edge detection . . . . .	60
5.4	Examples of ROW filtered images . . . . .	61
5.5	Examples of poor ROW filtered images . . . . .	61
5.6	Two categories of the profile of the breast boundary . . . . .	63
5.7	Division of the breast boundary into two single valued parts . . . . .	63
5.8	Breast boundary extraction for mdb003 . . . . .	65
5.9	Breast boundary extraction for mdb068 . . . . .	65
5.10	Examples of bad nipple preservation . . . . .	66
5.11	Example of contour smoothing around nipple area (mdb003) . . . . .	66
5.12	Dropped image case: mdb097 . . . . .	67
5.13	Dropped image case: mdb106 . . . . .	68
6.1	Axis of the ellipse having the same normalized second central moments as the component . . . . .	71
6.2	Radial distance of component . . . . .	71
6.3	The coordinate system for MLO view mammogram . . . . .	73
6.4	ROC curve for 3 different combinations of features . . . . .	75
6.5	Distribution of the combination of the features used in this study . . . . .	76
6.6	Distribution of the best combination of the features . . . . .	76
7.1	Ambiguity spatial representation by using centroid of objects . . . . .	78
7.2	Fuzzy spatial relation representation . . . . .	78
7.3	Problem with graph constructed based on neighborhood relation of objects . . . . .	80
7.4	Example of global offset of mass-like objects . . . . .	82
8.1	Outline of three experiments . . . . .	90
8.2	Example of matching results for a relabelled image . . . . .	91
8.3	Example of matching results for a relabelled and shifted image . . . . .	93
8.4	Example of matching results of mdb017 and its relabelled and warped image . . . . .	95
8.5	Example of matching results for a relabelled and warped image . . . . .	96

8.6	Examples of malignant mass components . . . . .	99
8.7	Examples of manual matching . . . . .	100
8.8	Example of a good match . . . . .	101
8.9	Example of an average match . . . . .	101
8.10	Example of a poor match . . . . .	102
8.11	Example of an unknown match . . . . .	102
8.12	Example of matching results . . . . .	103
8.13	ROC curves with and without graph matching . . . . .	103
8.14	Example of differently positioned breasts . . . . .	105
8.15	Another example of differently positioned breasts . . . . .	105
8.16	Example of a falsely rejected true mass in the training set . . . . .	106
8.17	False rejection of a true mass in the training set . . . . .	107
8.18	False rejection of a true mass in the testing set . . . . .	107
9.1	Example of poor boundary resulting in false matches . . . . .	109

# List of Tables

3.1	Mean and STD of the proportion of possible components matched for AP and MST . . . . .	34
3.2	The proportion of pairs in each group with match scores less than 0.25. . . . .	34
3.3	Mean and STD of RMSD and Av. diff: measurements of SV . . . . .	35
4.1	FP and FN proportion and distribution according to the area method: pectoral muscle boundary extraction results of 4 methods . . . . .	47
5.1	FP and FN proportion and distribution: breast boundary extraction results of three methods . . . . .	64
6.1	List of component features . . . . .	73
8.1	Matching results for relabelled images . . . . .	92
8.2	Matching results for relabelled and shifted images . . . . .	92
8.3	Matching results for relabelled and warped images . . . . .	94
8.4	Composition of the real temporal datasets . . . . .	98



# List of Abbreviations

CAD	Computer-Aided Detection
MLO	Medio-Lateral Oblique
CC	Cranial-Caudal
ROI	Region of Interest
ROC	Receiver Operating Characteristic
$A_z$	Area under the ROC Curve
AP	Adaptive Pyramid
MI	Mutual Information
SV	Shift Variance
MST	Minimum Spanning Tree
CSI	Common Subgraph Isomorphism
RMSD	Root Mean Square Difference
Av. dif	Average Difference
STD	Standard Deviation
Mini-MIAS	Mammographic Image Analysis Society Database
ARBE	Average Right Boundary Error
FP	False Positive
FN	False Negative
RNE	Row Normalized Error
ROW	Real Orthogonal Wavelets
MRF	Markov Random Field
ICM	Iterated Conditional Modes
GT	Ground Truth
LDA	Linear Discriminant Analysis
cmr	Correct Match Rate
me	Match Efficiency

# Summary

Sequential mammograms contain important information, such as changes of the breast or developments of the masses, for diagnosis of disease. Comparison of sequential mammograms plays an important part for radiologists in identifying malignant masses. However, currently computer-aided detection (CAD) programs can not use such information efficiently. The difficulties lie in the registration of sequential mammograms.

Most of current methods register sequential mammograms based on control points and image transformations. For these methods to work, extraction and correspondence of the control points is essential. This thesis presents a new approach in registering mammograms. The proposed method registers mammograms by associating mass-like objects in sequential mammograms directly. The mass-like objects appear in the images of normal breasts as well as images of breast with cancer. When the mass-like objects in sequential mammograms are accurately associated, measurements of changes in mass-like objects over time become possible. This is an important way to distinguish mass-like objects associated with cancer from cysts or other benign objects.

The proposed method is based on graph matching. It uses the internal structure of the breast represented by the spatial relation between the mass-like objects to establish a correspondence between the sequential mammograms. In this method, the mammogram is firstly segmented into separate components using an adaptive pyramid (AP) segmentation algorithm. A series of filters, based on the features of components, is then applied to the components to remove the undesired ones. The remaining components, the mass-like objects, are represented by a complete graph. The spatial relations between the remaining mass-like objects are expressed by fuzzy spatial relation representation and are associated to the edges of the graph as weights. Association of the mass-like objects of two sequential mammograms is realized by finding a common subgraph of the corresponding two graphs using the backtrack algorithm.

The segmentation methods developed in the course of this work were tested on a separate problem in computer-aided detection of breast cancer, namely the automatic extraction of the pectoral muscle.

The graph matching method was tested independently of the segmentation method on artificially distorted mammograms and the full process, including the

segmentation and the graph matching, was evaluated on 95 temporal mammogram pairs. The present implementation indicates only a small improvement in cancer detection rates but also presents opportunities for a substantial development of the basic method in the future.

# Publications

1. Ma, F., Bajger, M. & Bottema, M. J. (2005), Extracting the pectoral muscle in screening mammograms using a graph pyramid, *in* B. C. Lovell & A. J. Maeder, eds, 'APRSWorkshop on Digital Image Computing', The University of Queensland, Griffith University, Brisbane, Australia.
2. Bajger, M., Ma, F. & Bottema, M. J. (2005), Minimum spanning trees and active contours for identification of the pectoral muscle in screening mammograms, *in* B. C. Lovell, A. J. Maeder, T. Caelli & S. Oursellin, eds, 'Digital Image Computing Techniques and Applications', IEEE Computer Society Conference Publishing Service, Cairns, Qld Australia.
3. Ma, F., Bajger, M., Slavotinek, J. P. & Bottema, M. J. (2006), Validation of graph theoretic segmentation of the pectoral muscle, *in* 'Digital Mammography, IWDM 2006, 8th International Workshop', Springer, Manchester, UK, pp. 642-649.
4. Ma, F., Bajger, M., Slavotinek, J. P. & Bottema, M. J. (2007), 'Two graph theory based methods for identifying the pectoral muscle in mammograms', *Pattern Recognition* **40**, 2592-2602.
5. Ma, F., Bajger, M. & Bottema, M. J. (Dec. 2007), Robustness of two methods for segmenting salient features in screening mammograms, *in* '9th Biennial Conference of the Australian Pattern Recognition Society on Digital Image Computing Techniques and Applications (DICTA 2007)', IEEE., Glenelg, South Australia, pp. 112-117.
6. Yu, L., Ma, F., Jayasuriya, A., Sigelle, M. & Perreau, S. (2007), A new contour detection approach in mammogram using rational wavelet filtering and MRF smoothing, *in* '9th Biennial Conference of the Australian Pattern Recognition Society on Digital Image Computing Techniques and Applications (DICTA 2007)', IEEE., Glenelg, South Australia, pp. 106-111.
7. Susukida, H., Ma, F. & Bajger, M. (2008), Automatic tuning of a graph-based image segmentation method for digital mammography applications, *in* 'Proc. IEEE International Symposium on Biomedical Imaging (ISBI08)', Paris. pp. 89-92.

8. Ma, F., Bajger, M. & Bottema, M. J. (2008a), A graph matching based automatic regional registration method for sequential mammogram analysis, *in* 'Medical Imaging 2008: Computer-Aided Diagnosis', Vol. 6915, SPIE, San Diego, CA, USA, p. 69151Z.
9. Ma, F., Bajger, M. & Bottema, M. J. (2008b), Temporal analysis of mammograms based on graph matching, *in* 'Digital Mammography / IWDM', Springer, Tucson, AZ, USA, pp. 158-165.

# Certification

I certify that this thesis does not incorporate without acknowledgement any material previously submitted for a degree or diploma in any university; and that to the best of my knowledge and belief it does not contain any material previously published or written by another person except where due reference is made in the text.

As requested under Clause 14 of Appendix D of the *Flinders University Research Higher Degree Student Information Manual* I hereby agree to waive the conditions referred to in Clause 13(b) and (c), and thus

- Flinders University may lend this thesis to other institutions or individuals for the purpose of scholarly research;
- Flinders University may reproduce this thesis by photocopying or by other means, in total or in part, at the request of other institutions or individuals for the purpose of scholarly research.

Signed

Dated

Fei Ma

# Acknowledgements

First and foremost, I am deeply indebted to my supervisor, Associate Professor Murk Bottema for his guidance, support and encouragement all the way through my PhD studies. His extensive knowledge in mammography and excellence in mathematics have been of great help in solving many problems I confronted. The work in this thesis would not have been carried out without his profound insight and advice at every stage of my thesis research. One simply could not wish for a better or friendlier supervisor.

I am sincerely grateful to my co-supervisor Dr. Mariusz Bajger for his invaluable advice, discussion and cooperation on many issues that this thesis involved. His carefulness is mostly impressive and he shared with me a quality workstation which much of work has been done on. I am also grateful for his constructive feedback and the efforts he made in proof reading this thesis.

I wish to thank Dr. John Slavotinek for his support on this project and Dr. Ray Booth for providing me opportunities of teaching assistant work and always correcting me my spoken English.

I am grateful to the secretaries and technical staffs of school of Computer Science, Engineering and Mathematics of Flinders for always being friendly and helpful.

I would like to thank Flinders Medical Centre Foundation (FMC) and Drake Food Markets for awarding me the "2004 Drake Food Markets Award For Breast Cancer Research". I also wish to thank National Breast Cancer Foundation for providing the funds for this study.

I wish to thank my entire extended family, my brother, my sister, and my uncles for always being supportive.

Last but not least, I wish to thank my grandparents, my parents, my parents in law and my wife Limin Yu for their unconditional caring and support. I would also like to thank my 10 months old daughter Annie for being quiet during the night while I can have quiet time to write my thesis. She seems quite a keyboard lover and was always trying to take over it whenever she was close to it. This thesis is dedicated to all of them.