RECENT ADVANCES IN
Breast Imaging, Mammography, and Computer-Aided Diagnosis of Breast Cancer
RECENT ADVANCES IN
Breast Imaging, Mammography,
and Computer-Aided Diagnosis
of Breast Cancer

Jasjit S. Suri
Rangaraj M. Rangayyan
Editors

SPIE PRESS
Bellingham, Washington USA
Dr. Jasjit S. Suri dedicates this book to his children Harman and Neha, his wife Malvika, and his dear friends and collaborators all around the world who have made this possible.

Dr. Rangaraj M. Rangayyan dedicates this book to his students, fellow researchers, and clinical collaborators.
Contents

List of Contributors / xvii
Preface / xxi
Acknowledgments / xxxi

Chapter 1. The Subgross Morphology of Normal and Pathologically Altered Breast Tissue / 1
Tibor Tot

1.1 Introduction / 2
1.2 Subgross Breast Anatomy / 3
1.3 The Normal Mammogram / 15
1.4 In Situ Development of Malignant Tumors / 20
1.5 Invasive Carcinomas / 30
1.6 Time as Morphologic Factor / 45
References / 47

Dee H. Wu, Ann G. Archer, L. Jill Hast, Brenda Elledge, Douglas Beall, Max Walter, Susan M. Edwards, Heather R. Webb, Barry J. Greer, and Erika Rubesova

2.1 Introduction / 52
2.2 Consequences of Composition, Architectural, and Functional Evaluation in Breast MR Imaging / 59
2.3 Breast Composition and Hormonal Influences (Fat, Ducts, Secretions, and Breast Implants) / 60
2.4 Region of Interest Definition of Tumors / 63
2.5 Technological Fundamentals of Breast MRI / 64
2.6 Summary / 102
Acknowledgments / 102
References / 103

Hilary Alto, Rangaraj M. Rangayyan, Raman B. Paranjape, J.E. Leo Desautels, and Heather Bryant
3.1 Introduction / 110
3.2 Databases of Mammograms / 111
3.3 The Indexed Atlas Concept / 112
3.4 Design of the University of Calgary Indexed Atlas of Mammograms / 114
3.5 Use of Mobile Software Agents with the Indexed Atlas / 119
3.6 Discussion / 120
    Acknowledgments / 122
    References / 122

Chapter 4. Genetic Algorithms in CAD Mammography / 129
Renato Campanini and Nico Lanconelli
4.1 Introduction / 130
4.2 CAD Critical Issues / 133
4.3 Genetic Algorithms: A Brief Overview / 136
4.4 GA for Parameters Optimization / 141
4.5 GA for Feature Selection / 151
    References / 156

Chapter 5. Mammographic Mass Detection by Robust Learning Algorithms / 159
Aize Cao, Qing Song, Xulei Yang, Zhimin Wang, and Yan Shui
5.1 Introduction / 160
5.2 Robust Information Clustering for Automatic Mass Detection / 161
5.3 Vicinal Support Vector Machine for Mass-Pattern Analysis / 178
    References / 192

Chapter 6. Analysis of Bilateral Asymmetry in Mammograms via Directional Filtering with Gabor Wavelets / 197
Ricardo J. Ferrari, Rangaraj M. Rangayyan, J.E. Leo Desautels, and Annie F. Frère
6.1 Introduction / 198
6.2 Bilateral Asymmetry in Mammograms / 200
6.3 Construction of Gabor Wavelets / 200
6.4 Directional Analysis / 205
6.5 Analysis of Asymmetry in Mammograms / 211
6.6 Results / 215
6.7 Discussion and Conclusions / 224
    Acknowledgments / 224
    References / 224
Chapter 7. Support Vector Machines in CAD Mammography / 229
Renato Campanini, Nico Lanconelli and Matteo Roffilli

7.1 Introduction / 230
7.2 Support Vector Machines: A Qualitative Approach / 231
7.3 SVMs for CAD / 237
7.4 Novel Featureless Approach / 244
7.5 SVMs: Mathematical Details / 251
References / 260

Chapter 8. A Weighted Gaussian Mixture Model with Markov Random Fields and Adaptive Expert Combination Strategy for Segmenting Masses in Mammograms / 263
Sameer Singh and Keir Bovis

8.1 Introduction / 264
8.2 Weighted Gaussian Mixture Models / 266
8.3 Combination of Experts / 269
8.4 Experimental Details / 274
8.5 Results / 277
8.6 Conclusions / 285
References / 286

Chapter 9. Detection of Microcalcifications in Mammograms / 291
Begoña Acha, Carmen Serrano, Rangaraj M. Rangayyan, and J. E. Leo Desautels

9.1 Detection of Microcalcifications: Background and Motivation / 292
9.2 State of the Art / 293
9.3 Detection of Microcalcifications Using the 2D Linear Prediction Error / 297
9.4 Results / 305
9.5 Conclusions / 307
References / 308

Chapter 10. Using Computational Intelligence for Computer-Aided Diagnosis of Screen-Film Mammograms / 315
Walker H. Land, Jr., Daniel W. McKee, Frances R. Anderson, Timothy Masters, Joseph Y. Lo, Mark Embrechts, and John Heine

10.1 Evolutionary Programming and Evolutionary Computation / 317
10.2 Evolutionary Programming/Adaptive Boosting Hybrid / 326
10.3 Another Evolutionary Programming Approach / 332
10.4 EP-Derived Support Vector Machines / 338
10.5 A Support Vector Machine (SVM) Generalized Regression Neural Network (GRNN) Oracle / 350
Chapter 11. New Approach for Breast Skin-Line Estimation in Mammograms / 377
Yajie Sun, Jasjit Suri, Rangaraj M. Rangayyan, and J.E. Leo Desautels

11.1 Introduction / 379
11.2 A Brief Overview of the Proposed System / 381
11.3 Initial Skin-Line Boundary Estimation / 383
11.4 Initial Confirmed Portion Extraction: A Greedy Approach / 385
11.5 Extraction of Stroma Edge / 388
11.6 Skin-line Estimation: A Dependency Approach / 392
11.7 Performance Evaluation System / 396
11.8 Results: Dependency Approach versus Deformable Model / 401
11.9 Discussion and Conclusions / 405
Acknowledgments / 406
References / 406

Chapter 12. Computerized Mass Detection for Digital Breast Tomosynthesis / 409
Ingrid Reiser and Robert Nishikawa

12.1 Introduction / 410
12.2 CADe Based on the Reconstructed Breast Volume / 411
12.3 CADe Based on the Sequence of Projection Images / 420
12.4 Summary / 425
Acknowledgments / 426
References / 426

Chapter 13. Breast-Imaging Registration: A Review / 429
Yujun Guo, Jasjit Suri, and Radhika Sivaramakrishna

13.1 Introduction / 430
13.2 Registration Background / 434
13.3 Intramodality Breast-Image Registration / 440
13.4 Intermodality Breast-Image Registration / 458
13.5 Biomechanical Breast Model / 463
13.6 Validation of Breast-Registration Methods / 467
13.7 Discussion and Conclusions / 471
References / 474
Chapter 14. A Mammographic Registration Framework Based on Anatomical Linear Structures / 487
Robert Martí, Caroline M.E. Rubin, Erika R.E. Denton, and Reyer Zwiggelaar

14.1 Introduction / 488
14.2 Correspondence of Mammographic Images / 489
14.3 Identifying Salient Linear Structures / 501
14.4 Registration Using Linear Structures / 508
14.5 Detection of Abnormalities / 513
14.6 Tracking of Linear Structures / 515
14.7 Automatic MR Correspondence Based on Linear Structures / 518
14.8 Conclusions / 524
References / 525

Chapter 15. AMDI – Indexed Atlas of Digital Mammograms that Integrates Case Studies, E-Learning, and Research Systems via the Web / 529
Denise Guliato, Ernani V. de Melo, Ricardo S. Bôaventura, and Rangaraj M. Rangayyan

15.1 Breast Cancer and Mammography / 530
15.2 Indexed Atlases and Telemedicine / 530
15.3 Overview of AMDI / 531
15.4 Conclusion / 552
Acknowledgments / 553
References / 553

Daisuke Fukuoka, Takeshi Hara, and Hiroshi Fujita

16.1 Introduction / 558
16.2 Material and Methods / 558
16.3 Results / 564
16.4 Discussions / 565
16.5 Conclusions / 566
References / 566

Chapter 17. Computer-Aided Diagnosis for 2D/3D Breast Ultrasound / 569
Ruey-Feng Chang, Chia-Ling Tsai, Sheng-Fang Huang, Wen-Jia Kuo, Dar-Ren Chen, Woo Kyung Moon, Yu-Len Huang, Wei-Ming Chen, and Wen-Jie Wu

17.1 Introduction / 571
17.2 Texture-Based Computer-Aided Diagnosis for 2D Breast Ultrasound / 572
17.3 Shape-Based Computer-Aided Diagnosis for 2D Breast Ultrasound / 577
17.4 Classification Techniques for Breast US CAD / 582
17.5 Computer-Aided Diagnosis for 3D Breast Ultrasound / 590
17.6 Conclusion / 607
  References / 608

Chapter 18. Automatic Pectoral Muscle Segmentation on Mediolateral Oblique View Mammograms / 613
Sze Man Kwok, Ramachandran Chandrasekhar, Yianni Attikiouzel, and Mary T. Rickard

18.1 Introduction / 614
18.2 Overall Algorithm / 616
18.3 Orientation and Notation / 617
18.4 Straight-Line Estimation and Validation / 618
18.5 Iterative Cliff Detection / 624
18.6 Experimental Setup / 627
18.7 Results / 629
18.8 Discussion / 632
18.9 Conclusions / 635
  Acknowledgments / 636
  References / 636

Chapter 19. Performance evaluation of CADe algorithms in mammography / 639
Michael A. Wirth

19.1 Introduction / 640
19.2 Performance Evaluation in CADe / 645
19.3 Evaluating Image-Processing Algorithms / 650
19.4 Evaluating Enhancement Algorithms / 655
19.5 Little Boxes Made of Algorithms / 659
19.6 Performance Evaluation Framework / 661
19.7 Mammogram Databases / 667
19.8 Breast-Region Segmentation: Examination of a Performance-Evaluation Process / 671
19.9 Recommendations / 683
  References / 686

Chapter 20. A Simple Method for Automatically Locating the Nipple on Mammograms / 701
Ramachandran Chandrasekhar and Yianni Attikiouzel
CONTENTS

20.1 Introduction / 702
20.2 Review of Previous Work / 703
20.3 Outline of Method / 703
20.4 Notation / 705
20.5 Detailed Description of Algorithm / 705
20.6 Experimental Method / 708
20.7 Results and Discussion / 712
20.8 Conclusions / 720
Acknowledgments / 721
References / 721

Chapter 21. Algorithms for Segmenting Small Low-Contrast Objects in Images / 723
Isaac N. Bankman, Tanya Nizialek, Inpakala Simon, Olga B. Gatewood, Irving N. Weinberg and William R. Brody
21.1 Introduction / 724
21.2 Segmentation Algorithms / 727
21.3 Results / 731
21.4 Conclusion / 736
References / 737

Chapter 22. Computer-Aided Diagnosis of Breast Cancer on MR Imaging / 739
Qiu Wu and Mia K. Markey
22.1 Medical Imaging for Breast Cancer Detection and Diagnosis / 740
22.2 Magnetic Resonance Imaging of the Breast / 740
22.3 Dynamic Contrast-Enhanced Breast MRI / 741
22.4 Computer-Aided Detection and Diagnosis / 744
22.5 Developing CADe/CADx for DCE Breast MRI / 745
22.6 Future Directions / 753
Acknowledgments / 754
References / 755

Chapter 23. Review on Real-Time Magnetic Resonance Gad-Enhanced Breast Lesion Characterization / 763
Jasjit S. Suri, Alexander X. Falcao, Laura Reden, Jianbo Gao, and Swamy Laxminarayan
23.1 Introduction / 764
23.2 Data Acquisition and Scanning Protocols / 766
23.3 Three Techniques for MR Breast Tumor Detection and Analysis / 769
23.4 Issues Related to Real Time and Graphical User Interfaces / 782
23.5 Conclusions and Future Challenges / 784
Acknowledgments / 784
References / 785

Chapter 24. Breast MRI Computer-Aided Diagnosis Systems / 791
Lina Arbash Meinel and Joseph M. Reinhardt
24.1 Introduction / 792
24.2 Breast MRI Segmentation / 793
24.3 Selection of the Shape, Texture, and Contrast-Enhancement Features / 815
24.4 Breast MRI Classification / 819
24.5 Validation / 826
24.6 Future research / 827
References / 828

Chapter 25. Automatic Assessment of Mammogram Adequacy and Quality / 833
Ramachandran Chandrasekher and Sze Man Kwok
25.1 Introduction / 834
25.2 The Mediolateral Oblique View Mammogram / 836
25.3 Adequacy Assessment Algorithms / 837
25.4 Results / 843
25.5 Discussion / 843
25.6 Conclusions / 844
Acknowledgments / 844
References / 844

Chapter 26. Probability Modeling of CAD Systems for Mammography / 847
John Maleyeff and Frank C. Kaminsky
26.1 Introduction / 848
26.2 Background and Motivation / 850
26.3 Probability Modeling in CAD / 851
26.4 Analysis of Mammography Systems / 857
26.5 Illustrative Model Results / 861
26.6 Conclusion / 866
References / 868

Chapter 27. Computer-Aided Diagnosis in Breast Imaging: Where Do We Go after Detection? / 871
Joseph Y. Lo, Anna O. Bilska-Wolak, Jay A. Baker, Georgia D. Tourassi, Carey E. Floyd and Mia K. Markey
27.1 Introduction / 872
27.2 CADx Classifier Models / 873
Chapter 28. The Current Status and Likely Future of Breast Imaging CAD / 901
Jasjit S. Suri, Ramachandran Chandrasekhar, Nico Lanconelli, Renato Campanini, Matteo Roffilli, Ruey-Feng Chang, Yujun Guo, Radhika Sivaramakrishna, Tibor Tot, Begoña Acha, Carmen Serrano, Ingrid Reiser, Robert M. Nishikawa, Dee H. Wu, Koon-Pong Wong, Ashwini Kshirsagar, Yajie Sun, Michael Wirth, Aize Cao, J.E. Leo Desautels, and Rangaraj M. Rangayyan

28.1 Introduction / 903
28.2 Shift in Breast Imaging Paradigms / 905
28.3 Different Imaging Modalities for Breast Imaging / 905
28.4 Current and Future Challenges for CAD / 918
28.5 Commercial Breast CAD Systems and Their Role in Clinical Settings / 935
28.6 Resources in Breast Imaging: Research Centers, Conferences, Databases, Publications, and Patents / 940
28.7 Conclusions / 942
Acknowledgment / 944
References / 944

Index / 963
List of Contributors

Begoña Acha
University of Seville
Seville, Spain

Hilary Alto
University of Calgary
Calgary, AB Canada

Frances R. Anderson
Our Lady of Lourdes Memorial Hospital
Binghamton, NY USA

Ann G. Archer
University of Oklahoma
Health Sciences Center
Oklahoma City, OK USA

Yianni Attikiouzel
Murdoch University
Murdoch, WA Australia

Jay A. Baker
Duke University Medical Center
Durham, NC USA

Isaac N. Bankman
Johns Hopkins University
Laurel, MD USA

Douglas P. Beall
University of Oklahoma
Health Sciences Center
Oklahoma City, OK USA

Anna O. Bilska-Wolak
Duke University Medical Center
Durham, NC USA

Ricardo S. Bôaventura
Federal University of Uberlândia
Uberlândia, MG Brazil

Keir Bovis
Met Office
Exeter, UK

William R. Brody
Johns Hopkins University
Baltimore, MD USA

Heather Bryant
Alberta Cancer Board
Tom Baker Cancer Centre
Calgary, AB Canada

Renato Campanini
University of Bologna
Bologna, Italy

Aize Cao
Vanderbilt University
Nashville, TN USA

Ramachandran Chandrasekhar
The University of Western Australia
Crawley, WA Australia

Ruey-Feng Chang
National Chung Cheng University
Chiayi, Taiwan

Dar-Ren Chen
Changhua Christian Hospital
Changhua, Taiwan

Wei-Ming Chen
National Dong Hwa University
Hualien, Taiwan
LIST OF CONTRIBUTORS

Erika R. E. Den ton
Norfolk and Norwich University Hospital
Norwich, UK

Ernani V. de Melo
Federal University of Uberlândia Uberlândia, MG Brazil

J. E. Leo Desautels
Screen Test, Alberta Program for the Early Detection of Breast Cancer Calgary, AB Canada

Susan M. Edwards
University of Oklahoma Health Sciences Center Oklahoma City, OK USA

Brenda Elledge
University of Oklahoma Health Sciences Center Oklahoma City, OK USA

Mark Embrechts
Rensselaer Polytechnic Institute Troy, NY USA

Alexander Falcao
University of Campinas Campinas, SP Brazil

Annie F. Frère
University of Mogi das Cruzes Mogi das Cruzes, SP Brazil

Ricardo J. Ferrari
University of Calgary Calgary, AB Canada

Carey E. Floyd
Duke University Medical Center Durham, NC USA

Hiroshi Fujita
Gifu University Gifu, Japan

Daisuke Fukuoka
Gifu University Gifu, Japan

Jianbo Gao
KLA-Tencor Milpitas, CA USA

Olga B. Gatewood
Johns Hopkins Medical Institutions Baltimore, MD USA

Barry J. Greer
Wilford Hall Air Force Medical Center Lackland AFB, TX USA

Denise Guliato
Federal University of Uberlândia Uberlândia, MG Brazil

Yujun Guo
Kent State University Kent, OH USA

Takeshi Hara
Gifu University Gifu, Japan

L. Jill Hast
University of Oklahoma Health Sciences Center Oklahoma City, OK USA

John Heine
University of South Florida Tampa, FL USA

Sheng-Fang Huang
National Chung Cheng University Chiayi, Taiwan

Yu-Len Huang
Tunghai University Taichung, Taiwan

Frank Kaminsky
University of Massachusetts Amherst, MA USA
Ashwini Kshirsagar  
R2 Technologies  
Sunnyvale, CA USA

Wen-Jia Kuo  
Yuan Ze University  
Taoyuan, Taiwan

Sze Man Kwok  
Dynamic Digital Depth Research Pty. Ltd.  
Bentley, WA Australia

Nico Lanconelli  
University of Bologna  
Bologna, Italy

Walker H. Land, Jr.  
Binghamton University  
Binghamton, NY USA

Swamy Laxminarayan  
Idaho State University  
Idaho Falls, ID USA

Joseph Y. Lo  
Duke University Medical Center  
Durham, NC USA

Mia K. Markey  
University of Texas, Austin  
Austin, TX USA

Robert Martí  
University of Girona  
Girona, Spain

Timothy Masters  
TMAIC  
Brackney, PA USA

John Maleyeff  
Rensselaer Polytechnic Institute  
Hartford, CT USA

Daniel W. McKee  
Binghamton University  
Binghamton, NY USA

Lina Arbash Meinel  
University of Iowa  
Iowa City, IA USA

Woo Kyung Moon  
Seoul National University Hospital  
Seoul, South Korea

Robert M. Nishikawa  
The University of Chicago  
Chicago, IL USA

Tanya Nizialek  
Central Intelligence Agency  
Washington, DC USA

Raman B. Papanjape  
University of Regina  
Regina, SK Canada

Rangaraj M. Rangayyan  
Department of Electrical and Computer Engineering and Department of Radiology  
University of Calgary  
Calgary, AB Canada

Laura Reden  
Phillips Medical Systems  
Cleveland, OH USA

Joseph M. Reinhardt  
University of Iowa  
Iowa City, IA USA

Ingrid Reiser  
The University of Chicago  
Chicago, IL USA

Mary Rickard  
State Radiologist Breast Screen NSW  
North Parramatta, NSW Australia

Matteo Roffilli  
University of Bologna  
Bologna, Italy

Erika Rubesova  
Jules Bordet Institute  
Brussels, Belgium
Caroline Rubin
Royal South Hants Hospital
Southampton, UK

Carmen Serrano
University of Seville
Seville, Spain

Radhika Sivaramakrishna
Synarc, Inc.
San Francisco, CA USA

Yan Shui
No. 202 Hospital
of People's Liberation Army
Shenyang, China

Inpakala Simon
The MathWorks, Inc.
Natick, MA USA

Sameer Singh
Loughborough University
Loughborough, UK

Qing Song
Nanyang Technological University
Nanyang, Singapore

Yajie Sun
Kodak Health Group
Rochester, NY USA

Jasjit S. Suri
College of Engineering and Idaho
Biomedical Research Institute
Idaho State University
Pocatello, ID USA
and
Biomedical Technologies, Inc.
Westminster, CO USA

Tibor Tot
Central Hospital
Falun, Sweden
and
Uppsala University
Uppsala, Sweden

Georgia D. Tourassi
Duke University Medical Center
Durham, NC USA

Chia-Ling Tsai
National Chung Cheng University
Chiayi, Taiwan

Zhimin Wang
Nanyang Technological University
Nanyang, Singapore

Heather Webb
Baylor University Medical Center
Dallas, TX USA

Irving N. Weinberg
PEM Technologies
Bethesda, MD USA

Michael Wirth
University of Guelph
Guelph, ON Canada

Koon-Pong Wong
Hong Kong Polytechnic University
Hung Hom, Kowloon Hong Kong

Dee H. Wu
University of Oklahoma
Oklahoma City, OK USA

Qiu Wu
The University of Texas, Austin
Austin, TX USA

Wen-Jie Wu
Chang Gung University
Taoyuan, Taiwan

Xulei Yang
Nanyang Technological University
Nanyang, Singapore

Reyer Zwiggelaar
University of Wales
Aberystwyth, UK
Preface

Breast cancer is the most common type of cancer in women worldwide. About ten percent of women are confronted with breast cancer in their lives. Breast cancer can be most efficiently treated if detected at an early stage. This book focuses on the application of computer vision for lesion identification in mammograms and breast imaging volumes called computer-aided diagnosis (CAD) and computer-aided detection (CADx). The book is divided into four parts: Part I presents the anatomic, histopathology, and mammographic views of the breasts, and the physics of different breast imaging modalities. Part II presents the techniques for lesion detection, mass detection through CAD. Part III presents the applications of different computer vision fields in breast-image registration. Finally, Part IV presents the performance evaluation section for breast CAD techniques.

Chapter 1 summarizes 20 years of Dr. Tibor Tot’s experience in routine diagnostics using breast imaging. The group at Uppsala University, the Sweden has more than 5,000 operated breast lesions documented on large 2D histological sections, more than 400 of them are also examined in thick 3D sections. Their statistical work-up was carried out during the period of 1996–2003, corresponding to more than 1,700 breast carcinoma cases. This chapter not only aims to describe the morphologic findings in their static state, but attempts to place them in a perspective of the dynamic changes involving pathologically altered breast tissue: an ambition similar to describing a life-long movie with a couple of words and photographs.

Breast MRI has shown great potential as a diagnostic tool and is rapidly becoming part of the standard of care in breast cancer evaluation. The Chapter 2 describes the clinical science of breast MRI from clinical presentation, composition, and scientific first principles. Major technological advances and recent emergent technologies in breast MRI, including anatomically oriented pulse sequences; human factors in imaging; and molecular imaging techniques are discussed. The reader is introduced to concepts, clinical presentations, and manifestations of disease. As such, the goal is to provide a resource for scientists and clinicians to be able to better understand the multitude of decision-making capabilities of breast MRI by understanding established techniques, as well as emerging new technologies for this major women’s health issue.

Computer-aided diagnostic systems are being developed to assist radiologists in the interpretation of ambiguous mammographic features corresponding to possible signs of early breast cancer. Databases of digital mammograms are needed
for testing such systems. Chapter 3 presents an overview of a few such databases. Most databases are limited to single-exam sets of two or four mammograms on which a diagnosis was made, some ground-truth information related to the position of diagnostically significant mammographic features, and the diagnosis. The chapter presents the design of a comprehensive, indexed atlas of digital mammograms. The design of an appropriate indexing scheme facilitates the implementation of content-based retrieval techniques needed for efficient access to and retrieval of relevant cases from the atlas. Finally, the chapter proposes the use of mobile software agents for facilitating remote consultation of the atlas. Mobile agents can move between data sources such as the atlas and hospital repositories, perform computational tasks at each site, and return only relevant data to the user. These features reduce the computational requirements of the local computer system, bandwidth requirements, and overall network traffic. Proposed applications of the atlas include research, remote consultation, teaching, evaluation of CAD systems, and self-evaluation by radiologists.

The Chapter 4 focuses on the application of genetic algorithms (GAs) in computer-aided diagnostics (CAD). An overview of the GAs is supplied, with a special focus on their use as optimization techniques. In particular, the use of GAs for optimizing the choice of the numerous parameters involved in a CAD detection method is described. Major advantages induced by the use of a GA in CAD detection issues are described, both in terms of performance improvement and of the investigation of the importance of the different CAD parameters.

Effective mass detection and analysis are important steps in mammography. Chapter 5 discusses a study showing two aspects: (a) automatic detection of masses surrounded by glandular or dense glandular breast tissues, based on robust image-segmentation techniques that cluster information to ensure that suspicious masses are isolated from background breast tissue and as few false positives (FP) as possible; and (b) mass-pattern analysis to classify the region of interest (ROI) into normal or abnormal, and benign or malignant cases by a semi-automatic analysis approach, where a new classification of vicinal support-vector machine is proposed. Experimental results based on the Mini-MIAS* database demonstrate that the proposed algorithms are effective for mammographic mass detection and analysis.

Chapter 6 presents a procedure for analysis of left–right (bilateral) asymmetry in mammograms. The procedure is based on the detection of linear-directional components using a multiresolution representation based upon Gabor wavelets. A particular wavelet scheme with 2D Gabor filters as elementary functions with a varying tuning frequency and orientation specifically designed to reduce the redundancy in the wavelet-based representation, is applied to the given image. The filter responses for different scales and orientation are analyzed by using the Karhunen–Loève (KL) transform and Otsu’s method of thresholding. The KL transform is applied to select the principal components of the filter responses, preserving only the most relevant directional elements appearing at all scales. The selected principal

*Mammographic Image Analysis Society, London, U.K.
components, thresholded by using Otsu’s method, are used to obtain the magnitude and phase of the directional components of the image. Rose diagrams computed from the phase images and the statistical measures computed thereof are used for quantitative and qualitative analysis of the oriented patterns. A total of 80 images from 20 normal cases, 14 asymmetric cases, and six architectural distortion cases from the Mini-MIAS database were used to evaluate the scheme using the leave-one-out methodology. Average classification accuracy rates of up to 74.4% were achieved.

Chapter 7 focuses on the use of machine-learning techniques such as support vector machines (SVM) in CAD issues. First, an introduction of SVMs is presented, with a particular attention to their use as classifiers. A brief theory preamble and a survey of the advantages of SVMs over other classifiers is provided. Finally, examples of mass and microcalcification detection based on SVMs are described and reviewed. Particular emphasis is given to detection techniques that do not make use of extracted features for isolating the suspect regions.

In Chapter 8, a novel methodology for the unsupervised and supervised segmentation of mammograms for the purpose of detecting masses is proposed using weighted Gaussian mixture models and Markov random fields (MRF), consisting of a total of four image segmentation models. The results of implementing these models on the randomly selected Brodatz composite images and DDSM database are shown and discussed. Then a novel adaptive weighted model for the combination of experts based on different features using one of the four segmentation models, show it to perform significantly better at 5% significance level to the conventional ensemble-combination rules strategy.

Chapter 9 first presents a small review of the most significant existing methods to detect microcalcifications in mammograms. Next, a method developed by the authors for detecting microcalcification is exposed. The method is based on a seed selection procedure, which consists in an analysis of the prediction error obtained after applying a 2D linear-prediction-adaptive filter to the image. Subsequently, a region growing algorithm is performed in order to identify the microcalcifications. The method was tested on 23 mammograms from the Florida DDSM database. Two parameters were calculated to measure the performance of the algorithm: sensitivity (S) and positive predictive value (PPV), obtaining a value of $S = 82.72\%$ and $PPV = 88.39\%$, respectively.

Chapter 10 discusses the application of several computational intelligence paradigms to the classification and diagnosis of breast cancer using mammogram screen-film data sets from several different institutions. Specifically, the theory, application, and results obtained for the following paradigms has been discussed: evolutionary programming, evolutionary programming/adaptive boosting hybrid, probabilistic neural network (PNN), generalized regression neural network (GRNN), support vector machines (SVM) with several different kernels, SVM/GRNN oracle hybrid, differential evolution, partial least squares, and kernel partial least squares. The approach discusses the theories of each of these paradigms followed by a description of their specific application to screen-film.
mammogram data sets. These discussions are followed by evaluating these theories against specific measures of performance such as area under the receiver operating characteristic (ROC) curve, partial $A_c$, specificity, and positive predictive values (PPV) and specificities at clinical relevant sensitivities.

Accurate breast skin-line estimation is an important prerequisite for both enhancement and analysis of mammograms for computer-aided diagnosis of breast cancer. In Chapter 11, the authors proposed a novel system for skin-line estimation. First an initial estimate of the skin line is first computed using a combination of adaptive thresholding and connected-component analysis. Due to noise, this skin line is susceptible to errors in the top and bottom portion of the breast region. Using the assumption that the Euclidean distance from the edge of the stroma to the actual skin line is usually uniform, the chapter develops a novel dependency approach for estimating the skin-line boundary of the breast. In this dependency approach, first the constraints are developed between the stroma edge and initial skin-line boundary using the Euclidean distance. These constraints are then propagated to estimate the upper and lower skin-line portions. The selection of the constrained region is based on a greedy algorithm, which is also a new component in the system. The authors evaluate the performance of their skin-line estimation algorithm by comparing the estimated boundary with respect to the ground-truth boundary drawn by an expert radiologist. Two different metrics for error measurement are used: the polyline distance measure, and the Hausdorff distance measure. As part of the protocol, the dependency approach methodology is compared with a deformable model strategy (proposed by Ferrari et al.1). On a dataset of 82 images from the MIAS database, the dependency approach yielded a mean error ($\mu$) of 3.28 pixels with a standard deviation ($\sigma$) of 2.17 pixels using the polyline distance measure. In comparison, the deformable model strategy yielded $\mu = 4.92$ pixels with $\sigma = 1.91$ pixels. The improvement is statistically significant. The results are clinically relevant and appealing according to the radiologists who evaluated the results.

Chapter 12 is the application of CAD on 3D digital tomosynthesis data sets. Digital tomosynthesis has recently emerged as a new and promising modality in breast imaging. Digital breast tomosynthesis (DBT) produces a quasi-3D data set that is reconstructed from a small number of projections of the compressed breast. The 3D data set consists of 1-mm thick slices through the breast. As a result, the radiologist is typically required to read 50 images of each breast. Computer-aided detection (CADe) may be useful in helping radiologists read this large image set. The chapter shows two different approaches to detect mass lesions in the DBT. The first is a 3D method to examine the reconstructed image slices. The second is to operate directly on the set of raw projection images. The second technique has several advantages including independence from the exact reconstruction algorithm used. This is important since reconstruction algorithms for this DBT are not yet fully optimized and can produce considerable artifacts in the reconstructed slices.
It is known that a number of breast imaging methods for diagnosis and biopsy of suspicious lesions are available. X-ray mammography, magnet resonance imaging (MRI), and sonography are the methods used most often. Chapter 13 focuses on image registration as an important problem in breast imaging. It is used in a wide variety of applications that include better visualization of lesions on pre- and post-contrast breast MRI images, speckle tracking and image compounding in breast ultrasound images, alignment of positron emission, and standard mammography images on hybrid machines, etc. It is a prerequisite to align images taken at different times, using different imaging modalities, on different breast sections. The inhomogeneous, anisotropic nature of the soft-tissue within the breast, and its inherent nonrigid body behavior, in addition to temporal changes of the breast tissue, breast position, and the imaging conditions, all make breast-image registration a challenging task. This chapter gives an overview of the current state-of-the-art in the breast-image registration techniques. Methods are classified according to the modalities involved in the registration process. For the intramodality registration techniques, x-ray and MRI are the primary focus of interest in the literature. Multimodality techniques cover the combination of x-ray and ultrasound, x-ray and MRI, and more.

Two-dimensional mammography is the most common modality and 3D MRI is second. The Chapter 14 focuses on multilevel framework for 2D and 3D registration of mammographic data, which uses the following distinct steps: (a) extraction of anatomical linear structures, (b) selection of salient linear structures, (c) extraction of local features, and (d) matching the set of feature points. Temporal and contralateral 2D x-ray and temporal 3D MR registration are used as examples.

Chapter 15 describes AMDI – Atlas Indexado de Mamografias Digitais, an indexed atlas of digital mammographic images that includes four views for each case, the patient’s clinical history, global and specific radiological findings, contours of the breast and diagnostic features, and details of features, such as the number of individual calcifications present in each cluster as identified by an authorized specialist. AMDI integrates three systems: a mammogram database registration system, a research system, and a teaching system. AMDI includes concepts related to Web-based medical databases and ontologies for the representation of knowledge in the area of mammography and computer-aided diagnosis of breast cancer. The system facilitates the entry of new cases and related mammograms, radiological information, clinical information, and information related to the health and life style of a patient by a registered and authorized clinical user. The atlas incorporates a teaching system and a research system. The systems are designed to permit computer-aided diagnosis, teleradiology, telemedicine, content-based case or image retrieval, data mining, and distance learning. All the resources of AMDI are available via the Web to authorized users.

Chapter 16 presents the current status of breast screening in Japan and the sophisticated detection, classification, and visualization techniques are described. Breast screening using ultrasound images has started in some regions of Japan for early detection of breast cancer. Although the mammography is also recommended
for screening, the effectiveness of ultrasound testing is recognized for dense breasts of women aged over 40. A CAD scheme for detection of breast masses using a free-hand probe and 3D imaging ultrasound devices has been developed. The scheme includes a detection technique for breast lesions based on active contour and balloon models in 2D and 3D spaces, a classification step using statistical approaches using image features, and a fine visualization browser using virtual B- and C-mode images to confirm the shape and the position of the lesion.

In addition to distinguishing cysts from solid breast tumors, ultrasound is a valuable adjunct to mammography in breast imaging. Chapter 17 focuses on 3D ultrasound for distinguishing benign and malignant lesions. Ultrasound criteria for the classification of solid breast masses include lesion shape, orientation, margin, echogenicity, and acoustic transmission. Recently, similar criteria were applied to CAD and promising results were obtained for the classification of breast lesions. The conventional 2D ultrasound of the breast is increasingly used in surgical clinical practice because it offers many benefits compared with other medical imaging techniques. Nevertheless, conventional 2D ultrasound images are not enough to transmit the entire US information of a solid breast lesion, while the 3D ultrasound can offer comprehensive information of all 2D lesion aspects and provide, in addition, simultaneously, the coronal plane. This additional information has been proved to be helpful for both clinical applications and CAD. The 2D CAD and 3D CAD are expected to be a useful CAD tool for classifying benign and malignant tumors in ultrasonograms, and can provide a second reading to help reduce misdiagnosis.

When mammograms are analyzed by computer, the pectoral muscle should be excluded from processing that is intended for the breast tissue. For this and other reasons, it is important to identify and segment out the pectoral muscle. In Chapter 18, a new, adaptive algorithm is proposed to automatically extract the pectoral muscle on digitized mammograms; it uses knowledge about the position and shape of the pectoral muscle on mediolateral oblique (MLO) views. The pectoral edge is first estimated by a straight line, which is validated for correctness of location and orientation. This estimate is then refined using iterative “cliff detection” to delineate the pectoral margin more accurately. Finally, an enclosed region, representing the pectoral muscle, is generated as a segmentation mask. The algorithm was found to be robust to the large variations in appearance of pectoral edges, to dense overlapping glandular tissue, and to artifacts such as tape. The algorithm has been applied to the entire Mammographic Image Analysis Society (MIAS) database. The segmentation results were evaluated by two expert mammographic radiologists, who rated 83.9% of the curve segmentations to be adequate or better.

Image processing algorithms are the foundation for designing systems such as CADe to automatically process mammograms for tasks such as identifying potential abnormalities. A major limitation in the design of image processing algorithms lies in the difficulty of demonstrating that algorithms work to an acceptable measure of performance. Chapter 19 explores some of the issues, successes, and short-
comings related to existing performance evaluation paradigms for image processing algorithms in mammography, particularly in the context of image enhancement, segmentation, and registration. It reviews common algorithms in each category, the role that mammogram databases play in the performance evaluation of algorithms, and some of the challenges of designing image processing for mammograms.

Chapter 20 presents a simple, fast, and accurate method for automatically locating the nipple on digitized mammograms that have been segmented to reveal the skin-air interface. If the average gradient of the intensity is computed in the direction normal to the interface and directed inside the breast, a sudden and distinct change in this parameter close to the nipple is found. A nipple in profile is located between two successive maxima of this parameter; otherwise, it is near the global maximum. Specifically, the nipple is located midway between a successive maximum and minimum of the derivative of the average intensity gradient; these are local turning points for a nipple in profile, but are global otherwise. The method has been tested on 24 images, including both oblique and cranio-caudal views, from two digital mammogram databases. For 23 of the images (96%), the rms error was less than 1 mm at image resolutions of 400 and 420 µm/pixel. Because of its simplicity, and because it is based on both the observed behavior of mammographic tissue intensities and on geometry, this method has the potential to become a generic method for locating the nipple on mammograms.

Automated detection of microcalcifications in mammograms is particularly challenging because microcalcifications are small and have low contrast. Typically, an automated system for detection of microcalcifications includes algorithms for segmentation, feature extraction, and classification that perform separation of candidate objects from the background, representation of candidate objects with informative metrics, and decision making, respectively. In Chapter 21, sequential process segmentation has a seminal role and dictates the performance of the entire system. Candidate objects must be delineated appropriately to allow effective feature extraction and classification. This chapter presents algorithms that specialize in segmentation of small, low-contrast objects, and illustrates their application to segmentation of microcalcifications.

Noninvasive assessment of microcirculatory characteristics of tissues using MRI is one of the emerging technologies as discussed in Chapter 22. Dynamic contrast-enhanced (DCE) breast magnetic resonance imaging (MRI), in which the breast is imaged before, during, and after the administration of a contrast agent, enables a truly 3D examination of breast tissues. This functional angiogenic imaging technique provides a noninvasive assessment of microcirculatory characteristics of tissues in addition to traditional anatomical structure information. The use of DCE breast MRI is increasing, and it is recommended as an adjunctive breast screening modality to mammography. Traditional manual interpretation of DCE breast MRI is time-consuming, tedious, and can lead to oversight errors due to the large size of 4D data sets (three spatial dimensions plus time). Manual interpretation is also subject to inter- and intra-observer variability. There is a great need for computer-aided detection and diagnostic systems capable of increasing the efficiency, accuracy, and
consistency of breast MRI interpretation. In this chapter, the underlying principles of DCE breast MRI are reviewed the challenges of registration, segmentation, and classification in the design of CADe/CADx systems for breast MRI discussed, the progress made in this arena to date explored, and future directions for research suggested.

The pre- and postcontrast Gd-DTPA MR images of any body organ hold diagnostic utility in the area of medicine, particularly for breast lesion characterization. The Chapter 23 reviews state-of-the-art tools and techniques for lesion characterization, such as uptake curve estimation (functional segmentation), image subtraction, and velocity thresholding, differential characteristics of lesions such as maximum derivation of image sequence, steep slope and washout, fuzzy clustering, Markov random fields, and interactive deformable models such as live-wire.

Research has shown that 10 to 30% of cases missed by mammography can be detected using breast MRI (BMRI). And while BMRI has increased sensitivity, it suffers from limited specificity. Chapter 24 discusses BMRI, which is more difficult to interpret than mammography because it generates significantly more data; however, there are fewer people qualified to use it for diagnosis because it is not the standard breast imaging modality. Mammographers appear to be the best qualified, and certainly the most likely to read BMRI, but they are accustomed to reading 4–6 images per patient as compared with the 200–400 images per patient that BMRI generates. Also, some mammographers may be uncomfortable interpreting MR images. A user-friendly computerized system for BMRI presentation and lesion classification may help mammographers overcome their objections and anxieties concerning BMRI. Such a system would reduce the time required to read BMRI, making the technique a more practical clinical tool. Research shows that the diagnostic accuracy of mammography is increased when two radiologists view the same mammogram, or when the same radiologist rereads a mammogram. Using such strategies decreases the number of missed cancers, which leads us to the fundamental reason of using CAD systems—that is, to replace the second pair of human eyes with a set of “electronic eyes.” The development of dependable, low-cost CAD systems for breast lesion detection and classification is of great practical interest. In this chapter, examples of CAD systems are shown that were developed to provide computer assistance for humans reading BMRI data and classifying BMRI lesions.

Before looking at a mammogram in detail, a radiologist scans it globally to ensure that it is adequate and of acceptable quality. Adequacy means that all of the relevant breast tissue has been captured on the mammogram. Image quality covers a multitude of attributes like exposure, sharpness, etc. Adequacy and image quality ensure that a subsequent decision on the presence or absence of an abnormality may reasonably be based on the information presented by the mammogram. With computer-aided diagnosis, it is equally important to discard inadequate, poor quality images before they are analyzed further, because such analysis would be futile. The automatic assessment of mammogram adequacy and quality is thus an important quality assurance step in computer-aided diagnosis of mammograms.
Chapter 25 describes how aspects of image adequacy and quality may be assessed automatically by computer using guidelines established by radiologists themselves.

Visual inspection in medical care has always been a tedious and costly task that is prone to errors. Because of these errors, computer imaging systems have been designed to assist the human inspection process in the provision of better health care. Chapter 26 presents the analysis of the economic feasibility of any proposed system: costs associated with equipment operation, human inspection, as well as false positives, and false negatives that must be taken into account. Practical mathematical models based on probability theory can be used effectively to assist the decision-maker in the purchase of a computer-assisted imaging system by predicting its operational and financial performance implications. This chapter describes a mathematical model for the economic analysis of a computer-assisted imaging system for the detection of breast cancer.

Breast imaging is currently limited by inadequate sensitivity and specificity. About one in five breast cancers is missed by mammography screening, and when suspicious lesions are found and referred to biopsy, about 4 in 5 biopsies turn out to be benign and were thus arguably unnecessary. Chapter 27 addresses sensitivity, computer-aided detection has come a long way, with multiple commercial products now available and promising results from large clinical studies. On the other hand, specificity remains a major challenge, and to date there are still no commercially viable options due to medicolegal risks, lack of information explaining the computer diagnoses, and difficulties in clinical trial design. This chapter reviews the considerable research to date in computer-aided characterization in breast imaging, describes those current problems, and proposes some possible new approaches that may lead to eventual clinical translation of this important technology.

In Chapter 28, the book is concluded in contemplation of the future of computer aided detection. The future work that needs to be done to make the system more robust is discussed, as well as what it takes to develop a product, stages for FDA approval, and clinical trials. Finally, the chapter projects this research into the next decade.

Jasjit S. Suri, Ph.D.
Rangaraj, M. Rangayyan, Ph.D.
February, 2006
Acknowledgments

This book is the result of collective endeavors from several noted engineering and computer scientists, mathematicians, physicists, and radiologists. The authors are indebted to all of their efforts and outstanding scientific contributions.

We would like to express our appreciation to SPIE Publishers for helping create this invitational book. We are particularly thankful to Sharon Streams, whose discussions led to the idea of putting this CAD book together. We are also thankful to Merry Schnell who worked very to get all components of this book rolling. We also thank IEEE Press, Academic Press, Springer Verlag Publishers, and the several medical and engineering journals for permitting us to use some of the images previously published in their journals.

Dr. Suri would like to thank Philips Medical Systems, Inc., for the MR data sets and encouragement during his experiments and research. Special thanks are due to Dr. Larry Kasuboski and Dr. Elaine Keeler from Philips Medical Systems, Inc., for their support and motivation. Thanks are also due to Dr. Suri’s past Ph.D. committee research professors, particularly Professors Linda Shapiro, Robert M. Haralick, Dean Lytle, and Arun Somani, for their encouragement. Special thanks go to Professor Swamy Laxminarayan, Associate Director of Idaho State University Biomedical Research Institute for his strong support and encouragement. Dr. Laxminarayan was a true visionary for the field of biomedical engineering. Dr. Suri would also like to thank all his friends and collaborators all over the world who has worked with him in writing other books that cover different topics in the field of engineering in medicine and biology.

Finally, Jasjit Suri would like to thank his wife Malvika Suri for all the love and support she has showered over the years; and his children Harman and Neha, whose presence is always a constant source of pride and joy. He also expresses his gratitude to his father, a mathematician, who inspired him throughout his life and career; and to his late mother, who most unfortunately passed away a few days before his doctoral graduation, for her love and support: you will always be there in my mind and heart. Special thanks to Mr. Pom Chadha and his family from Tortonto, who has been a constant source of inspiration in Dr. Suri’s life. Dr. Suri would also like to thank his in-laws, the Rekhi family, who have a special place in his heart and have shown lots of love and care for him.

Rangaraj M. Rangayyan would like to thank his many graduate students, post-doctoral fellows, research associates, clinical collaborators, and colleagues for working with him on several research projects: much of the material reported in his works would not have been possible without their active participation.